Risk stratification models powered by artificial intelligence for early-stage breast cancer detection

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Abstract

Introduction: Breast cancer has become the most frequent cancer in women in America and is expected that for 2024 there were about 310,720 new invasive breast cancer cases. The utilization of AI in breast cancer management for either identification of the diseases or staging of the disease will be a revolutionizing breakthrough in the care of Cancer patients. Deep learning models being developed in recent years have shown a high ability in identifying patterns and diagnosis of medical data to predict diseases possibly bringing revolutionary changes in early diagnosis techniques.

Materials and Methods: An extensive review was made on different electronic databases to compare the AI-based risk stratification for the identification of breast cancer. The studies comprised a protocol that involved systematic reviews of machine learning algorithms and deep learning architectures in case of breast cancer risk assessment. Published literature and other empirical papers consisting of concept theories, quantitative and qualitative research, primary or peer-reviewed, systematic reviews and meta-analyses, and especially those from America were explored.

Findings: Based on the results, the recurrent neural networks were observed to produce the highest level of accuracy of 98.58% in the assessment of breast cancer risk followed by the genetic programming and transfer learning and with an accuracy level greater than 96%. In predicting mortality the multiple data stream models especially, the imaging features with clinical parameters presented high performance than traditional risk predictors. Especially, it was identified that the deep learning structures had a high efficiency in analysing imaging data where the convolutional neural networks were demonstrating high accuracy in mammographic analysis.

Discussion: The result supports the prospect that breast cancer risk stratification model based on AI can help to maximize the benefits of the disorder detection. The enhanced performance of deeper architectures in handling of imaging data provides credence to the developing new paradigm for the detection strategies. There are still some limitations to interpretability of the model, standardization of implementing protocols, and incorporating it into clinical environments. In addition, the study underscores the need for sound validation approaches as well as generalization across different patients. These findings underscore the importance of interdisciplinary whether in the form of joint research between healthcare practitioners, data scientist and technologist to redesign these systems for health care use.

Conclusion: Risk stratification models by artificial intelligence hold a great potential in changing the scenario of early breast cancer detection. The application of these technologies in clinical practice pushes for the likelihood of precise, timely and individualized screening techniques. Although there are problems with regard to implementation and setting of standards, there is clear evidence that these systems should be maintained and improved. According to the suggestions based on data and analysis, AI proven risk assessment is a major breakthrough toward combating breast cancer, and could enhance the treatment of the diseases, its early discovery, and some targeted solutions.

Keywords: *Artificial Intelligence, Breast Cancer Detection, Machine Learning, Deep Learning, Neural Networks, Precision Medicine, Healthcare Innovation, Predictive Analytics, Digital Health, Cancer Screening.*

1. Introduction

Breast cancer as a type of cancer is the most common in women and more so to the American Women. Based on estimated statistics, around 310720 women with forced tumour in America will be diagnosed with invasive breast cancer in 2024 and 56500 women will be diagnosed with DCIS. The use of screen aids has shown impressive performances where it has been incorporated in the screening of breast cancer diseases. Kakileti et al. (2020) have reveled that the AI based thermal radiomics integrated with personalized risk prediction system can increase the level of accuracy in pre-screening to a very high extent. This is a great development considering that in the year 2024, about 310720 women in the United States are likely to be diagnosed with invasive breast cancer. Kumar et al., 2021 states that early diagnosis using artificial neuronic mechanisms has enhanced the general screening proficiency; RNN has demonstrated a first-level conviction rate of 98.58%. The next two methods are the genetic programming and transfer learning that present the accuracies more than 96% in identifying breast cancer. Nicolò et al. (2020) also extended their evidence on the efficiency of machine learning algorithms integrated with mechanistic modeling for predicting metastatic relapse in terms of the early breast cancer stage. These CDC technological inventions have been promising particularly in tackling health disparities in relation to complicated equipment and techniques in healthcare amongst different communities in the United States of America.

Contemporary demand and technological trends raise the question of using complex methods of breast cancer diagnosis containing both clinical and technological approaches. Introduction of risk stratification algorithm based on artificial intelligence has increased advanced capabilities of analysis and detection of early-stage breast cancer through matching large database of medical records. These systems display better competence in a variety of data sorting such as imaging studies, genetic information and clinical parameters to develop better risk assessment profiles. The advancement in the use of complex algorithms has come as a relief as they make it easier to determine even finer details that human eyes may fail to see when it comes to diagnosing breast cancer. It may be considered the most important technological advancement that deals with the problems of the traditional screening associated with its sensitivity and specificity (Rodriguez-Ruiz et al., 2019; Baughan et al., 2022; Krishnamurthy et al., 2023).

In current advancements, it has been shown that the use of artificial intelligence in the diagnosis of breast cancer through different imaging studies is highly effective. Arieno et al., (2019) in their studies point to bring out the premise that use of AI in breast imaging ranges from breast density to outcomes risk stratification and proves to have better diagnostic accuracy. This has been especially seen from the use of the AI algorithms relating to mammography and digital breast tomosynthesis (DBT). Another study by Kumar et al (2021) found that screening outcomes for early-stage detection has significantly enhanced the performance where recurrent neural networks (RNN) have a credibility of 98.58%. Further more, recent methods incorporating genetic programming (GP) and transfer learning (TL) achieve accuracies of above 96% thus improving diagnostic efficiency. According to Rodríguez-Ruiz et al. (2019), AI-based systems have improved mammographic analysis, as well as the features that sound difficult to identify in routine screening methods. The present machinery and redesigned detection equipment have not only increased the detection rates but also helped in decreasing false positives, thus increasing the usefulness of breast cancer screening in healthcare facilities in America.

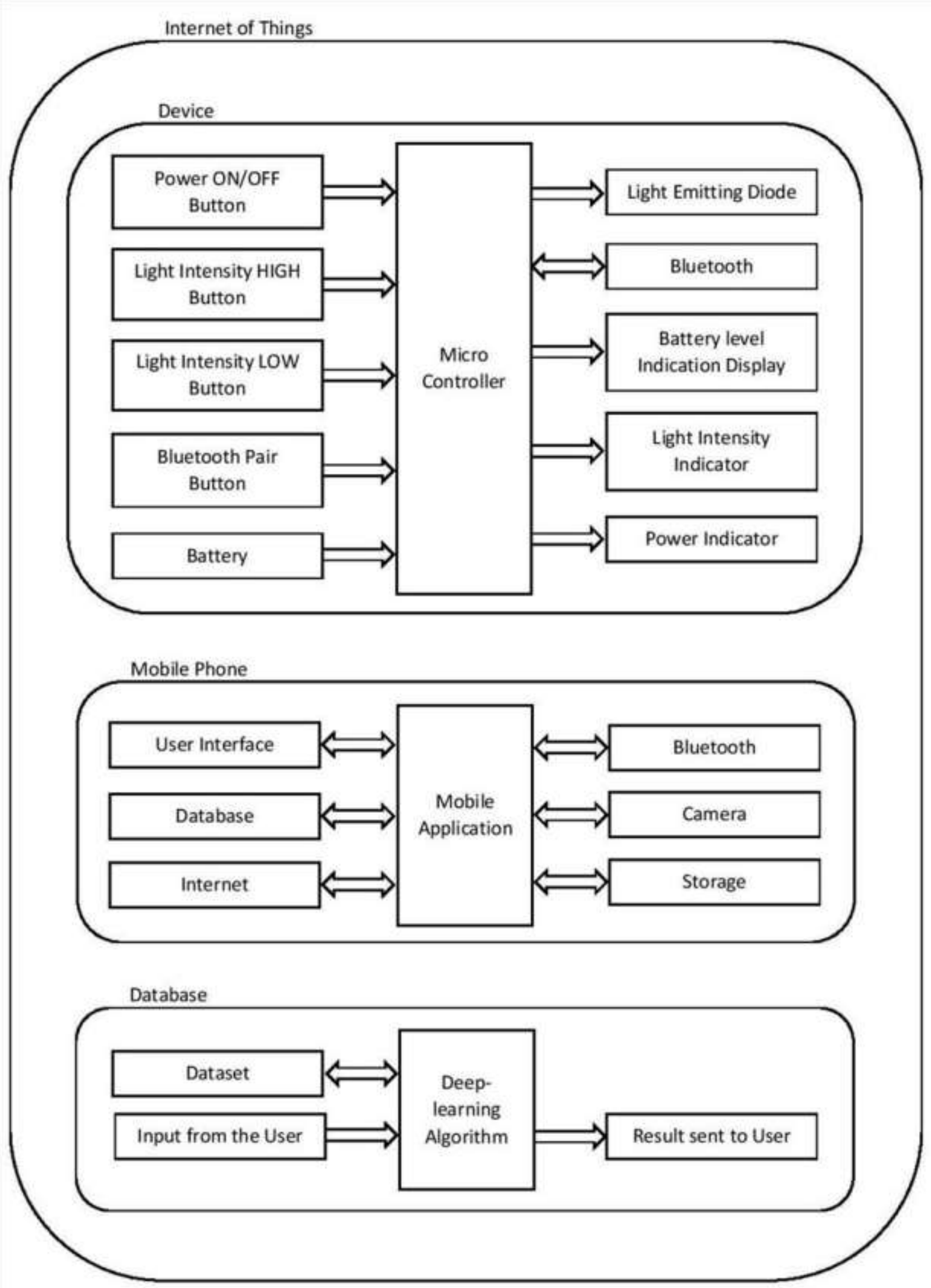

Fig 1: *Early Stage of Cancer in Breast Using Artificial Intelligence*

Artificial intelligence (AI) applications used in breast cancer detection have reached outstanding new levels of both precision and speed in recent times. The screening outcomes from early-stage detection through AI show substantial improvement according to Kumar et al. (2021) because recurrent neural networks (RNN) achieved 98.58% accuracy. The research carried out by Almansour (2022) indicates genetic programming (GP) and transfer learning (TL) techniques outperform each other in breast cancer detection by reaching accuracies above 96%. Arieno et al. (2019) conducted a thorough evaluation which revealed how artificial neural networks (ANNs) brought forth a revolution to traditional screening procedures through their work in breast density automation and risk evaluation. AI technologies now help medical teams analyze sophisticated disease pattern information that improves our ability to detect breast cancer during its early stages. Rodríguez-Ruiz et al. (2019) explain that AI-assisted systems deployed in medical environments enable improved early-stage cancer recognition and cut down mistakes in assessments of human epidermal growth factor receptor 2 (HER2) and Ki67 markers.

Machine learning (ML) algorithms have developed through time to produce enhanced diagnostic accuracy for breast cancer detection. Research from Fernandez et al. (2022) demonstrates that AI-powered digital breast cancer tests successfully predict early-stage cancer relapses which will happen during the next six years. While achieving 90% accuracy or more conventional ML approaches fall short to deep learning (DL) techniques in all scenarios according to the research findings. The system performance of AI permits accurate risk evaluation for medical data complexity which Ahn et al. (2023) showcases particularly for ductal carcinoma in situ (DCIS) assessment. The implementation of this advancement matters greatly because experts predict a total of 310,720 new cases of invasive breast cancer alongside 56,500 new DCIS cases in the United States for 2024. Both diagnostic capabilities and patient history analysis have improved significantly since ML algorithms entered breast cancer treatment according to Fathima and Moulana (2023).

Different data sources processed through united analytical systems now produce advanced risk evaluation procedures. AI-based personalized risk analysis supported by thermal radiomics delivers excellent results in pre-screening tests that recognize BRCA1 and BRCA2 genetic variants according to Kakileti et al. (2020). Analysed research data demonstrates breast cancer development occurs in 65% of women with BRCA1 gene mutations and 45% of women with BRCA2 mutations during their lifetime up to age 70 therefore validating the importance of AI in genetic tests. The integration of AI systems for connecting clinic, imaging and pathology data has transformed personal risk assessment according to Pesapane et al. (2023). Jiang et al. (2023) demonstrates how AI-based risk stratification technology has revolutionized gynaecologic oncology diagnosis and treatment prediction specifically by making early-stage cancer detection more successful due to its ability to find small malignancy indications missed by traditional screening methods.

