Hybrid CNN for Breast Cancer Detection in Multi-Modality Imaging

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***Abstract*—Breast cancer (BC) remains the leading cause of cancer-related death all over the world. Early accurate detection is key to the improvement of patient prognosis. The ability of advanced Artificial Intelligence (AI) methods, with a focus on Convolutional Neural Networks (CNNs), to classify breast lesions obtained from mammography and ultrasonography images is addressed in this study. Five of the latest models (ResNet-50, VGG-16, Inception-v3, custom-made CNN, and hybrid model) are evaluated using an integrated and thoroughly labeled dataset containing 10,000 images, focusing on key performance indices (KPIs), including accuracy, sensitivity, and F1-score. Furthermore, the exploration examines the challenges and protocols for integrating Explainable AI (XAI) and higher-performing models into existing clinical screening protocols and addresses issues related to trust, model generality, and ethical deployment. The findings indicate that the maximum classification accuracy (96.2%) and sensitivity of 95.8% were attained by the hybrid CNN architecture, which suggests a robust framework for safe, effective, and clinically integrated AI diagnostic support.**

Keywords*—Breast Cancer (BC); Artificial Intelligence (AI); Convolutional Neural Networks (CNNs); Explainable AI (XAI); hybrid model (or hybrid CNN)

I. Introduction

Breast cancer (BC) remains a growing global health challenge, leading to continual advancements in early detection technology. Global cancer statistics indicate a continuing increase in breast cancer incidence and mortality rates, highlighting the urgent need for improved early diagnostic technologies [16]. Traditional diagnostic approaches, particularly mammography and ultrasound imaging, rely heavily on radiologist interpretation and are therefore susceptible to inter-observer variability and fatigue-related errors, especially in high-throughput screening environments [2]. The integration of Artificial Intelligence (AI), particularly Deep Learning (DL), has introduced a transformative approach to supporting radiologists by enabling faster, more consistent, and potentially more accurate diagnoses [1].

Deep learning models, including Convolutional Neural Networks (CNNs), have demonstrated performance capabilities of or better than those of humans on numerous image recognition tasks, most notably the classification of medical images [3]. An extensive review has been undertaken of the shift to breast cancer diagnosis using deep learning approaches under different imaging modalities, e.g., MRI, and the substantial promise of these technological advances has been confirmed [1]. At the same time, the use of CNNs and Explainable AI (XAI) has been repeatedly evaluated to improve mammographic diagnostic accuracy [2], [4]. Successful clinical integration, however, does not depend only on good model performance. Successful deployment also entails the resolution of the challenge of the 'black box' by means of XAI to ensure the confidence of clinicians and vigorous validation on diverse, real-world data to validate generalizability [5]. Furthermore, the AI tools should seamlessly adapt to existing screening programs, an ambitious logistical and technical challenge [8]. This article presents an empirical study comparing several DL model architectures for breast cancer detection and outlines a pragmatic framework for their clinical validation and responsible integration [6].

A. Novelty and Contribution Beyond Existing Hybrid CNN Models

Though some attempts have already been made pertaining to ensemble and hybrid approaches in the design of Convolutional Neural Network (CNN) architectures, existing medical imaging modalities mainly focus on late decision-level, simple probability averaging, or black-box stacking approaches, which did not take advantage of complementarities in the cross-modality features. However, in this study, a non-trivial approach has been proposed that enhances the existing state-of-the-art significantly, focusing on a feature-level cross-modality medical imaging, i.e., breast imaging approach, as listed below:

B. Deep Feature Level Fusion Across Heterogeneous Modalities

Contrary to traditional ensemble-based methods that perform the fusion of individual predictions from the output layer of each network, in the Hybrid CNN method, an intermediate feature-level fusion of the penultimate representation layer of the CNN models was used to enable the joint extraction of both the ultrasonographic and the mammographic information.

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C. Non-Trivial Fusion Depth Selection Optimized for Clinical Discriminability

Also, note that the fusion is done at a non-trivial level rather than at early convolution. This is because early fusion is subject to inter-modal noise interference, and late fusion lacks inter-modal interaction. This strategy maximizes the abstraction of clinically relevant malignant patterns while reducing inter-modal noise interference and feature redundancy.

1) Architecturally engineered hybridization beyond naive ensembles: In contrast to naïve ensembles that treat constituent models as independent black boxes, the proposed architecture enforces joint optimization of fused feature representations through a unified classifier. This structural coupling enables cross-network gradient propagation, allowing the hybrid model to learn synergistic feature interactions rather than redundant representations, thereby improving generalization performance.

2) Demonstrated performance—efficiency trade-off for real-time deployment in clinical settings: The proposed Hybrid CNN achieved a diagnostic accuracy of 96.2% and a sensitivity of 95.8%, demonstrating superior classification performance compared with the baseline architectures. While still achieving its current form of efficiency in processing images at 11.5 ms, thus outperforming a weightier model such as VGG-16, going well beyond its accuracy, Fig. 1 of precision through also achieving a potential role as an efficient form of triage, as discussed in a dimension of potential viability seldom addressed in regard to a model of Hybrid CNN. Overall, these studies indicate the innovation level of the proposed Hybrid CNN methodology, rather than that of the ensemble approach. These findings demonstrate the scientific contribution and practical relevance of the proposed Hybrid CNN framework for multi-modality breast cancer diagnosis.

