

# Artificial Intelligence in Cardiology and Cardiac Surgery

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# What is “Intelligence”?

- “. . . the ability of a system to act appropriately in an uncertain environ- ment, where appropriate action is that which increases the probability of success, and success is the achievement of behavioral subgoals that support the system’s ultimate goal.” J. S. Albus [1]
- “Any system . . . that generates adaptive behviour to meet goals in a range of environments can be said to be intelligent.” D. Fogel [10]
- 6
- “Achieving complex goals in complex environments” B. Goertzel [12]
- “Intelligent systems are expected to work, and work well, in many different environments. Their property of intelligence allows them to maximize the probability of success even if full knowledge of the situation is not available. Functioning of intelligent systems cannot be considered separately from the environment and the concrete situation including the goal.” R. R. Gudwin [15]
- “[Performance intelligence is] the successful (i.e., goal-achieving) perfor- mance of the system in a complicated environment.” J. A. Horst [18]
- “Intelligence is the ability to use optimally limited resources – including time – to achieve goals.” R. Kurzweil [20]
- “Intelligence is the power to rapidly find an adequate solution in what appears a priori (to observers) to be an immense search space.” D. Lenat and E. Feigenbaum [23]
- “Intelligence measures an agent’s ability to achieve goals in a wide range of environments.” S. Legg and M. Hutter [21]
- “...doing well at a broad range of tasks is an empirical definition of ‘intelligence’ ” H. Masum [24]
- “Intelligence is the computational part of the ability to achieve goals in the world. Varying kinds and degrees of intelligence occur in people, many animals and some machines.” J. McCarthy [25]
- “. . . the ability to solve hard problems.” M. Minsky [26]
- “Intelligence is the ability to process information properly in a complex environment. The criteria of properness are not predefined and hence not available beforehand. They are acquired as a result of the information processing.” H. Nakashima [27]
- “. . . in any real situation behavior appropriate to the ends of the system and adaptive to the demands of the environment can occur, within some limits of speed and complexity.” A. Newell and H. A. Simon [29]
- “[An intelligent agent does what] is appropriate for its circumstances and its goal, it is flexible to changing environments and changing goals, it learns from experience, and it makes appropriate choices given perceptual limitations and finite computation.” D. Poole [31]
- “Intelligence means getting better over time.” Schank [32]
- “Intelligence is the ability for an information processing system to adapt to its environment with insufficient knowledge and resources.” P. Wang [39]
- “. . . the mental ability to sustain successful life.” K. Warwick quoted in [4] 7
- 18. “. . . the essential, domain-independent skills necessary for acquiring a wide range of domain-specific knowledge – the ability to learn anything. Achiev- ing this with ‘artificial general intelligence’ (AGI) requires a highly adap- tive, general-purpose system that can autonomously acquire an extremely wide range of specific knowledge and skills and can improve its own cog- nitive ability through self-directed learning.” P. Voss [38]

- “The ability to use memory, knowledge, experience, understanding, rea- soning, imagination and judgement in order to solve problems and adapt to new situations.” AllWords Dictionary, 2006
- “The capacity to acquire and apply knowledge.” The American Heritage Dictionary, fourth edition, 2000
- “Individuals differ from one another in their ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, to overcome obstacles by taking thought.” American Psychological Association [28]
- “The ability to learn, understand and make judgments or have opinions that are based on reason” Cambridge Advance Learner’s Dictionary, 2006
- “Intelligence is a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, com- prehend complex ideas, learn quickly and learn from experience.” Com- mon statement with 52 expert signatories [13]
- “The ability to learn facts and skills and apply them, especially when this ability is highly developed.” Encarta World English Dictionary, 2006
- “...ability to adapt effectively to the environment, either by making a change in oneself or by changing the environment or finding a new one . . . intelligence is not a single mental process, but rather a combination of many mental processes directed toward effective adaptation to the envi- ronment.” Encyclopedia Britannica, 2006
- “the general mental ability involved in calculating, reasoning, perceiving relationships and analogies, learning quickly, storing and retrieving infor- mation, using language fluently, classifying, generalizing, and adjusting to new situations.” Columbia Encyclopedia, sixth edition, 2006
- “Capacity for learning, reasoning, understanding, and similar forms of mental activity; aptitude in grasping truths, relationships, facts, mean- ings, etc.” Random House Unabridged Dictionary, 2006
- 2
- “The ability to learn, understand, and think about things.” Longman Dictionary or Contemporary English, 2006
- “: the ability to learn or understand or to deal with new or trying situa- tions : . . . the skilled use of reason (2) : the ability to apply knowledge to manipulate one’s environment or to think abstractly as measured by objective criteria (as tests)” Merriam-Webster Online Dictionary, 2006
- “The ability to acquire and apply knowledge and skills.” Compact Oxford English Dictionary, 2006
- “. . . the ability to adapt to the environment.” World Book Encyclopedia, 2006
- “Intelligence is a property of mind that encompasses many related mental abilities, such as the capacities to reason, plan, solve problems, think abstractly, comprehend ideas and language, and learn.” Wikipedia, 4 October, 2006
- “Capacity of mind, especially to understand principles, truths, facts or meanings, acquire knowledge, and apply it to practise; the ability to learn and comprehend.” Wiktionary, 4 October, 2006
- “The ability to learn and understand or to deal with problems.” Word Central Student Dictionary, 2006
- “The ability to comprehend; to understand and profit from experience.” Wordnet 2.1, 2006
- “The capacity to learn, reason, and understand.” Wordsmyth Dictionary, 2006
- 3 Psychologist definitions
- This section contains definitions from psychologists. In some cases we have not yet managed to locate the exact reference and would appreciate any help in doing so.
- “Intelligence is not a single, unitary ability, but rather a composite of several functions. The term denotes that combination of abilities required for survival and advancement within a particular culture.” A. Anastasi [2]
- “...that facet of mind underlying our capacity to think, to solve novel problems, to reason and to have knowledge of the world.” M. Anderson [3]
- “It seems to us that in intelligence there is a fundamental faculty, the alteration or the lack of which, is of the utmost importance for practical life. This faculty is judgement, otherwise called good sense, practical sense, initiative, the faculty of adapting ones self to circumstances.” A. Binet [5]
- 3
- “We shall use the term ‘intelligence’ to mean the ability of an organism to solve new problems . . . ” W. V. Bingham [6]
- “Intelligence is what is measured by intelligence tests.” E. Boring [7]
- “. . . a quality that is intellectual and not emotional or moral: in measuring it we try to rule out the effects of the child’s zeal, interest, industry, and the like. Secondly, it denotes a general capacity, a capacity that enters into everything the child says or does or thinks; any want of ’intelligence’ will therefore be revealed to some degree in almost all that he attempts;” C. L. Burt [8]
- “A person possesses intelligence insofar as he has learned, or can learn, to adjust himself to his environment.” S. S. Colvin quoted in [35]
- “. . . the ability to plan and structure one’s behavior with an end in view.” J. P. Das
- “The capacity to learn or to profit by experience.” W. F. Dearborn quoted in [35]
- “...in its lowest terms intelligence is present where the individual ani- mal, or human being, is aware, however dimly, of the relevance of his behaviour to an objective. Many definitions of what is indefinable have been attempted by psychologists, of which the least unsatisfactory are 1. the capacity to meet novel situations, or to learn to do so, by new adaptive responses and 2. the ability to perform tests or tasks, involving the grasp- ing of relationships, the degree of intelligence being proportional to the complexity, or the abstractness, or both, of the relationship.” J. Drever [9]
- “Intelligence A: the biological substrate of mental ability, the brains’ neu- roanatomy and physiology; Intelligence B: the manifestation of intelligence A, and everything that influences its expression in real life behavior; In- telligence C: the level of performance on psychometric tests of cognitive ability.” H. J. Eysenck.
- “Sensory capacity, capacity for perceptual recognition, quickness, range or flexibility or association, facility and imagination, span of attention, quickness or alertness in response.” F. N. Freeman quoted in [35]
- “. . . adjustment or adaptation of the individual to his total environment, or limited aspects thereof ...the capacity to reorganize one’s behavior patterns so as to act more effectively and more appropriately in novel sit- uations . . . the ability to learn . . . the extent to which a person is educable . . . the ability to carry on abstract thinking . . . the effective use of concepts and symbols in dealing with a problem to be solved . . . ” W. Freeman
- “An intelligence is the ability to solve problems, or to create products, that are valued within one or more cultural settings.” H. Gardner [11]
- 4
- “...performing an operation on a specific type of content to produce a particular product.” J. P. Guilford
- “Sensation, perception, association, memory, imagination, discrimination, judgement and reasoning.” N. E. Haggerty quoted in [35]
- “The capacity for knowledge, and knowledge possessed.” V. A. C. Henmon [16]
- “. . . cognitive ability.” R. J. Herrnstein and C. Murray [17]
- “. . . the resultant of the process of acquiring, storing in memory, retriev- ing, combining, comparing, and using in new contexts information and conceptual skills.” Humphreys
- “Intelligence is the ability to learn, exercise judgment, and be imagina- tive.” J. Huarte
- “Intelligence is a general factor that runs through all types of perfor- mance.” A. Jensen
- “Intelligence is assimilation to the extent that it incorporates all the given data of experience within its framework . . . There can be no doubt either, that mental life is also accommodation to the environment. Assimilation can never be pure because by incorporating new elements into its earlier schemata the intelligence constantly modifies the latter in order to adjust them to new elements.” J. Piaget [30]
- “Ability to adapt oneself adequately to relatively new situations in life.” R. Pinter quoted in [35]
- “A biological mechanism by which the effects of a complexity of stimuli are brought together and given a somewhat unified effect in behavior.” J. Peterson quoted in [35]
- “. . . certain set of cognitive capacities that enable an individual to adapt and thrive in any given environment they find themselves in, and those cognitive capacities include things like memory and retrieval, and problem solving and so forth. There’s a cluster of cognitive abilities that lead to successful adaptation to a wide range of environments.” D. K. Simon- ton [33]
- “Intelligence is part of the internal environment that shows through at the interface between person and external environment as a function of cognitive task demands.” R. E. Snow quoted in [34]
- “. . . I prefer to refer to it as ‘successful intelligence.’ And the reason is that the emphasis is on the use of your intelligence to achieve success in your life. So I define it as your skill in achieving whatever it is you want to attain in your life within your sociocultural context — meaning that
- 5
- people have different goals for themselves, and for some it’s to get very good grades in school and to do well on tests, and for others it might be to become a very good basketball player or actress or musician.” R. J. Sternberg [36]
- “...the ability to undertake activities that are characterized by (1) dif- ficulty, (2) complexity, (3) abstractness, (4) economy, (5) adaptedness to goal, (6) social value, and (7) the emergence of originals, and to maintain such activities under conditions that demand a concentration of energy and a resistance to emotional forces.” Stoddard
- “The ability to carry on abstract thinking.” L. M. Terman quoted in [35]
- “Intelligence, considered as a mental trait, is the capacity to make im- pulses focal at their early, unfinished stage of formation. Intelligence is therefore the capacity for abstraction, which is an inhibitory process.” L. L. Thurstone [37]
- “The capacity to inhibit an instinctive adjustment, the capacity to redefine the inhibited instinctive adjustment in the light of imaginally experienced trial and error, and the capacity to realise the modified instinctive ad- justment in overt behavior to the advantage of the individual as a social animal.” L. L. Thurstone quoted in [35]
- “A global concept that involves an individual’s ability to act purposefully, think rationally, and deal effectively with the environment.” D. Wech- sler [40]
- “The capacity to acquire capacity.” H. Woodrow quoted in [35]
- “. . . the term intelligence designates a complexly interrelated assemblage of functions, no one of which is completely or accurately known in man ...” R. M. Yerkes and A. W. Yerkes [41]
- “. . . that faculty of mind by which order is perceived in a situation previ- ously considered disordered.” R. W. Young quoted in [20]

# Recurring concepts

- 1. The ability to acquire and apply knowledge and skills
- 2. The ability to learn or understand or to deal with new or trying situations

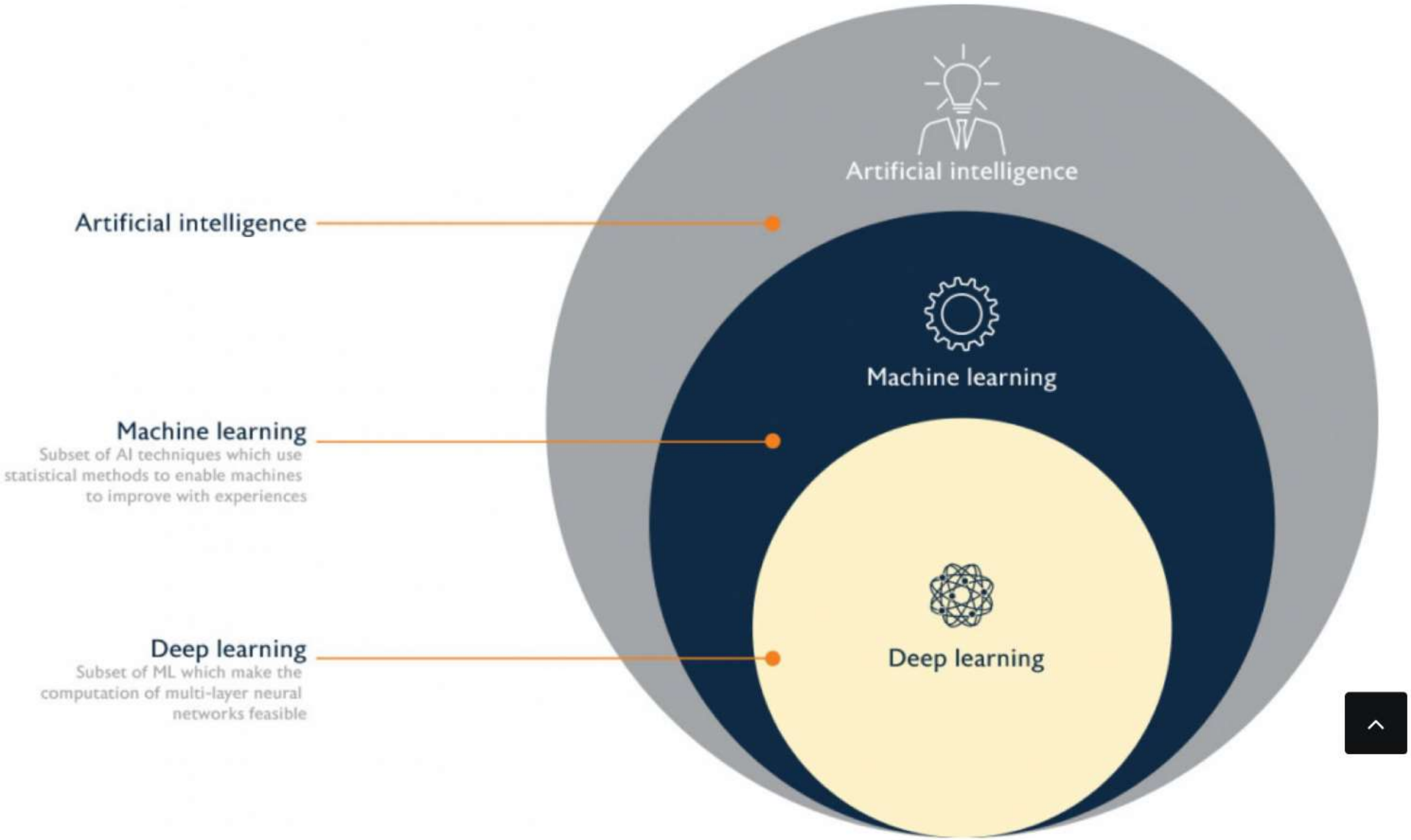
Original definition of Artificial Intelligence:

A branch of computer science that deals with the development of systems able to mimic human behavior.

