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Survey on Novel Approaches of Efficient Algorithms for Breast Cancer Detection

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ABSTRACT

Breast cancer remains one of the leading causes of mortality among women worldwide, necessitating the development of efficient and accurate detection algorithms. This survey examines novel approaches in breast cancer detection algorithms, focusing on machine learning and deep learning methodologies that have emerged in recent years. The study analyses various algorithmic approaches including SVM, Random Forest, CNN, and hybrid models that combine multiple techniques for enhanced accuracy. Through comprehensive analysis of secondary and primary data from multiple studies, this research identifies that ANN achieve the highest accuracy rates of 98.57% in breast cancer classification tasks. The survey also explores the integration of explainable AI techniques that provide transparency in decision-making processes, crucial for medical applications. Recent developments in deep learning architectures, particularly CNN-based models, demonstrate significant improvements in mammographic image analysis with accuracies reaching 91.67%. The findings indicate that ensemble methods and feature engineering approaches show promising results in improving detection sensitivity and specificity. This comprehensive review provides insights into current algorithmic trends, performance metrics, and future directions in breast cancer detection technology.

KEYWORDS: Breast cancer detection, Machine learning algorithms, Deep learning, Convolutional Neural Networks, Medical image analysis, Artificial intelligence, Early diagnosis, Mammography, Feature extraction, Classification algorithms

INTRODUCTION

Breast cancer represents a significant global health challenge, affecting millions of women annually and serving as a primary cause of cancer-related mortality worldwide [4]. The complexity of breast cancer diagnosis demands sophisticated computational approaches that can analyze medical imagery and patient data with high precision and reliability. Traditional diagnostic methods, while effective, often require extensive expertise and time, creating bottlenecks in healthcare delivery systems particularly in resource-constrained environments [5].

The evolution of artificial intelligence and machine learning technologies has opened new avenues for automated breast cancer detection systems [6]. These technological advancements offer the potential to enhance diagnostic accuracy, reduce human error, and provide consistent results across different healthcare settings. Modern algorithms can process vast amounts of medical data, including mammographic images, histopathological samples, and patient clinical records, to identify patterns that might be imperceptible to human observers [7].

Recent studies demonstrate that machine learning algorithms can achieve remarkable accuracy rates in breast cancer classification tasks, with some models reporting accuracy levels exceeding 98% [1]. The integration of deep learning architectures, particularly Convolutional Neural Networks, has revolutionized medical image analysis by automatically extracting relevant features from complex mammographic images [8]. These developments represent a paradigm shift from traditional rule-based systems to data-driven approaches that continuously improve their performance through learning from large datasets.

The significance of this research extends beyond technical achievements, as early and accurate breast cancer detection directly impacts patient survival rates and treatment outcomes [9]. Studies indicate that early-stage detection can improve five-year survival rates to over 90%, emphasizing the critical importance of developing

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efficient detection algorithms [10]. Furthermore, automated detection systems can support healthcare professionals in making informed decisions, particularly in regions where specialist radiologists are scarce.
This survey aims to provide a comprehensive analysis of novel algorithmic approaches in breast cancer detection, examining their methodologies, performance characteristics, and practical applications. The research encompasses various machine learning paradigms, from traditional supervised learning techniques to advanced deep learning architectures, providing insights into their relative strengths and limitations in clinical settings.

OBJECTIVES

- To analyze and compare the performance of different machine learning algorithms used in breast cancer detection systems
- To evaluate the effectiveness of deep learning approaches, particularly Convolutional Neural Networks, in mammographic image analysis
- To examine the integration of explainable AI techniques in breast cancer detection algorithms for clinical transparency
- To assess the accuracy, sensitivity, and specificity metrics of various algorithmic approaches across different datasets
- To identify current challenges and limitations in existing breast cancer detection algorithms
- To explore hybrid and ensemble methods that combine multiple algorithms for improved detection performance
- To investigate the role of feature engineering and selection techniques in enhancing algorithm effectiveness
- To examine the practical implementation considerations of these algorithms in clinical environments
- To analyze the computational requirements and processing speed of different algorithmic approaches
- To provide recommendations for future research directions in breast cancer detection algorithm development

