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Mammography AI in EDRN Imaging

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Imaging and AI in Early Cancer Detection

Early Detection Research Network

EARLY DETECTION RESEARCH NETWORK
National Cancer Institute Division Of Cancer Prevention

JUNE 30-JULY 1 2020

Background | Early AI in mammo

- Mammography and Digital Breast Tomosynthesis
  - Primary modalities for breast cancer screening
  - Full-field digital mammography (FFDM) still SOC, but tomo quickly replacing
- Computer-aided detection (CAD)
  - Earliest AI in medical imaging, CAD for mammo approved 1998
  - Quickly adopted universally due to reimbursement
  - Serve as “second reader” to point out where rad may have missed.

Background | Early AI in mammo

- 15+ yrs later… mammo CAD did not work
  - Lehman *et al.*, 2015 JAMA Int. Med.
  - 324k women, 626k exams
  - "Screening performance was not improved with CAD on any metric assessed"

Diagnostic Accuracy of Digital Screening Mammography With and Without Computer-Aided Detection

Constance D. Lehman, MD, PhD[1]; Robert D. Wellman, MS[2]; Diana S. M. Buist, PhD[2]; et al

» Author Affiliations | Article Information

JAMA Intern Med. 2015;175(11):1828-1837. doi:10.1001/jamainternmed.2015.5231

- Why did mammo CAD fail?
  - Commercial success killed new research
  - Early AI limited by computer power, algorithms
  - Trained on small data sets, no data sharing
  - Limitations of 2nd reader paradigm

Background| New era of mammo AI

Massive datasets of 10-100k cases, 1-2 orders larger than old CAD

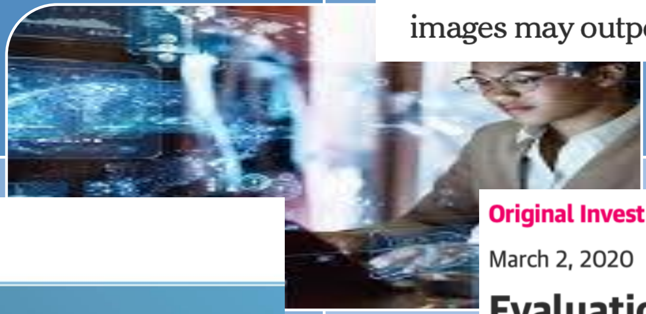
Breakthrough levels of performance, ≥ expert breast imaging rads

Nature Jan 2020: Google/UK, 29k
AUC 0.89, rel. to rads: -6% FP, -9% FN

The New York Times

A.I. Is Learning to Read Mammograms

Computers that are trained to recognize patterns and interpret images may outperform humans at finding cancer on X-rays.



THE LANCET
Digital Health

ARTICLES | VOLUME 2, ISSUE 3, E138-E148, MARCH 01, 2020

Changes in cancer detection and false-positive recall in mammography using artificial intelligence: a retrospective, multireader study

Hyo-Eun Kim, PhD † · Hak Hee Kim, MD † · Boo-Kyung Han, MD † · Ki Hwan Kim, MD · Kyunghwa Han, PhD · Hyeonseob Nam, MS · Eun Hye Lee, MD · Eun-Kyung Kim, MD · Show less · Show footnotes

Open Access · Published: February 06, 2020 · DOI: https://doi.org/10.1016/S2589-7500(20)30003-0

Original Investigation | Imaging

March 2, 2020

Evaluation of Combined Artificial Intelligence and Radiologist Assessment to Interpret Screening Mammograms

Thomas Schaffter, PhD[1]; Diana S. M. Buist, PhD, MPH[2]; Christoph I. Lee, MD, MS[3]; et al

» Author Affiliations | Article Information

JAMA Netw Open. 2020;3(3):e200265. doi:10.1001/jamanetworkopen.2020.0265

Lancet Mar 2020: KR/US/UK, 170k
AUC AI 0.94 >> rads 0.85

JAMA Netw Open Mar 2020: US/SE, 154k
AUC 0.90, rad > AI, but AI+rad > rad

Background | Different roles of AI

Computer aided detection (CADe)

- Where is the lesion?
- Calcs? Mass? Other?

Computer aided diagnosis (CADx)

- Benign or malignant?
- DCIS or invasive?

