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Medical Diagnostic Systems for Breast Cancer

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Abstract: Breast Cancer is one of the diseases where females have the highest mortality rate. Early detection is the way to diminishing the rate and helps increase the lifespan of suffering patients. Mammography is the method of using low energy X-rays for examination and screening the human breast. A team of radiologists required for the analysis of mammograms, but even experienced experts can misjudge in their evaluation.so Computer-Aided Detection (CAD) systems are having more pervasive for the purpose. There are various abnormalities, including micro-calcifications, are identified from mammograms. This study takes a look at all techniques that are helpful in detecting calcification. Several works of literature have been reviewed to explore and learn the outstanding way in different cases and situations for the sensing of classification in cancer of breast.

Keywords: X-ray, Breast Cancer, CAD, Mammogram

I. Introduction

The most frequent invasive cancer amongst females is bosom cancer. Breast cancer rises after age 40, and approximately at the age of 50, 80 percent of instances happened in women. The rank of bosom cancer is second among all the women who suffers from cancer. The cancer of the breast is cancer that structures in cells of the bosoms. Mammography is the precise type of breast imaging that uses low energy X-rays to differentiate between benign and malignant. World Health Organization said that in India, 50% of diagnosed cases are in stage 3 or stage 4, there is no treatment for breast cancer. There are many reasons for the late treatment, like the patient's shyness, delay of treatment, and not proper medical resources. In 2012, the World Health Organization's International Cancer Research Agency revealed 1.67 million breast cancer cases and about 0.5 million deaths attributed to breast cancer [1]. Breast cancer has various abnormalities such as micro calcifications (MCs), which are small calcium deposits that become appear as small shiny white spots and masses on the mammogram. MCs are short in size between 0.33 to 0.7 mm and burnished than adjoining tissues. MCs are, accordingly, challenging to find in the analysis programs by radiologists, they show low resemblance because of their small form [2]. The significance of identifying the clusters of micro calcifications is that they can be both premature warning marks and the only indication of breast cancer [3].

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The radiologists determined the existence of the disease or not according to MC's shape. Nevertheless, breast cancer diagnosis errors occur 30-50 percent early due to MCs clusters are being there.

The literature has suggested different algorithms for the recognition and calcification of MCs, utilizing an isolated patient's mammogram [4-7]. The foremost downside of the methodologies is the inadequacy of preliminary understanding about the timeline of appearance of MC, something radiologists generally evaluate. Several experiments have carried out to determine temporal characteristics to upgrade the classification accuracy of mass lesions [8-10].

II. Literature Review

Jelena Bozek et al. (2009) reviewed various image processing algorithms. These algorithms design to detect masses and calcifications. This work provided a summary of algorithms in every stage of the mass detection algorithms [11]. These steps included segmentation, extraction of the features, selection of the features, and classification. In this study, Wavelet detection techniques and other existing techniques suggested for detecting calcification. This work provided a summary of methods for contrast enhancement and noise equalization along with the overview of calcification classification approaches.

Keith Chikamai et al. (2015) emphasized the total automatic recognition of micro-calcifications in digital mammogram pictures [12]. This work also studied the difference between cancerous and non-cancerous subclasses of micro-calcifications. Finally, the micro-calcifications had been amplified by optimally integrating wavelet and Laplace filters. Afterward, post-processing implemented to deplete the list of false positives. It shows the sensitivity rate of 100% by the merged filter model in the detection of all existing calcifications in all mammograms. Specialist radiologists differentiated this, based on associated ground truth. This study depicted the efficiency of merging the probability maps from different filters to improve the recognition of calcification objects as per its aims**.**

R. Bhanumathi et al. (2015) attempted to design an automated system for the classification of digital mammogram pictures. These pictures classify into cancerous or non-cancerous. A classification framework on the basis of the Support vector machine (SVM) had been proposed in this work [13]. The main objective of this classifier was to identify the micro-calcification at every place in the mammogram pictures. There were three phases in which the proposed technique had implemented. These stages were preprocessing, feature extraction, and SVM classification. A database named Mammographic Image Analysis Society applied to evaluate the suggested technology.

The tested results revealed that the SVM approach showed a micro calcification recognition rate of 94.94% in mammograms in contrast to various other existing methodologies.

C. Abirami et al. (2016) aimed to design an automated system for the classification of digital mammogram representation [14]. These were classified into cancerous or non-cancerous images. In this work, a classification model on the basis of the Artificial Neural Network proposed for detecting the microcalcification at every place in the mammogram pictures. A database named Mammogram Image Analysis Society (MIAS) was used in this work to evaluate the proposed technique. The tested results depicted that RBF showed a microcalcification detection rate of 93% in mammograms in contrast to various other existing methods.