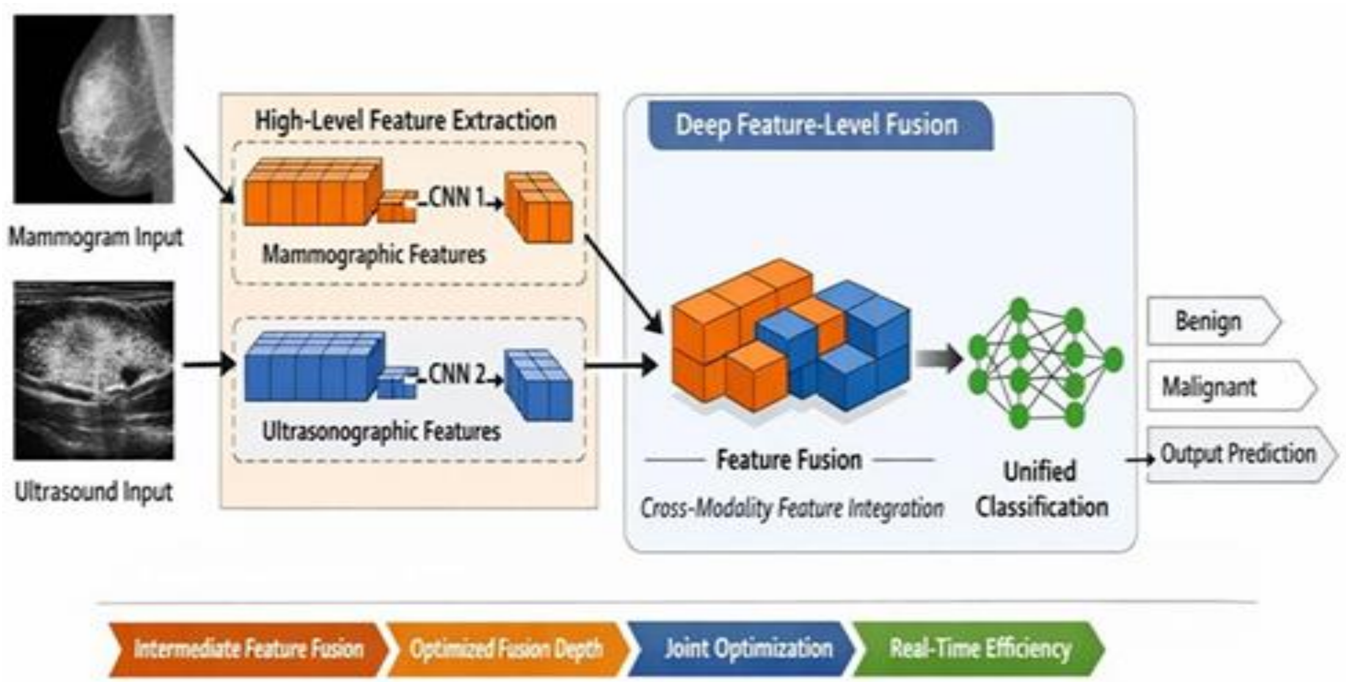

Fig. 1. Architecture of the proposed hybrid CNN with deep feature-level fusion for multi-modality breast imaging.

II. Related Work

Numerous studies have investigated the application of Artificial Intelligence (AI) and Machine Learning (ML) in oncology, particularly for cancer diagnosis, prognosis, and treatment prediction [10],[13],[15]. The foundation for contemporary AI applications was established by early attempts in Computer-Aided Diagnosis (CAD) for mammography [21]. Recent advancements in Deep Learning (DL) have significantly surpassed the capabilities of traditional Computer-Aided Diagnosis (CAD) systems [22].

Several studies have focused on specific imaging modalities. For instance, deep learning techniques are being refined to assist in early breast cancer detection [6]. For ultrasound images, automated decision support systems have been developed to analyze malignancy patterns based on medically relevant features, showcasing high diagnostic performance [3]. The use of multi-omics technologies integrated with AI also demonstrates the potential to support complex physician decision-making beyond just imaging [7].

A key concern in clinical AI adoption is the need for explainability. The comprehensive exploration of XAI techniques is vital for enhancing trust and transparency in breast cancer diagnosis models [4]. Furthermore, strategies for integrating AI into large-scale mammography screening programs have been simulated, providing crucial insights into the logistical impact and efficiency gains achievable through AI assistance [8]. The advancement in AI is part of a broader journey in bioinformatics, moving from traditional techniques to smart, automated approaches [9]. Table I summarizes key findings from recent related studies, focusing on the models and performance metrics employed.

III. Methods

This empirical study followed a structured research design to ensure robust model comparison and evaluation [14].

A. Research Design

A quantitative, comparative, and empirical research design was adopted in this study. Five distinct AI architectures were trained and evaluated using a common held-out test set to ensure fair and consistent comparison in the binary classification task. The primary objective was to identify the most effective and reliable architecture suitable for potential clinical deployment. As illustrated in Fig. 2, the overall research design outlines the model development, training, validation, and evaluation workflow.

