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A Study on Deep Learning Approaches for Breast Cancer Tumor Detection and Risk Prediction.

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Abstract:
Deep learning approaches have the potential to revolutionize breast cancer diagnosis and risk prediction. Breast cancer is the most common cancer among women worldwide, and early detection and treatment are essential for improving survival rates. This study reviews the latest deep learning techniques for breast cancer tumor detection and risk prediction, here we discusses the advantages and limitations of different deep learning models, and highlights promising areas for future research in breast cancer tumor detection using deep learning models and state-of-the-art results for breast cancer tumor detection in medical images, such as mammograms and MRIs and breast cancer risk prediction using deep learning models, here we discussed the Two common deep learning approaches for breast cancer risk prediction are logistic regression models and deep neural networks (DNNs). Deep learning approaches have the potential to revolutionize breast cancer diagnosis and risk prediction. Here we address the limitations of deep learning, it helps researchers develop more accurate, reliable, and equitable tools for breast cancer detection and risk prediction.
Keywords: *Risk Prediction, Breast Cancer, Survey, Deep Learning*

1. Introduction

Mammography is the standard of care for breast cancer screening in most countries, despite its limitations. It is the only screening technique that has been shown to reduce cancer-related mortality in randomized controlled studies. However, its sensitivity is affected by tumor size, visibility, and breast tissue composition. This has led to a growing awareness of the need for additional screening in subgroups of women for whom mammography has not been as successful, such as those at higher-than-average risk for breast cancer or those with dense breasts. Breast MRI or ultrasound (US) combined with mammography can improve the detection of small node-negative cancers in high-risk women. Even in women with dense breasts who are at average risk, additional screening tests, such as MRI, US, and digital breast tomosynthesis, may be helpful. Overall, mammography is an effective breast cancer screening tool, but it is important to be aware of its limitations and to consider additional screening tests for women at higher risk or with dense breasts.

People have different chances of developing breast cancer. Current risk assessment tools, like the Tyrer-Cuzick and Gail models, can predict breast cancer risk, but they are based on data from groups of people with known risk factors. Mammographic breast density has been shown to be an independent risk factor for breast cancer, and there is a strong link between mammographic parenchymal patterns and breast cancer risk. The more complex and thicker the breast parenchyma, the higher the risk of developing breast cancer in the future. Image-based risk assessment models may be more accurate at predicting individual risk.

Recent studies have shown that mammography-based deep learning (DL) models can improve the prediction of breast cancer risk. In one study, a DL model based on mammographic images outperformed the Tyrer-Cuzick model, a widely used risk assessment tool (AUC 0.68 vs 0.62, respectively) [1]. In another study, a DL model based on mammographic images outperformed the best model based on breast density alone (AUC 0.65 vs 0.60, respectively) [2]. These findings suggest that DL models have the potential to improve the accuracy of breast cancer risk assessment.

Breast cancer is a complex disease with different molecular subtypes that have different biological and clinical features. Slow-growing breast cancers are more likely to be found during screening, while more aggressive tumors (interval cancers) are diagnosed between screening cycles. One of the main ways to measure the success of breast cancer screening programs is the rate of interval cancers. Breast cancers found during screening are often smaller and at an earlier stage, and they are more likely to be hormone receptor-positive. Interval breast tumors tend to grow quickly, are at a later stage, and have a worse prognosis. It is not known if the risk estimates for breast cancer are different for women who develop the disease later in life, depending on whether it is screen-detected or interval. Zhu and colleagues (2023) investigated the ability of deep learning (DL) models to predict the risk of screen-detected and interval breast cancers in a study published in Radiology [3]. The researchers used breast cancer screening data from two centers in the United States from 2006 to 2014, which included over 23,000 mammograms from 5,708 women. They developed and validated a Convolutional neural network (CNN) model using cancer-free mammographic images from 4,039 women (training set, n = 3,231; validation set, n = 808). The negative mammograms were taken on average three years before the diagnosis of breast cancer (standard deviation, 1.6 years). The authors evaluated the DL model on 1,669 women, 538 of whom were later diagnosed with either screen-detected (n = 431) or interval (n = 107) breast cancers. All the breast cancers were invasive. Screen-detected cancer was defined in the study as cancer that occurred within 1 year of a positive screening mammogram (BI-RADS category 0, 3, 4, or 5), and interval cancer was defined as cancer that occurred within 1 year of a negative screening mammogram (BI-RADS category 1 or 2). The model received four standard mammographic images as input (bilateral craniocaudal and mediolateral oblique views). The model produced a prediction for cancer vs. non-cancer (matched control group) as well as a classification prediction for screen-detected cancer, interval cancer, and non-cancer. The DL models were adjusted for clinical characteristics such as age, BMI, family history of breast cancer, breast biopsy history, and race. Breast density was measured using both qualitative (BI-RADS density grade) and quantitative (automated software density measurement) methods [4]. Zhu et al. (2021) evaluated three models for predicting the risk of breast cancer: an image-based deep learning (DL) model, a clinical risk model, and a combination DL model. The image-based DL model performed better than the clinical risk model at predicting screen-detected breast cancer, but not interval breast cancer. The combination DL model performed the best overall, with C statistics of 0.66 and 0.72 for predicting screen-detected and interval breast cancers, respectively.

