Deep learning models trained for BMI prediction show capability for BIRADS classification, revealing common underlying mammographic signals.

BMI Prediction from Mammography Images and its Implications for Breast Cancer Risk

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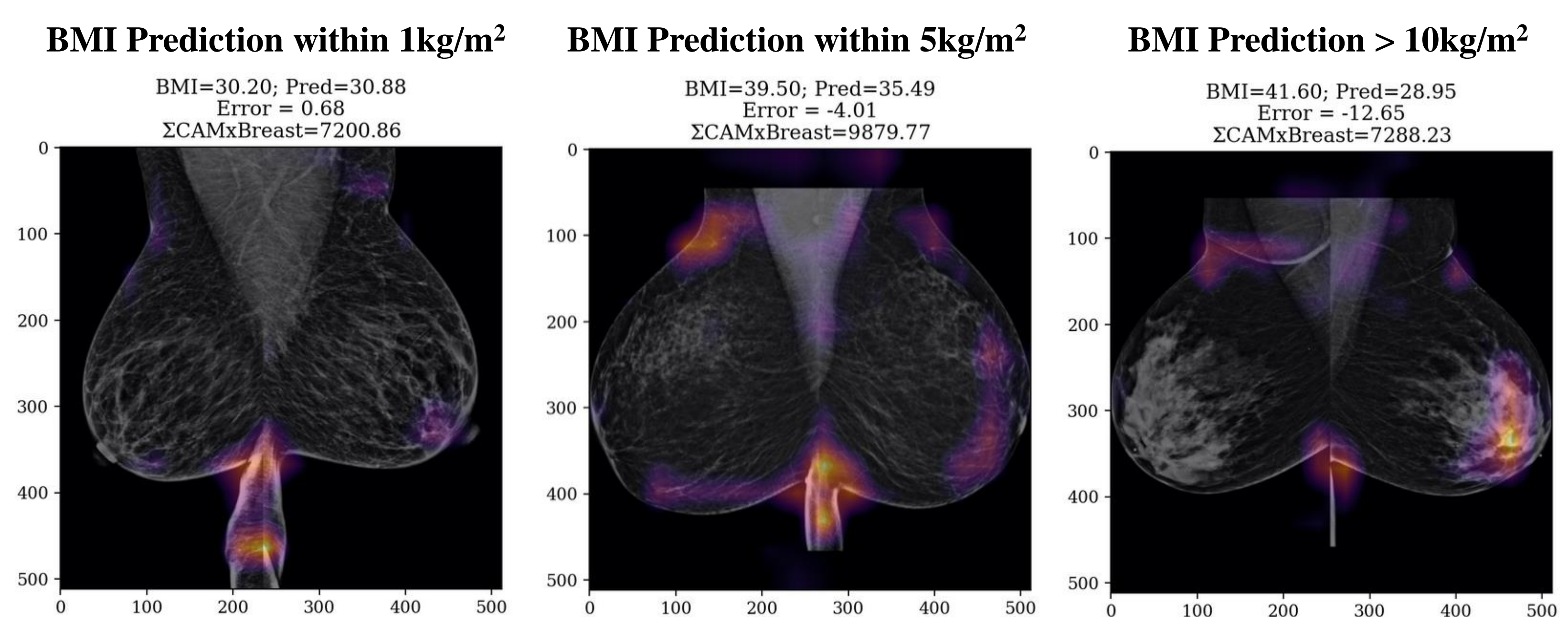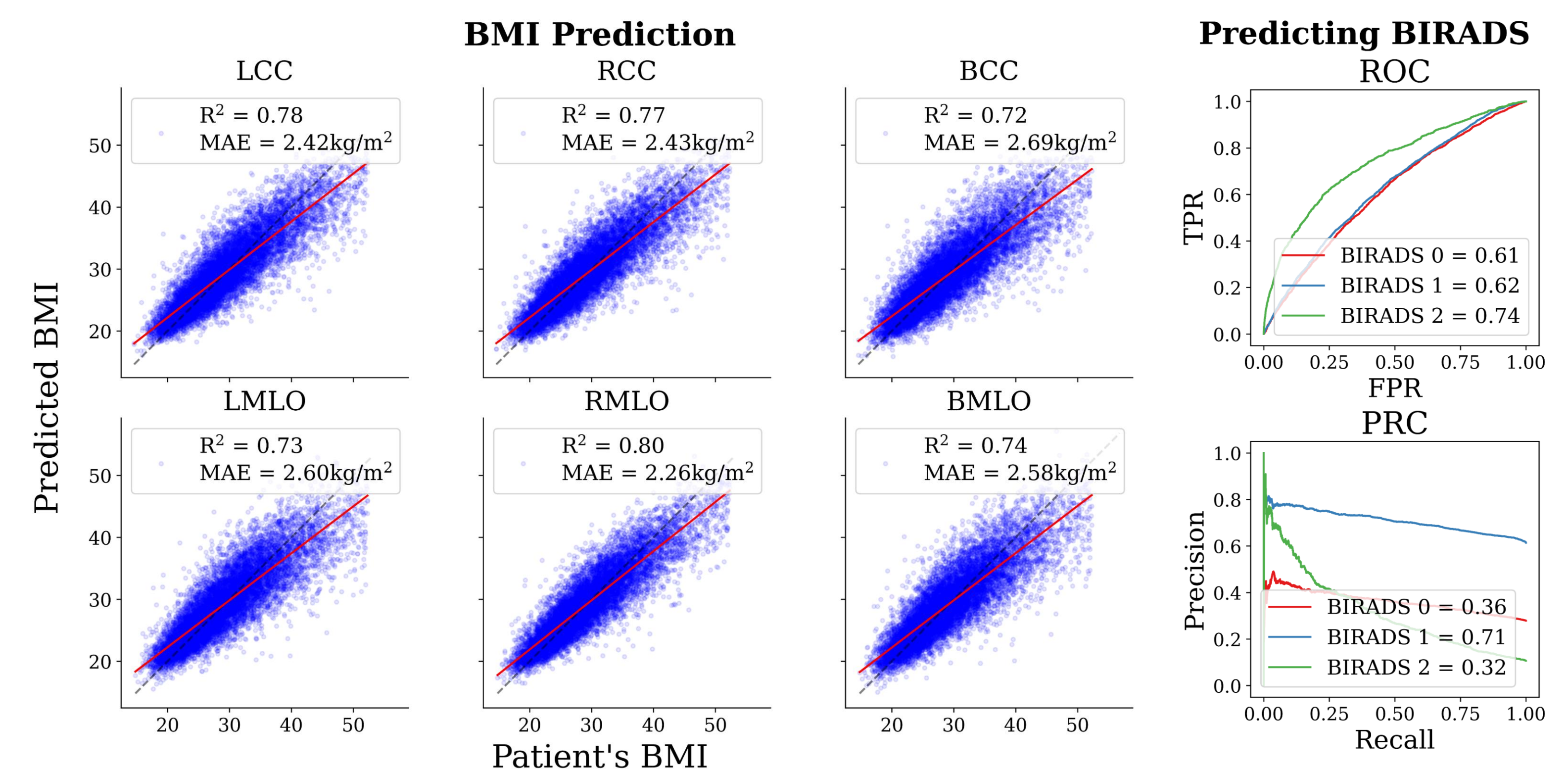
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Background: Traditional breast cancer risk models often underperform, especially in minority populations. Recent advances like the image-based deep learning models Mirai[1] outperform these traditional models but lack explainability of the image features influencing their predictions. Body mass index (BMI) is a well-known, explainable risk factor for breast cancer, affecting pre- and post-menopausal women differently.
This study aims to predict BMI from mammograms, potentially shedding light on explainable features within deep-learning-based breast cancer risk prediction models.

