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RESEARCH PAPER

Comprehensive Study for Breast Cancer Using Deep Learning and Traditional Machine Learning

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A B S T R A C T:
Breast cancer is one of the most dangerous diseases and the second largest cause of women cancer death. Techniques and methods have been adopted for early indications of the disease signs as it's the only effective way of managing breast cancer in women. This review explores the techniques used for breast cancer in Computer-Aided Diagnosis (CAD) using image analysis, deep learning and traditional machine learning. It primarily gives an introduction to the various strategies of machine learning, followed by an explanation of the various deep learning techniques and particular architectures for breast cancer detection and their classification. After the review, the researcher recommended the need for the inclusion of deep learning in machine learning because it performs multi-functions in enabling medical diagnosis. Also, it is important to involve the integration of more than learning methods in medical learning to improve the process of medical diagnostic imaging and their benefits and limitations, recent advancements and development are discussed by reviewing the existing secondary sources. This study reviews papers published from 2015 (early publications on breast cancer) to 2021. This paper is a review of the latest works and techniques have done in the field with the future trends and problems in breast cancer categorization and diagnosis.

KEY WORDS: Breast Cancer, Convolutional Neural Network (CNN), Computer-aided Diagnosis (CAD), Deep Learning, Machine Learning, MRI image CT scan image
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1.INTRODUCTION :

Computer-Aided Diagnosis (CAD) is a technology of computer-based used by radiologists to detect medical issues and thus guide further investigations that need to be done. CAD has a pattern recognition software that enhances the radiologists 'attention to suspicious features on images under study. It uses a computer system that enables disease detection and identification of diseases, improves accuracy in interpretation of images, and reduces high chances of false-negative interpretations.

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CAD has improved effectiveness in the use of mammograms in breast cancer detection (Henriksen et al., 2019). A cancer diagnosis can be done by use of various approaches that include biopsy, laboratory tests, physical exams and imaging tests. Diagnosis for breast cancer can be done by the use of various tests, a mammogram, biopsy, ultrasound and magnetic resonance imaging (MRI) (Wang, 2017). Breast cancer is documented as a significant medical concern for women globally, especially women above 40 years. The American Cancer Society advises women to start early mammogram screening at age of 40, however, at the age of 45, they should start yearly check-ups, while at 55 years they should be very consistent with yearly mammograms. Breast cancer is a high-risk factor for women of age 50 and a cause of death, its early detection, diagnosis and treatment helps in minimizing mortality rate and morbidity (Smith et al., 2018). Imaging tests have been considered effective in tumors examinations, diagnosis and detection of early breast cancer signs, and internal organs. Breast Cancer, CAD and Diagnosis have been adopted for use in medical treatment as they are effective.

1.2. Medical Image.

Rapid tumor detecting and diagnosing by techniques of machine learning and image processing nowadays could help improve the preciseness in the diagnosis of breast cancer. Medical imaging is critical for the diagnosis of clinical disease, evaluation of treatment, and detection of a defect in various organs of the body, including in the eye (Akbar et al., 2018). Medical imaging refers to a collection of techniques for analyzing the human body for identifying, monitoring, or treating a disease. Any kind of technology provides detailed information on the body part being examined or treated (Rajinikanth et al., 2017). Investigations in medical imaging aim to categorize the position, measure, and features of the intended organ, which is thought to be a useful tool to extract valuable data out of vast amounts of information. As a result, some researchers concentrated their efforts on developing and interpreting medical images to categorize the huge percentage of disorders (Khan et al., 2019). As a result, diagnostic images aid in disease detection, the detection of abnormal lesions, the clinical care of the patient, as well as the interference of various medical issues. In recent years, artificial intelligence and machine learning have made significant advances and had a significant function in the field of medicine including image processing. Medical imaging through the frequent employment of several modalities including CT, mammography, PET, and MRI, as well as ultrasounds of duplex and radiography, is one of the most successful approaches for identifying breast cancer (Ashour et al., 2016).

1.2.1. Mammography Images.

A mammography or mammogram test is a mammography examination in women that aids in the early detection and diagnosing of breast cancer. Professional radiologists may review these mammograms and see whether any abnormalities in the breast can be found. Improvement in two or more mammograms over one or two years could indicate the presence of early cancer(Society, 2019).

1.2.2. Ultrasound Images.

It is another form of breast cancer screening that utilizes frequencies of low dosage for producing breast images while keeping the image of contrast minimal. The image of ultrasound could improve mammography screening and abnormalities detection, specifically in women that have big breasts. Nodes of breast mass could be detected and located by ultrasound, and it's typically applied for convenience (Qi et al., 2019).

1.2.3. Magnetic Resonance Imaging.

Magnetic resonance imaging (MRI), in addition to mammography and ultrasound, is another approach to the early detection of cancer cells. MRI uses magnetic fields instead of X-rays to create extremely exact transverse images of three-dimensional (3D). MRI of the human body, to obtain correct breast 3D images, needs a radiation of high dosage (Tesfaye et al., 2016).

