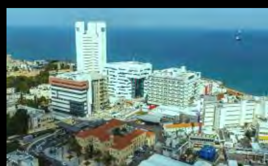
Chicago International Breast Course
The Westin Chicago River North
November 1-3, 2019

CIBC 2019

DEMYSTIFYING
Artificial Intelligence in Women's Imaging



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Learning Objectives

1) Describe WI unique culture of care→ predicts successful adoption of AI
2) Outline opportunities & challenges in AI
3) Consider: Who owns data? Ethical questions?
4) What are cybersecurity vulnerabilities?
5) ***The Holy Grail***: Integrated Radiomic models to provide personalized risk assessment

Is AI in everyday Life?

- smartphones
- self-driving cars
- drones
- video games
- music & media streaming
- banking
- security
- traffic

https://kapitiseniornet.files.w… ress.com/2… /smartphones-2.jpg

Artificial Intelligence

- 'Artificial Intelligence' 1956 Dartmouth Asst Prof John McCarthy:
- AI is "the science and engineering of making intelligent machines, especially intelligent computer programs."

Artificial Intelligence

- AI: machines perform cognitive functions like humans such as perception, reasoning, learning, problem solving
- AI combines big data with fast, iterative processing and intelligent algorithms
- Software/machines/Bots learn automatically from patterns or features in the data

Machine Learning:
Can computers learn without explicit rules?

- 1959, Arthur Samuel defined machine learning as a "field of study that gives computers the ability to learn without being explicitly programmed."
- ML algorithms learn and predict !!!
  - Unlike rules-based algorithms
  - Improve and learn from exposure to new data
  - Data is used for training, testing, and validation

Types of Machine Learning

1) Supervised Learning
   - Data labels are given to the algorithm in training phase
2) Unsupervised Learning
   - No data labels
   - Data is grouped or clustered
3) Reinforcement
   - Computer gets feedback from consequences without being taught
   - Finds patterns, filters signals

Performance Metrics for AI/ML/DL?

- "Validation" = model development & optimization
- "Testing" = external evaluation of AI performance
- Confirm clinical utility
  - Sensitivity, Specificity, Disease Prevalence, Costs
- ROC Curve
- Calibration Plot (fit: predicted vs real probabilities)
- External Data, Prospective
- Outcomes Data & Clinical Trials

REF: Park SH, Han K, Methodologic guide f[illegible]luating [illegible]ical performance an[illegible]t of artificial intelligence technology for medical diagn[illegible] Radiology 2[illegible] 01-809, 2018.

AI or ML?

- CAD (computer aided diagnosis) is a form of AI
- CAD has rule-based algorithms
- CAD is not ML!

ML improves with experience.

Deep Learning

- DL: type of ML
  - Processes many data resources
  - Requires less data preprocessing by humans
  - May be more accurate than traditional ML
- Interconnected layers of software-based calculators known as "neurons" →form a neural network
  - CNNs combine info from voxels spatially close together
- Learns complex patterns in large datasets
- Use what is learned to process new data

Neural Networks

- NN: interconnected units (like neurons)
  - processes info by responding to external inputs
  - relays info between units
  - multiple passes @ data finds connections & meaning
  - Kernels are filter elements
- Neurons are interconnected
  - output of one neuron = input for another
- Hidden layers allow deep neural networks to learn features of the data in a 'feature hierarchy'

VALUE OF ML: identify, flag, triage

- ML can
  - offer advice to radiologist
  - speed up workflow/acquisition time/time critical actions
  - improve image quality
  - improve diagnostic accuracy
  - segment abnormal from normal tissue
  - uncover hidden information, patterns
  - generate 'synthetic' images from current images
  - predict continuous variables (e.g.-bone age from hand XR)

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What's the AI BIG DEAL?

- Automation of repetitive high-volume tasks
- Improvement of performance and accuracy
- Computer leaning and adaptive intelligence
- Uncover/analyze deep data and hidden information
- Data has the information (Is Data IP?)

What changed all of a sudden?

- New algorithms, More IT computing power
- GPU technology stores 100s of teraflops of data
  - 1 TFLOP = 10^{12} (trillion) floating point operations/second
- Big Data more and more available
- Improved cloud-based services
- Leverage data to ***unlock valu***

$$$$$$$$$$$$$$$

BIG COMPUTING, BIG DATA, BIG CHANGES

- Now: Storage

EMR, PACS, RIS, CODING, BILLING, IMAGING, PATH, LABS, etc.

