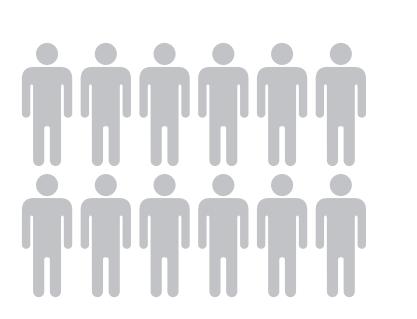


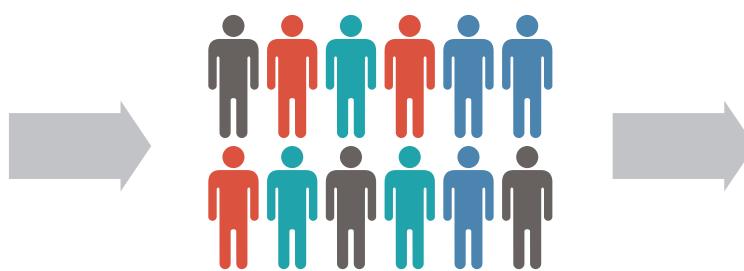
Combined PET and MRI Radiomics with Breast Cancer Outcomes

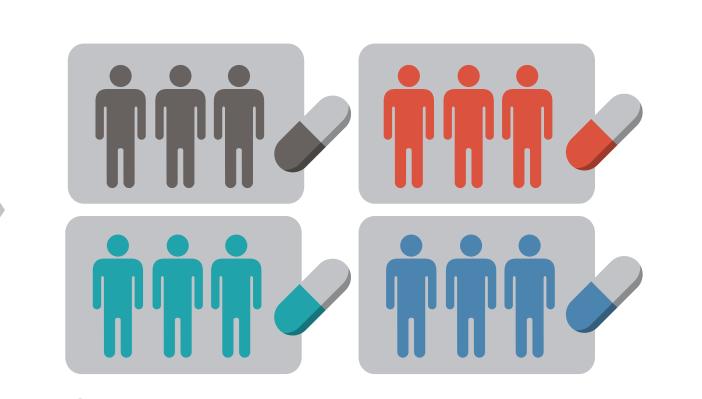
Shih-ying Huang, Benjamin L. Franc, Roy Harnish, Timothy Copeland, Vignesh Arasu Ella F. Jones, Nola M. Hylton, and Youngho Seo, Senior Member, IEEE

Why Radiomics?

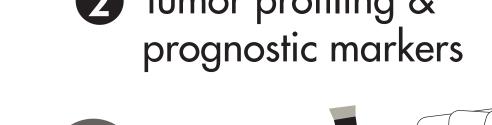
- Improve cancer treatment with more precise and personalized disease management
- Radiomics from 3D imaging modalities has been shown useful for discovering imaging biomarkers¹





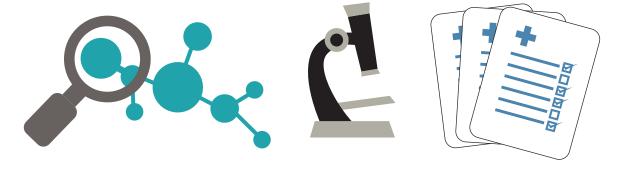








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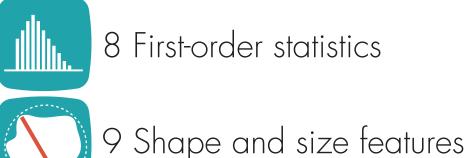


Radiomics Workflow

Data Collection

- PET and dynamic-contrast-enhanced MR (DCE-MRI) images from patients diagnosed with invasive breast cancer in 2003 - 2005
- All images were acquired prior to any surgery/treatment
- Gathered clinical data from the medical records and cancer registry including:
- tumor histology, grade, T/N/overall stages • estrogen receptor (ER), progesterone receptor (PR), human epidermal growth factor receptor 2 (HER2) status
- recurrence site, status, and duration until recurrence/death since diagnosis

Radiomic Feature Extraction





25 3D Gray level co-occurrence



- matrix (GLCM) texture features • Images were re-sampled to isotropic voxel size
- GLCM matrices were created with fixed bin width
- Computed with in-house Python-ITK² software and validated with pyradiomics open-source software³

