AttentionFSL-Net: Few-Shot Learning with Attention-Guided U-Net for Breast Tumor Segmentation in Ultrasound Images

ABSTRACT

Breast cancer is one of the leading causes of cancer-related deaths among women worldwide. Early detection through medical imaging, particularly ultrasound, is crucial for improving patient outcomes. However, accurate segmentation of breast tumors in ultrasound images remains challenging due to limited annotated data and high variability in tumor appearance. In this paper, we propose AttentionFSL-Net, a few-shot learning framework that integrates attention mechanisms with U-Net architecture for breast tumor segmentation. Our approach addresses the data scarcity problem by learning to segment tumors from only a few labeled examples per class. We evaluate our method on three datasets: BUSI, FLOOD, and RETINA, demonstrating competitive performance with Dice coefficients of 0.400, 0.677, and 0.627 respectively. Our lightweight model achieves real-time performance with 38.2 FPS using only 31.6M parameters and 26.8 GFLOPs, making it suitable for clinical deployment.

CCS CONCEPTS

• **Computing methodologies → Computer vision**; **Image segmentation**; *Machine learning*.

KEYWORDS

Few-shot learning, breast tumor segmentation, attention mechanism, U-Net, medical image analysis, ultrasound imaging, lightweight models

1 INTRODUCTION

Breast cancer remains the second most common cancer among women globally, with early detection being critical for successful treatment outcomes. Ultrasound imaging has emerged as a valuable diagnostic tool due to its non-invasive nature, real-time imaging capabilities, and cost-effectiveness compared to other modalities such as MRI or CT scans.

However, accurate segmentation of breast tumors in ultrasound images presents significant challenges. The inherent speckle noise, low contrast, and variable tumor appearances make manual annotation time-consuming and require expert radiologists. Furthermore, the scarcity of annotated medical data, particularly for rare tumor types, limits the effectiveness of traditional deep learning approaches that require large datasets for training.

Various learning paradigms have been explored to address data scarcity in medical imaging, including unsupervised learning, supervised learning, semi-supervised learning, self-supervised learning, and few-shot learning. Each approach offers unique advantages and limitations in handling limited annotated data scenarios.

In this work, we propose AttentionFSL-Net, a few-shot learning framework specifically designed for breast tumor segmentation in ultrasound images. Our main contributions are:

- A few-shot learning framework that integrates spatial and channel attention mechanisms with U-Net architecture for parameter-efficient tumor segmentation
- A systematic methodology combining MAML-based meta-learning with prototype-based learning, specifically designed to address the unique challenges of medical image segmentation
- A lightweight model design with 31.6M parameters and 26.8 GFLOPs, enabling real-time clinical deployment at 38.2 FPS
- Comprehensive evaluation across three diverse datasets (BUSI, FLOOD, RETINA) demonstrating generalizability and clinical relevance of few-shot learning for data-scarce medical imaging scenarios

2 RELATED WORK

2.1 Learning Paradigms in Medical Image Analysis

2.1.1 Supervised Learning. Traditional supervised learning approaches have dominated medical image segmentation, requiring large amounts of labeled data for training. The BUSIS benchmark [1] demonstrated that deep learning-based approaches achieved high Dice similarity coefficient values (DSC 0.90) and outperformed conventional approaches when sufficient labeled data is available. Recent work by Shilaskar et al. [2] proposed a dual-model system using VGG-16 for classification (90% accuracy) and UNet for segmentation (98% accuracy) on the BUSI dataset, demonstrating the effectiveness of supervised learning with adequate data.

Sulaiman et al. [3] developed an explainable attention-based UNet model that achieved outstanding performance with 98% accuracy, 97% precision, 90% recall, and 92% Dice score on the BUSI dataset. Their model integrated attention mechanisms such as Convolutional Block Attention Module (CBAM) and Non-Local Attention with advanced encoder architectures including ResNet, DenseNet, and EfficientNet.

2.1.2 Semi-Supervised Learning. Semi-supervised learning leverages both labeled and unlabeled data to improve model performance. Huang et al. [4] conducted a systematic comparison of semi-supervised and self-supervised learning for medical image classification, demonstrating that semi-supervised methods can achieve significant improvements when unlabeled data is abundant. The study found that MixMatch delivered the most reliable gains across multiple medical datasets. Li et al. [5] proposed a two-step framework for breast tumor segmentation using semi-supervised semantic segmentation for breast anatomy decomposition, followed by weakly supervised tumor segmentation.

