A Review of Classifications Techniques and computer aided used for Breast Cancer Detection

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Abstract

One of the most prevalent and deadly diseases in women is breast cancer due to the increasing incidence, many researchers have become interested in it in recent years. Due to the difficulty of distinguishing with high accuracy the infected and non-affected breast tissue, computer-assisted diagnostic techniques were introduced, as the correct diagnosis requires the use of methods for extracting the distinctive characteristics of breast tissue. Pre-processing, features extraction, and classification are the three primary processes that make up the machine learning method for detecting breast cancer. Because it has a significant impact on the accuracy of the extracted system, as the methods used to extract the distinctive characteristics of breast tissue and thus affect the patient's life, so several methods were used. This research paper aims to study, analyze and compare the methods used to determine the characteristics of breast tissue for the purpose of accurate diagnosis of breast cancer.

Keywords: Breast cancer, CNN, Computer-aided diagnosis (CAD), Feature Extraction, Medical image analysis

1.Introducation

Compared to other cancers, breast cancer is the most common cause of mortality among women, especially in middle and low-income countries[1]. This disease is characterized by with a large number of harmful cells in a state, leaving them without initial diagnosis and treatment leads to the formation of slow-growing tumors that may lead to the death of the patient. Due to the changes that may occur, deoxyribonucleic acid may lead to the emergence of abnormal cells as a result of a genetic mutation and become malignant[1].

Breast tissue is made up of Various connective tissues, lymph nodes, blood vessels, and lymphatic vessels as shown in Figure 1. Cancer usually forms when breast tissue expands abnormally and cell division is uncontrolled, resulting in the formation of a tumor. A tumor that develops may be invasive or non-invasive, and usually begins in the milk ducts or lobules[2]. Invasive cancer may begin in the lymph nodes and spread to other organs through blood vessels, but the cancer is often separated from the tumor[1].

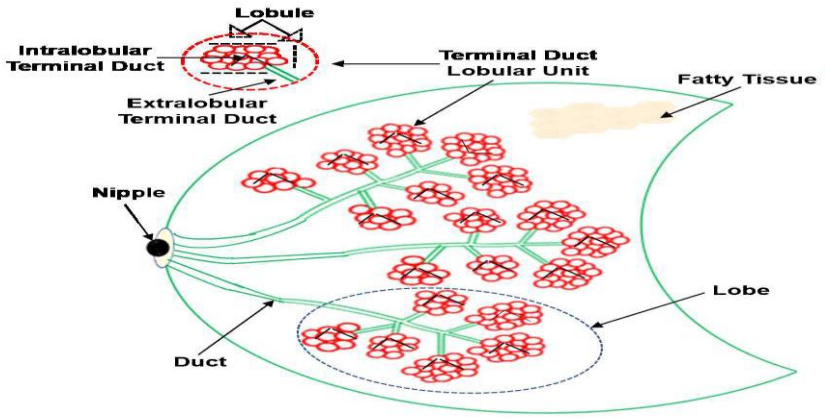


Fig 1: Female breast anatomy[1].

Early detection and diagnosis significantly reduces mortality and greatly increases cure rates. In the United States, for example, more than 3.1 million women have been diagnosed with breast cancer. Obesity, age, history of nursing, and menarche age are some of the factors linked to breast cancer. Early screening is achieved by identifying symptoms and routine examination, which helps to recover easily and prevent death [3].

As for the Middle East and Iraq in particular, breast cancer represents 23% of all cancers that affect women in the world. According to official statistics, breast cancer represents 32% of the other types of cancer that affect Iraqi women, and thus occupies the first place compared to the rest of the types that the Iraqi individual afflicts. Those diagnosed have been late, which greatly affects the possibility of successful treatment and thus increases the number of deaths[4].

Breast cancer diagnosis can be difficult due to the vast range of morphological characteristics that can be subtle and difficult to detect, as well as the necessity to consider numerous data sources, such as imaging modalities or patient-specific meta-knowledge. As a result, computer-aided detection/diagnosis (CAD)[5][6] systems are presented as a means of assisting radiologists in their decision-making. Pre-processing and Segmentation, Feature extraction, and Classification for decision making are the three primary phases of a CAD system[7][8][9] as seen in Figure 2 below[10].