TURING TEST

# AI = Ability of a computer system to:

- Acquire large amounts of data (Deep Learning)
- Analyze those data with regard to the system's goal (requires training algorithms and enormous computing power / Neural Networks)
- Provide an output
- Gather feedback and use it to confirm/validate or modify the initial algorithms (Machine Learning)


Artificial intelligence
Machine learning
Subset of AI techniques which use statistical methods to enable machines to improve with experiences
Deep learning
Subset of ML which make the computation of multi-layer neural networks feasible
Artificial intelligence
Machine learning
Deep learning

**Artificial Intelligence. Genuinely unintelligent without high quality data**

# The Importance of DATA


OUTLOOK
Climate change
nature
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
BEING HUMAN
Cataloguing the effects of genetic variation on gene expression in healthy tissues PAGES 190, 204, 239, 244 & 249
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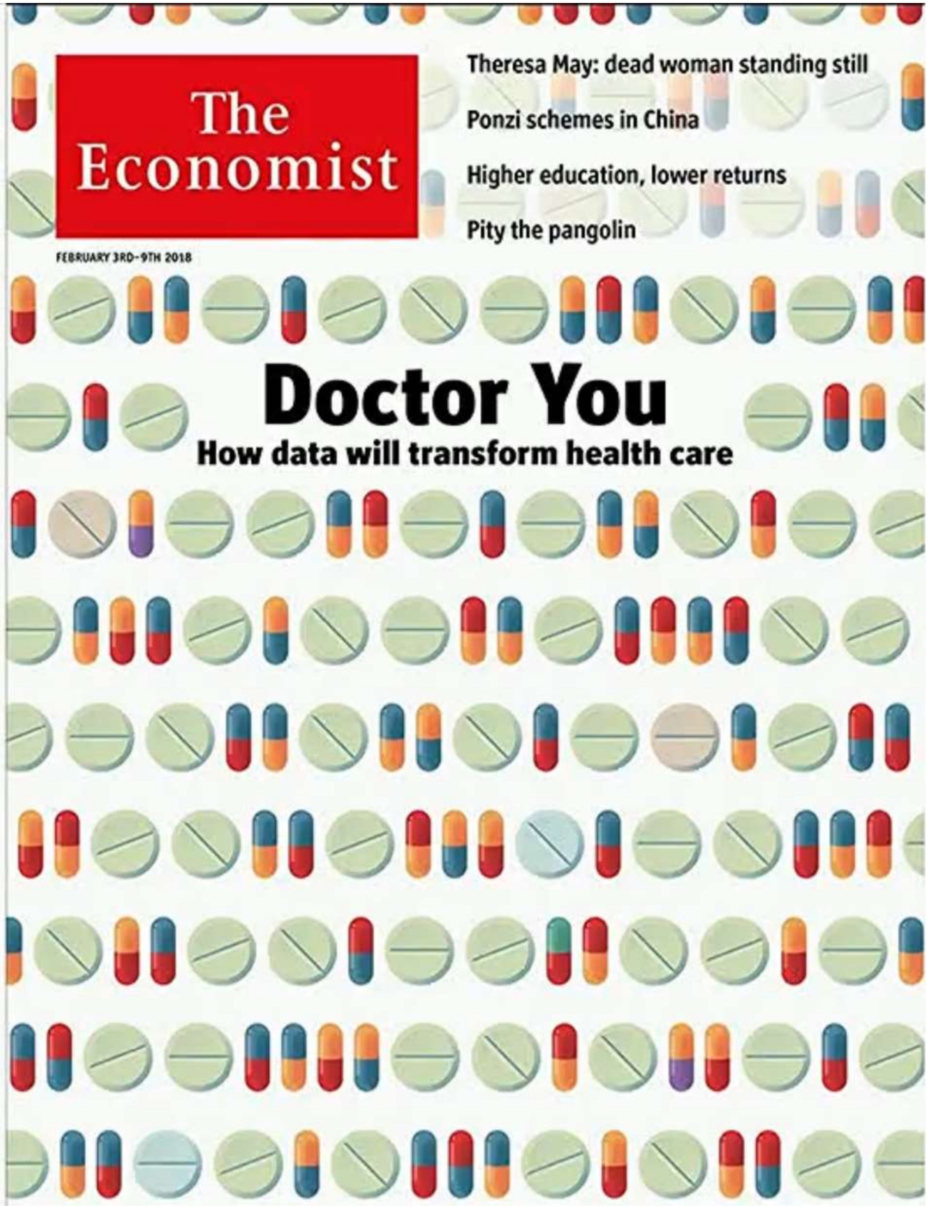
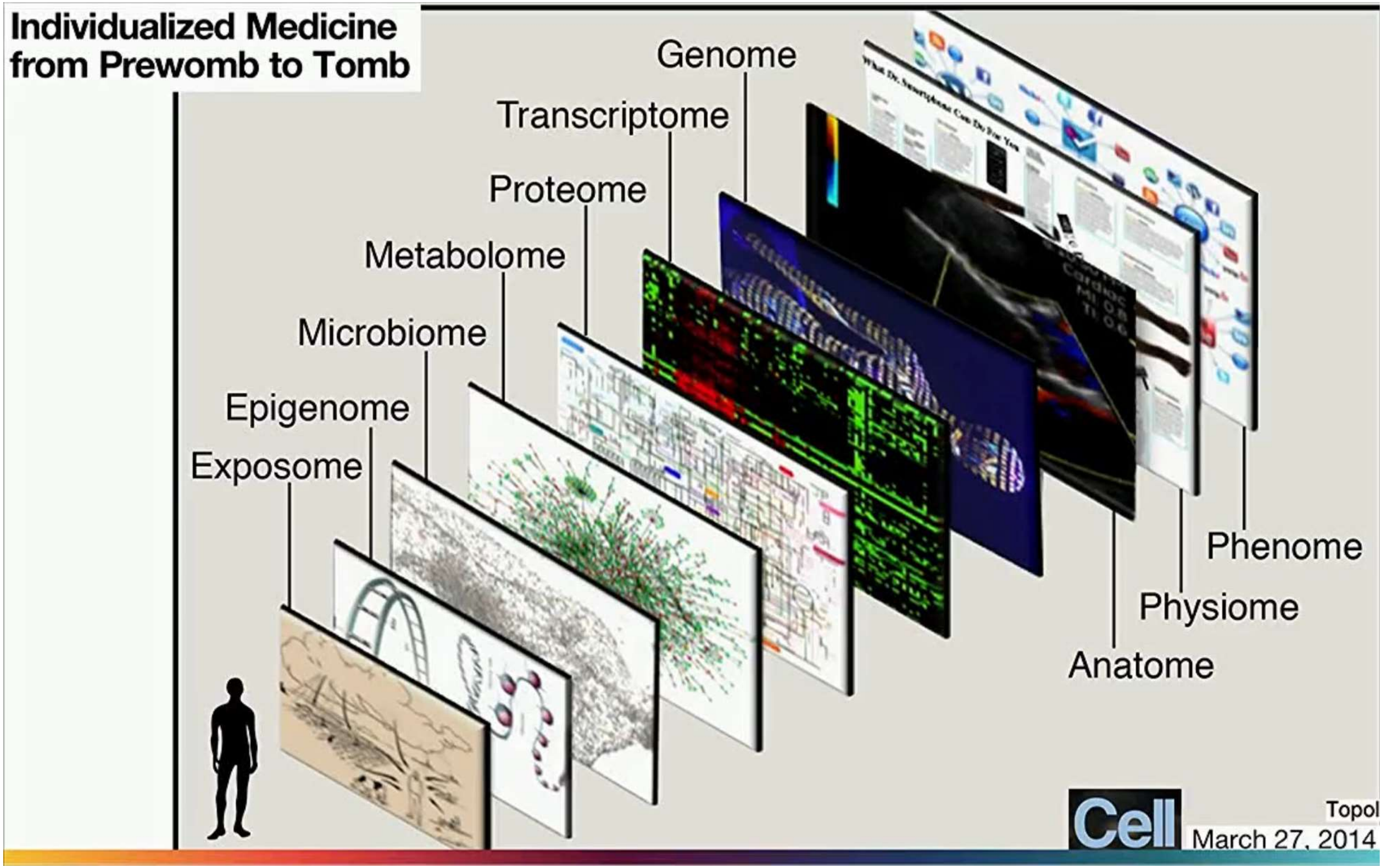
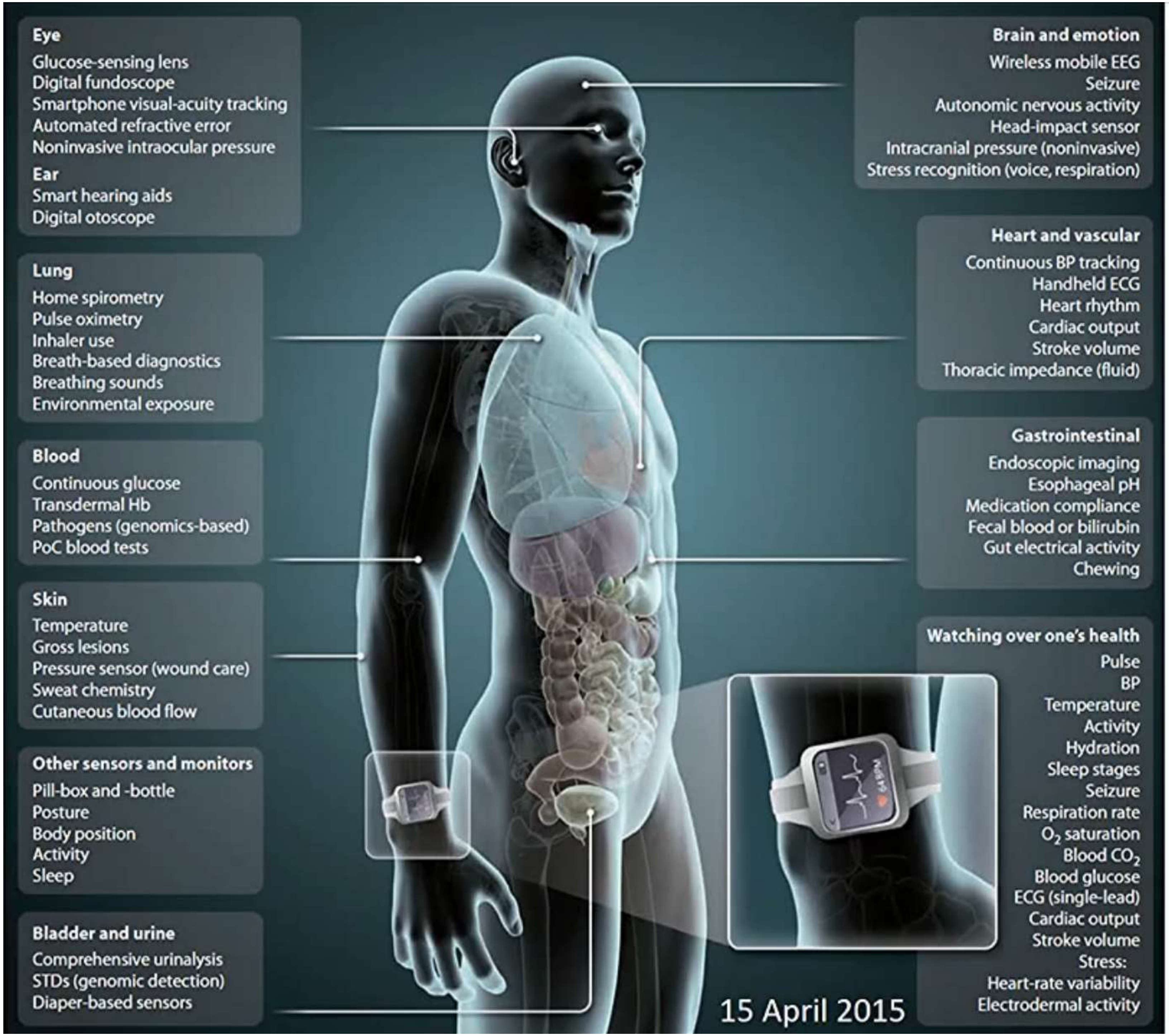
NATURE.COM/NATURE
12 October 2017
Vol. 550, No. 7675


The Economist
Theresa May: dead woman standing still
Ponzi schemes in China
Higher education, lower returns
Pity the pangolin
FEBRUARY 3RD-9TH 2018
Doctor You
How data will transform health care


Individualized Medicine
from Prewomb to Tomb
Genome
Transcriptome
Proteome
Metabolome
Microbiome
Epigenome
Exposome
Phenome
Physiome
Anatome
Cell
Topol
March 27, 2014



Eye
Glucose-sensing lens
Digital fundoscope
Smartphone visual-acuity tracking
Automated refractive error
Noninvasive intraocular pressure
Ear
Smart hearing aids
Digital otoscope
Lung
Home spirometry
Pulse oximetry
Inhaler use
Breath-based diagnostics
Breathing sounds
Environmental exposure
Blood
Continuous glucose
Transdermal Hb
Pathogens (genomics-based)
PoC blood tests
Skin
Temperature
Gross lesions
Pressure sensor (wound care)
Sweat chemistry
Cutaneous blood flow
Other sensors and monitors
Pill-box and -bottle
Posture
Body position
Activity
Sleep
Bladder and urine
Comprehensive urinalysis
STDs (genomic detection)
Diaper-based sensors
Brain and emotion
Wireless mobile EEG
Seizure
Autonomic nervous activity
Head-impact sensor
Intracranial pressure (noninvasive)
Stress recognition (voice, respiration)
Heart and vascular
Continuous BP tracking
Handheld ECG
Heart rhythm
Cardiac output
Stroke volume
Thoracic impedance (fluid)
Gastrointestinal
Endoscopic imaging
Esophageal pH
Medication compliance
Fecal blood or bilirubin
Gut electrical activity
Chewing
Watching over one's health
Pulse
BP
Temperature
Activity
Hydration
Sleep stages
Seizure
Respiration rate
$O_2$ saturation
Blood $CO_2$
Blood glucose
ECG (single-lead)
Cardiac output
Stroke volume
Stress:
Heart-rate variability
Electrodermal activity
15 April 2015


63
BPM
10:09
MON 9
150
50
10 PM
Record EKG
10:09
Kardia
Record your EKG
Your heart rate increased from 68 bpm to 94 bpm.
Record EKG
63
BPM
27
Speed: 25 mm / s
Gain: 10 mm / mV


ECG
10:09
Hold your finger on the crown.

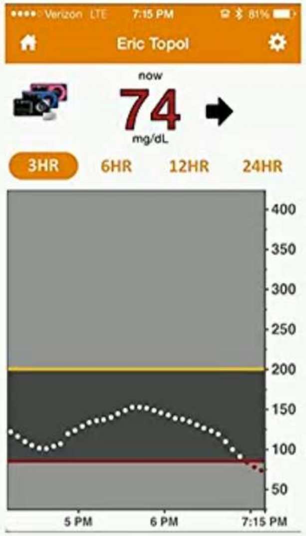

ECG
10:09
Sinus Rhythm
76 BPM AVERAGE
This ECG does not show signs of atrial fibrillation.
ECG
10:09
Atrial Fibrillation
76 BPM AVERAGE
This ECG show signs of AFib.


10:09
Kardia
082
Possible Hyperkalemia
High
K+ = ~5.8 mmol/L
Caution:
Investigational device. Limited by Federal (or United States) law to investigational use only.


SYS
mmHg
127
DIA
mmHg
84
PULSE
/min
72
01/10 7:30 AM

# Continuous Glucose Sensors







THE MEDICALIZED SMARTPHONE


# 'Alexa, Check My Heart', AI Tool to Detect Cardiac Arrest During Sleep

news18.com · PTI

Cardiac arrest patients are often unconscious, and have agonal breathing sounds. AI tools can help determine whether the patient needed...

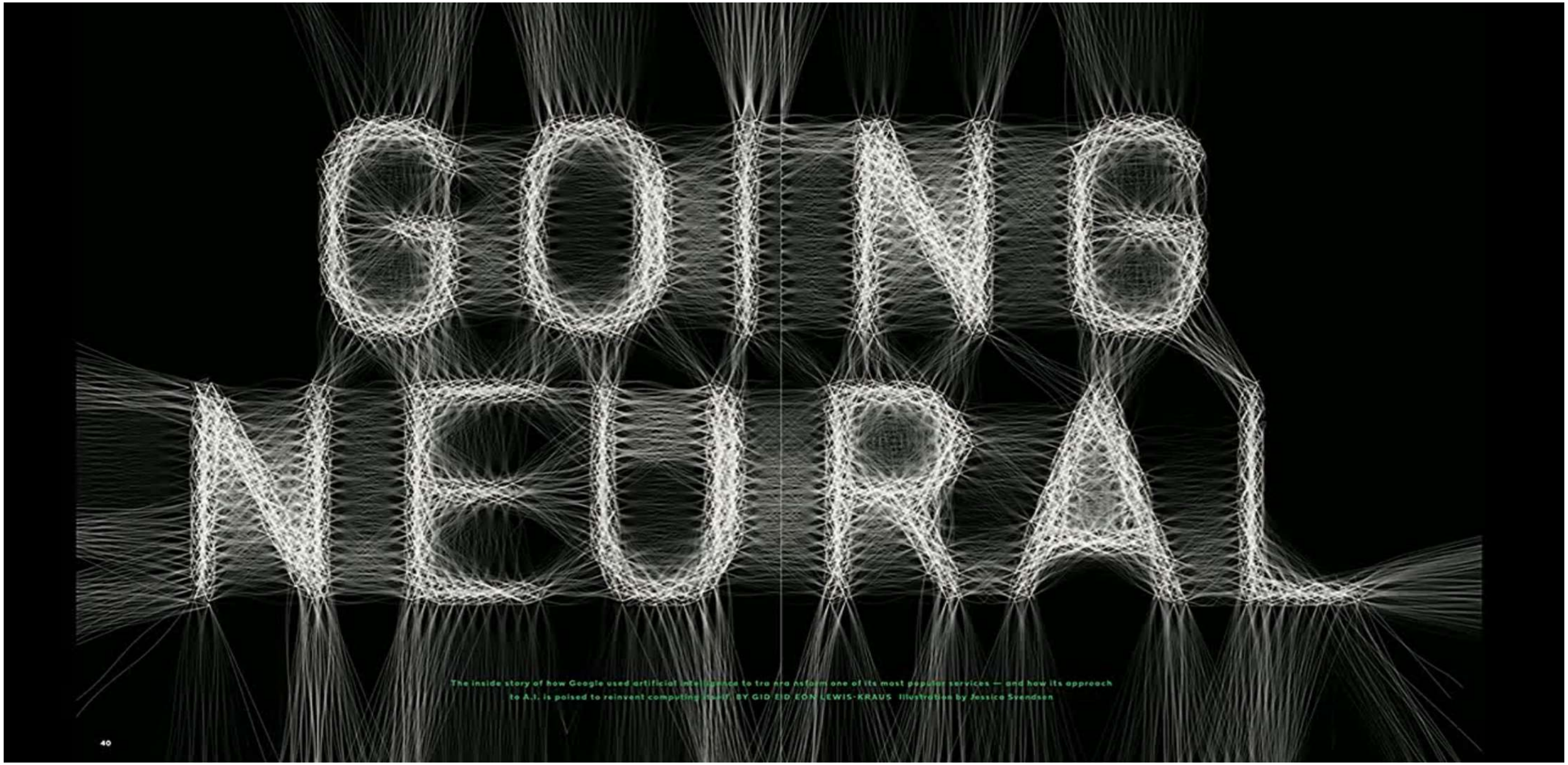
"A lot of people have smart speakers in their homes, and these devices have amazing capabilities that we can take advantage of," said Shyam Gollakota, an associate professor at UW.

