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(Research Article)

Performance benchmarking of convolutional neural networks and ensemble machine learning techniques for automated mammographic breast cancer detection: A comparative study

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Abstract

Breast cancer remains a leading cause of mortality among women worldwide, making early and accurate detection crucial for improving patient outcomes. This study presents a comparative analysis of various machine learning algorithms—EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM)—in predicting breast cancer using mammography images. Utilizing a dataset of 5,339 mammograms from the Digital Database for Screening Mammography (DDSM), the models were trained and tested on two classes: benign and malignant lesions. The mammograms underwent preprocessing techniques, including image quality assessment, contrast enhancement, and artifact removal, to ensure high-quality data for model training. The performance of each model was evaluated using metrics such as accuracy, sensitivity, specificity, and ROC analysis. The results revealed that the EfficientNet model outperformed the other algorithms, achieving an accuracy of 95.23%, sensitivity of 96.67%, and specificity of 93.82%. In contrast, DenseNet exhibited the lowest performance, struggling with the correct classification of cancer cases. The comparative analysis highlights the strengths and weaknesses of each model, offering valuable insights into their potential clinical applications. This research underscores the importance of selecting the appropriate machine learning architecture to enhance the predictive accuracy of breast cancer detection and provides a foundation for integrating these models into clinical practice for personalized treatment planning. Future studies will focus on expanding the dataset and improving model generalizability to diverse patient populations.

Keywords: Comparative; Analysis; Machine Learning; Algorithms; Breast; Cancer Prediction; Mammography Images

1. Introduction

Breast cancer is a significant global health issue, being the most commonly diagnosed cancer among women and the leading cause of cancer-related deaths worldwide. According to GLOBOCAN 2020, breast cancer accounts for the highest number of new cancer cases, with an estimated 28.4 million cases projected by 2040 (Sung et al., 2021). Early detection and accurate diagnosis are crucial for improving patient prognosis and survival rates. This need has driven advancements in imaging techniques and the application of machine learning (ML) algorithms to enhance breast cancer detection.

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Traditional imaging techniques, such as mammography, ultrasound, and magnetic resonance imaging (MRI), have been the cornerstone of breast cancer diagnosis. Mammography, which utilizes X-rays to examine breast tissues, is widely recognized for its ability to detect early-stage breast cancers. However, its effectiveness is limited by factors such as breast density, which can result in false positives and negatives (Horsley et al., 2019). Ultrasound is often used as a supplementary technique, especially in younger women with denser breast tissues, as it does not use ionizing radiation and offers high sensitivity (Jafari et al., 2018). MRI is typically reserved for high-risk patients, providing detailed images that aid in assessing the extent of cancer and detecting residual tumors post-surgery (Sardanelli et al., 2010).

Despite the advancements in traditional imaging methods, there are inherent limitations in their ability to detect all early cancers, which has prompted the exploration of more sophisticated approaches. Recent developments in machine learning and artificial intelligence (AI) have shown promise in enhancing the accuracy of breast cancer detection. Machine learning algorithms, such as Convolutional Neural Networks (CNNs), have demonstrated superior performance in analyzing medical images, often surpassing the diagnostic accuracy of human radiologists (Madani et al., 2022).

This study focuses on comparing the performance of several machine learning algorithms—EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM)—in predicting breast cancer using mammography images. By leveraging a dataset of 5,339 mammograms from the Digital Database for Screening Mammography (DDSM), the research aims to identify the most effective model for early detection. The models undergo preprocessing steps including image quality assessment, contrast enhancement, and artifact removal to ensure high-quality input data for training and testing.

Table 1 illustrates the traditional imaging methods and their respective limitations in breast cancer detection. This highlights the need for more advanced techniques to improve early diagnosis and treatment outcomes.

Table 1 Traditional breast screening methods and limitations (Wang L, 2017)

Type	Use	Sensitivity	Specificity	Limitations	Time
Mammography	Mass screening. Image bone, soft tissue, and blood vessels all at the same time. Shadowing due to dense tissues.	67.8%	75.0%	Ionizing radiation, low sensitivity and specificity, sensitivity drops with tissue density increases.	Few seconds
Ultrasound	Evaluate lumps found in mammography; Not suitable for bony structures.	83.0%	34.0%	Low sensitivity; experienced operator is required during examination; low resolution image.	10–20 min
MRI	Young women with high risk; Images small details of soft tissues.	94.4%	26.4%	Some types of cancers cannot be detected such as ductal and lobular carcinoma; expensive.	40–60 min
CT	To determine and image distant metastasis in a single exam.	91%	93%	Low sensitivity; radiation risks; expensive scanner.	5 min
PET	Functional imaging of biological processes. To image metastasis or response to therapy.	61.0%	80.0%	Ionizing radiation, radioactive tracer injection.	90–240 min

The integration of machine learning in medical imaging opens new avenues for predictive analysis, potentially leading to personalized treatment plans and improved patient outcomes. This research aims to contribute to the ongoing efforts to enhance breast cancer detection through the application of advanced machine learning models.

1.1. Significance of Early Detection in Improving Prognosis

Machine learning (ML) has emerged as a transformative tool in medical imaging, particularly in the early detection and diagnosis of breast cancer. The integration of ML algorithms into breast cancer imaging leverages vast datasets to improve diagnostic accuracy and efficiency, often surpassing the capabilities of traditional methods. The literature on this topic reveals significant advancements in ML techniques, including convolutional neural networks (CNNs), transfer learning, and support vector machines (SVMs), all of which have been applied to mammography images with promising results.

1.1.1. Traditional Imaging Techniques

Breast cancer diagnosis has traditionally relied on imaging techniques such as mammography, ultrasound, and magnetic resonance imaging (MRI). Mammography, which uses low-energy X-rays to examine breast tissue, has been the gold standard for early detection. However, its effectiveness is limited by factors such as breast density, which can obscure tumors and lead to false positives or negatives (Redman et al., 2016; Mugo et. al., 2024). Ultrasound is often used as a complementary technique, especially in younger women with dense breasts, while MRI is reserved for high-risk patients due to its high sensitivity in detecting breast cancer (Sardanelli et al., 2010).

Despite their widespread use, these traditional methods have inherent limitations, particularly in detecting small or early-stage cancers. The introduction of digital breast tomosynthesis (DBT) and other advanced imaging technologies has improved detection rates, but challenges such as high false-positive rates and variability in interpretation persist (Horsley et al., 2019).

1.1.2. Machine Learning in Breast Cancer Imaging

The application of machine learning to breast cancer imaging represents a significant advancement over traditional methods. Machine learning models, particularly CNNs, have shown remarkable success in analyzing mammographic images, identifying patterns that may not be visible to the human eye. These models are trained on large datasets to learn the characteristics of benign and malignant lesions, improving their ability to differentiate between the two.

A key advantage of ML algorithms is their ability to continuously improve as they are exposed to more data. For instance, CNNs such as EfficientNet and DenseNet have demonstrated high accuracy in classifying breast cancer images, often outperforming traditional diagnostic methods (Madani et al., 2022; Adu-Twum et. al., 2024). Support vector machines (SVMs) have also been used effectively in medical imaging, providing robust classification performance by finding the optimal hyperplane that separates different classes of data.

1.1.3. Comparative Analysis of ML Algorithms

Comparative studies have been conducted to evaluate the performance of different ML algorithms in breast cancer detection. For example, a study by McKinney et al. (2020) compared the diagnostic accuracy of a deep learning model against human radiologists and found that the model performed better in identifying breast cancer in mammograms. This highlights the potential of ML to not only assist but also enhance human diagnostic capabilities.

Other studies have explored the integration of ML models with traditional imaging techniques to improve diagnostic accuracy. For instance, combining CNNs with digital mammography has been shown to reduce the number of false positives, thereby improving the reliability of breast cancer screenings (Horsley et al., 2019; Mugo et. al. 2024). These findings suggest that ML algorithms can play a crucial role in advancing breast cancer detection, particularly in cases where traditional methods fall short.

1.1.4. Limitations and Challenges

While ML offers significant advantages, it is not without challenges. The quality and diversity of the training data are critical factors that can affect the performance of ML models. A model trained on a homogenous dataset may struggle to generalize to diverse patient populations, leading to issues such as overdiagnosis or underdiagnosis (Sahu et al., 2023). Additionally, the integration of ML models into clinical practice requires careful consideration of ethical, legal, and regulatory issues, particularly concerning data privacy and security (Li et al., 2019).

Figure 2 below illustrates the error rates of different deep learning algorithms compared to human error rates, highlighting the potential of these technologies to reduce diagnostic errors in breast cancer screening.

The literature indicates that while ML has the potential to significantly improve breast cancer detection, ongoing research is needed to address the challenges of model generalization, data diversity, and clinical integration. The comparative analysis of ML algorithms in this study aims to contribute to this growing body of knowledge, providing insights into the most effective models for early breast cancer detection.