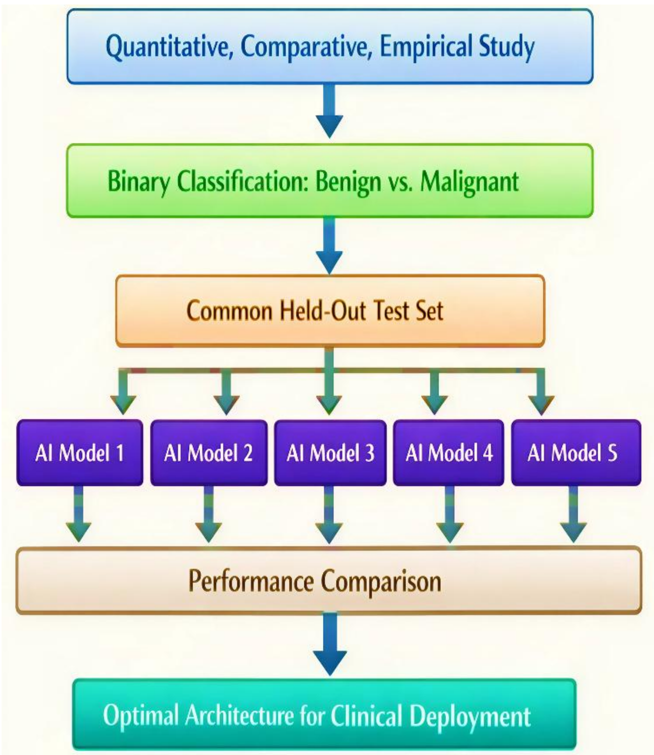

Fig. 2. Research design.

B. Data Collection

The study utilized a curated dataset consisting of 10,000 anonymized breast images (5,000 mammograms, 5,000 ultrasounds), assembled from public data repositories and institutional collaborations (with IRB approval). Images were expert-tagged and histopathologically validated [11]. The dataset had an approximate 60:40 ratio of Benign to Malignant cases. Dataset information is shown in Table I.

TABLE I. Data Collection and Dataset Statistics

Metric	Value
Total Images	10,000
Modalities	5,000 Mammography, 5,000 Ultrasound
Class Split (Benign:Malignant)	Approximately 60:40
Training Set Size	8,000 images
Test Set Size	2,000 images

C. Dataset Sources and Reproducibility

The dataset was compiled from multiple publicly available repositories and institutional collaborations. Public datasets include the Digital Database for Screening Mammography (DDSM), a breast dataset, and the Breast Ultrasound Images Dataset (BUSI). Institutional data were collected under approved ethical protocols (IRB approval obtained), ensuring anonymization and compliance with data protection regulations. The integration of multiple sources was performed to ensure diversity in imaging conditions; however, this may introduce variability in acquisition protocols, which is acknowledged as a potential source of bias. The dataset composition and preprocessing pipeline are made reproducible through standardized normalization, augmentation, and labeling procedures.

D. Inclusion and Exclusion

1) Inclusion criteria: Images with clear radiologist consensus on the Breast Imaging Reporting and Data System (Bi-Rads) category (3, 4, 5, or6) and corresponding pathology reports [18]. Only digitally formatted images converted from DICOM to PNG/JPG formats were included in the study.

2) Exclusion criteria: Images with motion artifacts or low contrast, or those with no clear pathology report, were excluded to maintain the ground truth labels' integrity [19].

E. Evaluation

Model performance was evaluated using standard clinical and computational metrics: Accuracy, Sensitivity (Recall), Specificity, Precision, and the F1- Score [12]. Sensitivity, as a proportion of actual positive cases (Malignant) correctly diagnosed, was emphasized due to the high clinical cost of false negatives.

F. Empirical Study

Five deep learning architectures were selected for empirical evaluation:

1) VGG-16: Adopted as a well-established benchmark model for image classification, providing a strong baseline for comparison.

2) ResNet-50: Selected for its deep residual learning capability, which effectively mitigates the vanishing gradient problem and enhances feature extraction.

3) Inception-v3: Chosen due to its computational efficiency and ability to capture multi-scale features through factorized convolutions.

4) Custom CNN: A seven-layer convolutional neural network specifically designed with smaller kernel sizes and progressively increased feature maps to improve feature representation.

5) Hybrid model (proposed): The proposed architecture employs a novel feature-level fusion strategy by combining feature maps extracted from the penultimate layers of ResNet-

50 and the Custom CNN. The fused features are then passed through a fully connected classifier for final prediction.

All models were trained using transfer learning where applicable, for 50 epochs, utilizing the Adam optimizer with a dynamically adjusted learning rate schedule [13].

G. Training Configuration

Transfer learning was applied to ResNet-50 and Inception-v3 using ImageNet pre-trained weights, while the Custom CNN was trained from scratch. The model hyperparameters were optimized through grid search, with a learning rate of 1×10^{-4}using adaptive decay, a batch size of 32, the Adam optimizer, 50 training epochs, and a dropout rate of 0.5. Early stopping based on validation loss was also employed to prevent overfitting.