"We envision a contactless system that works by continuously and passively monitoring the bedroom for an agonal breathing event, and alerts anyone nearby to come provide CPR. And then if there's no response, the device can automatically call 911," said Gollakota.

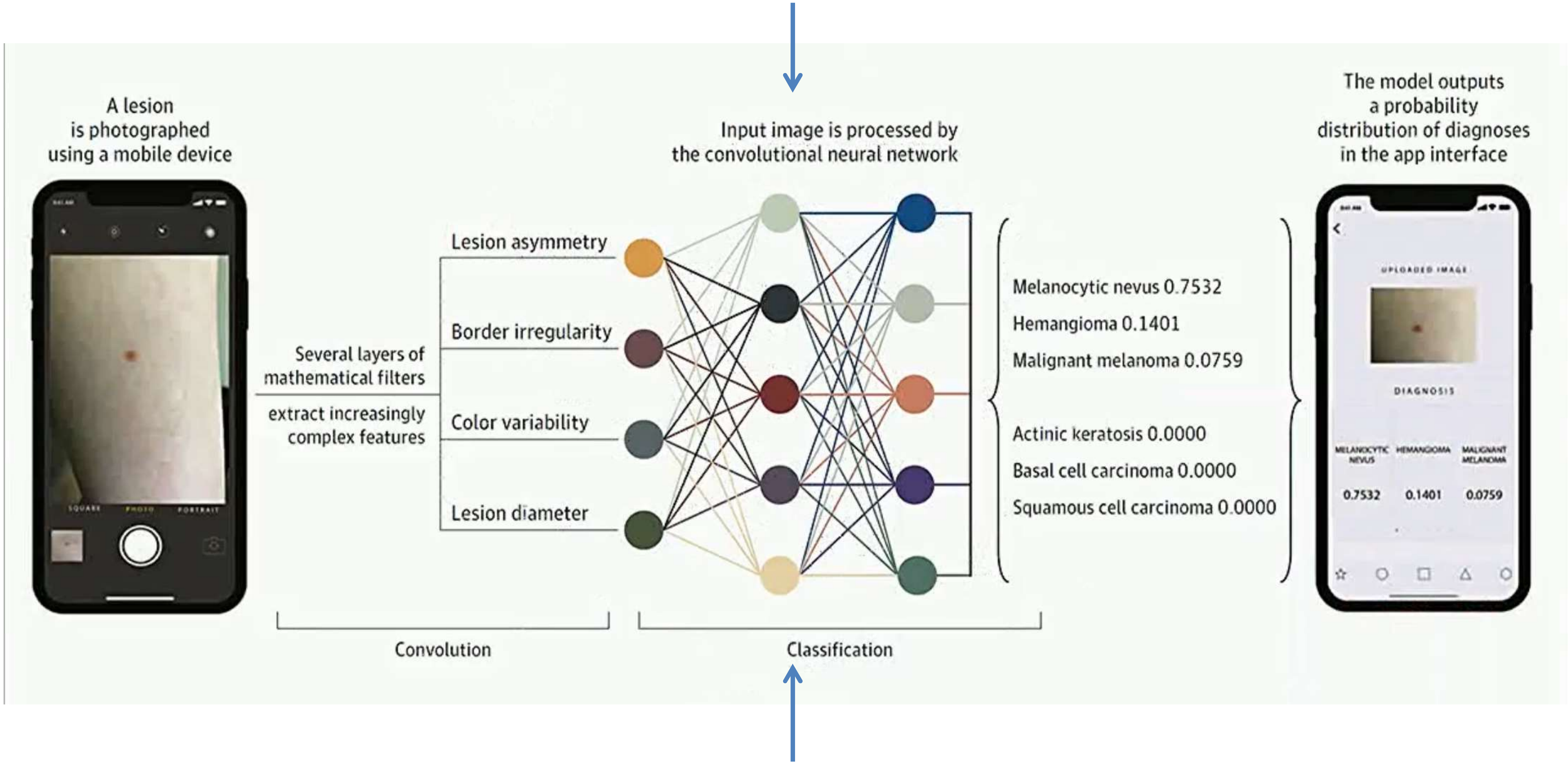
Agonal breathing is present for about 50 per cent of people who experience cardiac arrests, and patients who take agonal breaths often have a better chance of surviving.

"This kind of breathing happens when a patient

# Step 2: the analysis of data: Neural Networks



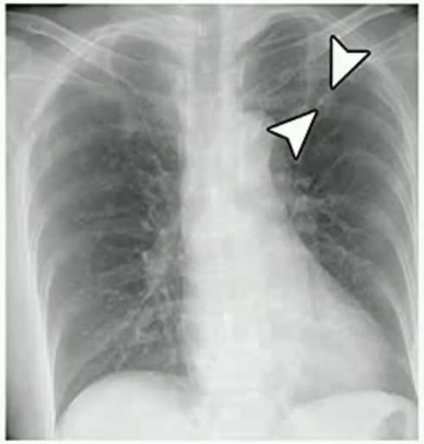
TRAINING




FEEDBACK (Machine Learning)

Radiology
RSNA®

# Development and Validation of Deep Learning–based Automatic Detection Algorithm for Malignant Pulmonary Nodules on Chest Radiographs



34,676 patients; 43,292 Chest X-rays
13 board-certified radiologists, 4 centers

| | Radiograph Classification Performance | | | | Nodule Detection Performance | | |
|---|---|---|---|---|---|---|---|
| Parameter | AUROC | Sensitivity (%) | Specificity (%) | F1 Score (Precision, Recall) | JAFROC FOM | Sensitivity (%)* | Rate of FP Findings (%)† |
| Seoul National University Hospital | 0.92 | 79.0 (94/119) [70.8, 85.4] | 95 (59/62) [86.2, 98.9] | 87.0 [94.9, 79.0] | 0.885 | 69.9 (100/143) [62.0, 76.9] | 0.34 [61/181] |
| Boramae Hospital | 0.99 | 91.1 (112/123) [84.6, 95.1] | 98 (58/59) [80.2, 100] | 94.9 [99.1, 91.1] | 0.924 | 82.0 (114/139) [74.7, 87.6] | 0.30 [54/182] |
| National Cancer Center | 0.94 | 71.2 (79/111) [62.1, 78.9] | 100 (70/70) [93.8, 100] | 83.2 [100, 71.2] | 0.831 | 69.6 (80/115) [60.6, 77.3] | 0.02 [3/181] |
| University of California San Francisco Medical Center | 0.96 | 88 (78/89) [79.0, 93.1] | 93 (56/60) [83.6, 97.8] | 91.2 [95.1, 87.6] | 0.880 | 75.0 (78/104) [65.8, 82.4] | 0.25 [37/149] |

**Conclusion:** This deep learning–based automatic detection algorithm outperformed physicians in radiograph classification and nodule detection performance for malignant pulmonary nodules on chest radiographs, and it enhanced physicians' performances when used as a second reader.

September 2018

# US Radiologists

Read 20,000 scans/yr; 50-100/day
False negative rate >25%; false positive 2%
31% are sued (almost all due to medical diagnoses)

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800 Million scans (50 Billions images) in US/yr

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30% hospitals use teleradiology, such as vRad w/ > 500 radiologists

vRad®
a MEDNAX® Company

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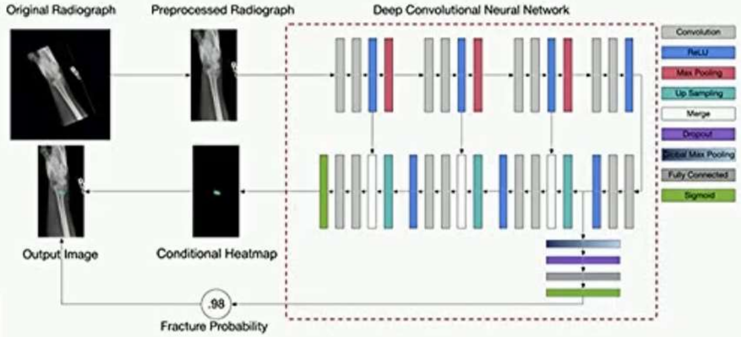
Zebra Medical, by late 2017, in 50 hospitals, > 1 million scans, $1 dollar per scan, ~10,000 times faster

zebra™

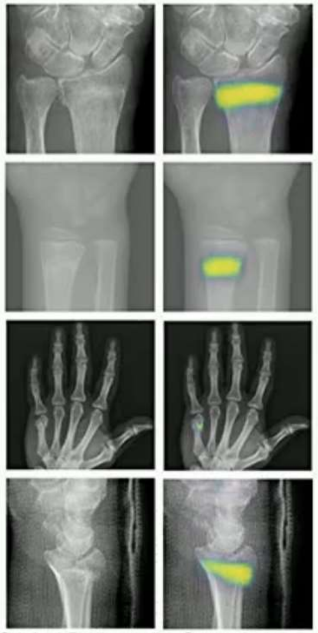
PNAS

# Deep neural network improves fracture detection by clinicians

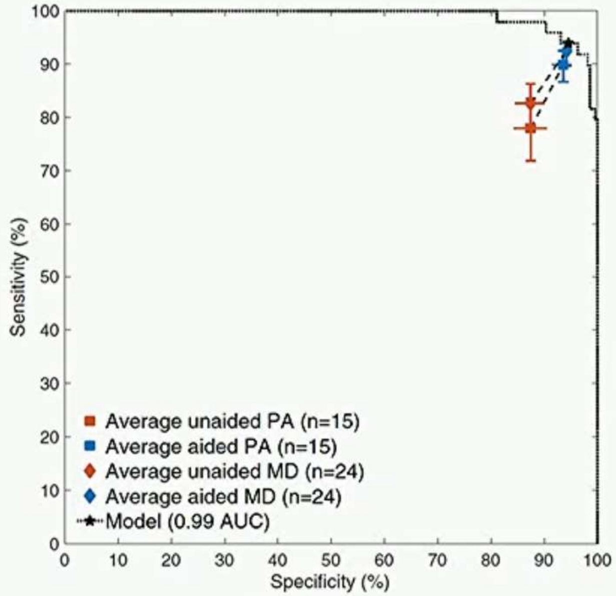



135, 409 wrist X-rays, 18 senior orthopedist
Tested in Emergency Medicine MDs
47% reduction in misinterpretation

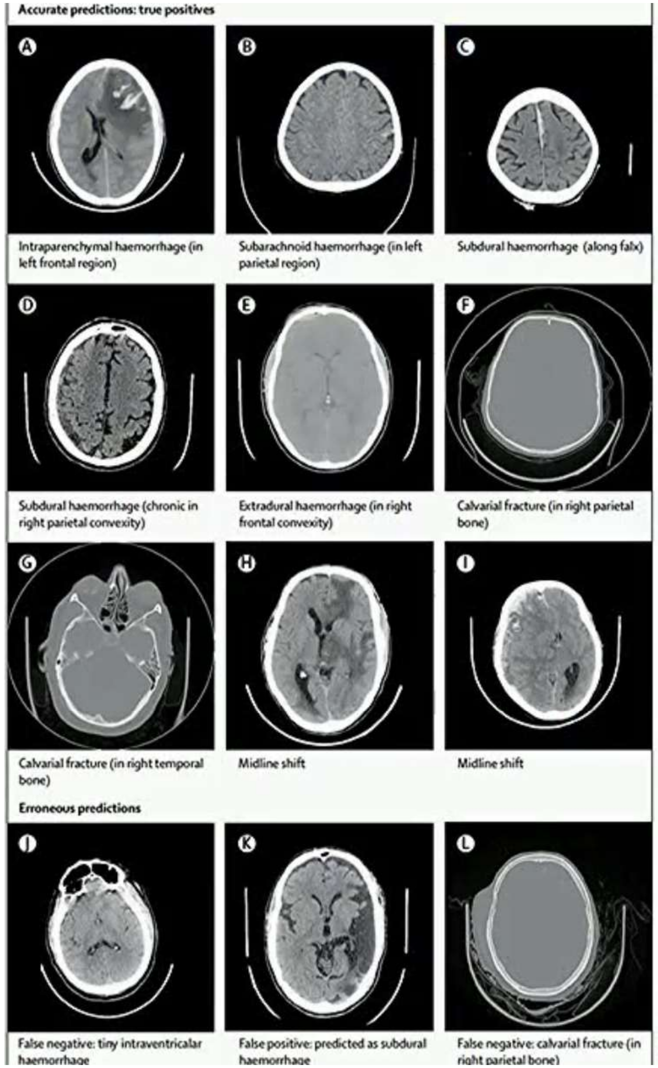

Original Radiograph Output Image



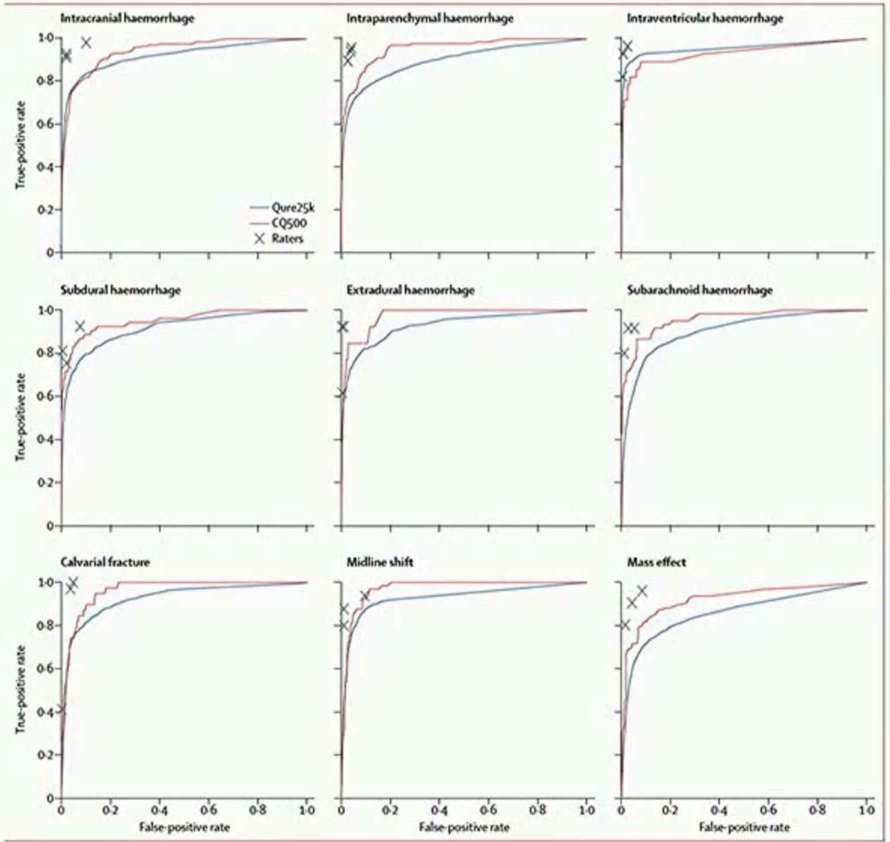
Original Radiograph Output Image




Lindsey et al,
22 October 2018




# Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study




313,318 Head CT scans
20 centers India

qure.ai

THE LANCET

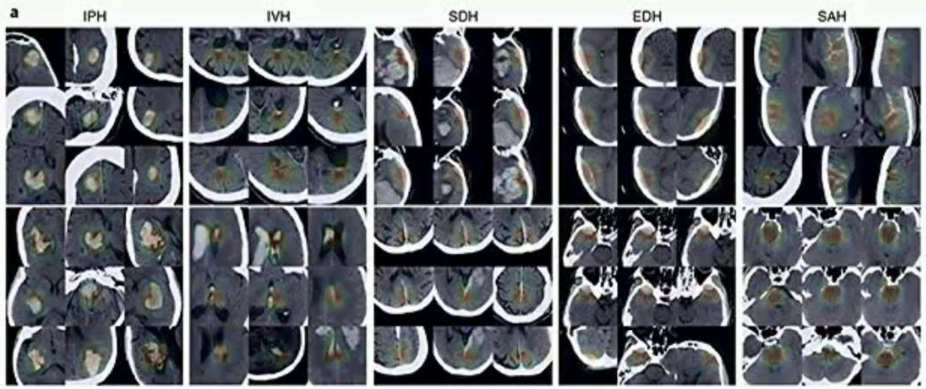
**Interpretation** Our results show that deep learning algorithms can accurately identify head CT scan abnormalities requiring urgent attention, opening up the possibility to use these algorithms to automate the triage process.

