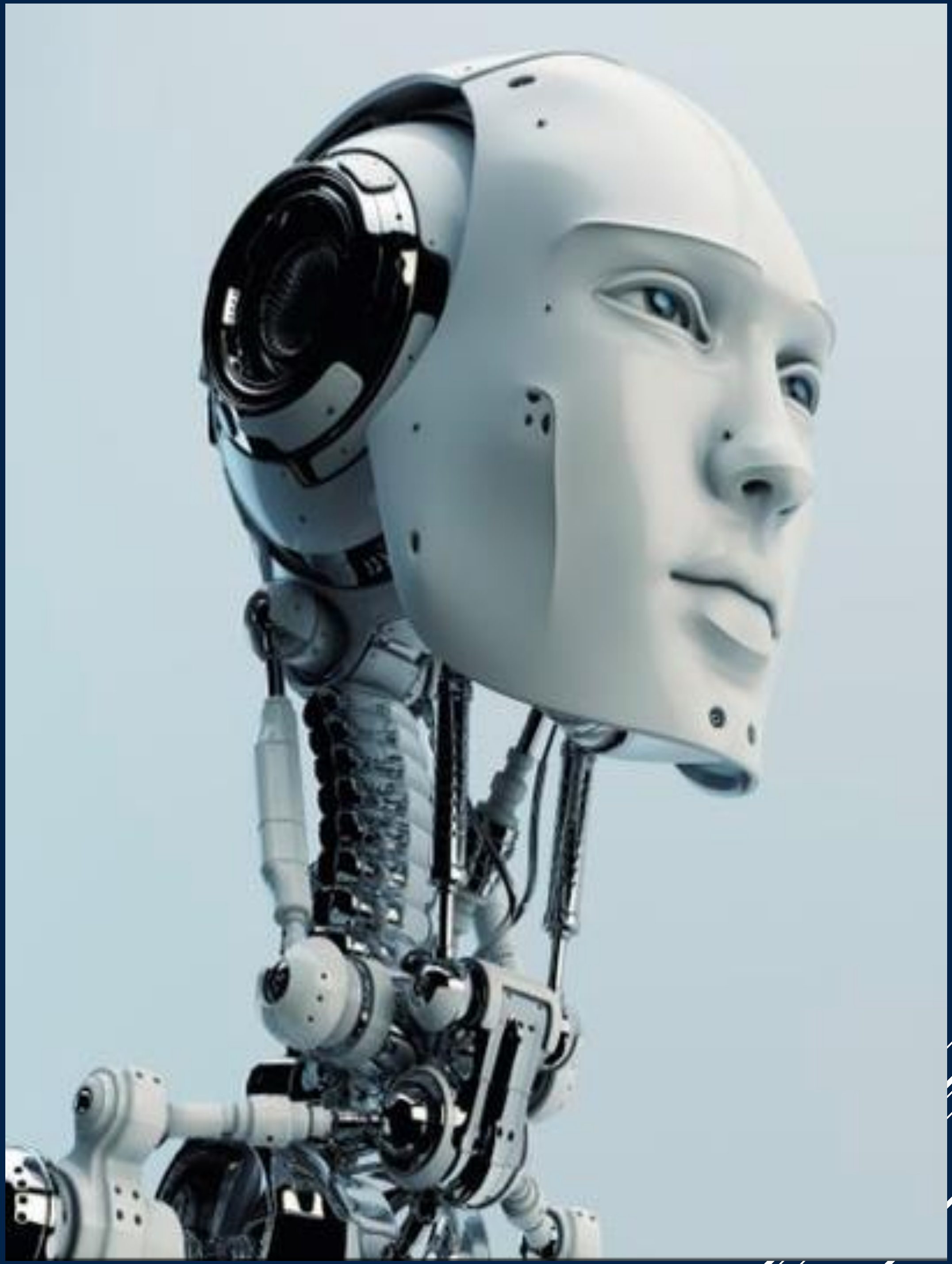
ARTIFICIAL INTELLIGENCE IN GASTROENTEROLOGY



Paul A. Lucha Jr., DO, FACOS, FAOCPr
VAMC Salisbury, NC

- Star Trek
- Lost in Space
- Isaac Asimov- I Robot
- Dune- thinking machines

- Internet Search
- Dragon Dictation
- Medical phone app for ddx

ARTIFICIAL INTELLIGENCE ??

OUTLINE

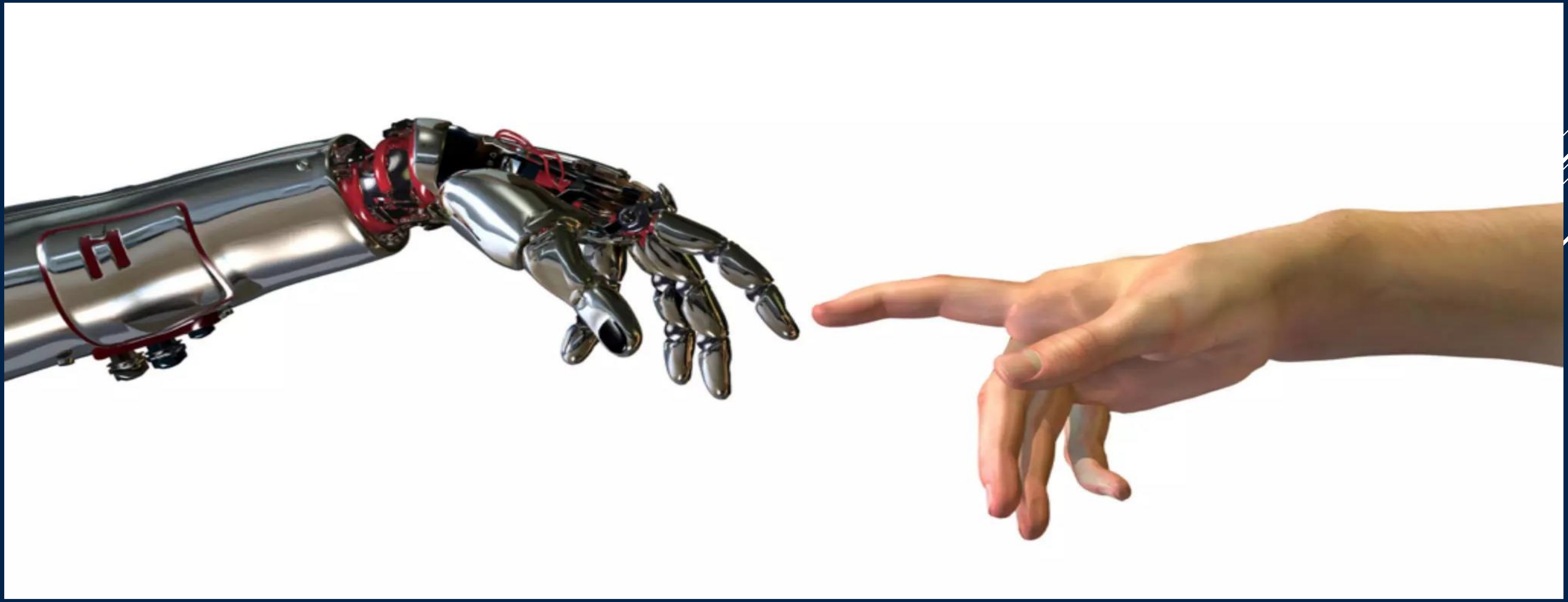
- Introduction
- What is the need for AI in endoscopy?
- Application in Endoscopy

A. Colonoscopy

B. Wireless capsule endoscopy

C. Upper endoscopy

D. Robotics endoscopy



INTRODUCTION

- A computer system that is able to perform tasks normally requiring human intelligence like visual perception, speech recognition and decision making and translation between languages

- Artificial intelligence means machine intelligence that mimics human cognitive functions like learning, to comprehend, thinking, reasoning

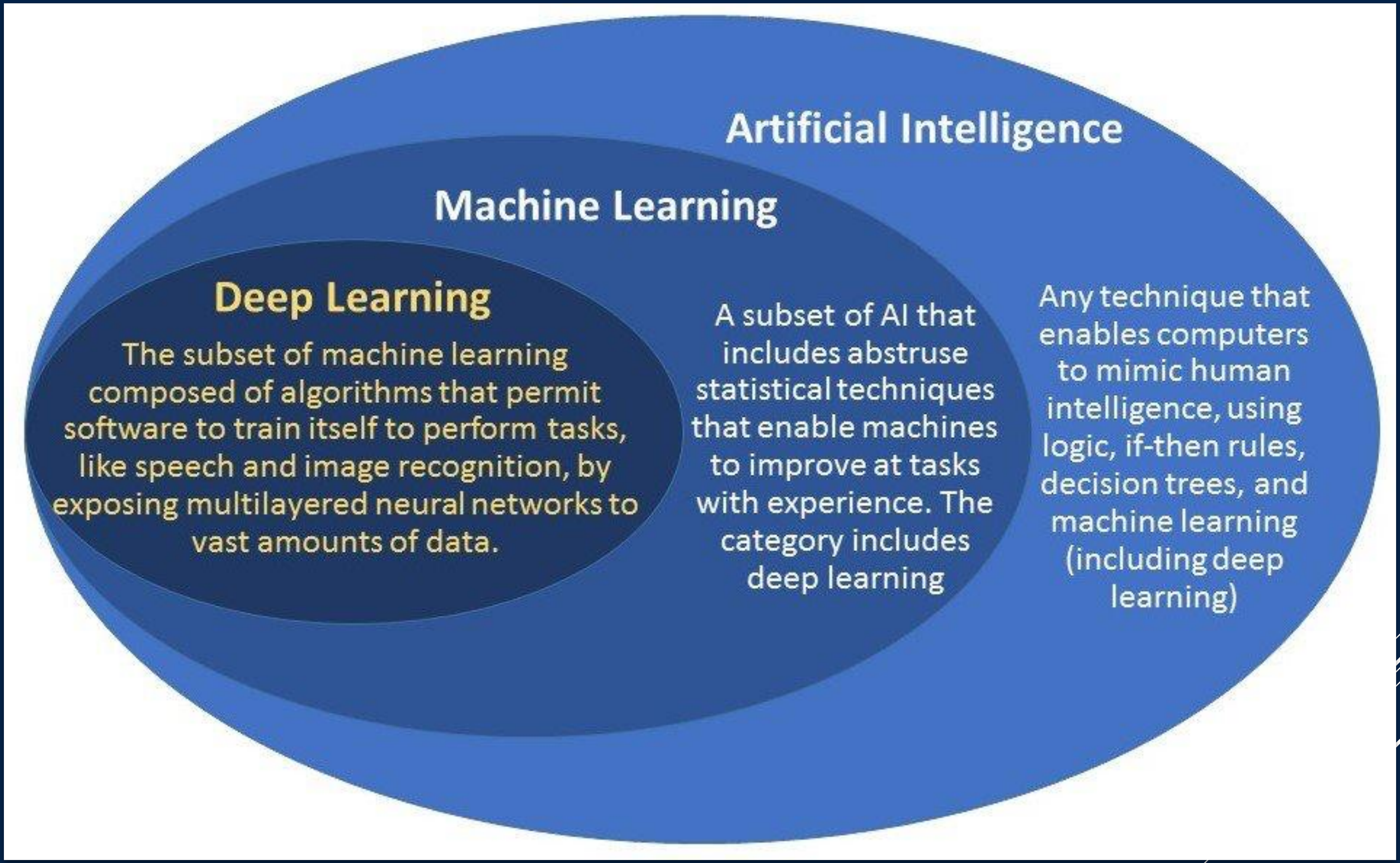
- Ability of a computer to perform a task associated with intelligent beings like cognitive functions that might mimic the human mind like the ability to ‘learn’

