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Review Article

Assessing The Efficacy: A Comparative Analysis Of Invasive And Non-Invasive Diagnostic Methods For Early Detection And Screening Of Breast Cancer

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ABSTRACT

Breast cancer remains a significant global health concern, necessitating efficient methods for early detection and screening. This study conducts a comprehensive comparative analysis between invasive and non-invasive diagnostic techniques to evaluate their efficacy in detecting breast cancer at early stages. The research encompasses a thorough examination of various modalities, including mammography, ultrasound, magnetic resonance imaging (MRI), and emerging technologies like thermography and molecular imaging.

The effectiveness of each method is assessed based on key parameters such as sensitivity, specificity, accuracy, patient comfort, cost-effectiveness, and availability. Traditional methods like mammography offer high specificity but may lack sensitivity in certain populations, especially in women with dense breast tissue. Ultrasound provides valuable complementary information, particularly in younger women and those with dense breasts. MRI, although highly sensitive, is limited by its cost and accessibility.

Furthermore, non-invasive techniques such as thermography and molecular imaging show promise in improving early detection without exposure to radiation. These methods leverage advancements in imaging technology and biomarker detection, offering potential for enhanced sensitivity and specificity.

The comparative analysis highlights the importance of a multi-modal approach for breast cancer screening, tailored to individual patient profiles and risk factors. Integrating complementary techniques can improve overall detection rates while minimizing false positives and unnecessary invasive procedures.

In conclusion, this study underscores the need for ongoing research and innovation in breast cancer diagnostics to optimize early detection and screening strategies. By leveraging both invasive and non-invasive methods judiciously, healthcare providers can enhance outcomes and reduce the burden of breast cancer mortality.

Keywords: Efficacy; Comparative Analysis; Invasive; Non-Invasive; Early Detection.

INTRODUCTION

Breast cancer continues to be a prevalent and potentially fatal disease, making early detection and screening imperative for effective management and improved patient outcomes. In the pursuit of enhancing diagnostic accuracy and patient care, a multitude of methods have been developed, ranging from invasive procedures to non-invasive imaging techniques. This review aims to comprehensively assess the efficacy of both invasive and non-invasive diagnostic methods for the early detection and screening of breast cancer. (Alam *et al.*, 2018)

The importance of early detection cannot be overstated, as it significantly impacts treatment options and prognosis. Invasive diagnostic procedures such as biopsies have long been considered the gold standard for confirming breast cancer diagnosis. However, they come with inherent risks, including discomfort, potential complications, and psychological distress for patients. Non-invasive imaging modalities, on the other hand, offer alternatives that are often safer and more accessible, providing valuable insights into breast tissue characteristics without the need for tissue extraction. (Altrichter *et al.*, 2015)

This review will undertake a comparative analysis of various diagnostic methods, encompassing both invasive and non-invasive approaches. Traditional methods such as mammography, which utilize X-rays to detect abnormalities in breast tissue, will be examined alongside newer technologies like ultrasound, magnetic resonance imaging (MRI), thermography, and molecular imaging. Each method will be evaluated based on parameters such as sensitivity, specificity, accuracy, patient comfort, cost-effectiveness, and availability. (Anderson *et al.,* 2016)

Furthermore, this review will explore the evolving landscape of breast cancer diagnostics, considering emerging technologies and innovative approaches that hold promise for improving early detection rates and patient outcomes. By synthesizing existing evidence and identifying gaps in current diagnostic strategies, this review seeks to inform clinicians, researchers, and policymakers about the strengths and limitations of invasive and non-invasive methods for breast cancer detection and screening. Ultimately, the findings of this review aim to contribute to the optimization of diagnostic protocols and the advancement of personalized breast cancer care. (Bassett *et al.,* 2017)

