

# Breast Cancer Detection and Diagnosis Using Gradient-Weighted Class Activation Mapping and Deep Learning

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## Abstract

Breast cancer is the most common cancer among women worldwide, posing significant diagnostic challenges. Traditional diagnostic techniques, while foundational, often lack precision and fail to provide clear insights into their decision-making processes. This limitation underscores the need for advanced diagnostic tools that enhance both accuracy and interpretability. This study aims to integrate cutting-edge deep learning algorithms with Gradient-weighted Class Activation Mapping (Grad-CAM) to improve the accuracy and transparency of breast cancer diagnostics through mammographic analysis. We proposed robust approaches using MobileNet, Xception, and DenseNet models, enhanced with Grad-CAM, to analyze mammogram images. This integration facilitates a deeper understanding of model decisions, highlighting critical diagnostic features through visual explanations. The models were rigorously tested on the MIAS dataset to evaluate their diagnostic performance and reliability, achieving a diagnostic accuracy of 94.17%, demonstrating superior performance compared to traditional methods. The findings show significant potential for clinical application, promising to enhance patient outcomes through more accurate and transparent diagnostic practices in oncology.

## Keywords

Breast Cancer, Deep Learning, Detection, Gradient-Weighted, Machine Learning

## 1. Introduction

Breast cancer is the most commonly diagnosed female worldwide malignancy, with about 2.3 million new cases being diagnosed each year, and it ranks second to lung cancer as a cause of female cancer-related deaths. It falls just under a quarter of all female malignancies [1]. Knowledge of different types of various lesions and the potential outcome in a woman's life, arising from the uncontrolled cellular proliferation of breast tissue, which classically presents as a palpable mass or lump [2], is of paramount importance [3].

In 2020, breast cancer was responsible for 685,000 fatalities, making it the most common cause of cancer-related death among women globally [4]. The use of breast cancer imaging has been pivotal in decreasing these mortality rates. Early detection through screening programs significantly enhances treatment options and improves survival chances compared to cancers identified at later stages [5]. Additionally, imaging techniques are crucial for tracking and assessing the effectiveness of cancer treatments. Various imaging techniques for breast cancer, ranging from traditional screen-film mammography to the more recent digital breast tomosynthesis, are employed by radiologists for cancer screening. Moreover, compared to other medical imaging techniques such as mammography, magnetic resonance (MR), and computed tomography (CT), histopathological imaging is considered the definitive standard for diagnosing breast cancer. These methods have successfully identified various breast cancer anomalies, such as masses, microcalcifications, architectural distortions, and bilateral asymmetry. Despite their effectiveness, these modalities face challenges such as the overlapping of breast tissues, which can obscure critical details and conceal potentially suspicious lesions [6].

MRI provides superior imaging of breast tissues, which is sensitive to subtle structures that cannot be visualized through mammograms or ultrasound [7]. With these imaging features, the differentiation between benign and malignant lesions can be done specifically, hence preventing unnecessary biopsies [8]. MRI uses no ionizing radiations and, therefore, is much safer for some patients with an important number of specific concerns [9]. However, it is imperative to remember that MRI access might be limited and costly for some patients [10].

### 1.1. Choosing the Right Approach

The optimal diagnostic approach for each patient hinges on various factors, including:

- Age: Younger women with dense breast tissue may benefit from more frequent ultrasound screenings owing to mammography limitations in dense tissue [11].
- Breast density: Women with dense breasts may require additional imaging with ultrasound or MRI to complement mammography [12].
- Symptoms: The presence of symptoms such as lumps or nipple discharge can

influence the choice of tests, with ultrasound often employed for initial evaluation [13].

- Medical history: A personal or family history of breast cancer may necessitate more aggressive diagnostic strategies, including MRI [14].

Although other modalities, MRI and ultrasound, have their place in particular scenarios, mammography presents some advantages for the diagnosis of breast lesions: wider availability, lower cost, better ability to detect the early stages of diseases, more detailed tissue visualization, and better-lowered exposure to radiation. Mammography remains the cornerstone for the screening and diagnosis of breast cancer [15] [16]. Computer-aided diagnosis (CAD) and machine learning models have really revolutionized medical diagnoses and give a number of advantages over routine methods [17] [18]. Such advanced tools increase the accuracy of diagnosis, the overall efficiency of the clinical workflows, and provide personalized care for the patients. Among such tools, CAD and ML systems are probably the best for objective and precise analysis of medical images, which human analysis can never achieve. The identification of subtle abnormalities or patterns helps to detect the disease in its early stages and, in this way, drastically increases the possibility of its effective treatment and increases the survival rates of patients [19]. Moreover, with the automation of the analysis of medical images, CAD and ML systems attain a higher level of workflow efficiency and free radiologists from routine work, giving more time to complex cases [20]. This is also directly transferred into cost savings for the system of medical care and gives better possibilities for patients to get a referral to specialists [1] [21].

### 1.1.1. Objectivity and Consistency

Human interpretation of medical images, while invaluable, inherently carries the risk of subjective biases and human errors that can diminish the accuracy and reliability of diagnoses [22]. Some of the key technological breakthroughs in this regard have been CAD systems and ML models. Such systems and models guarantee that the analyses are objective and consistent, and hence they negate diagnostic biases, with their results repeatable over various scenarios. These systems provide the general way of interpretation of the medical image; they contribute to the fairness and accuracy of the medical diagnosis, thus providing the equitable and accurate medical results to be offered to all patients [23].

### 1.1.2. Personalized Medicine and Improved Outcomes

ML models, when trained on extensive datasets, can discern patterns and predict individual disease risks based on factors such as medical history and genetic information. This capability facilitates the development of personalized treatment plans tailored to each patient's unique needs, ultimately leading to improved prognosis and better health outcomes [24].

### 1.1.3. Making Advanced Diagnostics Accessible

CAD systems and ML models can address healthcare disparities by offering advanced diagnostic tools in resource-limited settings. Their deployability in areas

with limited infrastructure can broaden access to high-quality care, particularly benefiting under-served populations [25].

#### **1.1.4. Drawbacks and Ethical Considerations**

Notwithstanding their numerous benefits, ML models pose challenges, particularly concerning explain-ability, where the rationale behind their decisions can be opaque and challenging to comprehend [26]. This opacity raises concerns regarding transparency and accountability, particularly in high stake medical applications. Additionally, overfitting may occur in ML models trained on small datasets, leading to less-than-ideal performance when presented with new, unlabelled data. In order to guarantee that the model can be used effectively in real-world scenarios and is generalisable, it is crucial to thoroughly evaluate the quantity and variety of the training data [27].

Missing or biased results for certain patient groups may result from ML models unknowingly learning and reinforcing biases in the training data [28]. Addressing these biases and promoting fair healthcare applications requires meticulous data curation and analysis.

The use of ML models in healthcare has brought new concerns about data security and privacy. Ensuring the secure gathering, storage, and use of sensitive patient data necessitates strong security protocols [29].

If we want to make the most of ML in healthcare, we need to solve these problems and encourage responsible growth. Promoting openness, accountability, justice, and ethical use of these potent technologies requires continuous study and cooperation between medical experts and AI specialists.

### **1.2. Novel Contribution**

Several new advancements in the detection of breast cancer are brought to light in our study:

- 1) Combining cutting-edge deep learning models with Gradient-weighted Class Activation Mapping (Grad-CAM), we were able to achieve a substantial increase in diagnostic accuracy, outperforming conventional approaches.

- 2) To provide a deeper understanding of AI model decision-making processes in breast cancer diagnostics, enhancing transparency and building trust in the model's predictions through visual explanations generated by Grad-CAM.

- 3) To conduct a comprehensive analysis of breast cancer images using advanced deep learning models, including MobileNet, Xception, DenseNet, and MobileNet-LSTM, combined with Grad-CAM technology, thus contributing to a more thorough examination of diagnostic features.

