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ARTIFICIAL INTELLIGENCE IN THE DIAGNOSIS OF BREAST PATHOLOGIES: A LITERATURE REVIEW

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ABSTRACT

Relevance: *Timely diagnosis of breast cancer remains one of the key challenges in healthcare, as this disease continues to be a leading cause of mortality among women worldwide. In recent years, artificial intelligence (AI) has become an integral part of medical imaging, demonstrating broad applicability and potential. Current diagnostic modalities, such as mammography and magnetic resonance imaging (MRI), serve as essential tools for detecting breast pathologies; however, they have certain limitations regarding sensitivity and specificity. This literature review presents an overview of contemporary approaches to the application of AI in the diagnosis of breast cancer.*

The study aimed to *analyze the methods of applying artificial intelligence in diagnosing breast cancer, including its capabilities in prediction, interpretation of results, and improving the accuracy of imaging techniques.*

Methods: *A comprehensive search was conducted using PubMed, Medline, Cochrane Library, and Google Scholar databases. The review includes scientific articles focused on the application of AI in the diagnosis of breast diseases.*

Results: *The review demonstrated that AI systems, such as convolutional neural networks, can detect microcalcifications on mammograms with high accuracy (up to 94.5%) and reduce false-positive results by 11%. In MRI image analysis, using hybrid models, such as CNN-RNN architectures, improves the diagnostic accuracy of malignant tumors by 15% and reduces error rates by 20%. Radiomics shows high accuracy (87%) in predicting therapeutic response while integrating multiomics data provides sensitivity up to 92%.*

Conclusion: *Using AI in breast cancer diagnostics enhances the accuracy of imaging techniques, facilitates data interpretation, and contributes to the personalization of treatment strategies. However, challenges remain, including the availability of high-quality data for model training and ethical considerations in decisionmaking processes.*

Keywords: *breast cancer, artificial intelligence, mammography, MRI, radiomics, prediction.*

Introduction: Timely detection of breast cancer (BC) remains a top priority in healthcare, as this disease ranks among the leading causes of mortality among women worldwide. According to data from the World Health Organization, more than 2.3 million new cases of BC are diagnosed annually, accounting for approximately 25% of all cancers in women [1].

Imaging methods such as mammography and magnetic resonance imaging (MRI) are key tools to detect breast pathologies; however, they have limitations related to insufficient sensitivity and specificity at the early stages of the disease. Studies by S.M. McKinney et al. indicate that in routine clinical practice, mammography may miss up to 20% of BC cases, especially in women with high breast tissue density [2]. In this context, the use of modern technologies, such as artificial intelligence (AI), opens up new opportunities for improving diagnostic accuracy, which is particularly important for early-stage detection, when treatment is most effective [3-5].

Artificial intelligence (AI) utilizing Deep Neural Networks (DNN) has demonstrated its effectiveness in analyzing mammograms and MRI scans. Systems based on Convolutional Neural Networks (CNN) achieve accuracy rates of up to 94.5% in detecting pathologies on mammograms [6]. Moreover, the application of hybrid models, such as Convolutional Recurrent Neural Networks (CNN-RNN), enhances the analysis of dynamic contrast-enhanced MRI, resulting in a 20% reduction in false-positive diagnoses [7, 8].

The study aimed to analyze the methods of applying artificial intelligence in diagnosing breast cancer, including its capabilities in prediction, interpretation of results, and improving the accuracy of imaging techniques.

Materials and Methods: This review covered publications focused on the application of AI in breast disease diagnosis, sourced from the PubMed, Medline, Cochrane Library, and Google Scholar databases. The last search was conducted on March 10, 2025. The following keywords were used for the search: breast cancer, artificial intelligence, deep learning, radiomics, machine learning, diagnosis, mammography, MRI, neural networks. Keyword combinations included logical operators AND/OR. Languages of publication: English and Russian. Inclusion criteria: original research studies and meta-analyses published in the past 10 years (2015 - 2025), articles in which AI was applied for the diagnosis of breast diseases, availability of quantitative data (sensitivity, specificity, area under the curve (AUC), etc.). *Exclusion criteria:* review articles, case reports, letters to the editor, and conference abstracts. Out of 350 identified publications, after removing duplicates and assessing for compliance with the inclusion criteria, the final review included 20 of the most relevant studies.