INTRODUCTION

- Types of AI

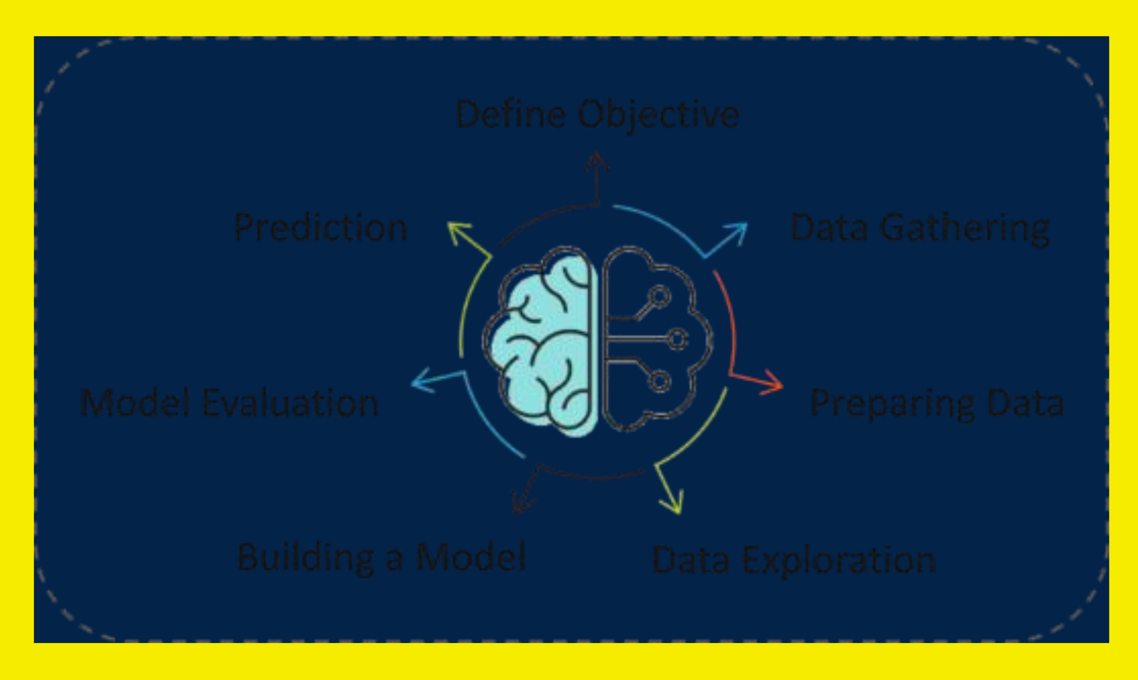
1. Artificial narrow intelligence (weak AI): applying AI to only a specific task
    - Only type available widely at present
2. Artificial general intelligence (strong AI): machines that perform any intellectual task that human can (like thinking and reasoning)
    - Not available yet
3. Artificial super intelligence: capabilities of computers surpasses human beings
    - Hypothetical as of now

INTRODUCTION



MACHINE LEARNING PROCESS

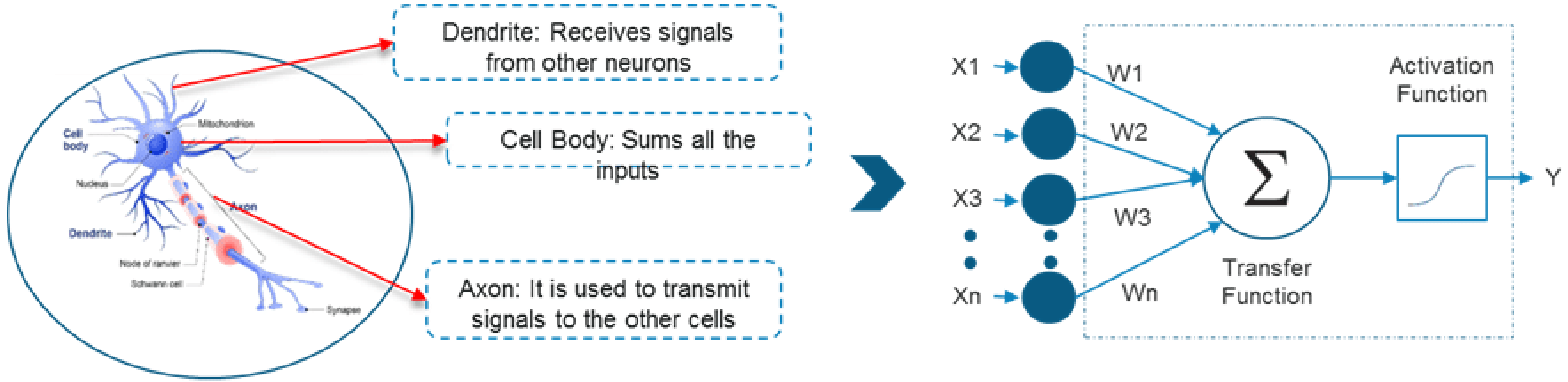
1. Define objective of the problem
2. Data gathering
3. Data preparation and cleaning
4. Data exploration and analysis
5. Building a model using algorithms
6. Testing the model for accuracy
7. Prediction of the problems



DEEP LEARNING

- Deep learning mimics our brain functions that it learn from experience
- Are capable of learning to focus on right features by themselves without guidance of programmer
- Features: extraction happens automatically based on desired outcome
- Self-learning without human interventions
- It includes artificial neural networks (DNN)

ARTIFICIAL NEURAL NETWORK

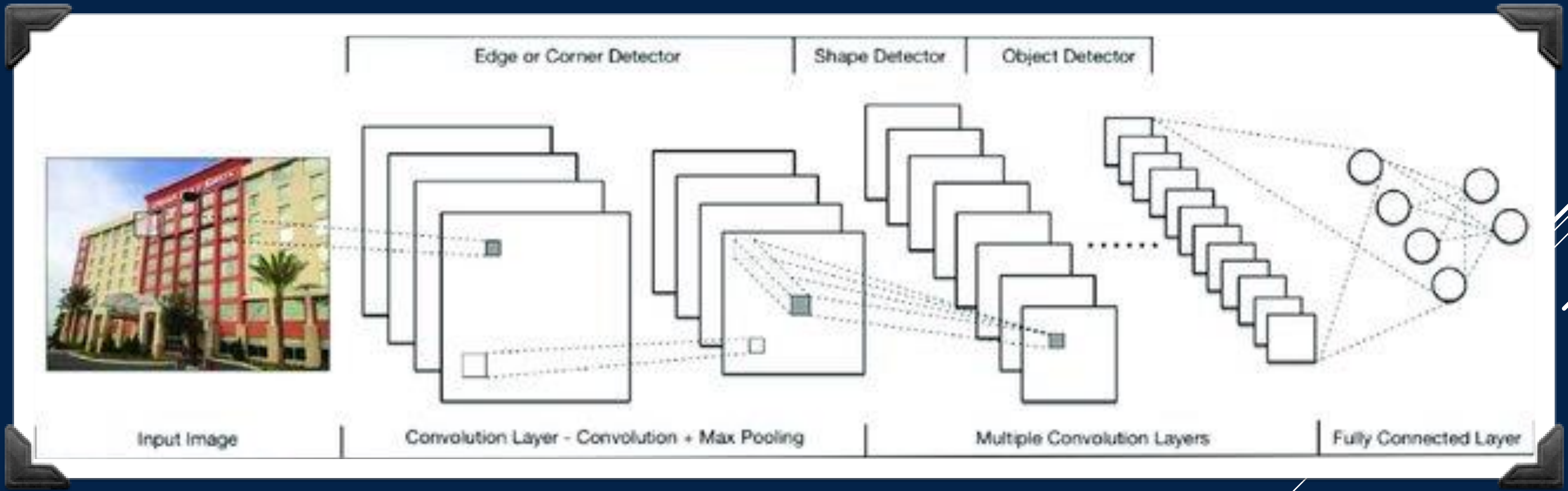


Neuron

Schematic for a neuron in a neural net

CONVULALATED NEURAL NETWORK

- Type of recurrent neural network
- Neuron in layer will only be connected to small layer of region before it instead of all of the neuron in a fully connected manner
- Mainly useful in image analysis and recognition process



WHAT IS THE NEED OF AI IN ENDOSCOPY?

- Endoscopist simultaneously performing endoscopy and interpreting findings has various limitations like Intra observers and inter observers variability and fatigue
- By now we have generated enormous data and to use that data in guiding and making evidence decisions AI can be applied
- To apply concepts of personalised medicine in field of endoscopy rather that the traditional medicine which means "one size fits all"

COLONOSCOPY

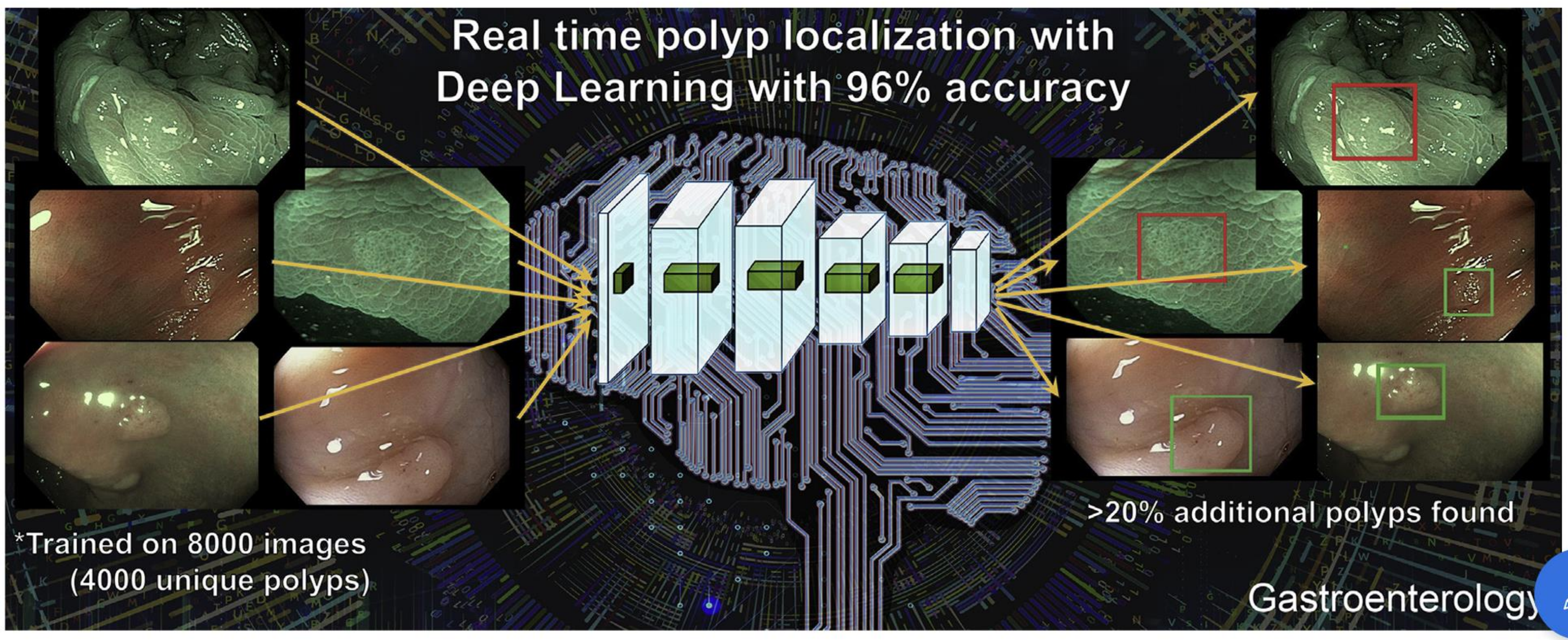
- CRC arises from precancerous polyps with a mean dwell time of at least 10 years
- 70% to 90% of CRCs are preventable with regular colonoscopies and removal of polyps.
- 1% increase in the ADR, the interval cancer rate was decreased by 3%
- In tandem colonoscopies, 22%–28% of polyps and 20%–24% of adenomas were missed
- So there is need to improve ADR to prevent CRC
- Artificial intelligence with it’s deep learning model convulated neural network is very promising in improving ADR

COLONOSCOPY

Deep Learning Localizes and Identifies Polyps in Real Time With 96% Accuracy in Screening Colonoscopy

