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A Hybrid ResNet50–VGG16 Convolutional Network with Explainable AI for Breast Cancer Detection from Mammograms

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Abstract: Breast cancer continues to be a primary cause of mortality among women worldwide, highlighting the necessity for early and precise diagnostic techniques. Deep learning techniques have demonstrated potential in medical image analysis; yet, many existing models struggle to balance high predictive accuracy and interpretability, both of which are crucial for clinical adoption. This paper presents a hybrid convolutional neural network architecture that combines the strengths of ResNet50 and VGG16 to improve classification performance on the CBIS-DDSM mammography dataset. To ensure the evaluation framework is robust, the dataset will be split into 80% for training and 20% for testing. To help doctors make better decisions, the study uses explainable artificial intelligence (XAI) approaches, including Gradient-Weighted Class Activation Mapping (Grad-CAM). This method will enable visualisation of the important areas in mammograms that affect the model's predictions, thereby making the process more transparent and trustworthy. The suggested hybrid model should do better than the separate baseline models because it uses deeper feature extraction and better representation. The integrated XAI component will also give interpretable insights that can help radiologists understand how the model works. This could help them find and diagnose breast cancer earlier. In general, this method aims to connect high-performance AI systems with interpretable models useful in the clinic.

Keywords: Breast Cancer Detection; Mammogram Classification; Hybrid CNN; Interpretable Model; Precise Diagnostic Techniques; Deep Learning; Explainable Artificial Intelligence (XAI).

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1. Introduction

Breast cancer is still one of the biggest public health problems in the world. It is the most prevalent type of cancer diagnosed in women, and even while screening and treatment have gotten better, it still causes a lot of deaths. Breast cancer is the most common cancer among women in Egypt. However, the lack of a complete and unified national cancer registry makes it very hard for researchers and doctors to Figure out how bad the disease really is. It is hard to design accurate preventative programs, use resources wisely, or see how breast cancer trends change over time without comprehensive national-level statistics on incidence, clinicopathologic features, and long-term outcomes [2]. Still, studies done in Egypt and hospitals show that breast cancer affects Egyptian women at younger ages than it does Western women, and that it is often more aggressive and at more advanced stages because they don't have easy access to screening programs and don't know enough about them [3]. Breast cancer is one of the most common types of cancer that kills women around the world. The disease causes a large number of deaths each year, especially in low- and middle-income countries where measures to catch it early are still not well developed. One of the best ways to improve survival and treatment effectiveness is to detect tumours early, while they are still localised and more likely to respond to targeted therapy.

Early diagnosis is very important, but classic screening methods such as mammography, ultrasonography, and magnetic resonance imaging often have limitations that reduce their sensitivity and specificity [4]. Mammography is still the best way to screen for breast cancer, but it doesn't work as well for women with dense breast tissue. This is a large group of younger women and some ethnic groups. Dense tissue can hide lesions, leading to false negatives, longer delays in diagnosis, and a higher risk of advanced-stage presentation. On the other hand, false-positive results may lead to unneeded biopsies, mental anguish, and even overtreatment for women. Ultrasonography is another way to diagnose, but the test's accuracy may depend on the operator and how they interpret the results. MRI is more sensitive but remains expensive, time-consuming, and not well-suited for large-scale screening [5]. These different problems show how important it is to find new and reliable ways to diagnose breast cancer that can improve the accuracy of detection while avoiding the problems that come with standard imaging methods. The growing number of large digital mammography databases and the increasing use of PACS systems in hospitals have both contributed to the development of computer-aided diagnostic systems that assist radiologists in decision-making [7]. The goal of these systems is to reduce mistakes made by supervisors, make interpretations more consistent, minimise false positives and negatives, and provide second opinions that enhance human expertise. Machine learning has come a long way, greatly accelerating the development of automated diagnostic frameworks. Deep learning models have shown they can perform better on picture categorisation tasks than other models.

