

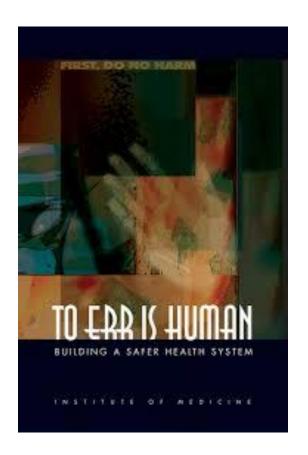
Al in healthcare Beyond deep learning in imaging

May 09, 2017

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Healthcare is dangerous and wasteful

IOM 1998/2012: 98.000 deaths



30% excess Medicare spending \$690 billion IOM 2012

Estimates of Waste in US Health Care Spending in 2011, by Category

	Cost to Medicare and Medicaid ^a		Total cost to US health care ^b			
	Low	Midpoint	High	Low	Midpoint	High
Failures of care delivery	\$26	\$36	\$45	\$102	\$128	\$154
Failures of care coordination	21	30	39	25	35	45
Overtreatment	67	77	87	158	192	226
Administrative complexity	16	36	56	107	248	389
Pricing failures	36	56	77	84	131	178
Subtotal (excluding fraud and abuse)	166	235	304	476	734	992
Percentage of total health care spending	6%	9%	11%	18%	27%	37%

SOURCE Donald M. Berwick and Andrew D. Hackbarth, "Eliminating Waste in US Health Care," JAMA 307, no. 14 (April 11, 2012):1513–6. Copyright © 2012 American Medical Association. All rights reserved. **NOTES** Dollars in billions. Totals may not match the sum of components due to rounding. alncludes state portion of Medicaid. Total US health care spending estimated at \$2.687 trillion.



Information overload

70 Min time spent on alarm management

240 Information categories in ICUs

5 Times increase # of sophisticated tests

Times increase of archival capability

Likelihood of missing information increased 200-500%



"Mrs. J is a 78 year old patient of mine whose chart contains multiple physicians' notes, laboratory and Information x-ray reports, hospital and home health summaries in Information scatter differing formats. Many of the physician notes are overload created using templates and contain large amounts of redundant boilerplate text, making it hard to pick out important information. She was recently discharged from the hospital, but the clinical summary, laboratory reports and medication changes from that Information hospitalization are not available in my office. underload Follow-up lab work was not done. I was unaware that the patient had an echocardiogram done as an Information outpatient." The nurse is unable to reconcile the conflict various medication lists with what she thinks she is taking from the hospital. She is upset and crying (1 Information am not sure why) and her husband, who is also in the overload Erroneous room, is clearly frustrated. He tells me that she had information a bad reaction to a "heart drug" in the hospital, but it turns out later that she did not.



Work overload

4070 report symptoms of physical burnor	46%	report symptoms	s of physical burnou
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22%	ordered	unneeded	tests	due	to time
ZZ /U	Olacica	annecaca		uuc	

5%	Patients suffer	ed adverse events
O		

Times increase of archival capability

Likelihood of missing information increased 200-500%



Data accuracy in healthcare

Data in EMRs are not accurate

Patient records are incomplete

70% Semantically incorrect when from other sources

Healthcare data is difficult



Heterougenous biology - Precision medicine

Digital Health = advanced analytics based on multi-modal data

Health Care Internet of Things = sensors, apps, and remote diagnostic or care delivery

Preventive Medicine =
Digital Twin for a Person's Health based on multiple data types

genomic data, i.e. nucleotide polymorphisms, whole human or exome sequencing, epigenetics, RNA expression data, metabolomics, microbiomics, environmentalomics, and diseasomics, personal and family health history, images, blood test data and other laboratory results, and prescription histories, sensors - wearable or implantable, and diagnostics raw data



Optimism bias and decision making

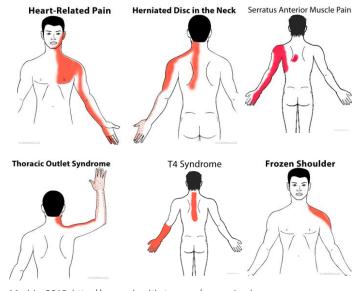
Patient with pain in his left arm

Cardiologist: Coronary

Neurosurgeon: Cervical Disc

Orthopaedic: Shoulder, Muscle

Angiologist: Vascular



Modric, 2015: http://www.ehealthstar.com/arm-pain.php

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Healthcare decision making's complex



Efficiency in healthcare

- 1/3 expenditure don't improve health
- US #50/55
- Germany #37/55
- Throughput 1/5 compared to aviation, automotive

