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A survey of approaches in Deep Learning techniques for the detection and classification of mammography abnormalities.

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***Abstract*—Mammography is currently the most widely used laboratory study for the early detection of precursor abnormalities of breast cancer, which is one of the main causes of mortality worldwide since this disease generates the appearance of large volumes of cancerous cells in the breast.**

Thus, Computer-aided detection or diagnosis (CADe and CADx) can help the specialist improve the accuracy of the diagnosis, providing the patient with a better treatment and disease management assessment. Unfortunately, there are several circumstances in which it is possible to obtain an erroneous diagnosis, such as subjectivity on the part of the radiologist due to the size or morphology of the anomalies detected, as well as the fact that mammograms may include embedded noise.

For this reason, this manuscript seeks to provide the reader with a more general overview of how this issue has been addressed in recent years (2016 onwards) through the compilation of various scientific research focused on the detection and classification of breast cancer precursor anomalies based on the implementation of artificial intelligence techniques, where it is possible to visualize the performance of each of the proposed models through the implementation of various metrics such as F1 Score, AUC, accuracy, etc. Thus, these studies have been obtained from recognized multidisciplinary scientific sites in the world such as Nature, Springer, IEEE Xplorer, and PubMed, among others.

Keywords— Anomalies, breast cancer, Artificial Intelligence, metrics.

I. INTRODUCTION

According to the World Health Organization (WHO), breast cancer is estimated to be the leading cause of death in women, with more than 2.2 million cases in 2020, and some 685,000 women died from the disease [1]. Breast cancer is a pathology associated with aging, unhealthy lifestyles and changes in reproductive patterns. This disease can initially present in different parts of the breast.

Nowadays, laboratory studies are indispensable tools to evaluate the patient's state of health, as is the case of mammography, which is an X-ray imaging modality used to classify subtle changes in breast tissues.

In developing countries, there is a higher percentage of mortality in the female population because it is usually detected at a very advanced stage, this is due to the lower access to health services for early detection, treatment, and control [2].

Due to their visual interpretation complexity, several recent types of research have emerged using image processing and artificial intelligence techniques.

Therefore, this paper reviews the state of the art to provide the reader with a clearer view of the deep learning techniques that have been implemented in recent years as essential tools to support the radiologist in detecting and classifying abnormalities in mammograms.

II. LITERATURE REVIEW

The present research attempts to find answers to several questions focused on breast cancer classification using Deep learning techniques. The following points are considered while developing this document: types of datasets used for deep learning classification models, metrics used to evaluate breast cancer models, and recent types of deep learning classifiers used for breast cancer.

For this reason, several well-known multidisciplinary scientific websites: PubMed, Nature, Springer, IEEE Xplorer, etc., are explored using keywords such as breast cancer in mammography for detection and classification of suspicious abnormalities and masses using deep learning schemes; where the most relevant articles published since 2016 were selected.

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A. Imaging Modality: Mammography

Mammography is a laboratory study, which allows physicians to identify subtle changes in the breast tissue, where most of them cannot be detected during a breast examination.

This modality is commonly used by medical specialists as a tool to obtain a better visualization of each breast through the visualization of the mediolateral oblique view (MLO) and the caudal cranial view (CC). In addition, it has a standardized breast lesion categorization system known as Breast Imaging Reporting and Data System (BI-RADS) [3], which was created by the American College of Radiology (ACR).

This system is divided into six categories (as shown in Table I), which are commonly implemented for the interpretation of mammography results, as it provides specialists with a guide to define the degree of suspicion of any abnormality, reducing discrepancies in interpretation.

TABLE I. BI-RADS SYSTEM CATEGORY.

