Using AI as a tool for the Dx Medical Physicist

Samuel Brady, M.S. Ph.D. DABR
samuel.brady@cchmc.org
7/14/2020

Terminology

- Artificial intelligence (AI)

  A branch of computer science that explores the ability for a computer/machine to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, etc.

  – AI is an umbrella term for machine learning and deep learning

The Promises of Artificial Intelligence

- Why have this conversation now?
  - Artificial Intelligence (AI) has the potential of being a disruptive force in medicine and radiology specifically
    - It WILL be a central player in medicine in the future
    - It WILL be used on all our imaging devices
    - It WILL be on all our PACs systems
    - It WILL be used as an algorithm behind the scenes controlling everything from supply management, billing, to medical management (both Dx and Tx)

The Promises of Artificial Intelligence

- The medical physicist (MP) is, generally, the technology consult to the department
  - We need to know how to use AI
  - We need to know how to manage AI

- But what about using AI to our advantage?

The Promises of Artificial Intelligence

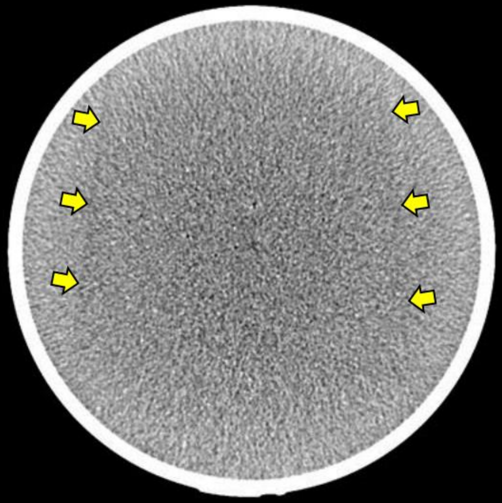
- How can AI help the Dx MP?
  - Reduce workload by performing repetitive tasks:
    - Clinical patient image quality (IQ) review
    - Analyze routine phantom data [e.g., daily/weekly MRI, CT, Nuc Med artifact review]
  - Find trends
    - Enterprise CT dosimetry [e.g., Radimetrics-like software is passive]
    - Inconsistent protocol parameters
    - Artifacts coming from one scanner
  - Act as a normalizer
    - Provide help for institutions w/o full time MP
    - Provide help for institutions w/ only one (*over worked*) MP

Terminology

- Machine learning (ML)

  An application of AI that uses computer programing and statistics to train a computer algorithm to learn and improve <u>without</u> being explicitly programmed.

  - Limitation: e.g., to train for artifact recognition, requires careful feature selection
    - Difficult to account for different types of artifacts
    - Same artifact may appear differently on different scanners, vendors, & institutions
    - Algorithm will be best suited to detect what it has been trained to find



James M. Kofler, Ph.D.
Mayo Clinic Rochester

Terminology

- Deep learning convolution neural network (DCNN)

Is an ML technique that has a learning structure similar to the human brain (using neural networks). Improves with larger “deeper” sets of data

  - Emulate human visual feature extraction
  - Requires more computing power than ML
  - Requires large data sets w/ normal and non-normal images
    - Transfer learning allows for retooling a previously trained network by re-training a subset of parameters using a smaller data set

Transfer Learning

- General transfer learning principles
  - Early DCNN layers learn low-level features common to most computer vision problems
  - Later DCNN layers learn high-level features which are more application-specific
    - Thus, adjusting the last few layers of a DCNN is how you “transfer” the networks knowledge to your specific task
  - Good networks to use for transfer learning:
    - VGGNet, ResNet, Inception, Xcaption
      - Each network was pretrained on ImageNet
      - Good networks for feature extraction and classification tasks

Tajbakhsh, N., et al. IEEE transactions on medical imaging 2016 35(5): 1299-1312.

