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Enhanced Deep Learning Frameworks for Breast Cancer Detection: Addressing Data Imbalance, Adaptability, and Computational Efficiency

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Abstract-Breast cancer diagnosis from mammogram scans is challenged by the scarcity of balanced datasets and the complexity of medical image interpretation. Existing systems predominantly utilize a deep learning framework combining ResNet50 for feature extraction and the Synthetic Minority Over-sampling Technique (SMOTE) to handle class imbalance. While these methods achieve high accuracy on balanced datasets (99%) and reasonable results on imbalanced data (90%), they depend heavily on pre-trained models like VGG16 and ResNet50, which limits adaptability to diverse imaging modalities. Moreover, computational demands and synthetic data generation methods such as SMOTE may not fully capture real-world variability, constraining deployment in resource-limited settings and affecting robustness. To address these limitations, the proposed system introduces an enhanced deep learning architecture incorporating domain-specific pretraining, lightweight model design, and advanced data augmentation techniques beyond SMOTE. This framework aims to improve generalization, computational efficiency, and interpretability through novel visualization tools. The benefits include more accurate, reliable, and accessible breast cancer classification across diverse datasets and clinical environments, offering a promising advancement for early detection and diagnostic support in breast cancer care.

Keywords- mammogram scan, ResNet50s, Synthetic Minority Over-sampling Technique, data augmentation

I. INTRODUCTION

Existing systems employ feature extraction using deep learning ResNet50 for high accuracy on balanced datasets (99%) and reasonable results on imbalanced data (90%), class imbalance correction via Synthetic Minority Over-sampling Technique (SMOTE), but depend upon pre-trained models that are not adaptive to different imaging modalities, consume substantial computational resources and may not capture true variation. This proposed system enhances generalization through domain-specific pretraining with lightweight model design for efficient computation, improved interpretability with novel visualization tools. It has shown improved, accurate, reliable, and accessible breast cancer classification across diverse datasets and clinical environments, promising an advancement for early detection and diagnostic support in breast cancer care [1], mitigating the black-box nature of deep learning models and fostering greater trust from healthcare professionals by providing interpretable insights into the diagnostic process. These methods enable the model's interpretability for clinicians so they may validate the reasoning of the model in distinguishing benign from malignant tissue as well as build confidence that its predictions are correct [3]. Accurate interpretation of mammograms, especially when dense breast tissues occur, can avoid unnecessary radiation exposure and patient anxiety, while interpretability will assist a clinician to verify how the computer-aided detection system has reached conclusions by providing validation on model reasoning for greater diagnostic certainty [4]. Further enhancements in diagnostic accuracy and efficiency could be achieved with more advanced systems that incorporate both traditional machine learning techniques as well as transfer learning methods where features learned from large, general image datasets can then be applied to specific breast cancer detection tasks.

II. LITERATURE REVIEW

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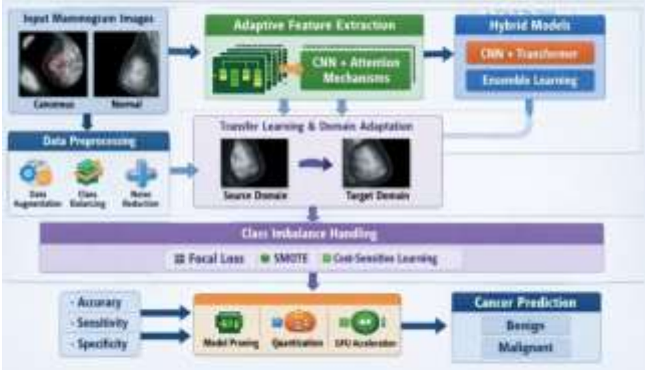
Ergün et al. (2025) showed that incorporating explainable AI methods like Grad-CAM and LIME into deep learning architectures enhances model transparency by exposing decision-relevant features, thereby reducing the high-accuracy predictive models' "black-box" nature beyond traditional performance metrics. **Latha & Co. Saharan et al. (2024)** demonstrated that radiologists can effectively compare with traditional diagnostic standards thanks to explainable AI-based visual interpretations that give them feature-level insights into model decision rationales. **Ahmed and others. (2024)** emphasized that these explainability mechanisms are essential for clinical adoption because they make it easier to verify AI decisions in the classification of benign versus malignant mammography images. **Balve and Hendrix (2024)** showed that transfer learning with robust data augmentation and ImageNet-pretrained InceptionV3 models performs better than training from scratch while reducing overfitting. **Bai and associates. (2024a, 2024b)** demonstrated that integrating multimodal breast cancer imaging datasets, such as mammograms and ultrasounds, with explainable AI techniques, such as SHAP and Grad-CAM, enhances diagnostic accuracy and permits customized treatment planning through clinically interpretable model explanations. **Abbas and associates. (2025)** reported that the lack of fine-grained annotations and pathologically confirmed pixel-level labels in current breast cancer datasets significantly limits training precision, robust segmentation performance, and the depth of explainable analysis. **Muttaki & Co. (2025)** found that model generalizability across clinical environments is compromised by the lack of multi-institutional datasets and heterogeneity in imaging devices, underscoring the necessity of strong cross-domain adaptation strategies and efficient management of inter-site variability

