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A Systematic Review on Early Detection of Breast Cancer Using Machine Learning and Deep Learning Techniques

B. Srinivas[1], M.Sriram[2], V.Ganesan[3]

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Abstract: The use of deep learning in the computer-aided diagnosis (CAD) of breast cancer is an area of active research, and it has shown promising results in recent years. Deep learning algorithms, such as convolutional neural networks (CNNs), have demonstrated superior performance in image analysis tasks, including medical image analysis. With the help of deep learning algorithms, the proposed CAD framework can extract and learn complex features from mammograms, which can be challenging for traditional image analysis techniques. This can lead to more accurate and reliable detection of suspicious lesions in mammograms, which can aid radiologists in making a more informed diagnosis. Using pre-trained deep CNNs such as AlexNet, GoogleNet, ResNet50, and Dense-Net121 is a common approach in deep learning-based image classification tasks, including breast cancer diagnosis. These pre-trained models are trained on large datasets such as ImageNet and can extract relevant features from images effectively. In the proposed experimentation, using pre-trained deep CNNs is likely to yield high accuracy in breast cancer diagnosis. The pre-trained models can be fine-tuned on a smaller dataset of mammogram images, and the learned features can be used for classification. This approach can potentially save time and computational resources compared to training a deep CNN from scratch. This work has produced a number of intriguing discoveries that will help scholars and researchers in evaluating and planning their future directions.

Keywords: *Deep Learning algorithm, CNNS, Computer-Aided Diagnosis and Mammogram image segmentation.*

1. Introduction

One in eight women globally receives a breast cancer diagnosis. Due to their promise to deliver precise and effective solutions, machine learning and deep learning techniques have attracted a lot of interest recently [1]. One important step in the detection and diagnosis of breast cancer is the segmentation of breast images to identify and isolate the region of interest (ROI). Different segmentation processes have been proposed, including edge-based, region-based, threshold-based techniques, and clustering-based methods. Each of these methods has its advantages and disadvantages, and the choice of method depends on the specific application and dataset [2]. After segmentation, various features can be extracted from the ROI, such as texture features, shape features, and intensity features. These features can be used to train classifiers for detecting early-stage breast cancer. Different classifiers have been proposed, including Decision trees, support vector machines, artificial neural networks, and random forests [3]. Deep learning approacheshave shown promising results in breast cancer detection and diagnosis. CNNs can automatically learn features from the raw image data and have been shown to outperform traditional machine learning approaches in many applications [5].
Breast cancer occurs when abnormal cells in the breast tissue begin to grow and multiply uncontrollably, forming a tumor. While it primarily affects women, men can also develop this condition, although it is relatively rare[6].

It can also occur in men, but this is rare. Breast cancer can start in different parts of the breast, such as the milk ducts or lobules, and can be classified as invasive or non-invasive. Invasive breast cancer means that the cancer cells have spread beyond the ducts or lobules into surrounding breast tissue, while non-invasive breast cancer means that the cancer cells have not spread beyond the ducts or lobules. Breast cancer can be diagnosed through various methods, including mammography, ultrasound, magnetic resonance imaging (MRI), and biopsy [7]. Early detection and treatment of breast cancer are critical for improving outcomes and increasing survival rates. [8]. A Computer-Aided Diagnosis (CAD) framework is a computer system that assists medical professionals in the diagnosis of diseases, such as cancer, by providing computerized analysis of medical images, such as X-rays, MRI scans, or mammography images [9-10]. The CAD framework can detect abnormalities in medical images, quantify their characteristics, and provide diagnostic decision support to radiologists, pathologists, or other healthcare professionals.

[1] Bharath Institute of Higher Education and Research,Research Scholar, School of Computing, Department of CSE, Chennai, Tamilnadu, India,ORCID: 0000-0002-4879-145X, srinu1032@gmail.com.
[2] Bharath Institute of Higher Education and Research, Associate Professor, School of Computing, Department of IT,Chennai, Tamilnadu, India, msr1sriram@gmail.com.
[3] Bharath Institute of Higher Education and Research, Associate Professor, School of Electrical, Department of ECE, Chennai, Tamilnadu, India
vganesh1711@gmail.com

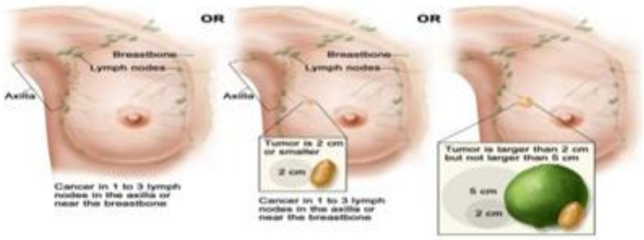

Fig 1: Shows the women with early stage positive beast cancer

The CAD framework typically consists of several components; including image preprocessing, and classification. In the image preprocessing stage, the medical images are first preprocessed to enhance image quality and reduce noise. In the feature extraction stage, features such as texture, shape, or intensity are extracted from the medical images to identify potential abnormalities [11]. In the classification stage, deep and machine learning algorithms are used to classify the abnormalities as benign or malignant. [12]. As a result of the CAD framework, diagnostic errors can be reduced, diagnostic accuracy can be improved, and diagnostic efficiency can be increased. However, CAD frameworks are not perfect and should always be used in conjunction with human expertise, as they may produce false positives or false negatives [13].

Mammography, an X-ray test of the breast tissue, and other imaging tests such as ultrasound and magnetic resonance imaging (MRI) can be used for breast cancer screening. Early detection and treatment can improve the chances of successful treatment and survival for women with breast cancer. It's important for women to discuss their individual risk factors and screening recommendations with their healthcare provider.2.1 million women are diagnosed with uncontrolled cell growth that leads to tumor development, according to many researchers [14].

Early detection of breast cancer is crucial for improving outcomes and reducing the rate of death and cost of treatment. When breast cancer is detected at an early stage, it is more likely to be treatable and may require less aggressive treatment than if it is detected at a later stage. Early detection also improves the chances of breast-conserving surgery, which can help preserve the breast tissue and avoid the need for mastectomy [15]. Early detection of breast cancer is key to improving outcomes and reducing the rate of death and cost of treatment. Women should talk to their healthcare provider about their individual risk factors and recommended screening recommendations [16].

One area of research focus has been on improving the accuracy of mammography, which is the most commonly used screening tool for breast cancer. Recent studies have looked at ways to improve the interpretation of mammography results algorithms to help radiologists detect subtle changes in breast tissue. Other research has explored the use of contrast-enhanced mammography, which involves injecting a contrast agent into the bloodstream to highlight abnormal blood vessels that may be indicative of cancer [17]. Another area of research has focused on developing new imaging technologies to detect early-stage breast cancer. For example, researchers have investigated the use of digital breast tomosynthesis (DBT), which creates a three-dimensional image of the breast tissue, to improve the accuracy of mammography. Other imaging technologies being studied include molecular breast imaging (MBI), which uses a radioactive tracer to detect cancer cells, and optical imaging, which uses light to create images of the breast tissue.In addition to imaging technologies, researchers have also explored the use of blood tests and other biomarkers to detect early-stage breast cancer.

