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Recognition and categorization of Lesions in Breast Ultrasound Images: A survey

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***Abstract:** Breast cancer is the world's second leading cause of death in women. The cause of the disease may be genetic or unknown. Since it is asymptomatic in the initial stage, early detection and diagnosis are critical for breast cancer prevention, it can increase the success of treatment and save lives. Ultrasound imaging is one of the most common screening techniques for identifying and classifying breast disorders. A computer-aided diagnosis (CAD) framework is a valuable and useful means for breast cancer identification and classification because it reduces operator dependence and increases diagnostic accuracy. In this paper clinical breast examination (CBE) methods and literature survey related to detection and classification of lesions/tumours in breast ultrasound images have been discussed.*

Introduction:

The cells in the breast tissue alter (or mutate) and continue to reproduce. These irregular cells normally form a tumour as they cluster together. These tumours can be benign or cancerous. When irregular cells enter other parts of the breast or migrate via the bloodstream or lymphoma, a tumour is called carcinomatous (or malignant). The milk-producing ducts of the breast (called lobules) or the tubular ducts that transport milk from the lobules to the nipple are where breast carcinoma normally begins. [1].

Breast cancer is the most common cancer in women and the second most common cancer worldwide. It affects 2100000 people per year and is the women foremost reason of decease from cancer. In 2018, 627 million women died from breast cancer, accounting for almost 15% of all cancer mortality. [2].

The occurrence and death rates from different recent national cancer registries were compared. Breast carcinoma is the most common cancer in Indian women, with a death rate of 12.7 per 100,000 women and an age-adjusted prevalence of 25.8 per 100,000 women in the year 2012 [3].

Breast cancer can be diagnosed and treated more quickly if detected early. Breast cancer screening refers to the process of examining a woman's breasts for cancer before the condition manifests itself in the form of signs or symptoms.

Portable Diagnostic Lab allows the delivery of high-quality diagnostic treatment in a reliable, cost-effective, and safe manner.

Early detection is critical for bettering the prognosis and survival of breast cancer patients. Breast cancer can be detected early using one of two methods: screening and diagnosis at an early stage. The majority of women are hospitalised late in low-resource environments with inadequate health treatment. An early intervention programmes focused on understanding early signs and symptoms and prompt referral of diagnosis and treatment should be prioritised.

Breast cancer can be detected early using a variety of imaging and pathological techniques. Few of the clinical breast examination (CBE) methods are as follows.

- **Doppler Ultrasound:** The blood flow in the breast is monitored using this procedure. The blood supply into the blood vessels is depicted. Doppler ultrasound waves travel through the breast and reverberate in the tissues. The picture created from the echoed waves is then projected on the projector. A transducer is a small handheld device is gently passed through the epidermis above the vessels of blood during Doppler ultrasound. It sends and absorbs sound waves that have been amplified. The sound waves reverberate off rigid surfaces, such as blood cells. Changes in the pitches of sound waves are caused by blood vessel activity. There will be no difference of pitch if there is no blood supply. The reflected sound waves are used to create a graph or an image, which is then analysed for tumour detection.

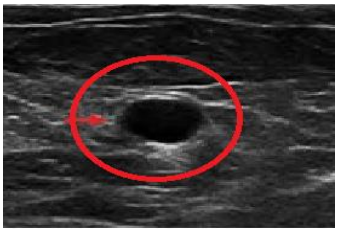

Fig 1. Breast containing tumour obtained from Ultrasound screening.

- **Diagnostic mammogram:** In mammography the X-ray is used as a diagnostic tool. Full-field optical mammography (FFDM) is another name for diagnostic mammogram. Low-dose X-rays are used to see inside the breast. It entails exposing a portion of the body to a low dose of radiation. Electronics replace the x-ray film, converting the x-rays into mammographic photographs of the breast. This system looks for irregular areas of density or mass in digitised mammographic images that could suggest the existence of cancer.

Mammography is often used to track conditions that have a high risk of false positives. It is not 100% accurate. There is a chance that the mammogram looks normal even if the cancer is present. This technique uses X-ray so the body is exposed to small amount of radiation which is harmful. It makes the patient feel uncomfortable during the test Mammography is painful during the screening process and is not recommended for younger patients.

