

Life After COVID

NAAMA 43rd National Medical Convention

Irvine, California | Sept 3rd - 5th



SEPT
4th
2021

Day 1: Medical Convention

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SEPT | 11:30 AM - 12:00 PM

4th

2021

Innovation And A.I. In Medicine



Munier Nazzal MD, MBA, CPE

Professor of Surgery Vice-Chair of Education and
Research. University of Toledo

President of University of Toledo Physicians

Artificial Intelligence in Healthcare Here to Stay

Munier Nazzal, MD, MBA, CPE, FRCS, FACS, DFSVS, FACCWS

Professor, Vice Chair of Research and Education

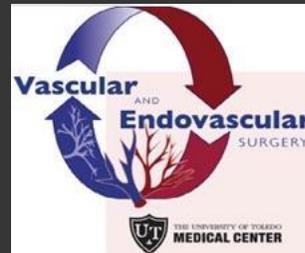
President of the University of Toledo Physicians

Director, Master of Clinical Research Program

Chief Division of Surgery Education and Surgery Simulation

Chief Division of Vascular, Endovascular and Wound Surgery

University of Toledo, Ohio



NAAMA
Education, Leadership, Philanthropy

Irvine, California, September 4-5, 2021



COVID-19

- COVID-19 pandemic has exposed the need for AI in the medical field
- Telemedicine long hailed truly become realized until 2020
- AI and ML the future of delivering health care at global public health scale.

**Survey of more
than 200
organizations
across industries**

The COVID-19 crisis presents an opportunity that few feel equipped to pursue.

Although most executives agree that innovating the business will be critical ...

90%

believe that the COVID-19 crisis will fundamentally change the way they do business over the next 5 years

85%

are concerned that the COVID-19 crisis will have a lasting impact on their customers' needs and wants over the next 5 years

... few feel equipped to face the challenge.

21%

have the expertise, resources, and commitment to pursue new growth successfully

2/3

believe that this will be the most challenging moment in their executive career

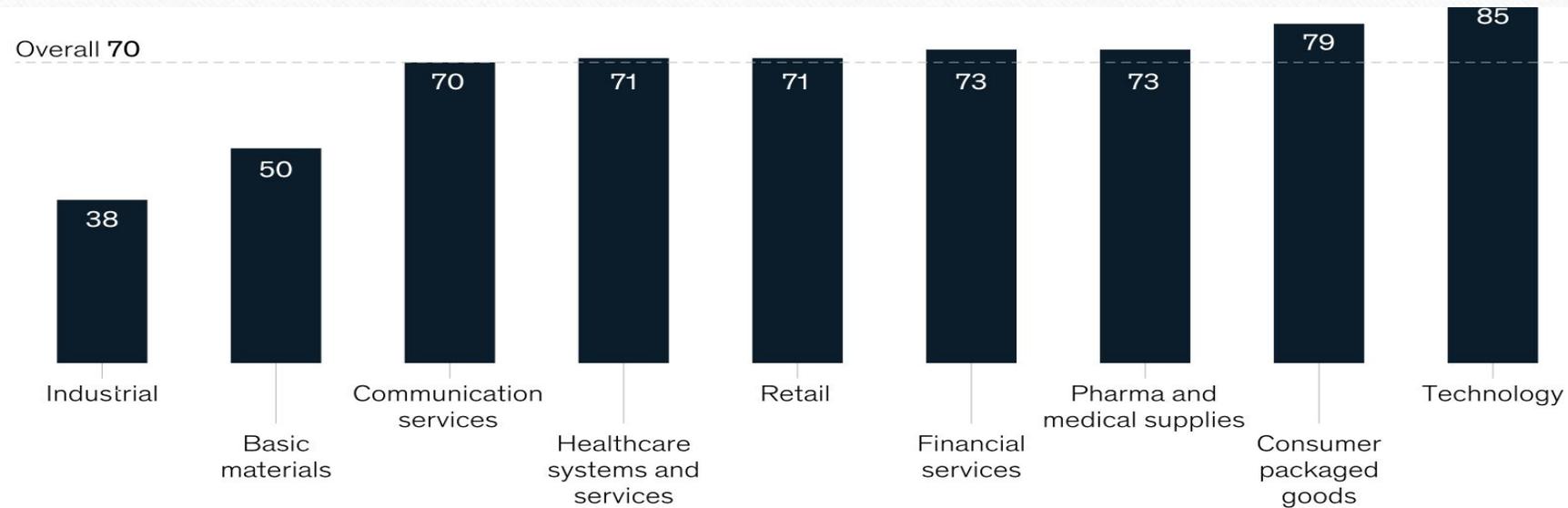
McKinsey
& Company



More than three-quarters of executives believe that the 2020 global health crisis will create significant new opportunities for growth.

"Throughout the COVID-19 crisis, the majority of organizations have been maintaining or even increasing their investments in artificial intelligence (AI), according to polling results from a Gartner webinar in May 2020."

COVID-19 Opportunity for Growth

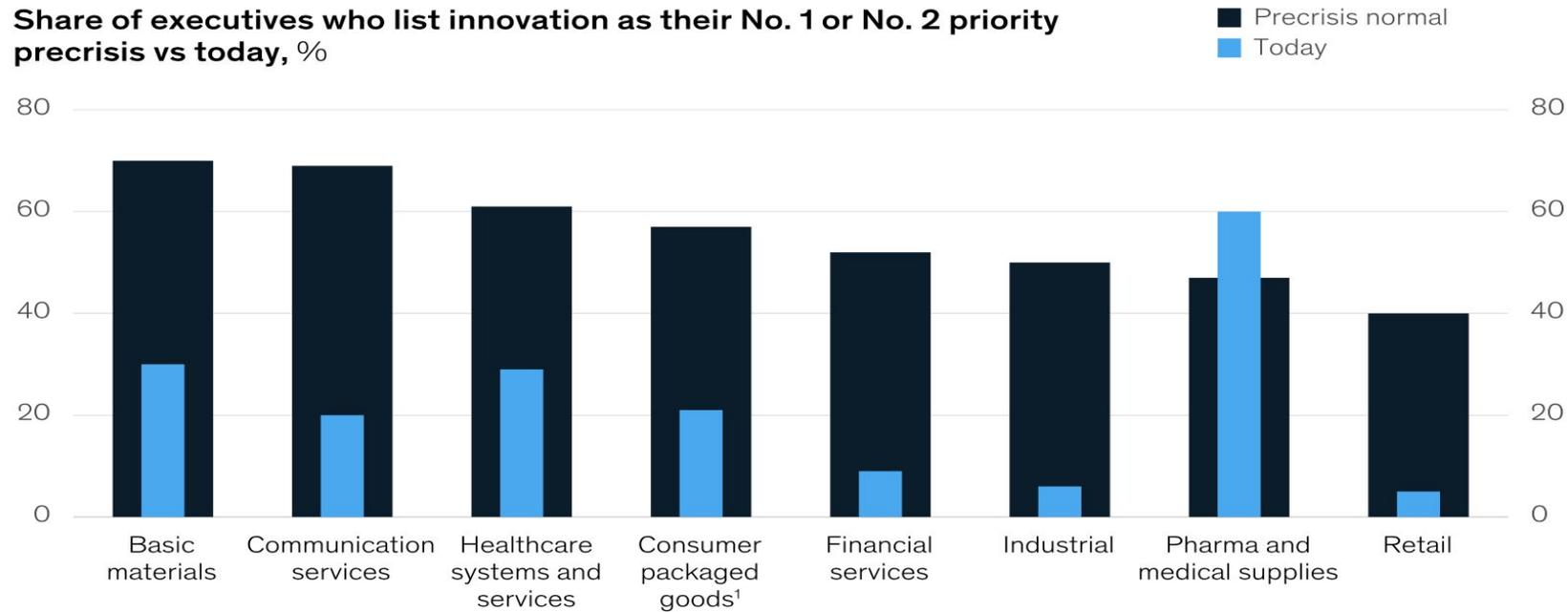


Source: McKinsey Innovation through Crisis Survey, April 2020

Nearly three of four executives agree that changes brought about by COVID-19 will be a big opportunity for growth, with variation across industries.

Across surveyed industries, only pharma and medical products has increased its focus on innovation during the COVID-19 crisis.

Share of executives who list innovation as their No. 1 or No. 2 priority precrisis vs today, %

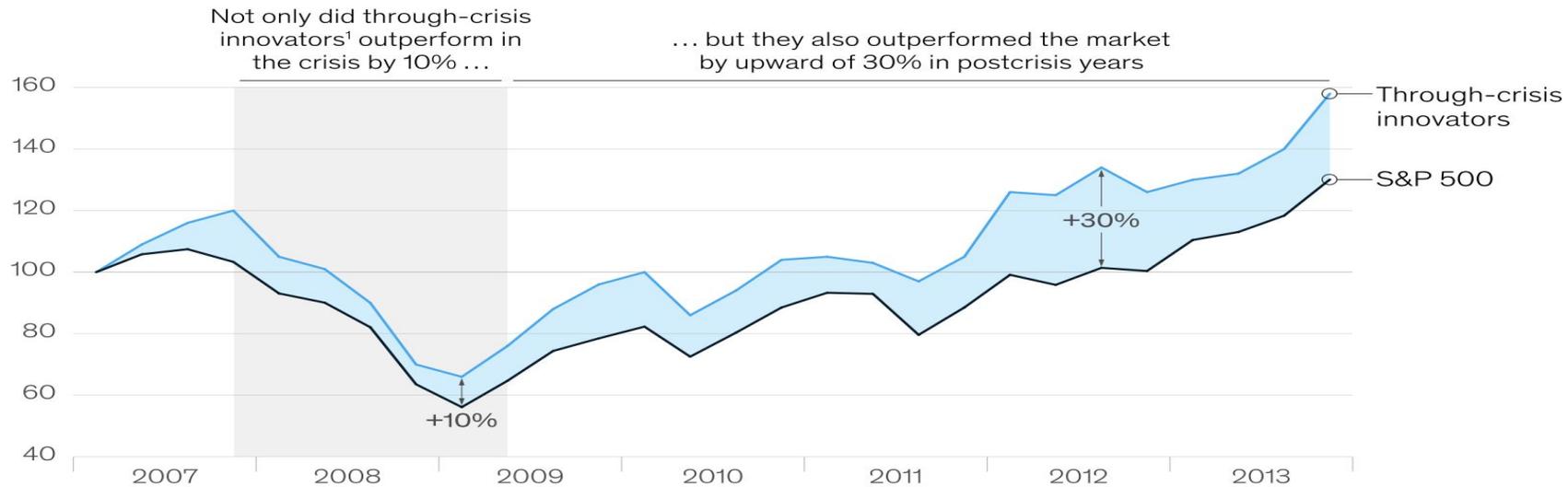


¹Includes grocery-retail businesses.

Source: McKinsey Innovation through Crisis Survey, April 2020

History suggests that companies that invest in innovation through a crisis outperform peers during the recovery.

Normalized market capitalization, index (Q1 2007 = 100)



¹Identified as companies on the *Fast Company* World's 50 Most Innovative Companies list for ≥ 2 years through a crisis, normalized to 2007.

What makes something a good idea?

Equation to use with valuable problems to solve



¹Willingness to pay is a proxy for customer ascribing meaningful value. Whether companies choose to charge and who pays is a business-model decision.

Radiomics

- Form of computer vision, to develop methods to instantaneously diagnose COVID-19 patients using CT imaging alone
- Uses imaging and algorithms to enhance diagnostic accuracy via interpretation of vast amounts of imaging data
- Tumors
- Response to treatment.
- AI and machine learning can predict fractures of the spine, ankle, and upper extremity better than orthopedic surgeons

overview

Artificial intelligence has endless applications

- Healthcare
- Banking and Finance
- Self-Driving Cars
- Surveillance
- Robotics
- Natural language processing

Focusing on using AI for human modeling and motion analysis



THE UNIVERSITY OF TOLEDO
MEDICAL CENTER

AI Future

The AI-associated healthcare market is expected to grow rapidly and reach USD 6.6 billion by 2021 corresponding to a 40% compound annual growth rate

Bohr A and Memarzadeh K, Artificial intelligence in HealthCare, 2020





AI

John McCarthy in his Dartmouth Summer Research Project in 1956

Analyze

Understand

Predict

Machines that
function
“appropriately”
and with
“foresight”

AI is the marriage of
numerical calculations
done with the aid of a
computer to create a
form of intelligence.

Use of a computer to interpret a situation and/or help accomplish a task, and in short to
make our lives easier and better

AI

Make decisions by Analyzing big data, these branches of AI have enormous potential to improve decision making



AI in Medicine



MACHINE
LEARNING



DEEP LEARNING

Machine Learning

- Machine learning is a field analyzing how computer algorithms and statistics can be used to autonomously improve through trial and error with pattern recognition



Deep Learning

- Deep learning, or deep structured learning, is a vaster application of machine learning concepts whose basis is centered around the formation and utilization of artificial “learning” or “neural” networks (ALNs and ANNs) that are based on the structure of biological brains, such as being multilayered



Natural Language Processing

Deals with pattern recognition of data that comes in unstructured formats

Types of Computer learning

In modeling risk, the computer is doing more than merely approximating physician skills but finding novel relationships not readily apparent to human beings.



