

Breast Cancer Classification based on Artificial Intelligence: State of the Art

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Abstract

Breast cancer, a formidable ailment, stands as a prominent contributor to global female mortality rates. The timely detection of breast cancer is of utmost importance as it significantly enhances the probability of a favourable prognosis while concurrently reducing the likelihood of the disease advancing to an incurable state. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as prominent methodologies for the precise detection and classification of breast cancer within Computer-Aided Diagnosis (CAD) systems. This paper provides a comprehensive overview of the existing body of literature pertaining to the application AI in the realm of breast cancer detection. The primary objective of this study is to underscore the significance of employing AI in the timely identification of breast cancer, thereby enhancing the efficacy of subsequent treatment interventions. Furthermore, an examination of different screening methodologies for the detection of breast cancer is presented. Furthermore, we explore the fundamental components of CAD system, including preprocessing, segmentation, feature extraction, and feature selection. This paper will extensively examine the various classification strategies employed in the identification of breast cancer.

Keywords: *Breast cancer, CAD system, Imaging Segmentation, Preprocessing.*

1. Introduction

Breast cancer is the deadliest form of the disease in females [1,2]. Therefore, early detection of breast cancer is crucial in preventing the spread of cancer cells and facilitating patients' participation in treatment, which in turn saves many lives. As shown in figure 1, there is a wide range of medical imaging options for detecting breast cancer. Mammography, thermography, ultrasonic imaging (sonography), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET) [3]. When it comes to aiding radiologists in their decision-making, a Computer-Aided Diagnosis (CAD) system is by far the most effective tool at their disposal. CAD was used as a pattern recognition system to spot breast cancer anomalies in imaging [9]. Because of its usefulness in diagnosing and categorizing diseases [9,10], computer-aided diagnosis (CAD) systems have risen to prominence in the medical industry. In the case of breast cancer, it is used to increase diagnostic accuracy. The primary goal of a CAD system is to use an automatic detection system to cut down on human errors. Various factors, such as inexperienced radiologists or distracting environmental factors, contributed to the high rate of human error. As a result, these

mistakes can be avoided through the use of a CAD system. Breast cancer detection through CAD can save lives, money, and time [11].

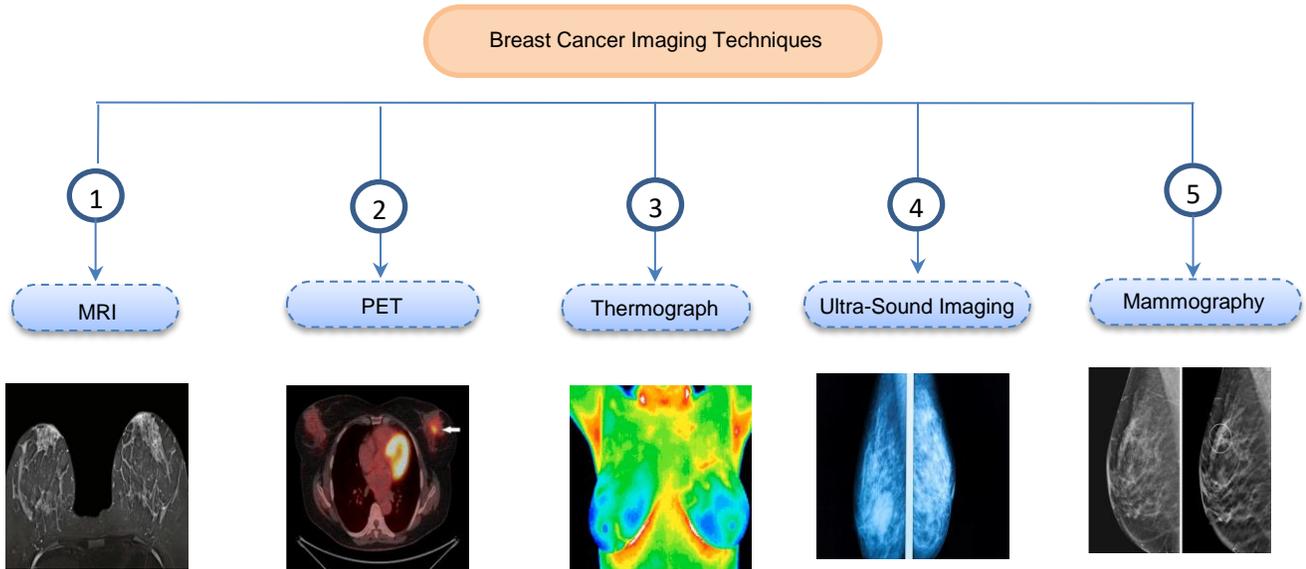


Figure 1, Different Breast Cancer imaging techniques.

The use of CAD systems has shown that Artificial Intelligence (AI) can be a useful tool in healthcare applications. The computers of today are getting more powerful, smaller, and quicker every year. These innovations are the backbone of AI and are being used to tackle some of the most intractable problems in the medical field and beyond [12]. Therefore, radiologists and pathologists should rely on AI and CAD for disease diagnosis. Both classical Machine Learning (ML) and Deep Learning (DL) fall under the umbrella of AI. The conventional ML framework typically consists of three primary stages, namely preprocessing, segmentation, and classification. It can be trained with a small number of features. Learning multiple representations at once through the construction of hierarchical features is central to DL, which is itself a subfield of ML. More features are needed for more effective training in DL [13]. In this paper, we present the results of an in-depth analysis of a CAD system for detecting breast cancer, which makes use of both conventional ML and DL.

1.1. Paper Organization

The rest of the paper is organized as follows; Section 2 describes the architecture of Computer-Aided Diagnosis (CAD) system for classifying breast cancer. It also explains its main parts in which image preprocessing, segmentation, feature extraction, feature selection, and classification will be reviewed. In the end, conclusions are presented in section 3.

2. Computer- Aided Diagnosis (CAD) system

When a quick decision is required in the medical field, automatic diagnosis has become crucial [14]. Radiologists can benefit greatly from the use of a CAD system. Initially created in the 1960s for the purpose of mammography-based breast cancer detection, its scope has since broadened to include the detection of lung cancer, brain tumours, etc. It was studied for several potential clinical

uses, and it turned out to be effective [15]. Therefore, CAD systems may help mostly radiologists arrive at a conclusive decision more rapidly and with more certainty [16]. With the help of CAD, doctors can zero in on the best course of action. There are typically two categories of CAD systems. Figure 2 illustrates a schematic representation of a computer-aided detection (CAD) system for breast cancer.

2.1 Image Preprocessing

Every CAD system starts with an image processing phase. Image processing's primary goal is to improve the quality of the input image so that false conclusions aren't drawn in later steps [17]. In other words, if you want good output, you need a high-quality input image. As can be seen in Figure 3, three primary operations—filtering, contrast enhancement, and data augmentation—are employed to achieve this goal.

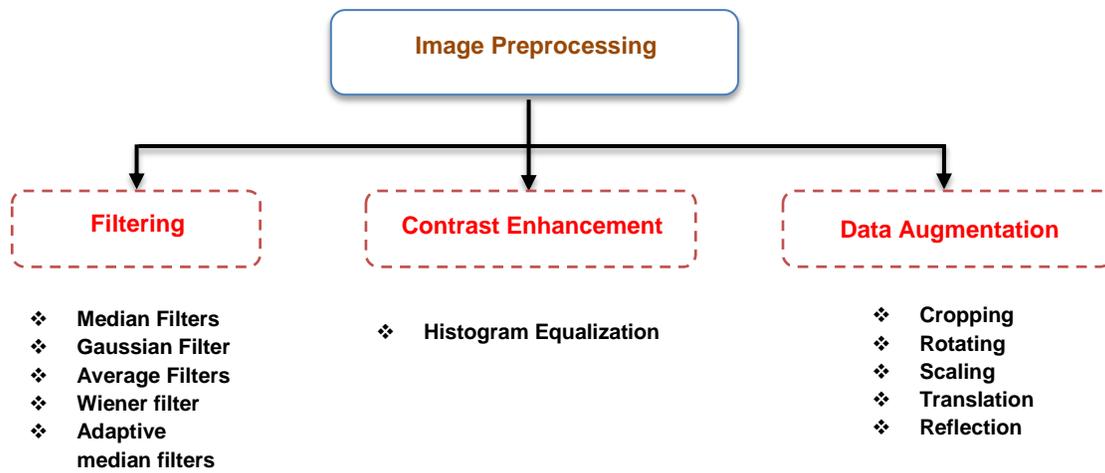


Figure 3, taxonomy of various image processing methods.

