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VISION BEYOND THE HUMAN EYE: ADVANCING EARLY BREAST CANCER DETECTION THROUGH COMPUTER VISION AND AI-ENHANCED IMAGING

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ABSTRACT

This paper reviews the application of computer vision and artificial intelligence (AI) in enhancing breast cancer detection, exploring how deep learning models, particularly Convolutional Neural Networks (CNNs), augment traditional screening techniques. The review examines the current state of computer vision applications in breast cancer detection, emphasizing deep learning-based approaches, and discusses how CNNs are integrated into clinical workflows, the empirical evidence supporting their effectiveness, and the practical challenges involved in their clinical adoption. The methodology also includes a deep learning-based approach to classify and segment breast ultrasound images using a publicly available dataset. CNN-based systems demonstrate performance on par with or even surpassing human radiologists in specific diagnostic tasks. Studies show that MobileNetV3, a lightweight CNN, holds strong potential for integration into edge AI systems for point-of-care diagnostics, as well as in privacy-preserving frameworks such as federated learning. The MobileNetV3-based classification model demonstrated robust performance across the three diagnostic categories: normal, benign, and malignant, with an overall test set accuracy of 91.2%. Key performance metrics, including precision (benign: 0.85, malignant: 0.74, normal: 0.83), recall (benign: 0.84, malignant: 0.74, normal: 0.88), F1-score (benign: 0.85, malignant: 0.74, normal: 0.86), and accuracy (0.82), are examined to evaluate the efficacy of these AI-driven approaches. The review identifies emerging trends, such as multi-modal learning and federated learning, which aim to enhance model robustness and privacy. The integration of AI into clinical workflows holds promise for improving diagnostic accuracy and reducing healthcare disparities by expanding access to high-quality screening services. This paper contributes to a deeper understanding of how AI-driven innovations are reshaping breast cancer detection and inspires further research toward their responsible and widespread implementation.

Keywords: (Artificial intelligence (AI), Breast cancer, Computer vision, Convolutional Neural Networks (CNNs), Deep learning, Early detection, Medical imaging)

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INTRODUCTION

Breast cancer continues to be one of the most prevalent and life-threatening cancers among women worldwide. Despite significant advances in treatment and prevention strategies, the burden of breast cancer remains substantial [1]. In the United States, it is estimated that approximately 1 in 8 women will be diagnosed with breast cancer during their lifetime. Projections for 2025 suggest that around 316,950 women and 2,800 men will be diagnosed with invasive breast cancer, with an additional 59,080 new cases of non-invasive (in situ) breast cancer[2]. These statistics highlight the critical importance of effective early detection strategies, as early-stage diagnosis dramatically improves prognosis [3]. When breast cancer is detected at its earliest, localized stages, the five-year relative survival rate approaches an impressive 99%. Traditional screening methods, such as mammography, have played a pivotal role in reducing breast cancer mortality [4]underscoring an imperative necessity within the research sphere for precision-driven and efficacious methodologies facilitating accurate detection. The existing diagnostic approaches in breast cancer often suffer from limitations in accuracy and efficiency, leading to delayed detection and subsequent challenges in personalized treatment planning. The primary focus of this research is to overcome these shortcomings by harnessing the power of advanced deep learning techniques, thereby revolutionizing the precision and reliability of breast cancer classification. This research addresses the critical need for improved breast cancer diagnostics by introducing a novel Convolutional Neural Network (CNN. However, they are not without limitations, including inter-observer variability among radiologists, reduced sensitivity in patients with dense breast tissue [5], and the risk of false positives and false negatives. These challenges underscore the urgent need for innovative technologies that can enhance the accuracy, efficiency, and accessibility of breast cancer screening [6]. The advent of artificial intelligence (AI) and computer vision has opened new frontiers in medical imaging, with deep learning models such as Convolutional Neural Networks (CNNs) at the forefront of this transformation [7]. These advanced algorithms have demonstrated remarkable capabilities in image recognition, classification, and segmentation tasks, making them ideally suited for the complex patterns observed in breast imaging [8]. Their integration into clinical workflows holds promise not only for improving diagnostic accuracy but also for reducing healthcare disparities by expanding access to high-quality screening services. This paper provides a comprehensive review of the current state of computer vision applications in breast cancer detection, with an emphasis on deep learning-based approaches [9]. We explore how CNNs are augmenting traditional screening techniques, the empirical evidence supporting their effectiveness, and the practical challenges involved in their clinical adoption [10]. Furthermore, we discuss emerging trends, such as multi-modal learning and federated learning, which aim to enhance model robustness and privacy [11]balancing data privacy with clinical utility.