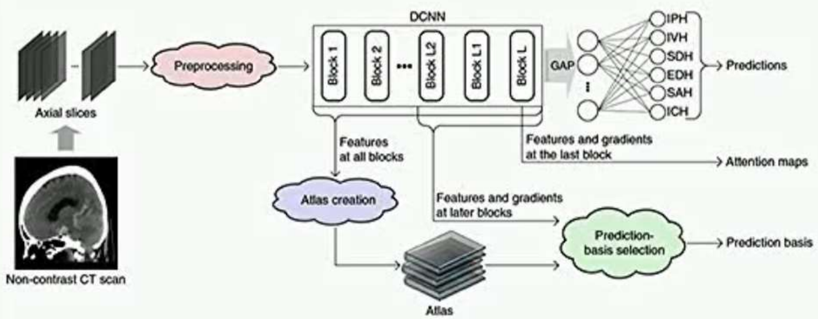
October 11, 2018

nature biomedical engineering
ARTICLES
https://doi.org/10.1038/s41551-018-0324-9

# An explainable deep-learning algorithm for the detection of acute intracranial haemorrhage from small datasets

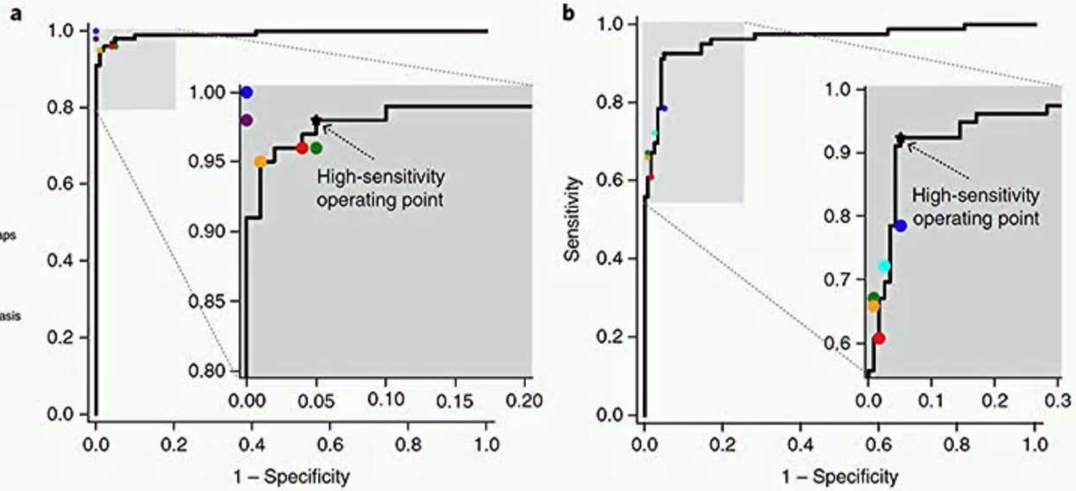
Hyunkwang Lee[1,2,3], Sehyo Yune[1,3], Mohammad Mansouri[1], Myeongchan Kim[1], Shahein H. Tajmir[1], Claude E. Guerrier[1], Sarah A. Ebert[1], Stuart R. Pomerantz[1], Javier M. Romero[1], Shahmir Kamalian[1], Ramon G. Gonzalez[1], Michael H. Lev[1] and Synho Do[1*]




Retrospective

Prospective



nature medicine
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https://doi.org/10.1038/s41591-018-0177-5

# Classification and mutation prediction from non-small cell lung cancer histopathology images using deep learning

Nicolas Coudray[1,2,9], Paolo Santiago Ocampo[3,9], Theodore Sakellaropoulos[4], Navneet Narula[3], Matija Snuderl[3], David Fenyö[5,6], Andre L. Moreira[3,7], Narges Razavian[8]* and Aristotelis Tsirigos[1,3]*

**Visual inspection of histopathology slides is one of the main methods used by pathologists to assess the stage, type and subtype of lung tumors. Adenocarcinoma (LUAD) and squamous cell carcinoma (LUSC) are the most prevalent subtypes of lung cancer, and their distinction requires visual inspection by an experienced pathologist. In this study, we trained a deep convolutional neural network (inception v3) on whole-slide images obtained from The Cancer Genome Atlas to accurately and automatically classify them into LUAD, LUSC or normal lung tissue. The performance of our method is comparable to that of pathologists, with an average area under the curve (AUC) of 0.97. Our model was validated on independent datasets of frozen tissues, formalin-fixed paraffin-embedded tissues and biopsies. Furthermore, we trained the network to predict the ten most commonly mutated genes in LUAD. We found that six of them—STK11, EGFR, FAT1, SETBP1, KRAS and TP53—can be predicted from pathology images, with AUCs from 0.733 to 0.856 as measured on a held-out population. These findings suggest that deep-learning models can assist pathologists in the detection of cancer subtype or gene mutations. Our approach can be applied to any cancer type, and the code is available at https://github.com/ncoudray/DeepPATH.**

According to the American Cancer Society and the Cancer Statistics Center (see URLs), over 150,000 patients with lung cancer succumb to the disease each year (154,050 expected for 2018), while another 200,000 new cases are diagnosed on a yearly basis (234,030 expected for 2018). It is one of the most widely spread cancers in the world because of not only smoking, but also exposure to toxic chemicals like radon, asbestos and arsenic. LUAD and LUSC are the two most prevalent types of non-small cell lung cancer[1], and each is associated with discrete treatment guidelines. In the absence of definitive histologic features, this important distinction can be challenging and time-consuming, and requires confirmatory immunohistochemical stains.

Classification of lung cancer type is a key diagnostic process because the available treatment options, including conventional chemotherapy and, more recently, targeted therapies, differ for LUAD and LUSC[2]. Also, a LUAD diagnosis will prompt the search for molecular biomarkers and sensitizing mutations and thus has a great impact on treatment options[3,4]. For example, epidermal growth factor receptor (*EGFR*) mutations, present in about 20% of LUAD, and anaplastic lymphoma receptor tyrosine kinase (*ALK*) rearrangements, present in <5% of LUAD[5], currently have targeted therapies approved by the Food and Drug Administration (FDA)[6,7]. Mutations in other genes, such as *KRAS* and tumor protein P53 (*TP53*) are very common (about 25% and 50%, respectively) but have proven to be particularly challenging drug targets so far[5,8]. Lung biopsies are typically used to diagnose lung cancer type and stage. Virtual microscopy of stained images of tissues is typically acquired at magnifications of 20× to 40×, generating very large two-dimensional images (10,000 to > 100,000 pixels in each dimension) that are oftentimes challenging to visually inspect in an exhaustive manner. Furthermore, accurate interpretation can be difficult, and the distinction between LUAD and LUSC is not always clear, particularly in poorly differentiated tumors; in this case, ancillary studies are recommended for accurate classification[9,10]. To assist experts, automatic analysis of lung cancer whole-slide images has been recently studied to predict survival outcomes[11] and classification[12]. For the latter, Yu et al.[12] combined conventional thresholding and image processing techniques with machine-learning methods, such as random forest classifiers, support vector machines (SVM) or Naive Bayes classifiers, achieving an AUC of ~0.85 in distinguishing normal from tumor slides, and ~0.75 in distinguishing LUAD from LUSC slides. More recently, deep learning was used for the classification of breast, bladder and lung tumors, achieving an AUC of 0.83 in classification of lung tumor types on tumor slides from The Cancer Genome Atlas (TCGA)[13]. Analysis of plasma DNA values was also shown to be a good predictor of the presence of non-small cell cancer, with an AUC of ~0.94 (ref. [14]) in distinguishing LUAD from LUSC, whereas the use of immunochemical markers yields an AUC of ~0.941[15].

Here, we demonstrate how the field can further benefit from deep learning by presenting a strategy based on convolutional neural networks (CNNs) that not only outperforms methods in previously

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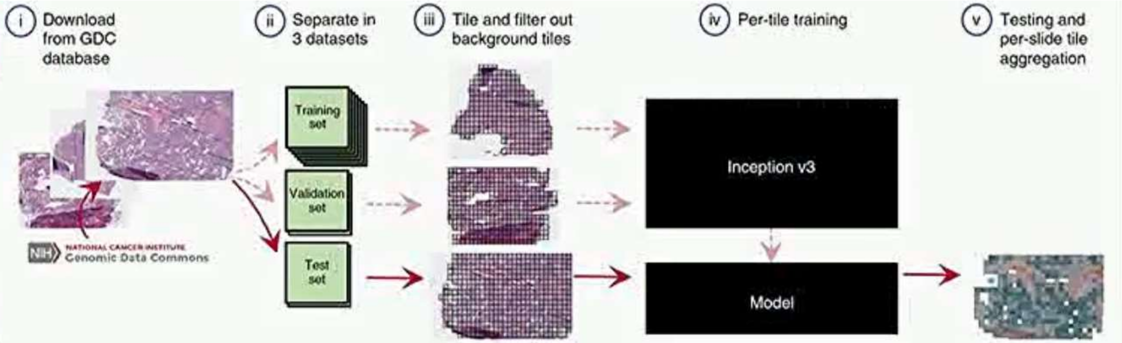


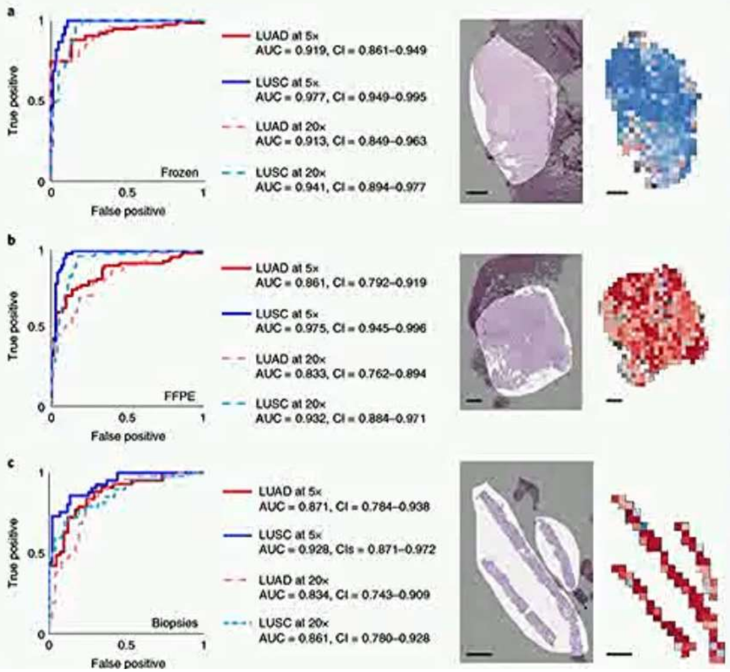
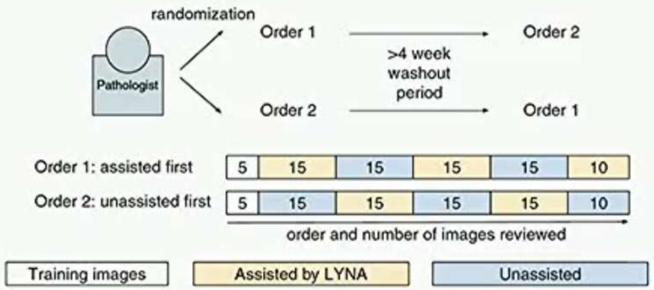




**Table 1 | AUC achieved by the network trained on mutations (with 95% CIs)**

| Mutations | Per-tile AUC | Per-slide AUC after aggregation by… | |
|---|---|---|---|
| | | … average predicted probability | … percentage of posit classified tiles |
| *STK11* | 0.845 (0.838-0.852) | 0.856 (0.709-0.964) | 0.842 (0.683-0.967) |
| *EGFR* | 0.754 (0.746-0.761) | 0.826 (0.628-0.979) | 0.782 (0.516-0.979) |
| *SETBP1* | 0.785 (0.776-0.794) | 0.775 (0.595-0.931) | 0.752 (0.550-0.927) |
| *TP53* | 0.674 (0.666-0.681) | 0.760 (0.626-0.872) | 0.754 (0.627-0.870) |
| *FAT1* | 0.739 (0.732-0.746) | 0.750 (0.512-0.940) | 0.750 (0.491-0.946) |
| *KRAS* | 0.814 (0.807-0.829) | 0.733 (0.580-0.857) | 0.716 (0.552-0.854) |
| *KEAP1* | 0.684 (0.670-0.694) | 0.675 (0.466-0.865) | 0.659 (0.440-0.856) |
| *LRP1B* | 0.640 (0.633-0.647) | 0.656 (0.513-0.797) | 0.657 (0.512-0.799) |
| *FAT4* | 0.768 (0.760-0.775) | 0.642 (0.470-0.799) | 0.640 (0.440-0.856) |
| *NF1* | 0.714 (0.704- | 0.640 (0.419-0.845) | 0.632 (0.405-0.845) |

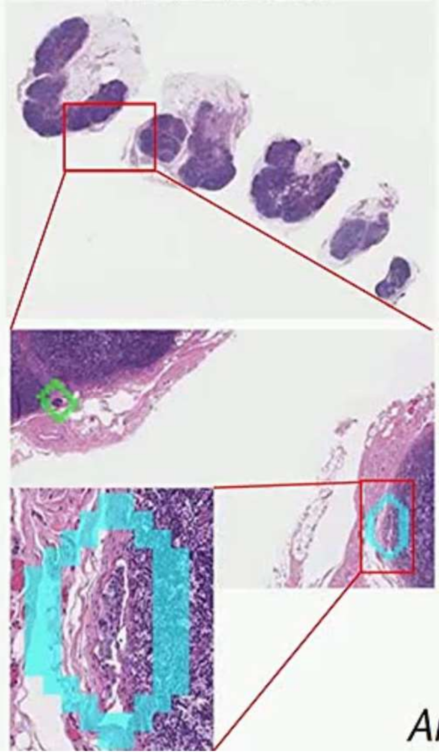
# Impact of Deep Learning Assistance on the Histopathologic Review of Lymph Nodes for Metastatic Breast Cancer

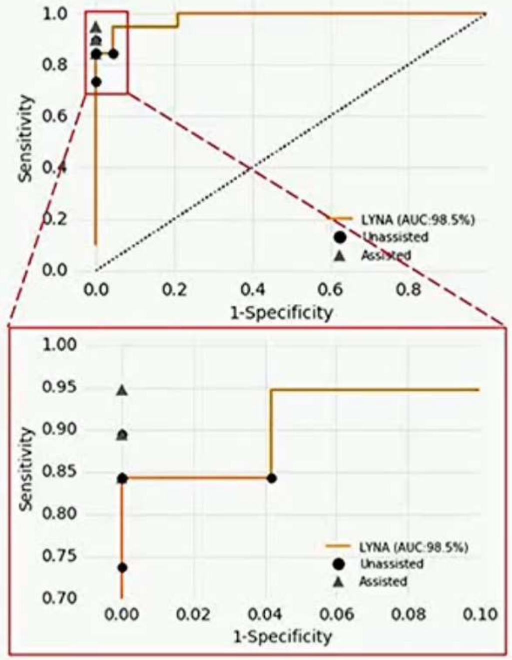
*David F. Steiner, MD, PhD,* Robert MacDonald, PhD,* Yun Liu, PhD,* Peter Truszkowski, MD,**
*Jason D. Hipp, MD, PhD, FCAP,* Christopher Gammage, MS,* Florence Thng, MS,†*
*Lily Peng, MD, PhD,* and Martin C. Stumpe, PhD**




6 pathologists/ 70 DSIs
AI + pathologist higher accuracy vs AI or path
LYNA algorithm AUC .985
Marked increase in speed of review for micrometastases: 61 v 116 secs

LYNA-assisted review






*Am J Surg Pathol* 12 October 2018

nature biomedical engineering

ARTICLES

https://doi.org/10.1038/s41551-018-0301-3

# Development and validation of a deep-learning algorithm for the detection of polyps during colonoscopy

Pu Wang[1], Xiao Xiao[2], Jeremy R. Glissen Brown[3], Tyler M. Berzin[3], Mengtian Tu[1], Fei Xiong[1], Xiao Hu[1], Peixi Liu[1], Yan Song[1], Di Zhang[1], Xue Yang[1], Liangping Li[1], Jiong He[2], Xin Yi[2], Jingjia Liu[2] and Xiaogang Liu[1*]

**The detection and removal of precancerous polyps via colonoscopy is the gold standard for the prevention of colon cancer. However, the detection rate of adenomatous polyps can vary significantly among endoscopists. Here, we show that a machine-learning algorithm can detect polyps in clinical colonoscopies, in real time and with high sensitivity and specificity. We developed the deep-learning algorithm by using data from 1,290 patients, and validated it on newly collected 27,113 colonoscopy images from 1,138 patients with at least one detected polyp (per-image-sensitivity, 94.38%; per-image-specificity, 95.92%; area under the receiver operating characteristic curve, 0.984), on a public database of 612 polyp-containing images (per-image-sensitivity, 88.24%), on 138 colonoscopy videos with histologically confirmed polyps (per-image-sensitivity of 91.64%; per-polyp-sensitivity, 100%), and on 54 unaltered full-range colonoscopy videos without polyps (per-image-specificity, 95.40%). By using a multi-threaded processing system, the algorithm can process at least 25 frames per second with a latency of 76.80 ± 5.60 ms in real-time video analysis. The software may aid endoscopists while performing colonoscopies, and help assess differences in polyp and adenoma detection performance among endoscopists.**

Colonoscopy is the gold-standard screening test for colorectal cancer[1–3], one of the leading causes of cancer death in both the United States[4,5] and China[6]. Colonoscopy can reduce the risk of death from colorectal cancer through the detection of tumours at an earlier, more treatable stage as well as through the removal of precancerous adenomas[5,7]. Conversely, failure to detect adenomas may lead to the development of interval cancer. Evidence has shown that each 1.0% increase in adenoma detection rate (ADR) leads to a 3.0% decrease in the risk of interval colorectal cancer[8].