2.1.1 Filtering

First, the input image must be cleaned of any distracting noise. Noise in medical images obscures vital details and features, preventing precise disease diagnosis. Consequently, the utilisation of an image filter is employed to augment the visual data encapsulated within the input images [18]. Among the many types of filters that are put to use, the median filter, the Gaussian filter, and the adaptive median filter stand out [19,20,21]. The primary objective of employing a filter in the context of image processing is to enhance the overall quality of the image while accentuating its edges. The primary objective of employing a filter in the context of image processing is to enhance the overall quality of the image while accentuating its edges [22]. A hybrid approach to denoising mammogram images was proposed and demonstrated in [23]. The proposed strategy involves a two-stage process. In the first place, mammograms were improved with the help of mathematical morphology. Next, the images were cleaned up using a Global Unsymmetrical Trimmed Median (GUTM) filter. In addition,

in [24], the Hybrid Denoising Filter (HDF) algorithm was used to preprocess the mammogram images to completely remove the noise.

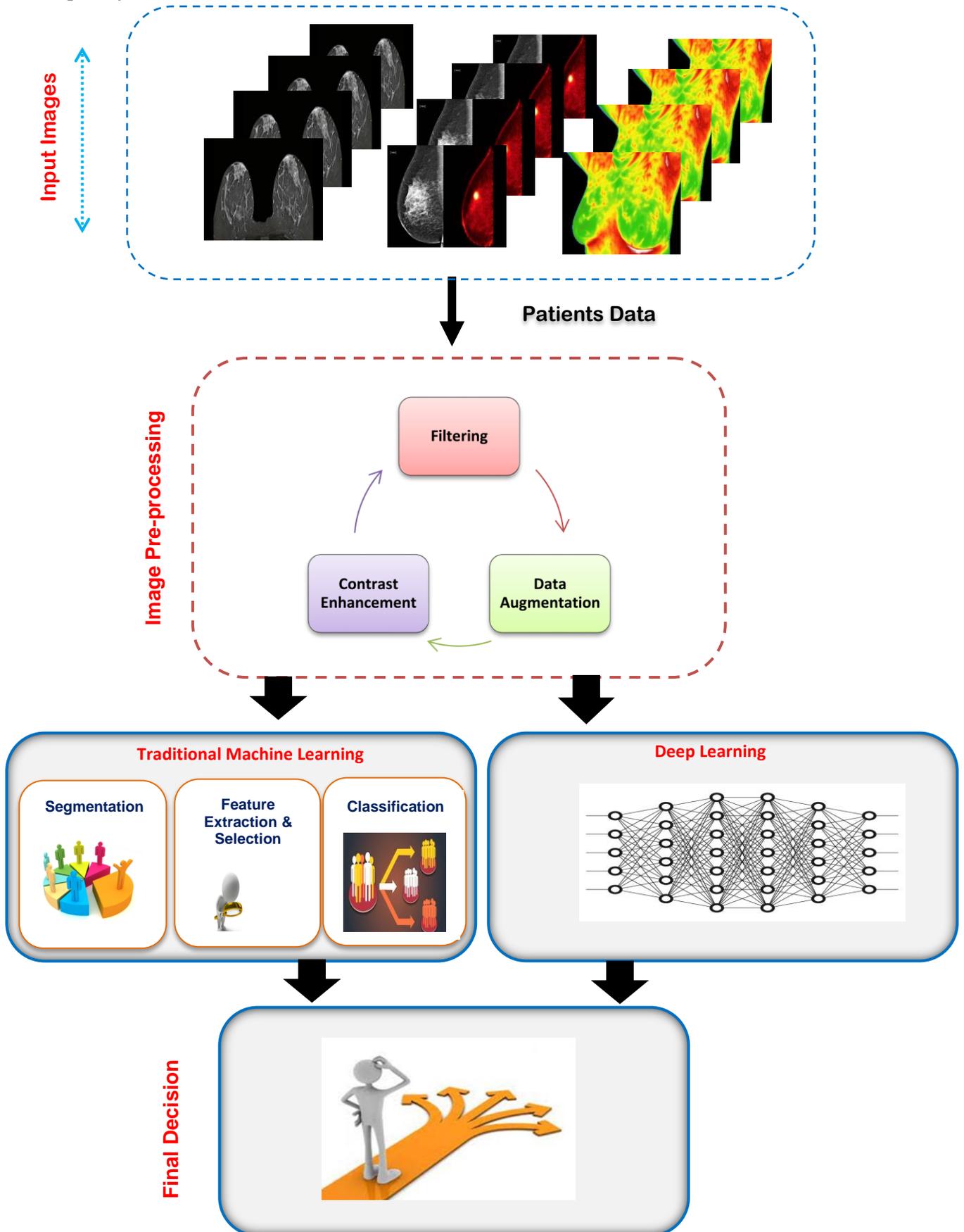


Figure 2, a block diagram of breast cancer CAD system.

2.1.2 Contrast Enhancement

Increasing the image contrast is another way to boost the quality of the input images. As a result, improving the contrast of an image is crucial and has numerous applications in the field of image processing, most notably in the medical field. It's meant to draw attention to details hidden by the image's limited dynamic range. Most commonly, Histogram Equalization (HE) is applied to improve image contrast [25]. The input images' contrast is improved as a result of the pixels' values being expanded to encompass the entire histogram [26,27]. When the useful information in an image is represented by relatively low contrast values, HE can improve the image's global contrast. This modification allows for more even intensity distribution across the histogram. It's most effective with pictures that have strong tonal contrasts between light and dark areas. This approach can be reversed with minimal time and effort investment [26].

The utilisation of HE has been extensively employed in a diverse range of published literature to enhance the contrast of images in the context of breast cancer. In their publication, the authors of reference [28] proposed a novel approach known as Adaptive Fuzzy logic based Bi-HE (AFBHE) in order to tackle the problem associated with conventional HE methods, which often result in images with a faded appearance and inconsistent alterations in luminance and brightness. When traditional higher education HE proved to be ineffective, we resorted to alternative forms of higher education, such as Alternative and Flexible Higher Education (AFBHE), as a potential remedy. The method proposed in this study demonstrates enhanced performance in comparison to existing alternatives with regards to visual quality, preservation of local information, and controlled contrast enhancement. This is evidenced by the results showcased in reference [28].

In [29], a new technique called the Self-Adaptive grey level HE Approach (SAHE) was introduced to improve the contrast of thermal infrared breast cancer images. The thermal infrared image of the breast cancer tumour was enhanced in colour using SAHE to aid in its early detection. No image-specific parameters need to be inputted by hand into the proposed SAHE. Early and accurate diagnosis in the medical field is aided by SAHE, as shown by research in [29]. In a similar vein, Contrast Limited Adaptive HE (CLAHE) was introduced as a means of enhancing contrast in [30]. As opposed to processing the entire image at once, the CLAHE operates on smaller sections of the image, or tiles. The goal of increasing the contrast of each tile is to create a histogram for the final area that is statistically equivalent to constant circulation. According to [30], testing showed that using CLAHE enhanced image contrast.

2.1.3 Data Augmentation

In the field of artificial intelligence, models, especially deep learning models, benefit from being trained on a sizable dataset in order to achieve better image classification. Acquiring substantial quantities of data for the purpose of training models poses significant challenges and incurs substantial costs, particularly in the context of medical applications. Data augmentation is a

technique that can be employed to augment the size of datasets. Therefore, image data augmentation is a method for making a training dataset larger than it actually is by creating altered versions of images already present in the dataset. Model performance and learning ability benefit from larger datasets [31,32]. Images undergo offline transformations like cropping, rotation, scaling, and translation as part of the data augmentation process [31,33]. Common data augmentation methods aim to make subtle adjustments to the provided image data, producing new images that are strikingly similar to those that result from natural variation.

When dealing with the issue of imbalanced data classification, Generative Adversarial Networks (GANs) can be used as an alternative method [34,35]. GANs are an effective tool for enhancing data. It is demonstrated that GANs can produce data for subclasses. It has the ability to simulate real data by producing synthetic results. Figure 4 illustrates the structural composition of a GAN, which comprises two primary elements, namely the generator and the discriminator. The generator and discriminator networks exhibit contrasting characteristics as they engage in a competitive process to generate the intended output. ML tasks benefit from GANs because of their ability to dive deep into data and interpret it in multiple ways [34,35].

