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Topic of Research: **Exploring Multiple Modalities for Efficient Detection of Breast Cancer using Deep Learning**

FINDINGS

This thesis systematically addressed critical challenges in breast cancer diagnosis by designing and validating novel deep learning frameworks across mammography, thermal, and ultrasound imaging modalities. The findings demonstrate that accurate diagnosis, computational efficiency, interpretability, and cross-modality robustness can be jointly achieved through carefully designed AI architectures.

The initial finding emerged from a **radiomics-based baseline framework** for molecular subtype classification, where handcrafted features were extracted and optimized using metaheuristic algorithms before classification with traditional machine learning models. While this approach established a meaningful performance benchmark, it exposed the limited capability of handcrafted features to capture complex and fine-grained molecular subtype characteristics. This limitation motivated the transition to end-to-end deep learning architectures capable of learning richer, discriminative representations directly from imaging data.

To overcome these constraints, the **MOB-CBAM model** was developed for mammographic analysis. By incorporating dual-channel attention mechanisms, the model enhanced lesion-specific feature localization and demonstrated robust performance in both coarse-grained and fine-grained molecular subtype classification tasks. Importantly, the model exhibited strong cross-dataset generalization, confirming its ability to learn clinically relevant features that are stable across heterogeneous mammography datasets.

For thermal imaging, the **LC-SCS model** was designed to achieve a balance between high diagnostic accuracy and computational efficiency. The findings show that a lightweight architecture with reduced parameters, memory-efficient operations, and low inference latency can maintain robust classification performance. This efficiency makes LC-SCS particularly suitable for real-time screening and deployment in resource-constrained clinical environments, supporting scalable and accessible breast cancer diagnosis.

The thesis further addressed interpretability through the **BreastFormer framework**, which integrates lesion classification with Grad-CAM–based visual explanations and Transformer-driven textual report generation. The results demonstrate that combining visual and textual explanations within a unified pipeline significantly enhances transparency and clinician trust. BreastFormer not only delivers accurate predictions but also provides interpretable evidence that supports clinical verification and informed decision-making.

For ultrasound imaging, the **SwinEff-AttentionNet** framework unified lesion classification and segmentation within a single model. By combining EfficientNet layers, Swin Transformer blocks, and efficient local self-attention mechanisms, the model effectively captured both global contextual information and fine-grained local details. The findings confirm reliable lesion delineation and accurate classification under variable imaging conditions, addressing operator dependency and data heterogeneity inherent in ultrasound imaging.

Collectively, these findings demonstrate the clinical value of deep learning systems that integrate molecular subtype classification, attention-driven interpretability, computational efficiency, and multi-task learning within robust and generalizable architectures. The proposed frameworks effectively address the challenges posed by heterogeneous imaging modalities, limited computational resources, and the need for transparent decision-making. Overall, this work establishes a strong foundation for clinically deployable, interpretable, and multimodal AI systems capable of supporting accurate and reliable breast cancer diagnosis across diverse healthcare settings.