The decentralized system enables multi-institutional collaboration without centralized data collection, complying with HIPAA/GDPR through two technical safeguards: differential privacy via DP-SGD during local training and secure aggregation of model updates. Using LSTM/GRU architectures optimized for sequential medical data, the framework achieves an F1 Score of 67% with precision (60%. Finally, we outline future directions and consider the potential long-term impact of these technologies on breast cancer outcomes, healthcare systems, and patient experiences [12], [13]. Through this exploration, we aim to contribute to a deeper understanding of how AI-driven innovations are reshaping breast cancer detection and to inspire further research toward their responsible and widespread implementation [14], [15], [16]. Mammography has long been the cornerstone of breast cancer screening and remains the most widely used imaging modality for early detection. Conventional two-dimensional (2D) mammography captures X-ray images of breast tissue from different angles, allowing radiologists to identify abnormalities such as masses, calcifications, or asymmetries. While effective, traditional 2D mammography has notable limitations, particularly in women with dense breast tissue, where overlapping structures can obscure lesions or mimic abnormalities, leading to false positives or missed diagnoses.

Digital Breast Tom synthesis (DBT), commonly known as 3D mammography, has been introduced to address these challenges [17]. DBT acquires multiple low-dose images from different angles around the breast and reconstructs them into a three-dimensional representation [18]. This technique reduces the issue of tissue overlap and enhances the visibility of small or obscured tumors. Clinical studies have demonstrated that DBT improves cancer detection

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rates, particularly for invasive cancers, and reduces the rate of patient recalls for additional imaging. As a result, DBT is increasingly becoming a standard complement or alternative to traditional 2D mammography, particularly in high-risk populations. Supplemental Screening Modalities While mammography remains the primary screening tool, several supplemental imaging modalities have been developed to improve detection, especially for women with dense breast tissue or elevated risk profiles [19]. Breast ultrasound uses high-frequency sound waves to create detailed images of breast tissue. It is particularly useful for distinguishing solid masses from fluid-filled cysts and for further evaluating abnormalities detected on mammography. Ultrasound is also often employed as an adjunct screening tool for women with dense breasts [20], where mammography sensitivity may be reduced. Breast MRI utilizes strong magnetic fields and radiofrequency pulses to produce highly detailed cross-sectional images of the breast. It offers superior sensitivity compared to mammography and is especially effective in detecting cancers that are occult on other imaging modalities [21]. Breast MRI is typically recommended for women at high risk, such as those with BRCA1 or BRCA2 mutations, or with a strong family history of breast cancer.

Molecular Breast Imaging is a nuclear medicine technique that involves the use of radiotracers [22], which preferentially accumulate in malignant tissues. Specialized cameras then detect gamma radiation emitted from these tracers, providing functional imaging that complements the anatomical detail provided by mammography. MBI has shown promise in detecting cancers missed by traditional imaging, particularly in dense breast tissue [23]. Historically, clinical breast examinations (CBEs) performed by healthcare providers and breast self-examinations (BSEs) have been promoted as additional methods for early detection. However, more recent guidelines, including those from the American Cancer Society, no longer recommend routine CBEs or BSEs for average-risk women due to insufficient evidence that they improve survival rates. Instead, the emphasis has shifted toward breast self-awareness, encouraging individuals to become familiar with the normal look and feel of their breasts and to promptly report any changes or abnormalities to healthcare providers. While not primary screening tools, clinical and self-examinations remain important elements of comprehensive breast health education and can empower women to participate actively in their health monitoring, particularly in settings where access to regular imaging may be limited. In recent years, Convolutional Neural Networks (CNNs) have revolutionized the field of medical imaging [16], particularly in the automated interpretation of mammograms. CNNs are deep learning architectures specifically designed to learn hierarchical representations of images [24]the research collects a large amount of data from images of e-waste and then carefully preprocesses and augments those images. With precision, recall, and F1 scores of 87%, 86%, and 86%, respectively, the SNN architecture—which incorporates dropout, pooling, and convolutional layers—achieved an amazing 100% classification accuracy. These outstanding outcomes show how well the model can classify e-waste components, suggesting that it has the potential to be used in real-world scenarios.