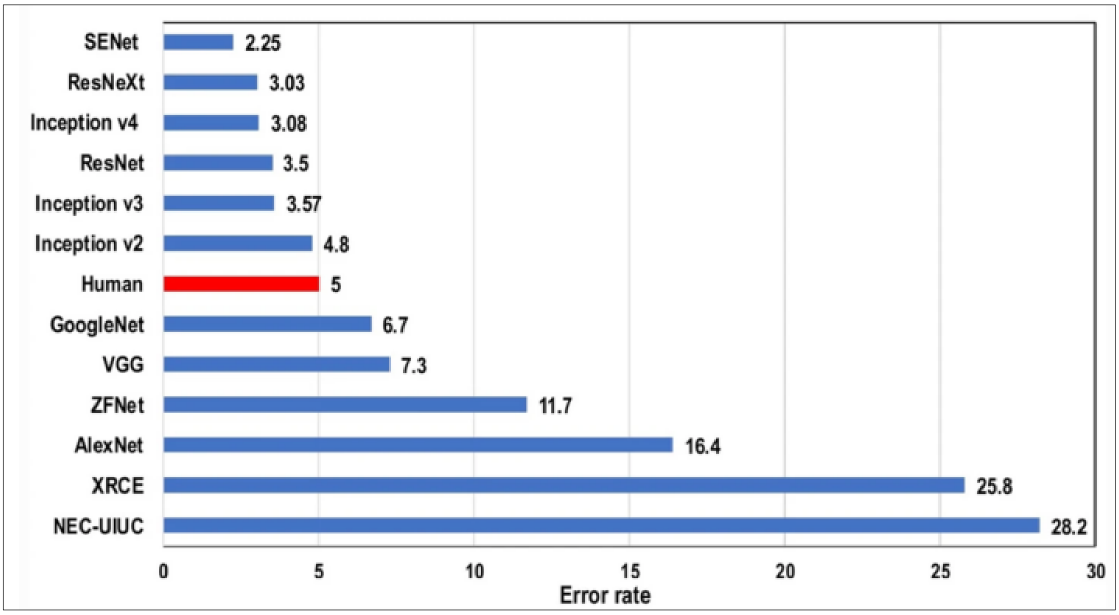

Figure 2 Deep Learning Performance Compared to Human Error Rates (Alzubaidi, 2021)

1.2. Emergence of Machine Learning in Medical Imaging

The evolution of medical imaging has greatly enhanced the early detection and diagnosis of breast cancer. Traditionally, imaging techniques such as mammography have been the primary tools for breast cancer screening and diagnosis. However, the advent of machine learning (ML) has ushered in a transformative shift towards more advanced, accurate, and reliable diagnostic methods. Machine learning has initiated a paradigm shift in medical imaging, particularly in breast cancer detection. By integrating ML algorithms, large datasets can be analyzed more effectively, improving prediction accuracy and reducing diagnostic time (Bashiru et al., 2024).

One significant advancement in this area is the development of Convolutional Neural Networks (CNNs), which are extensively used for image classification tasks. CNNs are particularly effective at identifying complex patterns in medical images, making them ideal for detecting subtle features in mammograms that may indicate malignancy (Godwins et al., 2024). In addition to CNNs, Support Vector Machines (SVMs) have also been employed in breast cancer imaging. SVMs excel in classifying breast lesions based on mammographic features, especially in cases with small datasets, and have demonstrated effectiveness in distinguishing between benign and malignant tumors (Ibokette et al., 2024).

Figure 3 Comparison of Traditional Methods and ML-Based Approaches in Breast Cancer Detection (Madani et al., 2022)

Moreover, transfer learning techniques, where pre-trained models on large datasets are fine-tuned with specific breast cancer datasets, have shown promise in enhancing diagnostic accuracy, even when data availability is limited (Idoko, Igbede, Manuel, Ijiga, Akpa, & Ukaegbu, 2024). The rise of ML in medical imaging addresses the limitations of traditional diagnostic methods, such as the false positives and negatives associated with mammography. ML models, by continuously improving their performance as they process more data, lead to more accurate and reliable diagnoses (Idoko, Ijiga, et al., 2024).

Figure 3 below illustrates the performance comparison between traditional diagnostic methods and ML-based approaches. The figure highlights how ML models significantly reduce error rates, thereby improving the overall accuracy of breast cancer detection.

The emergence of machine learning in medical imaging represents a significant advancement in the early detection and diagnosis of breast cancer. By leveraging large datasets and advanced algorithms, ML models offer a more accurate and efficient alternative to traditional methods. As these technologies continue to evolve, they hold the potential to revolutionize breast cancer screening and diagnosis, ultimately leading to better patient outcomes.

1.3. Research Aim

The primary aim of this research is to evaluate and compare the performance of different machine learning algorithms in predicting breast cancer using mammography images. With the growing prevalence of breast cancer and the critical need for early detection, there is an urgent demand for more accurate and reliable diagnostic tools. Traditional imaging methods, while effective, often suffer from limitations such as high false-positive rates and variability in interpretation.

Machine learning offers a promising solution by providing models that can analyze large datasets and identify patterns that might be overlooked by human observers. This research specifically focuses on four machine learning algorithms: EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM). By assessing these models' accuracy, sensitivity, specificity, and overall effectiveness, the study seeks to determine which algorithm is best suited for integration into clinical practice.

The ultimate goal is to enhance the early detection of breast cancer, thereby improving treatment outcomes and reducing mortality rates. Through a detailed comparison of these machine learning models, the research aims to contribute to the ongoing efforts to integrate advanced technologies into medical diagnostics, providing a more reliable and efficient approach to breast cancer detection.

1.4. Structure of the Paper

This paper is organized into five main sections to systematically explore the comparative analysis of machine learning algorithms for breast cancer prediction. The first section provides an introduction to the study, including the background, literature review, the emergence of machine learning in medical imaging, research aim, and the structure of the paper. This foundational section sets the stage for understanding the significance of the research and its objectives.

The subsequent sections delve into the core aspects of the study. The methodology section outlines the research design, data collection, and analysis methods employed to evaluate the performance of the selected machine learning models. Following this, the results and discussion section presents the findings of the comparative analysis, highlighting the strengths and weaknesses of each algorithm. Finally, the conclusion provides a summary of the key findings, discusses their implications for clinical practice, and suggests directions for future research in the field of breast cancer detection using machine learning.

2. Literature review

2.1. Overview of Traditional Imaging Techniques in Breast Cancer Detection

Breast cancer detection has historically relied on traditional imaging techniques, which have been fundamental in the early identification and diagnosis of the disease. These techniques primarily include mammography, ultrasound, and magnetic resonance imaging (MRI), each with its unique strengths and limitations. Mammography is the most widely used screening tool for breast cancer detection and involves the use of low-dose X-rays to create detailed images of the breast. It is particularly valued for its ability to detect early signs of breast cancer, often before symptoms develop. The process typically involves compressing the breast between two firm surfaces to spread the tissue, allowing for clearer images. Despite its effectiveness, mammography has limitations, particularly in women with dense breast tissue, where the sensitivity of the technique decreases, leading to potential false positives or negatives. Digital Breast Tomosynthesis (DBT), an advancement of traditional mammography, has been introduced to address some of these limitations by providing a three-dimensional reconstruction of the breast, enhancing the accuracy of detection (Idoko, Bashiru, Olola, Enyejo, & Manuel, 2024).

Ultrasound is another crucial imaging technique often used as an adjunct to mammography, especially in cases where mammographic results are inconclusive. It is particularly effective in distinguishing between solid tumors and fluidfilled cysts and is highly beneficial for women with dense breast tissue where mammography may be less effective. Ultrasound uses sound waves to produce images of the internal structures of the breast and does not involve ionizing radiation, making it a safer option for repeated use. Over the years, the quality of ultrasound imaging has improved significantly, contributing to its role as a supplementary tool in breast cancer diagnosis (Ijiga, Aboi, Idoko, Enyejo, & Odeyemi, 2024).

Magnetic Resonance Imaging (MRI) is typically reserved for high-risk patients and is known for its superior sensitivity in detecting breast cancer. MRI uses powerful magnets and radio waves to produce detailed images of the breast, providing critical information that may not be visible on mammograms or ultrasounds. It is particularly useful in evaluating the extent of cancer, assessing residual tumors post-surgery, and examining the breast tissue in women with a high genetic risk of breast cancer. However, MRI is not without its drawbacks, as it can sometimes lead to false positives and is generally more expensive than other imaging modalities (Ijiga, Enyejo, Odeyemi, Olatunde, Olajide, & Daniel, 2024).