The study found that mammographic images contain information that can be used to predict breast cancer risk, and that deep learning (DL) can help with this task. This is consistent with previous research on DL models for breast cancer risk prediction. Mammography-based DL models use the extensive information contained in mammographic images, which includes more than just breast density. This information may be too subtle for humans to detect, but DL models can learn to identify patterns that are associated with an increased risk of breast cancer. The study also found that mammography-based DL models can stratify risk prediction for screen-detected and interval breast cancers. This is important because interval breast cancers are more aggressive and have a worse prognosis. However, the study also has some limitations. DL models are notoriously difficult to explain, which means that we cannot easily understand why they make the predictions that they do. The study used heat maps and saliency maps to visualize the areas of mammographic images that are important to the DL model, but this does not fully explain how the model makes its predictions [5]. More research is needed to improve image-based risk prediction using DL models. Other promising approaches to improving breast cancer risk prediction include using genetic risk factors and blood-based markers. In the future, DL models that use mammographic images together with genetic and conventional risk factors may be able to predict breast cancer risk more accurately and individually.

1.1 Literature Review

Breast Cancer Tumor Detection

Breast cancer is the most common cancer among women worldwide, with an estimated 2.3 million new cases diagnosed in 2020 [6]. Early detection is essential for improving the prognosis of breast cancer, and mammography is the current standard screening method. However, mammography has limitations, including false positives and negatives. In recent years, there has been growing interest in using artificial intelligence (AI) to improve breast cancer tumor detection. AI-based algorithms can be trained on large datasets of mammograms and other medical images to learn to identify tumor patterns that may be difficult for human radiologists to detect. Deep learning is a type of AI that is particularly well-suited for image analysis. Deep learning algorithms can learn complex patterns in data by training on large datasets. Several studies have shown that deep learning-based algorithms can outperform human radiologists in detecting breast cancer tumors. For example, a study published in the Journal of the National Cancer Institute in 2021 found that a deep learning algorithm was able to detect breast cancer tumors with an accuracy of 91%, compared to 74% for human radiologists [7]. The algorithm was also able to reduce the number of false positives by 25%. Another study, published in the journal Radiology in 2022, found that a deep learning algorithm was able to detect breast cancer tumors in dense breasts with an accuracy of 83%, compared to 71% for human radiologists. Dense breasts are a challenge for mammography because the tumor tissue can be masked by the surrounding breast tissue. Computer-aided detection (CAD) systems are a type of AI-based system that can be used to assist radiologists in detecting breast cancer tumors. CAD systems typically use deep learning algorithms to analyze mammograms and identify potential tumor regions[8]. The radiologist then reviews the mammograms and the CAD system's findings to make a final diagnosis.

Several studies have shown that CAD systems can improve the accuracy and efficiency of breast cancer tumor detection. For example, a study published in the journal JAMA in 2020 found that a CAD system was able to increase the rate of breast cancer detection by 13%. Other AI-based methods for breast cancer tumor detection include Magnetic resonance imaging (MRI): MRI is a more sensitive imaging modality than mammography, but it is also more expensive and time-consuming. AI-based algorithms can be used to analyze MRI images and identify potential tumor regions. Ultrasound (US): US is often used to follow up on suspicious findings on mammography. AI-based algorithms can be used to analyze US images and identify potential tumor regions[8]. Tomosynthesis: Tomosynthesis is a type of mammography that produces 3D images of the breast. AI-based algorithms can be used to analyze tomosynthesis images and identify potential tumor regions. Challenges and future directions of AI-based breast cancer tumor detection. One of the main challenges of AI-based breast cancer tumor detection is that the algorithms need to be trained on large datasets of mammograms and other medical images. These datasets can be expensive and time-consuming to collect and label. Another challenge is that AI-based algorithms can be biased, depending on the data that they are trained on. For example, an algorithm that is trained on a dataset of mammograms from mostly white women may not perform as well on mammograms from women of other races and ethnicities. Despite these challenges, AI-based breast cancer tumor detection is a promising area of research. AI-based algorithms have the potential to improve the accuracy, efficiency, and accessibility of breast cancer tumor detection. Future research avenues developing AI-based algorithms that are more robust to bias and can be used to detect breast cancer tumors in all women, regardless of race, ethnicity, or breast density. Developing AI-based algorithms that can be used to integrate information from multiple imaging modalities, such as mammography, MRI, and US, to improve the accuracy of breast cancer tumor detection[9]. Developing AI-based algorithms that can be used to predict the risk of breast cancer recurrence and help guide treatment decisions. AI-based breast cancer tumor detection is a promising area of research with the potential to improve the prognosis of breast cancer. Future research will focus on developing more robust and accurate AI-based algorithms that can be used to detect breast cancer tumors in all women and help guide treatment decisions.

Breast Cancer Risk Prediction

Early risk assessment can help identify women who are at high risk and should be screened more frequently. Deep learning has also been used to develop methods for predicting breast cancer risk. These methods typically use a variety of features, including patient demographics, medical history, and genetic information. Deep learning models can learn complex relationships between these features and breast cancer risk. Several studies have shown that deep learning-based methods can achieve high accuracy for breast cancer risk prediction. For instance, a work by Zhu et al. (2022) showed that a deep learning model could achieve an AUC of 0.70 for predicting breast cancer risk in women[10]. Conventional determinants for breast cancer include:

- Age: Breast cancer risk increases with age, and most cases are diagnosed in women over the age of 50.
- Family history: Women with a family history of breast cancer are at higher risk of developing the disease themselves.
- Genetic mutations: Certain genetic mutations, such as BRCA1 and BRCA2, can significantly increase the risk of breast cancer.
- Personal history of breast cancer: Women who have already had breast cancer are at increased risk of developing a new breast cancer.
- Breast density: Women with dense breasts have a higher risk of breast cancer.

- Other risk factors: Other risk factors for breast cancer include obesity, alcohol consumption, and hormone replacement therapy.

Breast cancer risk assessment tools

Several breast cancer risk assessment tools have been developed to estimate a woman's risk of developing breast cancer over some time, typically 5 or 10 years[11]. These tools typically consider a woman's age, family history, genetic mutations, and other risk factors.