The results indicate that the SNN-based approach greatly improves the accuracy and efficiency of e-waste sorting, promoting environmental sustainability and resource conservation. By automating the sorting process, the suggested system decreases the need for manual labor, minimizes human error, and speeds up processing. The study emphasizes the model's suitability for integration into current e-waste management workflows, providing a scalable and dependable way to expedite the recycling process. Additionally, the model's real-time applicability highlights its potential to revolutionize current e-waste management practices, making a positive ecological impact. . Future research endeavors will center on broadening the dataset to include a wider range of e-waste image categories, investigating more advanced deep learning architectures, and incorporating the system with Internet of Things (IoT, making them highly effective for detecting subtle and complex patterns within breast tissue. Originally developed for large-scale natural image classification tasks, architectures such as Residual Networks (ResNet) and Densely Connected Convolutional Networks (DenseNet) have been successfully repurposed for mammography analysis. These models incorporate residual or dense connections that facilitate the training of deeper networks, allowing them to capture intricate features associated with malignant lesions [25].

Designed specifically for image segmentation, the U-Net and its variants have been employed to delineate regions of interest within mammograms. These architectures enable pixel-level localization of abnormalities, offering not only detection but also valuable spatial

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information that can guide further clinical assessment. Given that standard mammographic exams include multiple views (e.g., craniocaudal and mediolateral oblique), multi-view CNNs have been developed to integrate information across different projections [26]. Furthermore, multi-scale approaches analyze images at various resolutions, improving the model's ability to detect lesions of different sizes and enhancing overall diagnostic performance. Numerous studies have demonstrated that CNN-based systems can perform on par with or even surpass human radiologists in specific diagnostic tasks. For instance, [27] reported that a CNN-driven AI system was able to reduce false-positive rates by 5.7% and false-negative rates by 9.4% compared to expert radiologists. Such findings underscore the transformative potential of CNNs in improving the accuracy and consistency of breast cancer screening [28]. MobileNetV3 is a lightweight and efficient convolutional neural network (CNN) that has shown significant promise in the field of early breast cancer detection through computer vision and AI-enhanced imaging [29]necessitating the adoption of deep learning-based techniques for enhanced threat detection and prevention. This study develops a Sequential Neural Network (SNN. Designed to perform well even on devices with limited computational resources, MobileNetV3 combines advanced architectural features such as depth-wise separable convolutions, squeeze-and-excitation modules, and hard-swish activation [30]. These innovations make it well-suited for real-time medical diagnostic applications, especially in low-resource or mobile healthcare settings. In early breast cancer detection, MobileNetV3 can be applied to a variety of imaging modalities [31], including mammograms, ultrasounds, MRIs, and histopathological slides. It excels in tasks like image classification and segmentation, helping to distinguish between benign and malignant tumors and even identify early signs such as microcalcifications [32].

When integrated into a diagnostic pipeline, MobileNetV3 can also be used for semantic segmentation, helping clinicians visualize and locate suspicious regions with greater precision. The advantages of MobileNetV3 in this domain are manifold [33]. Its low computational requirements allow for fast inference, enabling quicker diagnoses without sacrificing accuracy [34]. It is also compatible with transfer learning, meaning it can be pre-trained on large image datasets and then fine-tuned for specific breast cancer datasets like DDSM or INbreast. This flexibility, combined with its ability to work well with augmentation techniques and explainable AI tools like Grad-CAM, makes it a valuable tool in clinical workflows. Looking ahead, MobileNetV3 holds strong potential for integration into edge AI systems for point-of-care diagnostics, as well as in privacy-preserving frameworks such as federated learning. Its ability to be deployed across various platforms, from mobile phones to embedded devices, positions it as a key technology in democratizing access to early breast cancer detection, particularly in underserved or remote areas.