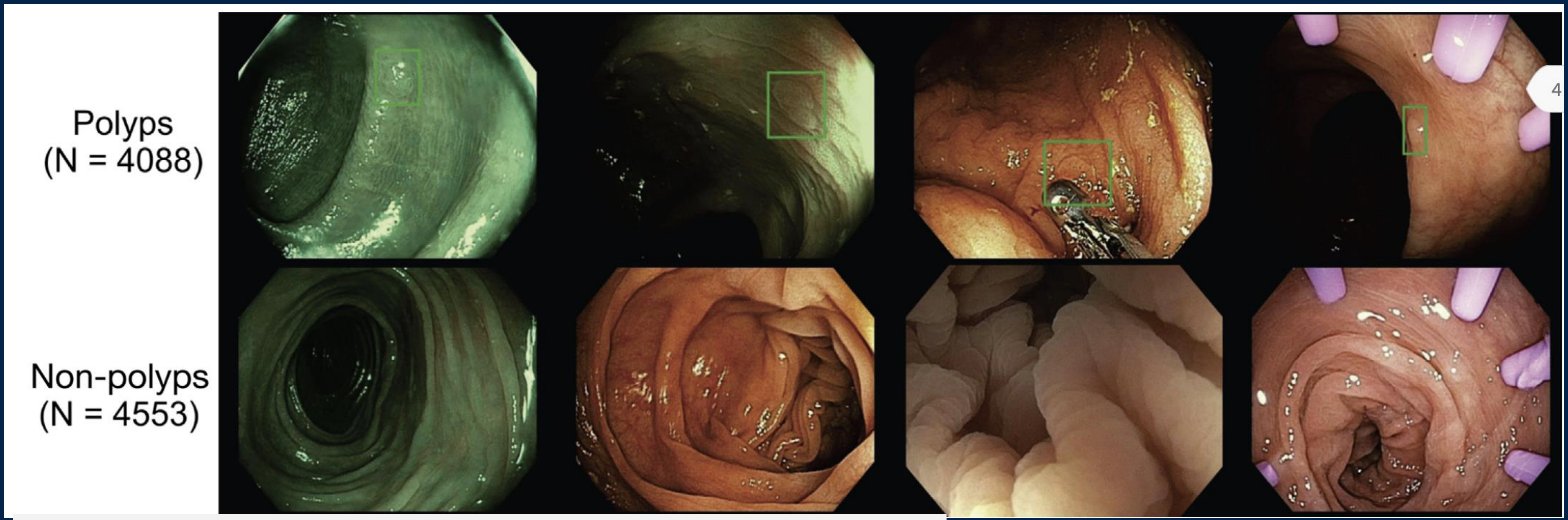
Gregor Urban,[1,2] Priyam Tripathi,[4] Talal Alkayali,[4,5] Mohit Mittal,[4] Farid Jalali,[4,5] William Karnes,[4,5] and Pierre Baldi[1,2,3]

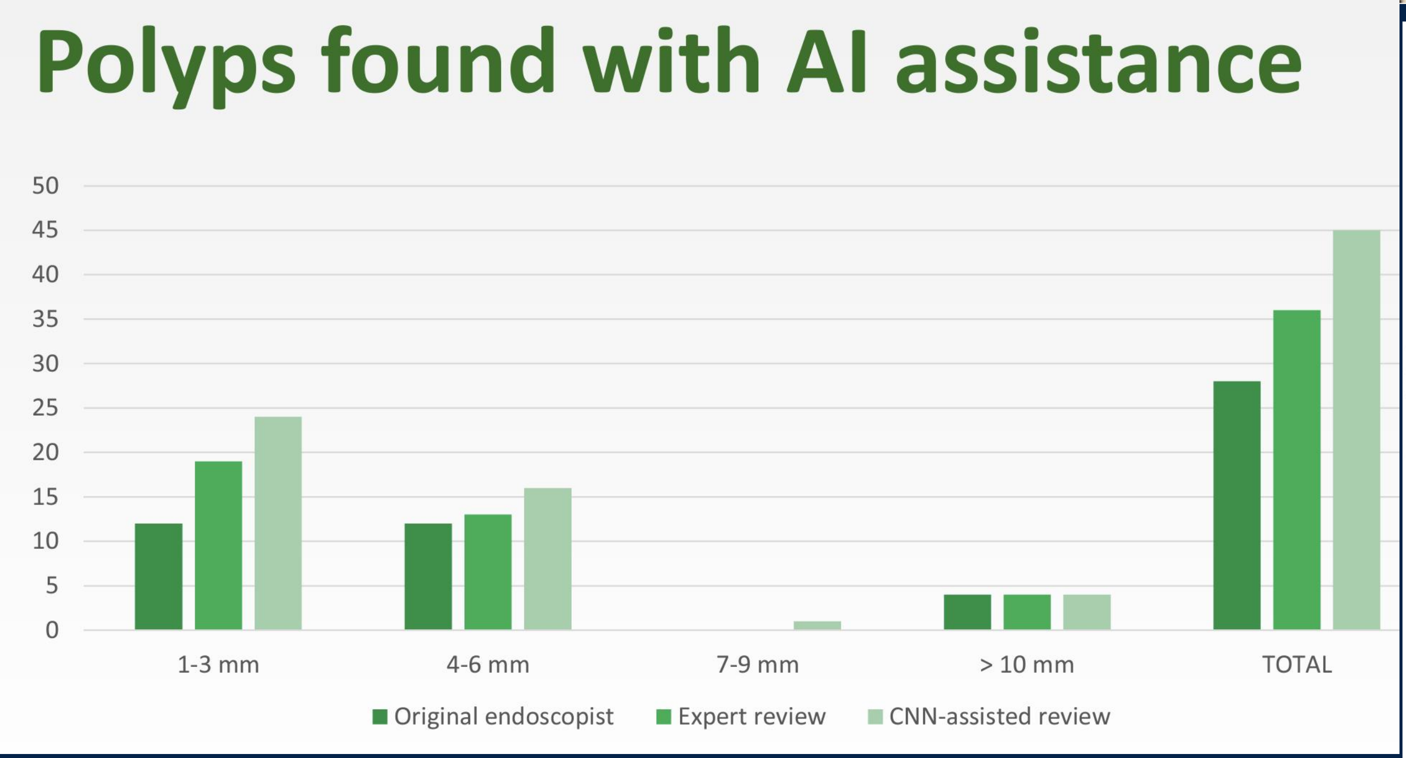
[1]Department of Computer Science, University of California, Irvine, California; [2]Institute for Genomics and Bioinformatics, University of California, Irvine, California; [3]Center for Machine Learning and Intelligent Systems, University of California, Irvine, California; [4]Department of Medicine, University of California, Irvine, California; and [5]H.H. Chao Comprehensive Digestive Disease Center, University of California, Irvine, California

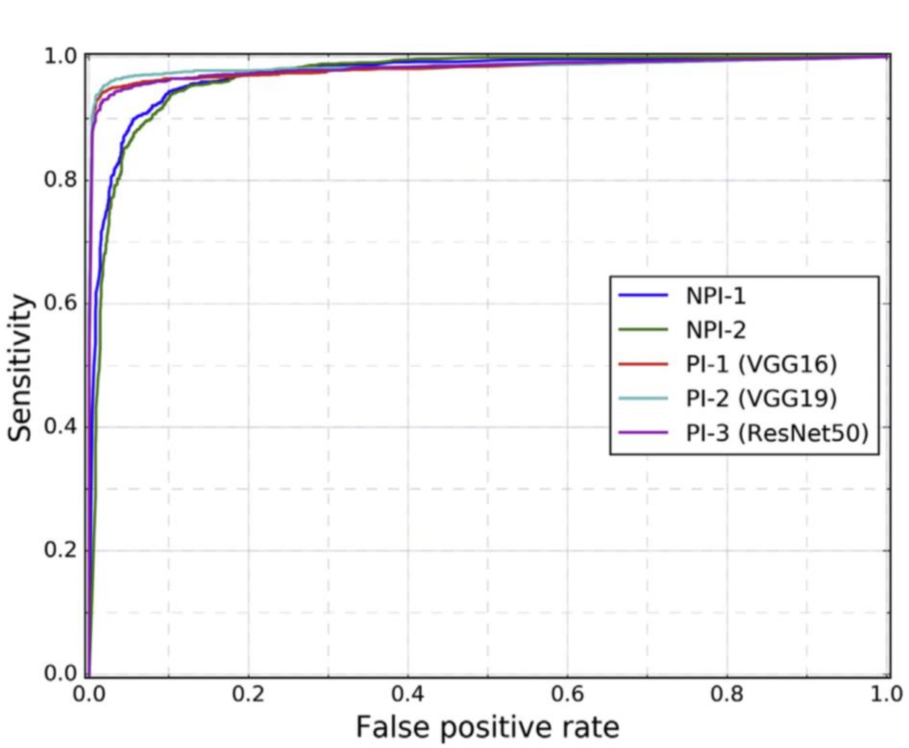


Gastroenterology 2018;155:1069–1078

COLONOSCOPY







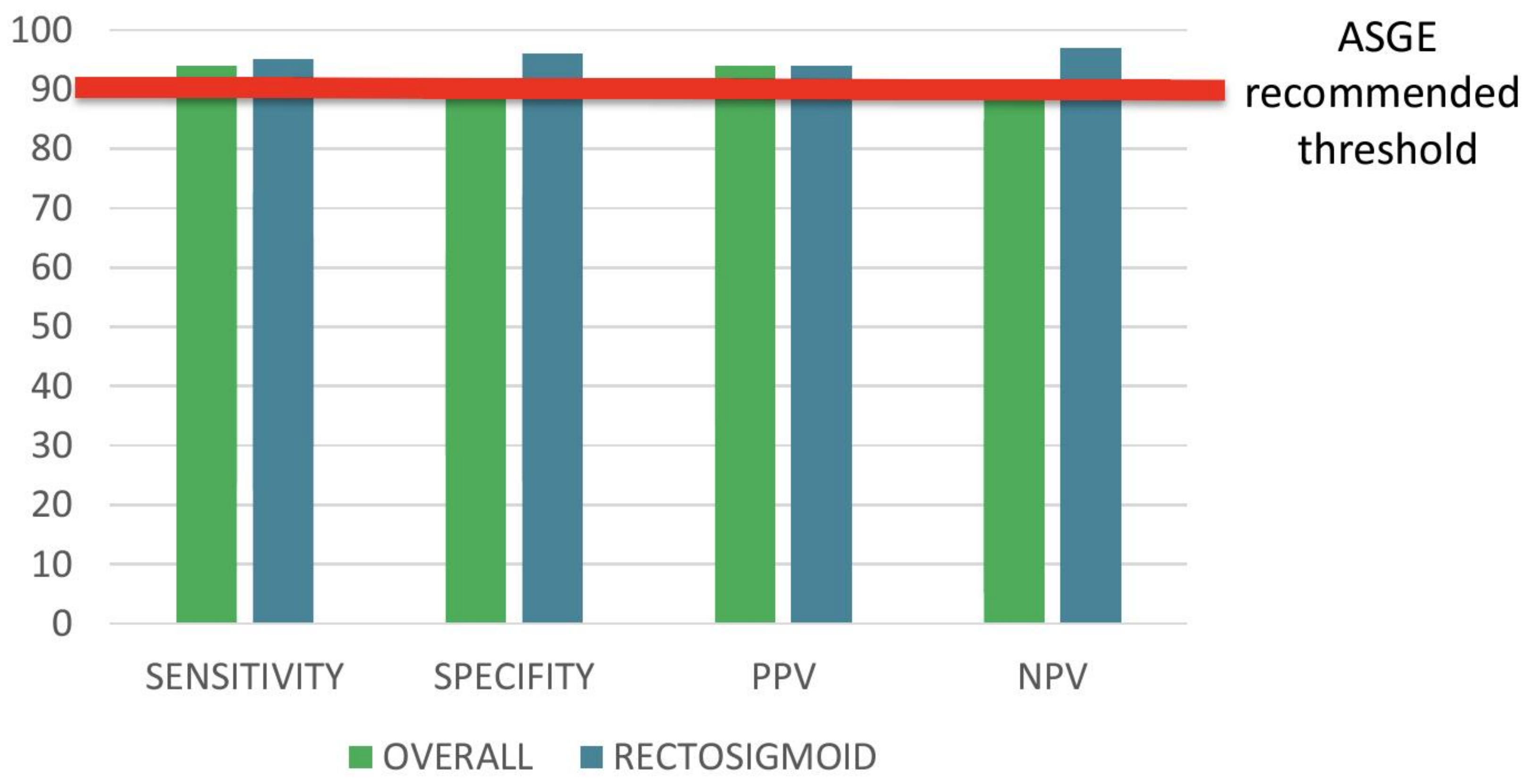
Gastroenterology 2018;155:1069–1078

COLONOSCOPY

Real-Time Use of Artificial Intelligence in Identification of Diminutive Polyps During Colonoscopy
A Prospective Study

Mori, Ann Intern Med 2018

- 466 $\leq$ 5 mm polyps
- 325 patients



Ann Intern Med. 2018.169:357–366.

