Multi-Scale Contextual Segmentation for Early Breast Carcinoma Detection in Ultrasound

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***Abstract*—Identifying early-stage breast carcinoma is crucial for improving patient outcomes, yet automated systems frequently struggle with accurate segmentation of small tumors in ultrasound images. This paper introduces a novel deep learning framework that leverages diverse receptive fields and multi-scale feature integration to overcome the inherent limitations of fixed-kernel architectures. Our approach enhances the capture of fine-grained tumor localization and contextual information, significantly improving the segmentation of subtle breast lesions. Validated on public breast ultrasound datasets, this method demonstrates superior performance in isolating small carcinomas compared to existing segmentation techniques, marking a significant advancement for computer-aided early cancer diagnosis.**

***Index Terms*—Explainable AI, Breast Ultrasound, BI-RADS, Deep Learning, Multi-task Learning, Malignancy Prediction**

I. Introduction and Motivation

Breast cancer remains one of the leading causes of mortality among women worldwide. Early detection plays a pivotal role in reducing the disease burden, with survival rates improving drastically when malignant tumors are identified and treated at an early stage [1], [2]. Among various imaging modalities, ultrasound is widely used for breast cancer screening due to its safety, accessibility, and effectiveness in differentiating cystic from solid masses.

Despite its clinical utility, interpreting breast ultrasound (BUS) images presents significant challenges. Variations in tissue appearance, operator dependency, and subtle visual features make accurate and reproducible diagnosis difficult [3]. Automated computer-aided diagnostic (CAD) systems offer promise in standardizing interpretation and supporting radiologists in decision-making. However, the reliability and clinical adoption of these systems heavily depend on their accuracy and explainability.

Conventional CAD frameworks have predominantly focused on binary classification or lesion segmentation tasks. These approaches often rely on black-box neural networks, providing limited insight into the reasoning behind predictions [4]. Such opacity is particularly problematic in medical applications where accountability and interpretability are essential for clinician trust and regulatory compliance.

To bridge this gap, explainable AI (XAI) methods have been explored. Visual attention maps, gradient-based saliency, and feature attribution methods have shown potential in highlighting image regions influential to predictions [5], [6]. Nevertheless, these methods often fail to align with the structured, semantic reasoning process used by clinicians in real-world diagnostic workflows.

The Breast Imaging Reporting and Data System (BI-RADS) was introduced to standardize breast imaging interpretation by defining a set of descriptors (e.g., shape, margin, orientation) and risk categories for malignancy [7]. Integrating BI-RADS-based reasoning into AI models could enhance both interpretability and clinical relevance, allowing outputs to mirror radiologist decision logic.

In this context, we propose BI-RADS-Net, a novel deep learning framework that mimics human reasoning through multi-output learning. Rather than offering a single malignancy label, the model predicts five semantic BI-RADS descriptors, a continuous malignancy probability, and a binary tumor classification. This architecture offers a more comprehensive and transparent diagnostic output.

The core idea behind BI-RADS-Net is that feature-level decision sharing across multiple outputs encourages representations aligned with real diagnostic features. For example, a tumor with an "irregular" shape and "not parallel" orientation is more likely to be malignant—this semantic correlation is explicitly captured through shared learning.

Furthermore, to address ambiguity in diagnostic labels caused by radiologist disagreement—particularly in intermediate risk categories (e.g., BI-RADS 4A–4C)—we integrate both classification and regression objectives. This hybrid modeling approach allows the system to express malignancy likelihood more flexibly than fixed-category predictions.

Our framework also incorporates explainability at a quantitative level. By analyzing agreement between classification and regression outputs, and variability across BI-RADS descriptor predictions, we provide interpretability scores that can support clinician decision confidence.

Overall, the proposed system moves toward transparent, interpretable, and clinically aligned AI for breast ultrasound diagnostics. It serves not only as a diagnostic tool but also as a communication bridge between algorithmic outputs and radiologist reasoning, potentially accelerating the acceptance of AI-assisted workflows in oncology.