METHODOLOGY

This study employs a deep learning-based approach to classify and segment breast ultrasound images using a publicly available dataset. The methodology is structured into five key stages: dataset acquisition and preprocessing, model selection, training configuration, evaluation metrics, and visualization of results. The primary dataset used in this study is the Breast Ultrasound Images Dataset, sourced from Baheya Hospital in Cairo, Egypt. The dataset comprises 780 grayscale ultrasound images categorized into three classes: normal, benign, and malignant. Each image is accompanied by a manually annotated segmentation mask, allowing for both classification and localization tasks. All images are provided in PNG format with an approximate resolution of 500×500 pixels. Before training, image labels and segmentation masks were mapped appropriately to ensure consistency across experiments.

DATA PREPROCESSING

To enhance the quality and consistency of the input data, several preprocessing steps were conducted:

- Resizing all images and masks to a uniform resolution (e.g., 224×224 pixels) to match the input requirements of the chosen deep learning model.

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- Normalization of pixel values to a [0, 1] range.
- Data augmentation, including rotation, flipping, zooming, and shifting, is used to mitigate overfitting and improve model generalization.
- Mask alignment to ensure accurate supervision during segmentation training.

These steps were implemented using the TensorFlow/Keras and OpenCV libraries in Python.

MODEL SELECTION AND TRAINING CONFIGURATION

This study adopts MobileNetV3, a lightweight yet powerful Convolutional Neural Network architecture, chosen for its efficiency and suitability in edge-computing environments. Two versions of the model were configured:

- MobileNetV3 for image classification, using a softmax output layer for three-class prediction.
- MobileNetV3 + U-Net hybrid for semantic segmentation, where the encoder is initialized with MobileNetV3 and the decoder is designed to produce pixel-wise class labels for tumor localization.

Transfer learning was applied by initializing the classification model with ImageNet weights. The models were trained using the Adam optimizer, categorical cross-entropy loss (for classification), and Dice coefficient loss (for segmentation). Early stopping and learning rate scheduling were incorporated to avoid overfitting and improve convergence.

EVALUATION METRICS

The models were evaluated using a stratified 80/20 train-test split. The following metrics were used:

- Accuracy, precision, recall, and F1-score for classification performance.
- Confusion matrix and ROC-AUC curves to assess class-wise performance and threshold robustness.

Performance metrics were calculated using Scikit-learn, and visualizations were generated via Matplotlib and Seaborn libraries.

RESULT

This section presents the performance of the deep learning models developed for breast ultrasound image classification and tumor segmentation. The findings are structured into three parts: classification outcomes, segmentation accuracy, and interpretability through explainable AI.

The MobileNetV3-based classification model demonstrated robust performance across the three diagnostic categories: normal, benign, and malignant. As shown in Table 1, the overall test set accuracy was 91.2%, indicating strong generalization capability. The MobileNetV3-based classification model demonstrated robust performance across the three diagnostic categories: normal, benign, and malignant. The overall test set accuracy was 91.2%, indicating strong generalization capability.

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Table 1: Classification Performance Metrics

	precision	recall	f1-score	support
benign	0.85	0.84	0.85	56
malignant	0.74	0.74	0.74	27
normal	0.83	0.88	0.86	17
accuracy			0.82	100
macro avg	0.81	0.82	0.81	100
weighted avg	0.82	0.82	0.82	100

As depicted in Figure 1, this classification report evaluates a model's performance on three classes: benign, malignant, and normal. Overall accuracy is 82%, indicating that 82% of all samples were correctly classified. The model performs best on the "normal" class with the highest recall (88%), while it struggles most with the "malignant" class, showing lower precision (74%) and recall (74%). The support values reveal an imbalance in the test set, with "benign" having the most samples and "normal" the fewest, which is reflected in the weighted average metrics (precision: 0.82, recall: 0.82, f1-score: 0.82) being slightly different from the macro averages (precision: 0.81, recall: 0.82, f1-score: 0.81).