COLONOSCOPY

Endoscopy

OPEN ACCESS

ORIGINAL ARTICLE

Real-time differentiation of adenomatous and hyperplastic diminutive colorectal polyps during analysis of unaltered videos of standard colonoscopy using a deep learning model

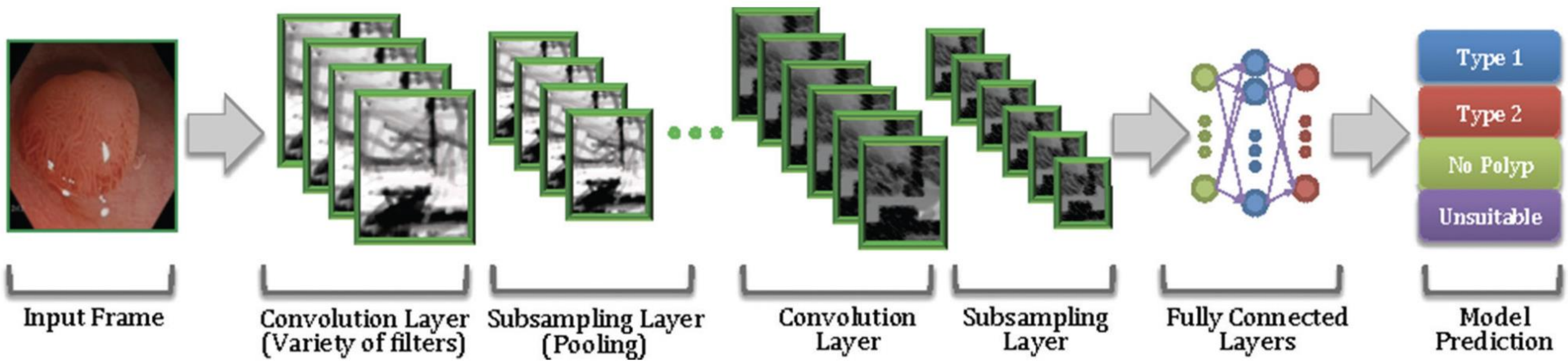


Figure 1 Schematic of the deep convolutional neural network model used.

- The model was tested on a separate series of 125 videos of consecutively encountered diminutive polyps that were proven to be adenomas or hyperplastic polyps

Byrne MF, et al. Gut 2019;68:94–100

COLONOSCOPY

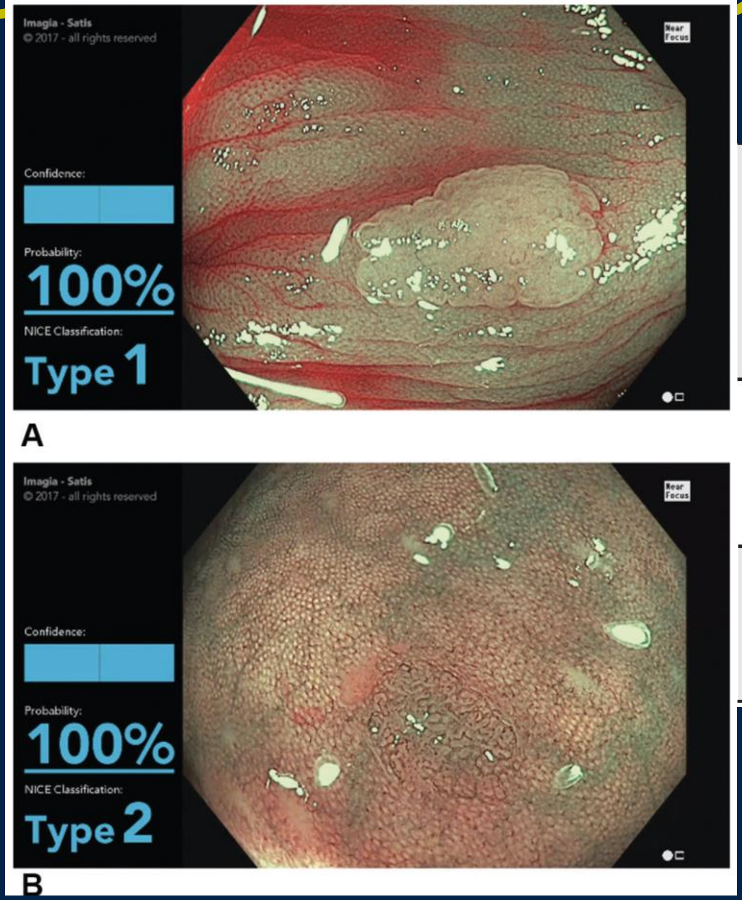


Table 1 Assignment of narrow band imaging International Colorectal Endoscopic classification (NICE) type 1 vs NICE type 2 compared with the pathology determined histology

		Predicted by the model	
		NICE type 1	NICE type 2
Pathology	Hyperplastic	33	7
	Adenoma	1	65

- For the 106 polyps, the accuracy of the model was 94% (95% CI 86% to 97%), the sensitivity for identification of adenomas was 98% (95% CI 92% to 100%), specificity was 83% (95% CI 67% to 93%), negative predictive value was 97% and positive predictive value was 90%.

Byrne MF, et al. Gut 2019;68:94–100

EGD

- Detection and characterization of gastrointestinal neoplasm
- Helpful in recognising anatomical location of EGD images with 99% accuracy
- Also discrimination of early neoplastic lesion in Barrett's esophagus
- Distinguishing between superficial esophageal cancer from advanced cancer
- Diagnosis of *H.pylori* infection using various image enhanced endoscopy

AI FOR ESOPHAGEAL NEOPLASM

Diagnostic outcomes of esophageal cancer by artificial intelligence using convolutional neural networks

Yoshimasa Horie, MD,[1,2] Toshiyuki Yoshio, MD,[1,3] Kazuharu Aoyama, MM,[4] Shoichi Yoshimizu, MD,[1] Yusuke Horiuchi, MD,[1] Akiyoshi Ishiyama, MD,[1] Toshiaki Hirasawa, MD,[1,3] Tomohiro Tsuchida, MD,[1] Tsuyoshi Ozawa, MD,[3,5] Soichiro Ishihara, MD,[3,5] Youichi Kumagai, MD,[6] Mitsuhiro Fujishiro, MD,[7] Iruru Maetani, MD,[2] Junko Fujisaki, MD,[1] Tomohiro Tada, MD[3,4,8]

Tokyo, Saitama, Japan

TABLE 1. Patient and lesion characteristics in the test image sets

Patient characteristics (n = 47)	Value
Sex, male/female	41/6
Median age, y (range)	70 (48-81)
Lesion characteristics (n = 49)	
Median tumor size, mm (range)	20 (5-700)
Tumor location, Ce/Ut/Mt/Lt/Ae	0/8/23/10/8
Macroscopic type	
Superficial cancer, 0-I/0-IIa/0-IIb/0-IIc	1/6/13/23
Advanced cancer 1/2/3/4	0/3/3/0
Depth of tumor, T1a/T1b/T2-4	40/2/7
Histopathology, ESCC/EAC	41/8

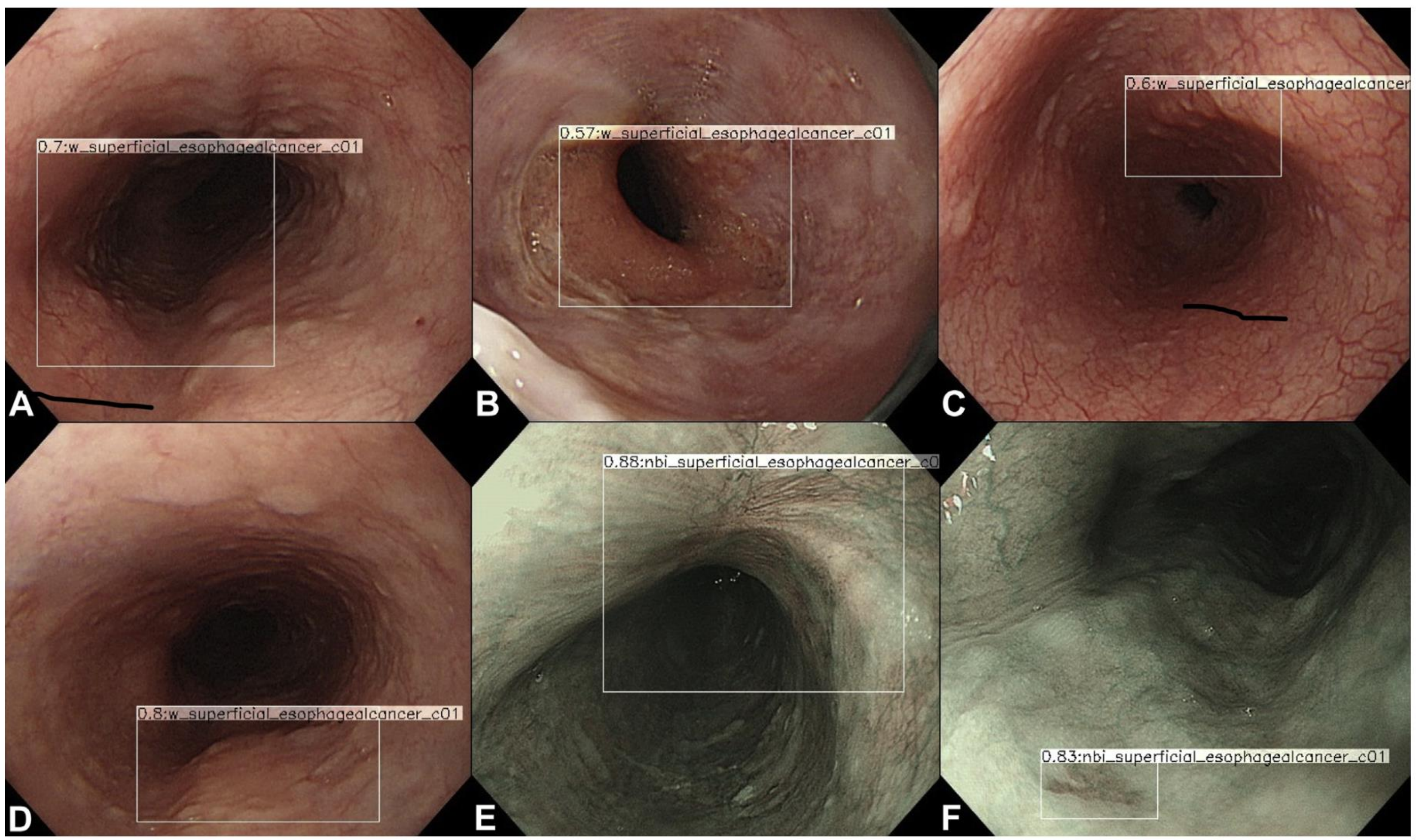
	Results of biopsy specimen	
	Cancer*	Noncanc
AI diagnosis by WLI		
Cancer	38	35
Noncancer	9	15
AI diagnosis by NBI*		
Cancer	41	28
Noncancer	5	22
Comprehensive AI diagnosis†		
Cancer	46	42
Noncancer	1	8

Volume 89, No. 1 : 2019 GASTROINTESTINAL ENDOSCOPY

AI FOR ESOPHAGEAL NEOPLASM

TABLE 4. Accuracy in diagnosing superficial versus advanced cancer

	WLI	NBI	All images
Superficial cancer, %	100 (75/75)	99 (67/68)	99 (142/143)
Advanced cancer, %	100 (14/14)	82 (9/11)	92 (23/25)
All cancer, %	100 (89/89)	96 (76/79)	98 (165/168)



re 3. Examples of false-positive images. The *white squares* here indicate areas that were misdiagnosed as cancer. **A,** Shadow. **B,** Esophagogas tion. **C,** Left main bronchus. **D,** Vertebral body. **E,** Post–endoscopic resection scar. **F,** Focal atrophy.

