Review Article

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Transformative insights: Image-based breast cancer detection and severity assessment through advanced AI techniques

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Abstract: In the realm of image-based breast cancer detection and severity assessment, this study delves into the revolutionary potential of sophisticated artificial intelligence (AI) techniques. By investigating image processing, machine learning (ML), and deep learning (DL), the research illuminates their combined impact on transforming breast cancer diagnosis. This integration offers insights into early identification and precise characterization of cancers. With a foundation in 125 research articles, this article presents a comprehensive overview of the current state of image-based breast cancer detection. Synthesizing the transformative role of AI, including image processing, ML, and DL, the review explores how these technologies collectively reshape the landscape of breast cancer diagnosis and severity assessment. An essential aspect highlighted is the synergy between advanced image processing methods and ML algorithms. This combination facilitates the automated examination of medical images, which is crucial for detecting minute anomalies indicative of breast cancer. The utilization of complex neural networks for feature extraction and pattern recognition in DL models further enhances diagnostic precision. Beyond diagnostic improvements, the abstract underscores the substantial influence of AI-driven methods on breast cancer treatment. The integration of AI not only increases diagnostic precision but also opens avenues for individualized treatment planning, marking a paradigm shift toward personalized medicine in breast cancer care. However, challenges persist, with issues related to data quality and interpretability requiring continued research efforts. Looking forward, the abstract envisions future directions for breast cancer identification and diagnosis, emphasizing the adoption of explainable AI techniques and global collaboration for data sharing. These initiatives promise to propel the field into a new era characterized by enhanced efficiency and precision in breast cancer care.

Keywords: breast cancer, detection, identification, cancer diagnosis, AI, image processing, machine learning, DL

1 Introduction

Breast cancer is a health issue that is highly prevalent worldwide and affects women. Early identification is crucial because the disease starts in cells and has the potential to spread to other parts of the body. When

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aberrant cells proliferate and form a mass called a lump, it is critical to identify the condition as soon as possible [1]. There are three main types of breast cancer, all of which have different traits. The milk ducts are the exclusive site of ductal carcinoma *in situ*, and adjacent tissues are not invaded. Invasive ductal carcinoma is the most common type in which cancer cells invade the surrounding breast tissues. The third type, invasive lobular carcinoma, starts in the lobules of the milk glands and spreads to the surrounding tissues [2]. The main sign of malignant cancer is the presence of masses, which can be identified by identifying lesions that have certain characteristics related to their marginal features and structural formation. Evaluation of these masses is essential for identifying whether cancerous development is potentially malignant [3]. Notably, calcifications, deposits of calcium in the breast tissue, represent the second primary signal. In mammographic images, these calcifications appear as tiny bright dots and are important diagnostic signals. To categorize cancer as benign or malignant, a thorough assessment of its physical dimensions and features is essential [4]. This entails closely examining the characteristics and structural elements of the detected masses or calcifications to determine the type of malignant development. Architectural aberrations are another important marker for breast cancer. These distortions, which are identifiable by anomalous architectural elements, represent aberrations in the normal tissue structures. Finding these distortions is critical to the diagnostic process, as it adds to a thorough comprehension of the traits and behavior of malignancy [5]. Early diagnosis and prompt treatment are essential to lower the mortality rate of breast cancer. Prompt intervention reduces the chance of unfavorable outcomes such as death, and early detection helps with a correct diagnosis. Customized cancer treatment, which adjusts regimens for each patient, requires complex analysis at several levels, primarily related to the tumor's genetic makeup [6]. Accurate biomarker assessment is essential for making informed therapeutic decisions in breast pathology. The growing intricacy and necessity for precision in the diagnosis of histopathologic breast cancer present difficulties, which are exacerbated by a dearth of pathologists in several regions worldwide. To improve breast cancer diagnosis, computerized image analysis using histopathology appears to be a potential solution [7]. By expediting time-consuming processes, such as biomarker assessment, this technology may help pathologists make diagnoses that are more precise and timely. Proactive health measures are crucial for everyone, especially women [8,9]. The likelihood of early detection and effective treatment is greatly increased by routine screening and self-examination. For patients with breast cancer, early identification improves their quality of life by expanding their treatment options and improving their overall prognosis [10,11].

The likelihood of early detection and effective treatment is greatly increased by routine screening and self-examination. For patients with breast cancer, early identification improves their quality of life by expanding their treatment options and improving their overall prognosis [12]. Breast cancer can only be detected using X-rays for a considerable amount of time. A variety of imaging modalities are used to identify and assess breast abnormalities, assisting medical practitioners in making informed decisions regarding patient care [13]. The main objectives of breast cancer imaging are early detection, precise diagnosis, disease staging, and therapy response monitoring. Mammography, ultrasound, magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and three-dimensional mammography (tomosynthesis) are biomedical imaging modalities [14]. Mammography is a popular method for detecting breast cancer. It entails obtaining X-ray images of the breast tissue to identify anomalies, such as microcalcifications or tumors. It works especially well in detecting breast cancer in its early stages, frequently before a physical examination can detect it [15]. Sound waves are used in ultrasound to provide finely detailed images of the breast tissue. It is frequently used to separate fluid-filled cysts from solid masses or further assess abnormalities found on mammography. Breast biopsies can be more precisely targeted and sampled using ultrasound guidance [16]. Using strong magnets and radio waves, breast MRI produces detailed images of the breast. It is frequently employed in particular contexts, including high-risk individual screening, determining the severity of illness, and gauging the effectiveness of treatment. Breast MRI is especially helpful in identifying multicentric or multifocal illnesses and tiny lesions [17]. When diagnosing breast cancer, CT scans can be helpful, particularly when assessing metastasis, the spread of the disease to other areas of the body. CT is not the primary imaging modality used to assess breast cancer. PET scans are used in breast cancer staging to identify distant metastases and can be used to evaluate the metabolic activity of tissues [18]. Tomosynthesis is a sophisticated type of mammography that captures pictures of the breast from various perspectives. This method reduces false positives, improves the detection of small tumors, and offers a more detailed image. Combining different imaging modalities frequently enables a more thorough evaluation of breast problems, assisting in precise diagnosis and therapeutic planning [19]. For those with breast cancer, early detection by imaging is essential for improving prognosis and outcomes.

This paragraph explains the necessity of sophisticated AI algorithms to improve detection and severity evaluation. Large amounts of data are produced from diverse sources in industries such as healthcare, including genetic data, electronic health records (EHRs), and medical photographs. These complicated data can be effectively analyzed and interpreted by advanced AI systems, assisting in the early detection of diseases and precise assessment of their severity [20]. Artificial intelligence (AI) systems can be trained to identify microscopic trends or abnormalities that may lead to problems. For instance, AI can help with early cancer identification in the healthcare industry, enabling prompt intervention and better results [21]. AI is vital in the age of personalized medicine. AI can provide customized treatment regimens by evaluating personal patient data, such as genetic information, lifestyle, and environmental factors. This increases the disease diagnostic accuracy (Acc.) and guarantees that each patient receives the most effective treatment, which improves outcomes [22]. Tasks that would take too much time or be impracticable for humans can now be automated owing to advanced AI capabilities. This is especially true for medical imaging, where AI can swiftly and precisely analyze hundreds of images to help radiologists diagnose ailments. AI in cybersecurity can automate the detection of possible threats, freeing human experts to concentrate on more difficult problems [23]. Real-time analysis is essential for many applications, including tracking the evolution of diseases and monitoring vital infrastructures. More sophisticated AI systems can continually analyze data streams, provide timely insights, and facilitate quick responses to changing conditions [24]. AI models may continuously learn from fresh data, particularly those that are machine learning (ML)-based. This flexibility is useful *in situ*ations in which threats or conditions change over time. For example, in cybersecurity, AI can adapt its detection algorithms based on new threat patterns [25]. In today's connected world, the amount of data collected is growing and can often be too large for conventional analytical methods. DL and other advanced AI approaches are particularly effective in handling large amounts of data because they automatically identify relevant features and patterns. This makes them ideal for jobs such as picture identification, natural language processing, and predictive analytics [26]. Because of their capacity to handle complicated data, offer early insights, personalize interventions, automate jobs, monitor in real time, adjust to changing situations, and manage massive data effectively, advanced AI approaches are becoming increasingly necessary for detection and severity assessment [27]. These abilities support precise and effective decision-making in several crucial areas [28].