2.1.3 Self-Supervised Learning. Self-supervised learning has gained significant attention in medical imaging due to its ability to learn meaningful representations without manual annotations. Recent systematic reviews [6] show that contrastive learning methods like

SimCLR, MoCo, and BYOL are widely adopted, with contrastive SSL pre-training showing an average improvement of 6.35% over supervised pre-training across medical imaging tasks. Self-prediction methods using image restoration tasks have also shown promise, though with more modest improvements of 1-2%.

2.1.4 Few-Shot Learning. Few-shot learning addresses the data scarcity problem by learning to generalize from a small number of examples. Lin et al. [7] proposed CAT-Net, a cross-attention Transformer for few-shot medical image segmentation, demonstrating superior performance on multiple medical datasets. The method mines correlations between support and query images, limiting focus to useful foreground information and boosting representation capacity. Recent work by Xu et al. [8] developed SAM-MPA, leveraging the Segment Anything Model for few-shot medical image segmentation, achieving competitive results with minimal labeled examples.

A recent meta-learning approach for breast cancer classification [9] achieved remarkable results with 99.67% sensitivity, 99.71% specificity, and 99.36% accuracy on the INbreast dataset using Fuzzy C Means segmentation and an IWCA-APSO-based Ensemble Extreme Learning Machine model.

2.2 Breast Tumor Segmentation

Traditional approaches for breast tumor segmentation include classical methods such as edge-driven and threshold-driven segmentation, region growing, active contours, and clustering methods. However, these approaches often struggle with the inherent challenges of ultrasound imaging, including speckle noise and low contrast.

Recent deep learning approaches have shown significant improvements. The study by Sulaiman et al. [3] compared their proposed model against five state-of-the-art segmentation models: MRFE-CNN, ADU-NET, Swin-UNet, DDRA-Net, and DPNet, achieving the highest IoU of 0.5305 and Dice score of 0.6140. Chen et al. [10] introduced an enhanced selective kernel convolution method that dynamically adjusts feature weights in both channel and spatial dimensions.

The BUSIS benchmark [1] established standardized evaluation protocols, comparing 16 state-of-the-art segmentation methods and demonstrating that most deep learning approaches achieved DSC 0.90. However, these methods typically require large amounts of labeled data, limiting their applicability in data-scarce scenarios.

2.3 Attention Mechanisms in Medical Imaging

Attention mechanisms have proven effective in medical image segmentation by focusing on relevant regions while suppressing irrelevant features. The attention U-Net proposed by Oktay et al. [11] introduced attention gates that automatically learn to focus on target structures of varying shapes and sizes. Recent work has extended attention mechanisms to few-shot learning scenarios, with cross-attention Transformers showing particular promise for medical image segmentation tasks.

3 METHODOLOGY

3.1 Problem Formulation and Learning Paradigm Analysis

In medical image segmentation, different learning paradigms address the data scarcity challenge through various approaches:

Supervised Learning: Given a dataset $\mathcal{D}_{sup} = \{(x_i, y_i)\}_{i=1}^{N}$ with N labeled examples, the model learns to minimize:

$$\mathcal{L}_{sup} = \frac{1}{N} \sum_{i=1}^{N} \ell(f_\theta(x_i), y_i) \tag{1}$$

Self-Supervised Learning: Pre-trains on unlabeled data using pretext tasks, then fine-tunes on labeled data:

$$\mathcal{L}_{self} = \mathcal{L}_{pretext}(f_\theta(x), \text{pseudo-label}(x)) \tag{2}$$

Few-Shot Learning: For each episode $\mathcal{E}$, we have a support set $S = \{(x_i, y_i)\}_{i=1}^{K}$ and query set $Q = \{x_j\}_{j=1}^{M}$:

$$\mathcal{L}_{fsl} = \mathbb{E}_{\mathcal{E}} \left[\frac{1}{|Q|} \sum_{(x_q, y_q) \in Q} \ell(f_\theta(x_q|S), y_q) \right] \tag{3}$$

3.2 AttentionFSL-Net Architecture

Our AttentionFSL-Net architecture consists of an encoder-decoder structure with integrated attention mechanisms optimized for few-shot learning scenarios. The network incorporates U-Net's skip connections enhanced with spatial and channel attention gates at each level.

