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A survey on different parametric based datasets, screening and deep learning strategies for diagnosis of breast carcinoma

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ABSTRACT

Breast carcinoma poses a serious concern to the public's health since it is the most usual type of tumor identified globally and the primary reason for women's cancer-related fatalities. As a result, early identification and medical intervention of malignant breast cancers can greatly improve patient outcomes and enable efficient therapy. Radiologists and physicians still struggle to provide accurate and consistent interpretations, which may result in misunderstandings and unnecessary biopsies. Many studies have investigated using Deep Learning (DL) techniques in conjunction with breast screening protocols to achieve accurate early detection of breast cancer. This review briefly presents the fundamental concepts of mammography and other screening methods and available datasets for deep learning in concern to breast cancer. This paper explores the usual recent advancements in Deep Learning algorithms systems used for breast tumor detection. Furthermore, it offers a succinct synopsis of datasets that are accessible to the public and investigates the most popular metrics for assessing computer-aided breast cancer diagnosis systems. Possible research directions in this emerging topic are finally described. In addition to providing a thorough analysis of the subject, this paper aims to encourage and point scientists, medical professionals, researchers, and other healthcare workers in the right direction when developing innovative applications for early breast cancer detection using Deep Learning.

INTRODUCTION

Globally, breast carcinoma is one of the main reasons for mortality for ladies, for which numerous applications have been created to enhance [1] early diagnosis. Being the most frequent cancer among women, breast cancer has an exceptionally high cancer fatality rate of 14% in India. While 12.5 % of women in Europe and the US are affected by BC, just 5% of Indian women are affected by it. Together, machine learning and artificial intelligence (AI) [3] can be accustomed to improve the identification of carcinoma of the breast and prevent overtreatment. However, combining AI with Machine Learning (ML) techniques facilitates precise prediction and judgment. For example, determining from the biopsy results whether the patient need surgery to detect breast cancer. This paper aims to examine the prospective applications of Deep Learning techniques for breast cancer screening procedures. This paper provides an overview of [4] Deep Learning techniques, data accessibility, and several breast cancer screening techniques, such as Magnetic Resonance Imaging, Thermography, Ultrasound, and Mammography. We will discuss literature study and examine deep learning in diagnostic breast imaging in this review. It is found that authors in various research papers state that Mammography, Thermography, Magnetic Resonance Imaging (MRI) and Ultrasound (US) might all be employed to identify breast cancer. The extracted tissue is dyed in the lab to improve visibility, and this entails an imaging analysis of the tissue. Another diagnostic tool for breast cancer is histological image analysis. Image micrographs of breast image micrographs of breast tissue called histopathological images are quite beneficial when treating cancer in its initial phases.

The important beneficiations of this survey are as follows:

1. Using various screening techniques, we investigate how current deep learning algorithms are applied to identify breast cancer.
2. A thorough analysis of the datasets on breast cancer that are currently accessible for each of the various modalities is given in our paper.
3. We go over incorporating machine learning and AI with screenings for breast cancer.

This review is coordinated in the consequently manner: Section 2 describes identification of breast cancer using different screening techniques, Section 3 explains the accessibility of data for different kinds of breast cancer screening, Section 4 gives detail analysis of Deep Learning studies in breast carcinoma detection, Section 5 explains the techniques for Breast Cancer Screening Overview of Recent Studies while at the end in Section 6 conclusion is presented.

Different Breast Cancer treatment methods:

1. *Different screening methods like Mammography, Thermography, MRI, and Ultrasound-* Investigators employed data based on [5] Mammography (X-rays), Thermography, Magnetic Resonance Imaging (MRI), Ultrasound (sonography) to examine breast cancer disease.
2. *Different datasets available for training Deep Learning Model -* MAIS, DDSM, Magic-5, The BancoWeb LAPIMO Database, INbreast, CBIS-DDSM, Breast Cancer Digital Repository (BCDR), Breast

Ultrasound Image, DMR-Database for Mastology Research-Visual Lab BUD, DCE MRI, OPTIMAM Medical Image Database, RIDER Breast MRI dataset are various datasets available publically depending on different screening methods for [6] Breast Cancer detection.

