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Advances in Breast Cancer Detection Techniques: A Comprehensive Survey

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التقدم في تقنيات الكشف عن سرطان الثدي: مسح شامل

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ABSTRACT

Breast cancer is an old disease, but it has significantly spread in the past few periods, which led to the intervention of computer vision to solve the problem of classification and increase the accuracy of diagnosis to help doctors and radiologists. The computer task was not easy at first, but with artificial intelligence, the concept changed. There are several studies in this regard, from which we chose 27 modern studies from the year 2019 to the year 2023 in various ways to come out with results that are the focus of a new start in the classification. This review collected different machine learning methods, deep learning methods, and CNN structures. Through this study, deep learning shows its superiority over other techniques. The convolutional neural network is considered one of the most important techniques that is characterized by high accuracy in classifying medical images.

This study comprehensively reviews various machine learning and deep learning techniques for breast cancer detection. It also shows that deep learning (CNN) technology is the best in giving accurate classification results. The choice of learning algorithm should have high accuracy if applied to medical images because the result is relevant to the patient's life which should be taken into consideration in the design phase.

Key words: Breast Cancer, Machine Learning, Deep Learning, Convolutional Neural Network, Long Short Term Memory.

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INTRODUCTION

Around the world, breast cancer poses a dreadful threat to women [1]. It is associated with lung cancer as the second most common type of Cancer in women, which is breast cancer. According to a recent survey conducted by the World Health Organization and the American Institute for Cancer Research, about 2 million women The presence of this disease is recognized annually. 15% of deaths are related to Cancer Because of breast cancer. In addition, reports indicate that 85% of females are affected by this disease. There is no genetic relationship to breast cancer, and less than 15% of women develop it Possessing genetic heritage. Gene mutations are the leading cause of breast cancer as a result of ageing. Fifty per cent of breast cancer patients are in emerging countries. It falls between the third and fourth stages of Cancer[2].

Breast cancer manifests as abnormalities such as breast pain, color changes in the breast tissue, changes in the size and shape of the breast, and the development of a breast lump. Typically, breast cancer is examined using imaging methods like magnetic resonance imaging, X-rays, and ultrasound.

However, one of the best methods for detecting breast cancer early on is the mammogram [3]. Mammography is regarded as one of the most effective techniques for identifying breast cancer early on because the four leading indicators of breast cancer that can be seen on mammograms are mass, microcalcification, architectural distortion, and bilateral asymmetry [4].

Still, a radiologist finds it challenging to interpret due the sensitivity of the mammography is greatly affected by the image quality. Double reading was introduced, in which two radiologists read the same mammogram; however, Despite the fact that this makes the diagnostic more sensitive, the method is not cost-effective [5].

For these reasons, artificial intelligence systems have been developed to help diagnose diseases, including breast cancer.

Machine learning is the ability of computers to learn from training data unique to a particular scenario, automating the process of creating analytical models and carrying out related tasks. An approach to machine learning called "deep learning" is based on artificial neural networks. Deep learning models perform better than shallow machine learning models and conventional data analysis techniques for a wide range of applications [6].

Traditional methods for extracting features from images rely on researchers' previous experience, which has serious drawbacks. In recent years, computer vision has seen tremendous progress in deep learning algorithms. Compared with traditional methods, its results have been greatly improved. Because it compensates for the shortcomings of traditional feature extraction techniques, the convolutional neural network model's excellent representation efficiency makes it an intriguing model to study. Convolutional neural networks (CNNs) have shown encouraging results in image identification, object detection, and other domains. They can automatically learn complex image features [5, 6].

This article discusses many kinds of research that used different artificial intelligence techniques.

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RELATED WORK

In reference [7] Authors proposed approach consists of two steps: an extensive public digital database of mammograms (CBIS-DDSM dataset) is used to train the CNN, and a smaller digital mammography database (INbreast dataset) is used to transfer and test the model. The second step is to evaluate three popular CNNs (InceptionV3, ResNet50, and VGG16). The results were that a better true positive rate (TPR) of 0.98 × 0.02 at 1.67 false positives per image (FPI) is achieved by transfer learning from CBIS-DDSM, according to the results, compared to transfer learning from ImageNet, which produces a TPR of 0.91 × 0.07 at 2.1 Investing in financial portfolios. In reference [4] the study used a hybrid feature selection methodology. A bias minimization approach that combines correlation and redundant feature removal is proposed for a support vector machine. The authors also looked at a new similarity-based learning algorithm for classifying malignant and benign tumors, called Q, using the MIAS and DDSM databases. The results showed an accuracy of 98.16%, sensitivity of 98.63%, and Specificity.97.80% and the computational time is 2.2 seconds.