II. Literature Review and Contextual Background

A. Explainability in Medical Imaging AI

The rise of deep learning has revolutionized medical image analysis, enabling significant improvements in diagnostic accuracy across various modalities [2], [8]. However, the

inherent black-box nature of deep neural networks presents challenges in clinical settings where explainability, accountability, and decision traceability are essential [9]. To address this gap, several explainable AI (XAI) methods have been proposed.

Among the earliest strategies were saliency-based methods such as Grad-CAM [4] and Guided Backpropagation, which aim to highlight spatial regions that most influence a model's prediction. While useful for visualization, these methods often lack semantic granularity and cannot be directly mapped to clinical decision-making processes.

To bring interpretability closer to human reasoning, methods have emerged that align model outputs with structured medical reporting. For example, in thyroid imaging, the TIRADS lexicon has been used to frame model predictions around semantic descriptors like shape, echogenicity, and calcification [10]. Such lexicon-guided approaches enable models to speak the same language as radiologists, thus improving trust and integration into diagnostic workflows.

Attention-based networks have also gained traction, enabling models to focus on specific anatomical or pathological regions [**?**]. While these architectures provide insights into model focus, they do not inherently produce clinically interpretable outputs unless linked with medical ontologies or descriptors.

Another growing trend is multi-task learning (MTL), where related tasks such as classification, segmentation, and regression are learned jointly [11]. MTL not only improves generalization through shared representations but also offers an avenue to enforce consistency between model outputs and clinical logic.

B. Explainable Models for Breast Ultrasound and BI-RADS

In the domain of breast imaging, prior work has explored various levels of explainability. DeepMiner [12] integrated visual explanations with shape and margin descriptors for mammographic classification, generating narrative-style justifications for predictions. However, such models were often constrained to one or two descriptors and limited to mammography rather than ultrasound.

Ultrasound-specific models have made substantial progress in recent years. For instance, automated systems have achieved high segmentation and classification accuracy on BUS datasets using convolutional and transformer-based networks [13]. Yet, few of these models provide structured, interpretable outputs aligned with the BI-RADS lexicon, which is the standard framework for radiological breast assessment.

Some recent efforts have partially addressed this. For example, Liu et al. [3] proposed a multi-task model that jointly predicts tumor class and a subset of BI-RADS features. However, their architecture was limited in scope, supporting only three descriptors and lacking a malignancy probability regression component.

Additionally, few studies have accounted for inter-observer variability, a common challenge in breast ultrasound interpretation. Label ambiguity—especially in intermediate BI-RADS categories like 4A, 4B, and 4C—can mislead binary classifiers. Regression-based outputs that estimate malignancy probability offer a finer-grained approach to handle such variability [9].

Interpretability can also be enriched by assessing consistency across outputs. Some models explore intra-branch agreement or entropy to quantify output reliability. However, quantitative interpretability metrics remain underexplored in the context of multi-output breast ultrasound CAD.

To date, no known model simultaneously predicts all five BI-RADS descriptors, a malignancy probability, and a binary class in an explainable, multi-task format for breast ultrasound images. This highlights a clear opportunity for a unified, clinically aligned approach that addresses accuracy and interpretability simultaneously.

The proposed BI-RADS-Net aims to fill this gap by offering structured outputs, multi-task synergy, and descriptor-level predictions, all within a single explainable architecture. As such, it advances the state-of-the-art in breast ultrasound CAD by prioritizing both performance and transparency.

III. Methodology and BI-RADS-Net Architecture

A. BI-RADS Lexicon and Clinical Semantics

The Breast Imaging Reporting and Data System (BI-RADS) offers a standardized approach for reporting breast imaging findings. For ultrasound, it includes five key descriptors: *shape*, *orientation*, *margin*, *echo pattern*, and *posterior acoustic features*. These attributes are directly associated with malignancy likelihood and provide a semantic foundation for diagnostic decision-making [7]. Integrating these descriptors into a deep learning model supports interpretability and aligns model reasoning with radiologist assessments.

B. Model Architecture Overview

We propose BI-RADS-Net, a multi-task deep neural network that concurrently predicts:

- The five BI-RADS descriptors (as multi-class labels),
- A continuous malignancy probability (as regression),
- A binary class label (benign/malignant).