- Next: Real time, Interoperable, Multi Source Integrated Healthcare Enterprise (PACS/RIS Workflow, Dashboard, DICOM, HL7 exchai e, integration, sharing, and retrieval of ele. onic health information.

Lack of Standards for

- De-ide ification of images and reports
- Structured reporting with common data elements
- Image quality
- Combining data-different sources
- Extract & Label EMR/Radiology Report data
- Data repositories minimizing bias
- Cybersecurity
- Image enhancement & reconstruction→ no training datasets to teach machines
- Patient engagement/trust??? with data sharing

data data data data data

Eth al Use of AI?: & n oral access rights to data

ment:

MII, CAR, AAPM

- Dat nsent, and Use
- Anonymiz
- Security - Gatekee
- Copyright, contract law,
- Profit motive and abuse potentia
- Liability

REF: Geis JR, et al, Ethics of Artificial Intelligence in Radiology: Summary of and North American Multisociety Statement. AOP- Oct 1 2019, Radiology/JACR/C Imaging 2019; 00:1–5 • https://doi.org/10.1148/radiol.2019191586

-MORE QUESTIONS THAN ANSWERS
-BEST PRACTICES LACKING
-OVERSIGHT IS DISORGANIZED

FAKE FINDINGS - FAKE NEWS?

- Mirsky et al (Ben Gurion Univ Cyber Security Research Center)
  - Malware altered lung CTs - adds or subtracts nodules
  - Fooled radiologists 99% of the time
  - Fooled again 60% after told about malware alterations
- Imaging data typically not digitally signed/protected
- Need Encryption and Updated Infrastructure ($$$$)
- **arXiv @ Cornell- NO PEER REVIEW**

CYBERATTACKS: insert/remove findings

ASSASSINS Everywhere!

character PNG Designed By yoneo from
Pngtree.com

- Generative Adversarial Network (GAN) on MMGs
  - 680 images w/ and w/o lesions
  - 302 cancers and 590 controls = test set
  - 3 rads read altered & original images: both hi and low res
- GANs: DL algorithms w/2 opposed neural networks
  - 1 GAN changes images; 1 GAN finds real vs altered images
  - @ low res, rads failed to id altered images
  - @ hi res, rads could id altered images but found fewer cancers (AUC 0.37 versus 0.80)

REF: Anton S. Becker, et al, Injecting and removing suspicious features in breast imaging with CycleGAN: A pilot study of automated adversarial attacks using neural networks on small images, European Journal of Radiology, 2019, *in press.*

Culture of Care in WI

- Large datasets → training
- Tumor Registries
- Standards (MQSA since 1994)
- Digital (PACS)
- BI-RADS: Risk stratification ~ pattern recognition
- Computer aided detection (CAD)

Impact of AI on WI

- Increasing Use of DBT for screening
- Increasing # of images per screening study
- Increasing interpretation time
- Increasing fatigue and imaging complexity

READING TIME
PERFORMANCE

POWER & POTENTIAL OF AI IN WI

1) IMPROVE WORKFLOW:

Remove Normals from 223,109 MMGs (2009 – 2016)→ decrease workload 19.3%

	No Algorithm	With Algorithm
Sensitivity	90,6%	90.1%
Specificity	93.5%	94.2%

Yale A, Schuster T, Miles R, Barzilay R, Lehman C, A Deep Learning Model to Triage Screening Mammograms: A Simulation Study. Radiology. 2019 Aug 6:182908. doi: 10.1148

2) INCREASE EFFICIENCY

250 2D MMGs comparing AI vs traditional CAD:

70% fewer false + marks per image

52% no marks by AI vs 17% no marks by CAD

Time savings ~ 64%

Possible 10% increase in MMGs read

	Traditional CAD	AI Based CAD
Sensitivity	90%	98%
False + marks per image	0.63	0.14
BI-RADS 0 cases (no marks)	17%	52%

Watanabe AT, Mayo RC, Chang Sen LQ, Kapoor M, Leung J, Artificial intelligence software to improve mammography workflow. Abstract #B-0696 14:17 , ECR 2019 Book of Abstracts, European Society of Radiology (ESR) European Congress of Radiology 2019 (Vienna, Austria, February 27 – March 3, 2019).