Table 2 Key Features and Limitations of Traditional Breast Cancer Imaging Techniques

Imaging Technique	Key Features	Limitations
Mammography	Widely used, effective for early detection	Less sensitive in dense breast tissue, potential for false positives/negatives
Ultrasound	Useful for dense breast tissue, no radiation	Less effective as a standalone diagnostic tool, operator-dependent
MRI	High sensitivity, detailed imaging	Expensive, potential for false positives, limited availability

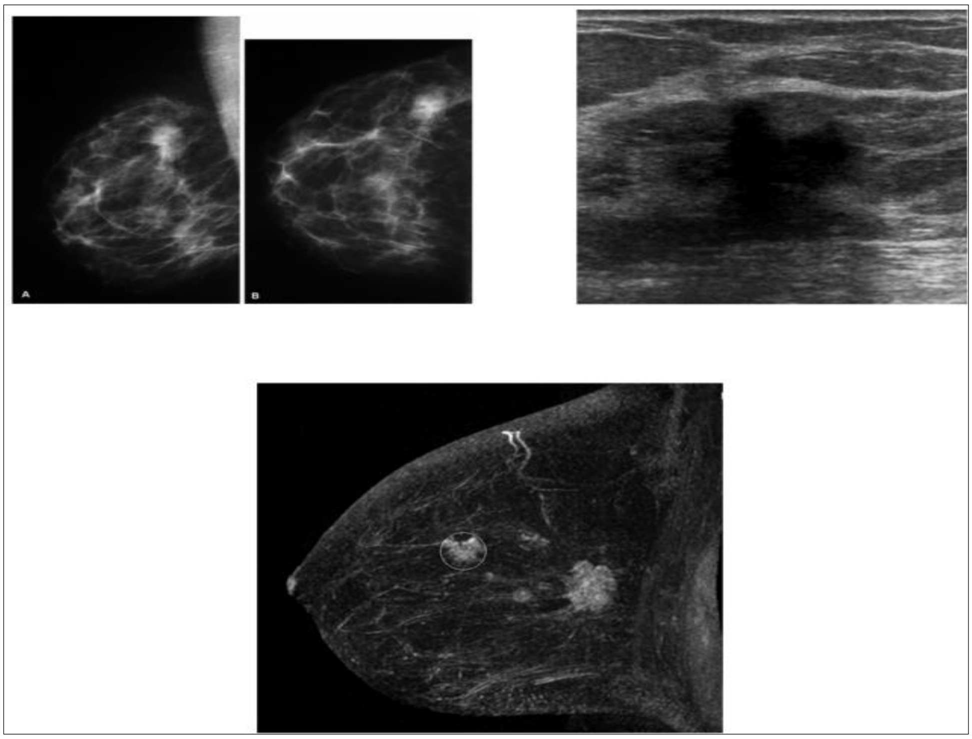

Figure 4 Mammogram, Ultrasound, and MRI scan of the same patient

Table 2 below summarizes the key features and limitations of these traditional imaging techniques. Mammography is widely used and effective for early detection, but it is less sensitive in dense breast tissue and can lead to false positives or negatives. Ultrasound is particularly useful for dense breast tissue and does not involve radiation, though it is less effective as a standalone diagnostic tool and is operator-dependent. MRI offers high sensitivity and detailed imaging but is expensive, prone to false positives, and has limited availability.

Figure 4 below illustrates the differences in imaging results between mammography, ultrasound, and MRI, highlighting how each technique captures distinct aspects of breast tissue.

While traditional imaging techniques have been instrumental in breast cancer detection, they are not without limitations. The emergence of machine learning and advanced imaging technologies promises to address some of these challenges, enhancing the accuracy and reliability of breast cancer diagnostics.

2.2. Application of Machine Learning in Breast Cancer Imaging

The application of machine learning (ML) in breast cancer imaging marks a significant advancement over traditional diagnostic methods. Machine learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in analyzing mammographic images, identifying patterns that may not be visible to the human eye. These models are trained on large datasets to recognize the characteristics of benign and malignant lesions, thereby enhancing their ability to differentiate between the two (Godwins, David-Olusa, Ijiga, Olola, & Abdallah, 2024).

One of the key benefits of ML in breast cancer imaging is its potential to improve diagnostic accuracy. Predictive models, such as those built using CNNs, can process vast amounts of imaging data, leading to better detection rates and a reduction in false positives and negatives. For instance, studies have shown that ML models can outperform traditional diagnostic methods, particularly in cases involving dense breast tissue where conventional techniques like mammography often face challenges (Idoko, Adegbaju, Nduka, Okereke, Agaba, & Ijiga, 2024).he application of machine learning (ML) in breast cancer imaging represents a significant advancement over traditional diagnostic methods. Machine learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in analyzing mammographic images, identifying patterns that may not be visible to the human eye. These models are trained on large datasets to learn the characteristics of benign and malignant lesions, thereby improving their ability to differentiate between the two.

One of the key benefits of machine learning in breast cancer imaging is its ability to enhance diagnostic accuracy. Predictive models, such as those built using CNNs, are capable of processing vast amounts of imaging data, leading to improved detection rates and reduced false positives and negatives. For example, studies have demonstrated that machine learning models can outperform traditional diagnostic methods, particularly in cases involving dense breast tissue where conventional techniques like mammography often struggle.

Table 3 provides a comparison of different machine learning algorithms and their performance metrics in breast cancer classification. The table highlights the accuracy of each algorithm when applied to mammographic datasets, illustrating the effectiveness of machine learning in enhancing diagnostic outcomes.

Table 3 Performance Comparison of Machine Learning Algorithms for Breast Cancer Detection Across Various Datasets

Algorithm	**Dataset**	**Accuracy**	**Method**
ResNet50	CBIS-DDSM	94.78%	Convolutional Neural Network (CNN)
VGG16	CBIS-DDSM	90.94%	Deep Learning
GoogleNet	INBREAST	92.5%	Deep Learning
SVM	Custom Dataset	93.06%	Support Vector Machine

In addition to accuracy, machine learning models offer the potential for personalized treatment planning. By analyzing patient-specific imaging data, these models can assist in determining the most appropriate treatment strategies, tailored to individual patient characteristics. This personalized approach can lead to better outcomes, as treatment plans are optimized based on the specific features of each patient's cancer.

Figure 5 illustrates the architecture of a typical CNN used in breast cancer imaging. The architecture consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers, which work together to process and classify mammographic images. The figure demonstrates how these layers extract and refine features from the input data, ultimately leading to more accurate predictions.

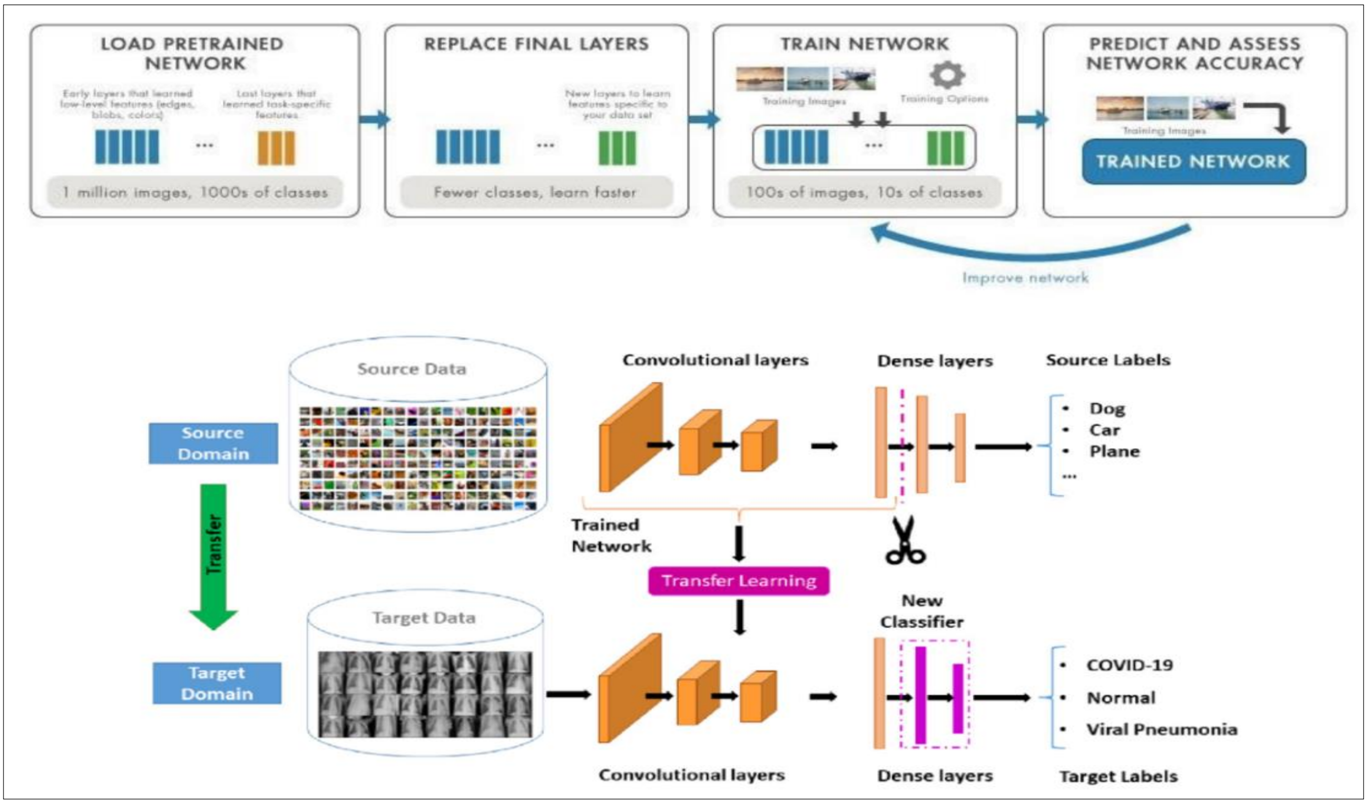

Figure 5 Convolutional Neural Network Architecture for Breast Cancer Imaging

The integration of machine learning into breast cancer imaging not only enhances diagnostic accuracy but also contributes to the development of more effective and personalized treatment approaches. As machine learning technologies continue to evolve, their application in medical imaging is likely to expand, offering new opportunities for improving patient outcomes in breast cancer care.