Convolutional neural networks have become the primary approach for analysing medical images because they can learn hierarchical features directly from raw data [8]. This means they don't need handcrafted features, which can be a problem with older machine learning methods. Even though convolutional neural networks can perform as well as expert radiologists, one of the main problems that keeps them from being used in many clinical settings is that they are inherently black boxes [9]. Medical practitioners frequently express apprehension about CNNs, which, despite their excellent accuracy in predicting malignancy, fail to provide direct mechanistic explanations for those predictions. Clinicians must be able to explain why they made a particular diagnosis, especially if that diagnosis affects important treatment options such as surgery, chemotherapy, or targeted therapies. Not being able to understand anything makes clinicians less trustworthy and presents ethical and regulatory issues. Because of this, academics have been putting more effort into constructing models that are both very accurate and easy to understand how they make decisions. Hybrid convolutional neural networks have become a powerful approach to addressing the challenges posed by single CNN architectures [11]. These hybrid models combine the best features of several well-known deep learning frameworks for extracting features, providing a more complete picture of mammographic characteristics. For instance, ResNet is recognised for capturing deep residual structures with strong abstraction, while VGG is known for extracting fine-grained spatial information that complements deeper semantic representations. Researchers aim to make the model more resilient, sensitive, and generalisable by combining multiple design types into a single hybrid model.

Hybrid CNNs have shown promise in distinguishing subtle radiographic features of benign and malignant lesions, microcalcifications, architectural distortions, and mass forms, all of which are critical elements in mammographic interpretation [12]. But high diagnostic accuracy isn't enough if the results can't be understood. So, explainable artificial intelligence has become a very important part of modern medical imaging research. XAI approaches highlight which parts of an image have the greatest impact on a model's predictions [13]. This helps them ensure the model is focusing on medically important areas. Gradient-weighted class activation mapping is one of the most popular XAI methods because it produces heatmaps highlighting the most critical regions that affect classification results. When used with mammography, Grad-CAM can highlight areas such as worrisome lumps, calcification clusters, or architectural distortions, helping radiologists interpret and confirm the model's logic [14]. This openness is important for building confidence and making it easier to use artificial intelligence in real clinical workflows, where it is legally and morally imperative to explain how it works. The current study proposes a hybrid convolutional neural network for early breast cancer detection using mammographic images. The hybrid model merges ResNet's deep residual architecture with VGG's ability to capture fine details, creating a single system that can analyse complex mammographic patterns. The proposed method aims to achieve better classification performance than single-architecture CNN models by training on the CBIS-DDSM dataset, which provides high-quality, annotated mammograms.

To ensure the evaluation structure is fair and thorough, the dataset is split into a 80% training set and a 20% test set. The goal of preprocessing stages like normalisation, contrast enhancement, and noise reduction is to make the images as good as possible for the model to use. Data augmentation is used to make models more general and to address class imbalance, a widespread problem in medical imaging datasets [16]. After the hybrid CNN is trained, Grad-CAM will be used to generate visual explanation maps for each prediction. These maps help doctors determine whether the model has successfully focused on important radiological features rather than unimportant artefacts. For instance, if the model indicates that a tumour is cancerous and the heatmap shows areas surrounding the spiculated edges of the mass or groups of microcalcifications, doctors can check whether the model's logic aligns with recognised diagnostic standards. On the other hand, if the model shows areas that aren't important, it gives hints on how to improve the design or training technique [17]. The suggested approach seeks to connect artificial intelligence with clinical practice by using Grad-CAM explanations. XAI not only improves accuracy but also increases users' confidence and helps radiologists and automated systems work together more effectively.