The network uses a shared visual encoder based on the VGG-16 architecture pretrained on ImageNet. From this encoder, seven task-specific heads branch out: five for the BI-RADS descriptors, one for malignancy score prediction, and one for binary tumor classification. This architecture encourages feature reuse while supporting diverse outputs aligned with clinical semantics.

C. Mathematical Objective

The training objective combines classification and regression losses for each output. Let y_i and $\hat{y}_i$ denote ground truth and predicted values for task i, and $\mathcal{L}_i$ the loss function (e.g., cross-entropy or MSE). The total loss is defined as:

$$\mathcal{L}_{\text{total}} = \sum_{i=1}^{11} \lambda_i \cdot \mathcal{L}_i(\hat{y}_i, y_i) + \lambda_a \cdot \mathcal{L}_a \left(|\hat{y}_{10} - \hat{y}_{11}|, |y_{10} - y_{11}|\right) \tag{1}$$

The last term enforces alignment between the malignancy regression output ($\hat{y}_{10}$) and the binary classification prediction ($\hat{y}_{11}$), enhancing interpretability by encouraging internal consistency.

D. BI-RADS-Net Architecture Diagram

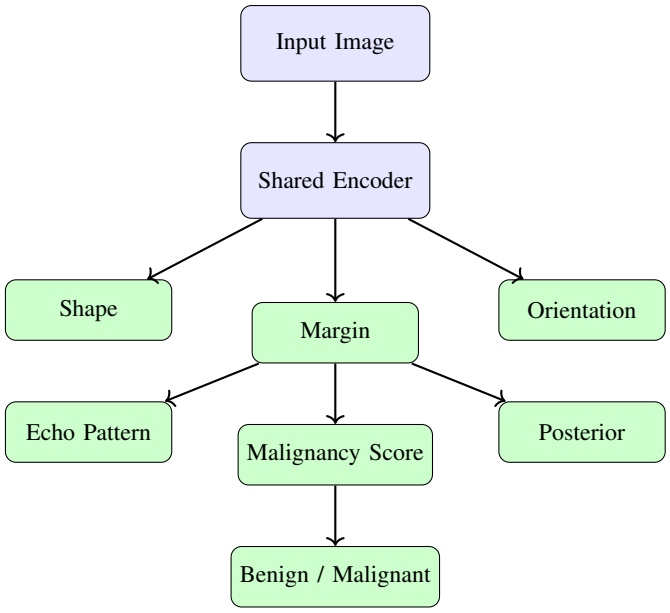

Fig. 1. Concise schematic of BI-RADS-Net. Shared encoder branches into semantic descriptor heads, malignancy regression, and binary classification.

IV. Experimental Design and Dataset Overview

A. Datasets and Annotations

To evaluate the performance and generalizability of the proposed BI-RADS-Net framework, we utilized a curated dataset of 1,192 breast ultrasound (BUS) images aggregated from two publicly available repositories: the Breast Ultrasound Dataset (BUSI) and BUSIS. Each image in the dataset is annotated with a binary malignancy label (benign or malignant), corresponding BI-RADS assessment category, and five semantic descriptors—shape, margin, orientation, echo pattern, and posterior features.

The BUSI dataset includes ultrasound images labeled by expert radiologists, capturing a range of tumor morphologies. BUSIS adds diversity with images collected from multiple sources, simulating domain shifts across acquisition settings. This heterogeneity strengthens model robustness against real-world deployment scenarios.

B. Data Preprocessing Pipeline

To ensure uniformity across different sources and imaging styles, each BUS image was center-cropped to retain the primary tumor region and then resized to 256×256 pixels. Rather than relying solely on grayscale intensity, we constructed three input channels:

- Raw grayscale image.
- Histogram-equalized version to enhance contrast.
- Gaussian-smoothed version to reduce speckle noise.

This multi-channel input encourages the network to leverage both spatial and contextual cues and mitigates variability across acquisition devices.