3. *Different deep learning techniques for Breast Cancer Diagnosis-* Researchers face difficulties in diagnosing BC illness. Many models and methods, including Transfer Learning, Deep Learning and Machine Learning are employed to address the issue of chest tumor [7].

In order to diagnose breast cancer at an initial phase breast cancer examining entails analysing the breasts utilizing imaging modalities to look for any odd signs or symptoms of the disease. The conventional and Artificial Intelligence embedded with Deep Learning methods for detecting breast cancer are depicted in the figure below.

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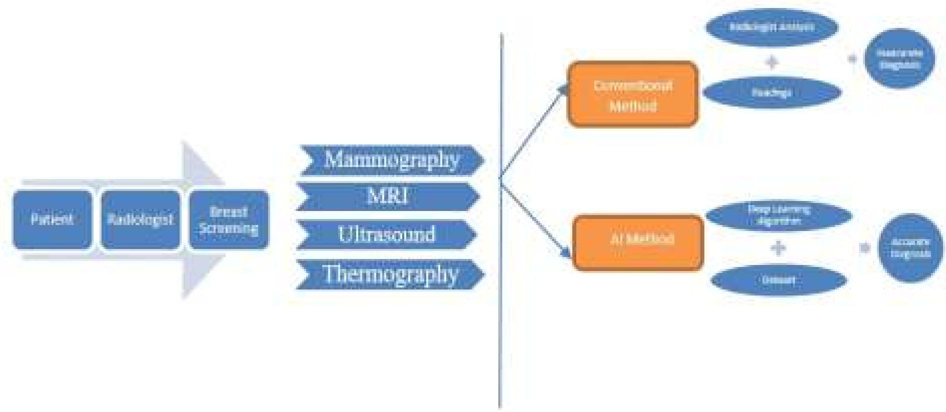

Fig. 1. Breast Cancer Detection Process

1. Mammography

One kind of breast cancer screening that [8] uses less radiation is mammography, which can identify the disease early. Mammograms come in three different varieties - Film mammography, Digital mammography and Digital Breast Tomosynthesis (DBT).

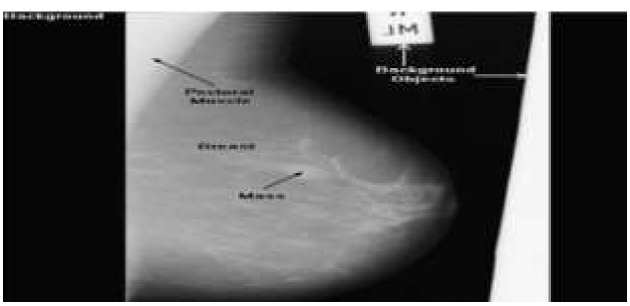

Fig 2. Sample Breast Mammogram image

Utilizing mammography with a CNN to identify breast malignancy was suggested in [11]. 322 breast exams from the original mini-MIAS database which was categorized as normal,
benign, or malignant were used in this investigation. The maximum accuracy attained with their suggested method was 82.71%.
An integrated approach was employed to create a cancer detection framework [12]. Their technique was an ensemble approach designed to identify chest structures cancers. On the MIAS and DDSM repositories, a nine-layer CNN model was used with a number of classifiers to identify cancer. The accuracy obtained with the CNN ensemble and feature extraction were 98.01% with the MIAS storehouse and 97.80% with the DDSM storehouse.
A method was suggested [14] for segmenting problematic areas on mammograms using an IRIS filter in order to identify cancerous tumor. Potential lesions were identified and segmented using an adaptive threshold that was applied after the mammograms were processed. A accuracy of 88.45% every picture was obtained based on lesion assessment whereas a sensitivity of 94.00% was attained every picture.
A new framework for segmenting and classifying images [15] of breast cancer was developed using multiple models. Breast areas from three separate databases—MIAS, DDSM, and CBIS-DDSM—were segmented using a modified U-Net model. The DDSM dataset yielded optimal outcomes when the Inception-V3 model was employed. With area under the curve (AUC) was 0.98, 98.88% sensitivity, and 98.87% accuracy, it attained its goals.

2.Magnetic Resonance Imaging (MRI)

Although MRI is less economical than mammography for population-based screening, it is typically more sensitive and provides more thorough pathophysiology information. Contrast-enhanced breast MRI has become the standard screening method. Using radio waves and strong magnets, [16] MRI generates finely thorough pictures within the chest. It is typically used to measure the cancer's size and find other breast cancers. Fig. 3 shows sample breast MRI image.