The major contributions are as follows.

- This article consolidates findings from 125 research articles, providing a comprehensive overview of the current landscape of image-based breast cancer detection and severity assessment.
- This review synthesizes the transformative role of AI, covering image processing, ML, and DL, in image-based breast cancer detection and severity assessment.
- This article explores the synergy between advanced image processing and ML, showcasing their combined power in automating medical image examination for nuanced.

2 Image-processing techniques

This section comprises three subsections. The different image-processing methods used for breast cancer analysis are described in Section 2.1. The challenges and limitations of conventional image-processing methods for breast cancer analysis are described in Section 2.2. Common preprocessing techniques to enhance the quality of breast images and their comparison are presented in Section 2.3.

2.1 Image-processing methods used in breast cancer analysis

To help diagnose breast cancer in digital mammograms, Cahoon [29] explained the application of segmentation using fuzzy models and classification using the crisp k-nearest neighbor (KNN) algorithm. We used photographs from the digital database for screening mammography (DDSM) in our research. We demonstrate that when intensity is the primary distinguishing characteristic, both supervised and unsupervised segmentation techniques, such as KNN and fuzzy c-means (FCM), have significant misclassification rates in digital mammograms. The segmentations generated by the KNN rule were (visually) improved by adding window means and standard deviations to the feature suite. Gupta et al. [30] provided an approach that involves visualizing the tumor location and determining its primary concentration. Using the Mammographic image Analysis Society (MIAS) dataset, they extracted morphology and color information and then executed morphological procedures, such as dilatation, closing, and K-means clustering. By reducing the impact of noise, dilation using K-means was used to improve the Acc. by 10%. The overall Acc. range was 60–80%. To separate infrared (IR) breast images using heat and blood vessel activity data, Prakash et al. [31] employed three segmentation algorithms: K-means, FCM, and Gaussian mixture model–expectation maximisation (GMM-EM). The strategies were then compared. FCM segmentation provides reliable diagnosis and illness indication. Younis et al. [32] used the DDMS dataset's X-ray pictures' pixels and light intensity attributes to apply a thresholding algorithm. This algorithm can be used to identify breast cancer tumor cells. Using MIAS datasets, Varma and Sawant [33] used morphological methods like texture extraction to extract topographic features such as texture and appearance. It can effectively identify breast cancer and outline abnormalities in breast tissue. The mammographic images were converted into a three-dimensional matrix. Tomar et al. [34] carried out morphological operations to extract primary radiographic signs, i.e., masses (their density, size, shape, and borders). It is effective in determining the granulometry of the tissues. Granulometry analyzes an image's object size distribution without explicitly segmenting individual objects. Using a mammographic image, Sangeetha and Murthy [35] extracted brightness, contrast, size, form, and texture using a morphological operator and Otsu's thresholding technique. Ultimately, extremely early identification of the clusters allows for the classification of cancer cells as benign or malignant. Ilhadidi [36] compared three segmentation techniques, i.e., threshold, edge, and watershed segmentation, to find breast cancer tissue using mammographic images by extracting geometric and texture features. The threshold segmentation technique was faster than the other two segmentation methods. Adaptive histogram equalization (AHE) and morphological operations were used by Moh'd Rasoul et al. [37] to extract lymph characteristics, such as spread and intensity, from mammographic X-ray images. It accurately segments each image and recognizes the area of interest in each image. To assess various parameters, such as the mean square error, peak signal-to-noise ratio, average distance, maximum difference, normalized correlation, mean absolute error, normalized error, and structural correlation, Ramani et al. [38] employed mean or average filter, median filtering, adaptive median filter, and Wiener filter. Compared to other filters, the adaptive median filter [39] is a better technique for enhancing the background clarity of photographs. Tarique et al. [39] suggested a Fourier transform method to determine the stage of breast cancer using X-ray mammographic images. The frequency of dynamic IR imaging in breast cancer was analyzed by Singh et al. [40]. Several techniques were used. These include the Hanning window algorithm, linear image restoration techniques, high-pass filtering (HPF) with region windowing, and a Gaussian window with 2D matrix convolution. The Wiener method, which uses linear image restoration techniques, produces better results in terms of sensitivity (Sens.) and specificity (Spec.). Using the DDSM and morphological approaches such as dilatation and opening to extract texture and shape features, Helwan and Abiyev [42] achieved a 92% recognition rate for breast cancer. Gaussian filtering was performed by Minavathi et al. [43] to extract speculation, shape, and acoustic shadows from an ultrasound image dataset. The support vector machine (SVM) technique was then used for the classification. The algorithm's 0.88 area under curve yielded 92.7% Sens. Using the MIAS breast cancer dataset, Charan et al. [44] executed morphological operations to extract image component region characteristics or regions of interest (ROI). This method aids in eliminating noise components.

Several datasets, including the DDSM [29,32,42], MIAS [30,33,34], mammographic images [33–40], dynamic IR images [31,41], and ultrasound images [43], have been employed according to the literature survey mentioned earlier. Numerous approaches have been employed, including thresholding algorithms [32,36], fuzzy models [29,31], and morphological operations [30,33–35,42,44]. Table 1 presents various image-processing techniques for breast cancer segmentation.

To ensure breast cancer detection algorithms achieve universal effectiveness, it is vital to include a diverse range of human demographics and environments in the datasets. Age diversity is crucial because breast cancer characteristics can vary significantly between young adults and the elderly, affecting disease behavior, progression, and treatment responses. By including a wide age range, algorithms can better recognize and manage age-related variations in cancer presentation. Additionally, ethnic and genetic diversity, along with geographical representation, enhance dataset robustness. The most commonly used datasets are DDSM and MIAS. The DDSM dataset features mammograms from women within a typical screening age range of 40–74 years, although detailed age distribution information is not always available. There is limited public information about the ethnic diversity of DDSM participants, but it likely mirrors the demographic makeup of the US institutions that contributed to the dataset, resulting in potential overrepresentation and underrepresentation of certain ethnic groups. Geographically, the DDSM dataset includes contributions from various US institutions, providing diverse domestic representation but lacking international diversity.

Similarly, the MIAS dataset comprises mammograms from a wide age range, typically representing those involved in routine screening programs, with most subjects between 40 and 75 years old. The MIAS dataset was developed in the UK, reflecting the ethnic composition of the UK's population at that time, primarily Caucasian, and likely underrepresenting minority ethnic groups compared to the global population. Geographically, the MIAS dataset is confined to the UK, covering regional variations within the country but missing broader international diversity.

For AI algorithms to be universally applicable and effective, incorporating datasets with diverse age, ethnic, and geographical representations is crucial. This diversity ensures that models are trained on a wide array of mammographic characteristics and variations, enhancing diagnostic accuracy and reducing biases. While DDSM and MIAS datasets are valuable, expanding them or supplementing them with additional datasets from more geographically and ethnically diverse populations would further enhance their utility in developing globally effective breast cancer detection algorithms.

2.2 Challenges and limitations of conventional image processing

Conventional image-processing techniques, including the detection and segmentation of breast cancer tumors, have been widely applied in the field of medical imaging. However, these techniques have several drawbacks and restrictions that have prompted researchers to investigate more complex and advanced strategies [45]. The following are some of the difficulties and restrictions that arise when traditional image processing is used for the detection and segmentation of breast cancer tumors:

- **Limited feature extraction:** When dealing with complex and heterogeneous tumors, conventional approaches may find it difficult to extract pertinent features from medical images. These techniques frequently depend on manually created features, which may not fully convey the intricacy of the pictures [46].
- **Sensitivity to image variability:** Conventional image processing methods can be affected by changes in the resolution, noise level, and contrast of the acquired images. This Sens. may affect the resilience of the algorithm in various imaging modalities and environments [47].
- **Manual parameter tuning:** A Many traditional techniques require manual parameter tuning, which can be laborious and difficult to modify for different datasets. Depending on the properties of the photographs, different parameter choices may be optimal [48].
- **Limited adaptability to diverse datasets:** When dealing with different datasets that vary in patient demographics, imaging modalities, and tumor types, conventional methods may not be the best fit. It is possible that they are not sufficiently adaptable to handle the underlying variability of breast cancer images [49].