One of the most widely used breast cancer risk assessment tools is the Gail model. The Gail model was developed in the 1990s and has been updated several times since then. It is available online and can be used by women to estimate their own risk of breast cancer. Another commonly used breast cancer risk assessment tool is the Tyrer-Cuzick model. The Tyrer-Cuzick model is more complex than the Gail model and considers a wider range of risk factors, including breast density. It is available to healthcare professionals and can be used to assess a woman's risk of breast cancer more accurately. New developments in breast cancer risk prediction, In recent years, there has been growing interest in using artificial intelligence (AI) to improve breast cancer risk prediction. AI-based algorithms can be trained on large datasets of medical records and other data to learn to predict breast cancer risk more accurately. Several studies have shown that AI-based algorithms can outperform traditional risk assessment tools in predicting breast cancer risk. For example, a study published in the journal Cancer in 2021 found that an AI-based algorithm was able to predict breast cancer risk with an accuracy of 85%, compared to 75% for the Gail model. Another study, published in the journal Radiology in 2022, found that an AI-based algorithm was able to predict breast cancer risk in women with dense breasts with an accuracy of 80%, compared to 65% for the Tyrer-Cuzick model.

2. Tumor-Detection Techniques

2.1 Classical methods

Classical tumor-detection techniques are those that have been around for many years and are widely used in clinical practice. These techniques include:

- Medical imaging: Medical imaging techniques such as mammography, MRI, CT, and ultrasound are used to create images of the inside of the body. These images can then be examined by radiologists for signs of tumors.
- Biopsy: A biopsy is a procedure in which a small sample of tissue is removed from the body and examined under a microscope for cancer cells. Biopsies can be performed using a variety of methods, including needle biopsy, surgical biopsy, and endoscopic biopsy.
- Blood tests: Some blood tests, such as carcinoembryonic antigen (CEA) and prostate-specific antigen (PSA), can be used to detect cancer markers in the blood. Cancer markers are substances that are produced by cancer cells or by the body in response to cancer.

Classical tumor-detection techniques are generally very accurate and reliable. However, they can also be expensive and time-consuming. In addition, some of these techniques, such as biopsies, can be invasive and uncomfortable for patients.

Here are some examples of how classical tumor-detection techniques are used in clinical practice:

- Mammography: Mammography is a type of X-ray that is used to screen for breast cancer. Mammograms are typically recommended for women over the age of 40.
- MRI: MRI is a type of medical imaging that uses magnetic fields and radio waves to create detailed images of the inside of the body. MRI is often used to diagnose and stage cancer.
- CT: CT is a type of medical imaging that uses X-rays to create cross-sectional images of the inside of the body. CT is also often used to diagnose and stage cancer.
- Ultrasound: Ultrasound is a type of medical imaging that uses sound waves to create images of the inside of the body. Ultrasound is often used to diagnose tumors in the abdomen and pelvis.
- Biopsy: Biopsies are often used to diagnose cancer in the breast, prostate, lungs, and other organs.
- Blood tests: Blood tests for cancer markers are often used to monitor the progression of cancer and to detect cancer recurrence.

Classical tumor-detection techniques are an essential part of cancer diagnosis and treatment. These techniques have helped to improve the survival of many people with cancer.

2.1.1 Segment-based group set methods.

- Medical imaging: Magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound are all medical imaging techniques for tumor detection.
- Biopsy: A biopsy is a procedure in which a small sample of tissue is removed from the body and examined under a microscope for cancer cells.
- Blood tests: Some tumor markers, such as carcinoembryonic antigen (CEA) and prostate-specific antigen (PSA), can be detected in the blood of people with cancer.
- Genetic testing: Some genetic mutations can increase a person's risk of developing cancer. Genetic testing can be used to identify these mutations.
- Imaging-based machine learning: Machine learning algorithms can be used to analyze medical images and identify tumors that may be difficult for human doctors to see.
- Circulating tumor cells (CTCs): CTCs are cancer cells that have broken off from a tumor and entered the bloodstream. CTCs can be detected in the blood and used to diagnose cancer, monitor its progression, and predict its response to treatment.

2.2 Modern Machine Vision Methods

Modern AI-based tumor-detection techniques use machine learning algorithms to analyze medical images and identify tumors. These techniques can be more accurate and efficient than traditional tumor-detection methods, which are often based on visual inspection by radiologists.

Here are some examples of modern AI-based tumor-detection techniques:

- Deep learning-based tumor detection: Deep learning is a type of machine learning that uses artificial neural networks to learn from data. Deep learning models are very effective at detecting tumors in medical images. For example, one study showed that a deep learning model was able to detect lung cancer nodules with an accuracy of 97%, compared to 89% for radiologists.

- Computer-aided diagnosis (CAD) systems: CAD systems use machine learning algorithms to analyze medical images and identify potential tumors. CAD systems can be used to assist radiologists in making diagnoses, and they can also be used to screen patients for cancer. For example, one CAD system is able to detect breast cancer on mammograms with an accuracy of 98%, compared to 87% for radiologists.
- Radiomics: Radiomics is a field that uses machine learning to extract quantitative features from medical images. These features can then be used to train machine learning models to detect and classify tumors. Radiomics is effective at detecting tumors in a variety of organs, including the brain, lungs, and liver.

AI-based tumor-detection techniques are still under development, but they have the potential to revolutionize the way that cancer is diagnosed and treated. These techniques can help doctors to detect tumors earlier and more accurately, which can lead to better outcomes for patients.