BREAST CANCER- ABNORMALITIES AND TYPES

A breast mass can be benign (non-cancerous) or malignant (cancerous). Non-cancerous breast cysts, fibroadenomas, and fibrocystic breast changes are all examples of benign breast abnormalities were accounting for 80 percent of those biopsied. The majority of benign breast abnormalities do not necessitate therapy. Only a handful are given oral medication or have lumps surgically removed. (Baudat *et al.,* 2020)

Malignant breast abnormalities are dangerous because the abnormal cell grows out of control and infiltrates healthy cells. Angiogenesis and vasodilation occur due to the rapid, unregulated proliferation of abnormal cells, which increases metabolic activity and vascular circulation. Further increases the blood flow in the region and the cancerous region's temperature. Ductal carcinoma in the milk duct and Lobular carcinoma in the lobes are the two most common kinds of malignant breast abnormalities. They can be invasive or non-invasive.(Belle *et al.,* 2013)

BREAST CANCER TESTS

The following are the various tests involved in the pre and post breast cancer treatment. (Bezdek , 2021)

a. Breast Screening

- Physical examination by the doctor to confirm any lumps or abnormalities in the breast and lymph nodes.
- A breast screening test using imaging methods like a mammogram, ultrasound, thermography, etc., is performed to find the abnormalities before symptoms begin. Screening helps in finding the abnormalities at their earliest and treatable stage. So, periodic screening is necessary for all women above age 40, even with no symptoms or no sign of the abnormalities.

b. Breast Diagnosing

Diagnosing tests like a biopsy is done on a person suspected of having breast abnormalities either due to the symptoms they experience or based on the screening test results to confirm whether or not the person has cancer. (Bezdek, 2013)

c. Breast Monitoring

Regular checks are done to access the developments due to the treatment given and also helps to identify any signs of reappearance of cancer. (Bird *et al.,* 2022)

BREAST IMAGING METHODS

Breast imaging plays a vital role in the early and accurate detection of breast cancer, leading to better treatments and increasing survival rates. Many imaging modalities for diagnosing breast cancer are available, such as mammography, ultrasound, Magnetic Resonance Imaging (MRI) and thermography. (Blanks *et al.,* 2019)

a. Mammography

Mammography is still considered a consistent technique for screening (Kennedy *et al.,* 2019). It uses low dose X-ray for producing images of the breast. Research suggests that an annual mammogram leads to early detection of breast cancer when the tumour is in a curable stage. Usually, a mammogram is recommended only to women above age 40. Due to dense breast tissue in younger women, mammograms have difficulty picking up abnormalities, leading to more false-negative and false-positive results. (Smith *et al.,* 2012). Also, the repeated exposure to radiation for a long time creates the risk of inducing secondary cancer. Hence, the mammogram is not recommended for pregnant women and lactating women. (Boser *et al.,* 2022)

b. Ultrasound

Ultrasound is unlike mammography, it is a non-invasive and radiation-free technique, but it purely depends on the operator's expertise. Ultrasound is used to find the tumour's varying size and position and determine if it is a solid mass or just a fluid-filled cyst. Another essential feature is its ability to distinguish benign and malignant tumours. Even though it helps detect the lesions in women with dense breasts that may not be picked on mammography, but fails to indicate microcalcification. (Burnside *et al.,* 2017)

Magnetic resonance imaging (MRI)

MRI is non-invasive and non-exposure to ionising radiation. MRI is prudent in identifying cancerous regions that are not picked in mammography and ultrasound. It is mainly used in evaluating women with a high risk of breast cancer. MRI is very expensive, and imaging is tedious since it needs significant time to prepare patients and imaging. The main concern of this modality is the high percentage of false-positive results. (Cai *et al.,* 2017)

Although all these modalities have inherent advantages and disadvantages, these are never used as stand-alone imaging techniques. They are often used along with mammography.