1.2.4. CT scan (Computed Tomography).

A CT scan allows accurate images of the inside of your body by combining x-rays taken from various angles and combining them with a monitor. This examination is most commonly used to check the chest for signs of breast cancer spreading to other organs (Hossam et al., 2018).

2. PROBLEMS AND CHALLENGES BREAST CANCER DIAGNOSIS.

Breast cancer detection and classification despite the positive results of the reviewed literature, there are still some limitations and challenges that need to be overcome based on ML techniques for breast cancer diagnosis. The lack of comprehensive training datasets has been a major challenge in the training of deep learning models for medical imaging. Automatic Diagnosis of breast cancer Using Deep Learning Models from CT or MRI images is a challenging task since lesions can appear at any location and have different intensity distributions. Incorrect identification (misclassification) of a malignant abnormality as benign. There are several breast cancer datasets for building Computer-Aided Diagnosis systems (CADs) using either deep learning or traditional machine learning models. Some Challenges faces the work the authors listed below in brief

1. Creating large medical imaging data is difficult because annotating the data requires a great deal of time and effort not only from an individual but from several experts to exclude human error.
2. Studies analyzed used different datasets.
3. Use of data expansion approaches rather than transferring learning to prevent overfitting.
4. Challenge of the time consuming for training the machine learning models for a Big dataset of breast cancer. The motivation for this review is to enable radiologists to utilize techniques of the machine and deep learning for improving the proportion of accurate and rapid breast cancer-detecting and classifying. This paper aims to find numerous researches that use techniques of the machine and deep learning for classifying breast cancer through various medical imaging modalities.

1. What imaging modalities have been shown to help classify breast cancer?
2. What is the limitation dataset is used in medical image classification models?
3. Which machine learning and deep learning methods are currently being used to classify breast cancer using medical imaging modalities?
4. Which algorithms are used in deep learning and machine learning to find tumors for breast cancer?
5. What kind of Convolutional Neural Network architecture is applied for classifying breast cancer?
6. What evaluation metrics are applied for evaluating the effectiveness of the categorization models?

This information presents an introduction to the different learning methods of machines and deeply applied in breast cancer research, MRI, CT scan, and segmentation and filtering, detecting and classifying breast cancer. The organization of the rest of this study is as below: Part 2 would deeply explore the overview of the techniques applied in the machine and deep learning, Usages of machine Learning in various algorithms used to find tumours for breast cancer would be explained in part 3, Usages of deep Learning in various modalities or algorithms and Convolutional Neural Network (CNN) architectures would be given in part 4, Part 5 is a comparison of machine learning and deep learning for breast cancer. Finally, part 6 presented the conclusion of the research review.

3. COMPUTER-AIDED DIAGNOSIS (CAD) FOR BREAST CANCER:

Computer-Aided Detecting and Diagnosing has developed and new techniques that are used in diagnostic tests include images of x-ray, nuclear medicine, ultrasound, (MRI)and (CT). (CT) is computerized x-ray imaging that generates tomographic images. It facilitates the quick identification of basic structures and abnormalities existing. The CT scans have become useful screening instruments for tumours or lesions detection in the Breast. In addition, to early diagnosis of breast cancer. There are risks associated with it that include radiation effects on the body (Al Mohammad et al., 2017). Various research studies conducted reveal that the application of Computer-Aided Detection is effective and has facilitated the early treatment of breast cancer at its initial stage. (Morra et al., 2015), in the research, evaluated system of computer-aided detection (CAD) of commercial tomosynthesis in a multicenter, independent dataset that revealed that the system detects a higher percentage of indicated masses and microcalcifications clusters (89%, 99 of 111) and also a low rate of false-positive (2.7 per breast view). System of CAD presented per-lesion sensitivity of 89% (99 of 111; 95% interval of confidence: 81%, 94%), with 2.7 ± 1.8 rates per view of false-positive (Morra et al., 2015). It has also been researched that there is a need for an automated dual view analysis for breast cancer identification in mammograms rather than relying on radiologists for two mammography examinations (Amit et al., 2015). In the artificial intelligence era, in research by (Gao et al., 2019) on breast imaging, a comparison was undertaken by reviewing traditional versus machine learning-based systems in breast imaging specifically on breast cancer. The latest adoption of artificial intelligence has led to an interest in (DL) which has been made easier because of advanced algorithms made efficient by computerization, greater storage and use of big data (Gao et al., 2019).