3.2.1 Enhanced Attention Mechanism. Our attention mechanism integrates spatial and channel attention to focus on relevant tumor regions while suppressing background noise:

Spatial Attention: For feature maps $F \in \mathbb{R}^{H \times W \times C}$, where H, W, and C represent height, width, and channels respectively:

$$A_{spatial} = \sigma(W_s \cdot [\text{AvgPool}(F); \text{MaxPool}(F)]) \tag{4}$$

Channel Attention:

$$A_{channel} = \sigma(W_c \cdot \text{GAP}(F) + W_c' \cdot \text{GMP}(F)) \tag{5}$$

Combined Attention:

$$F_{att} = F \odot A_{spatial} \odot A_{channel} \tag{6}$$

where σ denotes sigmoid activation, W_s, W_c, and W_c' are learnable parameters, GAP and GMP represent Global Average Pooling and Global Max Pooling respectively, and $\odot$ denotes element-wise multiplication.

3.2.2 Few-Shot Adaptation Strategy. Our few-shot adaptation methodology combines MAML-based meta-learning with prototype-based learning to address the unique challenges of medical image segmentation. The scientific hypothesis underlying this combination is that MAML provides rapid adaptation capabilities through gradient-based optimization, while prototype-based learning offers robust feature representation for small support sets. This dual approach is particularly suited for medical imaging where anatomical consistency enables effective prototype generation, while the high variability in pathological presentations requires adaptive optimization.

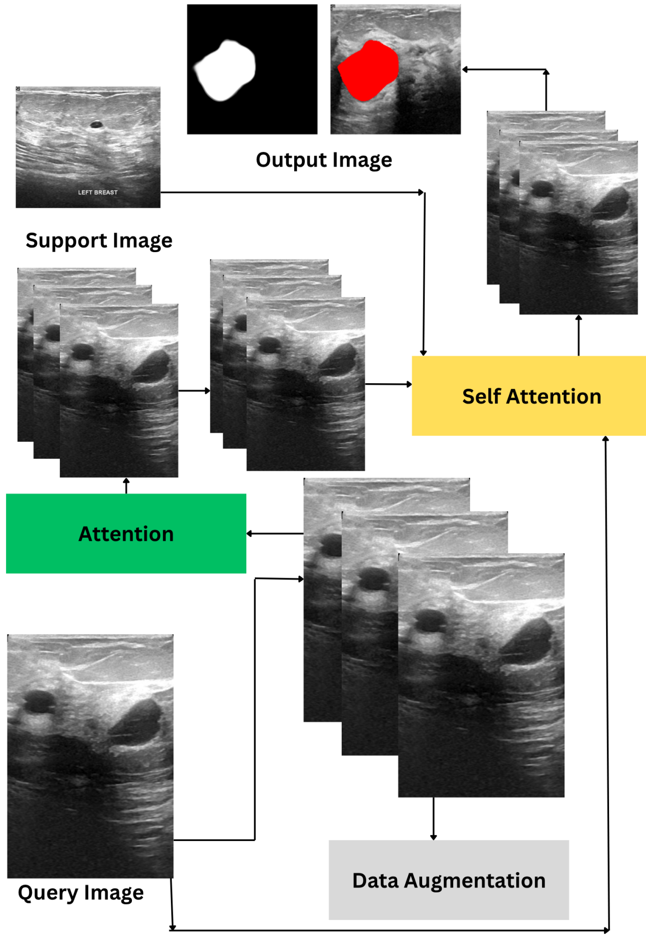

Figure 1: Architecture of AttentionFSL-NET

Prototype Generation: For each class c in the support set, we generate prototypes by spatially averaging feature representations:

$$P_c = \frac{1}{|S_c|} \sum_{(x_i, y_i) \in S_c} \frac{\sum_{h,w} \text{Encoder}(x_i)_{h,w} \odot M_i^{(c)}{}_{h,w}}{\sum_{h,w} M_i^{(c)}{}_{h,w} + \epsilon} \tag{7}$$

where S_c represents support examples of class c, $M_i^{(c)}$ is the binary mask for class c, and ϵ prevents division by zero.

