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An Enhanced Feature Selection Integrated Explainable Machine Learning Models for Prediction of Breast Cancers

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Abstract
The prediction of breast cancer has evolved significantly with the advent of machine learning models, which offer promising tools for early diagnosis and personalized treatment planning. This systematic literature review examines 31 peer-reviewed analyses undertaken between 2019 and 2024, targeting on the integration of enhanced feature selection methods within explainable machine learning models for breast cancer prediction. The primary goal is to assess how feature selection techniques contribute to model accuracy and interpretability, ensuring that predictions are both reliable and understandable to clinicians and researchers. The reviewed studies highlight a trend towards the use of sophisticated feature selection algorithms that refine input data, yielding models that not only enhance prediction accuracy but also generate actionable insights to inform decisions. This is especially important in healthcare, where the explainability of AI models can enhance trust and adoption by medical professionals, potentially improving patient outcomes. Despite these advancements, the review identifies several challenges, including the need for large, diverse datasets to ensure model generalizability and the difficulty of balancing model complexity with interpretability. Furthermore, the integration of these models into clinical workflows remains a significant hurdle due to varying levels of transparency and the potential for bias in feature selection. Gaps in the current literature suggest that future research concentrate on creating developing standardized frameworks for integrating feature selection with explainable models, ensuring that these tools are both effective and widely applicable in clinical settings. This review aims to guide future research and development efforts towards creating more robust, transparent, and clinically useful predictive models for breast cancer, ultimately contributing to more precise and personalized healthcare solutions.

Keywords: Breast cancer prediction, machine learning, feature selection, explainable AI, clinical decision support, model interpretability, healthcare AI.

1.INTRODUCTION

Breast cancer remains one of the leading causes of death among women globally, posing a significant health threat [1]. The importance of early detection and precise diagnosis cannot be overstated, as they are vital in improving survival rates and patient outcomes [2]. Recently, the advent of AI and ML has introduced promising advancements in breast cancer detection and diagnosis, offering enhanced accuracy, efficiency, and support in medical decision-making [3].

Research into using machine learning for predicting and classifying breast cancer has gained significant momentum, with various algorithms and approaches being explored [4]. These computational methods aim to address several challenges in breast cancer diagnosis, including the extensive number of dimensions present in contemporary datasets, the integration of multi-omics data, and the need for interpretable and explainable models [5].

The process of selecting the right features is crucial for building accurate machine learning models aimed at predicting breast cancer. By carefully choosing relevant features, the overall performance and reliability of these predictive models can be significantly enhanced. By identifying the most relevant and informative features from high-dimensional datasets, feature selection techniques can improve model performance, reduce computational complexity, and provide insights into the biological mechanisms underlying the disease [6]. Various feature selection techniques have been suggested, including filter-based approaches, wrapper methods, and embedded techniques [7].

In addition to feature selection, the choice of ML classifier substantially affects the performance of breast cancer prediction models. Researchers have investigated a wide range of algorithms, including various ML models [8]. Ensemble methods, such as gradient boosting and bagging, have also shown promise in improving classification accuracy and robustness.

While machine learning models have demonstrated high accuracy in breast cancer prediction, there is an increasing focus on creating models that are both understandable and transparent to users[9]. Explainable AI techniques, such as SHAP (SHapley Additive exPlanations), strive to shed light on the decision-making dynamics of intricate models, enhancing trust and acceptance among healthcare professionals [10].

This systematic literature review focuses on enhanced feature selection techniques integrated with explainable ML models for breast cancer prediction. By examining current advancements in feature selection methods, classification algorithms, and model interpretability, this evaluation aims is to offer a thorough summary. of the current cutting-edge techniques in breast cancer prediction through ML.

It will explore various aspects of breast cancer prediction models, including:

1. Attribute Filtering Strategies and Their Impact on Model Success
2. Comparative analysis of different machine learning classifiers
3. Integration of multi-omics data and its challenges
4. Explainable AI approaches for breast cancer prediction
5. Performance metrics and evaluation methodologies
6. Limitations and future directions in the field

Recent studies have demonstrated the potential of machine learning models in attaining optimal accuracy for breast cancer identification. For instance, support vector machines have shown promising results with accuracy rates of up to 92.7% [11]. Other approaches, such as the combination of Light Gradient Boosting Model (LGBM), CatBoost, and Extreme Gradient Boosting (XGB) for feature selection, have achieved accuracy rates of 96.49% when combined with Naive Bayes classifiers [12].