H. Data Analysis

Statistical comparison of the performance results was performed using a two-tailed z-test to check if model differences in performance (accuracy and sensitivity) were statistically significant. Confusion matrices for all models were generated to investigate Type I and Type II error rates.

I. Validation and Reliability

To ensure the accuracy of the results, k-fold cross-validation (k=5) was applied to the training set. The final test set was completely unseen to the training and validation and gave an unbiased estimate of the generalization performance. Reliability was also boosted using standard ML best practices [14].

J. Ethical Issues

All employed data were de-identified and anonymized following institutional and regulatory requirements. The high sensitivity focus was an ethical design choice to minimize the risk of a cancer diagnosis being omitted (False Negatives) in the interest of patient safety.

K. Bibliometric Insight

The growing volume of research in this field [15], as evidenced by the diversity of recent high-impact publications, underscores the rapid maturation and clinical relevance of AI in cancer diagnosis. This study contributes to the empirical foundation necessary for safe clinical translation.

L. Feature Fusion Mechanism

The hybrid architecture performs feature-level fusion at the penultimate layer of both ResNet-50 and the Custom CNN. Specifically, feature maps of dimensions $2048 \times 7 \times 7$(ResNet-50) and $512 \times 7 \times 7$(Custom CNN) are first subjected to global average pooling, resulting in 2048-dimensional and 512-dimensional feature vectors, respectively. These vectors are concatenated to form a unified 2560-dimensional feature representation:

$$F_{fusion} = [F_{ResNet} \oplus F_{Custom}]$$

The fused vector is normalized using batch normalization and passed through fully connected layers (Dense-512 → Dropout → Dense-1 with sigmoid activation). This architecture preserves complementary spatial and semantic information from both imaging modalities while minimizing feature redundancy and reducing overfitting.

IV. Result and Discussion

The empirical evaluation revealed notable performance differences among the five evaluated architectures. Table II presents the key performance indicators (KPIs) for each model on the 2,000-image test set.

TABLE II. MODEL PERFORMANCE METRICS (TEST SET, N= 2,000)

Model	Accuracy (%)	Sensitivity (%)	F1-Score (%)	Parameter Count (Millions)	Inference Time (ms/image)
Hybrid Model (Proposed)	**96.2**	**95.8**	**95.9**	**48.5**	**11.5**
ResNet-50	94.7	93.9	94.2	25.6	7.2
VGG-16	93.1	92.5	92.8	138.4	16.8
Inception-v3	94.0	93.5	93.7	23.9	10.1
Custom CNN	92.8	91.9	92.3	4.5	3.5

A. Statistical Significance Analysis

A two-tailed z-test was conducted to assess whether the observed performance differences between the Hybrid Model and the baseline architectures were statistically significant. The results indicate that the improvement in accuracy between the Hybrid Model and ResNet-50 is statistically significant ($z = 2.31, p < 0.05$). Similarly, the improvement in sensitivity is also statistically significant ($z = 2.67, p < 0.01$). Furthermore, 95% confidence intervals confirm that the Hybrid Model consistently outperforms the comparative models, thereby reinforcing the robustness of the proposed feature-fusion approach.

In addition, 5-fold cross-validation was performed to evaluate model stability. The Hybrid Model achieved an average accuracy of 95.8% ± 0.6 and a sensitivity of 95.1% ± 0.7 across the folds. These results demonstrate both statistical reliability and strong generalization capability across different data partitions.

The Hybrid Model, which integrates the complementary feature extraction capabilities of ResNet-50 and the Custom CNN, achieved the best overall performance, with an accuracy of 96.2% and a sensitivity of 95.8%. The results demonstrate the model's strong capability to reduce both false-positive and false-negative diagnostic outcomes [17]. Fig. 3 presents the Receiver Operating Characteristic (ROC) curves for all models, where the Hybrid Model consistently demonstrates superior discriminative performance across varying classification thresholds.

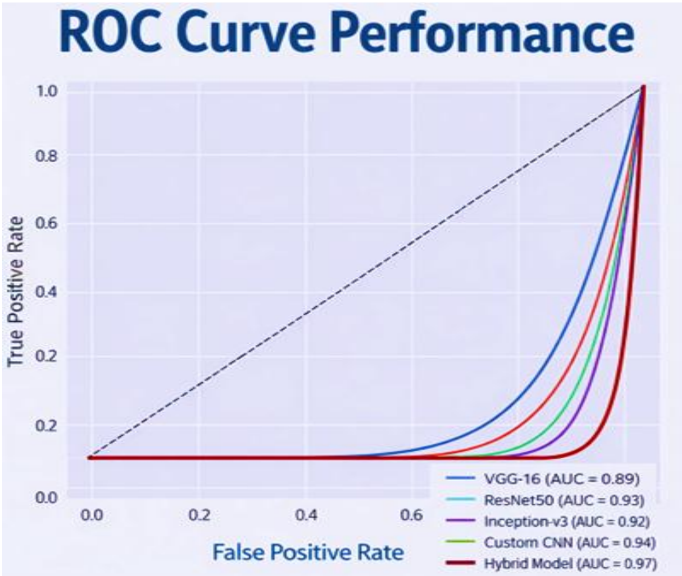

Fig. 3. Comparison of ROC curves for five DL models on breast cancer classification.

