

# Artificial intelligence (AI) for medicine and oncology: some concepts and applications

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# Outline of presentation

- Simple intro to AI
- AI in medicine
- AI in oncology
- AI in cancer genomics and transcriptomics
- *Use case: AI-based classification of cancers of unknown primary -> Later session*
- Conclusions and perspectives



<http://www.unehistoiredeplumes.fr/a-vol-doiseau/>

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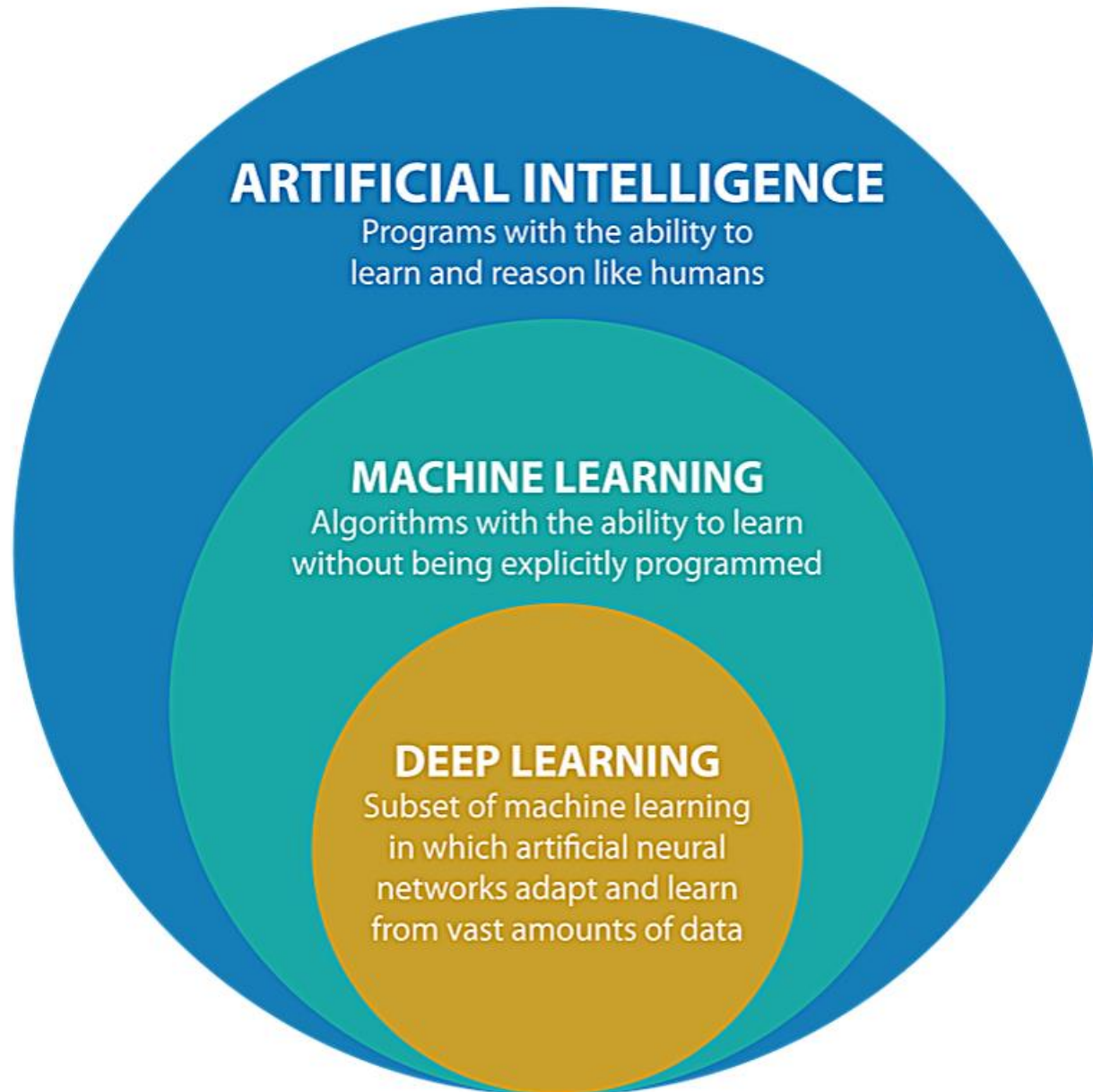