The integration of multiple data types, including genomic, clinical, and imaging data, has been explored to improve prediction accuracy [13]. However, this integration poses challenges in terms of data dimensionality and feature selection [14]. Researchers have proposed various strategies to address these challenges, including multi-stage feature selection frameworks and early integration schemes [15].

Explainable AI techniques have gained importance in recent years, addressing the "black box" nature ML models [16]. These approaches shows interpretable insights into model predictions, which is crucial for clinical adoption and trust-building among healthcare professionals.

This review aims to compile and evaluate recent research findings to pinpoint the most effective strategies for predicting breast cancer and to outline potential avenues for further investigation and enhancement. The conclusions drawn from this analysis are intended to advance the creation of more precise, understandable, and clinically applicable models for detecting and diagnosing breast cancer, thereby enhancing patient care and outcomes

2. BACKGROUND AND RELATED WORKS

Advances in ML and AI have surfaced as potent instruments in combating this disease, presenting opportunities for enhanced diagnosis and prognosis.

[17] presents a machine learning method for classifying the Surveillance, Epidemiology, and End Results (SEER) breast cancer dataset. This approach utilizes a two-phase feature selection process involving variance thresholding and principal component analysis, and subsequently applies classification through various supervised and ensemble learning algorithms, including AdaBoost, XGBoost, and Gradient Boosting.

Building on this, [18] compares eleven different machine learning algorithms to predict breast cancer recurrence. This comprehensive study found that the AdaBoost algorithm outperformed other methods, achieving the best prediction performance.

[19] introduces an innovative hybrid ML model that combines fuzzy logic and dimension reduction (MLF-DR) to enhance decision-making abilities and operational efficiency. This method integrates a fuzzy inference mechanism during the data analysis phase and applies dimension reduction methods in the preprocessing stage to identify the most effective features for optimization. The study reports that the Logistic Regression-Principal Component Analysis (LR-PCA) model achieved better accuracy in diagnosing breast cancer.

To further progress in this domain, [20] assesses and contrasts five distinct machine learning techniques utilizing a core dataset consisting of 500 patients. The research employs SHAP analysis to interpret the predictions of the XGBoost model and gain insights into the influence of each feature. After final evaluation, XGBoost attained the optimal model accuracy demonstrating the potential of this approach for breast cancer prediction. [21] the AdaBoost-Logistic algorithm achieved the peak accuracy on the Wisconsin Breast Cancer Dataset, outperforming previous techniques and showcasing its potential for clinical decision support.

In a novel approach, [22] integrates nanopipette dielectrophoresis with Surface-Enhanced Raman Scattering (SERS) analysis for cancer detection. This study employs Shapley Additive Explanations (SHAP), an explainable AI technique, to interpret complex SERS data from clinical samples. This implementation exposes the potential of combining advanced analytical techniques with explainable AI for cancer diagnostics. [23] presents an integrated framework combining CNNs and explainable AI for enhanced breast cancer diagnosis using the CBIS-DDSM dataset.

Addressing privacy concerns, [24] explores the intersection of explainable AI, privacy, and federated learning in breast cancer diagnosis. Using the Wisconsin Diagnostic Breast Cancer Dataset and Wisconsin Breast Cancer Dataset, the study demonstrates that federated learning can enhance user privacy while maintaining performance, achieving high accuracy and F1 scores across different models. [25] HHNN-E2SAT models outperformed standard algorithms, achieving over 98% on all performance metrics, highlighting the potential of these advanced techniques in improving breast cancer detection.

