

Artificial Intelligence (AI): Promise and Peril

Health Officers' Caucus - November 28, 2023

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Artificial Intelligence: Promise and Peril

- Definitions
- Historical perspectives
- Current accomplishments
- Evidence base for AI interventions
- Future directions

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2



2

Definitions and terminology related to artificial intelligence (AI)

- AI – “information systems and algorithms capable of performing tasks associated with human intelligence” (Rajpurkar, 2022; Sahni, 2023)
 - Predictive AI – use of data and algorithms to predict some output (e.g., diagnosis, treatment recommendation, prognosis, etc.)
 - Generative AI – generates new output based on prompts (e.g., text, images, etc.)
- A large part of modern success of AI due to machine learning – “computer programs that learn without being explicitly programmed” (McCarthy, 1990, attributed to Samuel, 1959; Shah, 2023)
 - Most success with deep learning, based on many-layered neural networks
- Other terms
 - Data science – science of learning from data (Donoho, 2017)
 - Data analytics – use of data and statistical analysis to build explanatory and predictive models and drive decisions and actions (Davenport, 2017)
 - Big Data – data characterized by large volume, velocity, variety and variability (Chang, 2019)



3

Machine learning (ML) (Shah, 2023)

- Overall goal is to build models that learn from data
- Initially two categories of models
 - Supervised – learn to predict from labeled data
 - Unsupervised – learn from naturally occurring patterns or groupings within data
- Now variations
 - Reinforcement learning – learning from experience with existing models
 - Transfer learning – applying learning trained for one task to another
 - Self-supervised learning – identify labels from patterns in data



4

Functionality of ML

Classification

- Models typically trained via supervised learning
- Clinical functions may include
 - Diagnosis
 - Treatment
 - Patient outcomes
- Methods include
 - Logistic regression
 - Bayesian
 - k-nearest neighbors (kNN)
 - Support vector machine (SVM)
 - Random forest
 - Neural networks

Regression

- Models typically trained via unsupervised learning
- Clinical functions may include
 - Risk stratification
 - Fitting line
 - Clustering
- Methods include
 - Linear regression
 - Bayesian
 - k-nearest neighbors (kNN)
 - Support vector machine (SVM)
 - Random forest
 - Neural networks



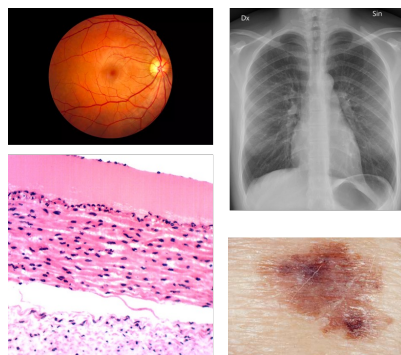
History of AI – first era in mid-20th century

- Earliest paper related to AI and biomedical informatics attributed to Ledley and Lusted (1959) aiming to model physician reasoning through symbolic logic and probability
- Warner (1961) developed mathematical model for diagnosing congenital heart disease
- In 1960s-1970s, emergence of “expert systems” – computer programs aiming to mimic human expertise (historical overview – Lea, 2023)
 - Rule-based systems – PhD dissertation of Shortliffe (1975) and subsequent work (Clancey, 1984)
 - Disease profiles and scoring algorithms – INTERNIST-1 (Miller, 1982) and DxPlain (Barnett, 1987)
- Limited by approach of manual construction and maintenance of knowledge
 - Not scalable or sustainable
 - Led to “AI winter” between 1990-2010
 - Main remnant is clinical decision support (CDS) for electronic health records (EHRs) that emerged in 1990s for electronic health records (Greenes, 2023)



Re-emergence of AI in 21st century

- “Predictive AI” driven by advances in ML, increasing availability of data, and more powerful computers and networks (Topol, 2019; Rajpurkar, 2022)
 - Deep learning in imaging advanced by Hinton (2006)
- Most success in image interpretation (Rajpurkar, 2023); examples include
 - Radiology – chest x-rays for diagnosis of pneumonia and tuberculosis
 - Ophthalmology – retinal images for diagnosis of diabetic retinopathy
 - Dermatology – skin lesions for diagnosis of cancer
 - Pathology – breast cancer slides to predict metastasis

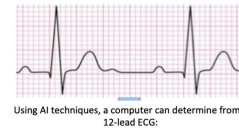


Predictive AI not limited to imaging

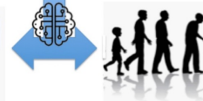
- Adverse events in hospitalizations from EHR data (Rajkomar, 2018)
- Generating clinical notes from patient and physician verbal interaction (Rajkomar, 2019)
- Protein folding from amino acid sequences (Jumper, 2021)
- ML model based on past ICD-10 codes and lab results to predict future diagnoses in office visits (Mukherjee, 2023)
- Semantic reconstruction of continuous language from fMRI brain recordings (Tang, 2023)
- Map chemicals to odors perceived by humans (Lee, 2023)
- Use across spectrum of infectious disease surveillance, tracking, and forecasting (Brownstein, 2023)

Also success in “seeing” where humans cannot (Topol, 2023)