- 4) To enhance the precision of breast cancer assessment, leading to more accurate diagnosis and treatment planning, by employing advanced image analysis techniques that highlight critical diagnostic features.

- 5) To distinguish itself from previous studies by leveraging sophisticated deep learning methods and Grad-CAM technology, rather than traditional machine

learning approaches that rely on features such as color histograms and Haralick textures, thereby demonstrating the advantages of modern AI techniques in medical diagnostics.

## 2. Related Works

Authors in [30] conducted a study on breast cancer classification using traditional machine learning (ML) and deep learning (DL) techniques. They achieved accuracy ranging from 93.25% to 93.97% by extracting features based on color histograms and Haralick textures. In [31], the authors proposed using machine learning models for breast cancer classification tasks, achieving an accuracy of 91% compared with the average accuracy of approximately 79% achieved by physicians. In [32], researchers utilized logistic regression, SVM, K-Nearest neighbor, and artificial neural networks for breast cancer image classification, achieving an average accuracy of 99.3%. The authors in [33] achieved a classification accuracy of 93.29% for skin cancer classification using deep learning techniques, whereas researchers in [34] used a DCNN to classify burnt human skin images, achieving an accuracy of 83.4%. Mahmood *et al.* [35] proposed a deep-learning approach to automatically detect and classify breast cancer using six DCNN models, with the ResNet50 model achieving the highest accuracy of 98.5% in detecting breast cancer, and the VGG16 model achieved the highest accuracy of 96.4% in classifying cancer types. In [36], the authors conducted an extensive study on classifying breast cancer images using deep learning and imaging techniques, analyzing 49 research works and outlining ten open research challenges to guide new researchers in the field. Mahmood *et al.* [37] proposed six deep learning-based methods for the early detection of breast cancer masses and calcification clusters using mammography, achieving a classification accuracy of 97.8%. The proposed model is compatible with conventional pathological practices and can reduce the workload of logists by analyzing mammography images. Existing research on breast cancer classification has shown impressive accuracy using various deep learning models, but these studies often lack interpretability and transparency in their AI models. Methods relying on specific feature extractions, such as color histograms and Haralick textures, may not generalize well across different datasets. Additionally, while high accuracy rates have been achieved, the black-box nature of these models limits their practical application in clinical settings. Our study aims to overcome these limitations by integrating Deep Learning with Grad-CAM, enhancing both the accuracy and interpretability of breast cancer detection. This approach provides clearer insights into model decisions, fostering greater trust and reliability in AI-driven diagnostics.

### 2.1. Related Work: Utilizing Grad-CAM with the MIAS Dataset

A number of studies in the recent past have tried to evaluate the effectiveness of Grad-CAM for visualizing regions of interest delineated by deep learning models trained on medical image analysis in the breast cancer detection and diagnosis

using the MIAS Mammographic Image Analysis Society. Chang *et al.* (2021) recently showed that Grad-CAM is effective in highlighting the optic nerve head and peripapillary nerve fiber bundles when weakly trained in limited training datasets, to improve the interpretability and generalizability of their model within the purview of glaucoma detection. Billah *et al.* (2022) used Grad-CAM in identifying the crucial characteristics responsible for cancer development in breast cancer histology images. The work shows that Grad-CAM could effectively visualize malignancy-related regions, leading to a guide on the model's decision process that could give potential utility in cancer diagnostic tasks. The released posters have indicated the relevancy of applying Grad-CAM-based model suggestions to multimodal deep learning to combine mammography and ultrasound images for the purpose of breast cancer classification and localization. They applied Grad-CAM for the visualization of RIO for both modalities, leading to better model prediction understanding and potentially enhancing the diagnostic accuracy for this decision.

**Table 1.** Recent studies using gradient-weighted class activation mapping and deep learning.

Related Studies	Used Approaches	Performance Evaluation	Limitation
Chang <i>et al.</i> (2021)	Grad-CAM	Successfully identifies optic nerve head and peripapillary nerve fiber bundles	Limited to glaucoma detection, not applicable to other diseases
Billah <i>et al.</i> (2022)	Grad-CAM	Effectively visualizes regions associated with malignancy	Requires further validation in larger datasets and clinical settings
Nguyen <i>et al.</i> (2023)	Grad-CAM	Provides a comprehensive understanding of model predictions in both mammography and ultrasound	Limited by the size and quality of available multimodal data
Sharma <i>et al.</i> (2023)	Grad-CAM	Successfully highlights relevant regions in mammograms and reduces false positives	May not be interpretable for all types of lesions and requires further investigation
Kim <i>et al.</i> (2023)	Grad-CAM, LIME, SHAP	Compares various explainable AI techniques in breast cancer diagnosis	Lacks a clear winner, requires consideration of specific application and interpretability needs
Santos <i>et al.</i> (2021)	Gradient Boosting	Achieved 0.809 accuracy and 0.839 AUC for Chronic Kidney Disease (CKD) progression prediction.	The study used a retrospective dataset and may not be generalizable to other populations or healthcare settings

Sharma *et al.* (2023) [9] researched the application of Grad-CAM to explain the inference made by deep learning models on the classification of mammographic masses and architectural distortions. They showed that Grad-CAM could highlight the salient regions in mammograms, hence giving a possible explanation of the model's decision process and, at the same time, reducing false positivity. Kim *et*

*al.* (2023)[38] compared a set of explainable AI methods, including Grad-CAM, to interpret deep learning models in diagnosing breast cancer. The present study discusses the effectiveness of identifying methodology for acquiring insights into the model's predictions and potential use in clinical settings. These are papers that show the Grad-CAM robustness and an immense opportunity for application in the field of medical image analysis, especially detection and diagnosis in breast cancer. Explanation of the model decisions and importance of highlighting important regions is achieved. Grad-CAM thus assists imperatively in model interpretation towards applications like diagnostic improvement and ultimately patient care. This study builds on the existing body of work on Grad-CAM by exploring its application in a novel context and proving its effectiveness in another domain. Therefore, the findings from this study will enhance the knowledge of the potential benefits and also possible limitations of Grad-CAM as a tool for explainable AI in medical imaging analysis. The recent studies summarized in **Table 1** illustrate how Grad-CAM and deep learning have been applied in similar contexts, providing the comparative background for our proposed method.

## **2.2. Importance of Deep Learning (DL) and Transfer Learning in Breast Cancer Diagnosis**

Medical image processing in deep learning is one of the few fields that can, with high certainty, be considered revolutionary and has enhanced to a larger extent the possibilities of increasing diagnostic accuracy, especially in mammography [39]. The traditional Computer Aided-Detection/Diagnosis (CAD) systems, beneficial as they are, face a few limits in the process of feature selection and adaptability. Recent studies by Kim *et al.* (2018) [40] and Nica *et al.* (2021) [9] have shown that there is potential for such models to overcome these shortfalls through integration of advanced machine learning techniques. Medical imaging has witnessed a revolution in the recent years with the appliance of deep learning and deep model architectures in Convolutional Neural Networks. Their capability to detect subtle patterns from the imaging data makes them ideal in tasks like breast cancer detection [41]; Kooi and Karssemeijer, 2017) [42]. However, the interpretability of the decision-making processes of DL models is a critical concern with respect to clinical applications. All the same, the main limitation of existing Computer-Aided Detection/Diagnosis systems, especially such as the feature selection and adaptability, the gap that this study aimed to fill in, is merged by the use of Grad-CAM. Grad-CAM gives visual explanations to the decisions of the CNN, highlighting the most influential regions in the images for the model prediction [43] [44]. Still, due to great leaps and bounds, the interpretability and adaptability of the models built on deep learning for imaging hold existing studies in significant limitation. Whereas traditional CAD systems form the basis of such studies, they often falter at optimal feature selection and adaptability across various datasets. This has been a matter of concern in black-box nature deep learning models for clinical application. Recent studies have shown that advanced machine learning techniques can outperform

human-powered precision in the solving of medical problems. This study uses state-of-the-art DL models like MobileNet, Xception, and DenseNet for the classification of breast cancer from mammograms. The selection of the models was made based on performances demonstrated on image classifications, as noted from the studies by Li *et al.* 2019 [45]. This research will advance diagnostic precision in medical imaging and artificial intelligence and give deeper insight into AI-based decision-making within the scope of breast cancer diagnostics, which has been a major gap highlighted in recent studies. The key points are as follows:

- Better detection with accuracy: DL-based models can help in detecting subtle patterns within medical images that enhance the accuracy of breast cancer detection compared to traditional methods [42].
- Early Diagnosis and Improved Outcomes: Transfer learning leverages knowledge from past tasks to diagnose breast cancer at an early stage, leading to improved outcomes and survival rates [46].
- Reduced False Positives and Unnecessary Biopsies: Deep learning models will be effective in distinguishing benign from malignant lesions, causing fewer than expected numbers of biopsies, and, in turn, decreasing the anxiety caused by that prospect in patients [47].
- Personalized Medicine: The proposed transfer learning is carried out at the level of individual patient data for the assessment of the risk of developing precancerous lesions and, thereby, preparation of personalized treatment strategies and preventive action [48].
- Expanding Access to Advanced Diagnostics: DL models may provide accurate and accessible diagnosis of breast cancers even in resource-constrained settings and thus contribute to excellence in the state of global health equity [49].

### 2.3. Deficiencies in Traditional Approaches

Breast cancer clinical diagnosis is an important field that seems to be making paramount steps. Still, it suffers from limitations that dim the positive outcome of patients. The techniques performed drastically for early detection of breast cancer even though in many cases, the techniques fail to perform as expected due to a limit in the tools or techniques associated with it. Limits of such traditional CAD systems are prominently associated with issues in feature selection and adaptability, either of which can lead to inconsistent diagnostic performance across diverse patient populations and imaging conditions. Viewing this issue, the incorporation into clinical use is further complicated by the black-box nature of the deep learning models. Even though CNNs and other deep learning technologies have achieved high sensitivity with high accuracy in the detection of breast cancer, their operation is normally opaque, a character that makes it hard for clinicians to trust and easily interpret its outputs. In clinical settings, this lack of transparency has proved to be the most significant obstacle to widespread deployment of the technologies.

Moreover, existing research has largely focused on improving diagnostic accuracy without placing equal emphasis on model interpretability and transparency. Studies

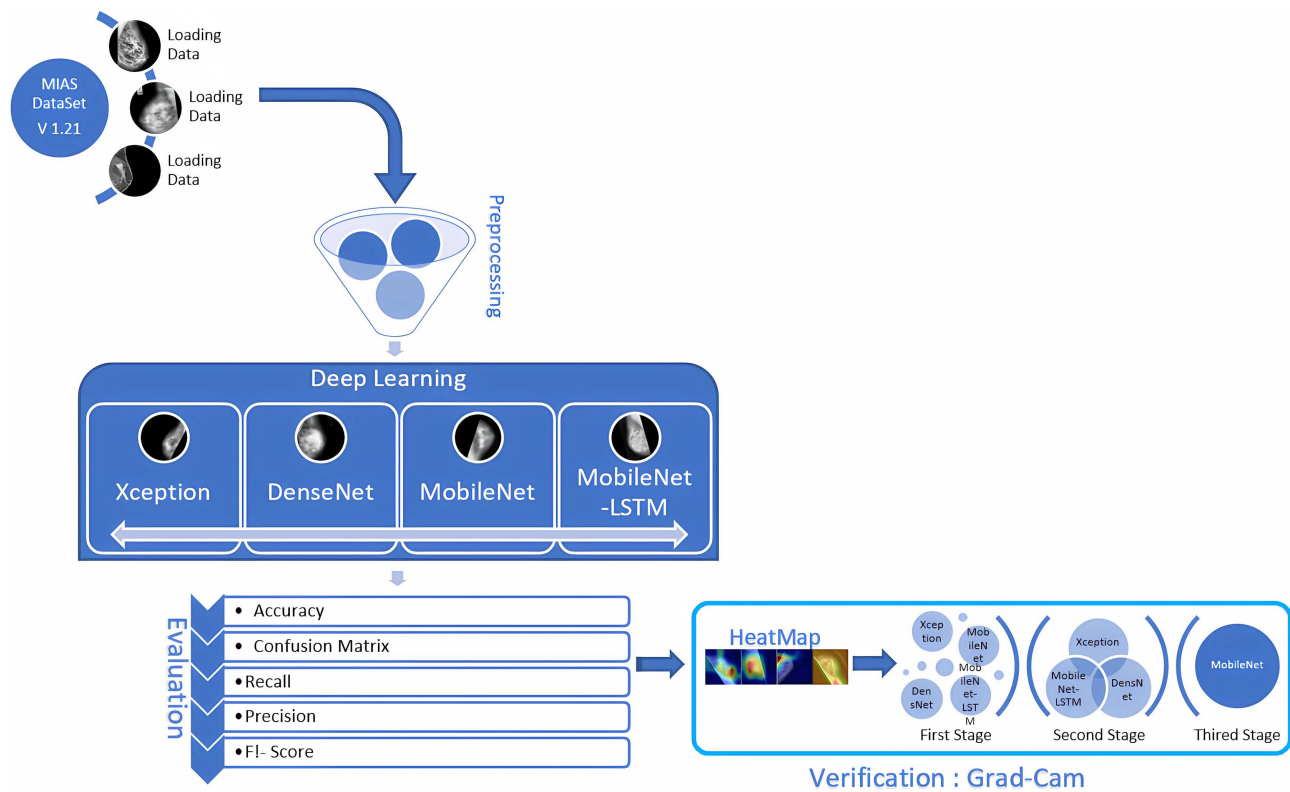
that use specific feature extraction methods, such as color histograms and Haralick textures, often face challenges in generalizing across different datasets, resulting in variability in diagnostic outcomes. Additionally, there is a critical need for cost-effective diagnostic technologies that can be deployed in resource-limited settings to ensure equitable access to healthcare. These inequalities are made worse by the expensive prices and technical requirements of modern imaging methods like MRI.

Personalised diagnostic methods that take into account the genetic and molecular features of certain tumours are also lacking in the present state of the art of research. In order to create individualised treatment programs and enhance patient results, such specialised tactics are crucial. Furthermore, less intrusive diagnostic procedures that put patient safety and comfort first without sacrificing diagnostic accuracy are critically needed.

In order to tackle these complex issues, our research improves the accuracy and transparency of breast cancer diagnosis models by combining transfer learning with Gradient-weighted Class Activation Mapping (Grad-CAM). In order to guarantee consistent performance across different datasets, transfer learning enhances model generalisation, while Grad-CAM offers visual explanations that emphasise the areas that have the greatest impact on model predictions. In addition to improving the diagnostic accuracy, this two-pronged strategy makes the decision-making process more visible, which in turn boosts confidence and dependability in AI-driven diagnostics. By bridging these critical gaps, our study aims to set a new standard in breast cancer diagnosis, ensuring that advanced AI technologies are both effective and interpretable, ultimately supporting better patient outcomes and more equitable healthcare solutions.