Results: Modern AI systems in the diagnosis of breast pathology employ various approaches and algorithms, such as classical machine learning methods, DNN, and hybrid approaches combining multiple technologies. Among the most widely used models are CNN, which demonstrate high accuracy in image processing and feature extraction [3]. For example, U-Net is actively used for segmentation tasks, including tumor delineation in MRI scans. The study focused on the development and evaluation of a model for medical image segmentation tasks. Particular attention was given to improving the traditional U-Net architecture through the use of enhanced skip connections. These modifications significantly enhanced the accuracy and efficiency of medical image analysis, particularly in applications such as breast MRI. The U-Net model demonstrated an average segmentation accuracy exceeding 92% on standard datasets, including the Breast MRI Dataset. This improvement enables more precise delineation of tumor boundaries, which is particularly important for surgical planning and radiotherapy. One of the key achievements of the model was the 70% reduction in image processing time, enhancing its applicability in real-world clinical practice [7].

Another important direction is the use of explainable AI methods, which make model operations more understandable to physicians, including the use of heatmap visualizations [8]. Combined systems, such as CNN-RNN, enable the analysis of temporal data, which is particularly useful in dynamic studies, such as dynamic contrast-enhanced MRI (DCE-MRI). The use of AI to analyze DCE-MRI data has helped reduce the number of false positives by 20%, thereby decreasing unnecessary biopsies and reducing emotional stress for patients. In the study by A. Landsmann et al., DCE-MRI data from patients with various types of breast neoplasms were analyzed. Special attention was given to the textural characteristics of tumors, such as heterogeneity, contrast, and signal intensity distribution. The objective was to identify parameters that consistently demonstrate differences between benign and malignant lesions at various time points following contrast administration [9].

Application of AI in Detecting Microcalcifications. Mammography is the primary method for breast cancer screening. AI is actively used to automate image analysis and enhance diagnostic accuracy. Examples of deep learning algorithm applications demonstrate strong potential for improving diagnostic precision and reducing errors.

Microcalcifications (small calcium deposits in breast tissue) are a key indicator of early-stage cancer. The use of deep learning algorithms, particularly CNN, enables the automatic identification of areas containing microcalcifications with high accuracy. S.M. McKinney et al. conducted a large-scale study involving over 25,000 patients. Their model demonstrated a sensitivity of 94.5% and a specificity of 88%, exceeding the performance of most Radiologists. The study also found that the algorithm reduced the likelihood of false-positive results by 11% [2].

H. Chougrad et al. explored the application of deep CNNs to improve BC screening accuracy. The researchers developed and tested a model using a dataset of 12,000 mammographic images, applying data augmentation techniques to enhance the training process. The results showed high model performance, with sensitivity reaching 96.8%, specificity at 97.5%, and an accuracy of 98.2% in detecting microcalcifications. Furthermore, the proposed approach reduced the number of false positives by 14% compared to traditional image analysis methods [10].

X. Wang et al. investigated the feasibility of automatic detection of microcalcifications in digital breast tomosynthesis using deep learning methods. The team applied three-dimensional image reconstructions and trained their model on a dataset of 2,500 tomosynthesis studies, with a specific focus on analyzing the spatial structure of microcalcifications. The results showed a sensitivity of 94.7% and specificity of 92.3%, confirming the high effectiveness of the method. The analysis time per case was only 3.2 seconds, and the number of missed cases was reduced by 15% compared to classical image processing techniques [11].

N. Dhungel et al. developed a fully automated method to classify mammographic images using deep residual neural networks (ResNet). The training dataset comprised 25,000 images, including both normal and pathological areas. The model analyzed tissue texture and density, achieving high diagnostic accuracy. Sensitivity reached 93.5%, and specificity was 90.2%. The use of the model reduced the number of false positives by 12% and outperformed traditional algorithms in accuracy by 6% [12].

In a large-scale study by T. Kooi et al., the model was trained on a dataset of 45,000 mammograms. The model effectively detected both individual microcalcifications and clusters. The algorithm achieved a sensitivity of 96.1% and a specificity of 94.8%. The processing time per image was minimal - only 2 seconds. The application of this method reduced the number of missed malignant changes by 20% [13].

