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Improving Performance of Breast Cancer Detection for Mammography Image Using Region Growing Algorithm

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ABSTRACT

One in eight women gets influenced by breast Cancer in their lifetime. Breast cancer, the most widely recognized invasive cancer in female worldwide. Breast cancer rates are much superior in developed countries contrasted with developing ones. So early detection of breast cancer is an important process. In this paper mammography image is considered to identify the abnormalities. In mammography image low dose X-ray is utilized so it does not cause any symptoms. In the accompanying lines some procedures are examined for the utilization of mammography image for early on detection of breast cancer. In this paper, by comparing other methods mammography image is enhanced using median filter. Filter is used to remove the noise from the mammography image. After that the enhanced image is segmented by region growing algorithm. This process isolates the ROI from the Background image. From the segmented image using genetic algorithm feature is selected from the image. Finally using Naive Bayes Classifier the images is classified into normal and abnormal tissues. By comparing various techniques we can easily detect the breast cancer through a classified image.

***Index Terms*:** Mammogram, ROI, Image Segmentation, Features, Region Growing Algorithm

1. INTRODUCTION

In Medical Imaging, the expert radiologist outwardly seeks the mammograms checking their shape, thickness, and edge [4]. Medical images are diverse in nature and require exceptional handling prior to diagnosis is made. Additionally there are an extensive variety of sources (machines) which deliver the human body parts images [5]. Image enhancement procedure helps specialists to distinguish cancer patients effortlessly. CT scanner, Ultrasound and MRI, mammography assumed control x-ray imaging by making the specialists to take a gander at the body's tricky third measurement [6].

Among all other tumors, breast cancer is a serious tumor that gets created in the tissue of breast. There is a 12% chance that every women will have Breast cancer sooner or later in her life. Breast cancer can happen equally in men and women, though is outstandingly uncommon within men. Consistently, for men there are around 2,400 of Breast disease occur and for women around 240,000 breast disease occurred. Breast tissue contains veins, lymph hubs, connective tissues and fat. Treatment and foundations intended for breast cancer are still in examination and because there is no broadly accessible preventive measure [7]. Breast cancer can initiate in cells of the lobules and in various tissues in the breast. Prominent cancer is Breast cancer that has spread from where it began in the channels or lobules to incorporating tissue [8]. Early recognition and compelling treatment is the main salvage to decrease Breast cancer fatality. Luckily, if Breast cancer is discovered precisely in a starting stage, restricted tumors can be dealt with effectively before the cancer spreads. In this way, exact diagnosis and successful aversion of Breast tumor is an essential and vital issue in medical science community [7].

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Mammography is basically the main generally utilized imaging methodology for screening process in breast cancer. Despite the fact that different modalities like MRI in addition to PET output could give important data to diagnosis, they are not prevalently received for different reasons including high cost, complexity and accessibility issues [9]. Be that as it may, mammography is compelling in lessening Breast cancer death rates in various studies [10]. Likewise the limit of mass is seen unmistakably, as it is portraying the mass from Breast parenchyma and it helps specialists to identify naturally threatening mass (cancer) and amiable mass (normal) [11].Mammography has a false-negative rate of no less than 10 percent. This is incompletely because of thick tissues clouding the cancer and the way that the presence of cancer on mammograms has a huge cover with the presence of ordinary tissues [12].

To utilize Mammography to identify tumors, it should be arranged to various classes. Typically doctors experience mammogram images and figure out whether a ladies has Breast cancer or not. This progression requires parcel of time and experience of doctor has critical impact in exact recognition. Hence, CAD assumes a vital part in successfully arranging Breast cancer image into various classes [13]. In [14], a multiscale contrast upgrade calculation taking into account Laplacian Pyramid is created to improve the contrast of the mammograms and enhance the perceptibility of the anomalous elements. Masses from the epithelial and connective tissues of Breasts and their densities on mammograms mix with parenchyma designs. A few studies have uncovered a positive relationship of tissue sort with Breast cancer dangers [15]. One advantage is mammograms contain highlights with shifting scale qualities, unpretentious components, for example, calcifications are for the most part contained inside little scales while bigger items with smooth outskirts, for example, mass are for the most part contained in coarse scales. In this manner diverse devices can be specifically improved inside various scales.

The remaining paper is arranged as, 1.2 depicts favorable position of mammography over different strategies. In 1.3 we have examined anomalies of breast cancer. In 1.4 contains examination of the breast cancer and it is contrasted with past strategies and finally, 1.5 contains a brief conclusion.

2. DIFFERENT IMAGING TECHNIQUES FOR BREAST CANCER DETECTION

Breast cancer may be perceived by method for a cautious examination of clinical history, physical examination, and imaging with either mammography or ultrasound. Nonetheless, conclusive diagnosis of a breast mass must be set up through fine-needle aspiration (FNA) biopsy, core needle biopsy, or excisional biopsy. In breast cancer identification, mammography, MRI and PET sweep could give profitable information to diagnosis [9]. X-ray and PET are not prevalently embraced for different reasons including high cost, unpredictability and availability issues. X-ray won't have the capacity to discover all cancers (i.e. breast cancers showed by micro calcifications) [16]. X-ray can't generally recognize malignant tumors or benign disease, (for example, breast fibro adenomas), which could prompt a false positive results. The test is effortless, yet tolerant need to lie still inside the thin barrel. Patient might be requested that hold her breath or keep as yet amid specific parts of the test.

In PET checking, Ultrasound results may distinguish a potential region of worry that is not malignant. The false-positive results can prompt for more methodology, together with biopsies that are redundant. Despite the fact that ultrasound is frequently utilized as a part of an endeavor to keep an obtrusive measure for diagnosis, now and then it can't figure out if or not a mass is malignant, and the biopsy will be suggested [17]. Calcifications that are noticeable on mammograms are not unmistakable on ultrasound examines, in this way avoiding early diagnosis of the portion of breast cancers that start with calcifications [18]. Similar to other therapeutic diagnosis systems, X rays are utilized as indicative instrument as a element of mammography for the inspection of human breast. These examinations are recorded as specific images which are then seen by radiologists for any conceivable abnormality [5]. The abnormalities in mammograms incorporate micro-calcifications (MCs), masses, structural distortion, and asymmetry [19]. Mortality lessening is the major objective of mammography screening. Chemotherapy may be more powerful in the premature stages, both are liable to add agreeably to the lessening of breast cancer mortality [19], [20]. Mammography aids in early discovery and it assumes an significant part in tumor treatment and allow a speedier recuperation for a large portion of the patients. Mammography is a particular kind of imaging that uses a low-dose X-ray framework, high-contract and high-determination film for examination of the breasts. Two process of mammography are specified as digital and film. Digital mammography is superior to anything film mammography since radiation rays can be lessened up to half and can in any case identify breast cancer, though in film mammography the standard radiation rays can't be decreased [21]. In mammography, twofold perusing has appeared to be highly beneficial, lessening the quantity of false-negative results by 4% to 14%, enhancing the rates of breast cancer identification [22]. Mammograms can delineate the greater part of the noteworthy changes of breast disease. The essential radio-realistic indications of cancer are masses (its thickness, site, shape, borders), spicular lesions and calcification content. These components might be extricated utilizing different recognition system [23].

