



Point/Counterpoint Live Debate: Artificial Intelligence Will Soon Change the Landscape of Medical Physics Research and Practice



Introduction to Artificial Intelligence

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Applications of AI in Medical Physics

- Tumor detection, segmentation, and classification
- Image landmark detection and registration
- Automatic treatment planning, dose prediction
- Outcome prediction (survival, toxicity, recurrence)
- Clinical workflow (QA, Tx strategy, etc.)
- Radiomics & radiogenomics
 - Tumor classification, segmentation
 - Outcome prediction



Recent Radiomics Studies

Table 2. Studies that have applied machine learning in the context of radiomics.

Radiomics aim	Dataset	Imaging modality	Features	Reference (last author, year)	
Radiomics in RT planning	Prostate	CT	1000	Wang et al. 2017 ¹	
		MR	1000	Park et al. 2017 ²	
	Lung	CT	1000	Wang et al. 2017 ³ , Wang et al. 2017 ⁴ , Wang et al. 2017 ⁵	
		CT	1000	Wang et al. 2017 ⁶	
	Breast	CT	1000	Wang et al. 2017 ⁷ , Wang et al. 2017 ⁸	
		MR	1000	Wang et al. 2017 ⁹	
		MR	1000	Wang et al. 2017 ¹⁰	
		MR	1000	Wang et al. 2017 ¹¹	
		MR	1000	Wang et al. 2017 ¹²	
		MR	1000	Wang et al. 2017 ¹³	
Radiomics in clinical research	Lung	CT	1000	Wang et al. 2017 ¹⁴ , Wang et al. 2017 ¹⁵	
		CT	1000	Wang et al. 2017 ¹⁶	
	Breast	MR	1000	Wang et al. 2017 ¹⁷	
		MR	1000	Wang et al. 2017 ¹⁸	
	Liver	CT	1000	Wang et al. 2017 ¹⁹	
		CT	1000	Wang et al. 2017 ²⁰	
	Pancreatic	CT	1000	Wang et al. 2017 ²¹	
		CT	1000	Wang et al. 2017 ²²	
	Radiomics in clinical research	Pancreatic	CT	1000	Wang et al. 2017 ²³
			CT	1000	Wang et al. 2017 ²⁴

1. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 2. Park J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 3. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 4. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 5. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 6. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 7. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 8. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 9. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 10. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 11. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 12. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 13. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 14. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 15. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 16. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 17. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 18. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 19. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 20. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 21. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 22. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 23. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078. 24. Wang J, et al. Radiomics in radiotherapy: A review. *Journal of Clinical Oncology*. 2017;35(26):3071-3078.

Br J Radiol 2017; 90: 20160642.

Big Data in Medical Physics

Information type	Brain examples
Baseline clinical data	Demographics (including co-morbidity and family history), TSM stage, date of diagnosis, histopathology
Diagnostic imaging data	Diagnostic CT, MR and PET imaging
Radiotherapy treatment planning data	Delineation/structure sets, planning CT, dose matrix, beam set-up, prescribed dose and fractions
Radiotherapy treatment delivery data	Contour beam CTs, orthogonal EPID imaging, delivered fractions
New radiotherapy treatment data	Surgery, chemotherapy
Outcome data	Survival, local control, distant failure, toxicity (including patient reported outcomes), quality of life
Follow-up imaging data	Follow-up CT, MR and PET imaging
Biological data	Sample storage, shipping, tracing and lab results
Additional study conduct data	Study design, protocol, eligibility criteria

Data types and approximate sizes for a single patient.		
Data type	Format	Approx. size
Clinical features	Text	10 MB
Word notes	Numbers	1 MB
Administrative	ICD-10 codes	1 MB
Imaging data	DICOM	400 MB
Radiation oncology data (planning and on-board imaging)	DICOM, RT-DCOM	500 MB
Raw genomic data	BAM: Position, base, quality	6 GB
Total		70 GB

10 GB per patient

Radiother Oncol. 2014 Dec; 113(3): 303-309.

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Challenges

- Improved ML methods, especially for unsupervised learning and reinforcement learning.
- Model verification, validation, and trust
 - > robust machine learning
- Potential pitfalls of model:
 - garbage in, garage out
 - bias data, biased results

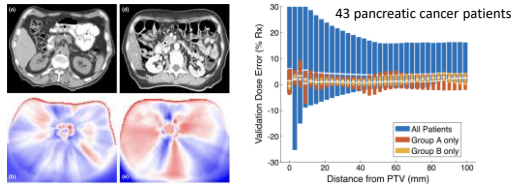
Thomas Dietterich, PhD, Oregon State University

Benefits and limitations of different machine learning (ML) methods

Algorithm	Advantages	Limitations
Decision Tree	<ul style="list-style-type: none"> Easy to understand Fast 	<ul style="list-style-type: none"> Classes must be mutually exclusive Results depend on the order of attribute selection Risk of overly complex decision trees
Naive Bayesian	<ul style="list-style-type: none"> Easy to understand Fast No effect of order on training 	<ul style="list-style-type: none"> Variables must be statistically independent Numeric attributes must follow a normal distribution Classes must be mutually exclusive
k-nearest Neighbors	<ul style="list-style-type: none"> Fast and simple Tolerant of noise and missing values in data Can be used for non-linear classification 	<ul style="list-style-type: none"> Less accurate Variables with similar attributes will be sorted in the same class All attributes are equally relevant Requires considerable computer power as number of variables increases
Support Vector Machine	<ul style="list-style-type: none"> Robust model Limits the risk of error Can be used to model non-linear relations 	<ul style="list-style-type: none"> Slow training Risk of overfitting Output model is difficult to understand
Artificial Neural Network and Deep Learning	<ul style="list-style-type: none"> Tolerant of noise and missing values in data Can be used for classification or regression Can be easily updated with new data 	<ul style="list-style-type: none"> Output model is difficult to understand (→ black-box x) Risk of overfitting Requires a lot of computer power Requires experimentation to find the optimal network structure

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Inter-observer Variation: neural network dose models for knowledge-based planning in pancreatic SBRT



- Remarkable improvements by training separate models for each physician

Med Phys, 2017, November, DOI: 10.1002/mp.12621



Figure 2 Farming is a useful metaphor for conceiving the errors in creating oncology databases in health care.

Advances in Radiation Oncology (2016) 1, 260-271

Where we are?

Health Informatics via Machine Learning for the Clinical Management of Patients

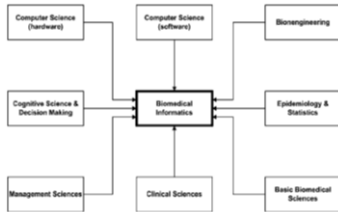
D. A. Clifton, K. E. Niehaus, P. Charlton, G. W. Colopy

Yonk Med Inform 2015;10:20-43
http://dx.doi.org/10.13067/2015-014
Published online August 13, 2015

4 Conclusions

We conclude by emphasising that the field of health informatics systems based on machine learning, drawing on disparate datatypes from the ICU, the wider hospital, and from (potentially very complex) EHR data, is in its infancy. While the majority of hospitals in the developed world have implemented EHR systems of some kind, the integrated use of the large quantities of data that arise from such systems is not employed at scale. This

Role of Physicist in AI Medicine



Kagadis et al.: Medical physicists and health care applications of Informatics, Med. Phys. 35 (1), January 2008



I used to be a medical physicist, but I did not learn AI.....

Medical Physics

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Artificial intelligence will soon change the landscape of medical physics research and practice

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