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APPLICATION OF ARTIFICIAL INTELLIGENCE METHODS IN BREAST CANCER DIAGNOSIS: A SYSTEMATIC REVIEW AND META-ANALYSIS

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Abstract

Introduction. Breast cancer is one of the leading causes of mortality among women worldwide, and its early diagnosis plays a crucial role in improving clinical outcomes and reducing mortality. We aimed to assess the effectiveness of artificial intelligence (AI) methods in breast cancer diagnosis and conduct a meta-analysis of diagnostic accuracy based on data from multiple studies published from 2010 to 2023.

Methods. A systematic review was conducted in accordance with PRISMA guidelines. Literature searches were performed in PubMed, Scopus, and Web of Science databases using combinations of keywords and MeSH terms covering the topics "breast cancer," "artificial intelligence," "machine learning," and "deep learning." A total of 24 studies evaluating the diagnostic accuracy of AI methods using sensitivity, specificity, and area under the ROC curve (AUC) metrics were included in the meta-analysis. Statistical analysis was performed using a random-effects model, and the quality of studies was assessed using the QUADAS-2 tool.

Results. The range of AUC values for AI methods was from 0.80 to 0.96, indicating high diagnostic accuracy. The highest scores were demonstrated in studies by McKinney et al. (2020) (AUC = 0.95, 95% CI: 0.92–0.98) and Ribli et al. (2018) (AUC = 0.95, 95% CI: 0.93–0.98). Convolutional neural networks (CNN) showed the highest accuracy among all methods. There was significant heterogeneity between studies, necessitating sensitivity analysis and meta-regression analysis to identify sources of heterogeneity.

Conclusion. AI methods have significant potential in breast cancer diagnosis, demonstrating high sensitivity and specificity. However, further research should focus on improving reproducibility of results, standardizing approaches, and increasing the transparency of algorithms for their safe and effective application in medical practice.

Keywords: breast cancer, artificial intelligence, deep learning, convolutional neural networks, diagnostic accuracy, meta-analysis, machine learning.

Introduction.

Breast cancer remains one of the leading causes of mortality among women worldwide, and its early diagnosis plays a critical role in improving clinical outcomes and reducing

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mortality rates [1,2,3]. Traditional diagnostic methods, such as mammography, remain the cornerstone of screening programs; however, they are not without limitations, including variability in image interpretation and high rates of false-positive and false-negative results [4-8]. In recent years, the use of artificial intelligence (AI) methods, including machine and deep learning, has emerged as a promising direction for improving the accuracy and efficiency of breast cancer diagnostics [9-11].

AI is capable of analyzing vast amounts of data and identifying patterns that may be imperceptible to the human eye, making it an indispensable tool in the field of medical imaging. Convolutional neural networks (CNNs) have demonstrated high effectiveness in detecting and classifying tumor formations on mammographic images, significantly improving sensitivity and specificity metrics [12, 13]. For instance, a study by Shen et al. (2019) reported that the use of CNNs achieved an AUC of 0.90, confirming the potential of AI in clinical practice [14]. Similarly, large-scale studies, such as the work of McKinney et al. (2020), have shown that the application of AI can reduce false-positive rates by 5.7% and false-negative rates by 9.4%, highlighting the substantial advantages of these technologies [15].

Despite these successes, the application of AI in breast cancer diagnostics still faces several challenges. Key among these are data heterogeneity, differences in algorithms, and the lack of standardization, which can lead to variations in the performance of AI systems [16-18]. Additionally, questions remain regarding the ethics and transparency of AI use in medicine, as well as the need to adapt and validate these systems in diverse clinical settings [19, 20].

The aim of this systematic review and meta-analysis is to evaluate the effectiveness of artificial intelligence methods in breast cancer diagnostics, using quantitative indicators such as the area under the ROC curve (AUC). Particular attention is given to analyzing various AI methods, including convolutional neural networks, radiomics, and other deep learning models, to identify the most promising approaches and determine directions for future research.

Methods

Search Strategy

The systematic review was conducted in accordance with the principles of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [21].