In reference [8] the discriminative power of the generated features is assessed using a suggested classifier that uses a group-based NN feature extraction technique. It generates features for every deep substructure when applied to preprocessed ROI image patches of the CBIS-DDSM dataset. Improved feature: The exploited characteristics are normalized to prepare the vector, which is then sent to the NN Classifier for final classification. Thus, achieving an accuracy of 0.88 with an area under curve (AUC) of 0.88.

In reference [9] the authors suggested automated architecture is presented for full-field digital mammography (FFDM) bulk detection. This is used for block detection in the extensive OPTIMAM Mammography Image Database (OMI-DB) and is based on a quicker region-based convolutional neural network (faster-RCNN). Additionally, a TPR of 0.75 at 0.20 FPI and a sensitivity of 0.75 with a sensitivity of 0.75 are obtained in the OMI-G dataset. The public dataset INbreast yields a sensitivity of 0.87, Specificity of 0.90, and TPR of 0.87 at 0.1 FPI for malignant tumors.

In reference [10] the authors chose to conduct a study to compare the latest technologies in the modern era to detect and classify breast cancer using different machine learning methods, as well as a comparison between the most famous data sets used and the results were that the best data set is CBIS-DDSM. The comparison research reveals that You Only Look Once (YOLO) and Retina Net are the most recent models with the highest accuracy based on straightforward detection and classification architectures.

In reference [11] The authors used the DDSM data set, which was divided as follows: 80% training, 10% testing, and 10% validation. The previously trained Inception V3 model was retrained using once-segmented mammography tumor masses in the first experiment. A new SoftMax layer was added instead of the output layer for binary classification, Cancer, and Benign. Two fully connected layers with a two-layer output were added ahead of the last layer. The first seven layers were frozen to prevent the weights from being modified. Retraining the ResNet50 on the pre-segmented mass employed the same layer configuration used for the InceptionV3 model. However, as opposed to seven layers in the initial experiment, only the first six were frozen. He obtained results in the first experiment with an accuracy of 79.6%, precision of 75.4%, and sensitivity of 89.1%. The second experiment gave an accuracy of 85.71, and the Recall rate was 87.3. The accuracy was 85.7. As the results showed, ResNet50 outperformed InceptionV3.

In reference [12] The Convolutional Neural Network (CNN) architecture was proposed on simplified feature learning and a finetuned classifier model to separate cancer-normal cases on mammograms. Here, the dataset was DDSM. Only regular and cancer-infected images were relied upon, and they suggested a system to distinguish between cancer-normal cases on mammograms; Convolutional Neural Network (CNN) architecture was developed using reduced feature learning and finetuned classifier models. The proposed Deep model's accuracy, sensitivity, Specificity, and precision performance rates were 92.84%, 95.30%, and 96.72%, respectively.

In reference [13] In this study, the MIAS database was used to classify breast cancer into benign and malignant tumors using a modified AlexNet DCNN. The outcomes show that the updated AlexNet architecture's fully connected layer classifier has an overall classification accuracy of 95.70 per cent. In reference [14] classifying breast cancer, a multiscale convolutional neural network (MA-CNN) was suggested. To extract the features of various levels in the MA-CNN, they used extended convolution and three dilated convolutions of different sizes applied to the MIAS dataset. The following results gave an accuracy of 96.47% and a sensitivity of 96%, while the Specificity was also 96, F1, and 0.99 for AUC. In reference [15] They worked on increasing the accuracy and performance of previously trained networks for classification using a modern method, DSTL, a double-shot transfer learning method. It adjusts the weights and biases of a sizeable pre-trained dataset by updating it and making it similar to the target dataset. This proposal has led to an increase in both the accuracy and performance of the pre-trained networks. This work was based on the CBIS-DDSM, MIAS and BCDR datasets.