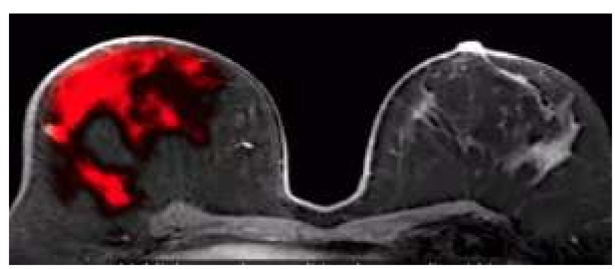

Fig. 3 Sample Breast MRI image

A mechanized [17] model was created for triage using 4580 breast MRI scans, removing the majority of scans that showed no abnormalities and identifying those that showed cancerous lesions. Performance was evaluated using an examination of receiver operating characteristics. In 90.70% of MRI tests with lesions, the model proposed was at 100.00% sensitivity for malignant lesions.
A system was created for Computer-Aided Detection (CAD) using the [18] physical data from the preliminary stage magnetic resonance imaging checks. This method uses a dynamic breast MRI technique that includes registered post-contract pictures as well as pre-contrast images. The suggested approach achieved a noticeably elevated average sensitivity of 64.29%.

3. Ultrasound

When mammography is not an option, an alternative technique for identifying breast cancer is called ultrasonography screening [23]. When the patient is younger than 25 and expecting or there is no way to look through the tissues, it can be helpful. Fig. 4 displays an example breast Ultrasound image.

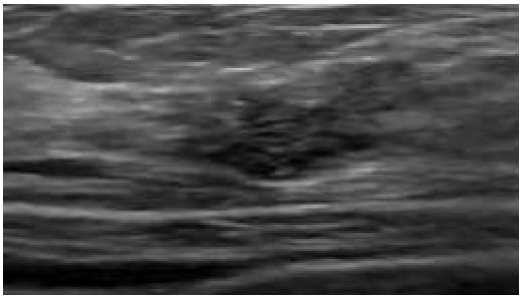

Fig. 4 Example Breast Ultrasound Image

A design was [25] created for segmenting breast ultrasound images using U-Net deep learning architecture. They used pre-processing techniques on a database of 221 photos to enhance the quality of the images. The similarity rate was 0.69 and the dice coefficient was 0.82.

Thermography

Thermography, also called infrared imaging, is a kind of breast cancer screening in which blood flow is measured and heat patterns within the body are identified using an infrared camera [31]. It takes the patient's breast skin temperature. Fig. 5 depicts the sample breast Thermogram image.

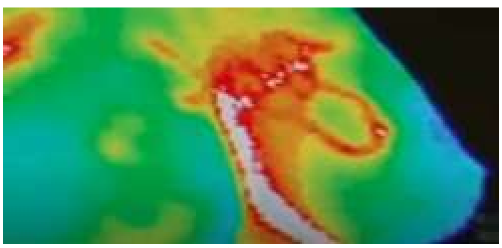

Fig. 5 Sample Breast Thermogram Image

A three-step strategy was suggested in [32] for segmenting breast tissue: axilla detection, infra-mammary fold detection and background removal. The data was then fed into a feed-forward neural network-based classifier. Results for their suggested approach indicated 89.73% specificity, 87.60% sensitivity, and 90.48% accuracy.

PUBLIC DATASETS USED FOR TRAINING THE DEEP LEARNING MODEL

There exist numerous databases pertaining to breast cancer. The various deep learning models are trained on images from these datasets. The modalities of the datasets vary, based on the screening technique employed to identify breast cancer. The databases listed below are accessible to the general public.