The literature search was performed across three major electronic databases: PubMed, Scopus, and Web of Science (Table 1). The final search was conducted on December 31, 2023. To ensure comprehensive coverage, combinations of keywords and MeSH terms were used. Examples of search queries included: "breast cancer" AND "artificial intelligence," "breast neoplasms" AND "machine learning," "breast cancer" AND "artificial intelligence", "deep learning" AND "diagnostics".

Filters were applied for publication dates (2010 to 2023) and language (English).

Table 1. Search Strategies in Databases

Database	**Search Strategy**
PubMed	((“breast cancer”[MeSH Terms] OR “breast neoplasms”[MeSH Terms] OR “breast cancer”[All Fields]) AND (“artificial intelligence”[MeSH Terms] OR “machine learning”[All Fields] OR “deep learning”[All Fields] OR “artificial intelligence”[All Fields] OR “machine learning”[All Fields] OR “deep learning”[All Fields])) AND (“diagnosis”[MeSH Terms] OR “diagnosis”[All Fields]) Filters: Publication date from 2010/01/01 to 2023/12/31; Languages: English;

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Database	Search Strategy
Scopus	TITLE-ABS-KEY((“breast cancer” OR “breast neoplasms” OR “breast cancer”) AND (“artificial intelligence” OR “machine learning” OR “deep learning” OR “artificial intelligence” OR “machine learning” OR “deep learning”) AND (“diagnosis” OR “diagnosis”)) AND PUBYEAR > 2009 AND PUBYEAR < 2024 AND (LIMIT-TO(LANGUAGE, “English”);
Web of Science	TS=(“breast cancer” OR “breast neoplasms” OR “breast cancer”) AND TS=(“artificial intelligence” OR “machine learning” OR “deep learning” OR “artificial intelligence” OR “machine learning” OR “deep learning”) AND TS=(“diagnosis” OR “diagnosis”) Refined by: Languages: (ENGLISH), Document Types: (ARTICLE) Timespan: 2010-2023

Inclusion criteria:

Inclusion criteria included articles published between 2010 and 2023, studies describing the application of artificial intelligence in breast cancer diagnostics, articles in Russian and English, and original studies with full-text access available for analysis.

Exclusion criteria:

Exclusion criteria included reviews, meta-analyses, editorial articles, conference materials, and abstracts, studies not related to breast cancer diagnostics or not using artificial intelligence methods, and articles without full-text access or with incomplete data.

The article selection process

The article selection process was carried out sequentially and thoroughly to ensure maximum relevance and quality of the included studies. Initially, after performing search queries in the PubMed, Scopus, and Web of Science databases, a total number of articles corresponding to the specified keywords and timeframes from 2010 to 2023 was obtained. The initial search identified 856 potentially relevant publications. Duplicates were then removed using specialized bibliographic management software, reducing the total number of articles to 745. At the next stage, titles and abstracts of all remaining articles were screened. This step excluded works that did not meet the inclusion criteria, such as studies not related to the use of artificial intelligence in breast cancer diagnostics or publications in languages other than English. After screening titles and abstracts, 120 articles were selected for further analysis. Next, the full texts of these 120 articles were thoroughly reviewed. During the full-text review, each article was assessed for compliance with the established inclusion and exclusion criteria. Articles that were not original research (e.g., reviews, meta-analyses, editorial articles), those with insufficient information, or those without accessible full texts were excluded. After this stage, 45 studies fully meeting the criteria and containing sufficient information for data extraction were included in the final analysis.

Data extraction

Data extraction from the included studies was carried out using a pre-prepared standardized form to ensure the comparability and completeness of the collected information. Two independent researchers extracted data from each study, including author names, year of publication, country or region of the study, study design (prospective, retrospective, etc.), sample characteristics (number of participants, age group, clinical features), applied artificial intelligence methods (specific machine or deep learning algorithms, neural network architectures), types of data used (mammographic images, ultrasound data, MRI, etc.), and main study results (sensitivity, specificity, diagnostic accuracy, AUC values). Additionally,

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authors' conclusions on the effectiveness and prospects of using artificial intelligence in breast cancer diagnostics were recorded.