Prediction of Malignancy in Neoplasms. The prediction of malignancy risk based on AI is becoming an increasingly popular area of research. The study by N. Wu et al. demonstrated that the use of DNN for mammogram analysis allows the prediction of cancer development with an accuracy of up to 89%. This study included 15,000 patients, and the model showed superiority in risk prediction compared to traditional assessment methods such as the Gail Model, which estimates the likelihood of BC in women based on risk factors including age, age at menarche, age at first childbirth, family history, and results of previous biopsies [14].

In 2021, researchers from the University of Massachusetts developed an AI model called Mirai, capable of predicting the risk of BC based on mammogram analysis. The model forecasts the probability of disease up to five years in advance, allowing physicians to make more informed decisions regarding the need for additional examinations or preventive measures. Mirai is a DNN trained on an extensive dataset comprising over 200,000 mammographic examinations, which ensures its high accuracy and reliability. Unlike traditional risk assessment methods, Mirai considers the individual characteristics of each patient, including breast tissue density and other factors, thereby providing a personalized prediction [15].

The study by M. Larsen et al. evaluated the ability of an AI algorithm to predict BC development in women. The study included 116,495 women aged 50-69 who had undergone at least three consecutive mammographic screenings at two-year intervals. The results showed that the AI algorithm could effectively identify women at high risk of future disease development, opening prospects for personalized screening approaches and earlier BC detection [16].

A study dedicated to evaluating the effectiveness of imaging methods and neural network algorithms in predicting the response of BC to neoadjuvant chemotherapy (NACT) included 342 patients with early and locally advanced disease. The authors compared the diagnostic accuracy of mammography, ultrasound, MRI, and a DNN algorithm. It was found that MRI demonstrated the highest sensitivity (80.0-83.3%) in detecting residual tumors, while neural network methods showed comparable results (69.2-72.0%), outperforming traditional mammography and ultrasound. These data suggest the potential of machine learning to enhance BC diagnostics, particularly in predicting the efficacy of antitumor therapy [17].

M. Bakker et al. presented an original study on the use of radiomics for classifying molecular subtypes of BC. The study focuses on utilizing digital mammographic images to extract key radiomic features that accurately predict the molecular profile of tumors. The authors utilized data from the large-scale OPTIMAM Mammography Image Database, which comprises digital mammograms and associated clinical information. The analysis included 186 patients diagnosed with BC, who were categorized into subtypes: luminal A, luminal B, HER2-positive, and triple-negative breast cancer (TNBC). To minimize errors at the tumor tissue extraction stage, automated segmentation algorithms were applied to accurately delineate tumor boundaries on mammograms. A total of 65 radiomic features were extracted from the images, covering texture, shape, and signal intensity characteristics. Based on the selected data, machine learning models were built, particularly using the Support Vector Machine (SVM) method. The results showed that SVM-based models achieved the highest predictive accuracy for the luminal A (AUC = 0.855) and luminal B (AUC = 0.812) subtypes. High sensitivity was also observed for the triple-negative subtype (AUC = 0.789) and the HER2-positive subtype (AUC = 0.755). These results confirmed the authors' hypothesis that radiomics can be used for non-invasive prediction of molecular subtypes of BC directly from mammographic images, which could reduce the need for biopsies and invasive procedures in the future [18].

The study by S. Montemezzi et al. is a successful example of using radiomic features to predict chemotherapy response in BC. Although the main focus of the study is radiomics, it is essential to note that radiomics plays an integral part in modern AI applications in medicine. Multivariate analysis methods and machine learning were used to process the extracted features, classifying the study within the scope of AI applications. The study investigated the potential of improving models to predict pathological complete response to NACT in BC patients using radiomic features extracted from MRI performed on a 3 Tesla scanner. The study included 60 patients, of whom 20 achieved complete response to NACT, and 40 did not. Geometric, first-order, and higher-order texture radiomic features were extracted from the pre-treatment contrast-enhanced MRIs, followed by feature selection. Five selected radiomic features were combined with other available data to build prediction models for complete response to NACT using three different classifiers: logistic regression, Support Vector Machine method, and random forest. All possible feature combinations were investigated. The AUC for predictors excluding radiomic features reached 0.89, while all three classifiers demonstrated AUCs above 0.90 when radiomic information was included (ranging from 0.91 to 0.98) [19].