Supervised learning: Predicting a known output, automated learning of EKG, classification tasks, automated lung nodule recognition, risk estimation

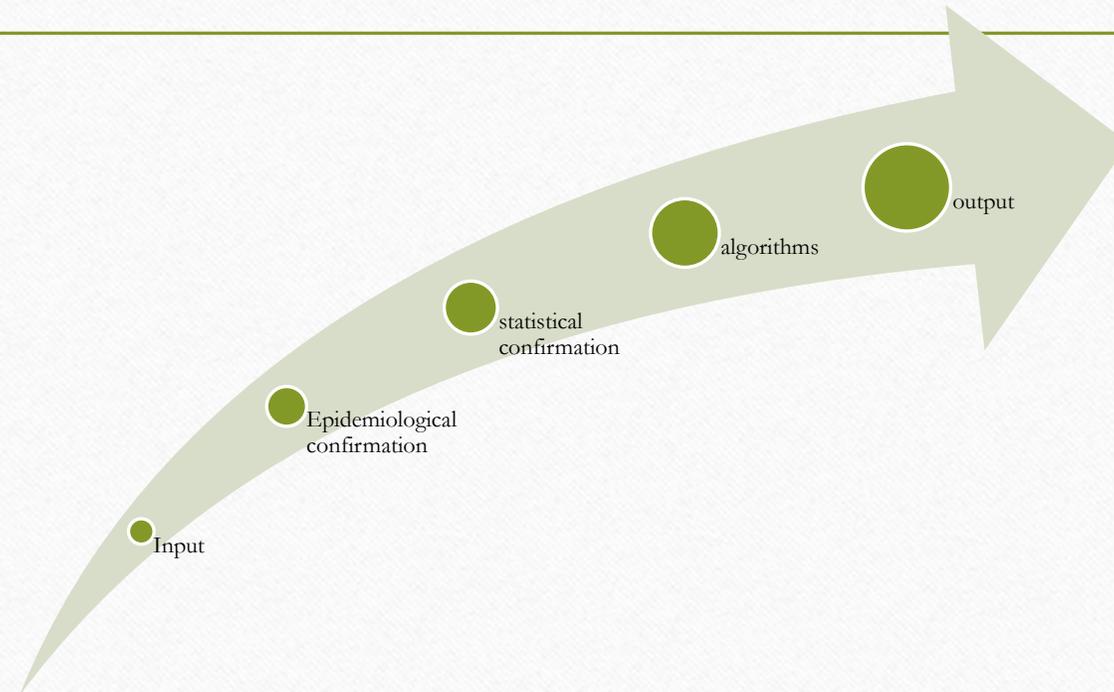


Unsupervised learning: No output to predict, find naturally occurring patterns or groupings within the data.

evaluated by its performance in subsequent supervised learning tasks

Precision medicine initiative

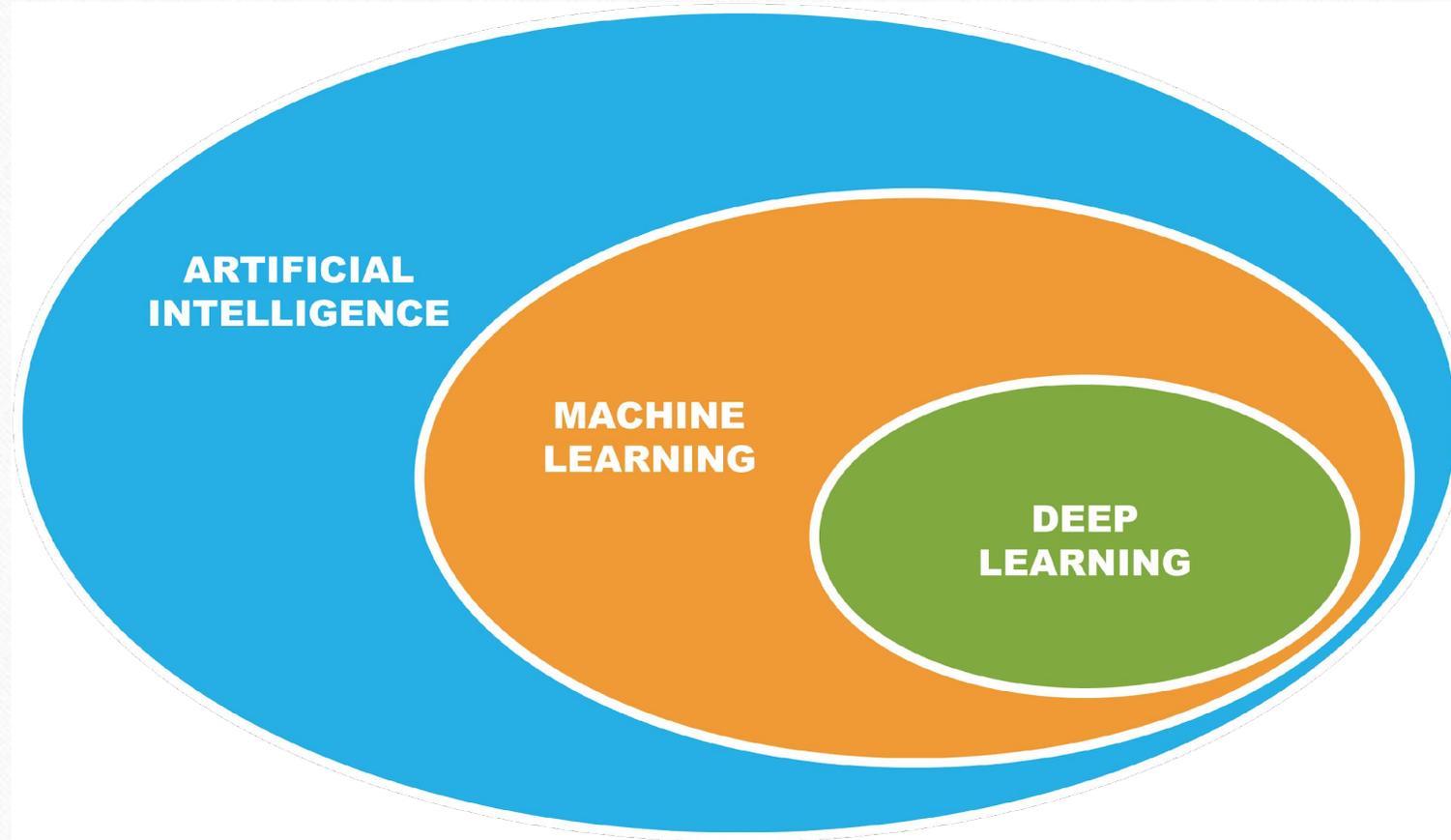
Stages in AI and ML



Inadequately addressing the epidemiologic and statistical principles may lead to misrepresentation

Often, overestimation, of the clinical performance and usefulness of the artificial intelligence tools.

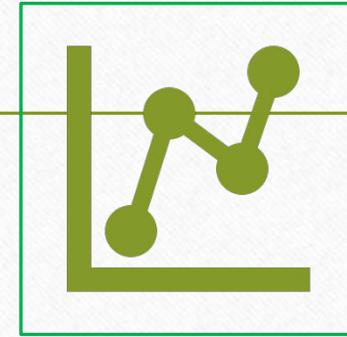
Deep learning



ML



Machine learning is the scientific discipline that focuses on how computers learn from data



Arises at the intersection of statistics, which seeks to learn relationships from data, and computer science, with its emphasis on efficient computing algorithms

Marriage of mathematics and computer science

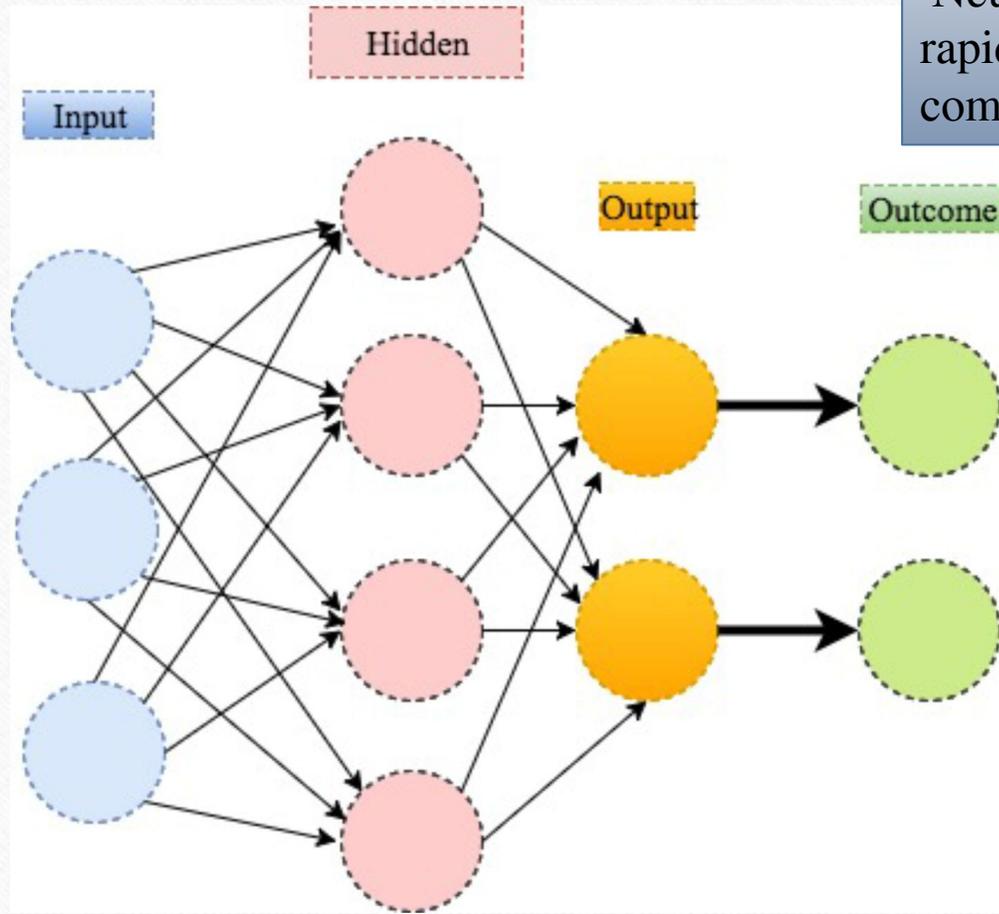
Artificial intelligence in healthcare: past, present and future

Fei Jiang,¹ Yong Jiang,² Hui Zhi,³ Yi Dong,⁴ Hao Li,⁵ Sufeng Ma,⁶ Yilong Wang,⁷
Qiang Dong,⁴ Haipeng Shen,⁸ Yongjun Wang⁹

June 2017

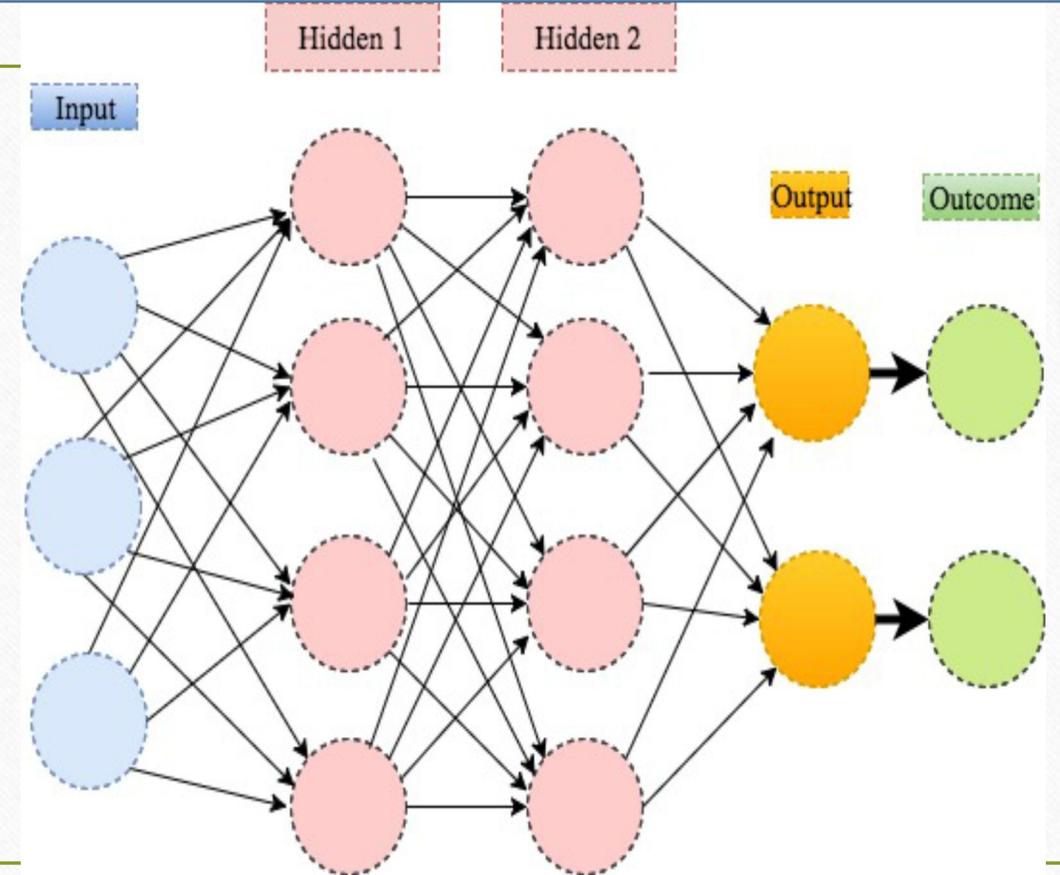
Neural network.

$$a_i = h \left\{ \sum_{k=1}^D w_{21k} f_k \left(\sum_{l=1}^p w_{1l} X_{il} + w_{10} \right) + w_{20} \right\}.$$



Deep learning with two hidden

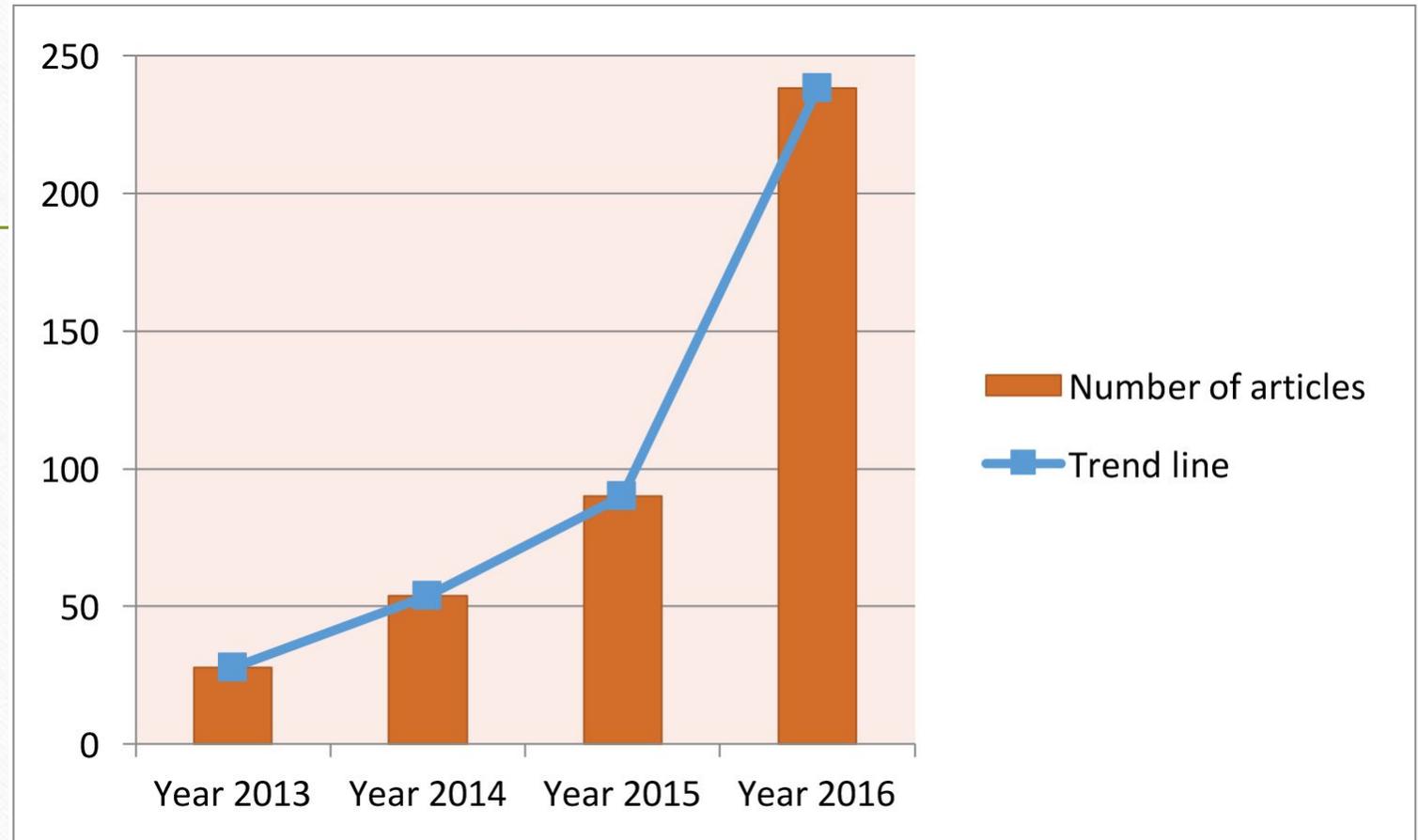
Neural network with many layers: Increase complexity of data, rapid development of modern computing. Can explore more complex non-linear patterns in the data.