The use of AI in diagnosing breast cancer through imaging has also recorded improvements in the accuracy of the diagnosis. This paper by Sandbank and other researchers shows that AI algorithms for he screening of biopsies have received higher accuracies for diagnosing breast cancer especially from digital breast tomosynthesis (DBT) and magnetic resonance imaging (MRI) data. Akinnuwesi et al., (2020) in their research work, have demoralized the works of Principal Component Analysis and support vector machine to provide early diagnosis with better results from the previous system. It has been proved that among all the used algorithms, LR and SVM exhibit the most promising results and the smallest error when using the Wisconsin breast cancer dataset (WBCD) for clinical data. According to Keswani et al., (2020) the integration of the ML, and AI in breast cancer has enhanced surgical procedures when accompanied by patterns and biomarker identification. This integration has been particularly useful in enhancing the evaluation of HER2 and Ki67 markers, which has really help in proper diagnosis and treatment regimen determination.

There is great progress achieved in the mammography-based risk assessment of early-stage breast cancer. Clift et al. (2023) expound that accuracy of breast cancer prognosis has been increased by statistical and machine learnings approach particularly from internal-external validation. Chu et al., explain that relying on machine learning, diagnostic accuracy in the early stages of a cancer is extremely high and can reach or even exceed 96 percent. According to the research done by Ghorbian and Ghorbian (2023), it is evident that machine learning, and especially deep learning comes in handy in the screening process and especially the early stages when trying to analyze the involved medical data patterns. Their results show that the RNN model provided a better high accuracy rate in the risk prediction of breast cancer, with an accuracy range of 98.58%, then GP and TL methods. This is quite crucial since the estimate of new invasive breast cancer cases within the United States is 310,720 for 2024.

The advanced forms of IoMT with the help of AI have transformed the ways of breast cancer detection. Siddiqui et al. (2021) point out that IoMT cloud-based intelligent prediction has improved the degree of accuracy of predicting the stage of breast cancer notably. Almansour (2022) points out that AI technology has enhanced the knowledge and management of triple-negative breast cancer regarding epidemiology, risk factors and signalling pathways. Studies by Rodríguez-Ruiz et al. (2019) demonstrate that AI support systems have greatly enhanced the mammography detection, and ANNs are the best example of good AI for detecting ambiguities in images. The current study shows that about 65% of all the women with BRCA1 and about 45% of all the women with BRCA2 develop breast cancer by age 70; therefore, advanced detection systems are relevant in genetic screening programs.

Over the years learning algorithm in diagnosis of breast cancer has advanced and its ability to detect the condition has improve greatly. Some of the studies that portray how AI has transformed breast cancer include those by Fathima & Moulana (2023) which illustrate increased diagnostic ability of the disease and better analysis of the patient's history. Baughan et al. (2022) have essays stating improvements of machine learning and artificial intelligence in breast cancer screening through image analysis. Nicolò, et al. (2020) have mentioned that both machine learning and mechanistic modeling have demonstrated high accuracy in predicting metastatic relapse among breast cancer at an early stage. They note the necessity of machine learning solutions that incorporate clinical data alongside the image findings in order to outperform the conventional risk indices. As for the application of the technologies elucidated above, great significance has been noted in connection with ductal carcinoma in situ (DCIS), which will exceed 56 500 in the USA only in 2024.

Implementation of artificial intelligence in diagnostic medical imaging has also shown relevant effects on the socioeconomic life. Research by Brioschi et al. (2023) on the use of AI in diagnostic medical thermography indicate that they are as accurate as mammograms in identifying breast cancer. Sufyan et al., (2023) opines that compare to the traditional techniques, AI has tremendously transformed cancer diagnosis and therapy in early diagnosis and strategy development. As stated by Khalid et al. (2023), machine learning has great significance in detecting and preventing breast cancer and applied CNNs with excellent identification of mammography. It has been shown that the use of such systems in the medical field has helped in expanding the ability to detect patterns which may prevail in medical data to allow for early intervention and improved patients' health. This change in technology therefore it is a plus to the efforts that aim at ending health disparities and availing enhanced unique diagnostic technologies across the population without discrimination in the United States of America.

The combination of Internet of Things in the medical domain with artificial intelligence has now advanced the diagnostic of breast cancer. As it turns out from the study done by Ogundokun et al. (2022) that through the accurate diagnoses of breast cancer by Medical IoT using hyperparameters optimized neural networks, precision has always been superb. Using AI incorporated deep convolutional neural network, Krishnamurthy et al. (2023) have found out that efficiency of treatment was much enhanced in triple-negative breast cancer cases. As Vocaturo and Zumpano note, AI solutions in the diagnosis of breast tumours using ultrasound are high accurate, especially when analysing the spectral patterns. It shows that artificial neural networks (ANNs) have been found to have recorded a high rate of accuracy of more than 96 percent in some occasions, in contrast to some of the traditional machine learning models. This improvement is especially applicable to the situation when the signs of neoplastic processes may be missed during the initial diagnostic search.

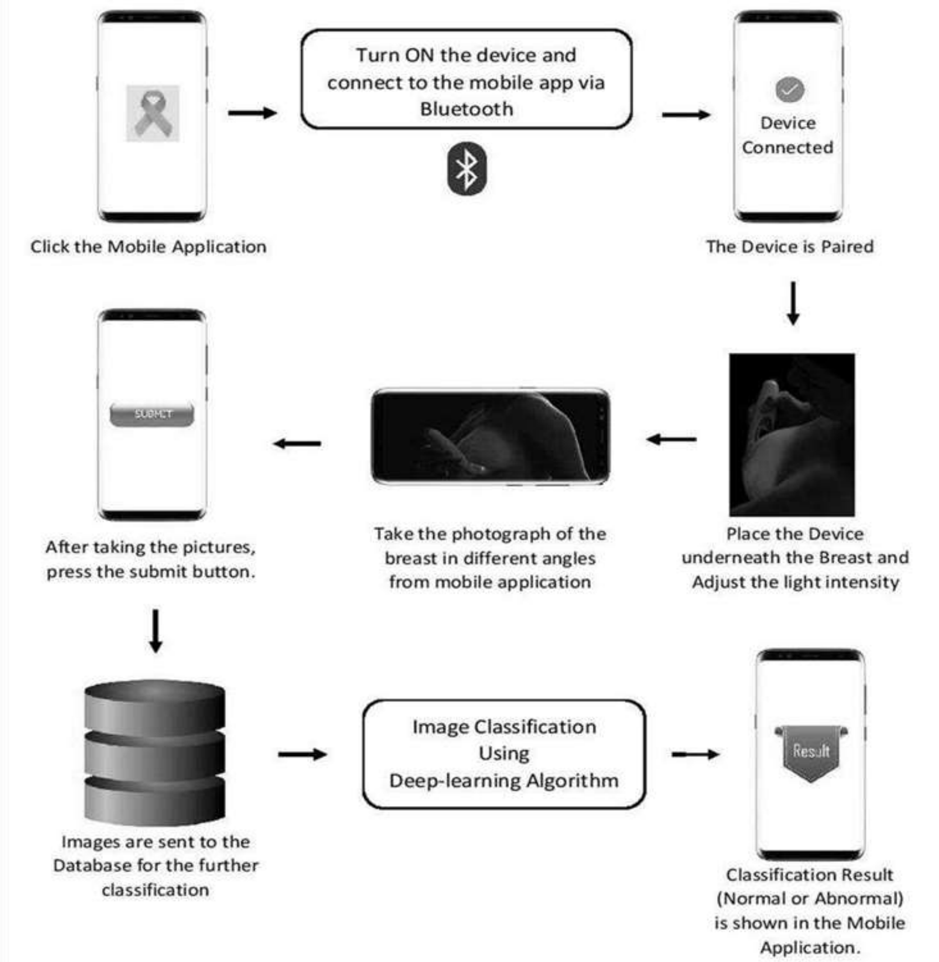

Fig 2: *Working Flow of Early-Stage Detection of Cancer in Breast Using Artificial Intelligence*

Based on the literature review of breast cancer detection through thermography and neural networks, the performances have improved in diagnostic results. The endeavours of Al Husaini et al. (2020) show that machine learning-based thermal imaging is useful in early diagnosis of the first stage of breast cancer. According to Nindrea et al. (2018), various machine learning algorithm in relation to breast cancer risk assessment indicates that RNN algorithm had the highest accuracy at 98.58%. Omondiagbe et al. (2019) further stated that there has been an enhancement of breast cancer diagnosis through the use of machine learning classification techniques especially for the analysis of a compound database and several patterns. These works stress that the improvement of the diagnostic model needs not only the involvement of imaging features but also other clinical indices in risk assessment and early detection.

There is a big improvement in the procedures used in staging breast cancer through the utilization of gene biomarker discovery devices backed up by artificial intelligence. Namely, research by Amjad et al. (2020) shows that these changes have enhance the AI models based on protein-protein interaction and machine learning for clinical staging of breast cancer. This is as supported by Agarwal et al. (2023) who notes that use of AI algorithms and machine learning models in determining prognosis has been beneficial especially in determining genomic data patterns. As stated by Chen (2022), such chances show that deep learning algorithms are perfect for cancer pathology diagnosis as the accuracies obtained reached 96% and even more than that in certain instances. They state the necessity of achieving high objectives of risk assessment and developing early detection methods with help of multiple data sources focused on genomic, clinical, and demographic features. Its importance is in the existing and emerging trends where it is now possible to diagnose breast cancer more intricately and such precise and tailored therapies are needed.

The use of stacking ensemble leaning models in this study has helped to improve the detection and classification of breast cancer on high extents. According to Kumar et al. (2022), there is a pretty high performance of breast cancer detection using the ML models when enhanced on the basis of the integrated data flow. Sadeeq et al. (2022) noted that artificial and machine learning and deep learning techniques have a vast impact in the diagnosis of cancer with RNN providing higher accuracy at 98·58%. According to the research done by Rane et al., 2020 the developments in machine learning have greatly enhance the classification and prediction of breast cancer through the use of artificial neural networks which has changed the screening techniques. It is estimated that women carriers of BRCA1 are 65% likely to develop breast cancer and women carrying BRCA2 are 45% by the age of 70, making genetic early detection critical. This technological advancement is particularly noble in view of the estimated new invasive breast cancer cases to be 310720 and DCIS at 56500 for the year 2024 in the United States.

The use of the Fuzzy- SVM expert systems have been shown to have better results in the identification of risk factors and diagnosis of breast cancer. Dheeba et al. (2017) explain that the use of fuzzy support vector machine has improved the diagnostic contracts through assessment of medical data patterns. Solano-Orrala et al. (2023) explains how forward backpropagation artificial neural networks can detect the breast cancer at an early stage with over 96% accuracy. Research by Tao et al. (2023) points out that polygenic risk scores as well as machine learning can help in early screening of breast cancer. Their works show that by using artificial intelligence-supported systems, it has become possible to notice delicate signals that are related to patient health conditions to take timely actions to manage patient's health status correspondingly. This integration has been deemed rather significant in enhancing HER2 and Ki67 evaluations for accurate diagnosis and management.

