APPLYING AI TO HEALTHCARE

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Overview

- Overview of Al
- Applications of Al to Healthcare
- Assessing Performance of Al tools

Background

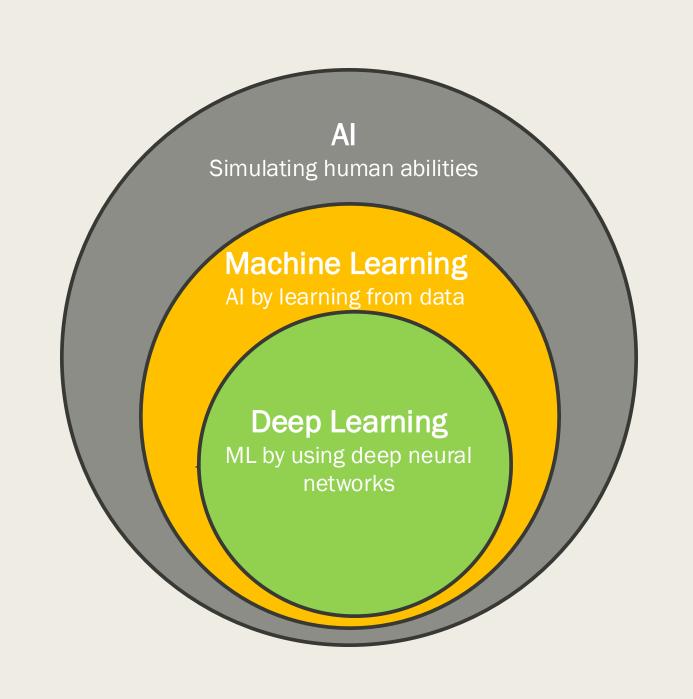
- Cardiology FellowshipStony Brook University Hospital
- Cardiac Imaging Research Fellowship
 Brigham and Women's Hospital
- Healthcare Al Research Fellowship Brigham and Women's Hospital
- BWH Innovation Fellowship
 Biofourmis (remote patient monitoring)

Healthcare Al

Technical aspects of Al techniques

Application of Al techniques to healthcare

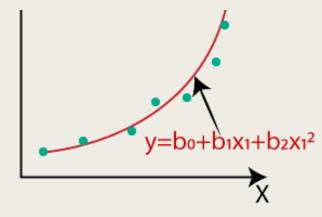
Overview of Al

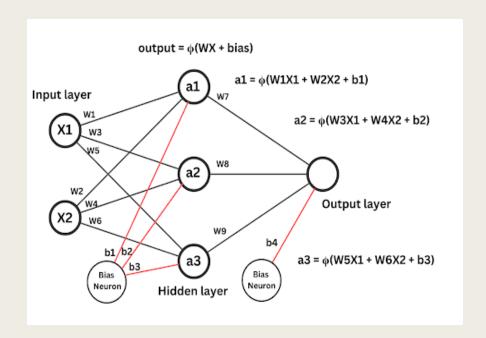


Deep Learning allows highly complex predictive models

Regression model

Here are 10 measurements from a patient's echocardiogram. What is the probability they will develop heart failure?





Neural Network model

Here is a clip from the patient's echocardiogram. Based on these 1 million pixels, what is the probability they will develop heart failure?

Deep Learning: President Identifier

Architecture

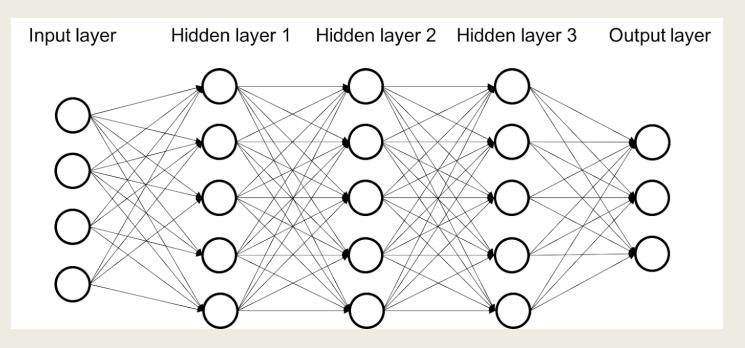
Skeleton of model created by data scientist