Linear data such as Cancer, stroke, etc

Complex and non linear such as imaging analysis

Deep Learning with non linear data



ML algorithms

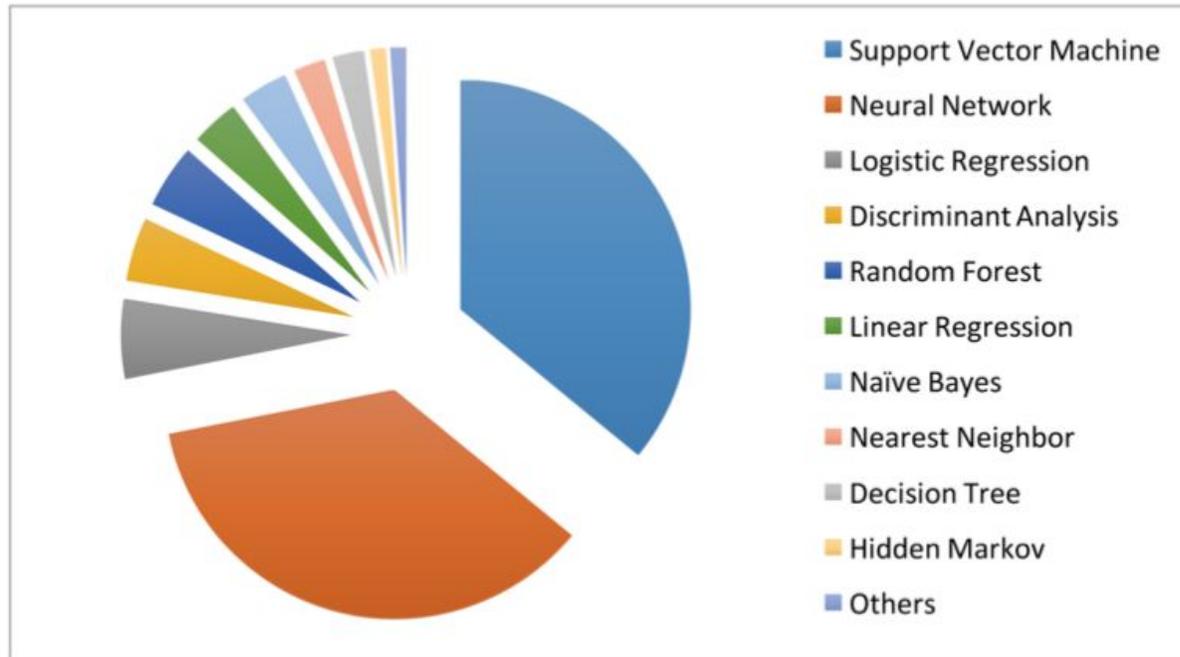


Figure 5 The machine learning algorithms used in the medical literature. The data are generated through searching the machine learning algorithms within healthcare on PubMed.

Based on Pubmed data

Can AI Defeat standard Medicine?

- Chess
- Jeopardy
- Law
- Labor
- Machine automation
- Furniture assembly
- Investment advice

- Imaging
- Dermatology
- Diagnostic
- Pathology
- Ophthalmology
- Drug discovery

Devices for monitoring health and for delivering treatment

AI in Medicine

- Wearable devices (Implantable nurse)
- Monitoring devices (implantable nurse)
- Triage nurses

Should we use AI and ML?



AI system can help to reduce diagnostic and therapeutic errors that are inevitable in the human clinical practice



AI system extracts useful information from a large patient population to assist making real-time inferences for **health risk alert** and **health outcome prediction** .



Improve accuracy and assist in decision making in cases requiring huge amount of data “genomics”

Data Types considered in AI literature

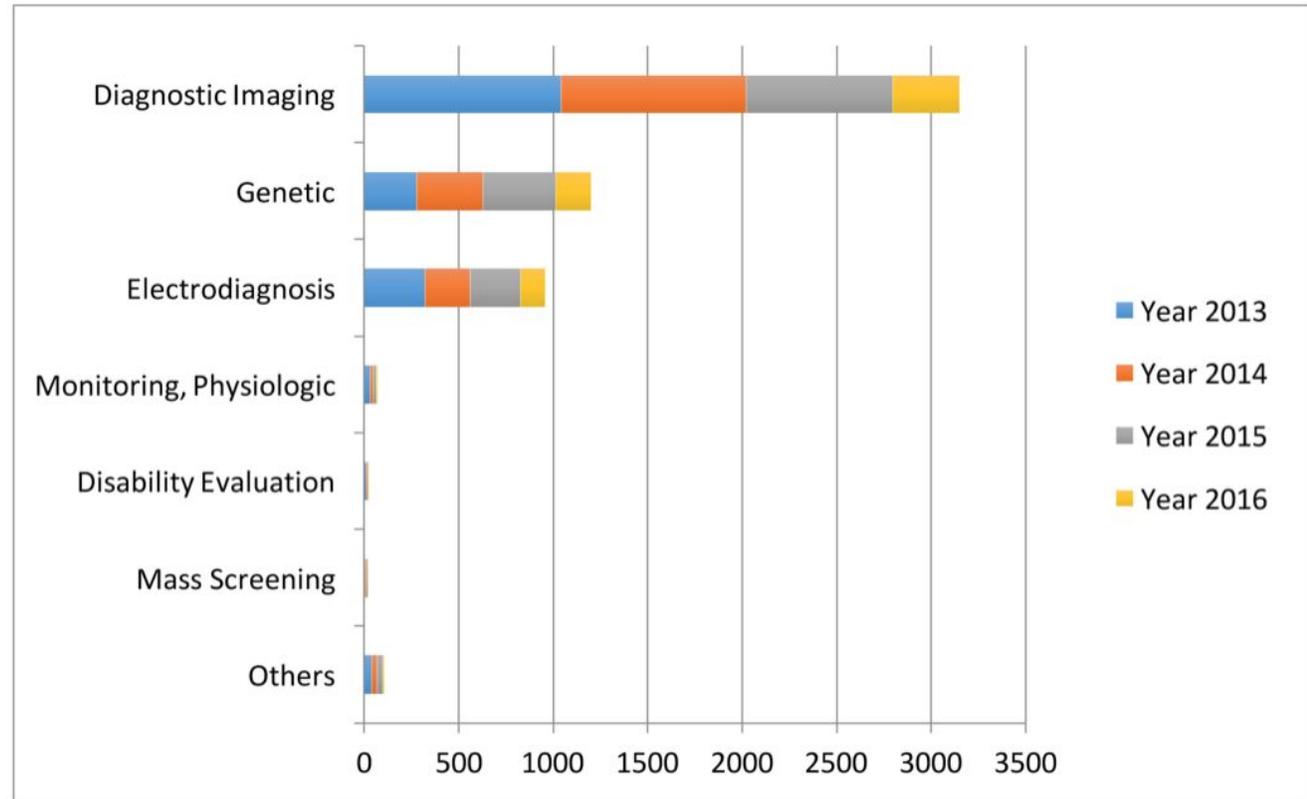
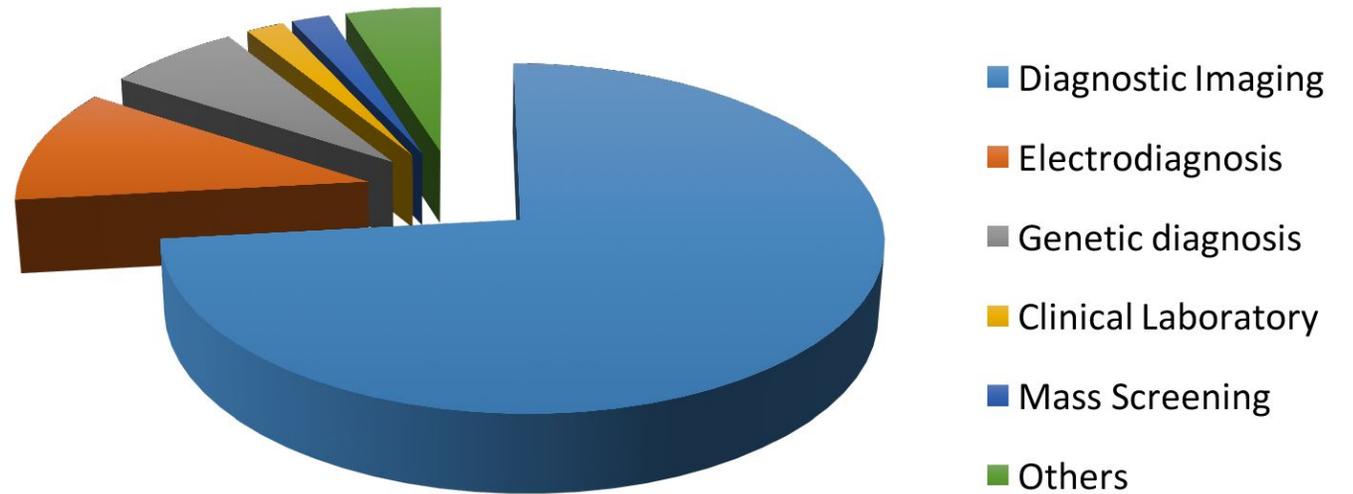


Figure 1 The data types considered in the artificial intelligence artificial (AI) literature. The comparison is obtained through searching the diagnosis techniques in the AI literature on the PubMed database.

Deep learning

- The data sources for deep learning.
- Based on Pub Med



Leading 10 disease types considered in the AI literature

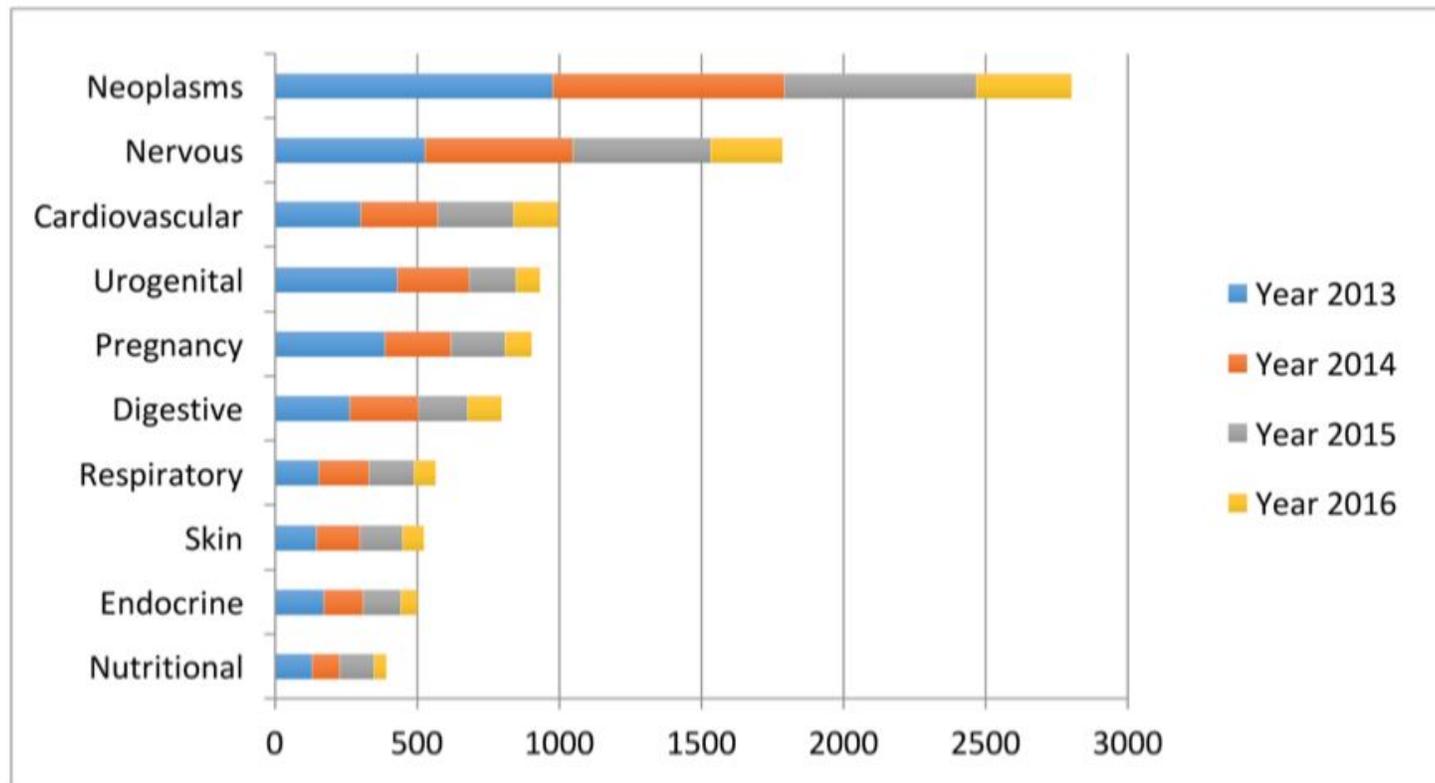


Figure 3 The leading 10 disease types considered in the artificial intelligence (AI) literature. The first vocabularies in the disease names are displayed. The comparison is obtained through searching the disease types in the AI literature on PubMed.

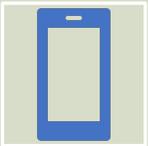
Examples of ML in Medicine

- **Diagnose cancer**, where the inputs are the PCs estimated from 6567 genes and the outcomes are the tumor categories
- **Predict breast cancer**, with the inputs being the texture information from mammographic images and the outcomes being tumor. Indicators.
- **Diagnose Parkinson's disease** based on the inputs of motor, non-motor symptoms and neuroimages.
- **Imaging analysis.**
- **Chest X-ray reports** would assist the antibiotic assistant system to alert physicians for the possible need for anti-infective therapy

Why AIS delayed?