Although more than 14 million colonoscopies are performed in the United States annually[2], the adenoma miss rate (AMR) is estimated to be 6–27%[9]. Certain polyps may be missed more frequently, including smaller polyps[10,11], flat polyps[12] and polyps in the left colon[13]. There are two independent reasons why a polyp may be missed during colonoscopy: (i) it was never in the visual field or (ii) it was in the visual field but not recognized. Several hardware innovations have sought to address the first problem by improving visualization of the colonic lumen, for instance by providing a larger, panoramic camera view, or by flattening colonic folds using a distal-cap attachment. The problem of unrecognized polyps within the visual field has been more difficult to address[14]. Several studies have shown that observation of the video monitor by either nurses or gastroenterology trainees may increase polyp detection by up to 30%[15–17]. Ideally, a real-time automatic polyp-detection system could serve as a similarly effective second observer that could draw the endoscopist's eye, in real time, to concerning lesions, effectively creating an 'extra set of eyes' on all aspects of the video data with fidelity. Although automatic polyp detection in colonoscopy videos has been an active research topic for the past 20 years, performance levels close to that of the expert endoscopist[18–20] have not been achieved. Early work in automatic polyp detection has focused on applying deep-learning techniques to polyp detection, but most published works are small in scale, with small development and/or training validation sets[19,20].

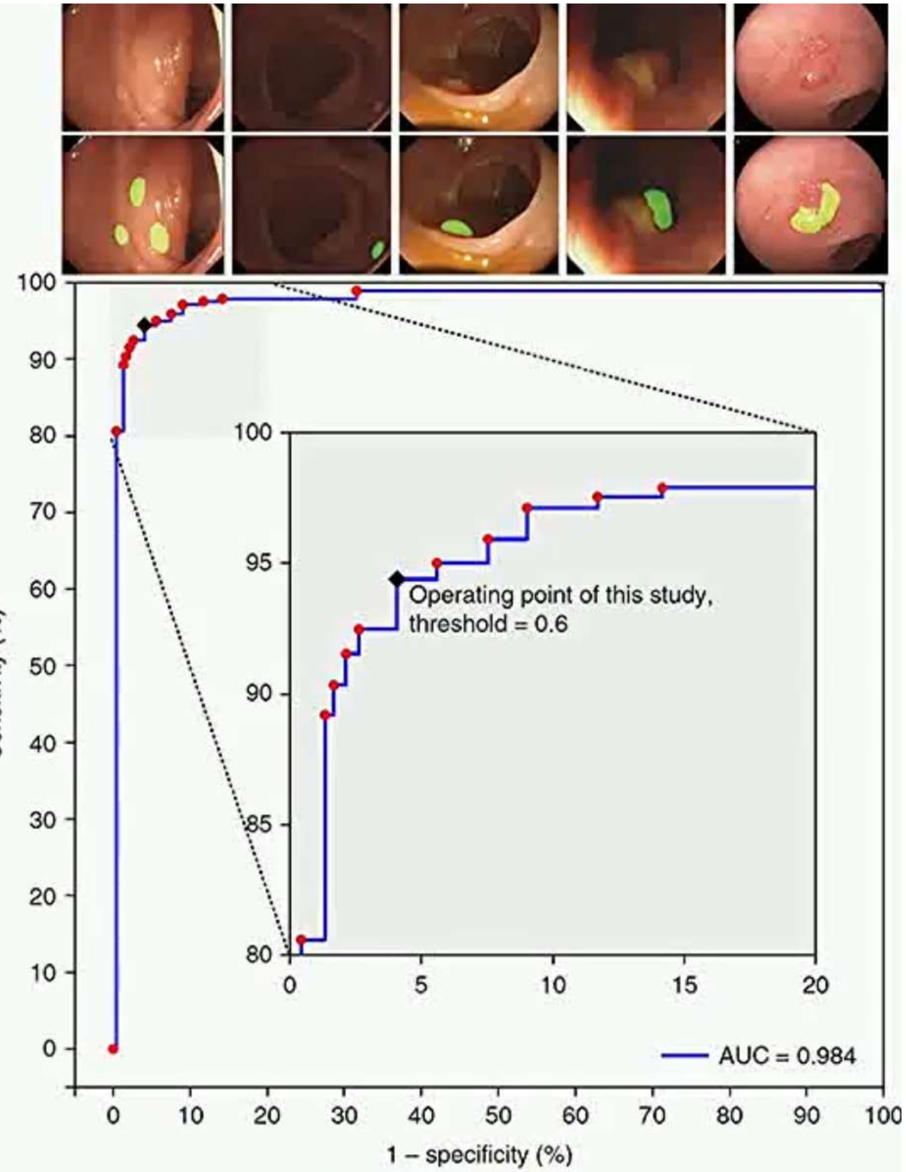
Here, we report the development and validation of a deep-learning algorithm, integrated with a multi-threaded processing system, for the automatic detection of polyps during colonoscopy. We validated the system in two image studies and two video studies. Each study contained two independent validation datasets.

## Results

We developed a deep-learning algorithm using 5,545 colonoscopy images from colonoscopy reports of 1,290 patients that underwent a colonoscopy examination in the Endoscopy Center of Sichuan Provincial People's Hospital between January 2007 and December 2015. Out of the 5,545 images used, 3,634 images contained polyps (65.54%) and 1,911 images did not contain polyps (34.46%). For algorithm training, experienced endoscopists annotated the presence of each polyp in all of the images in the development dataset. We validated the algorithm on four independent datasets. Datasets A and B were used for image analysis, and datasets C and D were used for video analysis.

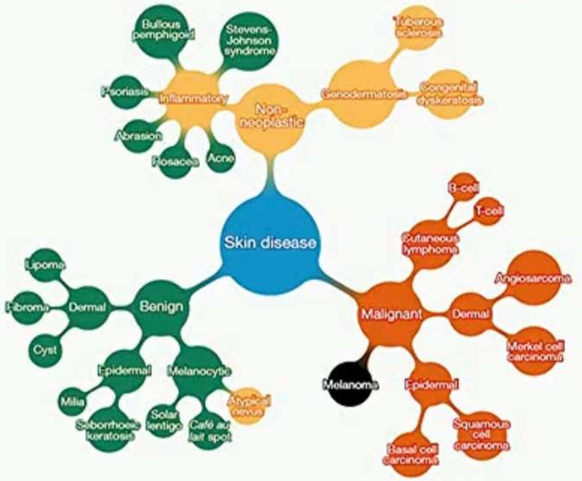
Dataset A contained 27,113 colonoscopy images from colonoscopy reports of 1,138 consecutive patients who underwent a colonoscopy examination in the Endoscopy Center of Sichuan Provincial People's Hospital between January and December 2016 and who were found to have at least one polyp. Out of the 27,113 images, 5,541 images contained polyps (20.44%) and 21,572 images did not contain polyps (79.56%). All polyps were confirmed histologically after biopsy. Dataset B is a public database (CVC-ClinicDB;

[1]Sichuan Academy of Medical Sciences & Sichuan Provincial People's Hospital, Chengdu, China. [2]Shanghai Wision AI Co., Ltd, Shanghai, China. [3]Beth Israel

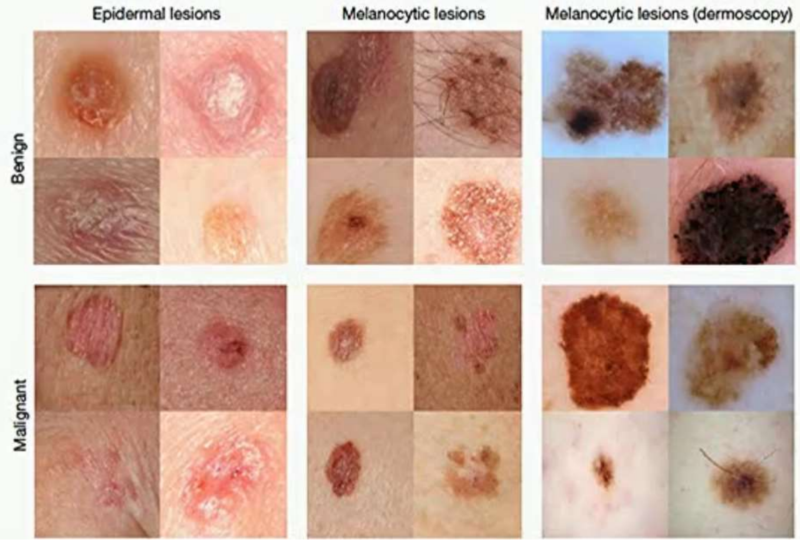


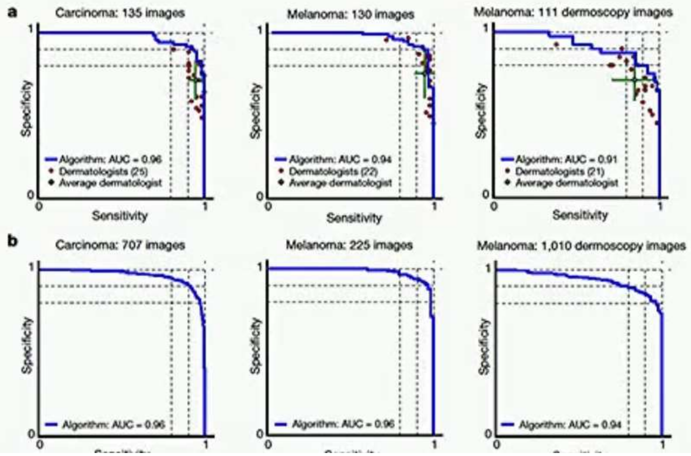
# Dermatologist-level classification of skin cancer with deep neural networks

nature

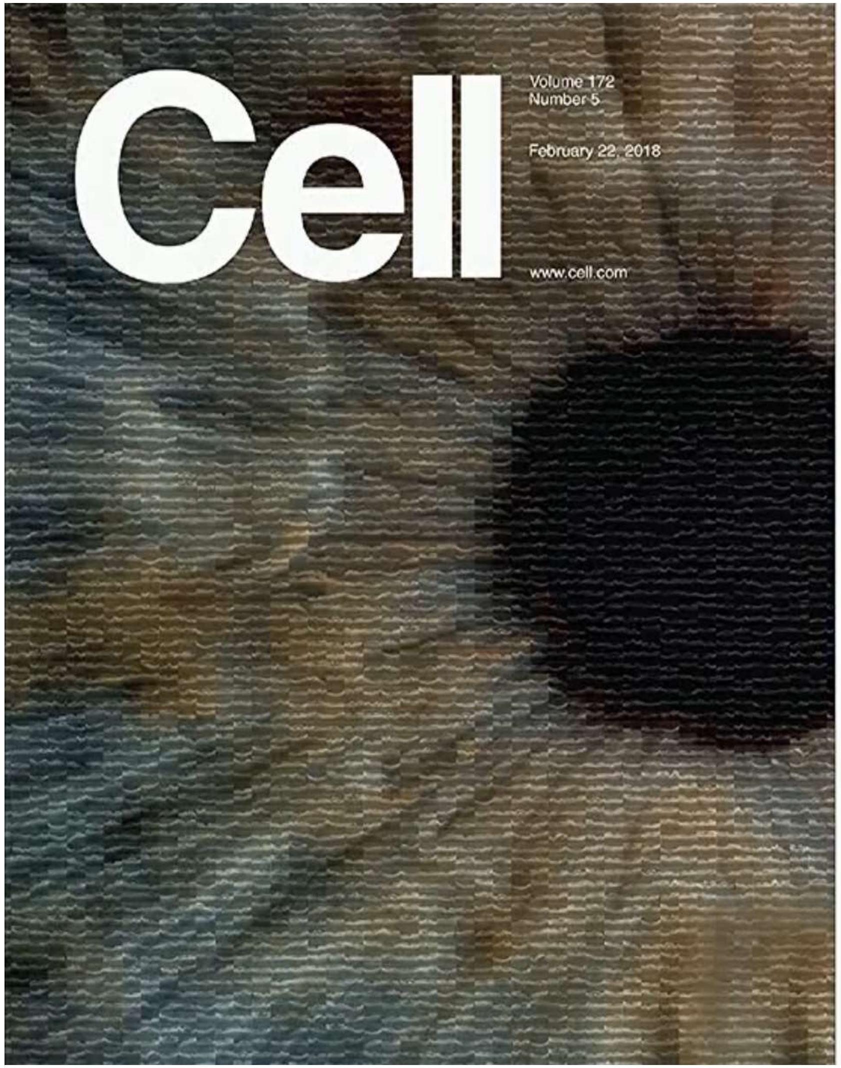



21 Board Certified Stanford Dermatologists
129, 450 images of 2,032 diseases
1.41 million AI training images



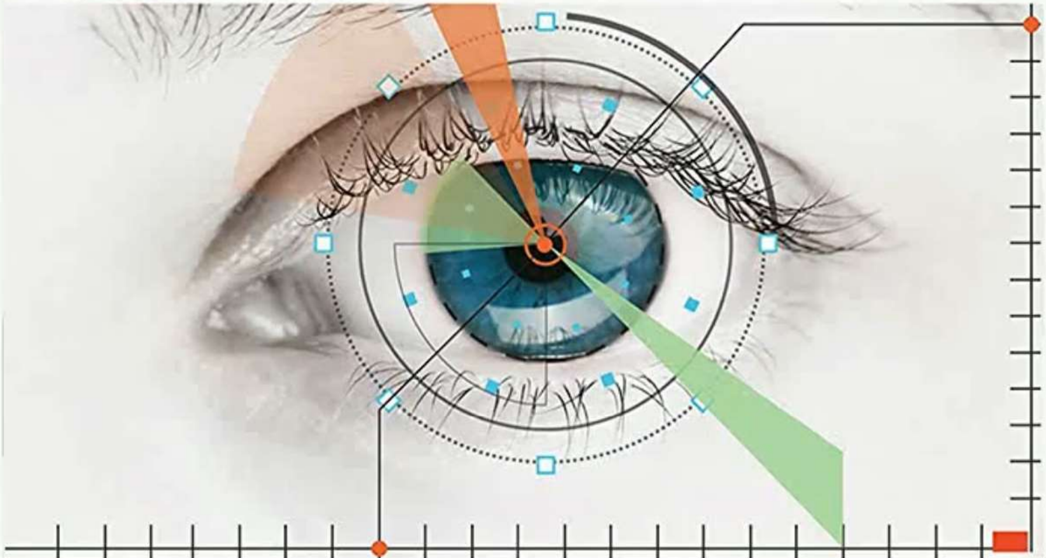

25 Jan 2017




# In the future, an AI may diagnose eye problems

New technology aims to speed medical care in places where specialists are scarce

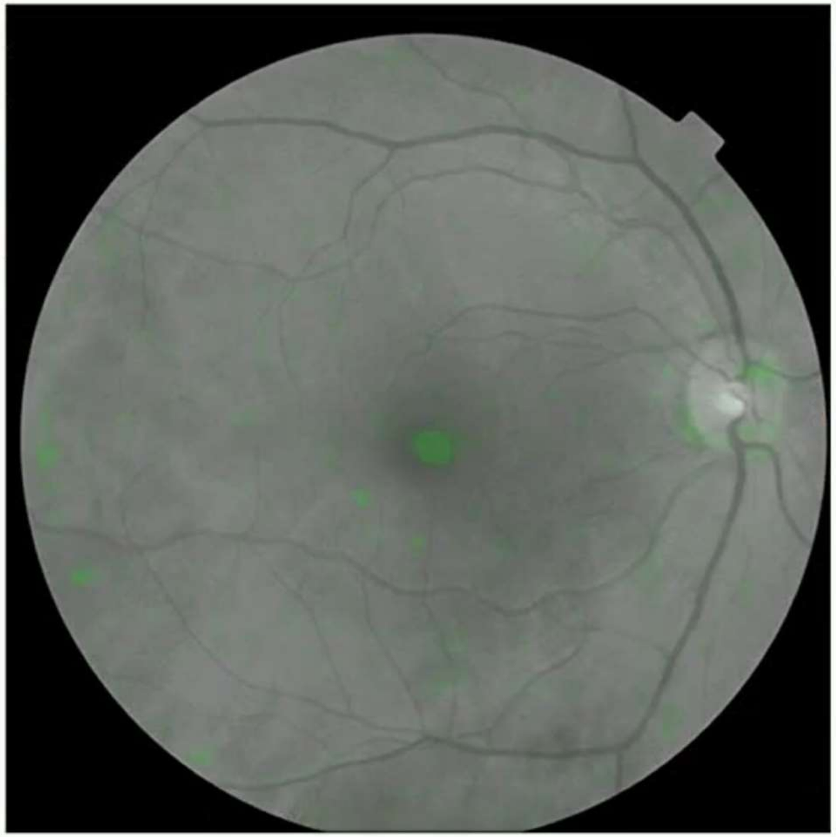
BY MARIA TEMMING 8:00AM, MARCH 4, 2018



**AI, M.D.** New AI programs coming down the pipeline can examine eye images to diagnose blinding diseases and potentially other health problems.

