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Artificial intelligence in diagnosing breast cancer imaging profile than other predicting markers. Current and best future emerging technology

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Abstract

Purpose: This research aims to underscore the significance of artificial intelligence in diagnosing breast cancer, contributing to precision medicine, and delves into current advancements and future requirements. **Procedure:** The data was collected from already published work on breast cancer imaging profile. Different websites including Google scholar etc were employed to fetch the relevant data for the current study. **Results:** The study reveals that diverse tools have been employed for precise image interpretation, assisting clinicians in prescribing accurate medications for more effective treatments. Artificial intelligence helps in medical science, such as computer-aided exposure and disease analysis, case-dependent reasoning, reasonable artificial intelligence, osteodetect method, and rainbow boxes, have demonstrated efficacy in diagnosing breast cancer. Different tools including Support vector machine, Cascade forward back-propagation network, Feed forward back-propagation network , k-nearest neighbor, Genetic algorithm as optimizer, Naive Bayes classifier, Deep learning technology show best performance for image processing and helpful in better medication prescriptions. **Conclusion:** In conclusion, it is crucial to recognize that the importance of artificial intelligence in interpreting breast imaging is evolving, not as a replacement for radiologists, but as a valuable aid, introducing new, effective, and efficient AI methodologies. Ongoing efforts are essential to further enhance artificial intelligence applications for more impactful outcomes in near future.

Keywords: Breast cancer, Mammography, Artificial intelligence, Computer-aided technique, Deep learning.

Introduction

Breast cancer BC remains the predominant cancer affecting females around world, ranks second in BC mortality with a death rate of 12.9 per 100k people. The frequency of breast cancer has shown an upward trend over the years (1-4). In US and the UK collectively, more than 42 million examinations are conducted annually (5, 6). Additionally, the prevalence of this disease is pronounced in less developed countries (2, 7). Notably, about 15% of all BC manifest as triple-negative breast cancer TNBC (8).

A paramount area of research centers on the application of image scrutiny in diverse clinical domains, encompassing breast tomography, numerical pathology, surgical preparation, and results assessment. The substantial volume of annotated digital imaging data, featuring well-defined features in both transmission and analysis, has facilitated the emergence of machine-learning-based results poised to integrate seamlessly into our medical practices in the imminent future (9). The study reveals that diverse tools have been employed for precise image interpretation, assisting clinicians in prescribing accurate medications for more effective treatments.

Breast cancer classification and predictor markers

In the context of early-stage BC, management choices are influenced by distinct clinical subtypes: (ER+ HER2−), amplified (HER2+), and (TNBC). These subtypes are characterized by existence or absence of receptors, and HER2 overexpression. However, this overarching arrangement fails to consider the substantial tumor evolution that occurs during disease progressions, influenced by selective pressure (10-14). For an extended period, the assessment of (ER) and (PR) status has been a key factor in establishing a patient's eligibility for endocrine therapy. More recently, the routine patient evaluation has incorporated testing for (HER-2/neu). This inclusion is driven by the acknowledgment of its significance, not only as a prognostic marker but especially in forecasting the response to trastuzumab (15).

TNBC is characterized by without (ER), (PR), and (HER2) overexpression. As per the guidelines established by the American Society of Clinical Oncology, ER/PR are deemed negative when less than 1% of tumor cells exhibit nuclear staining through immunohistochemistry (16, 17). TNBC manifests as a biologically and clinically diverse ailment, displaying a higher prevalence among young females and those with BRCA1 mutations. In recent years, various gene-expression-dependent classification for TNBC have surfaced (18-20). While many triple negative cases, identified through immunohistochemistry, align with the basal-like intrinsic subtype, a smaller subset falls into the non-basal-like category. This includes subtypes such as the luminal androgen receptor subtype and the HER2-enriched subtype

Mammography used for diagnosis

Mammographic screening initiatives have demonstrated a relative reduction of 20%-40% in breast cancer incidence (21, 22). However, the masking effect of dense breast tissue can result in the oversight of cancers during routine mammography screenings. Consequently, new guidelines are being formulated for females with dense breast undergoing screening, prompting the exploration of novel multimodality breast imaging techniques. These include full-field digital mammography (FFDM), dynamic contrast-enhanced (DCE), breast magnetic resonance imaging (MRI), digital breast tomosynthesis (DBT), and breast ultrasound, either as standalone methods or as adjuncts to mammographic screening (23-26). While mammography has gained extensive use, the interpretation of these images continues to pose challenges. Substantial variability exists in the accuracy of cancer detection among experts, and even the most skilled clinicians demonstrate room for improvement in their performance. The occurrence of false positive can contribute to patient depression, needless follow-up procedures, and invasive analytical interventions (27-29).