Surgeons not letting go.



Refusal to embrace robotic tele-manipulation technology



Reluctant to accept anything less than totally autonomous surgery as AIS

Robots that were independent of
surgeons



•Surgeons need to embrace surgical innovation so that we can evaluate it, understand it, and ultimately make it as safe as possible for our patients and us

Andrew Gumbs, et al, Art Int Surg 2021;1:1-10

AI in Surgery

- AI in surgery also involves movement
- “Surgery” we are also referring to endoscopy and interventional techniques and procedures

AIM reserved for instances where computer algorithms are used to better diagnose, manage or treat patients without a specific interventional procedure being done

AIS could be a term for autonomously acting machines that can do interventional gestures/actions.

Robotic telemanipulation technology

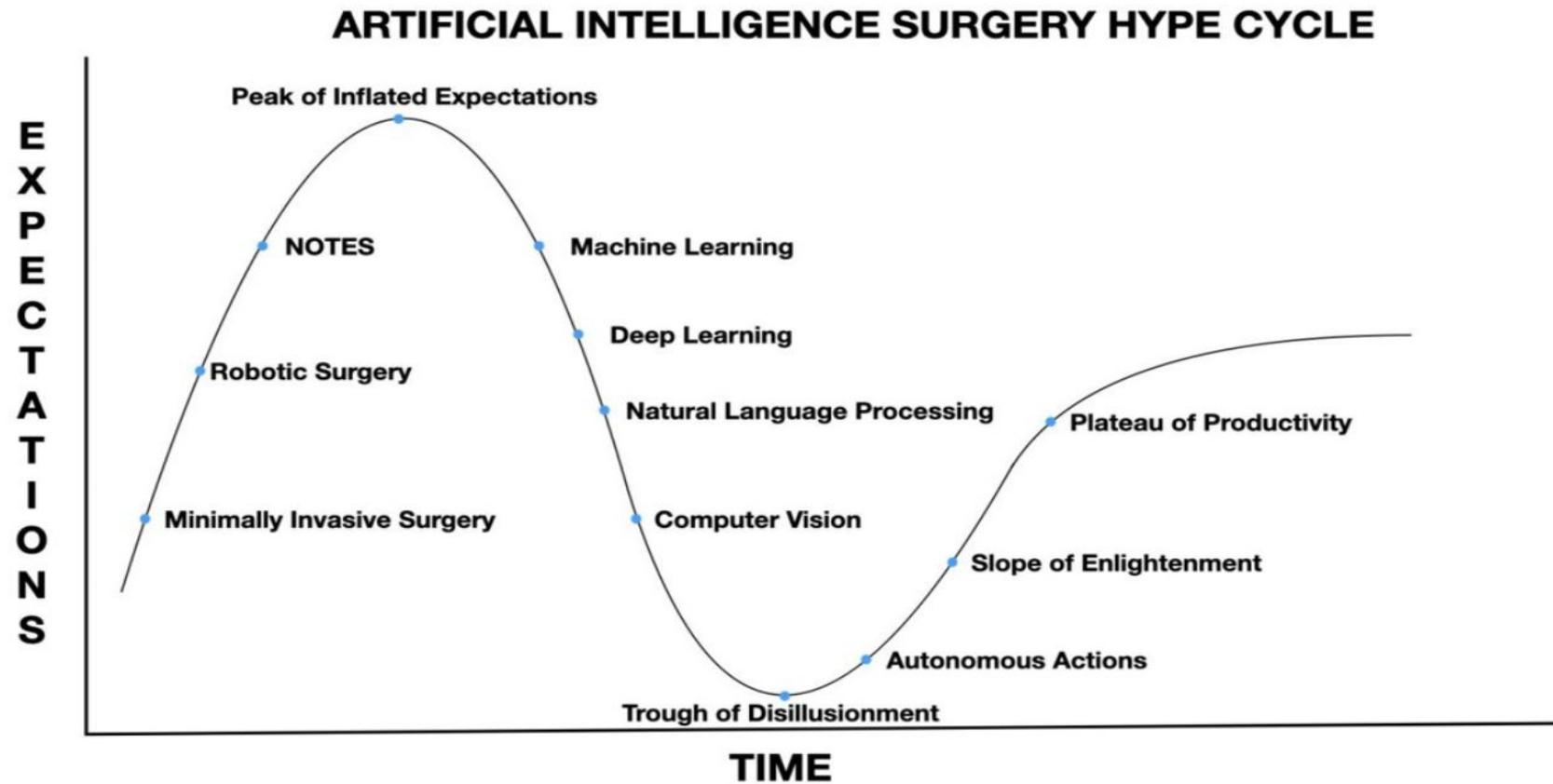


Figure 1. Artificial Intelligence Surgery Gartner Hype Cycle: NOTES = Natural Orifice Transluminal Endoscopic Surgery. Adapted from Gartner Hype Cycle for Artificial Intelligence, 2019 [gartner.com/smarterwithgartner](https://www.gartner.com/smarterwithgartner) and modifications by Oosterhoff et al^[10].

Surgical Decisions

- Decision to do surgery
- Surgical planning with three D printing
- Improve the workflow and resource utilization in the operating
- Robotic Automation
- Post operative care: using wearables and personal communication devices

Trauma Models

Prognostic Models for VBN



A prognostic model for tissue viability in patients with lower-extremity arterial trauma

VBN
A prognostic model for tissue viability in patients with lower-extremity arterial trauma

VBN HOME

VBN MODEL

VBN EVIDENCE

PUBLICATIONS

VBN HOME

VBN MODEL

VBN EVIDENCE

PUBLICATIONS

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TIC BN

This website presents information between the the **Risk and Trauma Sciences Unit**

Please click on the model

- **TIC BN: A prognostic model**
- **VBN: A prognostic model**

© 2019 Risk and Information Management (RIM) Research Group, Queen Mary University of London

Injuries to the blood vessels of the lower extremity are potentially devastating a disability or limb loss. Delays or errors in treatment decisions may lead to irreversible outcome. One of the most difficult surgical decisions is whether to attempt salvage severely injured extremity. Accurate risk stratification and outcome prediction, for potential to improve outcome by reducing delays and errors in decision-making vascular reconstruction and the projected tissue viability would inform treatment decisions.

The primary aim of the Lower Extremity Vascular Injury Bayesian Network (VBN) traumatic lower extremity with vascular injury after salvage is attempted. The model provides predictions when some of its input variables are unknown. The research is a collaboration of the **Information Management group, Queen Mary University of London**, the **Trauma London School of Medicine and Dentistry** and the **United States Army Institute of Surgical Research**.

A 10-predictor BN accurately predicted failed revascularization: area under the receiver operating characteristic curve (AUROC) 0.95

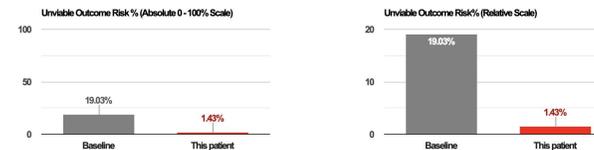
Perkins et al, Ann Surg 2020 Oct, 272 (4): 564-572

Home

VBN

Vascular Injury			Ischaemic Panel	
Level of Primary Vascular Injury <input checked="" type="radio"/> Femoral <input type="radio"/> Popliteal <input type="radio"/> Tibial - 1 Artery Injured <input type="radio"/> Tibial - 2 Arteries Injured <input type="radio"/> Tibial - 3 Arteries Injured <input type="radio"/> Unknown - Below Knee <input type="radio"/> Unknown - Above Knee	Management of Arterial Injury Vascular Repair <input checked="" type="radio"/> Primary <input type="radio"/> Interposition Graft <input type="radio"/> Unknown <input type="radio"/> Ligation	Vascular Injury at Multiple Levels <input checked="" type="radio"/> Yes <input type="radio"/> No <input type="radio"/> Unknown	Ischaemia Duration <input type="radio"/> 0 < t ≤ 1 <input checked="" type="radio"/> 1 < t ≤ 3 <input type="radio"/> 3 < t ≤ 6 <input type="radio"/> t > 6 <input type="radio"/> Unknown	Ischaemia Degree <input checked="" type="radio"/> Complete <input type="radio"/> Partial <input type="radio"/> None <input type="radio"/> Unknown

Associated Injuries & Conditions				MOI
Soft Tissue Injury <input type="radio"/> None <input checked="" type="radio"/> Mild <input type="radio"/> Moderate <input type="radio"/> Severe <input type="radio"/> Profound <input type="radio"/> Unknown	Associated Bone Fracture <input type="radio"/> Yes <input checked="" type="radio"/> No <input type="radio"/> Unknown	Shock <input type="radio"/> Yes <input checked="" type="radio"/> No <input type="radio"/> Unknown	Compartment Syndrome <input checked="" type="radio"/> Yes <input type="radio"/> No <input type="radio"/> Unknown	Mechanism of Injury <input checked="" type="radio"/> Penetrating <input type="radio"/> Blunt <input type="radio"/> Explosion <input type="radio"/> Unknown

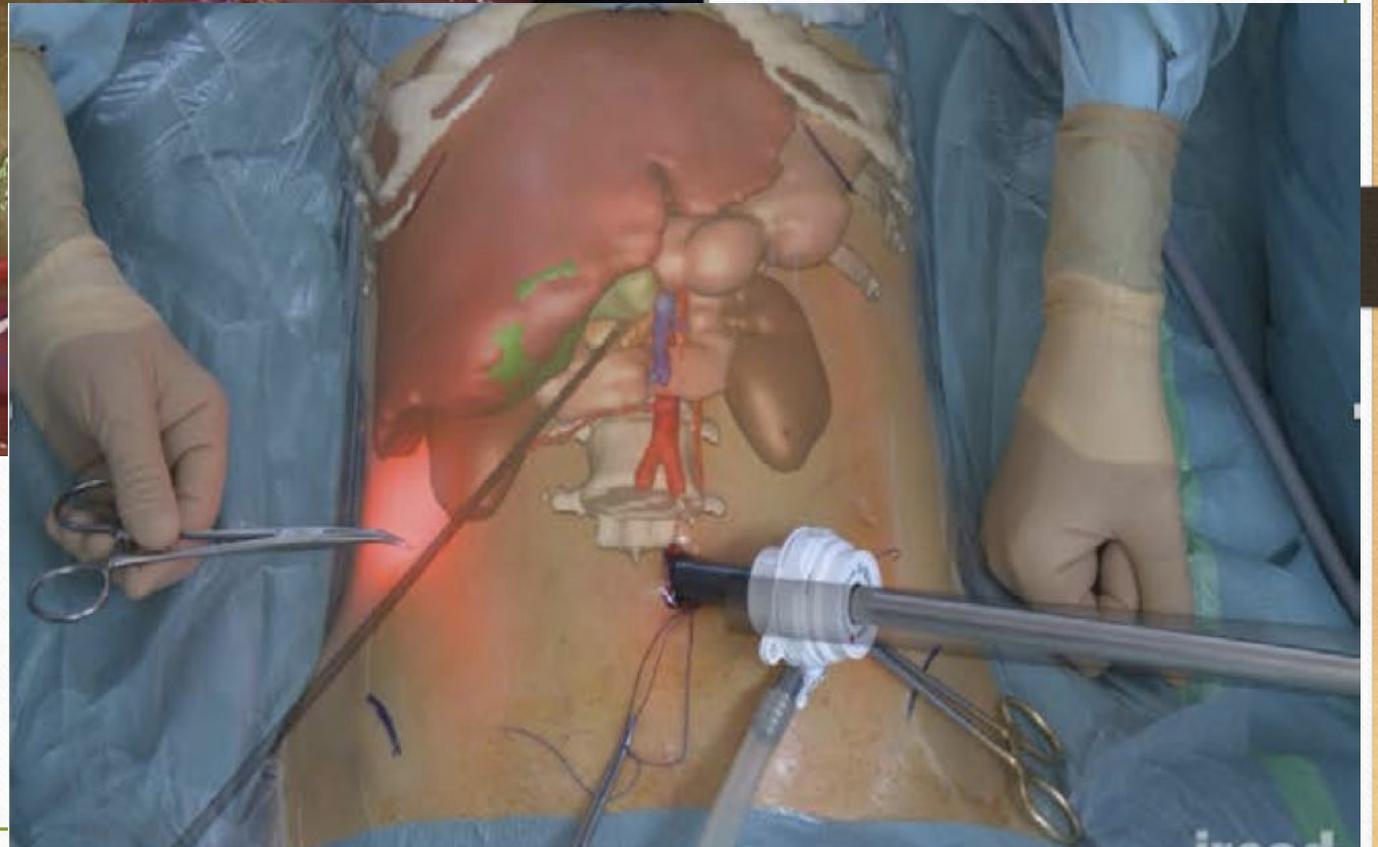
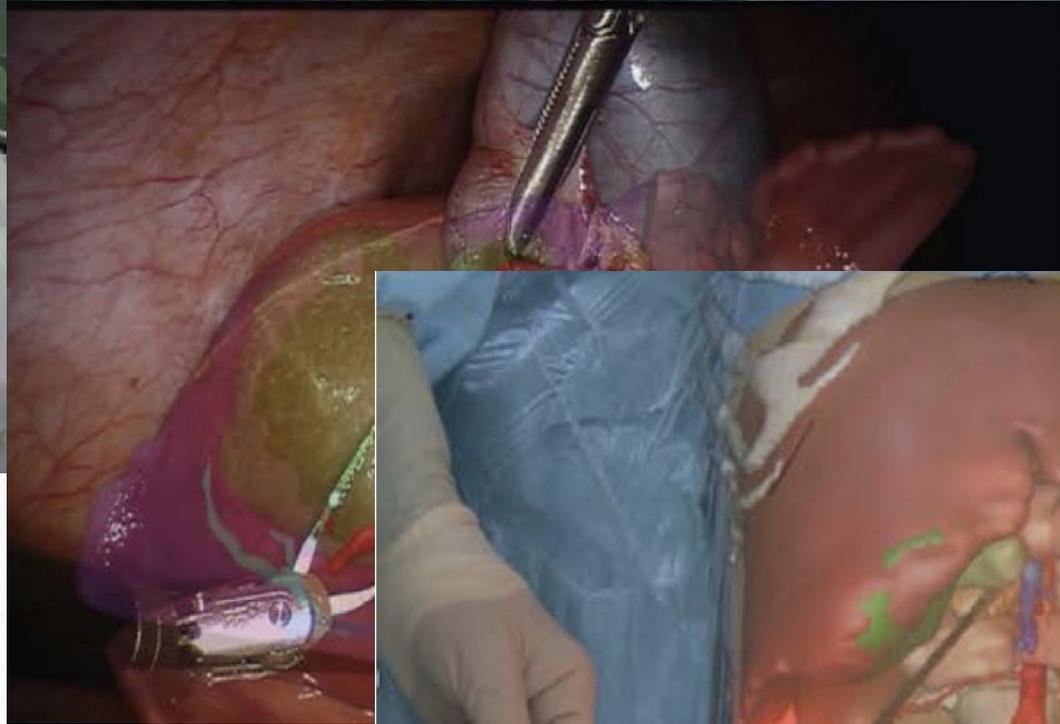