S. Kowsalya et al. (2016) used a median fuzzy c-means scheme to detect masses and macro-calcification in the pictures of mammogram [15]. For clustering of similar/dissimilar data based on the prototype, Median data clustering was a robust technique. The MFCM approach computed the median rather than evaluating the mean for every cluster for determining centroid and resulted in the reduction of an error on all groups concerning the 1- norm distance metric. This work considered contrary to the 2-norm distance metric square—a database named Mammographic Image Analysis Society used gathering of dataset. In contrast to clustering approaches with k-means and Fuzzy C-means, the spotting of masses and macro calcification gave more effective results.

Benjamin Kaltenbach et al. (2016) have analyzed 849 vacuum-assisted biopsies for assessing the probability of malignancy in BI-RADS4 and BI-RADS5 calcifications [16]. According to the BI-RADS lexicon morphology and distribution descriptors, it describes both categories of calcification. They were using the standardized matrix to combine the features of a group of classification with the type of BI-RADS. It found that 32% of lesions were malignant. 285/327/208/29 calcified tumors categorized into BI-RADS 4A/4B/4C/5 that indicates 16%/25%/55%/90% risk of malignancy. The morphology depictors estimated the malignancy risks as typically benign, indeterminate, and generally malignant. The distribution descriptors are compatible with the analysis of the fatal as diffuse, round or oval, regional, segmental, linear, and branching. This matrix becomes a useful tool for calcification detection and links between the description and lesion classification.

Vaia Koukou et al. (2017) present experimental dual-energy (DE) for microcalcifications visualization. Homogenous and inhomogeneous phantoms of breast used with the various calcification thicknesses in this method [17]. A contrast-to-noise was calculated for multiple surface doses from the DE subtracted images. In this 152 mm thickness of the calcification was visible at the acceptable levels with the mean glandular doses (MGD). The minimum depth of 93 mm was evident in the inhomogeneous breast phantom DE images. This dual-energy method improves visualization of the calcifications in the screening of the DE breast calcification.

Bhupendra Singh et al. (2017) proposed a novel approach that improved input image initially with the help of laplacian filtering [18]. Afterward, the obtained resemblance was categorised as cancerous or non-cancerous using wavelet, statistical, and a characteristic retrieved from the Histogram. The classification results obtained from Artificial Neural Network depicted that Daubechies-8 generated a 92.8% exact rate of detection and 12.5% false-positive rate with low-frequency elements of 50 percent in conjunction with statistical characteristics.

Juan Wang et al. (2018) proposed a context-sensitive deep neural network (DNN) to detect MC. For this purpose, both the local representation of attributes of an MC and its underlying tissue background considered. The proposed scheme assessed in terms of accuracy to detect both individual MCs [19]. The proposed approach used to identify clusters of MC on a compilation of 292 mammograms. The proposed method used free-response receiver operating characteristic (FROC) scrutiny to achieve this aim. The obtained outcomes revealed that the proposed scheme was able to get a considerably better accuracy rate to detect individual MCs. The proposed system integrated image related information in MC detection. It could prove advantageous to reduce FPs.

J. J. Mordang et al. (2018) presented a study to evaluate several times females with hidden calcifications in earlier testing mammograms were later identified with invasive cancer [20]. A radiologist could identify the calcifications related to the disease. A computer-based detection system on mammograms selected these calcifications. These considered cancer diagnosis before display-detection or interval: this ground reality and the pathology studies used to determine the responsiveness for recognition of calcification. The percentage of tumors with evident calcifications that originate into invasive cancer was also set on using these factors. It concluded that it was possible to detect 54.5% of cancer-related calcifications in the early stage. This work could significantly decrease the incidence of invasive cancers in the given populace.

Juntao Li et al. (2018) proposed a paper is to learn whether the DBT has the diagnostic merit over FFDM for suspicious breast calcification from diverse populations. In identification of breast cancer, DBT shows the higher diagnostic precision in the terminology of sensitivity, specificity, positive and negative predictive values for benign calcifications, as compared to FFDM [21]. It also has higher efficiency in the cases of premenopausal, postmenopausal, and dense breast than the FFDM. DBT reveals a more significant advantage in the fact of dense breast and benign calcification, although there is no advantage in the case of non-dense and malignant calcification.