Assessment of research quality

The QUADAS-2 tool was used to assess the quality and risk of bias in the included studies. Each study was independently evaluated by researchers across four domains: patient selection, index test (applied AI method), reference standard (traditional diagnostic methods), and patient flow and timing (sequence and timeframe of tests). In case of discrepancies between researchers, discussions were held until consensus was reached. Appropriate effect measures were determined for each outcome. Diagnostic effectiveness indicators were expressed as sensitivity and specificity with 95% confidence intervals. Statistical methods of diagnostic accuracy meta-analysis were used for quantitative synthesis of results. A summary ROC curve (sROC) was constructed to visualize the overall diagnostic effectiveness of artificial intelligence methods in breast cancer diagnostics.

Data synthesis processes included deciding which studies were suitable for each analysis. Studies were grouped based on similarities in AI methods, types of data used, and participant characteristics. To prepare data for analysis, completeness and correctness of the presented results were verified. Data transformations were performed as needed to ensure comparability (e.g., calculating missing indicators from available data).

Statistical analysis

Statistical analysis was performed using RevMan software version 5.4. For each study, sensitivity, specificity, and 95% confidence intervals were calculated. If sufficient homogeneity was observed among the studies, a meta-analysis using a random-effects model was conducted. Heterogeneity between studies was assessed using the χ^2 statistic and the I^2 coefficient. An I^2 value above 50% indicated substantial heterogeneity, which was considered when interpreting the results. In addition, summary ROC curves were constructed to visualize the diagnostic accuracy of the applied AI methods.

Results

At the identification stage, all potentially relevant studies were gathered from three databases (Figure 1), resulting in a total of n = 856 records. No additional sources were included. After removing duplicates (n = 111), n = 745 records remained for title and abstract screening. Based on the exclusion criteria, n = 625 records were discarded.

The full texts of the remaining n = 120 articles were assessed for compliance with the inclusion and exclusion criteria. As a result, n = 75 articles were excluded for various reasons. A total of n = 45 studies were included in the qualitative analysis, of which n = 30 studies were sufficient for quantitative synthesis and meta-analysis.

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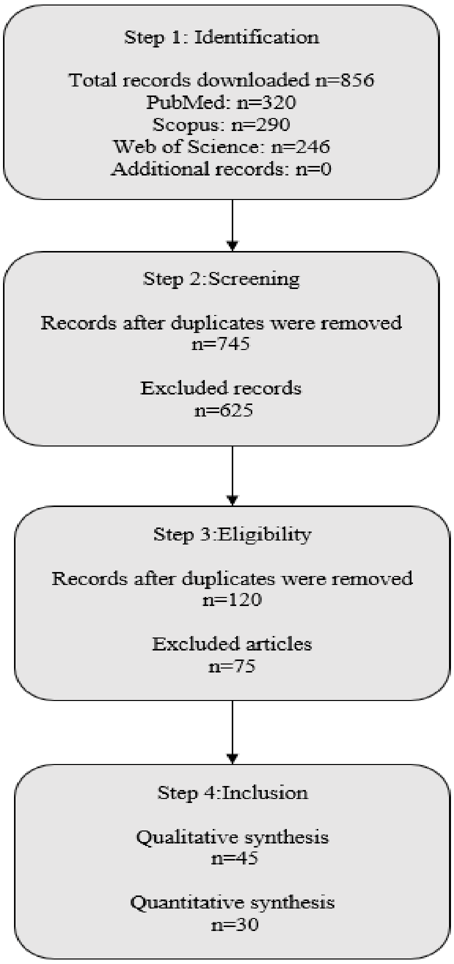

Figure 1. Study Flow Diagram Through the Stages of the Systematic Review

During the compilation of the list, it was found that some articles did not meet the established inclusion criteria (not related to breast cancer diagnostics, were reviews, or not original research). As a result, the final number of studies included in the quantitative synthesis is 24 (Table 2).