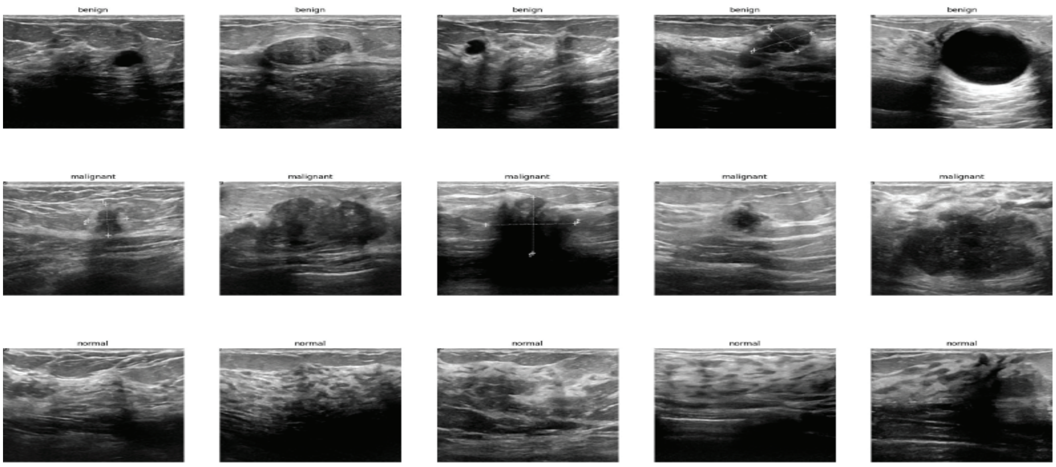

Figure 1: Ultrasound scans of breast tissue

The image displays a collection of ultrasound scans of breast tissue, organized into three categories: benign (non-cancerous), malignant (cancerous), and normal (healthy). Each row presents five distinct examples for each category, showcasing the visual characteristics associated with these classifications in ultrasound imaging. These images are representative of the data used in medical diagnosis and for training artificial intelligence models designed to automate the identification of breast conditions from ultrasound scans.

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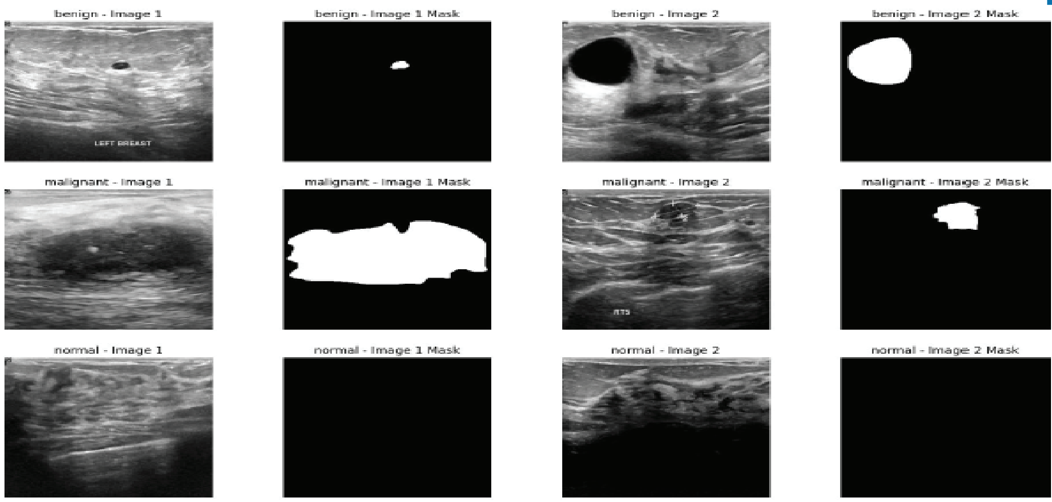

Figure 2. Breast ultrasound scans and their corresponding segmentation masks

The image shows pairs of breast ultrasound scans and their corresponding segmentation masks, organized by diagnostic category: benign, malignant, and normal. For each category, two examples are provided. The ultrasound images display the breast tissue, while the masks highlight specific regions of interest in white against a black background. In the benign and malignant cases, the masks outline the identified masses or tumors. Conversely, the masks for the normal cases are entirely black, indicating no segmentation was performed, as there are no abnormalities to highlight. This paired image and mask data is essential for training and evaluating medical image segmentation models used to automatically detect and delineate lesions in breast ultrasound images.