4. BASICS AND BACKGROUND FOR MACHINE LEARNING AND DEEP LEARNING:

4.1. Machine Learning.

Machine learning is also used to diagnose breast cancer in medical research from 2015 to 2021 according to knowledge from the databases of Scopus about machine learning and studies of breast cancer categorizing and detecting. Machine learning is regarded as a subset of artificial intelligence (de Filippis et al., 2019),(Syeda-Mahmood, 2018) also elaborate that digital imaging requires complex knowledge to understand the disease or pathogen, which presents the significant role of ML in identifying a disease-medical diagnosis of breast cancer. The processing techniques of digital imaging for medical diagnosis are embedded in different computer systems. The validation of image processing techniques is significant because it allows for the implementation of certain procedures. These procedures act as stimuli towards the performance of these systems. Hence, it avails decisions and actions depending on the techniques in medical imaging breast cancer, which helps in disease diagnosis by medics. (Langlotz et al., 2019) elaborate that imaging provides numerous fundamental and advanced image evaluation and visualization tools for improved disease identification. Thus, (Gao et al., 2019) (de Filippis et al., 2019)and (Langlotz et al., 2019) all accepted the fact that machine learning and imaging are complex and necessary in the medical diagnosis process. (Dwivedi et al., 2019) add that ML plays a significant role in achieving (AI) and that the best way to portray human intelligence is through AI. (Bera et al., 2019) also outlined that AI and machine learning are important in enabling medical diagnosis because of the imaging element. The authors further add the element of (DL), they explain combined with machine learning. Techniques of machine learning such as set classifiers, Support Vector Machines, (ANN), closest neighbor, Naive Bayes, and (DT) are commonly utilized in the development of CAD systems.

4.1.1. Support vector machine (SVM).

In 2013 Researchers suggested a mechanism for determining whether a tumor is benign or malignant. The MATLAB bioinformatics toolbox was used to train an SVM algorithm. The accuracy rate of the classifications obtained was 95%. Researchers suggested a technique using SVM to discriminate and classify regions derived from mammograms as mass and non-mass. Researchers proposed in 2017 an automated diagnostic approach that combined a two-step clustering algorithm and SVM to detect the secret patterns of malignant and benign tumors with a classification accuracy of 99.1%. Researchers found that using this method increases cancer prediction accuracy and reduces misclassification error (Yassin et al., 2018). It could be concluded that the kind of algorithm for classifying and detecting breast cancer it's good and gives the best result and accuracy.

4.1.2. Naïve Bayesian Network.

As a directed network of acyclic, the Bayesian Network (BN) uses probability to define a connection among several variables. The variables are represented by the graph nodes, while the relationships among the variables are represented by the arcs. It is a special instance of BN that is recognized as a simple classifier according to the Bayes theorem. Baye's theorem, often defined as Baye's law or Baye's rule, is the basis for the algorithm of Naive Bayes. The following equation expressed Baye's Theorem:

$$P(A/B) = \frac{P(B/A)P(A)}{P(B)}$$

P (A/B): An event occurring probability if event B occurs.

P (A) and P (B): Are event A and B probabilities, respectively.

P (B/A): The B event occurring probability if the A event occurs. (Chaurasia et al., 2018).

4.1.3. k-Nearest Neighbor.

KNN is one of the most basic supervised learning algorithms for classifying characteristics into distinct groups. It saves the complete data set of training and calculates the similarity among every instance of training and a sample of input for doing predictions. According to the forecast, the result is a class in which most of them are within the ‘K' closest neighbors. Breast cancer is classified using this system. (Sharma et al., 2018).

4.1.4. Decision Tree (DT).

As a technology of data mining, DT is s used to identify breast cancer in its early stages. It is a model in which classifications or regressions are presented as a tree structure. In this approach, the data set is divided into little sub-data, which are subsequently divided into even smaller sub-data. It is not susceptible to noise (Tahmooresi et al., 2018).

4.1.5. Artificial Neural Network (ANN).

In the brain of a human, an Artificial Neural Network (ANN) is equivalent to the linked network of neuronal biologics that connects all of the neurons. Feedback is an extensively used artificial neural network (ANN) for categorizing ANN issues, and it is utilized in conjunction with the training technique for backpropagation. In an ANN of direct-acting, the fundamental anatomy of a single neuron is shown. The input from other neurons is received by a single neuron in an artificial neural network (ANN), which multiplies every date by the relevant weight and utilizes a function of activation for generating an output of weighted (Murtaza et al., 2019).

4.1.6. Random Forest (RF) Algorithm.

It is necessary to utilize the RF method at a stage in the regularization process when model quality is maximum, bias and variance concerns are compromised. It is also essential to construct a large amount of DTs through a replacement and random samples to address the issue of DTs. Every tree categorizes its observations, and the choice is made based on the votes of the majority of the trees (Elgedawy, 2017).

4.1.7. AdaBoost Classifier.

This algorithm is applied for predicting the presence of breast cancer using regression and classification. It transforms weak learners into strong learners by integrating all weak learners into a single powerful rule. It obtains the node's weight and keeps changing it until reaching results accurately. It is, nevertheless, susceptible to feature quality and noise (Senkamalavalli and Bhuvaneswari, 2017).