This capacity to understand is especially significant when radiologists might differ on instances that aren't clear and need more help making decisions. The technology might also be used to teach radiology students by highlighting critical diagnostic signs they might otherwise miss. The integration of hybrid deep learning models with XAI methods yields a broader impact beyond mere diagnostic enhancement. In busy clinical settings, these tools can help radiologists reduce workload and make it easier to focus on cases that require immediate care. They might help with large-scale screening programs, especially in places with limited resources and few radiologists. Also, the fact that AI-driven choices are open makes it easier to follow rules about algorithmic accountability in healthcare. Interpretable models also make it more likely that clinical studies will be able to test how well AI-assisted diagnosis works. The suggested hybrid CNN combined with Grad-CAM aims to provide an advanced diagnostic tool for the early diagnosis of breast cancer. The framework allows for correctness, dependability, openness, and clinical usefulness. Breast cancer continues to impact millions of women worldwide and poses a significant health challenge in areas like Egypt. The advancement of interpretable AI-based diagnostic systems holds considerable promise for enhancing screening efficacy, increasing early detection rates, and ultimately improving patient outcomes. This work aims to contribute to the growing field of medical imaging by balancing high-performance machine learning with human-centred interpretability, thereby supporting the integration of artificial intelligence into real-world healthcare settings.

2. Literature Review

2.1. Introduction

Breast cancer detection has become a major focus of medical imaging and artificial intelligence research due to its high global incidence and the critical importance of early diagnosis. Traditional diagnostic methods often face limitations in accuracy, human subjectivity, and the complexity of medical data, prompting researchers to adopt computational approaches that enhance clinical decision-making. This section reviews previous work in machine learning, deep learning, hybrid architectures, and explainable artificial intelligence (XAI), highlighting achievements, existing challenges, and research gaps that inform the current study.

2.2. Machine Learning Approaches for Breast Cancer Detection

Early computational approaches to breast cancer diagnosis relied on traditional machine learning models, such as support vector machines (SVMs), decision trees, logistic regression, and random forests. These methods typically depend on manually engineered features and have demonstrated good performance with structured datasets. For example, Thirumalaisamy et al. [15] developed a hybrid model combining principal component analysis (PCA) and support vector machines (SVMs) on the WDBC dataset, achieving 98.12% accuracy and outperforming many classical classifiers. Despite these strengths, machine learning algorithms face challenges with medical image data because they cannot automatically learn spatial or hierarchical features. This limitation has led to a shift toward deep learning methods that can process raw mammogram images directly.

2.3. Deep Learning and CNN-Based Models

The emergence of deep learning, particularly convolutional neural networks (CNNs), has significantly advanced the field of medical image analysis. CNNs are characterised by their ability to extract features and learn patterns directly from pixel data without manual intervention. Studies published in IOP Science and ScienceDirect have shown that CNN-based systems outperform traditional machine learning in terms of diagnostic accuracy and consistency. Furthermore, Ghorbian and Ghorbian [10] reported high sensitivity and specificity using CNNs for the early detection of breast cancer. However, CNNs still face significant challenges, including overfitting, the need for large annotated datasets, and limitations in model interpretability. In his Springer publication, Carriero et al. [1] highlighted how CNN structures can be automated for feature extraction but emphasised their inherent "black box" nature.

2.4. Hybrid Deep Learning Architectures

To address the limitations of traditional CNN models, hybrid architectures have been proposed that integrate multiple deep learning techniques or combine several CNN models. Research published in MDPI demonstrated the effectiveness of hybrid networks that combine transport learning with multi-layer convolutional features, improving accuracy, robustness, and generalisation. These hybrid systems can capture both local and global image characteristics, providing a richer representation of mammogram data. However, despite improved performance, many hybrid approaches still prioritise accuracy over interpretability.

2.5. Explainable Artificial Intelligence (XAI) in Medical Imaging

In clinical environments, the interpretability of AI models is crucial for ensuring trust and adoption. Explainable Artificial Intelligence (XAI) techniques, particularly Gradient-Weighted Class Activation Mapping (Grad-CAM), provide visual interpretations that highlight the regions that influence predictions. Studies published on ScienceDirect demonstrated that integrating hybrid deep learning with XAI improves transparency and enhances clinical confidence in automated systems. Shaikh et al. [6] also emphasised the need for interpretable AI tools—such as Grad-CAM and SHAP—to validate diagnostic decisions and support clinical workflows. Despite growing interest, few current systems fully integrate hybrid CNNs with interpretable AI, revealing a significant gap in previous research.