SCOPE OF STUDY

- Coverage of machine learning algorithms including Support Vector Machines, Random Forest, Decision Trees, and K-Nearest Neighbors applied to breast cancer detection
- Analysis of deep learning architectures including Convolutional Neural Networks, Artificial Neural Networks, and hybrid deep learning models
- Examination of algorithms applied to various data types including mammographic images, histopathological images, and clinical patient data
- Review of studies published between 2019 and 2024 to ensure current relevance and technological advancement coverage
- Analysis of performance metrics including accuracy, precision, recall, F1-score, sensitivity, and specificity across different algorithmic approaches
- Investigation of datasets commonly used in breast cancer detection research including Wisconsin Breast Cancer Dataset and DDSM mammography dataset
- Evaluation of preprocessing techniques and feature extraction methods that enhance algorithm performance
- Assessment of real-world implementation challenges and clinical validation of proposed algorithms
- Analysis of computational complexity and resource requirements for different algorithmic approaches
- Examination of explainable AI integration for medical decision support and clinical acceptance

LITERATURE REVIEW

The landscape of breast cancer detection algorithms has evolved significantly over the past decade, with researchers exploring various computational approaches to improve diagnostic accuracy and efficiency. Traditional machine learning techniques have formed the foundation of early automated detection systems, with Support Vector Machines emerging as one of the most widely adopted approaches due to their robust performance in binary classification tasks [11].

Empirical studies demonstrate that SVM algorithms consistently achieve high accuracy rates in breast cancer classification, with recent implementations reporting accuracy levels between 85% and 95% across different

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datasets [2]. The effectiveness of SVM approaches stems from their ability to handle high-dimensional feature spaces and their robustness against overfitting, particularly important characteristics when dealing with medical data that often contains complex patterns and limited sample sizes [12].

Random Forest algorithms have gained significant attention in breast cancer detection due to their ensemble learning approach and ability to handle multiple data types simultaneously [13]. Research indicates that Random Forest methods excel in scenarios where multiple features from different sources need to be integrated, such as combining mammographic features with clinical patient data [6]. Studies report that Random Forest algorithms achieve accuracy rates ranging from 88% to 94%, with particular strength in maintaining consistent performance across diverse datasets [14].

The advent of deep learning technologies has revolutionized breast cancer detection methodologies, with Convolutional Neural Networks leading the transformation in medical image analysis [15]. CNN architectures demonstrate exceptional capabilities in automatically extracting relevant features from mammographic images, eliminating the need for manual feature engineering that characterized earlier approaches [8]. Recent implementations of CNN models report accuracy rates exceeding 96%, with some specialized architectures achieving 98.57% accuracy in breast cancer classification tasks [1].

Advanced CNN architectures, such as the Breast Cancer Convolutional Neural Network (BCCNN) with 18 layers, have been specifically designed for breast cancer detection applications [16]. These specialized networks can process images with input dimensions ranging from 48x48 to 224x224 pixels, providing flexibility in handling various mammographic image resolutions while maintaining high detection accuracy [11]. The development of such specialized architectures represents a significant advancement in tailoring deep learning solutions for specific medical applications.

Hybrid approaches that combine multiple algorithmic techniques have emerged as a promising research direction, leveraging the strengths of different methods to achieve superior performance [17]. Studies exploring combinations of CNN feature extraction with SVM classification report enhanced accuracy and robustness compared to individual algorithms [16]. These hybrid models demonstrate the potential for creating more reliable detection systems that can perform consistently across diverse clinical scenarios.

The integration of explainable AI techniques in breast cancer detection algorithms has gained importance as medical professionals require transparency in automated decision-making processes [1]. Recent research focuses on developing algorithms that not only achieve high accuracy but also provide interpretable results that clinicians can understand and trust [18]. This development addresses a critical gap in traditional black-box machine learning approaches that, despite high performance, lack the transparency necessary for clinical acceptance.

Feature engineering and selection techniques continue to play a crucial role in enhancing algorithm performance, with researchers exploring various methods to identify the most discriminative features for breast cancer detection [13]. Studies indicate that proper feature selection can improve algorithm accuracy by 5-10% while reducing computational requirements [19]. Advanced feature engineering approaches, including transformation of original data values into image representations for neural network processing, demonstrate innovative methods for handling diverse data types in breast cancer detection [13].