In addition to this, [26] introduces a transparent ML model designed to forecast postoperative complications in cancer patients undergoing significant surgical procedures. Using electronic health record data and the SHAP method, the model accurately predicts the risk of developing complications and provides insights into the contributing factors, demonstrating the potential of explainable AI in improving patient care. In reference [27], an enhancement technique is integrated into the Google Inception Network to improve breast cancer detection and classification. This enhanced model retains both local and global data, effectively addressing the diverse nature of breast tumor morphology. The model achieves high accuracy, recall, and sensitivity on a dataset of ultrasound images, showcasing its effectiveness in breast cancer detection. [28] compares various classifiers including KNN, SVM, Ensemble Classifier, and Logistic Regression on the Wisconsin Diagnostic Breast Cancer and Breast Cancer Coimbra datasets. The study introduces a Diagnostic Enhancement Technique (DET) to improve model performance, with the polynomial SVM. [29] proposes a comprehensive approach for breast cancer detection using the BreakHis dataset. The study employs adaptive filtering for noise removal, thresholding level set for segmentation, and a hybrid optimization technique for feature selection. The proposed method achieves high accuracy and other performance metrics, outperforming existing techniques on the BreakHis dataset.

In reference [30], a new method for data binarization is presented, aimed at enhancing the treatment of RNA sequencing data in cancer prediction models. This technique is evaluated across five distinct models using four cancer datasets, showcasing competitive performance with a reduced number of features. The research underscores the promise of data binarization in boosting the effectiveness and interpretability of RNA sequencing-based cancer prediction models.

Reference [31] assesses and contrasts five distinct machine learning approaches utilizing a primary dataset consisting of 500 patients from Dhaka Medical College Hospital.

Table 1 presents the summary of different existing techniques handled by the researches.

These advancements collectively contribute to more accurate, interpretable, and privacy-preserving breast cancer detection methods. As advancements in this domain progress, we anticipate enhanced capabilities for early detection, patient outcomes, and the overall management of breast cancer.

Table 1 Survey from the Different Authors

Ref	Methodology	Result/Accuracy	Limitations
[1]	Logistic Regression, SVM, KNN	SVM achieved highest accuracy of 92.7%	limited by dataset size and features
[2]	Light Gradient Boosting Model (LGBM), Catboost, Extreme Gradient Boosting (XGB)	Naive Bayes classifier achieved 96.49% accuracy	Limited to feature selection; may not generalize to other datasets
[3]	SVM, Random Forest, Logistic Regression, Decision Tree, KNN	SVM surpassed with 97.2% accuracy	Limited to specific algorithms; may not include newer techniques
[4]	SVM, KNeighborsClassifier, Random Forest	SVM and KNeighborsClassifier achieved best AUC of 0.82-0.83	Limited to survivability prediction; may not address other aspects of diagnosis
[5]	Logistic Regression, SVM, Bagging, Naive Bayes, Decision Tree, Gradient Boosting, KNN, Random Forest, AdaBoost, ExtraTrees, LDA, MLP	LGR + MLP attained highest accuracy (86%) and AUC (0.94)	Complex methodology may be difficult to implement in clinical settings
[6]	Random Forest, Neural Network, Gradient Boosting Trees, Genetic Algorithms	Random Forest presented highest performance (accuracy 80%, sensitivity 95%, specificity 80%, AUC 0.56)	Limited to specific dataset
[7]	Graph-based gene selection, explainable classifier	Improved accuracy and reduced execution time assessed to cutting-edge methods	May require complex computational resources
[8]	SVM, Random Forest, Extra Trees, XGBoost	Integrating ensemble models early and employing a two-phase feature selection process led to enhanced outcomes	Limited to multi-class classification; may not address binary classification needs
[9]	CNN Improvements for Breast Cancer Classification (CNNI-BCC) model, RF, DT, KNN, LR, SVC, Linear SVC	Proposed model highly efficient and accurate (specific accuracy not provided)	May require significant computational power for imaging methods
[10]	ANN with tuned hyperparameters, filter-based feature selection	Attained accuracy of 99.51%	Limited to specific feature selection methods; may not explore all possible combinations
[11]	Random Forest, XGBoost	Random Forest achieved highest performance (AUC: 0.793)	Focused on specific patient group; may not apply to all breast cancer cases
[12]	K-nearest neighbors, ANN	K-nearest neighbors achieved 97.7% accuracy, ANN achieved 98.6% accuracy	May not address complex, non-linear relationships in data

