

BI-RADS - A Composite Multi-Tasking Neural Network for Computer-Aided Diagnosis of Breast Cancer in Ultrasound Images with Semantic and Quantitative Explanation

Vasuki C ¹, Madhubala P ²

¹M.E., Computer Science and Engineering & Bharathiyar Institute of Engineering for Women, Salem.

Email id: vasukic2002@gmail.com

² Assistant Professor, Computer Science and Engineering & Bharathiyar Institute of Engineering for women, Salem. Email id: madhubalaprocse@gmail.com

Abstract— Breast cancer remains one of the most common causes of cancer-related mortality among women worldwide, highlighting the importance of early and accurate detection. Ultrasound imaging is widely used for breast cancer screening because it is non-invasive, relatively low cost, and effective for identifying abnormalities in dense breast tissue. However, the interpretation of ultrasound images largely depends on the expertise of radiologists, which may lead to variability and potential diagnostic errors. In recent years, computer-aided diagnosis (CAD) systems based on deep learning have been introduced to assist clinicians by providing automated and consistent analysis of medical images.

This study presents BI-RADS, a composite multi-tasking neural network designed for computer-aided diagnosis of breast cancer using ultrasound images. The proposed model integrates multiple related tasks within a single deep learning framework, including lesion segmentation, classification, and explanation generation. By performing these tasks simultaneously, the model can learn more comprehensive features and improve diagnostic performance. The system follows the Breast Imaging Reporting and Data System (BI-RADS) guidelines to generate both semantic and quantitative explanations, such as BI-RADS descriptors and visual attention maps that highlight important regions in the ultrasound images.

The architecture employs convolutional neural networks to extract meaningful spatial features from ultrasound images while dedicated modules handle lesion localization and classification. In addition, an explanation component enhances model transparency by providing interpretable outputs that help clinicians understand the reasoning behind the predictions. Experimental evaluations indicate that the proposed multi-task learning framework improves classification accuracy and segmentation quality compared to traditional single-task models. The results demonstrate that BI-RADS-V2 can effectively support radiologists by providing reliable diagnostic predictions along with interpretable explanations, thereby contributing to improved breast cancer detection and clinical decision-making.

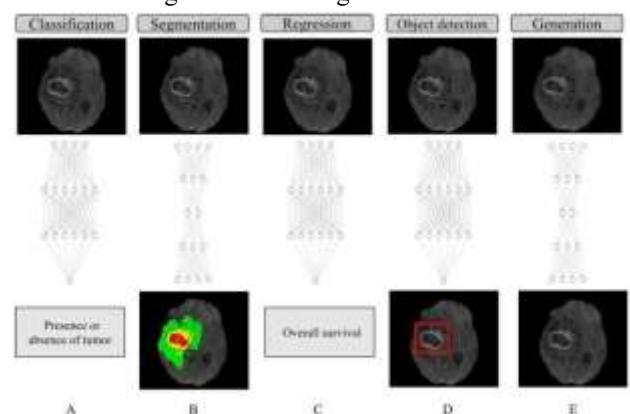
Keywords— Breast Cancer Detection, Ultrasound Imaging, Computer-Aided Diagnosis (CAD), Multi-Task Learning, Convolutional Neural Networks (CNN), BI-RADS, Medical Image Segmentation, Explainable Artificial Intelligence (XAI).

I. INTRODUCTION

Breast cancer remains one of the most common cancers affecting women globally, and early detection plays a crucial role in reducing mortality rates. Medical imaging techniques such as mammography, ultrasound, and MRI are widely used for breast cancer screening and diagnosis.

Among these modalities, ultrasound imaging is particularly useful for detecting tumors in dense breast tissues and for differentiating between cystic and solid masses. However, ultrasound images often contain noise, low contrast, and complex textures, which makes manual interpretation challenging even for experienced radiologists. This creates a need for intelligent computer-aided diagnostic systems that can assist in identifying suspicious lesions accurately and consistently.

Deep learning techniques have significantly improved medical image analysis by automatically learning complex features from large datasets. Traditional CAD systems mainly focus on classification tasks, which may not provide sufficient explanation for clinical decision-making. The BI-RADS standard is widely used by radiologists to describe lesion characteristics such as shape, margin, orientation, and echogenicity. Therefore, integrating BI-RADS-based semantic descriptions with automated classification can enhance model interpretability. The proposed BI-RADS multi-task neural network addresses this challenge by jointly performing lesion segmentation, classification, and semantic attribute prediction while generating quantitative explanations that align with clinical guidelines.