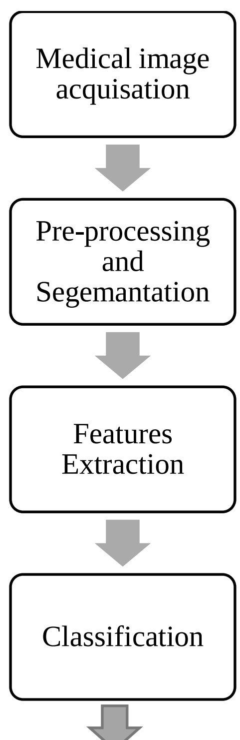


Fig 2: CAD based breast cancer detection system

The stage of features extractions plays a pivotal and important role in the diagnostic process, therefore there are many methods used for that. This work aims to review and compare them.

The remainder of this article is laid out as follows: In section 2 the Imaging modalities used for the purpose of diagnosis are reviewed. While section 3 reviews Preprocessing and Segmentation methods. Sections 4 identify and briefly explain the most frequent methods used for breast texture feature extractions, followed by Sections 5 and 6 which contain the Classification and Evaluation metrics discussion. Section 7 list the future directions and research gaps followed by Section 8 which is Conclusions.

2. 1 Breast Cancer Images Acquisition

Identification of breast abnormalities with imaging modalities begins with the analysis of a breast cancer image. When changes are detected early, the cure rate will increase; In the case of delayed detection and diagnosis, it leads to the spread of the disease, which is difficult to treat. There are many methods and technologies used to diagnose breast cancer that rely on a variety of imaging methods. Most common methods are reviewed bellow[11]:

2.1.1 Digital Mammography (DM)

A mammogram is an X-ray image of the breasts. They can be used either to detect breast cancer or for diagnostic purposes, such as to check for symptoms or unusual results on another imaging test. The breasts are squeezed between two firm surfaces during a mammography in order to stretch the breast tissue. The X-ray then takes black-and-white images that are displayed on a computer screen to check for signs of cancer[12]. Mammograms have an important role in detecting breast cancer. It can detect breast cancer before its signs and symptoms appear. Mammograms have been shown to lower the danger of breast cancer death[13].

2.1.2 Ultrasound (US)

Ultrasound is an imaging modality mainly used to detect the presence of lumps in the breast or any abnormal changes that the doctor finds during a clinical examination, on a mammogram, or in an MRI of the breast. Ultrasound of the breast does not replace mammography. Mammograms are required to examine the entire breast. Ultrasound sends a sound wave at a frequency higher than the human ear to the breast and the reflections of this sound on the ultrasound are shown as images[14].

2.1.3 Magnetic Resonance Imaging (MRI)

A non-invasive procedure used to identify medical issues is an MRI. An MRI creates precise images of your body's internal components using a powerful magnetic field, radio waves, and a computer[15]. X-rays are not used in an MRI. Doctors may study the body and find cancer using detailed MRI scans. A breast MRI provides valuable information about many breast conditions that cannot be obtained with other types of imaging tests such as radiography or ultrasound. A breast MRI is usually done after a positive cancer biopsy result[16]. A breast MRI can also reveal the extent of the disease[17]. A MRI along with a mammogram may also be used as a screening tool for breast cancer in some women, those with a strong family history of breast cancer, or those with hereditary breast cancer genetic changes. A MRI is not a substitute for mammography or ultrasound, but rather a complementary tool to it[18].