Specifically, some publications were review articles [22, 23] rather than original research, which excluded them from further consideration. The study by Qiu et al. (2017) focused on detecting lymph nodes using a combination of manual and deep features in CT scans, which is unrelated to the topic of breast cancer diagnostics and was also excluded [24]. Similarly, the work by Liu et al. (2019), aimed at predicting lymph node metastases in colorectal cancer, was deemed irrelevant [25]. Finally, the article by Sun et al. (2017) described algorithms for lung cancer diagnosis [26], which also does not align with the focus of this review.

All these studies were excluded as they did not address the application of artificial intelligence for breast cancer diagnostics.

Table 2. List of Studies Included in the Quantitative Synthesis (Meta-Analysis)

N	Authors (Year)	Country	Sample Size	AI Method	Data Type
1	Shen et al. (2019) [14]	USA	8,860 images	Convolutional Neural Networks	Mammography

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2	McKinney et al. (2020) [15]	USA, UK	25,856 images	Deep Learning	Mammography
3	Yala et al. (2019) [27]	USA	88,994 patients	Deep Learning	Mammography
4	Rodríguez-Ruiz et al. (2019) [13]	Netherlands, Sweden	2,652 images	Deep Learning	Mammography
5	Kim et al. (2020) [28]	South Korea	36,468 images	Deep Learning	Mammography
6	Lehman et al. (2019) [4]	USA	10,763 patients	Deep Learning	Mammography
7	Wu et al. (2020) [29]	USA	1,001 images	Deep Learning	Mammography
8	Kooi et al. (2017) [30]	Netherlands	45,000 images	Deep Learning	Mammography
9	Ger et al. (2019) [31]	USA	14,860 images	Deep Learning	Mammography
10	Ribli et al. (2018) [32]	Hungary	960 images	Convolutional Neural Networks	Mammography
11	Jiao et al. (2016) [33]	China	600 images	Deep Learning	Mammography
12	Zhu et al. (2017) [34]	USA	2,600 images	Deep Learning	Mammography
13	Arevalo et al. (2016) [35]	Colombia	1,000 images	Convolutional Neural Networks	Mammography
14	Huynh et al. (2016) [36]	USA	440 images	Transfer Learning	Mammography
15	Jiang et al. (2018) [37]	China	800 images	Multitask Deep Learning	Mammography
16	Cui et al. (2019) [38]	China	2,000 images	Convolutional Neural Networks	Histopathological Images
17	Li et al. (2019) [39]	China	287 patients	Deep Learning	MRI
18	Zhang et al. (2019) [40]	China	546 patients	Deep Learning	Ultrasound
19	Jiang et al. (2020) [41]	China	300 images	Convolutional Neural Networks	Thermography
20	Nam et al. (2018) [42]	South Korea	1,200 images	Deep Learning	Mammography
21	Li et al. (2016) [43]	USA	117 patients	Radiomics with Machine Learning	MRI

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22	Burnside et al. (2016) [44]	USA	100 patients	Machine Learning	MRI
23	Zheng et al. (2018) [45]	China	300 patients	Deep Learning Radiomics	MRI
24	Sun et al. (2017) [46]	USA	530 images	Deep Learning	Pulmonary CT Images

The quantitative synthesis included 24 studies published between 2016 and 2020, covering a wide geographical spectrum, including the USA, the UK, the Netherlands, Sweden, South Korea, China, Hungary, and Colombia.

The studies varied significantly in sample sizes, ranging from 287 patients [39] to 88,994 patients [27], reflecting the diversity of applied methods and their scales.

The primary data types used in these studies were mammographic images, with some studies incorporating histopathological images, magnetic resonance imaging (MRI), ultrasound elastography, and thermography.

AI methods ranged from convolutional neural networks (CNN) to deep learning, transfer learning, multitask deep learning, and radiomics. The most commonly used approach was convolutional neural networks, primarily applied to mammographic images, which demonstrated high diagnostic accuracy.