[13]	XGBoost, Random Forest, Logistic Regression, K-nearest neighbor	XGBoost model (8:2 data split) had best effects: recall 1.00, precision 0.960, accuracy 0.974, F1-score 0.980	Limited to specific algorithms; may not explore newer techniques
[14]	Pre-trained ResNet50V2 model, ensemble ML methods	Achieved higher accuracy of 95%, precision 94.86%, recall 94.32%, F1 score 94.57%	Complexity of hybrid approach may limit clinical implementation
[15]	Gradient Boosting Machine, XGBoost, LightGBM	LightGBM capable of maximum accuracy of 99%	Limited to mobile application context; may not be suitable for all clinical settings
[16]	MLP, KNN, AdaBoost, Bagging, Gradient Boosting, Random Forest	RF, GB, and AB models achieved 100% accuracy	Perfect accuracy may indicate overfitting; real-world performance may vary
[17]	Decision Tree, Random Forest, Logistic Regression, Naive Bayes, XGBoost	Decision Tree achieved best model accuracy of 98%	Limited to SEER dataset; may not generalize to other populations
[18]	Decision Tree, Random Forest, Logistic Regression, Naive Bayes, XGBoost, AdaBoost	AdaBoost algorithm had best prediction performance (specific accuracy not provided)	Focused on recurrence risk; may not address initial diagnosis challenges
[19]	Logistic Regression, Random Forest	LR-PCA (8 components) model achieved 99.1% accuracy	Complex integration of techniques may be challenging to implement widely
[20]	Decision Tree, Random Forest, Logistic Regression, Naive Bayes, XGBoost	XGBoost achieved best model accuracy of 97%	May not apply globally
[21]	Decision Tree, Stochastic Gradient Descent, Random Forest, SVM, Logistic Regression, AdaBoost	AdaBoost-Logistic algorithm achieved accuracy of 99.12%	May not explore more recent deep learning approaches
[22]	SERS analysis with Shapley Additive Explanations (SHAP)	Proof-of-concept model predictive of cancer from isolated exosomes (specific accuracy not provided)	Highly specialized technique; may not be widely applicable in all clinical settings
[23]	Fine-tuned ResNet50 with XAI methods (Grad-CAM, LIME, SHAP) on CBIS-DDSM dataset	Not explicitly stated; focuses on interpretability	Limited to a single dataset
[24]	Federated learning with ANN and XGBoost on Wisconsin datasets	97.59% accuracy (ANN), 97.14% accuracy (XGBoost)	Potential privacy concerns in federated learning
[25]	Genetic algorithms, Ant Colony Optimization, HHNN-E2SAT models	Over 98% on all performance metrics	Comparison limited to standard algorithms; potential overfitting
[26]	ML model using EHR data with	AUROC of 0.73, AUPRC of	Single-institution study;

	SHAP for explanations	0.52 on holdout test set	limited generalizability
[27]	Modified Inception network with locally preserving projection	99.81% accuracy, 96.48% recall, 93.0% sensitivity	Limited to ultrasound images; potential overfitting
[28]	KNN, SVM, Ensemble Classifier, Logistic Regression on WDBC and BCCD datasets	98.3% accuracy (Polynomial SVM)	Limited to specific datasets; potential overfitting
[29]	ASMDBUTMF for preprocessing, hybrid optimization for feature selection, CVAE for classification	99.4% accuracy, 99.2% precision, 99.1% recall	Complex methodologypotential overfitting
[30]	Binarilization technique with various ML models on NCI GDC datasets	Comparative performance with higher explainability	Limited to RNA sequencing data; potential loss of information in binarilization
[31]	Decision Tree, Random Forest, Logistic Regression, Naive Bayes, XGBoost with SHAP analysis	97% accuracy (XGBoost)	Limited to a single dataset from one hospital; potential bias in feature importance

3. SYSTEMATIC LITERATURE REVIEW

SLR is a critical process for synthesizing existing research, offering a comprehensive overview of the developments, challenges, and future directions in a particular field. This SLR focuses on the integration of enhanced feature selection techniques within explainable machine learning models for predicting breast cancers. The objective is to identify the current state of research, explore existing challenges, and uncover opportunities for innovation in creating accurate, interpretable, and clinically useful predictive models for breast cancer diagnosis and treatment.