A. Problem Statement

Breast cancer is one of the leading causes of death among women worldwide, and early detection plays a crucial role in improving survival rates. Ultrasound imaging is commonly used as a diagnostic tool for detecting breast lesions because it is non-invasive, affordable, and effective for examining dense breast tissue. However, the interpretation of ultrasound images is highly dependent on the experience and expertise of radiologists. This subjectivity can lead to variability in diagnosis, potential

misclassification of lesions, and delays in identifying malignant tumors.

Existing computer-aided diagnosis (CAD) systems have been developed to support radiologists in analyzing medical images. While many of these systems utilize deep learning models to classify breast lesions, most of them focus on a single task such as classification or segmentation. Single-task models may fail to capture the complex relationships between lesion characteristics, shape, and surrounding tissue structures, which can limit their diagnostic performance and reliability.

Another major challenge in medical image analysis is the lack of interpretability in deep learning models. Many existing systems function as “black boxes,” providing predictions without clear explanations. In clinical practice, radiologists require not only accurate predictions but also meaningful explanations that align with medical standards such as the BI-RADS guidelines. Without interpretable outputs, it becomes difficult for clinicians to trust and adopt automated diagnostic systems.

Therefore, there is a need for an advanced computer-aided diagnosis framework that can simultaneously perform multiple tasks, including lesion segmentation, classification, and explanation generation. Such a system should improve diagnostic accuracy while providing transparent and clinically meaningful outputs that assist radiologists in making informed decisions. The proposed BI-RADS composite multi-tasking neural network aims to address these challenges by integrating multiple diagnostic tasks and generating both semantic and quantitative explanations for breast ultrasound image analysis.

B. Objectives

The main objective of this research is to develop an effective computer-aided diagnosis (CAD) system for breast cancer detection using ultrasound images by employing a composite multi-tasking neural network known as BI-RADS. The proposed system aims to improve diagnostic accuracy while also enhancing the interpretability of deep learning models in medical image analysis. By integrating multiple tasks such as lesion segmentation, classification, and explanation generation within a single framework, the model can learn richer feature representations from ultrasound images and provide more reliable predictions.

Another important objective is to incorporate explanations that align with BI-RADS (Breast Imaging Reporting and Data System) guidelines so that the system can generate clinically meaningful outputs. These explanations include semantic descriptors and visual heatmaps that highlight suspicious regions in the ultrasound images. In addition, the study aims to evaluate the performance of the proposed multi-task learning model using standard evaluation metrics and compare it with traditional single-task deep learning methods. Ultimately, the goal is to develop a reliable and interpretable diagnostic tool that can assist radiologists in making more accurate and informed clinical decisions for early breast cancer detection.

C. Existing System

Existing computer-aided diagnosis systems for breast ultrasound imaging primarily rely on single-task deep learning models that perform binary classification of tumors into benign or malignant categories. These models typically use convolutional neural networks such as VGG, ResNet, or DenseNet for feature extraction and classification. While these models achieve good performance in detecting cancerous lesions, they often lack interpretability and clinical reasoning, making it difficult for radiologists to trust the system's predictions. Additionally, many models do not provide lesion localization or segmentation, which limits their usefulness in clinical practice.

Another limitation of existing systems is their inability to generate meaningful explanations for predictions. Most models only provide probability scores without describing why a particular lesion is classified as malignant or benign. This lack of transparency reduces the reliability and acceptance of AI-based diagnostic tools in healthcare. Furthermore, many existing approaches fail to incorporate BI-RADS descriptors that radiologists use for diagnostic interpretation. As a result, these systems do not fully align with clinical workflows and fail to provide comprehensive diagnostic support.

D. Disadvantages of Existing System

One major disadvantage of existing breast cancer detection systems is the lack of interpretability and explainability. Most deep learning models operate as black boxes, meaning they provide predictions without offering insights into the features influencing the decision. In medical applications, this limitation is critical because clinicians require transparent reasoning to trust automated systems. Without clear explanations such as lesion attributes or visual evidence, it becomes difficult for radiologists to validate the system's predictions and incorporate them into clinical decision-making.

Another limitation is that traditional models focus on a single task, usually classification, without considering other important diagnostic tasks such as lesion segmentation or attribute analysis. This results in incomplete diagnostic information and reduces the model's clinical relevance. Furthermore, single-task models often fail to capture complex relationships between lesion characteristics described in BI-RADS guidelines. As a result, they may produce inaccurate predictions when dealing with complex ultrasound images containing noise, artifacts, or ambiguous lesion patterns.