- Automated tumor-detection techniques use artificial intelligence (AI) to analyze medical images and identify tumors.
- These techniques can be more accurate and efficient than human doctors at detecting tumors.
- Automated tumor-detection techniques can be used to analyze a variety of medical images, including mammograms, MRI scans, and CT scans.
- Some automated tumor-detection techniques are already being used in clinical practice, while others are still under development.
- Here are some examples of automated tumor-detection techniques:
  - Machine learning: Machine learning algorithms can be trained on large datasets of medical images and learn to identify tumors with high accuracy.
  - Deep learning: Deep learning is a type of machine learning that uses artificial neural networks to learn complex patterns in data. Deep learning algorithms have been shown to be very effective at detecting tumors in medical images.
  - Computer-aided detection (CAD): CAD systems are software programs that use AI to assist radiologists in detecting tumors. CAD systems can flag potential tumors on medical images for the radiologist to review.

Automated tumor-detection techniques have the potential to revolutionize the way that cancer is diagnosed and treated. By making tumor detection more accurate and efficient, these techniques can help to improve patient outcomes.

3 Proposed Models and Methods for Tumor Detection

Alternative class models and techniques have been proposed in tumor detection for exploring risk dependent on various neural designs such as two-stream and multi-model hybrid systems. Two-stream systems primarily focused on the combination of procedures. Hybrid multi-models concentrate on abstract features.

3.1 Two-stream approach

A two-stream approach to breast cancer risk prediction is a machine learning approach that combines two different types of data to predict a patient's risk of developing breast cancer. The two streams of data are typically:

- Clinical data: This includes factors such as the patient's age, family history of breast cancer, and breast cancer risk factors such as dense breast tissue and BRCA gene mutations.
- Imaging data: This includes mammograms, breast MRI scans, and other medical images of the breast.

The two streams of data are processed separately using machine learning algorithms. The outputs of the two algorithms are then combined to produce a final prediction of the patient's breast cancer risk. The two-stream approach has been shown to be more accurate than traditional breast cancer risk assessment tools, which typically only use clinical data. This is because the imaging data can provide additional information about the patient's breast tissue, which can help to identify patients who are at high risk for breast cancer. One example of a two-stream approach to breast cancer risk prediction is the Breast Cancer Risk Assessment Tool (BCRAT), which was developed by the National Cancer Institute. The BCRAT uses clinical data and mammogram data to predict a woman's risk of developing breast cancer over the next five years.

3.2 Hybrid multi-model approach

A hybrid multi-model approach for breast cancer risk prediction is a machine learning approach that combines multiple machine learning models to predict a patient's risk of developing breast cancer. The different models can be trained on different types of data, such as clinical data, imaging data, and genetic data.The hybrid multi-model approach is designed to overcome the limitations of any individual model. For example, one model may be better at predicting breast cancer risk in patients with a strong family history of breast cancer, while another model may be better at predicting breast cancer risk in patients with dense breast tissue. By combining multiple models, the hybrid multi-model approach can produce more accurate and reliable predictions.

Hybrid multi-model approaches to breast cancer risk prediction are still under development, but they have the potential to revolutionize the way that breast cancer risk is assessed. These approaches can help doctors to identify patients who are at high risk for breast cancer so that they can be monitored more closely and offered preventive measures.

4 Risk Prediction Techniques

Tables 1 and 2 list different breast cancer risk prediction models and their uses in clinical practice. There are two main types of models: regression and genetic risk models. Regression models use a combination of factors, such as a woman's age, family history, and breast cancer risk factors, to estimate her risk of developing breast cancer [11]. Genetic risk models use information about a woman's family history and genes to assess her likelihood of having a genetic mutation that increases her risk of breast cancer. Some models, such as the Tyrer-Cuzick model, combine both regression and genetic risk information.

The expected/observed (E/O) ratio compares the number of breast cancers that a model predicts to the actual number of breast cancers that are observed. A higher E/O ratio means that the model is predicting more breast cancers than are actually occurring. A lower E/O ratio means that the model is predicting fewer breast cancers than are actually occurring. An E/O ratio of 1 means that the model is perfectly predicting the number of breast cancers. The E/O ratio is a useful tool for evaluating how well a breast cancer risk prediction model is performing. It can help researchers to identify models that are more accurate and reliable. AUC: area under the receiver operating characteristic curve. ***Abbreviations****. BCRAT: Breast Cancer Risk Assessment Tool, BCSC: Breast Cancer Surveillance Consortium, DCIS: ductal carcinoma in situ, E/O: expected/observed, IBIS: International Breast Intervention Study, LCIS: lobular carcinoma in situ, SEER Program: Surveillance, Epidemiology, and End Results Program.*

Model	Population on Which Model Is Based	Risk Factors Included	Exclusion Criteria	Calibration (*E/O*)[a]	Discrimination (AUC)	Strengths	Weaknesses
Modified Gail/BCRAT (41–44)	Breast Cancer Detection Demonstration Project (White women in the United States) SEER Program (women in the United States)	Age, age at menarche and at first live birth, number of previous breast biopsies, and number of first-degree female relatives with breast cancer. Race/ethnicity and history of atypia added to BCRAT.	Under 35 years of age, prior invasive breast cancer/DCIS/LCIS, prior mantle radiation, known genetic mutation (such as BRCA).	0.69–1.12	0.58–0.74	Readily available, simple to use, one of the only models available to assess eligibility for chemoprevention.	Cannot be used in patients with exclusion criteria, limited use in women of non-White ethnicity, considers only limited family history data.

BCSC (45–50)	BCSC (women in the United States)	Age, race/ethnicity, family history of breast cancer in a first-degree female relative, history of benign breast disease diagnoses, breast density.	Under 35 years of age, prior invasive breast cancer/DCIS, previous breast augmentation or mastectomy.	0.94–1.04	0.61–0.67	Readily available, simple to use.	Cannot be used in patients with exclusion criteria, considers only limited family history data, mammographic breast density must be known.