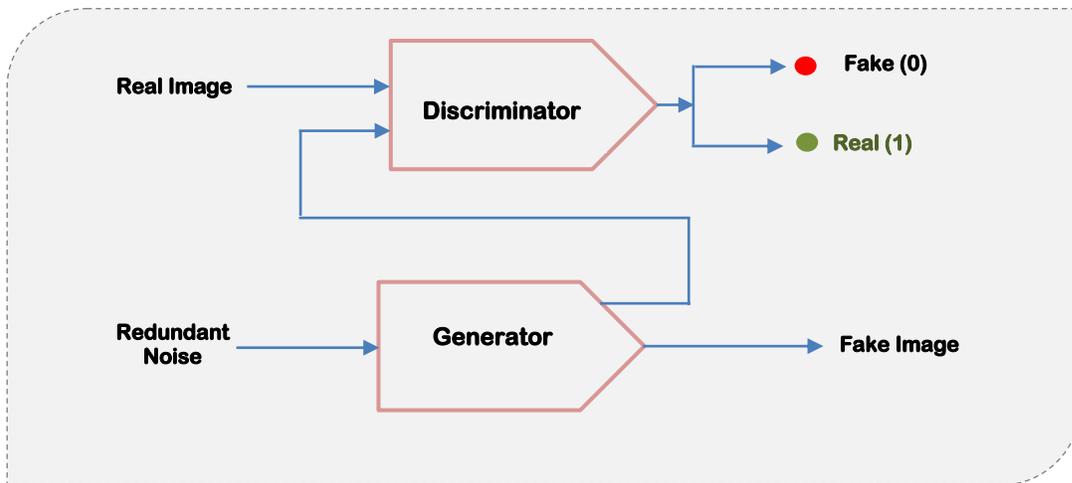


Figure 4, General GANs architecture.

Numerous studies have been conducted with the primary objective of identifying the most effective data augmentation technique to mitigate the problem of data inconsistency. Numerous contemporary research endeavours have already employed GANs for the purpose of augmenting data. In order to tackle the problem of disparate class representation, the scholarly article [36] introduces a novel approach known as Deep Convolution Generative Adversarial Networks (DCGAN). During the initial phase, the utilisation of DCGAN was employed to enhance the performance of the classifier by solely augmenting data for the minority class. The GANs methodology facilitated the accumulation of a sufficient quantity of medical images. However, it necessitates the availability of both input and labelled images, which in turn entails a laborious and time-consuming process of human annotation. In order to overcome the constraints associated

with GANs, the researchers in reference [37] developed a novel model aimed at improving the quality of ultrasound breast cancer image datasets. The methodology employed for enhancing data in breast ultrasound images is grounded in a semi-supervised Radiomics Model that utilises a GAN-based approach. The method under consideration effectively produces breast ultrasound masses of superior quality while concurrently alleviating the burden associated with annotation.

In order to generate different mass images in mammograms, the authors of [38] propose a novel approach based on GANs. As part of their strategy, they included binary masks as an adversarial learning condition. Producing many images with precise mask annotations is made possible by the binary masks. The artificial lesions are subsequently introduced into a standard screening setting through a procedure referred to as contextual filling. Consequently, the adversarial learning framework integrates the characteristics of authentic volumetric images in conjunction with their corresponding masks. The generator is able to learn the distribution of the actual mass images through the use of the combined features, as well as capture the matching shape, margin, and context information. The proposed method was shown to work in experiments in [38].

2.2 Traditional ML

The term of ML refers to a specific use of AI. It's a self-improving system that automatically learns from its own mistakes and errors [39]. The field of image processing, speech recognition, traffic prediction, etc., are just a few examples of the many uses for this technique. The diagnosis and categorization of diseases, such as breast cancer [40,41], is one of the most important medical uses of ML. Figure 2 depicts the typical progression of traditional ML, which includes segmentation, feature extraction and selection, and classification. In the sections that follow, you'll find detailed explanations of each stage.

2.2.1 Image Segmentation

The process of image segmentation is crucial in the field of image processing. The image is partitioned into multiple segments based on diverse criteria, including sets of pixels. The divided sections are uniform in terms of grayscale, contrast, texture, and brightness. One of the main purposes of image segmentation is to simplify image analysis [42]. Large regional variations and improperly illuminated images make breast cancer segmentation a difficult process [43]. Figure 5 illustrates the categorization of segmentation methods into two broad categories: classical segmentation methods and machine learning methods. There are various segmentation methods available; however, comprehensive testing of these methods on all conceivable image formats has not yet been conducted. The CNN-QA method, which utilizes Convolutional Neural Networks (CNNs), was developed in reference [44] as an automated Quality Assurance (QA) technique for automatic segmentation. The individual components of the proposed CNN-QA framework, namely the CNN model and the QA network built upon ResNet-101, operate autonomously without any interdependence. The proposed methodology comprises four distinct stages. Firstly, an automatic segmentation method is employed to generate segmentation probability maps.

Secondly, uncertainty maps are computed using the segmentation probability values. Thirdly, a classification model is utilized to predict the quality of the segmentation, incorporating information from the CT images, probability maps, and uncertainty maps. Lastly, the automatic segmentation is reviewed and revised by a physician, taking into consideration their expertise and the predicted segmentation quality. Despite its increased complexity, this approach exhibits the capability to autonomously forecast the quality of segmentation.

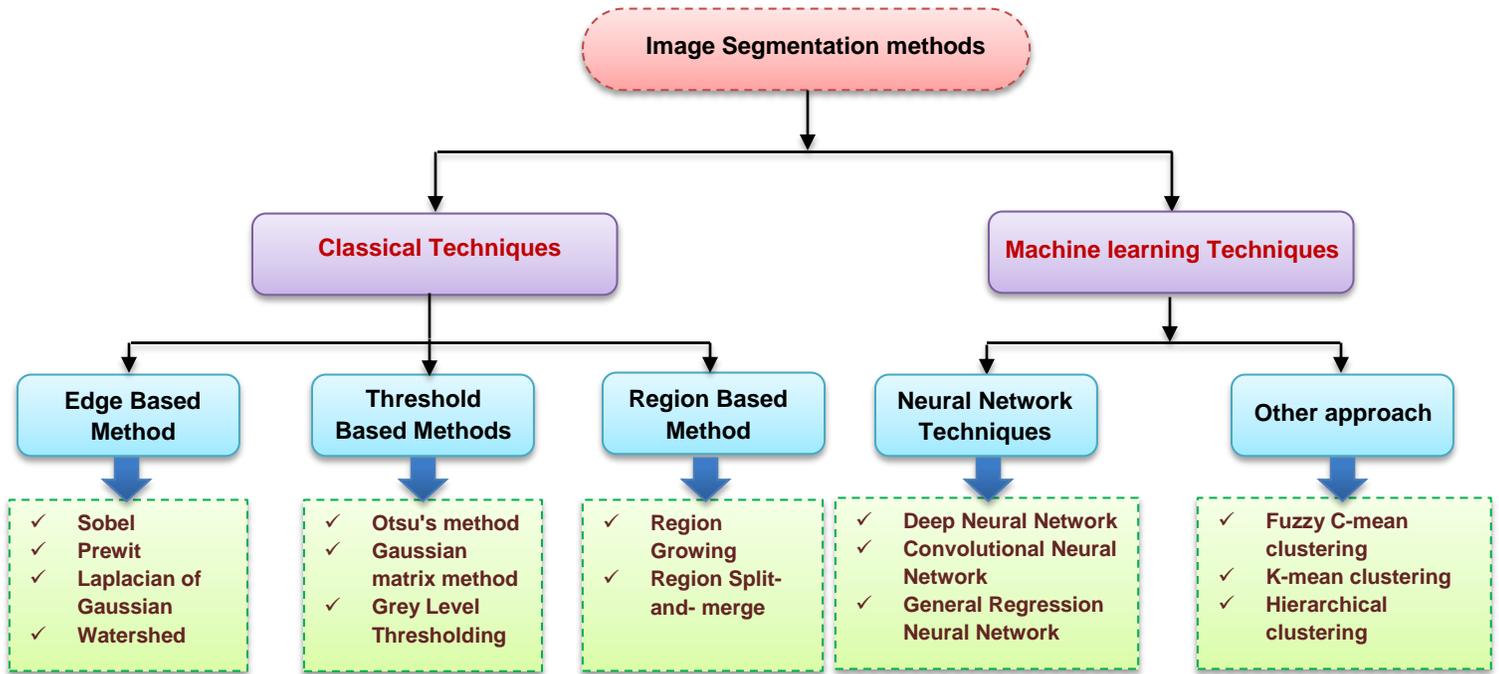


Figure 5, Different segmentation methods for classification breast cancer.