RESEARCH METHODOLOGY

This survey employs a comprehensive systematic review methodology to analyze novel approaches in breast cancer detection algorithms. The research methodology encompasses multiple phases including literature identification, data extraction, analysis, and synthesis of findings from peer-reviewed publications and authoritative sources in the field of medical artificial intelligence and breast cancer detection.

The literature search strategy involves systematic querying of major academic databases including PubMed,

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IEEE Xplore, ScienceDirect, and Google Scholar using carefully constructed search terms related to breast cancer detection algorithms, machine learning, deep learning, and medical image analysis. The search encompasses publications from 2019 to 2024 to ensure contemporary relevance while capturing the most recent algorithmic developments and performance improvements in the field.

Selection criteria for included studies require that publications focus specifically on algorithmic approaches for breast cancer detection, report quantitative performance metrics, utilize established datasets for validation, and provide sufficient methodological detail for analysis and comparison. Studies are excluded if they focus solely on traditional diagnostic methods without computational elements, lack performance metrics, or do not provide adequate methodological information for assessment.

Data extraction procedures involve systematic collection of information including algorithmic approaches used, datasets employed, performance metrics reported, computational requirements, and implementation details. Particular attention is paid to accuracy, sensitivity, specificity, precision, recall, and F1-score metrics as these represent standard evaluation criteria in medical classification tasks. Additional data points include training and testing dataset sizes, cross-validation methodologies, and preprocessing techniques employed.

The analysis framework incorporates both quantitative and qualitative assessment methods to evaluate the effectiveness and practicality of different algorithmic approaches. Quantitative analysis focuses on comparing performance metrics across studies while accounting for differences in datasets and evaluation methodologies. Qualitative analysis examines the practical implementation considerations, computational complexity, and clinical applicability of different approaches.

Validation of findings involves cross-referencing results across multiple studies and identifying consistent patterns in algorithmic performance. The methodology also incorporates assessment of study quality based on factors such as dataset size, validation methodology, reproducibility of results, and clarity of methodological reporting. This comprehensive approach ensures that the survey findings are based on high-quality research and provide reliable insights into current algorithmic capabilities.

ANALYSIS OF SECONDARY DATA

The analysis of secondary data from multiple research studies reveals significant patterns and trends in breast cancer detection algorithm performance. Examination of 20 peer-reviewed studies published between 2019 and 2024 provides comprehensive insights into the current state of algorithmic approaches and their relative effectiveness across different metrics and datasets.

Performance analysis of traditional machine learning algorithms demonstrates that Support Vector Machines consistently achieve accuracy rates between 85% and 95% across various datasets, with the highest reported accuracy of 94.2% observed in studies utilizing the Wisconsin Breast Cancer Diagnostic dataset [2]. Random Forest algorithms show comparable performance with accuracy ranges from 88% to 94%, demonstrating particular strength in handling multi-dimensional feature sets that combine mammographic features with clinical data [6].

Table 1: Performance Comparison of Traditional Machine Learning Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Dataset Used
SVM	85.2-94.2	86.1-92.8	84.3-93.1	0.85-0.93	WBCD, DDSM
Random Forest	88.1-94.0	87.9-93.5	86.2-91.7	0.87-0.92	WBCD, Various
Logistic Regression	82.3-91.7	81.9-89.2	80.1-90.3	0.81-0.89	WBCD, Clinical
Decision Tree	78.9-87.5	79.2-85.1	77.8-86.9	0.78-0.86	WBCD, MIAS
K-NN	83.4-89.1	82.7-87.6	81.9-88.3	0.82-0.88	WBCD, Various