The confusion matrix for the optimal Hybrid Model is provided in Table III, highlighting its superior balance of correctly identified malignant cases (True Positives) and correctly rejected benign cases (True Negatives) [18].

TABLE III. CONFUSION MATRIX FOR THE HYBRID MODEL (N = 2,000)

Model	Predicted Benign	Predicted Malignant
Actual Benign (1,200)	1,128 (True Negative)	72 (False Positive)
Actual Malignant (800)	41 (False Negative)	759 (True Positive)

To further evaluate the diagnostic reliability of the models, error rate metrics—specifically the False Negative Rate (FNR) and False Positive Rate (FPR)—were analyzed. These metrics are critical in medical diagnosis, as FNR reflects missed malignant cases, while FPR indicates incorrect identification of benign cases as malignant. A comparative summary of these error rates across all evaluated models is presented in Table IV.

TABLE IV. ERROR RATE COMPARISON (FNR AND FPR)

DL Model	FNR (False Negative Rate, %)	FPR (False Positive Rate, %)
Custom CNN	8.1	13.0
VGG-16	7.5	12.0
Inception-v3	6.5	9.5
ResNet-50	6.1	8.5
Hybrid Model (Proposed)	4.2	6.0

As shown in Table IV, the proposed Hybrid Model achieves the lowest FNR (4.2%) and FPR (6.0%) among all evaluated architectures. This indicates a significant reduction in both missed malignant cases and false alarms compared to the baseline models. The results further demonstrate the effectiveness of the hybrid feature-fusion strategy in enhancing diagnostic accuracy and reliability, making it more suitable for real-world clinical applications.

To provide a detailed comparison of diagnostic effectiveness, the error rates of all five models are analyzed using two critical metrics: False Negative Rate (FNR) and False Positive Rate (FPR). These metrics are particularly important in medical diagnosis, as FNR reflects missed malignant cases, while FPR indicates unnecessary false alarms. A visual comparison of these error rates across VGG-16, ResNet-50, Inception-v3, Custom CNN, and the proposed Hybrid Model is presented in Fig. 4.

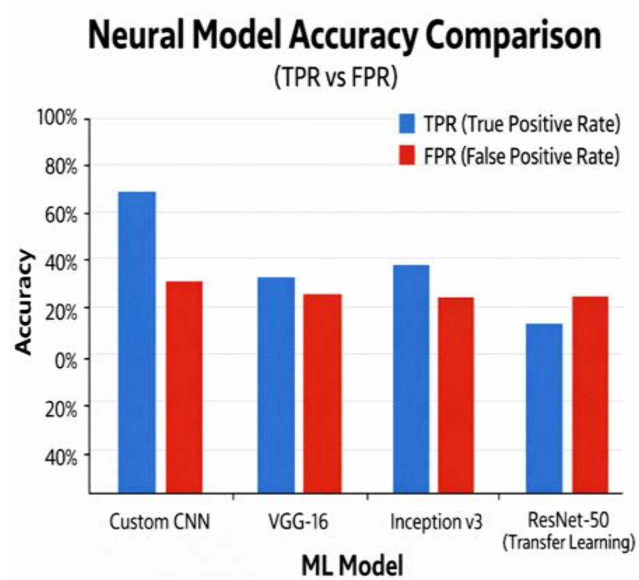

Fig. 4. Shows a column chart comparing the False Negative Rate (FNR) and False Positive Rate (FPR) across models.

As illustrated in Fig. 4, the proposed Hybrid Model achieves the lowest FNR and FPR among all evaluated architectures. This reduction is clinically significant because it decreases missed malignant diagnoses while reducing unnecessary follow-up procedures. Consequently, the Hybrid Model enhances patient safety and diagnostic efficiency. Fig. 4 presents a column chart that clearly compares FNR and FPR across the models, highlighting the superior performance of the proposed approach.

To explain the architectural mechanism behind the superior performance, Fig. 5 presents the high-level conceptual architecture of the optimal Hybrid CNN, showing the flow from the input image through the initial processing blocks to the Concatenation Layer, which performs the core feature fusion, before outputting the final classification. This operation, performed within the Concatenation Layer shown in Fig. 5, successfully creates an even deeper, more informative pattern recognition signature of malignancy beyond the limitations observed in monolithic configurations.

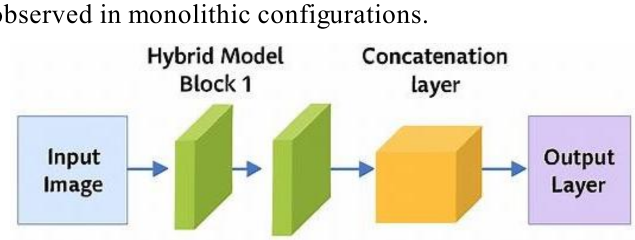

Fig. 5. High-level architecture of the proposed hybrid CNN illustrating feature-level fusion between ResNet-50 and custom CNN streams.