Category	*Description*	*Features*
0	Incomplete mammogram. Additional imaging evaluation is needed and/or previous mammograms for comparison.	Not assessable
1	Negative study	Normal, Symmetrical breasts, without nodules, distortions, or calcifications.
2	Negative study with benign findings	Fibroadenomas, skin or vascular calcifications, cysts, galactoceles, hamartomas, lymphatic ganglions, etc.
3	Probably benign findings	Amorphous and clustered calcifications, Normal solitary nodule, Density, Focal Asymmetry
4	Suspicious findings 4A: Low suspicion of malignancy 4B: Moderate suspicious for malignancy 4C: High suspicious for malignancy	Irregular nodules, Parenchymal-like density, Heterogeneous microcalcifications, Loss of breast architecture, Enlarged lymph nodes
5	High probability of malignancy	Irregular nodule, spiculated, Density greater than parenchymal, Microlobulated, Microcalcifications, linear morphology
6	Proved malignancy	Confirmed by biopsy

However, early detection of abnormalities possibly precursors of breast cancer often poses great challenges, as these abnormalities often go unnoticed by the human eye, due to different causes such as the morphology of the abnormality, breast density, etc.

As a consequence, humans have developed computer-aided detection and diagnosis (CAD) systems, which aim to increase the accuracy of image interpretation. These systems fall into two categories: Computer Aided Detection System (CADe), which are responsible for performing the task of lesion localization; and Computer Aided Diagnostic System (CADx), which focuses on lesion classification [4].

Currently, the scientific society has several public databases of mammograms [5], including the Mammographic Image Analysis Society (MIAS), which contains images in pgm format with MLO view [4], [6], [7], [8], [9]; Dataset of breast mammography images with masses (INbreast), contains images in dicom format with MLO and CC views [4], [6], [10], [11], [12], [13]; Digital Database for Screening Mammography (DDSM), contains images in jpeg format with MLO and CC views [6], [8], [14]; Curated Breast Imaging Subset of Digital Dataset of Screening Mammography (CBIS-DDSM), which is a new version of the DDSM database, contains images in .dicom format with MLO and CC views [7], [8], [12]; Breast Cancer Digital Repository (BCDR) contains images in. tiff format with MLO and CC views [6]; among others, which serve as an indispensable tool for scientific studies, since each of the datasets contains cases with suspicious and non-suspicious lesions of patients.

B. Artificial Intelligence

Currently, there is a wide variety of studies [5],[15], in which artificial intelligence techniques and specific deep learning techniques have been implemented together with preprocessing techniques to detect and diagnose mammograms with a high degree of containing malignant abnormalities.

For this reason, it is common to use metrics to evaluate the performance of the model in question, such as: True Positives (TP), where it is verified that the prediction correctly coincides with the positive actual value [16]; True Negatives (TN), where the prediction is found to correctly match the negative actual value [16]; False Negatives (FN), where the prediction is found to incorrectly match the positive actual value; False Positives (FP), where it is found that the prediction incorrectly coincides with the actual negative value; Accuracy (1), proportion of predicted true ratings (VP + VN) over the total sum of the sum (TP + TN + FP + FN) [4], [6], [8], [10], [13], [14], [17], [18], [19]; Precision (2), proportion of predicted true ratings (VP + VN) over the total sum of the sum (TP+FP) [4], [7], [9], [16]; Sensitivity (recall) (3), proportion of positive cases correctly classified [4], [12], [14], [16], [17], [20]; Specificity, proportion of correctly classified negative cases [4], [12], [14], [16], [17], [20]; F1 Score (4), harmonic measurement of metrics precision and sensitivity [4]; the area under the curve (AUC)(5), where the probability of correctly categorizing a positive class is determined [2], [4], [6], [11], [12], [16], [17], [21], [22], [23]; Curve ROC(6), is the ratio of the set of false positives to the set of true positives[24]; etc. [25].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\,Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

$$AUC = 1 - \frac{1}{2}\left(\frac{FP}{FP+TN} + \frac{FN}{FN+TP}\right) \quad (5)$$

$$ROC = \frac{\sqrt{Sensitivity^2 + Specificity^2}}{\sqrt{2}} \quad (6)$$

Each table (Table II and Table III) allows for visualizing certain characteristics of each study in question such as the database or set of databases implemented, the task performed, the deep learning technique or set of techniques used, their corresponding classification, as well as the results obtained, which show the performance of each of the proposed models of the evaluation metrics selected in the study, where it can be observed that the implementation of these metrics can correspond to the case of multiclass classification. This case can be approached by class binarization, where each class is computed as a binary classification problem after grouping the other classes as belonging to the second class; or by the per-class confusion matrices, where the True Negatives (TN) indicate that the other classes are not considered as belonging to class n.