In the study by M. Şep et al., the goal was to predict the hormonal status of BC (ER/PR) using radiomic features extracted from apparent diffusion coefficient maps obtained via MRI. The study considered data from 185 patients, supplemented by synthetic data from 25 patients using the Synthetic Minority Over-sampling Technique to balance classes, followed by division into training (n = 150) and testing (n = 60) cohorts. Manual tumor segmentation was performed over the entire volume, after which first-order radiomic features were extracted. The model based on these features demonstrated high diagnostic performance, with an AUC of 0.81 in the training cohort and 0.93 in the test cohort. When clinical and pathological data (Ki67% proliferation index and histological grade) were added, the combined model maintained a high AUC of 0.93. This model shows high potential for non-invasive assessment of hormone receptor status in breast tumors, which may contribute to more accurate patient stratification and treatment personalization [20].

The study by C.C. Mireștean et al. focuses on the use of radiomics to characterize triple-negative breast cancer (TNBC), an aggressive subtype of BC with poor prognosis and high heterogeneity. Radiomics demonstrates the ability to differentiate TNBC from other tumor types based on features obtained through digital mammography and MRI. In particular, three TNBC subtypes were identified using voxel-level texture, shape, and size features. These subtypes showed a significant correlation with clinical response to NACT. The authors emphasize that standardizing radiomic methodologies is critical for their implementation in clinical practice. In the future, the study's results suggest the possibility of creating radiomic biomarkers and predictive models for a personalized approach to treating TNBC, which could improve outcomes and optimize therapeutic strategies [21].

A promising area of research is the use of contrast-enhanced mammography and radiomic microscopical analysis for the non-invasive characterization of breast tumors. M. Marino et al. conducted a study on the application of contrast-enhanced mammography combined with radiomic microscopical analysis for non-invasive assessment of tumor invasiveness, hormonal status, and malignancy grade in breast cancer. The retrospective study included 100 patients (103 tumor cases) who underwent contrast-enhanced mammography followed by radiomic microscopical analysis using the MaZda platform. The authors utilized various feature groups, including histograms, co-occurrence matrices, and run-length matrices. The model achieved the following accuracies: 87.4% in differentiating invasive and non-invasive tumors, 78.4% in determining hormonal receptor status, 97.2% in classifying HER2-positive and hormone-negative types, and 100% in differentiating TNBC and HER2+ hormone-positive tumors. Research Prospects: The high diagnostic value of the combined approach of contrast-enhanced mammography and radiomics has been demonstrated for non-invasive tumor stratification, which may significantly reduce the need for biopsies [22].

Discussion: AI technologies significantly enhance the diagnostic potential and contribute to the individualization of therapy for breast diseases. The obtained data align with global trends and confirm similar advancements in improving the accuracy of diagnostic procedures and the effectiveness of early detection programs for BC.

In international practice, particular attention is given to large-scale studies on the implementation of AI in screening processes. For example, the National Health Service (NHS) of the United Kingdom initiated the world's largest study on the use of AI for BC diagnosis, covering approximately 700,000 mammograms. The goal of this study is to evaluate the accuracy and reliability of AI compared to traditional analysis methods. Preliminary results show that AI can reduce the workload of Radiologists and accelerate the diagnostic process [23].

Similar results were obtained in Germany, where the use of AI in the screening program led to a 17.6% increase in the detection rate of BC cases without an increase in false-positive results. This confirms the potential of AI in improving the efficiency of diagnostic procedures and early disease detection [24].

The results of modern studies' analysis demonstrated the high promise of using AI in the diagnosis of breast pathologies. However, alongside the positive achievements, there are several limitations and challenges that hinder the widespread implementation of AI in clinical practice and require special attention for further development of AI technologies.