The author in [45] employed a hybrid approach combining region-based active contour and neutrosophic theory to segment breast ultrasound images. The presence of speckle noise and tissue-related textures are identified as limitations in ultrasound imaging, prompting the proposal of this technique as a means to mitigate these challenges. The proposed method was applied to a dataset consisting of 36 ultrasound images of the breast for testing purposes. The initial enhancement of the input images involved the utilization of non-local means filtering and a fuzzy logic approach. Ultimately, the image underwent segmentation utilizing the Improved Weighted Region-Scalable Active Contour (IWRSAAC) methodology. In contrast to the commonly employed region-scalable fitting energy and weighted region-scalable fitting energy for active contour segmentation, the findings presented in reference [45] demonstrate the evident superiority of the proposed approach. In contrast, the method being proposed is a semi-automatic segmentation approach wherein the user is responsible for defining the initial contour.

In [46], a novel approach was proposed to classify breast cancers as either benign or malignant. It is suggested that you use a method known as the Optimized Region Growing (ORG) method. ORG relied on a swarm optimization method called Dragon Fly Optimization (DFO) to generate the best

possible initial seed points and thresholds. The proposed segmentation method was evaluated experimentally and found to introduce 90% accuracy as measured by the Jaccard index (results published in [46]). The hybrid method of breast region segmentation was first presented in [47]. The primary purpose of the proposed model is to demarcate the pectoral muscle and breast region in mammograms. The proposed segmentation model used ML (T-ML) methods that relied on Thresholding. In the first step, we applied novel thresholding methods to establish the breast boundary. Small objects were masked and removed using a morphological operation. In order to isolate the pectoral muscle and the ROI, neural network classifiers have been combined with ML and the Histogram of Oriented Gradient (HOG) feature. The obtained data validated the effectiveness of the suggested approach.

An automatic method for breast thermal image Region of Interest (ROI) segmentation was proposed in [48]. This technique was developed as a solution to the issue inherent in thermal images, in which hotter areas appear brighter and colder areas appear darker. Therefore, the proposed method employed a multi-stage procedure to achieve segmentation. colour values, thresholding operators, enhanced local contrast, and statistical operators are the steps involved. Average accuracy, sensitivity, and specificity were 90.167%, 89.336%, and 91% for the introduced method according to the results in [48].

An effective technique for the segmentation of breast cancer US images is presented in [49]. The proposed method segments US images of breast cancer using the Active Contour (AC) method. However, the active contour technique requires a starting point. In [49], the authors present a novel automatic procedure for initialization of active contours, which is essential for segmenting ultrasound images of breast cancer. The proposed method relies on combining data from multiple types of ultrasound scans, including elasticity and Doppler. The proposed method was successfully tested experimentally and the results were published in [49].

Breast cancer image segmentation is a particularly difficult task for current CAD systems. As a result, a great deal of effort is being put into developing an optimal segmentation method for breast cancer images. Breast cancer image segmentation using ML methods is of particular interest to this group [24,50,51,52,53,54]. In [24], the Optimized Kernel Fuzzy Clustering Algorithm (OKFCA) was proposed as a novel method for segmenting breast lesions in mammogram images. OKFCA was created to identify suspicious areas in mammograms, where cancer may be present. There were essentially three main steps in the execution of the proposed OKFCA. All that needs to be done is (i) some preliminary work on the mammogram images, (ii) noise removal using a Hybrid Denoising Filter (HDF), and (iii) cancer region segmentation using the proposed OKFCA. The accuracy of the proposed algorithm was confirmed by comparison to other traditional methods, as shown by the results presented in [24].

In [50], the authors proposed a ML-based automatic segmentation method for breast ultrasound images. The proposed method for segmenting 3D breast ultrasound images relied on the use of a Convolutional Neural Network (CNN). The proposed method involves segmenting 3D breast ultrasound images into skin, fibroglandular tissue, mass, and fatty tissue. To begin, CNNs take pixel-centered image blocks as input and output a tissue class. The images segmented by clinicians can then be used as a gold standard. Differentiating between skin, fibroglandular tissues, and masses is a breeze with the proposed CNN model. It's also a hands-off method that requires no human involvement whatsoever. The experimental results presented in [50] demonstrated the effectiveness of the proposed method for segmenting breast ultrasound images.

A novel approach to breast tumour segmentation using MRI was proposed in [51]. For breast tumour segmentation, the proposed method utilized Fully Convolutional Networks (FCN) within a Mask-guided Hierarchical Learning (MHL) framework. The proposed MHL method consists of three stages: (i) designing a two-cascading fully-convolutional neural network model to accurately detect tumour regions; (ii) developing a landmark detection method to select biopsied tumour from all detected tumour; and (iii) designing the FCN model to generate a 3D breast mask as the region of interest for each image. Despite the method's impressive success in breast tumour segmentation, it was unable to properly isolate tumours containing hematoma due to the influence of the tumor's complex morphology and texture.

Automatic breast cancer detection using deep learning and optimization algorithms was proposed in [53]. In order to pinpoint the cancerous area in a mammogram, DLOA was created. In reality, DLOA was accomplished in a few different ways. To begin, a median filter was applied to each of the input images to filter out any unwanted background noise. The cancerous area was then separated from the rest of the image using an optimized image segmentation method based on a Convolutional Neural Network (CNN) and a Grasshopper Optimization Algorithm (GOA). The primary goal of the proposed GOA-CNN is to optimize CNN by utilising GOA to set the network's hyperparameters.

To better identify, categorize, and segment mammographic cancer regions, researchers at [54] created a DL-CAD based on deep learning. Artefacts and the muscle region were first removed from the input image during preprocessing. Then, two state-of-the-art DL-based instance frameworks, DeepLab and Mask Recurrent CNN, were used to carry out the segmentation process. For its implementation, the proposed system relied on two open-source datasets: the Mammographic Image Analysis Society's (MIAS) and the Curated Breast Imaging Subset of Digital Database for Screening Mammography's (CBIS-DDSM) datasets. According to [54]'s experimental findings, mask RCNN and Deeplab achieve 80% and 75% average precision in the segmentation process, respectively. Table 1 provides a brief comparison of some of the most up-to-date approaches to breast cancer segmentation.

Table 1: Comparison of the recent breast cancer segmentation methods.

Segmentation Methods	Description	Imaging technique	Advantages	Disadvantages	Accuracy
CNN-Based Quality Assurance (CNN-QA) [44]	The CNN-QA technique is an automated segmentation approach utilised for breast cancer detection, employing CNN.	CT images	Capable of making automatic quality predictions for segmentation. It's also brisk and effective.	Complex	High
Improved Weighted Region-Scalable Active Contour (IWRASAC) [45]	IWRASAC algorithm is employed for the purpose of segmenting US breast cancer images. The proposed approach is a fusion of region-based active contour methodology and neutrosophic theory.	Ultrasound images	One must address inherent characteristics of ultrasound images, such as speckle noise and tissue-related textures, in order to mitigate their impact.	User-defined initial contour is used in this semi-automatic segmentation technique.	low
Optimized Region Growing (ORG) technique [46]	ORG is used to segment benign and malignant breast cancer. this method based on generation initial seed point using Dragon Fly Optimization	Mammogram images	Determine whether the masses are benign or cancerous with high confidence.	Depends on initial seed points.	High
Thresholding and Machine Learning (T-ML) techniques [47]	The T-ML approach is a hybrid method employed for the segmentation of the breast region and pectoral muscle in mammogram images. This approach combines thresholding techniques to identify the breast boundary and ML algorithms to determine the region of the pectoral muscle and ROI.	Mammogram images	It is advantageous to accurately delineate the boundary between the breast region and the pectoral muscle.	Cannot process the images whose histograms are nearly unimodal.	High
ROI method [48]	ROI method was used to automatically segment region of interest and extract first and second order statics features from thermograms.	Thermal Images (thermography)	One potential solution to address the issue of thermal images, wherein higher temperatures are depicted as brighter values and lower temperatures as darker values, is to employ a normalization technique.	This method based on extracting only horizontal texture features.	Moderate
Active Contour (AC) method [49]	AC is used to segment US breast cancer image using the fusion of a conventional US image with elasticity and Doppler images to generate initial contour	Ultrasound images	Good for segmenting and tracking objects with deformable motion and clear boundaries	Relatively slow and depends on the initial contour.	Moderate