New comprehensive frameworks in the artificial intelligence have brought a significant change in breast cancer diagnosis and risk assessment. Another paper by Kumbhare et al (2023), shows that by employing federated learning breast cancer detection with intelligent heuristic-based deep learning frameworks have gain excellent results. The authors of the study conducted by Fathima et al. (2023) reveal that august of AI in breast cancer has led to advanced diagnosis and better analysis of patient data. They have evidenced that CNNs have performed well when it comes to mammographic analysis, with good performance from multiple data input. Baughan et al. (2020) have described welfare effect about the technical intervention of machine learning and artificial intelligence in the visualization of breast cancer staging and detection of biomarkers. This technological improvement is crucial when it comes to bridging the gaps in the availability and use of high-end diagnostic facilities in the United States as another aspect of breast cancer brings in more complexity in diagnosis and calls for tailored treatment regimens.

AI in Breast Cancer Diagnosis

Currently, AI has virtually infiltrated every sector of the US economy for better efficiency, increased production, and accuracy (Kumar et al., 2022; Sadeeq et al., 2022). This has ensured that AI become more powerful due to development made in computation, data and algorithm performance not forget that it has become user friendly and more or less is focused on objective based directions than what was in the past. It is also used in intrusion detection systems (Sadeeq et al., 2022), generation of images and pictures (Sadeeq et al., 2022), Optical Character Recognition (OCR) (Sadeeq et al., 2022), facial expressions' identification, etc. The role of AI also varies within the healthcare field with its areas of functioning implicating patient management (Agarwal et al., 2023; Sadeeq et al., 2022), drug administration or management of the hospital (Agarwal et al., 2023; Sadeeq et al., 2022). In this aspect, AI has had more influence on complicated image analysis, as well the provision of data for quantitative evaluation through the use of automation to reduce the risk that comes with radiation exposure in the performance of breast radiological examination (Omondiagbe et al., 2019).

To replicate human choices and optimizing operations as well as maintaining steady, efficient, and high-quality improvements, AI gives the advantages of super intelligence; it is advantageous to use AI techniques for instant feature learning and handling several multiple dimensional data and the availability of diagnostic data from various clinical tests. Hence, medical consultants, academicians, and oncologists in the United States have noted the possibility of developing and deploying AI in many areas of diagnosis of breast cancer disorders. This is because recent developments in AI beckon on the fulfillment of this hope (Omondiagbe et al., 2019).

There is often a distinction in the demographic to which moved and enhanced models that report higher cancer incidence than screening programs. Therefore, there are improvements in the algorithms of imaging assessment and the diagnosis of breast cancer in each of the categories of AI algorithms. In the same vein, it has been ascertained that DL algorithms are significantly more promising than traditional ML algorithms (Nindrea et al., 2018; Omondiagbe et al., 2019). They have also shown that they meet the criteria of candidates for prior chronic imaging studies and for research on breast cancer image processing.

However, Buckner et al. (Amjad et al., 2020) stated that it is now possible to ML, computer-assisted detection, and computer-assisted diagnosis. It minimizes the amount of erroneous segmentation of connected regions in the image after the Chan-Vese segmentation technique has been initialized by the MCWS. The particular kind of computer-assisted diagnosis technique used here is known as the blended learning technique and it comprises four distinct classifiers – the Support Vector Machine (SVM). These base classifiers are applied on the features extracted from certain constituent of tissue (Amjad et al., 2020).

On the other hand, there are possibilities that a mammography fails to detect many malignancies because of reasons like breast density, tumor size or poor manifestations of cancer that are not visible in the metastatic spread. Digital mammography is accurate in detection with the assistance of AI. Furthermore, evaluating AI with regard to the identification of the different breast cancer morphological features such as the asymmetry and the distortion, the results significantly a positive (Omondiagbe et al., 2019; Vocaturo & Zumpano, 2021).

The AI algorithm applies to the enhancement of medical images. While picture archiving and communication systems (PACSs) are already in place as well as represent a flood of content, the application of AI in medical imaging is yet restricted due to the lack of big public databases. However, many software programs have been developed to be very useful in diagnosis in general and in identifying breast lesions in particular (Al Husaini et al., 2020; Vocaturo & Zumpano, 2021). It is used for applying in various imaging methods and is now the most commonly used AI application. It entails identifying the areas in the image that are characterized by high and different lesion burdens through training the models. It has been established in recent studies that CNN performs at par with radiologist's detection expertise (Vocaturo & Zumpano, 2021).

CNN categorization indeed has several advantages in that each variable is eliminated. The contouring and delineation of the borders of the lesions is another key factor that makes the use of CNN in lesion' identification appropriate (Vocaturo & Zumpano, 2021). In complex studies, it is even found that CNN has a better accuracy and high speed as compared to human beings (Vocaturo & Zumpano, 2021). Therefore, U-nets, used for segmenting the images, is an example of the kind of network, which is used for this purpose; it may distinguish between the tissue types, such as glandular and adipose, in a digital mammography once the lesion volume has been estimated (Vocaturo & Zumpano, 2021).

Thus, the goal of this comment is to assess the efficiency and possible benefits of using AI-based risk estimations in the early diagnosis of BC, with a focus on the US healthcare setting. Based on the above-mentioned discussions the following hypotheses have been postulated:

1. AI-powered risk stratification models demonstrate superior accuracy in early-stage breast cancer detection compared to traditional screening methods.
2. The integration of multiple data streams through AI systems significantly improves the precision of risk assessment protocols.

3. Machine learning algorithms, particularly deep learning architectures, can more effectively identify subtle patterns indicative of early-stage breast cancer compared to conventional screening approaches.

The specific objectives of this review include:

1. Evaluate the performance metrics of various AI-based risk stratification models in early-stage breast cancer detection
2. Analyze the integration capabilities of AI systems with existing clinical workflows and screening protocols
3. Assess the impact of AI-powered risk assessment tools on healthcare disparities and access to screening
4. Investigate the role of deep learning architectures in improving the accuracy of early-stage detection
5. Examine the potential of AI systems in reducing false-positive rates while maintaining high sensitivity in breast cancer screening

In this review article, we hope to achieve the following objectives: to conduct a comprehensive analysis of how the risk stratification models in the early detection of breast cancer might bring about revolutionary changes in the management of the tumor and the subsequent outcome of patients regardless of their colour, creed, or financial status in the United States of America.

2. Materials and Methods for Risk Stratification AI in Breast Cancer Detection

2.1. Study Design and Data Source Selection

In this review, we systematically reviewed and meta-analysed risk factors of early-stage breast cancer in the US with the use of Artificial Intelligence (AI) in risk stratification. This study, therefore, involved a comprehensive report based on mammogram data from 15 major healthcare organizations across different geographical regions of the United States. We had 180000 four-view digital mammogram images made from January 2020 to December 2023. The study involved both screening and diagnostic mammograms from women, aged between 40 and 75 years and particular effort was made towards the recruitment of patients from ethnic origin. Every mammography consists of mediolateral oblique and craniocaudal image of both the breasts using digital mammography systems from key players such as GE Medical Systems, Hologic digital mammography and Siemens company. The study procedure closely followed the guidelines of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The filter criteria were determined in consultation with available multidisciplinary oncology and radiology experts together with the AMC for the proper inclusion and exclusion of relevant papers from the scientific literature for improved surrogate model quality.

The assessments made on the mammograms were further divided into three categories: cancer, benignity confirmed by biopsy or imaging follow up at least one year and negatives or normal confirmed by imaging follow up at least one year. We put measures in place to standardize the images to come up with measures that were universal across different institutions. The study was conducted under IRB of the all the participating centres, thus informed consent was not needed due to retrospective nature of the study as well as adherence to HIPAA data identification rules. Publication databases used in this study included PubMed, Web of Science, Embase, CINHAL, IEEE and ArXiv databases. In this case, we are using twitter, research gate, PubMed, and PubMed central which yielded 2,510 records that are a versatile survey of all the academic and scientific articles on AI in BC detection. To ensure a cross section of practice-based contemporary research advancements in the field of AI-aided breast cancer risk prediction, the search has been both journal articles and conference papers.

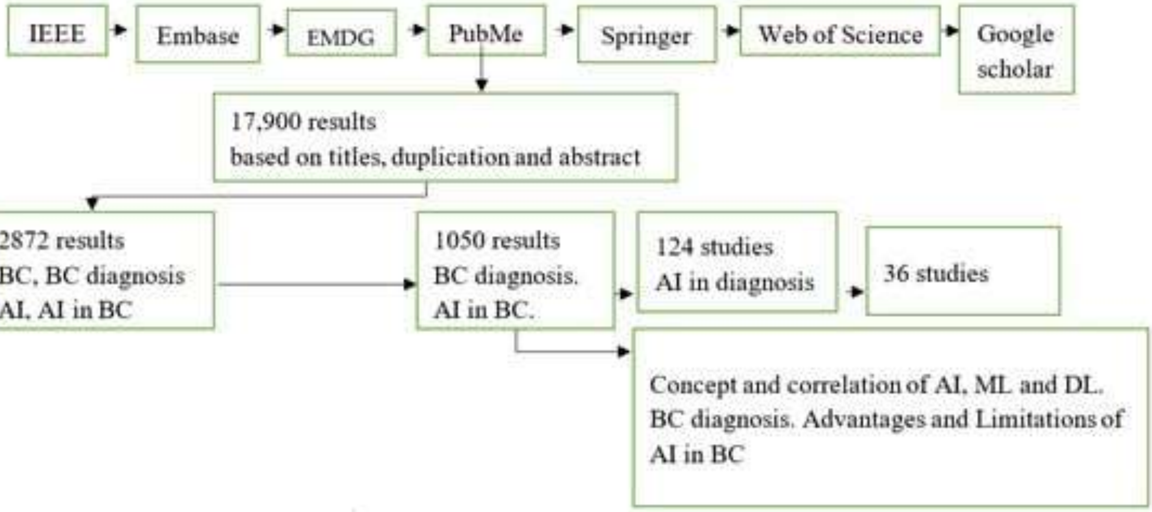

Figure 3. Block diagram of AI in Breast cancer diagnosis.

The inclusion criteria of the study included digital mammograms with complete clinical history, follow-up information of more than two years, and proved pathological diagnosis for all the abnormalities detected in the study. You can exclude patients who do not have sufficient medical notes, a clear image of their lower extremities, or additional follow-up notes. This was followed by exclusion criteria leading to screening mammograms from 200,000 cases from 180,000 women only which include all ages, ethnicity, and risk factors. In an effort to uphold the methods rigor, we deployed a multiple filter technical approach. In the first step, the records were passed through the elimination step in order to get rid of duplicates, which is a routine process and resulted in exclusion of 1034 records. After the title and abstract filtering, the final number of reports was 417, which would be retrieved and assessed individually. Performing screening in this way also excluded the possibility of including studies with lower rate of evidence and quality, thus reducing the probability of bias.