2.1.4 Breast Thermography

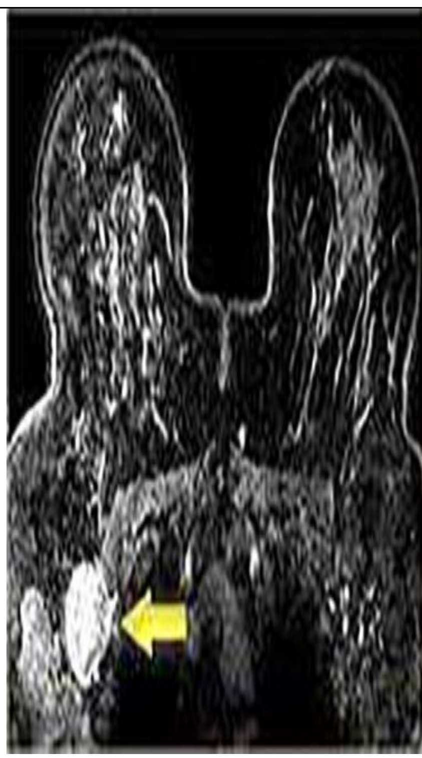
Thermography, also known as thermal imaging, is a technique for measuring the skin temperature on the breast's surface using a particular camera. It is a non-invasive and radiation-free diagnostic[10]. Thermography is founded on two principles: In a cancer tumor, blood flow and metabolism are increased due to the rapid growth and multiplication of cancer cells.

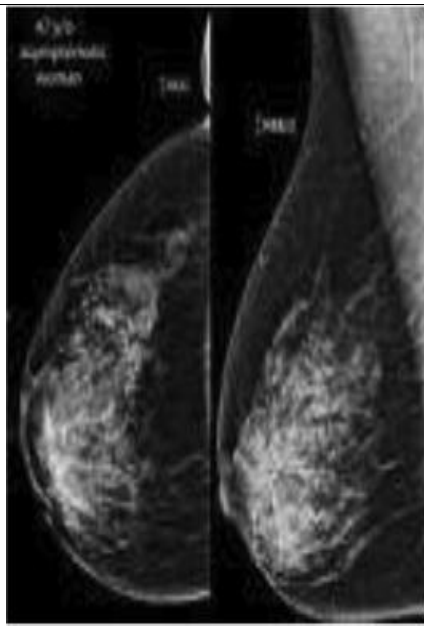
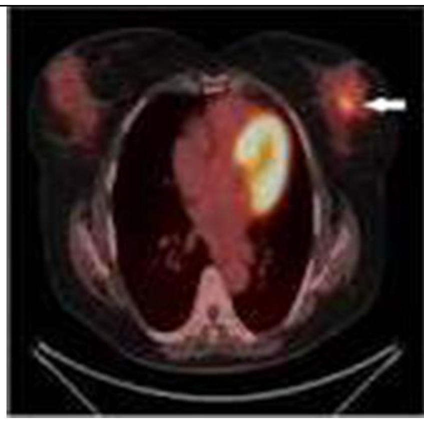
Skin temperature rises as blood flow and metabolism increase[19]. Although thermography has been used for decades, there is little evidence that it is a reliable screening technique for detecting cancer at an early stage, when it is most curable.

2.1.5 PET/CT Imaging

The positron emission tomography (PET) scan showed its sensitivity and accuracy in detecting many types of malignant tumors. The imaging device functions by indirectly detecting pairs of gamma rays that are released from radioactive isotopes that are positron sources (positively charged electrons)[20]. The radioactive chemical is concentrated in the organ to be inspected, such as the chest, by being injected into the patient's body after being attached to an active biomolecule (such as a sugar molecule). The computer then builds a three-dimensional image of the member using the measurements of the gamma rays it has produced. This image is then displayed on a screen attached to the computer[21].

Table 1 below summarize The imaging modalities[11][22][23].

Techniques		**Advantages**	**disadvantages**
Mammography		• The most common technique used by radiologists	• Exposure to low-dose radiation on a mammogram • A mammogram may fail to detect cancer if it is too small or is in a location that is difficult to image, such as the armpit. • Not recommended for women under the age of 40 who have thick breasts.
Breast MRI		• It's useful for women who have a highly risky factors. • Breast MRI is used to diagnose malignant tumors (cancer) in the breast in cases where a definitive diagnosis has not been made by mammogram or ultrasound of the breast. • • Breast MRI is a non-radioactive technology that does not expose the patient to radiation.	• Falsely positive result. After additional testing, such as a breast ultrasound or breast biopsy, a breast MRI may reveal suspicious spots that are benign tumors. • Sensitivity to the contrast dye. In order to make picture interpretation easier during a breast MRI, a dye is injected. People who already have kidney issues may experience major repercussions from this dye in addition to allergic reactions • Biopsies are recommended. • Not to be used by patients who have metal devices.

