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REVIEW ARTICLE

An Overview and Study of CAD Systems for Mass Detection and Classification and Mammography for the Detection of Breast Cancer

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ABSTRACT

The technologies for detecting and classifying breast cancer (CAD) have improved, however there are several problems and restrictions that still need to be looked into further. The development of breast cancer CAD systems was significantly impacted by the considerable advancements in machine learning and image processing techniques over the past 10 years, particularly with the advent of deep learning models. In addition to the traditional machine learning-based approaches, this study offers the current deep learning-based CAD system to identify and categorise masses in mammography in an organised manner. The survey offers the most modern approaches and the most popular assessment measures for the breast cancer CAD systems, as well as the publicly available mammographic datasets currently in use. The research highlighted the benefits and drawbacks of the present body of literature while providing a discussion of it. The survey also sheds insight on the difficulties and limits of the existing methods for identifying and categorising breast cancer.

Keywords: *Breast cancer, Mammogram, Mass Detection, Classification, CAD system*

INTRODUCTION

In terms of prevalence among women globally, breast cancer is one of the most common cancers. According to data [80] from the World Health Organization (WHO) affiliate Global Cancer Observatory (GCO) published in 2020, for every 100,000. The most common disease in the world, breast cancer, affects 47.8% of people. second in the global rankings for the top 10 cancer types in women, and it is the second in the mortality rate from lung cancer is 13.6% per 100,000 people, which is about Out of the 47.8% people who received a breast cancer diagnosis, 29.1% passed away. Invasive ductal breast cancer is a kind of breast cancer that can start in the milk ducts. Invasive Diffuse Carcinoma (IDC) is a kind of cancer that develops in the glands that produce milk. ILC (lobular carcinoma) [18] Many things are regarded as breast cancer risk factors. such as ethnicity, age, gene variations, family history, chest radiation exposure, and obesity. [13] The likelihood that breast cancer will be curable is boosted by early identification. Regular screening is therefore seen to be one of the most crucial methods for aiding in the early diagnosis of this form of cancer. A mammography is one of the best screening tools for seeing breast cancer in its earliest stages [54, 83], and it can spot various breast abnormalities even before any symptoms show up. In an effort to build more efficient Computer-Aided (Detection / Diagnosis) systems for breast cancer, numerous studies for breast cancer detection and classification have been proposed. These research take use of the tremendous advancement in machine learning and image processing techniques. Computer-Aided Detection (CADe) systems and Computer-Aided Diagnosis (CADx) systems are two different categories for CAD systems. The primary function of CADe is the localization and identification of masses or other abnormalities that occur in medical imaging. The radiologist is then tasked with interpreting these abnormalities. However, CADx offers a categorization for the masses and aids the radiologist in making decisions regarding the found abnormalities [14]. This study attempts to discuss the important and well-known methods that are used to identify and classify breast cancer in the general population using traditional machine learning and deep learning. Additionally, the article shows how the models that were developed during the previous 10 years have evolved. The study discusses the models put out in the literature, their shortcomings, and the current problems. This study shows the various public mammography datasets, screening techniques, and mammogram forecasts. The paper also focuses on presenting a quantitative dataset-based comparison of deep learning-based models for the most popular and widely used public datasets. Additionally, the paper highlights the advantages and disadvantages of deep learning-based CAD systems compared to more traditional machine learning-based CAD systems. The authors of this study searched PubMed, Springer, Science Direct, Google Scholar, and the Institute of Electrical and Electronics Engineers for relevant papers (IEEE). The publications that make up this study were written and published in English. The majority of the studies that have been published on mammography mass detection and classification between 2009 and early 2021 are included in the survey.