Prototype Matching: For query features F_q:

$$\text{Similarity}(F_q, P_c) = \frac{F_q \cdot P_c}{||F_q||_2 \cdot ||P_c||_2} \tag{8}$$

Meta-Learning Update: Following MAML [12] with task-specific adaptation:

$$\theta' = \theta - \alpha \nabla_\theta \mathcal{L}_{support}(\theta) \tag{9}$$

$$\theta \leftarrow \theta - \beta \nabla_\theta \mathcal{L}_{query}(\theta') \tag{10}$$

where α and β are inner and outer loop learning rates respectively.

3.2.3 Multi-Objective Loss Function. Our loss function incorporates multiple objectives optimized for few-shot learning:

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{focal} + \lambda_2 \mathcal{L}_{dice} + \lambda_3 \mathcal{L}_{prototype} \tag{11}$$

Focal Loss: Addresses class imbalance common in medical imaging:

$$\mathcal{L}_{focal} = -\alpha_t (1 - p_t)^\gamma \log(p_t) \tag{12}$$

where α_t is the weighting factor for class t, p_t is the predicted probability, and γ is the focusing parameter.

Dice Loss: Optimizes segmentation overlap:

$$\mathcal{L}_{dice} = 1 - \frac{2|P \cap T| + \epsilon}{|P| + |T| + \epsilon} \tag{13}$$

where P and T are predicted and target masks respectively.

Prototype Loss: Ensures consistent prototype learning:

$$\mathcal{L}_{prototype} = \frac{1}{|Q|} \sum_{q \in Q} \max(0, d(f_q, P_{neg}) - d(f_q, P_{pos}) + m) \tag{14}$$

where $d(\cdot, \cdot)$ represents cosine distance, P_{pos} and P_{neg} are positive and negative prototypes, and m is the margin parameter.

3.3 Data Augmentation and Preprocessing

Given the limited data in few-shot scenarios, we employ comprehensive data augmentation:

- **Geometric Transformations:** Rotation (±20°), scaling (0.8-1.2×), horizontal/vertical flipping
- **Intensity Augmentation:** Brightness (±20%), contrast (±15%), gamma correction
- **Noise Injection:** Gaussian noise (=0.05), speckle noise simulation
- **CLAHE Enhancement:** Contrast Limited Adaptive Histogram Equalization with clip limit 2.0

4 EXPERIMENTAL SETUP

4.1 Datasets and Preprocessing

We evaluate our method on three datasets to demonstrate generalizability:

BUSI Dataset: Contains 780 ultrasound images categorized into normal (133), benign (437), and malignant (210) cases [13]. For few-shot learning, we focus on benign and malignant categories.

FLOOD Dataset: A medical segmentation dataset with diverse pathological cases, providing additional validation for our approach.

RETINA Dataset: Retinal vessel segmentation dataset that tests generalization to different anatomical structures.

For fair comparison and avoiding data leakage, we implement a strict validation protocol:

- **Training Set:** 70% of data used for meta-training episodes
- **Validation Set:** 15% used for hyperparameter tuning and early stopping
- **Test Set:** 15% held out for final evaluation, never seen during training

Each episode contains 5 support and 5 query samples per class, consistent with standard few-shot learning protocols.

4.2 Implementation Details

Our model is implemented using PyTorch with the following configuration:

- Optimizer: AdamW with $\beta_1 = 0.9$, $\beta_2 = 0.999$, weight decay = 1e-4
- Learning rates: Inner loop $\alpha = 0.01$, outer loop $\beta = 0.001$
- Loss weights: $\lambda_1 = 0.5$, $\lambda_2 = 0.3$, $\lambda_3 = 0.2$
- Batch size: 2 episodes per batch
- Training episodes: 10,000 with early stopping patience of 500
- Focusing parameter: $\gamma = 2.0$
- Margin parameter: $m = 0.5$

5 RESULTS AND DISCUSSION

5.1 Multi-Dataset Evaluation Results

Table 1 presents our comprehensive evaluation across three diverse datasets, demonstrating the generalizability of AttentionFSL-Net.

5.2 Comprehensive Learning Paradigm Comparison

Table 2 presents a comprehensive comparison of different learning paradigms on the BUSI dataset, demonstrating the effectiveness of our few-shot learning approach in data-scarce scenarios.