3.1 Research Questions

The review explores the subsequent research questions to steer the analysis of the selected texts:

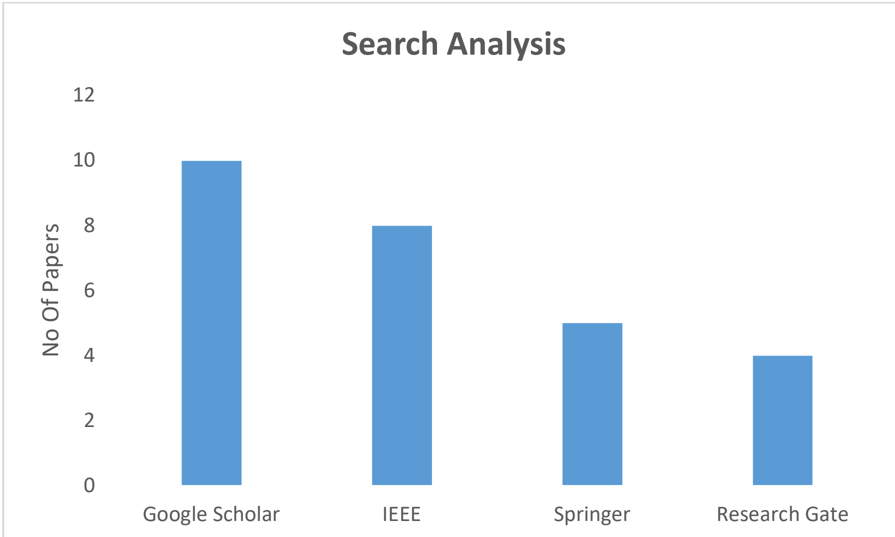
- **RQ-1:** What role do feature selection techniques play in improving the accuracy and interpretability of ML models for breast cancer prediction?
- **RQ-2:** How do explainable machine learning models improve the transparency and reliability of breast cancer predictions for clinical applications?
- **RQ-3:** What are the emerging challenges and potential solutions in integrating feature selection with explainable ML models for breast cancer prediction?
- **RQ-4:** How do existing models compare in terms of accuracy, interpretability, and clinical applicability when applied to breast cancer datasets?
- **RQ-5:** What best practices should be adopted for integrating feature selection with explainable machine learning to improve breast cancer prediction outcomes while ensuring model transparency?

3.2 Data Sources and Search Strategy

The review involved a comprehensive search across major databases such as Google Scholar, IEEE Xplore, Springer, and Research Gate, focusing on publications from 2019 to 2024. Keywords used included "feature selection for breast cancer prediction," "explainable machine learning in healthcare," "breast cancer diagnosis models," “DL based Breast Cancer Prediction” and "interpretable AI for medical predictions." These terms were incorporated using Boolean operators (AND, OR) to refine the search. Only peer-reviewed journal articles, conference papers, and technical reports were included, while non-peer-reviewed sources were excluded.

Abstracts were initially reviewed for relevance, followed by full-text reviews to ensure they met the research criteria. Additionally, citation tracking and manual searches were conducted to identify recent advancements and relevant studies not captured in the initial search. Figure 1 illustrates the process of organizing and selecting the studies.

Figure 1: Search analysis from different sources



3.3 Inclusion and Exclusion Criteria

The following inclusion and exclusion criteria were adopted as described in Table 2:

Table 2: Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Publication Date	Articles released between 2019 and 2024	Articles released before 2019 or after 2024
Article Type	Peer-reviewed journal articles, conference papers, and technical reports	Non-peer-reviewed sources, opinion pieces, and non-technical reports
Relevance	Focus on feature selection, explainable machine learning, and breast cancer prediction	Articles not related to feature selection, AI, or breast cancer prediction
Methodology	Empirical studies, case studies, systematic reviews with qualitative or quantitative data	Theoretical papers without empirical evidence or lack of rigorous methodology
Language	English	Non-English articles
Geographical Focus	Studies with global or regionally significant findings	Studies focused on highly localized issues with limited generalizability
Innovation and Impact	Studies presenting novel approaches, significant advancements, or impactful findings	Studies replicating known methods without new insights

3.4 PRISMA Methodology

The PRISMA methodology was adopted to ensure a systematic and transparent review process. The PRISMA flowchart (Figure 2) outlines the stages of the review, from the initial identification of studies to the final selection for in-depth analysis.

3.4.1 Search Results and Study Selection

The search yielded a total of 560 articles from the selected databases. After duplicates were excluded and relevant criteria enforced, 145 articles were shortlisted for detailed review. Following thorough abstract and full-text evaluations, 31 sources were determined to be relevant and factored into the final synthesis.