3. BREAST CANCER ABNORMALITIES

The fact that mammography is an exceptionally touchy however often a nonspecific examination must be appreciated by both the clinician and the radiologist to avoid false expectations. Genuine positive rates are cited from 10-30% of mammography abnormalities, contingent upon how aggressive and encountered the radiologist is. Mammography gives a false negative rate of l0-15% when a breast cancer is substantial [2]. Mostly (80-85%) breast cancers ordinarily can be viewed on a mammogram as a mass, a group of calcifications, or a blend of both. The acknowledgment of a mass smaller than 2 mm may be the perfect, yet reasonably, it is difficult to perceive most tumors smaller than 5 mm. Large, non-calcified masses might difficult to recognize in the thick glandular breast, which is regular in ladies of childbearing age. The edge for location of a cancer is variable and relies on the radiographic abnormality, the fat-glandular tissue ratio of the breast, the technical quality of the examination, and the diligence of the radiologist. [23].

3.1. Masses

In mass recognition, every mass ROI contains a solitary mass. Mass discovery can be evaluated by a free-response ROC analysis for various thresholds on the base nesting depth, the percentage of mass ROIs intersecting a location (i.e. the sensitivity) and the quantity of identifications intersecting no mass ROI (i.e. the quantity of false positives) per pathological mammogram [25].

By and large, dangerous sores have a more prominent radiographic thickness than an equivalent volume of fibro glandular breast tissue. Lucent injuries are constantly kind. Separated singular non-cystic densities should be assessed painstakingly. And when bigger than 8 mm in distance across, they should be considered for biopsy. More unpredictable the state of damage, more probable is the mass to be cancerous. A sporadic or speculated edge is a common imperative element showing that the mass is harmful. The cancers which are less infiltrating may have just marginally irregular or even all around circumscribed margins; papillary, medullary and colloid carcinomas are liable to be all around circumscribed. The margin of the mass will be sharply defined in a considerate injury, for example, a fibro adenoma or a cyst, till the mass having this appearance may be malignant in about 7% of cases. An intramammary lymph node is frequently very much circumscribed, small in size, and frequently found in the upper external quadrant of the breast. Asymmetric breast tissue nearly always can be recognized from a genuine mass by means of mammographic evaluation. The refinement of a small stellate mass from an early invasive breast cancer is often to a great degree unpretentious, so optimal system and careful interpretation are essential. Favorable stellate masses, for example, post-biopsy scamming and fat necrosis, as often as possible have a characteristic appearance.

One ought to take after rather than perform a biopsy on most nonspecific circumscribed masses because they generally are seen on mammograms and have an under 5% possibility of being malignant. A typical example of a probable kind injury is a non calcified‘ mass or knob with very much defined margins. Markowitz reported an investigation of 593 non calcified masses larger than 1.0 cm seen by mammography and found that about 2% of them ended up being malignant. More than half of these masses were appeared to be basic cysts on aspiration or on ultrasound evaluation. The etiology of most non calcified strong masses can be controlled by palpation or by ultrasound-guided final biopsy.

3.2. Micro-Calcifications

Large thick calcifications of an amiable, involutional fibro adenoma, when related with a lobulated mass, are diagnostic of favorable procedure; when an involutional procedure is creating, it may be indistinguishable from a malignant tumor, and biopsy need to be performed. Calcification might happen in fat necrosis or in the walls of a cyst. Punctuate, pointed irregular calcifications that are heterogeneous in size inside a mass, or fine, branching calcific deposits filling ducts, are solid indicators of cancer. Half of malignant masses have calcifications that can be seen by mammography. About 20-35% of radiographically identified clustered calcifications without a mass will be malignant, and the vast majority of these will speak to noninvasive cancer. Mammography is profoundly delicate in identifying breast calcifications; however the specificity in recognizing considerate from malignant calcifications is just 50-60% [24].

The cluster of couple of calcifications ought not be considered clearly considerate, rather, it ought to be considered at generally safe for being malignant and took after at 4 to 6 month intervals. At the point when more than a couple of calcifications are available without an associated mass, the choice to perform a biopsy may be more troublesome the most minor calcifications, as small as 0.2 mm, may be more suspicious than the 2-mm calcification. Kindhearted and malignant calcifications may coincide in the same breast. Calcifications associated with fibrocystic changes in the breast often impersonate those found in malignancy, leading to an unavoidable false constructive report. Skin and vascular calcifications must be recognized from mammary lesions, and biopsies don’t should be performed on them. Involvement in deciphering mammograms is necessary to minimize the quantity of biopsies that have amiable results.

3.3. Architectural Distortion of breast cancer

Architectural distortion is a regular mammographic appearance of non-palpable breast cancer, speaking to nearly 6% of abnormalities identified on screening mammography. Although its prevalence on mammography is small compared with calcification or unmistakable mass, architectural distortion is also harder to diagnose because it can be unobtrusive and variable in presentation. In fact, architectural distortion is a typical finding in review assessments of false-negative mammography and may speak to the earliest manifestation of breast cancer. Moreover, some surveys recommend that early location of architectural distortion may be associated with a more significant change in prognosis than earlier discovery of calcifications. Various computerized methods have been produced to raise the discovery ratio of architectural distortion, however they remain defective (identification rate of short of what one half with one strategy). The amiable and malignant causes of architectural distortion and illustrates its various manifestations in an effort to lessen undiagnosed architectural distortion on screening mammography [26].

3.4. Breast density

Report of mammogram also contains an assessment of breast density. Density breast is based on how fibrous and glandular tissues are conveyed in breast, versus amount of breast made up fatty tissue.

Thick breasts are not abnormal, but rather they are connected to a higher danger of breast cancer. We realize that thick tissues of breast can create it difficult to discover cancers on a mammogram. Still specialists do not accept the results from different tests, assuming objects, ought to be completed with mammograms in ladies with thick breast who does not have a high breast cancer hazard bunch (based on gene mutations, breast cancer in the family, or other factors).