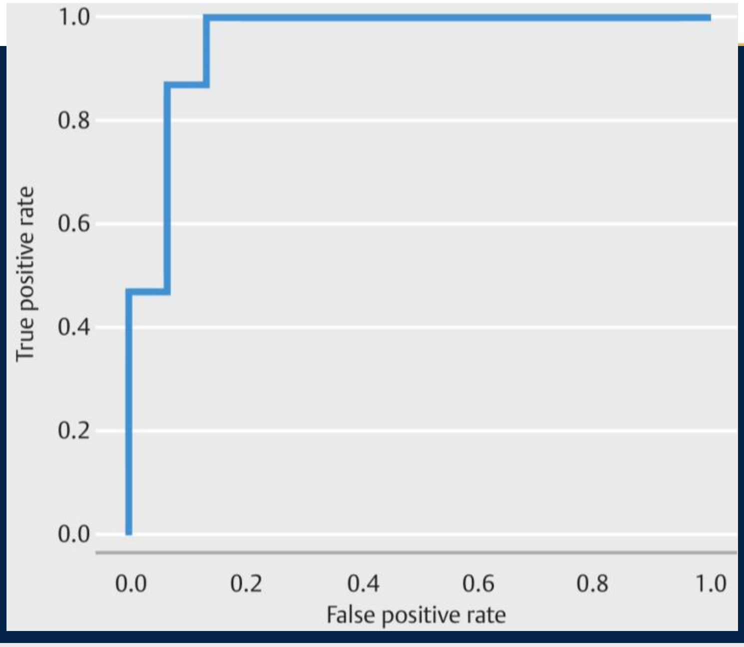
AI FOR *H.PYLORI*

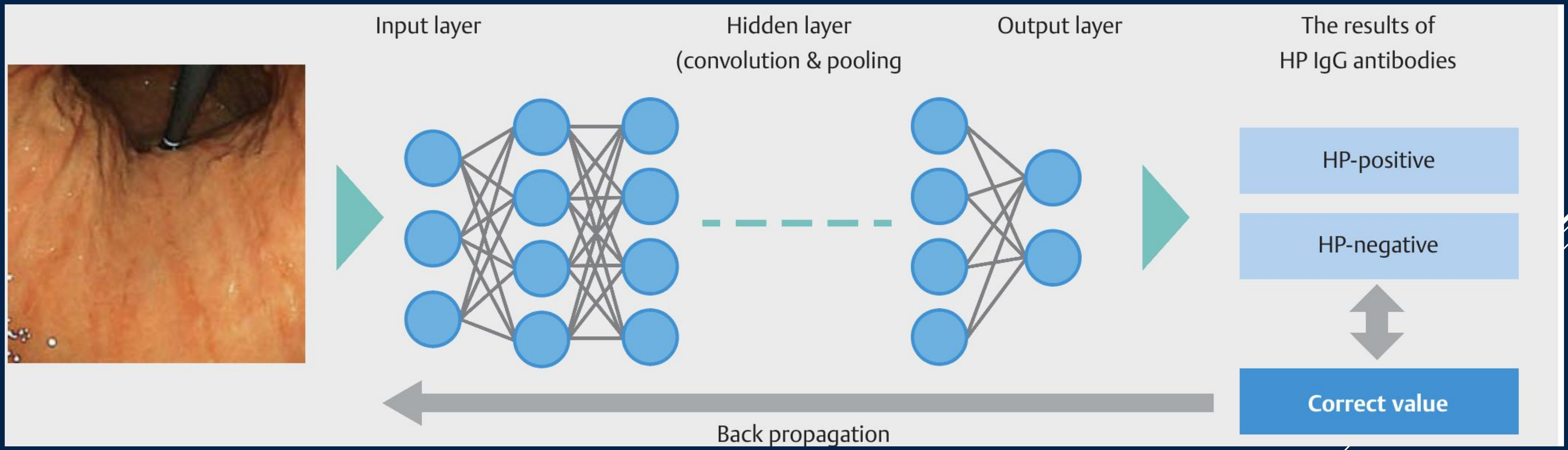
Original article

Thieme

Deep learning analyzes Helicobacter pylori infection by upper gastrointestinal endoscopy images

	HP infection status	No. of endoscopic images	No. of images after data augmentation
Training images	Positive	70	280
	Negative	79	316
Test images	Positive	15	–
	Negative	15	–



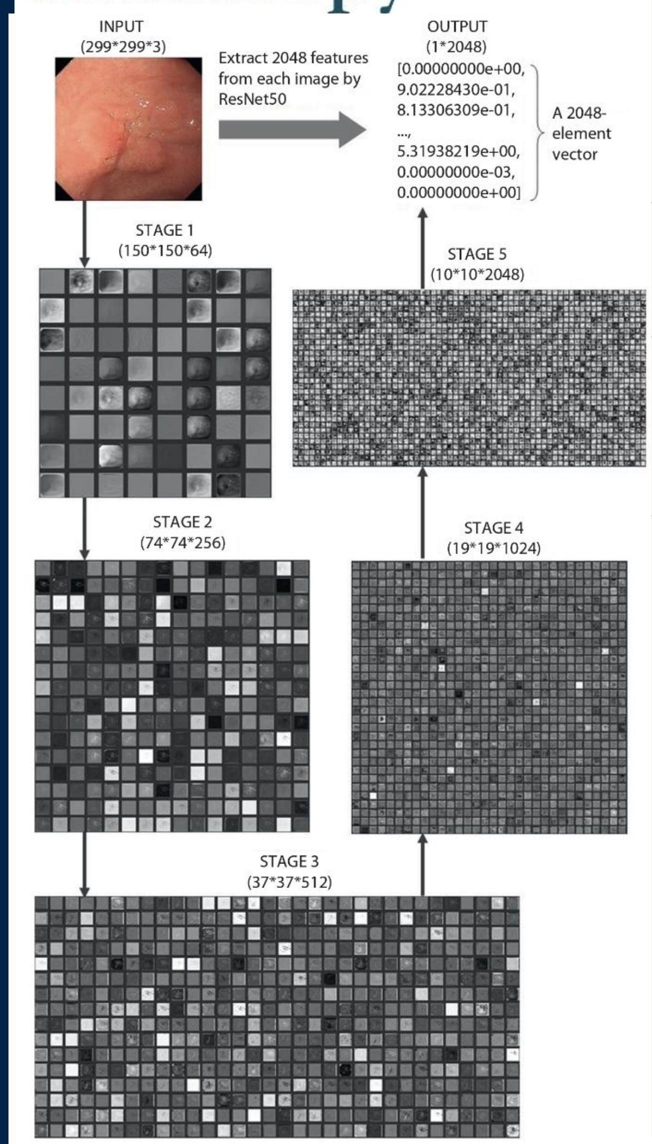


Endoscopy International Open 2018; 06: E139–E144

AI FOR GASTRIC CANCER

ORIGINAL ARTICLE: Clinical Endoscopy

Application of convolutional neural network in the diagnosis of the invasion depth of gastric cancer based on conventional endoscopy



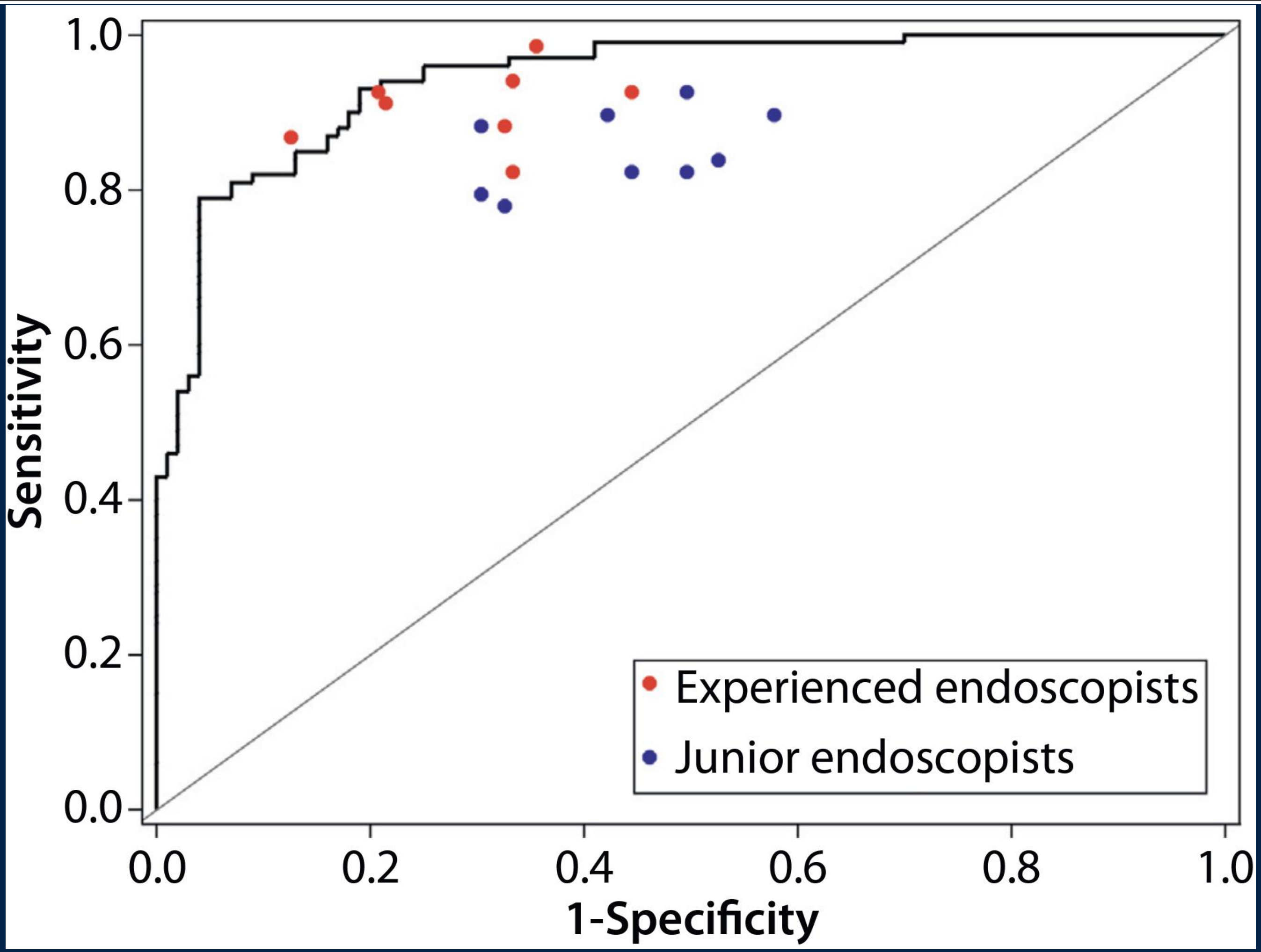
Characteristic	Development (n = 790)	Test (n = 203)
Gender		
Women	201 (25.4)	51 (25.1)
Men	589 (74.6)	152 (74.9)
Operation		
Surgical approach	526 (66.6)	131 (64.5)
Endoscopic resection	264 (33.4)	72 (35.5)
Location		
Upper	138 (17.5)	23 (11.3)
Middle	325 (41.1)	44 (21.7)
Lower	327 (41.4)	136 (67.0)
Macroscopic type		
Bormman type I	32 (4.1)	5 (2.5)
Bormman type II	82 (10.4)	33 (16.3)
Bormman type III	78 (9.9)	29 (14.3)
Bormman type IV	15 (1.9)	3 (1.5)
Type I	39 (4.9)	5 (2.5)
Type 2a	82 (10.4)	13 (6.4)
Type 2b	122 (15.4)	41 (20.2)
Type 2c	67 (8.5)	16 (7.9)
Type 3	44 (5.6)	15 (7.4)
Type 1+2a	1 (.1)	0 (0)
Type 2a+2c	199 (25.2)	39 (19.2)
Type 2c+2a	27 (3.4)	4 (2.0)
Type 2c+3	2 (.3)	0 (0)
Histologic type		
High-grade adenoma/dysplasia	252 (31.9)	65 (32.0)
Noninvasive carcinoma	189 (23.9)	48 (23.6)
Intramucosal carcinoma	104 (13.2)	22 (10.8)
Submucosal invasion by carcinoma	245 (31.0)	68 (33.5)
Degree of differentiation		
Differentiated	603 (76.3)	154 (75.9)
Undifferentiated	187 (23.7)	49 (24.1)
Invasion depth		
M	513 (64.9)	125 (61.6)
SM1	32 (4.1)	10 (4.9)
SM2	83 (10.5)	12 (5.9)
Muscularis propria	43 (5.4)	22 (10.8)
Subserosa	6 (.8)	12 (5.9)
Serosa	113 (14.3)	22 (10.8)
P0 or P1		
P0	545 (69.0)	135 (66.5)
P1	245 (31.0)	68 (33.5)