Convolutional Neural Networks (CNN) method [50]	CNN is an automatic method used for segmenting 3D-US images. It can distinguish between skin, fibroglandular tissues, and masses.	3D- ultrasound images	Fully automated method without any human intervention.	More complex.	Low
Mask-guided Hierarchical Learning (MHL) [51]	MHL was used to segment MRI breast image using Fully Convolutional Networks to accurately detect tumor regions.	MRI images	The proposed MHL method is better than the traditional segmentation method.	Failed to accurately segment tumors with hematoma.	Moderate
Grasshopper Optimization Algorithm and CNN (GOA-CNN) [53]	GOA-CNN is used to segment cancerous region from the background. GOA is used to determine the hyperparameters of CNN for better performance when compared with manual justification.	Mammogram images	CNN can accurately segment cancerous regions.	It suffers from the computational time.	Low
Deep Learning based Computer-Aided System (DL-CAD) [54]	DL-CAD is used to segment the cancerous region using two states of art based deep learning namely; DeepLab and RCNN.	Mammogram images	It is computationally expensive.	The proposed method cannot give optimal accuracy for cancerous region segmentation.	Low

2.2.2 Feature Extraction and Feature Selection

Feature Extraction is the step of breaking down a given image into its constituent parts. Feature extraction methods are used to glean the desired information. In order to reduce the size of a dataset, feature extraction methods typically work to derive new features from the existing ones (before discarding the original features) [55]. The primary focus of a CAD system developed for the purpose of breast cancer detection is centered on the extracted features. The importance of feature extraction in the domain of image processing is underscored by its significance [56]. The categorization of feature extraction methods can be delineated into several distinct categories, including texture-based, morphological, intensity-based, deep learning-based, and handcrafted approaches that involve the expertise of professionals such as radiologists [57]. The process of feature extraction involves the selection of the most efficient and illuminating features from a given set of extracted features. This method is commonly referred to as "feature selection."

Feature selection is deciding which data points will be the most useful [57]. The feature selection process's primary goal is to improve the classification model's performance, making it more efficient and accurate. In addition, the overfitting issue can be fixed by using feature selection [58, 59]. Because of the significant effect it has on the classification model's efficacy, feature selection is widely regarded as a central concept in machine learning. Figures 6 and 7 illustrate the primary divisions that can be made between feature selection methods: the filter and the wrapper.

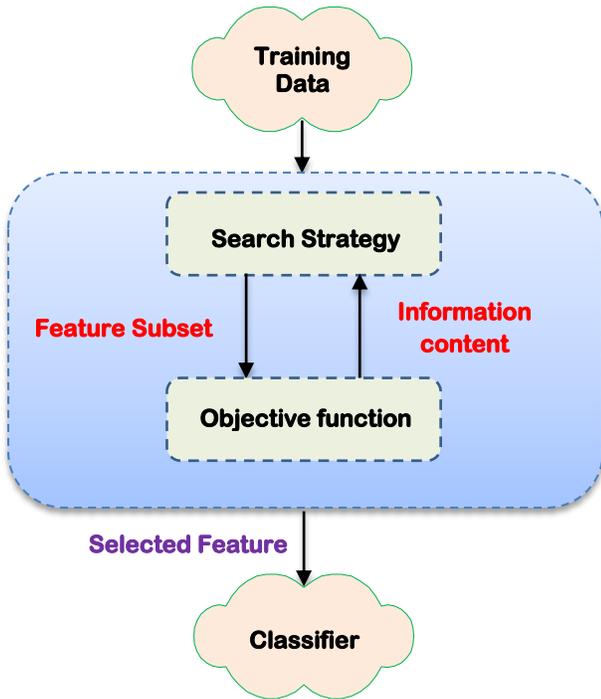


Figure 6, Filter based feature selection methods [55].

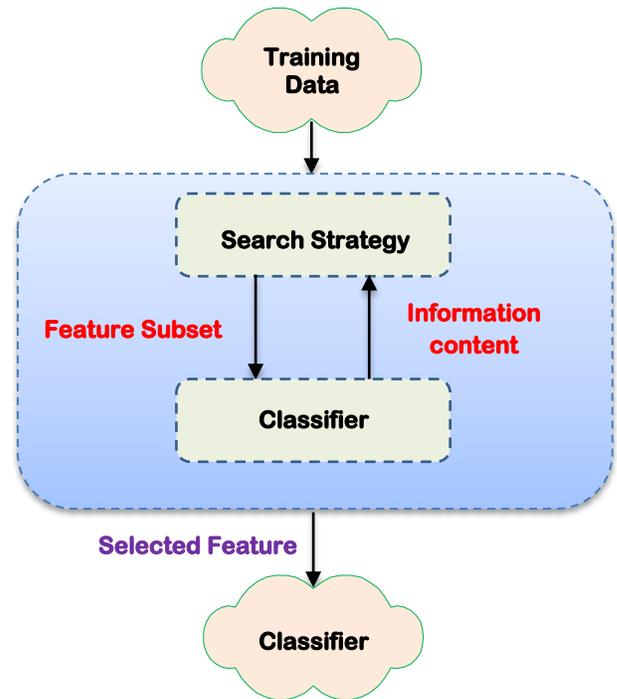


Figure 7, Wrapper based feature selection methods [55].

In order to select feature subsets autonomously, filter methods use statistical measures [60]. The selection of a feature is based on its degree, and features with a low degree are subsequently eliminated. In contrast, wrapper methods involve the identification of feature subsets through iterative evaluations of these subsets using a suitable classifier. This implies that wrapper approaches exhibit a high level of computational intensity [61]. While filter methods are considerably quicker than wrapper methods, they still fall short of what's needed in terms of precision. While wrapper approaches take into account the interplay between classifiers and features, filter methods do not [61,62].

In order to obtain the most accurate breast cancer classification, many researchers have dedicated their time and energy to discovering the most effective feature selection methods. In [63], the authors investigate how different feature selection strategies affect the performance of a classification algorithm when used to diagnose breast cancer. Particle Swarm Optimization (PSO) was used to select the most relevant and informative features. They conclude that by selecting the most important features, the classifier's performance was improved. In [64], Ant Colony Optimization (ACO) was first introduced as a method for selecting Raman spectral features for use in the diagnosis of breast cancer. Using ACO, we were able to determine the most helpful features connected to cancerous alterations, thereby increasing classification accuracy. Classification accuracy for normal, benign, and cancerous groups all improved by 14% and hit 87.7% when ACO was used to pick the best features, as shown in [64].

To further improve the diagnostic precision of CAD systems, a novel approach to feature selection was introduced, as shown in [65]. Opposition based enhanced Grey Wolf Optimization (OEGWO) is the name of the proposed method. Breast density classification is a problem that can be helped by using OEGWO to select features. It goes through the steps of population initialization based on competition, adjustment of the parameters that govern exploration and exploitation, and adjustment of the position updating step. The first step involved obtaining a collection of 45 texture features from mammogram images. After features were collected, OEGWO was used to select the most useful ones. The experimental results presented in [65] demonstrate that the proposed OEGWO is superior to alternative feature selection algorithms for the classification of breast density.

A novel approach to feature selection in breast mass classification is presented in [66]. Opposition-based Harris Hawks Optimization (OHHO) is the name of the proposed method. To begin fixing the issue of feature selection, the proposed OHHO was transferred into binary. There were 45 texture features and 9 shape features extracted, including mean, standard deviation, entropy, zernike moment 4th order, and compactness, compactness1, eccentricity, solidity, roundness, and roundness. The most crucial characteristic was then chosen using the proposed OHHO. According to [66], OHHO is superior to its rivals.

As shown in [67], the authors concluded that the system performance is excellent due to the selection of more appropriate features, highlighting the importance of selecting the most effective and informative features to improve the classification performance. As an additional means of improving classification precision, the Minimal Redundancy Maximal Relevance Feature Selection (MRMRFS) algorithms are presented in [68]. Selecting relevant features from the breast cancer datasets was accomplished with the help of MRMRFS. The SVM performance was enhanced due to the selection of more appropriate features using MRMRFS, as demonstrated by experimental results in [68]. The achieved accuracy of 99.71% was a direct result of this improvement.

In fact, many studies have investigated the effectiveness of combining feature selection methods to achieve optimal performance. In [69], a novel hybridization approach for feature selection was proposed using Grey Wolf Optimizer (GWO) and Rough Set (RS); this approach was given the name GWORS. Feature extraction and feature selection were crucial to the success of GWORS. We began by taking mass segmented mammogram images and manually extracting texture, intensity, and shape-based features. From among these extracted features, the most efficient and informative ones were chosen using GWORS. According to the findings in [69], GWORS provides superior accuracy, F-Measures, and receiver operating characteristic curve to competing methods.