2 Tumor Segmentation

- Manually segmented tumors from the SUV-converted PET images using MeVisLab
- Segmented tumors from the DCE-MR images by the signal-enhancment ratio (SER) map



Clustering and Statistical Analysis

- Performed unsupervised clustering using concensus clustering implemented in R⁴
- χ^2 test for significant association between the tumor clusters and tumor profiling variables
- Computed correlation coefficients for any inference between each radiomic feature to the outcome
- Ordered variables: Spearman's rank correlation coefficients
- Un-ordered variables: multiple-regression correlation coefficients

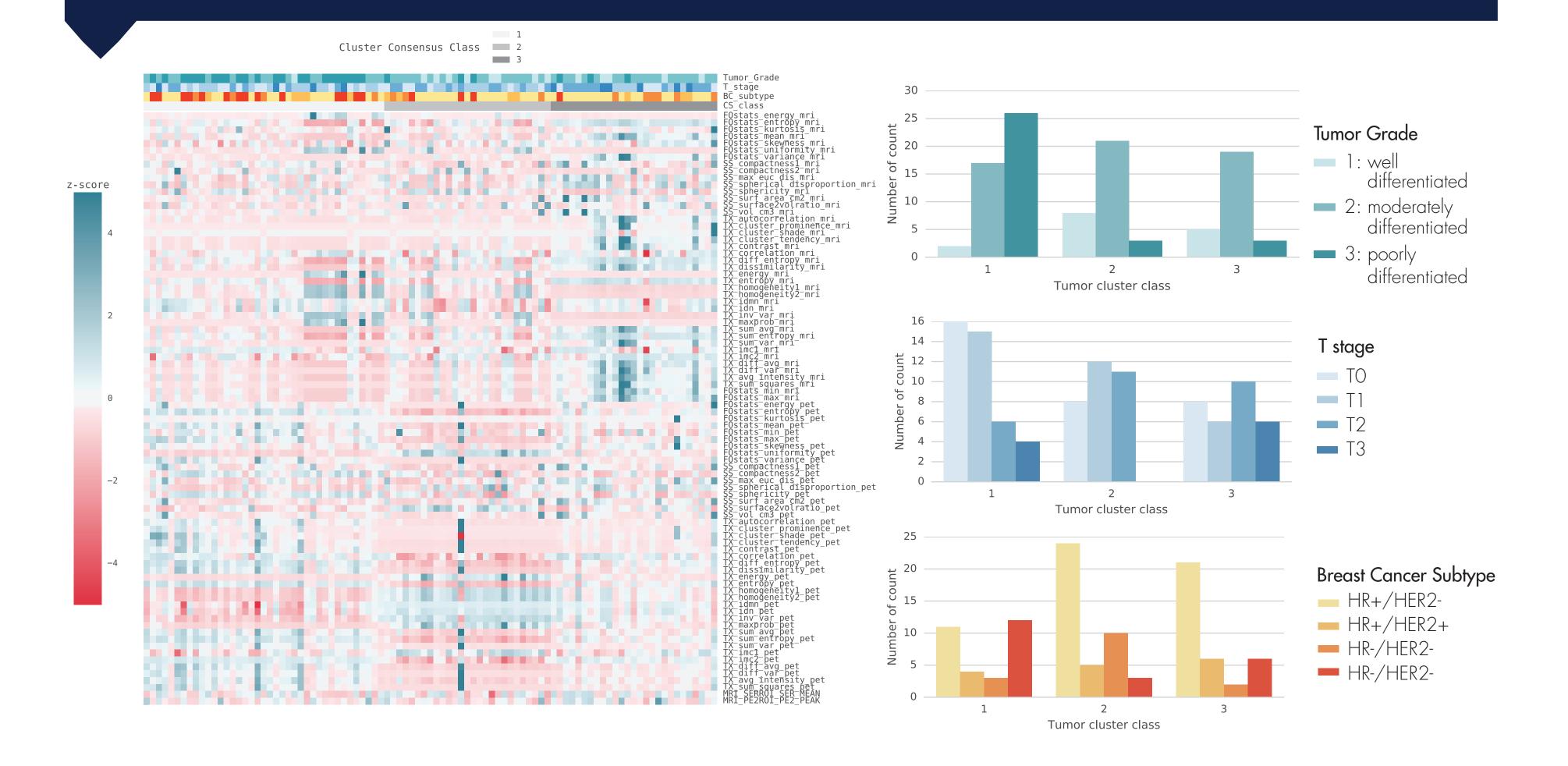
What Did We Find?