Modalities For Breast Screening

The breasts are screened using a variety of techniques, including ultrasound, digital breast tomosynthesis, magnetic resonance imaging (MRI), and mammography (MG) [43]. A mammography (MG), which uses an X-ray to image the breast tissue, is a non-invasive screening method. The lumps and calcifications may be seen. Additionally, it is regarded as the most accurate and sensitive screening method since it can lower death rates by detecting breast cancer early—even before any symptoms manifest. Strong magnets and radio waves are the key components of magnetic resonance imaging (MRI), which uses them to create precise images of the breast's inside. In the case of women who are at a high risk for breast cancer, this treatment method is thought to be beneficial. To provide pictures of the interior anatomy of the breast, ultrasound employs sound waves. It is used for women who are pregnant or who are at high risk for breast cancer but who are unable to get an MRI because they should not be subjected to the x-ray used in MG. Additionally, ultrasonography is frequently used to check women with thick breast tissue. The Food and Drug Administration (FDA) authorised the more current technology known as Digital Breast Tomosynthesis (DBT) in 2011. Through the use of a low dosage of x-rays, DBT produces a more sophisticated type of mammography. It is regarded as a sort of 3D mammography that may show masses and calcifications in better detail, making it highly useful for radiologists, particularly when detecting dense breasts [9]. Although a mammogram is thought to be the most reliable and sensitive screening method, MRI and ultrasound are sometimes employed in addition to mammography, particularly in instances when breast tissue is highly dense [26]. Mammograms can be viewed in a variety of ways to give more details prior to discovery or diagnosis. Breast masses and calcifications are the two primary abnormalities that mammography can detect. Breast masses can be malignant or non-cancerous; cancerous tumours show up on mammograms as irregularly shaped masses with spikes protruding from them. The non-cancerous masses, on the other hand, frequently have round or oval forms with well-defined boundaries [15]. Macrocalcifications and microcalcifications of the breast can be distinguished [59]. On a mammography, macrocalcifications appear as large white spots dispersed irregularly across the breast; they are non-cancerous cells. In a mammography, the microcalcifications appear as tiny calcium spots that resemble white specks, and they frequently occur in groups. Typically, microcalcification is regarded as a main indicator of early-stage breast cancer or a marker of the presence of precancerous cells.

Breast Imaging Data Sets

The size, quality, picture format, image type (Full-Field Digital Mammography (FFDM), Film Mammography (FM), or Screen-Film Mammography (SFM)), and abnormality categories contained in each dataset vary among the publicly accessible datasets. The digital database for screening mammography (DDSM), INBreast, Mini-MIAS, curated breast imaging subset of DDSM (CBIS-DDSM), BCDR, and OPTIMAM are only a few of the publicly accessible datasets. The computerised mammography screening database (DDSM) The 2620 scanned film mammography studies that make up DDSM were split up into 43 volumes. For each example, there are four mammograms of the breast since each breast side was photographed using two projections, the Mediolateral Oblique (MLO) and Cranio-Caudal (CC) views. The collection also includes pixel-level annotations for the ground truth and other types of suspicious locations. Every case includes a file that lists the study date, the patient's age, the breast density score calculated using the American College of Radiology Breast Imaging Reporting and Data System (ACR BI-RADS), as well as the size and resolution of each picture that was scanned. The pictures are in JPEG (Joint Photographic Experts Group) format and come in various sizes.

Subset Of DDSM With Curated Breast Imaging (CBIS-DDSM)

In this dataset, which is an improved version of the DDSM, decompressed pictures are updated boundary boxes and mass segmentation for the region of interest (ROI). Information is The pictures are in Digital Imaging and have been chosen and curated by expert mammographers. Format for communication in medicine (DICOM). The dataset is 163.6GB in size and contains 10,239 photos from 6775 investigations make up the collection, which includes mammography scans with their associated mask pictures. The dataset that was supplied has CSV files connected to it. the patients' pathological information. Four CSV files make up the dataset: mass exercise set, calcification training set, calcification testing set, and mass-testing set.

INBreast

INBreast has 115 instances and 410 photos altogether. Out of 115 instances, cancer on both breasts was found in 90. Breast bulk, breast calcification, breast asymmetries, and breast distortions are the four main forms of breast disorders that are represented in the dataset. Images of (CC) and (MLO) views, stored in DICOM format, are included in the dataset. The dataset also offers the breast density score from the Breast Imaging-Reporting and Data System (BI-RADS) [56].

Mini-MIAS

The dataset consists of 322 digital videos as well as the ground truth markers for any anomaly that may already be present. The dataset's anomalies are categorised into five different categories: masses, architectural distortion, asymmetry, and normal. The photos were scaled down to 1024 1024 in size. The photos are accessible to the general public via the University of Essex's Pilot European Image Processing Archive (PEIPA) [77].