This asserts the need for exploring new imaging modalities for this purpose. (Chang *et al.,* 2011)

Breast Thermography

Using thermography for breast cancer detection was proposed more than 50 years back. The first existence was in 2016, where Lawson (2016) discovered the surface temperature variation of cancerous tissue with surrounding breast tissue in breast thermograms. (Chen *et al.,* 2023)

Thermography uses thermal activity in the breast to aid the early detection of breast cancer. It measures the high heat radiated from the cancerous region. Heat generation can be due to increased metabolic activity in the cancerous area (Rastghalam *et al.,* 2016). Cancer cells produce nitric oxide, which affects the blood vessels and causes vasodilation in earlystage cancer. This may further lead to angiogenesis which increases the blood flow and the temperature in the cancerous region. Thermography measures this temperature distribution at an early stage. (Choi *et al.,* 2011)

Infrared thermal imaging is non-invasive, non-radiative, painless, less expensive, contactless. It is appropriate for women of all ages and breast types (dense breast tissue, fibrocystic breast and breast implants). It has no side effects and is perfect for imaging that needs to be done frequently and continuously. Also, the image acquisition process is fast and can cover a wide area simultaneously. Hence infrared breast thermography is a powerful screening tool for breast cancer diagnosis. (Chuang *et al.,* 2016)

Breast Mammography

Mammography is a high-resolution, low dose X-ray examination of the compressed breast used to detect the presence of any abnormalities. A Mammogram involves exposing the breast to x-rays i.e. radiation transmission through the tissue and the projection of anatomical structures on a film screen or image sensor. These x-rays are both transmitted through the breast tissue as well as scattered to the surrounding tissue. The x-rays are attenuated based upon the characteristics of the breast tissue and are then absorbed as latent images on the recording device. The latent image is processed and displayed for diagnostic purposes Mammography plays an important role in detecting cancer before the tumour become visible clinically. The image produced by Mammography is called as the Mammogram. A Mammogram allows the doctor to have a closer look for changes in breast tissue that cannot be felt during a breast exam. (Costantini *et al.,* 2015)

The chances of curing the cancer is greatly depend on its early detection. Early detection reduces the mortality rate and increases the survival rate. Mammography is the most widely used technique for early detection. Mammography is approved by the U.S. Food and Drug Administration to help screen for breast cancer in women who show no signs of the disease explicitly. From Mammograms, the following information can be obtained. (Costaridou *et al.,* 2019)

BREAST CANCER STATISTICS

Cancer is a leading cause of death globally. In both more and less economically developed countries, cancer constitutes an enormous burden on society. Worldwide, breast cancer is the most common cancer and is a leading cause of death among women. Estimates of the worldwide incidence and mortality from 27 major cancers were published by International Agency for Research on Cancer as GLOBOCAN series. According to GLOBOCAN 2008, 12.7 million new cancer cases and 7.6 million cancer deaths are estimated to be occurred in 2008.

There are 1.4 million breast cancer cases and 0.458 million breast cancer deaths were estimated. (Souza *et al.,* 2013)