Computer aided triage (CADt)

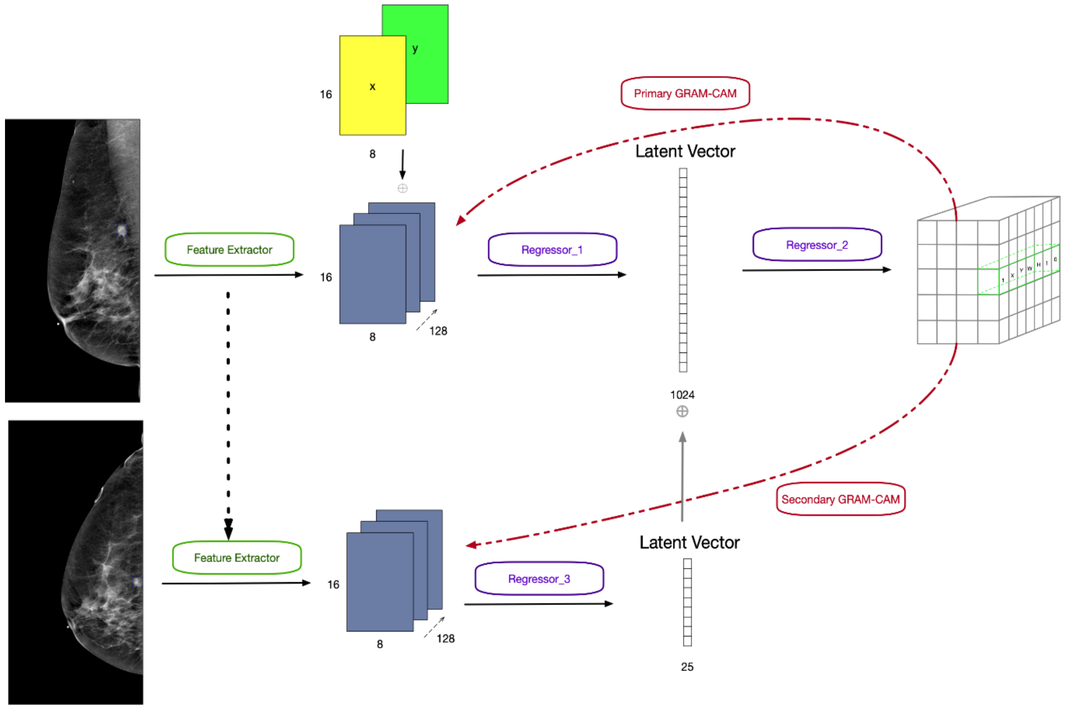
- "Stone cold negative" – skip or expedite
- Suspicious case – prioritize

Goals | Resource and Models

- Establish data resource
  - Multi-institution FFDM/DBT dataset
    - Duke + Moffitt
    - 1000 retro mammo, 1000 prospective mammo/DBT
    - Publicly available (only other one is UK OPTIMAM)
    - Focus on BI-RADS 4, ~2:1 benign to cancer
  - JPL LabCAS (Laboratory Catalog and Archive Services) resource
    - search, filter, preview, download
- Develop new models
  - Detection of lesions
  - Classification of benign/malignant
  - Shift from traditional radiomics/CAD to image-based machine learning
  - Integrate imaging and blood biomarkers