4. ANALYSIS TECHNIQUES FOR MAMMOGRAPHY

In this segment, we introduce the diverse methodologies of mammograms analysis expecting to identify irregularities, and the different strategies created in that reason. A survey of breast imaging methods other than X-ray can be found in Kopans (1984), Grobhadern (1992) and Sabel and Aichinger (1996). These imaging modalities include: ultrasonography (both checking modes and Doppler techniques); thermography; electrical impedance; strategies based on MRI; strategies utilizing X-ray radiation other than conventional mammography; imaging techniques with radio nuclides; PET; and different strategies. Some novel, rising techniques have as of now been produced industrially, for instance ultrasound and electrical impedance frameworks. Mammography is an exceptional kind of X-ray imaging of the breast to discover the tumor present in the breast. Early determination of the patient is the effective treatment of breast tumor.

Mammography assumes an essential part in early discovery of breast cancers. As indicated by the US FDA (Food and Drug Administration), mammography can discover 85–90 % of breast disease in ladies the individuals who are more than 50 of age and additionally can distinguish a lump for 2 years before it can be felt. Once a lump is identified, mammography can be a key in assessing the lump to figure out whether it is dangerous or not. While screening, mammography can recognize most breast malignancy, however it can miss up to 15 % of cancers.

A considerable measure of examination have been accomplished for early determination of breast micro calcifications from digitalized mammograms through utilizing highly developed image handling methods and distinctive preprocessing calculations proposed in various papers. Every one of these papers take after just about the same strides with some distinction in methods. The regular strides are preprocessing, breast image segmentation, feature extraction, tumor segmentation and extracted feature classification.

4.1. Feature upgrade

In [27], Discrete wavelet transform (DWT) is perform on the image, every wavelet coefficient of everything about band is then smothered and just the coefficients that are bigger than a specific threshold are upgraded. Subsequently, the pixels on the edge will be improved while the foundation noise will be decreased at the same time [28]. In [28] Bayesian estimator-based discriminator for image upgrade by isolating image and noise by expecting the noise as from the earlier Gaussian additive noise. Image upgrade systems have been broadly utilized as a part of screening mammograms. The gotten results from the proposed technique were discovered sensibly agreeable, contrasting them with those found by radiologists from the strategies proposed in the writing, while keeping up the low number of false positives, even with a slight noise enhancement which can be decreased [37].

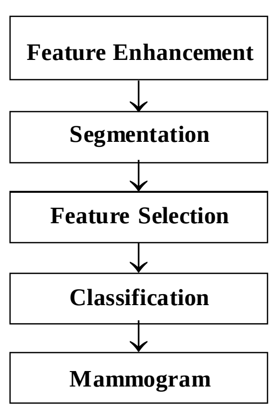

Figure 1:

The present study exhibited the capacity of GLCM-based texture analysis in measuring lesion heterogeneity communicated on improvement motor parameter maps for separating malignant from other breast lesions. Results recommended that texture features extracted from parametric maps that gave back the lesion failure properties (PIE and SER guide) can separate malignant from benign lesions more productively than texture features extracted from either the primary post contrast outline lesion range or from a parametric guide that reflects lesion introductory uptake (IE map) [39] .

We utilize median filter to diminish the noise in Mammography images. All smoothing methods are powerful at evacuating noise in smooth fixes or smooth locales of a sign, however unfavorably influence edges. For little to direct levels of (Gaussian) noise, the median filter is evidently superior to anything Gaussian obscure at expelling noise whilst safeguarding edges for a given, settled window size. In any case, its execution is not that greatly improved than Gaussian obscure for abnormal amounts of noise, while, for speckle noise and salt and pepper noise (hasty noise), it is especially compelling. As a result of this, median filtering is generally utilized as a part of advanced image handling [29].

4.2. Segmentation

A programmed segmentation of breast mass strategy based on patch merging technique and GHFCM. The ISODATA patch merging and clustering strategy is utilized to get the Adaptive Region of Interest and starting segmentation results, while the GHFCM technique which can conquer the drawbacks of impact of image commotion and Euclidean distance FCM which is touchy to outliers is utilized to acquire the exactly mass segmentation results [36].

A technique to look for ideal MRF highlights that fulfill contingent autonomy conditions by utilizing pair-wise restrictive shared data. Our multichannel MRF beats single channel MRF utilizing the best individual component from the same point of elements as utilized by the multichannel MRF. Our methodology likewise performs essentially better when contrasted with the understood normalized cuts segmentation algorithm and usually utilized past strategies for segmentation of breast cancer [36]. We have built up a completely robotized technique for the cell nuclei segmentation in Breast FNAC images. Using this process, we have successfully conquer the issue identified with the detection of nuclei areas. Also, we have effectively wiped out the false positive nuclei markers, which results in the productive segmentation of nuclei limits [40].

A robust atlas-based segmentation (ABS) algorithm was given two setups of sequence settings: intra and inter. Our method brings diverse ABS techniques into a single framework. It additionally proposes an atlas robust to intensity varieties which permits an atlas of one specific MR imaging sequence to be utilized to fragment images of an alternate MR sequence [43].

The segmentation of the improved filtered images is done utilizing two separate techniques. One utilizing k means segmentation and the other utilizing fuzzy C means segmentation. The principle thought of the image segmentation is to gathering pixels in homogeneous regions and the standard thing to do this is by basic component. In image segmentation, clustering algorithms are exceptionally famous as they are instinctive and are likewise simple to execute [51]. In this paper, we have proposed EFIS, which is a general segmentation conspire that depends on client feedback keeping in mind the end goal to enhance the nature of segmentation. The developing way of EFIS makes this methodology engaging for applications that consolidate top notch client feedback, for example, the examination of medicinal images. We proposed two forms of EFIS: one for single parameter yields and one for multi parameter yields (SEFIS and MEFIS, individually). Both techniques indicated promising results, with further handling of similar cases prompting constant and quantifiable enhancements. We likewise showed that for three unmistakable segmentation algorithms (worldwide thresholding, SRM, and RG), SEFIS can be utilized to fuse onlooker driven modification and accomplish a general help to segmentation exactness [58]. We built up a FCM-based strategy for predictable computerized breast lesion segmentation in three measurements from DCE-MRI information. Execution of the proposed strategy is similar to execution of an accomplished radiologist. The technique has the potential for precise, effective, and predictable segmentation of breast lesions in DCE MR Images [59].