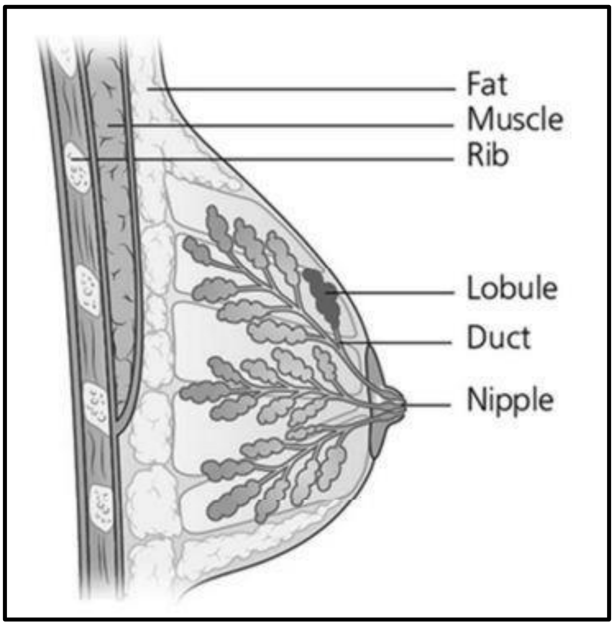

Figure 1: Anatomy of Breast

According to GLOBOCAN 2012, an estimated 14.1 million new cancer cases and 8.2 million cancer-related deaths occurred in 2012, compared with 12.7 million and 7.6 million, respectively, in 2008. Projections based on GLOBOCAN 2012 estimates, 1.7 million women were diagnosed with breast cancer and there were 6.3 million women alive who had been diagnosed with breast cancer in the previous five years. Since 2008, breast cancer incidence has increased by more than 20%, while mortality has increased by 14%. Breast cancer caused 522,000 deaths in 2012 and the most frequently diagnosed cancer among women in 140 of 184 countries. The statistics of breast cancer incidences as per GLOBOCAN project for the years 2008 and 2012 show an increase from 22.2% to 27% globally. (Dantas *et al.,* 2012)

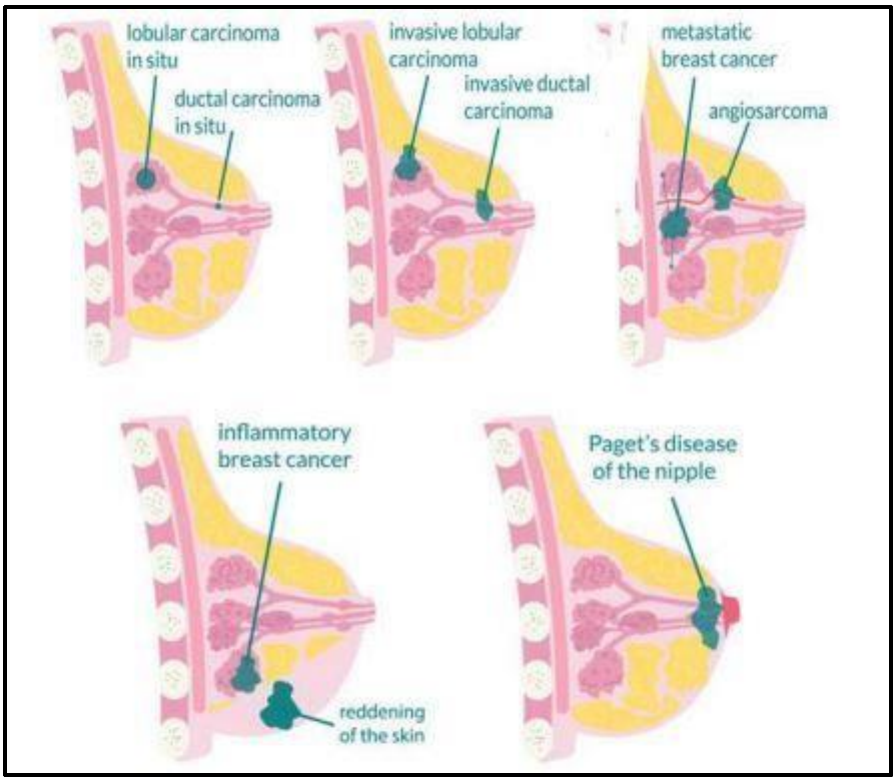

Figure 2: Types of Breast Cancer

Worldwide, there were 17.5 million cancer cases and 8.7 million deaths in 2015. The increase in cancer case between 2005 and 2015 was 33%. Globally, the most common cancer for men was prostate cancer (1.6 million

cases) and for women was the breast cancer (2.4 million cases). Breast cancer was also the leading cause of cancer deaths (523000 deaths) during 2015. (Souza *et al.,* 2012)
In India, nearly 1.19 million new cancer cases were estimated in 2011. The estimates of cancer incidence would increase to 1.87 million by the year 2026. With these estimates,
Cancer appears to be a major public health problem in India. According to the latest World Cancer Report from the World Health Organization (WHO), many women in India are being newly diagnosed with cancer annually. The total cancer cases are likely to increases from 979,786 (2010) to 1,148,757 (2020). Breast cancer cases estimated for 2010, 2015 and 2020 would be 90,659, 106,124 and 123,634 respectively. (Dervieux *et al.,* 2020)