Sanket Agrawal et al. (2018) explain the hybrid approach that is a combination of the neural network with linear classifiers for the spotting of the masses from the mammograms [22]. They used the VGG16 deep learning model for the feature extraction, then fed into linear classifiers formed on the neural networks that are effective for image processing.

This hybrid approach gives the outcomes of the mammogram that classifies into normal or abnormal. The former indicates that there was no tumor present, and the latter suggests that tumors, calcifications, distortions, and other masses are existed.

This method has been effective in achieving the possibility of success in finding the anomalies in mammograms.

Mohammed A. Al- masni et al. (2018) proposed a CAD system formed on the technique of deep regional learning, which is called YOLO means You Look Only Once. It is the ROI-based convolutional neural networks—the method used for both the detection and classification of masses simultaneously [23]. The proposed YOLO based CAD system consists of four stages, like pre-processing, extraction of features, mass detection, and mass classification. With 99.7% accuracy, this technique detects the mass locations and also differentiates the lesions that are benign and malignant with 97% precision. It also performs on some complex cases where over pectoral muscles and dense regions, the masses have been.

Jose M. Celaya-Padilla et al. (2018) explained that screening mammography includes images of the breast using the two standard views, and the critical feature for detecting breast cancer is the contralateral asymmetry. They proposed a approach to embrace such information on asymmetry into the CAD system to distinguish between healthy and risky subjects those having bosom cancer [24]. In this paper,the digital database for screening mammography (DDSM) and breast cancer digital repository (BCDP) used with analog and digital mammograms for validating the methodology. The method can classify the subjects from the other type of benign anomalies.

Relea et al. (2018) evaluate the effectiveness of the twinkling artifact on the Doppler ultrasound imaging for calcification diagnosis [25]. They were using Ultrasonography to examine the 46 patients suspected of the malignancy mammography looking for the twinkling artifact to identify the calcifications. After the calcification identified, core biopsy needle specimens of 11G needles are obtained and used the X rays for the existence of the calcifications, then by using the core needle, look over the percentage of the spotting of the microcalcifications. By using the twinkling artifact, they identified the 27 groups of calcifications. In ultrasound, the twinkling artifact is effective for microcalcifications that shows improvement in the ultrasound-guided biopsies and improves in marking of calcification group.

Fung Fung Ting et al. (2018) proposed the Convolutional Neural Network Improvement for Breast Cancer Classification (CNNI-BCC) for the experts of medical in breast cancer diagnostics [26]. The CCNI -BCC used the convolutional neural network to improve the classification of the breast cancer lesion that helps the experts in breast cancer diagnosing. It classifies the medical evidences into malignant, benign, and consists patients with 89.47% sensitivity, 90.50% accuracy, 0.901 ± 0.0314 area under the receiver operating feature curve (AUC), and 90.71% specificity.

Mina Yousefi et al. (2018) proposed a CAD framework formulated on DCNN and MIL for the identification of the masses in digital breast tomosynthesis [27]. It performs on a set of two-dimensional layers. This framework was used a multiple instance forest classifier to explain the DBT images. The size of the dataset was 87, and it reported accuracy of 86.81%, 86.6%sensitivity, and 87.5%specificity.

Mai S. Mabrouk et al. (2019) have presented their paper to show the improvement in the CAD system relies on the supervised classification that can be beneficial in detecting and diagnosing the modifications in bosom cancer by digitized mammograms better than the normal test programs [28]. The author represented their work centered on the integrated features like shape, texture, and invariant moment characteristics. The inclusion method achieves the best outcomes of sensitivity and specificity. This system's accuracy reached 96% in ANN automatic mode, while the best precision achieved by characteristics resulted from invariants moments that ANN automatically reached 97%.

Table 1: Table of Comparison

Authors Names	Year	Description	Outcomes
Jelena Bozek et al.	2009	Reviewed various image processing algorithms. These algorithms were designed to detect masses and calcifications	This work provided a summary of contrast enhancement and noise equalization techniques along with the summary of calcification classification approaches
Keith Chikamai et al.	2015	Emphasized on the total automatic recognition of micro-calcifications in digital mammogram pictures. This work also studied the difference between cancerous and non-cancerous subclasses of micro-calcifications	This study depicted the efficiency of merging the probability maps from different filters to improve the recognition of calcification objects as per its aims
R. Bhanumathi, et al.	2015	Attempted to design an automated system for digital mammogram pictures classification. These pictures were categorised into cancerous or non-cancerous	The tested results revealed that SVM approach showed micro calcification recognition rate of 94.94% in mammograms in contrast to various other existing techniques.
C.Abirami et al.	2016	In this work, a classification model formed on artificial neural network was suggested for detecting the microcalcification at every place in the pictures of the mammogram	The tested results depicted that RBF showed micro calcification detection rate of 93% in mammograms in contrast to various other existing techniques.