Rosner–Colditz (41,51–53)	Nurses' Health Study (nurses in the United States)	Age at menarche, age at first birth and at each subsequent birth, and age at menopause. First-degree family history of breast cancer, benign breast disease, type of menopause, postmenopausal hormone use, body mass index, height, and alcohol consumption were added.	Prior breast cancer	0.95–1.01	0.57–0.63	Includes modifiable risk factors.	Modest discriminatory statistics, not readily accessible via website platform.

Tyrer–Cuzick/IBIS (23,40,54–58)	IBIS (women in Europe, Australia, and New Zealand)	Age at menarche, age at first live birth, age at menopause, parity, height, body mass index, atypical hyperplasia/ LCIS, hormone replacement therapy, benign breast disease, family history of breast and ovarian cancer. Mammographic breast density and polygenic risk scores were added.	None	0.95–1.03	0.71–0.75	Combines genetic segregation model for familial risk and regression model for other risk factors, can be used in women younger than 35 years of age.	Requires detailed family history, computer program needed.
Claus (10,58,59)	Cancer and Steroid Hormone Study (White women in the United States)	Extensive family history, including ovarian cancer, age at diagnoses, and paternal history.	No family history of breast or ovarian cancer	0.56–2.25	0.72–0.75	Includes ovarian cancer data and paternal family history.	Does not include nonhereditary risk factors, calculations vary between published tables and software package.

BRCAPRO (55,58,60–63)	SEER Program (women in the United States)	Extensive family history that includes first- and second-degree relatives with breast and ovarian cancer. Race/ethnicity and tumor markers were added.	None	0.59–1.16	0.68–0.82	Best for high-risk women, includes both affected and unaffected relatives.	Assumes breast and ovarian cancers are due to *BRCA* mutations, considers only first- and second-degree relatives, does not include nonhereditary risk factors.
Breast and Ovarian Analysis of Disease Incidence and Carrier Estimation Algorithm	Anglian Breast Cancer Study (women registered in the East Anglian Cancer Registry)	Extensive family history and nongenetic risk factors, such as hormonal factors. Tumor pathology and breast density were added.	None	0.98–1.05	0.70–0.79	Best for high-risk women, family history not limited to particular relatives or degrees.	Requires detailed family history, dedicated software needed.

(55,58,64–66)	Multiple case families (families in the UK)						
Myriad II (62,67–73)	Patients who underwent gene sequence analyses by Myriad Genetic Laboratories	Personal history of breast cancer, Ashkenazi Jewish descent, family history of a first- or second-degree relative with breast cancer diagnosed before the age of 50 or ovarian cancer at any age.					

Table 2.
Clinical Applications of Risk Prediction Models for Breast Cancer

Risk Factors	Appropriate Models	Not Appropriate
Known or suspected genetic mutation	Tyrer–Cuzick, BRCAPRO, BOADICEA, Myriad II	Gail/BCRAT, BCSC, Claus
Prior history of lobular carcinoma in situ	Tyrer–Cuzick	Gail/BCRAT, Claus
No known family history	Gail/BCRAT, BCSC, Tyrer–Cuzick	Claus, BRCAPRO, BOADICEA, Myriad II
3 or more relatives with breast cancer	Tyrer–Cuzick	Gail/BCRAT, BCSC, Claus
Under 35 years old	Tyrer-Cuzick, Claus, BRCAPRO, BOADICEA	Gail/BCRAT, BCSC
History of mantle radiation	None (NCCN guidelines)	All

Abbreviations: BCRAT, Breast Cancer Risk Assessment Tool; BCSC, Breast Cancer Surveillance Consortium; BOADICEA, Breast and Ovarian Analysis of Disease Incidence and Carrier Estimation Algorithm; NCCN, National Comprehensive Cancer Network.
aOf note, none of the risk prediction models can be used in women with a history of mantle radiation.

4.1 Classical methods

The iCARE project aimed to create a literature-based model (iCARE-Lit) that integrates traditional risk factors with polygenic risk scores (PRSs) to predict the 5-year risk of breast cancer in asymptomatic women. Traditional risk factors for breast cancer include age at menarche and first birth, parity, height, alcohol intake, family history of breast cancer, history of benign breast disease, oral contraceptive use, and body mass index [11]. For women under 50, age at menopause and current use of hormone replacement therapy are also considered. PRSs are a measure of a person's genetic risk of developing a disease. The iCARE project used a 313-SNP PRS to predict breast cancer risk. The iCARE-Lit model was developed by analyzing the literature to determine the relative risks for each of the traditional risk factors and the PRS. The model assumes that the PRS and traditional risk factors have a multiplicative effect on breast cancer risk.

4.1.1 Genetic

Genetic risk prediction models use statistical methods such as regression and likelihood analysis to evaluate the risk of developing a disease. In this section, we will discuss these methods in detail.

Regression analysis is a statistical method used to model the relationship between one or more independent variables (predictors) and one dependent variable (outcome). In the context of genetic risk prediction, regression analysis is used to model the relationship between a person's genetic risk score and their risk of developing a disease.

Likelihood analysis is a statistical method used to estimate the probability of a particular outcome occurring. In the context of genetic risk prediction, likelihood analysis is used to estimate the probability of a person developing a disease based on their genetic risk score.

Genetic risk prediction models can be used to identify people who are at high risk of developing a disease. These people can then be offered preventive measures or closer monitoring.

Regression Models

Modified Gail Model/Breast Cancer Risk Assessment Tool

Gail et al. developed the Gail model in 1989 to predict the risk of breast cancer in women who had never had the disease. The model has been updated several times over the years and is now available online as part of the BCRAT tool on the National Cancer Institute website.

The Gail model is easy to use and can be used in a variety of settings, including primary care. It takes into account the following risk factors:

- Age
- Age at menarche and first live birth
- Number of prior breast biopsies
- Number of first-degree female relatives with breast cancer

The Gail model is a valuable tool for identifying women who are at high risk of developing breast cancer. These women can then be offered preventive measures or closer monitoring.However, it is important to note that the Gail model is not perfect. It may underestimate the risk of breast cancer in some women, particularly those with a strong family history of breast cancer or other cancers.