### 3. Methodology

The choice of models—MobileNet, Xception, DenseNet, and MobileNet-LSTM—was guided by their proven efficiency and accuracy in medical and natural image classification. MobileNet, for instance, is particularly lightweight and well-suited for real-time diagnosis applications. The proposed model for breast cancer detection integrates advanced preprocessing techniques such as normalization, noise reduction, and contrast enhancement with cutting-edge deep learning architectures using transfer learning methods for binary classification. We employ models such as Xception, DenseNet, MobileNet, and MobileNet-LSTM, all fine-tuned on mammographic images from the MIAS dataset. This approach ensures robust feature extraction and pattern recognition for classifying images into malignant or benign categories. To make this understandable, we added Gradient-weighted Class Activation Mapping (Grad-CAM) to show us visually which parts are used to make such a decision. This combination will increase the diagnostic accuracy but also make the AI decision process transparent and understandable for better trust and reliability in AI-driven diagnostics in healthcare. The approach proposed in detecting breast cancer is depicted in **Figure 1**.



**Figure 1.** The layered architecture of the proposed framework for breast cancer classification; 1) collection of mammography images from the MIAS dataset for algorithm training, and 2) denoising and enhancement of mammography images using diverse preprocessing techniques, 3) fine-tuning the proposed model to extract intrinsic features. Finally, model weights are modified to derive generic features specific to the classification task, resulting in the final prediction.

### 3.1. Dataset

The Mammographic Image Analysis Society (MIAS) database of digital mammograms (v1.21) [50] consists of 322 high-resolution digital mammogram images (161 pairs), especially selected for breast cancer research and detection. These images were in a Portable Gray Map (PGM) file format, which is highly used to represent grayscale images. This dataset will facilitate developing, testing, and improving machine-learning algorithms in the analysis of mammograms and contains ground truth information per image. Members of the Mammographic Image Analysis Society partially contributed a small amount of contradiction to the small remainder altruistically and without financial benefit. This work is supported from internally generated grant funding from the organization (RNAG/302). Creative Commons license, which allows others to distribute, remix, adapt, or otherwise build on this dataset, as long as the work is credited back to the authors. Additionally, the dataset incorporates the original project's study paper in PDF format alongside the mammogram images and a comprehensive README file, augmenting its utility. This collection serves as an invaluable asset for data scientists, academics, and medical professionals engaged in computer-aided diagnostics, mammography, and breast cancer detection [51]. The availability of high-quality images and meticulous ground truth data facilitates the development and enhance-

ment of machine learning algorithms, contributing to advancements in the early identification and diagnosis of breast cancer.

### 3.2. Preprocessing

Preprocessing is crucial in medical image analysis as it significantly impacts the accuracy and performance of the models used [52]. Proper execution of preprocessing steps is vital to avoid introducing artifacts or distortions that could compromise diagnostic accuracy. In our work, we use a publicly available preprocessed dataset and critically evaluate the preprocessing techniques applied to ensure they meet our analytical goals. This includes assessing data quality and confirming that no preprocessing-induced artifacts or errors are present. Key preprocessing steps involved are normalization, Image preprocessing techniques such as noise reduction and contrast enhancement play a vital role in improving image clarity and quality for subsequent analysis.

**1) Normalization:** This technique adjusts pixel intensities to a common range, enhancing the efficiency and stability of model training. Mathematically, normalization is expressed as:

$$I_{norm} = \frac{I - \mu}{\sigma} \quad (1)$$

where  $I$  is the original image,  $I_{norm}$  is the normalized image,  $\mu$  is the mean intensity value, and  $\sigma$  is the standard deviation.

**2) Noise Reduction:** In order to decrease picture noise, methods like median filtering and Gaussian blurring are used. Here is an instance where Gaussian noise reduction has been used:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

where the standard deviation of the Gaussian distribution is denoted by  $\sigma$  and the Gaussian function is represented by  $G(x, y)$ .

**3) Contrast Enhancement:** Histogram equalisation and other contrast enhancement techniques make medical picture features more visible. The formula for histogram equalisation is:

$$H_{eq}(v) = \sum_{j=0}^v \frac{n_j}{N} \quad (3)$$

where  $H_{eq}(v)$  is the equalized histogram,  $n_j$  is the number of pixels with intensity  $j$ , and  $N$  is the total number of pixels. It is essential to tailor these preprocessing techniques to the specific characteristics and needs of the dataset to optimize the performance of deep learning models used for analysis.

### 3.3. Deep Learning-Based Methods

Creating a sophisticated and accurate classification system for detecting breast cancer (BC) in mammography pictures is the main objective of this work. Xcep-

tion [53], DenseNet [54], and MobileNet [55] were part of the suite of deep learning (DL) models we used to achieve this. To improve picture categorisation accuracy, each model was hand-picked for its unique set of capabilities.

### 3.3.1. MobileNet

In this research, we look at how MobileNet—a mobile and embedded vision optimisation tool—can be used to identify breast cancer in mammograms. Achieving excellent performance while reducing computing needs and model size is the goal of MobileNet’s design. In order to improve diagnosis accuracy, we used a transfer learning strategy to tweak the model such that it was more sensitive to small breast cancer markers in mammography pictures.

By integrating MobileNet into the transfer learning paradigm, this study supports efficient case triage and flags cases requiring urgent treatment, which enhances patient care and healthcare system efficiency. Transfer learning with MobileNet allows exploration of various architectural and training strategies to strengthen diagnostic accuracy. Moreover, on-device processing with MobileNet ensures data privacy, as sensitive medical images remain confidential throughout the analysis process.

This study highlights the transformative potential of MobileNet and the transfer learning paradigm in breast cancer diagnosis based on mammogram images. By adapting MobileNet’s final layer and leveraging its computational efficiency, precision, and adaptability, this approach significantly enhances diagnostic accuracy and improves patient care outcomes.

### 3.3.2. Xception

This study is based on diagnosing breast cancer specifically, and the approach here presents the use of Xception, an advanced version of the Inception architecture. Xception is an adept, versatile tool that can be used in image analysis to better diagnostic precision and efficiency within the context of the mammograms. Xception will allow fine-tuning its layers using transfer learning, hence making it possible to identify the very soft notes of breast cancer in these images. The impact here is that it has brought a huge difference in the care and management of breast cancer. Being embedded into the transfer-learning paradigm is due to the seamless transition to the much less-dependant-on-massive-data-transfer mass, which means the very onerous case-based triage. Fast approaches deliver not only the best patient care but also improve health system efficiency. Use of Xception with transfer learning represents a quantitative leap in diagnosis of breast cancer with the use of mammogram images. The objectives of this study were to chart suitable integration in terms of partnership grade, in precision, efficiency, and commitment to data privacy, therefore making it an invaluable tool in the betterment of patient care and optimal efficiency of health care systems in breast cancer diagnosis.

### 3.3.3. DenseNet

The possibility to have fine-tuning in the layers, including the last layer, makes it very sensitive for very minor indicators in the mammogram images for finishing

the last layer of DenseNet meant for this job. This study targeted the rise of precision in diagnosis, which is perhaps the most central key goal in breast cancer diagnosis. The problems related to the detection of breast cancer can be solved by facilitating the triage of the cases. It also speeds actions to quantify cases that require immediate actions. With this capability, the vanishing gradient problem, which is a critical issue, becomes addressable. The DenseNet will provide a leaping improvement to mammogram-based breast cancer diagnosis with this integration. The results confirmed the actuality of DenseNet with regard to precision in breast cancer diagnosis.

### 3.4. Explainability with Grad-CAM

Explainable artificial intelligence (XAI) has emerged as a critical field in machine learning, addressing the need for transparency and interpretability in AI-driven decision-making processes [56] [57]. XAI enables users and stakeholders to understand, trust, and effectively manage AI solutions by providing insights into the model's reasoning. One notable technique within this domain is Gradient-weighted Class Activation Mapping (Grad-CAM), which enhances the interpretability of DL [58]. Grad-CAM works by producing visual explanations for decisions made by the model. It highlights the specific areas in an input image that are important for predictions, allowing users to see which features the model focuses on, thus demystifying the decision-making process and increasing trust in the technology, especially in critical applications.