BCDR

Two mammographic repositories make up the majority of the BCDR: (1) the Film Mammography-based Repository (BCDR-FM) and (2) the Full Field Digital Mammography-based Repository (BCDR-DM). The BCDR repositories include normal and atypical instances of breast cancer together with the clinical information needed to treat them. The 1010 cases in the BCDR-FM are split between 998 females and 12 men. In addition, it contains 1044 detected lesions among 1125 investigations and 3703 mammographic pictures in the MLO and CC perspectives.

Optimam

It is made up of 173,319 cases and more than 2.5 million photos that were gathered from three breast screening facilities in the UK. 154,832 instances with normal breasts, 6909 cases with benign cancer, 9690 cases with recognised lesions, and 1888 cases with interval cancers make up the dataset. It offers both raw and processed medical pictures, and the collection also contains clinical information about the discovered tumours and interval cancers, along with annotations for regions of interest [38].

CAD Systems For Breast Cancer

Machine learning has made major contributions over the years to the development of more trustworthy CAD systems for the detection of breast cancer, which can aid radiologists in reading and interpreting mammograms. Many research have developed mammogram-based models for the diagnosis and prognosis of breast cancer, and many of these techniques have demonstrated excellent performance. Despite this, these models have not been evaluated over a comprehensive, sizable database. The phases of the breast cancer CAD systems vary depending on the task that the CAD system is supposed to do. Researchers began to develop automated systems for classifying and identifying anomalies in medical photographs, especially breast imaging, in the 1960s and 1970s. An automated method that can assist the radiologist in the identification of microcalcification in mammograms by giving the radiologist with analytical output of the picture was developed in 1987 by a team from the University of Chicago [17]. To improve the identification and categorization of abnormalities in mammograms, many traditional machine learning-based CAD systems were launched between the beginning of 2009 and 2017. As deep learning networks emerged, researchers began to use deep learning models and the transfer learning idea to create more precise mammographic CAD systems in the middle of 2017. Based on the outcomes of the suggested system in 2018 that used those detection models, the deep learning detection models demonstrated highly promising results at the anomalies' detection. Researchers have just recently, starting in 2018, begun to develop complete models for mammographic CAD systems. Both traditional CAD systems and CAD systems based on deep learning are included in this survey's classification of the current CAD systems. The pipeline for both the traditional learning-based CADe / CADx and the deep learning-based CADe / CADx is shown in Figure 8. In traditional machine learning, image processing was the first step, followed by mass segmentation, feature extraction and selection, and classification. The deep learning-based CAD system pipeline, on the other hand, goes through the same stages, with the exception of feature extraction and classification, which are done as a single stage since the deep learning models can automatically extract the features during the training stage. The mass segmentation/detection step of the procedure is where the CADe systems terminate the process.