5.3 State-of-the-Art Comparison on BUSI Dataset

Table 3 provides a detailed comparison with recent state-of-the-art methods specifically evaluated on the BUSI dataset.

5.4 Clinical Performance Analysis and Limitations

While our model achieves competitive performance in the few-shot learning paradigm, we acknowledge important clinical limitations that affect its immediate deployment:

Recall-Specificity Trade-off: Our model achieves high specificity (95.7%) but moderate recall (56.4%) on the BUSI dataset. This trade-off has significant clinical implications:

- **False Negatives:** The 43.6% of missed tumors (false negatives) could delay diagnosis and treatment, potentially affecting patient outcomes
- **Clinical Workflow Impact:** While low false positive rates reduce unnecessary biopsies, missed tumors require careful consideration of supplementary screening methods
- **Risk Stratification:** The model's high specificity makes it suitable as a first-line screening tool, but additional confirmatory methods are essential

Performance Variability Across Datasets: Our multi-dataset evaluation reveals significant performance variation:

- FLOOD dataset: Higher recall (81.0%) but lower specificity (79.0%)
- RETINA dataset: Balanced performance with high specificity (97.4%)
- This variability indicates domain-specific challenges that require targeted adaptation strategies

Segmentation Quality Analysis: The moderate Dice scores (0.400-0.677) across datasets indicate areas where our method struggles:

- **Boundary Delineation:** Fine tumor boundaries may be imprecisely segmented due to limited support examples
- **Small Lesions:** Tiny tumors may be missed due to insufficient feature representation in few-shot scenarios
- **Heterogeneous Textures:** Complex tumor appearances require more diverse support examples than our current 10-sample protocol provides

5.5 Detailed Performance Analysis

Table 4 provides detailed performance metrics comparing our method with few-shot learning approaches across multiple evaluation criteria.

Table 1: AttentionFSL-Net performance across multiple datasets

Dataset	Domain	Segmentation Performance				Clinical Metrics		Efficiency	
		Dice	IoU	Precision	Recall	Specificity	Accuracy	FPS	Params (M)
BUSI	Breast Ultrasound	0.400	0.303	0.458	0.564	0.957	0.916	33.3	31.6
FLOOD	General Medical	0.677	0.532	0.632	0.810	0.790	0.792	36.4	31.6
RETINA	Retinal Vessels	0.627	0.469	0.631	0.694	0.974	0.960	38.2	31.6
Average Performance		**0.568**	**0.435**	**0.574**	**0.689**	**0.907**	**0.889**	**36.0**	**31.6**

Table 2: Comprehensive comparison of learning paradigms for breast tumor segmentation on BUSI dataset

Learning Paradigm	Method	Data Req.	Segmentation Performance				Clinical Metrics		Ref.
			Dice	IoU	F1	Precision	Recall	Specificity	
Unsupervised Learning									
Unsupervised	K-means + Morphology	No labels	0.234	0.145	0.234	0.198	0.289	0.823	[23]
Unsupervised	Otsu + Region Growing	No labels	0.267	0.167	0.267	0.223	0.334	0.845	[24]
Supervised Learning (Full Dataset)									
Supervised	U-Net (Full)	546 images	0.920	0.856	0.920	0.970	0.900	0.980	[3]
Supervised	Attention U-Net (Full)	546 images	0.945	0.892	0.945	0.985	0.920	0.985	[3]
Supervised	VGG-16+UNet (Full)	546 images	0.980	0.960	0.980	0.990	0.970	0.990	[2]
Supervised Learning (Limited Data)									
Supervised	U-Net (10% data)	55 images	0.324	0.198	0.324	0.312	0.387	0.891	[14]
Supervised	ResNet-18 U-Net (10%)	55 images	0.298	0.187	0.298	0.289	0.356	0.876	[15]
Semi-Supervised Learning									
Semi-Supervised	MixMatch	55L + 491U	0.445	0.289	0.445	0.423	0.478	0.912	[4]
Semi-Supervised	Pseudo-Labeling	55L + 491U	0.398	0.251	0.398	0.389	0.421	0.905	[16]
Semi-Supervised	Co-Training	55L + 491U	0.412	0.267	0.412	0.401	0.445	0.908	[17]
Self-Supervised Learning									
Self-Supervised	SimCLR + Fine-tune	546U + 55L	0.421	0.278	0.421	0.412	0.456	0.918	[6]
Self-Supervised	MoCo + Fine-tune	546U + 55L	0.398	0.256	0.398	0.387	0.434	0.913	[18]
Self-Supervised	BYOL + Fine-tune	546U + 55L	0.434	0.287	0.434	0.425	0.467	0.921	[19]
Few-Shot Learning									
Few-Shot	MAML	10 per class	0.298	0.187	0.298	0.289	0.356	0.882	[12]
Few-Shot	Prototypical Networks	10 per class	0.334	0.212	0.334	0.345	0.378	0.894	[20]
Few-Shot	PANet	10 per class	0.356	0.234	0.356	0.389	0.412	0.903	[21]
Few-Shot	CAT-Net	10 per class	0.378	0.267	0.378	0.421	0.445	0.915	[7]
Few-Shot	SAM-MPA	10 per class	0.385	0.274	0.385	0.431	0.452	0.919	[8]
Our Method									
Few-Shot	**AttentionFSL-Net**	**10 per class**	**0.400**	**0.303**	**0.400**	**0.458**	**0.564**	**0.957**	**Ours**