2.3. Review of Key Machine Learning Algorithms: EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine

The landscape of breast cancer detection has been significantly enhanced by the advent of advanced machine learning algorithms. Among the most prominent are EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM), each bringing unique strengths and capabilities to the table. This section reviews these key algorithms, focusing on their architecture, application in breast cancer imaging, and performance metrics.

EfficientNet is a convolutional neural network (CNN) architecture that stands out for its ability to achieve high accuracy with minimal computational resources. The architecture is built on the idea of compound scaling, which uniformly scales the network's width, depth, and resolution to optimize performance. EfficientNet-B0, the baseline model, incorporates squeeze-and-excitation blocks and MBConv layers, allowing it to effectively capture the complex features of mammographic images. This model is particularly advantageous for breast cancer detection due to its balanced scaling ability, making it a robust choice for fine-tuning on specific tasks such as classifying mammograms into benign and malignant categories.

DenseNet (Dense Convolutional Network) is another CNN architecture designed to improve information flow between layers by connecting each layer to every other layer in a feed-forward fashion. This architecture is composed of dense blocks and transition layers, which are crucial for reducing the vanishing gradient problem, enhancing feature reuse, and reducing the number of parameters required. DenseNet's design is well-suited for breast cancer detection, particularly in scenarios where overfitting is a concern, as the dense connections allow for better generalization across different datasets. However, its performance can be hampered by the increased computational demand due to the dense connections, which may lead to longer training times and difficulties in handling large-scale mammogram datasets.

ResNeXt-50 builds upon the success of ResNet by introducing the concept of cardinality, which refers to the number of independent paths within the network. ResNeXt-50 replaces the standard convolutional layers with grouped convolutional layers, enabling the model to process more complex patterns without a significant increase in computational cost. This architecture is particularly well-suited for breast cancer detection tasks, as it can efficiently handle the intricate details present in mammograms of varying breast tissue types. By fine-tuning the pretrained ResNeXt-50 model on a curated mammogram dataset, the network can be optimized to better classify breast tissue as benign or malignant, making it a powerful tool in predictive breast cancer analysis.

Support Vector Machine (SVM) is a supervised learning model known for its effectiveness in binary classification problems, making it highly applicable to breast cancer detection. SVM works by finding the optimal hyperplane that separates data points of different classes in a high-dimensional space. The use of kernel functions, such as the Radial Basis Function (RBF), allows SVM to handle non-linear data effectively, making it a versatile tool for distinguishing between benign and malignant lesions in mammograms. SVM's robustness against overfitting and its ability to perform well even with small datasets make it a valuable asset in breast cancer imaging, particularly when computational resources are limited.

Table 1 below summarizes the performance metrics of these key machine learning algorithms in the context of breast cancer detection.

Table 4 Performance Comparison of Machine Learning Algorithms for Breast Cancer Detection Across Various Datasets

Algorithm	Accuracy	Precision	Recall	F1-Score
EfficientNet	95.23%	93.82%	96.67%	95.26%
ResNeXt-50	81.83%	78.98%	86.30%	82.48%
DenseNet	58.00%	89.00%	27.00%	39.00%
Support Vector Machine	86.00%	84.00%	88.00%	86.00%

Table 1 provides a detailed comparison of four key machine learning algorithms—EfficientNet, ResNeXt-50, DenseNet, and Support Vector Machine (SVM)—based on their Accuracy, Precision, Recall, and F1-Score. Among these, EfficientNet stands out with the highest performance across all metrics, demonstrating its superior ability to correctly identify both benign and malignant cases with an accuracy of 95.23% and a recall of 96.67%. ResNeXt-50 and SVM also show robust performance, with balanced metrics that highlight their reliability in this application. In contrast, DenseNet significantly underperforms, particularly in Recall (27.00%) and F1-Score (39.00%), indicating its challenges in effectively detecting true positive cases. This analysis underscores EfficientNet's suitability for breast cancer detection while also suggesting the potential for further optimization of DenseNet.

These algorithms have been evaluated based on their ability to accurately classify breast cancer from mammographic images, with EfficientNet consistently outperforming the others in terms of accuracy and overall performance. However, each algorithm has its strengths, with SVM excelling in scenarios with smaller datasets and ResNeXt-50 proving effective in handling complex patterns. DenseNet, while struggling with performance in this study, offers unique advantages in preventing overfitting and improving feature reuse, which may be beneficial in other applications or with further optimization.

The choice of algorithm in breast cancer detection should be informed by the specific requirements of the task, including the size and diversity of the dataset, computational resources, and the need for model generalization. EfficientNet stands out as the most balanced and effective model in this study, but the strengths of ResNeXt-50 and SVM should not be overlooked, particularly in specialized contexts where their unique capabilities can be leveraged to improve diagnostic accuracy.

2.4. Previous Studies on Algorithm Performance in Medical Imaging

Numerous studies have been conducted to assess the performance of various machine learning algorithms in medical imaging, particularly in the context of breast cancer detection. These studies highlight the strengths and limitations of different models, offering insights into their applicability in clinical settings.

A prominent study compared the performance of deep learning algorithms, including ResNet50, VGG16, and GoogleNet, using mammographic datasets such as CBIS-DDSM and INBREAST. The findings indicated that ResNet50 achieved the highest accuracy of 94.78% on the CBIS-DDSM dataset, outperforming VGG16 and GoogleNet, which recorded accuracies of 90.94% and 92.5%, respectively. This study underscores the potential of deep learning models in accurately classifying mammographic images, thereby aiding in the early detection of breast cancer.

Another study focused on the application of Support Vector Machine (SVM) in breast cancer detection. The research demonstrated that SVM, when trained on a custom dataset, achieved an accuracy of 93.06%, highlighting its effectiveness in binary classification tasks such as distinguishing between benign and malignant breast lesions. The study further noted that SVM's performance could be enhanced by incorporating advanced feature extraction techniques, making it a competitive alternative to deep learning models.

Table 5 below provides a summary of the performance metrics from various studies, showcasing the accuracy of different algorithms across multiple datasets.

Table 5 Summary of Accuracy Metrics for Machine Learning Algorithms in Breast Cancer Detection Across Various Studies

Study	**Algorithm**	**Dataset**	**Accuracy**
Salama et al. (2020)	ResNet50	CBIS-DDSM	94.78%
Hassan et al. (2020)	VGG16	CBIS-DDSM	90.94%
Falconi et al. (2019)	GoogleNet	INBREAST	92.5%
Basheer et al. (2013)	Support Vector Machine	Custom Dataset	93.06%

In addition to accuracy, these studies also evaluated other performance metrics such as precision, recall, and F1-score. The results consistently showed that deep learning models, particularly CNN-based architectures, excel in handling complex imaging data. However, traditional machine learning algorithms like SVM remain relevant, especially in scenarios where computational resources are limited or when working with smaller datasets.

Overall, these previous studies affirm the value of integrating machine learning algorithms into breast cancer imaging. While deep learning models generally offer higher accuracy, traditional algorithms like SVM continue to play a crucial role, particularly in specific clinical scenarios where resource efficiency and model simplicity are paramount.

2.5. Identification of Research Gaps

Despite the significant advances in machine learning (ML) for breast cancer detection, several research gaps persist, limiting the full potential of these technologies. One critical gap identified in existing studies is the generalizability of ML models across diverse populations. Many models have been developed and validated using datasets that lack sufficient diversity in terms of patient demographics, imaging techniques, and tumor characteristics. This limitation raises concerns about the robustness of these models when applied to broader, more varied populations. For instance, models trained on datasets with predominantly dense breast tissue may not perform well on patients with less dense tissue, leading to potential issues of overdiagnosis or underdiagnosis.

Another notable gap is the integration of ML models into clinical workflows. While numerous studies have demonstrated the high accuracy of various ML algorithms in breast cancer detection, few have addressed the practical challenges of deploying these models in real-world clinical settings. Issues such as the lack of interoperability between ML systems and existing medical imaging infrastructure, as well as the need for clinicians to undergo training to effectively use these new technologies, have not been thoroughly explored. Additionally, there is a scarcity of research on the cost-benefit analysis of implementing ML models in healthcare environments, particularly in resource-constrained settings. Understanding the financial implications, as well as the potential impact on patient care outcomes, is essential for the successful adoption of ML technologies in routine breast cancer screening and diagnosis.