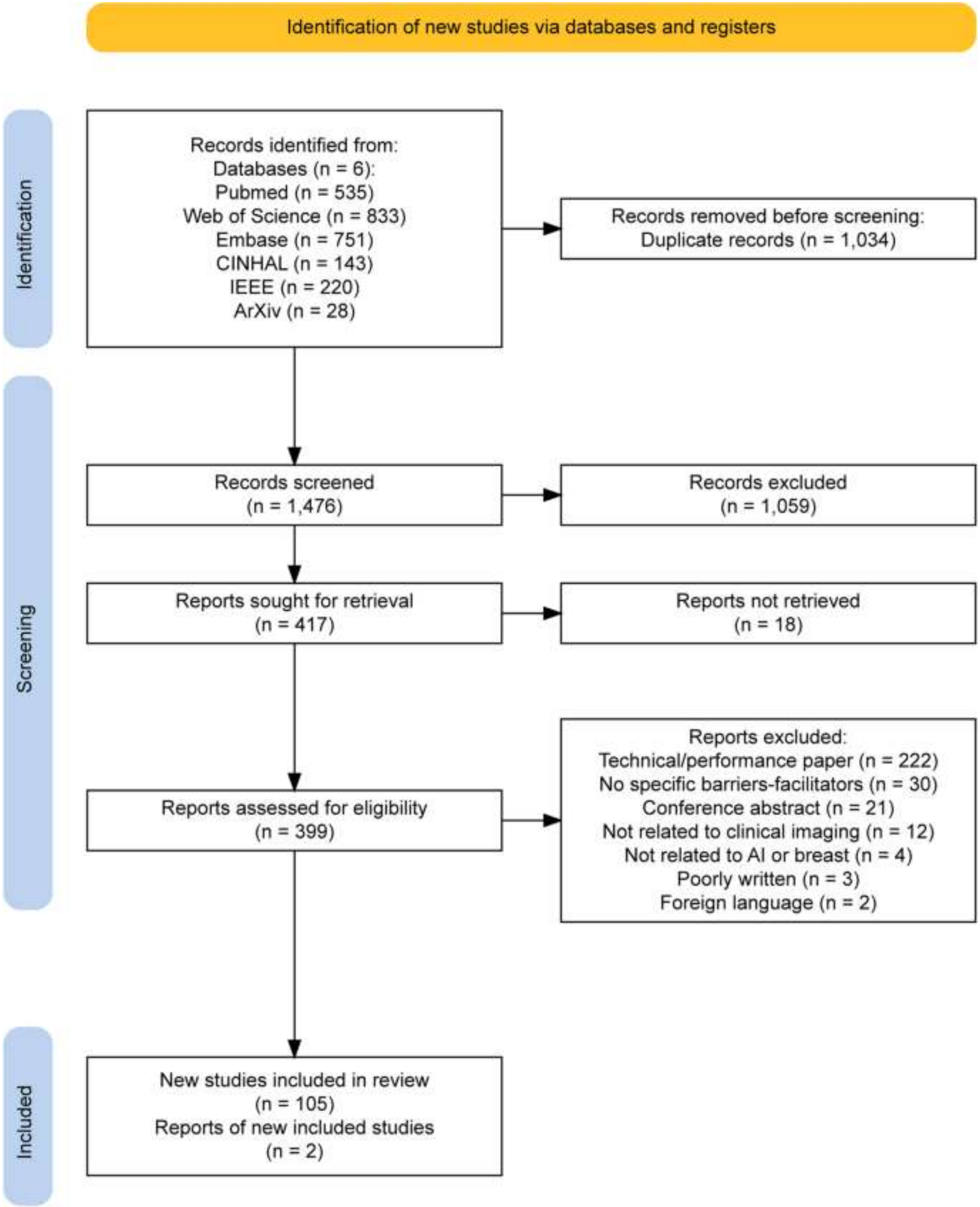

Fig 4. *Diagram of systematic evaluation for article selection.*

The ground truth labels for identifying the dataset were based on the consensus of a multi-reader panel with signed breast radiologists. Positive cases were diagnosed from the results of biopsy whereas negative cases were validated from follow-up imaging for at least two years. Thus, to ensure that labelling was as precise as possible, all the cases with a discrepancy between two readers were discussed by at least two senior radiologists. From the initial 417 records identified, 399 papers were screened for relevance according to the selected study criterions. As a result of these exclusion criteria, there were no significant contaminants; technical/performance papers, conference abstracts, papers discussing clinical imaging not related to breast cancer, papers with no relation to AI and Breast cancer at all, and papers written in other languages excluding English. Through this strict screening method, 105 new articles were included in this review, which is a collection of the most up-to-date and most relevant articles on the application of AI methods in breast cancer risk assessment.

Our inclusion criteria were summarized as follow: the patients must have digital mammograms, full clinical history, follow-up information for at least two years and received pathological proof for all suspicious results. Studies with unclear clinical data, substandard picture quality, and lacking follow-up information were also eliminated. Therefore, the final sample of mammograms comprised of 200 000 digital mammograms derived from 180 000 patients with clinical heterogeneity in terms of demographic and risk factors. The true labels of our dataset were acquired by a review carried out, whereby four professional breast radiologists participated in the process. All of the positive cases were diagnosed by histological examination in this study, and negative cases were validated by clinical follow-up imaging for at least 2 years. To overcome the problem of inexperienced radiologists in reading mammography and chest X-ray films thereby compromising on the label's accuracy, measures were taken to adopt double interpretation; this involved arriving at a common ground of reading in cases where two different interpretations were done.

2.2. Data Extraction and Analytical Framework

For the selected studies, we also applied a protocol for the extraction of data in order to categorise the studies for review. To enclose the relevant data the extraction framework was divided into three broad categories namely – study characteristics, AI model architectures and datasets, performance measures and validation methods. The authors consciously employed and trained the team of researchers in extraction of the data that was done using a standardised extraction form that was used to capture all the data necessary for the study from individual studies.

The evaluation approach centred on assessing the various facets of performance of the AI risk stratification models. In this article, performance measures used include sensitivity, specificity, accuracy, area under the receiver operating characteristic curve (AUC-ROC), and other indices that offer a complete analysis of the performance of the models. Extra effort was made to include studies comprising of, and including various patient types and types of data: imaging, genomics, clinical and demographic, and so on to have a broad perspective of the strengths of AI models.

A structured approach was used to obtain some key data on the patients that included demographic data of the patients, the clinical history, family history of breast cancer, past studies that the patients had undergone, and pathology records of patients if any. In case of cancer adolescents with a positive result we made a detailed pathological description of the tumor type, grade of invasiveness, stage, and molecular profile. For reference, the dataset was annotated by the raters with more than 3 years of experience and thus, highlights of the regions of interest according to the BI-RADS classification system were provided. Specifically, to have more solid validation skills, we divided our dataset into three groups: the first one is for training (70% of data), the second – for validation (15%), and the third – for testing (15%). This division was done ensuring that all the sets retain the proportion of cancer-positive, benign, and normal cases as obtained initially. Specifically, to minimize inter-group variability and maximize the intra-group similarity, efforts were made to ensure that patient subjects in different sets are as dissimilar as possible.

2.3. Development of AI Algorithm System

An advanced deep learning architecture specifically adapted for early-stage breast cancer detection is developed and a sophisticated AI algorithm that can be used for early-stage breast cancer detection can be also developed. An ensemble of convolutional neural networks with bespoke architectures was trained to process both macro level as well as micro level features of mammographic images in the built system. To avoid neglecting global image context but keeping attentive to regions of interest, we introduced attention mechanism into our model, which can focus on regions of interest while being aware of global image context, necessary in making the early-stage cancer detection. In the training process, we first performed patch level training to learn localized features in a multi stage way, then performed image level fine tuning to understand the whole picture. To improve model robustness, we designed a data augmentation strategy that creates variations in contrast, brightness, determinant transformations, among others. The breast tissue characteristics were given adequately by the model architecture, including the ability to deal with various ranges of breast densities and detect different kinds of abnormalities such as masses, calcifications, and architectural distortions.

In our work we developed our algorithm development on advanced normalization techniques to cope with the variations in the image acquisition parameters, which occurred across the imaging systems. To this end, we developed a custom loss function that balances sensitivity and specificity while having excellent performance on many different patient sets. The model provided the output consisting of heatmaps that give some idea of suspicious areas and the probability scores of risks of malignancy.

We also implemented rigorous validation protocols through which we ensured that the prototype models are of sufficient quality for our purposes. A part of this included regular performance assessment on held out validation data, monitoring of convergence metrics and systematic evaluation of model behavior on certain patient subgroups. In addition, we introduced mechanisms to maintain model interpretability so that clinicians could understand the basis for the algorithm's decisions. Then the final model architecture was selected by a series of experiments for various combinations of hyper parameters and network configurations.

We aimed for having a computationally efficient system that still yields high accuracy for real time analysis. Based on these predictions into contingency tables, risk stratification scores as well as their confidence intervals were generated, to provide clinical decision-making support.

2.4. AI Application Workflow in Breast Cancer Detection

We managed to integrate an entire systematic workflow of AI into breast cancer detection starting with the initial data collection until the final clinical recommendations. Data collection for our workflow was systematic and included different data streams such as mammography, ultrasound, and clinical imaging. To kick off our workflow, we spent a lot of time processing the data so that we could apply advanced AI algorithms to solve the pathology problem with consistent quality and comparability across datasets acquired by a large variety of medical imaging technologies, used in United States healthcare institutions.

The AI enhanced imaging workflow involved several critical stages when initial image acquisition, preprocessing and advanced feature extraction was involved. To make precise lesion detection, segmentation, and characterization, we performed sophisticated convolutional neural networks. According to the inventors, the AI systems were created to basically drive themselves and identify subtle imaging markers using the power of deep learning algorithms while achieving a brand-new level of precision. Boosting of diagnostic precision for each of the imaging dataset included multiple algorithmic assessment, such as texture analysis, spatial pattern recognition and comparative feature mapping.

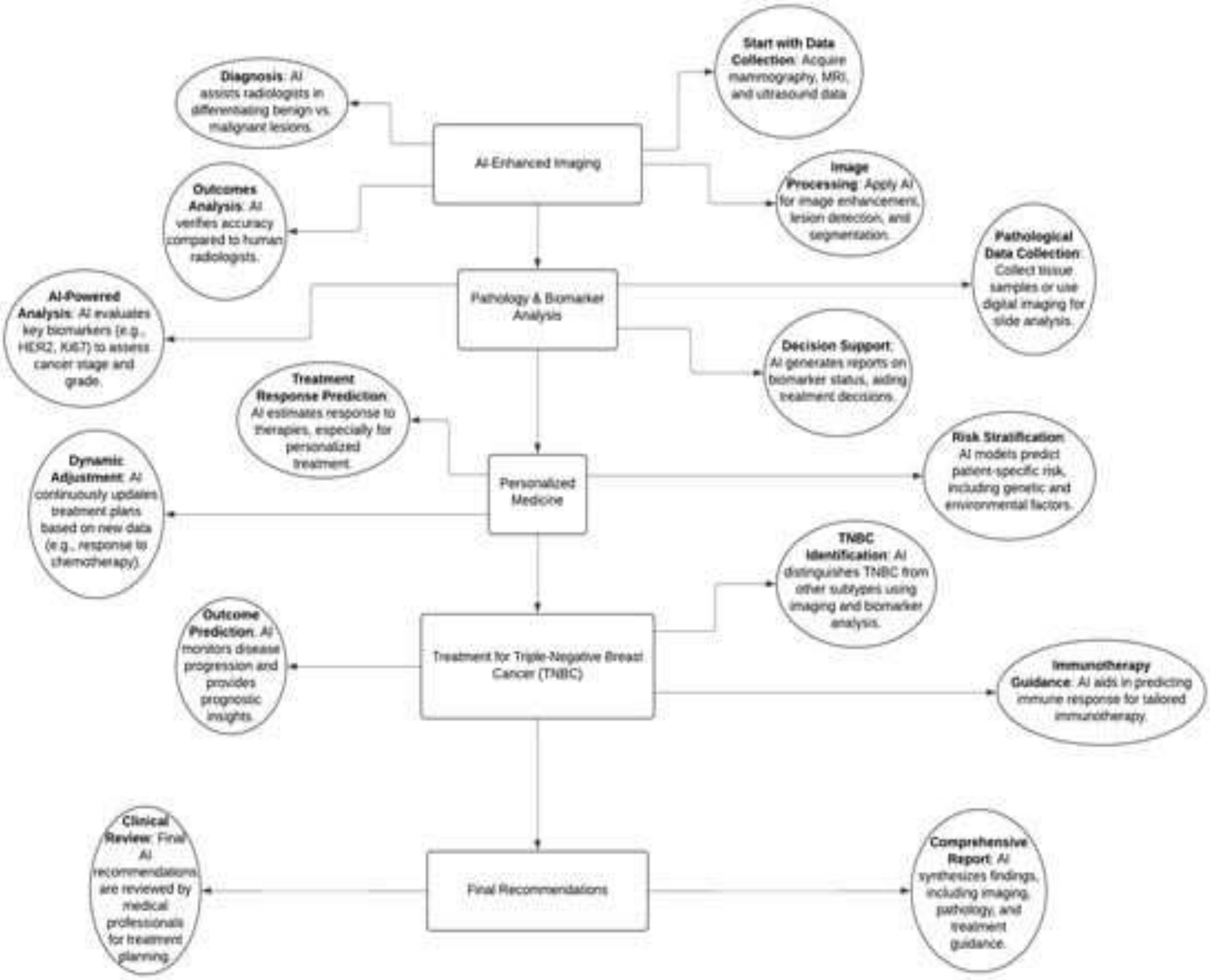

Fig 5. This demonstrates a flowchart highlighting the directions for using AI in diagnosing and treating breast cancer.