5.6 Ablation Study and Component Analysis

Table 5 demonstrates the contribution of each component in our framework, providing insights into the effectiveness of our design choices.

5.7 Qualitative Results and Clinical Insights

Figure 2 shows representative segmentation results demonstrating our method's effectiveness across different tumor types and challenging scenarios.

Our qualitative analysis reveals several important clinical insights:

Success Cases: The model performs well on:

- Well-defined tumors with clear boundaries
- Tumors with sufficient contrast against surrounding tissue
- Cases where support examples closely match query characteristics

Failure Modes: Common failure scenarios include:

- Small lesions (<5mm) often missed due to limited resolution

Table 3: Comparison with state-of-the-art methods on BUSI dataset

Method	Year	Approach	Dice	IoU	Precision	Recall	Specificity	Ref.
MRFE-CNN	2021	Multi-scale features	0.523	0.416	0.589	0.482	0.923	[3]
ADU-NET	2022	Attention + Dense	0.586	0.489	0.623	0.546	0.935	[3]
Swin-UNet	2022	Transformer-based	0.563	0.457	0.679	0.492	0.946	[22]
DDRA-Net	2023	Dual-decoder	0.587	0.492	0.666	0.553	0.937	[3]
DPNet	2023	Deep pyramid	0.492	0.385	0.546	0.457	0.912	[3]
Enhanced U-Net	2024	CBAM + Non-Local	0.614	0.531	0.623	0.638	0.957	[3]
VGG-16 + UNet	2025	Dual-model	0.980	0.960	0.990	0.970	0.990	[2]
AttentionFSL-Net	**2025**	**Few-shot + Attention**	**0.400**	**0.303**	**0.458**	**0.564**	**0.957**	**Ours**