The verification phase in our study leveraged the advanced capabilities of Grad-CAM for a nuanced assessment of our deep learning models applied to breast cancer detection. This method offers a compelling blend of qualitative insights and quantitative analysis, elucidating the model's decision-making process through sophisticated visualization techniques.

- **Grad-CAM Mechanism:** The core of Grad-CAM is a heatmap generation process, that underscores the regions within mammogram images that predominantly influence the model's classification outputs. The underlying principle of Grad-CAM is described by the following equation [58]:

$$L_{\text{Grad-CAM}}^c = \text{ReLU} \left( \sum_k \alpha_k^c A^k \right) \quad (4)$$

Here,  $L_{\text{Grad-CAM}}^c$  represents the class-discriminative localization map for a target class  $c$ , with  $\alpha_k^c$  denoting the neuron importance weights for the  $k^{\text{th}}$  feature map activation  $A^k$ . The application of the ReLU function ensures a focus on the positively influencing features of class  $c$ .

Incorporating Grad-CAM into our methodology brings forth several pivotal contributions:

**1) Enhanced Model Interpretability:** Grad-CAM significantly augments the interpretability of our models, offering intuitive visual explanations for their predictions. Establishing trust and understanding requires this level of openness, especially in a therapeutic setting where explainability is just as vital as

accuracy.

**2) Targeted Model Optimization:** By analysing Grad-CAM heatmaps, we may improve our models' accuracy and reliability in diagnostic prediction while simultaneously reducing bias.

**3) Contribution to AI Explainability:** By going beyond traditional performance verification, Grad-CAM helps us understand how deep learning models work in medical imaging. This has a big impact in the new field of explainable AI in healthcare.

**4) Alignment with Clinical Insights:** Our AI-driven diagnostic tools are more reliable and applicable in clinical settings when Grad-CAM marks the important diagnostic areas in the pictures. This guarantees that the model's decisions are in line with clinical interpretations.

By strategically using Grad-CAM, our work establishes a new standard for creating interpretable, clinically-aligned AI solutions for medical diagnostics and confirms the effectiveness of our models.

## 4. Results and Comparison

### 4.1. Evaluation Metrics

The effectiveness and accuracy of ML algorithms can only be determined by measuring their performance. For this goal, our technique makes use of a full suite of measurements and tools, such as a confusion matrix, ACC, PREC, REC, F1 score, and visual representations.

- The **Confusion Matrix** provides an in-depth look at the model's predictions, breaking them down into TP, TN, FP, and FN with relative ease. For those interested in learning how models behave when it comes to categorisation, it is an invaluable tool.
- **Accuracy (ACC)** is computed as the ratio of accurate predictions to total predictions; it is a crucial parameter in ML assessment.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

- **Precision (PREC)** measures the ratio of true positives to expected positives, which is defined as:

$$PREC = \frac{TP}{TP + FP} \quad (6)$$

- **Recall (REC)**, the fraction of true positives that are accurately detected, sometimes called sensitivity, is computed as:

$$REC = \frac{TP}{TP + FN} \quad (7)$$

- The **F1 Score** merges PREC and REC into one statistic, giving a fair assessment of the model's recall and precision:

$$F1\text{-Score} = 2 \cdot \frac{PREC \times REC}{PREC + REC} \quad (8)$$

- **Graphical Representations**, Visual insights into model performance are provided by tools like Receiver Operating Characteristic curves and precision-recall curves, which further aid in the assessment process.

Our approach innovatively incorporates advanced visualization techniques, dynamically displaying the relationship between accuracy and model loss over the training and validation phases. This visualization aids in assessing the learning process more effectively. Through such a detailed evaluation strategy, our model not only proves its efficiency in breast cancer (BC) detection but also facilitates ongoing enhancement and fine-tuning. This thorough analysis positions our deep learning-based model as a leading example of machine learning applications in medical diagnostics, showcasing the significant potential of advanced analytics in healthcare.

## 4.2. Experiment Setup

Our experiment involved a series of computational steps in a Python environment to analyze medical imaging data for breast cancer detection. The setup consisted of the following key components:

### Library and Dataset Preparation

- The installation of Python libraries, including Visuallkeras, which are crucial for our deep learning models, was the first step in our investigation.
- Into a specified data directory, the MIAS dataset—a world-renowned medical imaging collection for breast cancer studies—was extracted from its zip file.

### Data Preprocessing and Organization

- Ensuring the precise categorisation of photos into “malignant” and “benign” categories, we adjusted the directory names for uniformity.
- A comprehensive set of Python libraries, including TensorFlow, Keras, Pandas, NumPy, and Matplotlib, arrived from abroad. Our deep-learning models and data visualisation rely on these libraries.

### Initial Data Exploration

- We selected pictures from our dataset that belonged to the “benign” and “malignant” categories and used some code to make them visually appealing.
- Displaying a series of photographs in a matrix format helped us comprehend the dataset features during this early research.

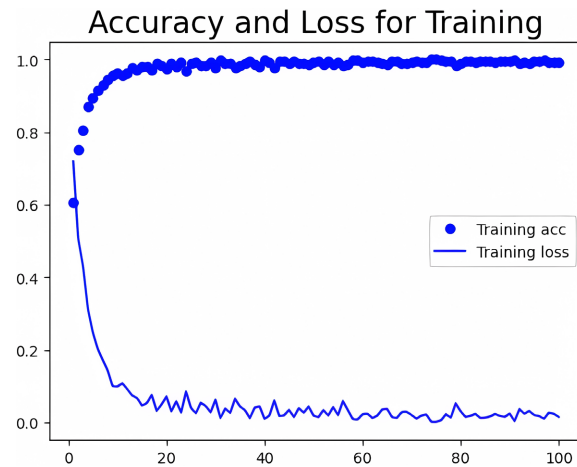
Following these procedures set the stage for training and analysing deep learning models using the Grad-CAM method. The success and dependability of our experimental method for identifying breast cancer using sophisticated image processing depends on this setting.

## 4.3. Results

At this pivotal point in our study, we submitted the challenge of breast cancer identification in mammography pictures to four state-of-the-art deep learning models: MobileNet, Xception, DenseNet, and each had its own unique architectural design.

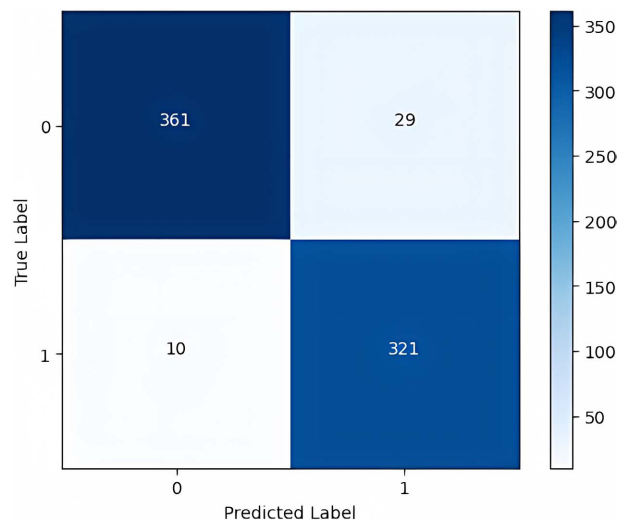
**MobileNet** sets itself apart by making use of depthwise-separable convolutional

layers, which improve model performance while maximising processing economy. **Figure 2** displays the MobileNet method’s training dynamics across 100 epochs, showcasing its accuracy and loss. The remarkable capacity of MobileNet to detect complex patterns in medical imaging data was shown in the 100th training epoch, when the network achieved an accuracy of 99.51% with a loss of just 0.0129.