II. RELATED WORKS

Breast cancer detection using medical imaging has been an important research area in recent years due to the increasing need for early and accurate diagnosis. Ultrasound imaging is widely used for breast examination because it is non-invasive, cost-effective, and particularly useful for detecting abnormalities in dense breast tissues. However, manual interpretation of ultrasound images is often challenging due to noise, low contrast, and variability in lesion appearance. To overcome these limitations, researchers have developed computer-aided diagnosis

(CAD) systems that assist radiologists in analyzing medical images and improving diagnostic accuracy.

Early CAD systems for breast cancer detection mainly relied on traditional image processing and machine learning techniques. Methods such as feature extraction, texture analysis, and classical classifiers including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees were used to distinguish between benign and malignant lesions. Although these approaches achieved moderate success, they required manual feature engineering and were often limited in capturing complex patterns present in ultrasound images.

With the advancement of deep learning, convolutional neural networks (CNNs) have become widely used for medical image analysis. CNN-based models automatically learn hierarchical features from images and have demonstrated superior performance in tasks such as image classification, segmentation, and object detection. Several studies have applied CNN architectures to breast ultrasound datasets to detect and classify tumors with higher accuracy compared to traditional machine learning methods. However, many of these models focus on a single task, such as classification or segmentation, which may limit their ability to capture comprehensive diagnostic information.

More recently, multi-task learning approaches have been introduced to improve the performance of CAD systems. These models simultaneously perform multiple related tasks, such as lesion segmentation, classification, and attribute prediction, within a unified framework. By sharing information across tasks, multi-task learning models can improve feature representation and enhance generalization performance. Additionally, researchers have begun to incorporate explainable artificial intelligence (XAI) techniques to provide interpretable outputs, such as heatmaps and attention maps, which help clinicians understand the reasoning behind the model's predictions.

Despite these advancements, challenges still remain in developing reliable and interpretable CAD systems for breast ultrasound imaging. Many existing models lack alignment with clinical reporting standards such as BI-RADS guidelines, which are widely used by radiologists for breast lesion evaluation. Therefore, there is a growing need for advanced frameworks that combine multi-task learning with explainable outputs while adhering to clinically meaningful standards. The proposed BI-RADS composite multi-tasking neural network addresses these challenges by integrating lesion segmentation, classification, and explanation generation to support more accurate and transparent breast cancer diagnosis.

III. PROPOSED METHODOLOGY

The proposed system introduces BI-RADS, a composite multi-task neural network designed to perform multiple diagnostic tasks simultaneously using breast ultrasound images. The architecture integrates lesion segmentation,

classification, and semantic attribute prediction into a unified framework. By combining these tasks, the system can analyze both visual and structural characteristics of lesions, enabling more accurate and interpretable predictions. The model also incorporates explainable AI techniques to generate visual heatmaps and attribute-based explanations aligned with BI-RADS descriptors.

In addition to semantic explanations, the proposed model provides quantitative analysis by measuring lesion size, shape, margin irregularity, and other statistical features. These quantitative metrics help radiologists understand the severity and nature of detected abnormalities. The system is trained using annotated ultrasound datasets containing segmentation masks and BI-RADS labels. By leveraging multi-task learning, the model improves feature sharing across tasks, leading to better performance and robustness. This approach enhances the reliability of computer-aided diagnosis systems and supports radiologists in making more accurate clinical decisions.

D. Advantages of Proposed System

The BI-RADS-V2 framework offers several advantages compared to conventional diagnostic systems. One key advantage is its multi-task learning capability, which allows the model to simultaneously perform lesion segmentation, classification, and attribute prediction. This integrated approach improves overall diagnostic accuracy while reducing computational redundancy. By sharing learned features across multiple tasks, the system can capture more meaningful representations of breast lesions, resulting in better detection performance.

Another important advantage is the explainability and interpretability of the model's predictions. The system generates both semantic explanations based on BI-RADS descriptors and visual explanations using attention maps or Grad-CAM heatmaps. These explanations help radiologists understand the reasoning behind each prediction, increasing trust and reliability. Additionally, the system provides quantitative metrics such as lesion size and shape characteristics, enabling clinicians to evaluate tumor progression more effectively. Overall, the proposed system enhances clinical decision-making and contributes to more accurate and transparent breast cancer diagnosis.