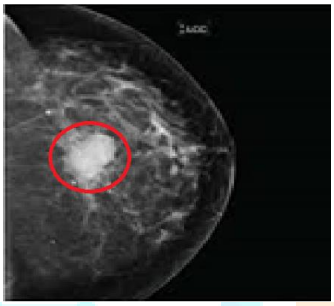

Fig 2. Breast containing tumour obtained from Diagnostic Mammogram.

- **Magnetic resonance imaging (MRI):** Magnetic fields and radio frequency signals are utilized in this process. Powerful magnetic rays are emitted into the body during an MRI. It is used to examine internal organs, tissues, and bones, among other things. Medical images are projected on a computer screen, and sent as an electrical signal, with the information written. This method, which does not use X- rays, is used for staging of cancer. They are able to take images of both breasts at the same time. It can spot any defects, tumours, or lymph nodes in the armpits with ease.

Since MRI is performed on an enclosed surface, people who are claustrophobic may have difficulty with it. MRI is noisy and is not an affordable screening method to low-income group.

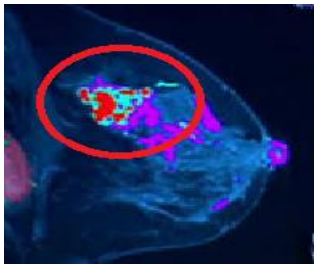

Fig 3. An MRI image of a tumour in the breast.

- **Biopsy:** This is a process in which breast tissue or blood is collected and inspected under a microscope before being subjected to further examination. Biopsies come in a different forms and sizes.

Biopsy is invasive procedure that causes bleeding or bruising. There is a possibility that this can infect the wound or damage the neighbouring tissue. Some people are concerned that the biopsy would cause cancer cells to spread to healthy tissue, resulting in new tumours.

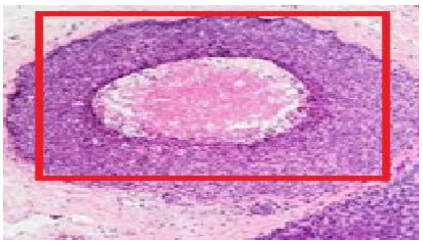

Fig 4. A biopsy image of breast cancer cells examined under a microscope using tissue/fluid taken from the breast.

- **Colour Doppler:** Colour Doppler is a simple instrument that is used with almost all ultrasonic imaging instruments. Vascularization of the tissues can be obtained. It is important to apply minimum pressure to the breast in order to show very slow flow and prevent compression of blood vessels. It monitors blood flow obstructions and blood flow through lumps, allowing the tumour to be diagnosed early.

The disadvantage of this is that the instrument performance affects the quality of blood flow imaging.

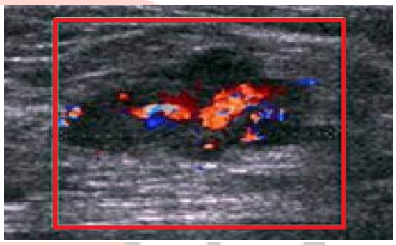

Fig 5. Breast containing tumour obtained from Colour Doppler.

- **Positron Emission Tomography PET:** This aids in identifying the infected region and cells. Fludeoxyglucose (FDG), a radiopharmaceutical, is inserted first into the blood stream which produces gamma rays. The scanner records the FDG, and the images are reconstructed and analysed. The abnormal area is located where the signals have collected heavily [4].

In Positron Emission Tomography, the image is not clear and in turn it is expensive. The radioisotope given during the procedure is only safe for the first couple of times. This method is used to identify metastasis.

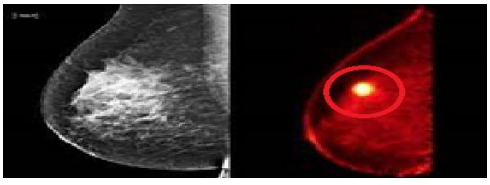

Fig 6. Breast tumour obtained from PET scan

Since ultrasound procedures are non-invasive, radiation free, affordable, simple, compact, and versatile, this imaging method is preferred for mass screening of breast cancer. MRI is used to detect the cancer stage; PET helps to identify metastasis and mammography is done after the biopsy to clarify the doubt whether the tumour is cancerous or not. Non-invasive, radiation-

free, portable and low-cost screening method is preferred for early detection.