Current Rank	2009 Rank	Change	Country/Region	Efficiency Score	Life Expectancy	Relative Cost %	Absolute Cost \$
1	1	-	Hong Kong	88.9	83.98	5.40	2,021
2	2	-	Singapore	84.2	82.65	4.92	2,752
3	8	5	Spain	72.2	83.80	9.03	2,658
4	7	3	S. Korea	71.5	82.16	7.37	2,060
5	3	-2	Japan	68.2	83.59	10.23	3,703
6	5	-1	Italy	67.7	82.69	9.25	3,258
7	4	-3	Israel	66.8	82.15	7.81	2,910
8	15	7	Chile	65.2	81.50	7.79	1,137
9	9	-:	U.A.E.	64.3	77.37	3.64	1,611
10	6	-4	Australia	62.0	82.25	9.42	6,031
11	33	22	Argentina	59.8	76.16	4.79	605
12	11	-1	Taiwan	59.7	80.20	6.34	1,389
13	22	9	Greece	59.0	81.29	8.08	1,743
14	10	-4	Switzerland	57.8	82.85	11.66	9,674
15	21	6	France	56.8	82.37	11.54	4,959
16	24	8	Canada	56.1	81.96	10.45	5,292
17	20	3	Mexico	55.3	76.72	6.30	677
18	27	9	Poland	54.6	77.25	6.35	910
19	19	-	China	54.3	75.78	5.55	420
20	13	-7	Norway	54.0	81.75	9.72	9,522
21	26	5	U.K.	52.9	81.60	9.12	3,935
22	16	-6	Malaysia	52.2	74.72	4.17	456
23	29	6	Czech Rep.	51.5	78.28	7.41	1,379
24	25	1	Finland	51.1	81.13	9.68	4,612



Healthcare & AI: three main pillars

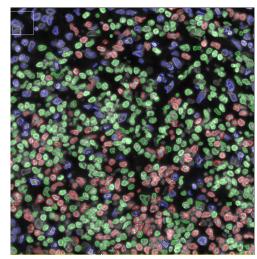
- 1. Imaging related decision making
- 2. Multi-modal Clinical Decision Support
- 3. Healthcare assets & predictive optimization



Deep Learning for Cell Classification

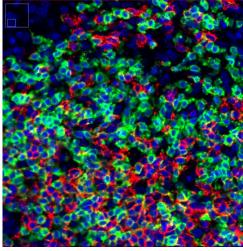
Example of cell classification in tissue samples using CD20 (B Cells) and CD3 (T Cells) markers





Markers: CD20 (red), CD3 (green), cell nuclei (blue)

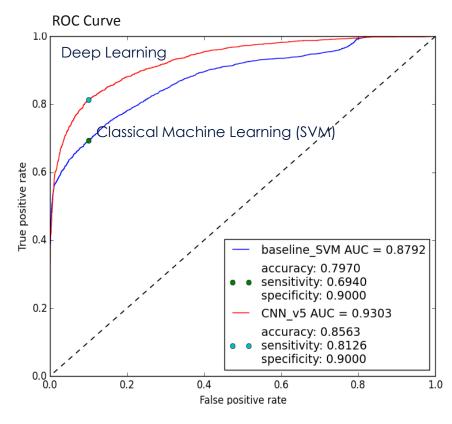
Classification



Classified CD20 (red), CD3 (green), double negative (blue)

Deep learning classification based on convolutional neuronal networks

Classified MultiOmyx® imaging data from cancer tissue from 747 colorectal cancer patients

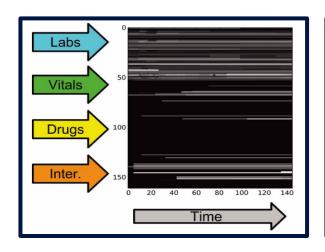


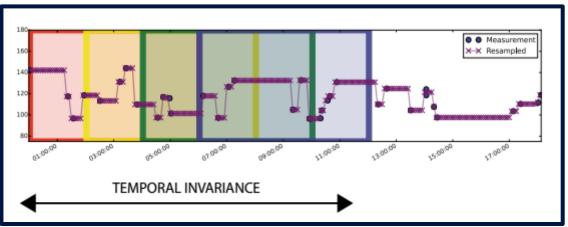
Performance comparison of learningbased methods

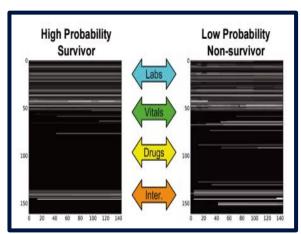




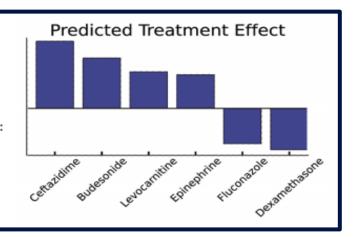
ICU's personalized recommendation for the most effective treatment







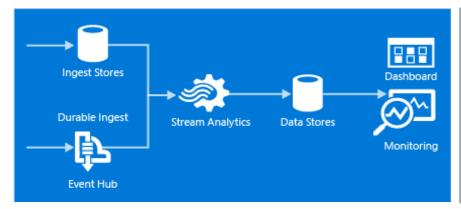
- · Patient diagnosed with:
 - Cardiac Arrest
 - Cardiomyopathy
 - Epileptic Seizures
 - Pneumothorax
- · Patient eventually treated with:
 - Piperacillin
 - Vancomycin
 - Epinephrine
 - Phenylephrine