IV. IMPLEMENTATION METHODOLOGY

A. Dataset Collection

The first stage in implementing the BI-RADS system is the collection of a suitable breast ultrasound image dataset. Breast ultrasound datasets are obtained from publicly available medical imaging repositories such as the BUSI (Breast Ultrasound Images) dataset and the UDIAT Breast Ultrasound dataset. These datasets contain ultrasound images categorized into three primary classes: benign, malignant, and normal. In addition to the class labels, many datasets also include segmentation masks that identify the tumor regions and annotations that correspond to BI-RADS descriptors used by radiologists for diagnosis. These

descriptors include characteristics such as lesion shape, margin irregularity, and orientation.

Collecting a well-annotated dataset is essential for training a reliable deep learning model. The dataset is divided into training, validation, and testing subsets to ensure proper model evaluation and generalization. The training dataset is used to train the neural network, while the validation dataset helps tune hyperparameters and prevent overfitting. The testing dataset is used to measure the final performance of the model. In some cases, additional private clinical datasets may also be incorporated to increase dataset diversity and improve the robustness of the proposed system.

B. Data Preprocessing

Data preprocessing is an essential step that improves the quality and consistency of ultrasound images before they are used for model training. Ultrasound images often contain noise, speckle artifacts, and low contrast, which can negatively affect the performance of deep learning models. To address these issues, several preprocessing techniques are applied. First, all images are resized to a uniform dimension such as 224×224 or 256×256 pixels to ensure compatibility with convolutional neural network architectures. Noise reduction techniques such as Gaussian filtering are applied to remove unwanted artifacts and enhance image clarity.

In addition to noise removal, contrast enhancement techniques such as histogram equalization are used to highlight important features within the ultrasound images. Data augmentation is also performed to increase the size and diversity of the training dataset. Augmentation techniques include rotation, horizontal and vertical flipping, scaling, and zooming. These transformations help the model learn invariant features and improve its ability to generalize to unseen images. The preprocessing pipeline is implemented using libraries such as OpenCV, NumPy, and TensorFlow/Keras to efficiently process large volumes of medical images.

C. Feature Extraction

Feature extraction plays a critical role in identifying meaningful patterns in ultrasound images that indicate the presence of tumors. In the proposed BI-RADS system, deep convolutional neural networks are used to automatically extract high-level features from input images. Pre-trained backbone architectures such as ResNet50, EfficientNet, or DenseNet121 are commonly used because they have already been trained on large-scale image datasets and can effectively capture complex visual patterns. These networks consist of multiple convolutional layers that learn hierarchical representations of image features.

The extracted features include important visual characteristics such as texture variations, lesion boundaries, internal echo patterns, and structural irregularities within the breast tissue. These deep features help differentiate between

benign and malignant lesions. By leveraging transfer learning, the system can utilize pre-trained weights to accelerate training and improve accuracy even with limited medical datasets. The feature extraction stage transforms raw ultrasound images into rich feature representations that can be further processed by the multi-task neural network for classification, segmentation, and attribute prediction.

D. Multi-Task Neural Network Architecture

The core component of the proposed system is a composite multi-task neural network architecture that performs multiple diagnostic tasks simultaneously. The network is designed with three main branches: a segmentation branch, a classification branch, and a semantic attribute prediction branch. The segmentation branch uses a U-Net architecture to identify and isolate tumor regions in ultrasound images. U-Net is particularly suitable for medical image segmentation because it captures both global context and fine spatial details using an encoder-decoder structure.

The classification branch receives deep features from the backbone network and predicts whether a detected lesion is benign or malignant using fully connected layers. Meanwhile, the semantic attribute branch predicts BI-RADS descriptors such as lesion shape, margin characteristics, orientation, and echo pattern. These attributes help provide clinical explanations for the classification results. By sharing features across these branches, the multi-task architecture improves efficiency and enables the model to learn correlations between lesion appearance and diagnostic attributes.

E. Explainable AI Module

Explainability is a crucial requirement in medical AI systems because clinicians must understand the reasoning behind automated predictions. The BI-RADS-V2 system integrates an Explainable AI (XAI) module that generates both visual and semantic explanations for its predictions. One of the key techniques used is Gradient-weighted Class Activation Mapping (Grad-CAM), which produces heatmaps highlighting the regions of the image that influenced the model's decision. These heatmaps allow radiologists to visually verify whether the model is focusing on the correct tumor regions.

