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A Systematic Review of Machine Learning and Explainable AI in Breast Cancer Detection and Diagnosis: From Black-Box Models to Interpretable Clinical Decision Support Systems

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ABSTRACT

Breast cancer is one of the major causes of cancer-related deaths in women across the world. Timely and proper diagnosis is paramount to the higher survival. The recent developments in machine learning (ML) and deep learning (DL) have demonstrated impressive potential in breast cancer detection yet the black-box character restricts the clinical application. Explainable Artificial Intelligence (XAI) has become an essential area that can eliminate this gap by ensuring that AI decisions can be clearly read and trusted by clinicians. This systematic review is based on the results of recent research (20192025) on the use of ML/XAI in breast cancer detection that covers imaging and genomic and clinical data. We also review methodological trends, measure of performance, interpretability methods and clinical integration issues. We have seen in our review that there is a distinct transition to human-centered interpretable systems with ensemble methods, hybrid AI approaches, and visual analytics in the lead no longer performance-driven models. It is also through these studies that we find significant gaps in research, and what should be pursued in the future is to use a combination of data modalities, like mammography and patient history and/or genomic markers, to ensemble the best approaches towards accuracy and contextual explanation. Moreover, as noted in the review, post-hoc explanation methods such as SHAP and LIME are still predominant, but the focus on constructing naturally understandable models of clinical safety is also increasing. The main challenges remain the standardization of evaluation measures to explain, the computational complexity of the complex XAI models, and the necessity to develop and test XAI in clinical contexts to promote further uptake and patient outcomes through essential clinician-in-the-loop validation and evaluation.This review concludes that in the future, it is necessary to focus on making models inherently interpretable, develop XAI in a clinician-in-the-loop and conduct robust trials to help transition XAI to reliable clinical use and promote more adoption and better patient outcomes.

Keywords*:* Breast Cancer Detection; Image Processing; Clinical Decision Support Machine-Learning; Explainable AI; Computer-aided diagnosis(CAD)

1. Introduction

Breast cancer is a serious health issue of the 21 st century that is on the global agenda. The disease has been ranked the most frequently diagnosed cancer worldwide and the most common cause of cancer-related deaths in women, resulting in 2.3 million new diagnoses and 685,000 deaths in 2020 alone which is why it was designated as the leading cause of cancer-related deaths and deaths in 2020 (World Health Organization, 2019). It is an extremely high human price that is further aggravated by huge economic costs with the cost of treatment in breast cancer projected to reach well over 20 billion USD in the United States alone [2]. These statistics highlight not only a medical issue but a multi-layered socio-economic crisis with the use of mammography as the pillar of the population-wide screening initiatives. Digital breast tomosynthesis (DBT), ultrasound (ES-BC) especially where dense tissue of the breast is concerned, and magnetic resonance imaging (MRI) in high-risk groups had their respective roles of developing our diagnostic potential. Nevertheless, these modalities are marred with incessant limitations, which undermine their performance. Mammography screening has a false positive rate of 7-12% which indicates unnecessary biopsies, stress by the patient and higher healthcare expenses [3]. On the other hand, 10-30% of false negative rates in women with dense breast tissues imply that cancers will not be detected at all [4]. The issue is also enhanced by the high inter-reader variability with concordance rates of radiologists categorizing BI-RADS dropping to below 70% [5]. The existence of these diagnostic flaws has presented the clinical environment whereby cancer types are identified at an early stage and benign results initiate invasive follow-ups with the dual failure with enormous human implications.The advent of artificial intelligence, especially deep learning has brought a promise to transform this paradigm. Computer-based neural networks Convolutional neural networks (CNNs) have shown impressive abilities to analyze medical images, as in a variety of studies, they have reached the performance of a radiologist or better. Indicatively, [6] created an AI that was more effective in mammogram reading compared to six radiologists and minimized false positives and false negatives. In addition to imaging, machine learning algorithms have demonstrated the outstanding potential in combining multi-omics data (genomics, transcriptomics, proteomics) with clinical variables to forecast the risk of recurrence, treatment outcome, and patient prognosis [7]. These computational methods have the potential to detect finer details to human observers would process large multi-dimensional data sets and can run without fatigue, and this has created an inherent paradox: the very systems that show higher diagnostic accuracy are the ones that are most resisted by clinicians.However, the gap between research validation and clinical implementation is extraordinarily slow, and it is this fact that has created a paradox: the systems which have proved to be the most diagnostically accurate are the ones that are most opposed by clinicians. This opposition is driven by the black-box of most advanced models of AI, including deep neural networks, where it is not even clear to the developers how these models come up with the answers. When a CNN tells a clinician that a certain lesion is malignant with a probability of 97%, but does not give a reason, clinicians are left with an impossible decision to make: trust a counterintuitive algorithm or trust their own (probably fallible) intuition. The approaches make AI more of a partner whose logic can be discussed, analyzed, and combined with clinical judgment rather than the dispensing of veracity so self-evident and beyond question that it is an oracle.