4.2. Methods used for Breast Cancer in Machine Learning.

The information and data that were used in this review were derived from secondary sources. These included books, internet sources, journals, and peer-reviewed articles. The review extracted information from multiple sources that analyzed the aspect of medical diagnosis for breast cancer imaging by machine learning, and the challenges faced in the process. There was a comparison of arguments by different researchers about the issue of machine learning to enable breast cancer imaging. Additionally, it allowed for the determination of the challenges faced in machine learning regarding breast cancer imaging. Thus, it aimed at explaining the evolvement of ML in enabling medical diagnostic for breast cancer imaging and how this has taken place over time. Also, using several types of algorithms in the field of machine learning to find breast cancer tumours and the best algorithm is (SVM) to find this disease and as it appears in the table according to best accuracy and results as shown in this Figure 1.

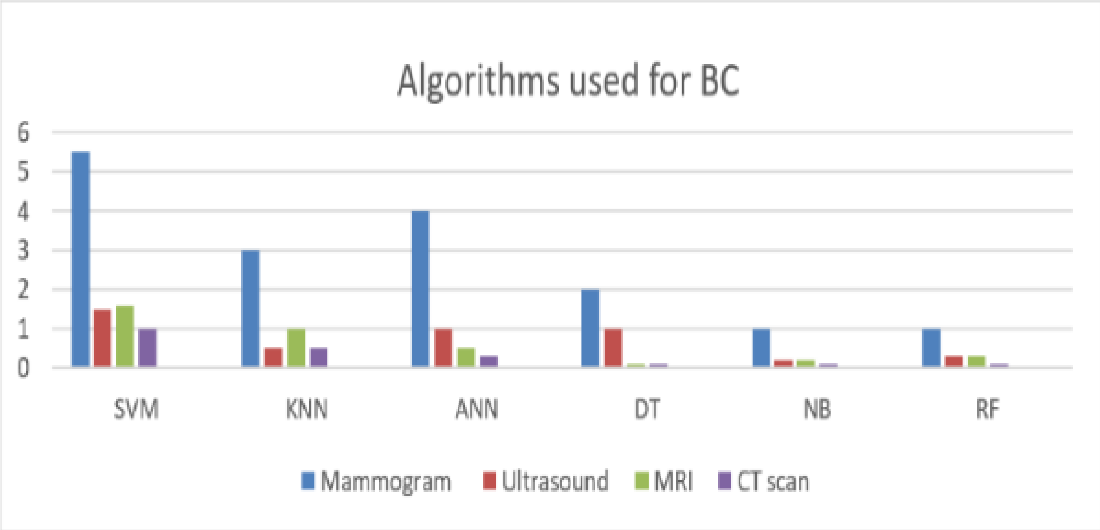

Figure 1. The number of algorithms utilized by machine learning for using different algorithms and images to find breast cancer.

4.3. Machine Learning Techniques for MRI (Magnetic Resonance Imaging).

Several types of research applied SVM, ANN, k-Nearest Neighbor, and Naïve Bayesian Network, for diagnosing and classifying breast cancer MRI. The researchers proposed an approach that uses the algorithm technique on a dataset of private to classify cancer of the breast as normal or non-normal (Benign or Malignant). The research (Obaid et al., 2018) suggested an approach. Three algorithms of machine-learning (Decision tree, K-nearest neighbors, and Machine of Support Vector) were utilized, and these classifiers performance was compared to see which one worked best for breast cancer categorization. The machine has the highest accuracy (98.1%) and the lowest rates of false discovery. KNN; Gradient Boosting; Xgboost; Forest of Random; Decision Tree; RBF machine of Support vector; machine of Linear Support vector; Gaussian Naive Bayes; regression of Logistic were among the machine-learning categorization techniques employed in the study (Obaid et al., 2018). Using both SL and SSL, the outcomes of every model is inspirational. Through only half of the training data, the SSL achieves good accuracy (90–98%). The DNN method was used in a study (Al-Azzam and Shatnawi, 2021) that showed (ML) approaches are used to diagnose breast cancer. Other algorithms like KNN, SVM, ANN, and others are also available. DNN, on the other hand, delivers a superior outcome in terms of accuracy. The accuracy of average increased to 89.77 per cent, while the high accuracy increased to 96 per cent. Machine learning techniques have several features attributes, such as the variable of independent and variable of dependent binary, and the main goal of them is building a categorization model from a dataset with named classes. The dataset training and validation are the two key stages in machine algorithms. The various techniques of machine learning for breast cancer are shown in Table 1.

Table 1: Results comparison of breast cancer through various algorithms of machine learning.