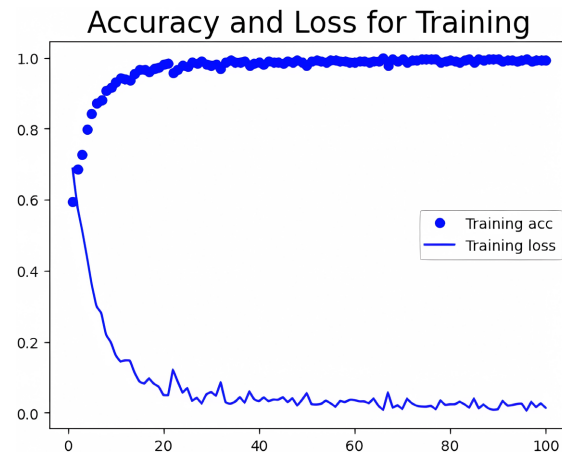
**Figure 2.** Training of the mobilenet model for medical image analysis.

**Figure 3** illustrates the confusion matrix for the MobileNet model, displaying the classification results between benign (label 0) and malignant (label 1) breast cancer cases. The matrix shows that the model correctly predicted 361 cases as benign and 321 cases as malignant. However, there were 29 benign cases misclassified as malignant and 10 malignant cases misclassified as benign. This matrix effectively captures the model’s accuracy in distinguishing between the two classes, demonstrating a high degree of sensitivity and specificity in its predictions.



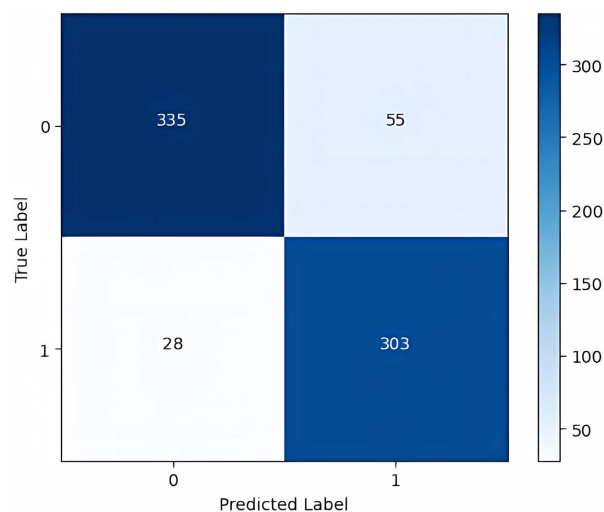
**Figure 3.** Confusion matrix for the MobileNet.

**Xception**, with its three dense layers, showed robustness in feature extraction, as reflected in its high accuracy of 99.31% and a loss of 0.0200. Designed for complex image recognition tasks, its architecture is particularly effective for medical image analysis. **Figure 4** showcases the training dynamics over 100 epochs, illustrating a rapid improvement in accuracy concurrent with a decrease in loss. This visualization confirms the model's robust learning capabilities and underscores its suitability for high-stakes environments like medical diagnostics.



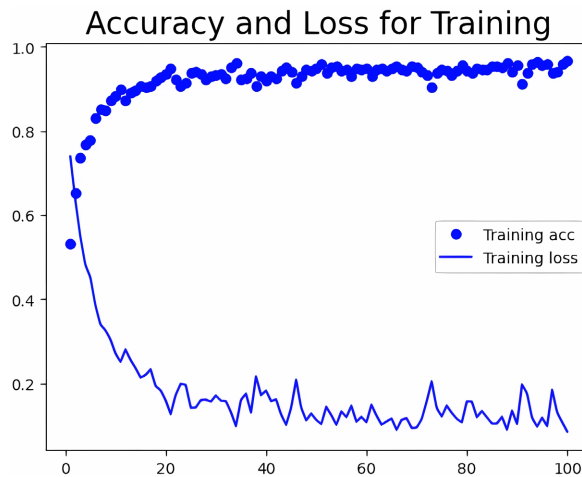
**Figure 4.** Training of the Xception model for medical image analysis.

**Figure 5** presents the confusion matrix for the Xception model, used to classify breast cancer cases as either benign (label 0) or malignant (label 1). The matrix indicates that the model successfully identified 335 cases as benign and 303 cases as malignant. On the other hand, there were 55 instances where benign cases were incorrectly labeled as malignant, and 28 malignant cases were misclassified as benign. This visual representation highlights the model's diagnostic accuracy and areas where further tuning could enhance its ability to differentiate between the two categories more precisely, ensuring a more reliable clinical assessment tool.



**Figure 5.** Confusion matrix for the Xception.

**DenseNet** leverages a unique configuration of dense layers interconnected by dropout layers to achieve an accuracy of 96.56% and a loss of 0.0857 by the 100th training epoch, as shown in **Figure 6**. The model exhibits rapid enhancements early on, marked by a sharp increase in accuracy and a swift decrease in loss. Following these initial gains, the loss levels off and remains low, while the accuracy continues to climb, demonstrating DenseNet's ability to effectively fine-tune its performance over time. This graph underscores the model's robust learning curve and its adeptness at maintaining a consistently low error rate, affirming DenseNet's efficacy and suitability for complex tasks like medical image analysis.



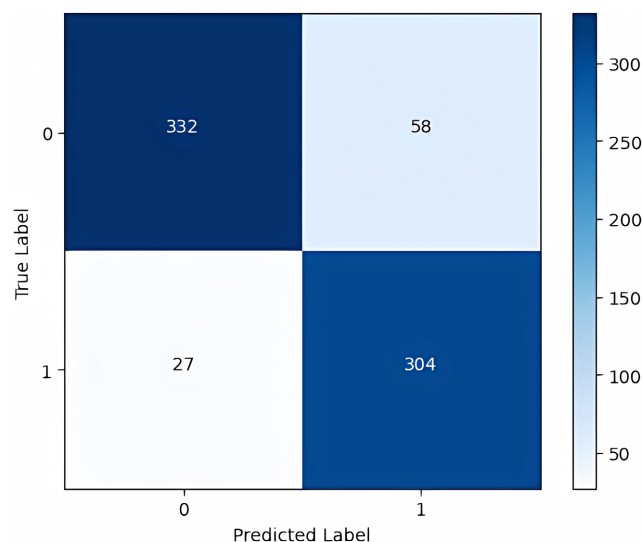
**Figure 6.** Training of the DenseNet model for medical image analysis.

**Figure 7** displays the confusion matrix for the DenseNet model used in classifying breast cancer into benign (label 0) and malignant (label 1) categories. The matrix reveals that the model correctly identified 332 benign cases and 304 malignant cases. However, there were 58 false positives, where benign cases were incorrectly classified as malignant, and 27 false negatives, where malignant cases were misclassified as benign. This visualization provides a clear depiction of the model's performance, highlighting its strengths in accurate classification as well as areas where improvements could be made to reduce misclassification.

**Interpretation and Implications:** The comparative performance evaluation of deep learning models, as summarized in **Table 2**, reveals distinct differences in the outcomes achieved by MobileNet, Xception, and DenseNet under the same training conditions. MobileNet outperforms the other models with an impressive accuracy of 94.17% and the lowest loss in the last training epoch at 0.0129. Its architecture, featuring depthwise-separable convolutional layers combined with ReLU and Softmax activation functions, and optimized using Adam, enables high efficiency and effectiveness, as reflected in its F1-scores of 0.95 for benign and 0.94 for malignant classifications.

Xception, which utilizes three dense layers and the same activation functions and optimizer, shows a lower performance with an accuracy of 85.17% and a loss of 0.0200. Its F1-scores for both benign and malignant classifications are equal at

0.86, indicating a balanced performance but with room for improvement in accuracy and loss reduction.