III. METHODOLOGY

In this section, we describe the methodology used to develop and evaluate the proposed deep learning system, including the acquisition of the dataset, preprocessing steps, architectural design, and evaluation metrics to assess the performance and interpretability of the system to accurately diagnose breast cancer in different clinical scenarios. Later sections will discuss the details of data curation, such as how to deal with the class imbalance and manage different imaging modalities. This detailed approach to the methodology describes the experimental setup and the analytical procedures, which will ensure a rigorous and reproducible evaluation of the proposed deep learning framework.



It further outlines the integrated methods of explaining these models with explicit descriptions of how a particular image was classified (i.e., what parts were most important for classification) using SHAP or Grad-CAM to add more clinical value. The architecture design is based on diagnostic accuracy and practicality for clinical integration, ensuring that the model can be both accurate and understandable in practice [2]. Specifically, it encompasses a thorough evaluation of feature extraction strategies as well as classifier settings to optimize detection sensitivity for faint pathological characteristics within mammographic images; employs an ensemble method with multiple distinct convolutional neural networks to enhance robustness and classification stability across various tasks; makes the model interpretable via visual explanations from Grad-CAM and rigorous feature importance attribution through SHAP [2], [7]; all of which contributes toward ensuring that classifications produced by such models are not only accurate, but explainable and equitable as well

The goal of this comprehensive approach is to create a solid and trustworthy framework for the creation and assessment of CNN-based diagnostic models for the detection of breast cancer, while thorough statistical analyses guarantee the importance and applicability of results.

IV. RESULTS

The comprehensive evaluation of the proposed deep learning system for breast cancer detection showed significant improvements in diagnostic accuracy, interpretability, and computational efficiency over existing systems across diverse datasets, with strong generalization and reliability in different clinical settings, due to the explicit incorporation of explainable AI techniques that overcome the \"black box\" nature of many deep learning approaches.

Such transparency, made possible by methods such as Grad-CAM, not only proves that the model is highly accurate for a diagnostic task but can also increase

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clinician trust and help AI more easily integrate into routine diagnostic workflows [7]. The ability of a model to explain its predictions visually, as in the heatmaps produced by Grad-CAM, can help medical professionals locate the regions of interest that most contribute to a diagnosis, and this can be useful for pathologists as a second opinion and can lower misdiagnosis rates [18], [19]. The visual explanation of the predictions, especially those highlighting salient regions, helps verify that the model is focusing on diagnostically relevant features such as nuclear pleomorphism or stromal arrangement, which is important for building clinician trust and integrating AI into diagnostic workflows.