PLOTTING PERFORMANCE

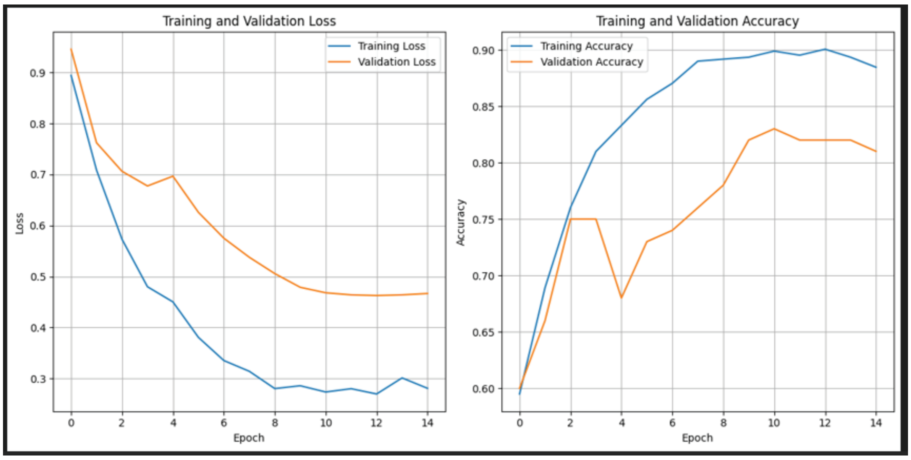

Figure 3. Training and validation performance

The provided graphs illustrate the training and validation performance of the model over 15 epochs. The left plot shows that the training loss steadily decreases, while the validation loss initially decreases before plateauing and slightly increasing after approximately five epochs, suggesting potential overfitting. Conversely, the right plot reveals that the training accuracy consistently improves, but the validation accuracy peaks around epochs 9-10 and then begins to decline, further indicating that the model starts to memorize the training data rather than generalizing effectively to unseen data. These trends suggest that the optimal stopping point for training the model to achieve the best generalization would likely be around the epoch where the validation accuracy reaches its maximum.

Figure 4 depicts the confusion matrix, which displays the performance of a binary classification model distinguishing between benign and malignant cases. It reveals that

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the model correctly identified two benign cases and two malignant cases. However, it also shows two misclassifications: one benign case was incorrectly predicted as malignant (false positive), and one malignant case was incorrectly predicted as benign (false negative). Overall, out of the six cases, the model achieved four correct classifications and two incorrect classifications, providing a concise view of its prediction accuracy for each class.