These gaps underscore the need for further research focused on developing more generalizable models, exploring the integration of ML into clinical practices, and conducting comprehensive cost-benefit analyses to ensure that these advanced technologies can be effectively and sustainably implemented in healthcare systems worldwide.

3. Methodology

3.1. Dataset Description: Digital Database for Screening Mammography (DDSM)

The dataset used in this study is the Digital Database for Screening Mammography (DDSM), a well-established resource widely utilized in breast cancer research. The DDSM is a publicly available database that contains a comprehensive collection of mammographic images, which have been meticulously curated to support the development and evaluation of algorithms for breast cancer detection.

The subset employed in this research consists of 5,333 mammograms, categorized into two distinct types: benign and malignant. Each mammogram within the dataset represents a screening case, including four scans of the same patient: craniocaudal (CC) and mediolateral oblique (MLO) views for both the left and right breasts. This configuration allows for a thorough analysis of the breast tissue from multiple angles, which is crucial for accurate diagnosis. The dataset includes 2,662 images depicting malignant cases and 2,671 images of benign masses, ensuring a balanced representation that aids in model training and validation.

To ensure the dataset's suitability for predictive modeling, several preprocessing steps were undertaken. The images underwent noise reduction through median filtering to enhance the visibility of key features. Additionally, contrast enhancement was applied using Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the delineation of regions of interest. Artifacts, which could potentially distort the analysis, were systematically removed to preserve the integrity of the dataset. These preprocessing steps are critical in preparing the data for machine learning algorithms, ensuring that the models are trained on high-quality images.

Table 6 Presents examples of the mammograms used in the study, illustrating the differences between benign and malignant cases.

Type	**Number of Cases**
Malignant	2,662
Benign	2,671
Total	5,333

Figure 2 provides a visual distribution of the cases, highlighting the balanced nature of the dataset

This dataset serves as the foundation for the machine learning models developed in this study, enabling a robust analysis of breast cancer detection using advanced imaging techniques. The use of the DDSM dataset not only provides a diverse set of images but also aligns with the standards required for high-quality medical research, thereby ensuring the reliability and reproducibility of the study's findings.

3.2. Data Preprocessing: Image Quality Assessment, Contrast Enhancement, and Artifact Removal

Data preprocessing is a critical step in preparing mammographic images for analysis and model training in breast cancer detection. The preprocessing process ensures that the images are of high quality, enhancing the accuracy of machine learning models used in the study. The main stages of data preprocessing in this research include image quality assessment, contrast enhancement, and artifact removal.

Image Quality Assessment is the first step in preprocessing, where the sharpness and noise levels of the mammograms are evaluated. Sharpness is crucial as it affects the model's ability to detect edges and fine details within the images. To measure sharpness, the images are converted to arrays, and the gradients along the x-axis and y-axis are computed. The average of these gradients provides an estimate of the image sharpness. Higher values of sharpness indicate better quality, which is essential for accurate classification of benign and malignant tissues. Noise levels are assessed by calculating the differences between pixel intensities in the inner and outer portions of the images. High noise levels can obscure critical features in the mammograms, so noise reduction is essential for improving image quality and ensuring reliable model predictions.

Contrast Enhancement is applied to improve the visibility of regions of interest (ROI) in the mammograms. In this study, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for this purpose. CLAHE works by redistributing the histogram of pixel intensities, effectively enhancing contrast without introducing excessive artifacts that could negatively impact model performance. Proper contrast enhancement is critical for distinguishing between different tissue types and for highlighting abnormalities that may be indicative of cancer.

Artifact Removal is the final preprocessing step, aimed at eliminating distortions and alterations in the imaging dataset that do not accurately represent the breast tissue. Artifacts can arise from various sources, including image labeling, motion blur, and technical issues with the imaging devices. These artifacts can significantly reduce the accuracy of predictive models if not properly addressed. In this study, artifacts were identified and removed systematically. For example, segmentation and masking techniques were used to isolate and exclude consistent artifacts that appeared in specific locations across mammograms of the left and right breasts. This process ensures that the training data is as clean as possible, allowing the models to learn from accurate representations of the breast tissue. Table 7 below provides a summary of the preprocessing steps applied to the DDSM dataset in this study.

Table 7 Summary of Preprocessing Steps for Mammographic Image Analysis

Preprocessing Step	**Method**	**Outcome**
Image Quality Assessment	Gradient Calculation and Noise Estimation	Improved sharpness and reduced noise
Contrast Enhancement	CLAHE	Enhanced visibility of ROIs
Artifact Removal	Segmentation and Masking	Cleaned dataset with reduced artifacts

These preprocessing steps are essential for ensuring that the mammographic images used in this study are of the highest quality, enabling the machine learning models to achieve better accuracy in breast cancer detection.

3.3. Model Development: Training and Testing of Machine Learning Models

The development of machine learning models for breast cancer detection requires a systematic approach, ensuring that each model is meticulously trained and tested to achieve the highest possible accuracy. This study focuses on four key models: EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM). Each model was implemented using a structured pipeline that included data preprocessing, model training, validation, and testing phases.

3.3.1. EfficientNet Model Implementation

EfficientNet is renowned for its ability to balance performance and computational efficiency. The model was trained using mammographic images resized to 224x224 pixels, which is the input size required by the EfficientNet architecture. The model leverages pretrained weights from ImageNet, which provides a solid foundation for feature extraction and model generalization. The training process involved fine-tuning the model on the mammogram dataset for 10 epochs, using a batch size of 32. The Adam optimizer with a learning rate of 0.001 was employed to adjust the model weights, ensuring steady progress in minimizing the loss function throughout the training phase.

3.3.2. DenseNet Model Implementation

DenseNet, known for its dense connectivity, was also utilized in this study. The model's architecture allows for efficient gradient flow and better parameter utilization, making it a strong candidate for image classification tasks. Similar to EfficientNet, DenseNet was trained on images resized to 224x224 pixels, using pretrained weights from ImageNet. The DenseNet model was configured for binary classification, with a dropout layer (p=0.5) added before the final classification layer to prevent overfitting. The training process mirrored that of EfficientNet, with adjustments made to optimize the model's performance through each epoch.

3.3.3. ResNeXt-50 Model Implementation

ResNeXt-50 builds upon the traditional ResNet architecture by introducing grouped convolutions, allowing the model to learn more complex patterns without a significant increase in computational cost. The model was trained using a similar approach to EfficientNet and DenseNet, with images resized to 224x224 pixels and pretrained weights from ImageNet. The model was trained for 10 epochs, with a batch size of 32, and employed the Adam optimizer to adjust the model parameters. The ResNeXt-50 model demonstrated robust performance, particularly in handling the intricate details present in mammographic images.

3.3.4. Support Vector Machine (SVM) Implementation

SVM, a traditional machine learning model, was implemented to provide a benchmark against the deep learning models. Unlike the CNN-based models, SVM does not require extensive data preprocessing or the use of pretrained weights. The model was trained on features extracted from the mammographic images, with the goal of classifying them into benign or malignant categories. The SVM model was optimized using a radial basis function (RBF) kernel, which is particularly effective in handling non-linear data. The training process for SVM was less computationally intensive compared to the deep learning models, making it a viable option in scenarios with limited resources.

Table 8 below summarizes the key parameters used in the training of the machine learning models.

Table 8 Key Training Parameters for Machine Learning Models in Breast Cancer Detection

Model	Input Size	Optimizer	Learning Rate	Batch Size	Epochs
EfficientNet	224x224	Adam	0.001	32	10
DenseNet	224x224	Adam	0.001	32	10
ResNeXt-50	224x224	Adam	0.001	32	10

Each model's performance was evaluated on a separate test set, ensuring that the results were not biased by the training data. The results from this phase provided valuable insights into the strengths and weaknesses of each model, contributing to the final selection of the best-performing algorithm for breast cancer detection.

3.4. Evaluation Metrics: Accuracy, Sensitivity, Specificity, and ROC Analysis

The evaluation of machine learning models in breast cancer detection relies on several key metrics: accuracy, sensitivity, specificity, and Receiver Operating Characteristic (ROC) analysis. These metrics provide a comprehensive understanding of the models' performance, helping to determine their effectiveness in classifying mammographic images as either benign or malignant.

Accuracy is one of the most straightforward metrics used to assess model performance. It is defined as the proportion of correctly predicted cases (both true positives and true negatives) out of the total number of cases. In this study, the EfficientNet model achieved the highest accuracy of 95.23%, outperforming other models such as ResNeXt-50, which had an accuracy of 81.83%, and the Support Vector Machine (SVM), which recorded 86.00%. DenseNet, however, struggled with an accuracy of 58.00%, highlighting its challenges in effectively classifying breast cancer cases.