Training Dataset

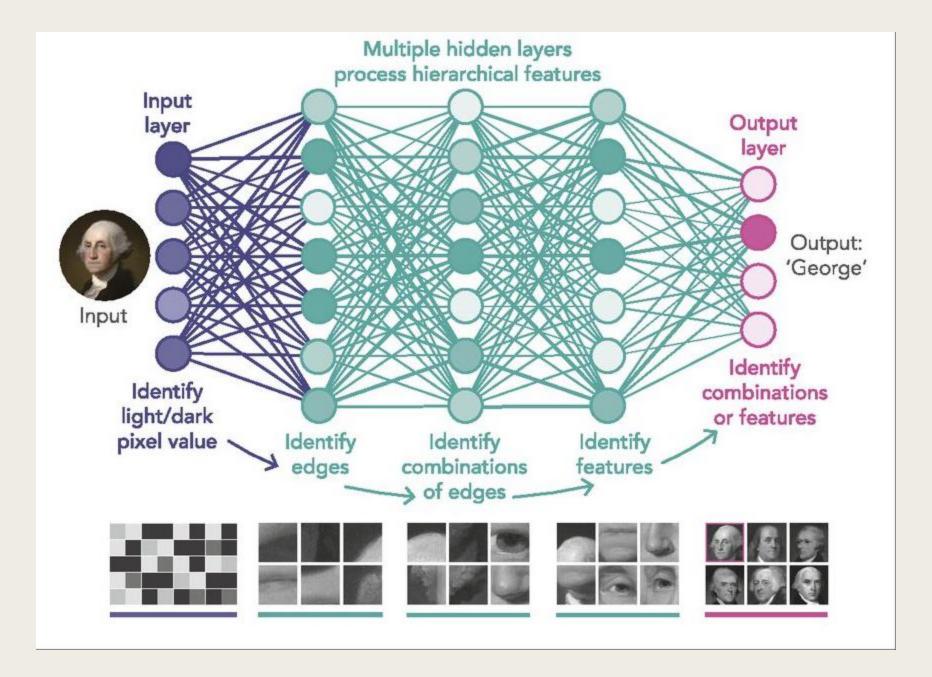
1,000 different pictures of US presidents with their names

Training process

Algorithm learns to find patterns in the pictures that help predict the name







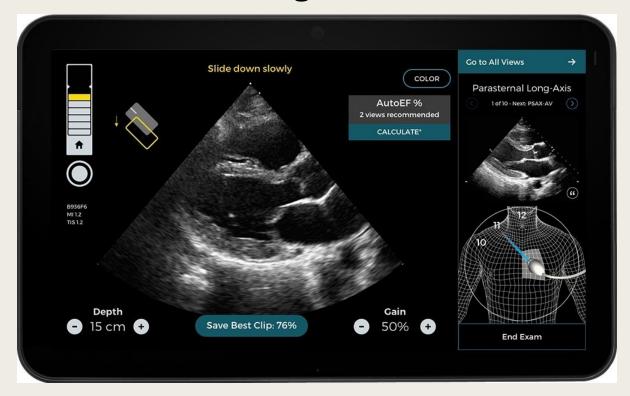
Applications of Al to Healthcare

Al in Healthcare

Improve what we already do



Allow us to do things we couldn't before



Al in Healthcare

- Over 500 FDA-approved AI tools
 - #1: Radiology (including cardiac imaging) ~75%
 - #2: Cardiology ~11%
- Many more AI tools that are not FDA regulated (e.g. administrative tools)
- Despite this, most physicians may not consider themselves as using Al
 - Low level of implementation
 - Replacement of non-Al tools with Al tools may be seamless
 - Many tools have Al versions and non-Al versions
 - Sepsis prediction score
 - Automated radiology measurements
 - Analysis of remote patient monitoring data
 - Predicate for >1/3 of FDA 510(k)-cleared AI tools is a non-AI tool

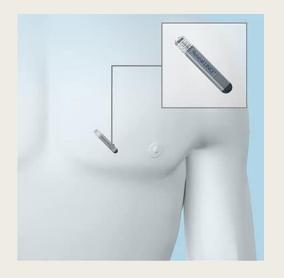
Challenges

- Challenging to acquire the right data to create Al models
 - Need datasets that are:
 - Large enough
 - Appropriate representative of all the settings the tool will be used in
 - Have information in a consistent format (variables may vary across institutions)
 - Groups addressing: Nightingale Health, MAIDA, Atropos, Rhino Health
- Challenging to choose AI tools to implement
 - Difficult to figure out what tools are available and popular Process sometimes relies on clinical champions
 - Often unclear how well a tool performs
 - Groups addressing: ACR Al Central, Dandelion Health
- Challenging to implement AI tools
 - Outdated hardware and software
 - Limited interoperability across different software
 - Limited IT dept capabilities
- Challenging to gain clinician acceptance
 - Clinicians often wary of new tech, especially after poor experiences with prior software
 - Fear of clinicians being replaced ("Augmented Intelligence" is a term being used more)
 - Unclear legal ramifications of following/not following Al-generated advice