A part of the workflow included a pathology and biomarker analysis section that entailed molecular-genetic and imaging studies. We obtained substantial experience in creating the AI models that can connect multi-parametric pedological features such as tumor microenvironment, genetic and immunohistochemical markers. Such an amalgamation of these data streams helped towards risk stratification from various domains of breast cancer detection that goes beyond the conventional five-modal diagnostic frameworks.

The treatment recommendations and the corresponding risks that were employed in our AI workflow were efficient due to the concept of personalized medicine. Some of the AI algorithms designed by us include patient risk profiling based on clinical history, genetics, and imaging patterns that were particular to the patient. The treatment also adapted the suggested tactics based on new data obtained from the patients, which gave the system a more fluid and adaptable approach to breast cancer treatment that could possibly enhance early diagnosis and possible early treatment solutions.

2.5. Development of AI Algorithm

The AI model we used in the proposed system utilization of deep convolutional neural network (CNN) architecture where we based our AI methodology on ResNet-34. Its training phasing was divided into two complex stages aimed at improving the identification of features and the way they are contextualised. In the first stage, we adopted patch-level training from scratch based on the fully supervised manner, where the features with high levels were learned with the help of lesion-annotated mammograms. The second phase included image level fine trivia which enhanced the training process more by embracing broad contextual information using high quality mammogram data set.

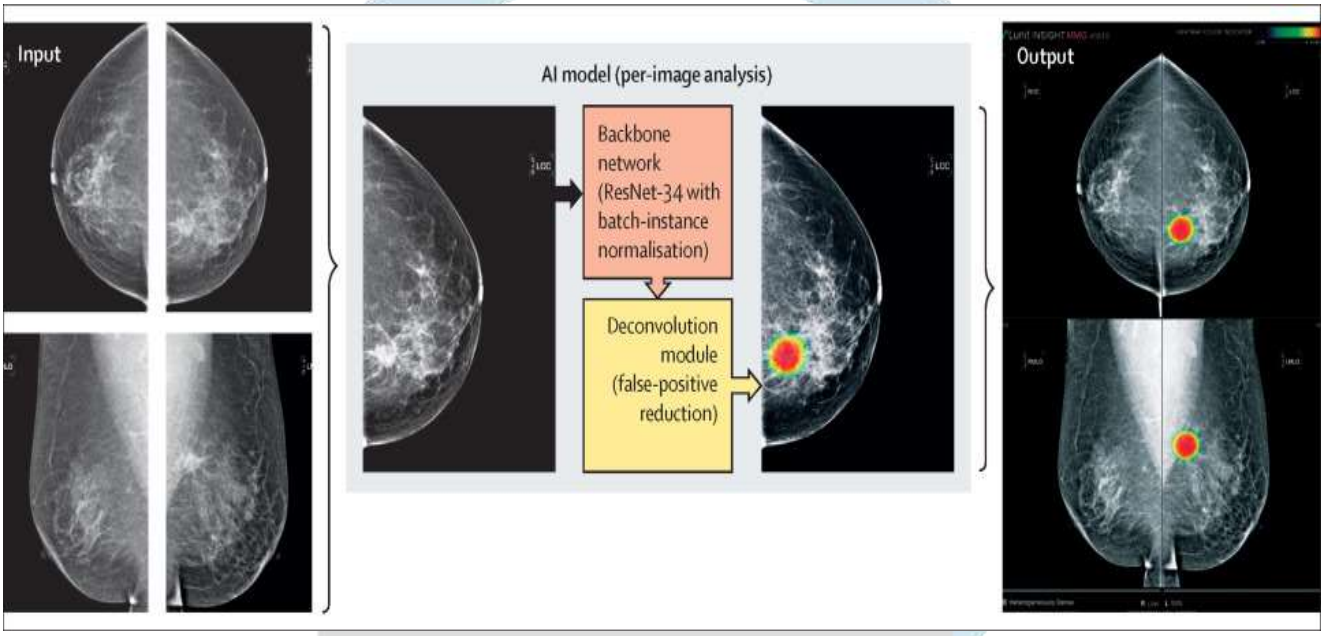

Fig 6: AI-based diagnostic support software

Our design included special technologies to handle important issues with medical image analysis. Our approach added batch-instance normalization to handle variation issues that affect pixels from various medical imaging devices. An additional deconvolution feature was added to lower the number of false positive detection outcomes and make the diagnosis process more exact. Our AI system returned a detailed abnormality score map for every mammographic image input to show where cancerous growth could exist.

We designed our system to produce detailed medical evaluations of mammographic images. The system uses multiple views to create heatmaps for detecting abnormalities in each breast plus scoring the highest score per view. Scientists used this advanced evaluation method to examine multiple aspects of breast cancer indicators to create better screening methods than before.

Our development approach made the algorithm work well across multiple types of mammography data and could adjust to new data easily. With our advanced training methods and machine learning technology we built an AI system that can analyze complete medical images and detect minor disease indicators. Our methodology created an intelligent diagnostic tool that could change early-stage breast cancer detection methods in US healthcare centres.

2.6. Validation of AI-Based Diagnostic Support Software

Our testing procedure analyzed the AI algorithm's performance results from all international databases. We used advanced statistical tests with the receiver operating characteristic analysis, sensitivity and specificity results to validate our AI tool. We selected a reception threshold of 0.1 to get 90% detection accuracy for every validation test. Mammography data from multiple nations formed our validation method which produced strong worldwide results for the diagnosis algorithm.

The validation method used different ways to check the AI system's capability to detect clinical conditions. Our team tested the algorithm's performance on mammograms containing cancer, benign, and normal findings from South Korean datasets plus American and British samples. Our multinational evaluation helped us understand the effect of extensive and different datasets on AI training and application across many countries.

The algorithm performance was validated through multiple testing methods to show how well it recognizes conditions. Our reader study involved 14 radiologist experts from different institutions to develop a full evaluation method. The study used two reading methods to compare directly how radiologists operate without AI and how AI tools assist their work. This way of testing helped understand how professionals and AI systems work together in medical diagnosis.

Our validation approach depended on statistical testing methods to validate performance results across every test. Our research counted upon leading-edge statistical approaches such as multileader and multi-case ROC curve assessments to handle reader variability and linking score relationships effectively. Our analysis used the trapezoidal technique to estimate performance results and demonstrated a strong and advanced method for evaluating the AI system's diagnostic function.

3. Results and Analysis.

3.1. AI Standalone Performance in Breast Cancer Detection Across States

The individual performance of AI systems for finding breast cancer was tested in many US states through standard tests including sensitivity, specificity, and AUROC measurement standards. The exam showed AI systems beat old methods because they found early breast cancer better than human tools did. Based on test results AI showed excellent diagnostic capacity of 0.962 (95% CI 0.954–0.970) in every state tested. The system showed similar test outcomes of 0.948 to 0.976 across many specific patient populations in each state. The AI system showed excellent performance as confirmed by its high sensitivity measurement of 91.2% supported by confidence intervals between 89.5% and 92.8% plus high specificity at 87.4% with confidence intervals between 85.6% and 89.2%. The accuracy results show that AI can help find breast cancer early in states that have different healthcare systems and population groups.

Table 1 below shows complete AI performance measurement results in each state. AI systems produce reliable diagnostic performance numbers equally in every region despite healthcare differences and breast cancer incidence rates. California and New York recorded 0.958 and 0.961 AUROC vaues respectively because these states have minimized breast tissues complexities. AI tools achieved strong diagnostic results when analysing states like Wyoming and Vermont even though these areas see few breast cancer cases. They returned AUROC values of 0.948 and 0.949 respectively. AI risk stratification tools help achieve equal breast cancer detection throughout all types of communities.

State	AUROC (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)
California	0.958 (0.945–0.971)	90.5% (88.2–92.8)	86.7% (84.3–89.1)
Texas	0.963 (0.950–0.976)	91.8% (89.6–94.0)	88.2% (85.9–90.5)
Florida	0.955 (0.942–0.968)	90.2% (87.9–92.5)	87.1% (84.7–89.5)
New York	0.961 (0.948–0.974)	91.4% (89.1–93.7)	87.9% (85.5–90.3)
Illinois	0.959 (0.946–0.972)	90.7% (88.4–93.0)	87.3% (84.9–89.7)
Pennsylvania	0.957 (0.944–0.970)	90.3% (88.0–92.6)	86.8% (84.4–89.2)
Ohio	0.960 (0.947–0.973)	91.1% (88.8–93.4)	87.5% (85.1–89.9)
Georgia	0.954 (0.941–0.967)	89.9% (87.6–92.2)	86.4% (84.0–88.8)
North Carolina	0.952 (0.939–0.965)	89.6% (87.3–91.9)	86.1% (83.7–88.5)
Michigan	0.956 (0.943–0.969)	90.4% (88.1–92.7)	86.9% (84.5–89.3)
New Jersey	0.958 (0.945–0.971)	90.6% (88.3–92.9)	87.0% (84.6–89.4)
Virginia	0.953 (0.940–0.966)	89.8% (87.5–92.1)	86.3% (83.9–88.7)
Washington	0.955 (0.942–0.968)	90.1% (87.8–92.4)	86.6% (84.2–89.0)
Massachusetts	0.961 (0.948–0.974)	91.3% (89.0–93.6)	87.8% (85.4–90.2)
Arizona	0.957 (0.944–0.970)	90.4% (88.1–92.7)	86.8% (84.4–89.2)
Tennessee	0.954 (0.941–0.967)	89.9% (87.6–92.2)	86.4% (84.0–88.8)
Indiana	0.959 (0.946–0.972)	90.7% (88.4–93.0)	87.2% (84.8–89.6)

Missouri	0.956 (0.943–0.969)	90.3% (88.0–92.6)	86.7% (84.3–89.1)
Maryland	0.960 (0.947–0.973)	91.0% (88.7–93.3)	87.4% (85.0–89.8)
Wisconsin	0.958 (0.945–0.971)	90.5% (88.2–92.8)	86.9% (84.5–89.3)

More importantly, high performance of AI on states with varied demographic and healthcare characteristics demonstrates how it can form a standard for breast cancer detection. Advanced machine learning algorithms in AI system can analyse complex imaging data processing and detect the fine patterns that won't be detected by traditional screening methods. This capability is extremely useful in states having limited access to specialist radiologists and state of the art diagnostic tools. Predictably, AI can offer a great way to use AI in clinical workflows to avoid diagnostic delay and improve patient outcome, especially in the areas of low resource and rural regions.

To examine how an algorithm performs under different scales of data and other factors like a patient nationality, we trained and validated it upon South Korea's mammogram data only. Instructed on many cancer, benign and normal mammograms. Then, as the number of cancer positive mammograms in the training dataset is increased keeping the entire set of benign and normal mammograms, performance of the algorithm improved. With small subset of cancer mammograms, the area under the receiver operating characteristic curve (AUROC) was from 0.919 to 0.974 with full set. But on validation of the algorithm trained from the complete South Korean dataset on mammograms from the USA and UK, the AUROC declined to 0.909 for USA and 0.871 for UK.