3) IMPROVE PERFORMANCE

Use of CAD (AI) with DBT:

↓ reading time 55.9% subspecialists, 48.5% generalists

↑ diagnostic performance 24 readers, 260 DBT cases
13 breast imagers, 11 generalists

CASE LEVEL AVERAGE	AI	W/O AI	NOTES
AUC	0.852	0.795	22/24 readers had > AUC w/AI
Sensitivity	85%	77%	Avg Sens increase 0.80
Specificity	69.6%	62.7%	Avg Spec increase of 0.069
Mean Read Time	30.4 secs (decrease 52.7%)	64.1 sec	Avg improved 52.7% w/AI

Conant EF, Toledano AY, Periaswamy S, et al, Improving Accuracy and Efficiency with Concurrent Use of Artificial Intelligence for Digital Breast Tomosynthesis. Radiology: Artificial Intelligence 2019 1:4

4) IMPROVE DBT PERFORMANCE IN DENSE BREAST TISSUE

24 readers of 260 DBT studies included 65 cancers and 65 benign lesions
AI improved AUC DENSE AND NONDENSE, shortened read time, improved Sensitivity & Specificity

	W/O AI	W/ AI
AUC DENSE	0.81	0.87
AUC NON DENSE	0.78	0.84
READ TIME secs DENSE	65.8	28
READ TIME secs NONDENSE	62.5	32.8
SENSITIVITY DENSE	77%	84%
SENSITIVITY NONDENSE	77%	86%
SPECIFICITY DENSE	66%	75%
SPECIFICITY NONDENSE	60%	64%

Emily F. Conant, MD, Concurrent Use of Deep Learning Based Artificial Intelligence Improves Detection of Breast Cancer and Reading Time with Digital Breast Tomosynthesis in Women with Dense and Non-Dense Breasts, 2019 SBI/ACR Breast Imaging Symposium, April 4, 2019, Hollywood, FL

5) IMPROVE DIAGNOSTIC ACCURACY: DM DREAM CHALLENGE- 2017

Digital Mammography for Reverse Engineering Assessments and Methods

- Sage bionetworks with NCI funded BCSC registry
- 640,000 de-identified DM images with 1,114 images of breast cancer (0.34%) in 86,000 ♀♀
- Competition for improved accuracy using ML
  - Sens ~87% (Radiologists Sens ~88%)
  - Spec ~82% (similar to Radiologists in CCS data)
- Ann Arbor & Therapixel shared firs place using DL
- Now in collaboration phase - sha rce code, annotated data, devel AI-CAD t s

AUTOMATION USING AI

- Image segmentation
- Lesion detection
- Measurement
- Labelling
- Comparison to prior studies
- Structured reports (NLP)
- Semantic error detection in reports
- Data mining
- Workflow, dashboards
- Performance improvement, outcomes analysis

WHA ABOUT AI AUTOMATED " ORMAL" REPORTS?

- Normal MMGs never seen by docs?
  - PAP smears in Pathology already done
  - Reduces cost
  - Focus attention on abnormals
- Complexity of each remaining case is greater!!!
  - Pay for cognitive difficulty ???
  - AI Tools may add to work and time needed

ML in omen's Imaging

- Workflow
  - Scheduling, Prioritizing Worklists, Distribution of Labor
  - Safety Screening (e.g.- MRI safety, iv injections)
- Quality Improvement
  - Reduce acquisition time
  - Improve scan technique, noise reduction, completeness
  - Detect artifacts
- Automated Lesion Detection and Characterization: CADe, CADx

CAD

- CADe marks findings; CADx evaluates findings;
- Steps:
  - Preprocessing- image noise reduction, optimize contrast
  - Segmentation
  - ROI analysis (morphology, size, pixel values)
  - Classification Algorithm (probability of true positive)
  - Highlight lesions reaching threshold
- HIGH SENSITIVITY LOW SPECIFICITY