Assessing Performance of Al Tools

Considerations Broadly Applicable to Health Tech Tools

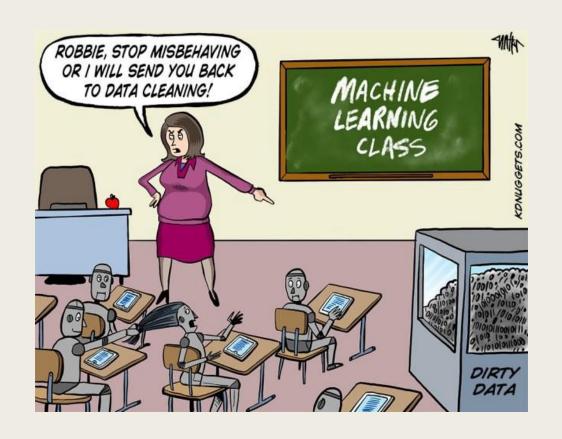
- Technical performance vs clinical performance
 - Meaningful metrics
 - Accounting for human-machine interaction
- Outcome impact
 - Impact of low-hanging fruit like remote monitoring for arrhythmias
- Improvement from the tool? Or from simultaneous improvements in workflow?



Considerations Applicable To Data-Driven Tools

The data used to create the model:

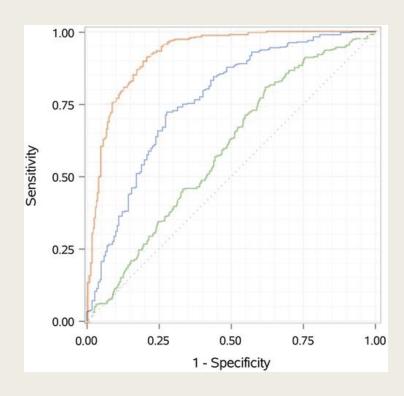
- Inadequately cleaned
- Uses variables inappropriately
- Not representative of all the settings the tool will be used in



Considerations Applicable To Data-Driven Tools

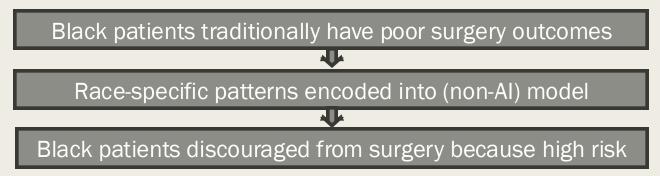
The data used to create the model:

- Excludes low-quality samples
- Has inadequate coverage of values that will be encountered in practice
 - Hypertrophic cardiomyopathy (HCM) and healthy
 - HCM, severe hypertension, aortic stenosis, healthy
- Is no longer as applicable to the current clinical environment (model drift / model shift)
- Has insufficient samples of a particular sex or selfreported race - can lead to algorithmic bias



Algorithmic Bias

- Can be problematic to include self-reported race in algorithms
 - STS cardiac surgery risk score



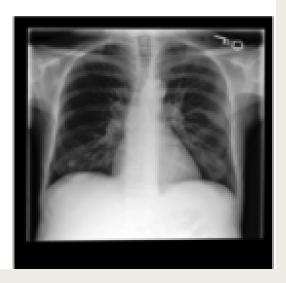
- Can be problematic to simply disregard self-reported race in algorithms
 - Optum risk score Who should get additional support to lower healthcare costs?