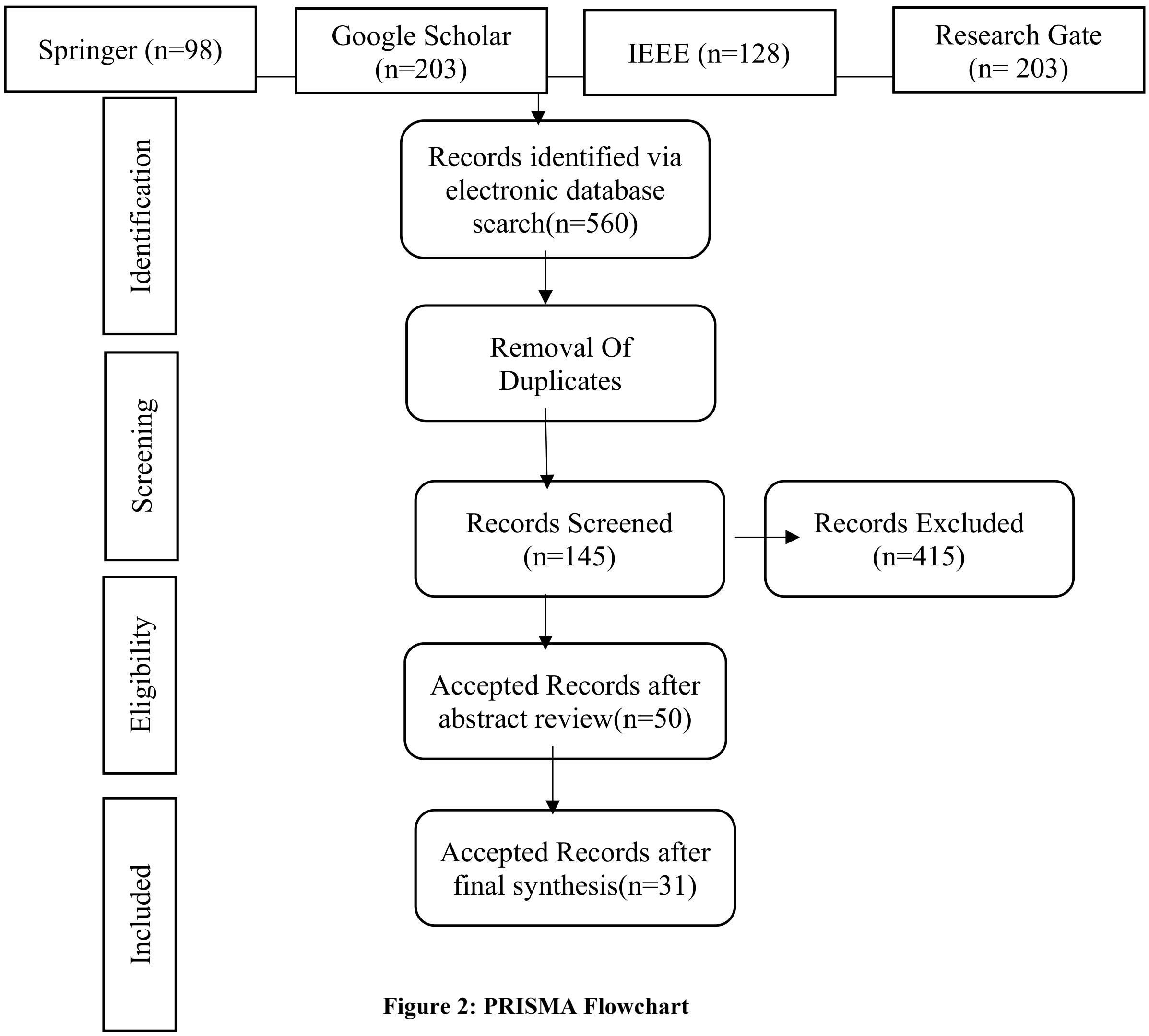


Figure 2: PRISMA Flowchart

3.5 Overview of Selected Studies

The selected studies cover various aspects of feature selection, explainable machine learning, and their applications in breast cancer prediction. Key observations include:

- **Advancements in Feature Selection:** Recent research highlights significant progress in feature selection techniques, particularly in refining input data to improve model accuracy and interpretability for breast cancer prediction.

