

Point/Counterpoint Live Debate:

AI Will Soon Change the Landscape of Medical Physics Research and Practice

Lei Xing, Department of Radiation Oncology, Stanford University

Elizabeth Krupinski, Department of Radiology, Emory University

Jing Cai, Department of Health Technology & Informatics, PolyU, HK

Stanford University
Department of Radiation Oncology
School of Medicine

Disclosure

- Dr. Lei Xing has received speakers honoraria from Varian Medical Systems.
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- Scientific advisor for Huyihuiying Med Tech Co.
- Founder of Luca Medical Systems.

WHY DO WE NEED AI?

WHAT AI CAN DO FOR US?


HOW WELL CAN AI DO OUR JOBS?

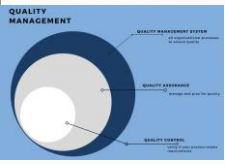
WHEN GENERAL AI WILL BE AVAILABLE?

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WHY DO WE NEED AI?

I'm too busy to tell people how busy I am.






The Cost of Health Care
How does it compare?

If other prices had grown to quality as health care costs since 1960...



a dollar today
\$55



a gallon of milk
\$48



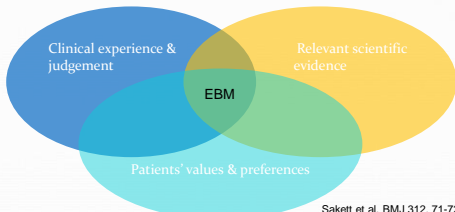
a dollar's worth
\$134

Approximately 1 in 3 Health Care Dollars is Waste
Can We Afford This?



Category	Amount
Unnecessary Services (Excess Imaging, etc.)	\$800
Excess Administrative Costs (Excess Billing, etc.)	\$720
Inefficient Care Delivery (Excess Tests, etc.)	\$495
Excess Prices (Excess Charges, etc.)	\$400
Excess Specialty Care	\$285
Preventable Problems (Excess Medication, etc.)	\$210
Total Wasted Spending per Person	\$2,910

Current medical practice is evidence-based



Sakett et al, BMJ 312, 71-72, 1996

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Problems and concerns with current EBM

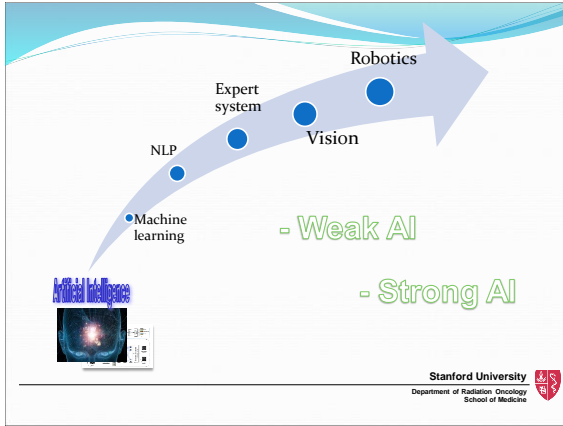
- Quality of the evidence
- Hypocognition
- Care provider dependent
- Efficiency & cost (not only the healthcare delivery process....)
- Lag between when the RCT is conducted and when its results are published/adopted
- Not individualized
- Human cognitive capacity???

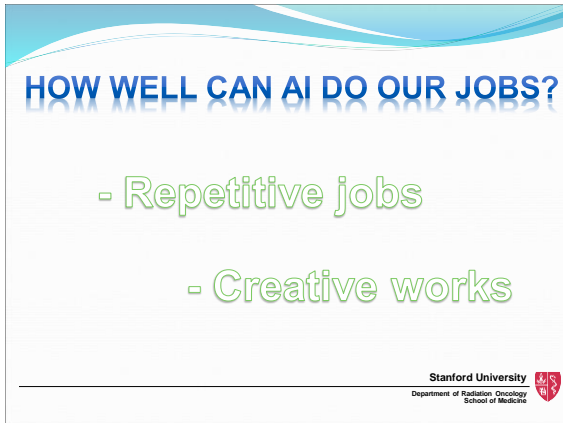
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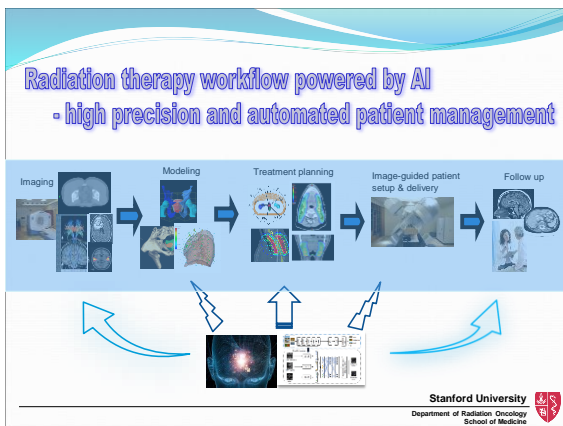