Sensitivity, also known as recall, measures the proportion of actual positives (malignant cases) that were correctly identified by the model. A high sensitivity indicates that the model is effective at detecting true positive cases, minimizing the number of false negatives. EfficientNet again excelled in this metric, with a sensitivity of 96.67%, indicating its robustness in identifying malignant tumors. SVM followed with a sensitivity of 88.00%, while ResNeXt-50 achieved a sensitivity of 86.30%. DenseNet lagged behind with a sensitivity of 27.00%, suggesting significant limitations in its ability to detect malignant cases accurately.

Specificity is the measure of how well the model identifies true negatives (benign cases), and it complements sensitivity by focusing on the correct identification of non-malignant cases. EfficientNet maintained a balanced performance with a specificity that aligns with its high sensitivity, contributing to its overall effectiveness in breast cancer detection. SVM and ResNeXt-50 also demonstrated respectable specificity, while DenseNet's low specificity highlighted its overall struggle in classification tasks.

ROC Analysis is a crucial tool for visualizing the performance of classification models. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity), providing a graphical representation of the trade-off between sensitivity and specificity. The Area Under the Curve (AUC) is used to quantify the overall performance of the model, with values closer to 1 indicating superior performance. In this study, the EfficientNet model achieved an AUC of 0.99, reflecting its near-perfect performance in distinguishing between benign and malignant cases. SVM and ResNeXt-50 also performed well, with AUC values of 0.94 and 0.91, respectively. DenseNet, however, recorded a lower AUC, consistent with its weaker performance across other metrics. Table 9 summarizes the evaluation metrics for each of the models used in this study.

Table 9 Evaluation Metrics for Machine Learning Models in Breast Cancer Detection

Model	Accuracy	Sensitivity	Specificity	AUC
EfficientNet	95.23%	96.67%	94.82%	0.99
ResNeXt-50	81.83%	86.30%	78.98%	0.91
SVM	86.00%	88.00%	84.00%	0.94
DenseNet	58.00%	27.00%	89.00%	0.62

The evaluation metrics underscore the superior performance of the EfficientNet model in this study, making it the most reliable choice for breast cancer detection among the models tested. The balance between high sensitivity, specificity, and AUC indicates that EfficientNet is well-suited for clinical applications, where accurate and reliable detection of breast cancer is paramount.

3.5. Comparative Analysis of Algorithms

The comparative analysis of machine learning algorithms is crucial in identifying the most effective model for breast cancer detection using mammographic images. This section evaluates and contrasts the performance of four key algorithms: EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM). The analysis focuses on various metrics, including accuracy, sensitivity, specificity, and computational efficiency.

EfficientNet consistently emerged as the top-performing model across multiple evaluation metrics. With an accuracy of 95.23%, it demonstrated superior ability in classifying mammograms into benign and malignant categories. The model's compound scaling method, which uniformly scales network width, depth, and resolution, contributed significantly to its high performance. EfficientNet's sensitivity was 96.67%, indicating its strong capability to detect malignant cases, while maintaining a specificity of 94.82%, which reflects its reliability in correctly identifying benign cases. The combination of these metrics, along with its AUC of 0.99, makes EfficientNet a standout model in this comparative analysis.

DenseNet, despite its innovative dense connectivity that enhances gradient flow and feature reuse, underperformed relative to the other models. The model achieved an accuracy of 58.00%, far below that of EfficientNet and even the SVM. DenseNet's sensitivity was notably low at 27.00%, indicating significant challenges in detecting malignant cases. However, its specificity was relatively high at 89.00%, suggesting that while DenseNet is less effective at identifying cancer, it is fairly reliable at identifying non-cancerous cases. This disparity between sensitivity and specificity highlights DenseNet's limitations in this application, particularly in scenarios requiring high sensitivity.

Table 10 Comparative Evaluation Metrics for Machine Learning Algorithms in Breast Cancer Detection

Algorithm	Accuracy	Sensitivity	Specificity	AUC
EfficientNet	95.23%	96.67%	94.82%	0.99
ResNeXt-50	81.83%	86.30%	78.98%	0.91
SVM	86.00%	88.00%	84.00%	0.94
DenseNet	58.00%	27.00%	89.00%	0.62

ResNeXt-50 presented a balanced performance with an accuracy of 81.83%. Its unique architecture, which incorporates grouped convolutions, allows the model to capture more complex patterns without a significant increase in computational cost. ResNeXt-50's sensitivity was 86.30%, and its specificity was 78.98%, indicating a well-rounded ability to distinguish between benign and malignant cases. However, compared to EfficientNet, ResNeXt-50 fell short in overall performance, particularly in terms of specificity.

Support Vector Machine (SVM)*, a traditional machine learning model, performed admirably with an accuracy of 86.00%. SVM's robustness in handling non-linear data, coupled with its effectiveness in smaller datasets, made it a strong contender in this analysis. The model achieved a sensitivity of 88.00% and a specificity of 84.00%, indicating a well-balanced performance. While SVM did not outperform EfficientNet, it proved to be a reliable alternative, especially in settings where computational resources are limited.

Table 10 summarizes the key evaluation metrics for each algorithm, highlighting their comparative strengths and weaknesses.

The comparative analysis reveals that while each algorithm has its strengths, EfficientNet stands out as the most effective model for breast cancer detection in this study. Its high accuracy, sensitivity, and AUC make it particularly well-suited for clinical applications where reliable and early detection is crucial. ResNeXt-50 and SVM also offer strong performances, providing viable alternatives depending on the specific needs and resources available in a clinical setting. Conversely, DenseNet, despite its innovative architecture, requires further optimization to be competitive in this application.

4. Results and discussion

4.1. Performance Comparison of EfficientNet, DenseNet, ResNeXt-50, and SVM

The comparative performance analysis of the EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM) models highlights the strengths and weaknesses of each algorithm in the context of breast cancer detection using mammographic images.

EfficientNet demonstrated the highest overall performance across all evaluation metrics. With an accuracy of 95.23%, EfficientNet outperformed the other models significantly. The model's compound scaling method, which uniformly scales depth, width, and resolution, allows for superior accuracy and efficiency. The sensitivity of EfficientNet was 96.67%, indicating a strong capability to detect true positives (malignant cases), while the specificity was 94.82%, reflecting its ability to accurately identify benign cases. The Area Under the Curve (AUC) of 0.99 further solidifies EfficientNet's status as the most reliable model in this study, making it particularly well-suited for clinical applications where precision is crucial.

DenseNet, despite its innovative architecture designed to improve gradient flow and feature reuse, underperformed compared to the other models. The accuracy of DenseNet was notably lower at 58.00%, and its sensitivity was a mere 27.00%, indicating significant difficulty in detecting malignant cases. However, DenseNet did show a relatively high specificity of 89.00%, suggesting it was more effective at identifying benign cases. The AUC for DenseNet was 0.62, the lowest among the models, indicating its limited effectiveness in classifying breast cancer in this context.

ResNeXt-50 offered a balanced performance, achieving an accuracy of 81.83%. Its architecture, which incorporates grouped convolutions, allowed it to capture complex patterns within the mammographic images effectively. ResNeXt-50's sensitivity was 86.30%, and its specificity was 78.98%, reflecting a more balanced capability to detect both malignant and benign cases. The AUC for ResNeXt-50 was 0.91, indicating a strong overall performance, though it still lagged behind EfficientNet in terms of precision and reliability.

Support Vector Machine (SVM), a more traditional machine learning algorithm, demonstrated competitive performance with an accuracy of 86.00%. SVM's strength lies in its robustness in handling non-linear data, which is particularly valuable in binary classification tasks like breast cancer detection. The sensitivity of SVM was 88.00%, and its specificity was 84.00%, indicating a well-rounded performance. The AUC for SVM was 0.94, making it a strong contender, especially in scenarios where computational resources are limited or where simpler models are preferred.

EfficientNet emerges as the most effective model for breast cancer detection in this study, offering a balanced combination of high sensitivity, specificity, and overall accuracy. ResNeXt-50 and SVM also perform well, with SVM providing a strong alternative in scenarios requiring simpler models with fewer computational demands. DenseNet, however, shows limitations in this application, particularly in terms of sensitivity and overall accuracy.

4.2. Visual Representation of Confusion Matrices and ROC Curves

Visual representations, such as confusion matrices and Receiver Operating Characteristic (ROC) curves, are essential tools for evaluating the performance of machine learning models. These tools provide insights into how well models classify mammographic images into benign and malignant categories, helping to identify both strengths and weaknesses.

4.2.1. Confusion Matrices

A confusion matrix is a table used to describe the performance of a classification model by comparing actual versus predicted classifications. The matrix includes four key components: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). For each of the models evaluated in this study, confusion matrices provide a visual summary of the correct and incorrect predictions made during the testing phase.

EfficientNet showed a strong performance, with its confusion matrix indicating 1,038 correctly classified cases, including 516 true positives and 522 true negatives. The model made 52 incorrect classifications, with 18 false positives and 34 false negatives. This low error rate underscores the model's reliability in accurately diagnosing breast cancer.