GASTROINTESTINAL ENDOSCOPY Volume89, No.4:2019

AI FOR GASTRIC CANCER

TABLE 2. Diagnostic accuracy of CNN-CAD system versus endoscopists

		Endoscopists		
	CNN-CAD system	All (n = 17)	Experienced (n = 8)	Junior (n = 9)
Accuracy, %	89.16	71.49 (8.47)	77.46 (6.52)	66.17 (6.24)
Sensitivity, %	76.47	87.80 (5.69)	90.81 (4.96)	85.13 (5.11)
Specificity, %	95.56	63.31 (12.21)	70.74 (10.18)	56.71 (10.17)
Positive predictive value, %	89.66	55.86 (9.24)	62.04 (8.76)	50.36 (5.60)
Negative predictive value, %	88.97	91.01 (4.19)	93.95 (3.12)	88.40 (3.21)



GASTROINTESTINAL ENDOSCOPY Volume89, No.4:2019

CAPSULE ENDOSCOPY

- Interpretation of capsule endoscopy images by endoscopist is very time consuming process and also depends on reviewers ability and effort

- AI has potential to overcome this problems and very promising for predicting accurate diagnosis

Ref.	Published year	Aim of study	Design of study	Number of subjects	Type of AI	Outcomes
Leenhardt *et al*[62]	2019	Detection of gastrointestinal angiectasia	Retrospective	600 control images and 600 typical angiectasia images (divided equally into training and test datasets)	CNN	Sensitivity: 100%, specificity: 96%, PPV: 96%, NPV: 100%.
Zhou *et al*[63]	2017	Classification of celiac disease	Retrospective	Training set: 6 celiac disease patients, 5 controls. Test set: additional 5 celiac disease patients, 5 controls	CNN	Sensitivity: 100%, specificity: 100% (for test dataset)
He *et al*[64]	2018	Detection of intestinal hookworms	Retrospective	440000 images	CNN	Sensitivity: 84.6%, specificity: 88.6%

World J Gastroenterol 2019 April 14; 25(14): 1640-1782

ROBOTICS ENDOSCOPY

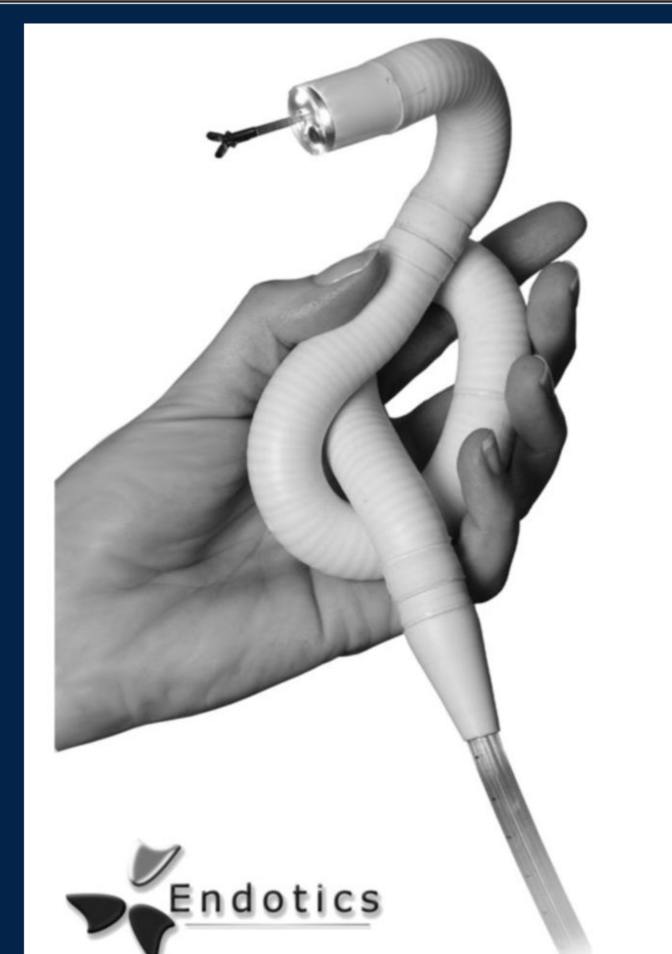
- The main goal of this biotechnology is to improve precision, effectiveness, safety and reliability, enhance the interventional capabilities of endoscopists and to augment the field of possible interventions
- Robots available today are capable of doing polypectomy, mucosectomy and endoscopic submucosal dissection (ESD)
- Robotic endoscopy is rapidly gaining popularity for ESD and NOTES procedures as a result of potential reduction in procedural time, safety and efficacy.
- The potential of robotic endoscopy is enormous even if today we are still in the evolution phase with very few clinical human trials carried out worldwide

Digestive Endoscopy 2019; 31:119–124

ROBOTICS ENDOSCOPY

Table 1 Endoscopy robots

Name	Development status	Animal trials	Human trials
Robotic-driven endoscope locomotion			
Aer-O-Scope (GI View Ltd, Ramat Gan, Israel)	FDA, CE	Yes	Yes
Endotics (ERA Endoscopy SRL, Peccioli, Italy)	CE		
Invendoscope (Invendo Medical GmbH, Kissing, Germany)	FDA, CE	Yes	Yes
Robotic-driven instrumentation of the endoscope			
MASTER (EndoMASTER Pte, Singapore)	Finalizing	Yes	Yes
ISIS-Scope/STRAS system (Karl Storz/IRCAD, Tuttlingen, Germany)	Finalizing	Yes	Waiting



Digestive Endoscopy 2019; 31:119–124

STRENGTH

- Able to solve problems related to quality, improve detection and characterization of colonic lesions
- Space for improvement: the more you train, the better performance you get
- Improvement of computer systems
- Operator independent hence universally reproducible
- Can provide same level of diagnostic certainty across all level of health care system (Top to bottom)

LIMITATIONS

- Need of multicenter and real life validation
- Need of high quality procedures: appropriate withdrawal time and withdrawal technique
- Possible effect on inspection behaviour
- Deep learning performance may vary by indication
- Need of cost-effectiveness validation: colonoscopy time, pathology costs, irrelevant findings,…
- Legal and regulatory doubts, reimbursement

TAKE HOME MESSAGE

- Artificial intelligence is an exciting frontier for endoscopic diagnosis of various GI problems
- CNN is main model for image recognition in endoscopy by artificial intelligence
- Data should be stored in Electronic Medical Record so that can be used in future for developing AI models and algorithms

The Four Industrial Revolutions

First (1760 to 1840): the steam engine

Second (1870 to 1914): the telegraph, the telephone, the light bulb; industries powered by steam & electricity

Third (1969 to 2000): New information and communication technology (Internet) converge with renewable electricity to digitize global manufacturing

Fourth (2000 to future): Artificial Intelligence, Big Data, and Machine Learning are general purpose technologies like steam engine and electricity


USD 2.1 Billion
USD 36.1 Billion
2018
2025
CAGR
50.2%
▪ AI in healthcare market estimated to be valued at USD 2.1 billion in 2018 and further expected to reach USD 36.1 billion by 2025, at a CAGR of 50.2% during forecast period
▪ Machine learning technology expected to hold major share of the AI in healthcare market in 2018
▪ Among machine-learning technologies, deep learning expected to hold largest size of AI healthcare market
▪ Availability of big data and demand to reduce healthcare cost drive the growth of AI in healthcare market

Technologies That Will Transform Health Care

Artificial Intelligence
Machine Learning
Predictive Analytics
Precision Medicine
Cloud Computing

High Performance Medicine
Eric Topol, Nature Medicine, Jan 2019

Medicine is at crossroad of major trends

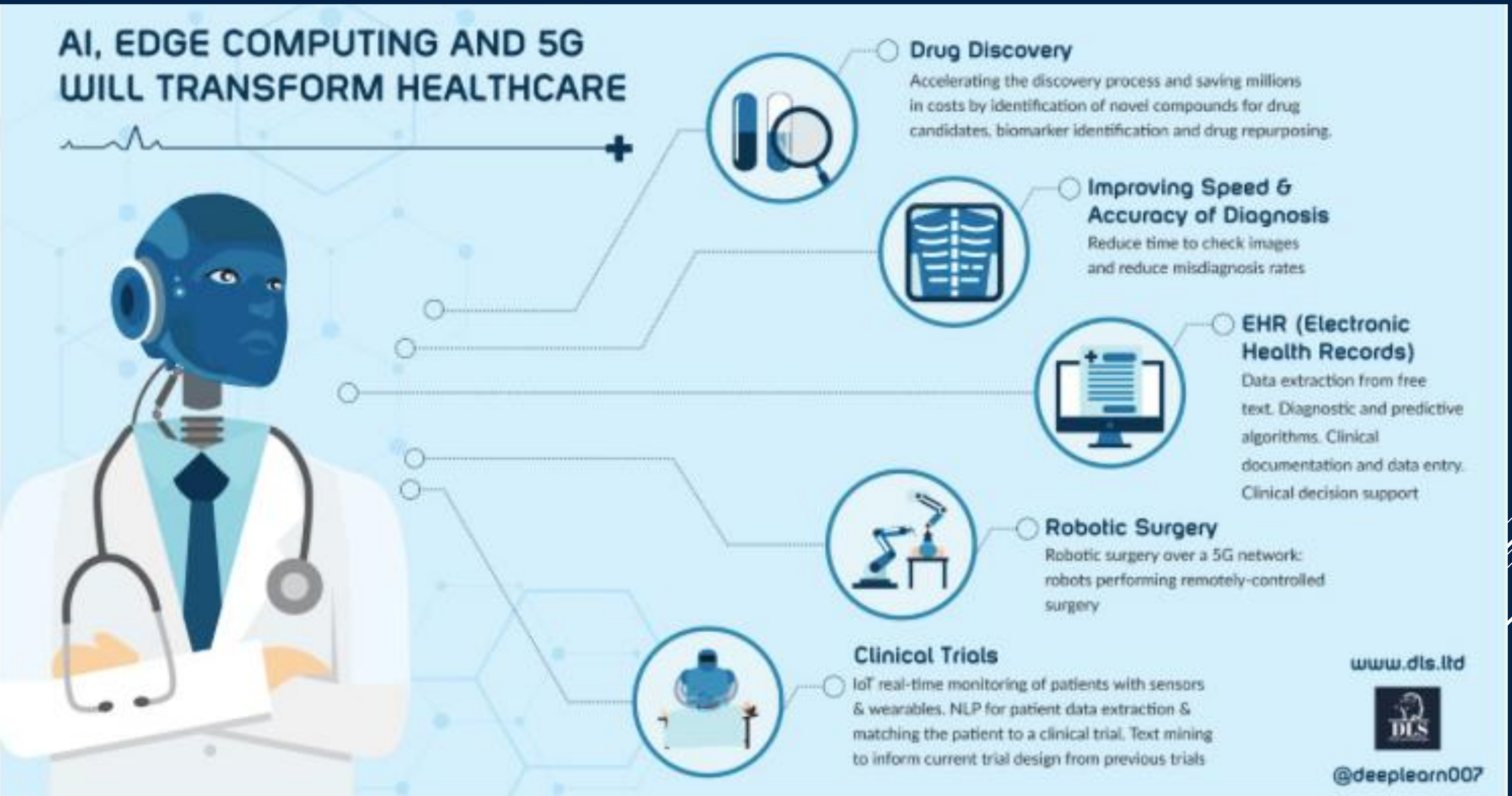
Disruption of a failed business model

Generation of data from imaging, biosensors, genome sequencing, and electronic medical records that exceeds ability of human analysis and requires machine learning.