2. Literature Review

Early stage breast cancer detection is a vital topic in the medical field and various methods have been proposed for detection and diagnosis. In this progressive review section, the authors have discussed different segmentation processes, features and classifiers along with their merits and demerits for early stage breast cancer detection. Deep learning approaches have been discussed for early-stage breast cancer detection and their role for detection and diagnosis of breast cancer and assistance in the treatment, recovery and decrease the chances of critical situations has been discussed. Shewtha K et al. [18] Machine learning algorithms can also be used for breast cancer detection and diagnosis, particularly in situations where the available data is limited or the computational resources required for deep learning methods are not available. In addition, hybrid approaches that combine machine learning and deep learning techniques have also been proposed, which can leverage the strengths of both approaches for improved accuracy and efficiency. S. Shamy et al. [19]. The use of texture feature extraction methods can help capture important information about the structure and texture of breast tissue, which can be useful for detecting and classifying different types of breast lesions.

K-means and Gaussian mixture model (GMM) are clustering algorithms that can be use to group similar regions of interest (ROIs) in the breast images, which can improve the accuracy of subsequent classification tasks. Using a CNN algorithm for breast cancer detection and segmentation can also be effective, as CNNs can learn to extract relevant features from images and can achieve high accuracy with appropriate training. The use of the MIAS dataset is also appropriate, as it is a used dataset for cancer detection research and contains a variety of images representing different breast abnormalities.

V Sansya Vijayam et al. [20] Clustering algorithms like Lloyd's algorithm can help identify regions of interest in histopathology images, which can improve the accuracy and efficiency of subsequent classification tasks. The use of CNN for classification is also appropriate, as CNNs can automatically learn relevant features from histopathology images and achieve high accuracy with appropriate training. The achieved accuracy of 96% is impressive and indicates the potential of deep learning methods for breast cancer diagnosis using histopathology images.

Puspanjali Mohapatra et al. [21] the use of deep learning methods can capture complex patterns and features in histopathology images that are difficult to discern with traditional machine learning methods.

Chandra Churh Chatterjee et al. [22] the achieved accuracy of 99.29% and AUROC score of 0.9996 indicate that the model was able to accurately distinguish between IDC and non-IDC cases in the dataset. Their architecture allows them to effectively capture the features of the input images and learn complex relationships between them. Additionally, the use of residual connections allows the network to overcome the degradation problem that arises when deep neural networks are trained. Canh Phong Nguyen et al. [23] By increasing the size of the dataset, the model has more examples to learn from, which can help it better capture the patterns and relationships in the data. Deep learning models often require large amounts of data to achieve good performance, especially when dealing with complex tasks such as image classification. By extending the dataset, the model can better learn the variations and subtleties present in the data, leading to more accurate predictions. However, it's important to note that simply increasing the size of the dataset is not always sufficient to improve model performance. The quality of the data, the diversity of examples, and the balance between different classes are also important factors to consider when building a deep learning model. Additionally, overfitting can be a risk when working with large datasets, so techniques such as regularization and data augmentation may also need to be employed to ensure the model generalizes well to new data. Varsha J. Gaikwad et al. [24] SVM is a popular classifier in machine learning and has been successfully used for many classification problems, including medical image analysis. The model went through several stages, starting with preprocessing and segmentation, which is essential for removing noise and extracting regions of interest (ROIs) that are most relevant for diagnosis. Feature extraction is also a critical step in image analysis, as it allows the model to identify key characteristics of the ROIs that are most indicative of breast cancer. SVM was used as a classification algorithm, Achieving an accuracy of 83% on this dataset is a promising result and indicates that the model is capable of accurately diagnosing breast cancer from mammogram images.. Tina Elizabeth Mathew et al. [25] they may be utilised to classify a variety of issues, including medical Wisconsin trees are a common classifier in machine learning, and the suggested model is based on Decision Tree classifier on breast cancer. The paper also mentions other classification algorithms such as naïve Bayes tree, rotation forest, adaptive boosting, bagging, boosting, and REPtree, which suggests a comprehensive study on different algorithms. The WEKA environment is a popular open-source tool for machine learning and data mining, and it provides a range of algorithms and tools for analysis. The use of different algorithms and techniques for classification, such as adaptive boosting, bagging, boosting, and REPtree, is an effective way to compare the performance of different approaches and identify the most suitable algorithm for a particular dataset. The paper's focus on accuracy indicates a rigorous evaluation of the performance of each algorithm. However, it's important to note that the accuracy achieved on the Wisconsin breast cancer dataset may not necessarily generalize to other datasets or clinical settings. Additionally, the model's performance may be affected by factors such as data quality, variability in imaging techniques, and differences in patient populations. Therefore, further evaluation on independent datasets is necessary to assess the model's generalizability and suitability for clinical use. Deepa B G et al. [26]The suggested approach for classifying breast cancer is based on augmentations of classifiers. Augmenting classifiers is a technique that can improve the performance of machine learning models by combining multiple classifiers and taking advantage of their individual strengths. The use of feature selection methods based on correlation and information is also a useful technique in machine learning, as it can help identify the most important features for a particular problem and reduce the dimensionality of the dataset. The evaluation of the model's performance with and without feature selection methods indicates a comprehensive analysis of the impact of these techniques on the accuracy of the classifiers. The use of five classifiers provides a good comparison of different algorithms, which is important to identify the most suitable classifier for a particular dataset. However, it's important to note that the accuracy achieved on the breast cancer dataset may not necessarily generalize to other datasets or clinical settings. Additionally, the model's performance may be affected by factors such as data quality, variability in imaging techniques, and differences in patient populations. Therefore, further evaluation on independent datasets is necessary to assess the model's generalizability and suitability for clinical use.. Badal Soni et al. [27] the proposed model based on the augmentations of classifiers for breast cancer classification sounds like an interesting approach. The use of feature selection methods based on correlation and information is also a useful technique in machine learning, as it can help identify the most important features for a particular problem and reduce the dimensionality of the dataset. The evaluation of the model's performance with and without feature selection methods indicates a comprehensive analysis of the impact of these techniques on the accuracy of the classifiers. The main objective is this study is to develop a deep learning system that can accurately classify breast cancer cases as either benign or malignant, with the goal of detecting breast cancer early and reducing errors in the classification process.