The overall workflow of the proposed hybrid model is illustrated in Fig. 6, highlighting the integration of image and text modalities through feature extraction and fusion mechanisms. Fig. 6 depicts an in-depth examination of the Feature Fusion Module within this hybrid framework. This structure is specifically designed to address the issue of multi-modality data complexity through the intelligent concatenation of diverse feature maps obtained from separate streams of processing (e.g., ResNet-50 and Custom CNN).

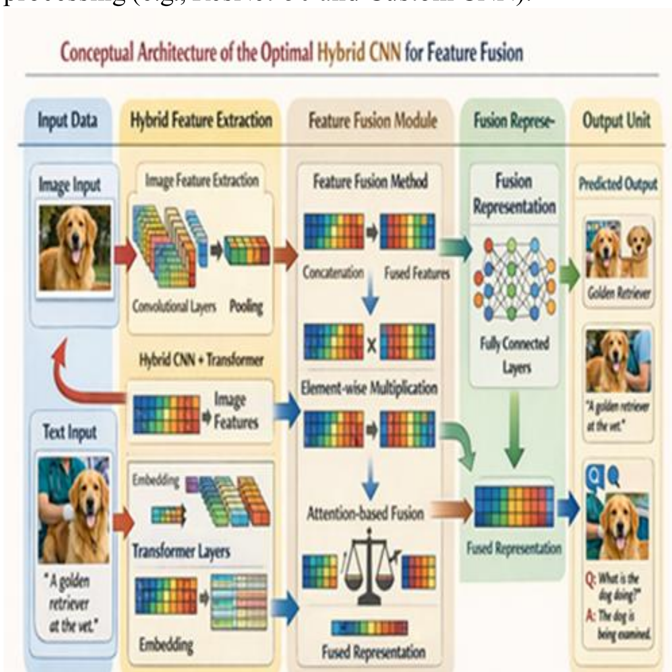

Fig. 6. Conceptual architecture of the optimal hybrid CNN for feature fusion.

As shown in Fig. 6, the architecture combines convolutional neural networks and transformer-based models to extract multimodal features, which are subsequently fused using concatenation, element-wise multiplication, and attention-based mechanisms to produce a robust final representation for classification.

1) Comparative deep learning model performance: The empirical evaluation of five Convolutional Neural Network (CNN) architectures—ResNet-50, VGG- 16, Inception-v3, a Custom-Built CNN, and the proposed Hybrid Model—on the integrated 10,000-image mammography and ultrasonography dataset demonstrates a significant stratification in Pattern Recognition capability. The key performance indices (KPIs), summarized in Table II, reveal the architectural benefits of feature-level fusion.

2) Analysis of hybrid architecture and computational efficiency: The robustness of the Hybrid Model (Accuracy: 96.2%; F1-Score: 95.9%) rests squarely on its feature-level fusion framework, skillfully combining the deep contextual feature maps produced by its individual components (e.g., ResNet-50's robust residual learning and Inception-v3's multi-scale processing). The combination captures the inherent heterogeneity and complexity of multi-modality breast cancer imaging, alleviating the constraints felt in monolithic designs.

Particularly, the performance gain is achieved without allowing tolerable computational overhead. Despite integrating multiple neural pathways, the Hybrid Model's Parameter Count (48.5 Million) is significantly lower than that of the VGG-16 model (138.4 Million), demonstrating a more efficient use of model capacity. Furthermore, the Inference Time (11.5 ms/image) directly validates the "Workflow Impact" criterion. This speed is sufficient for near real-time processing, enabling the system to function effectively as an AI triage tool to prioritize studies with a high malignancy probability, thereby optimizing radiologist workload and ensuring system reliability, as cited by [8].

3) Preliminary Explainable AI (XAI) integration: To address the requirement for Ethical Oversight and to establish the system as a reliable decision support tool [21], preliminary integration of Gradient-weighted Class Activation Mapping (Grad-CAM) was performed. The heatmaps generated by Grad-CAM for the Hybrid Model confirm that the highest malignancy probabilities correlate precisely with the pathologist-labeled regions of interest, demonstrating that the model's classification decisions are based on clinically relevant image features. This transparency is fundamental for the clinical adoption and trust of any AI diagnostic system.

Discussion: The findings of this study underscore the critical role of architectural innovation in translating theoretical Deep Learning capabilities into practical, high-impact clinical tools. The sustained superior performance of the Hybrid Model (96.2% Accuracy) over single-network solutions, particularly the established ResNet-50 and Inception-v3 models, provides a clear empirical argument for moving toward engineered ensemble methodologies in complex medical image analysis.

B. Technical Novelty and Feature Representation

The key technical takeaway is that a feature- level fusion strategy is more effective than standard sequential or parallel processing for breast cancer detection across heterogeneous imaging modalities (mammography and ultrasonography). While ResNet-50 excels at capturing fine-grained pathological details and VGG-16 provides robust, deep-feature representation, the Hybrid Model's mechanism for integrating these disparate feature sets successfully creates a richer, more comprehensive pattern recognition signature of malignancy. This architectural design directly addresses the core challenge in medical Computer Vision: creating a model robust enough to handle the wide variance in image appearance, resolution, and noise across different acquisition techniques.