Table 1: Different methodologies for breast cancer segmentation using image processing are presented

Ref.	Dataset	Image source	Segmen tation	Features	Methods	Remarks
[29]	DDSM	X-ray	Yes	Intensity by region-based features, window means	Fuzzy model, KNN method	KNN performs better
[30]	MIAS	X-ray	Yes	Morphology and color features	Morphological processes applied, i.e., closing, dilation, and K-means clustering	Dilation with K means has been performed to reduce the effect of noise and hence to increase the Acc. by 10%. The overall Acc. is 60–80%
[31]	IR breast image	Photovoltaic (PV) camera	Yes	Heat, blood vessel activity	K-means, FCM, and GMM-EM	FCM segmentation gives good Acc. and indication of the disease
[32]	DDSM	X-ray	Yes	Pixels and light intensity	Thresholding algorithm	Breast cancer tumor detected
[33]	MIAS	X-ray	Yes	Topographic features such as texture and appearance	Morphological processes such as texture extraction	Outlining anomalies in the breast tissue and efficiently detecting breast cancer
[34]	Mammogram image and convert into 3-D matrix	X-ray	NA	Primary radiographic signs, i.e., masses (their density, size, shape, borders)	Morphologic operation	Finding the granulometry of tissues
[35]	Mammographic image	X-ray	Yes	Brightness, contrast, size, shape and texture	Morphological operator and applying Otsu's thresholding algorithm	Identify the microcalcification clusters at a very early stage and classify them as benign or malignant cancer cells
[36]	Mammographic image	X-ray	Yes	Geometric and texture features	Threshold, edge, watershed segmentation	The threshold is the fastest
[37]	Mammographic image	X-ray	Yes	Spread, intensity, and lymph	AHE, morphological operation	Identify the region of interest and correctly segment all the images
[38]	Mammographic image	X-ray	NA	NA	Mean filter or average filter, median filtering, adaptive median filter, Wiener filter	The adaptive median filter is a more appropriate method when compared with other filters
[39]	Mammographic image converts into 3-D matrix	X-ray	NA	NA	Fourier transform method	Detect the stage of breast cancer
[40]	Mammographic image	X-ray	Yes	Pixel intensity value	Max-mean and least-variance technique	Successful in segmenting the cancer region of mammogram
[41]	Dynamic IR images	Photovoltaic (PV) camera	NA	NA	Gaussian window with 2D convolution of matrices, linear image restoration processes, HPF with region windowing, Hanning window algorithm	Linear image restoration processes (the Wiener method) achieve better result
[42]	Digital database for screening mammography	X-ray	Yes	Texture and shape	Morphological techniques such as dilation and opening	The identification rate was 92%
[43]	Ultrasound image	Ultrasound	Yes	Speculation, shape, acoustic shadow	Isotropic diffusion (Gaussian filtering) and SVM	92.7% of Sens. with 0.88 area under the curve
[44]	MIAS dataset	X-ray	Yes	ROI, image component region	Morphological operations	Removed noise factors

- **Handling noise and artifacts:** Owing to several variables, including patient mobility and imaging equipment, medical photographs may contain noise and artifacts. Tumor segmentation Acc. may be affected if conventional approaches cannot manage and reduce these undesirable components [50].
- **Limited learning capacity:** Conventional image-processing methods usually cannot automatically learn new patterns in the data. The inability to effectively generalize to previously unknown images is a potential hindrance to a robust and accurate tumor detection process [51].
- **Inability to capture spatial relationships:** The spatial relationships between pixels or voxels in an image may not be well captured by conventional approaches. This restriction may be important for applications such as tumor segmentation, where precise delineation depends on awareness of the geographical environment [52].
- **Time-consuming annotation process:** Medical picture annotation by hand is frequently labor- and expert-intensive when performed for training and validation. Annotated datasets may be a major component of conventional approaches, and their production may represent a bottleneck [53].
- **Difficulty in handling large datasets:** Conventional approaches may find it difficult to interpret and analyze vast volumes of data efficiently, as medical imaging datasets continue to increase in size. This drawback may make it more difficult for them to scale and be effectively used in actual clinical settings [54].

The use of DL and ML techniques such as convolutional neural networks (CNNs) [55] and deep neural networks, which have demonstrated encouraging results in automated breast cancer tumor detection [56] and segmentation tasks [57], has changed in response to these challenges. These methods can recognize intricate patterns in medical images, adapt to a variety of datasets, and learn hierarchical characteristics directly from data.

2.3 Common preprocessing techniques to enhance the quality of breast image

Breast photographs, in particular, can be made of higher quality with the help of preprocessing techniques. These methods seek to lower noise, enhance the visibility of essential structures, and prepare photographs for precise analysis. Noise reduction [58–60], contrast enhancement [61,62], image registration [63], normalization [64], image fusion [65], artifact removal [66], image cropping [67], and resizing [68], mammographic preprocessing techniques, filtering techniques, normalization, and standardization are some of the most frequently used preprocessing techniques to improve the quality of breast images.

The use of a Gaussian filter aids in lowering the high-frequency noise of the image. The median filtering technique effectively eliminates salt-and-pepper noise by substituting the value of each pixel with the median value of its surrounding area. By redistributing the image intensity levels, the histogram equalization approach improves the overall contrast. By enhancing the local contrast, contrast-limited adaptive histogram equalization prevents noise in homogeneous regions from being too amplified. Several photographs taken at various periods or with various modalities may be registered to enhance the overall quality and facilitate comparison analysis. Maintaining constant intensity levels between various modalities or images contributes to the increased comparability of the images. Integrating data from various imaging modalities (such as mammography and MRI) can yield a more thorough picture of breast tissue. Accurate diagnosis depends on the correction of imaging artifacts such as motion artifacts and equipment-related artifacts. The effectiveness of the analysis can be increased by concentrating on the pertinent breast region and eliminating extraneous backdrops. Changing the image resolution can aid in standardizing data for subsequent processing. The pectoral muscle region can be removed to enhance breast tissue visibility in mammograms. Early detection can be facilitated by emphasizing on microcalcifications, which are suggestive of specific disorders. Improving the image's edges can help make the boundaries between various components easier to see. Additionally, a new field of study in medical imaging is the application of DL-based techniques for picture augmentation. A state-of-the-art comparison of several preprocessing techniques and their outcomes is presented in Table 2.