Author & Ref	**Method**	**Dataset**	**Findings**	**Limitation**
Gao et al.[28]	The segmentation network uses a U-Net architecture to segment the breast region from the ultrasound image, while the classification network uses a VGG-16 architecture.	The authors used a dataset of 385 ultrasound images of breast lesions, consisting of 209 malignant and 176 benign cases.	The proposed method achieved an overall accuracy of 92.73% for cancer detection and classification on the dataset. The segmentation network achieved a mean dice coefficient of 0.892 for breast region segmentation.	The method relies on the availability of large amounts of annotated data. The authors not compare the proposed method with non-deep learning methods and not consider the interpretability of the deep learning method.
Lee, J., Lee, J.H., Kim, M.S. et al.[29]	The method used a convolutional neural network (CNN) architecture called the U-Net, which was trained on a dataset of 238 breast cancer cases, containing 546 histopathological images.	Researchers used the following dataset in their research of 238 breast cancer cases, containing 546 histopathological images. The dataset was obtained from the Seoul National University Hospital (SNUH).	In the identification and segmentation of early-stage breast cancer in histopathology pictures, the suggested strategy demonstrated great accuracy.	For the identification and segmentation of breast cancer, deep learning techniques outperform conventional approaches. To train the deep learning model, a lot of labelled data and computing power are required.
J. Chen et al.[30]	The detection network is R-CNN method, which is trained on a large dataset of mammograms. The segmentation network is a U-Net model, which is also trained on the same dataset of mammograms.	The authors used the Digital Database for Screening Mammography (DDSM) dataset, which contains 2,620 mammograms with annotations.	The area under the receiver operating characteristic curve (AUC), sensitivity, specificity, accuracy, and other measures were used by the authors to evaluate their approach. They succeeded in the segmentation task with an AUC of 0.918 and the detection task with an AUC of 0.905.	The author may not include the need for large amounts of labeled data and computational resources to train the deep learning model, as well as potential ethical concerns related to the use of medical images.
N. P. Jayashree, et al.[31]	Using a deep convolutional neural network trained on a sizable dataset of mammography pictures, the technique includes the identification of malignant areas in mammography	The uses the Digital Database for Screening Mammography dataset, which contains a total of 2,620 mammography images, including 1,582 normal cases and 1,038 abnormal	The authors claim that their method achieves an accuracy of 97.34% in detecting breast cancer.	sLimitation on the dataset size or variety used to train and evaluate the algorithm used for deep learning, or potential biases in the labeling of the medical images.

	images.	cases.		
V. M. Patel et al.[32]	A convolutional neural network (CNN) architecture with several convolutional and pooling layers was employed in the suggested technique.	The authors used the Digital Database for Screening Mammography (DDSM) dataset,	The method achieved an overall accuracy of 95%, which outperformed several other segmentation.	The authors not include need for large data and computational resources to train the deep learning model.
Yang Zhang et al.[33]	The method involves the use of a deep CNN that is trained on a large dataset of breast cancer histology images.	This research uses the BreakHis dataset, which contains a total of 7,909 breast cancer histology images, including 2,480 benign and 5,429 malignant cases.	The authors claim that their method achieves an accuracy of 91.16% in classifying the breast cancer histology images.	The authors not include interpretability of the deep learning model, which may limit its clinical utility, and the potential biases in the dataset, which may affect the validity of the findings.
M. Hemalatha and S. Subathra et al.[34] .	The authors used a U-Net architecture, which is a type of CNN network to segment the breast tumor from mammogram images.	The dataset used for training and testing the model was the DDSM (Digital Database for Screening Mammography) dataset	The proposed deep learning method achieved promising results for the earliest stage breast cancer detection and segmentation. The authors reported an accuracy of 97.2% and a sensitivity of 97.9% for the breast cancer detection task..	The optimal configuration of deep learning models for this task, such as the choice of network architecture, the number of layers, or the pre-processing steps.
Wang, J et al.[35]	CNN networks and its derivatives, including U-Net, a popular design for segmentation tasks, are the most often used deep learning approaches.	The datasets used for training and validation vary, but some of the commonly used ones include the Digital Database for Screening Mammography (DDSM).	This may lead to better patient outcomes by aiding in the detection and management of breast cancer.	The authors not include of thorough comparison and evaluation of the deep learning methodperformance and the potential limitations of the studies reviewed, such as small sample sizes, biased datasets, or limited generalizability.
Li, Z et al.[36]	The proposed method used a CNN network to extract features from the mammography images and classify them as either normal or abnormal.	Using the Digital Database for Screening Mammography, the suggested approach was assessed, which contains mammography images from 2,620 patients with biopsy-proven breast cancer.	The deep learning approach that was succeeded accuracy of 94.8% for breast cancer detection and a dice coefficient of 0.85 for breast cancer segmentation improve the accuracy and efficiency of breast cancer diagnosis.	The authors not include interpretability. If the proposed method does not provide any insights into the underlying mechanisms of the model's decision-making process.
H. Khan et	The researcher	It contains the Breast	In contrast to GANs, which	The authors do not mention

al.[37]	various deep learning techniques, including CNN's, RNN's networkS and generative adversarial networks (GANs), that have been applied to the problem of breast cancer detection and segmentation.	Imaging Reporting and Data System (BI-RADS), the INbreast dataset.	have been used to create artificial mammograms, the scientists highlight that CNNs have demonstrated good outcomes in diagnosing breast cancer from mammography pictures. RNNs have also been applied for breast cancer detection from ultrasound and MRI images.	that it is crucial to evaluate the performance of the suggested strategy against that of other cutting-edge approaches in order to confirm its efficacy.
Dhiraj K et al.[38]	A CNN network was employed in the first step of the suggested approach, which had two stages, to identify breast cancer in mammography pictures.	The authors used the (DDSM) dataset for their experiments. It consists of 2,620 mammography images from 262 patients, including both normal and abnormal cases.	The suggested technique achieved accuracy of 96.5% for the detection of breast cancer and a 0.78 Dice coefficient was used to segment breast lesions.	The dataset used for training and evaluation is limited in size or diversity, the proposed method's performance may not generalize well to other datasets.
O. Elazab et al. [39]	To segment and categorise the mammograms into normal and abnormal instances, the suggested technique used a CNN architecture with a U-Net-like encoder-decoder structure.	The DDSM datasets was used to assess the suggested approach, which contains 2,620 digitized film mammograms from 1,265 women.	The recommended method has a 93.44% accuracy, 94.14% sensitivity, 93.14% specificity, and an F1-score of 93.64% on the testing dataset.	The authors proposed method does not provide any insights into the underlying mechanisms of the model's decision-making process.
Akselrod-Ballin et al. [40]	The researcher various deep learning techniques, including CNN's FCN,s and RNN's network that have been applied to the problem of breast cancer detection and segmentation.	The authors used the INbreast dataset, which is a publicly available mammogram dataset with 115 cases, including both benign and malignant cases. The dataset is annotated with regions of interest (ROIs) indicating suspicious regions.	The recommended method achieved an overall accuracy of 89% for breast tissue segmentation and 81% for classifying the suspicious regions into benign or malignant. The study showed that the proposed deep learning-based method can effectively detect and segment suspicious regions in mammograms, which can help in early breast cancer detection.	Deep learning models require a significant amount of data to be trained accurately, and authors the dataset used for training and evaluation is limited in size or diversity, the proposed method's performance may not generalize well to other datasets.
Chengyue Gong et al. [41]	The proposed method a CNN network is used to detect suspicious regions in mammography images.	The authors used the DDSM dataset, which contains 2,624 mammography images from 262 patients.	The proposed method achieved a sensitivity of 94.4% and a specificity of 88.1% in detecting malignant tumors, and a sensitivity of 85.7% and a specificity of 97.7% in segmenting	The performance of the suggested approach must be compared to that of other cutting-edge methods for the authors to validate its efficacy.