CAD LIMITATIONS

- By 2010, 74% MMGs read with CAD
  - REF: Rao VM, et al, How widely is CAD used in screening and diagnostic mammography?, J Am Coll Radiol 2010; 7(10):802-805.
- More recalls, higher biopsy rate
  - REF: Gilbert FJ, et al, Single reading with CAD for screening mammography. N Engl J Med 2009; 359(16):1675 – 1684.
- 20% longer reading time, False (+)s
  - REF: Tchou PM, et al, Interpretation time of computer aided detection at screening mammography. Radiology 2010; 257(1): 40 – 46.
- ***CAD MUST CHANGE → ML CAD***
  - ***TIME, WORKFLOW, COST, REVENUE***

ML: MMG SOLUTIONS

- RISK Modeling & Screening
- Reader Assistance
- Second Reader?
- Cancer Detection & Characterization

BEWARE - MANY VENDORS: angular range, technique, pixel binning, reconstruction algorithms, etc.

BREAST DENSITY

- Automated
- DL ALGORITHM quantifies breast density
- NN trained to recognize density
  - 41,479 digital screening MMGs in 27,684 patients
- Test set 8,677 MMGs in 5741 patients
- Clinical practice 10,763 MMGs vs 8 radiologists
  - **Very good agreement (k = 0.85; 95% CI: [illegible])**

REF: Lehman CD, Yala A, Shuster T, et al, Mammographic breast density assessment using deep learning: clinical implementation. Radiology 290(1): [illegible]-58, 2019. Epub [illegible], 2018.

AI PREDICTING BREAST CANCER?

- IBM's AI Model – from Haifa IL (Maccabi, Assuta)
- 52,936 images from 13,234 women
- menarche age, hormonal status, br density, FH, meds, Sx, …
- TRAINING DATA: 9,611 MAMMOGRAMS & EHRs
  - Records available for at least one year prior
- Validated in 1,055 patients
- Tested in 2,548 patients
- RESULTS:

AI IDENTIFIED 34/71 (48%) FALSE (-) MMGs

REF: Akselrod-Ballin A, et al, Predicting Breast Cancer by Applying Deep Learning to Linked Health Records and Mammograms. Radiology. 2019 Jun 18:182622. Epub AOP

STRATEGIES TO PAY FOR AI

- January 20[illegible] 1st FDA approved AI algorithm
- < 1/4 Algorithms have FDA 510k clearance
- Some AI Vendors may not submit 510k applications
  - Software = adjunct to radiologist readings
  - Must be integrated into existing systems, PACS
    - Requires Validation by Vendor
- What is the Business Plan? Low CAD reimbursement.
- CAD ≠ AI …. Throughput
- Liability?

REGULATORY REQUIREMENTS

- Build, maintain, deploy, scale AI tools
- FDA accelerated clearance of AI tools in 2018
  - >12 Medical AIs approved
- FDA intends to regulate digital health tools as part of a drug delivery type system
- FDA will regulate companies, not just products

HOW WILL FDA REGULATE PRODUCTS THAT EVOLVE, LEARN AND IMPROVE? INCORPORATE NEW EVIDENCE?

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FUTURE OF AI

- Interoperable cross-specialty DATA
  - DATA Mining on a Massive Scale
- Personalized Medicine
  - Preventative Medicine
  - Diagnosis
  - Prognosis
  - Tailored Treatment Selection
  - Surveillance
- Predictive Analytics: Px, RECIST

WORK PRODUCT OF FUTURE AI RADIOLOGISTS

- AI RADS = Data Scientists
- Astronauts driving digital platforms to new heights
- Infrastructure in Evolution
- Safety & Efficacy before Clinical Use
  - CIO: Chief Info. Officer - quality, saf , effectiveness
  - CDO: Chief Data Officer - data quality validation, training ML systems, compli ce
- COMMON STANDARDS → rability & Integration of AI

ACR AI-LAB

- AI Democratization
- No programming skills required
- Imaging database, ACR AI –LAB access
- Software tools, Imaging Algorithms → clinical
- Without programming language
- Software and integration provided
- MGH, OSU, Lahey, Emory, UW, UCSF, &W

Doe AI Have Predictive Value?

- Predictions are useless unless used to improve clinical outcome - quick, safe, and effective
- Metrics
- Partnership
- Transparency
- Innovation
- **TRUST**

RO PEC DESIGN: respon le development & plement ion of AI in Medicine