A completely mechanized segmentation technique consolidating another an enhanced watershed algorithm and fuzzy active contour model for breast cancer cell images. Initial, another fuzzy active contour model containing statistical region data is proposed for the contour detection of cell nuclei. At that point, an improved watershed technique based on concave vertex diagram is connected on the pre-fragmented image keeping in mind the end goal to separate covering and touching nuclei. The proposed segmentation algorithm is contrasted with late techniques with show the change of the segmentation precision [60].

In [27], adaptive region growing algorithm is utilized for section the cancer zone. The normal angles of the edges are additionally employs to access the best portioned contour as the most extreme likelihood examination. Region growing techniques can give the first images contains precise boundary with great segmentation results. To identify the breast range, splendid zones should be recognized. Be that as it may, this is insufficient: on the grounds that image intensity diminishes close to the breast edges, these edges are generally dark. By and by, breast edges are sharp, so distinguishing sharp ranges too guarantees that breast is not under-fragmented [25].

The region based segmentation is process to partitioning the image into similar/homogenous regions of associated pixels through the use of homogeneity/similarity criteria. Each of the pixels in a region is similar as for a few qualities or registered property, for example, shading, intensity and/or surface [62]. The programmed segmentation strategy proposed in this study could analyze breast cancers, however the last result still should be affirmed by the radiologists. It can likewise be reached out to manage the issue of distinguishing proof of the illness sort utilizing the same methodological framework [45].

4.3. Highlight selection

One critical task in the partition of malignant and benign tumors is highlight selection and computation. In [30], Region growing algorithm is utilized component selection procedure to decide the great seed position, tried 10 territories of-interest chose at various distances and introductions from the injury focus. The proposed DF-BrCanD framework utilizes taxonomic indices, statistical measures and local binary patterns based components for arrangement of mammogram images as cancerous and non-cancerous utilizing SVM with RBF kernel. Grouping execution as far as exactness is better in half and half element space of taxonomic indices, statistical measures and LBP when contrasted with highlight space of just taxonomic indices and highlight area depends on statistical values and LBP [47].

The effectiveness of the principal request statistical parameters in breast asymmetry detection from infrared breast thermo gram. It has been found that, the element estimations of right and left breast of a normal breast thermo gram are very similar while, in the event of an abnormal breast thermogram, there is a critical difference in the component estimations of both breasts. Statistical components like mean difference, kurtosis, skewness, and entropy demonstrate a perceptible difference between the left and right breast of an abnormal breast thermogram contrasted with different elements [61].

The point of this paper is to enhance the detection of associated regions containing some write with injury. In the proposed work we have planned another CAD strategy to recognize the mass region in the mammogram. Portioned image contains the suspected region which is given for highlight extraction process. The separated elements are characterized into abnormal and normal region .The got exactness was 95.6% while the affectability and specificity were observed to be 96.5% and 89% separately. The proposed framework gives quick and exact representation of breast cancer [66]. In our proposed framework, Genetic Algorithm is utilized for highlight selection reason. It is utilized to extricate the elements from the ROIs.

4.4. Naïve Bayes classifier

To fix the issues, detecting breast cancer based on textural features has not been examined in depth. Other linear and non-linear classifiers were also employed to be compared to the SVM performance. SVM was able to achieve better classification accuracy [32]. For each tumor region extract, morphological features are extracted to categorize the breast tumor. Finally the SVM classifier is used for classification [34]. This paper has investigated a proposed SCBDL approach which has achieved over 97% classification accuracy on test set which is much higher than the standard MLP classifier and other existing techniques. This research demonstrate that the soft clustering based direct learning classifier has a significant impact on improving overall classification accuracy. The values for both specificity and sensitivity were much better than that obtained with a standard MLP style classifier [44].

Reversible Round-Off Non recursive 1-D Discrete Periodic Wavelet Transform is used to classify the tumor, which used a modified wavelet transform to simplify high octave decomposition at a cost of classification performance [50]. Greater part of the productions concentrates on characterizing malignant and benign lesions (as a rule called injury arrangement), and a portion of the articles concentrate on ordering lesions and non-lesions (more often than not called sore detection), and just a couple of them spotlight on both. Injury detection is fundamental before sore characterization. Oftentimes utilized linear classifiers for bosom disease detection and arrangement are linear discriminator analysis and logistic regression (LOGREG). The main idea of LDA is to find the linear combination of the features which best separate more than two classes of the data [56]. Noise Distance based Fuzzy C-Means (NDFCM) algorithms are based on the objective operation of basic fuzzy C-means method [6].

The outlier and the noise detection technique explained in previous methods are stringent. Along with the actual outliers, some of the Support Vector Machines (SVMs) based classifier in comparison with Bayesian classifiers and ANN for the prognosis and diagnosis of breast cancer disease. In this section we discuss the problem of automated diagnosis of benign vs. malignant breast cancer instances in the case of the WDBC patient data. New classifiers based on SVMs, Bayesian classifiers and Artificial Neural Networks

Table 1
Classification methods compared with Naïve Bayes Classifier

Classifier	*Advantages*	*Disadvantages*
Linear classifiers: Construct decision boundaries by optimizing certain criteria: LDA and LOGREG	Simple and effective for linearly separable data	Poor performance for non-linearly Separable data. Poor adaptability for complex problem.
ANNs: Construct non-linearmapping functions: Back-propagation, SOM and hierarchical ANN	Robustness, no rule or explicit expression is needed, and widely applicable	Long training time, initial value dependent, un repeatable, over-parameterization and over-training.
BNN: A probabilistic approach to estimate the class conditional probability Density functions	Priori information can incorporate in models, useful when there is finite training data	Need to construct model and estimate the associated parameters
Decision tree: A tree structure with classification rules on each node.	Low complexity	Accuracy depends fully on the design of the tree and the features
Template matching: Uses retrieval technique to find the most alike image in the database and assign the query image to the class of the most alike image.	No training process needed, new data can be directly added to the system	Requiring large size database, images should come from the same platform to archive better performance
Naïve Bayes: Naive Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables in a learning problem.	Simple technique, need small amount of training, Fast model, used in high dim-ensional problems, value independent. Stable algorithm.	Small change in training data cause big change in model.

have been developed in order to procure a reliable automated system of breast cancer diagnosis. Several SVM models with different kernel functions were tried in order to find the leading classifier that would be characterized by high performance indices (in terms of accuracy, specificity, sensitivity) [65] The classifiers use nuclei features, which capture the deviations in the nuclei patterns, to acquire how to separate nuclei into other different classes. For feature extraction, there are two kinds of information available in the image: 1) the intensity values of pixels; and 2) their spatial interdependency [68]. The SOM–RBF classifier improves the performance of the distance-comparison-based SOM learning procedure [71].