Observed PET and MR radiomics pattern among the tumor clusters

Higher grade tumors found in tumor cluster 3 $(\chi^2 \text{ test P-value} = 7.9 \times 10^{-6})$

Lower T-stage tumors found in tumor cluster 2 $(\chi^2 \text{ test P-value} = 4.0 \times 10^{-2})$

Triple-negative tumors found in tumor cluster 1 $(\chi^2 \text{ test P-value} = 8.9 \times 10^{-3})$



Tumor Grade Potential • PET image 1st-order entropy and imaging uniformity • PET image texture difference biomarkers average and dissimilarity

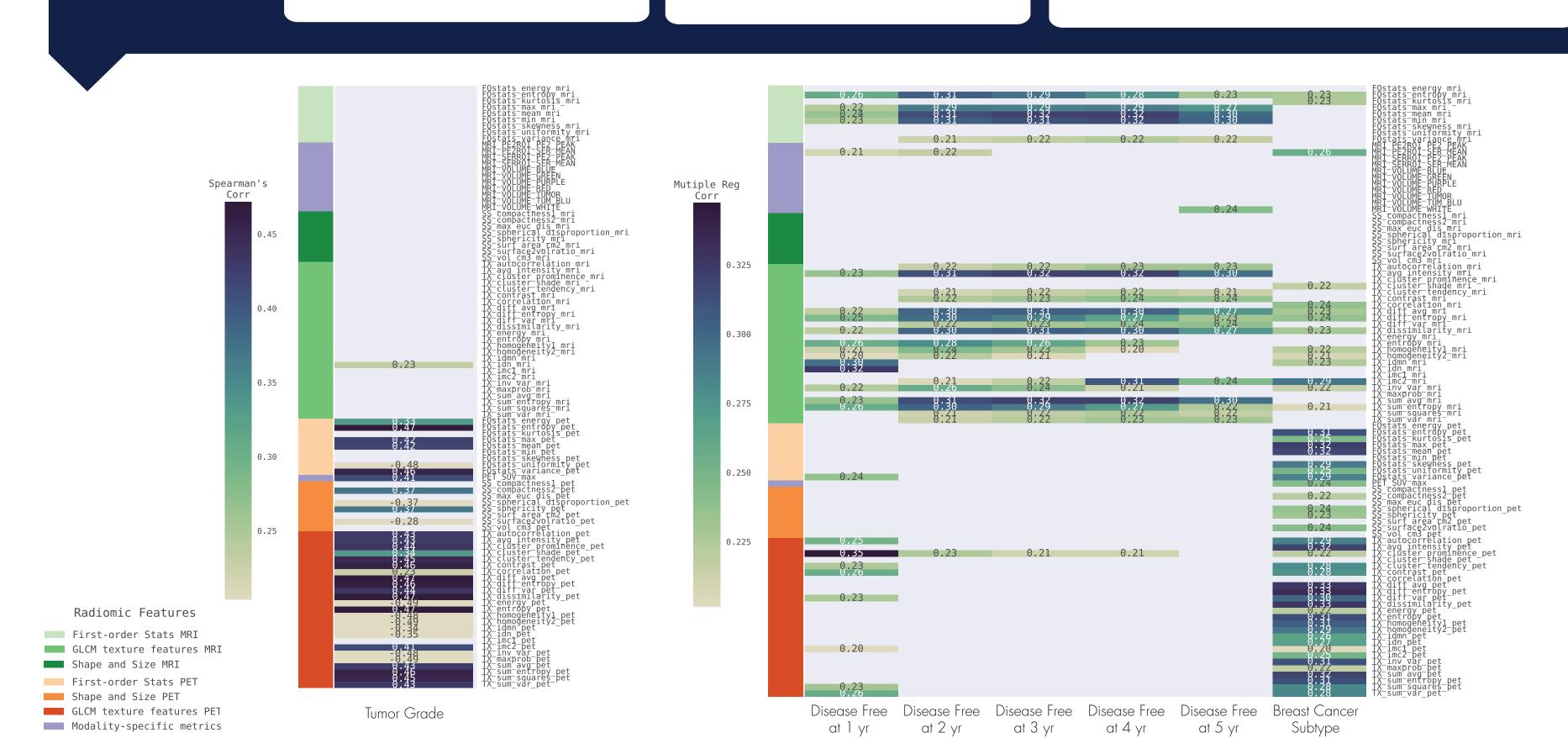
Breast Cancer Subtype PET image texture difference