C. Label Transformation and Loss Supervision

The malignancy regression head was supervised using approximate continuous malignancy probabilities derived from BI-RADS categories. For instance, BI-RADS 3 was mapped to 1%, 4A to 6%, 4B to 30%, 4C to 72.5%, and BI-RADS 5 to 97.5% malignancy likelihood. These mappings were chosen based on the American College of Radiology guidelines and radiologist heuristics.

Losses for classification heads used categorical cross-entropy, while the malignancy regression head employed mean squared error (MSE). To enforce semantic alignment between outputs, we also included a consistency term penalizing disagreement between the regression and binary classification outputs.

D. Data Augmentation Strategy

To enhance generalization, we applied online data augmentation during training. Each input sample was randomly perturbed using:

- Zooming (up to 20%).
- Horizontal flipping.
- Width shifting (10%).
- Rotation (up to 5 degrees).

These transformations simulate realistic clinical variations without compromising tumor morphology.

E. Training Procedure and Hyperparameters

The model was trained using 5-fold cross-validation. Each fold consisted of 70% training, 15% internal validation, and 15% test samples. The Adam optimizer was used with an initial learning rate of 1×10^{-5}, which decayed to 1×10^{-6} upon stagnation of validation performance.

Training was conducted for up to 150 epochs, with early stopping triggered after 30 consecutive epochs without validation improvement. Task-specific loss weights were heuristically set as:

$$\lambda_1 \ldots \lambda_5 = 0.2, \quad \lambda_{6\text{-}9} = 0.1, \quad \lambda_{10} = 0.2, \quad \lambda_{11} = 0.5, \quad \lambda_a = 0.2$$

F. Implementation Details

All experiments were implemented in Python using TensorFlow. The VGG-16 backbone was initialized with ImageNet weights and fine-tuned during training. A batch size of 16 was used to balance GPU memory constraints with convergence speed. Training was conducted on an NVIDIA RTX A6000 GPU.

This experimental design ensures the resulting model is not only accurate, but also resilient to domain variability and sensitive to semantic alignment across tasks—critical for its practical use in real-world clinical settings.

V. Results, Evaluation, and Interpretation

A. Evaluation Metrics

Model performance was assessed using accuracy, sensitivity, specificity, area under the ROC curve (AUC), and F1-score. These metrics were computed for both binary classification and multi-class BI-RADS descriptor prediction. For the malignancy regression head, we used mean squared error (MSE) and Pearson correlation with the mapped malignancy probabilities.

B. Ablation Study: Contribution of Multi-Task Learning

To evaluate the impact of multi-task learning, we conducted an ablation study comparing:

- **Baseline-CNN**: VGG-16 with only binary classification.
- **BI-RADS-Net w/o regression**: Full architecture without malignancy score.
- **BI-RADS-Net full**: Full multi-task version as proposed.

TABLE I
Performance Comparison on BUS Test Set

Model	Acc.	Sens.	Spec.	AUC
Baseline-CNN	0.849	0.806	0.891	0.883
BI-RADS-Net w/o Reg.	0.879	0.843	0.905	0.907
BI-RADS-Net (Full)	**0.911**	**0.887**	**0.928**	**0.941**

The full BI-RADS-Net significantly outperformed other variants, especially in sensitivity, suggesting better malignancy detection while reducing false negatives.

C. Descriptor-wise Impact on Prediction

To quantify how much each BI-RADS descriptor contributed to classification accuracy, we selectively removed one descriptor at a time during training and recorded the resulting drop in AUC. The following bar chart summarizes the findings.