Cloud Computing

Ability to preform predictive analytics on huge amounts of data

Predict and Prevent Precision Medicine



AI, EDGE COMPUTING AND 5G
WILL TRANSFORM HEALTHCARE
Drug Discovery
Accelerating the discovery process and saving millions in costs by identification of novel compounds for drug candidates, biomarker identification and drug repurposing.
Improving Speed & Accuracy of Diagnosis
Reduce time to check images and reduce misdiagnosis rates
EHR (Electronic Health Records)
Data extraction from free text. Diagnostic and predictive algorithms. Clinical documentation and data entry. Clinical decision support
Robotic Surgery
Robotic surgery over a 5G network: robots performing remotely-controlled surgery
Clinical Trials
IoT real-time monitoring of patients with sensors & wearables. NLP for patient data extraction & matching the patient to a clinical trial. Text mining to inform current trial design from previous trials
www.dls.ltd
@deeplearn007

AI Will Affect All of Health Care

Drug discovery

Robotic surgery

Personalized medicine

Managing medical records and other data

Health monitoring via wearable trackers

Medication management

Healthcare system analysis

Workflow and administrative tasks

AI & Pharma

Batting average of turning compound into medicine is 0.100
Price tag of developing new drug $2.6 billion
Mature data sets: curating safety reports
Drug design: identify targets (receptor on cells); identify compounds bind to target; identify compounds that can travel to target in the body
Biological understanding

Verb Surgery

Google J&J joint venture

All surgical robots are connected via Internet

Record data from each procedure and apply ML to learn best surgical practices

Called Surgery 4.0 with integration of virtual reality and 3-D video microscopy

ML draws upon intraoperative imaging as well as relevant patient clinical data will redefine past practice and improve outcomes

Workflow & Administrative Tasks

Accenture estimates could save $18 billion a year
Save time on routine tasks
Johns Hopkins and GE AI for scheduling bed assignments and managing requests for unit assistance
Nuance cut documentation time and improve report quality by Computer assisted physician documentation

Hospitals & Health Systems

Detect patterns & normalize data
To map care pathways and processes
Reduce costs in care
Improve outcomes
MACRA & MIPS have bonus payments and decreased payments based on quality and efficiency of care delivered by individual physicians

Stat News

Casey Ross, May 13, 2019

Cleveland Clinic, Yale New Haven, Johns Hopkins
Central Monitoring Units
77,000 phone calls to nurses in one month
Alert nurses to cardiac emergency about to occur
Machine learning utilized to spot emerging emergencies

Health Care Applications of AI

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5568844/

Kaiser Permanente Medical Group studied 650,000 hospitalized patients, 20,000 required ICU care

20,000 in ICU are four times more likely to die than if deterioration was prevented in first place

Created predictive analytic model to identify which patients today are most likely to end up in ICU tomorrow

Monitor health status of all patients and alert physicians via automated early warning system to patients who are at risk of needing ICU care

Definitions

Artificial Intelligence (AI): the mimicking of human cognition by computers that can reason, discover meaning, generalize, and learn from experience

Machine Learning (ML): Algorithms sift through vast numbers of variables looking for patterns that predict outcomes by combining them in nonlinear and highly interactive ways without explicit programming. Computer learns from data over time and allows us to use large amounts of new kinds of more complex data.

- Supervised learning: Goal of predicting a known output or target. Automated EKG interpretation; automated detection of lung nodule on CT scan.
- Unsupervised learning: No outputs to predict. Finding naturally occurring patterns or groupings within the data. Redefine disease according to pathophysiologic mechanisms. Eosinophilic subtype of asthma which responds to therapy targeting eosinophil secreted cytokine IL-13.
- Deep learning: Uses a cascade of multiple layers of nonlinear processing units for pattern recognition. Each successive layer uses output from previous layer as input for analysis.

Definitions

Algorithm: Set of rules that precisely defines a sequence of operations that lead to a goal or output

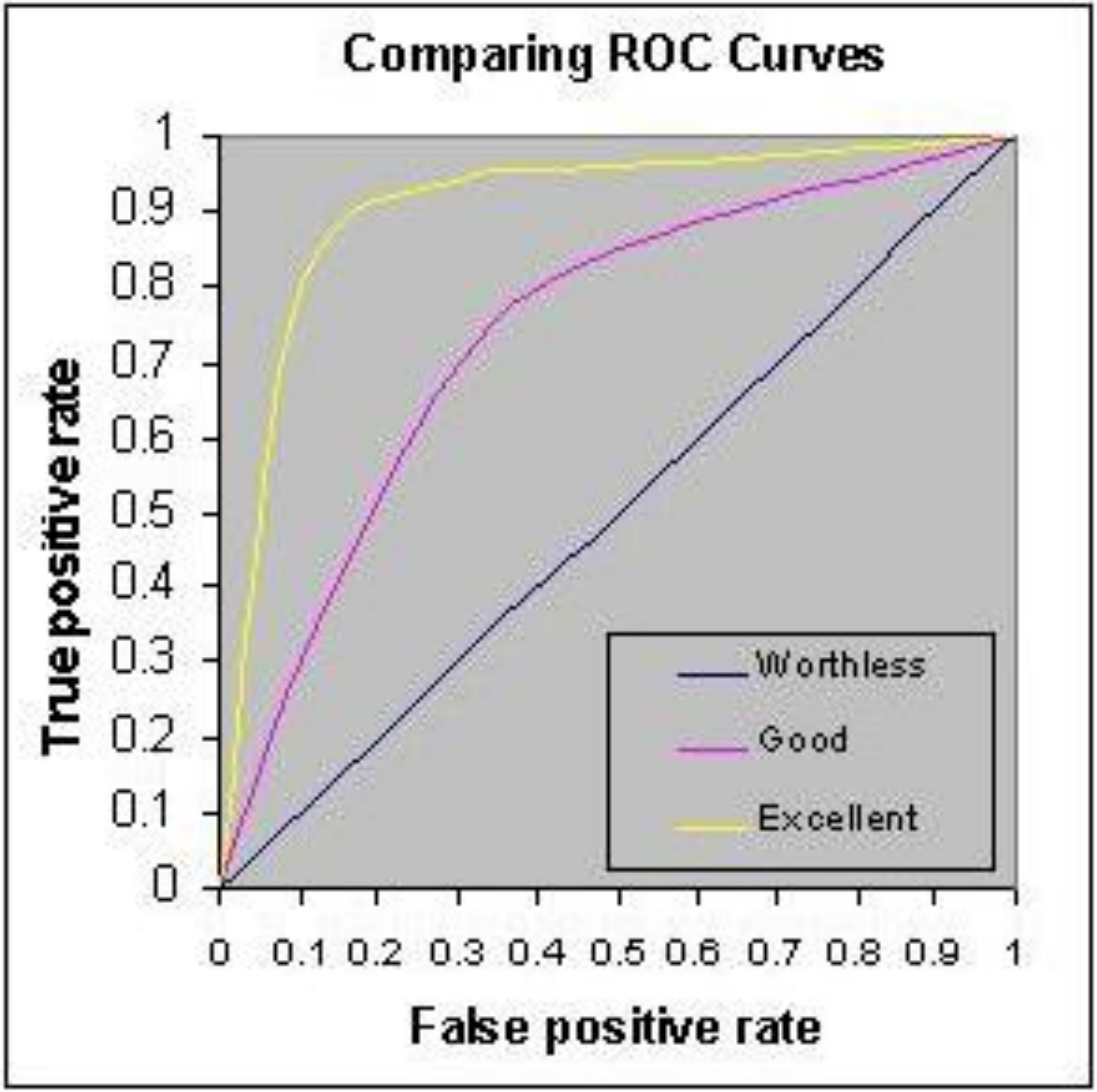
Artificial neural network (ANN): Computing systems inspired by human brain that perform tasks by looking for patterns without being programed with task specific rules. ANN learn from data.

Natural language processing (NLP): Computer being able to process and analyze large amounts of human language data for syntax, semantics, discourse, and speech recognition

Computer vision (CV): Interdisciplinary field studies how computers can acquire, process, and analyze digital images to extract high dimensional data from pictures and videos.

Table 3 | Selected reports of machine- and deep-learning algorithms to predict clinical outcomes and related parameters

Prediction	*n*	AUC	Publication (Reference number)
In-hospital mortality, unplanned readmission, prolonged LOS, final discharge diagnosis	216,221	$0.93^{*}0.75^{+}0.85^{\#}$	Rajkomar et al.[96]
All-cause 3-12 month mortality	221,284	0.93^{*}	Avati et al.[91]
Readmission	1,068	0.78	Shameer et al.[106]
Sepsis	230,936	0.67	Horng et al.[102]
Septic shock	16,234	0.83	Henry et al.[103]
Severe sepsis	203,000	$0.85^{@}$	Culliton et al.[104]
Clostridium difficile infection	256,732	0.82^{++}	Oh et al.[93]
Developing diseases	704,587	range	Miotto et al.[97]
Diagnosis	18,590	0.96	Yang et al.[90]
Dementia	76,367	0.91	Cleret de Langavant et al.[92]
Alzheimer's Disease (+ amyloid imaging)	273	0.91	Mathotaarachchi et al.[98]
Mortality after cancer chemotherapy	26,946	0.94	Elfiky et al.[95]
Disease onset for 133 conditions	298,000	range	Razavian et al.[105]
Suicide	5,543	0.84	Walsh et al.[86]
Delirium	18,223	0.68	Wong et al.[100]



Comparing ROC Curves
True positive rate
False positive rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Worthless
Good
Excellent

AI Equals or Outperforms Physician

Cardiologist-level arrhythmia detection with convolutional neural networks. arXiv preprint arXiv: 1707.01836

Development & validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundal photographs. JAMA 316, 2402-2410. 10.1001/jama. 2016. 17216 [PubMed]

Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. JAMA 318, 2199-2210. 10.1001/jama 2017.14585 [PubMed]

Dermatologist-level classification of skin cancer with deep neural networks. Nature 542: 115. 10.1038/nature21056 [PubMed]

Predicting non-small cell lung cancer prognosis by fully automated microscopic pathology image features. Nat Commun. 2016; 7(7): 12474.

Google DeepMind AI Diagnoses Eye Diseases

Jeffrey De Fauw, et. al. Nature Medicine, 13 August, 2018

94% of patient optical CT scans at Moorsfield Eye Hospital were correctly diagnosed based on AI

Identified portions of optical coherence tomography scans used to make AI diagnosis

AI identified 50 different eye diseases

Across all cases AI error rate 5.5% vs top two human specialists (6.7% & 6.8%)

Radiology

2 billion CXR performed worldwide
AI outperformed 4 radiologists in detecting pneumonia over 112,000 CXR with AUC of 0.76
AI outperformed 17/18 radiologists in detecting cancerous nodule over 34,000 CXR
AI outperformed ED MDs in diagnosing wrist fractures increasing sensitivity from 81% to 92% and reducing misinterpretation by 47%

Radiology

AI applied to bone films for fracture and estimation of aging, classification of TB, CT scans for lung nodules, liver masses, pancreatic cancer, coronary calcium scores, brain scans for hemorrhage, head trauma, MRI, echocardiograms, and mammograms.