The successful treatment of breast cancer relies on early detection. Therefore, it is crucial to employ effective screening methods for identifying the initial signs of breast cancer. Several imaging techniques are available for breast cancer screening and diagnosis, with mammography, ultrasound, and thermography standing out as the most significant (30, 31). Mammography holds a key role as an early diagnostic method for breast cancer. However, for dense breasts where mammography may be less effective, ultrasound or diagnostic sonography techniques are recommended. Recognizing that small masses may go undetected by radiography, thermography emerges as a potentially more powerful tool for diagnosing smaller cancerous masses compared to ultrasound (32, 33).

Conventional methods benefits and their drawbacks

There are many advantages and drawbacks of conventional methods of diagnosis.

Advantage

Mammography offers benefits by utilizing low levels of X-rays for imaging, making it particularly effective in detecting ductal carcinoma in situ (DCIS) and calcification. It serves as the gold standard for identifying early-stage BC before lesions become clinically intense. On the other hand, ultrasounds are widely available, easily accessible, noninvasive, and provide quick results. They exhibit high sensitivity, making them suitable for women with dense breasts. Thermography is a noninvasive method, further adding to the array of options available for breast cancer detection (31).

Drawbacks

Mammography has its drawbacks, including the associated radiation risks and other potential threats like wrong alarms. The low contrast in mammograms makes it challenging for radiologists to interpret results accurately. Double reading of mammograms increases the overall price of recognition. Mammography, when used alone, may miss many cancer types in women with dense breasts. Ultrasounds, while widely accessible, have limitations. The quality and clarification of ultrasound images are highly dependent on persons skill conducting scan. Thermography, as a method, faces challenges related to image quality and resolution. Physicians may encounter difficulty interpreting images due to the low quality images captured by old infrared imaging cameras (31).

Artificial intelligence AI

Over the past decades, the potency of AI in various systematic domains, especially in medication, has emerged as a valuable means for effective analysis and disease management (34). The integration of radiomics and AI holds the potential to furnish clinicians and patients with information that can guide treatments, personalize therapeutic strategies, minimize delays in diagnosis, and may even contribute to the field of preventative oncology (35).

Artificial intelligence (AI) holds unique potential to address challenges in the field. Recent studies have shown that AI can not only match but also surpass the performance of human professionals in various medical image scrutiny tasks. With less mammography experts posing a threat to the capability of breast screening facilities globally, the scalability of artificial intelligence presents an opportunity to enhance access to good-quality treatment for a broader population (36-44).

The additional papers featured the application of artificial intelligence in various aspects of breast imaging, including transmission, analysis, and prediction, along with predicting cancer response to treatment. These papers provide comprehensive reviews and discussions that consider the current status of previous roles (45-48). Artificial intelligence stands to enhance efficiency in screening plans loaded by screen-reading workloads and can complement radiologists' interpretation. They delve into various approaches to integrating AI into screening in this issue (47), while others emphasize the necessary paths for validating and diversifying algorithms to ensure their applicability in screening practices (45).

Computer-aided detection CAD technique

The introduction of (CAD) software for mammography occurred in the 1990s, and various assistive tools have received approval for medical use. Despite initial optimism, this initial wave of software in the 1990s failed to demonstrate improvements in reader performance in practical, real-world settings (28, 49-53). However, there has been a resurgence in the field more recently, attributed to the success of deep learning techniques. Some studies have indicated that breast cancer prediction systems leveraging deep learning exhibit standalone performance that approaches that of human experts (54, 55).

CAD, a type of artificial intelligence assistance, has been in development and clinical use since 1996 (56-58). As computers have advanced in terms of both computing power and memory, there has been rapidly increasing in exploring the applications of artificial intelligence in different tasks within breast imaging. This extends beyond the early use in CAD to encompass analysis, prediction, response to therapies, risk valuation, and even in the discovery of cancer. Artificial intelligence approaches are evolving for computer-aided detection (CADe) and analysis (CADx), for triaging (CADt), and with aspirations for autonomous reading, sometimes without adequate attention for its impact on radiologists' observation, cognitive presentation, and workflow.