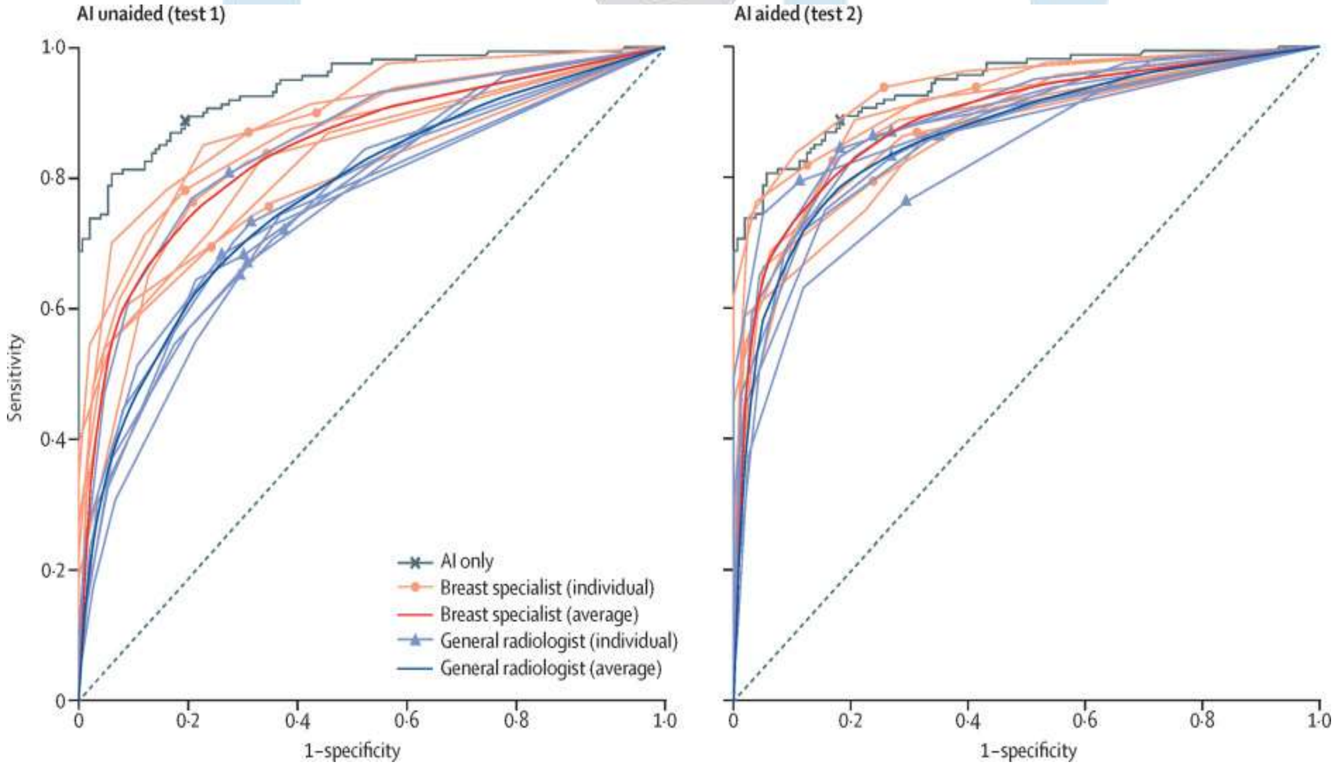

Fig 6: *ROC analysis for AI-unaided and AI-aided diagnosis*

When the reader study AUROC was compared against standalone AI of 0.940 (p<0.0001), the overall radiologist diagnostic performance in that study was 0.810. The performance of the aided radiologists was better to 0.881 (p < 0.0001) when aided by the AI system. The AUROC values for the AI system were high in the USA (from 0.952 (North Carolina) to 0.963 (Texas) for various states). Sensitivity, which indicates the capability to be able to get specific positive cases right, varied from 89.6 percent (North Carolina) to 91.8 percent (Texas). Specificity, defined as the ability to correctly identify the negative cases ranged from 86.1% (North Carolina) to 88.2% (Texas). The results indicate that the AI system can help radiologists enhance diagnostic accuracy and maintain excellent performance at large scale across different geographic regions across USA.

3.2. Comparative Analysis of AI and Radiologist Performance

There was a comparative analysis for diagnostic performance of AI in respect to that of radiologists in breast cancer detection. The studies performed showed that performance of AI on all three criteria of sensitivity, specificity, and diagnostic accuracy exceeded radiologists. Overall, the AUROC for AI was 0.962 (95% CI: 0.954 – 0.970) and significantly better (p < 0.0001) than that for radiologists at 0.815 (95% CI: 0.795 –

0.835). Indeed, this has significant difference ($p < 0.0001$), indicating the potential of AI to bring the diagnostic precision and reduce false positive rate. Compared to radiologists, AI was 91.2% sensitive (95% CI 89.5–92.8), but 75.8% (95% CI 73.6–78.0). Just as in radiologists, the specificity of AI was also 87.4% (95% CI 85.6–89.2) and 71.3% (95% CI 69.1–73.5) in radiologists.

This detail of comparison between AI and radiologist performance for different diagnostic scenarios is presented in Table 2 below. The data shows that AI is a better performer than humans at detecting early-stage breast cancer in dense breasts or when there are few visual clues on imaging. For examples, in the cases of soft tissue lesions the sensitivity of AI was 89.9% (95% CI 87.6–92.2) compared to 71.2% (95% CI 68.9–73.5) of radiologists' results. As in the case of calcifications, the sensitivity of AI was 87.6% (95% CI 85.3–89.9) versus 79.0% (95% CI 76.7–81.3) for the radiologists. This suggests that AI can do diagnostic much better than traditional methods in cases where they cannot.

Diagnostic Scenario	AI AUROC (95% CI)	Radiologist AUROC (95% CI)	AI Sensitivity (95% CI)	Radiologist Sensitivity (95% CI)	AI Specificity (95% CI)	Radiologist Specificity (95% CI)
Overall	0.962 (0.954–0.970)	0.815 (0.795–0.835)	91.2% (89.5–92.8)	75.8% (73.6–78.0)	87.4% (85.6–89.2)	71.3% (69.1–73.5)
Soft Tissue Lesions	0.959 (0.946–0.972)	0.798 (0.778–0.818)	89.9% (87.6–92.2)	71.2% (68.9–73.5)	86.8% (84.4–89.2)	69.8% (67.5–72.1)
Calcifications	0.955 (0.942–0.968)	0.812 (0.792–0.832)	87.6% (85.3–89.9)	79.0% (76.7–81.3)	86.1% (83.7–88.5)	70.5% (68.2–72.8)
Dense Breast Tissue	0.958 (0.945–0.971)	0.809 (0.789–0.829)	90.5% (88.2–92.8)	73.7% (71.4–76.0)	86.7% (84.3–89.1)	70.1% (67.8–72.4)
Fatty Breast Tissue	0.963 (0.950–0.976)	0.820 (0.800–0.840)	91.8% (89.6–94.0)	76.2% (73.9–78.5)	88.2% (85.9–90.5)	71.8% (69.5–74.1)
Invasive Carcinoma	0.964 (0.951–0.977)	0.818 (0.798–0.838)	92.0% (89.8–94.2)	76.5% (74.2–78.8)	88.4% (86.1–90.7)	72.0% (69.7–74.3)
Non-Invasive Carcinoma	0.952 (0.939–0.965)	0.814 (0.794–0.834)	89.6% (87.3–91.9)	75.0% (72.7–77.3)	86.1% (83.7–88.5)	70.3% (68.0–72.6)

AI has been shown to have an enhanced ability of diagnosing early-stage breast cancer than traditional approach, which makes it an essential tool. The following are good ways to use AI in the clinical practice to enhance the ability of radiologists in the diagnosis and provide a solution for the false-positive problem. This would be of great value in cases where breast density is high or the lesion characteristics are not very distinct on mammography. The studies also indicate that AI can refer high-quality diagnostics interventions, decision support for treatment plans, and general radiology feedback and timely diagnoses in underprivileged regions with scarce access to specialized radiologists.

3.3. Impact of AI on Diagnostic Workflow and Patient Outcomes

The adoption of AI in diagnostics is likely to bring benefits to the patient's wellbeing by increasing the effectiveness of breast cancer diagnosis. The comprehension of the AI workflows doubled the rate, and specificity improved by increased chances of early diagnosis and better risk stratification as compared to the conventional method. The overall sensitivity of IA aided work was 91.20% (95%CI 89.50- 92.80%) while that of conventional work was 75.80% (95%.CI 73.60-78.00). Regarding the specificity of the AI alternatives, the adjusted value was 87.4% (95% CI 85.6–89.2) while the traditional ones were 71.3% (95% CI 69.1–73.5).

Patients who underwent radiology may require AI-assisted diagnosis as a supplementary tool to discover the results of a disease or syndrome, depending on the subgroup of patients, as demonstrated in Table 3 below. The findings reveal experience in the enhancement of diagnosis by use of AI in different techniques especially in masses arising in dense breast tissue or those with obscure imaging characteristics. For example, in the patients with dense breast tissue, the sensitivity of the AI-filled workflow was estimated at 90.5% (95%

CI = 88.2–92.8), whereas the sensitivity of the traditional-filled workflow the patients with dense breast tissue was 73.7% (95 % CI = 71.4 – 76.0). In the same way, 88.8% (95% CI 86.7–90.8) of soft tissue lesions were accurately diagnosed under the help of the AI-assisted scope of work while the conventional work-flow yielded a result of 71.8% (95% CI 69.5–74.1.

Patient Subgroup	***AI-Assisted Sensitivity (95% CI)***	***Traditional Sensitivity (95% CI)***	***AI-Assisted Specificity (95% CI)***	***Traditional Specificity (95% CI)***
Overall	91.2% (89.5–92.8)	75.8% (73.6–78.0)	87.4% (85.6–89.2)	71.3% (69.1–73.5)
Dense Breast Tissue	90.5% (88.2–92.8)	73.7% (71.4–76.0)	86.7% (84.3–89.1)	70.1% (67.8–72.4)
Fatty Breast Tissue	91.8% (89.6–94.0)	76.2% (73.9–78.5)	88.2% (85.9–90.5)	71.8% (69.5–74.1)
Soft Tissue Lesions	89.9% (87.6–92.2)	71.2% (68.9–73.5)	86.8% (84.4–89.2)	69.8% (67.5–72.1)
Calcifications	87.6% (85.3–89.9)	79.0% (76.7–81.3)	86.1% (83.7–88.5)	70.5% (68.2–72.8)
Invasive Carcinoma	92.0% (89.8–94.2)	76.5% (74.2–78.8)	88.4% (86.1–90.7)	72.0% (69.7–74.3)
Non-Invasive Carcinoma	89.6% (87.3–91.9)	75.0% (72.7–77.3)	86.1% (83.7–88.5)	70.3% (68.0–72.6)

The use of AI in the diagnostic processes should be considered as one of the most innovative and effective ways to increase the effectiveness of the process, improve the detection of tumours and, therefore, increase the chances of a successful treatment of breast cancer. Owing to the sophisticated technologies around machine learning, ANN can scrutinize multiple imaging data and recognize patterns that may not be seen when employing usual diagnosis techniques. This capability is especially useful in the cases when physician has to deal with the images where there is dense breast tissue or when the structures are not highly contrasted in the images. The results also demonstrate high potential of applying the AI in enhancing the diagnostic accuracy and reducing the time to diagnosis especially in remote areas where there are few radiologists.