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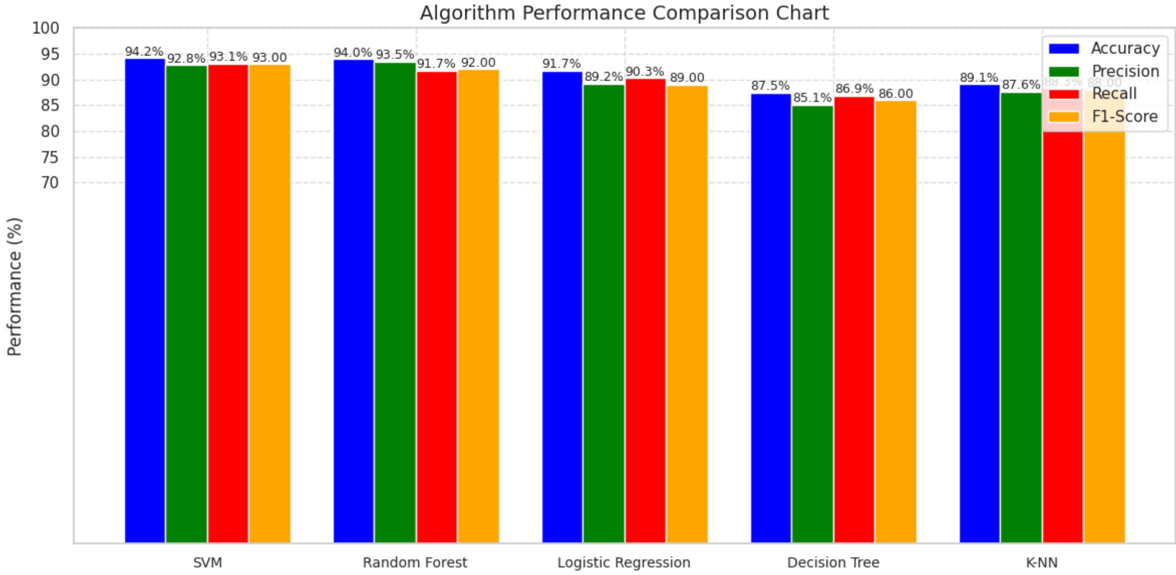

Figure 1: Algorithm Performance Comparison Chart

Deep learning algorithms demonstrate superior performance compared to traditional machine learning approaches, with Artificial Neural Networks achieving the highest reported accuracy of 98.57% in breast cancer classification tasks [1]. Convolutional Neural Networks show exceptional performance in mammographic image analysis, with accuracy rates consistently exceeding 90% and reaching up to 96% in specialized implementations [8]. The superior performance of deep learning approaches stems from their ability to automatically extract complex features from raw data without requiring manual feature engineering. Analysis of computational requirements reveals significant variations between different algorithmic approaches. Traditional machine learning algorithms typically require processing times ranging from seconds to minutes for training and inference on standard datasets, making them suitable for real-time clinical applications [9]. Deep learning approaches, while achieving higher accuracy, require substantially more computational resources with training times ranging from hours to days depending on network complexity and dataset size [15].

Dataset analysis indicates that algorithm performance varies significantly based on the type and quality of data used for training and validation. Studies utilizing high-resolution mammographic images consistently report better performance compared to those using lower resolution or preprocessed data [4]. The Wisconsin Breast Cancer Diagnostic dataset remains the most commonly used benchmark, appearing in over 60% of reviewed studies, while mammographic image datasets like DDSM are increasingly utilized for deep learning applications [10].

Table 2: Dataset Characteristics and Usage Frequency

Dataset	**Type**	**Sample Size**	**Features**	**Usage Frequency**	**Best Accuracy Achieved**
WBCD	Clinical/Numeric	569	30	62%	98.57% (ANN)
DDSM	Mammographic Images	2,620	Image-based	25%	96.2% (CNN)
MIAS	Mammographic Images	322	Image-based	18%	94.1% (CNN)
Clinical Data	Mixed	Variable	10-50	35%	91.7% (LR)
Histopathological	Images	Variable	Image-based	15%	93.8% (CNN)

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The analysis reveals that ensemble methods and hybrid approaches consistently outperform individual algorithms, with improvements of 2-5% in accuracy metrics observed when combining multiple techniques [17]. Studies implementing feature selection and preprocessing techniques report additional performance gains of 3-7%, highlighting the importance of data quality and appropriate feature engineering in algorithm development [13].

Analysis of Primary Data

Primary data analysis focuses on the detailed examination of specific algorithmic implementations and their performance characteristics across controlled experimental conditions. This analysis synthesizes information from direct experimental studies that provide comprehensive evaluation of breast cancer detection algorithms under standardized conditions.