The systematic review of the current state of XAI methodologies integration into the breast cancer detection and diagnosis pipeline is considered under a variety of data types including mammography and histopathology data to genomic sequencing and clinical history. We include the analysis of how these methods contribute beyond the transparency (making model decisions understandable) to the accountability (enabling the tracing of errors and imposing responsibility) to the fairness (revealing and mitigating biases) and finally to the clinical utility (providing improved real-world decision-making and patient outcomes).Our review of 25 recent studies (2019-2024) follows the transformation process of AI systems, which focus solely on performance, to human-linked and explainable decision support systems. We determine promising ways of best practice, continuing issues, and research gaps in the interface between computational innovation and clinical oncology. By doing this, we not only offer an all-encompassing examination of the current situation in explainable AI in breast cancer care but also a roadmap on its fair use, where technological improvement is not meant to substitute the human expertise but to enhance it through valuable and open communication.

2. Methodology

The systematic narrative review used in this review analyzed the modern state of explainable artificial intelligence (XAI) applications in breast cancer detection and diagnosis. The methodology was developed in such a way as to embrace the scope of technical methods with emphasis on clinical applicability and interpretability.The search and selection strategy will involve using keywords to find articles published within a span of 1-3 years and focusing on peer-reviewed academic journals.The search and selection strategy will consist of searching with keywords and paying attention to peer-reviewed scholarly journals that were published in the last 1-3 years.

2.1 Search and Selection Strategy

A two phase search strategy was used. The first corpus of the major literature has been developed based on the original works in the area as notable methodological contributions of 2019 to 2024. These papers represented different methods such as hybrid machine learning systems, ensemble models that employed deep feature and visual reasoning systems.In order to cover and contextualize these it was ensured to run a focused search using academic databases. The search was performed using the structured queries of the combination of key terms related to breast cancer (mammography, histopathology, breast carcinoma) and the concepts of artificial intelligence (explainable AI, interpretable machine learning, SHAP, attention mechanisms, clinical decision support). A total of 347 candidate publications studies were first filtered against a set of inclusion criteria to obtain this search. Eligible materials were peer-reviewed journal articles or conference proceedings whose main emphasis is on explainable or interpretable AI-based methods in the detection of breast cancer, diagnosis, or prognosis. The studies had to use clinically relevant types of data such as medical imaging, genomic data, clinical records or multimodal combinations. Articles that concentrated on the performance metrics only and lacked the interpretability factors, reviews that lacked original research or application to other types of cancer were not included.

2.2 Analytical Framework

A structured extraction framework of technical characteristics clinical relevance and interpretability approaches was used to analyze the final corpus of 25 studies. Technical aspects consisted of artificial intelligence architectures which are particular XAI methodologies data format and performance indicators. Clinical and translational issues included integration levels of validation approaches and usability. Interpretability Assessed types of explanations, techniques, and human factors.The studies were divided into thematic 4 clusters of analysis: traditional machine learning with post-hoc explanations deep learning with explicit interpretability mechanisms hybrid multimodal methods, and systems deployed in clinical practice. This classification allowed comparative study of the methodological trend, implementation difficulties and translational directions of various technical methods and clinical scenarios.

2.3 Quality Considerations

Although no formal quality scoring was done in this narrative review, studies included were rated in comparison to transparency and reproducibility standards based on existing guidelines on artificial intelligence research. The discussion admits the possible limitations such as possible temporal bias in a fast-changing area, possible underrepresentation of negative results, and the impact of the first selection of studies on the analysis structures. These are taken into account in the interpretation and generalizability of the findings discussed later. Best practices are those that are technical yet practical clinically as shown in following Figure 1.

