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Breast Cancer Segmentation Using a Modified U-Net with Dynamic Whale Optimization Algorithm (DWOA) Channel Selection

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Extended Abstract

Accurate segmentation of breast cancer lesions in medical imaging is pivotal for diagnosis, treatment planning, and monitoring progression [1]. While U-Net architectures have become a cornerstone in medical image segmentation, redundant feature maps in convolutional layers often hinder performance by diluting critical tumor-related information [2]. This study addresses this limitation by integrating the Dynamic Whale Optimization Algorithm (DWOA)—a metaheuristic technique inspired by humpback whale foraging behavior—into a U-Net model [3]. The primary objective is to enhance segmentation accuracy through dynamic channel selection during training, optimizing feature relevance while maintaining computational efficiency and model interpretability.

The proposed architecture modified the U-Net framework by embedding a custom WOA-based channel selection layer within encoder blocks [4]. During training, the WOA module iteratively refined channel selections by evaluating feature map activations, prioritizing those most discriminative for tumor boundaries and texture. The algorithm initializes "whale" agents representing candidate channel subsets, which evolve over iterations using exploration-exploitation strategies. Channels associated with higher activation magnitudes were weighted dynamically during max-pooling to amplify their contribution. The encoder-decoder structure retained spatial hierarchies through skip connections, while transpose convolutions in the decoder enable precise localization. The model was trained on breast ultrasound and mammography [5] datasets using IoU loss, with evaluation metrics including the Dice Coefficient and Intersection-over-Union (IoU) to quantify overlap with ground truth masks.

Unlike static or attention-based methods, the WOA layer adaptively selects channels by balancing global exploration (diversifying candidate subsets) and local exploitation (refining high-scoring solutions). This reduces redundancy and focuses computation on tumor-salient features. Channel selection occurs exclusively during training, ensuring inference efficiency. Selected channels are encoded into a binary mask, combined with batch normalization to stabilize learning. Additionally, each encoder block processes features via dual convolutional layers, followed by WOA-driven selection and weighted pooling. The bottleneck layer expands the receptive field to capture contextual tumor features before reconstruction.

Experimental results demonstrate a 4.1% improvement in IoU over the baseline U-Net, alongside a 3.05% increase in Dice Coefficient, validating the efficacy of WOA-driven feature optimization. The model exhibits robustness in heterogeneous tumor morphology and low-contrast imaging scenarios, achieving faster convergence due to reduced parameter redundancy. Computational overhead during training remains manageable, with a 12% increase in time per epoch compared to the standard U-Net, while inference latency matches conventional architectures. These advancements address critical challenges in medical imaging, such as generalizability across diverse datasets and interpretability of feature importance, bridging the gap between complex deep learning models and clinical usability.

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