In [70], the authors propose a novel intelligent diagnosis strategy for breast cancer. A novel strategy for feature selection is proposed, and it goes by the name; Information Gain with Simulated Annealing Genetic Algorithm Wrapper (IGSAGAW). To begin, the extracted features

are ranked using the IG algorithm. Then, we used SAGAW to select the m-best features to feed the classifier. Classification is simplified thanks to IGSAGAW, and the accuracy gains and waste reductions caused by its use are both noteworthy.

A new Hybrid Feature Selection (HFS) method [71] was recently introduced to determine which features are most important when classifying patients into malignant and benign categories. The proposed framework consists of several steps. To begin, Principal Component Analysis (PCA) and the Bhattacharyya Distance (BD) are used to create a novel feature importance index that ranks the extracted features. The combination of PCA and BD parameters highlighted features with higher variance and discriminant power. If a feature has a low importance score, the index suggests dropping it before continuing classification on the remaining features. The outcomes demonstrated in [71] validated the proposed method.

Composite Hybrid Feature Selection (CHFS) and Optimized Genetic Algorithm (OGA) are two examples of new hybrid feature selection models presented in [72] with the goal of enhancing the classifier's performance. In CHFS-OGA, the benefits of both the filter method and the wrapper method OGA have been combined. Features are extracted and selected via an Optimized Genetic Algorithm (OGA) in CHFS-OGA. To begin prioritizing the features, Information Gain (IG) and Gain Ratio (GR) were applied to the extracted data. The top-ranked features were then used to seed a genetic algorithm to produce an optimized subset. Based on the results presented in [72], it is clear that the proposed CHFS-OGA model is superior to the individual filter methods.

In [73], a novel Relieff-and-Entropy-based-Genetic-Algorithm (EGA) based Hybrid Feature Selection Algorithm (HFSA) was proposed for breast cancer diagnosis. When working with high-dimensional datasets and associated uncertainties, HFSA was used to combine the benefits of filter and wrapper approaches. We began by using the Relieff ranking method as a filter to determine the importance of each feature and to evaluate the resulting weights. Next, we used EGA as a wrapper technique to better eliminate superfluous features. In [73], experimental results show that the proposed method not only generates a small subset of informative and significant features, but also provides substantial classification accuracy for large datasets.

2.2.3 Classification

The term "classification" refers to the procedure of assigning a label to each data point. In order to solve a classification problem, one must first decide into which class the new information will fall [74]. There are two stages to the classification process: training and testing. In the training phase, features are extracted from the breast cancer image and used to train a classifier. The learned classifier is put to the test in the testing phases, where it is asked to differentiate between data that was not seen during training [14,75]. A variety of features are used to determine whether the latest breast cancer image is benign or malignant. It is challenging to create a valid classification model to deal with the breast cancer classification issue [76]. Different breast cancer classification strategies have been developed using a wide range of machine learning algorithms, including K-Nearest Neighbor (KNN), Naive Bays (NB), Support Vector Machine (SVM), Random Forest

(RF), Decision trees (DT), logistic regression method, etc. [77]. When it comes to classifying images, KNN is one of the simplest, most effective, and flexible methods [78].

Despite its apparent ease of use, it can be ensnared. Several examples of the KNN trapping problem are depicted in Figure 8. Many researchers are currently focusing on fixing KNN's issues. In [79], eight distinct KNN distance functions, along with their respective optimal K values for locating effective KNN, were introduced. These distance functions yield optimum K values between 1 and 59. The proposed technique was applied to the Wisconsin breast cancer (WBC) and Wisconsin Diagnostic Breast Cancer (WDBC) datasets available in the UC Irvine ML repository. The experimental results in [79] show that KNN achieves the highest accuracy rate compared to state-of-the-art models when the optimal K value and distance function are used. The proposed technique was applied to the Wisconsin breast cancer (WBC) and Wisconsin Diagnostic Breast Cancer (WDBC) datasets available in the UC Irvine ML repository. The experimental results in [79] show that KNN achieves the highest accuracy rate compared to state-of-the-art models when the optimal K value and distance function are used.

As demonstrated in [80], a new method has been developed to improve KNN's accuracy in the detection of breast cancer. Gaussian Brownian Motion Optimization with Kernel Neural Networks (GBMO-KNN) describes the proposed approach. For this reason, each gas molecule keeps track of information representing the subset of features used to determine KNN and K value. In practice, the classification was performed using three UCI benchmark breast cancer datasets, and the results were compared to those obtained by other breast cancer detection algorithms. The experimental results reported in [80] validated GBMO-KNN's efficacy.

In addition, a new method called Optimized KNN (OKNN) was proposed by the authors of [81] to speed up the KNN procedure. OKNN employing a filtering system based on clustering and attributes. In reality, OKNN entails three distinct steps: class instance clustering, attribute selection, and similarity reflection using reliability coefficients. The OKNN algorithm took into account the reliability coefficient of each attribute in determining how much of a distance an individual instance could be from the centre of each cluster. The proposed method not only minimizes the number of distances calculated but also gets rid of the ones that aren't useful. The experimental results in [81] show that the proposed method has the highest F-measure.

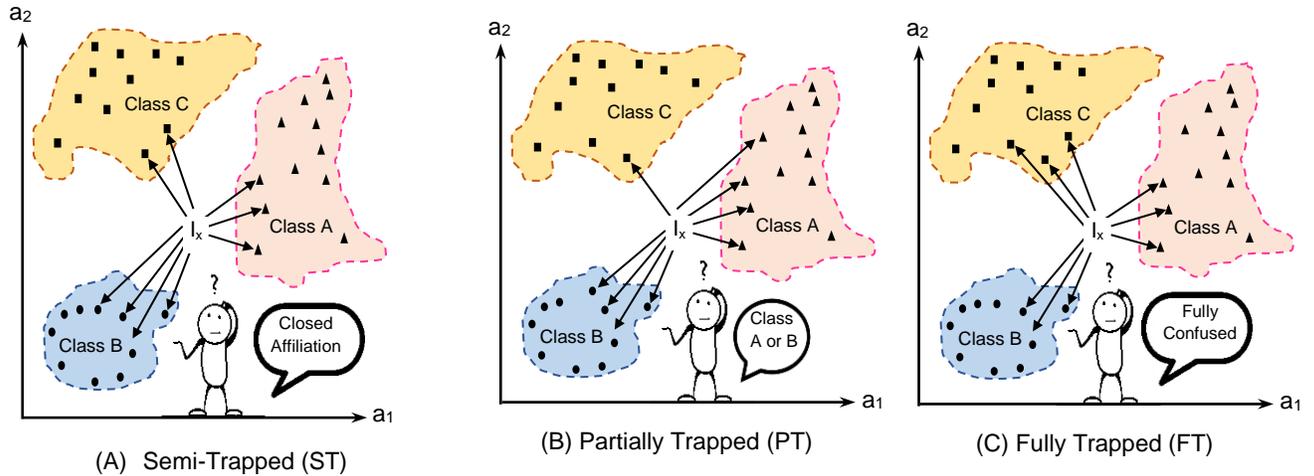


Figure 8, Different types of KNN trapping [58].

Since Support Vector Machines (SVMs) have demonstrated impressive classification performance, they have also been considered for use in breast cancer classification. For this reason, SVM is most effective when there are clear boundaries between classes. SVM is a flexible machine learning algorithm because it can be utilized for both classification and regression. Protein structure prediction, handwriting recognition, intrusion detection, and breast cancer diagnosis are just some of the many applications where this method has proven to be the gold standard [82–84]. Compared to other classifiers, SVM has lower risks of overfitting and better computational complexity, as well as several other benefits, including (i) being relatively memory efficient, (ii) being more efficient and working well in high dimension space, (iii) having models with generalization in practice. It's hard to pick the best kernel function, and it's sensitive to outliers.

In fact, SVM has been used in a number of breast cancer classification studies [70,85,86,87,88,89]. To distinguish between benign and malignant ultrasound breast tumours, a new method was proposed in [85] that combines a Deep Residual Network model with a Support Vector Machine. In an effort to improve classification performance while decreasing physician workload, the proposed DRN-SVM was developed. First, the convolutional layer of the trained DRN was used to extract image features. The extracted feature was then classified using SVM equipped with a sequential minimal optimization solver. Twenty-nine hundred and ninety-nine unlabeled two-dimensional breast ultrasound images were used with the proposed DRN-SVM. The results presented in [85] demonstrated the method's potential usefulness.