Author(s)	Algorithms/Techniques used	Dataset	Accuracy of machine learning in medical diagnosis	Implementation tool
(Sharma et al., 2018)	KNN	Wisconsin Diagnosis Breast Cancer (WDBC)	95.90%	Machine learning libraries in Python
(Chaurasia et al., 2018)	Naïve Bayes	uci machine learning repository datasets	97.36%	
(de Lima et al., 2016)	SVM	MIAS	94.1%	MATLAB
(Benhassine et al., 2020a)	ANN, SVM, NB	MIAS	100%, 94.1%, 92.6%	MATLAB
(Arafa et al., 2019)	SVM	MIAS	91%	MATLAB
(Benhassine et al., 2020b)	ANN, SVM, RF, NB	MIAS	99.1% 99.4% 98.2% 97.7%	MATLAB
(Silva et al., 2019)	GRNN and FFBPN, SVM, DT and Naive Bayes	Breast Cancer	GRNN 83.33%, FFBPN 85.18%, NB 72.2%,DT 70.83% & SVM: 77.77%	MATLAB
(Hazra et al., 2016)	NB, SVM, Ensemble	WDBC	SVM: 98.5%, NB &Ensemble: 97.3%	
(Bharat et al., 2018)	SVM, C4.5, NB, KNN	WBC	SVM outperform others: 97.13%	WEKA

4.4. Deep Learning Overview

Due to its ability to learn on its own, DL is a machine learning subcategory, and AI focuses on a complicated image features hierarchy, dissimilar to conventional algorithms of ML extraction. Deep learning is created from multilevel neural networks that use raw input images to generate a hierarchical structure of features. While remaining insensitive to variations of image, DL algorithms can practice with millions of images. DL has become more well-known as a result of recent successes, especially in image segmentation and classification. DL methods have been developed for a variety of purposes, including object recognition and segmentation, and disease classification (Dargan et al., 2019). Explain that this phase of the machine is at its advanced level. It mainly applies neural networks for learning and to enable data forecasting. Because of the complexities of neural networks and other elements, it is evident that this mode of ML requires in-depth and extensive knowledge and learning. (Korotcov et al., 2017) elaborate that this ML type is a group of diverse

algorithms. These algorithms enable the planning of a composite to generalize system with the capability of handling any challenge and providing prediction/diagnosis. Deep learning makes the application of the deep graph that

contains multiple processing layers to help identify the presence of a disease (Chen et al., 2017). However explain that though deep learning can solve and enable the prediction of many diseases, it cannot predict all the diseases because

machines are not always 100% efficient (Kong et al., 2015). The neural network is used to critique situations where a cell is normal with extreme assurance where every individual network contains just two outcomes–it will be either a normal cell or cancer. The ability to provide outcomes revealed that the neural network has the potential of achieving a high level of exactness, and a minimal level of false-negative analysis. Deep learning techniques. CNN's are one of the most interesting deep learning approaches. CNN, like those used in the competition of Image Net, has swiftly become a state-of-the-art approach for image processing through effectively utilizing local connection patterns with weights of shared. Networks of deep convolutional are one of the most applied algorithms of deep learning in analysis of medical image. This research presents a detailed overview of present high quality medical image processing utilizing networks of deep convolutional. These methodologies' limitations and possibilities are also emphasized, as seen in f Figure 2.

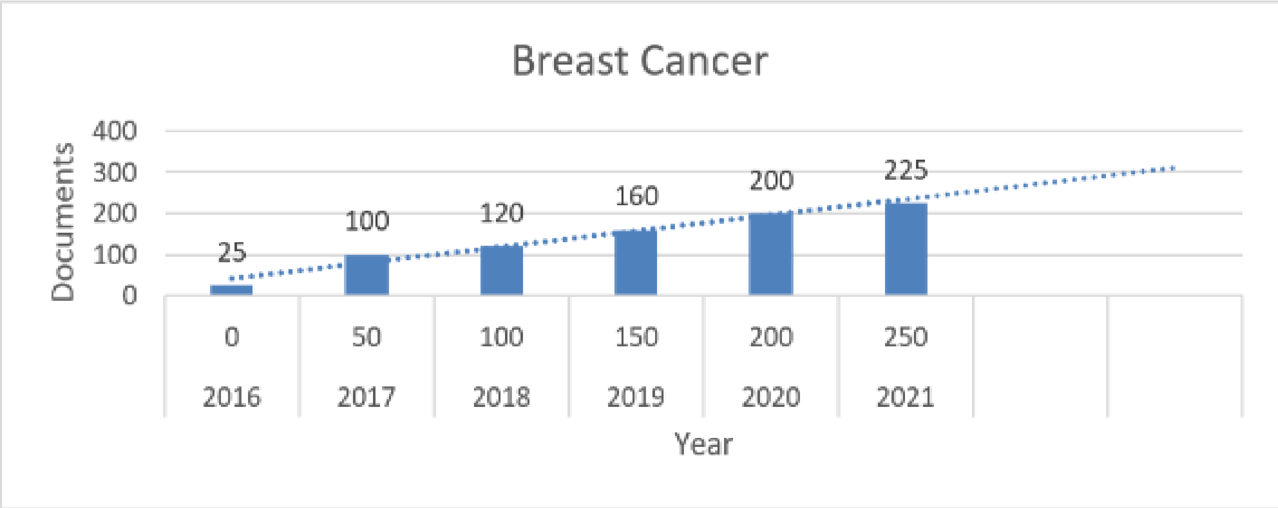

Figure 2. Histogram of deep learning for breast cancer classification and detection published