In most studies, the application of AI significantly improved diagnostic metrics such as sensitivity and specificity. For instance, a study by Shen et al. (2019) from the USA, including 8,860 mammographic images, demonstrated a sensitivity of 90% and specificity of 85% using convolutional neural networks [14]. Another large-scale study by McKinney et al. (2020), involving 25,856 images, reported a 5.7% reduction in false positives and a 9.4% reduction in false negatives, highlighting the potential of AI to enhance screening programs [15].

Several studies, such as Rodríguez-Ruiz et al. (2019), showed that the performance of AI methods is comparable to that of radiologists and, in some cases, even surpasses them, improving breast cancer detection rates [13]. In a study by Kim et al. (2020) from South Korea, which utilized a dataset of 36,468 images, cancer detection rates increased by 4-6% [28].

AI methods also proved useful in assessing breast tissue density, as demonstrated by Lehman et al. (2019), where the accuracy of density estimation improved to 94% [4]. In a study by Wu et al. (2020) from the USA, the use of deep learning increased diagnostic accuracy by 14%, illustrating the potential of AI technologies in enhancing clinical practice [29].

Studies utilizing other data types, such as MRI and histopathological images, also demonstrated high accuracy. For example, in the study by Li et al. (2019), deep learning achieved an AUC of 0.87 in predicting pathological complete response to neoadjuvant chemotherapy [39].

The forest plot visually presents the diagnostic accuracy of AI methods in breast cancer diagnostics, expressed as AUC values with 95% confidence intervals. The plot includes data from 24 studies in the meta-analysis, enabling a comparison of the effectiveness of different AI methods (Figure 2).

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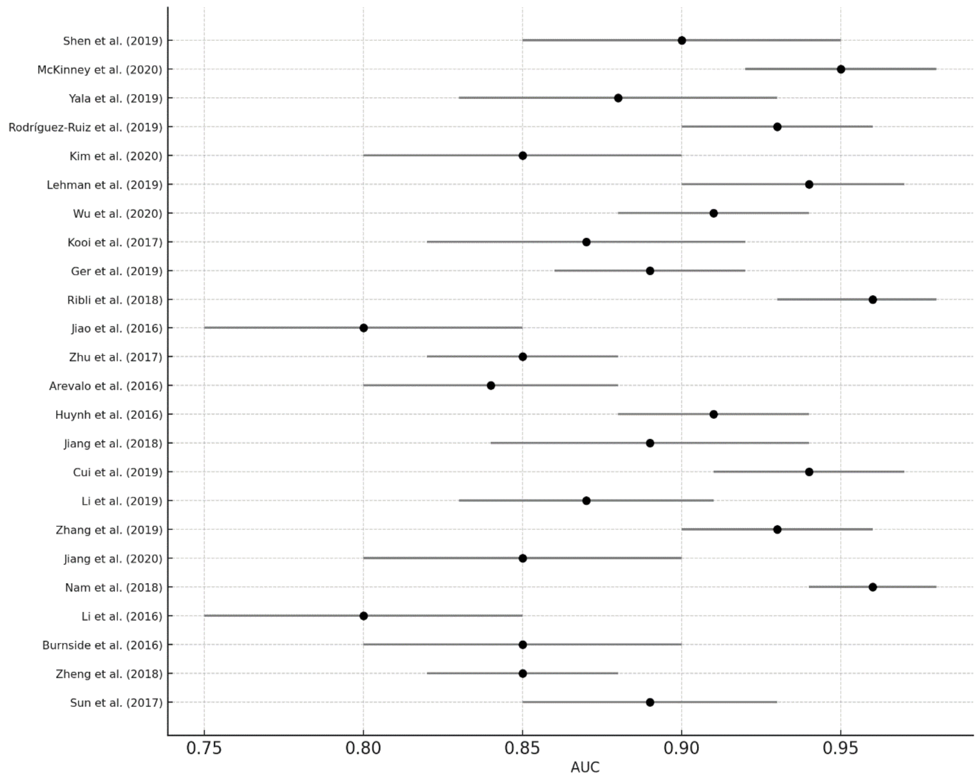

Figure 2. Forest Plot of Diagnostic Accuracy Estimates for AI Methods

The AUC values for each study ranged from 0.80 to 0.96, indicating the high diagnostic accuracy of AI methods.