In addition to visual explanations, the system generates semantic explanations based on predicted BI-RADS attributes. These attributes describe the characteristics of the detected lesion, such as irregular margins or heterogeneous echo patterns, which are clinically relevant indicators of malignancy. The system also performs quantitative analysis by calculating measurements such as lesion size and shape irregularity. By combining visual heatmaps with semantic descriptors, the explainability module enhances transparency and helps clinicians interpret the results with greater confidence.

F. Model Training

Once the model architecture is designed, the next step is to train the multi-task neural network using the prepared dataset. Training involves optimizing the model parameters so that it can accurately perform segmentation, classification, and attribute prediction tasks. Different loss functions are used for each task. Dice Loss is applied for the segmentation branch to measure the overlap between predicted and ground truth masks. Cross-entropy loss is used for classification tasks, while multi-label loss functions are used for predicting BI-RADS attributes.

The model is trained using the Adam optimizer, which adjusts learning rates dynamically to improve convergence speed and stability. Training typically runs for 50 to 100 epochs depending on dataset size and model complexity. A batch size of 16 or 32 images is commonly used to balance memory efficiency and training speed. The training process is implemented using deep learning frameworks such as TensorFlow or PyTorch, which provide efficient GPU acceleration for handling large-scale neural network computations.

Model Evaluation

After training, the model's performance is evaluated using several standard metrics to measure its effectiveness in diagnosing breast cancer. For classification tasks, metrics such as accuracy, precision, recall, and F1-score are calculated to assess how well the model distinguishes between benign and malignant lesions. The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (ROC-AUC) are also used to evaluate the model's ability to differentiate between classes at different decision thresholds.

For the segmentation task, the Dice coefficient is used to measure the similarity between the predicted segmentation mask and the ground truth mask. A higher Dice score indicates better segmentation accuracy. Visualization techniques such as confusion matrices and ROC curves are used to analyze model performance and identify potential weaknesses. Additionally, Grad-CAM heatmaps are generated to visually verify that the model is focusing on the correct regions of the ultrasound images during prediction.

V. RESULTS AND DISCUSSION

The performance of the proposed BI-RADS composite multi-tasking neural network was evaluated using breast ultrasound image datasets to analyze its effectiveness in lesion detection, segmentation, and classification. The model was trained and tested using standard evaluation metrics such as accuracy, precision, recall, F1-score, and segmentation performance measures such as Dice coefficient and Intersection over Union (IoU). These metrics help assess both the classification capability and the quality of lesion localization in ultrasound images.

The experimental results indicate that the proposed multi-task framework achieves strong performance in distinguishing between benign and malignant breast lesions. The classification module of the model demonstrated high accuracy due to the ability of convolutional neural networks to capture important spatial patterns and texture features in ultrasound images. Compared with traditional single-task models, the multi-task architecture was able to learn richer feature representations by simultaneously performing segmentation and classification tasks.

The segmentation component of the proposed model effectively identified and localized suspicious regions within ultrasound images. By accurately outlining lesion boundaries, the system helps provide clearer visual information to radiologists regarding the size, shape, and location of detected abnormalities. The Dice coefficient and IoU results demonstrate that the segmentation network can reliably capture lesion structures even in images with noise or low contrast.

Another important contribution of the proposed model is the explanation module, which generates interpretable outputs aligned with BI-RADS descriptors. Visual heatmaps and semantic attributes highlight the regions that influenced the model's predictions, allowing clinicians to better understand the reasoning behind the classification results. This improves the transparency and reliability of the CAD system, making it more suitable for clinical applications.

Overall, the experimental results demonstrate that the BI-RADS-V2 multi-task model outperforms traditional single-task approaches in both diagnostic accuracy and interpretability. The integration of segmentation, classification, and explanation generation within a single framework enhances the overall effectiveness of the computer-aided diagnosis system. These results suggest that the proposed approach can serve as a valuable decision-support tool for radiologists in the early detection and diagnosis of breast cancer using ultrasound imaging.

VI. CONCLUSION AND FUTURE SCOPE

Breast cancer remains one of the most significant health challenges affecting women worldwide, and early detection is essential for improving survival rates and treatment outcomes. Ultrasound imaging plays an important role in breast cancer screening due to its non-invasive nature, affordability, and effectiveness in detecting abnormalities in dense breast tissues. However, manual interpretation of ultrasound images can be difficult and may vary depending on the experience of radiologists. Therefore, intelligent computer-aided diagnosis systems are needed to assist clinicians in making accurate and consistent diagnostic decisions.