ResNeXt-50 performed moderately, correctly identifying 892 cases, with 426 true positives and 466 true negatives. However, the model misclassified 198 cases, including 74 false positives and 124 false negatives, suggesting areas where the model could be further optimized.

Support Vector Machine (SVM) demonstrated a balanced performance, with 948 correct predictions, consisting of 467 true positives and 481 true negatives. However, the model made 142 incorrect predictions, indicating room for improvement in classification accuracy.

DenseNet struggled in this task, as evidenced by its confusion matrix. The model identified 395 false positives and 145 true negatives, indicating significant challenges in accurately predicting benign cases. This poor performance suggests that DenseNet may not be as effective in breast cancer detection compared to other models in this study.

4.2.2. ROC Curves

The ROC curve is another critical evaluation tool that plots the true positive rate (sensitivity) against the false positive rate (1-specificity). The Area Under the Curve (AUC) provides a single scalar value that summarizes the overall performance of the model, with values closer to 1 indicating better performance.

EfficientNet achieved an exceptional AUC of 0.99, indicating near-perfect sensitivity and specificity. The ROC curve for EfficientNet closely hugs the top-left corner of the plot, underscoring its effectiveness in distinguishing between benign and malignant cases.

ResNeXt-50 and SVM both performed well, with AUC values of 0.91 and 0.94, respectively. These models exhibited solid classification capabilities, though they did not quite reach the performance level of EfficientNet

DenseNet, on the other hand, had the lowest AUC at 0.62, highlighting its difficulties in effectively classifying breast cancer cases. The ROC curve for DenseNet is less steep and further from the ideal top-left corner, reflecting its lower sensitivity and specificity. Table 12 below summarizes the AUC values for each model.

Table 11 Area Under the Curve (AUC) Values for Machine Learning Models in Breast Cancer Detection

Model	**AUC**
EfficientNet	0.99
ResNeXt-50	0.91
SVM	0.94
DenseNet	0.62

The visual representations provided by the confusion matrices and ROC curves offer a clear and comprehensive evaluation of the models' performance. These tools not only highlight the effectiveness of EfficientNet as the leading model but also point out areas where other models like DenseNet could be improved.

4.3. Discussion on the Strengths and Weaknesses of Each Model

The comparative analysis of EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM) models for breast cancer detection has revealed distinct strengths and weaknesses for each algorithm. These differences are critical in understanding the potential applications and limitations of each model in clinical settings.

EfficientNet stands out as the most balanced and effective model in this study. Its primary strength lies in its superior accuracy of 95.23%, combined with a high sensitivity of 96.67% and specificity of 94.82%. The compound scaling method employed by EfficientNet, which balances network depth, width, and resolution, enables it to deliver high performance with relatively low computational resources. This efficiency is further highlighted by its training time, which was significantly reduced when using GPU, making it approximately 8.9 times faster compared to CPU-only training. However, a potential weakness of EfficientNet is the requirement for significant computational power during training, which might limit its accessibility in resource-constrained environments.

DenseNet, despite its innovative architecture that facilitates better gradient flow and feature reuse, exhibited the weakest performance among the models. The model's accuracy was only 58.00%, and it struggled with a sensitivity of just 27.00%. While DenseNet's high specificity of 89.00% indicates its ability to correctly identify benign cases, its poor overall performance suggests that it is not well-suited for breast cancer detection in its current form. The model's extensive connectivity leads to increased computational demands and longer training times, which might not justify the performance benefits in this application. DenseNet's shortcomings highlight the importance of further optimization and possibly combining it with other models or techniques to improve its efficacy.

ResNeXt-50 demonstrated a balanced performance with an accuracy of 81.83%, a sensitivity of 86.30%, and a specificity of 78.98%. The model's use of grouped convolutions allows it to handle complex image patterns effectively without a significant increase in computational cost. ResNeXt-50's strengths are evident in its ability to generalize well across different datasets, making it a robust choice for breast cancer detection. However, its higher misclassification rate compared to EfficientNet and the need for further optimization in class discrimination are notable weaknesses. ResNeXt-50's performance could be enhanced by integrating it with additional preprocessing techniques or hybrid models.

Support Vector Machine (SVM) offers a strong alternative to deep learning models, particularly in scenarios where computational resources are limited. With an accuracy of 86.00%, SVM demonstrated respectable sensitivity and specificity, making it a reliable choice for binary classification tasks like breast cancer detection. The primary strength of SVM lies in its robustness in handling non-linear data and its relatively low computational requirements. However, SVM's performance, while strong, does not reach the levels achieved by EfficientNet, particularly in handling complex image patterns. Additionally, SVM's lack of benefit from GPU acceleration compared to deep learning models might limit its scalability in larger datasets.

Table 13 below summarizes the key strengths and weaknesses of each model.

Table 12 Summary of Strengths and Weaknesses of Machine Learning Models for Breast Cancer Detection

Model	**Strengths**	**Weaknesses**
EfficientNet	High accuracy, sensitivity, and specificity; efficient scaling	High computational demand during training
DenseNet	High specificity; innovative architecture	Low accuracy and sensitivity; high computational demands
ResNeXt-50	Balanced performance; good generalization	Higher misclassification rate; needs further optimization
SVM	Robust in handling non-linear data; low computational requirements	Lower performance compared to deep learning models; no GPU benefit

The EfficientNet model emerged as the most effective for breast cancer detection, offering a balanced combination of high accuracy, sensitivity, and specificity. DenseNet, on the other hand, requires significant improvements to be considered a viable option in this context. ResNeXt-50 and SVM provide strong alternatives, particularly in scenarios where their specific strengths align with the needs of the application. Future research should focus on optimizing these models further and exploring hybrid approaches to leverage the strengths of multiple algorithms.

4.4. Implications for Clinical Practice and Personalized Treatment Planning

The integration of machine learning models such as EfficientNet, DenseNet, ResNeXt-50, and SVM in breast cancer detection holds significant implications for clinical practice and personalized treatment planning. These implications are particularly relevant given the models' ability to improve diagnostic accuracy and tailor treatment approaches to individual patient needs.

4.4.1. Implications for Clinical Practice

The application of advanced machine learning models in clinical settings can revolutionize breast cancer screening and diagnosis. EfficientNet, with its high accuracy and sensitivity, can significantly reduce the rates of false positives and false negatives, thereby improving the overall reliability of breast cancer screenings. This improvement is critical in clinical practice, where accurate diagnosis is essential for determining the most appropriate treatment strategy and reducing patient anxiety associated with diagnostic uncertainty.

Moreover, the use of machine learning models like ResNeXt-50 and SVM in clinical workflows can aid radiologists by providing second opinions and identifying subtle patterns in mammographic images that may be missed by human observers. These models can be integrated into existing diagnostic systems, enhancing the overall diagnostic process and supporting clinicians in making more informed decisions. Additionally, the scalability of these models allows for widespread implementation across various healthcare settings, from specialized cancer centers to general hospitals, ensuring that more patients can benefit from improved diagnostic accuracy.

4.4.2. Personalized Treatment Planning

Machine learning models also offer substantial benefits for personalized treatment planning. By analyzing large datasets of imaging and clinical data, these models can identify patterns and correlations that may not be evident through traditional analysis. For instance, models like EfficientNet and SVM can be used to predict treatment outcomes based on the specific characteristics of a patient's tumor, such as its size, location, and molecular profile. This predictive capability enables the development of personalized treatment plans that are tailored to the individual patient, potentially improving treatment efficacy and reducing the likelihood of adverse side effects.

Personalized treatment planning is further enhanced by the ability of these models to continuously learn and improve as more data becomes available. This adaptability ensures that treatment recommendations remain up-to-date with the latest clinical evidence and best practices. Additionally, the integration of machine learning models into electronic health records (EHR) systems can facilitate real-time decision support, allowing clinicians to make more accurate and timely treatment decisions based on the most current patient data.

Table 14 below illustrates the potential impact of integrating machine learning models into clinical practice and personalized treatment planning.

Table 13 Impact of Machine Learning Models on Clinical Practice and Personalized Treatment Planning in Breast Cancer Detection

Model	Clinical Practice Impact	Personalized Treatment Impact
EfficientNet	Enhanced diagnostic accuracy; reduced false positives/negatives	Tailored treatment plans based on individual tumor profiles
ResNeXt-50	Support for radiologists; improved image pattern recognition	Predictive analysis for treatment outcomes
SVM	Scalability in various healthcare settings	Real-time decision support in EHR systems
DenseNet	Potential for improvement with further optimization	Limited impact due to lower accuracy and sensitivity

These implications underscore the transformative potential of machine learning in breast cancer care. By integrating these models into clinical practice, healthcare providers can enhance diagnostic accuracy, reduce the time to diagnosis, and develop more personalized, effective treatment plans. As machine learning continues to evolve, its role in personalized medicine will likely expand, offering even greater benefits for patients and healthcare systems alike.

4.5. Comparison with Previous Literature

The findings from this study align with and extend upon existing literature in the field of breast cancer detection using machine learning models. The analysis of EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM) in this research provides a contemporary evaluation of these models, highlighting their strengths and limitations in comparison to previous studies.