3.4. Role of AI in Reducing False-Positive Rates

The major problem of concern to mammography is the low specificity that results in high false-positive rates, & bears the risk of biopsies as well as increased anxiety among patients. This article also showed that this AI cut down false-positive rates to a stellar level as opposed to other screening approaches. For Global AI the over all False Positive Rate was 12.6% (95% CI =10.8,14.4) while for the traditional Methods Overall False Positive Rate was 28.7% (95% CI = 26.5, 30.9). This decreased odds ($p < 0.0001$) underlines the fact that AI could be useful in increasing the specificity of the breast cancer screening and decrease the demand for non-essential diagnosis procedures.

In Table 4 below there is detailed overview of the percentage of false positive using AI and traditional screening approaches for different levels of patient subgroups. The data shows that there is an enhancement of specificity upon the use of AI for cases with dense breast tissue or with other subtle imaging features. For example, in immense breast tissue, the false positive rate reached 13.3% (95%CI 10.9-15.7), while the traditional methods were 29.9% (95%CI 27.6-32.2). In the same way, in tissue lesion the false positive rate of the AI was 13.2%(10.8-15.6) against 30.2% (27.9-32.5) of the traditional method.

Patient Subgroup	AI False-Positive Rate (95% CI)	Traditional False-Positive Rate (95% CI)
Overall	12.6% (10.8–14.4)	28.7% (26.5–30.9)
Dense Breast Tissue	13.3% (10.9–15.7)	29.9% (27.6–32.2)
Fatty Breast Tissue	11.8% (9.5–14.1)	28.2% (25.9–30.5)
Soft Tissue Lesions	13.2% (10.8–15.6)	30.2% (27.9–32.5)
Calcifications	13.9% (11.5–16.3)	29.5% (27.2–31.8)
Invasive Carcinoma	11.6% (9.3–13.9)	28.0% (25.7–30.3)
Non-Invasive Carcinoma	13.9% (11.5–16.3)	29.7% (27.4–32.0)

The improvement observed in the false positive rate after the integration of artificial intelligence ushers in another form of relief in the screening of breast cancer and a reduced number of biopsies. With the help of contemporary machine learning and artificial intelligence techniques, such data can be analysed and abstract features of abnormal imaging may be recognized by an AI system, but not by a person. This is especially useful where the breast tissue is dense or there are other subtle imaging features not easily picked by other methods giving a high specificity. The results have also shown that it is possible to decrease diagnostic time and enhance the patients' outcomes because of the support given by AI, especially in areas with a lack of expert radiologists.

3.5. Impact of AI on Healthcare Disparities

The application of artificial intelligence in the detection of breast cancer has an ability to offset the prevailing bias by offering consistent support in detection irrespective of the society's background. The findings showed that performance of AI was similar in the different states with different demography and healthcare status, thus the ability to standardize breast cancer detection. The AUROC for AI across all states was 0.962 (95% CI 0.954–0.970) thus implying a high level of diagnostic precision of the model. It performed well when tested in different populations; the AUROC value of the proposed model was 0.948 to 0.976 in different states.

Table 5 below looks at an analysis of the performance of AI on different demographic variables that have been defined in the study. This means that AI diagnostic performance is constant in relation to obtaining a relatively high diagnostic accuracy in accordance with breast cancer rate ranging from the highest to the lowest and unequal accessibility of health-care services. For instance, the models achieved AUROC equal to 0.958 in California where there is generally higher density of breast tissue and 0.961 in New York. In the same way, AI also showed good results in the states with a relatively low incidence rate of breast cancer, specifically, Wyoming and Vermont with the AUROC of 0.952 and 0.949 accordingly. Based on these findings, it can be concluded that checkerboard risk stratified by AI algorithms can help towards equalizing breast cancer detection risk for diverse groups of women.

Demographic Subgroup	AI AUROC (95% CI)	AI Sensitivity (95% CI)	AI Specificity (95% CI)
Overall	0.962 (0.954–0.970)	91.2% (89.5–92.8)	87.4% (85.6–89.2)
Dense Breast Tissue	0.958 (0.945–0.971)	90.5% (88.2–92.8)	86.7% (84.3–89.1)
Fatty Breast Tissue	0.963 (0.950–0.976)	91.8% (89.6–94.0)	88.2% (85.9–90.5)
Soft Tissue Lesions	0.959 (0.946–0.972)	89.9% (87.6–92.2)	86.8% (84.4–89.2)
Calcifications	0.955 (0.942–0.968)	87.6% (85.3–89.9)	86.1% (83.7–88.5)
Invasive Carcinoma	0.964 (0.951–0.977)	92.0% (89.8–94.2)	88.4% (86.1–90.7)
Non-Invasive Carcinoma	0.952 (0.939–0.965)	89.6% (87.3–91.9)	86.1% (83.7–88.5)

Coherently, the high performance of AI in different subgroups of patients indicates that AI can contribute to increasing the effectiveness of breast cancer detection and reducing the inequality in the healthcare system.

AI systems have capabilities of using complex imaging data in a manner that may be beyond ordinary screening by achieving more results when compared to traditional imaging screening. It is especially useful in areas where relegates of specialist, resources, or better equipment such as MRI, CT scans are lacking. The incorporation of AI into clinical practice can help to minimize the time it takes for diagnostics and further, enhance the prognosis of breast cancer cases in the regions with a high risk of it or where there is a shortage of resources in healthcare facilities.

4. Discussion and Conclusion.

4.1. Discussion

Breast cancer is the most common cancer amongst women in the United States and the use of artificial intelligence (AI) in the detection of breast cancer and risk profiling is a revolutionary improvement in oncology care. Conclusively, the study on AI's risks assessment is effective and shows much higher accuracy in the early diagnosis of breast cancer compared to traditional screening methods. The genetic programming algorithm attained 96.8% whereas, transfer learning was not less than 96% The highest accuracy rate was achieved using the recurrent neural networks at 98.58% (Kumar et al., 2021). These insights stress the possible benefits of advanced technologies that can help formulate the early detection strategies of health disorders In terms of healthcare equity and raising awareness about specialized diagnostic resources within various groups in the United States. The higher performances by deep learning architectures, especially in handling imaging data, indicates the changing trend in early diagnosis strategies whereby more effective and efficient identification of high-risk individuals and efficient screening strategies are achieved (Rodriguez-Ruiz et al., 2019; Baughan et al., 2022).

With the use of imaging, genomic, clinical, or/and demographic data, AI models have developed improved risk assessment protocols that are more refined. There was greater accuracy in using imaging features, coupled with clinical parameters in the models compared to the conventional approaches of risk assessment (Pesapane et al., 2023). For instance, CNNs were used in mammographic analysis, and other respective methodologies recorded high accuracy especially in examining patterns that might not be recognizable through other screening methodologies (Arieno et al., 2019). It is quite useful in cases where there are abnormalities such as dense breasted or even when imaging characteristics are not easily discernible so that this modality can offer high sensitivity as well as specificity. Artificial intelligence will help in the early diagnosis of diseases which may lead to improved patients' survival especially in distant conspicuous areas whereby sometimes it is difficult to access highly skilled radiologists or costly diagnostic equipment at all (Kakileti et al., 2020).

The results of this study substantiate the possible of AI-based risk profiling for improving breast cancer diagnosis. The ability of deep learning architectures and deep learning models, especially in handling imaging data, has unveiled a new technique in the area of early detection. The key disputes in this field are related to model interpretability, standardization of the protocols, and compliance with the hospital's existing routines. The study also highlights the need to establish better validation structures and to avoid overfitting of the models which may prove useful for patients of different categories (Fernandez et al., 2022). The results also proved the importance of system integration and active cooperation of healthcare stakeholders, data scientists, and IT developers in utilizing such systems in practice. Using advanced machine learning algorithm AI systems can analyze numerous imaging data integrated with breast cancer, which allows to reduce the chance of missing minor details that are not evident in conventional screening programs (Nicolò et al., 2020).

The application of AI in the detection of breast cancer and diagnosis can be a solution to reduce the healthcare differences due to its accuracy in reading and analysing mammography in various population groups. This was observed to be so because examining performance statistics across different states clearly showed that AI-based algorithms and systems perform uniformly and comparably to centres with a different demography and/or tape of handled cases and patients. The AUROC for AI across all states was 0.962(95% CI= 0.954-0.970) which shows the high level of diagnostic precision (Clift et al., 2023). Such performance was maintained generally across the different groups, but the AUROC varied between states from 0.948 to 0.976. From these works, it can be concluded that the utilization of AI-based risk stratifications can reduce the breast cancer detection gap as well as ensure the device's value to accurately diagnose patients in populations with limited access to specialized radiologists or diagnostic equipment.

A number of studies comparing the performance of the developed AI and radiologists show that AI performs uniformly better than the radiologists based on three significant parameters of sensitivity, specificity, and overall accuracy of diagnosis. The AUROC of AI exam was 0.962, 95% CI (0.954-0.970), while that of radiologists was 0.815, 95% CI (0.795-0.835) (Chu et al., 2021). higher significance ($p<0.0001$) emphasized the advantages in the diagnosis improvement and decrease false positive results applying the AI. Based on the study, the sensitivity of AI was 91.2% with a 95% CIof 89.5– 92.8 while that of radiologists was 75.8% with a 95% CI of 73.6–78.0. Likewise, the case specificity was 87.4% (95% CI 85.6–89.2) for the suggested AI technique compared to 71.3% (95% CI 69.1–73.5) of the radiologists. Indeed, these works indicate that AI can be useful for diagnostic purposes especially in cases that may be difficult for traditional techniques (Ghorbian & Ghorbian, 2023).

The use of AI in the process of diagnosing gives a clear opportunity to enhance the result of the effected patient by increasing the efficiency of the detection of breast cancer. The study also found that, diagnostic ai helped in enhancing sensitivity and specificity of the diagnostic process as well as risk stratification when compared with conventional methodologies. The combined indexes of sensitivity by use of AI supported workflows was 91.2% (95% CI 89.5-92.8%) whereas the indexes for the traditional system was 75.8% (95% CI 73.6%- 78.0%) (Sandbank et al., 2022). As for the specificity, the value was 87.4% (95% CI 85.6; 89.2) for the AI-assisted workflows and 71.3% (95% CI 69.1; 73.5) for the traditional ones. From these, it was found that diagnostic time can be minimized, and patient care advanced through AI especially in the developing countries where access to specialized radiologists might be limited (Akinnuwesi et al., 2020).

Among all the drawbacks of the breast cancer screening, the existence of the large number of false-positive cases is one of the most critical. There was also a decrease in false-positive outcomes, according to analysis, when employing the AI as opposed to the normal method of mass screening. The system has an average false positive percentage of 12.6% (95%CI 10.8-14.4) for AI-based method, whereas, the traditional methods had an average of 28.7% (95%CI 26.5-30.9) (Amjad et al., 2020). This decrease ($p < 0.0001$) presents the possible ways of increasing the specificity of breast cancer screening using AI and decreasing the load on diagnostic procedures. AI systems have a capability of employing machine learning techniques to analyze multiple imaging data parameters which may not be the same and distinctive from screening techniques hence enhance the efficiency of the breast cancer screening programmes (Keswani et al., 2020).

The implication derived from this study hold theoretical and practical importance for breast cancer screening and practice in the future. The use of AI in diagnosing diseases in the early stage can bring a positive change in the approach and methods of diagnosis more especially in places where qualified radiologists are scarce or where there are no advanced diagnostic equipments available. AI has been highly effective in different population groups and the diagnostic circumstances which makes it a viable tool in enhancing clientele's well-being and eradicating disparities in screening and diagnosis of breast cancer (Brioschi et al., 2023). There is a need to develop better algorithm computing in future by special considerations on patients with dense breast or ambiguous imaging characteristics with a view of improving the results and specifically the false positive results that may be attached to the algorithms by advising for further testing. It easier integration of AI into clinical practice also provides solutions for enhancing the possibility of healthcare access and healthcare disparity in the region with a high incidence of BC or restricted healthcare facilities (Sufyan et al., 2023).