4.4.1. Convolutional Neural Network.

A network of convolutional neural is a network of deep neural which is often applied for categorizing visual pictures in deep learning. CNN is a network of feed-forward that is capable of extracting an image's topological features. Multilayer models of perceptron-based are known as CNN's (Yap et al., 2017). In general, a layered perceptron refers to a network that is fully linked, with one neuron in a single layer connected to every neuron of the following layer. CNN is similar to neural networks in that they have three layers: fully linked, pooling, and convolutional. There is a distinct function for every layer as shown in Figure 3. (Stenroos, 2017)

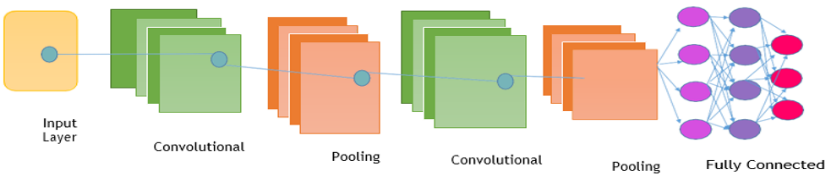

Figure 3. Convolutional Neural Network example(Houssein et al., 2020)

1. Convolutional Layers: The layers of convolutional are organized in maps of features using the local connection notion and theory of weight distribution. Every unit in a map of feature is linked to patches of local in the previous phase through a filter bank, which is a weight group and referred to as local connectivity. (Cai et al., 2015).
2. Layer of pooling: The layer of pooling uses a subsampling technique for combining identical

convolutional layer characteristics into a single layer (semantically) (Cai et al., 2015).

3. Layer of fully connected: These units` layers are linked to every unit in the layer before it, as in a typical neural network (multilayer perceptron) (Cai et al., 2015). Architectures of CNN: The performance and efficiency of CNN are largely determined by its architecture. The organization of the levels, the pieces utilized in every layer, and the way they are structured all have an impact on the speed and accuracy with which certain activities may be completed. CNN's success has been excellent in recent years as they have grown rapidly. (ImageNet, LeNet-5, AlexNet, GoogleNet, VGGNet, Inception-v4, ResNet-50, Inception-ResNet, Xception, Inception-v3, Inception-v1, ResNetXt-50). (Stenroos, 2017).

4.4.2. Recurrent Neural Networks (RNNs).

The model generates features from a variety of clinical text types, such as Magnetic Resonance Imaging (MRI) of Nuclear, Tomography of Computed (CT), X-rays, and B-ultrasound, using several recurrent neural networks (RNNs), and then gradually integrates the produced features. Lastly, according to integrated produced characteristics, a greater network layer of recurrent neural for identifying breast cancer of malignant and benign (Chen et al., 2017).

4.4.3. Deep Belief Networks (DBNs).

Deep Belief Network's (DBN) study uses segmentation of active contour for distinguishing aberrant images, which Deep Belief Network can classify. In the technique of restoration of low-dosage medical images, the suggested algorithm is applied for removing the attributes of the function of the point spread and restoring the rebuilt image quality. (Malathi et al., 2021).

4.4.4. Long Short Term Memory Networks (LSTMs).

The memory networks of long short-term are a form of RNN which could learn dependencies of long-term while overcoming the vanishing gradient issue. To capture extended dependencies in a series, the LSTM incorporates a mechanism of the gate and a unit of memory. The phrase memory of long short-term was used to describe the following phenomenon. Weights in networks of simple RNN provide the memory of long-term. (Malathi et al., 2021).

4.5. Deep Learning Techniques for Breast Cancer.

This section summarizes the most recent developments in breast cancer detection, classification, and diagnosis. Various researches utilized DL for detection and classification of MRI, Mammogram Imaging Ultrasound imaging and other types of medical images to find breast cancer. The researchers offer assessment outcomes of breast lesion detecting in (Malathi et al., 2021), demonstrating that the detector of YOLO can obtain general detecting accuracies of 99.17 per cent and 97.27 per cent, respectively, and F1-scores of 99.28 per cent and 98.02 per cent for the datasets of breast and DDSM. At the same time, for the datasets of INbreast and DDSM, during the testing time, the detector of YOLO predicted 71 frames per second (FPS). The classification models of InceptionResNet-V2, ResNet-50, and CNN for the dataset of DDSM obtain promising average general accuracies of 94.50 per cent, 95.83 per cent, and 97.50 per cent, respectively, and for the dataset of DDSM 88.74 per cent, 92.55 per cent, and 95.32 per cent, respectively. The researchers suggest a breast cancer histopathology image automated classification according to a fusion of deep features and improved routing (Al-Antari et al., 2020). To begin, a unique structure with channels of dual is developed that may extract characteristics of capsule and features of convolution at the same time, as well as merge spatial and sematic characteristics into newer capsules to acquire additional discriminative information. On the public BreaKHis of the dataset, the suggested technique FE-BkCapsNet has been tested. The suggested technique is effective for breast cancer categorization in clinical settings, as shown by experimental findings (400×: 93.54, 200×: 94.03%, 100×: 94.52%, 40×: 92.71%). They (Wang et al., 2021) employed strong CNNs and got better results than other state-of-the-art approaches for categorizing datasets of the same public. The database of BCDR had 96.67 per cent accuracy and 0.96 AUC, the database of INbreast had 95.50 per cent accuracy and 0.97 AUC, and the database of DDSM had 97.35 per cent accuracy and 0.98 AUC. The Screening Framework of Breast Cancer was built based on the model of CNN that produced the greatest results, with a 98.94 per cent accuracy (Feng et al., 2020) table 2 shows breast cancer detection using different deep learning algorithms.