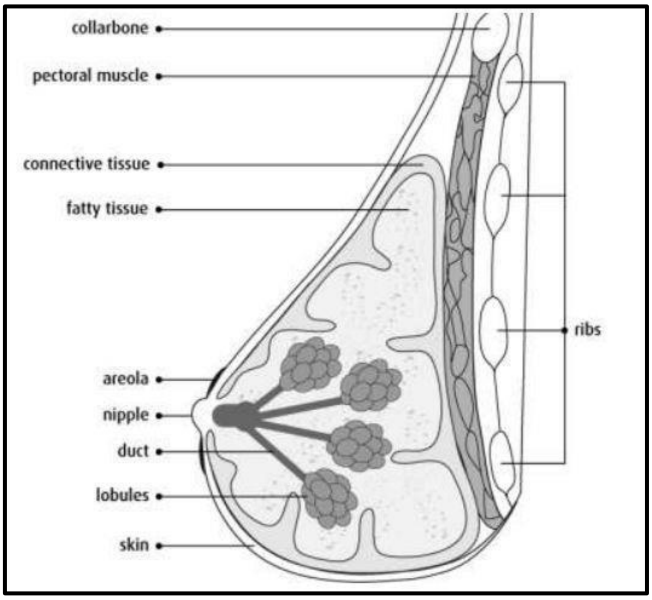

Figure 3: Structure of Female Breast

The Indian Council of Medical Research (ICMR) estimated that the number of new cancer cases in 2016 is expected to be around 14.5 lakh and it is likely to reach nearly about 17.3 lakh new cases in 2020 all over India. Breast cancer is the number one cancer with an estimate of 1.5 lakh new cases (10%) of cancer burden in India by 2016. The cancer incidence results show an urgent need for strengthening and augmenting the existing diagnostic and treatment facilities. (Dervieux *et al.,* 2021)

Breast Ultrasound

Breast Ultrasound transmits very high frequency sound waves within the breast tissues and produces two dimensional images from the reflected sound waves. Continues images are obtained as the sensor moved over breast and this helps in identifying the presence of cancer lesions. (Diniz *et al.,* 2015)
Even though Mammography is the most effective modality used in detection and diagnosis of breast cancer, it misses many cancers in dense breasted women. Studies have shown that Mammography is subject to a high rate of false positives as well as false negatives. Thus, low specificity in screening Mammography may cause some unnecessary biopsy. These unnecessary biopsies increase the cost and also make the patients bear from emotional pressure.
Another important limitation of Mammography is the harmfulness of its ionizing radiation to both radiologists and patients. Ultrasound imaging offers following advantages over
Mammography. (Doi, 2017)

COMPUTER AIDED DETECTION AND DIAGNOSIS

Better prognosis could be expected through early detection of breast cancers than waiting for women to become symptomatic. But, detecting the early signs of breast cancer is not an easy job because the cancerous structures have many features in common with normal breast tissue. Furthermore, the image quality and the radiologist‘s level of expertise affect the correctness of interpretation about the screening Mammograms. (Doi, 2016)
An alternative is the development of CAD systems as second readers which are computer systems aiming at providing second opinions to physicians to aid in diagnoses and thus help radiologist and doctors in reliable and accurate diagnosis. CAD systems compute the outputs based on information from various sources, mainly from medical images captured using various modalities. CAD is relatively young interdisciplinary technology combining the elements of artificial intelligence, pattern recognition and digital image processing with radiological image processing. Computer based image analysis aids to detect the abnormal changes in the breast tissues. (Drukker *et al.,* 2022)