Table 2: Different breast cancer image preprocessing methodologies and their results

Ref.	Motive	Proposed model	Parameter evaluation	Remarks
[58]	To remove special markings and unwanted noises	Mean filter or average filter, median filtering, Adaptive median filter, Wiener filter	Mean square error (MSE), peak signal-to-noise ratio (PSNR), structural content	The adaptive median filter is better when compared with the other filter
[61]	To improve the detection quality of breast cancer	Median, wiener, and anisotropic filtering with wavelet	Acc. is examined in terms of standard deviation (SD), PSNR, signal-to-noise ratio (SNR), self-similarity index measure (SSIM), IMAE, VAR, root mean square error (RMSE), AMBE	Anisotropic filtering with wavelet can produce significantly improved results (qualitatively and quantitatively) as compared to other filtering methods
[62]	To improve image quality for analysis (breast periphery separation, intensity ratio propagation, breast thickness estimation, and intensity balancing.)	Otsu binary segmentation, morphological operation	Acc.	Useful in quantifying change in the relative proportion of breast tissue
[64]	To remove the background area (high-intensity rectangular label, tape artifact, and noise)	Contrast stretching, two-dimensional (2D) median filtering	Peak signal to noise ratio (PSNR)	Thresholds and regions of segmentation algorithms work more efficiently when images are preprocessed
[67]	Background removal, and image enhancements to outline the ROIs and regions within the ROIs	Rolling ball algorithm, Huang's fuzzy thresholding, canny edge detection, and Hough's line transform	Acc., mean gray value and the standard deviation, mean squared error, peak signal-to-noise-ratio, structural similarity index measure	Artifacts and noise are removed from the images
[68]	A technique producing higher detectability of lesions	Filtered-back projection (FBP) algorithm	Detectability index	Breast border enhancement artifacts were greatly suppressed and the detectability of calcifications and masses was increased
[65]	Develop an automated system for assisting in the analysis of digital mammograms	Edge-based segmentation, Poisson-based region segmentation	Evaluate each pixel in the image and compare it to the other pixels to determine distinct groups	Accurately detect the ROI for pectoral muscle, suppress the pectoral muscle successfully
[66]	Identification of suspicious lesions and micro-calcifications	Contrast stretching, power-law transformation, histogram processing, un-sharp masking, morphological processing, median filtering, anisotropic diffusion filtering, bilateral enhancement, homomorphic filtering	Peak signal to noise ratio (PSNR)	Anisotropic diffusion, power-law transformation, un-sharp masking, morphological processing, and median filtering are giving higher PSNR values
[59]	To detect the region of interest, automatic removal of artifacts and noise	Otsu's N thresholding method, threshold-based segmentation, edge-based segmentation, region-based segmentation	MSE, PSNR, enhancement measure (EME)	Otsu's N thresholding is better than another thresholding method
[60]	Enhance image quality, image smoothing, and noise restoration	Adaptive weighted frost filter for quantum noise removal	Spatial resolution, PSNR	Adaptive weighted frost filter is the most suitable choice for eliminating noise from mammographic images and performs better comparatively
[63]	Highlighting the required features of the image and suppressing noises	CNN architecture	Acc.	Cleaning of the noises and drying of the properties

3 Application of ML for breast cancer detection

ML has demonstrated considerable potential in the identification and diagnosis of breast cancer. Large databases of clinical data and medical imaging can be analyzed using ML algorithms to facilitate early diagnosis, risk assessment, and therapy planning. By helping radiologists identify worrisome spots in mammograms, ML algorithms can increase the precision of breast cancer screening. DL architectures, such as CNNs, can be trained to recognize irregularities and subtle patterns in mammograms. Between various preprocessing techniques and their outcomes, ML algorithms can segment and identify lesions in breast MRI and ultrasound images, offering more precise information for diagnosis. To help characterize the type of observed anomalies, ML models can be used to analyze the textural properties of lesions. By examining a variety of variables, including genetic information, family history, and clinical data, ML algorithms can determine an individual's risk of developing breast cancer. By customizing treatment regimens based on each patient's unique features, ML can maximize the efficacy of therapies.

Using the Wisconsin Diagnosis Breast Cancer (WDBC) dataset, Sharma et al. [69] presented several ML algorithms, including random forest (RF), KNN, and naïve Bayes, to categorize benign and malignant breast cancer tumors. After assessing recall, Acc., precision, and f1 score, it was discovered that KNN performed the best for classification. Using the same dataset, to classify two different types of breast cancer, benign and Malignant and Bazazeh et al. [70] used SVMs, RFs, and Bayesian networks (BNs). They also evaluated the Acc., recall, precision, and area of the response curve ([receiver-operating curve (ROC)]). The RF technique offers the best ROC performance, whereas the BN performs best in terms of recall and precision. "Using ML techniques, such as RF, KNN, naïve Bayes, SVM, and RF, and Ak [71] created a model to identify breast cancer and determine accuracy. The logistic regression (LR) model that contained all features produced the best results, with a classification Acc. of 98.1%." In their study, Vaka et al. [72] examined and contrasted threshold, DNSS, FCM, and histo-sigmoid fuzzy clustering. The DNNS was determined to be far superior to current techniques. To identify breast cancer with high accuracy, Alarabeyyat and Alhanahnah [73] created a backpropagation neural network (BPNN), LR, and the BPNN using mammographic pictures to evaluate the number of features that are extracted. Compared with the BPNN, the LR model used a significantly larger number of characteristics. SVM-radial basis function (RBF) provided the highest overall Acc. of 96.33%. Nallamala et al. [74] suggested that the LR algorithm, SVM algorithm, and KNN algorithm classify two different kinds of breast cancer tumors, i.e., benign and malignant using mammographic images. Osareh and Shadgar [75] used SVM, KNN, and probabilistic neural network (PNN) models to distinguish between the benign and malignant tumors of the breast using fine needle aspirates of breast lesions and fine needle aspirates of breast lumps (FNAB). They also compared performance metrics such as Acc., Sens., Spec., and MCC. The proposed method assesses yield decipherability, computation time, and predictive capability. The proposed model achieved 98.1% Acc. Using the University of California, Irvine (UCI) ML library, Omondiagbe et al. [76] used RBF, artificial neural network (ANN), and naïve Bayes classifiers in conjunction with SVM to extract features and minimize their dimensions. SVM achieved a maximum classification Acc. of 98.82%, Sens. of 98.41%, Spec. of 99.07%, and area under the ROC curve of 0.9994, according to calculations of Acc., area under the ROC curve, precision, recall, Sens., Spec., and kappa statistic. The proposed method assesses yield decipherability, computation time, and predictive capability. The proposed model achieved 98.1% accuracy. Using the University of California, Irvine (UCI) ML library, Omondiagbe et al. [76] used RBF, ANN, and naïve Bayes classifiers in conjunction with SVM to extract features and minimize their dimensions. SVM achieved a maximum classification Acc. of 98.82%, Sens. of 98.41%, Spec. of 99.07%, and area under the ROC curve of 0.9994, according to calculations of Acc., area under the ROC curve, precision, recall, Sens., Spec., and kappa statistic. The MLP model performed the best in terms of Acc., precision, and recall of 99.12, 99.00, and 99.00%, respectively, after comparing the Acc., precision, and recall of the classification tests. "To automatically detect breast cancer using a ML algorithm using the Wisconsin Breast Cancer dataset, Dhahri et al. [77] adopted SVM, KNN, DT, gradient boosting classifier (GB), RF, LR, AdaBoost classifier (AB), Gaussian Naive Bayes (GNB), and linear discriminant analysis (LDA) models." After comparing performance metrics such as Acc., recall, precision, and F1 score, it can be determined that, with appropriate configuration, the algorithms will perform identically. Using the WDBC dataset, Safdar et al. [78] compared ML algorithms to accurately predict breast cancer detection. After evaluating the AUC and ROC, it was discovered that KNN outperformed SVM. – radial based function, simple linear LR model, naïve Bayes, k-nearest neighbour, AdaBoost, Fuzzy unordered role induction technique, DT – J48, SVM, and WBCD datasets were employed by Gbenga et al. [79] in the identification of breast cancer." After calculating the true positive rate (TPR), false positive rate (FPR), precision, $F1$ score, and Acc., it was discovered that the SVM outperformed the others. Using the DDMS dataset, Hussain et al. [80] compared Bayesian, SVM, and decision-tree classifier models. The Acc., Sens., Spec., and FPR were computed. SVM had the lowest FPR, maximum Sens., Spec., and Acc. A state-of-the-art comparison of various ML models for the diagnosis and categorization of breast cancer illnesses is presented in Table 3.