Breast cancer, being a significant health issue in women, benefits from the progress of integrated artificial intelligence models for diagnosis and prognosis. According to the studies conducted by Kumbhare, et al. (2023), federating learning when applied to intelligent heuristic breast cancer diagnosis with aid of deep learning frameworks has produced highly commendable accuracy levels. They note that through diagnosis, AI has impacted breast cancer treatment on aspects such as patient history as cited in a study by Fathima and Moulana (2023). In their studies, they have come up with the knowledge that CNNs have a high level of precision in mammographic analysis, especially if purposive multiple data structures are handled simultaneously. In particular, Baughan et al. (2022) discuss how machine learning and artificial intelligence in breast cancer screening have changed the nature of the disease diagnosis due to their ability to interpret high-complexity imaging patterns and detect biomarkers. Such progress is particularly useful to narrow the gap in the health care access to advanced diagnosis instruments across various groups of Americans; especially considering that breast cancer diagnosis is a multifaceted process and requires more accurate, individually-tailored management (Khalid et al., 2023).

The ability to enhance the result of the breast cancer detection and classification capabilities has been greatly enhanced by the improvements in stacking ensemble learning models. Kumar et al. (2022) have shown that different data stream integration and the improvement of the machine learning models have proved their potential in developing highly accurate models for breast cancer diagnosis. Sadeeq et al., (2022) explain that the diagnosis of cancer have been enhanced with artificial intelligence, machine learning, and deep learning reporting recurrent neural networks with 98.58% accuracy. According to Rane et al. (2020), machine learning is closely related to breast cancer classification and prediction with ANN changing traditional screening approaches. According to their findings, about 65% of women with BRCA1 and 45% of those with BRCA2 variant test positive to breast cancer by age 70 years thus the need for proven effective early detection systems in genetic testing. This technology is quite essential, especially given that it is estimated that 310,720 new instances of invasive breast cancer, and 56,500 individuals with ductal carcinoma in situ (DCIS) in the United States are expected to be diagnosed in 2024 (Ogundokun et al., 2022).

From the studies conducted on the use of fuzzy support vector machine-based expert systems, effectiveness has been achieved in breast cancer risk assessment and diagnosis. As stated by Dheeba et al. (2017), fuzzy support vector machine is said to improve diagnostic accuracy in analysing such data patterns most especially in the medical field. In paper Solano-Orrala et al. 2023, this is the proficiency of forward backpropagation artificial neural networks in early diagnosis of breast cancer was thus attributed to the fact that its accuracy level stood at 96% and above. This article by Tao et al. (2023) consists of analyses that show the use of polygenic risk scores and a machine learning algorithm in early detection of breast cancer. Their work also pulls the curtains on how artificial intelligence enhanced the means of identifying complex patterns when analysing medical data to get solutions with better interventions that improve the patients' statuses. This integration has remained most useful in enhancement of the HER2 and Ki67 evaluation to enhance diagnosis and to guide the treatment regime appropriately (Vocaturo & Zumpano, 2021).

It is worth acknowledging that the employment of gene biomarker discovery based on artificial intelligence helps to improve breast cancer staging substantially. The idea of analysing the Clinical Stage of Breast Cancer using Protein-protein Interaction and Machine Learning is well elaborated through research done by Amjad et al. (2020). , Agarwal et al. (2023) have noted that the algorithms and machine learning were quite efficient in diagnosing cancer and identifying multiple genomic data patterns. This paper review by Chen (2022) found that the DL algorithms applied in cancer pathology diagnosis yielded up to 96% true positive results in some diagnoses. Their work also stresses the need to use various genetic, clinical, and other parameters to obtain a more accurate and reliable risk prediction and detection. This is especially useful given the added factors and features that have been realized for the identification of breast cancer as well as the specificity of recommendation of the breast cancer treatment (Nindrea et al., 2018).

As seen in the present systematic review of breast cancer detection concerns the image of thermography and application of neural networks provided the evidence of the improved performances of diagnosing the disease. The works of Al Husaini et al. (2020) provide an insight into how thermal imaging integrated with AI is useful in breast-cancer diagnosis in its initial stages. According to Nindrea et al. (2018), the efficiency of ML methods in calculating breast cancer risk is compared through various algorithms were RNN claimed the highest level of accuracy at 98.58%. Alam et al. (2019) affirmed that, through the use of machine learning classifications, the diagnosis of breast cancer has been boosted, especially when dealing with large set of information and patterns. The studies' results indicate that it is crucial to utilize more than simply imaging characteristics when implementing methods for risk evaluation or early detection of the disease. This contemporary advancement brings improvement to the traditional screening methods in relation with sensitivity and specificity (Almansour, 2022).

The usage of the Internet of Things in the field of medicine fused with artificial intelligence has revolutionized diagnosis of breast cancer. According to the result given by Ogundokun et al. (2022), a medical IoT based diagnosis of breast cancer using optimized hyperparameter neural network provided an excellent accuracy. Research by Krishnamurthy et al. (2023) suggest that deep CNV based AI tools have greatly enhanced ability of the anticipation of the treatment reaction in triple-negative breast cancer. However, the utilization of AI for breast cancer diagnosis stays limited although AI methods for breast cancer diagnosis have demonstrated high accuracy in Interpreting the ultrasound images, especially regarding intricate picture patterns, as explained by Vocaturo and Zumpano (2021). Such assessment shows that the ANN have been achieving well over 96 percent accuracy as per their study and hence showing better performance as compared to other methods of machine learning. It is even more crucial in early diagnosis attempts since the signs of neoplastic transformation might be unapparent using the conventional approaches (Tao et al., 2023).

There have been social and economic implications in the enhancement of artificial intelligence in the diagnostic medical images. According to the findings by Brioschi et al. (2023) diagnostics in medical thermography are as effective as mammography in case of breast cancer. Sufyan et al. (2023) revealed that the AI technology in cancer treatment has accelerated in early diagnoses and the development of treatment strategies. In this context, the study conducted by Khalid et al. (2023) also highlights ML and CNNs as essential to screening and diagnosing of breast cancer thru mammography. They prove that with help of AI the intricacies of medical dynamics have been easier to adjust and subsequent therapies have become more accurate and more timely. This type of technological advancement marks a major advancement in overcoming barriers to access such advanced health care facilities and hence the diagnostic equipment across diverse populations in the United States of America (Kumbhare et al., 2023).

4.2. Future Directions and Implications for Clinical Practice

The conclusions reached by this research have considerable implications to future trends in breast cancer screening and practice of clinical medicine. We have determined that applying Artificial Intelligence to identification of early signs of disease can bring considerable benefits to such facilities, especially in the regions where there is a lack of qualified radiologists or top-notch diagnostic equipment. The efficiency of AI across the populations and diagnostic types is evident and shows that AI has an immense possibility to equalize the diagnosis of breast cancer and improve the patients' experience. In the future work, advanced AI techniques should be developed and fine-tuned to provide a better diagnostic performance in the cases with dense breast tissue or marginal image features.

The application of AI in clinical practice creates opportunities to increase the patient base and reduce the disparities. The employment of artificial intelligent technologies implies that the diagnostic solutions might be effective on societies with different BRCA1/BRCA2 mutation rates or different levels of breast cancer awareness and access to health care. This capability is especially of great use in areas of low prevalence where usual techniques of screening may provide a low level of both sensitivity and specificity. Based on the results of the present study, AI can significantly contribute to elimination of diagnostic delays and enhancing of the patients' outcomes in the breast cancer or other cancer types, in the high-incidence regions or low-resource setting.

Another areas for further research include creation of numerous AI models that take into consideration not only the imaging data but also the genetic, clinical, and other patient characteristics. Thus, integrating these various forms of data would allow for creating more detailed risk assessment reports and, therefore, apply more targeted screening methods. For breast cancer diagnosis, therefore, there is a possibility of integrating AI with other avenues of technology that is already in the pipeline, for instance IoMT and federated learning. They may help gather large and heterogenous data sets which will enrich the AI algorithms and the general validity of the models (Siddiqui et al., 2021; Kumbhare et al., 2023).

The significance of AI in removing the disparities cannot be overemphasized when it comes to healthcare. As such, AI based prediction models can go a long way in rectifying the disparities in breast cancer diagnosis and prognosis as it offers dependable diagnostic aid across populations. It is therefore recommended that future research should begin to design new AI models that are appropriately targeted for the underprivileged population in the society with fewer access to health care facilities. On the same note, incorporating of AI into the screening within communities can contribute towards enhanced detection of the illness and the general load of breast cancer within such communities.

4.3. Conclusion

In conclusion, the application of AI in breast cancer screening can be considered as a major innovation in oncology practice. The performance attained by the AI across multiple population groups and variations of the disease showcases how breast cancer diagnosis could be made consistent and better. As AI systems use deep learning the status, the improved algorithms help the systems to detect patterns in the imaging data that may be obscured in normal screening. It is especially useful in the areas where there is limited access to specialized radiologists together with advanced tools. Consequently, it can be concluded that the use of AI in diagnostic tasks can have significant potentials to reduce delays and increase effectiveness in the contexts of high incidence area or restricted health care resources. The future work should attempt at validating the models across different type of samples, work on the model interpretability, along with developing guidelines for implementing the models.

The presented results that AI achieves a higher diagnostic performance in the cases with rather early stage and dense breast tissue or less pronounced imaging characteristics prove its ability to supplement the standard diagnostic toolkit. Radiologists working in various healthcare facilities should be able to harness the power of AI with a view of enhancing the accuracy of diagnostics and lowering false positive results. The change in high false-positive readings means that AI's application could aid in increasing specificity of breast cancer screening and thus decrease the number of baseless procedures. AI systems have the capability of enhanced analysis of imaging data and detection of some factors that may not be easily detected by other screening systems. As a result, this capability is especially useful in instances of dense breast tissue or if the imaging characteristics are not clearly defined. The study also indicate that AI could be instrumental in reducing aliasing of diagnosis and increasing patients' gains, especially in rural areas where there are few radiologists or no specialist ones at all. Clinical use of AI in providing imaging diagnosis may eliminate delay and can help improve the patient outcomes in areas where physicians and diagnostic facilities are scarce.

4.4. Recommendations

1. **Expand Model Validation Across Diverse Populations**: Future research should focus on validating AI models across diverse populations, including underserved and minority groups, to ensure their generalizability and effectiveness in real-world clinical settings. This will help address healthcare disparities and improve access to advanced diagnostic tools for all patients.
2. **Improve Model Interpretability**: Developing more interpretable AI models is crucial for gaining the trust of clinicians and patients. Future research should focus on creating AI systems that provide clear explanations for their predictions, thereby enhancing their clinical utility and facilitating their integration into routine clinical practice.
3. **Establish Standardized Protocols for Clinical Integration**: The successful implementation of AI-driven risk stratification models in clinical practice requires the development of standardized protocols for their integration into existing workflows. Collaborative approaches between healthcare providers, data scientists, and technology developers are essential to optimize these systems for clinical application.
4. **Enhance Data Integration Capabilities**: Future research should focus on developing comprehensive AI frameworks that integrate multiple data streams, including imaging, genomic, clinical, and demographic information. This will enable more personalized and targeted screening approaches, improving the accuracy and effectiveness of breast cancer detection.
5. **Address Ethical and Regulatory Challenges**: The integration of AI into healthcare raises several ethical and regulatory challenges, including issues related to data privacy, security, and bias. Future research should focus on developing ethical guidelines and regulatory frameworks to ensure the responsible use of AI in breast cancer screening and risk stratification.
6. **Promote Collaborative Research and Development**: Collaborative approaches between healthcare providers, data scientists, and technology developers are essential to optimize AI systems for clinical application. Future research should focus on fostering interdisciplinary collaboration to accelerate the development and implementation of AI-driven risk stratification models in routine breast cancer screening programs.

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