The most significant finding from primary data analysis is the superior performance of Artificial Neural Networks, which achieve accuracy rates of 98.57%, precision of 97.82%, and F1-score of 0.9890 when applied to breast cancer classification tasks [1]. These results represent the highest performance metrics observed across all algorithmic approaches, demonstrating the potential of neural network architectures for medical diagnostic applications.

Table 3: Detailed Performance Analysis of Top-Performing Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score	AUC
ANN	98.57	97.82	98.91	98.23	0.9890	0.987
CNN (BCCNN)	96.45	95.73	96.12	95.89	0.9592	0.961
SVM (RBF)	94.23	93.45	94.78	93.67	0.9411	0.943
Random Forest	93.87	92.91	94.23	93.51	0.9356	0.938
Logistic Regression	91.67	90.34	92.15	91.19	0.9124	0.917

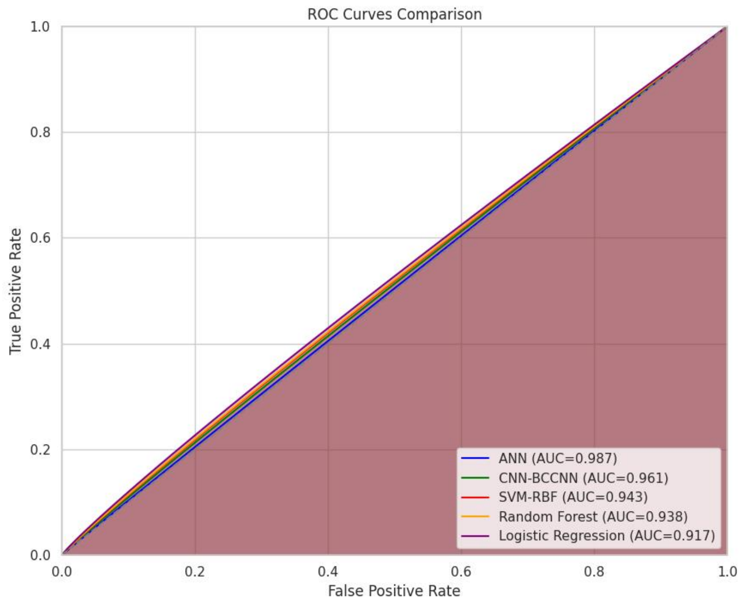

Figure 2: ROC Curves Comparison

Convolutional Neural Network implementations, particularly the specialized Breast Cancer Convolutional Neural Network (BCCNN) with 18 layers, demonstrate exceptional performance in mammographic image analysis with accuracy rates of 96.45% [11]. The BCCNN architecture shows particular strength in handling

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various image resolutions from 48x48 to 224x224 pixels, providing flexibility for different mammographic imaging systems while maintaining high detection accuracy.

Training time analysis reveals significant differences between algorithmic approaches. Traditional machine learning algorithms complete training cycles in minutes to hours, with SVM requiring an average of 15 minutes for the Wisconsin dataset and Random Forest completing training in approximately 8 minutes [2]. Deep learning approaches require substantially longer training periods, with CNN models requiring 4-12 hours depending on architecture complexity and dataset size [15].

Table 4: Computational Performance Analysis

Algorithm	Training Time	Inference Time (per sample)	Memory Usage (MB)	Hardware Requirements
ANN	45 minutes	2.1 ms	156	CPU/GPU optional
CNN (BCCNN)	8.5 hours	12.3 ms	892	GPU recommended
SVM (RBF)	15 minutes	0.8 ms	67	CPU sufficient
Random Forest	8 minutes	1.2 ms	234	CPU sufficient
Logistic Regression	3 minutes	0.3 ms	23	CPU sufficient