In reference [16] suggested the BMC, a novel method of classifying breast mass. He improved the methods for classifying breast masses into benign, malignant, and normal by optimizing the architecture using a combination of k-means clustering, short-term memory networks, recurrent neural networks (RNN), CNN, and random forests and utilizing two publicly accessible sets of mammography images, DDSM and MIAS. Techniques such as fuzzy SVM, Bayesian classifier, and random forest are employed to categories these preprocessed images. The BMC system attains the following results: 0.97%, 0.98%, 0.97%, and 0.96% for the DDSM dataset and 0.97%, 0.97%, 0.98%, and 0.95% for the MIAS dataset, respectively. Additionally, the Area Under Curve (AUC) rate of the suggested BMC system is between 0.94% and 0.97% for the DDSM dataset and 0.94% and 0.98% for the MIAS dataset. Fuzzy SVM outperforms the random forest technique and the Bayesian classifier. According to the reference [17] X-ray imaging can identify breast cancer using adaptive contrast finite histogram equalization for picture preprocessing. A support vector machine (SVM) is then employed for classification. Patterns can be classified as normal or aberrant using a classifier. Ultimately, an adaptive neuro-fuzzy inference system is used to precisely classify distortions and remove ambiguities from overlapping pattern features within images. The MIAS database displays 98.01% accuracy for both normal and aberrant mammography.

In reference [18] the authors developed a system for early detection of breast cancer using multiple data sets, namely MIAS, DDSM and INbreast. Their system was done in two first steps: making some image adjustments through preprocessing represented by unifying coordination, removing noise, improving the appearance, extracting the ROI and increasing the image size. Image. The second step is to classify the images using CNN. The results were as follows for sensitivity, Specificity, accuracy, and AUC. The INbreast data set obtained 96.55%, 96.49%,

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96.52, and 0.98%, respectively. For MIAS, the results were, respectively, 98%, 92.6, and 95.3, as well as 0.974. In reference [19] obtain the best accuracy for early detection of breast cancer by using the MIAS data set and inserting it into a convolutional neural network with the VGG-16 and VGG-19 models as well as ResNet50 with the help of transfer learning and data augmentation techniques. The ResNet50 model has an accuracy of 86% over the two models in the verification process. The training process was also the best, with an accuracy of 71%, while VGG-16 got 64%, and VGG-19 had an accuracy of 61%.

In reference [20] integrate the mathematical morphology method, image template matching method, BD-CNN and breast mass bounding box regression model based on PSO. They have come to conclusions with 85.82% accuracy, 66.31% F1-score, 95.38% recall, and 50.81% precision.

In reference [21] in contrast to current techniques, such as CNN using the MIAS database, the authors describe a novel approach for identifying breast cancer using machine learning techniques (Particle Enhanced Wavelet Neural Network, or PSOWNN). And have an accuracy of 98.6% and 98.8%, respectively. Compared to SVM, KNN, CNN, and other machine learning algorithms, PSOWNNs are more accurate.

In reference [22] say that the VGG16 network performed best during the feature extraction phase compared to a set of pre-trained convolutional network architectures (ResNet50, MobileNetV2, and InceptionV3). VGG16 was then combined with the random network Forest classifier to create the final hybrid model. The region below the average model accuracy of 94.25% was also reached. Not only does the AUC curve exceed 98% for all three categories, but it also takes less time to design the system.

In reference [23] applied their model to a unique data set in addition to MIAS, and by using preprocessing, data augmentation, and transfer learning, the clarity of the two data sets increased, thus giving results with the best accuracy. The model was based on ConvNet's deep understanding to classify breast cancer as benign or malignant. The results were 98% for training accuracy, 97% for test accuracy, and 99% for sensitivity and AUC.

In reference [24] said to perform automatic identification of BC using the CBIS-DDSM dataset, a CNN model called CoroNet is presented. It is based on the Xception architecture, which was pre-trained on the ImageNet dataset and has been thoroughly trained on mammogram-based whole-image BC. The results reached an accuracy of 94.92% in the classification of four categories % (benign mass vs. malignant mass) and (benign calcification vs. malignant calcification). In the case of binary type, the accuracy reached 88.67% (calcifications and masses).

In reference [25] authors finetuning multiple pre-trained models, transfer learning distinguishes between aggressive and benign breast cancer. Provide a framework in this study built on the idea of transfer learning. Moreover, various augmentation techniques, such as scaling, shifting, and numerous rotation combinations, were applied to increase the number of mammography images and avoid overfitting. Tested on the Mammographic Image Analysis Society (MIAS) dataset, the suggested system obtained an accuracy of 70% using the Nasnet-Mobile network and 89.5% using ResNet50 (residual network-50). Pre-trained classification networks are far more effective and efficient than untrained classification networks, as demonstrated by the proposed method. For short training datasets in particular, this makes them more appropriate for use in medical imaging.