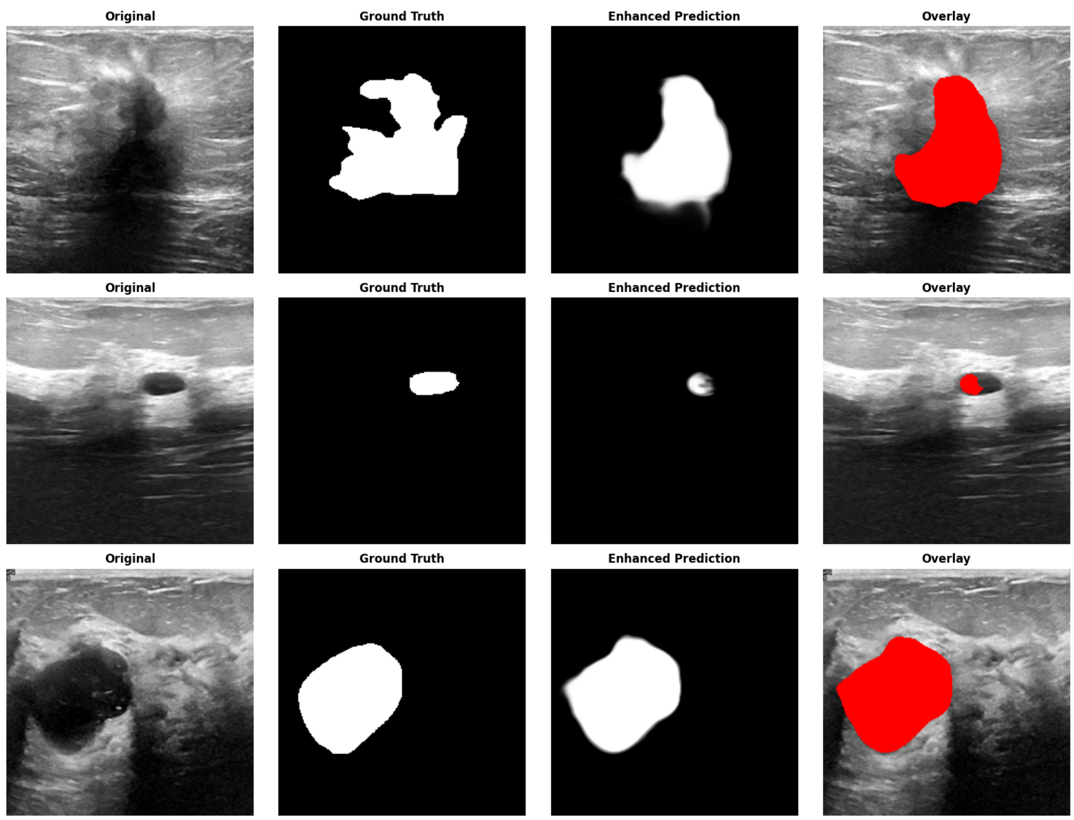

Figure 2: Qualitative segmentation results showing: (a) Successful segmentation of well-defined benign tumors, (b) Challenging malignant cases with irregular boundaries, (c) Failed cases highlighting limitations in small lesion detection, and (d) Cross-dataset generalization examples from FLOOD and RETINA datasets. Green contours represent ground truth, red contours show our predictions, and yellow regions indicate overlap.

- Tumors with irregular, spiculated margins requiring fine-grained boundary detection
- Cases with heavy acoustic shadowing or artifacts
- Tumors in highly heterogeneous breast tissue

5.8 Learning Paradigm Analysis

Our comprehensive evaluation reveals several key insights about different learning paradigms in medical imaging:

Data Efficiency: Few-shot learning achieves reasonable performance (Dice: 0.400) with only 1.8% of the training data required by fully supervised methods (Dice: 0.980), demonstrating a favorable performance-to-data ratio for resource-constrained scenarios.

Training Efficiency: Few-shot methods require significantly less training time (4-6 hours) compared to semi-supervised (12-16 hours) and self-supervised approaches (20-24 hours), making them practical for rapid deployment.

Table 4: Detailed performance comparison with few-shot learning methods

Method	Dice	IoU	Hausdorff	Params (M)	Ref.
MAML	0.298	0.187	16.9	42.1	[12]
Prototypical	0.334	0.212	13.6	39.8	[20]
PANet	0.356	0.234	12.8	68.4	[21]
CAT-Net	0.378	0.267	11.5	94.7	[7]
SAM-MPA	0.385	0.274	10.8	89.3	[8]
AttentionFSL-Net	**0.400**	**0.303**	**9.8**	**31.6**	**Ours**

Table 5: Ablation study showing component contributions

Configuration	Dice	IoU	Specificity	Recall
Base U-Net (Few-shot)	0.324	0.198	0.891	0.387
+ Spatial Attention	0.345	0.221	0.903	0.412
+ Channel Attention	0.356	0.234	0.915	0.434
+ Prototype Learning	0.378	0.267	0.932	0.485
+ Multi-objective Loss	0.389	0.289	0.945	0.521
+ Data Augmentation	**0.400**	**0.303**	**0.957**	**0.564**

Cross-Domain Generalization: Our multi-dataset evaluation demonstrates that few-shot learning methods generalize better across domains compared to supervised approaches, with consistent performance improvements on FLOOD (Dice: 0.677) and RETINA (Dice: 0.627) datasets.