Literature survey was carried out to study about the methodology to segment the lesions, extract features and to classify as lesions and non-lesions using BUS image. Few of the referred papers are discussed below.

Literature Survey:

Navid Ibtehaj Nizam [5] suggested using quantitative ultrasound (QUS) biomarkers to identify breast lesions. A novel closest neighbourhood average regression line fitting (NNARLF) technique was used to measure the ESD. For MSS estimation, an improved EEMD domain autoregressive (AR) spectral estimation method was used. The ESD had high sensitivity, precision, and consistency values of 95.45 percent, 95.79 percent, and 95.68 percent, respectively, when used for binary classification of 139 lesions. The receiver operating characteristic (ROC) curve's area under the curve was 0.95. As ESD was combined with even better sensitivity, accuracy and specificity, the results were 97.73 percent, 96.40 percent, and 95.79 percent, respectively. In addition, the region under the ROC was raised to 0.97. The ability of these QUS parameters to be used as non-invasive biomarkers for breast cancer diagnosis is demonstrated by their high classification efficiency.

Combining conventional signal processing-based pre-processing steps with deep neural networks could be the best way for enhancing ultrasonic tissue classification efficiency in the future.

Mohammad I. Daoud [6] suggested a new CAD scheme to enable correct BUS picture recognition. Improved texture analysis was applied, in which the tumour was separated into a series of nonoverlapping regions of interest (ROIs). To evaluate the tumour type predictor, each ROI is examined using gray-level cooccurrence matrix features and a support vector machine classifier. The tumour type markers from both ROIs are merged using a voting system to estimate the tumour class. In addition, the tumour is classified using morphological analysis. Using a probabilistic approach, the classification findings of the multiple-ROI texture analysis and morphological analysis were fused. The proposed method was used to identify 110 BUS photographs, 64 of which were benign and 46 of which were malignant tumours. The proposed method achieves precision, specificity, and sensitivity of 98.20 percent, 98.40 percent, and 97.80 percent, respectively. These findings show that the proposed method can effectively distinguish between benign and malignant tumours.

Esme Uzunhisarcikli [7] created a two-layer, high-success-rate classifier model based on Type-2 fuzzy inference that classifies the tumour as benign or malignant based on its BI-RADS class by integrating expert doctors' opinions. The accuracy tests yielded a 99.34 percent success rate in benign/malignant classification and a 92 percent success rate in group classification (BIRADS 2, 3, 4, 5). These findings suggest that the CAD method is useful for offering a second diagnostic opinion during mass diagnosis by radiologists.

Ahmed Hijab [8] proposed using transfer learning to develop a deep learning technique for classifying breast cancer in ultrasound images. A deep convolutional neural network was trained using the training data, which included hundreds of images of benign and malignant cases (CNN). The researchers proposed a baseline approach, in which the CNN architecture is learned from scratch, a transfer-learning approach, in which the pre-trained VGG16 CNN architecture is further trained with ultrasound images, and a fine-tuned learning process, in which the deep learning parameters are fine-tuned to overcome fitting problem. With pre-training on US photos, the results were 0.97 accuracy and 0.98 AUC. Using medical imaging data to create pre-trained models will undoubtedly increase deep learning outcomes in biomedical applications.

To help in the detection of breast lesions, **Yongdong Chen** [9] suggested a novel diagnosis scheme. A function scoring scheme was applied to product feature data in this approach. The results of blustering mining were then used to find the most powerful diagnostic patterns, which were then used to turn the original features into advanced hidden features. The advanced features were then used as input data for a Biclustering Mining and Neural Network to train a classifier that could distinguish between benign and malignant breast tumours. The test was performed on a database of 238 breast tumour cases (115 benign cases and 123 malignant cases), and the results were compared to other traditional approaches. The accuracy, sensitivity, and specificity of tumour classification were 96.1 percent, 96.7 percent, and 95.7 percent, respectively.