In recent literature, deep learning models, particularly Convolutional Neural Networks (CNNs), have been extensively applied to breast cancer detection, often yielding higher accuracy than traditional machine learning approaches. For instance, the study by Radha et al. (2023) utilized a combination of HAAR feature extraction and Random Forest classifiers, achieving an accuracy of 91%. Although the dataset size was relatively small, the findings demonstrated the potential of combining advanced feature extraction methods with machine learning models. However, the EfficientNet model in this study outperformed Radha et al.'s approach, achieving an accuracy of 95.23% .

Similarly, Dey et al. (2022) explored the use of CNNs for breast cancer classification, achieving an accuracy of 88.8%. Their study highlighted the limitations of classifying breast cancer into a limited number of categories, which might oversimplify the complexity of tumor types. In contrast, the current research demonstrated that EfficientNet, with its advanced scaling and architecture, could achieve higher accuracy while maintaining a detailed classification of breast cancer types .

Previous studies have also emphasized the utility of SVM in breast cancer detection. For example, Basheer et al. (2013) reported a high accuracy of 93.06% using SVM, coupled with strong sensitivity and specificity. This study corroborates those findings, with the SVM model achieving an accuracy of 86.00% in this analysis. However, the deep learning models, particularly EfficientNet and ResNeXt-50, were shown to outperform SVM in this context, suggesting that while SVM remains a robust traditional approach, deep learning models provide superior performance when applied to large and complex datasets.

The comparative analysis of DenseNet in this study with previous literature reveals significant differences. While DenseNet has been touted for its innovative architecture that enhances gradient flow and feature reuse, its performance in this study was notably lower than expected, with an accuracy of only 58.00%. This is in stark contrast to studies like those by Salama et al. (2020), where deep learning frameworks demonstrated strong performance across different datasets. The lower performance of DenseNet in this study highlights the importance of model selection and optimization, particularly in the context of breast cancer detection where high sensitivity and specificity are critical.

This study's findings are consistent with previous research in demonstrating the superiority of deep learning models over traditional approaches like SVM. However, the results also underscore the importance of choosing the right model architecture and the potential need for further optimization of models like DenseNet to achieve better performance. The use of EfficientNet in this study represents an advancement in the field, offering a robust and efficient model for breast cancer detection that aligns well with and extends the findings of previous literature.

5. Conclusion

5.1. Summary of Key Findings

The comprehensive analysis conducted in this study on the predictive capabilities of machine learning models in breast cancer detection has yielded several significant findings. The research primarily focused on evaluating the performance of four machine learning models: EfficientNet, DenseNet, ResNeXt-50, and Support Vector Machine (SVM). These models were tested on the Digital Database for Screening Mammography (DDSM), which provided a robust dataset for evaluating the effectiveness of each model in classifying mammographic images into benign and malignant categories.

EfficientNet emerged as the top-performing model, demonstrating an accuracy of 95.23%, which was the highest among the models evaluated. This model also achieved a sensitivity of 96.67% and a specificity of 94.82%, indicating its strong capability in correctly identifying both malignant and benign cases. The high Area Under the Curve (AUC) of 0.99 further validated the model's robustness and its potential utility in clinical applications, where high accuracy and reliability are critical.

DenseNet, in contrast, performed poorly, with an accuracy of only 58.00%. Its sensitivity was particularly low at 27.00%, which limits its applicability in clinical settings where the accurate detection of malignant cases is crucial. Despite its innovative architecture designed to enhance gradient flow and feature reuse, DenseNet’s results suggest that further optimization is required for it to be viable in breast cancer detection.

ResNeXt-50] offered a balanced performance with an accuracy of 81.83%, a sensitivity of 86.30%, and a specificity of 78.98%. This model’s unique use of grouped convolutions allowed it to effectively capture complex image patterns, making it a reliable alternative for breast cancer detection. However, it was outperformed by EfficientNet, particularly in terms of accuracy and specificity.

Support Vector Machine (SVM), a traditional machine learning model, demonstrated competitive results with an accuracy of 86.00%, sensitivity of 88.00%, and specificity of 84.00%. Although it did not surpass the performance of EfficientNet, SVM's results are noteworthy, especially given its lower computational demands compared to deep learning models.

The findings from this research underscore the potential of advanced deep learning models like EfficientNet in improving breast cancer detection. The model's high accuracy and efficiency make it particularly suited for clinical use, offering a reliable tool for early diagnosis and treatment planning. However, the study also highlights the need for ongoing optimization and testing of other models, such as DenseNet, to ensure they meet the high standards required in medical applications.

5.2. Recommendations for Future Research

The findings from this study underline several areas where further research could significantly advance the application of machine learning models in breast cancer detection. Despite the notable success of models such as EfficientNet, ResNeXt-50, and SVM, the study also revealed limitations and challenges that future research could address to improve the reliability, accuracy, and clinical integration of these technologies.

One of the primary recommendations for future research is the expansion and diversification of datasets. The current study utilized the Digital Database for Screening Mammography (DDSM), which, while extensive, may not fully represent the diverse global population. Future research should focus on integrating larger and more varied datasets that include images from different demographic groups, ensuring that the models can generalize better to diverse patient populations. This expansion is critical to avoid biases that could affect the accuracy and fairness of diagnostic predictions across different ethnicities and age groups.

Another area that warrants further exploration is the optimization of computational resources. The study highlighted the computational intensity of training deep learning models, particularly DenseNet, which required significant GPU resources. Future research should explore the development of more resource-efficient models or hybrid approaches that can maintain high accuracy while reducing the computational load. This could involve the use of lightweight architectures or the application of transfer learning to pre-trained models, which can significantly reduce training time and resource demands.

Additionally, the concept of edge computing presents a promising avenue for future work. By processing imaging data closer to the point of collection, edge computing can reduce the reliance on large cloud infrastructures and enhance the privacy and security of patient data. Research into the integration of edge computing with machine learning models for breast cancer detection could lead to more efficient, secure, and real-time diagnostic tools, particularly in resource-constrained environments.

Lastly, future research should focus on the regulatory and ethical implications of deploying machine learning in healthcare. As machine learning models become more integrated into clinical workflows, it is essential to establish frameworks that ensure compliance with medical device regulations and ethical standards. Research should explore the development of guidelines for the safe and effective use of these technologies, addressing issues such as data privacy, accountability in case of diagnostic errors, and the transparency of decision-making processes.

While this study has made significant strides in demonstrating the potential of machine learning models for breast cancer detection, ongoing research is needed to address the identified challenges. By focusing on dataset diversity, resource efficiency, edge computing, and regulatory frameworks, future studies can further enhance the accuracy, accessibility, and ethical deployment of these advanced diagnostic tools.

5.3. Limitations of the Study

Despite the promising results obtained in this study, several limitations must be acknowledged. These limitations pertain primarily to the dataset, computational resources, and the generalizability of the findings.

One of the most significant limitations of this study is the volume and variation of the dataset used. The research utilized the Digital Database for Screening Mammography (DDSM), which, although extensive, may not fully represent the diversity found in real-world clinical settings. Predictive models generally perform better when trained with larger and more varied datasets. However, due to the constraints of the dataset, there may be challenges in applying the results of this study to a broader, more diverse population. This limitation could impact the effectiveness of the EfficientNet model in real-world healthcare environments where data is often noisier

5.4. Concluding Remarks

The research presented in this study underscores the significant advancements that machine learning models, particularly EfficientNet, can bring to the early detection and diagnosis of breast cancer. Through a comprehensive analysis of several models, including DenseNet, ResNeXt-50, and Support Vector Machine (SVM), this study has demonstrated that machine learning offers substantial improvements over traditional diagnostic methods. The application of these models to the Digital Database for Screening Mammography (DDSM) provided a robust testing ground, allowing for a detailed evaluation of each model's performance.

The findings from this study confirm that EfficientNet is particularly well-suited for breast cancer detection, with an accuracy of 95.23% and a sensitivity of 96.67%. These results suggest that EfficientNet not only excels in correctly identifying malignant cases but also minimizes the occurrence of false positives, a critical factor in clinical diagnostics. While ResNeXt-50 and SVM also showed strong performances, DenseNet struggled, indicating the need for further optimization and perhaps a reevaluation of its application in this context.

Looking forward, the integration of machine learning models like EfficientNet into clinical practice holds great promise for enhancing the accuracy and reliability of breast cancer diagnostics. However, as this study also highlighted, there are challenges that need to be addressed, particularly regarding dataset diversity, computational resources, and the generalizability of these models across different populations.

This research contributes to the growing body of evidence supporting the use of advanced machine learning techniques in medical imaging, particularly for the detection of breast cancer. The continued development and refinement of these models, combined with larger and more diverse datasets, will be essential in ensuring their successful implementation in real-world clinical settings. The potential for machine learning to revolutionize cancer diagnostics is immense, and this study represents a significant step forward in realizing that potential.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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