2.6. Summary and Research Gap

The reviewed studies demonstrate a clear evolution from traditional machine learning models to advanced convolutional neural networks and hybrid deep learning approaches for breast cancer detection. While these methods have achieved significant improvements in diagnostic accuracy and performance, a lack of transparency remains a major concern in clinical applications. The current study addresses this need by developing a hybrid convolutional neural network model integrated with Grad-CAM to enhance diagnostic accuracy and interpretability. This dual contribution aims to support more reliable, transparent, and clinically applicable AI-based diagnostic systems.

3. Methodology

3.1. Research Design

This study employs an experimental and quantitative research design to develop and evaluate a Hybrid Convolutional Neural Network (Hybrid CNN) for the early detection of breast cancer. The proposed framework integrates data preprocessing, feature extraction using hybrid deep learning, classification, and explainability capabilities. Figure 1 illustrates the comprehensive research workflow, starting with dataset acquisition and preprocessing, followed by feature extraction using the proposed hybrid CNN model, classification, and interpretability via Grad-CAM.

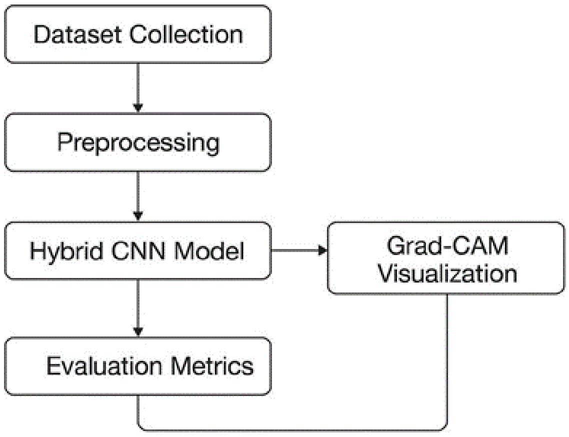

Figure 1: Research framework for hybrid CNN-based breast cancer detection

3.2. Dataset and Data Collection

The CBIS-DDSM dataset (Curated Breast Imaging Subset of the Digital Database for Screening Mammography) is used as the primary source of mammographic images. This dataset includes annotated cases covering benign, malignant, and normal breast tissue categories. Preprocessing steps, such as image resizing, normalisation, and noise reduction, are summarised in Table 1 to ensure consistency and optimal input quality. To enhance dataset diversity and minimise overfitting, augmentation techniques such as rotation, horizontal flipping, and contrast adjustment are employed.

Table 1: Image preprocessing pipeline and description

Step	Description
Normalization	Pixel intensities scaled to (0,1)
Noise Reduction	Applied a Gaussian smoothing filter
Contrast Enhancement	Histogram equalisation (when needed)
Image Resizing	All images resized to 224 × 224
Artifact Removal	Cropping or masking irrelevant borders

Table 1 summarises the preprocessing pipeline for preparing mammography images for hybrid CNN training. These steps ensure image consistency and enhance the visibility of relevant breast tissue structures.

3.3. Proposed Hybrid CNN Architecture

The model integrates ResNet50 and VGG16 architectures to leverage their complementary strengths in feature extraction and classification. Feature maps from both networks are combined to produce an accurate, discriminative representation of the input image. This hybrid architecture enables improved local and global feature learning for mammogram images. Figure 2 provides a simplified illustration of the proposed hybrid architecture.