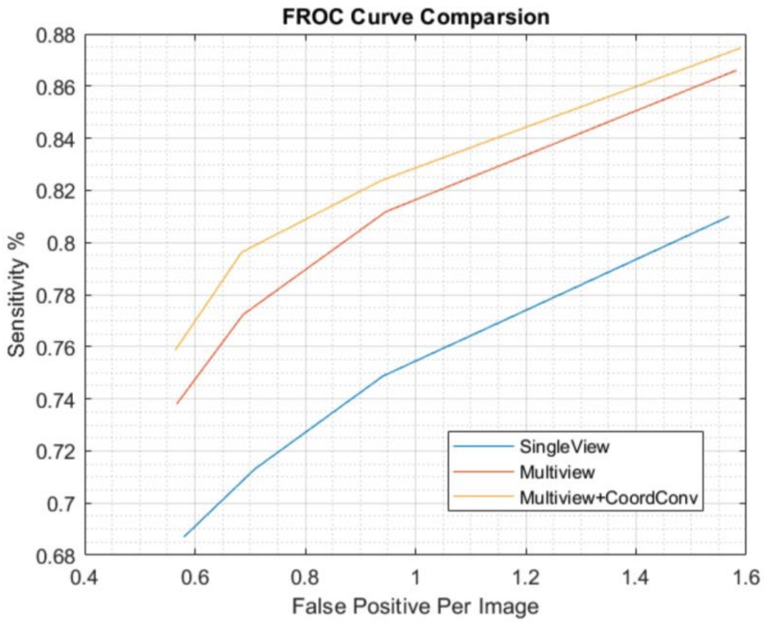
Progress | AI detection

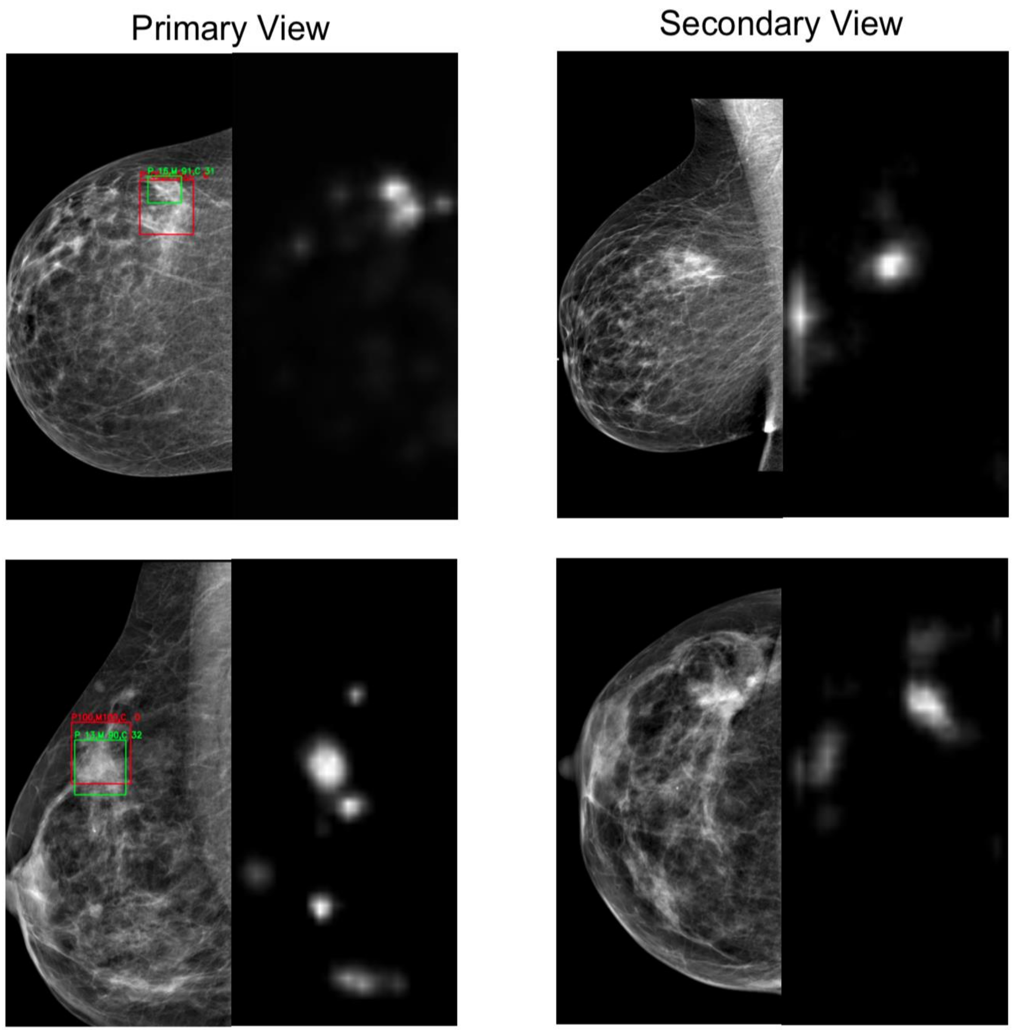
- Multi-view deep learning detection
  - You Only Look Once (YOLO) model
  - shared feature extraction
  - inject latent features from 2nd view
  - Efficient combination of information from 2 images (vs. brute force concatenation)



Progress | AI detection

- Multi-view deep learning detection
  - 2nd view improves performance
  - Class activation maps confirm contribution from correlating lesion in 2nd view