Table 2: Results comparison of breast cancer detection by using different Deep Learning algorithms.

Author(s)	Algorithms/Techniques used	Dataset	Accuracy of deep learning in medical diagnosis	Implementation tool
(Ahmed et al., 2020)	Deep Lab Mask-RCNN	MIAS CBIS-DDSM	95.0% 98.0%	libraries in Python
(Baffa and Lattari, 2018)	CNN's	DMR	98% for static and 95% for dynamic protocol	libraries in Python
(Roslidar et al., 2019)	DenseNet201 ResNet101 MobileNetV2 ShuffleNetV2	Database for Mastology Research (DMR)	MobileNetV2 has an accuracy of 100% for static datasets and 99.6% for dynamic datasets	MATLAB
(Zuluaga-Gomez et al., 2020)	Proposed CNNs	DMR-IR database	92%	libraries in Python
(Yari et al., 2020)	CNN, DensNet, ResNet	BreakHis dataset	100%	libraries in Python
(Kim et al., 2020)	CRNN	Breast Ultrasound Image - Mendeley Data	99.75%	OpenCV-python
(Byra et al., 2019)	CNN based on VGG19	BI -RADS	Acc value: 88.7% TP value: 84.8% TN value: 89.7% AUC value: 93.6%	Python
(Yap et al., 2017)	FCN-AlexNet	datasets of US images.	98%	
(Ismail and Sovuthy, 2019)	VGG16- ResNet50	IRMA dataset	94% 91.7%	
(Li, 2021)	CNN	BCDR-F03	89%	

4.6. Steps in Machine Learning and Deep Learning in Breast Cancer.

Breast cancer diagnosis needs some steps involved in deep learning and machine learning algorithms to achieve diagnosis based on MRI or CT images. These can be shown in Figure 4. below:

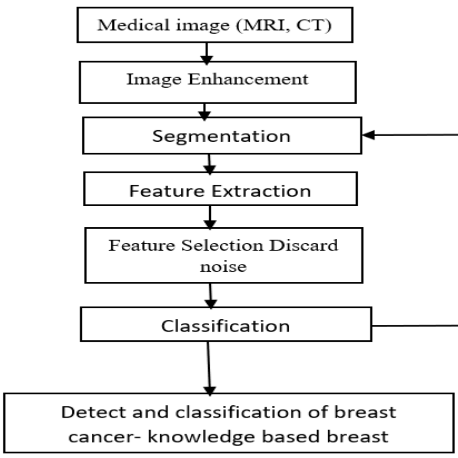

Figure 4. Machine and Deep Learning algorithms workflow in medical diagnostic imaging for breast cancer.

Image enhancement algorithms are commonly applied to remotely sensed data to improve the appearance of an image and a new enhanced image is produced. The objective of image segmentation is to make things simpler and transform the representation of medical images into a meaningful subject. The feature extraction of image methods is more and more used in medical image analysis, which increases the diagnostic accuracy and works an efficiency of doctors. Medical image classification is one of the most important problems in the image recognition area, and it aims to classify medical images into different categories. Overall, breast cancer image classification can be divided into two steps it's non-cancerous (benign) breast lumps or malignant.

In this part, the results of the proposed method are compared with other states of the machine learning and deep learning methods the results show that our model performed better which are presented in Tables 1 and 2, have been compared the results of the proposed method with another state of machine learning and deep learning methods and the comparison shows that our model provides promising results. In the proposed review study, types of deep and machine learning are used for the detection of breast cancer using MRI, CT-scan and mammography images also, in Table 3 shows deep learning architectures performance. The types of datasets that are used in the study. The accuracy achieved by the proposed method in deep learning it's better for machine learning. Authors (Yari et al., 2020) presented a deep learning-based method for the classification of breast cancer from (BreakHis) dataset by using CNN, DensNet, ResNet the study shows an accuracy of 100%. Authors, presented a CNN based model for the classification of breast cancer using MIAS, CBIS-DDSM DMR, Database for Mastology, Research (DMR) DMR-IR database, BreakHis dataset, Breast Ultrasound Image - Mendeley Data, stained images this study shows an accuracy of 95.0%, 98.0%, 98% for static and 95% for dynamic protocol MobileNetV2 has an accuracy of 100% for static datasets and 99.6% for dynamic datasets. The CNN model is quite deep as it comprises layers but still, the architecture failed to provide promising results.