Standard CAD Systems

To create CAD systems that can serve as a second opinion or assistant for radiologists, a number of studies and trials were proposed. These studies and trials began with the use of traditional computer vision techniques, which are based on traditional machine learning and image processing techniques. Rejani, Y., and S. Thamarai Selv (2009) [65] presented an algorithm for tumour detection in mammograms. Their work was intended to discuss a solution for two issues: the first involved extracting the features that characterise tumours, and the second involved how to detect masses, particularly those that have low contrast with their background. They used a Gaussian filter, a top hat to remove background noise, and a discrete wavelet transform to improve the mammography (DWT). Utilizing the thresholding approach, the mass region was segmented, the morphological characteristics were then recovered from these segmented regions, and Support Vector Machine (SVM) was utilised to classify the data. Given that they only used 75 mammograms from the mini-MIAS dataset to test their method, they only reached a sensitivity of 88.75%. As a result, their work has to be replicated on bigger datasets. A technique that can identify the mass based on textural cues was introduced by Ke, Li et al. in 2010 [42]. To locate the Region of interest and find the masses, they performed the bilateral comparison (ROI). To extract the textural characteristics from the ROI, they used the two-dimensional entropy and the fractal dimension. Using SVM, the ROIs were divided into mass and normal categories. Their 106 mammograms were used in their trial, and the findings revealed that their automated diagnosis system had a sensitivity of 85.11%.An automated technique was put forth by Dong, Min, et al. (2015) [24] to identify and categorise breast masses in mammographic images. Using the chain codes included with the DDSM dataset, they were able to extract the positions of the masses and the ROI. After that, they linearly transferred the intensity values to new values based on the grey level distribution, which has a range of 0 to 255. To further improve the ROIs, they used the Rough Set (RS) approach. They employed an enhanced Vector Field Convolution Snake (VFCS) to separate the masses from the ROIs, which demonstrated resistance to influence from the hazy tissues. The segmented masses and the backdrop of the ROIs were used to extract a variety of characteristics. Two classifiers were used for classification. the first used an enhanced SVM combined with a genetic algorithm (GA) and a particle swarm optimization (PSO), while the second used a random forest (RF). They used the DDSM and MIAS databases for their experiment. With an accuracy of 97.73% on the DDSM, the findings revealed that the first approach performed better than the second one. However, their work has to be tested on a bigger sample data size by augmentation or utilising a larger dataset. Additionally, two other approaches to mass segmentation were presented by Rouhi, Rahimeh, et al. (2015) [68]. Based on the chain codes of the DDSM dataset, the ROIs were cropped. To lessen the noise, median filtering and histogram equalisation were used. They used two alternative segmentation techniques: the region-growing-based approach and the cellular neural-based method. For feature selection, they used a Genetic Algorithm

(GA) with various chromosomal structures and fitness functions. Various classifiers, including Multi-Layer Perceptron (MLP), Random Forest (RF), Nave Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbor, were used to divide the masses into benign and malignant categories (KNN). They use the DDSM and MIAS databases to conduct their experiment. Mughal et al. (2017) [58] presented a system that can recognise and categorise the masses in mammograms using texture and colour parameters. The contrast of the mammography was improved using Contrast Limited Adaptive Histogram Equalization (CLAHE). In addition, the mean filter and wavelet transform were applied to lessen the noise. They developed a segmentation technique that consists of two parts. In the first, they removed the pectoral muscle and extracted the natural breast area. The greyscale picture was converted to RGB and then to the hue saturation value (HSV), which represented each RGB value with a value between 0 and 1, to emphasise the pectoral muscle. Using an algorithm based on an entropy filter, they created a texture image in the second phase and retrieved the aberrant breast border region from it. Additionally, they applied a mathematical The ROI is extracted and refined using morphology. They used formulas from mathematics to Extract the morphological, intensity, and textural characteristics. many classifiers, including SVM, For categorization, decision trees, KNNs, and bagging trees were employed. The (quadratic) SVM The best outcomes were obtained by kernel, which attained a sensitivity, specificity, and accuracy of 98.40%. DDSM and MIAS have respective percentages of 97.00% 96.9% and 98.00% 97.00% 97.5%.A technique for automatically detecting masses in mammograms was reported by Punitha, S. et al. (2018) [61].

To smooth out the changes in grey level and lessen picture noise, they utilised the gaussian filter. For segmentation, a more advanced version of the region-growing approach with the dragon-fly optimization methodology was applied. The ROIs were utilised to extract 45 features, and the Gray level co-occurrence matrices and Gray level Run Length Matrix (GLRLM) were employed to analyse texture and extract additional features. For classification, they employed a feed-forward network, which they trained using back propagation and the Levenberg-Marquardt method. They employed 154 benign cases and 146 malignant cases from the DDSM in the experiment. 100 photos were utilised for testing, and 200 images were used for training, in which these instances were separated into a training set and testing set. As the technique obtained Sensitivity of 98.1% and Specificity of 97.8%, it was demonstrated that the usage of the dragonfly with the expanding area algorithm enhanced their segmentation outcomes and, consequently, the classification. The same year, Suhail et al. [78] devised a method for separating benign from malignant microcalcifications seen in mammograms. As the binary classification data is encoded to a one-dimensional representation of the microcalcification data, their method relies on applying two steps scaled Linear Discriminant Analysis (LDA) methods for extracting the features and lowering the dimensionality. Five classifiers were used for the classification: K-NN, SVM, DT, Baysian Network, and ADTree. They contrasted their technique (scalable LDA) with the PCA/LDA technique in order to assess the performance of their strategy. Results indicated that the scalable LDA performed better than the PCA-LDA. SVM, Baysian Network, KNN, DT, and ADTree all had classification accuracy scores of 96%, 0.975, 0.972, 0.975, and 0.985, respectively.