Progress | AI image synthesis

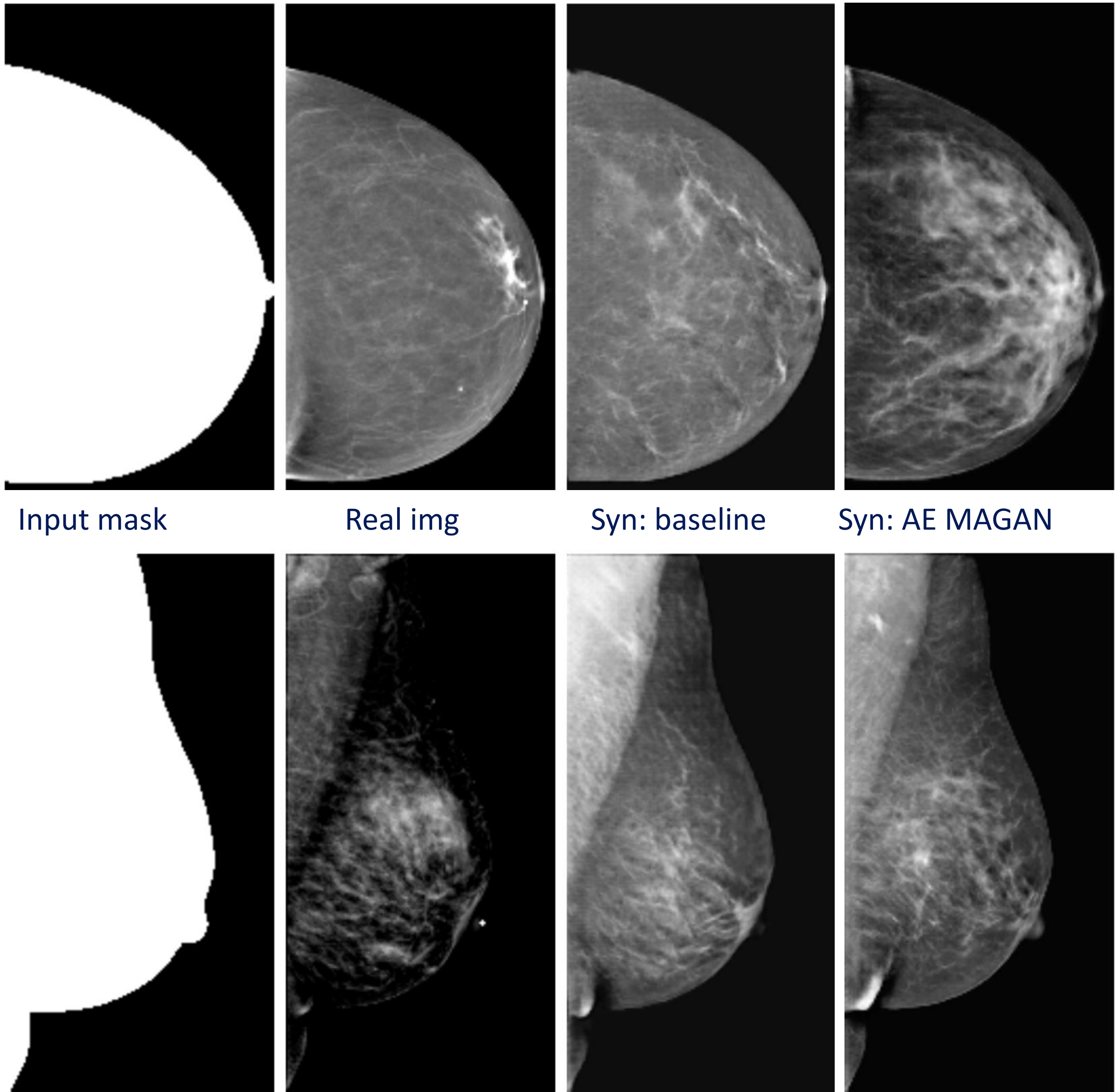
- Deep learning image synthesis
  - Generative Adversarial Network (GAN)
  - Image synthesis may address lack of data for modeling
  - Need to control image content and feature distribution
  - Balance diversity vs. realism
  - Our innovations:
    - mask embedding
    - autoencoder-guided multi-agent

edges **real** **syn1** **syn2** **syn3** **syn4**

Row: different "fakes" based on same edges from real
Col: different styles from same random noise input

Progress | AI image synthesis

- Image synthesis
  - Skin line defines breast shape, create different interior parenchyma
  - Future: also synthesize lesions
- Images L to R:
  - Input mask
    - skin line from real mammo
  - Real img
    - real mammo example input
  - Baseline GAN mask embed
    - blurry, only local structures
  - Auto-encoder Multi-Agent GAN
    - long, sharp structures
    - diverse frequency content



Plans | Potential Outcomes

- Large mammo/DBT dataset
  - Comparable to DDSM analog mammo from 1990s
  - All cases are biopsy proven (most difficult to accrue)
  - Facilitate future "super" dataset: >3k Bx, >10k neg?
- Improve screening performance
  - Today: ~70% sensitivity, 10% recall rate, PPV 6% 4a / 19% 4b, κ~0.4 observer variability
- Reduce benign biopsies
  - Today: ~3M biopsies/yr, only 25-30% cancer
- Integrate imaging and blood biomarkers
  - Complementary information, requires careful coordination