Applications of conventional methods and AI

Mammography indeed plays a crucial role as the gold standard in imaging and diagnosing early stages of breast cancer. Ultrasounds are particularly suitable for imaging dense and soft tissues, providing valuable information in various medical contexts. Thermography, on the other hand, is often deemed suitable for visualizing temperature variations and blood flow, making it applicable for examining muscle tissues. Each imaging modality has its unique strengths and applications, contributing to a comprehensive approach in the diagnosis and evaluation of breast health (31).

AI role in medical science encompass a range of functionalities, including CAD and disease analysis, case-dependent reasoning, reasonable AI, osteodetect machine learning, and rainboxes (34). When applied to digital pathology for BC, machine learning offers analytical and predictive application that not only complements the daily work of breast pathologists but also enhance diagnostic precision. As outlined in a comprehensive review (59), AI in breast cancer pathology has the potential to provide information beyond what can be gleaned through visual assessment alone, and may even offer a cost-effective alternative to certain expensive multigene assays. Unlike imaging and pathology, where AI tools are already present and important applied search exists, the subspecialties in local handlings of BC are comparatively lagging behind in the adoption of artificial intelligence applications. The utilization of artificial intelligence in the context of local treatments for BC has not progressed as extensively, highlighting a gap in the integration of AI technologies within this specific domain of medical practice (9).

The continuous development of deep learning (DL) and artificial intelligence techniques for different computer-aided detection applications is a continuing process. However, as of now, there have been no clinical research conducted to comprehensively assess the influence of new generation of artificial intelligence -based CAD on clinicians. In the realm of breast imaging, a particularly intriguing application is the use of AI to alleviate radiologists' workload in broadcast mammography, which represents the highest volume in breast imaging but with a relatively low cancer frequency of less than 1%. While several studies explored the probability of employing artificial intelligence-based CAD for screening mammograms as either low risk or high risk for BC, enabling radiologists to arrange their reading and enhance workflow, substantial clinical validation is still required in this evolving field (60). The figure 1 shows the previous methods and current AI impact in breast cancer image processing.

AI role in diagnosis

In early 1980s, a notable rise in application of neural network in fields of image and signal processing. Given the inherent difficulty in diagnosing breast cancer, statistical methods and (AI) methods have become crucial in this context. Artificial intelligence is defined as an intelligent machine capable of responding to diverse situations similar to an intelligent human. This encompasses understanding complex scenarios, feigning intellectual procedures and human reasoning approaches, as well as indicating accurate responses, learning capabilities, knowledge acquisition, and reasoning skills for problem-solving (61, 62). For instance, they utilized a particle swarm-optimized wavelet neural network (PSOWNN) to identify BC in mammograms. This technique, useful with real data, demonstrated a sensitivity and accuracy of 94% and 92%, respectively. The results indicated an outstanding presentation with an area under receiver operating characteristic (ROC) arch of 0.96. Additionally, new tools, including image processing tools, have been established to enable the analysis of BC masses. Image processing approaches contribute to the identification of abnormal features in medical images. Through the integration of image processing, pattern recognition, and artificial intelligence, scholars have successfully devised techniques that accurately detect breast cancer masses (31).

The evaluation of a breast lesions for analysis takes place during the examination following its detection through screening mammography or alternative methods, like physical breast exam. This process involves classifying the lesions rather than localizing it, as is the case in screening. In screening scenarios, radiologists assign a BI-RADS rating to a detected suspicious lesion, demonstrating either it is normal (BI-RADS 5 1), probably benign (BI-RADS 5 2), and uncertain, needing further investigation (BI-RADS 5 0) (63). In the diagnostic phase, the objective is to evaluate the probability of the lesion being cancerous and determine whether a biopsy is necessary for pathological confirmation. Multiple imaging modes, like mammography, ultrasound (64), or MRI (26), are often used to enhance the characterization of the suspicious lesion. Upon confirming a cancer diagnosis, additional imaging of tumor is performed to assess the extent of disease, aiding in determining patient management. Therefore, artificial intelligence plays a role in integrated diagnostics. This is indicated in figure 1.