Breast Ultra-Sound		• Do not expose the patient to a dose of radiation. • Suitable for examining women with dense breasts It contains many glands and connective tissue • Painless technique during examination. • It is used with pregnant women who are difficult to examine using MRI, or Mammogram	• Covering the entire breast is difficult. • Resolution is poor.
PET		• It gives an accurate diagnosis and shows the extent of the disease's spread to other parts of the body. • It is not affected by breast density.	• Costly • Uses a radioactive substance injected into the patient • However, it is recommended that the patient not approach children or pregnant women until the patient has exposed the radioactive material. • Resolution is restricted. • Imaging speed is slow
Thermography		• non-invasive, • quick imaging duration, • suited for thick breasts	• In accurate procedure. It gives a wrong diagnosis if the body temperature is not the same

3. Preprocessing and Segmentation:

The fundamental principle of preprocessing is to transform RGB image to grayscale, LAB, or HSV mode, remove noise, and then clean and prepare the image for the next stage[24]. In general, images pre-processing operations for Breast cancer include augmentation, ROI extraction, scaling, image resizing, and normalization to remove artifacts and characteristics.

Augmentation or geometric transformation such as rotation a flipping, ROI extraction such as region growth, nucleus segmentation, the Otsu approach, and the Markov random model[25]. Scaling such as bilinear interpolation, bi-cubic interpolation Gaussian pyramid[20]. Images normalization and enhancement to eliminate noise and irrelevant parts are all common image pre-processing operations for Breast Cancer such as histogram equalization, median, Wiener filter, log transforms, adaptive mean filters[26]. When raw images (without pre-processing) are used in machine learning, the results of categorization are frequently skewed, and the output might often be poor[2].

After preprocessed breast images, the fundamental idea for the segmentation step is to separate the right and left breasts from an images that also contains the background, arms, and neck. Segmentation is the technique of automatically or semi- automatically drawing the borders within an image to divide it into various relevant segments (with similar features). These segments correspond to distinct tissue classes, diseases, organs, or other biological structures in medical imaging[14].Segmentation can be done in a variety of ways, including edge-based ,region-based, and threshold-based procedures. Sobel, Canny edge detector, corners detection, and other segmentation methods such as Hough transform, morphological operators and optimal cluster selection [19][27] .

4. Features Extraction

Over a CAD framework, extraction of features is the most critical phase in breast cancer diagnosis[28]. This procedure can only be carried out if the suspicious structures, such as tumors that are benign or malignant, are appropriately described. In addition to having a convenient representation, the extracted characteristics must be small enough to be practical and computationally efficient[29].The human designer expends a lot of effort in traditional CAD systems to extract and develop handcrafted details, such as the shape and density information of the malignant area in medical photos. This is a difficult undertaking since the method takes a long time, and the derived handcrafted features may not have enough discrimination ability to diagnose malignant regions[26].Whether it's binary, colored, or grayscale image processing, it's all the same. For identification, classification, diagnosis, classification, clustering, recognition, and detection, image processing can be done via extracting features. The feature extraction approach is used to extract as much information from an image as feasible. The selection and effectiveness of selected features, as well as their extraction, are currently a serious challenge. There are a variety of ways for extracting features, including Geometric features, Statistical features, Texture features, and Color features[30].

Several research has been conducted in the domain of breast cancer detection. This section provides a summary of several works that provide information on various detection strategies.

Dian C. R. Novita sari and et.al [3] This work suggested using statistical methods to extract characteristics of breast tissue such as Gray Level Co-occurrence Matrix(GLCM)[31],Gray Level Run Length Matrix(GLRLM) and, Gray level Difference Method(GLDM) . The author used Error Computing output code support vector machine (ECOC SVM) as classifier, which is built using three kernel comparisons: linear, RBF, and polynomial. According to author, the best kernel is polynomial kernels with statistical features produced using GLRLM, with an accuracy rating of 93.9757%.