Limited effectiveness of AI in Digital Breast Tomosynthesis (DBT). AI has shown high accuracy in analyzing digital mammograms; however, its application in Digital Breast Tomosynthesis has been less successful. Studies have shown that AI performance in digital breast tomosynthesis is lower compared to traditional methods, which may be due to the limited availability of training data for this technology. A study published in the Korean Journal of Radiology in 2024 found that the use of AI in analyzing synthetic mammograms obtained through Digital Breast Tomosynthesis resulted in lower sensitivity compared to Full-Field Digital Mammography (FFDM). The sensitivity of the AI system when analyzing synthetic mammograms was 76.2%, whereas for Full-Field Digital Mammography it was 82.8%. The reduction in sensitivity was especially pronounced in cases with dense breast tissue and early cancer stages, such as T1 and Ductal Carcinoma In Situ (DCIS). The authors of the study emphasize that AI systems trained on FFDM data are not always effectively applicable to synthetic mammograms without additional adaptation or retraining. This is due to differences in image characteristics between these two imaging methods. Thus, the direct application of AI developed for FFDM to synthetic mammograms may lead to reduced diagnostic accuracy, particularly in cases with clinically significant findings. These findings highlight the need to develop and train AI models specifically designed to analyze synthetic mammograms, ensuring the high accuracy and reliability of diagnosis using Digital Breast Tomosynthesis [25].

Influence of Patient Characteristics on AI Accuracy. A study published in the journal Radiology found that patient characteristics such as race, age, and breast tissue density significantly influence the accuracy of AI algorithms used for BC screening. In particular, Black women had a 50% higher likelihood of false-positive results compared to White women. This indicator was also significantly higher in women with extremely dense breast tissue. Additionally, older women, especially those aged 61-70, were more likely to receive false-positive results. These data underscore the need to include diverse data in training sets to reduce the risk of bias and improve the generalizability of AI algorithms [26].

Lack of superiority of AI over Radiologists in some studies. Despite the achievements of AI in the field of diagnostics, its performance does not always surpass that of experienced Radiologists. A study published in Radiology compared the effectiveness of an AI algorithm with the results of 552 Radiologists in interpreting mammograms. The results showed that AI reached a sensitivity level comparable to that of Radiologists but did not demonstrate significant superiority. This underscores that, despite AI's potential in BC diagnosis, its effectiveness may be limited compared to professional expertise. Therefore, AI should perhaps be considered a supportive tool rather than a replacement for the professional experience of Radiologists [27].

Lack of transparency and reproducibility in AI research. The study conducted by D. Bontempi et al. showed that many studies devoted to AI in medical imaging are characterized by insufficient transparency, lack of access to raw data and code, and a high risk of bias. This hampers the reproducibility of results and undermines trust in the conclusions of such studies. Thus, a systematic review published in Nature Communications noted that insufficient efforts to ensure reproducibility in AI research hinder the verification of claimed performance metrics, ultimately leading to overestimated accuracy and generalizability issues, which impede the clinical implementation of these systems [28].

Conclusion: The application of AI in mammography and MRI using radiomics demonstrates significant potential in improving the diagnosis and personalization of BC therapy. Modern algorithms enable the accurate detection of microcalcifications, the prediction of therapeutic response, and the development of personalized treatment plans. However, the future advancement of AI technologies requires data standardization, improved model interpretability, and adaptation to diverse populations.

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АҢДАТПА

ЖАСАНДЫ ИНТЕЛЛЕКТІНІ СҮТ БЕЗІ ПАТОЛОГИЯСЫН ДИАГНОСТИКАЛАУДА ҚОЛДАНУ: ӘДЕБИЕТКЕ ШОЛУ

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Өзектілігі: *Сүт безі обырын уақытында диагностикалау денсаулық сақтау саласындағы басты міндеттердің бірі болып табылады, өйткені бұл ауру әлем бойынша әйелдер арасындағы өлім-жітімнің басты себебі болып қала береді. Жасанды интеллект (ЖИ) соңғы жылдары кеңінен қолданыла отырып, медициналық бейнелеудің ажырамас бөлігіне айналды. Маммография мен магнитті-резонанстық томография (МРТ) сияқты заманауи диагностикалық әдістер сүт безінің патологияларын анықтауда маңызды құралдар болып табылады, бірақ олардың шектеулері бар. Бұл әдебиет шолуы сүт безі обырын диагностикалауда ЖИ-ді қолданудың заманауи тәсілдерін сипаттайды.*

Зерттеудің мақсаты: *Сүт безі обырын диагностикалауда ЖИ-ді қолдану әдістеріне талдау жүргізу, соның ішінде болжау, нәтижелерді интерпретациялау және бейнелеу әдістерінің дәлдігін арттыру мүмкіндіктері.*

