Abstract Number: 1534

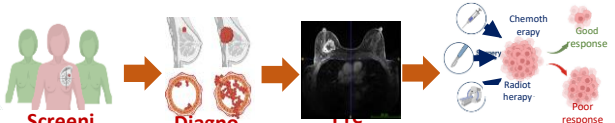
Optimizing Transfer Learning for Early Prediction of Pathologic Complete Response in Breast Cancer: A Multicenter Study Using Pretreatment DCE-MRI

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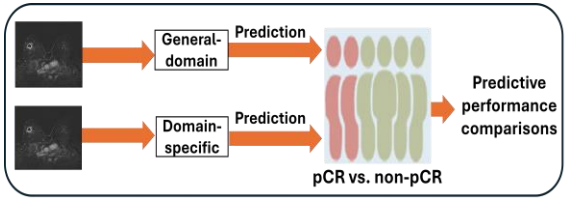
* corresponding author

Background

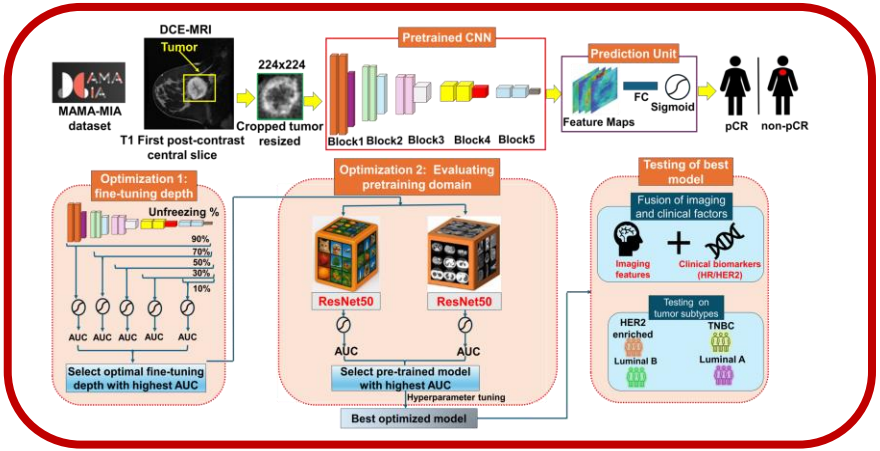


Pathological complete response (pCR)

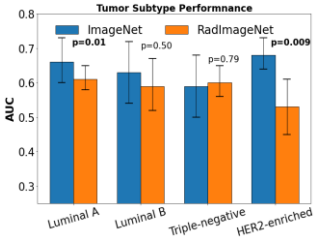
Strong indicator of better survival and disease-free outcomes.



Methods



Results



P-value compares ImageNet vs. RadImageNet AUCs via DeLong's tests.

- ImageNet outperformed RadImageNet in transfer learning for pCR prediction.
- Performance gains varied across tumor subtypes.

Study Dataset (MAMA-MIA)[1]

Inclusions N = 1506 → **Exclusions N = 149** → **Final Data N = 1357**

- Women diagnosed with invasive breast cancer.
- Women undergoing NAT.
- With pretreatment DCE-MRI available.

- Lacked pCR.
- Incomplete pathology data.
- Non-complete MRI sequences.
- Image artifacts.

- **T1W pre-contrast sequence.**
- Two postcontrast T1W phases: **Phase 1**, Phase 2.
- Tumor annotations.

Final dataset:
424 pCR and 933 non-pCR

Results

Model	AUC [95% CIs]	Balanced Accuracy [95% CIs]	PPV [95% CIs]	NPV [95% CIs]	P-value
ImageNet	0.63 [0.59, 0.66]	0.59 [0.58, 0.61]	0.41 [0.40, 0.43]	0.75 [0.74,0.77]	**P = 0.02**
RadImageNet	0.59 [0.57, 0.61]	0.56 [0.54, 0.58]	0.39 [0.37, 0.40]	0.73 [0.71,0.75]	
ImageNet + clinical	0.68 [0.62, 0.75]	0.64 [0.61-0.67]	0.41 [0.40, 0.43]	0.84 [0.80-0.89]	**P = 0.04**

p-values denote AUC differences for ImageNet vs RadImageNet and ImageNet + clinical via DeLong's tests.

Conclusions

- Our study highlights the potential of transfer learning for pCR prediction with pre-treatment DCE-MRI.
- Optimized performance with ImageNet indicates the importance of initial knowledge domain in transfer learning and the potential benefit from diverse feature learning from large datasets.
- Future steps include external validation experiments, extensions to other clinically relevant endpoints, and multimodal imaging approaches.

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