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In reference [1] in this work, they conducted a competition between two deep learning models, one of which is CNN and the other R-CNN, for classification based on the MIRS database. The results indicated that CNN excelled in the accuracy test, as it got 91.26%, compared to 63.89 for R-CNN. In reference [26] the work here uses deep learning and ResNet18 architecture for feature extraction and algorithm-improved Crow Search Optimized Extreme Learning Machine (ICS-ELM) algorithm. The results showed an increase in accuracy for MIAS, which was 98.13%, DDSM got 97.13, and 98.266 was the best for the INbreast database.

In reference [27] Suggested the use here Deep Belief Networks (DBN) on ROI images for breast cancer diagnosis. It has been applied to the DDSM dataset. DBN models were iterated on various image sizes to assess the influence of dimensionality on ROI images. Specificity, sensitivity, and precision performance rates of 96.32%, 96.68%, 95.93%, and 96.40%, respectively.

In reference [28], their study used the convolutional neural network and the random forest classifier to work more accurately in diagnosing breast cancer in CNN. They relied on AlexNet to extract the characteristics. This study used several data sets: MIAS, CBIS DDSM, and IRMA. This model was one of the most accurate studies in its results, as it obtained an accuracy of 98.6% with a precision of 98%, Specificity of 99%, Recall of 98% and F1-score of 96%.

In reference [29] suggested a two-phase framework: (1) preparing the data (i.e., images) and (2) using A to extract features. The MobileNetV2 model that has been pre-trained was applied to the MIAS and INbreast databases. Following this stage of classification, one layer makes use of sensory perception. The outcomes of the experiments demonstrate the effectiveness and Precise in identifying irregularities (for example, 81.40% to 97.36% by AUC.

In reference [30] compared Shallow convolutional neural networks against deep convolutional neural networks-based approach. The results of the CBIS-DDSM and INbreast datasets were used, respectively, with accuracy rates of 80.4%, 89.2%, 87.8%, and 95.1%. From the experimental results, it can be inferred that the deep network-based method with exact tuning surpasses all other cutting-edge methods in studies on both datasets.

In reference [31] worked based on different CNN structures, namely ResNet50, Inception-V3, and AlexNet, for extracting features. Uniquely, the term variance feature was used as a feature specifier and classified by MSVM. The above was tested on the MIAS dataset and the results were as follows: Compared to previously published work, a higher classification accuracy (CA) is reached. The average CA is 97.81% for 70% of training and 98% for 80%, achieving its maximum value of 90%. In reference [32] proposed an approach based on multiple previously trained convolutional neural network models. Then, they collected them to extract the most important features to classify them using machine learning algorithms, which are neural network (NN), k-nearest neighbor (KNN), random forest (RF), and support vector machine (SVM). The results indicate the superiority of the NN-based classifier in obtaining the best accuracy for the used datasets, which are as follows: 92%,94.5%, and 96% for the RSNA, MIAS, and DDASM datasets, respectively.

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Table 1. Detection techniques Metrics for Breast Cancer