			malignant tumors.	
R. Sudha et al.[42]	The proposed technique uses a CNN’s network architecture called U-Net.	The authors use the publicly available DDSM dataset.	The proposed method achieved a high accuracy of 98.9% for breast cancer detection and 95.6% for segmentation.	It is possible that the authors may not provide enough details on the deep learning architecture or the training process, which could limit the reproducibility of the results.
Li, W et al. [43]	The framework consisted of three parts: a multi-scale feature extraction module, a region proposal network (RPN)	The dataset was divided into two parts: a training set of 220 cases and a testing set of 56 cases.	The authors reported an overall accuracy of 94.1%, a sensitivity of 94.9%, a specificity of 93.2%, and a Dice coefficient of 0.832.	It is not the most appropriate metric for imbalanced datasets like those encountered in breast cancer detection.
H. K. Verma et al. [44]	They proposed a model called Convolutional Neural Network-based Feature Extractor (CNFE) that extracts	They used the BreakHis dataset, which contains 9,109 breast histopathological images of benign and malignant tumors.	They showed that their proposed CNFE model can effectively classify benign and malignant breast tumors with an accuracy of 92.2%.	The generalizability of the suggested strategy to other demographics and imaging technologies may be seen by the authors via validation on an external dataset.
A. E. A. Gharib et al. [45]	The CNN is used to extract features from mammogram images, and the SVM is used to classify the images as benign or malignant.	They used the DDSM dataset, which contains mammogram images of benign and malignant tumors.	They demonstrated that their proposed system can accurately detect breast cancer with an accuracy of 93.3% on the DDSM dataset.	The performance of deep learning models heavily depends on the quality and quantity of the dataset used for training and evaluation. If the dataset used in this study is small or limited in diversity, the proposed method's performance may not generalize well to other datasets or clinical settings.
Li, H., Giger, M. L., & Huo, Z et al.[46]	The used deep learning techniques in this field are convolutional neural networks (CNNs) and their variations, such as U-Net.	The datasets used for training and validation vary, but some of the commonly used ones include the DDSM, the Breast Cancer Histopathological Image Classification (BreakHis) dataset, and the Cancer	The findings of these studies show that deep learning methods can accurately detect and segment breast cancer in its earliest stages, with high sensitivity and specificity. This can potentially improve the diagnosis and treatment of breast cancer, leading to better patient outcomes.	The authors focus on deep learning methods for image analysis in breast cancer diagnosis and prognosis. However, other aspects of breast cancer diagnosis and prognosis, such as genomics and proteomics, are not adequately covered. the field.
K. Vijaya Lakshmi and K. Kalaiselvi at el. [47]	The method uses a pre-trained convolutional neural network (CNN) for feature extraction and a modified U-Net	The dataset used for the study is the publicly available DDSM (Digital Database for Screening	The proposed method achieved an accuracy of 97.2% for breast cancer detection and a Dice coefficient of 0.89 for segmentation, which	The author may not provide a comprehensive evaluation of the proposed deep learning method, including its performance, robustness, and generalizability.

	architecture for segmentation.	Mammography) dataset.	outperformed existing state-of-the-art	Without such an evaluation, it is challenging to assess the effectiveness of the proposed method in real-world scenarios and compare it with other state-of-the-art methods
L. Wang, L. Chen, and J. Liu, et al. [48]	The method used a convolutional neural network (CNN) with multiple layers to learn the features of the images and classify them as cancerous or non-cancerous.	The authors used the publicly available BreakHis dataset, which contains over 7,000 breast histopathological images with different magnification levels.	The authors reported an accuracy of 95.1% in detecting breast cancer and an average Dice coefficient of 0.86 in segmenting cancerous regions.	The authors should provide clear details on the evaluation metrics used to assess the performance of the proposed method. If the evaluation metrics are not well defined, it may be challenging to compare the results with other studies.
Alaa Khamis and Hala Elsaadany, et al. [49]	They used a deep convolutional neural network (CNN) to extract features from the mammograms. The CNN architecture used was VGG16, which has been proven to be effective in image classification	The authors used the publicly available DDSM (Digital Database for Screening Mammography) dataset, which contains 2,620 mammograms with annotations indicating the presence or absence of	The proposed deep learning-based approach achieved an accuracy of 93.38% in detecting breast cancer in mammograms. The segmentation results showed an accuracy of 94.85%.	The authors not include comparison with other state-of-the-art methods or the lack of a thorough evaluation of the proposed method's performance on diverse datasets. Additionally, it is possible that the author does not address ethical considerations related to the use of deep learning for breast cancer detection and segmentation.
Wang, S., Liu, Z., Li, L., Yao, J., Chen, Y., & Chen, X. et al. [50]	Deep learning methods have shown great potential in the early detection and segmentation of breast cancer. The most commonly used deep learning techniques in this field are convolutional neural networks (CNNs) and their variations, such as U-Net,	The datasets used for training and validation vary, but some of the commonly used ones include the Digital Database for Screening Mammography (DDSM), the Breast Cancer Histopathological Image Classification (BreakHis) dataset, and the Cancer Imaging Archive (TCIA).	The findings of these studies show that deep learning methods can accurately detect and segment breast cancer in its earliest stages, with high sensitivity and specificity. This can potentially improve the diagnosis and treatment of breast.	The authors briefly mentions the performance metrics used to evaluate deep learning models, but it does not provide a comprehensive analysis of the performance of different approaches..
M. H. Kabir et al. [51]	The authors used a fully convolutional network (FCN) to detect the breast cancer region in the	The authors used the DDSM (Digital Database for Screening Mammography)	The proposed method achieved an overall accuracy of 98.1% for the breast cancer detection task and a dice similarity coefficient (DSC)	The authors does not address the issue of interpretability, which is an important consideration in

	mammogram image and a modified U-Net architecture to segment the cancerous region from the detected breast cancer region.	dataset for experimentation. This dataset contains 2620 mammograms from 262 patients.	of 0.91 for the breast cancer segmentation task.	medical imaging.
A. Karthikeyan, et al. [52]	In the feature extraction stage, a deep convolutional neural network (CNN) was used to extract relevant features from the mammogram images.	The authors used the Digital Database for Screening Mammography (DDSM) dataset, which consists of 2,620 mammogram images from 262 patients.	The proposed method achieved an overall accuracy of 96.87% for the classification of cancerous and non-cancerous mammogram images	The authors does not address the issue of Deep learning models are often considered as black boxes, and it can be challenging to understand the underlying reasons for their predictions

3. Conventional Methods for Earliest Breast Cancer Detection

Breast self-examination, clinical breast examination, and mammography are the traditional techniques for the early diagnosis of breast cancer.