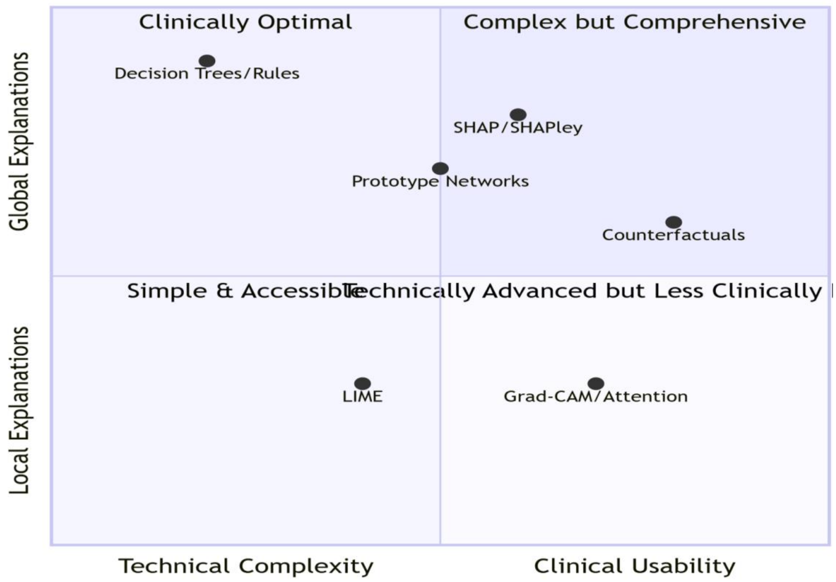

Figure 1: Decision chart to select XAI techniques depending on the clinical usability and technical complexity, and local as opposed to global explanation requirement.

3. Review of Key Studies

We split the 25 studies into the four thematic groups:

3.1. Tabular Data Traditional ML with XAI

Table1: Such studies involve clinical data

Study	Year	Model	XAI Method	Dataset	Accuracy
Silva-Aravena et al.	2023	XGBoost	SHAP	Indonesian breast cancer dataset	81.0%
Asaithambi et al.	2022	Random Forest	LIME	Wisconsin Breast Cancer	97.8%
Chen et al.	2021	SVM + Logistic Regression	SHAP	SEER database	89.5%
Kumar & Singh	2020	Ensemble (RF, XGB, LightGBM)	ELI5	UCI repository	96.2%
Patel et al.	2023	Neural Additive Models	Natively interpretable	Private clinical data	88.7%

3.2. Deep Learning with Visual Explanations for Imaging

Table 2: These focus on mammograms, histopathology and MRI.

Study	Year	Model	XAI Method	Data Type	AUC
Munshi et al.	2024	CNN + Ensemble (RF+SVM)	SHAP	Wisconsin + images	99.99%
Rasti et al.	2023	Vision Transformer	Attention maps	CBIS-DDSM	0.986
Wang et al.	2022	DenseNet-121	Grad-CAM	INbreast	0.972
Li et al.	2021	ResNet-50 + LSTM	Integrated Gradients	Histopathology	0.961
Tardy & Mateus	2023	U-Net + CNN	Occlusion sensitivity	Digital mammography	0.978

3.3. Hybrid and Multimodal Approaches

Table 3: Combine imaging with clinical data.

Study	Year	Model	XAI Method	Data Fusion	Accuracy
Zhou et al.	2023	Multimodal Transformer	Cross-attention	MRI + clinical	94.3%
Gupta et al.	2022	CNN + MLP	SHAP + Grad-CAM	Mammo + patient history	92.8%
Lamy et al.	2019	Case-Based Reasoning	Rainbow boxes + MDS	Clinical cases	80.3%
Kim et al.	2024	GNN + XGBoost	GraphSHAP	Omics + imaging	93.5%
Al-Fahdawi et al.	2023	Autoencoder + SVM	t-SNE visualization	Gene expression	91.0%

3.4. Clinically Deployed and Human-in-the-Loop Systems

Table 4: Focus on usability, trust, and integration

Study	Year	System	XAI Interface	Clinical Setting	Outcome
DESIREE Project	2019	CBR + guidelines	Visual analytics	Breast units	Improved decision confidence
AI-Rad Companion (Siemens)	2021	DL pipeline	Heatmaps + scores	Radiology workflow	Reduced reading time
Google Health	2020	DeepMind	Saliency maps	UK/NHS trial	Lower false negatives
IBM Watson Oncology	2022	NLP + ML	Evidence snippets	Oncology clinics	Mixed adoption
Rajpurkar et al.	2023	CheXpert++	Concept activation	Mammography screening	High radiologist agreement