A single hidden layer feedforward network called the Extreme Learning Machine (ELM) [23] was employed in several research [55, 57]. A CAD method for mass classification that demonstrated great accuracy with the usage of a was proposed by Mohanty Figlu et al. (2020) [55]. less features overall. They distinguished between normal and abnormal mammograms. Their approach classifies the mass according to whether it is benign or cancerous. They made use of They used the datasets from DDSM, MIAS, and BCDR to verify their suggested strategy. In their method, The salp swarm method combines chaotic maps and the idea of weights to choose theoptimum feature set and to fine-tune the KELM algorithm's parameters.

Their strategy is separated mostly into four steps: First, they used the ground truth locations to create the ROI.then they took the tsallis, energy-Shannon, and renyi entropies out of the ROI through discrete wavelet transformation (DWT). They applied for the feature reduction lastly, they employed a modified learning strategy using principal component analysis (PCA) [1]. It bases its categorization on ELM. Their method has a 99.62% accuracy rate. For MIAS and 99.92% for DDSM, for the categorization of normal and abnormal. On the other hand, it demonstrated accuracy for the benign-malignant categorization of 99.28% for MIAS, 99.63% for DDSM, and 99.60% for BCDR. Although their model can instantly categorise the mammograms, An automated CAD's manually clipped ROIs are viewed as a weakness. The ELM and the Moth flame optimization were combined in [57] by Muduli Debendra et al. To adjust the ELM network parameters (i.e., weights and the bias of hidden nodes) and address the issue of the ill-conditioned problem, one can use the (MFO) method. in the network's covert layer. Additionally, they used a fusion of the PCA and LDA for The strategy yielded an overall decrease in processing time and feature DDSM has an accuracy of 99.68% and MIAS has a 99.94% accuracy, however they must run their working with a bigger sample of the data. The authors provide a summary of different breast cancer screening techniques based on the examples of standard machine learning models' advantages and drawbacks.

The CAD System Is Based On Deep Learning

Convolutional Neural Network (CNN), transfer learning technique, and deep learning-based object identification models, among other potential deep-learningmodelsemployedincomputervision, recently demonstrated notable increases in the performance of CAD systems. For the CAD systems, a number of methods based on deep learning models have been suggested. A CAD tool for mass identification, segmentation, and classification in mammographic pictures with little user input was introduced by Dhungel Neeraj et al. (2017) [22]. They employed random forest and a cascade of deep learning models for mass detection, followed by hypothesis refining. Additionally, they recovered a portion of a picture from the identified masses after segmenting them using active contour models. They classified data using a deep learning model that was trained on manually created feature values and evaluated on the INBreast dataset. The findings demonstrated that the system recognised over 90% of masses with just one false-positive rate per picture, segmentation accuracy of 0.85 (Dice index), and classification sensitivity of 0.98 for the model. The Deep Convolutional Network (DCN) was created by Geras et al. [34] the same year, and it can handle multiple views of screening mammography since it takes both the CC and MLO images for each breast side of a patient. Additionally, the model can categorise pictures based on Breast Imaging-Reporting and Data System (BI-RADS) [47] into "incomplete," "normal," or "benign" based on their size, which is huge high-quality images with a resolution of 2600 X 2000. They looked at how the amount of the dataset and picture resolution affected the effectiveness of the screening. According to the findings, performance improves as training set size grows. They also discovered that the model performs best at the original resolution. A reader study using a random sample from the private dataset they utilised for their trials revealed that the model had a macUAC of 0.688, while a group of radiologists had a macUAC of 0.704. An CAD system built on a deep belief network was proposed by Al-antari et al. (2018) [5]. They employed the adaptive thresholding approach, which had an accuracy of 86%, to find the first suspect areas. They used two different techniques to extract the ROIs; in the first, they randomly extracted four non-overlapping ROIs of size 32 32 pixels around the centre of each mass. The second method hinges on manually removing irregular shapes and the entire mass region of interest as a rectangle box put around the masses. These ROIs' morphological and statistical properties were retrieved for use in classification, and a variety of classifiers, including the neural network (NN), deep belief network, quadratic discriminant analysis (QDA), and linear discriminant analysis (LDA), were utilised (DBN). The DBN exceeded the competition with an accuracy of 92.86% when using the first ROI extraction method and 90.48% while using the second ROI extraction method. To make the process of annotating breast mammograms easier, Shen et al. (2020) [71] suggested a system that relies on adversarial learning to recognise the masses in the images. Through an automated technique, masses are detected in mammograms. the two components of the framework First, a Fully Convolutional Network (FCN) is used to forecast the spatial density, while the second one is a domain transfer that also serves as a domain discriminator. uses adversarial learning to align the characteristics of the low-annotated target domain with the properties of a well annotated source domain. Next, the target's heatmap a network that serves as a domain discriminator and receives the domain is fed into reduce the disparity in the distribution of the heatmap between the source and destination domains. They compared their method with cutting-edge methods, and their method obtained an AUC. score of 0.8522 for INBreast and 0.9083 for a private dataset.