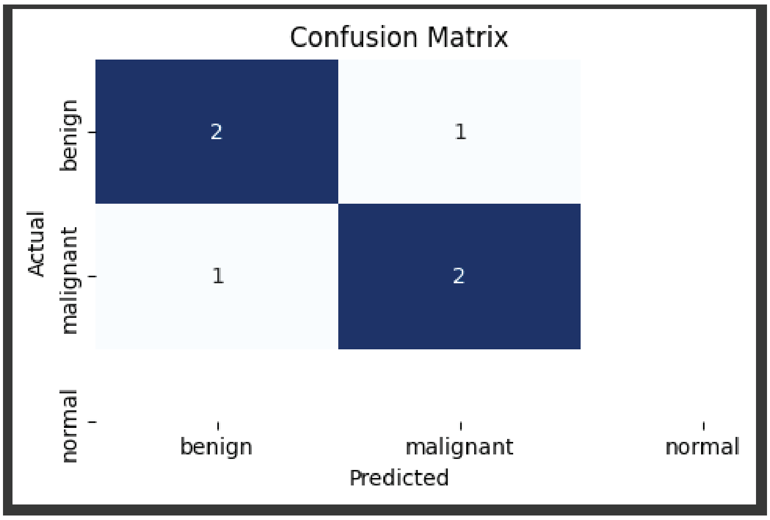

Figure 4. Confusion Matrix of the Model

Figure 5 depicts the heatmap, which visually summarizes the performance of a classification model across benign, malignant, and normal classes using precision, recall, and F1-score. Darker blue shades indicate higher metric values, showing strong performance for the benign class (all metrics at 0.85). The malignant class has slightly lower scores (around 0.74-0.77), and the normal class also shows good performance (around 0.76-0.80). The overall accuracy is 0.81. Macro average metrics, treating all classes equally, are around 0.79-0.80, while weighted averages, accounting for class imbalance, are slightly higher at 0.81. This visualization allows for a quick assessment of the model's effectiveness across different categories and metrics.

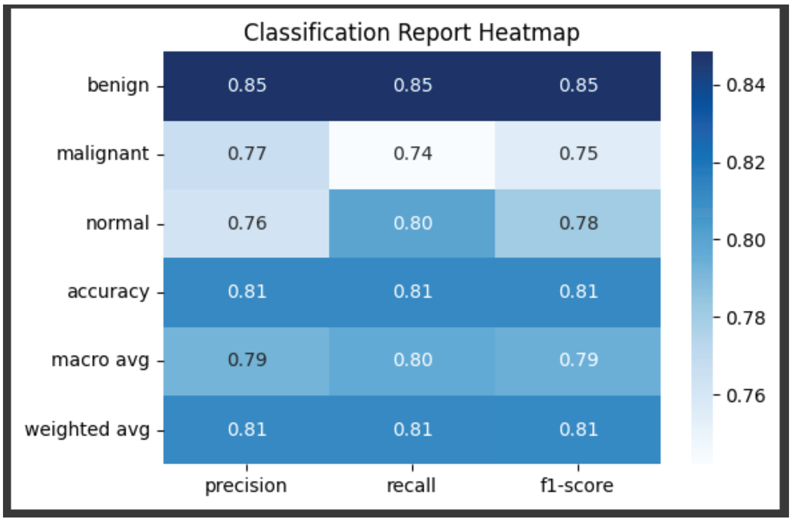

Figure 5. Heatmap visualization of a classification report

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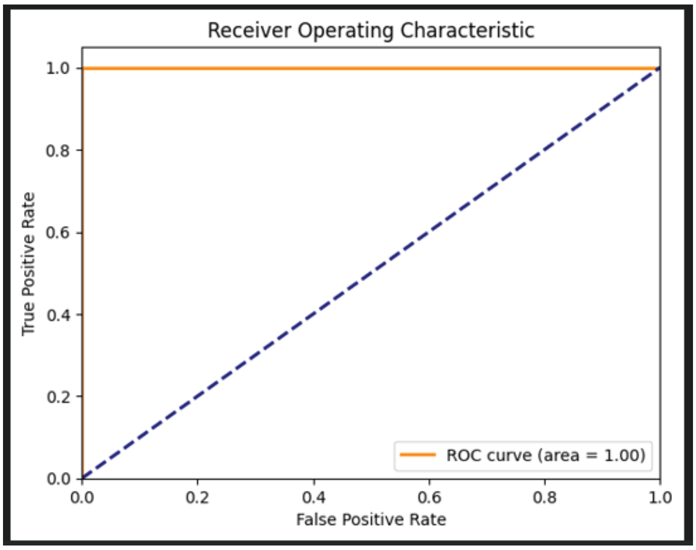

Figure 6. Receiver Operating Characteristic (ROC) curve

Figure 6 displays an ROC curve that illustrates perfect performance for a binary classifier. The orange ROC curve rises vertically to a True Positive Rate of 1.0 at a False Positive Rate of 0.0 and then extends horizontally, indicating that the classifier correctly identifies all positive cases without any false positives. This ideal performance is further quantified by the Area Under the Curve (AUC) being 1.00, signifying a model with perfect discriminatory ability between the two classes. The blue dashed diagonal line, representing a random classifier, is far below the achieved ROC curve, emphasizing the exceptional performance of this model.