WHO
IS GOING TO
SAVE US ?

WHAT AI CAN DO FOR US?







On-going AI related research at Stanford Radiation Oncology Department



- ✓ AI-aided image analysis, reconstruction, super-resolution imaging, and tumor target segmentation
- ✓ Autonomous treatment planning driven by deep learning
- ✓ RT delivery guided by multiple layers of neural network
- ✓ AI-aided clinical decision-making, toxicity and survival prediction
- ✓ AI-facilitated QA
- ✓ NLP auto-annotation and clinical notes transcription

JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhraveer Venugopalan, MS; Kasumi Hether, MS; Tom Madams, MEng; Jorge Calzadilla, MD, PhD; Ramarany Kim, MD, DMSc; Rajiv Raman, MS, DMSc; Philip C. Nelson, BS; Jessica L. Meigs, MD, MPH; Dale R. Webster, PhD

Editorial pages 2366 and 2368
Supplemental content

IMPORTANCE Deep learning is a family of computational methods that allow an algorithm to program itself by learning from a large set of examples that demonstrate the desired behavior, removing the need to specify rules explicitly. Application of these methods to medical imaging requires further assessment and validation.

OBJECTIVE To apply deep learning to create an algorithm for automated detection of diabetic retinopathy and diabetic macular edema in retinal fundus photographs.

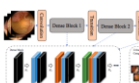
DESIGN AND SETTING A specific type of neural network optimized for image classification called a deep convolutional neural network was trained using a retrospective development dataset of 128 175 retinal images, which were graded 3 to 7 times for diabetic retinopathy, diabetic macular edema, and image gradability by a panel of 54 US licensed ophthalmologists and ophthalmology senior residents between May and December 2015. The resultant algorithm was validated in January and February 2016 using 2 separate data sets, both graded by at least 7 US board-certified ophthalmologists with high intergrader consistency.

EXPOSURE Deep learning-trained algorithm.

Automatic Polyp Recognition by Densely Connected Neural Network with Unbalanced Discriminate and Category Sensitive Constraint

Yizhou Yuan, Weiqiao Qiu, Bin Han, Xia, Q-H. Meng, Feliu, IEEE, Lei Xing

Fig. 1. Workflow of this paper.



The first step is to preprocess the input polyp images. The second step is to extract features using a densely connected neural network. The third step is to classify the features using a loss function that is sensitive to unbalanced data. The fourth step is to post-process the results to improve the accuracy of the classification.

The loss function is designed to be sensitive to the unbalanced data. The loss function is defined as follows: $L = -\sum_{i=1}^N \log(p_i)$, where p_i is the probability of the class i . The loss function is minimized by adjusting the weights of the network. The loss function is also used to evaluate the performance of the network.



Segmentation of organs-at-risks in head and neck CT images using convolutional neural networks

Bulat Ibragimov¹ and Lei Xing

¹Department of Radiation Oncology, Stanford University School of Medicine, Stanford, California 94305, USA

(Received 2 May 2016; revised 31 October 2016; accepted for publication 23 November 2016; published 13 February 2017)

Purpose: Accurate segmentation of organs-at-risk (OARs) is essential for radiation therapy planning. In this paper, we propose a deep learning-based algorithm, for segmentation of OARs in head and neck CT images, against state-of-the-art automated segmentation methods.