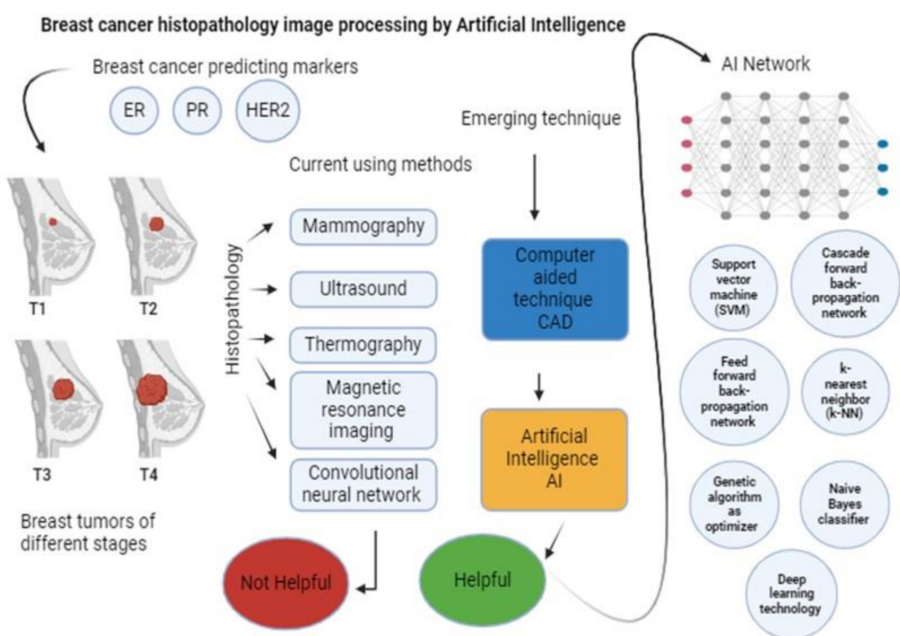

Figure 1: Indicates the previous methods and current AI role in diagnosing breast cancer images

Different AI techniques to process images

Different AI techniques play role in good processing of breast cancer imaging. This is indicated in figure 1.

Support vector machine (SVM)

The extensively employed method for diagnosing BC is Support Vector Machine. SVM is a prominent algorithm inspired by statistical learning model and has become an integral part of machine learning. This technique addresses the overfitting issue in training data, allowing the identification of a large training set with smaller subsets of training points. Additionally, SVM has the capability to operate on optional features without the requirement to generate independent hypotheses. Its versatility and effectiveness make SVM a valuable tool in the realm of breast cancer diagnosis within the machine learning framework (65-67)

Cascade forward back-propagation network

In this network, the postpropagation algorithm could be a method for updating weights during or after the backpropagation process. The statement about every layer of neuron being linked to all early neuron layers suggests a fully connected architecture, where every neuron is connected to other neurons in previous layers (68).

Feed forward back-propagation network

The described model is a standard feedforward neural network architecture, comprising inputs, outputs, and unseen layers. It employs the widely used backpropagation learning algorithm for training. During the training process, data is input into the network, and computations are conducted sequentially from the input layer to hidden and then to output layers, producing predictions. Subsequently, the error or the disparity between the predicted output and the actual target is computed. The backpropagation algorithm is then employed to propagate this error backward through the layers. As a result, the weights of the connections between neurons are iteratively adjusted to minimize the error, enhancing the network's capability to make precise predictions. The connectivity of each layer to the previous layers enables the network to capture intricate relationships within the data, facilitating the learning process (68).

k-nearest neighbor (k-NN)

This algorithm operates by selecting a group of K records from training dataset that are close to test record in terms of similarity or distance metrics. The algorithm then makes a decision about the class of test record depends on the majority class within this selected neighborhood. In other words, it looks at the labels or classes of the K nearest records and assigns the class that occurs most frequently among them to the test record. This straightforward approach makes k-NN a simple and intuitive algorithm for classification tasks, where the class of a data point is determined by the classes of its nearest neighbors in the feature space (69).

Genetic algorithm as optimizer

The genetic algorithm is known for its ability to efficiently explore a wide range of potential solutions and eliminate suboptimal choices without compromising the final outcome. It operates based on its own set of rules, making it particularly suitable for solving problems that are defined in irregular or unconventional ways. The algorithm mimics the process of natural selection, involving the evolution of a population of potential solutions over successive generations. By applying principles such as selection, crossover, and mutation, the genetic algorithm iteratively refines the candidate solutions, converging towards an optimal or near-optimal solution for complex problems with irregular structures or unconventional definitions (67, 70).