Transfer Learning

- Two approaches to AI network generation:

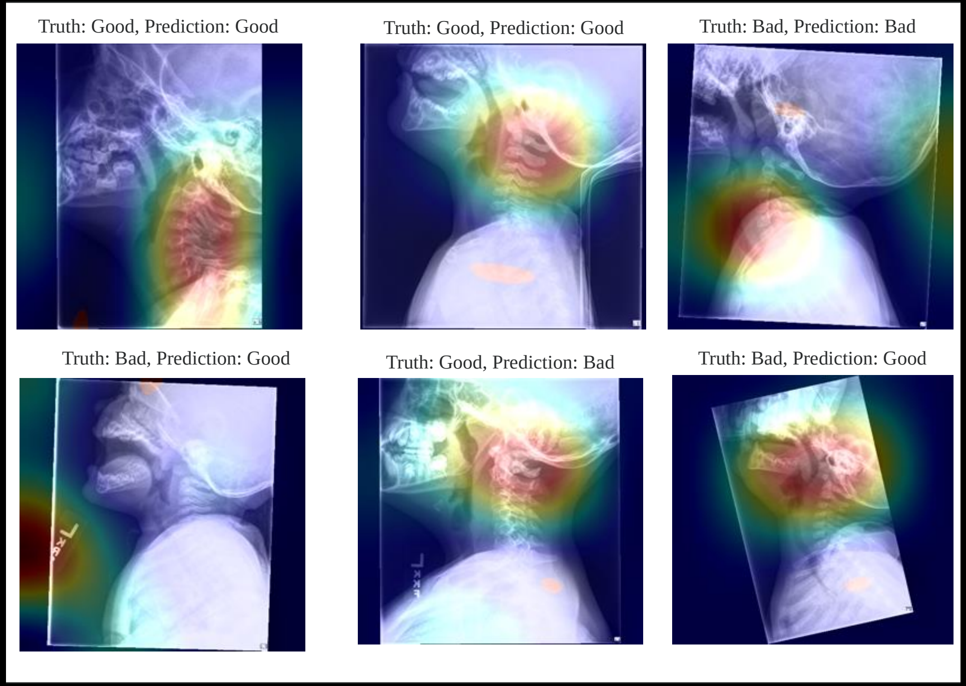
1. Unsupervised AI (*less common*)
   - Group unsorted information according to similarities, patterns and differences w/o prior training of data
     - Use unsupervised AI to:
       - Identify specific imaging protocols that are different using natural language processing
   - Cannot be used for regression or classification
     - Algorithm does not know what is "Truth"

Google

Transfer Learning

- Two approaches to AI model generation:

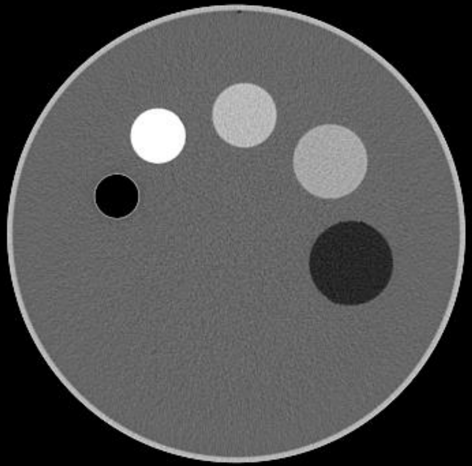
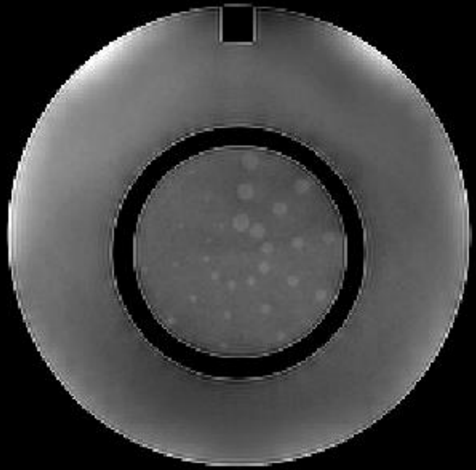
2. Supervised AI
   - Specifically train algorithms to look for:
     - Key features as they appear in an image
     - Images have adequate contrast and signal
     - Patients are positioned correctly
     - Etc.
   - Requires collaboration between MP and Radiologists to establish “truth”