Calculate VBN

VBN is powered by **asend RISK**

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<https://www.traumamodels.com/vbn/vbn.jsp>



Procedure Planning

Mariano Giménez et al Ann Surg 2020

A New Model for Algorithmic Prediction of Amputations in Diabetics

*Stavros Stefanopoulos, Qiong Qiu, Gang Ren, F.C.
Brunicardi, Ayman Ahmed, Mohammad Osman,
Munier Nazzal*

AIM and Methods



AIM: To create a new predictive model of major amputation in DFU patients



Methods:

2018-2014 NIS data using ICD9 codes and AHRQ comorbidity codes

Odds ratio, T-Test, and Chi square for descriptive statistics

Binary logistic regression for selection of top 5 and top 10 most predictive variables

Decision tree model for top 5 and top 10 variables

Data set then boosted and compared to non boosted predictive performance

Demographics

Numerical variables	No Major Amputation	Major Amputation	Mean-Diff	CI 95%	P-value
	Mean ± Stdev	Mean ± Stdev			
Age	62.315 ± 14.075	64.049 ± 13.235	1.735	1.531 - 1.939	<0.001
No. chronic conditions	8.65 ± 3.159	9.464 ± 3.194	0.814	(0.768 - 0.86)	0.033
Length of stay (Days)	7.307 ± 7.427	12.854 ± 10.443	5.547	(1.531 - 1.939)	<0.001
Total charges (USD)	51436 ± 63868	93566 ± 105989	42,130	(41,143 - 43,117)	<0.001

Chronic Kidney Disease	No	71.911	94.752	5.248	0.821	<0.001	Primary Expected payer	Medicare	59.11	93.55	6.45	<0.001
	Stage 1	0.17	94.775	5.225				Medicaid	13.684	94.157	5.843	
	Stage 2	1.262	94.362	5.638				Private insurance	19.071	95.213	4.787	
	Stage 3	8.978	94.003	5.997				Self-pay	4.996	95.417	4.583	
	Stage 4	3.812	94.02	5.98				No charge	0.595	96.587	3.413	
	Stage 5	0.611	94.274	5.726				Other	2.544	94.406	5.594	
	End stage	13.256	90.497	9.503								
BMI	(0,18)	0.451	86.93	13.07	-1	<0.001	Median Household Income Quartile of ZIP Code	0-25th	34.463	93.377	6.623	-1
	[18,25)	0.583	89.795	10.205				26th to 50th (median)	26.563	93.981	6.019	
	[25,30)	0.848	92.8	7.2				51st to 75th	22.485	94.584	5.416	
	[30,40)	4.123	95.245	4.755				76th to 100th	16.489	94.991	5.009	
	[40,+)	5.387	95.638	4.362								
Race	White	63.271	94.767	5.233	0.679	<0.001	Age Group 2	[18,30]	1.123	99.507	0.493	<0.001
	Black	18.893	92.118	7.882				(30,40]	4.819	96.873	3.127	
	Hispanic	12.83	93.631	6.369				(40,50]	13.939	88.362	11.638	
	Asian or Pacific Islander	1.222	93.817	6.183				(50,60]	25.485	74.835	25.165	
	Native American	1.096	93.658	6.342				(60,70]	25.13	73.041	26.959	
								(70,80]	17.873	79.949	20.051	
				(80+)	11.63	87.433	12.567					

Demographics

Risk Factors

Gangrene	19.744	11.842	11.466 - 12.231
Peripheral Vascular Disease	41.727	3.09	2.996 - 3.187
Weight Loss	6.191	2.638	2.525 - 2.755
Systemic Infection	14.25	2.445	2.365 - 2.527
Anemia, Chronic Blood Loss & Deficiency	34.622	1.782	1.731 - 1.835
Age >= 40	94.058	1.726	1.598 - 1.864
Osteomyelitis	30.292	1.679	1.63 - 1.73
Paralysis	2.911	1.63	1.518 - 1.75
Renal Failure	38.045	1.511	1.467 - 1.555
Chronic Kidney Disease	28.089	1.49	1.445 - 1.536
Fluid and Electrolyte Disorders	29.021	1.464	1.42 - 1.509
Valvular Disease	3.881	1.418	1.328 - 1.514
Diabetes, Complicated	58.974	1.404	1.362 - 1.448
Hypertension	74.78	1.276	1.231 - 1.322
Other Neurological Disorders	6.037	1.135	1.071 - 1.203
Depression	12.597	1.121	1.074 - 1.169
Congestive Heart Failure Total	24.801	1.036	1.002 - 1.071
Urinary Tract Infection	8.956	1.029	0.978 - 1.082
Hyperchylomicronemia	0.002	1	1

Non predictive Factors and protective factors

Smoking	23.668	0.965	0.933 - 0.999	0.046
Psychoses	4.666	0.963	0.898 - 1.033	0.296
Peptic Ulcer Disease	0.025	0.941	0.94 - 0.942	0.023
Hyperlipidemia	0.589	0.93	0.764 - 1.131	0.466
Chronic Obstructive Pulmonary Disease	12.483	0.93	0.889 - 0.973	0.002
Hypercholesterolemia	6.836	0.901	0.848 - 0.956	<0.001
Coagulopathy	3.706	0.883	0.814 - 0.958	0.003
Female	36.21	0.873	0.847 - 0.901	<0.001
Pneumonia	4.607	0.862	0.801 - 0.928	<0.001
Hypothyroidism	10.492	0.843	0.801 - 0.886	<0.001
Alcohol Abuse	2.764	0.793	0.719 - 0.874	<0.001
Liver Disease	2.999	0.771	0.701 - 0.848	<0.001
Cellulitis	36.697	0.745	0.721 - 0.768	<0.001
Acquired Immune Deficiency Syndrome	0.172	0.74	0.495 - 1.106	0.14
Rheumatoid Arthritis/Collagen Vascular Diseases	2.407	0.738	0.662 - 0.822	<0.001
Obesity	20.681	0.733	0.705 - 0.763	<0.001
Solid Tumor without Metastasis	0.955	0.731	0.615 - 0.868	<0.001
Race, White	63.271	0.73	0.708 - 0.753	<0.001
Diabetes, uncomplicated	18.384	0.698	0.669 - 0.728	<0.001
Drug Abuse	3	0.682	0.617 - 0.754	<0.001
Lymphoma	0.439	0.647	0.495 - 0.846	<0.001
Social Determinants	1.075	0.595	0.499 - 0.711	<0.001
Metastatic Cancer	0.541	0.588	0.457 - 0.757	<0.001
Elevated C-reactive Protein	0.023	0.43	0.106 - 1.751	0.225
Hyperglyceridemia	0.394	0.366	0.253 - 0.529	<0.001
Elevated Sedimentation Rate	0.055	0.361	0.134 - 0.974	0.036

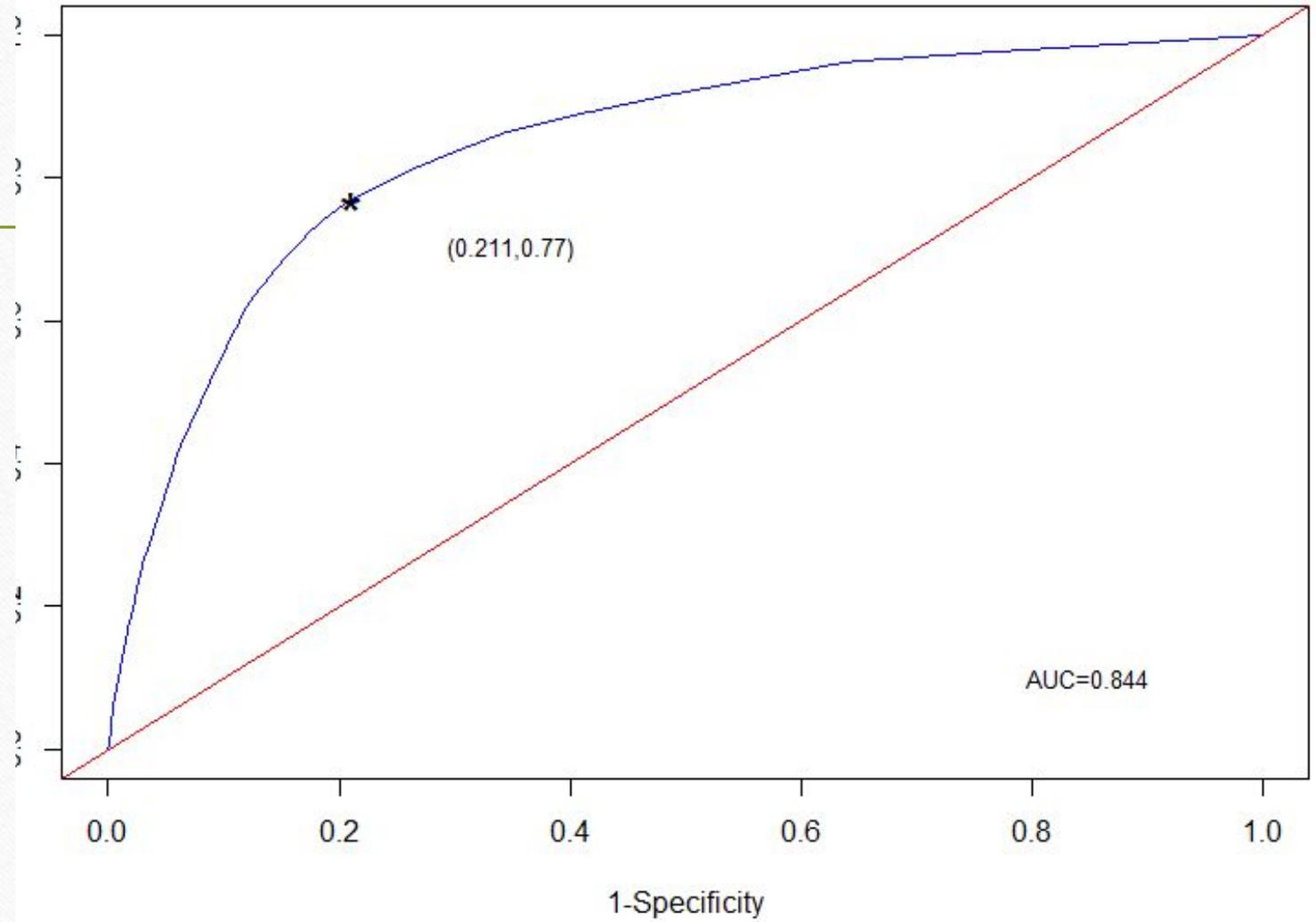
10-factor Model

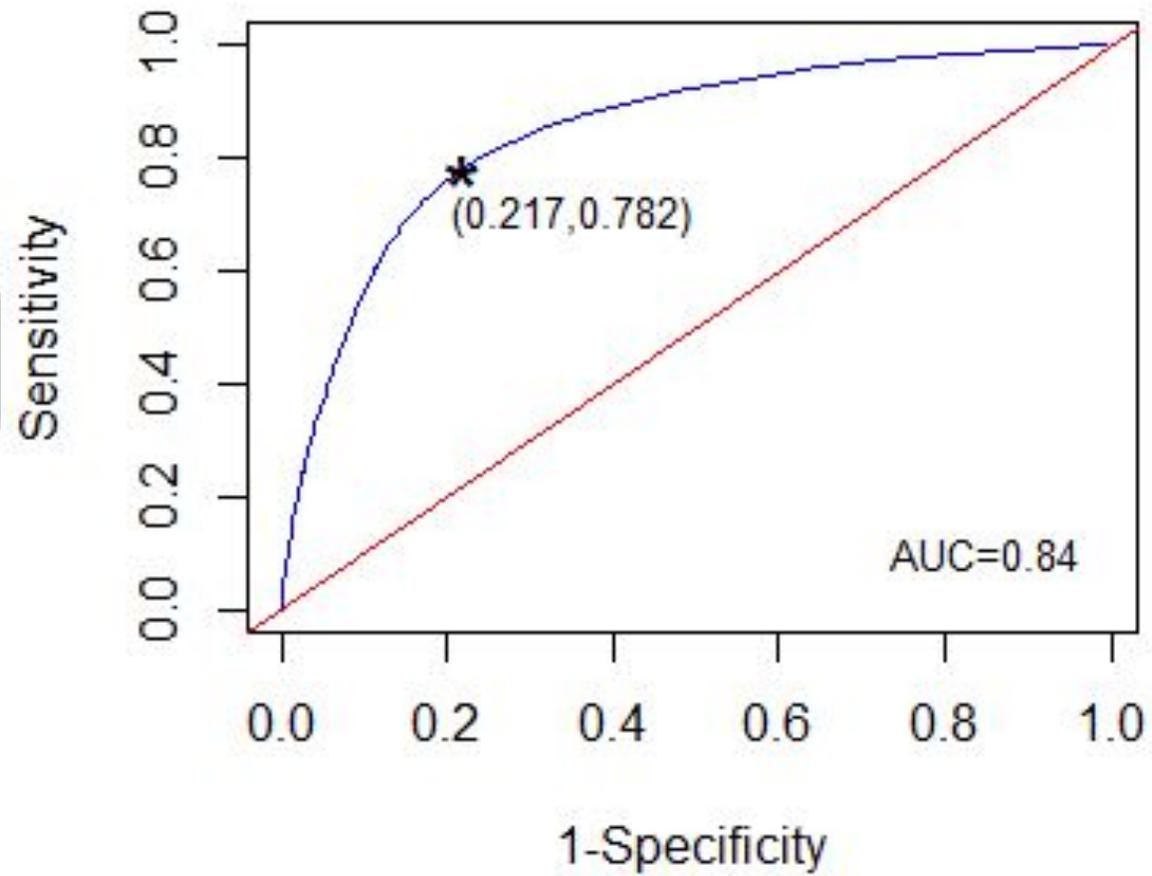
Covariant

Gangrene	2.238
Systemic Infection	0.753
Peripheral Vascular Disease	0.598
Weight Loss	0.527
Osteomyelitis	0.316
Paralysis	0.311
Anemia, Chronic Blood Loss & Deficiency	0.286
Depression	0.249
Chronic Obstructive Pulmonary Disease	0.219
Fluid and Electrolyte Disorders	0.162