- **Explainable ML Models:** There is a growing trend towards developing machine learning models that are not only accurate but also interpretable, assuring that clinicians find the decision-making process clear and transparent.

- **Challenges in Model Integration:** Integrating feature selection with explainable AI models presents challenges, including balancing model complexity with interpretability and validating model effectiveness across multiple datasets.

3.6 Comparative Analysis

A comparative analysis of the methodologies, feature selection techniques, and performance metrics across the selected studies reveals the following:

- **Accuracy:** Choosing relevant features significantly strengthens the predictive accuracy of models by focusing on the most essential features, thereby reducing noise and improving model performance.
- **Interpretability:** Explainable AI models provide insights into how predictions are made, which is crucial for clinical adoption. Yet, the extent of interpretability shifts depending on the complexity of the model and the methods employed.
- **Clinical Applicability:** While many models demonstrate high accuracy and interpretability, Their relevance in practical clinical contexts depends on factors like data readiness, model robustness, and the ease of adapting them to current clinical workflows.

3.7 Key Insights and Observations

The review of the 31 selected articles provides insights into the state-of-the-art in integrating feature selection with explainable ML models for breast cancer prediction. It included:

- **Enhanced Model Accuracy:** The utilization of feature selection has significantly refined the accuracy of predictive models for breast cancer, making them more reliable for clinical use.
- **Advances in Interpretability:** Explainable AI models offer transparent and understandable predictions, which are essential for clinical decision-making.
- **Ongoing Challenges:** Despite these advances, challenges such as balancing model complexity with interpretability and assuring that models are applicable across a wide range of patient groups is a vital area for ongoing research.

4.FINDINGS

This analysis aims to answer the research questions (RQs) established for this systematic literature review. Data extraction was conducted on the selected research articles (n=31), and the findings are examined in relation to the study's RQs. Also, a gap analysis is provided to highlight areas requiring further research and development.

4.1 Solutions to RQs:

RQ-1: What role do feature selection techniques play in enhancing the accuracy and interpretability of ML models for breast cancer prediction?

By identifying the most relevant features from high-dimensional datasets, these techniques can significantly improve model performance while reducing computational complexity. Taghizadeh et al. (2022) demonstrated that careful feature selection led to enhanced classification accuracy and robustness in breast cancer prediction models. Their study utilized transcriptome profiling data and employed various feature selection methods, resulting in more accurate and interpretable models. Similarly, Prustya et al. (2023) proposed an integrated machine learning-fuzzy and dimension reduction approach, which not only enhanced prediction accuracy but also improved the model's interpretability by reducing the feature space to the most significant predictors. This approach highlights how feature selection can bridge the gap between model complexity and clinical interpretability, a critical factor in the adoption of AI-driven diagnostic tools in healthcare settings.

RQ-2: How do explainable machine learning models refine the transparency and reliability of breast cancer predictions for clinical applications?

These models provide insights into the decision-making process, allowing healthcare professionals to understand and trust the predictions. Vrdoljak et al. (2023) applied explainable machine learning models to detect breast cancer lymph node metastasis, demonstrating how these models can provide clinically relevant insights. Their approach not only achieved high accuracy but also offered interpretable results that could be easily understood by clinicians, potentially improving the adoption of AI in clinical decision-making. Khater et al. (2023) further emphasized the importance of explainability in their study, developing an explainable artificial intelligence model for breast cancer classification. Their model provided clear explanations for its predictions, enhancing trust and facilitating better integration of AI-driven diagnostics into clinical workflows. These studies underscore the critical role of explainable AI in bridging the gap between complex machine learning algorithms and practical clinical applications, ultimately leading to more reliable and actionable breast cancer predictions.

RQ-3: What are the emerging challenges and potential solutions in integrating feature selection with explainable machine learning models for breast cancer prediction?