Similarly, an SVM classifier and Hough Transform (SVM-HT) based early breast cancer detection method was presented in [86]. Features were extracted using HT from mammograms of breast cancer. The data was then classified using SVM. Ninety-five mammography images were used to test the accuracy of the proposed method for categorizing mammograms into normal and abnormal categories. Breast tumour detection using a support vector machine-based system was developed by the authors of [87]. Principle Component Analysis (PCA) based Differential Evolution (DE)

algorithm and Support Vector Machine (PCA-DESVM) is the name of the proposed diagnostic system. The PCA-DESVM system is a three-stage diagnostic procedure. First, we used Principal Component Analysis (PCA) to eliminate superfluous details from the raw data and draw out meaningful patterns. Differential Evolution (DE) was then used to find the best possible settings for each SVM parameter. When it came down to it, (PCA-DESVM) was used to split incoming tumours apart.

In fact, there is a lot of enthusiasm for applying various machine learning strategies to the task of breast cancer classification. In order to accurately detect and classify breast cancer, many researchers have dedicated their time to finding the best classification method [90–96]. The Random Forest (RF) and Extremely Randomized Trees (ET) algorithms (RF-ET) were introduced in [93] as new tools for breast cancer classification. To arrive at its final classification, the RF- ET model employs decision trees as effective classifiers. The RF-ET model consists of four main steps: input identification, optimum tree number determination, voting analysis, and decision making. According to the results presented in [93], the RF-ET model is both the most user-friendly and most effective in terms of classification.

In [94], the authors present a fresh method for spotting breast cancer by combining the Extremely Randomized Tree algorithm (BCD-WERT) with efficient features derived from the Whale optimization. Dimensionality reduction and feature selection are accomplished by BCD-WERT via the Whale Optimization Algorithm (WOA). In the meantime, the Extremely Randomized Tree (ERT) algorithm was used to sort the data. It has been shown experimentally that BCD-WERT is more accurate than competing methods. In [96], researchers created an enhanced version of a rule extraction technique called Improved Random Forest (IRFRE) for diagnosing breast cancer. Decision tree ensemble accuracy and interpretability were achieved with the help of IRFRE. First, the many different kinds of decision rules we have today were all developed using IRF. Next, a method for extracting rules from trained trees is created so that decisions can be made more quickly. Finally, a multi-objective evolutionary algorithm with a focus on finding the best balance between accuracy and interpretability was used to find the best possible base predictor.

2.3 Deep Learning (DL) techniques

To put it simply, Deep Learning (DL) is a branch of AI's machine learning field. Its foundation is in analyzing code in order to learn and improve. Therefore, it can function independently of human intervention. Over the past few years, DL has made significant contributions to the medical field, particularly in the areas of disease diagnosis and classification. The reason is that DL can adapt better to new circumstances and is less susceptible to noise in the data. To top it all off, features are elicited and optimized automatically. Therefore, this saves time compared to more conventional machine learning methods that necessitate feature extraction before use [97]. Numerous computer-assisted methods have been developed to help doctors make decisions. There has been a lot of effort put into developing DL models in recent years. Since DL models already exist, they can be quickly implemented using a trained network.

Artificial neural networks with many layers are the engines of DL. DNNs are capable of performing complex tasks on each of their layers, such as medical image classification. Like the human brain, neural networks typically have multiple "layers" or "tiers" of nodes. A network's depth is measured by the number of layers it contains. Images are used as data in deep learning models. Next, the most informative features are extracted automatically with a deep work flow [98,99]. In addition, DL engages in end-to-end learning, in which a network is taught to automatically carry out a task by being presented with data for that task, such as classification. The accuracy of DL models for computer vision tasks like medical image classification can be improved through automatic feature extraction [100]. CNNs are among the most well-known types of DL models. CNN's ability to automatically extract features from images is responsible for this. As the network is trained on the dataset, it picks up the features automatically. A CAD system developed using deep CNN is shown in Figure 9.

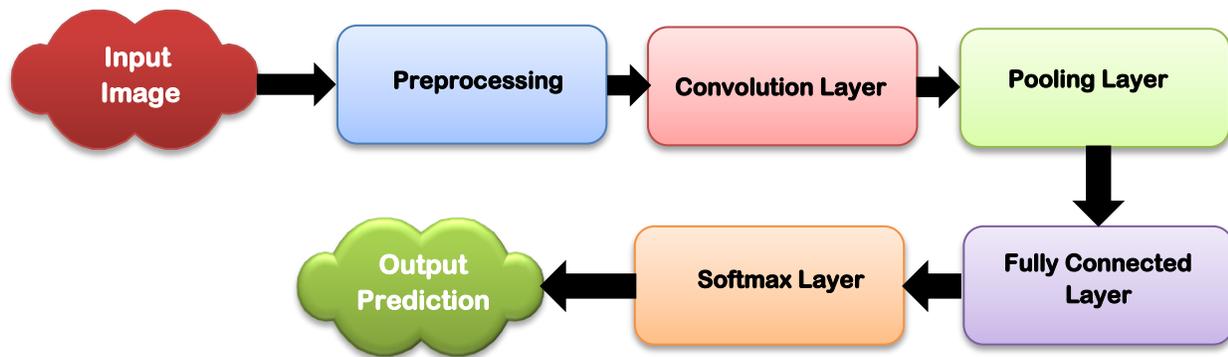


Figure 9, DL (CNN) architecture-based CAD system.

In Figure 10, we see the many layers that go into making a CAD-based CNN a reality. A convolution layer, pooling layer, fully connected layer, and softmax layer are all examples of these layers. A convolution layer is used to apply a fixed-size n-convolution filter to an input image in order to produce feature maps, which can then be used for feature extraction. While pooling, features extracted from multiple input maps are combined using a window of a fixed size to produce a single output map. In this case, a pooling layer is used to reduce the feature extraction dimension. The features are then used as input for a fully connected layer that terminates in a softmax unit, where classification is performed and the classifier model is trained. In addition, a gradient descent update rule and back propagation can be used to fine-tune the model's parameters for optimal performance [99-101].