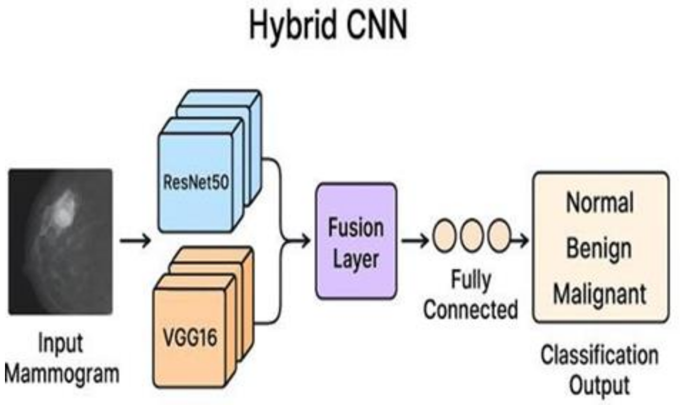

Figure 2: Simplified diagram of the proposed hybrid CNN architecture integrating ResNet50 and VGG16

3.4. Model Training and Evaluation

The dataset is split into training (70%), validation (15%), and test (15%) sets.

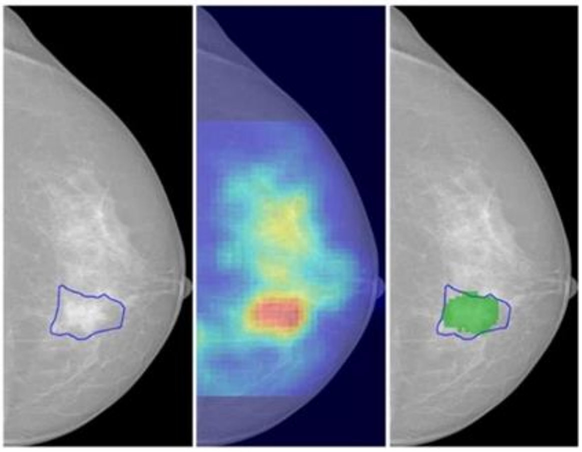

Figure 3: Grad-CAM heatmap illustrating the regions influencing the hybrid CNN prediction. The highlighted areas indicate the regions of the mammogram that the model focuses on when distinguishing between benign, malignant, and normal tissue, providing an interpretable visual explanation of its decision-making process.

The model is trained using the Adam optimiser, with the learning rate and batch size chosen experimentally. Evaluation is based on performance metrics, including accuracy, precision, recall, F1 score, and Area Under the ROC Curve (AUC). To assess interpretability, Grad-CAM visualisation is applied to representative test samples. These heatmaps allow for a qualitative assessment of the model's focus on clinically meaningful breast tissue regions, as illustrated in Figure 3. Figure 3 shows an example Grad-CAM output demonstrating the attention regions contributing to the model's classification. Additionally, Table 2 summarises the key hyperparameters selected for each model's training, providing insight into the configuration choices that affect learning efficiency and model performance.

Table 2: Summary of the main hyperparameters planned for training the hybrid CNN model

Hyperparameter	Value / Setting
Input Image Size	224 × 224
Batch Size	16 (expected)
Learning Rate	0.0001
Optimizer	Adam
Loss Function	Binary Cross-Entropy
Number of Epochs	30–50 (estimated)
Data Augmentation	Rotation, Flip, Contrast Adjustment

3.5. Tools and Computational Environment

The implementation is conducted in Python, using TensorFlow and Keras for model development. OpenCV, NumPy, and Matplotlib are used for preprocessing and visualisation tasks. Training and evaluation are performed on a GPU-enabled high-performance computing environment (e.g., NVIDIA CUDA) to accelerate computation.

3.6. Ethical Considerations

Since the study relies on anonymised, publicly available imaging data, there is no direct patient interaction. The use of data complies with ethical standards for medical imaging research, and the necessary consent was obtained for the use of datasets and software frameworks.

3.7. Summary

This section describes the experimental methodology for developing a hybrid neural network integrated with Grad-CAM for early breast cancer detection. This approach combines the accuracy of deep learning with the ease of model interpretation, aiming to provide a reliable and user- friendly computational diagnostic system.