Integrating feature selection with explainable ML models for breast cancer prediction presents several emerging challenges, along with potential solutions. One significant challenge is balancing model complexity with interpretability while maintaining high predictive accuracy. Meshoul et al. (2022) addressed this challenge by proposing an integrative feature selection approach combined with explainable multi-class classification for breast cancer subtyping. Their method demonstrated how careful feature selection could enhance both model performance and interpretability. Another challenge lies in handling diverse data types and ensuring model generalizability across different patient populations. Taminul Islam et al. (2024) tackled this issue by developing a predictive model for breast cancer classification specifically for Bangladeshi patients, incorporating explainable AI techniques. Their approach highlights the importance of considering population-specific factors in feature selection and model development. A potential solution to these challenges involves the development of hybrid approaches that combine advanced feature selection techniques with interpretable model architectures. For instance, Sharmin et al. (2023) proposed a hybrid deep feature extraction and ensemble-based machine learning approach, which achieved high accuracy while maintaining a degree of interpretability through feature importance analysis.

RQ-4: How do existing models compare in terms of accuracy, interpretability, and clinical applicability when applied to breast cancer datasets?

Some models prioritize high accuracy at the expense of interpretability, while others focus on maintaining a balance between performance and explainability. Zhou et al. (2024) conducted a comprehensive comparison of multiple machine learning algorithms for breast cancer prediction, finding that ensemble methods like AdaBoost often achieved the highest accuracy but lacked straightforward interpretability. In contrast, Briola et al. (2024) developed a federated explainable AI model for breast cancer classification that maintained high accuracy while providing interpretable results, demonstrating a potential path forward for clinically applicable models. The clinical applicability of these models also varies, with some requiring extensive computational resources or specialized data that may not be readily available in all clinical settings. Hernandez et al. (2024) addressed this issue by developing an explainable ML model to predict postoperative complications in cancer patients, focusing on practical implementation in clinical workflows. Their approach highlights the importance of considering not just model performance, but also the feasibility of integration into existing healthcare systems when evaluating breast cancer prediction models.

RQ-5: What best practices should be adopted for integrating feature selection with explainable machine learning to improve breast cancer prediction outcomes while ensuring model transparency?

Firstly, it's crucial to employ robust feature selection techniques that consider both statistical significance and clinical relevance. Chen and Kabir (2024) demonstrated this by developing an explainable ML approach for cancer prediction through binarization of RNA sequencing data, which improved both model performance and interpretability. Secondly, the chosen machine learning algorithms should inherently support explainability or be paired with post-hoc explanation methods. Admass et al. (2024) exemplified this by integrating feature enhancement techniques with a modified Google Inception network, achieving high accuracy while maintaining interpretability through visualization techniques. Lastly, continuous validation and refinement of models using diverse datasets is essential to ensure generalizability and robustness. Some authors addressed this by emphasizing the importance of adaptive feature selection techniques in maintaining model performance across different datasets.

4.2 Gap Analysis:

Despite significant advancements in integrating feature selection with explainable machine learning for breast cancer prediction, several gaps remain. There is a need for standardized frameworks that can seamlessly combine feature selection techniques with explainable AI models across different types of breast cancer data. Additionally, more research is required to develop models that can effectively handle multi-modal data (e.g., combining genomic, clinical, and imaging data) while maintaining interpretability. Furthermore, there is a gap in long-term studies evaluating the clinical impact of these models on patient outcomes and treatment decisions. Future research should also emphasize on developing more robust methods for quantifying and comparing the interpretability of different models, as current approaches often lack standardization.

5.CONCLUSION

This systematic literature review explored the integration of enhanced feature selection techniques within explainable ML models for breast cancer prediction. The analysis identified significant advancements in model accuracy, interpretability, and clinical applicability. However, the review also highlighted ongoing challenges, such as the need for scalable frameworks, better data integration methods, and a balance between model complexity and transparency. Future research should prioritize developing standardized, robust, and interpretable models that can be widely adopted in clinical settings to improve breast cancer diagnosis and treatment outcomes. The findings underscore the ability of combining feature selection with explainable AI to create more accurate, transparent, and clinically useful predictive models for breast cancer.

1.1 **Data Availability**

1.2 **The dataset supporting this study's findings is available from the corresponding author upon request.**

1.3 **Conflicts of Interest**

1.4 **The authors declare no conflicts of interest related to this publication.**

1.5 **Funding Statement**

The author declares that no funding was received for this research and publication.

Ethical Approval

This article does not involve studies with human participants or animals.

Author Contributions

All authors declare equal contribution to this work.

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