Abu Sayeed Md. Sohail [10] introduced a system for classifying ultrasound medical images that addressed two key issues: I the best function subset selection for representing ultrasound medical images, and (ii) improving classification accuracy by eliminating outliers. An analytical function incorporating the principles between class distance and within-class divergence within the training dataset was proposed as a feature selection assessment criterion. The Multi-Objective Genetic Algorithm (MOGA) was used to find the best subset of features (MOGA). This criterion is used to describe a subset of Grey Level Co-occurrence Matrix (GLCM) and Grey Level Run Length Matrix (GLRLM) based statistical texture descriptors that optimise separability among the training dataset's groups. The Fuzzy Support Vector Machine (FSVM), which decreases the influence of outliers by considering the significance level of and training set, was used to prevent the impact of noisy data during classification. Six hundred and seventy-nine ultrasound ovarian photographs were examined, with an overall classification accuracy of 89.60 percent.

Wilfrido Gómez Flores [11] devised a method for compiling texture features and morphological that are commonly used in BUS image computer-aided diagnostic systems. 641 BUS images yielded a total of 1465 texture and 26 morphological elements. The discrimination power of different feature subsets was evaluated using a feature selection approach based on shared knowledge and statistical tests. The 632 bootstrap method was used to estimate the classification utility of each function subset using the local Fisher discriminant analysis (LFDA) with linear kernel as classifier and the area under the ROC curve (AUC) as output index. AUC=0.942, obtained by a morphological collection with five characteristics, was found to be the best classification output in the experiments. Furthermore, with an AUC of 0.897, this morphological collection outscored the best four-feature texture collection. This morphological feature set outpaced the classification performances of 11 feature sets proposed in the literature.

Hoda Nemat [12] examined 21 shape-based features, 24 texture-based features and 810 contour-based features in their research.

They used a Bayesian extension of logistic regression in conjunction with an Automatic Relevance Detection Mechanism to exclude unnecessary functions. For a private database, the findings were excellent. With 93.75 percent sensitivity, 97.12 percent accuracy, and 98.61 percent specificity, the algorithm outperformed six state-of-the-art methods for BUS picture classification by a wide margin.

The methodology for classifying lesions in breast ultrasound images can be derived from the above literature review. The system level block diagram for computer-aided design (CAD) approach to diagnose and classify lesions is as shown in Fig. 7.

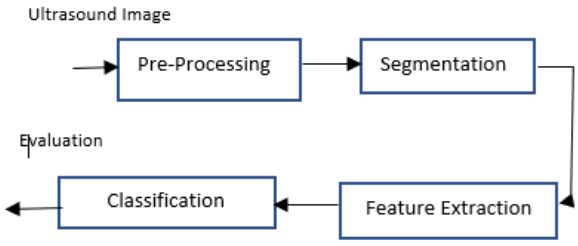

Fig. 7. A computer-aided design (CAD) approach to diagnose and classify lesions.

The input to the system is the breast ultrasound image. Since the US images have inherent speckle noise embedded in it, the image is degraded considerable. The pre-processing methods are used to increase image clarity by eliminating speckle noise from breast ultrasound (BUS) images without removing essential diagnostic features. The image pre-processing stage also has some enhancement methods to create contrast between the tumour and its background.

The aim of segmentation is to make an image more coherent and easier to interpret by simplifying and/or changing its representation. Image segmentation distinguishes and extracts the tumour from the surroundings by dividing the image into partitions of non-overlapping areas. The regions which contain the tumour/lesions are referred as region of interest (ROIs). These ROIs are then used for feature extraction.

The Feature extraction stage finds a feature collection of breast cancer lesions that can reliably discriminate lesion from non-lesion or benign from malignant.

The purpose of feature selection is to choose the most suitable feature. Since all of the extracted features which fail to detect lesions in the breast image, only the most successful features are used.

The classification of lesions is based on the features chosen; the suspected regions are classified as lesion/non-lesion or benign/malignant using a variety of classification methods.

Performance analysis is needed to evaluate the efficiency of the suggested method or algorithm. This would determine whether or not the algorithm used to classify lesions in a Breast Ultrasound Image is correct.

Conclusion:

In this paper, we reviewed CAD systems for breast cancer detection and classification using ultrasound images in the literature. The aim is to implement the best method to detect and classify the lesions in breast ultrasound images using image processing techniques and SVM as classifier which yields the results with highest accuracy, sensitivity and specificity in the further research.

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