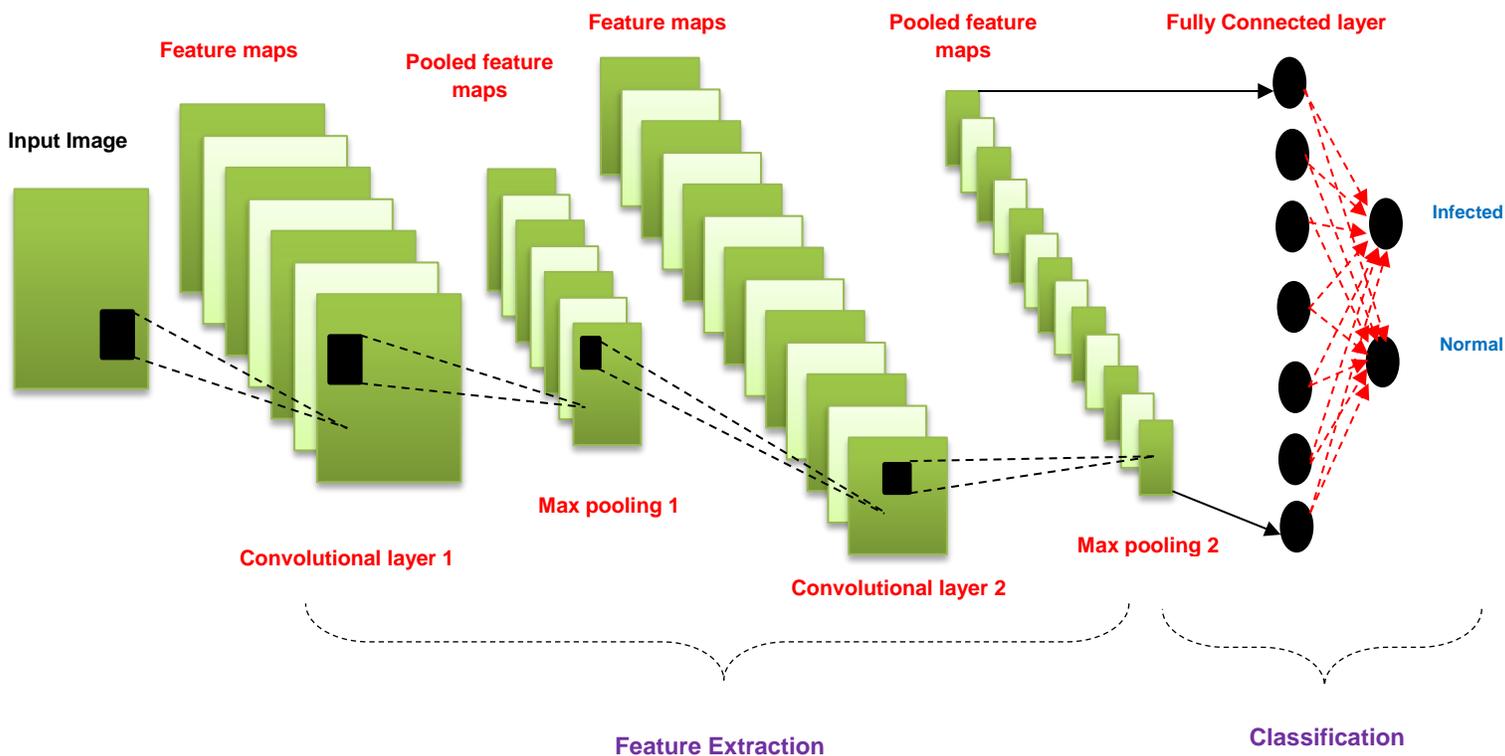


Figure 10, The architecture structure of CNN process.

In recent years, researchers have presented and proposed a range of papers [100-111] regarding the application of DL in the classification of breast cancer. The authors of [102] presented a novel CAD system designed for the detection of breast cancer. The proposed CAD system exhibited a dependence on deep learning-based methods for both feature extraction and classification. The proposed system was put through its paces in four experimental setups. The first involves enhancing the classification accuracy via pre-trained fine-tuned Deep CNN (DCNN) networks architectures like AlexNet, GoogleNet, ResNet-18, 50, and 101. The second was accomplished by feeding an SVM classifier the deep features extracted with DCNNs. In the third test, deep features fusion was used to boost the classifier's efficiency. In the end, the features vector was compressed using PCA.

Similarly, in [103], the Feature Extraction BreakHis CapsNet (FE-BKCapsNet), which is based on deep feature fusion and enhanced routing, was proposed for automatically classifying breast cancer. A combination of a CNN and a Capsule Network (CapsNet), FE-BKCapsNet is a neural network architecture. While CNNs were used to emphasise semantics, CapsNets zeroed in on position and posture details. The proposed CNN-CapsNet actually uses a two-stage process. To begin, we first perform a simultaneous extraction of convolution features and capsule features. Then, new capsules are constructed using these features to generate even more distinct characteristics. To classify the BreakHis dataset, the proposed FE-BKCapsNet was used. The proposed model improved the classification accuracy of identifying malignant tumours from breast cancer, as shown by experimental results in [103].

In [104], the authors propose a hybrid transfer learning-based model for detecting breast cancer. Two separate models, Modified VGG (MVGG) and ImgeNet, make up the proposed model. Both

2D and 3D mammograms were used with the proposed model. When combined with ImageNet, MVGG actually outperformed using MVGG alone to perform classification. The proposed MVGG-ImageNet achieved an accuracy of approximately 94.3%, while the proposed MVGG achieved an accuracy of approximately 89.8%, according to experimental results presented in [104]. Therefore, the proposed hybrid pre-trained network performs better than state-of-the-art alternatives like CNN.

A novel DL Framework (DLF) for early breast cancer detection and classification is presented in [105]. DLF is predicated on the theory of transfer education. Two procedures were used to carry out the proposed DLF. GoogLeNet, VGGNet, and Residual Networks (ResNet) are three examples of pre-trained CNN architectures that were used to extract image features in the first stage. The extracted features were then fed into a fully connected layer where average pooling classification was used to categorize cells as either malignant or benign. According to the findings presented in [105], the proposed DLF is more accurate at detecting and classifying breast tumours than any of the other deep learning architectures tested.

To better distinguish between cancer and normal cases on mammograms, a new DL model was proposed, as shown in [106]. CNN architecture, which is dependent on easy feature learning and a well-tuned classifier model, is used in the DL model. CNN architecture also allows for the seamless incorporation of deep learning models into mobile networks and real-time medical image analysis devices. The primary aim of the proposed DL model is to enhance the learning capability of DL models in order to achieve accurate breast cancer diagnosis through the utilisation of CNNs. This is accomplished by evaluating the efficacy of various feature learning models. The effectiveness of the proposed DL model is demonstrated through experimental results presented in reference [106], with regards to accuracy, sensitivity, specificity, and precision.

In [107], the authors propose a novel method for identifying the immunohistochemical response to breast cancer by searching for thermal heterogeneous patterns in the affected region. The proposed procedure involves a number of stages. Initially, a ResNet-50 pre-trained model is used in conjunction with sparse principal component analysis to extract deep high-dimensional features from a low-rank thermal matrix approximation. Then, a Deep Sparse Autoencoder (DSA) specifically built and trained for this purpose was used to reduce the dimensionality of these features. In reality, there are just 16 latent space thermomic features left. The participants were then categorized using Random Forest (RF). The proposed model (ResNet-50-DSARF) performed exceptionally well, as demonstrated by the results in [107].

Using DL methods, breast tumour MRI images were classified into one of three molecular subtypes in [108], where CNN with transfer learning between two centers was used. The proposed algorithms required both standard CNNs and the Convolutional Long Short-Term Memory (CLSTM). Experimental results from [108] showed that using 10-fold cross-validation, CLSTM was more accurate on average than CNN. However, the mean accuracy of CNN and CLSTM was enhanced through the use of transfer learning. Similar to this is the DenseNet CNN deep learning

approach presented in [109]. The proposed method's primary objective is to categorize breast tumours as either benign (fibroadenoma) or malignant (lobular carcinoma). The proposed DenseNet CNN model for multiclass breast cancer classification achieves an accuracy of 96% in experiments, as shown in [109].

It was proposed in [110] that a CNN be used to create a Patch-Based Classifier. Automatic breast cancer classification into normal, benign, in situ, and invasive carcinoma was accomplished using PBC-CNN. One Patch in One Decision (OPOD) and All Patches in One Decision (APOD) are two implementations of the proposed PBC-CNN. Class labels for each patch were predicted using OPOD mode. Even though in OPOD mode, class labels were extracted alongside each extracted patch, in APOD mode, a majority voting system was used to determine the image's classification. Patch-wise classification accuracy of 77.4% for 4 classes and 84.7% for 2 classes were reported by the proposed OPOD mode in [110]. Whereas, the APOD method was able to achieve an accuracy of 90% for 4-class classification and 92.5% for 2-class classification using only visual cues.

Moreover, radiogenome associations in breast cancer are discovered with the help of DL methods. Dynamic Contrast-Enhanced Magnetic Resonance Imaging (DCE-MRI) was studied in 270 patients, for instance [111]. The primary objective of this research is to classify tumours into Luminal A or other subtypes using patches of MRIs. There were three distinct deep learning methods used to accomplish this. In the first method, only tumour patches are used for training; in the second, networks are pre-trained on normal images with tumour patches; and in the third, features are extracted and classified SVM. Different network architectures, including GoogleNet, VGG, and CIFAR, were used in the experiment described in [111]. According to the findings, transfer learning outperforms starting from scratch. Since this is the case, DL is crucial in establishing radiogenomic associations in breast cancer.

3. Conclusions

In terms of female cancer mortality, breast cancer ranks second. The World Health Organization (WHO) and the American Society for Clinical Oncology (ASC) both agree that early detection of breast cancer is crucial because it gives patients and doctors a better chance of making an informed choice about which treatment protocol will be most effective. Several types of imaging are actually used to search for breast cancer. Radiologists face a difficult challenge when they must rely solely on imaging methods to identify breast cancer. In addition, their expertise is crucial to making an accurate diagnosis. Therefore, relying on computers is crucial in order to dodge difficulties. Machine learning and artificial intelligence can be used as a second opinion to help radiologists make the best decision when classifying breast cancer. So, it saves time and prevents mistakes made by humans. The medical community relies heavily on CAD systems for accurate disease diagnosis and classification. This overview looks at the various imaging methods used to detect breast cancer and discusses the benefits and drawbacks of each. The latest findings from machine

learning and deep learning studies on breast cancer are also discussed. In addition, the three primary phases of CAD system are discussed: preprocessing, segmentation, and classification.

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