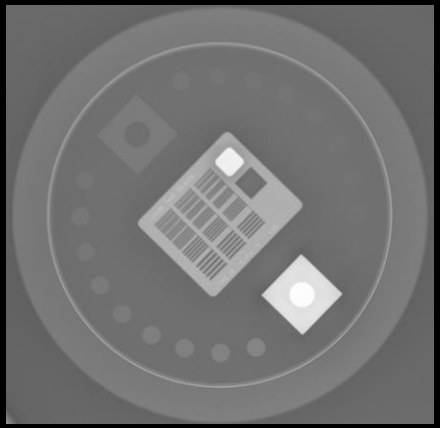
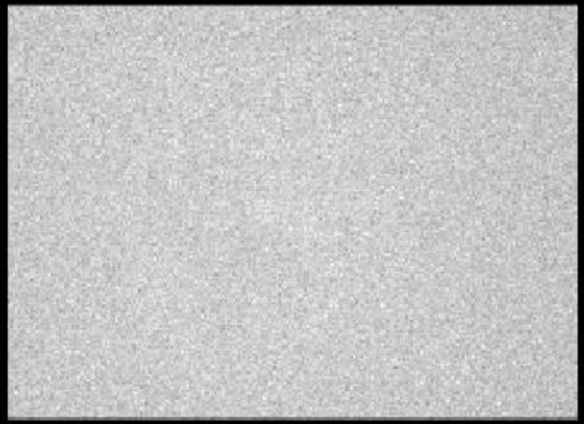


Somasundaram, E et al. Radiology:AI 2020 (In press)

AI for DX MP

- Clinical patient image quality (IQ) review
  - Analyze routine phantom data
    - E.g., daily/weekly MRI, CT, Nuc Med artifact review