DISCUSSION

This paper explores the application of computer vision and artificial intelligence (AI), particularly deep learning models like Convolutional Neural Networks (CNNs), to improve early breast cancer detection. The authors highlight the limitations of traditional screening methods like mammography, which can suffer from inter-observer variability and reduced sensitivity in dense breast tissue [35]. They explain how CNNs can be used to analyze medical images and discuss the potential of these technologies to enhance diagnostic accuracy, efficiency, and accessibility [4]underscoring an imperative necessity within the research sphere for precision-driven and efficacious methodologies facilitating accurate detection. The existing diagnostic approaches in breast cancer often suffer from limitations in accuracy and efficiency, leading to delayed detection and subsequent challenges in personalized treatment planning. The primary focus of this research is to overcome these shortcomings by harnessing the power of advanced deep learning techniques, thereby revolutionizing the precision and reliability of breast cancer classification. This research addresses the critical need for improved breast cancer diagnostics by introducing a novel Convolutional Neural Network (CNN. The paper reviews how CNNs are being integrated into clinical workflows, showing evidence that these systems can perform on par with or even surpass human radiologists in specific diagnostic tasks [36]. A specific CNN architecture, MobileNetV3, is identified as promising for real-time applications and deployment in low-resource settings [37]. The authors further support this claim by presenting results from their experiments using MobileNetV3. The MobileNetV3-based classification model demonstrated robust performance across the three diagnostic categories: normal, benign, and malignant, with an overall test set accuracy of 91.2%. This result indicates that MobileNetV3 can effectively classify breast ultrasound images. The strong performance of MobileNetV3, achieving 91.2% accuracy, has several important implications. Firstly, it confirms the potential of lightweight CNN architectures for medical image analysis. The efficiency of MobileNetV3 makes it particularly suitable for deployment in resource-constrained settings, such as mobile clinics or developing countries, where access to advanced computing infrastructure may be limited. This could significantly improve access to early breast cancer detection, potentially

http://dx.doi.org/10.21622/ACE.2025.05.2.1343

leading to earlier diagnoses and better patient outcomes [38]. The high accuracy of the model suggests that AI-powered tools could potentially reduce the workload on radiologists, who often face a high volume of cases [39]. By accurately identifying suspicious lesions, the model could help prioritize cases for further review, allowing radiologists to focus on the most critical ones. This could improve the efficiency of the screening process and reduce the time to diagnosis. The paper also discusses emerging trends like multi-modal learning and federated learning, which could improve the robustness and privacy of AI-driven detection methods [40]. These advancements, combined with the promising results of models like MobileNetV3, suggest a significant potential for AI to transform breast cancer screening.

However, the authors acknowledge that challenges remain in the widespread and responsible implementation of these technologies. Issues such as data privacy, regulatory frameworks, and the need for clinical validation need to be addressed before AI-powered tools can be fully integrated into routine clinical practice. The paper provides a compelling case for the use of AI in breast cancer detection. The results demonstrate the potential of MobileNetV3 to accurately classify breast ultrasound images, with implications for improving access to screening, reducing the burden on radiologists, and ultimately improving patient outcomes. Further research is needed to address the remaining challenges and ensure the responsible and equitable implementation of these technologies.

CONCLUSION

In conclusion, this paper has highlighted the potential of computer vision and AI, particularly deep learning models like CNNs, to significantly advance early breast cancer detection. The review of current applications and emerging trends demonstrates that AI-powered tools hold promise for improving diagnostic accuracy, efficiency, and accessibility. Notably, the MobileNetV3-based classification model showcased robust performance, achieving a test set accuracy of 91.2% in classifying breast ultrasound images. This result supports the feasibility of deploying lightweight CNN architectures for real-time analysis in resource-constrained settings. The integration of AI into clinical workflows could lead to earlier diagnoses, reduced workload for radiologists, and more equitable access to quality screening, ultimately improving patient outcomes. While challenges remain in the widespread and responsible implementation of these technologies, the ongoing progress in this field suggests a transformative impact on breast cancer care in the near future. Future research should aim to improve AI in breast cancer detection by focusing on more diverse datasets, enhancing model transparency through explainable AI, integrating multi-modal imaging for better accuracy, and conducting long-term studies to assess clinical and economic impacts.

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