Based on the highest and minimum temperatures of the right and left breasts, authors in [32]. In this works, 233 thermograms were used to classify cancer and non-cancer patients into binary and multi-class categories (malignant, benign, cyst, and normal). Furthermore, to eliminate classifier bias, the current database was balanced by the creation of synthetic vectors. The sensitivity of a classifier based on Sequential Minimal Optimization (SMO) was 94.73 percent for binary class and 80.77 percent for multi-class analysis.

Yeakel an et.al in [33]. Authors proposed using multi-convolution Neural Network (MCNN) as classifier with local and global mammography images features. The traditional manual features extraction stage is avoided due to the structure of MCNN, which sends a mammography image to numerous deep CNN with varying sizes and resolutions. The suggested method outperforms traditional state-of-the-art methods in terms of classification rates, allowing for a safer Computer-Aided Diagnosis of patient's state of cancer. Based on Author, using the multiscale convolution technique achieves a diagnosis accuracy of 97% ±3, demonstrating the efficacy of the proposed method.

Wavelet, Curve let, and Contour let transforms were used by Jayantha et al.in [34] . Authors suggested to derive characteristics from thermograms then characteristics were assessed using a one-sample t-test and an independent t-test. The thermograms medical images were separated into normal and abnormal categories with a Mean Square Error (MSE) of 0.3 using a Multilayer Perceptron back-propagation Neural Network.

Sure J. Mohammed and et al. in [35] proposed using statistical features to classify mammography breast images. A multiclass support vector machine (SVM) classifier is utilized to classify these tumor images. Using two evaluating classifier approaches, a hold-out method and one of the cross-validation methods, the accuracy of this classifier for classifying mammography tumors into malignant, benign, or normal cases is evaluated.

Ahmet H.Y. and et al. in [18] suggested using CNN with MRI images for early detection of breast cancer. Because of its superior soft tissue imaging capability, MRI is the highly recommended approach for identifying and screening breast cancer tumors and analyzing lessoned regions. Furthermore, it is a time-consuming technique involving an experienced radiologist. Convolutional neural networks (CNNs), on the other hand, have showed superior image classification performance when compared to feature-based methods and have shown promise in medical imaging.

Zhu et al. in [15] suggested using pre-trained Google Net with 16 layers was used to extract features from MRI. A total of 131 patients had their images taken, with 35 of them having aggressive cancer and the remainder having ductal carcinoma in situ DCIS. Data augmentation was used after the ROIs were generated from the original pictures using random translation and rotation. The SVM with different types of kernel functions (polynomial, linear, and RBF) was trained, evaluated, and verified using cross-validation (10 fold). Deep features from convolutional layer 13 had the best AUC value (0.68) when compared to other features.

Mayidili N. and et.al in [16] proposed using T2-weighted imaging (T2WI), dynamic contrast-enhanced (DCE) imaging, diffusion-weighted imaging (DWI), and apparent diffusion coefficient (ADC) imaging yielded a total of 1409 radiomic characteristics. To find the features most linked with LVI, researchers used a three-step feature selection process that included SelectKBest, interclass correlation coefficients (ICC), and least absolute shrinkage and selection operator (LASSO). Then, to construct single-layer radiomic models and fusion radiomic models, a Support Vector Machine (SVM) classifier was developed.

5. Classification

For all classes, such as malignant, benign, and normal, a sample of medical photos is taken from the given database[36]. After extracting features from pre-processed breast photos, the values are sent into the classifier, which determines whether the case is normal or abnormal. Ad boost, Neural Network[33], decision tree (DT), K-nearest neighbor (KNN), Support vector machine (SVM)[37], Random forest (RF), logistic regression (LR), and other classifiers are used to assign labels or classes to various groups[35].

6. Evaluation Metrics and Result Analysis

The model used to diagnose breast cancer patients is evaluated and tested using the Confusion matrix. It shows how the expected and actual values are related as seen in Table 2[23].

	Predicated Positive	Predicated Negative
Genuine Positive	True Positive (TP)	False Negative (FN)
Genuine Negative	False Positive (FP)	True Negative (TN)

There are four scenarios that can be used to differentiate between normal and abnormal breasts: When an abnormal breast is successfully diagnosed as abnormal, it is called a true positive (TP). When a normal breast is wrongly classified as abnormal, this is known as a false positive (FP).True negative (TN) refers to when a normal breast is correctly classified as normal; false negative (FN) refers to when an ill breast is incorrectly diagnosed as normal[23][10].