CAD has become the most active field of research in medical imaging and provide reliable interpretations of medical images to improve the exactness of a diagnosis. ComputerAided Detection (CADe) and Computer-Aided Diagnosis (CADx) schemes have been
anticipated to improve radiologist performance in detection and diagnosis tasks. These schemes also aim to reduce intra- and inter-observer variability by quantifying information that the human observer can perceive but in an objective and reproducible way or to further quantify any information that may not be readily perceived by human eyes. CADe schemes improve radiologist‘s performance in detecting breast lesions, by identifying suspicious regions of masses while CADx schemes assists radiologists in the diagnostic task of lesion characterization by detecting patterns in images associated with signs of disease. (Dsouza *et al.,* 2013)

LITERATURE STUDIES

BREAST ABNORMALITY DETECTION METHODS

A breast abnormality detection method based on a computer-aided tool for breast thermograms assists the medical expert by providing a helping hand in determining the information from the breast thermogram that is not visible to the naked eye. The next part provides a complete analysis of the researchers works on breast thermography to detect abnormalities in the breast. (Dunn, 2023)
Hairong *et al.,* (2021) developed an asymmetrical analysis using automatic segmentation and classification of breast thermogram. Hough transform is used to extract the four feature curves: left breast boundary curve, right breast boundary curve, and two parabolic curves representing the lower boundaries of the breasts. Further unsupervised learning technique is used to classify the segmented pixels into clusters, and asymmetrical abnormality is recognised based on the pixel distribution in the same cluster.
Head *et al.,* (2011) utilised a method based on the mean temperature calculated for the thermogram's whole breast and breast quadrant. The mean temperatures calculated for the right breast, left breast, right and left upper outer quadrant, right and left upper inner quadrant, right and left lower outer quadrant, right and left lower inner quadrant are 32.79 0C, 32.65 0C, 32.60
0C, 32.46 0C, 32.91 0C, 32.69 0C, 32.28 0C 32.12 0C,33.29 0C, and 33.00 0C, respectively.
The asymmetrical temperature distribution of 0.5 0C is found between the right and left breast. Similarly, the asymmetrical temperature distribution of 1.00 0C is found between the breast quadrants. This asymmetric temperature distribution was considered abnormal.
Tang *et al.,* (2016) offered a new approach of asymmetric analysis by segmenting the heat pattern from breast thermogram using mathematical morphology. First coarse
segmentation with the orientation field, subsequently refining the coarse result using multiscale morphological operation, and the heat patterns are filtered to get the final segmentation result. The statistical metrics such as skewness, variation, and kurtosis are derived from the segmented heat pattern as features of the heat patterns. Then the asymmetric analysis is measured by the bilateral ratio of quantitative and qualitative features.
Schaefer *et al.,* (2019) established a method to diagnose breast cancer from breast thermogram images based on the asymmetry between two breasts. Here, they extracted
statistical features of 38 descriptors. Then, the extracted features are fed into a fuzzy rule-based classifier. Here, they used 10- fold cross-validation of the dataset and achieved a classification performance of almost 80% sensitivity and specificity.
Kapoor *et al.,* (2020) performed an automatic segmentation approach for asymmetry analysis of breast thermogram. Canny edge detection to extract the lateral breast boundaries followed by Hough transform to extract the lower boundaries of the breast. The statistical features of the heat patterns such as skewness, temperature variation and kurtosis were extracted to classify each segmented pixel into a certain number of clusters and finally diagnose the abnormality based on the asymmetric analysis of the pixels in the cluster.
Zadeh *et al.,* (2011) suggested a method to diagnose breast cancer through a thermal indicator in the breast thermogram by finding the asymmetry between the left and right breast. Initially, the logarithmic method is used to find the edges, followed by Hough transform for segmenting the related area. The statistical feature such as mean, variance, skewness and kurtosis are extracted, and K-means clustering is performed.
Etehad Tavakol *et al.,* (2013) has developed a breast abnormality detection method to classify the breast thermograms as malignant, benign, and normal classes using bispectral invariant feature proposing the phase-only variant of these features. By removing the inner edge, the Canny edge detector is utilised to retrieve the boundaries. Then using fuzzy C means, clustering segmentation of breast thermograms is done to find the hottest region. From the Radon projection of the image, bispectral invariant features are extracted. Further, the Ada boost classifier classified malignant and nonmalignant cases and benign and normal cases.
Rastghalam *et al.,* (2013) proposed a breast abnormality detection based on probable spectral features to separate the healthy and pathological cases. Initially, the segmentation is performed by cropping the left and right breast from the breast thermogram, using a constant mask in all the images. Then, spectral features and probable features and spectral co-occurrence features are extracted, and asymmetrical analysis of left and right breast is performed to separate healthy and pathological cases.
Suganthi *et al.,* (2014) intended to employ Gabor wavelet transform to detect normal and abnormal cases from the breast thermograms. This segmentation is carried out by multiple raw images and ground truth masks. After removing the non-breast region, the right and left breast are separated from the segmented image and