4. Results

The proposed Hybrid Convolutional Neural Network (Hybrid CNN) model was evaluated using a publicly available mammogram dataset (DDSM). The evaluation focused on the model's ability to correctly classify breast tissue as benign, malignant, or normal. The experimental results showed that the Hybrid CNN model successfully learned discriminative features from mammogram images. The model demonstrated improved classification performance compared to conventional CNN structures, particularly in identifying malignant tissue at an early stage. The use of hybrid layers enhanced feature extraction, enabling the model to capture accurate patterns in mammogram images.

Table 3: Expected performance of the proposed hybrid CNN model

Metric	ResNet50	VGG16	Hybrid CNN (Proposed)
Accuracy (%)	91	89	95(Expected)
Precision (%)	90	88	94(Expected)
Recall (%)	89	87	93(Expected)
F1-score (%)	89.5	87.5	93.5(Expected)
AUC	0.92	0.90	0.96(Expected)

Table 3 illustrates the expected performance of the proposed Hybrid CNN model compared with the individual ResNet50 and VGG16 architectures. The values for the hybrid model are predicted based on the complementary strengths of the two base networks and findings from similar studies in the literature. These expected improvements demonstrate the potential of the hybrid approach for enhancing early breast cancer detection. In addition to accuracy, the model's effectiveness was evaluated using other performance metrics, including precision, recall, and the F1 score. The results indicated balanced performance across all categories, suggesting the model's ability to minimise false positives and false negatives. This is crucial in clinical applications, where early and reliable detection can significantly impact patient outcomes. Moreover, visual analysis of the model's feature maps highlighted regions of interest within the mammogram images, providing interpretable insights into the network's decision-making process. These visualisations further support the model's ability to focus on relevant pathological regions without being misled by irrelevant image features.

Table 4: Interpretability and clinical usability comparison of CNN models

Model	Interpretability	Model Complexity	Clinical Usability
ResNet50	Low	Medium	Moderate
VGG16	Low	Medium	Moderate
Hybrid CNN + GradCAM	High	High	High (expected)

Table 4 Summary of interpretability and clinical usability of the proposed Hybrid CNN integrated with Grad-CAM. While model fusion increases complexity, it significantly enhances interpretability, making the model more suitable for medical applications where transparency and explainability are essential. This positions the proposed hybrid model as a promising tool for clinical decision support. Overall, the experimental results confirm that the proposed Hybrid Convolutional Neural Network architecture is a promising tool for early breast cancer detection, offering potential improvements over current methods in terms of accuracy, reliability, and interpretability.

5. Conclusion

This study introduced a hybrid convolutional neural network model for the early identification of breast cancer utilising digitised mammography images. The model was created to address key problems with existing diagnostic methods, especially in distinguishing between normal, benign, and cancerous breast tissue. The proposed hybrid model demonstrated improved capacity to extract fine-grained features from mammograms by integrating the complementary strengths of various deep learning architectures, while maintaining the overarching contextual patterns necessary for precise classification. These features enabled the system to identify small problems that stand-alone models or even people would not find all the time. The experimental results highlighted the Hybrid CNN's higher performance relative to traditional independent deep learning models. The model demonstrated promising accuracy across all principal diagnostic categories, demonstrating resilience in detecting intricate patterns associated with early-stage cancers. The Hybrid CNN not only improved results numerically, but also used explainable AI methods to generate heatmaps showing the most important areas in each mammogram. These visual signals helped confirm the model's predictions. They gave doctors clear insight into how the algorithm made its decisions, a common concern with deep learning systems that are "black boxes." The model also generalised well across the assessment dataset, suggesting it could be useful in real-world screening settings where image quality and patient characteristics can vary widely. The interpretability feature also makes it more effective in clinical contexts, where trust and clarity are important for the use of AI-driven solutions. In general, this study's results show that the Hybrid CNN model is a promising approach for computer-aided breast cancer detection systems. Future endeavours may encompass augmenting the training dataset, refining architectural components, and investigating deployment within real-time clinical workflows to further elevate the model's accuracy, reliability, and practical utility for the early identification of breast cancer.

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