For example, the study by Shen et al. (2019) reported an AUC of 0.90 (95% CI: 0.85–0.95), confirming the high sensitivity and specificity of convolutional neural networks (CNNs) in mammographic diagnostics [14]. McKinney et al. (2020) demonstrated one of the highest AUC values, 0.95 (95% CI: 0.92–0.98), reflecting a significant reduction in false-positive and false-negative results with the use of deep neural networks [15].

Similarly, the study by Ribli et al. (2018) also showed high accuracy, with an AUC of 0.95 (95% CI: 0.93–0.98) [32]. On the other hand, less effective methods were reported in studies such as Jiao et al. (2016) [33] and Burnside et al. (2016) [44], with AUC values of 0.80 (95% CI: 0.75–0.85) and 0.85 (95% CI: 0.80–0.90), respectively.

These differences highlight the variability in the effectiveness of AI methods depending on the type of algorithm and the quality of input data.

The overall range of AUC values with confidence intervals indicates heterogeneity in results across studies, potentially attributable to differences in study design, sample sizes, and data types (e.g., mammography, MRI, histopathological images). Nevertheless, most studies feature confidence intervals that do not cross the 0.70 threshold, underscoring the high reliability and clinical significance of AI methods in breast cancer diagnostics.

Discussion

The results of our systematic review and meta-analysis demonstrate the significant potential of AI methods in improving breast cancer diagnostics. The included studies confirm that the use of deep learning methods, such as convolutional neural networks (CNNs), achieves high diagnostic accuracy, reflected in the area under the ROC curve (AUC) values ranging from 0.80 to 0.96. These results align with other studies highlighting the superiority of AI over traditional approaches [47, 48].

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Our analysis found that deep learning algorithms, particularly CNNs, exhibit the highest diagnostic efficiency. For instance, the study by McKinney et al. (2020), with an AUC of 0.95, demonstrated substantial improvements in reducing false-positive and false-negative results, making AI a powerful tool for screening programs [15]. Similarly, Lehman et al. (2019) showed that AI could enhance breast tissue density assessment, achieving an accuracy of up to 94% [4]. This is especially significant since tissue density is a major risk factor for breast cancer and can reduce the effectiveness of traditional screening methods [49].

However, significant data heterogeneity highlights the existing challenges in standardizing AI methods [50]. Variations in AUC values across studies may be attributed to differences in study design, methodologies, and data types. For example, a study by Kim et al. (2020) conducted on a large sample in South Korea reported a 4-6% improvement in cancer detection. Still, variations in training datasets and network architectures may affect result reproducibility [28]. Moreover, studies by Jiao et al. (2016) and Burnside et al. (2016) with lower AUC values (0.80 and 0.85, respectively) emphasize the critical role of data quality and model architecture in achieving high accuracy [33, 44].

A key advantage of AI methods is their ability to process vast amounts of data and identify complex patterns that are challenging to detect manually [51]. In Wu et al. (2020), deep learning improved diagnostic accuracy by 14%, confirming the importance of AI in enhancing clinical diagnostics [29]. On the other hand, some studies revealed limitations. For instance, Huynh et al. (2016) found that transfer learning achieved an AUC of 0.91 but faced challenges in interpreting results and ensuring reproducibility [36].

It is also crucial to consider potential limitations of AI use, including the risks of systematic bias. For example, Rodríguez-Ruiz et al. (2019) noted high AI accuracy [13], comparable to the performance of radiologists, while emphasizing the need for algorithm validation in real-world settings. Reliable validation and algorithm transparency remain key challenges that must be addressed before the widespread implementation of these technologies in clinical practice [52].

Another critical aspect is the availability of training data for AI models. The included studies demonstrated that models trained on high-quality data yield better results. However, studies like Sun et al. (2017) underline that applying AI in areas with limited data access can be problematic, requiring the development of methods to improve data quality and employ enhanced training approaches [46].