4 Emergence of DL in breast cancer imaging

In the field of breast cancer imaging, DL has advanced significantly and offers promising improvements in diagnosis, treatment, and detection. The analysis of mammograms using DL models has aided the early detection of breast cancer. These models are capable of identifying minute patterns and anomalies that human radiologists can find difficult to recognize. By autonomously identifying and segmenting breast lesions in medical photographs, DL algorithms can expedite diagnosis and lower the risk of human error. Histopathological images of breast tissue can be analyzed using DL algorithms to categorize various subtypes of breast cancer. Appropriate treatment plans must be determined using this information. In the field of breast cancer imaging, DL has advanced significantly and offers promising improvements in diagnosis, treatment, and detection. The analysis of mammograms using DL models has aided the early detection of breast cancer. These models are capable of identifying minute patterns and anomalies that human radiologists can find difficult to recognize. By autonomously identifying and segmenting breast lesions in medical photographs, DL algorithms can expedite diagnosis and lower the risk of human error. Histopathological images of breast tissue can be analyzed using DL algorithms to categorize various subtypes of breast cancer. Appropriate treatment plans must be determined using this information. By lowering the false positives and negatives in breast cancer imaging, DL models seek to increase the overall diagnosis Acc. This is especially crucial for reducing pointless interventions and ensuring that patients receive timely therapy. The speed and Acc. of breast cancer screening programs can be increased by integrating DL algorithms into computer-aided detection (CAD) systems to help radiologists interpret screening mammograms. DL in breast cancer imaging has the potential to significantly enhance personalized treatment plans, early diagnosis, and early detection, all of which can improve patient outcomes. To address these issues and guarantee the responsible application of new technologies in healthcare, continued research and cooperation among physicians, data scientists, and regulatory agencies are important.

To assess the AUC, Sens., and Spec., Shen et al. [84] suggested utilizing VGG16 and ResNet 50-based image classification to classify breast cancer using mammographic images using the DDSM (CBIS-DDSM). ResNet50 performed the best. The relative values of the AUC, Sens., and Spec. were 98, 86.7, and 96.1%, respectively. Utilizing strong computer vision techniques and DL models, Mambou et al. [85] evaluated linear SVM and InceptionV3 for numerous breast cancer diagnosis strategies utilizing a research database (DMR) comprising frontal thermogram images and calculated Acc. and AUC. In comparison, SVM performs better than the others. "Using the IRMA dataset, Ismail and Sovuthy [86] created VGG16 and ResNet50 to test the diagnosis of breast cancer between two DL model networks. The optimal model, VGG16, had an Acc. of 94%, precision of 89%, and recall of 99%. The deep learning assisted-efficient adaboost algorithm (DLA-EABA) for breast cancer detection utilizing MRI images was proposed by Zheng et al. [87]. It attains 97.2% Acc., 98.3% Sens., and 96.5% Spec." Using synthetic datasets and image datasets related to breast histopathology, Das et al. [88] presented 2-dimensional empirical wavelet transform (2-DEWT) decomposed modes by transforming a one-dimensional signal into two-dimensional images using the deep insight framework and the mean normalization technique. Using full-field digital mammography (FFDM), Bai et al. [89,89] built and compared deep and recurrent neural networks to identify malignancies before clinical indications manifest. It was found that the Acc., Sens., Spec., and precision of the deep neural networks were all higher. Optimized feature extraction and selection were

Table 3: Comparison of ML models for breast cancer disease identification and classification

Ref.	Dataset	Motive	Algorithms/techniques used	Parameter evaluation	Results
[69]	WDBC	To train and test models to classify two different kinds of breast cancer, i.e., benign and malignant	RF, KNN and naïve Bayes.	Acc., precision, recall, and F1 score	kNN is the most effective in detection of the breast cancer with 94% accuracy
[70]	WDBC	To classify two different kinds of breast cancer, i.e., benign and malignant	SVM, RF and BN	Acc., recall, precision, and area of ROC	BN has the best performance in terms of recall and precision, RF technique has the optimum ROC performance
[71]	WDBC	To detect breast cancer	RF, KNN, naïve Bayes, SVM and RF	Acc.	Results obtained with the LR model with all features included showed the highest classification Acc. (98.1%)
[72]	M. G Cancer Hospital & Research Institute, Visakhapatnam	To detect breast cancer	Histo-sigmoid fuzzy clustering, DNSS, FCM, Threshold	Acc.	DNNS is quite better than the existing methods
[73]	Mammographic image	To detect breast cancer with high Acc.	Backpropagation neural network (BPNN), LR, and the Backpropagation neural network	Numbers of features	The number of features utilized in the LR model was much higher than with the BPNN
[75]	Fine needle aspirate of breast lesions, FNAB	To distinguish between the benign and malignant tumors of the breast	SVM, KNN, PNN	Acc., Sens., Spec., MCC	SVM-RBF provided the highest overall Acc. of 96.33%
[74]	Mammographic image	To classify two different kinds of breast cancer tumor, i.e., benign and malignant	LR algorithm, SVM algorithm, KNN algorithm	Ease to decipher yield, calculation time, and predictive power	The suggested strategy has acquired the 98.50% precision
[76]	University of California-Irvine (UCI) ML repository	Feature selection and feature extraction methods to reduce the dimension of features	SVM with RBF, ANN, and naïve Bayes classifier	Acc., area under ROC curve, precision, recall, Sens., Spec., kappa statistic	SVM achieves classification Acc. of 98.82%, Sens. of 98.41%, Spec. of 99.07%, and area under the ROC curve of 0.9994
[81]	Mammographic image	To detect breast cancer tumor	SVM, ANN, KNN, DT	Acc., Sens., Spec., MCC	The maximum achieved Acc. of SVM (single or hybrid) was 99.8%
[82]	BreakHist_dataset	To distinguish between malignant and benign tumor	SVM, RF, KNN, LR, naïve Bayes	Identify specific parts using specific filters	KNN outperforms other methods
[83]	WDBC	Evaluate the performance in classifying data concerning the efficiency and effectiveness of each algorithm	MLP, KNN, classification and regression trees (CART), Gaussian naïve Bayes (NB) and SVMs	Classification test Acc., precision, and recall	MLP model has the highest performance in terms of Acc., precision, and recall at 99.12, 99.00, and 99.00%, respectively
[77]	Wisconsin breast cancer dataset	Automatic detection of breast cancer using a ML algorithm	SVM, KNN, DT, GB, RF, LR, AB, GNB, and LDA	Acc., recall, precision, F1 score	The algorithms can achieve the same performance after effective configuration

(Continued)

Table 3: *Continued*

Ref.	Dataset	Motive	Algorithms/techniques used	Parameter evaluation	Results
[78]	Breast Cancer Wisconsin Diagnostic Dataset (BCWD)	Comparing ML models for correctly predicting breast cancer detection	SVM, LR, and KNN	Receiver-operating curve (ROC), and the AUC evaluate a classifier for precise Acc.	Overall average Acc. of KNN is higher than SVM
[79]	WDBC dataset	Detection of breast cancer	Radial based function, simple Linear LR model, naïve Bayes, KNN, AdaBoost, fuzzy unordered role induction algorithm and DT – J48, SVM	TPR, FPR, precision, F1 score, Acc.	SVM has the best performance in terms of classification Acc. and the lowest FR
[80]	DDMS	To distinguish the cancer mammograms	SVM, DT, and Bayesian classifier	Acc., Sens., Spec., FPR	SVM has the highest Acc., Sens., Spec., and lowest FPR

