SEABED: Secure and Efficient AI-Based Breast Cancer Detection Using Low-Cost Edge Devices

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AI-powered breast cancer diagnostics remain inaccessible in low-resource settings due to patient privacy constraints, high hardware costs, and bandwidth limitations. This project designed and validated SEABED, a federated learning (FL) system enabling breast cancer detection on a $170 Raspberry Pi 5 edge node without transmitting raw patient data. SEABED combined two algorithmic innovations: (1) Frozen-Backbone Subspace Optimization, restricting training to a 961-parameter Active Learning Head atop a frozen MobileNetV3Large backbone; and (2) Top-K Gradient Sparsification with residual accumulation, compressing client uploads to sub-kilobyte payloads. A novel Performance-Weighted aggregation rule ($S_i = n_i \times AUC_i$) replaced standard FedAvg to counter non-IID data heterogeneity. The system was trained on CBIS-DDSM over 300 federated rounds across two physical nodes, with four sparsification rates (k = 1%, 5%, 10%, 100%) evaluated across different random seeds. SEABED at k=10% achieved AUC = 0.715, approaching the centralized model benchmark (AUC = 0.740) and matching FedAvg (0.717, ? = -0.18%, $p = 0.50$), while reducing per-round upload by 80% (0.75 KB vs. 3.75 KB). Network traffic analysis confirmed zero raw pixel transmission across all 763 training rounds. At k=1%, AUC dropped to 0.686, revealing a cliff effect at extreme compression. These results demonstrate that advanced medical FL is deployable on sub-$200 hardware with near-baseline diagnostic accuracy and structural privacy guarantees. Future work includes asynchronous FL for intermittent connectivity, multimodal EHR integration, and quantized LLM clinical auto-reporting.

Awards Won:

Fourth Award of $600