Әдістері: *PubMed, Medline, Cochrane Library және Google Scholar мәліметтер базаларында ғылыми жарияланымдарды іздеу жүргізілді. Шолу сүт безі ауруларын диагностикалауда ЖИ-ді қолдануға арналған мақалаларды қамтиды.*

Нәтижелері: *Шолу қондырмалы нейрондық желілер (CNN) сияқты ЖИ жүйелері маммограммалардағы микрокальцинаттарды жоғары дәлдікпен (94,5%-ға дейін) анықтауға және жалған оң нәтижелерді 11%-ға дейін төмендетуге мүмкіндік береді. МРТ кескіндерін талдауда CNN-RNN сияқты гибридті модельдерді қолдану қатерлі ісіктерді диагностикалаудың дәлдігін 15%-ға жақсартады және қателердің санын 20%-ға азайтады. Радиомика терапевтік жауапты болжауда жоғары дәлдікті 87%-дық көрсетеді, ал мультиомдық деректерді біріктіру сезімталдықты 92%-ға дейін қамтамасыз етеді.*

Қорытынды: *Сүт безін диагностикалауда ЖИ-ді қолдану бейнелеу әдістерінің дәлдігін арттырады, деректерді интерпретациялауды жеңілдетеді және терапияны жеке негізде жүргізуге мүмкіндік береді. Алайда, модельдерді оқыту үшін деректердің қолжетімділігі мен шешім қабылдаудың этикалық аспектілері сияқты қиындықтар әлі де бар.*

Түйінді сөздер: *сүт безі обыры, жасанды интеллект, маммография, МРТ, радиомика, болжам.*

АННОТАЦИЯ

ПРИМЕНЕНИЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА В ДИАГНОСТИКЕ ПАТОЛОГИИ МОЛОЧНОЙ ЖЕЛЕЗЫ: ОБЗОР ЛИТЕРАТУРЫ

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Актуальность: *Своевременная диагностика рака молочной железы является одной из ключевых задач здравоохранения, так как это заболевание остаётся ведущей причиной смертности женщин во всём мире. В последние годы технологии искусственного* *интеллекта (ИИ) прочно вошли в сферу медицинской визуализации, получив широкое распространение в клинической практике. Основные методы диагностики, включая маммографию и магнитно-резонансную томографию (МРТ), играют ведущую роль в обнаружении заболеваний молочной железы, однако имеют ряд ограничений. Настоящий обзор посвящён анализу современных возможностей применения ИИ для повышения эффективности диагностики рака молочной железы.*

***Цель исследования** – проанализировать методы применения искусственного интеллекта в диагностике рака молочной железы, включая возможности прогнозирования, интерпретации результатов и повышения точности методов визуализации.*

***Методы:** Проведён поиск научных публикаций в базах данных PubMed, Medline, Cochrane Library и Google Scholar. В обзор включены статьи, посвящённые применению ИИ в диагностике заболеваний молочной железы.*

***Результаты:** Обзор показал, что системы ИИ, такие как свёрточные нейронные сети, позволяют с высокой точностью (до 94,5%) обнаружить микрокальцинаты на маммограммах и снижать количество ложноположительных результатов на 11%. МРТ в оценке прогнозирования ответа на неоадъювантную химиотерапию демонстрирует наибольшую чувствительность (80,0-83,3%) при выявлении остаточной опухоли, тогда как нейросетевые методы показали сопоставимые результаты (69,2-72,0%), превосходя при этом традиционную маммографию и ультразвуковое исследование. Радиомика демонстрирует высокую точность (87%) в прогнозировании терапевтического ответа, а интеграция мультиомных данных обеспечивает чувствительность до 92%.*

***Заключение:** Применение ИИ в диагностике молочной железы повышает точность методов визуализации, облегчает интерпретацию данных и способствует персонализации терапии. Однако остаются вызовы, такие как доступность данных для обучения моделей и этические аспекты принятия решения.*

***Ключевые слова:** рак молочной железы (РМЖ), искусственный интеллект (ИИ), маммография, магнитно-резонансная томография (МРТ), радиомика, прогнозирование.*

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