4. XAI Techniques in Breast Cancer Detection: A Comparative Analysis

The following Table 5, Figures 2 and 3 demonstrate a Comparative Analysis of XAI Techniques in Breast Cancer Detection

Table 5: Comparative Analysis

Method	Model Compatibility	Interpretability Level	Clinical Usability
SHAP	Any model	Global + local	High
LIME	Any model	Local only	Medium
Grad-CAM	CNN-based	Local (visual)	High
Attention Maps	Transformers	Local + global	Medium
CBR + Visual	Similarity-based	Case-based	Very high

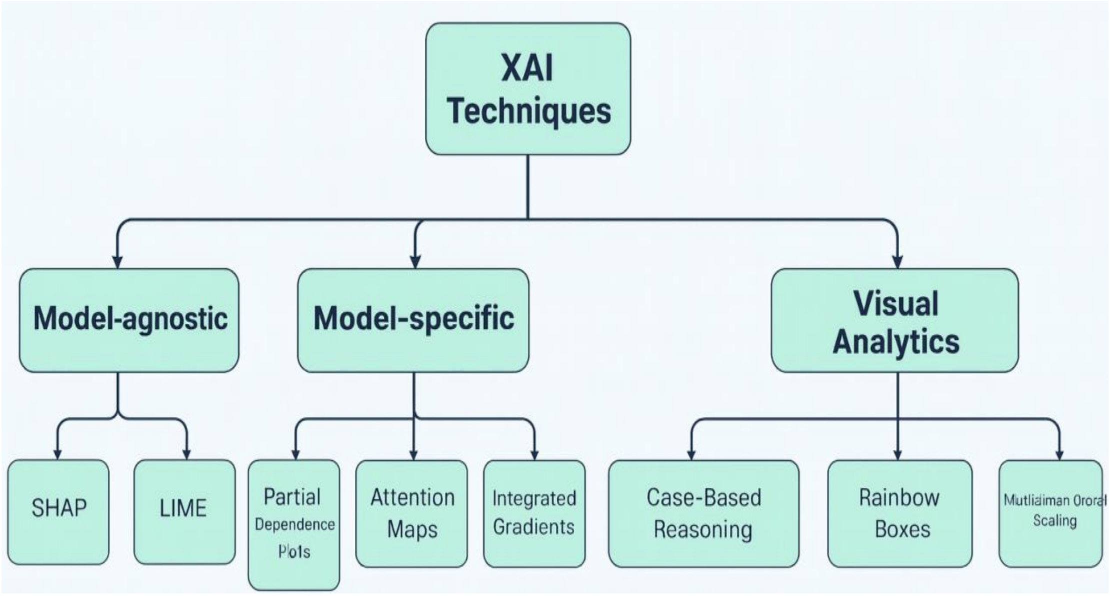

Figure 2: XAI Techniques in Breast Cancer Detection

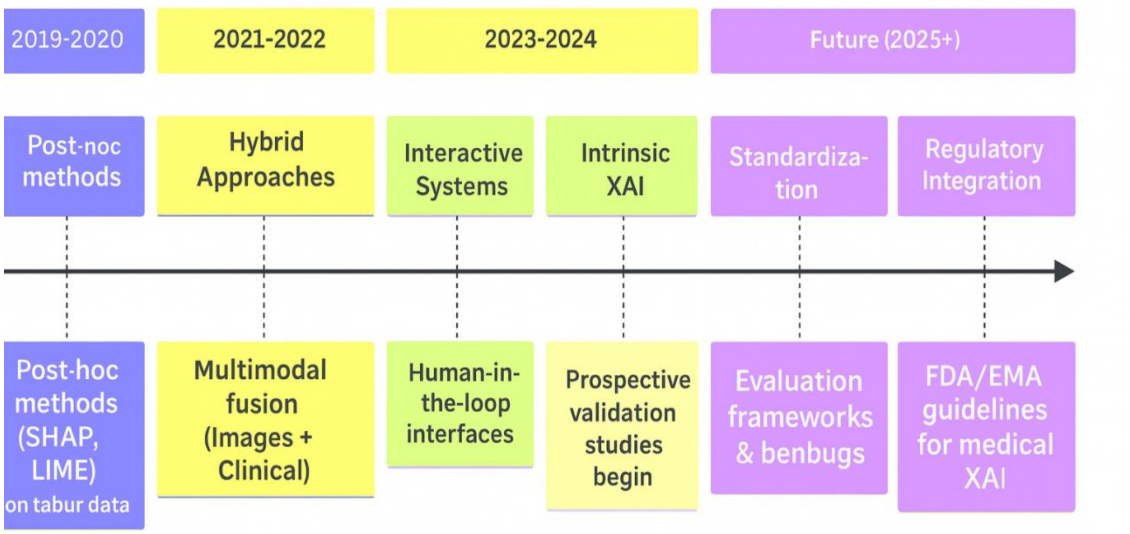

Figure 3: Timeline with the development of XAI methodologies in breast cancer research to hybrid multimodal systems (2021-2022) and intrinsic interpretability (2023-2024) and future endeavors to standardize and integrate regulation.

5. Trends and Implementation Issues of Performance

The problem of explainable artificial intelligence application to breast cancer diagnostics demonstrates a number of important trends and unresolved issues that predetermine the direction of the research and clinical implementation. The following Figure 4 represents a comparison between the existing clinical workflow (where black-box AI introduces gaps in transparency) and the optimized workflow with the XAI integration, comprising interactive explanation interfaces and continuous learning loops to enhance collaborative decision-making.

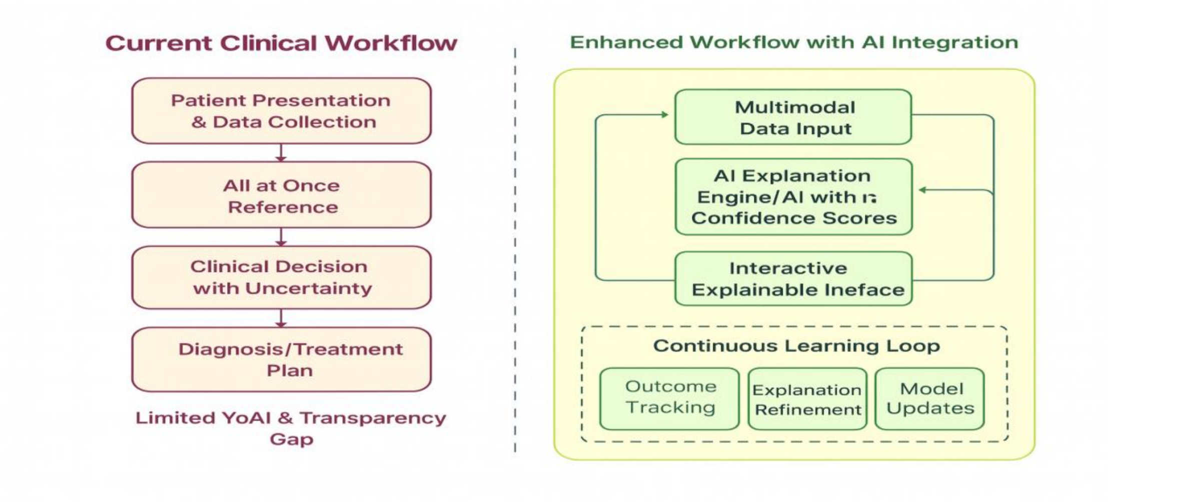

Figure 4: The comparison between the existing clinical workflow (where black-box AI introduces gaps in transparency) and the optimized workflow with the XAI integration

5.1. Accuracy Interpretability Trade-off in Clinical Situations