Naive Bayes classifier is a probabilistic classifier based on the Bayes' theorem, considering a strong (Naive) independence assumption. Naïve Bayes classifier is compared with other classification techniques in Table 1. Thus, a Naive Bayes classifier considers that all attributes (features) independently contribute to the probability of a certain decision. The testing diagnosing accuracy, that is the fundamental execution measure of the classifier, was around 74.24%, as per the execution of other surely understood Machine Learning systems [31].

4.5. Comparison

Image enhancement procedures have been proposed to enhance the quality and coherence of mammograms or to recognize abnormalities on the grounds that mammographic images generally have poor contrast and deceivability of points of interest. The objective of image enhancement is to enhance the image features so

Table 2
Comparison between segmentation algorithms

Segmentation Algorithm	*Advantages*	*Limitations*
Digital Mammography	Calcification, circumscribed, speculated and other imprecise masses can be diagnosed	Frequent intensity changes may not give 100% diagnostic results
KNN and fuzzy means algorithm	Change in intensity levels is used as a discriminating feature	–
Vector quantization	Nonappearance of over and under segmentation	Bundle of segmentation areas andinformation
MRF and HPACOalgorithm	Success rate of the algorithm is 94.8%	
Image segmentation with 3D structure analysis	Exact size and thickness of tumor can be calculated	CAD system have to be combined with the segmentation algorithm to obtain highest success rate
Multi-wavelet and hardthreshold	Provides good outcome in case of dense mammograms by noise cancellation	–
Screening Mammography	Identification is based on the unevenness(among normal and tumor tissues)	–

Table 3
Image Acquisition techniques comparison

Image AcquisitionTechnique	*Affordable*	*Performance / Accuracy*	*Reliable*
Mammography	Yes	97%-98%	Yes
Thermal Infrared Imaging	Very less	85%-90%	Yes and no side effects
Microscopic slide Images	Yes	99%	Yes
Ultrasound	Less	97.92%	Yes but has side affects
MRI and CT Scan	Less	97%-99%	Yes

that handled image is superior to the real image for a particular application or an arrangement of destinations. The enhancement technique was connected in the wavelet domain by manipulating the contrast values computed using the high-recurrence and low-recurrence information. The upsides of the proposed image enhancement innovation lie in [128]: 1) simplicity of change by end clients (for instance, adjusting a single parameter); 2) the image enhancement innovation can be connected to JPEG 2000 compressed images in the decompression stage to lessen the time required for image enhancement, which alters the wavelet coefficients obtained in the decompression stage; and 3) the proposed image enhancement innovation alters a multiscale measure that matches the human visual system, resulting in the upgraded images having a superior visual quality [33].

To condense, the anatomical breast coordinate system is relevant for breast cancer risk evaluation where the discriminative components are not pivot invariant but rather should be measured as for some anatomical reference introduction in the ML or MLO mammograms. Moreover, employing such coordinate transformations for classifying introduction highlights in mammograms yields preferable discrimination over radiologist-helped scoring, for example, BIRADS for thickness and the rate thickness. In principle, the breast coordinate transform could be also reached out to cranial-caudal (CC) sees. In contrast to the ML and MLO sees, this methodology is tricky as a result of the nonappearance of the pectoral muscle, which we utilized as an anatomical landmark. The expansion of the coordinate system for the CC perspectives is in this way left for future work [38].

We have exhibited and assessed an arrangement of new components for the portrayal of contrast specialist uptake kinetics in ultrafast MR acquisitions. Our study findings demonstrate that the classification performance of kinetics got from the ultrafast (100 s) TWIST obtaining imaging contrast operator uptake, is fundamentally higher than the performance of kinetics got from a much lengthier (510 s), commonly utilized VIBE (3-D GRE) securing. The performance of morphological descriptors for the portrayal of breast lesions was not essentially distinctive between the TWIST and VIBE acquisitions. The bigger cut thickness of the TWIST acquisitions appears not to hinder the performance and even the transient blurring that happens because of sharing of outer k-space information does not appear to influence accuracy. The restrictions of this study include the moderate size of our database. Particularly in analyses where both kinetic and morphological elements are combined, the quantity of tests in the training fold is low compared to the quantity of elements. A bigger database could decrease the fluctuation of the outcomes and might enhance the outcome and hugeness of the results [41].

In our work we introduced a novel non-unbending surface-based enlistment approach that handles missing information up to 30% and accounts for volumetric deformation impacts known to be available in soft tissues. We connected the technique to MR-TRUS combination, where a full segmentation from MR was fit to a possibly halfway segmentation from TRUS. In this paper, we utilized a linear, homogeneous material to make the finite component model of the prostate [46].

It is demonstrated that higher request otherworldly elements are fit for differentiating between various classes, for example, malignant, benign and normal in breast thermogram. The thermogram are initially converted to rectangular images of problem area regions using a progression of image processing steps. Bispectral invariant elements separated from their Radon projections are appeared to perform well in discriminating amongst malignant and non-malignant cases. Normalized bispectrum forms of these elements perform better for discriminating amongst benign and normal cases. The proposed technique is appropriate for fast usage making utilization of the FFT, little dimensionality of the list of capabilities and parallel execution of Radon projections at various points and highlight extraction along various slopes and can be utilized for mass preliminary screening of breast thermogram before X-beams and biopsies are recommended for a much littler subset.[48].

In this article, we propose a novel methodology GALASSO to construct a combinatorial regulatory network of TF and miRNAs. GALASSO utilize a Gaussian graphical model with adaptive tether punishments to integrate the sequence computational forecasts with the gene expression profiles. It is a comprehensive technique to systematically contemplate the gene direction. The recreation study demonstrates that GALASSO has higher accuracy than the past strategies. Meanwhile, the comparison of trial studies and the investigation of gene co-expression patterns likewise confirm the accuracy of GALASSO. Besides, we investigate the structure of the regulatory network and discover a few network motifs. These network motifs serve as the littlest practical modules of the entire network [52].

In outline, a Kelly approach forces considerations of what is an underlying reasonable diversion, considerations of risk and reward, asymmetry, and a margin of security. Above all, it recognizes that there is no law that expresses that each case (instance) in a dataset ought to be characterized. The essential objective is to find where flags that brief activity will offer clarity, and dodge activity based on commotion (where I[X; Y] = 0). Those with proficiency in information hypothesis may have the best capacity to facilitate grow Kelly thought [62]. This paper surveys the examination of information mining methods connected to proteomics for cancer detection/diagnosis. This study proposes that it is attainable to combine serum protein profiling with counterfeit consciousness learning algorithms to arrange cancer tests from benign and/or normal controls with a top—down methodology. Since these m/z values were observed to be reproducibly distinguishable, onlym/z values (a total of ten values in our study) are required to make an accurate detection. Their characters at the protein or atomic level are a bit much for classification reason.