1. Mammographic Image Analysis Society Digital Mammogram Database
   The Mammographic Image Analysis Society Digital Mammogram Database (MIAS) [35] comprises of 323 pictures that were taken in 1994 from 161 patients and kept in the 8 bits per pixel portable gray map file format (PGM). There are three classes in this database: normal, malignant, and benign.
2. Magic-5
   Magic-5 [36] is an information source of digitalized mammography images gathered by a team of physicists in 1999. 3369 photographs recorded in a DICOM format, categorized by lesion kind, morphology, breast tissue and pathology type are included in the database, which was gathered from 967 patients. These photos came from a variety of viewpoints such as lateral, cranial-caudal (CC), and lateral to median oblique (MLO). The dataset is partitioned into 1601, 1456 and 312 photos in the CC, MLO, and lateral views.
3. The BancoWeb Database
   The BancoWeb Database [23] includes 1474 photos that were gathered from 320 cases in 2010. Images with a resolution of 12 bits are available in TIFF format, contains three types of data: normal, malignant, and benign.
4. INbreast
   INbreast [38] is a digital mammography data repository made up of 411 pictures. Out of the 115 instances, 90 contain two perspectives of each chest from the median oblique (MLO) and cranial-caudal (CC) perspectives. Six classes make up the dataset: masses, calcifications, asymmetries, numerous discoveries, and architectural aberrations. The DICOM format containing these images has a pixel resolution of 14 bits. Each image's region of interest and associated data are saved in XML format.
5. Digital Database for Screening Mammography
   The Digital Database for Screening Mammography (DDSM) [25] consists of 2621 instances of digital mammography with four normative views— median oblique, oblique and cranial-caudal — from each case are included in this database. The 10,481 photos are categorized into three categories: non-cancerous, malignant and normal.
6. CBIS-DDSM
   The CBIS-DDSM [40] is uniformed and upgraded variant of the DDSM comprises a portion of the DDSM data that has been formatted into DICOM. It has 1644 instances with 16 bits per pixel spatial resolution, updated bounding boxes and ROI segmentation and diagnosis of pathology for training purposes.
7. OPTIMAM Medical Image Database
   OMI-DB [41] has been gathered to offer researchers a consolidated, completely labelled dataset. CRUK assembled a dataset of 2,889,312 pictures from 173,319 women. The DICOM format is accessible for these pictures.
8. Breast Cancer Digital Repository
   The Breast Cancer Digital Repository (BCDR) [42] is a set of individual's information from the University of Porto in Portugal's Hospital São João verified by radiologists. The dataset consists of 1010 instances, comprising 3703 digitalized pictures from picture mammography in .tiff form with a closure of 15 bits per pixel, medical background, BI-RADS categorized divided lesion and image-based descriptors. 795 lesions were segmented from MLO and CC images.
9. DMR-Database for Mastology Research Lab
   The Dimentionally Modelled Data dataset [43] has gathered by the UFF, Database for Mastology Research Lab. On the other hand, the five-minute sequence of thermograms that make up the dynamic photos is taken every 15 seconds. 5760 photos in total, broken down into three categories—healthy, ill, and unknown—are accessible in JPG format.
10. Breast Ultrasound Image
    Breast Ultrasound Image (BUS) [44], this is a publicly accessible Mendeley dataset that was gathered in 2017. There are 250 photos of breast cancer in the dataset; 150 are malignant and 100 are benign. The photos have dimensions of 72 × 72 pixels, with breadth varying from 57 to 61 pixels and lengths spanning from 75 to 199 pixels.
11. Breast Ultrasound Dataset
    The Breast Ultrasound Dataset [45] is in dicom format. Every image underwent pre-processing to eliminate redundant images and unutilized boundaries. The dataset consisted of 133, 487, and 210 photographs per class—normal, benign, and malignant—those were separated into three categories. Every image has 500 by 500 pixels and is in the PNG format.
12. Dynamic Contrast-Enhanced Magnetic Resonance Images (DCEMRI)
    Dynamic contrast-enhanced magnetic resonance pictures of breast carcinoma individuals with tumour locations (Duke-Breast-Cancer-MRI) [46] are kept in the Cancer Imaging Archive of the NCI. The dataset contains demographic data, clinical, pathological and treatment outcomes information, as well as 922 DCE-MRI images of patients with invasive BC prior to therapy. The database was collected in the prone position using 1.5 T or 3 T scanners, and it is accessible in DICOM format.
13. RIDER Breast MRI
    The Reference Image Database to Evaluate Therapy Response (RIDER) Breast MRI [47] was gathered in early 20s to create protocols for assessing the effectiveness of medications or radiation therapy. The collection, which is kept in the Cancer Imaging Archive of the NCI, consists of 1500 DICOM-formatted pictures.