average and entropy PET image texture sum average

PET SUV_{max} and SUV_{avg}

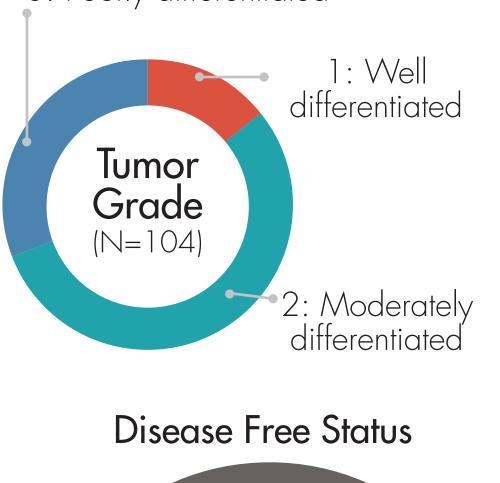
Disease Free Status

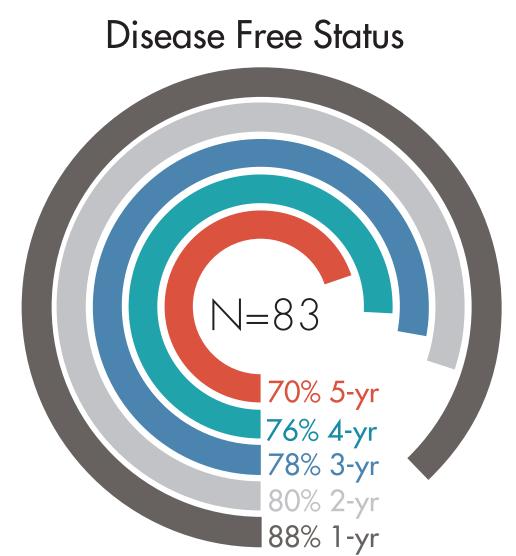
- MR image mean and minimum
- MR image texture features average intensity, sum average, difference average, and dissimilarity
- PET image texture cluster prominence



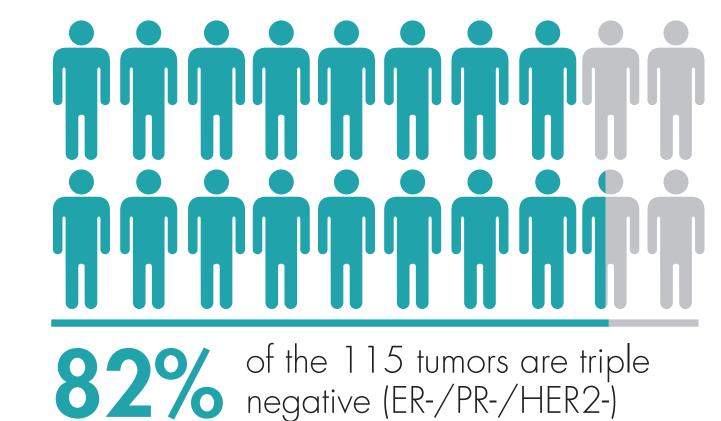
Patient Demographics

Γ stage (N=102) 3: Poorly differentiated





Breast cancer subtypes (N=107)→ HR+/HER2-HR-/HER2- •— HR-/HER2+ •— HR+: ER+ or PR+ HR-: ER- or PR-HR+/HER2+



Conclusion

- Extracted and validated PET and MR image radiomics
- Unsupervised clustering show radiomic features have potential for predicting tumor profiling
- Texture features of PET and MR images, in addition to first-order image statistics, could be key imaging biomarkers in building a predictive model for breast cancer diagnosis and prognosis

Thank You

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