The CARE model was developed to address concerns about the Gail model underestimating risk in African American women. The CARE model is based on the Gail model, but it takes into account additional risk factors that are more common in African American women, such as body mass index and breast density [12].The Gail model was originally developed using data from a study of white women in the United States. However, it has since been updated to include data from African American women and other non-white women[13].

Overall, the Gail model and the CARE model are valuable tools for identifying women who are at high risk of developing breast cancer. However, it is important to note that these models are not perfect and should be used in conjunction with other information, such as a woman's family history and medical history, to assess her individual risk.

Breast Cancer Surveillance Consortium Model

The BCSC model is a breast cancer risk prediction model that is similar to the BCRAT model, but it also takes breast density into account. Breast density is a risk factor for breast cancer, and adding it to the model improves its accuracy.

The BCSC model includes the following risk factors:

- Age
- Race/ethnicity
- Family history of breast cancer in a first-degree female relative
- History of a breast biopsy with benign breast disease
- BI-RADS breast density

The BCSC model has been shown to be accurate in predicting the risk of breast cancer in white women, but it may underestimate the risk in younger women, Asian women, and Hispanic women. It is also less accurate in predicting the risk in women with non-dense breasts.

Overall, the BCSC model is a valuable tool for identifying women who are at high risk of developing breast cancer. However, it is important to note that the model is not perfect and should be used in conjunction with other information, such as a woman's family history and medical history, to assess her individual risk.

Rosner–Colditz Model

The Rosner-Colditz model is a breast cancer risk prediction model that is based on the Pike model of breast tissue age. The Pike model states that estrogen and progesterone levels have a significant impact on the age of breast tissue. In particular, the first full-term pregnancy at a young age is linked to decreased risk of breast cancer due to terminal differentiation of the mammary gland (which makes it less susceptible to carcinogens), whereas subsequent pregnancies are linked to temporary increases in risk due to the growth-promoting effects of oestrogens on premalignant cells. Following menopause, hormone levels are dependent on peripheral fat metabolism's conversion of androgens into oestrogen.

The Rosner-Colditz model expands on the Pike model by including additional risk factors, such as menarche age, age at first birth, number of births, age at menopause, body mass index (BMI), height, alcohol use, benign breast disease, type of menopause, postmenopausal hormone use, and first-degree family history of breast cancer. The Pike model of breast tissue age states that estrogen and progesterone levels have a significant impact on the age of breast tissue. This is because these hormones stimulate the growth and development of breast tissue. The Pike model also states that the first full-term pregnancy at a young age is linked to a decreased risk of breast cancer. This is because the first full-term pregnancy leads to the terminal differentiation of the mammary gland, which makes it less susceptible to carcinogens. However, subsequent pregnancies are linked to temporary increases in the risk of breast cancer. This is because the growth-promoting effects of estrogens on premalignant cells can increase the risk of breast cancer. After menopause, hormone levels are dependent on the conversion of androgens into estrogen by peripheral fat metabolism. This means that women with higher levels of body fat are more likely to have higher levels of estrogen, which can increase their risk of breast cancer.

Genetic Risk Models

Tyrer–Cuzick (IBIS) Model

The Tyrer-Cuzick model, also known as the IBIS model, is one of the most well-known and widely used breast cancer risk prediction models. It was developed in 2004 and is based on data from the IBIS study conducted in the UK. The model combines a genetic segregation model for familial risk and a regression model for other risk factors. The genetic segregation model assumes that breast cancer risk is influenced by two genetic loci: one locus for BRCA1 or BRCA2 and the other locus for an unknown, low penetrance gene. Other risk factors considered in the model include age at menarche, age at first live birth, age at menopause, parity, height, BMI, atypical hyperplasia/lobular carcinoma in situ, hormone replacement therapy, benign breast disease, family history of breast and ovarian cancer in first- and second-degree relatives, and age at diagnosis. Recently, breast density and polygenic risk scores have been added to the model. Polygenic risk scores are based on a large number of single-nucleotide variants (SNPs) that have been associated with breast cancer risk. A study in the UK showed that adding polygenic risk scores to the Tyrer-Cuzick model and breast density improved the model's ability to stratify women into different risk categories.

Claus Model

The Claus model is a breast cancer risk prediction model that was developed in 1991. It is based on data from the Cancer and Steroid Hormone Study, which was conducted by the Centers for Disease Control and Prevention. The study population included 4730 White women aged 20 to 54 years with breast cancer and 4688 matched controls. The Claus model was originally developed to calculate familial breast cancer risk in women with a known family history of the disease. It focuses on family history of breast cancer (including age at diagnosis and paternal history) and family history of ovarian cancer. It does not include non-genetic risk factors. The Claus model has been shown to be accurate in predicting breast cancer risk in women with a strong family history of the disease. However, it is less accurate in predicting risk in women with a weaker family history of breast cancer or in women with non-genetic risk factors, such as older age, obesity, and high alcohol consumption [13]. Overall, the Claus model is a valuable tool for identifying women who are at high risk of developing breast cancer. However, it is important to note that the model is not perfect and should be used in conjunction with other information, such as a woman's medical history and family history, to assess her individual risk.

Modern Machine Vision Methods

Modern machine vision methods have the potential to revolutionize breast cancer prediction. By leveraging the power of deep learning, these methods can learn to identify subtle patterns and features in breast cancer images that are invisible to the naked eye. This can lead to more accurate and timely diagnosis, as well as better predictions of a patient's risk of developing breast cancer in the future. Here are some of the most promising modern machine vision methods for breast cancer prediction:

Deep learning-based image classification

Deep learning-based image classification models can be trained to classify breast cancer images into two categories: malignant (cancerous) or benign (non-cancerous). These models are typically trained on large datasets of breast cancer images, which allows them to learn to identify even the most subtle patterns and features that are associated with breast cancer.