Table II shows a compilation of various scientific investigations corresponding to the possible existence of malignant, benign, or absence of malignant anomalies; whiles Table III shows several scientific investigations corresponding to the identification of the types of densities present in breast tissues.

TABLE II. ARTIFICIAL INTELLIGENCE TECHNIQUES FOR BREAST CANCER DETECTION AND CLASSIFICATION.

Database	***Classification***	***Method used***	***Task***	***Results***		***Ref.***
Private	BI-RADS (0,1,2,3,4A, 4B,4C,5)	EfficientNet	Diagnostic Bi-RADS 0,1,2,3,4A, 4B,4C,5	Ave_Sensitivity: 95.51% Ave_Specificity: 99.15% Accuracy: 94.22% AUC: 0.972		K. J. Tsai, et al., 2022 [17]
MIAS, CBIS-DDSM	Benign, Malign	CNN, CNN-wavelet, GAN	Convolutional Neural Network of data-augmented wavelet decomposition and transform for breast cancer detection using digital mammography.	CNN Precision: 0.86832 Precision val: 0.8722	CNN-wavelet Precision: 0.8716 Precision val: 0.87514	O.N. Oyelade, and A.E.S. Ezugwu, 2022 [7]
MIAS, INbreast	Benign, Malign, Normal, Mass (Benign, Malign)	AlexNet, GoogleNet, ResNet50, VGG19	Classification of breast cancer in mammograms with Deep Learning	GoogleNet AUC: 99.29% F1 Score: 91.92% Accuracy: 91.92% Precision: 92.15% Sens: 91.70% Spec: 97.66% AlexNet AUC: 98.60% F1 Score: 88.27% Accuracy: 87.87% Precision: 87.67% Sens: 87.87% Spec: 96.58%	VGG19 AUC: 99.50% F1 Score: 91.18% Accuracy: 91.16% Precision: 92.21% Sens: 91.16% Spec: 97.66% ResNet50 AUC: 98.53% F1 Score: 85.81% Accuracy: 85.73% Precision:85.89% Sens: 85.73% Spec: 96.13%	S. Castro-Tapia, et al., 2021 [4]
Private ImageNet	Benign, Malign	DenseNet-201 Ensemble Inception-v3 InceptionResNet-v2 ResNet-101 Xception	Convolutional deep learning model for improved mammographic diagnosis of breast microcalcification	DenseNet-201 AUC: 0.83 Sens: 82.47% VPN: 86.92% Xception AUC: 0.82 Inception-v3 AUC: 0.79	ResNet-101 AUC: 0.84 Precision: 81.54% Spec: 91.41% VPP: 81.82% InceptionResNet-v2 AUC: 0.84 Ensemble AUC: 0.86	D. Kang, et al., 2021 [16]
DDSM PINUM	Benign, Malign	FC-DSCNN	Computer vision-based microcalcification detection.	PINUM Accuracy: 0.90 Sens: 0.99 Spec: 0.82	DDSM Accuracy: 0.87 Sens: 0.97 Spec: 0.83	K. Ur Rehman, et al., 2021 [14]
DDMS, INbreast, BCDR, MIAS	Benign, Malign	Transfer Learning (TL), Pulse-Coupled Neural networks (PCNN), Convolutional Neural Networks (CNN)	Identify and classify mammography mass lesions.	AUC: 0.99 Accuracy: 98.77%		M. M. Altaf, 2021 [6]
MIAS DDSM CBIS-DDSM	Benign, Malign	InceptionV3, DenseNet121, ResNet50, VGG16, MobileNetV2, U-Net	Segmentation and classification of breast cancer images.	DDSM Accuracy: 98.87%		W. Salama, and M. H. Aly, 2021 [8]