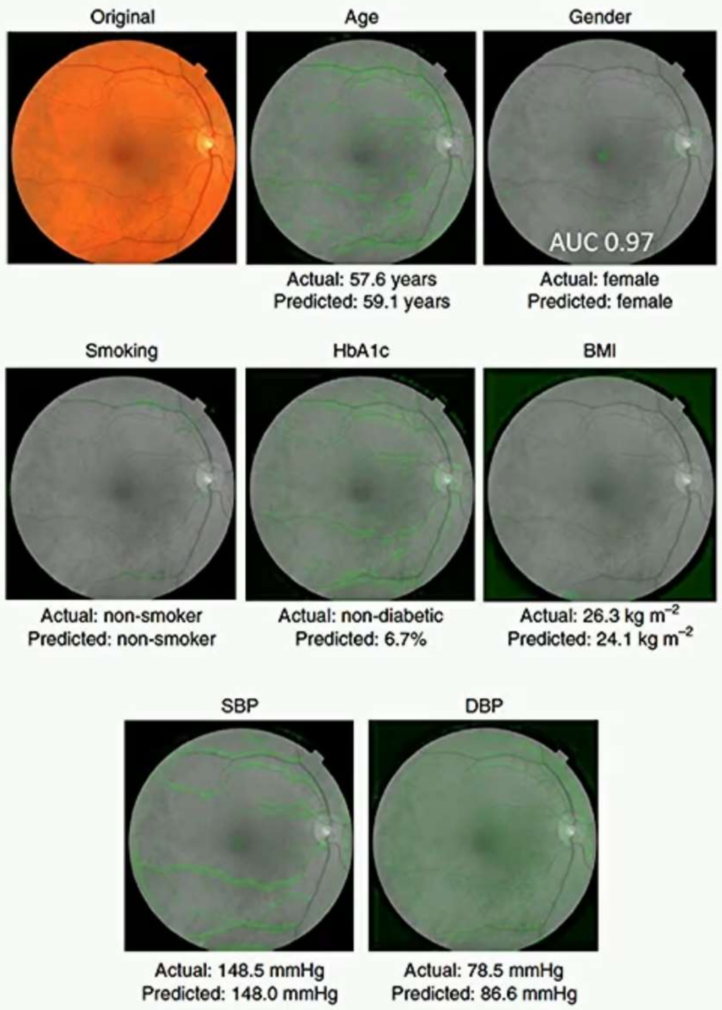
ScienceNews

## Gender



Actual: Female
Predicted: Female

# Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning



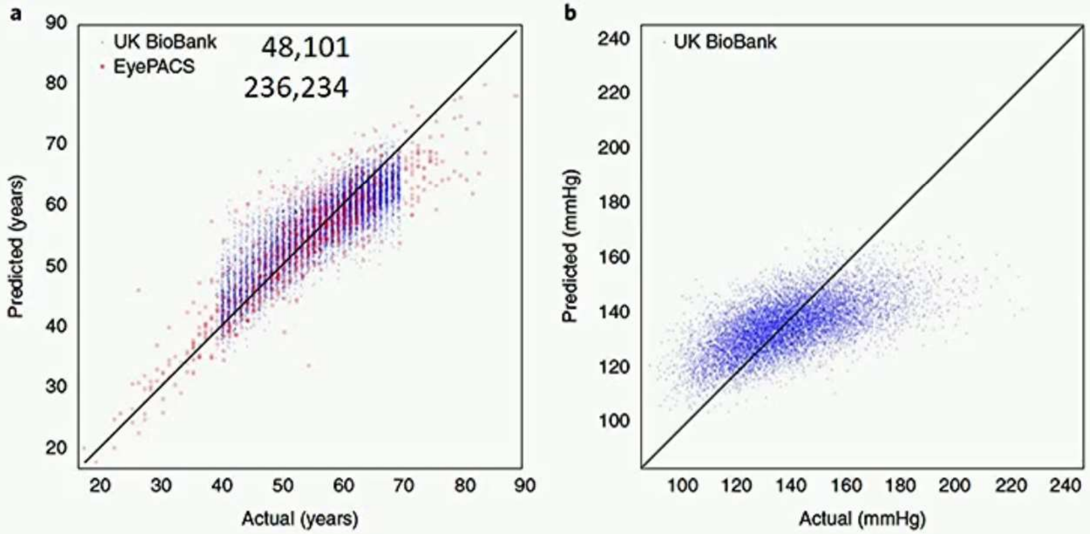
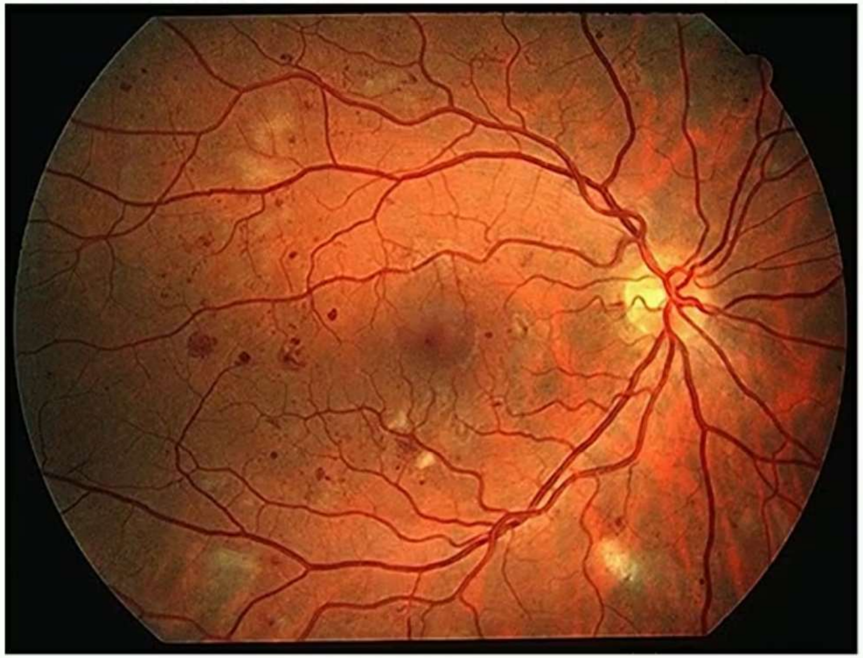




**Fig. 1 | Predictions of age and SBP.**

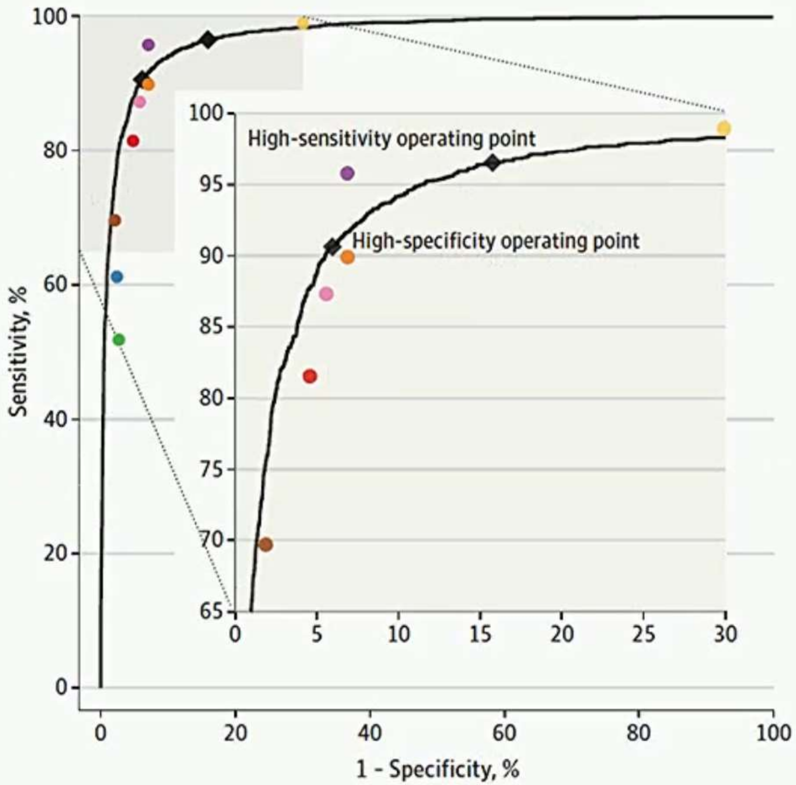
nature biomedical engineering February 2018

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



**JAMA** December 13, 2016

Figure 3. Validation Set Performance for All-Cause Referable Diabetic Retinopathy in the EyePACS-1 Data Set (9946 Images)




Performance of the algorithm (black curve) and ophthalmologists (colored circles)

ARTICLE OPEN

## Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices

Michael D. Abràmoff[1,2,3,4], Philip T. Lavin[5], Michele Birch[6], Nilay Shah[7] and James C. Folk[1,2,3]

AI system diagnostic accuracy

| | Point estimate | 95% CI |
|---|---|---|
| Sensitivity | 87.2% | 81.8%–91.2% |
| Specificity | 90.7% | 88.3%–92.7% |

## AI alone now making the diagnosis

By Rachel Z. Arndt

Modern Healthcare | October 8, 2018

EDITORIAL OPEN

## With an eye to AI and autonomous diagnosis

Pearse A. Keane[1] and Eric J. Topol[2,3]
[1]*NIHR Biomedical Research Centre for Ophthalmology, Moorfields Eye Hospital NHS Foundation Trust and UCL Institute of Ophthalmology, London, UK;* [2]*Scripps Translational Science Institute,*

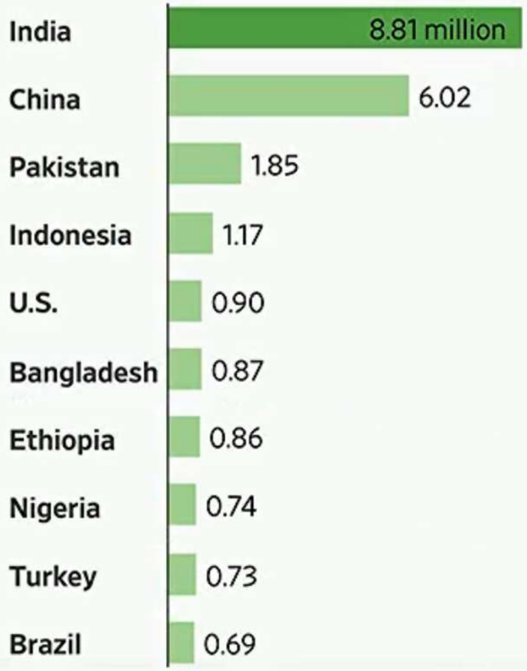
nature
npj | Digital Medicine 28 August 2018

# Google's Effort to Prevent Blindness Shows AI Challenges

Company's AI can detect a condition that causes blindness in diabetes patients, but in rural India it doesn't always work

## Lacking Vision

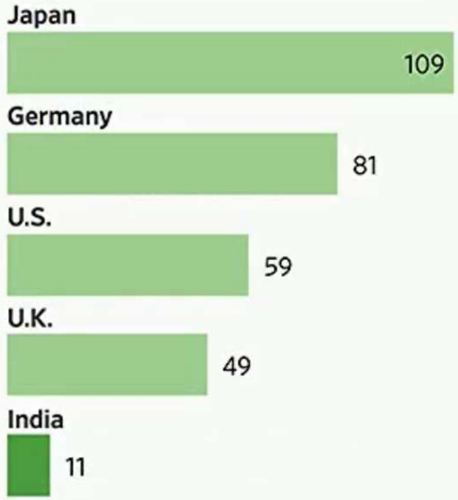
India has the greatest number of people who are blind.




## Lacking Doctors

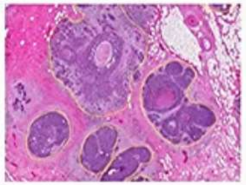
India has a shortfall of ophthalmologists.

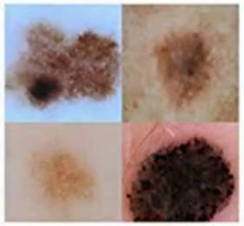
**Ophthalmologists per million people**




28 January 2019

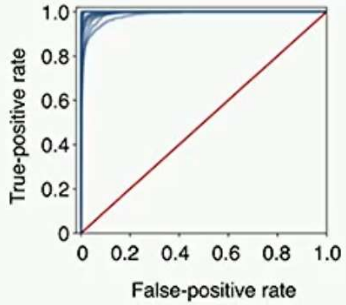
THE WALL STREET JOURNAL.

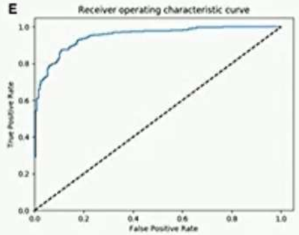


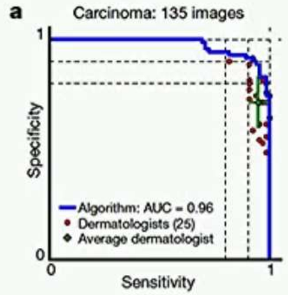


# How AI Will Transform Clinical Practice

| Clinician Category | Data Interpretation |
|---|---|
| Radiologists | Scans |
| Pathologists | Slides |
| Dermatologists | Skin Lesions |
| Ophthalmologists | Eye Exams |
| Cardiologists | ECG, Echo |
| Psychiatrists | $\Psi$ Status |
| Gastroenterologists | Scopes |
| Oncologists | Omics, Rx |
| Geneticists | Face, BAM file |
| Palliative Care | Predictions |
| All Doctors | Delete Keyboards |
| Nurses | Vital signs |
| Pharmacists | Drugs |



# Digital Medicine Clinical Trials

| Condition | Digital Intervention | Impact | Citation |
|---|---|---|---|
| Asthma | Inhaler Sensor + GPS for hot spots | Reduce rescue inhaler use by 78%; 48% more symptom-free days (Louisville Air) | Barrett, Health Affairs, April 2018 |
| Hypertension | Smartphone app RCT | Improved medication adherence | Morawski, JAMA Internal Med 2018 |
| Diabetes | Telemedicine RCT | Improved control of Type 2 diabetes | Wild et al, PLOS Medicine, 2016 |
| Heart failure | Telemedicine RCT | Less hospital admission and mortality | Koehler, Lancet, 2018 |
| Inflammatory Bowel Disease | Telemedicine RCT | Striking reduction in outpatient visits and hospital admissions | De Jong, Lancet 2017 |
| Cancer | Smartphone app RCT | Improved survival in lung cancer | Denis, ASCO 2018 |
| Headaches | Telemedicine RCT | As effective as traditional consultations | Muller, Neurology, 2017 |
| Visual Impairment | Smartphone app RCT | Marked improvement of detection among school children in Kenya | Rono, Lancet Global Health, 2018 |
| Insomnia | Digital CBT RCT | Major reduction in insomnia among patients with mental health conditions | Freeman, Lancet Psychiatry, 2017 |
| Attention deficit disorder | Video game RCT | Significant improvement of attention performance in children and adolescents | Kollins, December 2017 and Proof of Concept PLOS One, 2018 |
| Schizophrenia | Avatar CBT RCT | Significant reduction of hallucinations | Craig, Lancet Psychiatry 2017 |
| Low Back Pain | Digital care RCT | Significant reduction of pain | Shebib, NPJ Nature Digital Medicine, 2019 |