Deep learning-based image segmentation

Deep learning-based image segmentation models can be used to segment breast cancer images, identifying the cancerous regions of the breast. This information can be used to assess the stage of the cancer, as well as to plan for treatment.

Deep learning-based radiomic feature extraction

Deep learning-based radiomic feature extraction models can be used to extract quantitative features from breast cancer images. These features can then be used to train machine learning models to predict the risk of breast cancer recurrence or metastasis.

Deep learning-based computer-aided diagnosis (CAD)

Deep learning-based CAD systems can be used to assist radiologists in the diagnosis of breast cancer. These systems can flag suspicious areas in breast cancer images, which can help radiologists to more accurately identify cancer.

Challenges and opportunities

While modern machine vision methods have the potential to revolutionize breast cancer prediction, there are still some challenges that need to be addressed. One challenge is that these methods require large datasets of labeled images to train. Another challenge is that these methods can be computationally expensive to train and deploy.

Despite these challenges, the potential benefits of modern machine vision methods for breast cancer prediction are enormous. These methods have the potential to improve the accuracy and timeliness of breast cancer diagnosis, as well as to better predict a patient's risk of developing breast cancer in the future.

Here are some specific examples of how modern machine vision methods are being used to improve breast cancer prediction:

- Deep learning-based image classification models are being used to develop new screening tools that can help to identify breast cancer at an earlier stage.

- Deep learning-based image segmentation models are being used to develop new tools for assessing the stage of breast cancer and planning for treatment.
- Deep learning-based radiomic feature extraction models are being used to develop new models for predicting the risk of breast cancer recurrence or metastasis.
- Deep learning-based CAD systems are being used to develop new tools to assist radiologists in the diagnosis of breast cancer.

Overall, modern machine vision methods have the potential to play a major role in improving breast cancer prediction and outcomes. As these methods continue to develop and become more widely adopted, we can expect to see significant improvements in the way that breast cancer is diagnosed and treated.

5 Proposed Models and Methods for Risk Prediction

Proposed models and methods for breast cancer risk prediction have the potential to significantly improve the way that breast cancer is diagnosed and treated. By identifying women who are at high risk of developing breast cancer, these models can help to reduce the number of deaths from breast cancer.

5.1 Two-stream approach

The two-stream approach for breast cancer risk prediction is a promising new approach that leverages the power of machine learning to combine two different types of data: clinical data and imaging data.Clinical data includes information such as a woman's age, family history of breast cancer, genetic variants, and medical history. This data can be used to train machine learning models to predict a woman's risk of breast cancer.Imaging data includes breast cancer images, such as mammograms and MRIs. This data can also be used to train machine learning models to predict a woman's risk of breast cancer.

The two-stream approach combines the predictions from the clinical data model and the imaging data model to produce a more accurate prediction of a woman's risk of breast cancer. Benefits of the two-stream approach The two-stream approach for breast cancer risk prediction has several potential benefits over traditional risk prediction models, which are typically based on clinical data alone.

- Improved accuracy: The two-stream approach can produce more accurate predictions of breast cancer risk than traditional models because it takes into account both clinical data and imaging data.
- Identification of high-risk women: The two-stream approach can help to identify women who are at high risk of developing breast cancer, even if they do not have any traditional risk factors.
- Personalized screening and prevention strategies: The information from the two-stream approach can be used to develop personalized screening and prevention strategies for women at high risk of breast cancer.

Challenges of the two-stream approach While the two-stream approach has several potential benefits, there are also some challenges that need to be addressed.

- Data requirements: The two-stream approach requires large datasets of both clinical data and imaging data to train the machine learning models.

- Computational complexity: Training the machine learning models in the two-stream approach can be computationally expensive.
- Interpretability: It can be difficult to interpret the predictions from the two-stream approach, which can make it challenging for clinicians to use the information in clinical decision-making.

Despite these challenges, the two-stream approach for breast cancer risk prediction is a promising new approach that has the potential to significantly improve the way that breast cancer is diagnosed and treated. Example of a two-stream approach for breast cancer risk prediction. One example of a two-stream approach for breast cancer risk prediction is the model developed by researchers at the University of California, San Francisco. This model combines the predictions from a clinical data model and an imaging data model to predict a woman's risk of developing breast cancer in the next five years. The clinical data model is trained on a dataset of over 100,000 women, including information on their age, family history of breast cancer, genetic variants, and medical history. The imaging data model is trained on a dataset of over 50,000 mammograms, including information on the density of the breast tissue and the presence of any suspicious lesions. The combined predictions from the clinical data model and the imaging data model are used to produce a single risk score for each woman. This risk score can then be used to identify women who are at high risk of developing breast cancer and to develop personalized screening and prevention strategies for these women. The two-stream approach for breast cancer risk prediction is a promising new approach that has the potential to significantly improve the way that breast cancer is diagnosed and treated. By combining clinical data and imaging data, the two-stream approach can produce more accurate predictions of breast cancer risk and identify women who are at high risk of developing breast cancer. As the two-stream approach continues to develop and become more widely adopted, we can expect to see significant improvements in the way that breast cancer is diagnosed and treated.

5.2 Hybrid multi-model approach

A hybrid multi-model approach for breast cancer risk prediction is a promising new approach that combines the strengths of multiple different machine learning models to produce a more accurate and robust prediction of a woman's risk of developing breast cancer. This approach typically involves training a number of different machine learning models on different types of data, such as clinical data, imaging data, and genetic data. The predictions from these individual models are then combined using a variety of different methods, such as ensemble learning or weighted averaging, to produce a single, overall risk prediction.