**Figure 7.** Confusion matrix for the DenseNet.

**Table 2.** Comparative performance evaluation of deep learning models.

Model	Architecture Details	Activation Functions	Optimizer	Accuracy	Loss (in last epoch)	F1-Score (Benign)	F1-Score (Malignant)
MobileNet	Depthwise-separable conv layers, fully connected layers	ReLU, Softmax	Adam	94.17%	0.0129	0.95	0.94
Xception	3 dense layers	ReLU, Softmax	Adam	85.17%	0.0200	0.86	0.86
DenseNet	5 dense layers, 3 dropout layers	ReLU, Softmax	Adam	87%	0.0523	0.87	0.86

DenseNet, incorporating five dense layers interspersed with three dropout layers, achieves an accuracy of 87% and a higher loss of 0.0523. Similar to Xception, its F1-scores are slightly better at 0.87 for benign and 0.86 for malignant, which suggests good model reliability but highlights potential areas for optimization in terms of loss reduction and overall accuracy.

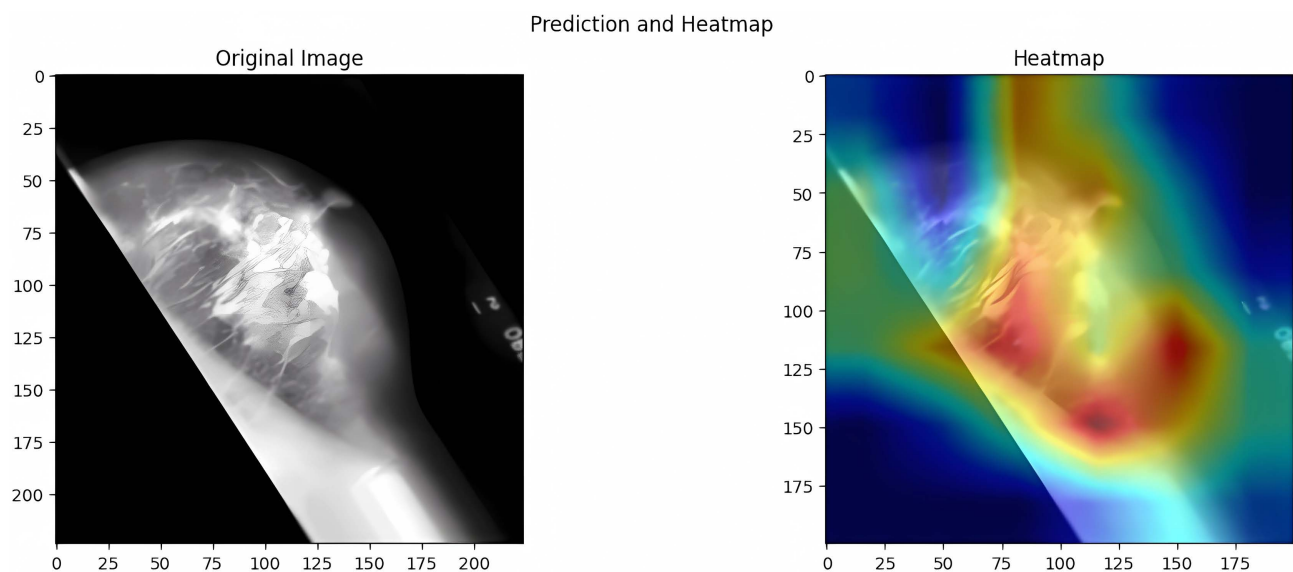
- The high accuracy and low loss values across these models underscore the advancements in deep learning applied to medical imaging, marking a significant stride in the field of breast cancer diagnostics.
- The balanced F1 scores observed in MobileNet illustrate their potential to reduce false positives and negatives, which is paramount in medical diagnosis.
- The diversity of model architectures provides insights into the versatility of deep learning approaches, catering to various aspects of image-based diagnosis, from feature extraction to sequential pattern recognition.

#### 4.4. Comparison

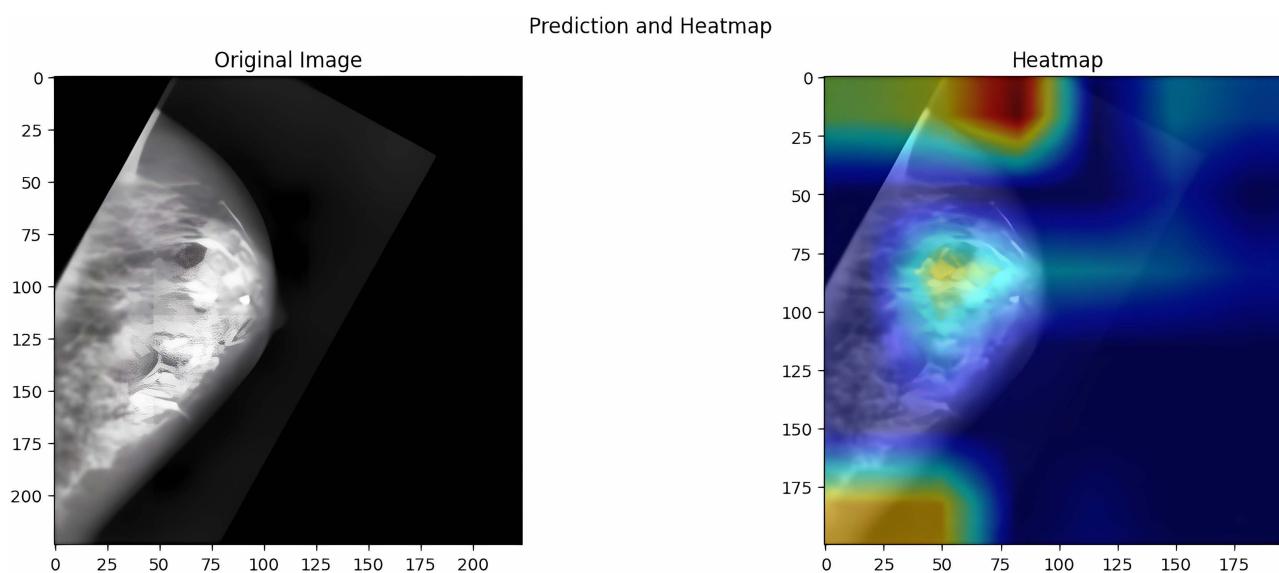
The interesting findings of a comparative investigation regarding the model's performance in classifying two categories of breast cancer are benign and malignant were presented. We did an evaluation of performance in terms of accuracy, which becomes a very important indicator for using medical imaging applications. Of the models for performance evaluation, MobileNet was at the top with an average correct classification of 94.17%. DenseNet and Xception showed a difference in accuracies of 86.68% and 85.71%, respectively. This shows, very well, that MobileNet is the best effective model in our study for the detection of breast cancer from mammogram images. Further justification towards the performance superiority of MobileNet was made through a gradient-weighted class activation mapping (Grad-CAM) technique. It is an advanced visualization tool that allows us a window into the areas of focus of the model while predicting and shows the features of the image that are mostly important in taking the decision about the presence of breast cancer.

##### Insights from Grad-CAM Analysis:

- **Figure 8** and **Figure 9** show Grad-CAM visualizations for MobileNet and Xception. Notably, the Grad-CAM output for MobileNet was markedly more defined and coherent, reflecting its higher accuracy for breast cancer detection.
- The visualizations for MobileNet distinctly highlight the regions of the mammogram images that contribute most significantly to the classification decisions. This precise focus on relevant features underpins its robust diagnostic capability.
- In contrast, the Grad-CAM results for Xception appear more dispersed and less focused, indicating a less targeted approach to feature detection. This could partly explain its lower accuracy compared to that of MobileNet.