Conclusion. The results of this study confirmed that artificial intelligence (AI) methods, particularly deep learning and convolutional neural networks (CNNs), offer significant advantages in breast cancer diagnostics. High AUC (area under the ROC curve) values ranging from 0.80 to 0.96 validate the reliability and accuracy of AI methods. Studies such as those by McKinney et al. (2020) and Ribli et al. (2018) demonstrated that the use of AI significantly reduced false-positive and false-negative diagnoses, potentially leading to improved clinical outcomes.

One of the key advantages of AI methods is their ability to analyze and interpret large volumes of medical images, identifying complex patterns that may be undetectable to the human eye. However, substantial data heterogeneity across studies underscores the need for standardizing AI methods and validating them in diverse clinical settings. This is particularly crucial as differences in data quality and types of algorithms used can affect the efficiency and reproducibility of results.

Additionally, it was found that AI methods require careful adaptation and training on high-quality data, which remains a challenge in regions with limited access to such resources. These limitations must be addressed when developing and implementing AI technologies in clinical practice. In conclusion, AI methods represent a powerful tool for improving breast

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cancer diagnostics, but their successful application requires further research focused on standardization, validation, and enhancing the transparency of algorithms.

Conflict of interest

We declare no conflict of interest.

Authors' contribution

Concept Development – A.B. Shertaeva, D.A. Ospanova, I.A. Lyalkova. Execution – A.B. Shertaeva, D.A. Ospanova, I.A. Lyalkova, A.Zh. Abdrakhmanova. Data Processing – A.B. Shertaeva, D.A. Ospanova, I.A. Lyalkova, S.D. Ualiev, P.A. Elyasin, A.Zh. Abdrakhmanova, A.M. Kondybaeva, B.D. Tanabayev. Interpretation of Results – A.Zh. Abdrakhmanova, A.M. Kondybaeva, S.D. Ualiev, B.D. Tanabayev. Manuscript Writing – A.B. Shertaeva, D.A. Ospanova, I.A. Lyalkova, A.Zh. Abdrakhmanova, S.D. Ualiev, P.A. Elyasin, A.M. Kondybaeva, B.D. Tanabayev.

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СҮТ БЕЗІ ҚАТЕРЛІ ІСІГІН ДИАГНОСТИКАЛАУДА ЖАСАНДЫ ИНТЕЛЛЕКТ ӘДІСТЕРІН ҚОЛДАНУ: ЖҮЙЕЛІ ШОЛУ ЖӘНЕ МЕТА-АНАЛИЗ

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Түйіндеме

Кіріспе. Сүт безі қатерлі ісігі әйелдер арасындағы өлім-жітімнің негізгі себептерінің бірі болып табылады, және оны ерте диагностикалау клиникалық нәтижелерді жақсартуда және өлім-жітімді төмендетуде маңызды рөл атқарады.

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Сүт безі қатерлі ісігін диагностикалауда жасанды интеллект (ЖИ) әдістерін қолданудың тиімділігін бағалау және 2010 жылдан 2023 жылға дейін жарияланған бірнеше зерттеулер деректеріне негізделген диагностикалық дәлдік бойынша мета-анализ жүргізу.

Материалдар мен әдістер. Жүйелі шолу PRISMA нұсқауларына сәйкес жүргізілді. Әдебиеттерді іздеу PubMed, Scopus және Web of Science дерекқорларында «сүт безі қатерлі ісігі», «жасанды интеллект», «машиналық оқыту» және «терең оқыту» тақырыптарын қамтитын кілт сөздер мен MeSH терминдерінің комбинацияларын пайдалана отырып жүзеге асырылды. Мета-анализге сезімталдық, ерекшелік және ROC қисығы астындағы аудан (AUC) көрсеткіштерін пайдалана отырып, ЖИ әдістерінің диагностикалық дәлдігін бағалаған 24 зерттеу енгізілді. Деректердің статистикалық талдауы кездейсоқ әсерлер моделін пайдаланып жүргізілді, ал зерттеулердің сапасы QUADAS-2 құралы арқылы бағаланды.