3.1. Breast self-examination:

Breast self-examination is a simple technique that women can perform themselves at home. It involves feeling the breasts for any lumps, changes in texture or size, or other abnormalities. Women should perform breast self-examination once a month, usually a few days after their menstrual period, when the breasts are less likely to be tender or swollen. Although breast self-examination is not a substitute for mammography or other imaging tests, it can help women become familiar with their breasts and notice any changes that may require further evaluation.

3.2. Clinical breast examination:

A clinical breast examination is a physical assessment of the breast done by a medical practitioner, such as a doctor or nurse. During the examination, the healthcare provider will feel the breasts for any lumps or abnormalities and examine the surrounding lymph nodes for swelling or tenderness. Clinical breast examination is typically recommended as part of a routine check-up for women over the age of 20 and should be performed every 1-3 years.

3.3. Mammography:

Mammography is the most commonly used imaging test for breast cancer screening. Mammography is recommended for women over the age of 50, although some organizations recommend starting screening at an earlier age for women with certain risk factors [43]. Mammography is considered the gold for breast cancer screening and has been shown to reduce breast cancer mortality by detecting cancers at an early stage when they are more treatable. The combination of breast self-examination, clinical breast examination, and mammography is the current conventional approach to detecting breast cancer at the earliest stage possible [63].

4. Earliest Breast Cancer Identification, Detection And Segmentation Methods

In recent years, there have been several advancements in the field of breast cancer detection and segmentation. Here are some of the earliest breast cancer identification, detection, and segmentation methods.

4.1. Digital Breast Tomosynthesis (DBT): DBT is an advanced form of mammography that captures multiple images of the breast from different angles to create a 3D image.

4.2. Magnetic Resonance Imaging (MRI):

A magnetic field and radio waves are used in MRI to provide precise pictures of the breast tissue. Women with a high risk of breast cancer or when mammography and ultrasonography are unreliable frequently have MRI scans.

4.3. Automated Breast Ultrasound (ABUS):

ABUS is a newer technology that uses ultrasound to generate images of the breast tissue.

4.4. Artificial Intelligence (AI) and Machine Learning (ML):

AI and ML have shown promise in improving breast cancer detection and segmentation. These technologies can analyze mammography and other imaging data to identify patterns and anomalies that may be indicative of cancer.

4.5. Thermography:

Thermography uses infrared imaging to detect changes in temperature that may be indicative of cancerous tissue. While still considered a relatively experimental technology, thermography has shown promise in detecting breast cancer at an early stage.

5. Research Work Carried Out to Detect the Earliest Stage Breast Cancer

There have been several research studies conducted in recent years to detect the earliest stage of breast cancer.

5.1. AI for Breast Cancer Screening:

In 2019, a research study published in Nature investigated the use of artificial intelligence to get better breast cancer screening. The study found that an AI algorithm was able to identify breast cancer on mammograms with greater accuracy than human radiologists.

5.2. Blood Test for Early Detection:

The test works by identifying antibodies in the blood that are produced in response to cancer cells.

5.3. Liquid Biopsy:

In 2020, a study published in Nature Communications investigated the use of liquid biopsy to detect early-stage breast cancer. Liquid biopsy involves analyzing a patient's blood or other bodily fluids for the presence of cancer cells or DNA fragments. The study found that liquid biopsy was able to detect early-stage breast cancer with a high degree of accuracy.

6. Imaging Modalities

- Mammography
- Ultrasound
- MRI Scan
- CT Scan
- PET Scan

7. Machine Learning Models

In order to identify breast cancer in mammography pictures, various machine learning algorithms were applied to the MIAS dataset.

7.1. Decision trees

Information gain measures the reduction in uncertainty about the class labels achieved by splitting the data based on a particular feature. Decision trees are easy to interpret and visualize, making them useful for understanding the relationships between input features and class labels.

7.2. Random forests

Instead of using a single decision tree, random forests generate a set of decision trees by randomly sampling the training data and the input features. The algorithm works by constructing a large number of decision trees, where each tree is trained on a subset of the training data and a random subset of the input features. During prediction, the output of the random forest is obtained by aggregating the predictions of all the individual trees. Random forests are often used for classification and regression tasks and have several advantages over a single decision tree. They are less prone to overfitting, more robust to noisy or irrelevant features, and can handle a large number of input features. Additionally, they are relatively easy to interpret and visualize, and can provide information on the importance of input features.

7.3. Support Vector Machines (SVMs)

The SVM algorithm works by mapping the input data points into a high-dimensional feature space, where a linear hyperplane can be used to separate the classes. The hyperplane is determined by finding the optimal set of weights that maximize the margin between the classes. This is done by solving a constrained optimization problem that minimizes the classification error subject to the margin constraint. SVMs have several advantages over other classification algorithms, such as the ability to handle non-linear decision boundaries by using kernel functions to map the input data into a higher-dimensional space. SVMs are also effective in handling high-dimensional data and can perform well with a small number of training examples. Additionally, they can handle class imbalance and are robust to noise.

8. Deep Learning

Deep learning models are able to learn to extract features from data automatically, which makes them highly effective in a variety of applications such as computer vision, NLP, and speech recognition [60]. The perceptron, on the other hand, is a simple neural network model with a single layer that can only learn linearly separable patterns.

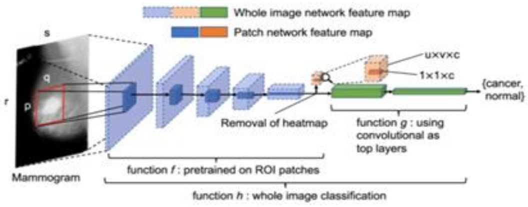

Fig 2: Shows the Deep Learning for Better Screening Mammography Breast Cancer Detection.

Deep learning has shown great promise in breast cancer detection, particularly in the analysis of mammography images [61]. These algorithms can learn to analyze mammography images and identify features associated with breast cancer, such as the presence of microcalcifications or masses.

These algorithms can then be used to classify new mammography images as either benign or malignant. There have been many studies that have demonstrated the effectiveness of deep learning in breast cancer detection. For example, in 2019, a team of researchers from Google Health published a study in which they used a deep learning algorithm to analyze mammography images from over 76,000 women in the United States and the United Kingdom [59]. The algorithm achieved a better performance than radiologists in terms of reducing false positives and false negatives. However, it is important to note that deep learning algorithms are not perfect and still require human oversight. In clinical practice, deep learning algorithms can be used as a tool to assist radiologists in making more accurate diagnoses, but they should not be relied on as a standalone diagnostic tool.