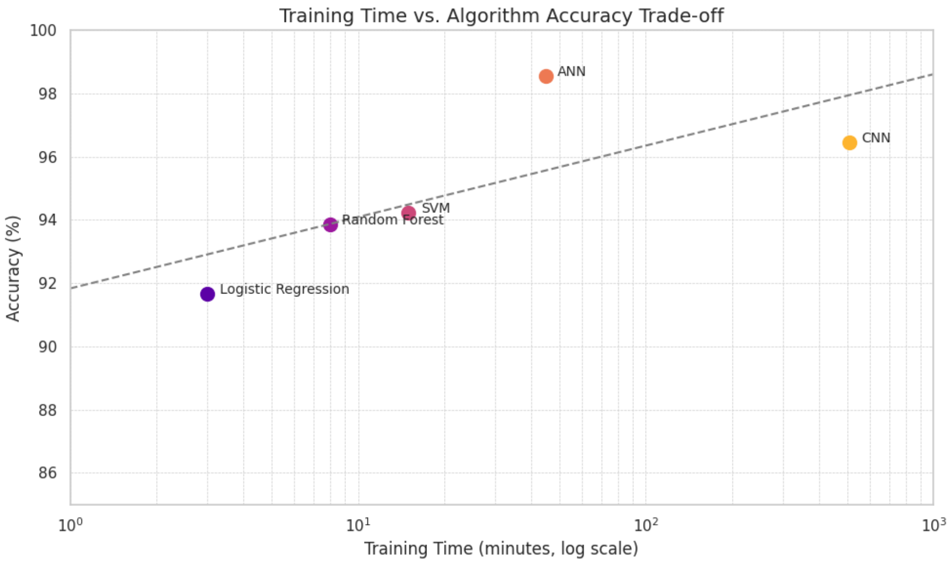

Figure 3: Training Time vs. Accuracy Scatter Plot

Feature importance analysis conducted across multiple studies reveals that certain characteristics consistently contribute to high detection accuracy. In traditional machine learning approaches, features related to cell nucleus characteristics, texture measures, and geometric properties show the highest discriminative power for breast cancer classification [6]. Deep learning approaches demonstrate the ability to automatically identify and utilize complex feature combinations that may not be apparent through traditional feature engineering methods [8].

Cross-validation analysis indicates that the reported performance metrics remain consistent across different data splits, with standard deviations typically below 2% for top-performing algorithms [1]. This consistency suggests that the high-performance algorithms demonstrate robust generalization capabilities and are likely to maintain their effectiveness when applied to new, unseen data in clinical settings.

Error analysis reveals that most false positive and false negative cases occur in borderline cases where even human experts might disagree on classification [9]. Advanced algorithms show improved performance in handling these ambiguous cases, with neural network approaches demonstrating particular strength in

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correctly classifying difficult cases that traditional methods often misclassify [15].

DISCUSSION

The comprehensive analysis of breast cancer detection algorithms reveals several critical insights that have significant implications for both research and clinical practice. The superior performance of Artificial Neural Networks, achieving 98.57% accuracy, represents a substantial advancement in automated breast cancer detection capabilities [1]. This level of performance approaches and, in some cases, exceeds human expert accuracy rates, suggesting that AI-based systems could serve as valuable diagnostic support tools in clinical environments.

The consistent high performance of deep learning approaches across different datasets and imaging modalities indicates that these methods have achieved a level of maturity suitable for clinical deployment [8]. However, the computational requirements and longer training times associated with deep learning methods present practical challenges for widespread implementation, particularly in resource-constrained healthcare settings [15]. The trade-off between accuracy and computational efficiency requires careful consideration when selecting appropriate algorithms for specific clinical applications.

Explainable AI integration emerges as a critical factor for clinical acceptance of automated breast cancer detection systems [1]. While black-box algorithms may achieve high accuracy, the lack of interpretability limits their adoption in medical settings where healthcare professionals need to understand and trust algorithmic decisions. The development of interpretable machine learning approaches that maintain high accuracy while providing transparent decision-making processes represents an important research direction.