Methods:

- We acquired a dataset of 11,874 patients who had undergone 4-view screening mammography at Emory Healthcare with corresponding BMI measurements from 2012 to 2021.

- Mammograms were labeled with the BMI at the time of the study and divided into 80/20 training and testing splits at the patient level.

- Bilateral images were created by stitching together left and right view position images.

- We trained six ConvNext-based models for different views (LMLO, LCC, RMLO, RCC, BMLO, BCC).

- Model performance was evaluated on MAE and R^2 metrics and GradCAM++ was used for model explainability.

- Subgroup analyses were conducted on race, sex, age, marital status, tissue density, and BIRADS score subgroups.

- Finally, we took the pre-logit layer from the model and used it to predict BIRADS as well as pathological severity.

BMI Prediction — LCC ($R^2=0.78$, MAE = 2.42kg/m²), RCC ($R^2=0.77$, MAE = 2.43kg/m²), BCC ($R^2=0.72$, MAE = 2.69kg/m²), LMLO ($R^2=0.73$, MAE = 2.60kg/m²), RMLO ($R^2=0.80$, MAE = 2.26kg/m²), BMLO ($R^2=0.74$, MAE = 2.58kg/m²). Predicting BIRADS ROC: BIRADS 0 = 0.61, BIRADS 1 = 0.62, BIRADS 2 = 0.74. PRC: BIRADS 0 = 0.36, BIRADS 1 = 0.71, BIRADS 2 = 0.32.

BMI Prediction within 1kg/m²: BMI=30.20; Pred=30.88, Error = 0.68, ΣCAMxBreast=7200.86. BMI Prediction within 5kg/m²: BMI=39.50; Pred=35.49, Error = -4.01, ΣCAMxBreast=9879.77. BMI Prediction > 10kg/m²: BMI=41.60; Pred=28.95, Error = -12.65, ΣCAMxBreast=7288.23.