8.1. Perceptron

A perceptron is a type of ANN algorithm use in supervised learning for classification tasks. It was one of the earliest and simplest forms of neural networks, invented by Frank Rosenblatt in 1957. The basic idea behind a perceptron is to make a model that can learn to classify input data into different categories. It does this by taking in a set of input values (features), multiplying each input by a corresponding weight, and then summing the weighted inputs to produce a single output value. This output value is then passed through an activation function, which produces the final classification output. During the training phase, the perceptron adjusts the weights associated with each input to reduce the error between the predict output and the true output [58]. This process is known as gradient descent and is used to update the weights in each iteration of the training process. The perceptron algorithm is a linear model and can only learn to classify data that is linearly separable. However, multiple perceptrons can be combined to create a multilayer perceptron (MLP) that can learn more complex nonlinear relationships in data.

8.2. The First Neural Network Perceptron

The perceptron was indeed one of the earliest network models, and it was invented by Frank Rosenblatt in 1957. Rosenblatt was interested in creating a machine that could learn from experience, and he was inspired by the way neurons in the brain process information..

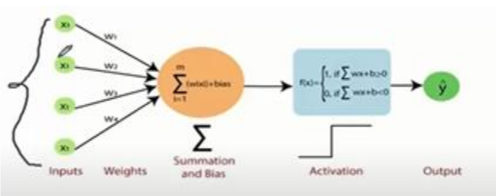

Fig 3: Shows the Neural Network Perceptron

The perceptron was initially hailed as a breakthrough in artificial intelligence and was seen as a potential model for creating machines that could learn from experience. However, it was soon discovered that perceptrons could only learn linearly separable patterns, and could not learn more complex patterns that were not linearly separable.

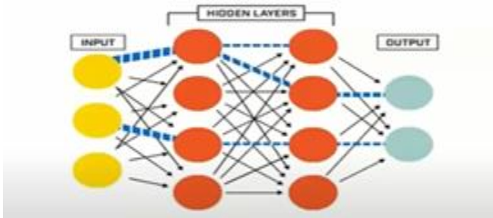

Fig 4: Shows the Neural Network Perceptron

8.3. Multilayer Perceptron

A multilayer perceptron (MLP) is a kind of neural network with many layers of nodes, such as an input layer, one or more hidden layers, and an output layer.

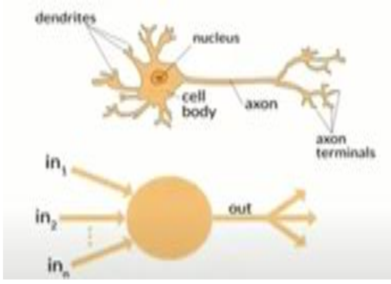

Fig 5: Shows the Multilayer Perceptron

The main advantage of MLPs over single-layer perceptrons is their ability to learn complex, nonlinear patterns in data. This is because the hidden layers in an MLP can learn intermediate representations of the data, which are then used by the output layer to make predictions. By using multiple hidden layers, MLPs can learn increasingly complex representations of the input data, allowing them to model highly nonlinear relationships.

9. Image Processing Using Deep Learning for Segmentation and Classification

Deep learning has revolutionized image processing, and there are a variety of deep learning techniques that can be used for tasks such as categorization, creation, segmentation, and object identification in images. CNNs are designed to automatically learn hierarchical representations of the input data by using convolutional filters to extract local features and pooling layers to reduce the dimensionality. This makes CNNs highly effective in tasks such as image recognition, where the input images can have a large number of pixels. Object detection is another important application of deep learning in image processing. This involves detecting the presence and location of objects in an image. Segmentation involves dividing an image into regions that correspond to different objects or parts of objects [53].

This can be achieved using techniques such as semantic segmentation, which assigns a label to each pixel in the image based on the object or class that it belongs to, or instance segmentation, which assigns a unique label to each instance of an object in the image. Finally, deep learning can also be used for image generation, such as generating new images from scratch or enhancing the quality of existing images. The GMM algorithm clusters the pixels of the mammogram image into different groups based on their intensity values, which allows for the identification and segmentation of breast nodules.

9.1. Convolutional Neural Networks (CNNs)

They are designed to routinely learn hierarchical representations of images by using convolutional filters to extract local features and pooling layers to reduce the dimensionality of the feature maps. Each filter is small (typically 3x3 or 5x5 pixels), and it slides over the entire input image, computing a dot product at each position to produce a new value in the feature map [54].

The output of the convolutional layer is typically passed through a non-linear activation function (such as ReLU) to introduce nonlinearity into the model. This is followed by a pooling layer, which reduces the spatial dimensionality of the feature maps by downsampling them. Max pooling is a common type of pooling, where the maximum value in each pooling window is retained. The resulting feature maps are then passed through additional convolutional and pooling layers to extract increasingly complex features from the input image.

Finally, the feature maps are flattened into a vector and fed into one or more completely connected layers, which execute the classification or regression task. CNNs are widely used for image classification, where the goal is to assign a label to an image based on its contents. They are also used for object detection, where the goal is to locate and classify objects in an image, and for semantic segmentation.

CNNs are designed to work on image data and have achieved state-of-the-art results in various image-related tasks. They are trained on a large dataset of labeled images, where the network learns to extract relevant features from the input image by applying multiple convolutional and pooling layers [55]. The final output is a probability distribution over the classes, which indicates the likelihood of the input image belonging to each class. Object detection is another task where CNNs have been successfully applied. In this task, the purpose is to identify the location of objects in an image and classify them.

9.1.1. CNN-Based Object Detection

In order to extract characteristics from the input picture and produce suggestions for regions that are likely to contain objects, CNN-based object identification algorithms like Faster R-CNN and YOLO combine convolutional and pooling layers. These regions are then refined and classified using additional convolutional and fully connected layers. Semantic segmentation is another image-related task that can be solved using CNNs. In this task, the goal is to assign a label to each pixel in the input image based on its semantic meaning.

9.1.2. CNN-Based Semantic Segmentation

CNN-based semantic segmentation algorithms using an encoder-decoder architecture where the encoder makes advantage of convolutional and pooling layers to extract features from the input image and the decoder uses upsampling and convolutional layers to generate a dense pixel-wise output. Finally, CNNs can also be used for image generation, such as generating new images from scratch or enhancing the quality of existing images.

9.1.3. Generative Adversarial Networks (GANs)

GANs are a popular type of CNN-based image generation algorithm, where two networks are trained simultaneously - a generator network that generates fake images and a discriminator network that tries to distinguish between the fake and real images. To produce more convincing pictures that can trick the discriminator, the generator network is trained.

