Selective Phase-Aware Training of nnU-Net for Robust Breast Cancer Segmentation in Multi-Center DCE-MRI

Team FPixel | Paper ID: 0073

Beyza Zayim, Aissiou Ikram, Boukhiar Naima

MICCAI2025 Daejeon REPUBLIC OF KOREA

INTRODUCTION

Breast tumor segmentation in dynamic contrast-enhanced (DCE-)MRI is critical for diagnosis and treatment planning. However, models trained on multi-institutional data often fail to generalize to new clinical centers. This work investigates strategies to improve model robustness for reliable clinical deployment across diverse datasets (DUKE, NACT, ISPY1, ISPY2).

OBJECTIVE

This study had two primary objectives:

1. To diagnose the generalization gap in breast tumor segmentation models when applied to multi-center DCE-MRI data, moving beyond simple in-dataset performance metrics.
2. To validate two targeted strategies for improving model robustness:
   - The use of phase-aware training (utilizing multiple contrast phases).
   - Strategic dataset curation (prioritizing data quality and consistency over sheer quantity).

METHODS

- **Model:** 3D full-resolution nnU-Net (state-of-the-art biomedical segmentation framework).
- **Preprocessing:** Isotropic resampling & z-score normalization.
- **Strategy:** 5-fold cross-validation.
- **Postprocessing:** Retain only the largest connected component to focus on the primary tumor.

We evaluated two key scenarios to diagnose generalization issues:

- **Sanity-Check (In-Distribution):** Mamma Mia Challenge (DSC 0.93, top-8 result).
- **Validation (Generalization):** External test sets (DSC 0.72).

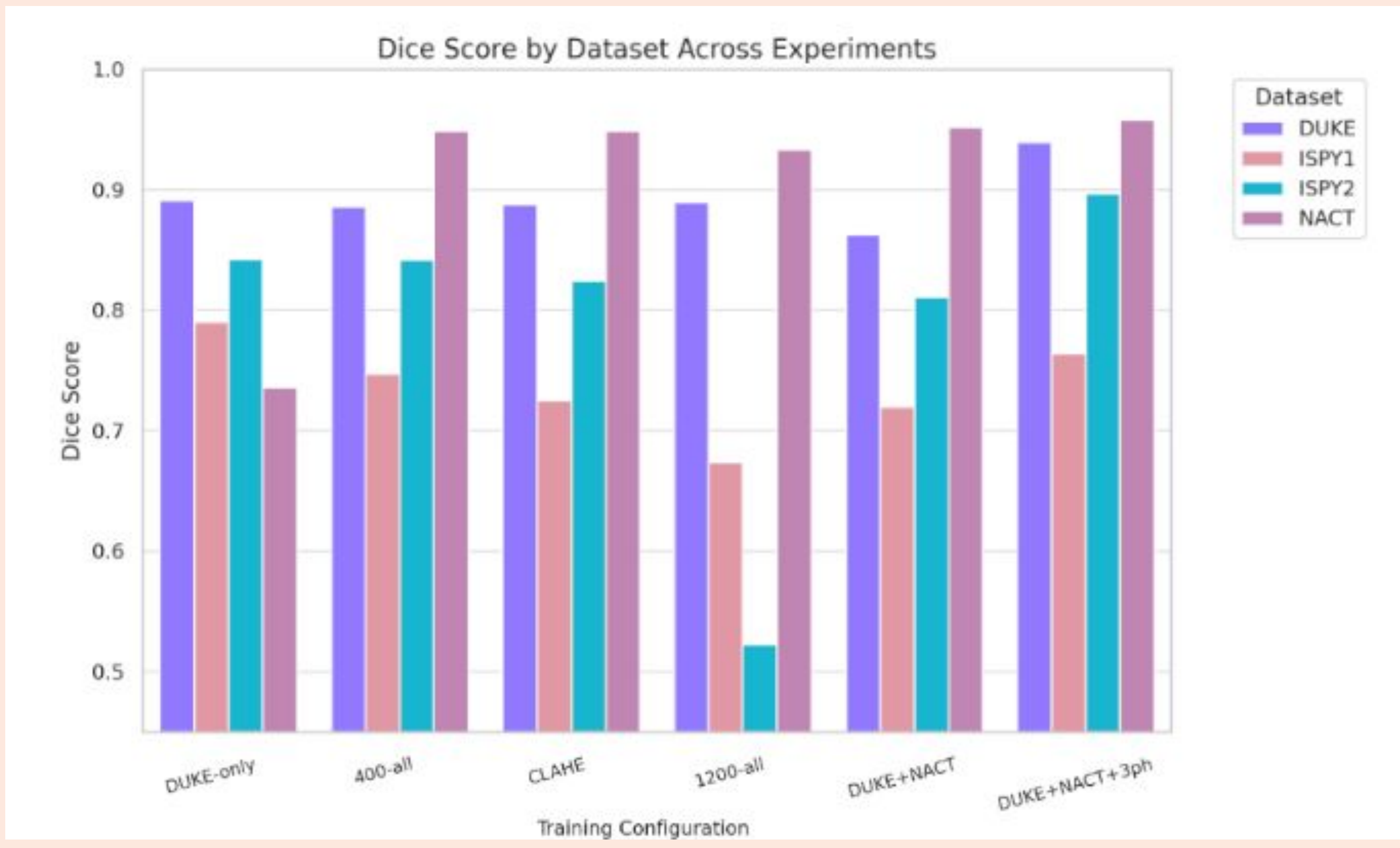
To bridge this performance gap, we proposed and tested two selective training strategies:

- **(a) Phase-Aware Training:** Comparing models trained on a single DCE-MRI phase vs. a 3-phase ensemble.
- **(b) Dataset Curation:** Comparing training on all available data vs. a curated subset (DUKE+NACT only).

RESULTS

Our selective training strategies significantly improved model generalization on external validation sets.

Strategy	Performance Gain (DSC)	Key Insight
Phase-Aware Training	**+0.10**	Utilizing multiple contrast phases provides complementary information.
Dataset Curation (DUKE+NACT only)	**+0.17**	Data quality and consistency trump sheer quantity.



Key Finding: A model trained on a small, high-quality curated subset (n=20 cases from DUKE+NACT) outperformed a model trained on a larger, more heterogeneous pool of data from all collections.

CONCLUSION

The conventional "more data is better" assumption can be detrimental for multi-center breast MRI segmentation. Selective, phase-aware training and rigorous dataset curation are essential for enhancing model robustness and generalization.

- **Clinical Impact:** These strategies are a critical step toward translating reliable AI segmentation tools into diverse clinical settings.
- **Future Work:** Motivated by these results, we are investigating automated, quality-based data selection pipelines to build optimal training sets without manual intervention.

REFERENCES