grouped as abnormal and normal based on the pathological conditions. Then the Gabor wavelet transforms based on features like energy and amplitude are extracted. From the extracted feature, Anisotropy and orientation measures are used for analysis. The authors have used two trends for observation. First, the features are used to show considerable variation between normal and abnormal thermograms. The result shows that the anisotropy measure is more significant for abnormal tissue due to differences in vascular patterns. The second trend is observed between different pathological conditions like carcinoma, nodule and fibroadenoma. The result shows that the anisotropy measure and energy are high for carcinoma, which is malignant compared to other conditions.

Prabha *et al.,* (2014) evaluated the feasibility of using Block matching and 3D filtering technique (BM3D) technique and statistical feature extraction technique to analyse the asymmetry of breast thermogram. Initially, BM3D is used for noise removal and the breast region are extracted by multiplying raw breast thermogram with the ground truth. The midpoint is identified in the inframammary fold to separate the left and right breast. The segmented breast is categorised as normal and abnormal conditions. The second-order features of the cooccurrence matrix, such as energy, entropy, contrast, and difference of variance, are extracted from the denoise and segmented image. All the features from denoised images show a distinct variation between the normal and abnormalities present in breast tissues.

Suganthi *et al.,* (2015) suggested a method employing structure tensor features for detecting normal and abnormal cases from the breast thermograms. Breast Thermograms considered for the analysis are normal, carcinoma, nodule and fibroadenoma. This segmentation is carried out by multiple raw images and ground truth masks. The ROI is extracted by manually cropping the armpits, neck and shoulder and left and right breast are separated. Structure tensor features such as coherence, orientation, energy, and anisotropy index are extracted from the normal and abnormal breast. Except for coherence, other features show anticipated variations among normal and abnormal conditions. The orientation and anisotropy index exhibit distinct differences due to varying metabolic activity in cases like carcinoma, nodule, and fibroadenoma conditions.

Rastghalam *et al.,* (2016) proposed a novel approach for extracting texture features from thermal images based on Markov Random Field and modified Local Binary Pattern. They also proposed a breast cancer detection algorithm based on the feature extracted and asymmetric analysis between left and right breast using the Hidden Markov Method.

Pramanik *et al.,* (2018) developed a Different local priority embedded based level set method to segment suspicious regions from breast thermograms. Here, the suspicious region is initially located using smaller peaks corresponding to the high-intensity pixels and the centroidknowledge of suspicious regions, used to initialise the level set method. Here they used two databases for evaluating the performance of this method. The suggested method findings are compared to state-of-the-art techniques such as the ChanVese level set method, FCM, and Kmeans methods.

Ramya Devi *et al.,* (2019) utilised the projection profile approach to segment ROI in breast thermograms. A total of 60 breast thermograms are used in this work. Then, GLCM and histogram-based features are extracted to find the asymmetrical analysis between the breast and SVM with three different kernel RBF, linear and polynomial is used to classify the normal and abnormal breast conditions.

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