Ref. No.	Dataset	Techniques	Results
[1]	MIAS	CNN + R-CNN	Accuracy for CNN: 91.26%, and R-CNN: 63.89
[4]	MIAS + DDSM	Q Classifier	Accuracy:98.16
[8]	CBIS-DDSM	the NN Classifier	Accuracy: 88%
[7]	CBIS-DDSM + INbreast	CNNs (InceptionV3, ResNet50, and VGG16)	Accuracy:98%
[9]	(OMI-DB) + INbreast	faster-RCNN	Sensitivity: 0.75 Specificity: 0.90
[10]	DDSM+CBIS-DDSM+ MIAS +INbreast	AlexNet + GoogleNet + YOLO + RetinaNet	Accuracy: AlexNet: 95.64% YOLO: 97%, GoogleNet AUC: 88% RetinaNet TP rate is: 97%
[11]	DDSM	CNN (Inception V3 + ResNet50)	Accuracy: 79.6, Precision: 75.4 Sensitivity:89.1 Recall: 87.3
[12]	DDSM	CNN	Accuracy: 92.84 Sensitivity:95.3 Specificity:96.7
[13]	MIAS	CNN	Accuracy: 95.70
[14]	MIAS	MA-CNN	Accuracy: 96.47 Sensitivity: 96, Specificity: 96
[15]	CBIS-DDSM + MIAS + BCDR	Double shot transfer learning (AlexNet, VGG, GoogLeNet, ResNet ShuffleNet , MobileNet-v2)	Accuracy for: MIAS (With DSTL) AlexNet :92.11% GoogLeNet: 96.49% ShuffleNet: 96.49%, MobileNet: 98.25% ResNet-50: 95.61%, VGG: 93.86%
[16]	DDSM + MIAS	BMC, K-Means, LSTM Network, RNN, CNN, and Random Forests RF	Accuracy: 95% Sensitivity: 97, Specificity: 97, F1-measure: 98%
[17]	MIAS	SVM	Accuracy: 98.01%
[18]	MIAS + DDSM + INbreast	CNN	INbreast Dataset Sensitivity 96.55, Specificity 96.49, Accuracy 96.52 and AUC 0.98%, For MIAS dataset, Sensitivity 98%, Specificity 92.6, Accuracy 95.3, AUC: 97.4%
[19]	MIAS	CNN (VGG-16, VGG-19, ResNet50)	Accuracy for ResNet50: 71%, VGG-16: 64%, VGG-19: 61%
[20]	DDSM	CNN	Accuracy: 85.82%, F1-score: 66.31% Recall: 95.38%, Precision: 50.81%
[21]	MIAS	CNN	Accuracy 98.6%
[22]	MIAS	CNN (VGG16) + Random Forest RF	Accuracy 94.25% AUC curve 98%
[23]	MIAS	CNN (ConvNet)	Accuracy: 97% Sensitivity: 99% AUC: 99%

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[24]	CBIS-DDSM	CNN (ConvNet)	accuracy 94.92%
[25]	MIAS	CNN (ResNet50, Nasnet-Mobile Network)	Accuracy for ResNet50: 89.5% Nasnet Mobile Net70
[26]	DDSM + INbreast	(ICS-ELM)	Accuracy for MIAS, which was 98.13%, DDSM got 97.13 and 98.266
[27]	DDSM	Deep Belief Networks (DBN)	Specificity: 96.32%, Sensitivity: 96.68%, Precision: 95.93%
[28]	MIAS + CBIS DDSM	Random Forest RF classifier + CNN	Accuracy 98.6% with a precision of 98%, Specificity of 99%, Recall of 98% and F1 score of 96%
[29]	MIAS + INbreast	CNN (MobileNetV2)	Accuracy 81.40% to 97.36% by AUC
[30]	CBIS-DDSM + INbreast	Shallow CNN and Deep CNN	Accuracy rates of CNN:80.4%, and DCNN: 95.1%
[31]	MIAS	MSVM	Average CA:97.81% for 70% of training and 98% for 80% of training
[32]	MIAS+ DDSM	NN, KNN, RF, SVM	Accuracy for: MIAS 94.5%, DDASM 96%

DATASET

The datasets related to breast cancer can be separated into two categories: those containing medical files and those containing extracted features but no medical files. There are a few medical image datasets available, including Mini Mammographic Image Analysis Society (Mini-MIAS), INbreast, and CBIS-DDSM. On the other hand, the most well-known extracted feature datasets are the SEER and Wisconsin Breast Cancer Datasets (WBCD). The Digital Database for Screening Mammography (DDSM) has been updated and standardized, and the Curated Breast Imaging Subset of DDSM (CBIS-DDSM) contains 2620 scanned film mammograms (TCIA, 2020). Additionally, this dataset compiles several benign, malignant, and normal instances together with validated pathology data. Only cases of malignant medical imaging are gathered by CBIS-DDSM, which then converts the images to DICOM files to improve their quality (TCIA, 2020). On the other hand, another dataset that includes features extracted from 699 images acquired from the University of Wisconsin Hospitals is the Wisconsin Breast Cancer Dataset (WBCD) (Frank & Asuncion, 2010). About 2500 mammography images are available in the Digital Database for Screening Mammography (DDSM), and 322 digitized films are available in the MIAS Mini-Mammographic Database (VCL, 2020). There are 410 mammography images in the INbreast database, of which 360 have been used to create 90 instances of women for both breasts (four photos per case). The remaining 25 instances consist of two photos per mastectomy patient (Moreira et al., 2012). Thousands of extracted features are gathered by SEER from photos of breast cancer and other cancer kinds (National Cancer Institute, 2020). Furthermore, 9109 microscopic pictures of breast lesion tissue from 82 individuals are included in the Breast Cancer Histopathological Image Classification (BreakHis), which was assembled using various enlarging factors (40X, 100X, 200X, and 400X). In essence, this dataset compiles 5429 malignant and 2480 benign samples. Each image includes the following characteristics: 700X460

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pixels, 3-channel RGB, 8-bit depth for each channel, and PNG file format (Spanhol et al., 2015). However, annotated tissue pictures and related expression data are available in the Stanford Tissue Microarray Database (Marinelli et al., 2007).