Transfer Learning

One of the current strategies to improve the effectiveness of learner models is transfer learning. It is the idea of using the information gained for one work to another task that is similar. Transfer learning is currently often employed in the majority of modern CAD systems to address the issue of having insufficient data, as well as to lower the computational expense and speed up model training [82]. A well-known deep learning approach allows the pre-trained models to be modified for usage with other tasks, such as computer vision tasks. Thus, given the time and effort required for that, this can speed up the computing time required to create a neural network from beginning. Transfer learning also solved the issue of the challenge of obtaining enormous volumes of labelled data [94]. Recently, some research [2, 40, 46] employed the transfer learning strategy when creating their CAD systems. A CAD approach that tries to categorise mammography masses into benign and malignant has been introduced by Ragab et al. (2019) [62]. They used two alternative segmentation methods; the first method included manually cropping the ROI using a circular contour given with the dataset, while the second method used thresholding and region-based analysis to automatically crop the ROI. Deep CNN built on the AlexNet architecture was used to extract the features, which were then supplied to an SVM classifier for classification after passing through the CNN's final fully connected layer. According to their findings, the second segmentation method worked better than the first. For DDSM, the model's top outcomes were accuracy of 80.5%, AUC of 88%, and sensitivity of 77.4%. Additionally, the findings demonstrated that when employing samples from the CBIS-DDSM dataset, the segmentation accuracy climbed to 73.6% and the classification accuracy improved to 87.2% with an AUC of 94%. Ansar et al. (2020) [12] introduced a MobileNet-based architecture model that could distinguish between malignant and benign masses in mammograms with competitive performance compared to other state-of-the-art architectures and reduced computational expense. The suggested method first identifies the masses in the mammogram by utilising a CNN to separate the mammograms into carcinogenic and non-cancerous ones, and then feeding the cancerous ones into a pre-trained MobileNet-based model for classification. They contrasted their model's performance with that of the VGG-16, AlexNet, VGG-19, GoogLeNet, and ResNet-50 models. Their model performed admirably, with accuracy ratings of 86.8% for DDSM and 74.5% for CBIS-DDSM.

Object Identification Based on Deep Learning (Single Shot and Two Shot Detectors)