Database	*Classification*	*Method used*	*Task*	*Results*	*Ref.*
Sheba Medical Center, INbreast	Normal, Anormal	FCN	Automatic feature extraction of groups of microcalcifications.	AUC:0.99, 0.98, Respectively	R. Zamir, et al., 2021 [13]
University of Chicago Department of Radiology data set.	Benign, Malign	Convolutional Neural Networks (CNN)	Detection of microcalcifications as benign or malignant.	AUC=0.669, 0.561, Respectively	J. Wang, et al., 2021 [22]
MIAS	Normal, Tumor	Convolutional Neural Networks (CNN)	Mammographic image classification with deep fusion learning	Model 1 Precision: 0.8906 Model 2 Precision: 0.875	X. Yu, et al., 2020 [9]
Private	Normal. Benign, Malign	Principal Component Analysis (PCA), Multi-layer perceptron (MLP), artificial neural network.	Combined texture analysis and machine learning for distinguishing suspicious mammographic calcifications	ROC= 0.82, 0.832, Respectively	P. D. Stelzer, et al., 2020 [24]
Sun Yat-Sen University Cancer Center (SYSUCC), Nanhai Affiliated Hospital of Southern Medical University (Foshan,China).	Benign, Malign	Convolutional Neural Network (CNN), Support Vector Machine (SVM)	Discrimination of microcalcifications for breast cancer detection.	Sens: 86.89 Spec: 89.32	H. Cai, et al., 2019 [20]
CBIS-DDSM INbreast	Benign, Malign	Convolutional Neural Networks (CNN)	Deep learning to improve breast cancer detection in screening mammography	ResNet-ResNet, ResNet-VGG, VGG-VGG, VGG-ResNet AUC:0.95 Model Average AUC:0.98, Sens: 86.7%, Spec: 96.1%	L.Shen, et al., 2019 [12]
Private	Normal, Abnormal	Convolutional Neural Networks (CNN)	Detect and segment breast microcalcifications.	Accuracy: 98.22%, 97.47%, Respectively	G.Valvano, et al., 2018 [18]
INbreast	Benign, Malign	Faster R-CNN	Detect and classify malignant or benign lesions on a mammogram	AUC: 0.95	D. Ribli, et al., 2018 [11]

Through the present tables, it is possible to observe the tendency of current research to implement deep learning techniques, as well as the combination of artificial intelligence techniques, due to the promising potential that these represent for a wide variety of tasks such as the case of automatic anomaly detection [16].

However, a very frequent obstacle in the training phase is that the vast majority of public databases do not contain enough images to be used individually in this phase.

On the other hand, the use of private databases poses an important challenge in preserving the anonymity of patients' privacy, as expressed by the following authors [20], [21], [16], [24], [17], [18], [22], [26], [13], where the origin of the database in question was omitted since these sets contain confidential information, which could be exposed to the general public [27].

Therefore, several studies make use of the combination of several public datasets [4], [6], [7], [8], [12]; the use of private databases [13], [16], [17], [18], [20], [21], [22], [24], [26]; as well as the generation of new databases through the implementation of Generative Adversarial Neural Networks (GANs) [7] to increase the number of images and thus achieve an improvement in the performance of the model [12].

It is worth mentioning that, among the articles corresponding to the classification of benign or malignant anomaly, some of them presented results higher than 0.90, as was the case of [4], where the GoogleNet model and the VGG19 model obtained in the F1 Score metric: 91.92% and 91.18%, respectively. Likewise, [6] and [8], presented an accuracy of 98.77 and 98.87, respectively. While [11] and [12] presented values of 0.95 and 0.98 in the AUC metric, respectively.

Thus, concerning the classification of the presence or absence of anomaly, [13] stands out, since it presented AUC results higher than 0.97. Likewise, [18] obtained accuracy values above 97%.