Because of the way that knowing the personalities of these discriminating substances is basic in understanding their organic part these peptide/proteins may have in the oncogenesis of ovarian cancer, and in identifying potential remedial targets. For this, we take the difference of intensity (let us allude it as mistake) of every edge pixel from the original loud image and the image, smoothed by various filtering strategies. At that point we assess the normal of these intensity mistakes over all the edge pixels.se intensity errors over all the edge pixels.

We find that the average error in the proposed method is 18%, 10% and 5% less than the errors of AD, SLH and LGM respectively. Thus our method follows the edge more closely compared to other methods and thereby performs better edge preservation. Hence, the proposed edge preserving filter makes the cell and background regions more homogeneous and performs better edge preservation compared to AD, SLH and LGM method [69].

5. CONCLUSION

In this survey paper, Mammography is currently regarded as one of the best ways to detect breast cancer in the early stage, Also made on the different types of methods and algorithms used for cancer detection Identification of abnormalities in mammogram images to classify masses and micro calcification. In this paper, median filter is used to enhance the mammography image. Followed by that segmentation is handled by Region Growing Algorithm. After that Genetic algorithm select the Features from segmented ROI. Finally Naïve Bayes classifier classifies the image it will provide the better detection of breast cancer.

REFERENCES

[1] Vikhe, P. S., and V. R. Thool. “Mass Detection in Mammographic Images Using Wavelet Processing and Adaptive Threshold Technique.” *Journal of medical systems* 40.4 (2016): 1-16.

[2] Vikhe, P. S., and V. R. Thool. “Intensity Based Automatic Boundary Identification of Pectoral Muscle in Mammograms.” *Procedia Computer Science* 79 (2016): 262-269.

[3] Sinare Swati S., and Pratap S. Vikhe. “Fuzzy C-means Clustering Algorithm for Breast Cancer Detection.” *International Journal of Advanced and Innovative Research (IJAIR)* (2012): 307-310.

[4] Singh, Satya P., Shabana Urooj, and Aimé Lay-Ekuakille. “Breast Cancer Detection Using PCPCET and ADEWNN: A Geometric Invariant Approach to Medical X-Ray Image Sensors.” *IEEE Sensors Journal* 16, no. 12 (2016): 4847-4855.

[5] Yasmin, Mussarat, Muhammad Sharif, and Sajjad Mohsin. "Survey paper on diagnosis of breast cancer using image processing techniques." *Research Journal of Recent Sciences ISSN* 2277 (2013): 2502.

[6] Rao, K. M. M., and V. D. P. Rao. "Medical Image Processing." In *Proc of Workshop on Medical Image Processing and Applications*. 2006.

[7] Arya, Chandresh, and Ritu Tiwari. "Expert system for breast cancer diagnosis: A survey." In *2016 International Conference on Computer Communication and Informatics (ICCCI)*, pp. 1-9. IEEE, 2016.

[8] http://thecentertx.com/cancer%20type/breast-cancer/, 2010.

[9] Qi, Hairong, and Nicholas A. Diakides. "Thermal infrared imaging in early breast cancer detection." In *Augmented Vision Perception in Infrared*, pp. 139-152. Springer London, 2009.

[10] Andreea, Gheonea Ioana, R. A. L. U. C. A. Pegza, L. U. A. N. A. Lascu, S. I. M. O. N. A. Bondari, Z. O. I. A. Stoica, and A. Bondari. "The role of imaging techniques in diagnosis of breast cancer." *J. Curr. Health Sci* 37, no. 2 (2011): 241-248.

[11] Spandana, P., and Kunda MM Rao. "Novel image processing techniques for early detection of breast cancer, mat lab and lab view implementation." In*2013 IEEE Point-of-Care Healthcare Technologies (PHT)*, pp. 105-108. IEEE, 2013.

[12] "Mammography-leaflet; Screening for breast cancer with mammography". Retrieved 2012-06-24.

[13] Gc, Sailesh, Ravi Kasaudhan, Tae K. Heo, and Hyung D. Choi. "Variability measurement for breast cancer classification of mammographic masses." In*Proceedings of the 2015 Conference on research in adaptive and convergent systems*, pp. 177-182. ACM, 2015.

[14] Liu, Xiaoming, J. Tang, Si Xiong, Zhilin Feng, and Zhaohui Wang. "A multiscale contrast enhancement algorithm for breast cancer detection using Laplacian Pyramid." In *Information and Automation, 2009. ICIA'09. International Conference on*, pp. 1167-1171. IEEE, 2009.

[15] Cheng, H. D., X. J. Shi, Rui Min, L. M. Hu, X. P. Cai, and H. N. Du. "Approaches for automated detection and classification of masses in mammograms." *Pattern recognition* 39, no. 4 (2006): 646-668.

[16] "MRI Scan" http://www.cancerquest.org/mri-advantages-and-disadvantages.html

[17] "Breast Ultrasound" Radiology Info (07-10-2007) [http://www.radiologyinfo.org/en/info.cfm?PG=breastus]

[18] "Ultrasound." Breastcancer.org (07-10-2007) [http://www.breastcancer.org/testing_ultrasound.html]

[19] Li, Y., H. Chen, L. Cao, and J. Ma. "A Survey of Computer-aided Detection of Breast Cancer with Mammography." *J Health Med Informat* 7, no. 238 (2016): 2.

[20] Heywang-Köbrunner, Sylvia H., Astrid Hacker, and Stefan Sedlacek. "Advantages and disadvantages of mammography screening." *Breast care* 6, no. 3 (2011): 199-207.

[21] Al-Shamlan, Hala, and Ali El-Zaart. "Feature extraction values for breast cancer mammography images." In *Bioinformatics and Biomedical Technology (ICBBT), 2010 International Conference on*, pp. 335-340. IEEE, 2010.

[22] Calas, Maria Julia Gregorio, Bianca Gutfilen, and Wagner Coelho de Albuquerque Pereira. "CAD and mammography: why use this tool?." *Radiologia Brasileira* 45, no. 1 (2012): 46-52.

[23] Tomar, Ranjeet Singh, Tripty Singh, Sulochana Wadhwani, and Sarita Singh Bhadoria. "Analysis of breast cancer using image processing techniques." In *Computer Modeling and Simulation, 2009. EMS'09. Third UKSim European Symposium on*, pp. 251-256. IEEE, 2009.