CBT-cognitive behavioral therapy, RCT-randomized controlled trial

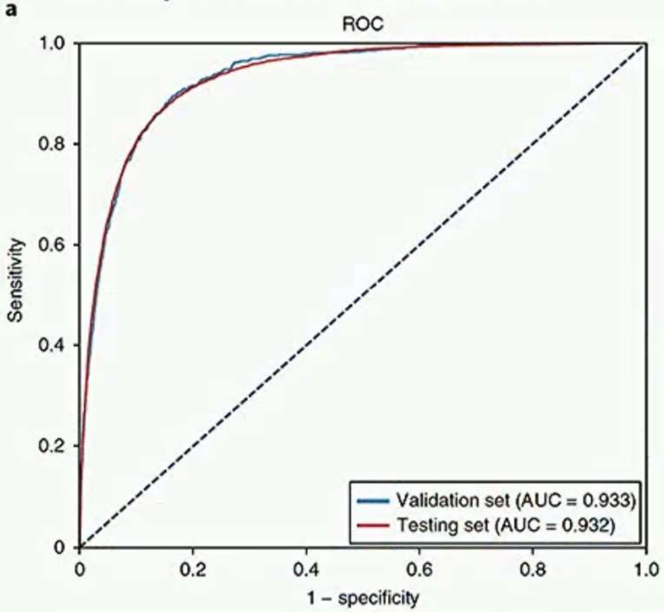
# FDA AI Approvals Are Accelerating

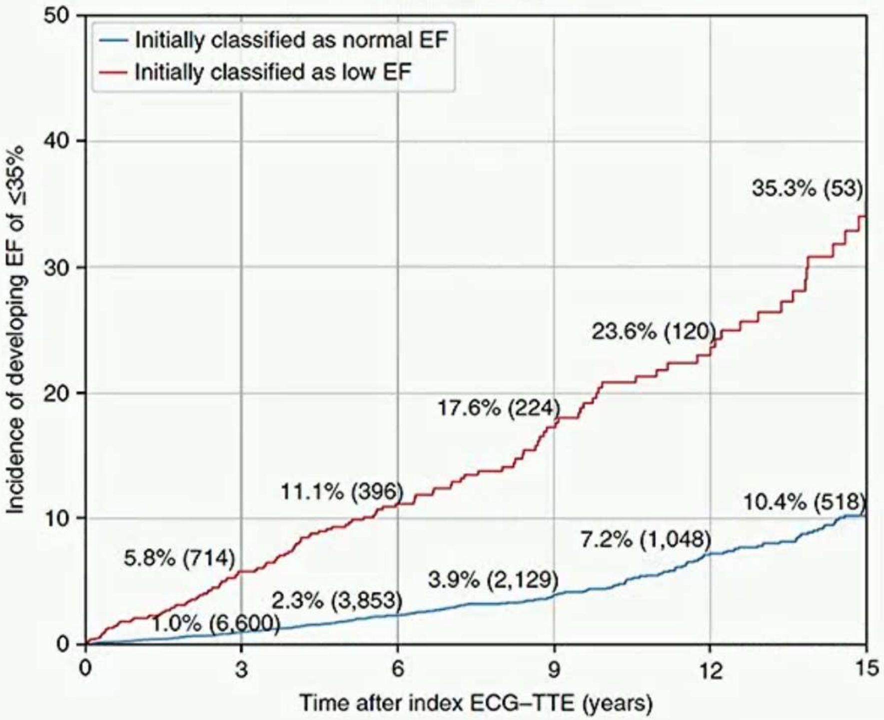
| Company | FDA Approval | Indication |
|---|---|---|
| Apple | September 2018 | Atrial fibrillation detection |
| Aidoc | August 2018 | CT Brain bleed diagnosis |
| iCAD | August 2018 | Breast density via mammography |
| Mirada Medical | July 2018 | Radiation therapy planning |
| Zebra Medical | July 2018 | Coronary calcium scoring |
| Bay Labs | June 2018 | Echocardiogram EF determination |
| Neural Analytics | May 2018 | Device for paramedic stroke diagnosis |
| Densitas | April 2018 | Breast density via mammography |
| IDx | April 2018 | Diabetic retinopathy diagnosis |
| Icometrix | April 2018 | MRI brain interpretation |
| Imagen | March 2018 | X-ray wrist fracture diagnosis |
| Viz.ai | February 2018 | CT Stroke diagnosis |
| Arterys | February 2018 | Liver and lung cancer (MRI,CT) diagnosis |
| MaxQ-AI | January 2018 | CT Brain bleed diagnosis |
| Alivecor | November 2017 | Atrial fibrillation detection via Apple Watch |
| Arterys | January 2017 | MRI heart interpretation |

nature medicine

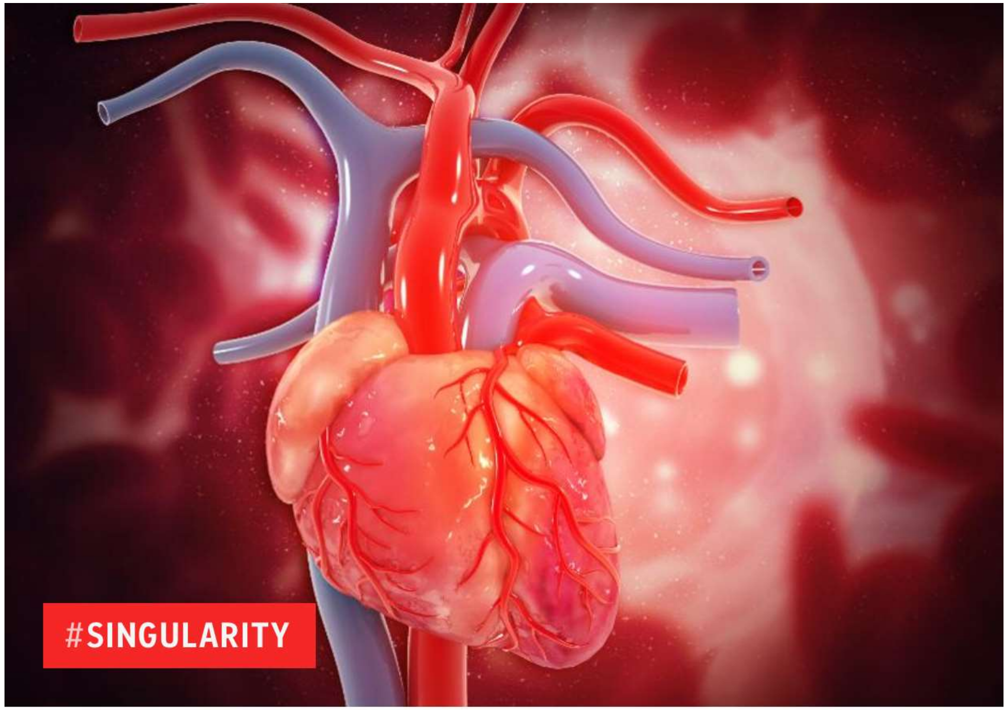
# Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram

Training set 44,959 patients: ECG +Echo
Validation in 52,870 patients
Ventricular dysfunction = EF ≤ 35%




Attia et al
Jan 2019




# Artificial Intelligence Detects Heart Failure From One Heartbeat With 100% Accuracy

Forbes · Nicholas Fearn

Doctors can detect heart failure from a single heartbeat with 100% accuracy using a new artificial intelligence-driven neural network. That's according to a recent study published in Biomedical Signal Processing and Control...

Forbes

Unlike existing methods that are often time-consuming and inaccurate, their model combines advanced signal processing and machine learning tools on raw ECG signals to improve detection rates dramatically.

Dr Sebastiano Massaro, associate professor of organizational neuroscience at the University of Surrey, said: "First, by assessing ECG directly, we confirm that with AI it is possible to accurately detect CHF looking beyond heart rate variability analysis. Thus, we have in general results that are more adherent to the real behavior of the affected heart."

In another part of the experiment, a specific CNN model was used to improve the accuracy of CHF detection while taking into account comparable models.

"We focus on the detection of the pathology from one single heartbeat in excerpts of 5-minutes rather than in 24-hours recordings," said Massaro.


# Artificial intelligence could create heart attack early warning system

sciencefocus.com · Jason Goodyer

The creators believe the system "could be saving lives within the next year." Technology developed using artificial intelligence could identify people…

Now, researchers at the University of Oxford have developed a new method of identifying future risk of heart attack using machine learning - an application of artificial intelligence that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.

Dubbed the fat radiomic profile (FRP), the system looks for signs of inflammation, scarring and changes to the blood vessels that supply blood to the heart.

"Just because someone's scan of their coronary artery shows there's no narrowing, that does not mean they are safe from a heart attack," Professor Charalambos Antoniades, BHF Senior Clinical Fellow at the University of Oxford.

"By harnessing the power of AI, we've developed a fingerprint to find 'bad' characteristics around people's arteries. This has huge potential to detect the early signs of disease, and to be able to take all preventative steps before a heart attack strikes, ultimately saving lives. We genuinely believe this

# SmartECHO: 1D/2D/3D/4D Echocardiography to solve the workflow and quality demands of cardiac imaging

Cardio-testing and ECHO laboratories

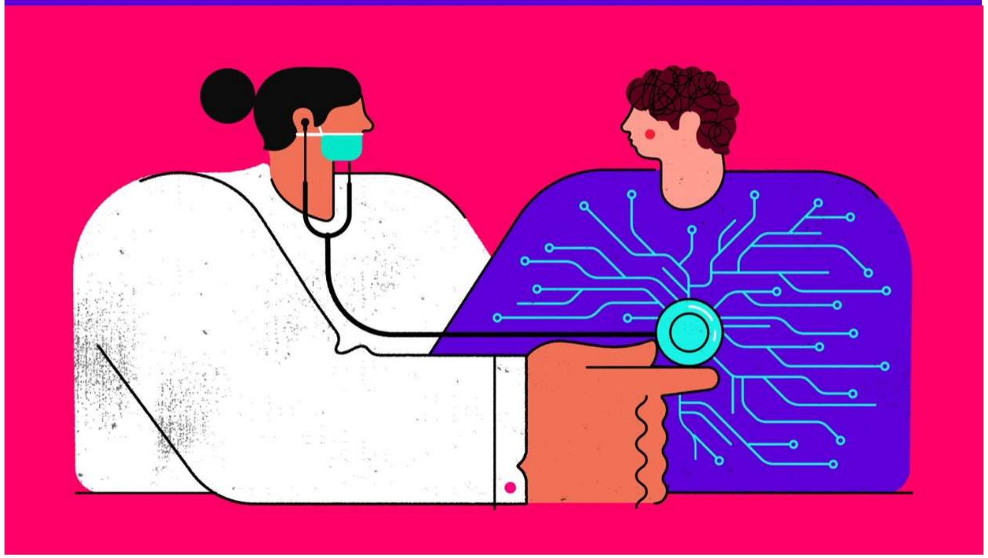
St Louis University Medical Center

St Louis, MO Steven Smart MD, PhD

TECHNOLOGY

# How hospitals are using AI to save their sickest patients and curb 'alarm fatigue'

Early tests show artificial "assistants" can help doctors and nurses spot potentially deadly problems in time to take life-saving action.



— Early tests suggest artificial intelligence can improve patient care in hospitals' intensive care units while helping curb "alarm fatigue." Woody Harrington / for NBC News

In a traditional ICU, nurses respond to an alarm every 90 seconds, two thirds of which turn out to be false alarms, meaning they don't signal real danger. Some doctors and nurses have been known to tune out – and even turn off – alarms, a phenomenon called "alarm fatigue." In 2011, the FDA warned that alarm-related problems contributed to more than 500 patient deaths from 2005 to 2008.

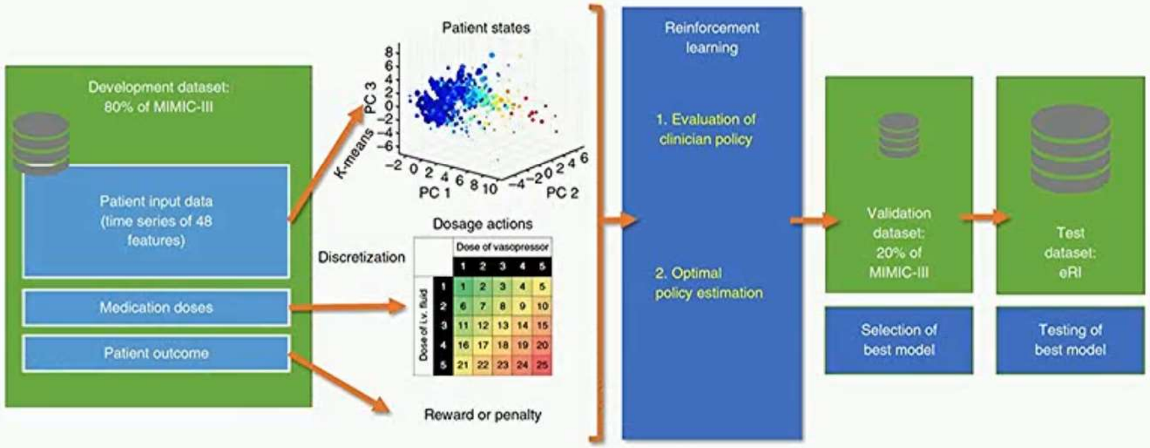
Unlike a conventional monitoring system, AI is often able to predict problems hours in advance; doctors and nurses get a calm, text-message warning rather than having to respond to an urgent alarm signaling that a patient is already in trouble.

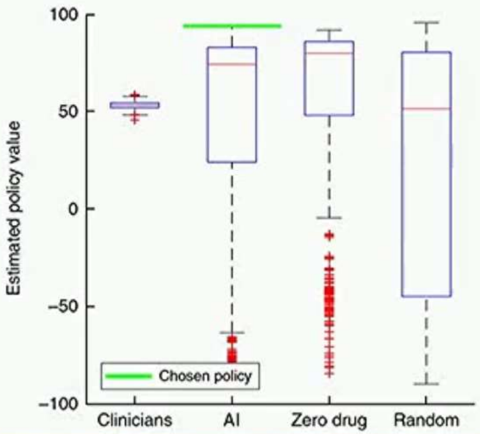
Barton said he received positive feedback from floor nurses during the AI study at UCSF. "The charge nurse of the floor will report that the number of false alarms has gone way down," he said. "It's making their work faster and more efficient."

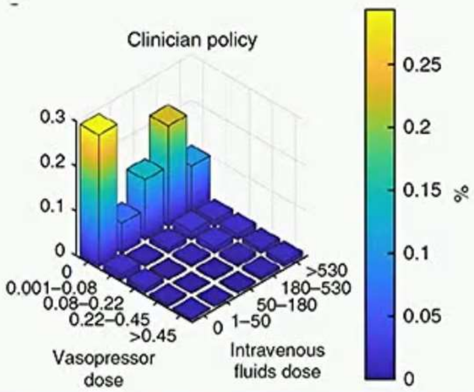
nature medicine

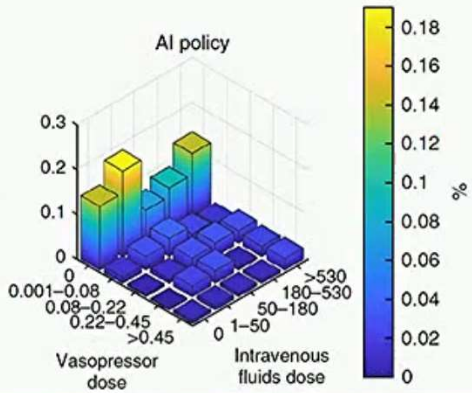
# The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care

17,803 admissions | 5 ICUs
79,073 admissions | 128 hospitals
Model for individualized patient
AI: Better use of (less) IV fluids, (higher dose) vasopressors, medications
“AI Clinician is on average reliably higher than human clinicians”