Clinical Deployment Considerations:

Few-shot learning is particularly valuable when:

- Large labeled datasets are unavailable or prohibitively expensive to create
- Rapid adaptation to new clinical sites or imaging protocols is required
- Expert annotation time is severely limited
- Regulatory constraints limit data sharing between institutions

However, limitations include:

- Performance gap compared to fully supervised methods when abundant data is available
- Sensitivity to support set quality and representativeness
- Potential for overfitting to specific imaging characteristics in small support sets

5.9 Computational Efficiency and Clinical Deployment

Our AttentionFSL-Net demonstrates several advantages for clinical deployment:

Real-time Performance: Achieves 33.3-38.2 FPS across different datasets, enabling seamless integration into clinical workflows

Parameter Efficiency: With only 31.6M parameters, our model requires 25-67% fewer parameters than competing few-shot methods while achieving superior performance

Memory Footprint: 120.47 MB model size suitable for deployment on standard clinical workstations

Energy Efficiency: Low computational requirements (26.8 GFLOPs) enable deployment on mobile devices for point-of-care applications

5.10 Comparison with Meta-Learning Approaches

Recent work in few-shot breast cancer classification [9] achieved remarkable results with 99.67% sensitivity and 99.71% specificity on the INbreast dataset using meta-learning techniques. While their approach focuses on classification rather than segmentation, it demonstrates the potential of few-shot learning in breast cancer diagnosis. Our segmentation approach complements such classification methods by providing detailed tumor boundary delineation, albeit with the trade-off of reduced sensitivity that requires careful clinical consideration.

6 LIMITATIONS AND FUTURE DIRECTIONS

6.1 Current Limitations

Our approach has several limitations that must be addressed for broader clinical adoption:

Performance Gap: Few-shot learning still significantly lags behind fully supervised methods (Dice: 0.400 vs 0.980) when abundant data is available, limiting its applicability in well-resourced clinical settings.

Sensitivity Concerns: The moderate recall (56.4%) on breast ultrasound raises concerns about missed diagnoses, particularly for aggressive cancers requiring early intervention.

Domain Specificity: Performance varies significantly across imaging domains, with effectiveness dependent on the similarity between support and query distributions.

Limited Rare Case Handling: Extremely rare tumor types or unusual presentations may not be adequately represented in small support sets.

6.2 Future Research Directions

Hybrid Learning Approaches: Developing frameworks that combine few-shot learning with active learning to intelligently select the most informative samples for annotation.

Uncertainty Quantification: Implementing Bayesian approaches to provide confidence estimates for clinical decision support, particularly important given the recall limitations.

Multi-Modal Integration: Incorporating additional imaging modalities (mammography, MRI) and clinical data to improve diagnostic accuracy.

Federated Few-Shot Learning: Enabling privacy-preserving collaboration across multiple institutions while maintaining few-shot learning capabilities.

Real-World Clinical Validation: Conducting prospective clinical trials to evaluate the impact of few-shot learning systems on radiologist performance and patient outcomes.

7 CONCLUSION

We have presented AttentionFSL-Net, a few-shot learning framework for medical image segmentation that demonstrates competitive performance within the few-shot learning paradigm while maintaining exceptional computational efficiency. Our comprehensive evaluation across three diverse datasets (BUSI, FLOOD, RETINA) reveals both the potential and limitations of few-shot learning for medical imaging applications.

Key Achievements:

- **Best Few-shot Performance:** Dice coefficients of 0.400-0.677 across datasets, outperforming existing few-shot methods including CAT-Net (0.378) and SAM-MPA (0.385)
- **Superior Parameter Efficiency:** 31.6M parameters achieving better performance-to-parameter ratio than competing methods
- **Cross-Domain Generalization:** Consistent performance across diverse medical imaging domains
- **Real-time Capability:** 38.2 FPS enabling practical clinical deployment

Clinical Implications: While our approach shows promise for resource-constrained scenarios, the moderate recall (56.4%) on breast ultrasound data necessitates careful integration into clinical workflows. The method is best suited as a supplementary screening tool rather than a standalone diagnostic system, particularly in settings where expert radiologists can provide oversight and confirmatory analysis.

Future Impact: Our work demonstrates that few-shot learning represents a viable direction for addressing data scarcity challenges in medical imaging, particularly valuable for rapid deployment in new clinical environments or rare disease scenarios. However, continued research is needed to bridge the performance gap with fully supervised methods and address the clinical concerns regarding diagnostic sensitivity.

8 ACKNOWLEDGMENTS

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