Public databases and their characteristics

Dataset	Modality	No. of Images	Resolution / Bit Depth	Image Type	Categories / Annotations
MIAS	Mammography	322	8 b/p	PGM	CaD, Mass-C, Mass-S, Mass-I, Arch, Asym, Norm, Ben, Mal, BenWC
Magic-5	Mammography	3,369	16 b/p	DICOM	-
BancoWeb	Mammography	1,473	12 b/p	TIFF	-
INbreast	Mammography	410	14 b/p	DICOM	B, M, NORM
DDSM	Mammography	10,480	8 or 16 b/p	LJPEG	B, C, NORM, BWC
CBIS-DDSM	Mammography	3,468	16 b/p	-	NORM, B, M
OPTIMAM	Mammography	2,889,312	-	-	-
BCDR	Mammography	3,703	14 b/p	-	NORM, B, M
DMR-Database	Thermography	5,760	-	-	-
BUS	Ultrasound	250	-	-	-
Breast Ultrasound Dataset	Ultrasound	780	-	-	-
Duke-Breast-Cancer-MRI	MRI	922	-	-	-
RIDER Breast MRI	MRI	1,500	-	-	-

DEEP LEARNING FOR RESEARCH ON BREAST CANCER

In the field of medicine, Artificial Intelligence technology is crucial to diagnosis and decision-making [34]. Machine learning and Deep Learning is used extensively in applications to help with a diversity of tasks, including the segmentation identification and categorization of breast carcinoma. Deep learning is the mostly used approach at the moment.

A subfield of machine learning known as "deep learning" uses multiple processing layers to extract data attributes pertinent to a specific task [21]. After being trained on a vast amount of labelled data and employing numerous layers of neural network topologies, models are able to classify objects based on text, images, or sounds [22].

Numerous investigations on the utilization of pictures or genomics in the recognition of breast carcinoma had done. The authors of [57] provided an overview of the numerous methods for categorizing breast cancer through histological image analysis (HIA), which is based on various Artificial Neural Network (ANN) architectures. It was evident that Deep CNNs were very useful for earlier breast cancer diagnosis which resulted in more successful treatment.

Algorithms for natural inspired computing (NIC) have been developed and used to examine a range of Situations of humanity. Five insect-based NIC methods were displayed by the authors in [37] and are utilized in the diagnosis of cancer and diabetes. The authors discovered that it performed exceptionally well in identifying several cancer forms, including ovarian, lung, prostate, and breast cancer. More precisely, a hybridization of directed ABC and Neural Networks was used to identify breast carcinoma.

The authors of [52] examined current works using various imaging modalities and deep learning in the context of breast carcinoma. The features of dataset, architecture, application and assessment were used to structure these investigations. They focused on Deep Learning structures created for three distinct types of breast imaging: MRI, mammography and ultrasound. Through the use of DLR-based CAD systems, they sought to present cutting-edge results about breast cancer imaging.

DL models used till now:

Inception V3, Inception-V2 (Novel CNN deep learning model) ResNet, VGG16, VGG19 and ResNet50 are the different Deep Learning Models used for Breast Cancer detection. Bilateral filtering (BF) Image pre-processing, LEDNet Model -Segmentation, Residual Network (ResNet-18) - Feature Extractor, SEO-RNN classifier are the different classifiers used for Breast Carcinoma detection.

Transfer Learning as Deep Learning technique in breast cancer detection:

Using a technique called transfer learning [2], a CNN model is trained to acquire characteristics for a variety of domains. AlexNet is the foundation of the most recent TL technique research.

Three of the eight layers in AlexNet's learnable architecture are fully connected layers and the remaining are convolutional layers. Every layer has irregular initiation function called ReLU. Later convolutional layers use adjustment to excerpt generic features from pictures, such as edge detection. Pre-trained convolutional neural network (CNN) architecture such as Inception V3, ResNet50, Visual Geometry Group networks (VGG)-19, VGG-16 and Inception-V2 ResNet are used as transfer learning technique. TL of the VGG16 model gives 98.96% accuracy.

