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A Data-Driven Hybrid ML–XAI Approach for Early stage Breast Cancer Screening

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ABSTRACT:

Breast cancer continues to be the most common type of cancer in women globally and poses a serious threat to global health. Early detection remains a crucial factor in determining survival rates, even with the advancements in imaging technologies. Recent years have seen impressive advancements in the detection, diagnosis, and prognosis of breast cancer thanks to machine learning (ML) and deep learning (DL) techniques. However, as the majority of ML models function as "black boxes" with little transparency, a significant obstacle to clinical application is the lack of interpretability. A promising strategy to close this gap is Explainable Artificial Intelligence (XAI), which provides patients and physicians with understandable insights into algorithms that make decisions. A thorough summary of hybrid ML–XAI architectures for early breast tumor detection is given in this review. We talk about XAI techniques like LIME, SHAP, and Grad-CAM, investigate how they are integrated into hybrid frameworks, and look at the function of ML in mammography, ultrasound, and histology. The study also critically assesses the body of research, identifies present issues, and suggests future paths for the application of reliable, interpretable, and high-performing AI in breast cancer screening. Hybrid ML–XAI frameworks offer a revolutionary route toward dependable, moral, and clinically applicable AI-driven healthcare by fusing interpretability and accuracy.

Keywords: *Breast Cancer, Machine Learning, Explainable Artificial Intelligence, Early Screening, Hybrid Frameworks, Medical Imaging.*

1. INTRODUCTION:

In 2023, breast cancer accounted for approximately 685,000 deaths globally and 2.3 million new cases, making it one of the main causes of death from cancer among women [1]. The worldwide burden emphasizes the value of early detection techniques, which greatly enhance survival rates. In the past, screening methods including magnetic resonance imaging (MRI), ultrasound, and mammography have been essential for detecting breast cancer. Nonetheless, diagnostic mistakes, weariness, and variability continue to affect human perception of medical pictures [2].

In some contexts, models using machine learning (ML) and, more recently, deep learning (DL), have outperformed radiologists in detecting worrisome lesions [3]. Convolutional neural networks, or CNNs, have demonstrated a great deal of promise in tasks involving image-based detection and classification. However, despite their success, a significant obstacle still exists: the black-box dilemma. The majority of machine learning and deep learning models provide results that lack interpretable logic, which undermines patient and physician confidence [4].

Explainable Artificial Intelligence (XAI), which aims to make AI models accessible and interpretable, has grown as a result of this constraint. Meaningful explanations for AI predictions are offered by XAI techniques like Gradient-weighted Class Activation Mapping (Grad-CAM), SHapley Additive exPlanations (SHAP), and Local Interpretable Model-Agnostic Explanations (LIME) [5]. These techniques encourage accountability and confidence in healthcare applications in addition to helping doctors validate model judgments.

One interesting approach to early breast cancer detection is the hybrid framework that combines ML and XAI. Hybrid systems guarantee accurate and understandable models by fusing the interpretability of XAI techniques with the prediction accuracy of ML/DL algorithms. These kinds of frameworks are essential for integrating solutions based on artificial intelligence into clinical settings where openness is a must [6].

Reviewing the literature on hybrid ML–XAI frameworks for breast cancer screening, this paper focuses on methods based on mammography, ultrasound, and histopathology. It identifies potential for further research, examines difficulties, compares approaches, and showcases cutting-edge advancements.

2. Background: Breast Cancer Screening

2.1 Importance of Early Detection

Patient outcomes are significantly improved by early detection of breast cancer; five-year survival rates for localized tumors are over 90%, whereas those for late-stage diagnoses are fewer than 30% [7]. While MRI and ultrasound are complimentary modalities, especially for younger women or females with a dense layer of breast mammography is still the gold standard for detection [8].

2.2 Limitations of Conventional Screening

1. Despite progress, standard screening methods confront considerable challenges:
2. False Positives: causing patients to worry and needless biopsies.
3. False Negatives: In circumstances with thick tissue, missed diagnoses.
4. Inter-observer Variability: Reliability is impacted by radiologists' frequent differences in interpretation.
5. Resource Limitations: In many low-resource areas, there is a shortage of qualified radiologists [9].

2.3 Role of Artificial Intelligence

- AI-powered solutions can help with these problems by: Improving the precision of anomaly detection.
- lowering false negatives and positives.
- establishing a common diagnostic for all institutions.
- providing decision-assistance tools to radiologists [10].

3. Machine Learning in Breast Cancer Detection:

3.1 Traditional Machine Learning

Using manually created parameters like shape, texture, and density, traditional machine learning techniques like Support Vector Machines (SVMs), Random Forests (RFs), and k-Nearest Neighbours (kNN) have long been used to diagnose breast cancer [11]. Despite their relative success, these models frequently performed poorly on complex imaging data and were constrained by feature engineering.