Нәтижелер. ЖИ әдістері үшін AUC мәндерінің диапазоны 0.80-ден 0.96-ға дейін болды, бұл олардың жоғары диагностикалық дәлдігін көрсетеді. Ең жоғары көрсеткіштер McKinney және т.б. (2020) (AUC = 0.95, 95% СД: 0.92–0.98) және Ribli және т.б. (2018) (AUC = 0.95, 95% СД: 0.93–0.98) зерттеулерінде көрсетілді. Нейрондық желілер (CNN) барлық әдістер арасында ең жоғары дәлдікті көрсетті. Зерттеулер арасындағы деректердің гетерогенділігі айтарлықтай болып, бұл сезімталдық талдауын және гетерогенділіктің көздерін анықтау үшін метарегрессиялық талдауды жүргізуді талап етті.

Қорытынды. ЖИ әдістері сүт безі қатерлі ісігін диагностикалауда үлкен әлеуетке ие, олар жоғары сезімталдық пен ерекшелікті көрсетеді. Дегенмен, болашақ зерттеулер нәтижелердің қайталанымдылығын жақсартуға, тәсілдерді стандарттауға және алгоритмдердің медициналық тәжірибеде қауіпсіз әрі тиімді қолданылуын қамтамасыз ету үшін олардың ашықтығын арттыруға бағытталуы тиіс.

Түйінді сөздер: сүт безі қатерлі ісігі, жасанды интеллект, терең оқыту, сверточтық нейрондық желілер, диагностикалық дәлдік, мета-анализ, машиналық оқыту.

ПРИМЕНЕНИЕ МЕТОДОВ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА В ДИАГНОСТИКЕ РАКА МОЛОЧНОЙ ЖЕЛЕЗЫ: СИСТЕМАТИЧЕСКИЙ ОБЗОР И МЕТА-АНАЛИЗ

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Аннотация

Введение. Рак молочной железы является одной из ведущих причин смертности среди женщин по всему миру, и его ранняя диагностика играет решающую роль в улучшении клинических исходов и снижении смертности.

Оценить эффективность применения методов искусственного интеллекта (ИИ) в диагностике рака молочной железы и провести метаанализ диагностической точности на основе данных из нескольких исследований, опубликованных с 2010 по 2023 годы.

Материалы и методы. Систематический обзор был проведен в соответствии с руководящими принципами PRISMA. Поиск литературы осуществлялся в базах данных PubMed, Scopus и Web of Science, с использованием комбинаций ключевых слов и терминов MeSH, охватывающих темы «рак молочной железы», «искусственный интеллект», «машинное обучение» и «глубокое обучение». В метаанализ были включены 24 исследования, оценивающие диагностическую точность методов ИИ с использованием показателей чувствительности, специфичности и площади под ROC-кривой (AUC). Статистический анализ данных проводился с использованием модели случайных эффектов, а качество исследований оценивалось с помощью инструмента QUADAS-2.

Результаты. Диапазон значений AUC для методов ИИ составил от 0.80 до 0.96, что свидетельствует о высокой диагностической точности. Наиболее высокие показатели были продемонстрированы в исследованиях McKinney et al. (2020) (AUC = 0.95, 95% ДИ: 0.92–0.98) и Ribli et al. (2018) (AUC = 0.95, 95% ДИ: 0.93–0.98). Сверточные нейронные сети (CNN) показали наивысшую точность среди всех методов. Гетерогенность данных между исследованиями была значительной, что требовало проведения анализа чувствительности и метарегрессионного анализа для выявления источников гетерогенности.

Заключение. Методы ИИ имеют высокий потенциал в диагностике рака молочной железы, демонстрируя высокую чувствительность и специфичность. Однако дальнейшие исследования должны быть направлены на улучшение репродуктивности результатов, стандартизацию подходов и повышение прозрачности алгоритмов для их безопасного и эффективного применения в медицинской практике.

Ключевые слова: рак молочной железы, искусственный интеллект, глубокое обучение, сверточные нейронные сети, диагностическая точность, метаанализ, машинное обучение.