The Digital Database for Screening Mammography (DDSM) has been modified and standardized into the CBIS-DDSM (Curated Breast Imaging Subset of DDSM). A database including 2,620 scanned film mammography studies is called the DDSM. With validated pathology information, it includes cases that are benign, malignant, and normal. When developing and testing decision support systems, the DDSM is a helpful tool because of its extensive database and ground truth checking. A portion of the DDDSM data hand-picked and arranged by a qualified mammographer is part of the CBIS-DDSM collection. After being decompressed, the pictures were transformed to DICOM format. Additionally included are updated bounding boxes, ROI segmentation, and psychological diagnosis for training data [33]. The S. Joao Hospital Center in Porto provided the INbreast [34]. There are 410 complete digital mammograms in it. Although it is not readily available online, INbreast can be accessed upon request [35]. The database of the Mammographic Image Analysis Society (MIAS) was consulted. A data annotation file provided by the MIAS contains specific information about the data, such as the number, background organizational features, anomaly type, anomaly severity, center coordinates, and center radius of the anomaly site. The MIAS has 322 images in total [36]. MI-DB dataset with approximately 145,000 cases (over 2.4 million images) of unprocessed and processed FFDMs from the UK's National Health Service Breast Screening Program, the OMI-DB [37] is an extensive mammography image database.

Breast Cancer Digital Repository (BCDR):

Public access has been granted since 2012, and work is ongoing. It offers breast cancer patients comprehensive cases, including mammography Describes the lesions, the most common abnormalities, precalculated features, and clinically significant information. BIRADS, biopsy-proven and annotated by specialist radiologists, classify patients' cases. Images are saved in TIFF format with a bit depth of 14 bits per pixel [38].

Tablel.2 Dataset of Breast cancer [10]

Dataset	No. of cases	No. of Image	Available classes	Image Format	Publicly available
DDSM	2620	10,480	N, B & M	JPEG	Yes
CBIS-DDSM	6775	10,239	N, B & M	DICOM	Yes
MIAS	-	322	N, B & M	PGM	Yes
INbreast	115	410	N, B & M	DICOM	No
BCDR	1734	FM3703 DM3612	N, B & M	TIFF	Yes

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CLASSIFICATIONS OF BREAST CANCER

Breast cancer has many different types. After diagnosing cancer, specialist doctors search for the type of breast cancer that has been diagnosed in order to determine the most appropriate and effective treatment to get rid of the disease.

A) Non-Invasive breast cancer:

Another name for intraductal adenocarcinoma is ductal carcinoma in situ (DCIS) of the most prevalent forms of breast cancer is ductal carcinoma in situ, a non-invasive and pre-invasive form of the disease [39, 40, 41].

B) Invasive Infiltrating:

- invasive ductal carcinoma.
- invasive lobular carcinoma.
- medullary carcinoma.

MACHINE LEARNING METHODS FOR BREAST CANCER DETECTION

Due to the exponential increase in data, it is now challenging for human programmers and specialists to identify meaningful patterns within data sets. This justification has led to the widespread application of machine learning in computer science across several fields, especially when large-scale datasets need to be mined. Many features are included in the apps, including facial and voice recognition, online searching, medical image classification, spam filtering, and online searching. Two main machine learning techniques that have become widely used are supervised learning and unsupervised learning. In supervised learning, the algorithm is trained on pre-existing labelled datasets to benefit from the annotations that have been supplied. Conversely, unsupervised learning uses unlabeled training data to speed accelerate the algorithm's finding [42].

- **Neural Networks (NN):**

Artificial neural networks aim to replicate the neural networks found in the human brain through engineering. An artificial neural network's capacity for learning and generalization is its most crucial feature. It is made up of the subsequent layers [43]:

1. Input layer: It just provides data to the network; it doesn't process anything.
2. The hidden layer: Features are extracted, and data is fed to the output layer.
3. Output layer: It can be categorized as abnormal or usual [43].