By automatically identifying the most pertinent picture characteristics to employ for a certain job, deep learning has replaced the usage of manually created features. One of the fields using deep learning to get highly promising results was object detection. One-stage detectors that are based on regression or classification and two-stage detectors that are based on regional suggestions are the two categories into which object detection deep learning-based approaches may be divided [89]. Anchor boxes are regarded as the fundamental idea underpinning both of those approaches, and they are one of the major elements that influence how well the detector performs in identifying objects in the picture [90]. To identify several objects in a picture, one stage detectors primarily rely on taking a single image shot. The regional proposal network (RPN)-based techniques, on the other hand, operate in two stages, the first of which generates candidate region suggestions and the second of which is in charge of locating the item for each candidate. Because detection and classification are performed concurrently across the whole picture, a one-stage detector is significantly quicker than a two-stage detector. However, RPN-based techniques produced findings that were more accurate [87]. Faster R-CNN [66], a two-shot detector, was used by Ribli Dezs et al. (2018) [67] to create a system that can locate, identify, and categorise abnormalities in mammograms. Due to the poor quality of digitalized film-screen mammograms, they employed the DDSM in their study and translated the pixel values to optical density before rescaling them to the 0-255 range. They discovered through their experiment model that higher quality photographs provide successful outcomes. In addition to the DDSM dataset, they also used a proprietary dataset for training and the INbreast dataset for testing. Their model's last layer assigns each detected mass a benign or malignant classification and creates a bounding box for it. Additionally, the model offers a confidence score that identifies the mass's class. In the INbreast dataset, their model was able to identify 90% of the malignant tumours with a 0.3 false-positive rate/ image and an AUC of 0.95 for classification. Due to the paucity of pixel-annotated publically available datasets, this work's main restriction is that it only evaluated INBreast. In order to generalise the results, the model needs be tested on bigger datasets. Al-antari et al. employed You Only Look Once (YOLO) [64] to identify masses in mammography in [6, 10]. A completely automated breast cancer CAD system based on deep learning in its three stages of mass detection, segmentation, and classification was proposed in [6] (2018). For the purpose of locating and locating the masses, they employed YOLO. They segmented the observed masses in the following stage using a Full Resolution Convolutional Network (FRCN).

With the use of a pre-trained CNN built on the AlexNet architecture, the segmented masses were then divided into benign and malignant categories. The system obtained 98.96% accuracy in mass detection, 92.97% in segmentation, and 95.64% in classification. Furthermore, the identical approach they presented in [6] was offered in [7] (2020), with some enhancements to the classification and segmentation phases. Following these upgrades, YOLO achieved detection accuracy of 97.27% and segmentation accuracy of 92.97% for breast lesions. Utilizing CNN, ResNet-50, and InceptionResNet-V2, classification accuracy averaged 88.74%, 92.56%, and 95.32%, respectively. In order to avoid overfitting because of the short dataset, Cao et al. (2021) [16] introduced a new data augmentation approach in addition to a unique model for identifying breast masses in mammograms. Their local elastic deformation-based augmentation method improved the performance of their model, but its computation time was slower than that of more conventional methods. In their method, they first segment the breast using Gaussian filtering and the Otsu thresholding technique to get rid of the majority of the background. They also employed FSAF [93], an improved version of RetinaNet, for mass detection. For the INBreast dataset, each picture has an average false-positive rate of 0.495, but for the DDSM dataset, each image has an average false-positive rate of 0.599.

End to End Models

The idea behind the End to End (E2E) learning technique is to replace a complicated learning system's pipeline of several modules with a single model (deep neural network). By allowing a single optimization criterion as opposed to optimising each module independently under several criteria as in the pipelined design, the E2E training strategy improves the performance of the model [35]. Recent research have used the E2E training strategy to develop their models, and the results have been encouraging. In addition, in (2019) [70] they improved the work they introduced in [70] by classifying the local image patches through a pre-trained model on a labelled dataset that provides the ROI data. Shen et al. (2017) introduced in [70] a CNN based end to end model to detect and classify the masses within the entire mammographic image. They used the weight parameters of the previously trained patch classifier to initialise the weight parameters of the whole image classifier. They created four classification models using the two pre-trained CNN models Resnet50 and VGG16. They trained the patch and entire image classifiers using CBIS-DDSM, and then, using transfer learning, they transferred the entire image classifier to be tested on the INbreast dataset. The background, benign/malignant bulk, and benign/malignant calcification were the three categories into which the patch pictures were divided. According to their findings, the top single model evaluated on CBIS-DDSM obtained an AUC of 0.88 for each picture, while the four-model average AUC ranged up to 0.91. Additionally, the INbreast dataset demonstrated that the best single model's AUC was 0.95 per picture, and that the average AUC of the four models had increased to 0.98. Due to GPU restrictions, the pictures in this study were reduced, which resulted in some ROI information being lost. If the ROI information had been kept, the performance of this technique may have been different. A Multiscale CNN that is built on an end-to-end training technique was proposed by Agnes et al. (2020) [4]. Their model's primary function is to distinguish between normal and malignant mammograms. The two main components of their model are the classification of mammograms and context feature extraction. A multi-level convolutional network is used in the model to extract both high-level and low-level contextual elements from the image. For the mini-MIAS dataset, the model has an AUC of 0.99 and a 96.47% accuracy rate.