Naive Bayes classifier

In a Naive Bayes classifier, the possibility of a particular class given a set of structures is calculated using Bayes' theorem. The model makes the simplifying assumption that the features are independent given in the class. The key advantage of this process is simplicity and efficiency. It performs well in scenarios with high-dimensional data and can handle categorical and continuous features. It is particularly effective in situations with a limited amount of training data, making it suitable for cases where collecting large labeled datasets is challenging (71).

Deep learning technology

In this system, a convolutional neural network (CNN), the architecture is characterized by a series of image processing layers that far surpass conservative image feature-based machine learning identifiers. Every layer within the network, including convolutional, pooling, and fully connected layers, constitutes a neural network. A notable departure from traditional approaches is that, instead of relying on manually or automatically selected image features calculated from data, deep learning networks directly take the raw input—in this case, images. Lower layers of

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the network autonomously learn and extract fundamental image features, such as edges or textures, while higher layers build upon these lower-level representations to discern more intricate and abstract patterns. This endows deep learning networks with the capability to automatically derive effective image features from the data, eliminating the need for explicit feature engineering. The approach has proven highly successful in a range of computer vision works, enabling the model to learn hierarchical representations for tasks like image cataloging, objects recognition, and image division (72, 73).

The investigation revealed that the Support Vector Machine (SVM) classification method outperformed other methods, showcasing higher accuracy across various types of medical images. Specifically, the SVM method demonstrated exceptional accuracy rates of 98.58% for ultrasound, 93.063% for mammography, and a perfect 100% for thermography. Notably, the SVM method's superior performance was attributed to the use of an appropriate segmentation method, allowing for precise extraction of the desired areas in the images. The study found that the intensity of extracted features played a pivotal role in cataloguing process. The mixture of gray-level co-occurrence matrix (GLCM) and Pratio feature, with morphological characteristics, yielded the most accurate results, highlighting the significance of feature selection and extraction methods in enhancing the performance of SVM-based classification in medical image analysis.

Previous work and current prospect

The previous work on image processing is shown in table 1. This includes the already work conducted and the new techniques to process images for better authentication and medication planning.

Table 1: Shows the previous work with emerging technique

Sr. no.	**Year**	**Image source**	**Tool used for image processing**	**Effective to date or not**	**AI used DL, CAD, (role) in future**	**Disease**	**Beneficial in future or not**	**Reference**

1	2018	Histopathology	Mammography, ultrasound, and thermography	Not	Helpful	Breast cancer	Yes	(74)
2	2019	Histopathology	Not used	Not confirmed	Helpful	Invasive ductal carcinoma IDC	Yes	(35)
3	2019	Histopathology	Computer-aided diagnosis (CAD)	Yes	Helpful	Breast cancer	Yes	(60)
4	2020	Not described	Not used	Not confirmed	Helpful	Breast cancer	Yes	(75)
5	2020	Histopathology	Mammography	Not	Helpful	Breast cancer	Yes	(76)
6	2021	Histopathology	Magnetic resonance imaging (MRI)	Not	Helpful	Breast cancer	Yes	(77)
7	2021	Not described	Not used	Not confirmed	Helpful	Breast cancer	Yes	(78)
8	2021	Histopathology	Convolutional neural network (CNN)	Yes	Helpful	Invasive ductal carcinoma IDC	Yes	(79)
9	2022	Not described	Not used	Not confirmed	Helpful	Triple negative Breast cancer	Yes	(80)
10	2024	Histopathology	Magnetic resonance imaging (MRI)	Not	AI enhanced MRI Helpful	Breast cancer	Yes	(81)

Conclusion

In conclusion, artificial intelligence plays a crucial role in image prediction, particularly in the diagnosis of breast cancer. While the accuracy of breast cancer diagnosis through AI can be high, it may not necessarily generalize uniformly across diverse sets of images. Hence, there is room for future research aimed at enhancing system performance and validating results through extensive testing on a broader array of images. Moreover, it is essential to recognize that the role of AI in interpreting breast imaging is an evolving one. Rather than replacing radiologists, AI serves as a valuable tool to assist them using innovative and efficient methods. Despite the longstanding presence of AI in the interpretation of breast cancer images, ongoing advancements persist as larger, well-curated datasets are amassed, and more sophisticated algorithms are devised. The imperative remains to continually refine AI for even more effective outcomes in the future.

Author's contribution

All authors contributed equally in the work.

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Conflict of interest

None

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