9.2. Convolutional Filters

Convolutional filters, also called kernels or feature detectors, are an essential component of CNNs. They are used to extract local features from the input image by performing a convolution operation between the filter and the image. A convolutional filter is a template of numerical values that slides over the input image, computing a dot product at each position to produce a new value in the output feature map. The size of the filter is typically small, such as 3x3 or 5x5 pixels, and the values within the filter are learned during the training process.

The convolution operation is a mathematical operation that combines two functions to produce a third function [56]. In the context of CNNs, the input image and the convolutional filter are the two functions being combined. The output of the convolution operation is a new feature map that represents the presence or absence of a particular feature at each position in the image. Convolutional filters are designed to detect different types of features in an image, such as edges, corners, and blobs [57]. The learned filters are often visualized as images themselves, and they resemble patterns that are commonly found in images. During the training process, the weights of the convolutional filters are updated using backpropagation to minimize the error between the predicted output of the network and the true labels [58].

This process allows the network to learn the most useful filters for the task at hand. In summary, convolutional filters are used in CNNs to extract local features from the input image by performing a convolution operation between the filter and the image [59]. The learned filters are updated during the training process to minimize the error and to learn the most useful filters for the task at hand.

9.3. Pooling Layers

The dimensionality of the feature maps generated by the convolutional layers is decreased using pooling layers, another crucial part of CNNs. They achieve this by subsampling the feature maps using a sliding window and applying an aggregation function such as max or average pooling to the values within the window. Max pooling is the most common type of pooling used in CNNs, where the maximum value within each pooling window is retained and the rest are discarded.

This has the effect of preserving the most important feature in each window and discarding the less relevant information. Average pooling, on the other hand, computes the average value within each pooling window and is less commonly used in CNNs. It has the effect of smoothing out the feature maps and reducing the sensitivity to small variations in the input image.

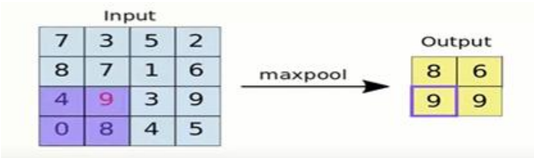

Fig 6: Shows the pooling layers

The pooling operation has several benefits for the CNN architecture. The main advantage is that it decreases the dimensionality of the feature maps, which lowers the number of parameters in the succeeding layers and aids in avoiding overfitting. Second, it introduces translation invariance into the network, meaning that small shifts in the input image. Pooling layers are typically inserted after the convolutional layers and before thecomplety connected layers in a CNN architecture.

They are often used in combination with stride and padding to control the size of the output feature maps. They achieve this by subsampling the feature maps using a sliding window and applying an aggregation function such as max or average pooling to the values within the window. Pooling layers help to reduce overfitting and introduce translation invariance into the network.

9.4. Connected Components

Connected components refer to groups of adjacent pixels in a binary or grayscale image that share the same value or intensity level. In other words, all the pixels in a connected component are connected to each other either directly or indirectly, and they form a distinct region or object in the image. Connected components are often used in image processing and computer vision applications for tasks such as object detection, segmentation, and recognition. One common algorithm for finding connected components in an image is the label propagation algorithm, which works by assigning a unique label to each connected component in the image.

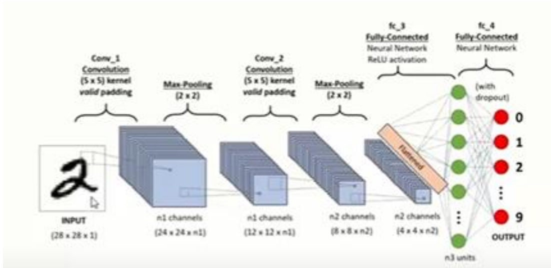

Fig 7: Shows the connected component in the image.

The label propagation algorithm starts by scanning the image from left to right and top to bottom. For each pixel, it checks if it belongs to a connected component that has already been labeled. If so, it assigns the same label to the current pixel. If not, it assigns a new label to the current pixel and updates a list of connected components with the pixel's label. After scanning the entire image, the label propagation algorithm performs a second pass to merge connected components that overlap or touch each other. This is done by checking the labels of adjacent pixels and merging the labels of connected components that share a boundary. The output of the label propagation algorithm is a labeled image, where each pixel is assigned a label that corresponds to the connected component it belongs to. This labeled image can be used for various image processing tasks, such as counting objects, measuring their size and shape, or segmenting them from the background. In summary, connected components are groups of adjacent pixels in an image that share the same value or intensity level.. The label propagation algorithm is a common method for finding connected components in an image, which assigns a unique label to each connected component in the image and merges overlapping or touching components.

10. Breast Cancer Detection Using A CNN Model

Breast cancer detection using a CNN model involves designing and training CNN to accurately classify mammogram images as either cancerous or non-cancerous. Here are the steps involved in creating a CNN model for breast cancer detection.

10.1. Data collection:

Collect a large dataset of mammogram images along with their corresponding labels indicating whether the image contains a cancerous lesion or not. The dataset should be diverse and representative of the population being diagnosed.

10.2. Data pre-processing:

Perform pre-processing steps on the dataset such as image resizing, normalization, and enhancement to make sure the pictures are of uniform size and quality and to increase the dataset size by creating variations of the original images.

10.3. Model design:

Create a CNN model architecture including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. According to how the model performs on the validation set, the architecture may be adjusted and improved.

10.4. Model training:

Train the CNN model on the pre-processed dataset using a suitable optimization algorithm such as stochastic gradient descent or Adam. The model should be trained on a high-performance computing platform with access to GPUs or TPUs for faster training.

10.5. Model evaluation:

Analyze the performance of the trained model with a different, unrelated test set. Accuracy, precision, recall, F1 score, and ROC curve analysis are the measures utilised for assessment.

10.6. Model deployment:

Deploy the trained model in a production environment, such as a web or mobile application, to enable real-time breast cancer detection for patients and healthcare providers.

10.7. Use of transfer learning:

Transfer learning involves using a pre-trained CNN model as a starting point for training a new model on a specific task. This approach can reduce the amount of training data required and improve the performance of the model.

10.8. Class imbalance:

The number of cancerous lesions in mammogram images is typically much smaller than the number of non-cancerous lesions, leading to class imbalance. Techniques such as oversampling, undersampling, and class weighting can be used to address this issue.

10.9. Interpretability:

It is important to ensure that the CNN model is interpretable, meaning that the features it learns can be understood and interpreted by healthcare providers. Techniques such as feature visualization and saliency mapping can be used to improve interpretability. In summary, building a CNN model for breast cancer detection involves data collection, pre-processing, model design, training, evaluation, and deployment. By using deep learning techniques, the accuracy and efficiency of breast cancer detection can be significantly improved, leading to earlier diagnosis and better patient outcomes.

11. Transfer Learning

This approach is especially useful when the new dataset is too small to train a neural network from scratch or when there is limited computational power or time available for training.

It taking a pre-trained neural network, usually trained on a large dataset such as ImageNet, and then removing the last layer(s) of the network. These layers are replaced with new layers, which are trained on the new dataset for the new task at hand.