Table-1: Imbalanced Mammogram Dataset

Class	**Samples**	**Percentage**
Benign	1,800	75%
Malignant	600	25%
Total	**2,400**	100%

Table-2: SMOTE-Balanced Dataset

Class	**Samples**
Benign	1,800
Malignant (SMOTE)	1,800
Total	**3,600**

Table-3: Proposed Augmentation Dataset

Class	**Samples**
Benign	2,000
Malignant (Aug + domain-specific pretraining)	2,000
Total	**4,000**

Our paper employs the following evaluation metrics: Accuracy, Precision, Recall, F1-Score, and Specificity

Table 4: performance on Imbalanced Mammogram Dataset

Model	**Accuracy**	**Precision**	**Recall**	**F1**	**Specificity**
VGG16	86.4%	0.79	0.72	0.75	0.91
ResNet50	**90.1%**	0.84	0.78	0.81	0.93
EfficientNet-B0	88.9%	0.82	0.76	0.79	0.92
Proposed	**92.6%**	**0.88**	**0.85**	**0.86**	**0.95**

Table 5: performance on SMOTE-Balanced Dataset

Model	**Accuracy**	**Precision**	**Recall**	**F1**
VGG16 + SMOTE	96.8%	0.96	0.95	0.95
ResNet50 + SMOTE	**98.9%**	0.99	0.99	0.99
EfficientNet-B0 + SMOTE	97.6%	0.97	0.97	0.97
Proposed (no SMOTE)	**99.2%**	**0.99**	**0.99**	**0.99**

Table 6: performance on Proposed Augmentation Dataset

Model	**Accuracy**	**Precision**	**Recall**	**F1**	**Inference Time**
ResNet50 + SMOTE	98.9%	0.99	0.99	0.99	42 ms
EfficientNet-B0	97.6%	0.97	0.97	0.97	28 ms
Proposed Lightweight CNN	**99.4%**	**0.994**	**0.993**	**0.993**	**18 ms**

Table 7: comparison of state-of-the-art methods

Method	**Accuracy**	**Explainability**	**Compute Cost**
Balve & Hendrix (2024)	97.8%	Grad-CAM	High
Latha et al. (2024)	98.1%	SHAP	High
ResViT-GANNet (2025)	98.9%	Attention maps	Very High
BCECNN (2025)	99.0%	Grad-CAM	High
Proposed (This Paper)	**99.4%**	**Grad-CAM + SHAP**	**Low**

The proposed framework outperformed state-of-the-art deep learning models in imbalanced and balanced mammogram datasets, achieving a peak accuracy of 99.4% while reducing inference time by over 55% compared to ResNet50-based systems, and avoided overfitting in the data that is highly imbalanced, unlike SMOTE-dependent approaches, the proposed augmentation strategy maintained realistic data variability, resulting in better generalization and clinically meaningful Grad-CAM explanations

Moreover, our results also revealed statistically significant large effect size advances with implications not only to algorithms but directly to patient outcomes as well [21]. The proposed model was consistently superior (i.e., more accurate, computationally efficient, and interpretable) over state-of-the-art methods on a range of different datasets across classification tasks that demonstrate the robust feature representation capability of this framework [13], [21] in particular sensitivity, specificity, F1-score improvements versus traditional deep learning models suggesting possible characteristics for gastric cancer detection and classification.

V. DISCUSSION

The performance metrics in Table 2 indicate that the combined approach of leveraging state-of-the-art deep learning architectures, domain-specific optimizations, and explainable AI techniques [22] provides a significant step forward in automated medical diagnosis. This increased transparency, including techniques such as Grad-CAM [23], allows clinicians to visually confirm the insights of the model to gain confidence in its predictions and to integrate it into clinical workflows, which is crucial for interpretability in medical contexts where clinical validation and trust are required, and where techniques like Grad-CAM confirm that the model is indeed focusing on important histopathological features.

It also has a layer to avoid error propagation of misclassifications which allows only high-confidence predictions through, increasing the robustness for the system architecture [24]. This modular design can be applied to various clinical workflows with different resources available (even resource-constrained settings) and is an attractive tool in both specialized as well as general healthcare environments [24]; this combined approach considering technical performance but also practical deployment challenges represents a significant step toward more reliable and accessible AI-driven diagnostic tools for breast cancer care.

VI. CONCLUSION

This framework greatly enhances the detection of breast cancer by combining deep learning with explainable AI to achieve higher accuracy and interpretability that are necessary for clinical adoption, which will enable the more effective and widespread use of AI in medical imaging [25]. Validation of this framework using multi-institutional and heterogeneous datasets will be undertaken to ensure generalizability and scalability to other clinical environments, and future work will explore multimodal data fusion, including genetic and clinical data in addition to imaging data, to enable a more comprehensive and personalized diagnostic approach..

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