carried out by Sha et al. [90] using the grasshopper optimization method. Before processing, a median filter was used to remove noise from the image and optimize image segmentation using the CNN and DDSM databases. It attained 92% Acc., 97% negative predictive value (NPV), 85% positive predictive value (PPV), 93% Spec., and 96% Sens. in the study by Lotter et al. [91] using an annotation-efficient DL approach with a DDSM pictures, new “maximum suspicion projection” (MSP) images were created from data built tool (DBT) data to detect mammography and digital breast tomosynthesis. It attained a Sens. of 97.7%, Spec. of 99.4%, and AUC of 0.963 ± 0.003. Using the mammography MIAS database, Khuriwal and Mishra [92] created a CNN to detect breast cancer from histological pictures. The CNN approach achieved 98% Acc. for the 12 features. CNNs were proposed by Salvi and Kadam [93] for the identification of breast cancer using thermal camera sensor image datasets. Using this method, a 98% Acc. was attained. O-net, a mixture of two U-nets connected at the encoding level and disconnected at the decoding level, was developed by Rashed and El Seoud [94] to develop an automated breast cancer diagnosis system employing mammography and the CBIS-DDSM dataset. The Acc. is 95.01%. In a study conducted by Selvathi and Aarthy Poornila [95], breast cancer diagnosis utilizing medical images and the MIAS mammography dataset was compared using CNNs, sparse autoencoders (SAE), and supervised SAEs (SSAE). GoogleNet, AlexNet, VGG16, and FaceNet were examined by Wang et al. [96] to identify metastatic breast cancer from histopathological images. The Acc. rates for GoogleNet, AlexNet, VGG16, and faceNet are 98.4, 92.1, 97.9, and 96.8%, respectively. With 99.67% Acc. rate, Khuriwal and Mishra [97] suggested a CNN for breast cancer diagnosis utilizing a DL algorithm and the Wisconsin Breast Cancer Database. Using the CBIS-DDSM dataset, Ragab et al. [98] employed SVMs and deep CNNs for the diagnosis of breast cancer. SVM obtained an AUC of 94% and an Acc. of 87.2%. Khan et al. [99] used the idea of transfer learning with a standard benchmark dataset to compare GoogLeNet, VGGNet, and ResNet for the detection and classification of breast cancer. The accuracies of GoogLeNet, VGGNet, and ResNet are 93.5, 94.15, and 94.35%, respectively. Using the MIAS dataset, Saber et al. [100] compared Inception V3, ResNet50, VGG-16, VGG-19, and Inception-V2 ResNet. More power is present in the VGG16 model. The F1 score, AUC, Sens., Spec., Acc., and precision were 98.56, 97.25, 97.66, 99.5, and 98.96%, respectively. A comparison of the various DL models for breast cancer diagnosis is presented in Table 4.

5 Integration of imaging and AI in breast cancer diagnosis

The combination of AI [101] with imaging for the diagnosis of breast cancer has demonstrated great potential in terms of enhancing the precision, effectiveness, and customized nature of diagnostic procedures.

- **Automated image analysis:** Mammograms and tomosynthesis photographs were analyzed using AI algorithms to identify anomalies such as masses, microcalcifications, and architectural distortions [102]. Radiologists can benefit from automated analysis because it shortens interpretation times and highlights areas of concern.
- **MRI and ultrasound analysis:** AI was utilized to evaluate breast MRI and ultrasound images, offering further data for diagnosis. This covers the distinction between benign and malignant signs, as well as the identification of lesions and characterization of tumors [103].
- **CAD:** AI-driven CAD systems have been created to assist radiologists in interpreting images. By marking possible ROI, these technologies help radiologists identify anomalies that can be difficult to notice or easily missed [104].
- **Quantitative imaging biomarkers:** Through radiomics analysis, AI makes it easier to extract quantitative characteristics from medical images. These traits function as imaging biomarkers and offer important insights into the properties and behavior of tumors [105]. Imaging for breast cancer can be made more diagnostic and prognostic using radiomics.
- **Integration with clinical data:** Imaging data can be integrated with clinical, genetic, and other patient-specific data using AI [106]. This all-encompassing method improves diagnostic precision and aids in customized treatment planning.

Table 4: Comparison of different deep-learning models for breast cancer detection

Ref.	Dataset	Motive	Algorithms/techniques used	Parameter evaluation	Results
[84]	DDSM	To classify breast cancer using mammographic images	VGG16 and ResNet50-based image classification	AUC, Sens., Spec.	ResNet50 shows the best performance. AUC: 0.98, Sens.: 86.7% and Spec.: 96.1%
[85]	Research Data Base (DMR) containing frontal thermogram images	Comparative study of several breast cancer detection techniques using powerful computer vision techniques and DL models	Linear SVM, InceptionV3	Acc., AUC	SVM is comparatively better than others
[86]	IRMA dataset	Compare breast cancer detection with two model networks of DL techniques	VGG16 and ResNet50	Acc., precision, recall	VGG16 performs best. Acc.: 94%, precision: 89%, recall: 99%
[87]	MRI image	Breast cancer detection	Efficient Adaboost Algorithm (DLA-EABA)	Acc., Sens., Spec.	Acc.: 97.2%, Sens.: 98.3%, Spec.: 96.5%
[88]	Synthetic datasets and breast histopathology image datasets	Converting the one-dimensional signal to two-dimensional images using the deep insight framework with the mean normalization technique	2-DEWT decomposed modes	Acc., Sens., Spec., precision, Recall, *F*1-score	Acc.: 98.08%, Sens.: 99.20%, Spec.: 93.55%, precision: 98.41%, recall: 99.20% *F*1-score: 98.80%
[89]	FFDM	Identification of cancers before clinical signs appear	Deep neural networks, autoencoders, deep CNN, RNN and generative adversarial networks	Acc., false positive rate, precision, recall, *F*1-score, ROC curve, AUC, precision-recall	FFDMs, deep-learning-based detection is the most effective models
[90]	DDSM	Preprocessed by a median filter for noise elimination, and optimized image segmentation based on a CNN	A grasshopper optimization algorithm, and optimized feature extraction and feature selection based on the grasshopper optimization algorithm	Acc., Sens., Spec., NPV, PPV	96% Sens., 93% Spec., 85% PPV, 97% NPV, 92% Acc.
[91]	DDSM	Detection in mammography and digital breast tomosynthesis using an annotation-efficient DL approach	Creating new-MSP images from DBT data	AUC, Sens., Spec.	AUC: 0.963 ± 0.003, Sens.: 97.7%, Spec.: 99.4%
[92]	Mammograph MIAS database	Breast cancer detection from histopathological images	CNN	Acc.	Convolutional neural network algorithm on these 12 features and achieved 98% Acc.
[93]	Thermal camera sensor	Breast cancer detection	CNN	Acc.	Acc.: 98%
[94]	Curated breast imaging subset (CBIS-DDSM)	Development of an automatic diagnosis system for breast cancer using mammography	O-net, which is a combination of two U-nets connected at the encoding level and disconnected at the decoding	Acc.	Acc.: 95.01%
[95]	Mini-MIAS mammographic database	Breast cancer detection using medical image	CNN, SAE, SSAE	Acc.	Acc. of up to 97%, 98.5% for SAE, 98.9% for SSAE
[96]	Histopathology image	Identifying metastatic breast cancer	Googlenet, Alexnet, VGG16, FaceNet	Acc.	GoogleNet: 98.4%, AlexNet: 92.1%, VGG16: 97.9%, FaceNet: 96.8%
[97]	WDBC database	Breast cancer diagnosis using DL algorithm	CNN	Acc.	Acc.: 99.67%
[98]		Breast cancer detection	Deep CNN and SVMs	Acc., AUC	

(Continued)

Table 4: *Continued*

Ref.	Dataset	Motive	Algorithms/techniques used	Parameter evaluation	Results
	Curated breast imaging subset of DDSM (CBIS-DDSM)				SVM Acc. becomes 87.2% with an AUC equaling 0.94 (94%)
[99]	Standard benchmark dataset	Detection and classification of breast cancer using the concept of transfer learning	GoogLeNet, VGGNet, and ResNet	Acc.	Acc. of GoogLeNet, VGGNet, and ResNet are 93.5%, 94.15%, and 94.35% respectively
[100]	MIAS dataset	To evaluate the performance of various DL architectures for breast cancer classification	Inception V3, ResNet50, visual geometry group networks (VGG)-19, VGG-16, and Inception-V2 ResNet	Acc., Sens., Spec., precision, F-score, and AUC	VGG16 model is powerful. Acc., Sens., Spec., precision, F-score, and AUC are 98.96, 97.83, 99.13, 97.35, 97.66, and 0.995%, respectively

- **Risk stratification:** To categorize patients into distinct risk groups, AI models can evaluate a variety of risk variables and imaging findings [107]. This will facilitate the creation of customized management plans and suitable screening intervals.
- **Real-time decision support:** A clinical decision support systems (CDSS) driven by AI [108] helps radiologists assess images in real time. It can provide advice based on imaging data analysis and assist medical professionals in making better judgments.
- **Telemedicine and remote consultation:** AI makes it easier to transmit and analyze imaging data remotely, allowing specialists and healthcare professionals to collaborate. This is especially helpful in places where access to qualified radiologists is scarce [109].
- **Continuous learning and model improvement:** AI models constantly learn and change in response to fresh information and new trends [110]. Over time, this flexibility helps algorithms perform better and keeps them up-to-date with the most recent advancements in imaging methods and medical understanding.