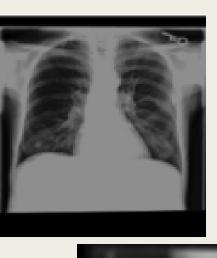


Algorithmic Bias

May be impossible to remove race as a feature within a model

Original



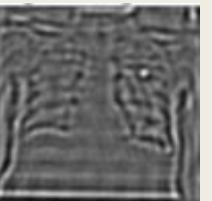








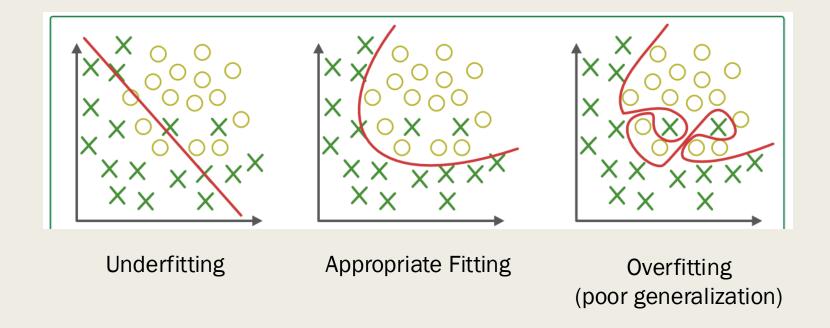




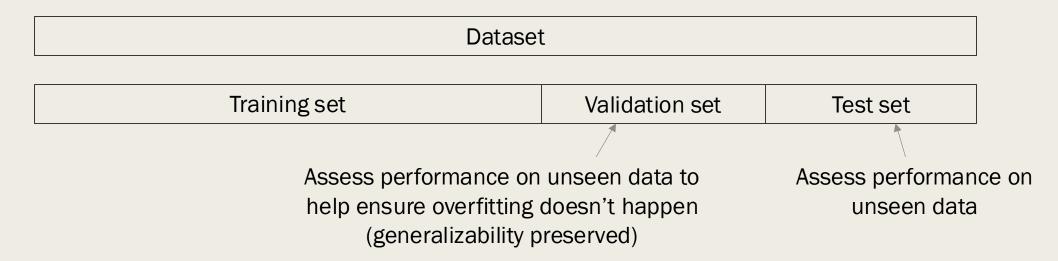
Gichoya, J. Lancet Digital Health (2022)

Considerations Specific to Al

Frequent issue: Overfitting



Overfitting



Test set performance may be artificially inflated

- Can use test dataset over and over -> overfitting to test dataset
- Similar studies from same patient used in training set and test set

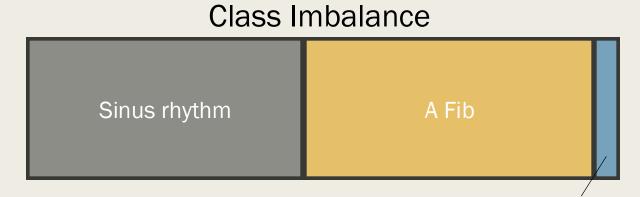
External Validation Dataset

Advantages of External Validation

- Not affected by overfitting to test set
- Not affected by some types of mistakes during model development
- Ensures generalizability to another healthcare setting, which may have different:
 - Patient demographics
 - Disease prevalence
 - Treatment approaches (e.g. outcomes may be different at academic center that is aggressive with procedures)
 - Available data points (deep learning generally doesn't handle missing data well)
 - Hardware / Software (e.g. different radiology vendors)

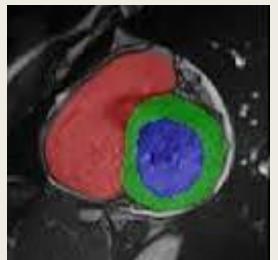
Adequate Evaluation of Al Model

- Overall performance metrics
- Condition subgroups
 Class imbalance may lead to poor subgroup performance
- Demographic subgroups
- Edge cases
- Failure cases



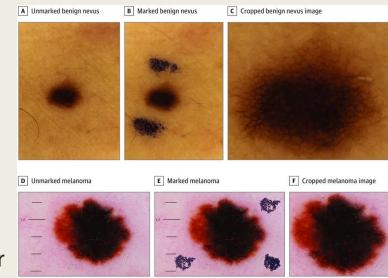
V. Tach

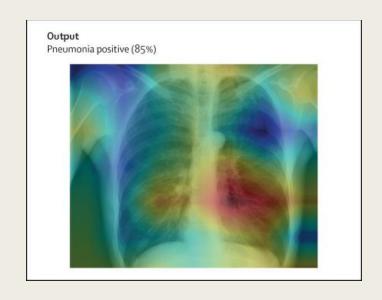
Cardiac MRI segmentation



Explainability

- Trade-off between performance and explainability
- Unintended features may be encoded within the "black box"
 - If a priest visits a patient, then the patient is likely to die soon
 - If a chest x-ray is done in the patient's room, the patient has a higher probability of having pneumonia
 - If a patient has labs drawn at night, they have a higher probability of having sepsis
 - If a freckle has presurgical markings, then it is probably melanoma
- Explainability methods
 - many argue for these, because Al models may occasionally fail in unexpected ways
 - do not fully explain individual model predictions
 - may be misleading and provide false reassurance