Other indicators for assessing a model's performance are given below[23]:

1. Accuracy = $\frac{TP+TN}{TP+TN+Fp+FN}$
2. Sensitivity (recall) =$\frac{Tp}{Tp+FN}$
3. Specificity =$\frac{Tp}{TN+Fp}$
4. Precision = $\frac{Tp}{Tp+Fp}$
5. F-measure = $\frac{2*precision*recall}{precision+recall}$
6. False Positive rate (FPR) = $\frac{Fp}{Tn+Fp}$
7. Area Under the Receiver Operating Characteristics (AUC-ROC) is a commonly used graphic tool for comparing different classification algorithms (ROC). To evaluate trade-offs between sensitivity and specificity in diagnostic procedures, a graphic representation of the relationship between the true positive rate and the false positive rate is used[10][23].

Table No. 2 gives a comprehensive summary of the previous work reviewed in this work in terms of the features extraction method, the type of classifiers used and the results obtained.

Table 2 Methods comparisons

Paper	**Features Extraction Techniques**	**Classification Method**	**Results**
[3]	GLCM, GLRLM, and GLDM	ECOC SVM	Accuracy =93.97% With mammography images
[32]	Statistical measures based on maximum and minimum temperature ,patients age	Multi-Layer Perceptron, Sequential Minimal Optimization (SMO), K-Nearest Neighbors (KNN), Bayes, Bayes Net, Random Tree,	Completely balanced extended thermogram categorization (SMO based) offers a binary class sensitivity of 94.73 % and a multi - class classification sensitivity of 80.77 %
[33]	Local and global features	Milti_Convolution Neural Network (MCNN)	Accuracy= 97% ±3 Sensitivity =95.9% Specificity= 94.85 In Mammography images
[34]	Curvelet Non-spaced ,Gabor wavelet, Contourlet, Dual Tree Wavelet, Curve let Wrapping	Multi-layer perceptron Back Propagation Neural Network	Gabor Wavelet features identified with a low mean square error (0.3).

[35]	Statistical features	Multi Class SVM	Accuracy = 0.9571% Sensitivity = 0.80%
[18]	Deep learning	Deep Convolution Neural Network	Accuracy =98.3% Sensitivity =1.0% Specificity= 0.9688% precision = 0.9655
[15]	Deep Learning	Google Net, SVM	Accuracy= 95%
[16]	dynamic Contrast-enhanced (DCE) imaging, diffusion-weighted imaging (DWI), and apparent diffusion coefficient (ADC),	Support Vector Machine (SVM)	Accuracy= 95% with ADC With MRI images

Figure 3 below summarize features extraction methods accuracy .