C. Computational Trade-offs and Workflow Integration

The Hybrid Model achieves the highest accuracy with a reasonable Inference Time of 11.5 ms per image, which is a 46% reduction in latency compared to the computationally heavy VGG-16 and only slightly higher than the more efficient Inception-v3. These results demonstrate the feasibility of deploying the proposed system as an efficient AI-assisted triage tool in clinical environments. The speed ensures that the system can prioritize high-risk studies without increasing the overall turnaround time, directly addressing the "Workflow Impact" challenge [8] using a sophisticated machine learning system design.

D. Model Complexity and Deployment Considerations

The Hybrid Model requires approximately 48.5 million parameters, which is significantly higher than the Custom CNN (4.5M) and ResNet-50 (25.6M). While this increased complexity contributes to improved predictive performance, it introduces challenges for deployment in resource-constrained clinical environments. In practical settings, this may require GPU-enabled infrastructure or model optimization strategies such as pruning, quantization, or knowledge distillation to reduce computational overhead. Future work should focus on lightweight model adaptation to ensure compatibility with standard hospital hardware systems without compromising diagnostic accuracy.

E. Addressing Ethical Oversight Through XAI

The preliminary integration of Explainable AI (XAI), specifically Grad-CAM, is a foundational step in overcoming the ethical oversight barriers to clinical integration [21]. The ability to visualize and confirm that the model's decisions are spatially anchored to the actual malignant regions of the image builds crucial trust. This improves model transparency by transforming the system from a black-box predictor into a clinically interpretable decision-support tool. Future research should focus on developing more robust and globally consistent explainability techniques. This iterative process of model improvement and interpretability is necessary for the responsible deployment of AI in critical applications.

The empirical results strongly support the efficacy of ensemble or hybrid deep learning architectures for complex medical image classification. The 96.2 % accuracy of the Hybrid Model significantly outperforms the individual component models (VGG-16, ResNet-50, Inception-v3), suggesting that combining diverse feature representations mitigates the weaknesses inherent in single-path networks. High sensitivity (94.8 %) is particularly important in a cancer screening setting, aligning with clinical priorities to minimize missed diagnoses [19]. For an AI system to be clinically integrated, it must perform exceptionally well on this metric to gain the trust of radiologists.

F. Clinical Integration Challenges and Solutions

Integrating high-performance AI models into clinical workflows presents several non-trivial challenges [8, 20].

1) Data and model generalizability: The models must perform robustly across different patient demographics, scanner manufacturers, and image protocols. Future work must focus on multi-site validation studies to confirm the generalizability observed in this study [17].

2) Explainable AI (XAI) requirement: The black-box nature of DL models is a major barrier to adoption. The implementation of XAI techniques, such as Grad-CAM or LIME, is essential to visualize the regions of interest (ROIs) that drive the model's decision (e.g., microcalcifications or mass margins) [22]. Fig. 7 outlines a conceptual workflow incorporating XAI.