Methods: Convolutional neural network (CNN) is used to study consistent intensity patterns in a previously unseen test CT image. Five intensity patches around voxels that passed through a sequence of CNN layers

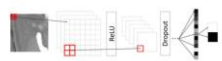
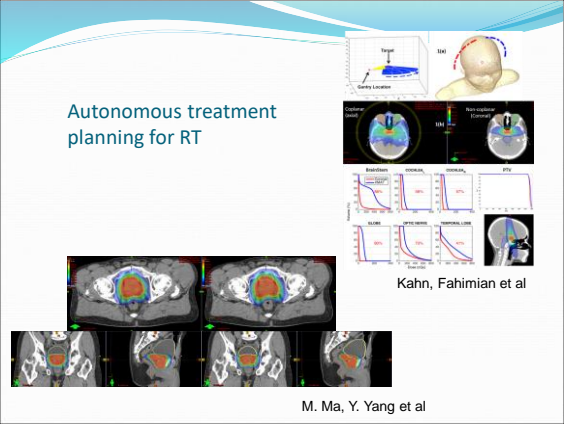


Fig. 1. A schematic diagram of the convolutional neural network architecture. The diagram shows the input CT image, the convolutional layer, the max pooling layer, and the output segmented OARs. The diagram also shows the intensity patches around voxels that passed through a sequence of CNN layers.

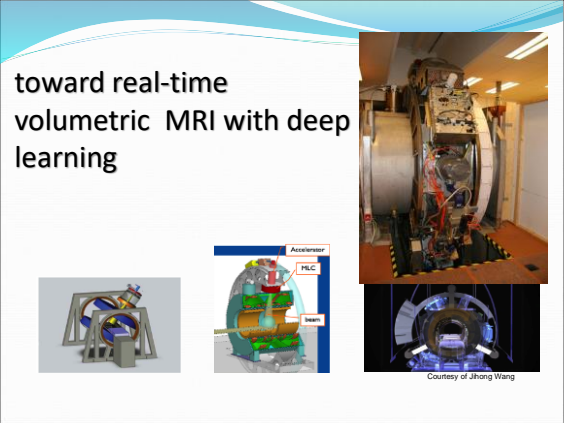
Autonomous treatment planning for RT



Kahn, Fahimian et al

M. Ma, Y. Yang et al

toward real-time volumetric MRI with deep learning



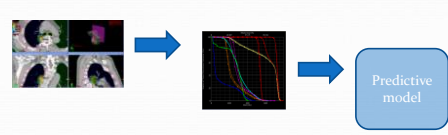
Courtesy of Jihong Wang

From population-average nomogram to deep learning-based toxicity prediction

— B. Ibrimbrow, D. Toesca, D. Chang, A Koong, L Xing

Current approach:

- (i) radiomics;
- (ii) NTCP/TCP types of modeling



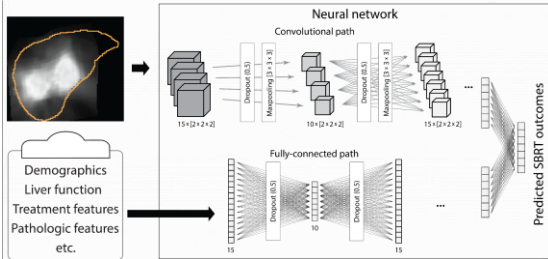
Predictive model

Machine learning-based toxicity/survival prediction

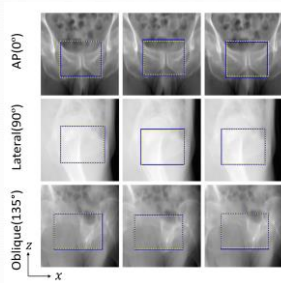
Deep dose analysis: combined

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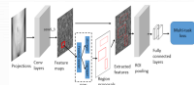
Multi-path network: 1) 3D CNN for dose plan; 2) fully-connected path for features



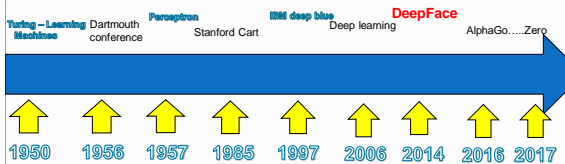
Visualizing the invisible soft tissue target



Zhao W, et al, RADIOLOGY, Submitted, 2018



WHEN GENERAL AI WILL BE IN THE CLINIC?



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SUMMARY

- APPLIED AI WILL SIGNIFICANTLY IMPROVE EFFICIENCY, QUALITY, AND REDUCE HEALTHCARE COST.

- WE ARE MARCHING INTO AN AGE OF GENERAL AI.

- MEDICAL PHYSICISTS SHOULD PLAY A MAJOR ROLE IN AI TECHNOLOGY.

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