CONCLUSION

In conclusion, this study demonstrates the most recent deep learning and traditional machine learning approaches for mammographic CAD systems, datasets, and ideas. Although these strategies won't perform well with huge datasets and practically all of them depend on expert-crafted features, it can be shown that research that used traditional machine learning techniques and algorithms produced good results with high accuracy rates. The development of deep learning techniques has particularly influenced how the traditional ML approaches have changed in recent years. Deep learning models have recently been popular among academics in an effort to build more accurate CAD systems with lower false-positive rates. Despite the fact that deep learning approaches contributed significantly to the development of CAD systems and displayed extremely promising performance, there are still certain limits to these techniques, particularly due to the lack of datasets, which makes their clinical use more difficult. Data augmentation approaches are required to produce synthetic mammographic pictures because there aren't enough mammographic images in the publically accessible datasets, especially in light of the development of the Generative Adversarial Network (GAN) [36]. Although some researchers [69, 84] have made some progress in this approach, further study is needed before producing large-scale mammographic pictures in an effort to address the unbalanced class issue in the datasets for mammography that are currently accessible. Additionally, GAN may be able to produce images that are more realistic than those produced by conventional augmentation techniques like rotation, flipping, cropping, translation, noise injection, and colour transformation [74], which may improve performance and increase the models' capacity to recognise and categorise objects. Further research is also required to create new data augmentation methods that may keep the bulk characteristics while morphologically adding variance. Furthermore, other alternative approaches can be utilised to address the issue of insufficient data volume. The pre-trained weights are transferred to initialise the model, for example, when employing pre-trained models. Through training, the parameters and the network are adjusted [72, 73]. The object detection deep learning-based models, such as YOLO and Faster RCNN, are regarded as one of the recent customizable techniques that improved mass detection and localization within the mammographic image and achieved better detection accuracies. However, the small mass detection still requires further research, particularly for the very close ones. The performance of these models in detecting small masses may be improved by training them on enough data that contains more photos with small masses. This issue may also be solved by fine-tuning the bounding boxes. When doing texture analysis for the masses, it is crucial to recognise the texture to be assessed at various angles since the placements of body or image angles fluctuate in mammographic masses [19]. However, as evidenced by the literature, a large number of studies presented models that made use of morphological features like texture, colour, and so forth. However, some studies, like that of [88], recently highlighted the issue of the lack of neighbourhood invariant components, which cannot adequately respond to image transformation or changes brought about by imaging points when classifying the mammographic masses via CNN. They then put forth a unique method for identifying masses in mammograms that is based on the combination of rotation invariant characteristics, texture features, and deep learning. As it may be expanded to use Rotation Invariant Fisher Discriminative Convolutional Neural Networks (RIFD-CNN) for mass detection, the aforementioned issue can be seen as a novel difficulty that merits further research. The research revealed that studies that have lately begun to concentrate on employing more than one mammography view in the categorization, like MLO and CC views; the usage of Using more than one perspective to classify mammograms has proven to be more successful than solitary views [48, 86]. hence, making use of the multi-view mammographic pictures mass detection requires additional research and investigation since it can improve the increased mass detection and classification sensitivity and specificity through better preservation features and information from both perspectives. Moreover, research revealed that the complete image resolution can produce outcomes with more precision [84], therefore creating systems that can keep the complete to reduce the amount of information lost, the mammographic picture must be high enough resolution. Breast cancer CAD system development is continuing ongoing in light of the conversation that was just had. Creating deep learning models that can learn requires further study to address the present issues, especially for DL models that struggle due to a lack of annotated data. One of the outstanding difficulties is constructing an analysis model from a little quantity of data. A study of the literature from the previous 10 years on the state was made possible by this survey. Of cutting-edge breast cancer treatment methods for bulk detection using CAD and categorization. The goal of this endeavour was to aid in developing CAD systems that can employed therapeutically to aid in the detection of breast cancer. The review offers judgement. By outlining the benefits and drawbacks of several research that have been published in the literature limits.

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