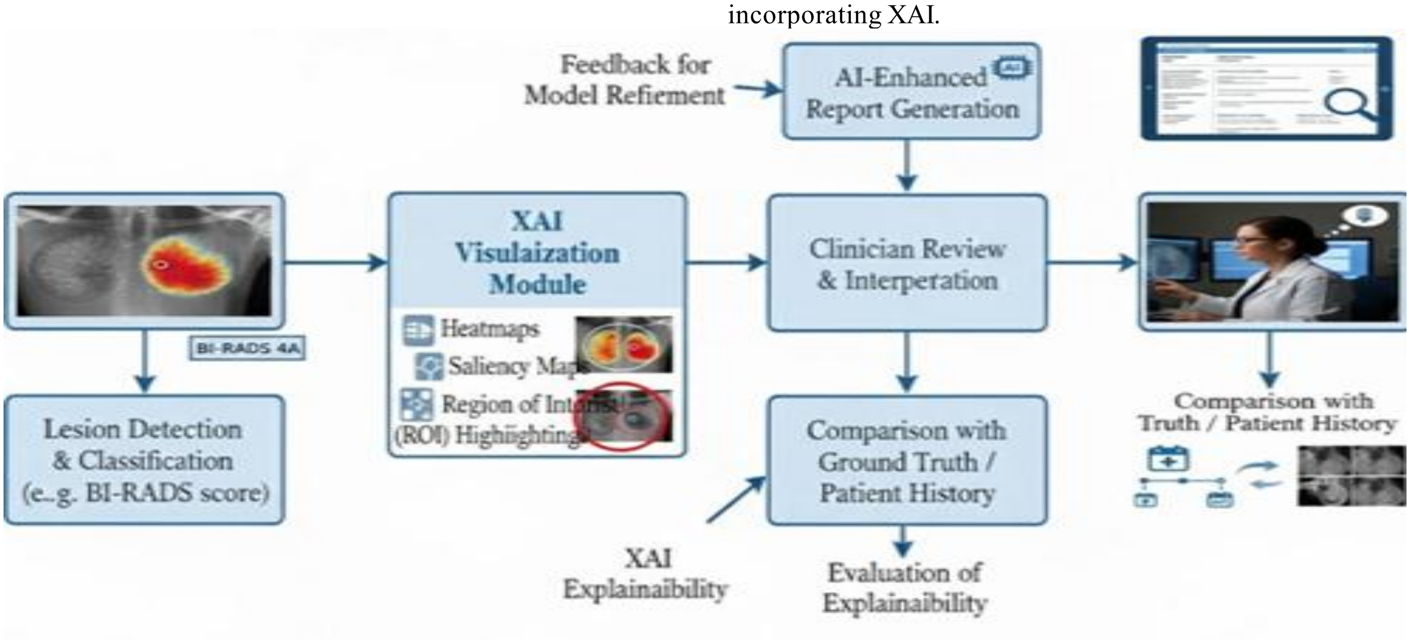

Fig. 7. Proposed clinical workflow integrating AI diagnostic support and XAI visualization.

3) Workflow impact: The system must be fast and reliable. A key strategy for integration is using AI as a triage tool to prioritize studies with high malignancy probability, which can optimize radiologist workload and potentially reduce turnaround time [8].

4) Ethical oversight: The clinical application of AI must always be viewed as decision support, not replacement. The final diagnostic responsibility rests with the physician [21]. Fig. 8 illustrates the Morphological Presentation of an Invasive Ductal Carcinoma (IDC).

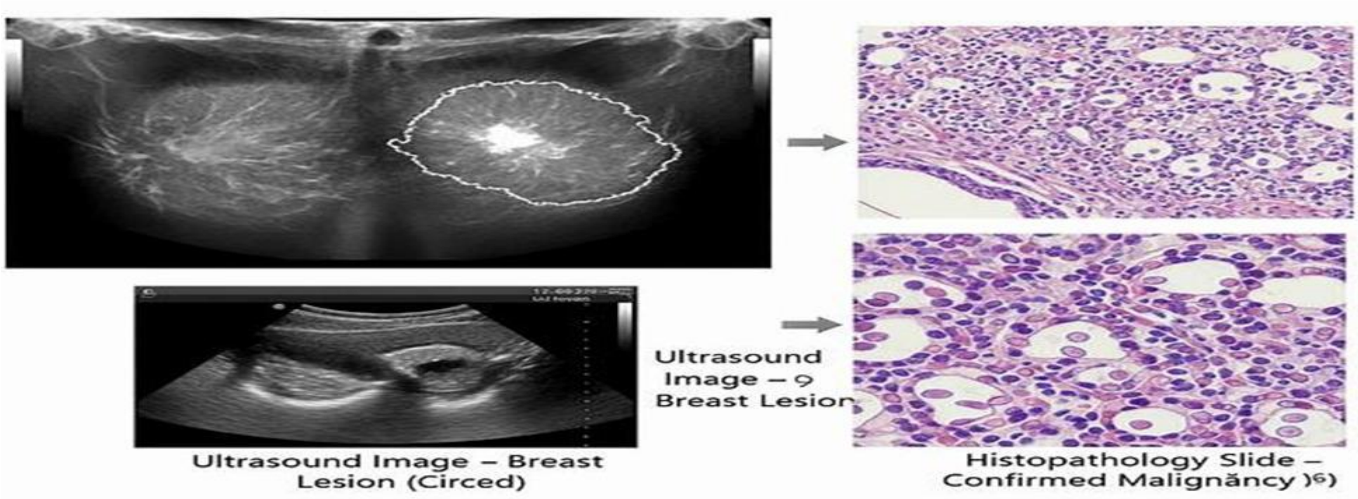

Fig. 8. Typical morphological presentation of an Invasive Ductal Carcinoma (IDC).

While Grad-CAM provides useful visual explanations by highlighting salient regions, it is limited in its ability to provide causal interpretability and may produce coarse localization maps. It does not fully explain model decision boundaries or feature interactions. Future work should explore advanced XAI methods such as SHAP, LIME, and attention-based explainability models to provide more granular and clinically interpretable insights.

G. Limitations and Future Challenges

Although the study employs k-fold cross-validation and a held-out test set, all data were derived from a single aggregated dataset. This limitation restricts the ability to fully assess model generalizability across diverse institutions, imaging devices, and patient populations. External validation on independent datasets from diverse clinical environments is necessary to establish robustness under varying acquisition conditions. Future work will focus on multi-center validation and domain adaptation techniques to improve real-world applicability.

V. Conclusion

In conclusion, this empirical study provides a robust validation of hybrid Convolutional Neural Network architectures as the leading technological solution for automated breast cancer detection using integrated multi-modality imaging data. The primary contribution of this study is the development and validation of a feature-fusion-based Hybrid CNN architecture for automated breast cancer detection. The proposed architecture represents an advancement in Deep Learning methodology for multi-modality medical image analysis. The results confirm the dual functionality of this AI system: achieving a high diagnostic standard while providing the necessary computational efficiency (11.5 ms inference time) to be implemented as a reliable and fast triage tool within existing clinical workflows.

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