**Top ten Model
predictive factors**

ROC Curve for Top ten factors





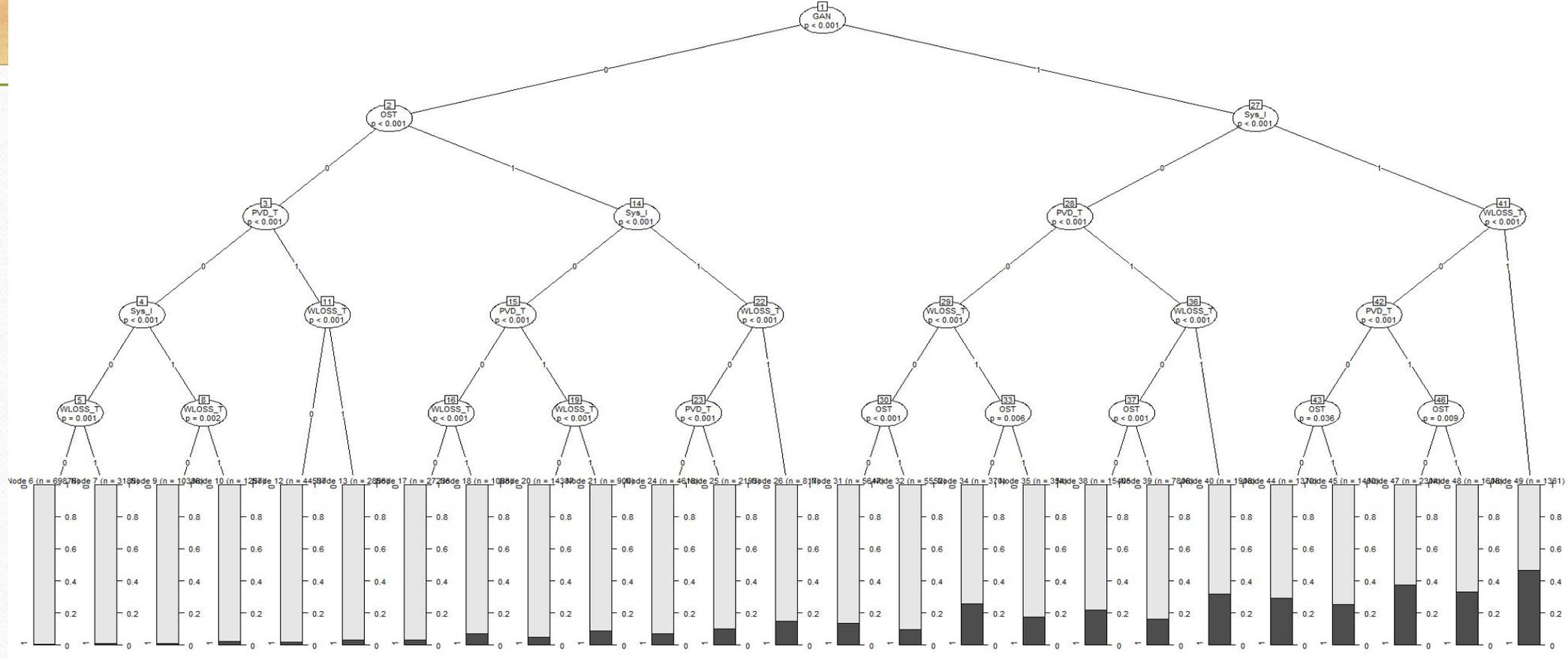
Boosted 10
variables

5-factor Model

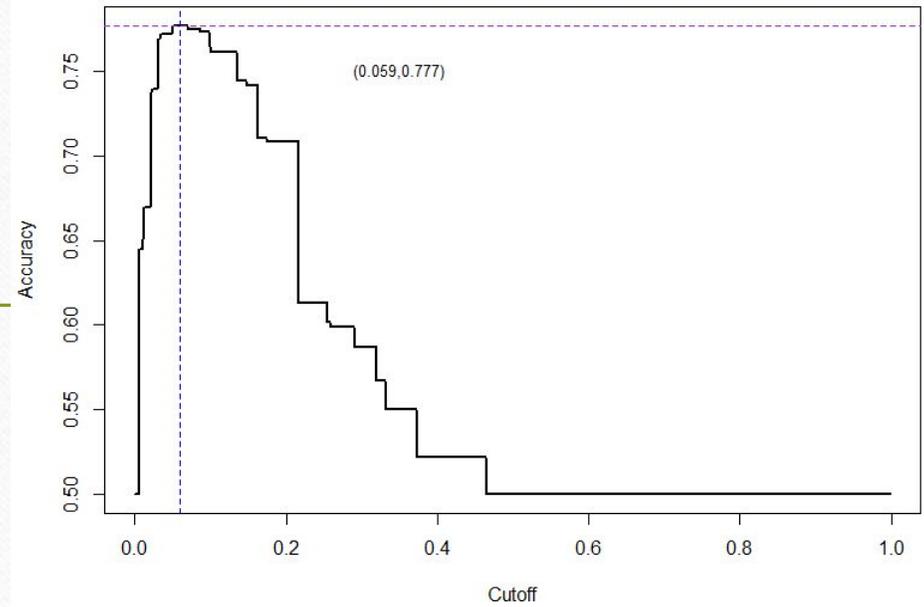
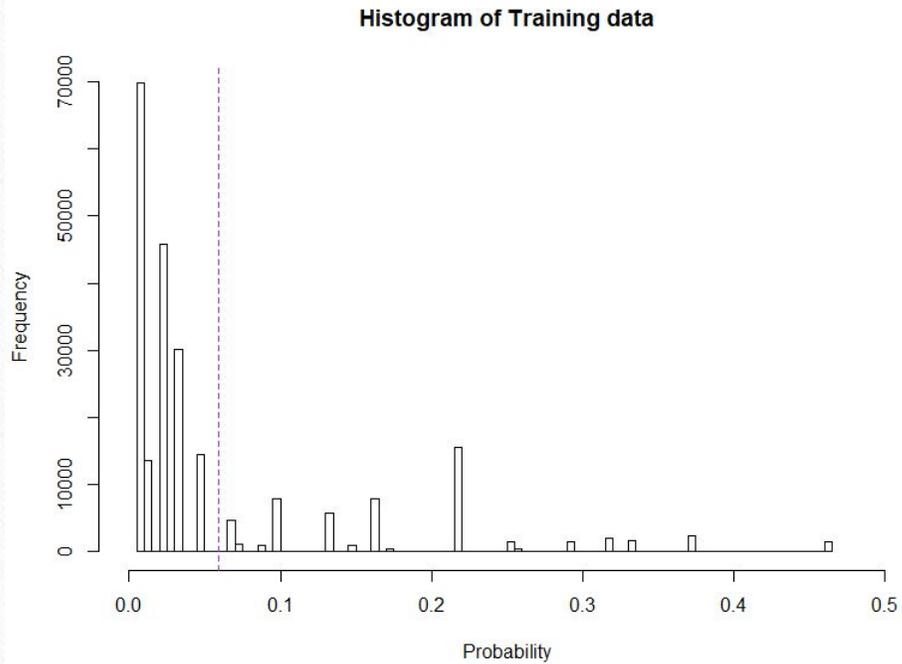
Covariant

Gangrene	2.295
Osteomyelitis	0.762
Systemic Infection	0.699
Peripheral Vascular Disease	0.687
Weight Loss	0.559