Table 3: Deep Learning Architectures Performance.

Reference	**Architecture**	**Category**	**Strength**	**Limitation**	Performance
(Amkrane et al., 2020)	Deep learning, Radiomics	Breast DCE-MRI image dataset Radiomics analysis, decision support	The dataset in this field is still limited to validate the developed method	Breast tumor response prediction using a Radiomics approach	High
(Hirra et al., 2021)	Deep Learning, deep belief network, DBN architecture	patch-based deep learning model is presented for the classification of breast cancer using histopathology images.	image dataset having images from four different data cohorts and achieved	The limitation of keeping the images of equal sizes	Medium
(Chen et al., 2021)	3D convolutional neural network (C3D) and the 3D ResNet (R3D)	validate our model on our Breast-CEUS dataset composed of 221 cases	The dataset is collected from one scanner, the model is applied to data collected from different scanners	classification models for breast cancer. The model consists of 3D convolution.	Medium
(Chougrad et al., 2018)	VGG16, ResNet50 and Inception v3 (FTM-ML)	Mammography, mass-lesion classification	Merged three datasets	Inadequate model evaluation	High
(Xie et al., 2019)	CNN (FTM-LL)	Histopathology, multi-class classification, clustering analysis	Solved the unbalanced distribution of samples	Lack ofimage pre-processing	High
(Mendel et al., 2019)	CNN (FTM-ML)	Mammography, digital Breast tomosynthesis, classification	Leave-one-out step-wise feature selection was used to eliminate redundant features.	Lack of training data	Medium
(Kumar et al., 2020)	VGGNet-16 (FTMML)	Histopathology, feature extraction, image classification	Analysis of effects of image pre-processing	Accuracy is influenced by magnification	High
(Das et al., 2021)	conv2-D,max_pooling2-D	deep learning-based CNN model is restored even after using EWT and VMD, image classification	Synthetic Gene Image Dataset, Breast histopathology image Dataset	the types of breast cancer that are not verified that can	High

		and clustering analysis		be considered in the future.	
(Yu et al., 2021)	CNN (FTM-ML)	Histopathology, image classification	Images are collected via the internet.	The quality of the images could be inadequate.	High
(Surendhar and Vasuki, 2021)	Deep learning algorithm, Relu, Sigmoid function, Softmax	classifying the sample data into benign or malignant	data-mammogram scanned image to a certain trained a cluster of 400 women	classification is good because if the input value even goes the output value as in the limit of zero to one	low
(Hu et al., 2020)	CNN (FTM-ML)	MRI, feature extraction	Pre-processing, large dataset, and extended training times are not required	Issue of class imbalance	Medium

5. FUTURE WORK.

For future work, our model could perform better and could provide better accuracy if more hardware resources are available like GPU, for using a large number of the dataset for breast cancer MRI and CT-scan images input it is used deep learning because the deep learning method convolutional neural network mostly used for image dataset classification for breast cancer. Since we will try with new features and also try with the real images dataset so that we can achieve the best result and accuracy for diagnosis cancer, and also try this method on different types in cancer not only for breast cancer and we can work on the classification between different types of cancers using this model.

6. CONCLUSION.

The involvement of deep learning is a type of machine learning that empowers systems to gain for a fact and comprehend the world regarding a pecking order of ideas. It is an organized system and it can play a significant role in medical diagnosis. Deep learning allows for object and image classification. Also, it enables organ and localization detection after the image or object is classified. Deep learning also helps in segmentation to enable the processing of organ substructures of medical pictures, especially in the quantitative evaluation of clinical features. Deep learning will also allow for registration which involves the practice of transforming diverse sets of data into a single coordinate system. Therefore, deep learning inclusion will be of crucial use. Some machine learning techniques already use it. Integration of more than one learning method is another recommendation that will enable efficient ML for medical diagnostic imaging. Each machine learning technique has its advantages, while it has individual shortcomings. Techniques adopted in CAD and Diagnosis for disease treatment and prevention have played a key role in the medical field as they have enabled radiologists to be accurate and efficient in image interpretation of women examinations thus has led to early management of breast cancer. The limitations of techniques used in disease prevention and treatment need to be addressed in the modern era by computerized technical solutions and ensure that CAD algorithms are customized for effective analysis and reduce chances of wrong and misleading results from occurring. It will, therefore, support and facilitate radiologists to be very effective and accurate in their image interpretation hence less human errors and timely breast cancer detection and diagnosis thus appropriate treatment to save women lives.

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