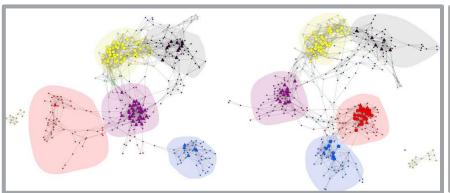
Deep learning Recommendation of Treatment from Electronic Data David Ledbetter, Melissa Aczon Virtual Pediatric Intensive Care Unit, Children's Hospital Los Angeles



Deep Learning and Streaming Analytics for Prediction of Adverse Events in the ICU



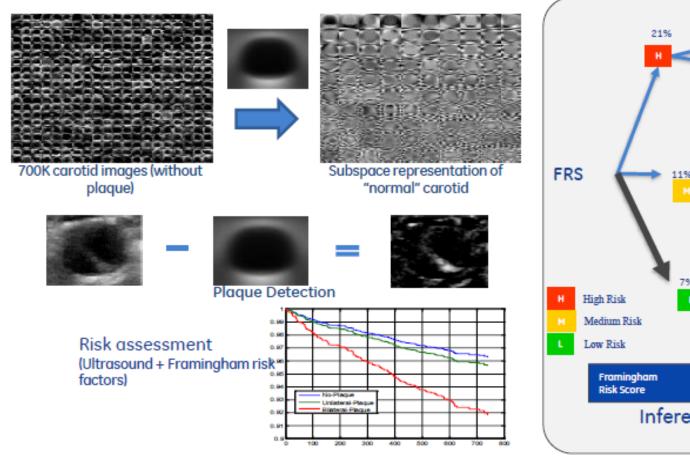
Transmits over 100,000 real-time data points per 100 beds, per second

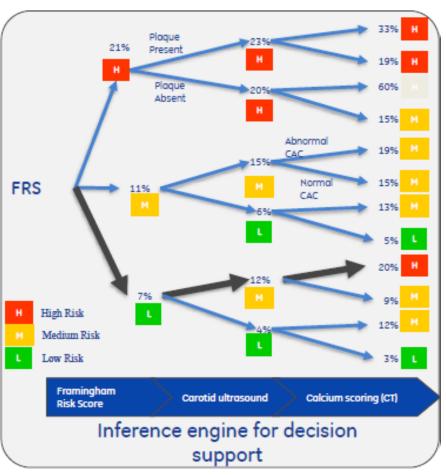


In-flight deep learning prediction model for onset of HAI, hypovolemia, sepsis



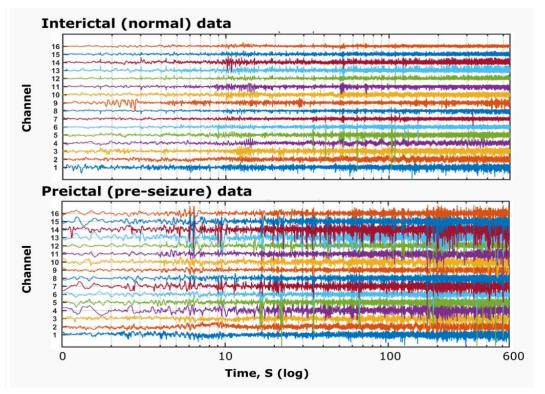
Ultrasound Carotid Plaque Analysis & Cardiac Risk Assessment

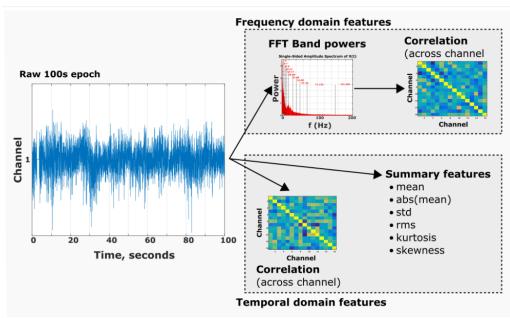






Deep learning seizure prediction





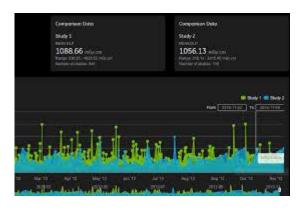
forecast the occurrence of seizures using intracranial EEG recordings deep learning networks stand out as a promising approach for neurological diagnosis on EEG data



Asset optimization using Deep Learning

Command Center based hospital throughput prediction





Digital Twin of CTs optimizes Radiation Dose

DL algorithm predicts likelihood of reimbursement denial





One thing for sure: 20 years from now (and hopefully sooner) we won't be saying "deep learning in medicine", "precision medicine

"clinical decision support", "personalized medicine", "digital medicine" and "genomic medicine"— it'll just be "medicine". Eric Topol June 27, 2015

"I predict that within 10 years no medical imaging study will be reviewed by a radiologist until it has been pre-analyzed by a machine"



2002 RSNA President Dr Nick Bryan, May 1, 2016