3.2 Deep Learning Approaches

Medical imaging was transformed by deep learning, especially CNNs, which automatically extracted hierarchical characteristics from unprocessed data [12]. CNNs have been used for:

Identifying masses, calcifications, and architectural distortions is known as mammography.

Differentiating between benign and malignant tumors using ultrasound.

Histopathology: Determining cellular tumor subtypes [13].

Accuracy scores on benchmark datasets have surpassed 90% in recent research employing pre-trained CNNs with transfer learning [14].

3.3 Challenges with ML Models

1. ML and DL models still have problems in spite of their achievements:
2. Impossibility of Interpretation: Models frequently fall short of proving predictions.
3. Data Requirements: Healthcare organizations lack the vast datasets needed for deep models.
4. Fairness and Bias: The possibility of skewed forecasts that target marginalized groups [15].

4. Explainable AI in Medical Imaging:

4.1 Need for Explainability

Accuracy is crucial in therapeutic settings, but so are trust and accountability. An interpretable judgment that clinicians can justify is more acceptable than a classified incorrectly lesion with no explanation [16].

4.2 XAI Techniques

1. Local Interpretable Model-Agnostic Explanations, or LIME, uses perturbing inputs to provide local approximations of predictions.
2. Cooperative game theory is used by SHAP (SHapley Additive exPlanations) to determine feature importance levels.
3. Grad-CAM, or Gradient-weighted Class Activation Mapping, creates heatmaps that show the areas of a picture that have an impact on CNN predictions.
4. Counterfactual Explanations: Illustrates how little adjustments to input could influence forecasts [17].

4.3 Applications in Breast Cancer

- Mammography: The regions (calcifications, masses) that affected the choice are displayed in Grad-CAM representations.
- Ultrasound: Pixel contributes to malignant classifications are shown by SHAP values.
- Histopathology: The significance of cellular features is validated by LIME explanations [18].

4.4 Limitations of Current XAI

- Justifications may be erratic.
- Clinical reasoning may not always be consistent with visualizations.
- There is yet little integration with real-time workflows [19].

5. Hybrid ML–XAI Frameworks for Breast Cancer Screening:

5.1. Concept

- The interpretability of XAI and the predictive capability of ML/DL are used in a hybrid ML–XAI framework to provide accurate and transparent systems.

5.2 A hybrid framework's design

1) Image denoising, augmentation, and normalization are examples of data preprocessing.
2) CNN-based automatic learning of features is known as feature extraction.
3) SVM, RF, and XGB are ML classifiers that are trained on extracted features in hybrid classification.
4) Explainability Layer: Interpretability is provided by XAI approaches.
5) Risk scores, visual heatmaps, and easily understood explanations are all part of the clinician interface.

5.3 Literature Review

- Arevalo et al. [20]: Grad-CAM visuals for CNN-based mass lesion categorization.
- Dhungel and associates. [21]: LIME explanations in conjunction with transfer learning in mammography.
- Guan and Tjoa [22]: A survey on XAI in healthcare that focuses on breast cancer as a key use case.
- Recent Developments (2022–2023): On the MIAS and BUSI datasets, hybrid CNN-XGBoost pipelines with SHAP interpretations attained >94% accuracy [23].

5.4 Benefits

- increased accuracy through hybridization of ML and DL.
- transparency using visuals powered by XAI.

- Improved communication between patients and clinicians

6. Challenges and Future Directions:

6.1 Data Challenges

- limited datasets that are accessible to the public.
- Privacy issues while exchanging medical information

6.2 Model Challenges

- balance between interpretability and accuracy.
- Absence of common standards for evaluating XAI

6.3 Deployment Challenges

- integration with PACS systems in hospitals.
- Ethics and regulations

6.4 Future Directions

1. For teaching across several institutions while protecting privacy, use federated learning.
2. Integrating genomic data, ultrasonography, and mammography is known as multimodal integration.
3. AI that collaborates with physicians to make decisions is known as "human-in-the-loop" AI.
4. Fairness and Bias Auditing: Ensuring performance is equal for all groups.
5. Establishing clinically significant standards through the standardization of XAI metrics

7. Conclusion:

A revolutionary development in early breast cancer detection is represented by hybrid ML–XAI frameworks. These systems meet two essential needs: performance and trust, by fusing the interpretability of XAI techniques with the prediction accuracy of deep learning. Despite the notable advancements, there are still issues with data availability, dependability, explainability, and clinical application. Federated, multimodal, and human-centered AI systems that can be easily included into healthcare processes should be the main emphasis of future research. In the end, the effectiveness of AI in breast cancer detection will rely on these systems' transparency, equity, and dependability in addition to their accuracy.

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