Considerations Not Yet Addressed by FDA

Generative AI - hallucinations

how do i convert digoxin dosing from iv to po?

Share

clair Answer

To convert digoxin dosing from intravenous (IV) to oral (PO), you need to consider the bioavailability of the drug. The conversion ratio for digoxin is 1:1, meaning that a 0.1-0.4 mg IV dose every 24 hours is equivalent to a 0.125-0.5 mg PO dose every 24 hours.

However, when switching from IV to PO formulations, allowances should be made for differences in bioavailability when calculating maintenance dosages.

For example, it's estimated that an oral tablet of digoxin of 0.5 mg has about the same bioavailability as 0.35 of digoxin given by slow intravenous infusion (or 0.4 mg if given faster).

When the maintenance dose is given IV, the onset and peak will occur earlier than with oral administration.

References

Digoxin bioavailability:
Formulations and rates of
infusions

DOI: 10.1002/cpt1976203253

Source:

https://pubmed.ncbi.nlm.nih.gov/9543

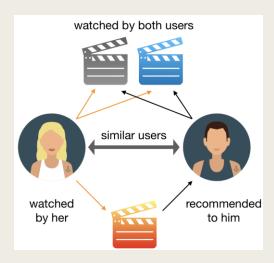
2. Effects of Amiodarone on Oral and Intravenous Digoxin Kinetics in Healthy Subjects

DOI: 10.1097/00005344-198704000-

Source:

https://pubmed.ncbi.nlm.nih.gov/2438

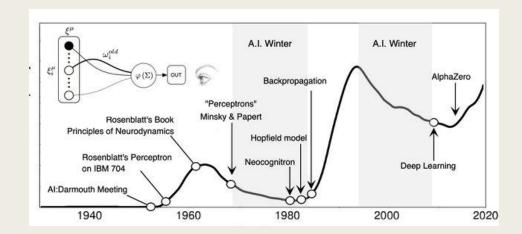
3. Conversion of atrial fibrillation to sinus rhythm and



Online learning – continuously updating model

Putting Healthcare Al Into Perspective

- Still potential for Al winter in healthcare?
- Stimulating investments into data infrastructure, upgrading technology, improving workflows
- ASCVD risk score for coronary heart disease uses 13 variables, based on decades-old data
 - How have advances in medical care in the past decades changed risk?
 - How does use of this risk score affect risk?
 - Is the risk same for a patient at a large academic medical center and a patient at a small rural clinic?
 - How accurate is this score for patients with kidney disease?
 - How accurate is this score for minority races?
 - How do social determinants of health affect risk?



Questions?

Al in Healthcare Examples

■ Viz.Al – triaging – low downside risk, high upside potential



Al in Healthcare Examples



- LumineticsCore (previously IDx-DR)
 - First FDA-approved autonomous healthcare AI product
 - Uses proprietary camera no vendor variability



Al in Cardiology Examples

- More robust predictive models
 - Is this person likely to develop X issue?
 - Do this patient's remote monitoring signals look like those from someone who is becoming ill?
- Large Language Models
 - Drafting clinician notes
 - Explaining info to patients
- Cardiovascular imaging
 - Automated measurements
 - Improved image post-processing
 - Motion correction for heartbeats and breathing
 - Simulation of contrast-enhanced images
 - Future potential uses
 - Extracting information from images that is not visible to human eye
 - Evaluating CT for heart muscle that is not getting enough blood
 - Integrating information across two different modalities e.g. echocardiogram and CT

Al in Healthcare

Improve what we already do

- Assist with repetitive tasks
- Avoid errors or missed diagnoses
- Improve management in the "gray zones" of medicine by setting up Learning Health Systems

Allow us to do things we couldn't before

- Diagnose conditions at earlier stages
- Novel tools such as a tool to guide novice users to perform an echocardiogram
- Draft clinical notes