Results: All 6 models performed similarly, with mean R^2 of 0.76 (SD: 0.03) and mean MAE of 2.5 kg/m2 (SD: 0.14 kg/m2). The RMLO model outperformed others with R^2 of 0.80, suggesting sufficient BMI encoding in unilateral mammograms. Subgroup analysis on race revealed higher model performance in White patients compared to Black patients across all models, notably RMLO ($R^2=0.81$ vs. $R^2=0.76$, respectively). Model performance was lower in postmenopausal-age women ($R^2=0.70$ vs. $R^2=0.76$, respectively). BIRADS Breast Density C and BIRADS score 1 yielded the highest performance with $R^2=0.67 - 0.69$ and $R^2=0.74$, respectively. Finally, pre-logit prediction showed signal in predicting BIRADS scores with AUROC= 0.61 - 0.74.

Conclusion:

DL models demonstrate the ability to predict BMI, a risk factor in breast cancer, from mammography exams with acceptable performance. Models trained for BMI prediction were also able to predict BIRADS scores by a classification head on the last layer.

Distribution of Patient BMI on Train and Test Datasets

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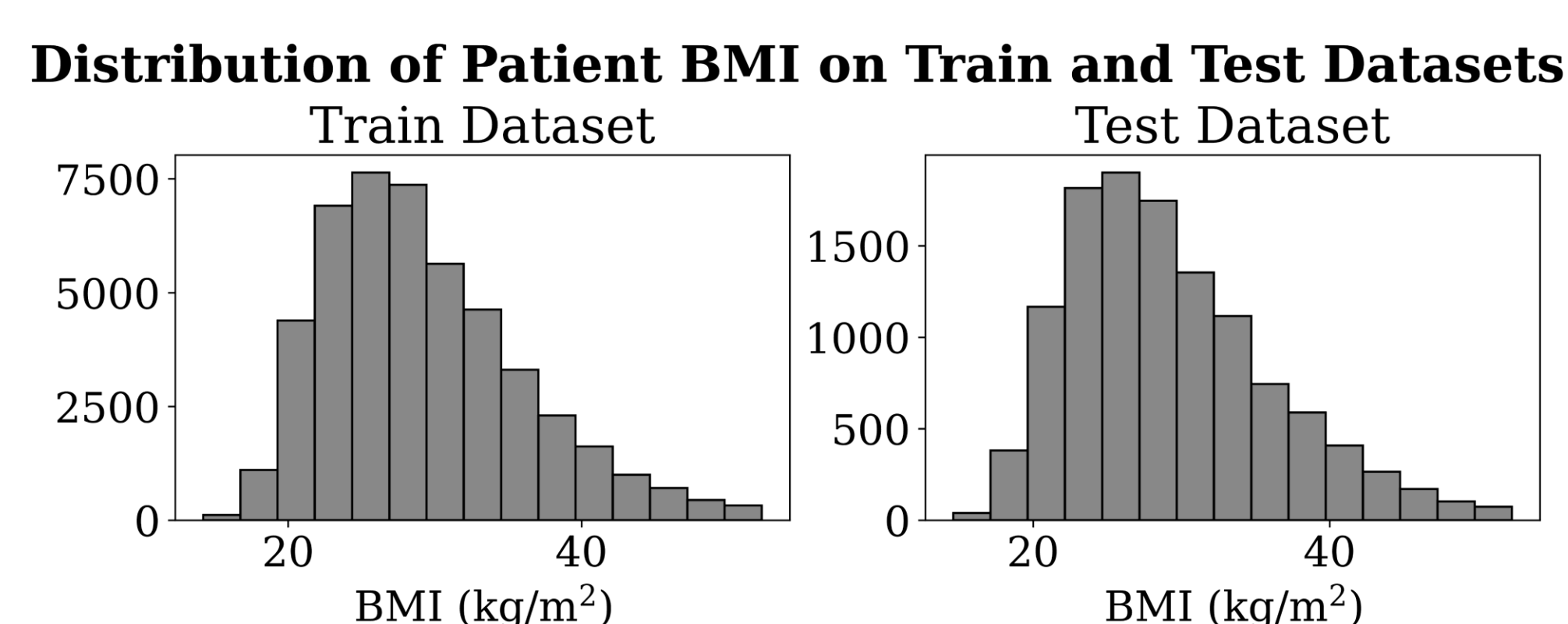
*) List of views
- LCC: Left Cranio-Caudal
- LMLO: Left Medio-Lateral Oblique
- RCC: Right Cranio-Caudal
- RMLO: Right Medio-Lateral Oblique
- BCC: Bilateral Cranio-Caudal
- BMLO: Bilateral Medio-Lateral Oblique

References:
1. Adam Yala et al. Toward robust mammography-based models for breast cancer risk.Sci. Transl. Med.13,eaba4373(2021).DOI:10.1126/scitranslmed.aba4373
2. Liu, Z., Mao, H., Wu, C.-Y., Feichtenhofer, C., Darrell, T., & Xie, S. (2022). A ConvNet for the 2020s. arXiv. https://doi.org/10.48550/ARXIV.2201.03545