**Figure 8.** Grad-CAM visualization for breast cancer detection: Focus on dense tissue regions.



**Figure 9.** Grad-CAM heatmap analysis: Highlighting areas of potential anomalies in breast tissue.

In **Figure 8**, the heatmap overlaid on the original mammogram reveals significant areas of interest that the model focuses on, predominantly along the denser regions of the breast tissue, which are critical for detecting malignancies. Similarly, **Figure 9** presents another heatmap highlighting areas where the model detects potential anomalies. These regions, marked by warmer colors (reds and yellows), indicate the zones most influential in the model's prediction process, thus providing valuable insights into the neural network's focus areas. Such visualizations not only aid in verifying the model's accuracy but also contribute to clinical decision-making by pinpointing specific areas within the breast that may require closer examination. These heatmaps validate the model's diagnostic reasoning and offer a transparent tool for clinicians to assess the AI's analytical process.

**Implications of Comparative Analysis:** The study compares deep learning models in medical image analysis, highlighting the importance of model architecture and feature detection strategies. The superior performance of MobileNet in breast cancer diagnostics was evident through quantitative metrics and qualitative Grad-CAM visualizations. This study highlights the need for continued advancements in this field, with a focus on more precise and reliable AI-based diagnostic tools. The analysis also highlights the value of visualization techniques, such as Grad-CAM, in interpreting and enhancing deep learning models for medical imaging, as shown in **Figure 8**.

A detailed comparison of our proposed methodology with conventional approaches is presented in **Table 3**. **Table 3** compares the performances of various studies employing machine learning and deep learning methodologies for image classification tasks. In our study, we used four different models: MobileNet, Xception, DenseNet, and MobileNet-LSTM, and achieved impressive results with high accuracy. Our results demonstrated that MobileNet (94.17%) outperformed the accuracies reported in other studies. For example, in [30], accuracies ranging from

93.25% to 93.97% were achieved using conventional ML and DL techniques, In contrast [31]’s ML-based models achieved an accuracy of 91%. [32]’s deep learning algorithms achieved an accuracy of 94.17%, slightly higher than our MobileNet model but lower than our Xception model. Moreover, our study’s performance surpassed that of [33], which achieved a classification accuracy of 93.29%. Similarly, our models demonstrated significantly higher accuracy than the DCNN models in [34], which reported classification accuracy ranging from 79.4% to 83.4%. [36] outlined ten open research challenges in deep learning and imaging techniques but did not report specific accuracies values.

**Table 3.** Accuracy comparison between proposed methodology with conventional methods. The experiments show that the suggested strategy is effective with a 0.94 accuracy.

Study	dataset	Methodology	classification	Results
[30]	BreakHis	Conventional ML and DL	Binary	Achieved accuracies ranging from 93.25% to 93.97%
[31]	DDSM, CBIS-DDSM, MIAS, INbreast and BCDR	ML-based models	Multi-class	Achieved an accuracy of 91%
[32]	Wisconsin Breast Cancer	DL algorithms	Binary	99.3%
[33]	Real data	DL techniques	Multi-class	Achieved a classification accuracy of 93.29%
[34]	two dataset	DCNN	Multi-class	Achieved a classification accuracy ranging from 79.4% to 83.4%
[36]	-	DL and imaging techniques	-	Outlined ten open research challenges
Our Study	MIAS	MobileNet, Xception, DensNet	Binary	MobileNet: 94.17%

## 5. Discussion

This extensive study was motivated by the urgent need for advanced and accurate tools for breast cancer classification using mammographic images. Breast cancer is a prevalent life-threatening disease that affects millions of individuals worldwide. Early detection is paramount, as it significantly improves treatment outcomes and patient survival rates. Mammography remains a frontline screening tool, but its accuracy can be enhanced by integrating cutting-edge deep-learning models. Our research demonstrates the remarkable potential of state-of-the-art deep learning models, specifically MobileNet, Xception, DenseNet, and MobileNet-LSTM, for revolutionizing breast cancer diagnosis. MobileNet, in particular, has emerged as a standout performer, exhibiting exceptional accuracy and minimal loss, signifying a groundbreaking advancement in medical-image analysis. The addition of Grad-CAM enriches these models by providing crucial insights into their decision-making processes, which is a key aspect of medical diagnosis. This interpretability facilitates a deeper understanding of how the models arrive at their classifications,

instilling confidence in their predictions and aiding healthcare professionals in making informed decisions. The significance of our findings extends beyond academic research. These findings have profound implications in clinical practice and patient care. The versatility of these deep learning models in feature extraction and sequential pattern recognition, as evidenced by their well-balanced F1 scores, holds immense promise for reducing both false positives and false negatives in breast cancer diagnosis. This not only improves diagnostic accuracy, but also minimizes the emotional and financial burden on patients by reducing unnecessary follow-up tests and treatments.

However, there are some challenges that need to be overcome. The reliance on a single dataset, the MIAS database, underscores the need for broader validation across diverse datasets to ensure the robustness and generalizability of our models. Moreover, the computational demands of deep learning models can be resource-intensive, potentially limiting their applicability in resource-constrained healthcare settings. Addressing these challenges through ongoing research is essential to realizing the full potential of these models in improving breast cancer diagnosis and ultimately saving lives. Our study represents a crucial step forward in this vital area of medical research by offering hope and inspiration for further advancements in breast cancer classification using mammography.

## 6. Conclusion

While our models show high accuracy on the MIAS dataset, a limitation of this study is the lack of validation on an external dataset. Future work should focus on evaluating the robustness of the models across diverse, real-world mammographic datasets. This study highlights the potential of deep learning algorithms and the Grad-CAM technique to improve breast cancer detection and diagnosis in medical imaging. MobileNet, a tested model, is the leader in terms of accuracy, and a significant breakthrough in medical image analysis. Integration of Grad-CAM technology enhances our understanding of how these models discern cancerous tissues, providing critical insights into their decision-making processes. The collaborative development of DL algorithms and Grad-CAM technology signifies a transformative force in diagnostic imaging, demonstrating the progress achieved through interdisciplinary collaboration and the pivotal role of advanced technology in improving healthcare outcomes. The application of Grad-CAM technology to BC image analysis holds promise for substantial improvements in accuracy, detection, and diagnosis, ultimately leading to improved patient care and outcome. This study demonstrated the potential of innovative technologies in medical diagnostics and the importance of interdisciplinary efforts to drive progress in healthcare.

## 7. Future Work

This study suggests several potential improvements for breast cancer detection. First, more advanced deep learning models can be explored to enhance the accu-

racy. Attention-based models have shown promise in medical image analysis. Second, a larger dataset can be used to train and test the models, ensuring their robustness and generalizability. Third, multimodal imaging, such as combining mammography and ultrasound images, can improve the BC detection accuracy. Finally, integrating advanced technologies such as computer-aided diagnosis could lead to more accurate and efficient detection and diagnosis. The results of this study show that MobileNet outperforms the other methods, with accuracies ranging from 93.25 to 93.97%. The study also found that deep learning algorithms achieved an accuracy of 94.17%, which is slightly higher than that of MobileNet model but lower than that of Xception.

This study revealed the exceptional performance of our models, with MobileNet achieving an impressive accuracy of 94.17%, surpassing other studies using conventional machine learning and deep learning techniques. Our models, including MobileNet, Xception, and DenseNet demonstrated efficacy in addressing complex image classification tasks and advancing breast cancer detection. These findings provide valuable insights for future research, emphasizing the need for advanced DL models, dataset expansion, multi-modal imaging, and CAD systems to improve breast cancer detection and patient outcome.

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### Informed Consent Statement

The requirement for patient consent was waived for the use of a local private dataset and was included after approval. There were no ethical implications for public datasets.

### Data Availability Statement

Two publicly available databases, MIAS [50] were used for the experiments in this study.

### Conflicts of Interest

The authors declare that they have no conflict of interest.

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