[24] McKenna, Robert J. "The abnormal mammogram radiographic findings, diagnostic options, pathology, and stage of cancer diagnosis." *Cancer* 74, no. S1 (1994): 244-255.

[25] Quellec, Gwenole, Mathieu Lamard, Michel Cozic, Gouenou Coatrieux, and Guy Cazuguel. "Multiple-Instance Learning for Anomaly Detection in Digital Mammography." (2016).

[26] Gaur, Shantanu, Vandana Dialani, Priscilla J. Slanetz, and Ronald L. Eisenberg. "Architectural distortion of the breast." *American Journal of Roentgenology* 201, no. 5 (2013): W662-W670.

[27] Cao, Ying, Xin Hao, Xiaoen Zhu, and Shunren Xia. "An adaptive region growing algorithm for breast masses in mammograms." *Frontiers of Electrical and Electronic Engineering in China* 5, no. 2 (2010): 128-136.

[28] Ganesan, Karthikeyan, U. Rajendra Acharya, Chua Kuang Chua, Lim Choo Min, K. Thomas Abraham, and Kwan-Hoong Ng. "Computer-aided breast cancer detection using mammograms: a review." *IEEE Reviews in Biomedical Engineering* 6 (2013): 77-98.

[29] WeiQiYan "Introduction to Intelligent Surveillance", 2013.

[30] Melouah, Ahlem. "Comparison of automatic seed generation methods for breast tumor detection using region growing technique." In *IFIP International Conference on Computer Science and its Applications_x000D_*, pp. 119-128. Springer International Publishing, 2015.

[31] Dumitru, Diana. “Prediction of recurrent events in breast cancer using the Naive Bayesian classification.” *Annals of the University of Craiova-Mathematics and Computer Science Series* 36, no. 2 (2009): 92-96.

[32] Al Mutaz, M. Abdalla, Safaai Deris, Nazar Zaki, and Doaa M. Ghoneim. “Breast cancer detection based on statistical textural features classification.” In *Innovations in Information Technology, 2007. IIT’07. 4th International Conference on*, pp. 728-730. IEEE, 2007.

[33] Tang, Jinshan, Rangaraj M. Rangayyan, Jun Xu, Issam El Naqa, and Yongyi Yang. “Computer-aided detection and diagnosis of breast cancer with mammography: recent advances.” *IEEE Transactions on Information Technology in Biomedicine* 13, no. 2 (2009): 236-251.

[34] Rejani, Y., and S. Thamarai Selvi. “Early detection of breast cancer using SVM classifier technique.” *arXiv preprint arXiv:0912.2314* (2009).

[35] Ashraf, Ahmed B., Sara C. Gavenonis, Dania Daye, Carolyn Mies, Mark A. Rosen, and Despina Kontos. “A multichannel markov random field framework for tumor segmentation with an application to classification of gene expression-based breast cancer recurrence risk.” *IEEE transactions on medical imaging* 32, no. 4 (2013): 637-648.

[36] Gu, Shenghua, Yunjie Chen, Jin Wang, and Jeong-Uk Kim. “A Novel Breast mass segmentation method based on patch merging and GHFCM.” *International Journal of Hybrid Information Technology* 8, no. 10 (2015): 427-436.

[37] Guerroudji, Mohamed Amine, and Zohra Ameur. “New approaches for Contrast enhancement of calcifications in mammography using morphological enhancement.” In *Proceedings of the International Conference on Intelligent Information Processing, Security and Advanced Communication*, p. 77. ACM, 2015.

[38] Brandt, Sami S., Gopal Karemore, Nico Karssemeijer, and Mads Nielsen. “An anatomically oriented breast coordinate system for mammogram analysis.” *IEEE transactions on medical imaging* 30, no. 10 (2011): 1841-1851.

[39] Karahaliou, Anna, Katerina Vassiou, N. S. Arikidis, S. Skiadopoulos, Theodora Kanavou, and L. Costaridou. “Assessing heterogeneity of lesion enhancement kinetics in dynamic contrast-enhanced MRI for breast cancer diagnosis.” *The British journal of radiology* (2014).

[40] George, Yasmeen M., Bassant M. Bagoury, Hala H. Zayed, and Mohamed I. Roushdy. “Automated cell nuclei segmentation for breast fine needle aspiration cytology.” *Signal Processing* 93, no. 10 (2013): 2804-2816.

[41] Platel, Bram, Roel Mus, Tessa Welte, Nico Karssemeijer, and Ritse Mann. “Automated characterization of breast lesions imaged with an ultrafast DCE-MR protocol.” *IEEE transactions on medical imaging* 33, no. 2 (2014): 225-232.

[42] Gubern-Mérida, Albert, Robert Martí, Jaime Melendez, Jakob L. Hauth, Ritse M. Mann, Nico Karssemeijer, and Bram Platel. “Automated localization of breast cancer in DCE-MRI.” *Medical image analysis* 20, no. 1 (2015): 265-274.

[43] Khalvati, Farzad, Cristina Gallego-Ortiz, Sharmila Balasingham, and Anne L. Martel. “Automated segmentation of breast in 3-d mr images using a robust atlas.” *IEEE transactions on medical imaging* 34, no. 1 (2015): 116-125.

[44] Verma, Brijesh, Peter McLeod, and Alan Klevansky. “Classification of benign and malignant patterns in digital mammograms for the diagnosis of breast cancer.” *Expert systems with applications* 37, no. 4 (2010): 3344-3351.

[45] Huang, Qinghua, Feibin Yang, Longzhong Liu, and Xuelong Li. “Automatic segmentation of breast lesions for interaction in ultrasonic computer-aided diagnosis.” *Information Sciences* 314 (2015): 293-310.

[46] Khallaghi, Siavash, C. Antonio Sánchez, Abtin Rasoulian, Yue Sun, Farhad Imani, Amir Khojaste, Orcun Goksel et al. “Biomechanically constrained surface registration: Application to MR-TRUS fusion for prostate interventions.” *IEEE transactions on medical imaging* 34, no. 11 (2015): 2404-2414.

[47] Rehman, Awais Ur, Naveed Chouhan, and Asifullah Khan. “Diverse and Discrimintative Features based Breast Cancer Detection using Digital Mammography.” In *2015 13th International Conference on Frontiers of Information Technology (FIT)*, pp. 234-239. IEEE, 2015.

[48] Etehad Tavakol, Mahnaz, Vinod Chandran, E. Y. K. Ng, and Raheleh Kafieh. “Breast cancer detection from thermal images using bispectral invariant features.” *International Journal of Thermal Sciences* 69 (2013): 21-36.