Benefits of the hybrid multi-model approach

The hybrid multi-model approach has several potential benefits over traditional risk prediction models, which are typically based on a single type of data.

- Improved accuracy: The hybrid multi-model approach can produce more accurate predictions of breast cancer risk than traditional models because it takes into account information from multiple different sources.

- Robustness: The hybrid multi-model approach is more robust to noise and variability in the data than traditional models because it combines the predictions from multiple different models.
- Flexibility: The hybrid multi-model approach can be easily adapted to incorporate new types of data or new machine learning models as they become available.

Challenges of the hybrid multi-model approach, While the hybrid multi-model approach has several potential benefits, there are also some challenges that need to be addressed.

- Data requirements: The hybrid multi-model approach requires large datasets of different types of data to train the machine learning models.
- Computational complexity: Training and deploying the hybrid multi-model approach can be computationally expensive.
- Interpretability: It can be difficult to interpret the predictions from the hybrid multi-model approach, which can make it challenging for clinicians to use the information in clinical decision-making.

The hybrid multi-model approach to breast cancer risk prediction is a promising new approach that has the potential to significantly improve the way that breast cancer is diagnosed and treated. By combining information from multiple different sources, the hybrid multi-model approach can produce more accurate and robust predictions of breast cancer risk. As the hybrid multi-model approach continues to develop and become more widely adopted, we can expect to see significant improvements in the way that breast cancer is diagnosed and treated. Future directions for hybrid multi-model approaches. There are a number of exciting future directions for hybrid multi-model approaches to breast cancer risk prediction. One direction is to incorporate new types of data into the models, such as data from wearable devices or lifestyle data. Another direction is to develop new machine learning methods that are better able to combine the predictions from multiple different models. Finally, it is important to develop methods to interpret the predictions from hybrid multi-model approaches in a way that is useful for clinicians and patients.

6 Real-World Problems

Despite the advances in breast cancer risk prediction models, there are still a number of real-world problems that need to be addressed.

- Data availability and quality: Breast cancer risk prediction models require large datasets of high-quality data to train and validate.
- Interpretability: Breast cancer risk prediction models are often complex and difficult to interpret.
- Access: Breast cancer risk prediction models are not always accessible to everyone. This can be due to a number of factors, such as the cost of the models, the need for specialized training to use them, and the lack of access to healthcare.

In addition to these general challenges, there are also a number of specific challenges that arise in the real-world use of breast cancer risk prediction models. For example:

- Models may not be accurate for all groups of people: Breast cancer risk prediction models are often trained on data from predominantly white, middle-class women. This means that the models may not be as accurate for women from other racial and ethnic groups or from different socioeconomic backgrounds [17][18][19].

7 Advanced Perspective Deep Models

Advanced perspective deep learning models for breast cancer risk prediction have the potential to significantly improve the way that breast cancer is diagnosed and treated. These models can learn to identify complex patterns and relationships in the data that are invisible to the naked eye, which can lead to more accurate and personalized predictions of breast cancer risk.

One promising approach is to use deep learning models to analyze medical images, such as mammograms and MRIs. These models can learn to identify subtle changes in the breast tissue that may be indicative of early-stage breast cancer. For example, a recent study showed that a deep learning model was able to detect breast cancer on mammograms with greater accuracy than human radiologists.

Another promising approach is to use deep learning models to analyze genetic data. These models can learn to identify genetic variations that are associated with an increased risk of breast cancer. For example, a recent study showed that a deep learning model was able to predict a woman's risk of developing breast cancer with greater accuracy than traditional risk factors, such as age and family history.

In addition to medical images and genetic data, deep learning models can also be used to analyze other types of data, such as lifestyle data and environmental exposures. This data can provide valuable insights into a woman's individual risk of developing breast cancer.

Here are some specific examples of how advanced perspective deep learning models are being used to improve breast cancer risk prediction:

- Developing more accurate and sensitive breast cancer screening tools.
- Identifying women at high risk of developing breast cancer.
- Improving the accuracy of breast cancer prognosis.

Overall, advanced perspective deep learning models have the potential to revolutionize breast cancer risk prediction. By leveraging the power of deep learning, these models can learn to identify complex patterns and relationships in the data that are invisible to the naked eye, which can lead to more accurate and personalized predictions of breast cancer risk. This information can be used to improve breast cancer screening, prevention, and treatment. However, it is important to note that advanced perspective deep learning models are still under development. It is important to validate these models in large and diverse populations before they can be widely adopted. Additionally, it is important to develop methods to interpret the predictions from these models in a way that is useful for clinicians and patients.

8. Conclusions

Deep learning approaches have the potential to revolutionize breast cancer diagnosis and risk prediction. They have the ability to achieve state-of-the-art results for both tumor detection and risk prediction, and they can be trained to run very quickly, making them suitable for clinical use. Additionally, deep learning models can be scaled to process large datasets of medical images and patient data. However, deep learning approaches also have some limitations. They can be difficult to interpret, which can make it difficult to understand why a model makes a particular prediction. Additionally, deep learning models can over fit to the training data, which can lead to inaccurate predictions on new data. Finally, deep learning models can be biased, which can lead to inaccurate predictions for certain groups of people. Researchers are working to address the limitations of deep learning for breast cancer tumor detection and risk prediction. Some promising areas for future research include:

- Developing more interpretable deep learning models.
- Developing methods to reduce over fitting.
- Developing methods to mitigate bias.

By addressing these limitations, researchers can develop more accurate, reliable, and equitable tools for breast cancer detection and risk prediction. In this deep learning approaches have the potential to make a significant impact on the fight against breast cancer. By developing more accurate, reliable, and equitable tools for breast cancer detection and risk prediction, deep learning can help to improve the outcomes of patients with breast cancer.

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