AUC for hip fracture 0.99

AUC for intracranial bleeding 0.84

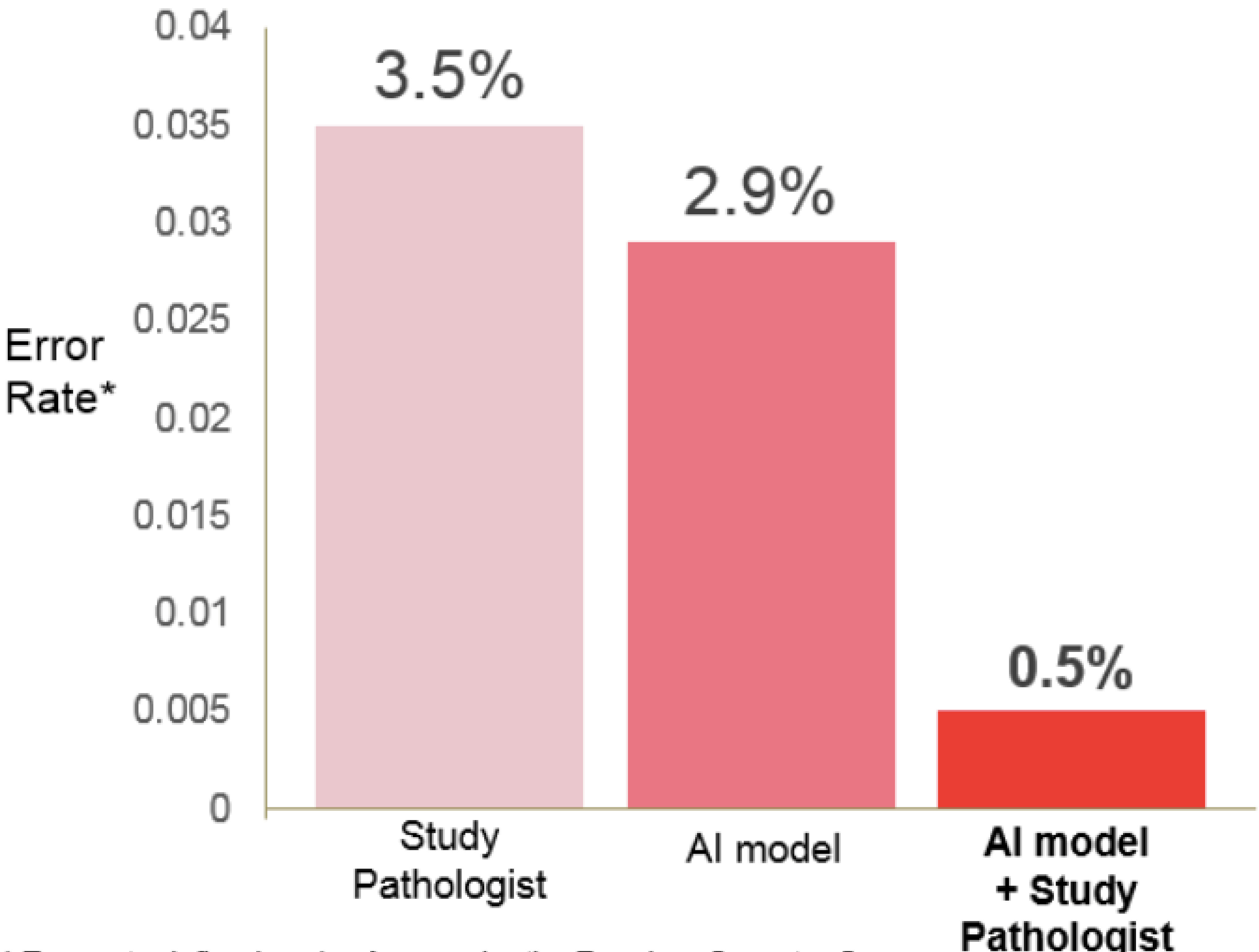
AUC for liver masses 0.84

AUC for acute neurologic screening 0.56

Pathology

Much slower to adopt digitization of slides
ML using brain tumor DNA methylation patterns led to improved classification compared with traditional histological approach
Combination of AI and pathologist working together led to best accuracy and faster results in study of breast cancer micrometastases

(AI + Pathologist) > Pathologist



* Error rate defined as 1 – Area under the Receiver Operator Curve

** A study pathologist, blinded to the ground truth diagnoses, independently scored all evaluation slides.

Dermatology

Study of 130,000 skin lesions AI AUC 0.96 for carcinoma and 0.94 for melanoma

AI vs. 58 international dermatologists to detect melanoma revealed AUC for AI of 0.86 and for doctors of 0.79

Most skin cancers worldwide are diagnosed by primary care physicians and not dermatologists and inaccuracy has been a documented problem

Cardiology

AI to diagnose MI on 549 ECG sensitivity of 93% and specificity of 90% similar to cardiologist readings
64,000 one lead ECG AI and cardiologist readings were similar for 14 different conduction disturbance
8000 echocardiograms analyzed by AI showed AUC 0.93 for hypertrophic cardiomyopathy, AUC 0.87 for cardiac amyloid, and AUC 0.85 for pulmonary artery hypertension

Gastroenterology

Finding <5 mm adenomatous or sessile polyps

Study of 325 patients with 466 tiny polyps revealed AI accuracy of 94% and negative predictive value of 96% during real time, routine colonoscopy

AI worked equally well for novice and expert

No need vital dye to detect the polyps

Mental Health

350 million have depression worldwide
Digital tracking of depression and mood via keyboard interaction, speech, voice, facial recognition, sensors, and use of interactive chatbots.
Facebook posts have predicted depression diagnosis later documented in medical record
ML predicting medication usage, depression, suicide, bouts of psychosis in schizophrenia

Digital Phenotyping of Mental State

Speech: volume, vowel space, word choice, length of phrases, coherence, sentiment

Voice: valence, tone, pitch, intonation

Keyboard: Reaction time, attention, memory, cognition

Smartphone: activity, movement, communication, social media, tweets, emoji

Face: Emotion, tics, smiles, look at ground, eye movement, eye contact

USC Software

74 acoustic features
Voice quality, shimmer, pitch, volume, jitter, prosody
Predicted marital discord as well or better than therapists

Sandy Pentland's Cogito

Honest signals: tone, fluidity, conversational engagement, energy
Monitor mental health of patients by recording audio diary
Real time analysis of conversation being used by insurance companies to handle customer calls
VA using with at risk veterans with 24/7 phone monitoring

AI and PTSD
Dave Philipps, NY Times, April 22, 2019

NYU & SRI International study

129 male vets, 32 years old, without depression, alcohol abuse

CAPS identified 52 with PTSD, 77 without PTSD

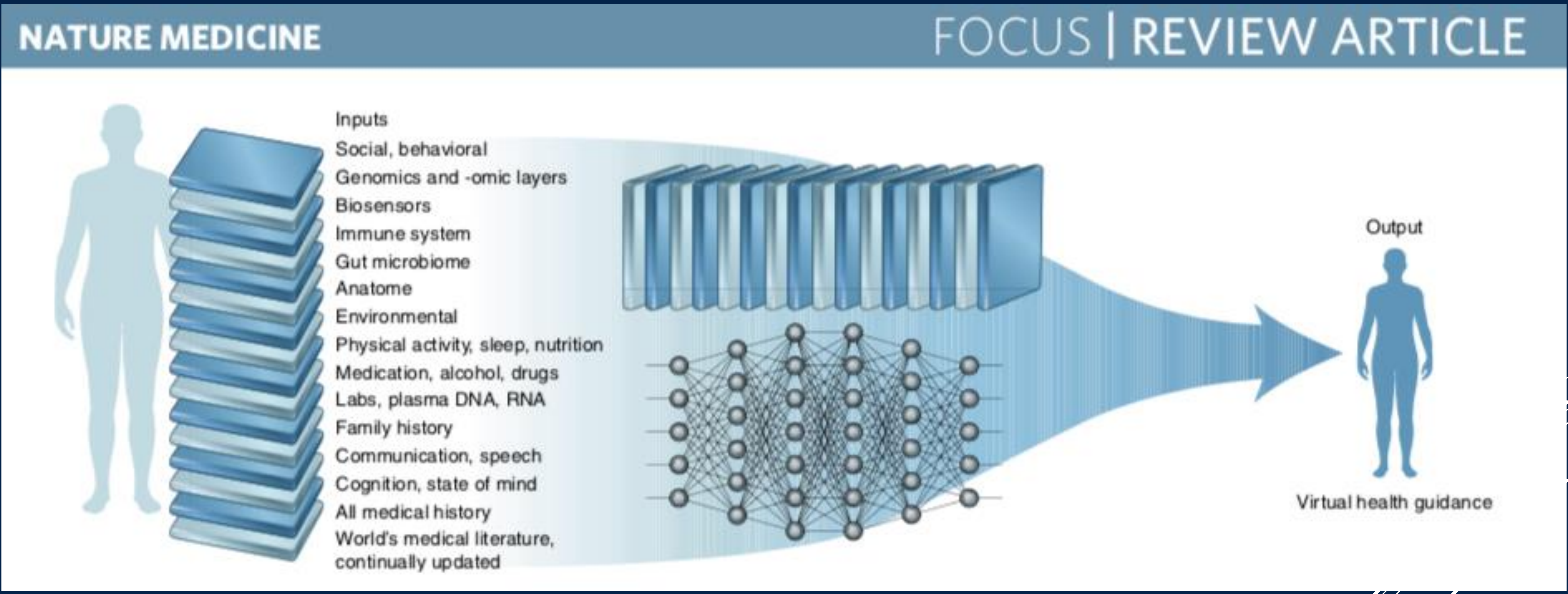
Interviews deconstructed into 40,526 features

AI searched the features and identified 18 features (flatter speech, less articulation of tongue, monotonous tone) predictive of PTSD 89% of the time

Experts thought best feature would be agitated speech

Table 2 | 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
Zebra Medical	July 2018	Coronary calcium scoring
Bay Labs	June 2018	Echocardiogram EF determination
Neural Analytics	May 2018	Device for paramedic stroke diagnosis
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
FOCUS | REVIEW ARTICLE
Inputs
Social, behavioral
Genomics and -omic layers
Biosensors
Immune system
Gut microbiome
Anatome
Environmental
Physical activity, sleep, nutrition
Medication, alcohol, drugs
Labs, plasma DNA, RNA
Family history
Communication, speech
Cognition, state of mind
All medical history
World's medical literature, continually updated
Output
Virtual health guidance

Michael Snyder
Nature Medicine 25, 792-804 (2019)

18 had Stage II hypertension
9 diabetes, but different paths to the disease
Patient with recurring strokes on wrong medicine
Genetic variant linked to enlarged weak heart
Lymphoma

A.I. Versus M.D.

Siddhartha Mukherjee, New Yorker, April 3, 2017

“I think if you work as radiologist you are like Wile E. Coyote in the cartoon. You’re already over the edge of the cliff, but you haven’t looked down. There’s no ground underneath. It’s just completely obvious that in five years deep learning is going to do better than radiologists. It might be ten years. I said this at a hospital. It did not go down too well.”

Geoffrey Hinton (father of Deep Learning), University of Toronto

Babylon Health

MRCGP exam in UK tests trainee general practitioners
Average passing grade 72% over last five years
Babylon Health received 82%
Chatbot asks questions of patient to come to dx.
NHS 26,000 citizens in London switched from GP clinics to Babylon

A.I. Versus M.D.

Siddhartha Mukherjee, New Yorker, April 3, 2017

"I'm interested in magnifying human ability…The industrial revolution amplified the power of human muscle. When you use a phone, you amplify the power of human speech…Did the phone replace the human voice? No, the phone is an augmentation device. The cognitive revolution will allow computers to amplify the capacity of the human mind in the same manner. Just as machines made human muscles a thousand times stronger, machines will make the human brain a thousand times more powerful."

Sebastian Thrun (Stanford, Google X) mother died of breast cancer at age 49.

Human + Machine: Reimagining Work in the Age of AI
Paul Daugherty & H. James Wilson, 2018

Human & machine intelligence synergistic, not competitive
Humans and AI Cobots will work together.
There are eight new fusion skills necessary for successful human and computer optimal results

Human + Machine: Reimagining Work in the Age of AI

Paul Daugherty & H. James Wilson, 2018

Rehumanizing Time: increase time available for distinctly human tasks like interpersonal interactions, creativity, and decision making

Responsible normalizing: Responsibly shaping the purpose and perception of human-machine interaction as it relates to individuals, businesses, and society

Judgment Integration: Ability to decide a course of action when machine is uncertain what to do

Intelligent interrogation: Knowing how best to ask questions of AI across levels of abstraction to the insights you need

Human + Machine: Reimagining Work in the Age of AI

Paul Daugherty & H. James Wilson, 2018

Bot-based empowerment: Working with AI to extend your human capabilities and create superpowers in business processes and careers

Holistic melding: The ability to develop robust mental models of AI agents to improve process outcomes

Reciprocal apprenticing: performing tasks with AI so they can learn new skills & on the job training for people so they can work well with AI enhanced processes

Relentless reimagining: Rigorous discipline of creating new processes and business models from scratch, rather than automating old processes

Why Physicians Should Learn to Code

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3622380/

Don't want technicians to define role of physician

Boost career

Important to be able to talk to data scientists

GitHub, Medium, Stack Overflow

ProgrammingForPhysicians.com

- Open access course
- 12 lessons
- 30-60 minutes each lesson

Adapting to Artificial Intelligence
Saurabh Jha & Eric J. Topol. JAMA November 29, 2016

Combination of big data and artificial intelligence will change medicine

Examine future of radiology & pathology

Radiology & pathology: transition from subjective perceptual skill to objective science

Operant conditioning trained pigeons to spot calcifications on mammograms and detect cancer on histology PLoS One. 2015; 10(11):e0141357

Adapting to Artificial Intelligence

Saurabh Jha & Eric J. Topol. JAMA November 29, 2016

To avoid being replaced by computers they must allow themselves to be displaced by computers

Radiology & pathology should merge into single entity (information specialist) whose job will not be extracting information from images and histology but to manage the information extracted by artificial intelligence in the clinical context of the patient