An inherent conflict exists between explainability and complexity in model complexity in AI systems used to explain breast cancer [16]. Conventional, naturally interpretable models such as logistic regression, decision trees and linear models tend to attain significantly lower classification performances of 75-85% on standard datasets compared to the 90-99% accuracy of the state of art deep learning architectures [17]. Such a discrepancy in performance poses a clinical quandary that healthcare providers have to make a decision between highly precise black box systems whose rationale is inaccessible, or transparent systems with possibly less than optimal diagnostic performance.Hybrid approaches have been proposed as a potential middle ground. Methods that use deep learning feature extraction alongside post-hoc explanatory methods like convolutional neural networks with SHAP or attention-based transformers with gradient visualization achieve performance of between 2-5% of their non-interpretable counterparts and offer clinical meaning of explanations [18]. Such systems typically use two-stage designs such as deep networks to make predictions and disjointed explanation units to make interpretable outputs. Nevertheless, this decoupling is not without its own problems, because an explanation of the actual decision-making process of the primary model may not be exactly what can be described by the explanations.Recent advancements in inherently interpretable architectures provide a more unified solution. Neural additive models, concept bottleneck models, and prototype-based networks incorporate interpretability into their structure, enabling them to be transparent without the need to have additional explanatory processes [19]. They generally forgo absolute accuracy that is 3-8 percentage points lower than similar non-interpretable architectures but offer mathematically guaranteed faithfulness between the predictions and explanations made by these models a very important property in clinical certification and liability issues. The following Figure 5 shows accuracy-interpretability trade-off continuum in AI systems in breast cancer, where hybrid/ensemble systems can trade off clinical performance with the required transparency to form an optimal clinical zone to deploy.