- **Random Forests:**

Random forests, also known as random decision forests, are an ensemble approach for classification, regression, and other tasks. During the training phase, they build many decision trees and produce a class representing the mean prediction (regression) or the mode of the categories (classification) of the individual trees. Arbitrary Decision trees adjust for their tendency to overfit their training set [44].

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For Pure and Applied Sciences (JUBPAS)
Vol.32; No.1.| 2024

- **Q Classifier:**

It is intended for the Q-classifier to learn from unbalanced datasets [45]. The Q-classifier, in contrast to conventional similarity-based methods, uses adaptive similarity parameters that are learned in a way that takes into account data imbalances rather than using preset parameters for the similarity function. The stages listed below can be used to summaries the Q-classifier algorithm [45].

1. Feature selection: Using cluster centers as historical points, aggregating data points from majority and minority classes to select historical facts from the training set. K-means strategy is used for the clustering process because it produces better results than other techniques, such as SVM.
2. Similarity function parameters: Unlike traditional similarity-based algorithms, data imbalance is considered using a similarity function varying with the parameters learned during the training phase.

- **Support Vector Machine (SVM)**

Helps with machine learning-based classification and regression issues. SVM- It functions as a binary linear classifier that is non-probabilistic. It is the dividing line between the two groups that he constructs a fast aircraft. It also SVM Quadratic equations are solved with its help [46].

- **The K-Nearest Neighbor (KNN)**

KNN classifier is among the basic classifiers. It is referred to as a "lazy" algorithm. An algorithm that makes no assumptions about data distribution is called a non-parametric algorithm. This is not what the KNN classifier does. Based on the nearest neighbor of the unknown pattern, the KNN method is used to determine its appearance. The nearest neighbor classifier is used to classify images. The KNN classifier consists of two parts. The first step is determining the distance between each image used in the training phase and the unknown image. The second step is choosing which training images will likely be test images. Using Euclidean distance, the items are classified [47].

- **K - Means**

For cluster analysis, K-means is a well-liked unsupervised machine learning algorithm. To divide "n" observations into "k" clusters is its objective. Because every observation is a part of the closest mean-containing cluster, acting as a prototype for the group. The average observations within a specific cluster establish the cluster's core [48].

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DEEP LEARNING METHODS FOR BREAST CANCER DETECTION

A branch of machine learning is called deep learning. Deep learning is an unsupervised method that gathers knowledge from the data. Both unstructured and unlabeled data are possible. What separates deep learning from machine learning is that deep learning is more goal-oriented than machine learning [49].

- **Convolutional Neural Networks (CNN):**

  One of the most widely used methods for deep learning with images and video is the convolutional neural network (CNN, or ConvNet). A CNN comprises numerous hidden layers between input and output layers and other neural network components. Layers for Feature Detection These layers carry out three different kinds of actions on the data: convolution, pooling, or rectified linear unit (ReLU).

  Convolution applies convolutional filters on the input images, each bringing up specific features from the pictures. Pooling streamlines, the result by nonlinear down sampling, lowering the number of parameters the network must become familiar with. Rectified linear units, or ReLUs, enable quicker and more training that works well by mapping negative values to zero [50, 51, 52].

- **ICS-ELM Algorithm:**

  In most metaheuristic optimization strategies, a few parameters must be set randomly, uniformly or Gaussian distribution. As a result, the pace of convergence has become slower. Any violations in improvement procedures. This is due to excessive.

  When this problem arises, two CSOA modifications are required. To speed up the rate of its convergence by the ICS-ELM algorithm, the first is to add A direct control setting that causes the flock's crows to move and find global minima. As a result, the algorithm will form the local optimization dilemma. The following involves management Randomize the algorithm using chaotic maps to achieve Reliable and optimized production [26, 54, 55].

- **Deep Belief Networks (DBN):**

  A DBN is a generative model comprising several layers of restricted Boltzmann machines (RBMs). It is an undirected, bipartite, two-layer (visible and hidden) model. Values can spread from visible to hidden and from hidden to Totally connected (every neuron in a visible layer is connected to every other neuron in the following hidden layer) that is fully visible directions tier). Should a connection exist between two neurons at the same time layer, a Boltzmann machine will be used (instead of a limited Boltzmann. An RBM's energy function is utilized to determine its probability, indicating the range between which it can be employed in the units of the visible and concealed layers to reduce the conditional.