Techniques for Breast Cancer Screening Overview of Recent Studies

Different breast cancer screening techniques are displayed in the above figure. Each screening technique, including ultrasound imaging, thermal imaging and MRI is displayed with a distinct study publication. The dataset, machine learning or deep learning model and the results obtained from it are displayed in the research publications. In ascending order based on the year of publication, all research papers are arranged.

A. Mammography

1. “Deep Learning-based Mammogram Classification for BC”

The employment of a CNN architecture was proposed in [24] to categorize mammograms into two groups: normal and malignant. The insight that pruned CNN architectures can be utilized to classify mammograms using a feature-based learning approach served as the basis for the contribution. With 18 layers, the top CNN model has 92.84% accuracy, 96.72% specificity and 95.30% sensitivity.

2. “Multi-class classification of BC abnormalities using DCNN”

A technique is presented [48] for categorizing and dividing chest anomalies, such as cancers called carcinomas calcium deposits, cancers, and irregularity, using deep convolutional neural networks (CNN). The images have undergone a number of filtering processes before the best one was chosen, such as median filters, inverse filtering and Wiener filters. Using a pre-trained ResNet-50 model on a bespoke dataset derived from the CBIS-DDSM and UPMC databases—UPMC consisting of tomosynthesis images with asymmetric chest anomalies and tumour pictures—they performed transfer learning. After that, a selection of photos based on multiple datasets was created via data augmentation. An improved CNN that could modify the learning rate was created in order to further optimize the model. The findings indicated that the anomalies were classified with an accuracy of 88.00%.

3. “DL in mammography: Automated CNN approach. “

A new framework is presented [15] for splitting up and classifying images of breast cancer using a range of models. For the purpose of segmenting the breast areas of three distinct databases—MIAS, DDSM, and CBIS-DDSM—an altered U-Net model was employed. Additionally, a variety of designs like Inception-V3, ResNet-50, VGG-16, DenseNet-121, and MobileNet-V2 were used to determine whether the DDSM, CBIS-DDSM and MIAS datasets were non-cancereous or cancereous. To enhance the system's performance, two distinct perspectives—the Medio lateral oblique (MLO) and the craniocaudally (CC)—were used. Using the Inception-V3 model on the DDSM database produced the best results. It obtained 98.98% sensitivity, 0.99 Area Under Curve (AUC) and 98.87% accuracy. The recommended structure worked good when the combined MLO and CC views were more effective than using just the MLO view.

4. **“BC detection: CNN and TF based approach”**

A cancer detection system [12] developed technique which was an ensemble approach designed to identify breast tissue cancers. The core elements of the ensemble model, which can improve classification effectiveness, were a CNN model and feature extraction. Pre-processing techniques like the median filter were applied to the photos to reduce noise and enhance contrast. The extraction-based approach depended on establishing texture features and projecting and approximating uniform manifolds to reduce their dimensionality. On the MIAS and DDSM repositories, a nine-layer CNN model was used with a number of classifiers to identify cancer. The accuracy obtained with the CNN ensemble and feature extraction was 98.00% with the MIAS dataset and 97.90% with the DDSM dataset.

5. **“BC Detection using DCNN and FEMT”**

A fuzzy deep learning constructed [39] CNN approaches like Inception-V4, ResNet-164, VGG-11, and DenseNet121 in order to create an ensemble approach based on a Gompertz function. Four mammography datasets, each containing 1145 normal, benign, and malignant pictures, were used in this study: BCDR, MiniMIAS, INbreast and DDSM. The recommended Inception-V4 ensemble model demonstrated accuracy of 99.32% as a result of the suggested methodology.

B. Thermography

1. **“Comparison of DL Architectures for Pre-Screening of BC Thermograms”**

Using automated techniques [33] assessed Deep Neural Networks DNN for the classification of breast thermograms. 173 photos were trained using various DL structures: AlexNet, GoogLeNet, ResNet-50, ResNet-101, InceptionV3, VGG-16, and VGG-19. Using a VGG-16 convolutional neural network, the greatest accuracy of 91.18% was attained, along with a sensitivity of 100.00% and a specificity of 82.35%.