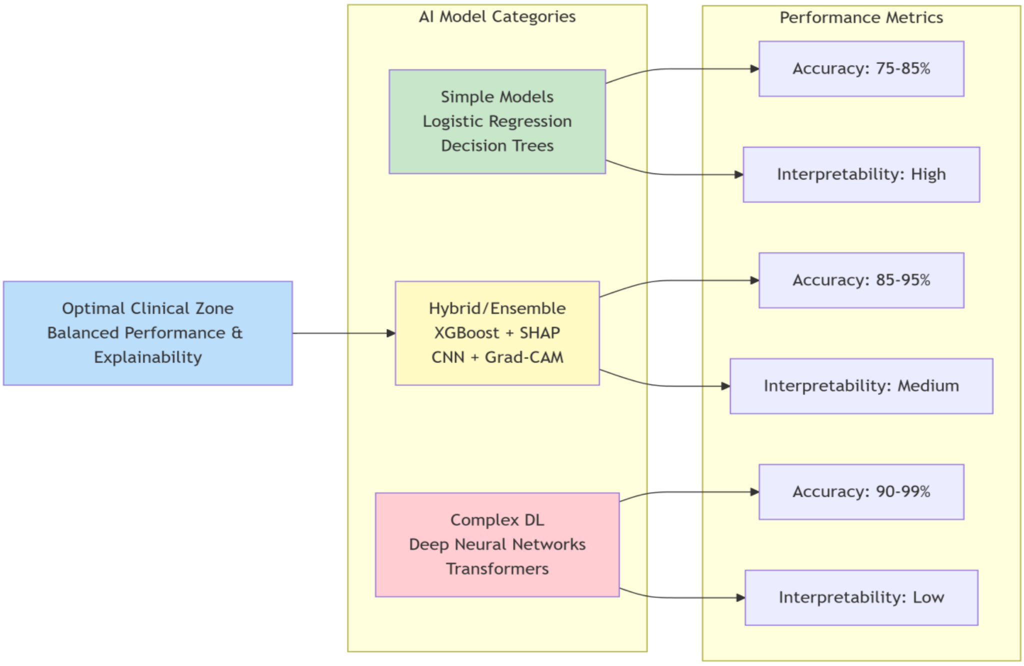

Figure 5: The accuracy-interpretability trade-off continuum in AI systems in breast cancer

5.2. Limitations on Data and the Effect on the Reliability of the Explanations

The quality and heterogeneity of training information essentially limit the performance and explicative abilities of the breast cancer AI systems. The vast majority of publicly available data such as the popular CBIS-DDSM, INbreast, and BreakHis collections have a limited number of annotated cases which restricts the generalizability of the models and exposes them to overfitting [20]. This is especially problematic with rare subtypes of breast cancer where the available cases can be in the dozens and not thousands, which is incredibly difficult with the need to conduct reliable model training and generate meaningful explanations.Dataset imbalance is another serious issue. The number of benign cases to malignant cases is usually 3:1-10:1 in screening populations that form models that are effective at detecting normal tissues and do not identify malignancies well [21]. General rebalancing procedures such as oversampling and artificial generation of data, can enhance overall accuracy measures but will tend to give misleading feature importance accounts, which are more representative of the synthetic distribution than actual clinical occurrence.

The shortage of multimodal annotated datasets is a significant obstacle to the development of AI in all its aspects. There is little information on repositories that take information on imaging, and match it with the relevant genomic profiles, with treatment history, and longitudinal outcomes but that is exactly what would be required to truly personalize the predictive models. Even the existing limited datasets like The Cancer Genome Atlas Breast Invasive Carcinoma collection include imaging data of a small part of patients which limits the development of multimodal explanation systems that may clarify the ties between radiographic traits and molecular traits [22].