[49] Gubern-Mérida, Albert, Michiel Kallenberg, Ritse M. Mann, Robert Marti, and Nico Karssemeijer. “Breast segmentation and density estimation in breast MRI: a fully automatic framework.” *IEEE journal of biomedical and health informatics* 19, no. 1 (2015): 349-357.

[50] Lee, Hsieh-Wei, Bin-Da Liu, King-Chu Hung, Sheau-Fang Lei, Chin-Feng Tsai, Po Chin Wang, Tsung Lung Yang, and Juen-Sean Lu. “Breast tumor classification of ultrasound images using a reversible round-off nonrecursive 1-D discrete periodic wavelet transform.” *IEEE Transactions on Biomedical Engineering* 56, no. 3 (2009): 880-884.

[51] Dinsha, D., and N. Manikandaprabu. “Breast tumor segmentation and classification using SVM and Bayesian from thermogram images.” *Unique Journal of Engineering and Advanced Sciences* 2, no. 2 (2014): 147-151.

[52] Su, Naifang, Ding Dai, Chao Deng, Minping Qian, and Minghua Deng. “Using graphical adaptive lasso approach to

construct transcription factor and microRNA's combinatorial regulatory network in breast cancer." *IET systems biology* 8, no. 3 (2014): 87-95.

[53] Chang, Jenny C., Eric C. Wooten, Anna Tsimelzon, Susan G. Hilsenbeck, M. Carolina Gutierrez, Richard Elledge, Syed Mohsin et al. "Gene expression profiling for the prediction of therapeutic response to docetaxel in patients with breast cancer." *The Lancet* 362, no. 9381 (2003): 362-369.

[54] Wang, Xiong, Tao Qin, Russell S. Witte, and Hao Xin. "Computational feasibility study of contrast-enhanced thermoacoustic imaging for breast cancer detection using realistic numerical breast phantoms." *IEEE Transactions on Microwave Theory and Techniques* 63, no. 5 (2015): 1489-1501.

[55] Wang, Teh-Chen, Yan-Hao Huang, Chiun-Sheng Huang, Jeon-Hor Chen, Guei-Yu Huang, Yeun-Chung Chang, and Ruey-Feng Chang. "Computer-aided diagnosis of breast DCE-MRI using pharmacokinetic model and 3-D morphology analysis." *Magnetic resonance imaging* 32, no. 3 (2014): 197-205.

[56] Cheng, H. D., Juan Shan, Wen Ju, Yanhui Guo, and Ling Zhang. "Automated breast cancer detection and classification using ultrasound images: A survey." *Pattern Recognition* 43, no. 1 (2010): 299-317.

[57] Kannan, S. R., R. Devi, S. Ramathilagam, and K. Takezawa. "Effective FCM noise clustering algorithms in medical images." *Computers in biology and medicine* 43, no. 2 (2013): 73-83.

[58] Othman, Ahmed A., Hamid R. Tizhoosh, and Farzad Khalvati. "EFIS—Evolving fuzzy image segmentation." *IEEE Transactions on Fuzzy Systems*22, no. 1 (2014): 72-82.

[59] Chen, Weijie, Maryellen L. Giger, and Ulrich Bick. "A fuzzy c-means (fcm)-based approach for computerized segmentation of breast lesions in dynamic contrast-enhanced mr images 1." *Academic radiology* 13, no. 1 (2006): 63-72.

[60] Mouelhi, Aymen, Mounir Sayadi, and Farhat Fnaiech. "Hybrid segmentation of breast cancer cell images using a new fuzzy active contour model and an enhanced watershed method." In *Control, Decision and Information Technologies (CoDIT), 2013 International Conference on*, pp. 382-387. IEEE, 2013.

[61] Gogoi, Usha Rani, Gautam Majumdar, Mrinal Kanti Bhowmik, Anjan Kumar Ghosh, and Debotosh Bhattacharjee. "Breast abnormality detection through statistical feature analysis using infrared thermograms." In *Advanced Computing and Communication (ISACC), 2015 International Symposium on*, pp. 258-265. IEEE, 2015.

[62] Kamdi, Shilpa, and R. K. Krishna. "Image segmentation and region growing algorithm." *International Journal of Computer Technology and Electronics Engineering (IJCTEE) Volume* 2 (2012).

[63] Dalton, Leslie W. "Information Theory, Kelly Betting, Risk, Reward, Commission, and Omission: An Example Problem in Breast Cancer." *IEEE Access* 2 (2014): 1272-1280.

[64] Li, Lihua, Hong Tang, Zuobao Wu, Jianli Gong, Michael Gruidl, Jun Zou, Melvyn Tockman, and Robert A. Clark. "Data mining techniques for cancer detection using serum proteomic profiling." *Artificial intelligence in medicine* 32, no. 2 (2004): 71-83.

[65] Maglogiannis, Ilias, Elias Zafiropoulos, and Ioannis Anagnostopoulos. "An intelligent system for automated breast cancer diagnosis and prognosis using SVM based classifiers." *Applied intelligence* 30, no. 1 (2009): 24-36.

[66] Patel, Bhagwati Charan, and G. R. Sinha. "Mammography feature analysis and mass detection in breast cancer images." In *Electronic Systems, Signal Processing and Computing Technologies (ICESC), 2014 International Conference on*, pp. 474-478. IEEE, 2014.

[67] Liu, Xiaoming, and Jinshan Tang. "Mass classification in mammograms using selected geometry and texture features, and a new SVM-based feature selection method." *IEEE Systems Journal* 8, no. 3 (2014): 910-920.

[68] Irshad, Humayun, Antoine Veillard, Ludovic Roux, and Daniel Racoceanu. "Methods for nuclei detection, segmentation, and classification in digital histopathology: a review—current status and future potential." *IEEE reviews in biomedical engineering* 7 (2014): 97-114.

[69] Paul, Angshuman, and Dipti Prasad Mukherjee. "Mitosis Detection for Invasive Breast Cancer Grading in Histopathological Images." *IEEE Transactions on Image Processing* 24, no. 11 (2015): 4041-4054.

[70] Cireşan, Dan C., Alessandro Giusti, Luca M. Gambardella, and Jürgen Schmidhuber. "Mitosis detection in breast cancer histology images with deep neural networks." In *International Conference on Medical Image Computing and Computer-assisted Intervention*, pp. 411-418. Springer Berlin Heidelberg, 2013.

[71] Mu, Tingting, and Asoke K. Nandi. "Breast cancer detection from FNA using SVM with different parameter tuning systems and SOM–RBF classifier."*Journal of the Franklin Institute* 344, no. 3 (2007): 285-311.