S. Kowsalya et al	2016	Used median fuzzy c-means scheme to detect masses and macro-calcification in pictures of mammogram	In contrast to k-means and Fuzzy C-means clustering approaches, the identification of masses and macro calcification gave more effectual results.
Benjamin Kaltenbach et al	2016	Used the matrix of morphology and distribution depictors with the BI-RAIDS calcification category	The morphology depictors estimated the malignancy risks as typically benign, indeterminate and typically malignant. The distribution descriptors compatible with the analysis of the malignant as diffuse, round or oval, regional, segmental, linear and branching
Vaia Koukou et al	2017	Dual energy subtraction method	152 m thickness of the calcification was visible and improves visualization of the calcifications
Bhupendra Singh et al.	2017	Proposed a novel approach that improved input image initially with the help of laplacian filtering.	The classification results obtained from Artificial Neural Network depicted that Daubechies-8 generated 92.8% true rate of detection and 12.5% positive false rate with low frequency elements of 50% in conjunction with statistical characteristics.
Juan Wang et al.	2018	Developed a context-sensitive deep neural network (DNN) to detect MC. For this purpose, both the local image characteristics of an MC and its underlying tissue background were considered	The achieved outcomes revealed that that the proposed scheme was able to get a considerably better accuracy rate to detect individual MCs. The proposed scheme integrated image related information in MC detection
J. J. Mordang et al.	2018	Presented a study to evaluate the number of times females with hidden calcifications in earlier testing of mammograms were later recognized with invasive cancer	It was concluded that it was possible to detect 54.5% of cancer related calcifications in early stage. This could significantly decrease the incidence of invasive cancers in the given populace
Juntao Li et al	2018	This paper shows the comparison between DBT and FFDM	DBT shows the 92.9% sensitivity, 87.9% specificity, 77.8% and 96.4% positive and negative predictive values than FFDM.
Sanket Agrawal1 et al.	2018	Hybrid approach of deep leaning model VGG16 and linear classification	Classify the mammograms into normal (no tumor present) or abnormal(tumor or calcification present)
Mohammed A. Al-masni et al	2018	YOLO-based CAD system	Detect mass locations with 99.7%accuracy and differentiate the benign and malignant with 97% accuracy
Jose M. Celaya-Padilla et al	2018	A CADx approach-Contralateral asymmetry	Discern between the healthy subjects and risky subjects and achieved AUC i.e. 0.738&0.767 and diagnostic odds ratio of 23.10 &9.00
A. Relea, J.A. Alonso, et al	2018	Ultrasonography for evaluating the effectiveness of the twinkling artifact on Doppler ultrasound	By twinkling sign they identify the 27 additional groups of calcifications.
Fung Fung Ting et al.	2018	Proposed algorithm called CNNI-BCC and used the convolutional neural network for identifying breast cancer	Classifies malignant, benign and healthy patients with 89.47% sensitivity, 90.50% accuracy and 90.71% specificity.
Mina Yousefi et al.	2018	Used CAD framework based on DCNN and MIL for mass detection	Reported an accuracy of 86.81%,86.6% sensitivity and 87.5% specificity.
Mai S. Mabrouk et al	2019	Integration of the features like shape, texture and invariant moment features.	96% accuracy is achieved in ANN automatic way and According to invariant moment features 97%accuracy is achieved.

III. METHODOLOGY

The steps to develop these medical diagnostic systems are as follow-

1. In first step, generally the data is collected from various reliable source like hospitals, doctors etc.
2. In second step, the pre-processing is done on the dataset taken is step 1. Some time data is incomplete, so it is required to complete the dataset. Basically, it is data analysis.
3. In this step, the artificial algorithm is decided. This artificial algorithm would be applied on this dataset.
4. Training and testing will be done in this step.

IV. CONCLUSION

A cancer diagnosis and treatment plan are essential component of any overall cancer prevention strategy. The main goal is to treat the patients who have cancer or extend their life significantly, make a sure good life. The epidemic mammography and many other techniques are quite famous and useful for the detection of calcification in breast cancer. This paper has taken charge of several strategies of calcification detection in breast cancer. These techniques are like mammography, ultrasound, CAD systems, artificial and image processing techniques.

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