Fig 8: Shows the Transfer learning

The pre-trained weights of the remaining layers are frozen, and only the weights of the new layers are updated during training. This allows the model to quickly adapt to the new dataset and achieve good accuracy even with a small number of training.

11.1. Feature extraction transfer learning:

In this approach, the pre-trained model is used as a fixed feature extractor, and the new layers are trained on top of the extracted features. The pre-trained model is typically modified to remove the last complete connected layer, and the output of the remaining layers is used as features for the work.

11.2. Fine-tuning transfer learning:

In this approach, the entire pre-trained model, or a subset of its layers, is fine-tuned on the new task. This approach allows the model to learn task-specific features in addition to the general features learned on the original dataset. Transfer learning has been successfully applied to a wide range of computer vision tasks such as object detection, image segmentation, and classification..

12. Mammogram Image Segmentation

Mammogram image segmentation refers to the process of identifying and isolating the relevant areas of a mammogram image for further analysis. This can be useful in various applications such as detecting breast cancer or evaluating the effectiveness of a treatment. One traditional method is the thresholding technique, where a threshold value is chosen to separate the image into foreground and background regions. Another method is the watershed segmentation, which is based on the concept of flooding regions with water from different starting points until the regions meet at watershed lines. Deep learning-based techniques have also shown promising results in mammogram image segmentation. One popular approach is the U-Net architecture, which is designed to handle medical image segmentation tasks by combining a contracting path to capture context and a symmetric expanding path to enable precise localization.

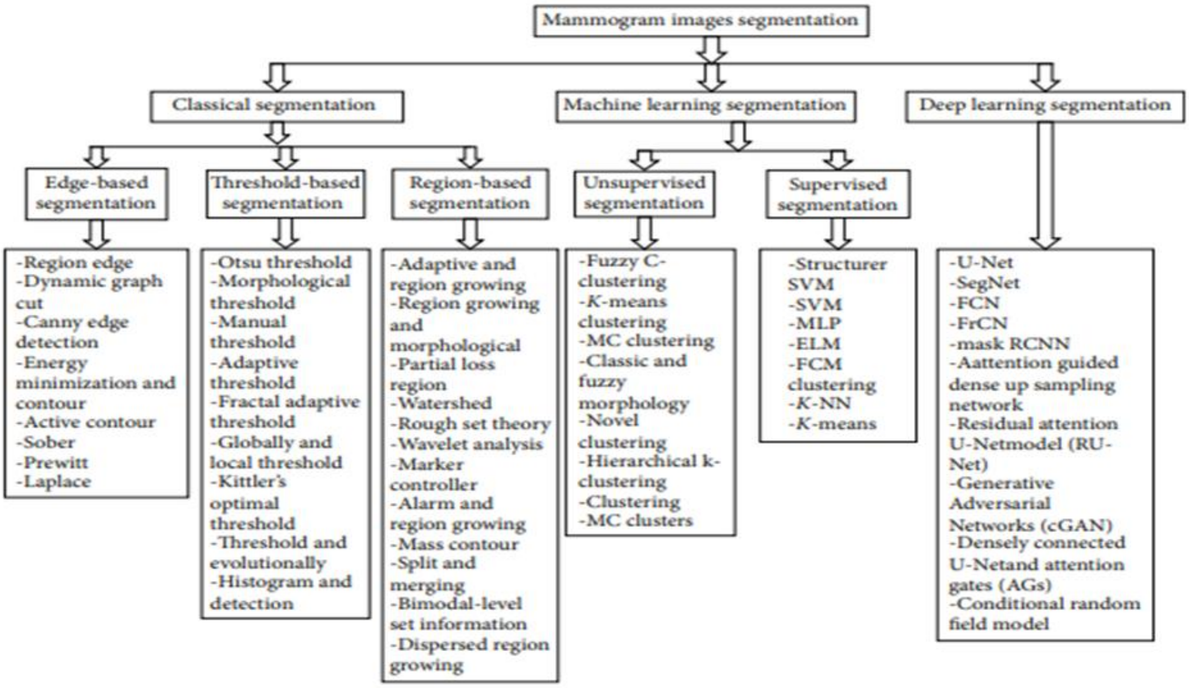

Fig 9: Shows Mammogram image segmentation

13. Deep Learning-Based CNN Architectures Mammogram Image Segmentation

There are several CNN architectures that have been developed over the years, each with their own unique features and strengths. Here are some of the most popular CNN architectures.

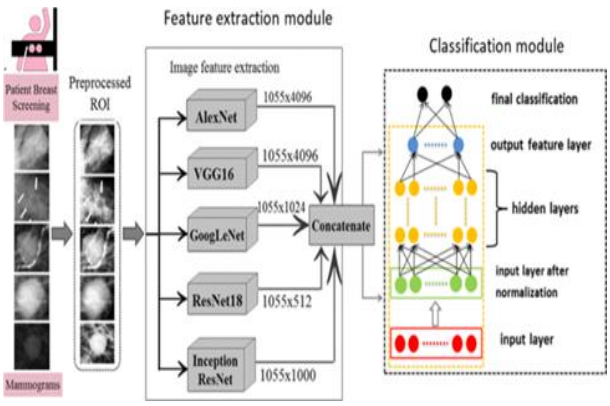

Fig 10: CNN Architectures Mammogram Image Segmentation

14. Evaluation

The true positive rate (TPR) vs the false positive rate (FPR) for various categorization criteria is plotted on the ROC curve. The area under the ROC curve, or AUC, gauges the classifier's general performance. The percentage of genuine positives over all anticipated positives is known as precision, and the harmonic mean of precision and recall is known as the F1 score. These evaluation tools are commonly used in machine learning to assess the performance of binary classifiers, including those used for breast cancer diagnosisis.

15. Conclusion

The use of machine learning and deep learning techniques for breast cancer detection is indeed a promising approach, as it has the potential to improve the accuracy and efficiency of breast cancer diagnosis. However, it is important to note that machine learning techniques are not limited to linear data and can be used

for nonlinear data as well. In fact, many machine learning techniques such as decision trees, random forests, and support vector machines have been successfully used for breast cancer classification on image data. However, it is true that deep learning techniques, particularly CNNs, have emerged as a powerful tool for image classification tasks, including breast cancer diagnosis. CNNs can automatically learn and extract relevant features from images, and their ability to handle large amounts of data makes them suitable for analyzing medical images. Moreover, the use of deep learning techniques can potentially overcome some of the limitations of traditional machine learning techniques, such as the need for handcrafted features and the difficulty in handling high-dimensional data. Therefore, the use of deep learning-based techniques such as CNNs for breast cancer diagnosis is a promising approach that can potentially improve the accuracy and efficiency of breast cancer detection. However, it is important to carefully evaluate and compare the performance of different deep learning models and techniques to identify the most optimal method for breast cancer diagnosis.

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