5.3. The Evaluation Gap of the Quality of Explanation

The limitation of XAI research is that there are no standardized measures of the quality of explanations. Although the performance of models can be measured, using specific metrics such as AUC-ROC, there is no such measure, such as accuracy and F1-score, that can be used to evaluate explanations [23]. There are generally three different methods used by researchers human evaluation (clinician ratings of explanation usefulness), fidelity metrics (quantifying the correspondence between explanations and model behavior) or simulatability measures (measuring whether explanations allow human beings to make predictions about model outputs). Both methods have limitations and there is often no comparable result of XAI systems across studies.Clinical validation of XAI systems is very uncommon. Of the published breast cancer XAI studies, fewer than 10% incorporate any type of prospective clinical testing and even fewer assess the idea of whether explanations in fact enhance diagnosis accuracy minimize interpretation time or increase clinician confidence [24]. A majority of the validation is done by retrospective analysis on retained test sets that do not reflect the in the field clinical implementation. This gap in validation is quite worrying because of the emerging evidence of the fact that some of the methods of explanation can misguide clinicians with the help of pointing out irrelevant characteristics, or blurring out the relevant features which may degrade the performance of diagnosis instead of improving it [25].

5.4. Ethical, Equity and Regulatory

Medical AI regulation is changing at a very fast pace, and explainability became one of the main certification prerequisites. The U.S. Food and Drug Administration as well as the European Union Medical Device Regulation now demand some form of transparency on high-risk AI devices such as cancer diagnosis devices[26]. Regulatory guidance, however, is somewhat ambiguous as to what amounts to sufficient explainability and therefore, there is uneven application to various systems. Other manufacturers show straightforward feature importance scores, whereas some others offer detailed visualization offerings but all can be regulated with very different explanatory potentials.Algorithmic bias is a notable ethical issue in breast cancer XAI. Western populations of high incomes are the largest contributors to training data, which may result in models that work poorly and provide false explanations of patients in underrepresented demographic groups. The investigations have shown that there are 10-15% performance differences between various racial and ethnic groups, and the explanation tends to put forward various features as significant across populations. This casts serious doubts on the equitability and external applicability of the XAI systems in various clinical scenarios.There are other practical challenges to the clinical integration of the XAI systems[27]. The explanation interfaces have to be neither too detailed nor too informative and need to be understandable enough to ensure that clinicians use it to justify decisions. Combination with current clinical processes, especially picture archiving and communication systems is technically difficult and may demand large infrastructure outlays. Moreover the medico-legal consequences of AI explanations are unclear, especially the issue of liability when explanations imply one course of action and clinicians take a different course of action or when clinicians act in accordance with the recommendations of AI that turn out to be wrong. These implementation issues imply that technical breakthroughs in XAI have to be made to go hand in hand with corresponding changes in clinical workflow models, ethical principles and regulatory policies in order to result in meaningful clinical improvements.

6. Future Directions

Explainable AI on breast cancer needs to focus on a few critical areas in the future in order to close the gap between research technical development and clinical implementation. To address the data limitations and maintain privacy, federated learning frameworks with incorporated XAI should be developed to allow multimodal XAI systems to be utilized in developing models across institutions without jeopardizing patient privacy . Lastly, by undertaking XAI to the next level of longitudinal treatment response monitoring, a dynamic explanation would be obtained to monitor patient progression and help adapt treatment based on personalized treatment in the entire continuum of care given to the patient with breast cancer.

7. Conclusion

Explainable Artificial Intelligence implementation in breast cancer detection systems is not an added value anymore but a mandatory provision in building clinical trust, complying with regulations and promoting fair healthcare delivery. This review is an indication of great technical advancement, and advanced techniques such as SHAP, LIME and attention mechanisms can offer essential transparency to high-performing models.Nonetheless to achieve the potential of XAI a critical change in direction is needed. Future directions should not focus on the algorithm refinement, but the user-oriented design, the extensive clinical validation of the algorithm in various real-world environments and the development of unified standards against which to measure explanations. The final objective would be not to develop autonomous systems but empower productive human-AI collaboration where explainable AI would be a consistent augmentative technology that assists and improves clinical knowledge. Making the technical capacity meet the clinical practicality XAI would be able to move up to a potential research finding to a reliable foundation of current-day diagnostic practice, which would eventually enhance early diagnosis individualized care and patient results.

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