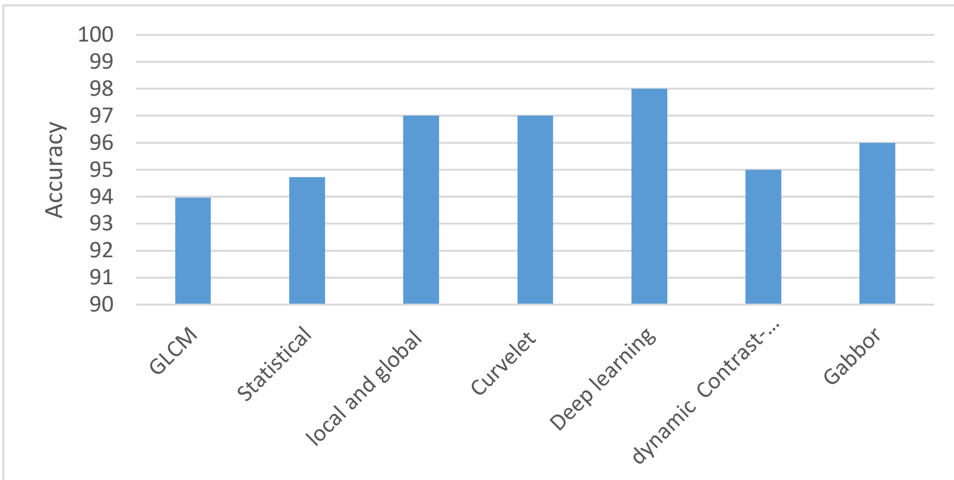


Fig 3: Methods Accuracy

7. Future Directions and Research Gaps

Breast cancer cases are rising at an alarming rate all over the world. In comparison to industrialized countries, fatality estimates in low- and middle-income countries are comparable to high. Early and accurate diagnosis are critical in improving long-term survival. The use of CAD to evaluate medical images has been proven to become the most effective method for early treatment and diagnosis. Deep learning is superior than traditional machine learning for the diagnosis of breast cancer, according to experimental data from studies by several authors. However, deep learning still has scope for development in terms of data integration, interpretability, security, temporal modeling, and the incorporation of expert knowledge. Deep learning is excellent for handling complex, diverse, unstructured, and data that has been inadequately annotated. Deep learning for breast cancer diagnosis has numerous advantages, but there are also some big challenges to overcome:

- Less large-scale, dependable datasets from medical experts for breast cancer classification are available. Deep learning algorithms require a large number of training images. Instead of using independent datasets, the majority of the authors used publically available datasets. Because independent datasets typically lack many photos from experienced doctors, most authors choose to use publically available datasets over others. However, because public datasets have already been pre-processed, models based on them are less dependable. As a result, if researchers are given massive annotated datasets from professional doctors, the health sector could be enhanced.

- Using non-imaging data to supplement imaging data. There are currently just a handful CAD models that combine radiomic characteristics with image data. More studies in future are required to incorporate non-imaging variables including analytical information, cancer history, and genetic information with image data to give early cancer detection for women at high risk.
- For breast cancer categorization, different imaging modalities. For breast cancer diagnosis, most investigations have relied on mammography, with only a few studies focusing on thermography, Ultrasounds, PET and MRI. As a result, many modalities may be used to diagnose the same patient in order to enhance the models' capacity for categorization, which boosts productivity and dependability.
- The majority of the papers that were chosen used supervised deep learning, or CNN, to diagnose breast cancer, which necessitates a big annotated dataset. However, gathering labeled datasets in the medical area is difficult, and the majority of the datasets available are unlabeled. As a result, further research is required to construct CAD models that make use of these unlabeled photos, which are an important source of data.
- The class imbalance problem, or the percentage of positive and negative samples, is another obstacle for CAD systems. Many of the existing datasets are still unbalanced. When training takes place on an imbalanced dataset, the prediction may be skewed towards a more common class and have a negative influence on the classifier's behavior. As a result, additional aspect that needs to be resolved is the lack of balanced datasets.

8.Conclusion

The deadliest malignancy in women is breast cancer. To reduce death rates, early diagnosis and treatment are essential. For early prediction and diagnosis in the healthcare sector, medical image analysis employing CAD has grown significantly. Our survey provides the most recent findings in breast cancer research using machine learning and deep learning approaches. The importance of early cancer diagnosis using imaging tools cannot be overstated, even though malignancy cannot be proven without a biopsy. Due to its high availability relative to alternatives, mammography is considered the "gold standard" for diagnosing breast cancer. However, it is being questioned for being ineffective for women who have dense breasts. Several imaging modalities, such as ultrasound, MRI, PET, and mammography, must be combined in order to obtain relevant results from extensive research. This survey also identifies problems with current research and offers suggestions for beginners in this field. The most common classifier for diagnosing breast cancer, according to machine learning research, is SVM. Additionally, deep learning techniques demonstrated exceptional performance for a variety of evaluation criteria, including accuracy, sensitivity, specificity, F-measure, etc. Deep learning model training takes a lot of time and resources from scratch. As a result, pre-trained models have been used in numerous research with impressive results. Results show that when the dataset is large, deep learning beats traditional machine learning in the diagnosis of breast cancer. Recent investigations that have identified research gaps show that practical and scientific research is urgently required to improve healthcare in the long run.

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