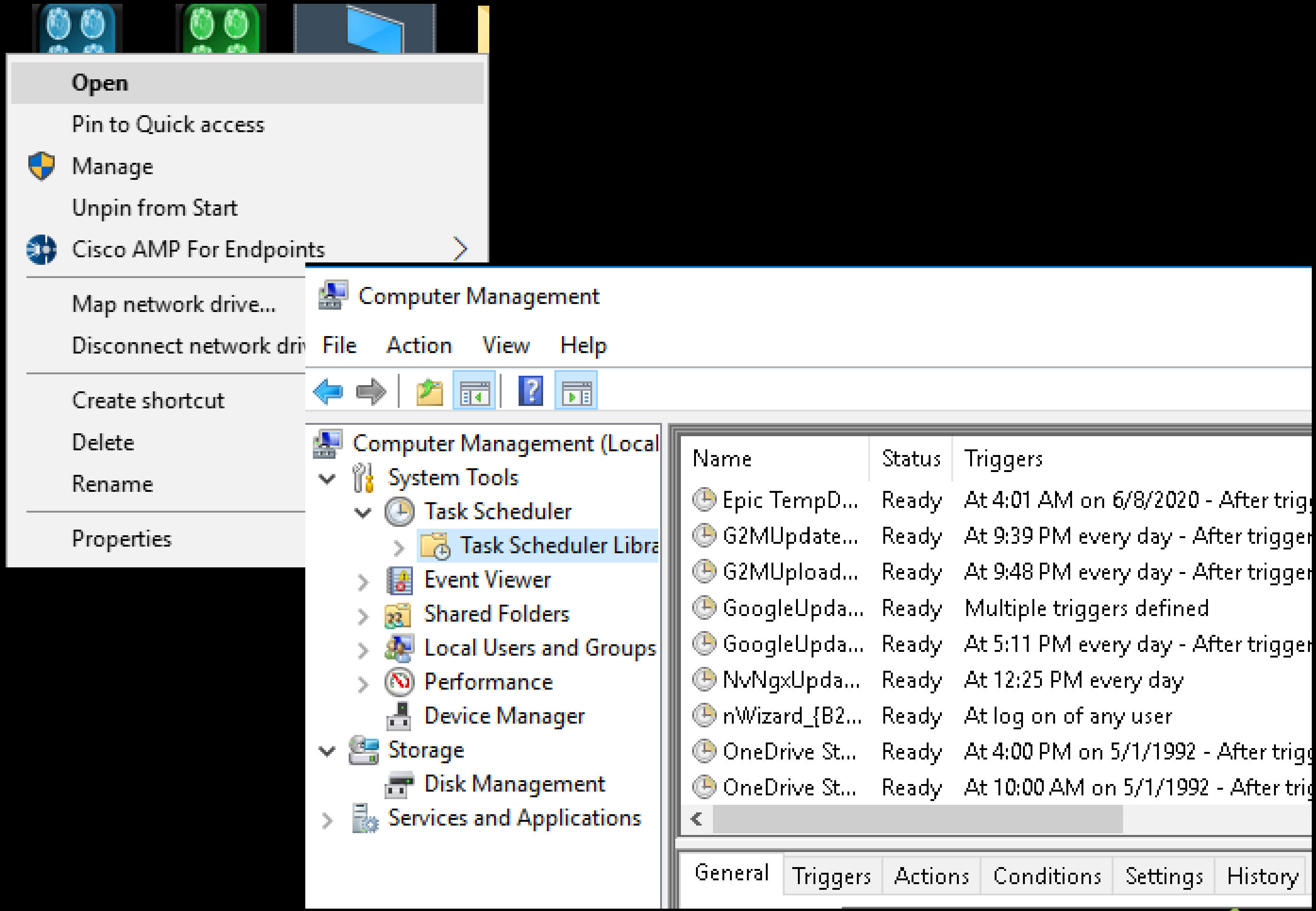
AI for DX MP

- Clinical patient image quality (IQ) review
  1. Collect all images in a local repository
     - Even small clinics will generate thousands of images a year
       - Produces large data sets for data mining
     - Data stored on PACS is not readily accessible for DL use (requires personnel to move around)
       - Its very easy to set up “rules” so that when a QC image is sent to PACS it will be auto-routed to a computer node
       - You can set up a computer in your office to act as a node/repository
         - » Cheaper than purchasing a server
         - » Limitation is that normal computers don’t come w/ RAID redundancy and limited automated backup capabilities

Implementation

– Set up simple scripts:
  - Process data
  - Back up computer
  - Etc.

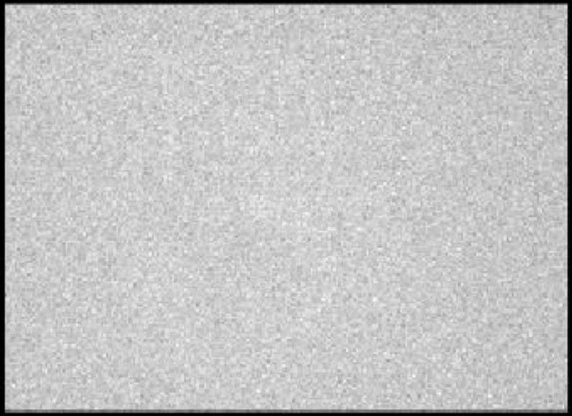
  - Use Computer Management
    – Create a “Task”
    – Set “Triggers”
      » e.g., specific times of the day
    – Set “Actions”
      » Run batch files