- Retinal images
 - Age, biological sex, and cardiovascular risk determination from retinal images (Poplin, 2018)
 - Race (Coyner, 2023)
- Electrocardiograms (ECGs)
 - Age and biological sex determination (Attia, 2019)
 - Diagnosis and risk stratification in occlusive myocardial infarction (Al-Zaiti, 2023)
 - Chronic kidney disease (Holmstrom, 2023)
 - Left ventricular systolic dysfunction from ECG images (Sangha, 2023)
- Chest x-rays
 - Race (Gichoya, 2022)
 - Cardiac function and valvular heart diseases (Ueda, 2023)
 - Diabetes (Pyrros, 2023)
 - Correlation with chronological age in healthy cohorts and, for various chronic diseases, difference between estimated age and chronological age (Mitsuyama, 2023)



Whether you are male or female with an accuracy of over 90%



Your age, if you're healthy, within 7 years ... And may determine your physiologic age if you have other comorbidities

And now, “generative AI”

- Introduction of ChatGPT in November, 2022 brought new type of AI into focus: generative AI
 - Initially based on GPT-3.5 model; added larger GPT-4 soon after
- Based on large language models (LLMs) processed by deep neural networks using large amounts of training data and tuned for specific tasks
 - Trained on massive amounts of text and other content, e.g., large Web crawls, books, Wikipedia, and more for ChatGPT (Roberts, 2022)
 - Use transformer models that predict words in sequence from billions/trillions of words and add measure of importance to “attention” words (Raschka, 2023)
 - Fine-tuned for specific tasks (Chung, 2022)
 - Activated by (and importance of) prompting (Liu, 2023)

Results of ChatGPT and other LLMs

- Medical board exams
 - USMLE “arms race,” starting with (Kung, 2023)
 - Claimed best – <https://www.openevidence.com/blog/openevidence-ai-first-ai-score-above-90-percent-on-the-usmle>
 - Even on “soft skills” (e.g., communication skills, ethics, empathy, and professionalism) questions (Brin, 2023)
 - Passing level on some board exams (clinical informatics – Kumah-Crystal, 2023; radiology – Bhayana, 2023) but not others (neonatology – Beam, 2023)
- Answering questions
 - Vary by subject domain and type, but sometimes wrong and/or incomplete (e.g., Antaki, 2023; Chen, 2023; Goodman, 2023)
 - Consistently provided evidence-based answers to public health questions, although primarily offered advice rather than referrals (Ayers, 2023)
- Solving clinical cases
 - Comparable to but not better than expert humans (e.g., Levine, 2023; Kanjee, 2023; Rao, 2023; Benoit, 2023; Levkovich, 2023)



Results of ChatGPT and other LLMs (cont.)

- Communicating with patients
 - Answer questions in public forums (Sarraju, 2023)
 - Write letters with comparable or better empathy (Ali, 2023, Ayers, 2023)
- Use of predictive AI (closing the AI loop)
 - Classifying CXR findings based on previous images and reports (Xu, 2023)
 - Generating CXR reports from new images in ED from prior images and reports (Huang, 2023)
 - Predicting cardiovascular risk comparable to Framingham models (Han, 2023)



But there are downsides to generative AI

- Equally compelling disinformation – humans cannot distinguish between true and false tweets generated by GPT-3 and written by real Twitter users (Spitale, 2023)
- Fabrication and errors in the bibliographic citations – asked to produce short literature reviews on 42 multidisciplinary topics (Walters, 2023)
 - 55% of GPT-3.5 citations and 18% of GPT-4 citations fabricated
 - 43% of real (non-fabricated) GPT-3.5 citations and 24% of real GPT-4 citations include substantive errors
- 8 dermatology questions asked of 4 LLMs recapitulated “harmful, race-based medicine” (Omiye, 2023)
- Performs worse than humans in abstraction and analogy problems (Moskvichev, 2023)
- Automated GPT detectors do not work well (Sadasivan, 2023; Odri, 2023)
 - More likely to classify non-native English writing as AI-generated (Liang, 2023)
 - Humans not able to discern AI writing either (Dell'Acqua, 2023)



What is the evidence base for AI?

- Models are an important foundation (basic science) but need evidence of improved patient outcomes, care delivery, or other benefits (clinical science)
- Best evidence for any clinical intervention is randomized controlled trial (RCT) or systematic review of RCTs
- Three recent systematic reviews (Zhou, 2021; Plana, 2022; Han, 2023)
 - Small numbers of RCTs (40-80) relative to modeling papers
 - Many papers with methodological concerns, i.e., risk of bias
 - Unequal distribution of topical coverage, e.g., excess of colonoscopy imaging studies



Will AI help or hinder medicine?

- Real-world use and evidence base still modest – only 21% of physicians in group practices have used AI applications (MGMA, 2023)
- “AI won’t replace radiologists, but radiologists who use AI will replace radiologists who don’t,” (Langlotz, 2019)
- Must also address bias in data and algorithms
 - AI may compromise care if not used properly (DeCamp, 2023)
 - Must be implemented in responsible (Dorr, 2023) and fair (Chen, 2023) ways



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Questions?

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