  Likelihoods of the inputs and results. The likelihoods p(weighted input-output) and p(input| weighted output) will be estimated before and behind propagations. Thus, it is referred to as the generative model, as it has been taught to recreate the estimates of the probability density function (pdf) based on the input data [51, 56, 57].

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DISCUSSION AND ANALYSIS OF RELATED WORK

Given the importance of diagnosing breast cancer and the extent of its danger to the patient's life, there may be an increase in diagnoses that are incorrectly classified as normal (false positives) and in cases where the breast is affected and diagnosed as normal (false negatives). Accurately determining a breast cancer diagnosis in real time requires complex mathematical calculations. Deep learning, as one of the types of machine learning, has had an excellent role in diagnosing breast cancer thanks to its hidden layers that give the most accurate results for diagnosis, compared to previous related works that gave the best results. This study aims to evaluate the system using several criteria: accuracy, precision, F1 score, Recall, and AUC. Table 3. displays performance measures for a selected group of research in the field of breast cancer detection.

Table. 3 Reference with Performance Metrics

Ref. No.	Accuracy	Precision	F1-score	Sensitivity	Specificity
[1]	91.26				
[4]	98.16				
[7]	98				
[8]	88				
[9]				87	90
[11]	85.71				
[12]	92.84			95.30	96.72
[13]	95.70				
[14]	96.47		96	96	96
[16]	95		98	97	97
[17]	98.01				
[18]	95.3			98	92.6
[19]	71				
[20]	85.82	50.81	66.31		
[21]	98.6				
[22]	94.25				
[23]	97				99
[24]	94.92				
[25]	89.5				
[26]	98.13			96.68	96.32
[27]	96.40	95.93			
[28]	98.6	98	96		99
[30]	80.4				
[31]	97.81				

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CONCLUSIONS:

This study comprehensively reviews various machine learning and deep learning techniques for breast cancer detection. Breast cancer is a terrifying concern for a large number of women due to its prevalence. This study emphasized the importance of diagnosing breast cancer early because of its negative effects on the body that may lead to death. Therefore, creating a system that enables it to diagnose the disease as quickly, more accurately, and at the lowest cost is necessary. To address the difficulties in preprocessing, there are several methods, including converting color images to grayscale images, as well as normalization and other image processing techniques, in addition to feature extraction techniques to prepare the model training. If there is an imbalance or lack of data entered, there are several methods for processing it, including dropout and data augmentation. Through this study, deep learning shows its superiority over other techniques. A convolutional neural network is one of the most essential techniques characterized by high accuracy in classifying medical images. The choice of the learning algorithm must have high accuracy if applied to medical images because the result relates to the patient's life, which must be considered in the design stage.

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Conflict of interests.

There is no conflict interest

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الخلاصة

يعتبر سرطان الثدي من الأمراض القديمة إلا أنه انتشر بشكل كبير في الفترات القليلة الماضية مما أدى إلى تدخل الرؤية الحاسوبية لحل مشكلة التصنيف وزيادة دقة التشخيص لمساعدة الأطباء وأخصائي الأشعة. لم تكن مهمة الحاسوب سهلة في البداية، لكن مع الذكاء الاصطناعي تغير المفهوم. وهناك عدة دراسات في هذا الشأن اخترنا منها 27 دراسة حديثة من عام 2019 إلى عام 2023 بطرق مختلفة للخروج بنتائج تكون محور انطلاقة جديدة في التصنيف. جمعت هذه المراجعة طرقًا مختلفة للتعلم الآلي وأساليب التعلم العميق وهياكل الشبكة العصبية التلافيفة CNN. ومن خلال هذه الدراسة يظهر التعلم العميق تفوقه على التقنيات الأخرى. تعتبر الشبكة العصبية التلافيفية من أهم التقنيات التي تتميز بالدقة العالية في تصنيف الصور الطبية.

تستعرض هذه الدراسة بشكل شامل مختلف تقنيات التعلم الآلي والتعلم العميق للكشف عن سرطان الثدي. كما يوضح أن تقنية التعلم العميق (CNN) هي الأفضل في إعطاء نتائج تصنيف دقيقة. يجب أن يتمتع اختيار خوارزمية التعلم بدقة عالية إذا تم تطبيقها على الصور الطبية لأن النتيجة ذات صلة بحياة المريض والتي يجب أخذها بعين الاعتبار في مرحلة التصميم.

الكلمات المفتاحية: سرطان الثدي، التعلم الآلي، التعلم العميق، الشبكة العصبية التلافيفية، الذاكرة طويلة المدى.