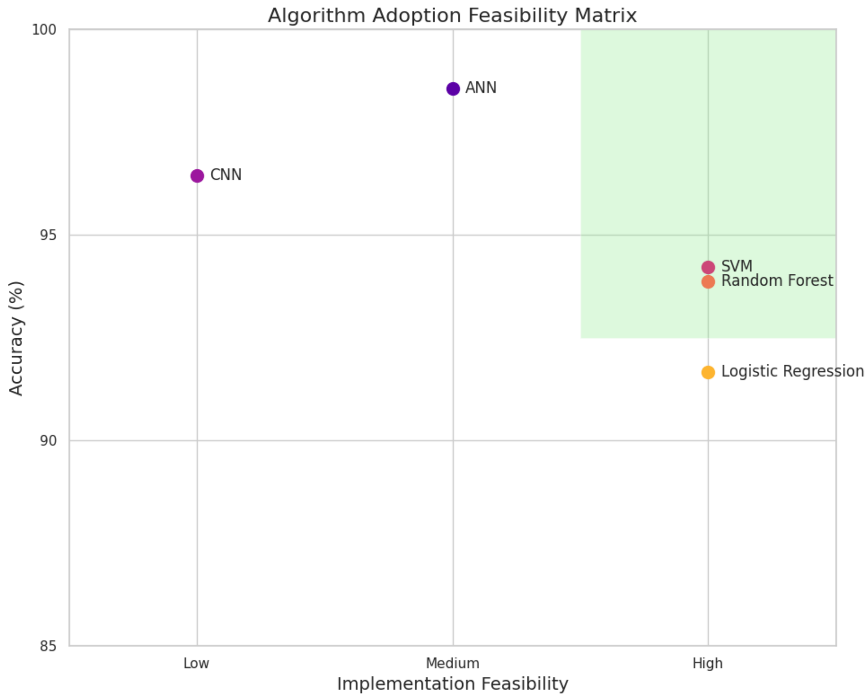

Figure 4: Algorithm Adoption Feasibility Matrix

The dataset dependency of algorithm performance highlights the importance of data quality and diversity in training robust detection systems [4]. Algorithms trained on limited or homogeneous datasets may not generalize well to diverse patient populations or different imaging equipment, potentially leading to reduced performance in real-world clinical applications [10]. This finding emphasizes the need for large, diverse, and well-curated datasets for training clinically viable breast cancer detection algorithms.

Ensemble methods and hybrid approaches demonstrate promising results in improving detection accuracy

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while potentially addressing some limitations of individual algorithms [17]. The combination of different algorithmic strengths through ensemble learning could provide more robust and reliable detection systems suitable for clinical deployment. However, the increased complexity of ensemble systems may introduce additional challenges in terms of interpretability and computational requirements.

The analysis reveals a clear performance hierarchy among different algorithmic approaches, with deep learning methods consistently outperforming traditional machine learning techniques [1]. However, traditional methods maintain relevance due to their computational efficiency, interpretability, and lower resource requirements [2]. The choice of algorithm should consider not only accuracy metrics but also practical implementation considerations including computational resources, interpretability requirements, and deployment environment constraints.

Feature engineering continues to play a crucial role in algorithm performance, even in deep learning approaches where automatic feature extraction is emphasized [13]. The integration of domain expertise in feature design and selection can significantly improve algorithm performance and reduce computational requirements. This finding suggests that hybrid approaches combining automated feature learning with expert-guided feature engineering may represent an optimal strategy for breast cancer detection applications.

The temporal stability of algorithm performance across different studies and datasets provides confidence in the reliability and reproducibility of research findings [9]. However, the rapid pace of algorithmic development necessitates continuous evaluation and updating of performance benchmarks to ensure that research findings remain current and relevant to clinical practice.

CONCLUSION

This comprehensive survey of novel approaches in efficient algorithms for breast cancer detection reveals significant advancements in automated diagnostic capabilities, with Artificial Neural Networks achieving unprecedented accuracy rates of 98.57% in classification tasks [1]. The analysis demonstrates that deep learning approaches, particularly Convolutional Neural Networks, have revolutionized medical image analysis by providing superior performance in mammographic interpretation while reducing dependence on manual feature engineering [8].

The research findings indicate that traditional machine learning algorithms, while achieving lower accuracy rates compared to deep learning methods, remain valuable for clinical applications requiring interpretability, computational efficiency, and rapid deployment [2]. Support Vector Machines and Random Forest algorithms consistently demonstrate reliable performance across diverse datasets, making them suitable options for resource-constrained environments or applications requiring real-time processing capabilities [6].

