Improving Model Adaptability: A Domain Knowledge-Integrated Deep Learning Approach for Ultrasound Image Segmentation and Classification

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Introduction: Ultrasound imaging is a non-invasive, widely-used imaging modality for breast cancer detection. We develop a model for breast ultrasound image segmentation and classification, focusing on its economical deployment across diverse clinical settings. We investigate the performance of our existing two-stage neural network model [1] when applied to breast ultrasound images collected from various hospitals, distinct from its initial training dataset. Moreover, we explore transfer learning using our pre-trained model, incorporating domain insights from the original ultrasound dataset, and demonstrate the adaptability of our model to new datasets.

Methods: We employ a two-stage model from our prior work [1], integrating image segmentation and classification. The first stage is built on a U-Net architecture, to generate segmented tumor masks, as shown in Figure 1, followed by the second stage of a convolutional neural network (CNN) for classifying tumor type. To enhance the model's efficiency, we introduce a new feature fusion method for the CNN input, fusing the predicted mask, the original ultrasound image, and their product representing the region of interest.

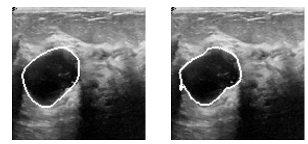

Figure 1: Ultrasound images with tumor mask boundaries (in white): ground truth mask (left) and predicted mask (right).

Our evaluation extends beyond the breast ultrasound images dataset (BUSI) [2], where our model was first trained, to include two additional datasets, the UDIAT Diagnostic Centre dataset (UDIAT) [3] and the Mendeley ultrasound dataset (BUSC) [4]. We initially apply the model trained on the original dataset directly to new datasets, establishing a baseline performance of the model when confronted with datasets sourced from different hospitals, with potential differences in the equipment and operator skill. Next, we analyze the impact of transfer learning, by comparing models with weights pre-trained on the original dataset and fine-tuned on additional datasets against models trained from scratch. We quantitatively evaluate the model's performance based on the segmentation intersection over union (IoU) and the classification accuracy (ACC).

Results: We first train our model on the BUSI dataset covering 2 tumor classes (benign and malignant), achieving a test IoU of 0.6071 and an ACC of 0.9385. Subsequently, we directly apply this trained model to the entire UDIAT and BUSC datasets, treating them as test sets. The results show an IoU of 0.5492 for UDIAT and 0.6852 for BUSC, along with an ACC of 0.7669 for UDIAT and 0.6080 for BUSC.

Table 1: Models' test performance without and with transfer learning (TL).

	Without TL		With TL	
	UDIAT	BUSC	UDIAT	BUSC
IoU	0.4986	0.7260	0.6613	0.8206
ACC	0.8182	0.9067	0.8788	0.9867

To better adapt our model to new datasets, we employ transfer learning. We split UDIAT and BUSC into 80 : 20 training and test sets, then train new models. In Table 1, we present a comparison between two groups of models on their test sets: models trained from scratch and models fine-tuned with pre-trained weights from BUSI. We observe that, transfer learning leads to an increase in segmentation IoU by 0.1627 for UDIAT and 0.0946 for BUSC. Concurrently, it increases the classification ACC by 0.0606 for UDIAT and 0.0800 for BUSC.

Conclusions: In this work, we enhanced the feature fusion phase in the classification stage and demonstrated the added value of transfer learning utilizing a medical dataset from the same imaging modality, verified across two datasets. This approach effectively integrates domain knowledge to improve the model's adaptability. To promote practical utility and generalizability of diagnostic decision-support models, we suggest future work to further tackle the inherent heterogeneity of data.

References

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