2. **“Breast cancer diagnosis using thermography and CNN”**

A novel feature extraction approach based on data, picture statistical analysis and picture data was proposed [26]. The suggested method used five processes: segmentation, feature extraction, data collecting, image processing and classification. Projection profile analysis was used for the breast segmentation process. By applying the Bayesian algorithm-optimized convolutional neural network (CNN), the segmented images were categorized as either normal or suspicious. Convolutional, max-pooling and fully linked layers were between the several layers that made up the suggested network, which engaged several steps. They achieved 98.95% accuracy using their suggested technique, which they used to 3895 thermal pictures.

3. **“Breast Cancer Detection using Thermal Images and DL”**

A Deep Convolutional Neural Network design was employed [27] to forecast breast carcioma. One Dropout Layer, one Fully Connected Layer, one Softmax Layer, one Classification Layer and five groups of Convolutional, Batch Normalization, and Rectified Linear Activation function (ReLU) layers made up the suggested network. Three max-pooling layers were also included. Using this technique, 680 thermal photos were preprocessed, segmented and categorized after being converted to grayscale. Consequently, 95.80% accuracy was attained, with 99.50% sensitivity and 76.30% specificity, respectively.

4. "Deep learning model for fully automated breast cancer detection system from thermograms"

A breast cancer method of identification centered on automatic segmentation was suggested in [28]. Utilizing the DMR-Database for Mastology Research Lab, the suggested approach was assessed. The breast regions were separated and kept apart from other internal parts using the U-Net network. In addition, a CNN model with two classes was trained from the beginning to distinguish between regular and pathological breast cells according to the thermal pictures. The suggested approach obtained accuracy, sensitivity and specificity of 99.43%, 99.90% and 99.68% respectively, using 1000 thermal pictures.

5. "Breast cancer classification on thermograms using DCNN and transformers"

A technique for detecting breast cancer based on the segmentation and categorization of breast thermograms was proposed [29]. TransUNet, a vision-based Transformer, was employed to part of the target chest part. The ability of all of the models—EffectiveNet-B7, ResNet-50, VGG-16 and DenseNet-201—to distinguish between sick, healthy and unknown types of segmented thermograms was assessed. From the DMR Lab, a total of 3989 breast Thermograms were used. The accuracy and sensitivity of the ResNet-50 model's output were 97.26% and 97.26%, respectively.

C. Ultrasound

1. "A DL framework for classification of BL in US images"

A Convolutional Neural Network called GoogLeNet was suggested in [30] to distinguish between different kinds of lesions and nodules on breast ultrasonography pictures. The collection contained 7408 pictures of the breast, of which 3154 were cancerous and 4254 were benign. The suggested solution made use of margin augmentation, image cropping and histogram equalization. Using the training data, ten-fold cross-validation was used to identify the ideal values. They discovered an approximate 90.00% accuracy, 86.00% sensitivity and 96.00% specificity as a result. Radiologists can distinguish between malignant tumors faster and with more accuracy using this procedure.

2. "BC Classification in US Images using TL"

A deep learning method for dividing breast sonography pictures into harmless and cancerous instances was presented in [31]. The suggested model was developed using three different methods: fine-tuning, Transfer-Learning, according to prior training VGG-16 CNN architecture and training from scratch. There were 1000 photos in the instruction pack and 300 photos from the examination collection of the dataset that was employed. To combat overfitting, the dataset was expanded and to improve accuracy, fine-tuning was combined with the VGG-16 pretrained model's bottleneck features. The fine-tuned method using a pretrained VGG-16 produced an accuracy of 97.00% and an AUC of 0.98.

3. "Prospective assessment of BC from MM US images via DL"

An Ensemble Deep Learning Framework for Breast Ultrasound Classification was proposed [32]. To find the best base model for breast cancer prediction, a comparison of several models, such as ResNet-18, VGG19, ResNet-50 and Inception-v3, every one implanted with the SENet block, was carried out. 11,815 breast ultrasound pictures from 635 patient cases with 722 lesions were used to train the suggested method. Better results were found when using the ResNet-18 model with the SENet backbone; the Area Under Curve (AUC) for multimodal images was 0.94, while it was 0.92 for bimodal images.

4. "BC Classification from US Images Using Probability-Based Optimal DL FF"

Based on ultrasound pictures a structure was established for the grouping of breast cancer [33]. DarkNet-53, a pre-trained deep model, was adjusted and lined up using augmented images. The best features selected by modified differential evolution and reformed gray wolf were fused utilizing a novel probability-based serial technique for classification based on machine learning techniques. The best accuracy recorded with 780 photos was 99.10%.