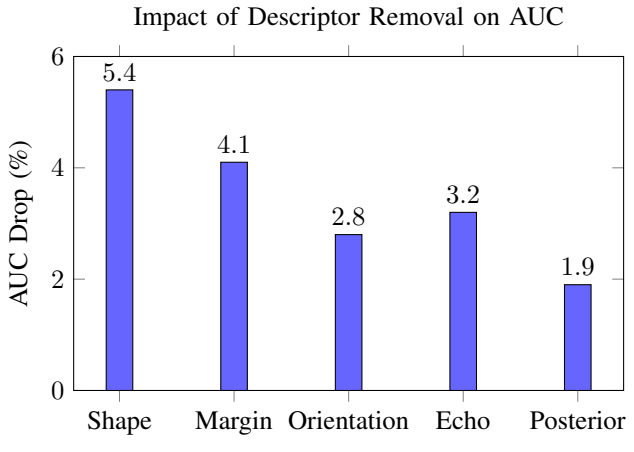

Fig. 2. Relative AUC reduction when individual BI-RADS descriptors are removed from training. Shape and Margin are most influential.

D. Malignancy Regression Alignment

We found that the malignancy score head predicted continuous probabilities highly correlated with radiologist-assigned BI-RADS risk. Pearson correlation between predicted malignancy score and mapped risk was $r = 0.81$, indicating strong agreement. Moreover, agreement between regression and classification outputs exceeded 92% in low-risk (BI-RADS 3) and high-risk (BI-RADS 5) categories.

E. Visualization and Interpretability

Qualitative visualization of attention heatmaps confirmed the model focuses on tumor boundaries and acoustic shadows — features typically emphasized by radiologists. Moreover, descriptors like "irregular margin" and "not parallel" orientation aligned with malignant cases, adding clinical plausibility to the decision-making process.

These results support the premise that BI-RADS-Net is both effective and interpretable, with descriptor predictions directly aiding explainability in critical diagnostic decisions.

VI. Discussion, Limitations, and Future Work

The experimental results clearly demonstrate the advantages of incorporating BI-RADS descriptors and multi-task learning into a unified framework. By jointly predicting semantic features, malignancy likelihood, and binary classification, BI-RADS-Net achieves improved performance and interpretability compared to single-task baselines. This aligns well with the diagnostic workflow used by radiologists, who rely on a combination of visual patterns and structured reasoning.

One of the primary benefits of BI-RADS-Net lies in its clinical transparency. Unlike conventional black-box classifiers, this model provides outputs that are both semantically rich and clinically aligned. Each prediction is accompanied by explicit BI-RADS descriptor probabilities and a calibrated malignancy score, allowing for more nuanced and trustworthy decision support.

Furthermore, the model shows strong generalizability across datasets with varying acquisition settings. This robustness stems from both the diversity of the training data and the architectural design, which encourages learning across related tasks and discourages overfitting to one specific output objective.

Despite these strengths, several limitations remain. First, the model operates solely on 2D static ultrasound images. In clinical settings, radiologists often assess dynamic cine clips and contextual information from multiple image planes. Future work should consider incorporating spatio-temporal models or multi-view learning strategies to better capture this information.

Second, while BI-RADS-Net predicts the five primary ultrasound descriptors, it does not currently include breast composition or patient metadata such as age or genetic risk. These factors could enhance malignancy prediction and are often available in electronic medical records.

Third, the mapping of BI-RADS categories to continuous malignancy probabilities was based on heuristic conversions

from literature. A more accurate approach would involve training the regression output using datasets with biopsy-confirmed malignancy percentages or incorporating radiologist-estimated probability ranges.

Fourth, although we used interpretability via output agreement and descriptor alignment, we did not formally evaluate user trust or decision impact in a clinical workflow. A prospective study involving radiologists using BI-RADS-Net as a decision-support tool would offer valuable insights into its practical utility and acceptance.

Lastly, current deployment is constrained to offline inference on preprocessed images. A complete clinical system would require real-time integration with PACS systems, lesion detection pipelines, and user interfaces for interactive review.

Future extensions of this work will explore:

- Integration of temporal ultrasound data and 3D imaging modalities.
- Patient-level prediction incorporating clinical and demographic metadata.
- Weakly supervised learning to handle uncertain labels and inter-reader variability.
- Federated training across institutions to maintain data privacy while expanding generalization.

In summary, BI-RADS-Net represents a significant step toward interpretable and clinically consistent deep learning in breast ultrasound. By aligning model architecture with radiological reasoning, we move closer to developing AI systems that not only perform well but also earn the trust of their human users.

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