Top 5 variables

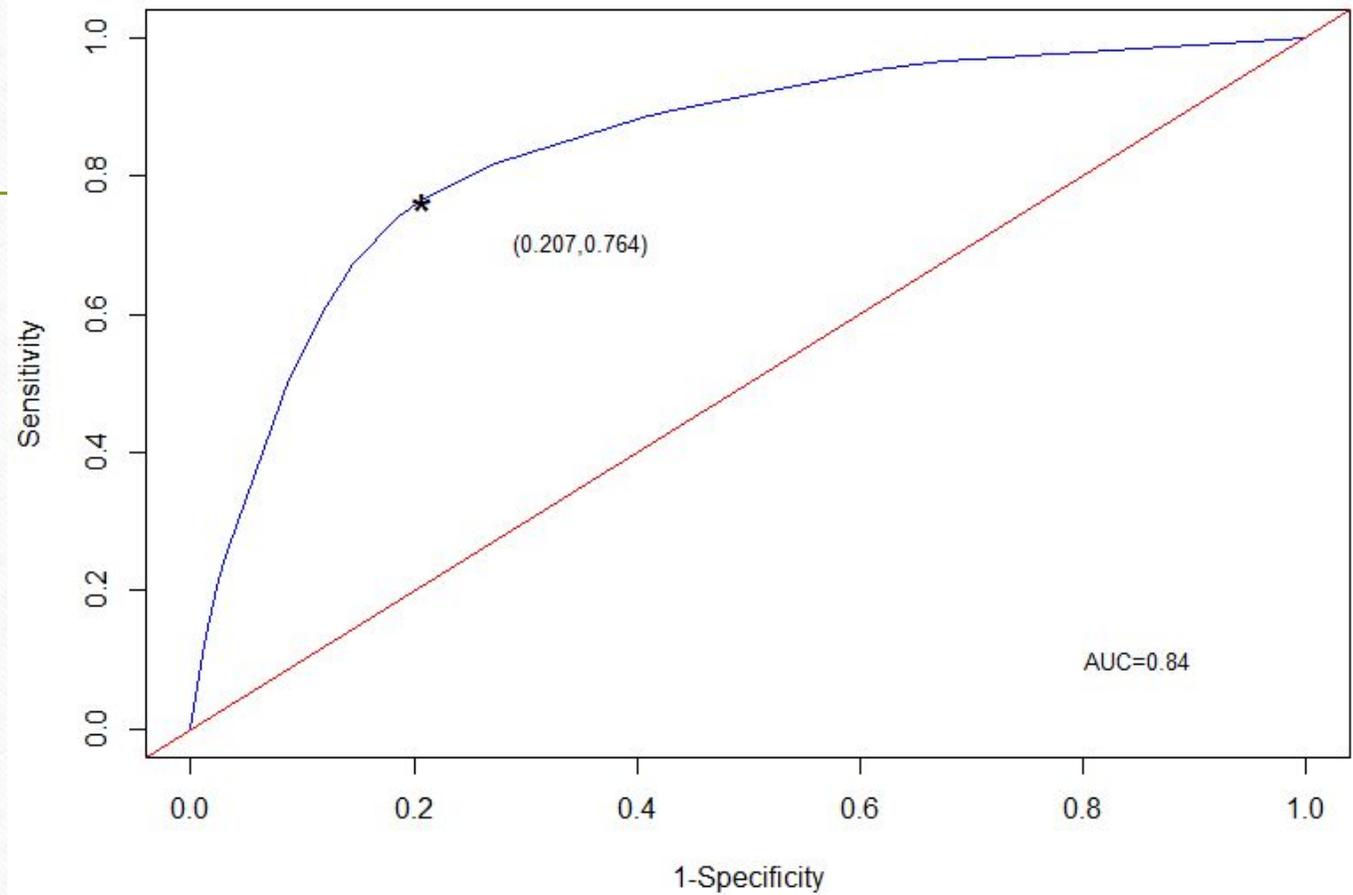


Decision tree top 5 variables

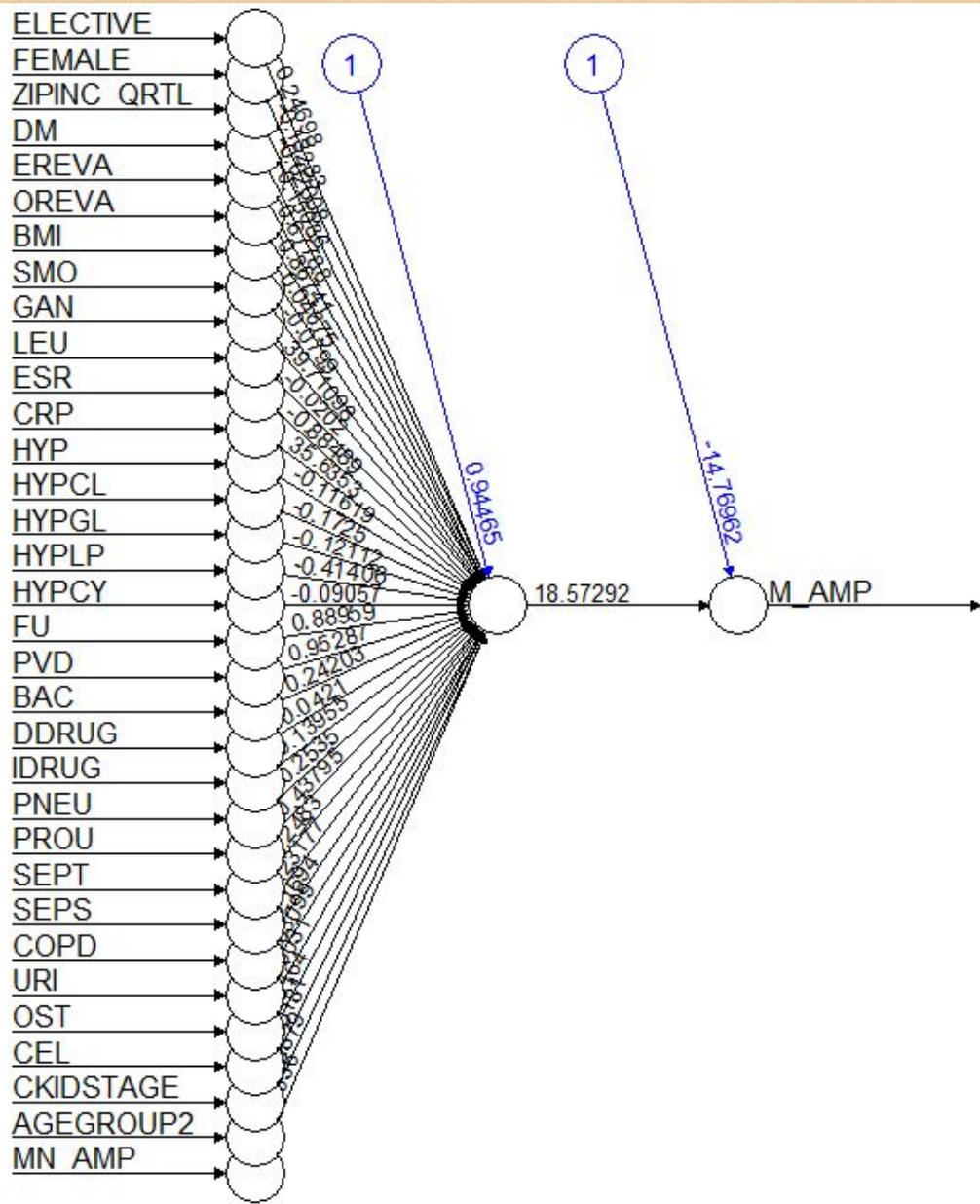


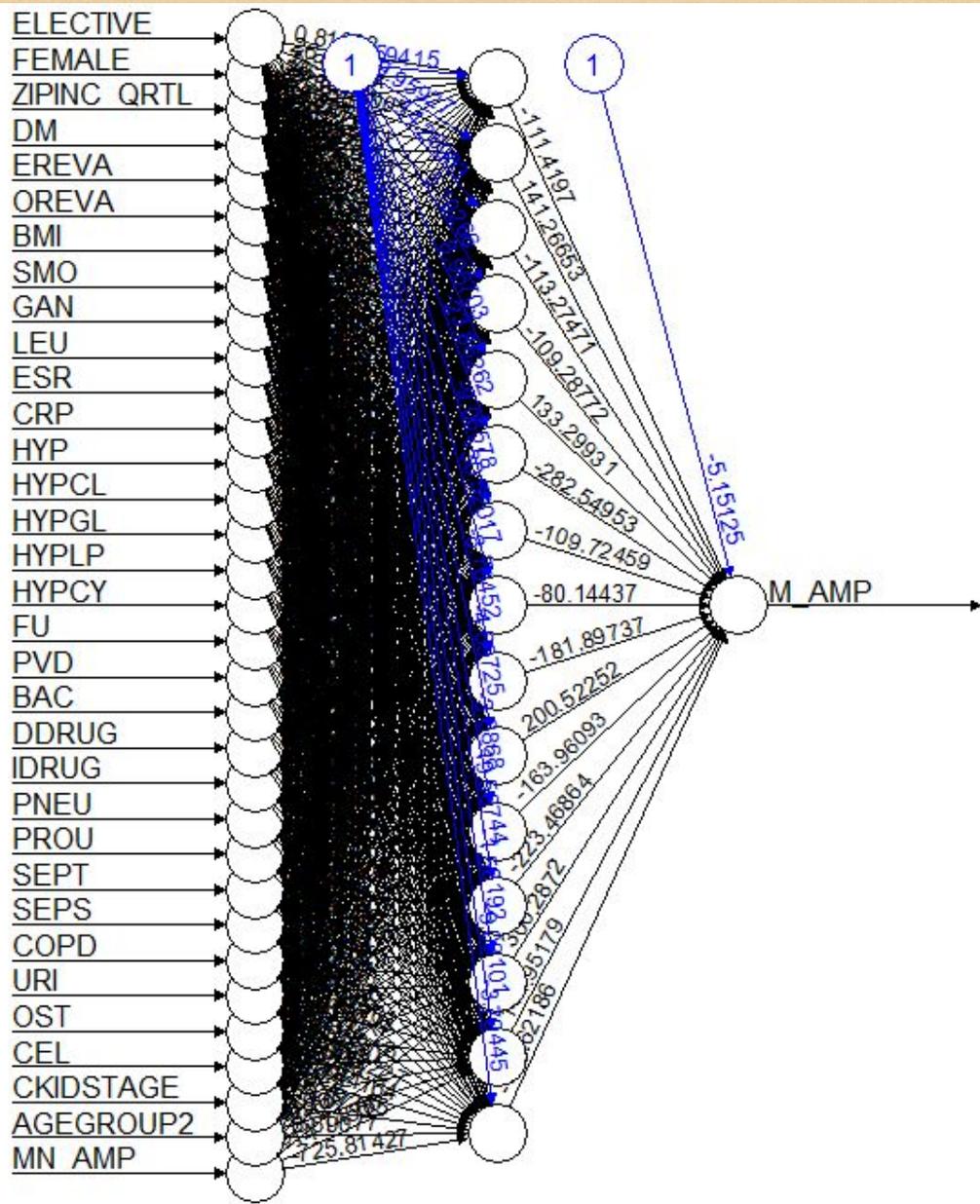
**Top 5 variables
accuracy cutoff**

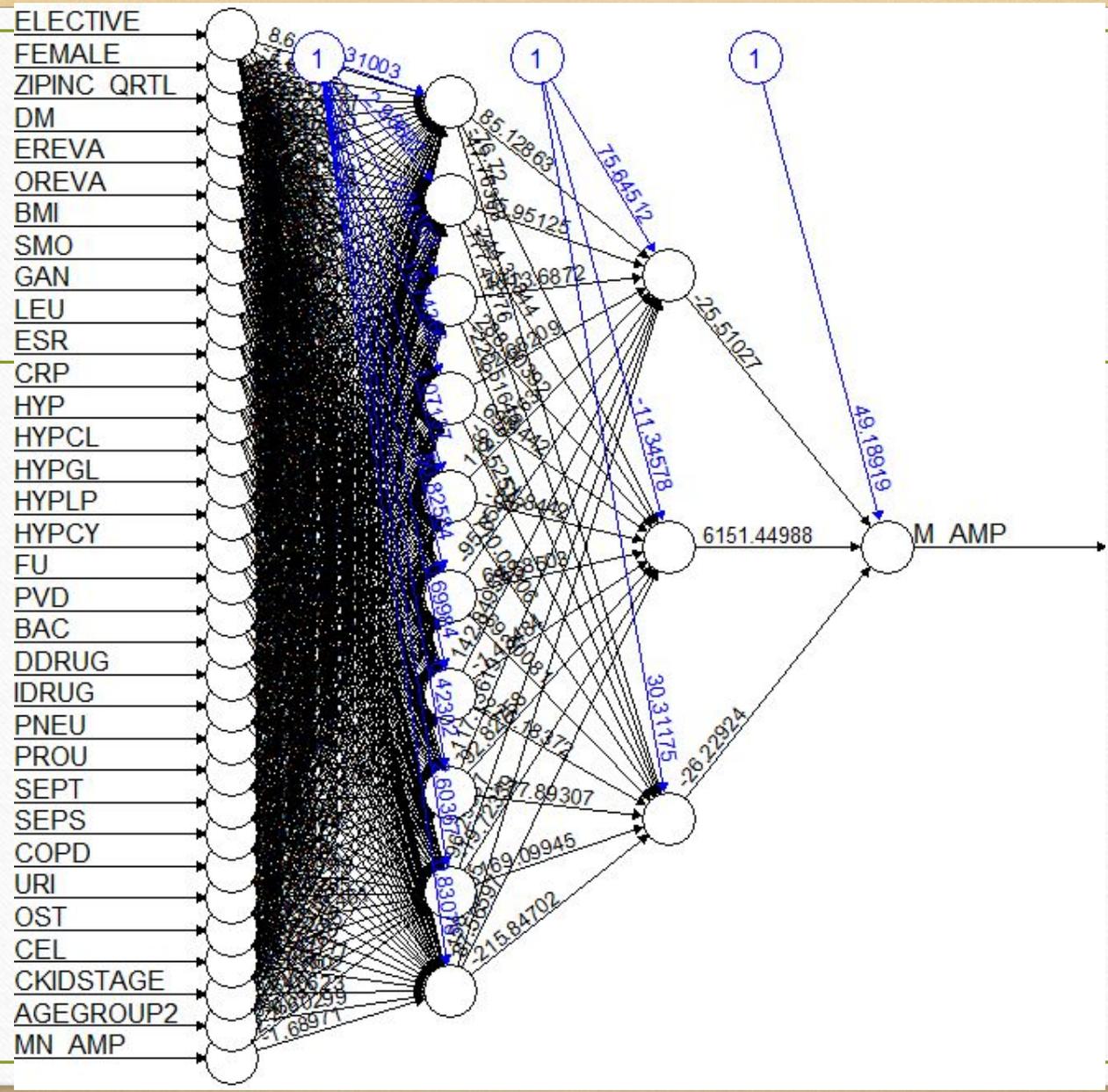
**Boosted top 5
variables**



Neural Network







Combined Results

		SENSITIVITY (%)	SPECIFICITY (%)	PERFORMANCE (%)
10 Varia bles	Testing	76.70	78.96	77.83
	Training	76.95	78.9	77.93
	Boosted	76.95	78.78	77.87
5 Varia bles	Testing	76.16	79.35	77.76
	Training	76.11	79.32	77.71
	Boosted	76.16	79.35	77.76

Highest risk Classification

Gangrene	Osteomyelitis	Sys. Infection	PVD	Weight Loss	Amp. Probability	Amp. Risk Multiplier
1	0	1	0	1	46%	7.85
1	0	1	1	1	46%	7.85
1	1	1	0	1	46%	7.76
1	1	1	1	1	46%	7.76
1	0	1	1	0	38%	6.36
1	1	1	1	0	33%	5.61
1	0	0	1	1	33%	5.53
1	1	0	1	1	30%	5.15
1	0	1	0	0	29%	4.92
1	1	1	0	0	26%	4.32

Lowest risk Classification

Gangrene	Osteomyelitis	Sys. Infection	PVD	Weight Loss	Amp. Probability	Amp. Risk Multiplier
0	0	0	0	0	1%	0.10
0	0	0	0	1	1%	0.19
0	0	1	0	0	1%	0.20
0	0	0	1	0	2%	0.34
0	0	1	0	1	3%	0.42
0	0	1	1	0	3%	0.44
0	0	0	1	1	3%	0.51
0	1	0	0	0	3%	0.53
0	0	1	1	1	4%	0.73
0	1	0	1	0	5%	0.85

grenut.shinyapps.io

-
- <https://grenut.shinyapps.io/amputation/>

Innovation in motion analysis with artificial intelligence

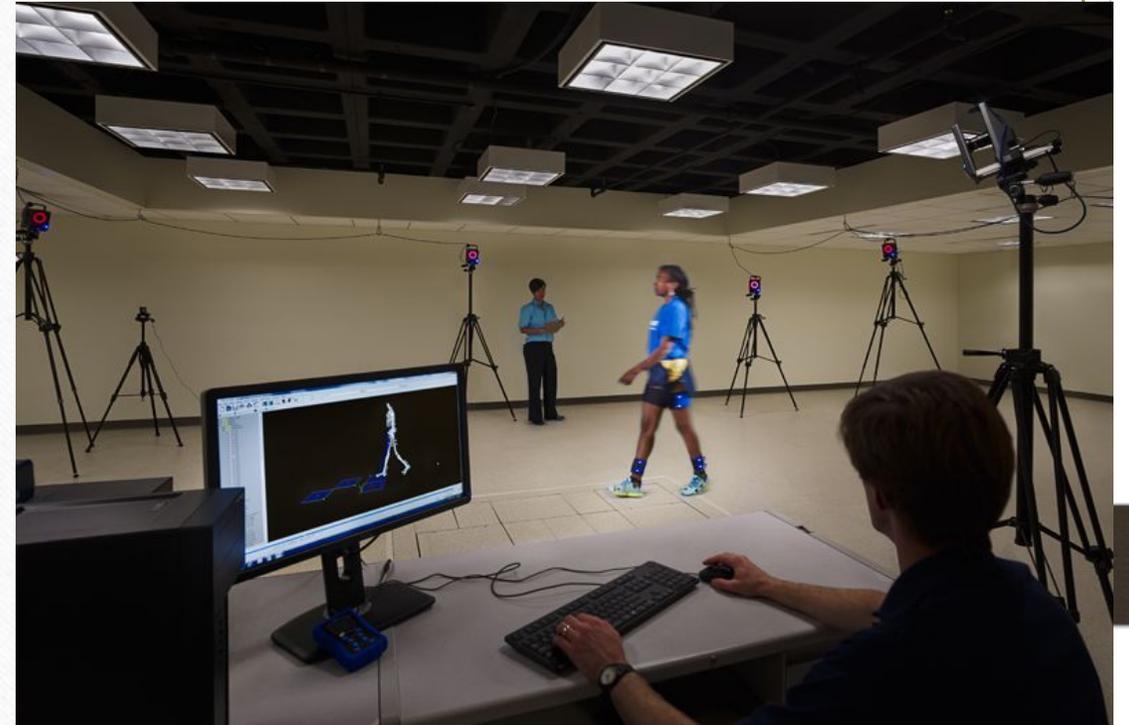
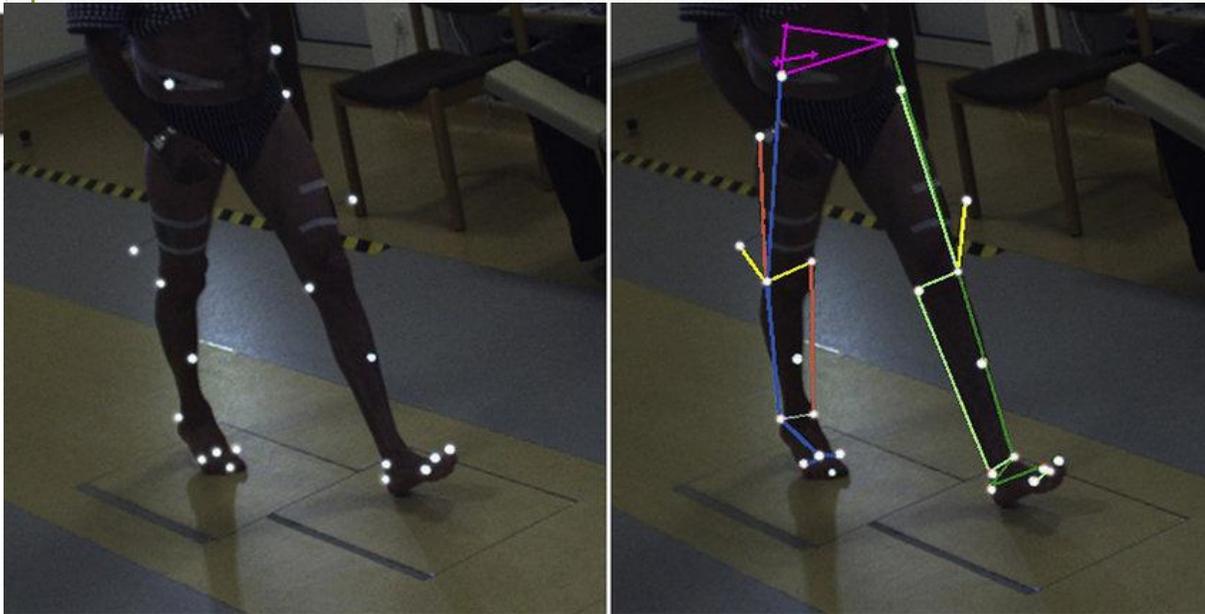
Lucas Haberkamp
B.S. Bioengineering