In this study, a BI-RADS composite multi-tasking neural network was proposed for breast cancer diagnosis using ultrasound images. The proposed framework integrates multiple tasks, including lesion segmentation, classification, and explanation generation, within a single deep learning architecture. By combining these tasks, the model can learn

more comprehensive feature representations and improve diagnostic performance. In addition, the system provides both semantic and quantitative explanations aligned with BI-RADS guidelines, enhancing the interpretability and reliability of the predictions. Experimental results demonstrate that the proposed multi-task model achieves improved accuracy and better lesion localization compared to traditional single-task models.

Overall, the proposed approach contributes to the development of more reliable and interpretable CAD systems for breast cancer detection. By providing accurate predictions along with clinically meaningful explanations, the system can support radiologists in diagnosing breast abnormalities and improve the efficiency of medical imaging analysis.

Future Scope

Future research can focus on expanding the proposed framework by incorporating larger and more diverse ultrasound datasets to further improve model generalization and robustness. Advanced deep learning architectures such as transformer-based models or hybrid CNN-transformer networks may also be explored to enhance feature extraction and classification performance.

Additionally, integrating real-time clinical decision-support systems and deploying the model in hospital environments could help evaluate its practical applicability in medical workflows. Further improvements can also include the development of more advanced explainable artificial intelligence techniques to provide clearer and more detailed diagnostic explanations for clinicians. Finally, extending the framework to analyze multi-modal medical images, such as mammography and MRI, could further enhance the effectiveness of breast cancer diagnosis and screening systems.

REFERENCES

- [1] J. Zhang, Y. Li, and H. Wang, "Deep learning-based computer-aided diagnosis for breast ultrasound image classification," *IEEE Access*, vol. 13, pp. 11234–11245, 2025.
- [2] S. Kumar and R. Patel, "Explainable artificial intelligence for breast cancer diagnosis using medical imaging," *Biomedical Signal Processing and Control*, vol. 92, pp. 105967, 2025.
- [3] M. Ahmed, L. Chen, and Q. Zhao, "Multi-task learning framework for breast lesion segmentation and classification in ultrasound images," *Computers in Biology and Medicine*, vol. 175, pp. 108245, 2025.
- [4] P. Singh and A. Kaur, "Deep convolutional neural networks for automated breast cancer detection in ultrasound imaging," *Expert Systems with Applications*, vol. 249, pp. 123456, 2025.
- [5] Y. Liu, H. Chen, and J. Wu, "Attention-based deep learning model for breast ultrasound image analysis," *IEEE Journal of Biomedical and Health Informatics*, vol. 29, no. 2, pp. 654–663, 2025.
- [6] T. Nguyen and D. Tran, "Explainable deep learning framework for medical image diagnosis," *Artificial Intelligence in Medicine*, vol. 148, pp. 102698, 2025.
- [7] R. Gupta and N. Sharma, "Computer-aided breast cancer detection using CNN and medical image segmentation," *Journal of Medical Systems*, vol. 49, no. 1, pp. 1–12, 2025.
- [8] H. Park, S. Lee, and K. Kim, "Multi-task deep learning network for breast tumor detection and segmentation in ultrasound images," *Pattern Recognition Letters*, vol. 182, pp. 35–43, 2025.
- [9] A. Rahman and M. Hassan, "Interpretable deep neural networks for breast lesion classification in ultrasound images," *IEEE Transactions on Medical Imaging*, vol. 44, no. 3, pp. 1120–1131, 2025.
- [10] L. Wang, Y. Zhang, and F. Li, "Deep learning-based CAD system for breast cancer diagnosis using ultrasound images," *Sensors*, vol. 25, no. 4, pp. 2156, 2025.
- [11] M. Patel and S. Desai, "Hybrid deep learning model for breast tumor classification in medical imaging," *Biomedical Engineering Letters*, vol. 15, pp. 201–212, 2025.
- [12] K. Roy and P. Das, "Explainable AI techniques for improving trust in medical image classification systems," *IEEE Access*, vol. 13, pp. 45670–45682, 2025.
- [13] N. Verma and A. Mishra, "Breast cancer diagnosis using multi-task convolutional neural networks," *International Journal of Medical Informatics*, vol. 192, pp. 105012, 2025.
- [14] J. Chen, Y. Zhou, and X. Li, "Deep learning-based lesion segmentation in breast ultrasound images," *Medical Image Analysis*, vol. 94, pp. 102978, 2025.
- [15] S. Ali and M. Farooq, "Computer-aided diagnosis of breast cancer using explainable deep learning techniques," *Diagnostics*, vol. 15, no. 3, pp. 478, 2025.