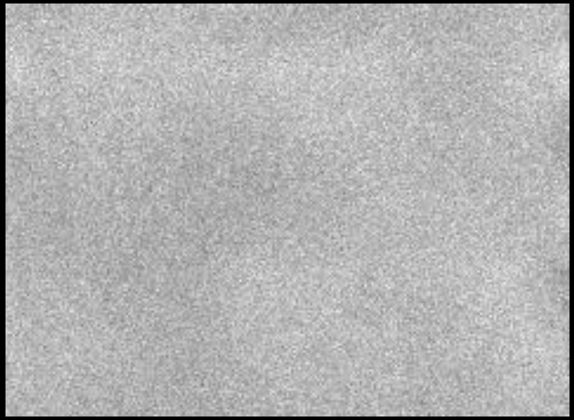
AI for DX MP

- Clinical patient image quality (IQ) review
  2. Train images to identify normal vs. abnormal
     - To train a network to identify the type/class of artifact requires manual labeling of data set
       – Very time consuming
     - Instead train the network to identify “abnormal” and flag the image for review by an MP
       – Establish a regression analysis of the probability for abnormal
     - In this example: want to minimize false negatives (i.e., maximize the Recall rate)

Normal

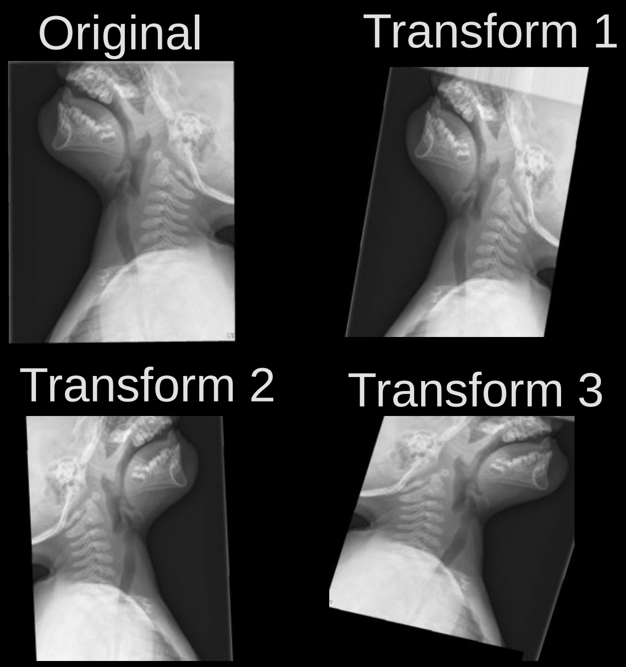


Abnormal



AI for DX MP

- Clinical patient image quality (IQ) review
  3. Training requires handling of imbalanced data sets
     - Normal artifact-free data abundance is typically > 99%
     - Need multi-institutional data sets to prevent overfitting to local data
     - Under-sample normal data set
     - Over-sample the abnormal data set
  – Data Augmentation
     - Augment or add to the data set by adding variation to the data set
     - Now one image will = 10s to 100s of images
     - Common: flip, rotate, zoom, shift, etc.



Somasundaram, E et al. Radiology:AI 2020 (In press)

Implementation

- Challenges for DL broad scale implementation → TRUTH
  - What is "truth" and who dictates it?
    - Option 1: Based on MP consensus
      - Need to analyze inter-observer accuracy
      - Need multi-institutional
      - Need multi-platform/vendor review
    - Option 2: Based on DL algorithm consensus
      - Compare multiple algorithms

Conclusion

- To implement AI in our daily practice you need to think like a computer
  - Look at our daily systems, what is automatable?
  - Remember, the task(s) MUST be structured for easy data access
  - Need to develop repositories and label our "data"

- For clinical AI, the roles for Medical Physicists are not established yet
  - Now is the time to define OUR role
  - Increasingly requires MP to interface and work with AI
    - You will need to learn the language of AI

Thank you

samuel.brady@cchmc.org