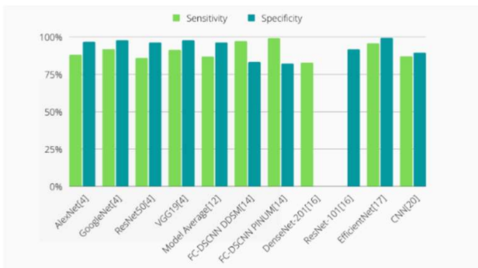

Fig. 1. Results of the Sensitivity and Specificity metrics of several Deep Learning models.

In terms of breast density classification, [10] and [19], where the accuracy metric is 98.95% and 96.80%, respectively, stand out. Likewise, [2] and [23], contain AUC results of 93.40 and 98.92, respectively.

However, it is important to mention the contribution provided by [17], which seeks greater interpretability of the information when classifying based on the categorization of the BI-RADS system [3], obtaining as shown in Figure 1 an average sensitivity and specificity metric of 95.51% and 99.15%, respectively. This study provides a more complete support tool, giving more detailed information for the doctor in decision-making.

TABLE III. ARTIFICIAL INTELLIGENCE TECHNIQUES FOR BREAST DENSITY DETECTION AND CLASSIFICATION.

Database	*Task*	*Method used*	*Task performed*	*Results*	*Ref.*
INbreast	Low density, High density	Convolutional Neural Networks (CNN)	Classify breast density as fatty, fibroglandular dense, heterogeneously dense, and extremely dense.	Accuracy: 96.80%	J. Xu, et al., 2018 [19]
ImageNet	Sparse, heterogeneously dense density	AlexNet	Distinguish chest density between sparse density and heterogeneous density.	AUC: 98.92	A. A Mohamed, et al., 2018 [2]
Private	Dense, Non-dense	CNN algorithms based on transfer learning.	CNN is used to classify dense and non-dense tissue.	AUC: 93.40	N. Wu, et al., 2017 [23]
INbreast	Predominantly adipose, Fibro-glandular density, Heterogeneously dense, Extremely dense	K-means, Backpropagation Algorithm	Separate mammographic images into breast density categories.	Accuracy: 92.9% Accuracy: 98.95%	P. C. Carneiro, et al., 2017 [10]
Dutch Breast Cancer screening	Denser end, less dense	Sparse convolutional autoencoder (CSAE)	Automatic segmentation and scoring of breast density features.	AUC: 61, 54, 59, respectively	M. Kallenberg, et al., 2016 [21]

C. Future work

In recent years, the area of technology has become more relevant in the field of medicine due to the various advances that have been presented in favor of timely diagnosis to the patient, as is the case of several studies that have been conducted around the world to determine that deep learning techniques provide satisfactory results concerning the early detection and classification of breast cancer.

However, even with a large number of documents on the detection and classification of breast cancer using various artificial intelligence techniques, many of these ideas tend not to materialize because they do not provide standardized information about possible precursor abnormalities of breast cancer. At the moment, a general model supported by a medical standard for the task of counseling in the interpretation of mammograms has not yet been defined and implemented. Therefore, it is envisaged for future work to provide this type of information to facilitate interpretation for medical personnel, as shown in Figure 2.

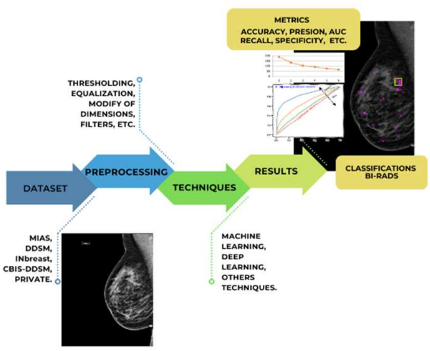

Fig. 2. Steps for the task of detecting and classifying abnormalities on mammography.

III. CONCLUSION

In summary, the use of artificial intelligence in the area of medicine, specifically in the detection and diagnosis of breast cancer precursor abnormalities, has had great relevance in the scientific community. However, there are still some challenges to tackle to obtain a more detailed description of the abnormalities by means of classification based on a medical standard approved by health authorities, as is the case of the BI-RADS system. Therefore, it has been intended to present to the reader a compilation of various papers published from 2016 onwards, which can serve as a guide for the detection of areas of opportunity for future research.

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