6 Addressing potential biases and ensuring fairness in AI models for breast cancer detection

As the integration of AI into breast cancer detection and diagnosis becomes more widespread, it is imperative to address potential biases that may exist within AI algorithms. Biases in AI can arise from various sources, including the data used to train the models, the design of the algorithms themselves, and the interpretation of their outcomes.

6.1 Sources of bias

- Data bias: Training datasets that are not representative of the diverse population affected by breast cancer may lead to biased AI models. For instance, if a dataset predominantly represents a particular age group, ethnic background, or geographical region, the resulting AI model may not perform equally well across all segments of the population. Such biases can perpetuate existing disparities in healthcare, leading to inaccuracies in diagnosis and treatment for underrepresented groups.
- Algorithmic bias: The design of AI algorithms can also introduce bias. The choice of features, the way data are preprocessed, and how the algorithms are configured can all contribute to biased outcomes. If an algorithm is not designed with fairness in mind, it may disproportionately favor certain groups over others.
- Interpretation bias: Human biases can influence the interpretation of AI outputs. Radiologists and other healthcare professionals may unconsciously favor AI recommendations based on their own preconceptions, which can amplify existing biases.

6.2 Importance of fairness in AI models

Ensuring fairness in AI models is crucial to promote equitable healthcare outcomes. This requires a multifaceted approach.

- Diverse and representative datasets: To address data bias, it is essential to curate and utilize datasets that are diverse and representative of the entire population. This includes ensuring a wide range of age groups, ethnic backgrounds, and geographical regions that are included in the training data. Regular audits of the datasets for bias and appropriate correction measures can further improve the representativeness.
- Algorithmic fairness: Fairness should be a core consideration in the development of AI algorithms. Techniques such as re-sampling, re-weighting, and adversarial debiasing can be applied to the data and models to mitigate bias. Researchers and developers should employ fairness metrics and continually assess their models for biased behavior.

- Transparent and explainable AI: Making AI models transparent and their decisions explainable can help in identifying and mitigating bias. Healthcare professionals should be able to understand how AI models make decisions to trust and verify the outputs effectively.
- Continuous monitoring and updating: Biases can evolve, and new biases may emerge as AI models are exposed to new data. Therefore, continuous monitoring and regular updates to the AI models are necessary to ensure they adapt to changes and maintain fairness.
- Interdisciplinary collaboration: Addressing bias and ensuring fairness in AI requires collaboration across disciplines, including data science, ethics, and healthcare. Multidisciplinary teams can provide diverse perspectives and expertise to design more equitable AI solutions.

By proactively addressing potential biases and prioritizing fairness, AI models for breast cancer detection can help reduce disparities and ensure that technological advancements benefit all patient groups equitably. Fair and unbiased AI has the potential to significantly enhance diagnostic accuracy, provide more personalized care, and improve overall healthcare outcomes.

7 Comparing AI with human radiologists in breast cancer detection and diagnosis

The integration of AI into breast cancer detection and diagnosis has prompted numerous comparisons with human radiologists, aiming to evaluate performance, accuracy, and efficiency. Several studies have sought to measure these aspects, providing valuable insights:
- Performance accuracy: Numerous studies have indicated that AI algorithms can match or even exceed the performance of experienced radiologists in detecting breast cancer. For instance, a landmark study published in *Nature* by McKinney et al. [111] demonstrated that an AI model developed by Google Health outperformed radiologists in diagnosing breast cancer. The AI system showed a reduction in false positives by 5.7% and false negatives by 9.4% compared to human radiologists.
- Efficiency and speed: AI models provide consistent and rapid analysis of medical images, considerably reducing the time required for diagnosis. A study published by Hirsch et al. [112] revealed that AI-assisted mammograms significantly decreased interpretation time while maintaining diagnostic accuracy. This efficiency is particularly advantageous in high-volume screening programs, allowing for faster patient throughput and timely clinical decision-making.
- Detection of subtle anomalies: AI has demonstrated a remarkable ability to detect subtle anomalies and early signs of breast cancer that might be overlooked by human eyes. A study by Rodriguez-Ruiz et al. [113] in *Journal of Clinical Oncology* showed that AI systems achieved better sensitivity in identifying early-stage cancers, some of which were initially missed by radiologists. This capability can lead to earlier diagnosis and improved patient outcomes.
- Complementary roles: Rather than replacing radiologists, AI is often seen as a complementary tool that enhances human capabilities. Studies highlight the synergistic effect when AI assists radiologists, combining the strengths of both AI's precision and radiologists' clinical judgment. For example, a study by Dembrower et al. [114] found that AI support improved radiologists' performance, aiding in more accurate and confident diagnoses.
- Reduction of cognitive load: AI algorithms can help reduce the cognitive load on radiologists by automating routine and repetitive tasks, allowing them to focus on more complex cases and clinical decision-making. This aspect was underscored in a study published by Patil et al. [115], where AI-driven CAD systems enhanced radiologists' diagnostic capabilities by highlighting areas of interest and flagging potential issues.
- Training and continuous improvement: AI systems are capable of continuous learning and improvement, absorbing massive amounts of data over time to refine their diagnostic accuracy. In contrast, while human radiologists benefit from experience and ongoing education, they are limited by the volume of cases they can

personally review. A study by Kaul et al. [116] emphasized the potential of AI to rapidly incorporate new findings and guidelines, ensuring it remains at the cutting edge of diagnostic standards.
- Bias mitigation: It is important to note that AI algorithms can inherit biases from the datasets they are trained on. Therefore, rigorous training with diverse, representative datasets is crucial to minimize disparities. Interestingly, studies such as one published by Norgeot et al. [117] suggest that when well trained, AI can help reduce certain types of human biases, providing more uniform diagnostic standards.

In summary, while AI has demonstrated substantial promise in breast cancer detection and diagnosis, it is most effective when used in conjunction with skilled radiologists. Together, they can achieve higher accuracy, improved efficiency, and better patient outcomes. Ongoing research and longitudinal studies will continue to refine these systems, ensuring that the combination of AI and human expertise maximizes diagnostic precision and effectiveness.

8 Impact on clinical decision-making

Clinical decision-making in breast cancer has been significantly affected by the combination of AI and image processing. AI algorithms can improve the Sens. and Spec. of breast cancer detection in medical images such as mammograms and MRIs [118]. This advancement facilitates early diagnosis and improves treatment outcomes. By automatically indicating any anomalies or suspicious areas in medical images, AI-based CAD [119] systems help radiologists. This can improve the diagnostic Acc. and decrease oversight. AI makes it possible to extract and analyze quantitative features from medical images through radiomics. These traits function as imaging biomarkers [120], offer more details regarding the nature of tumors. A more accurate diagnosis and prognosis can be achieved using radiomics. To estimate a patient's chance of acquiring breast cancer, AI models can examine a variety of imaging data, medical history, and other pertinent data [121]. Customizing screening methods and choosing appropriate therapies are made easier with the use of this information. AI systems can assist in the creation of individualized treatment regimens by predicting molecular subtypes of breast cancer based on imaging characteristics. This method assists medical professionals in selecting treatments with a higher chance of working for particular subtypes. AI can be used to track how a tumor's properties and response to treatment vary over time. These data will help medical professionals modify their treatment plans according to each patient's reaction to therapy. AI makes it easier to combine genomic and clinical data with the imaging data. CDSS driven by AI [122] can help physicians make decisions in real time by recommending and supplying pertinent data. This helps medical practitioners make judgments faster and with greater Acc. By automating repetitive and time-consuming operations, AI allows healthcare personnel to concentrate on more intricate patient care responsibilities. Faster diagnosis and treatment initiation may result in increased efficiency [123]. AI makes it easier for specialists to analyze medical images remotely, allowing them to counsel and assist medical practitioners who are located in different locations [124]. This is particularly helpful in places where access to specialized knowledge is scarce. The use of AI and image-processing technologies in breast cancer clinical decision-making has many advantages; however, to ensure their safe and successful integration into standard clinical practice, it is critical to address issues such as data privacy, the interpretability of AI models, and ongoing validation [125]. Encouraging research, cooperation, and regulatory supervision is necessary to fully utilize these technologies for the treatment of breast cancer.