THE UNIVERSITY OF TOLEDO
MEDICAL CENTER

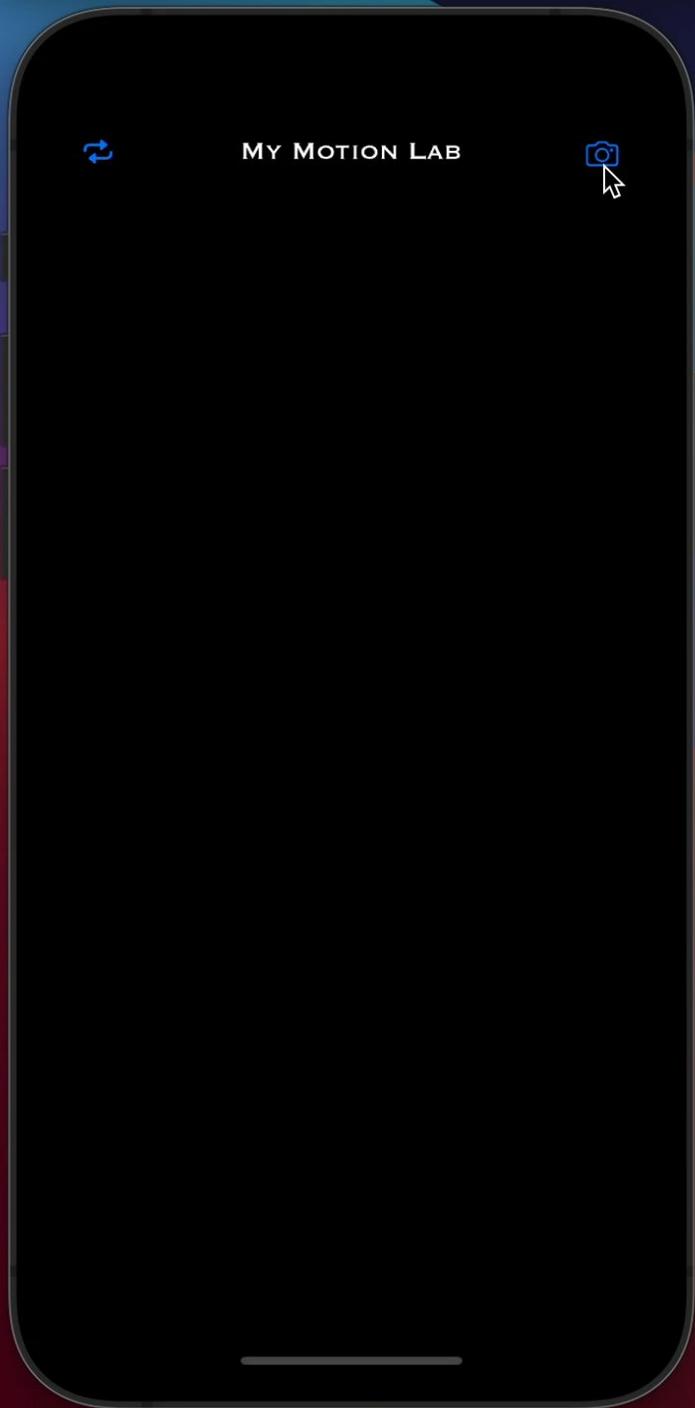
3D motion analysis – Background

Collect meaningful measurements
allowing for quantification of movement



Drawbacks...

AI in motion analysis



- Instantaneous feedback is achieved
 - Eliminates the need for user input and operator proficiency
- User friendly lowering the barrier for entry in biomechanical analysis
 - These algorithms can be employed in any smartphone or computer
 - Requires no coding knowledge for the practitioner to use
 - Free to use

Machine learning and drug discovery

- Machine learning used in the process of “targeted” drug discovery. Less expense and more accurate.
- ML and AI help extract insight about mechanism-of-action of drugs by applying techniques such as similarity metrics across all diseases to find shared pathways
- Identify potential side effects based before clinically reported.

Obstacles for AI in medical research

- Current regulations lack of standards to assess the safety and efficacy of AI systems.
- Data exchange.
- Current healthcare environment does not provide incentives for sharing data on the system

Barriers to adopt AI/ML in Medicine

- **Trust:** Both clinician and physician trust. (2018 survey). Trust affects outcome, affect true results, affect compliance
- Potential "**black box**" nature. Inputs and outputs are visible, the internal process of getting from the input to the output remains opaque.
- **Deep Learning:** Using historical data to train a computer model to make predictions about future data and to direct computer choices based on that data. Multiple layers depend on each other "Neural network"

Barriers to adopt AI/ML in Medicine

- **Lack of interpretability** in AI is often seen as a significant barrier to trust. 76% of CEO potential for biases and a lack of transparency were impeding AI adoption in their businesses.
- Figure out **technical problems** or vulnerabilities: Can it be manipulated, or abused by agencies.
- **Potential error in model**: Death/pneumonia Asthma model (AI was lower, reality higher).

Barriers to adopt AI/ML in Medicine

- Layers of deep learning: creating new hypothesis in each layer to reach conclusion (Neural layers).
- Company's unlikely to open the black boxes to avoid undermining the intellectual property interests.
- Regulations are lagging behind scientific advances

AI Prediction



Work flow will be automated



Triaging will be by ML and AI



by 2030 physicians may have digital assistants that listen in on health care encounters and simultaneously write notes for clinical care, the patient, and billing purposes.



Patient check follow up will be automated.

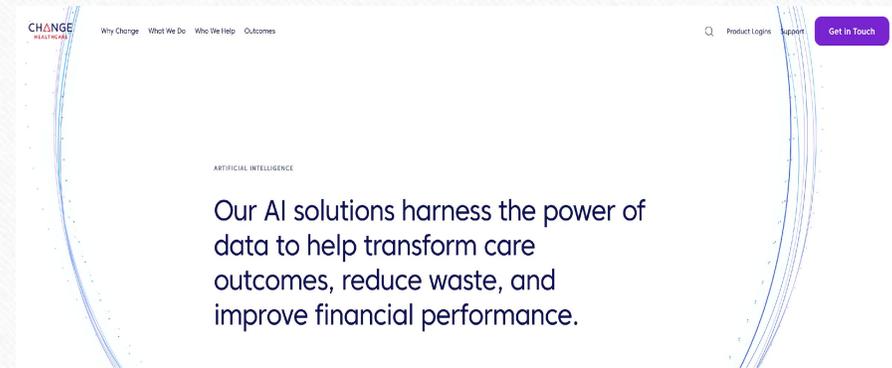


Imaging, dermatology, skin ulcers, wounds, diagnosis and management will be largely by ML and AI means

Future with AI

- AI and ML are here to stay
- Medical assistants will be mostly machines
- Integration of services automated.
- Registration and appointments will be automated
- Physicians and surgeons will not be obsolete but those who refuse to adopt part or all technological advances will be.

Future with AI



Cut health cost by \$150B by 2026: reactive to a proactive approach

Health management rather than disease treatment.

Fewer hospitalizations, less doctor visits, and less treatments .

Stay healthy via continuous monitoring and coaching.

Earlier diagnosis, tailored (precision) treatments, and more efficient follow-ups

Improve revenue cycle

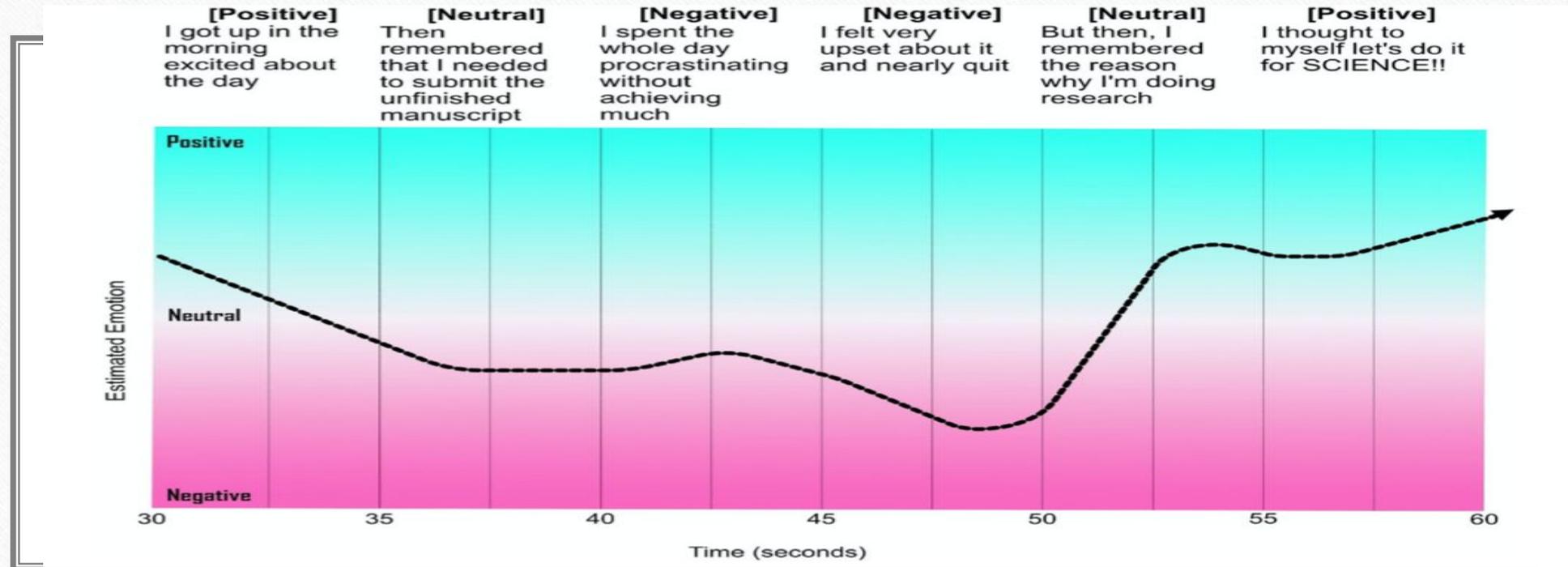
Bohr A and Memarzadeh K, Artificial intelligence in HealthCare, 2020

AI and Healthcare

- Precision medicine
- Genetics-based solutions
- Drug discovery and development
- Drug property and activity prediction
- De novo design through deep learning
- Drug target interactions
- Medical visualization
- Machine vision for diagnosis and surgery
- Deep learning and medical image recognition
- Augmented reality and virtual reality in the healthcare space
- Education and exploration
- Patient experience
- Intelligent personal health records
- Health monitoring and wearables
- Integration of personal records
- Robotics and artificial intelligence-powered devices
- Minimally invasive surgery
- Neuroprosthetics
- Ambient assisted living
- Smart home
- Assistive robots
- Cognitive assistants
- Social and emotional stimulation

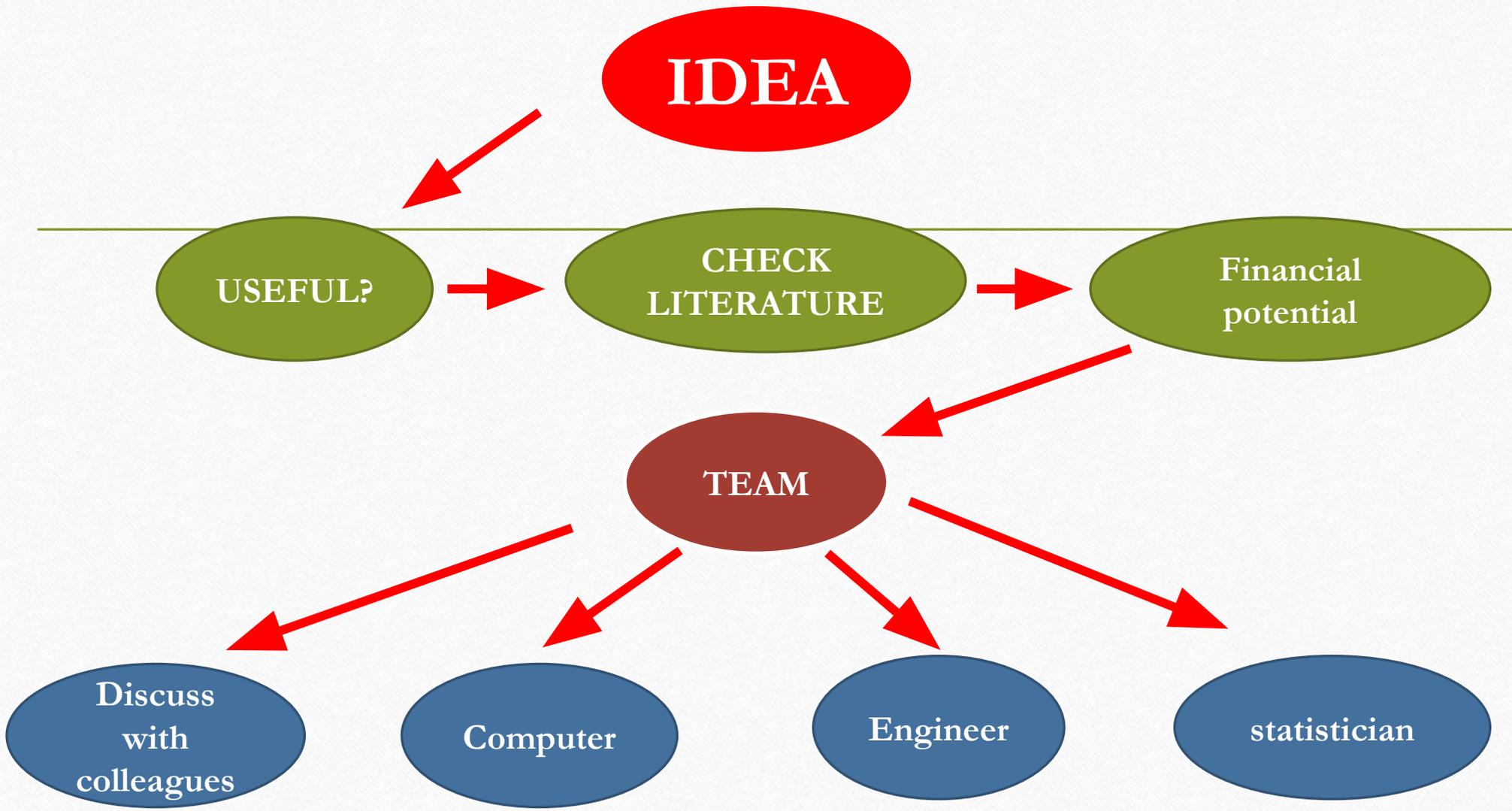
Precision Medicine

- Tailoring healthcare interventions to individuals or groups of patients:
 - Genomic variation
 - Contributing factors: Age, gender, geography, race, family history, immune profile, metabolic profile, microbiome, and environment vulnerability.
 - Individual biology rather than population biology



Early Detection of Mood Conditions

Predicted by analyzing the trend, tone of voice, and speaking style of individuals.





An International Conference Exploring AI's Role in Medicine

Artificial Intelligence & Innovation Conference

Virtual Conference
 August 14th, 2021
 11:00 am - 2:00 pm EST



- [Home](#)
- [Symposium](#)
- [UAlberta](#)
- [UBC](#)
- [Dalhousie University](#)
- [UToronto](#)
- [USask](#)



An interdisciplinary approach to health care

This organization aims to inform and educate students on the applications of Artificial Intelligence (AI) and Machine Learning (ML) in the medical field. From AI-controlled robotic surgery and intelligent prosthetics, to health outcome prediction and precision medicine, this interdisciplinary effort aims to foster a collaborative community between computing sciences, engineering, and medicine.