D. Magnetic Resonance Imaging (MRI)

1. "Detection of BC via DCNN using MRI"

A Convolutional Neural Network-based approach presented for classifying lesions [48] as benign or malignant using MRI images. A multi-layer CNN design with live data supplementation was developed using only image data. The suggested system was made up of Six ensembles of Convolutional Neural network, sequential Normalization, corrected Linear Activation Function (ReLU), five Max-Pooling, one Dropout layer, one Fully Connected and one Softmax Layer are included. There were 102 malignant and 98 benign tumorous locations of the 200 total malignant regions found in the chest Magnetic Resonance Imaging database. The suggested approach produced results with accuracy of 98.33%.

2. "A DL for BC diagnosis using MRI"

A deep transfer learning-based computer-aided diagnosis [49] technique using multipara metric magnetic resonance imaging. MRI pictures of 927 different masses on 616 ladies were included in this collection. In this study, T2-weighted and Dynamic Contrast-Enhanced (DCE) MRI patterns were utilised and a pre-trained CNN was utilized to extract features. Support-vector machine (SVM) classifiers were employed to categorize the dataset as benign or malignant. Image fusion, feature fusion, and classifier fusion were applied. AUCs for DCE and T2w with the single-sequence classifiers were 0.85 and 0.78, respectively, but the AUCs for Image Fusion, Feature Fusion, and Classifier Fusion with the multipara metric methods were 0.85, 0.87, and 0.86. The feature fusion produced the best results.

3. **"A DL for BC using dynamic contrast enhanced MRI"**

A fusion CNN model to increase the diagnosis of breast cancer based on dynamic variance improved MRI images was created [50]. The suggested system was formulated of two branches: a shallow branch that received input from seven analytical features and a deep branch that received input from a composite gray-scale tumor ROI image. Of the 130 patients, 71 had benign tumors while the remaining 59 had malignant ones. The CNN classification result was interpreted using three different forms of evidence criteria: contributing dynamic scan time points, feature visualization, and prediction likelihood. The suggested method obtained an accuracy of 87.71%, a precision of 91.22%, a sensitivity of 86.11%, and an AUC of 0.92 in a five-fold evaluation process.

4. **"Weakly supervised DL approach to breast MRI assessment"**

With no pixel-level segmentation a poorly supervised Deep Learning approach was formulated [51] with the goal of enhancing breast MRI lesion classification specificity. The ResNet-101 architecture served as the foundation for the suggested method. The collection included 288,685 picture slices from 438 patients in total. To improve its specificity, their network assessed the full slice of the MRI image rather than simply the region of interest (ROI). Compared with the manual definition of ROI boundaries, the suggested method decreased subjectivity-related mistakes. Breast MRI images were identified as benign or malignant using the suggested approach, which produced results including an AUC of 0.91, accuracy of 94.23%, sensitivity of 73.41% and specificity of 96.30%.

CONCLUSION

The detection of breast cancer is a difficult problem, despite being the most prevalent and dangerous disease. Numerous applications were able to identify breast cancer with the AI tool's assistance, even in cases when there was no obviously visible tumor. Radiologists can now diagnose medical images more easily, thanks to a number of deep learning applications and approaches. To find breast cancer early on screening techniques include Mammography, Thermography, Ultrasound and Magnetic Resonance Imaging (MRI) are used. Scientists trained the models and made numerous improvements to the early identification of breast cancer by utilizing various databases with varying screening techniques. Despite the Deep learning's efficacy in healthcare picture analysis there are insufficient balanced datasets related to breast cancer, which may result in incorrect diagnosis. Access to some helpful datasets, enlightening reviews, and an emphasis on real-world applications are all necessary for improving the accuracy of medical reports. One noteworthy observation is the extensive application of the CNN and Transfer learning algorithms to different images data. The other technique for detecting breast cancer is through genomics or genetic structure analysis. The field of radio-genomic research is a recent development that emphasizes the numerous scales connections between clinical imaging and genetic expression datasets. This article gives a summary of the most current findings on the use of Deep Learning in conjunction with visualization techniques to diagnose breast carcinoma, along with several methods that could be helpful in directing future research.

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