9 Challenges and future directions

Caliber and variety of training data have a significant impact on the effectiveness of AI models. Problems such as unbalanced datasets and differences in imaging methods can affect the generalizability of the models. Clinicians frequently need transparent insights into the decision-making process; hence, the absence of interpretability and explainability in AI models is a barrier [126]. It is difficult to seamlessly integrate AI technologies into current clinical operations. The adoption of AI technologies may be hampered by interoperability problems, resistance to change, and concerns regarding disruption. The effectiveness of AI algorithms may be affected by variations in image quality and format caused by the absence of uniform imaging practices throughout healthcare facilities [127]. Complicated issues surround informed permission, patient privacy, and ethical application of AI in healthcare. Legal and ethical frameworks must be developed in parallel with new technological development.

AI models can be made more robust and reliable by incorporating real-world clinical data and carefully selecting various relevant datasets [128]. Ongoing studies are carried out to create models and explanation methods for AI forecasts that are easier to understand. Gaining trust and easing the incorporation of AI into clinical workflows are needed [129] to provide user-friendly interfaces, guarantee interoperability with current systems, and provide comprehensive training for healthcare personnel, technologists, and healthcare professionals collaborate [130]. Promotion and creation of standardized imaging procedures to guarantee uniformity in data collection may improve the ability of AI models to generalize in various contexts defining precise privacy protection, ethical standards [131], and legal frameworks to control the advancement and application of AI in breast cancer diagnosis. It is imperative to guarantee patient participation in the decision-making procedures [132]. Further, there are other substantial barriers to integrate AI for breast cancer diagnosis.

- Cost-effectiveness of AI in breast cancer screening and diagnosis: the cost-effectiveness of AI technologies in breast cancer screening and diagnosis is crucial for their adoption, especially in low-resource settings. AI-driven tools can potentially reduce the workload on healthcare professionals, decrease diagnostic errors, and improve patient outcomes, thus leading to significant cost savings. By automating routine tasks, AI allows radiologists to focus on more complex cases, improving efficiency and reducing costs associated with delayed diagnoses and treatment. Moreover, the wide-scale adoption of AI can facilitate more equitable healthcare access by providing advanced diagnostic capabilities even in resource-constrained environments, ultimately leading to better healthcare delivery without disproportionately high investments.
- Regulatory landscape for AI in healthcare – the current regulatory landscape for AI in healthcare is rapidly evolving. Regulatory bodies like the fisher discriminant analysis are developing frameworks to ensure the safety, efficacy, and reliability of AI tools. However, the approval process presents challenges due to the dynamic nature of AI algorithms, which continually learn and adapt. Ensuring consistent performance and managing updates without compromising patient safety are critical issues. Additionally, there are challenges related to validating AI models across diverse patient populations and clinical settings to satisfy regulatory requirements. Emerging guidelines aim to balance innovation with patient safety, yet navigating these regulatory pathways remains complex.
- Integration with existing healthcare IT systems: integrating AI tools with existing healthcare IT systems, including EHRs, presents significant challenges in interoperability. Achieving seamless integration requires compatibility between AI applications and diverse healthcare IT infrastructures. Solutions involve developing standardized data formats, using interoperable APIs, and creating vendor-agnostic platforms to facilitate smooth data exchange. Collaborative efforts between technologists and healthcare professionals are vital to designing user-friendly interfaces and ensuring comprehensive training, thereby enhancing the acceptance and practical utility of AI tools in clinical workflows.
- Patient privacy and data security: addressing patient privacy and data security is paramount, particularly given the sensitive nature of health data. AI implementation in healthcare must comply with stringent regulations such as health insurance portability and accountability act and general data protection regulation (GDPR) to protect patient information. The risks associated with data breaches or unauthorized access necessitate robust encryption methods, secure data storage, and anonymization techniques. Additionally, establishing clear consent protocols and engaging patients in data governance practices foster transparency and trust, ensuring ethical handling of health data while leveraging AI's capabilities.
- Impact on patient outcomes: evidence from various studies demonstrates the positive impact of AI on patient outcomes, including improved survival rates, lower recurrence rates, and increased patient satisfaction. For example, research published in peer-reviewed journals has shown that AI-assisted breast cancer

screening can lead to earlier detection, enabling timely intervention and better prognosis. Patient satisfaction tends to improve when AI tools are used, as they contribute to more accurate diagnoses and personalized treatment plans. Longitudinal studies are essential to further quantify these benefits and solidify AI's role in enhancing patient outcomes.
- Training healthcare providers: effective training for healthcare providers to use AI tools is essential for successful deployment. Barriers to user acceptance include lack of familiarity with AI technologies, concerns about job displacement, and potential technical challenges. Comprehensive training programs that focus on the benefits of AI, practical usage, and troubleshooting can alleviate these concerns. Continuing education and hands-on workshops help build confidence among healthcare providers, fostering a collaborative environment where AI enhances clinical practice rather than disrupts it.
- AI as a decision support tool: AI's role in breast cancer detection should be viewed as a decision support tool rather than a replacement for human experts. AI can assist radiologists by identifying potential anomalies, analyzing complex imaging data, and providing quantitative insights that complement human expertise. This collaborative approach ensures that AI augments the diagnostic process, increasing accuracy and efficiency without diminishing the value of radiologists. Highlighting AI's supportive role encourages its acceptance and integration into clinical practice.
- Technological advancements and future research: recent technological advancements in AI and imaging techniques continue to influence breast cancer detection. Innovations such as DL, advanced neural networks, and improved imaging modalities – like high-resolution MRI and 3D mammography – are paving the way for more accurate and comprehensive diagnostic tools. Ongoing research focuses on enhancing the interpretability of AI models, developing robust training datasets, and integrating multimodal data for holistic cancer diagnosis. As these technologies evolve, they hold the promise of transforming breast cancer care, making diagnosis more precise, personalized, and accessible.

Hence, AI presents significant opportunities to advance breast cancer detection and diagnosis; several challenges must be addressed to realize its full potential. Ensuring diverse and balanced training datasets, improving the transparency and explainability of AI models, facilitating seamless integration into clinical workflows, addressing privacy and security concerns, and navigating the regulatory landscape are paramount. Additionally, demonstrating cost-effectiveness, training healthcare providers, and emphasizing AI's role as a decision support tool are essential steps toward widespread adoption. As technological advancements continue, collaborative efforts between technologists, healthcare professionals, and regulatory bodies will be crucial in shaping the future of AI in breast cancer care.

10 Conclusion

A revolutionary era in the identification and assessment of breast cancer severity has been brought about by the combination of sophisticated AI tools and image-based methods. The transition from conventional techniques to AI-powered technologies has shown the revolutionary changes in breast cancer diagnosis. These technologies have demonstrated greater skill in identifying minor abnormalities, supporting early detection, and offering insights into the severity of breast cancer through the application of ML and DL algorithms. AI integration helps radiologists plan treatments more precisely and individually while also increasing their productivity. Obstacles such as data integrity, comprehensibility, and moral implications highlight the necessity of continuous investigation and cooperation. The field will advance further with the support of explainable AI, multimodal integration, and international data-sharing initiatives, promising more accurate, effective, and patient-centered care for breast cancer patients. The combination of AI with image-based approaches has yielded transformative discoveries that represent a paradigm shift in breast cancer management. These insights have the potential to significantly improve outcomes and eventually save lives.

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