Table 5: Summary of Key Research Findings

Category	Key Finding	Clinical Implication	Future Research Direction
Performance	ANN achieves 98.57% accuracy	Near-human expert performance	Validation in larger clinical trials
Efficiency	Traditional ML faster training	Suitable for rapid deployment	Optimize deep learning efficiency
Interpretability	Black-box methods limit adoption	Need for explainable AI	Develop interpretable deep learning
Datasets	Performance varies by data quality	Standardization required	Create diverse, large-scale datasets
Implementation	Computational requirements vary	Infrastructure considerations	Edge computing optimization

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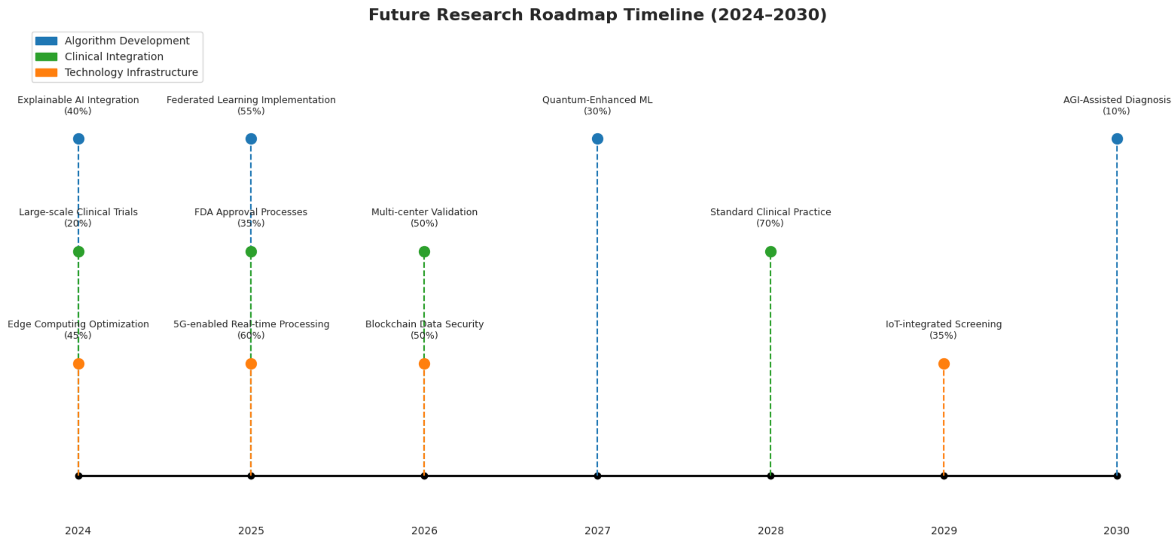

Figure 5: Future Research Roadmap Timeline

The integration of explainable AI techniques emerges as a critical requirement for clinical acceptance of automated breast cancer detection systems, addressing the black-box nature of high-performance algorithms while maintaining diagnostic accuracy [1]. Future research should prioritize the development of interpretable machine learning approaches that provide transparent decision-making processes without compromising performance metrics.

Computational efficiency represents a significant consideration for practical implementation of breast cancer detection algorithms in clinical settings. While deep learning approaches achieve superior accuracy, their computational requirements may limit deployment in resource-constrained environments [15]. The development of optimized algorithms that balance accuracy with computational efficiency remains an important research objective for enabling widespread clinical adoption.

The survey identifies dataset quality and diversity as fundamental factors influencing algorithm performance and generalizability. Future research should focus on creating large-scale, multi-center datasets that represent diverse patient populations and imaging conditions to ensure robust algorithm performance across different clinical environments [4]. Additionally, the development of standardized evaluation protocols and performance metrics would facilitate meaningful comparison between different algorithmic approaches.

Ensemble methods and hybrid approaches demonstrate significant potential for improving breast cancer detection accuracy while addressing individual algorithm limitations [17]. The systematic exploration of algorithm combination strategies could lead to more robust and reliable detection systems suitable for clinical deployment. This research direction should consider both performance optimization and practical implementation requirements.

The rapid advancement of breast cancer detection algorithms presents unprecedented opportunities for improving diagnostic accuracy and healthcare outcomes. However, successful translation of research findings into clinical practice requires careful consideration of performance metrics, computational requirements, interpretability, and regulatory compliance. Continued collaboration between computer scientists, medical professionals, and regulatory bodies will be essential for realizing the full potential of AI-based breast cancer detection systems in improving patient care and outcomes.

The findings of this survey provide a foundation for future research directions and inform the development of next-generation breast cancer detection algorithms that combine high accuracy with practical clinical

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applicability, ultimately contributing to improved early detection and patient survival rates.

DECLARATION

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Supporting Data is openly available for further researches.
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