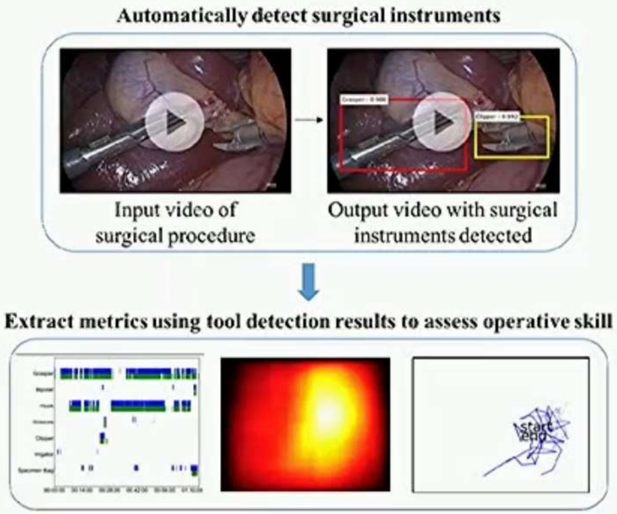



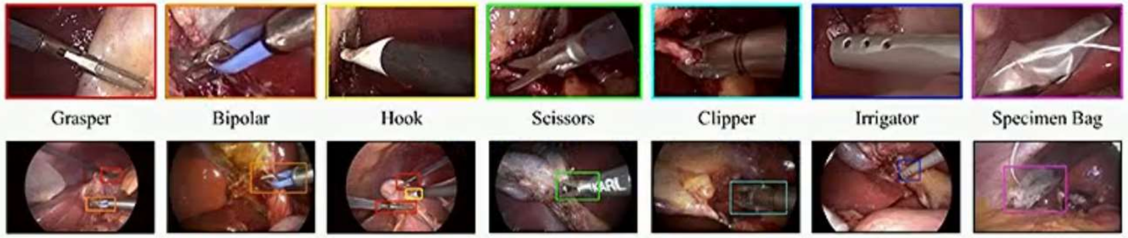



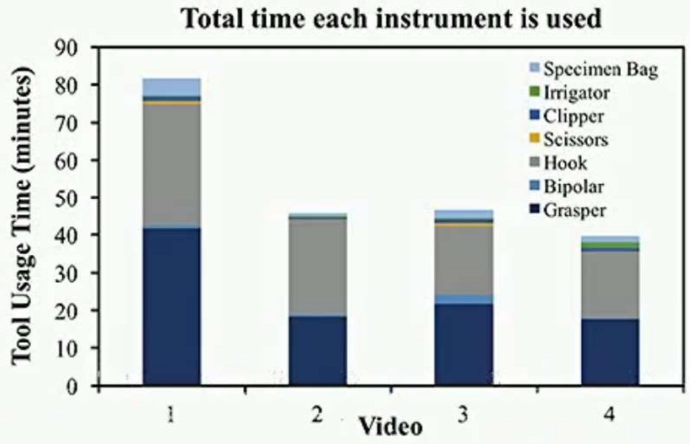

22 October 2018

# Tool Detection and Operative Skill Assessment in Surgical Videos Using Region-Based Convolutional Neural Networks

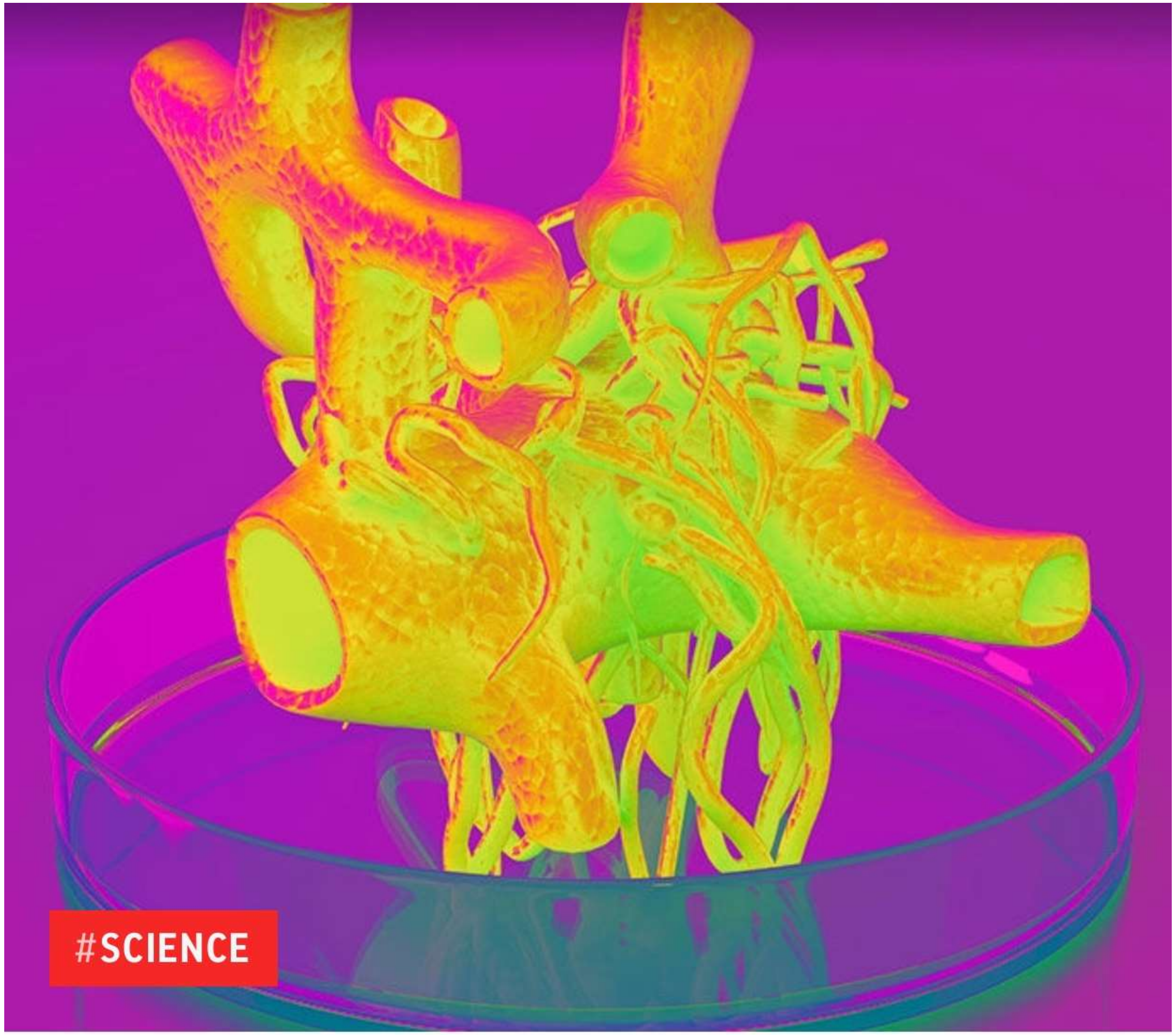



| | Video 1 | Video 2 | Video 3 | Video 4 |
|---|---|---|---|---|
| Depth Perception | 2.67 | 4.67 | 2.33 | 3.67 |
| Bimanual Dexterity | 3.00 | 4.67 | 2.00 | 3.33 |
| Efficiency | 2.00 | 4.67 | 2.33 | 3.00 |
| Tissue Handling | 2.33 | 4.67 | 2.67 | 3.33 |
| Total | 10.00 | 18.67 | 9.33 | 13.33 |



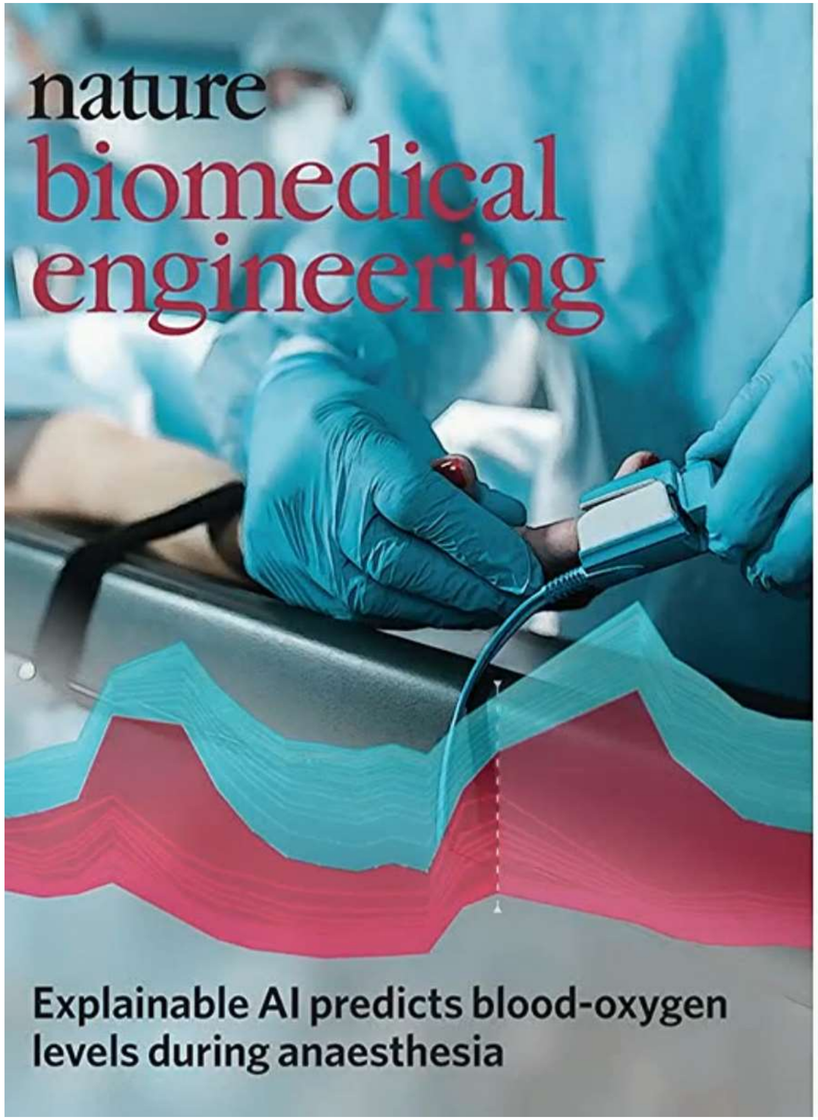

Jin et al, arXiv, 22 July 2018




# Prepping for surgery with 3D-printed organs may become commonplace

Selected reports of machine and deep learning algorithms to predict clinical outcomes and related parameters

| Prediction | N | AUC | Reference |
|---|---|---|---|
| In-hospital mortality, unplanned readmission, prolonged LOS, final discharge diagnosis | 216,221 | 0.93*<br>0.75+<br>0.85# | Rajkomar et al, Nature NPJ Digital Medicine, 2018 |
| All-cause 3-12 month mortality | 221,284 | 0.93^ | Avati et al, arXiv, 2017 |
| Readmission | 1,068 | 0.78 | Shameer et al, Pacific Symposium on Biocomputing, 2017 |
| Sepsis | 230,936 | 0.67 | Horng et al, PLOS One, 2017 |
| Septic shock | 16,234 | 0.83 | Henry et al, Science, 2015 |
| Severe sepsis | 203,000 | 0.85@ | Culliton et al, arXiv, 2017 |
| C. Difficile infection | 256,732 | 0.82++ | Oh et al, Infection Control and Epidemiology, 2018 |
| Developing diseases | 704,587 | range | Miotto et al, Scientific Reports, 2018 |
| Diagnosis | 18,590 | 0.96 | Yang et al, Scientific Reports, 2018 |
| Dementia | 76,367 | 0.91 | Cleret de Langavant et al, J Internet Med Res 2018 |
| Alzheimer's Disease (+ amyloid imaging) | 273 | 0.91 | Mathotaarachchi et al, Neurobiology of Aging, 2017 |
| Mortality after cancer chemotherapy | 26,946 | 0.94 | Elfiky et al, JAMA Open, 2018 |
| Disease onset for 133 conditions | 298,000 | range | Razavian et al, arXiv, 2016 |
| Suicide | 5,543 | 0.84 | Walsh et al, Clinical Psychological Science, 2017 |

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ARTICLES
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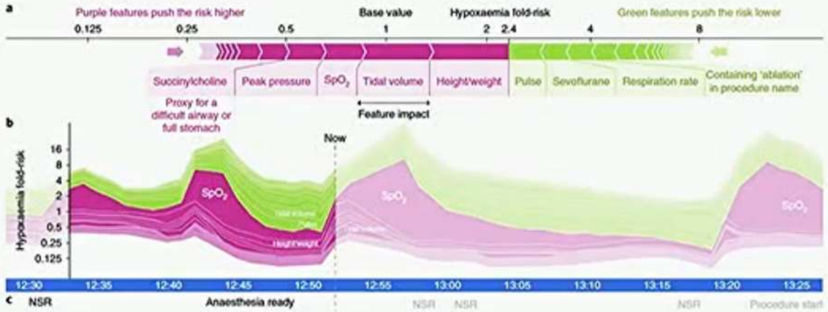
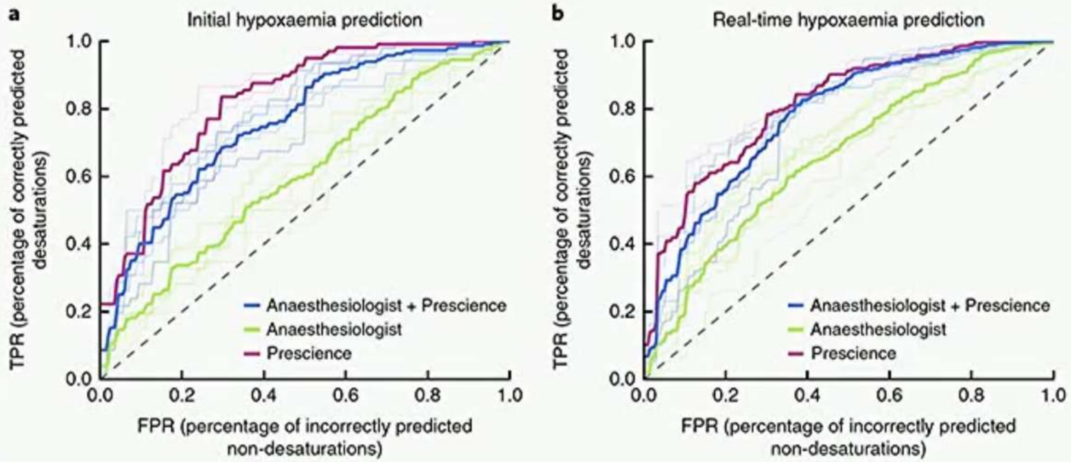
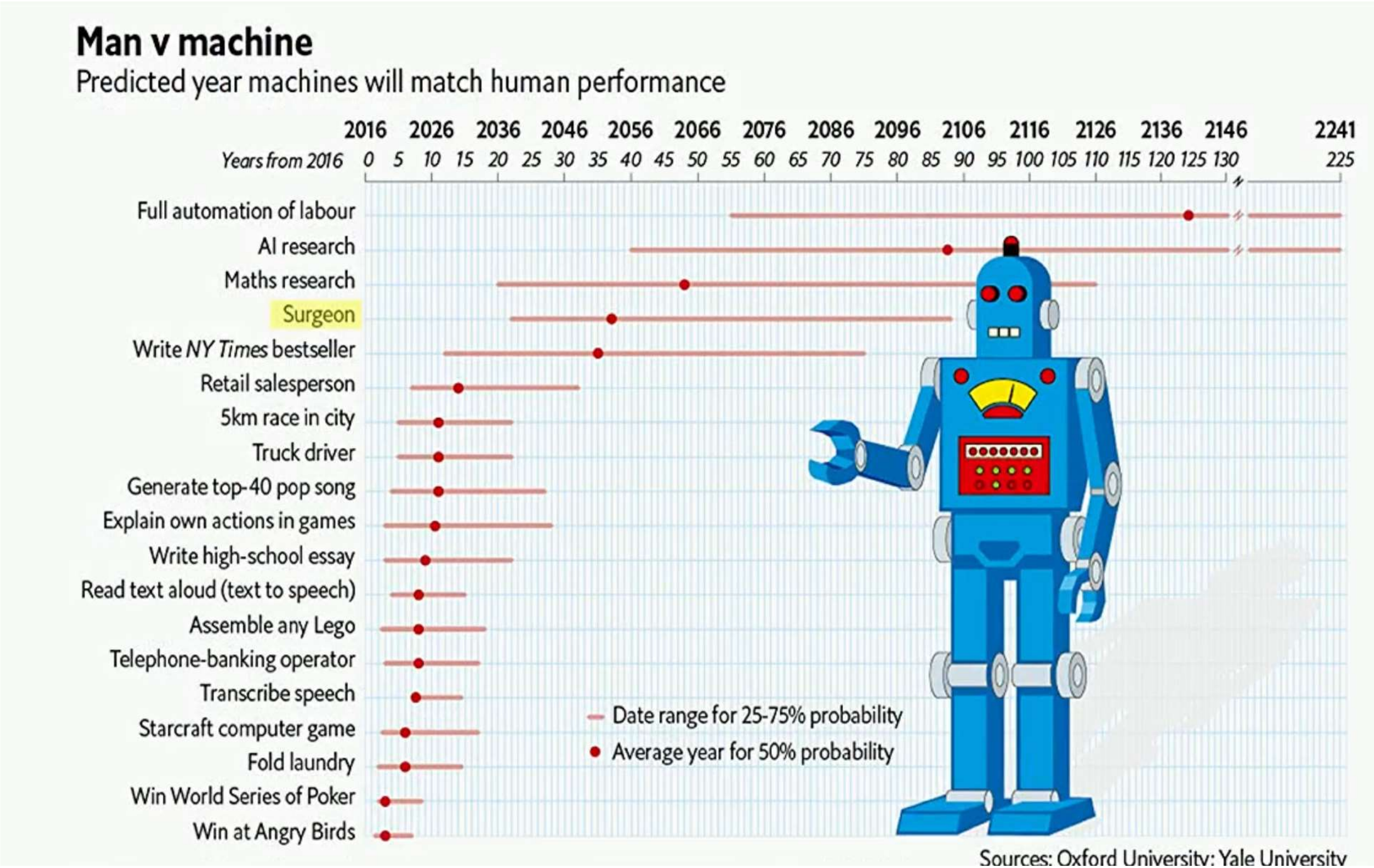
# Explainable machine-learning predictions for the prevention of hypoxaemia during surgery

Scott M. Lundberg[1], Bala Nair[2,3,4], Monica S. Vavilala[2,3,4], Mayumi Horibe[5], Michael J. Eisses[2,6], Trevor Adams[2,6], David E. Liston[2,6], Daniel King-Wai Low[2,6], Shu-Fang Newman[2,3], Jerry Kim[2,6] and Su-In Lee[1*]





Man v machine
Predicted year machines will match human performance
2016 2026 2036 2046 2056 2066 2076 2086 2096 2106 2116 2126 2136 2146 2241
Years from 2016 0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100 105 110 115 120 125 130 225
Full automation of labour
AI research
Maths research
Surgeon
Write NY Times bestseller
Retail salesperson
5km race in city
Truck driver
Generate top-40 pop song
Explain own actions in games
Write high-school essay
Read text aloud (text to speech)
Assemble any Lego
Telephone-banking operator
Transcribe speech
Starcraft computer game
Fold laundry
Win World Series of Poker
Win at Angry Birds
Date range for 25-75% probability
Average year for 50% probability
Sources: Oxford University; Yale University


Our most valuable intelligence isn't artificial.
HSBC
Bank
Together we th

# THANK YOU

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