<http://www.unehistoiredeplumes.fr/a-vol-doiseau/>

*Don't hesitate to interrupt and ask questions!*

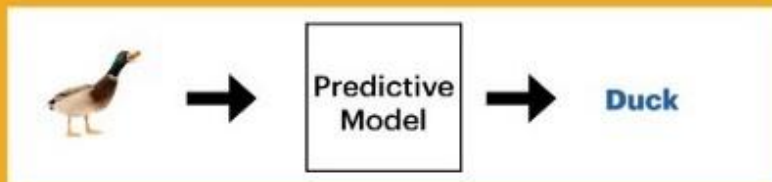
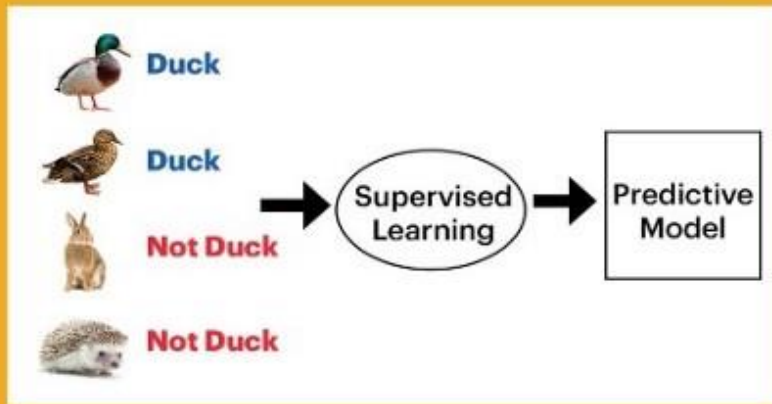
# Artificial intelligence (AI): some concepts

# Definitions

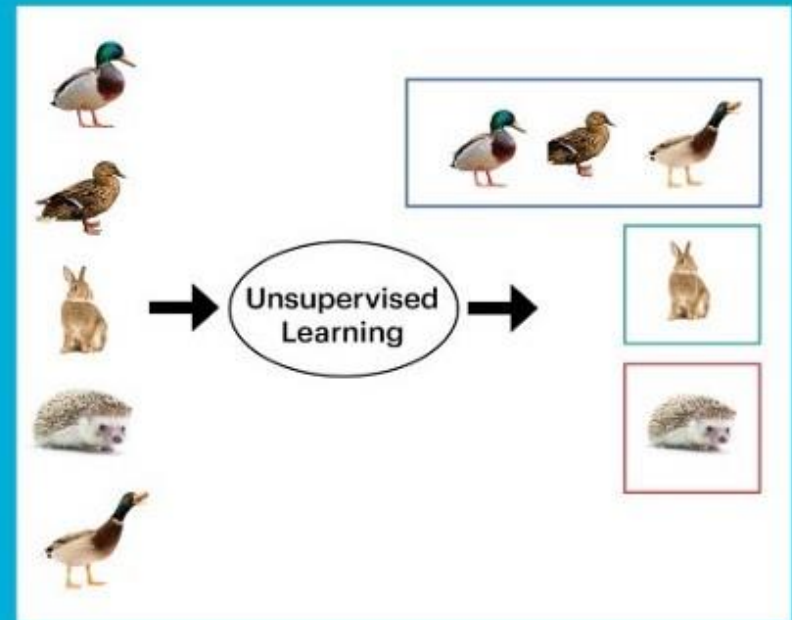


# Supervised/unsupervised learning

## Supervised Learning (Classification Algorithm)



## Unsupervised Learning (Clustering Algorithm)



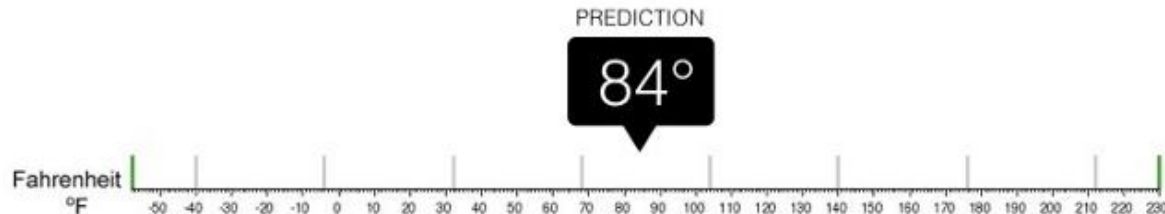
Western Digital.

# Regression or classification



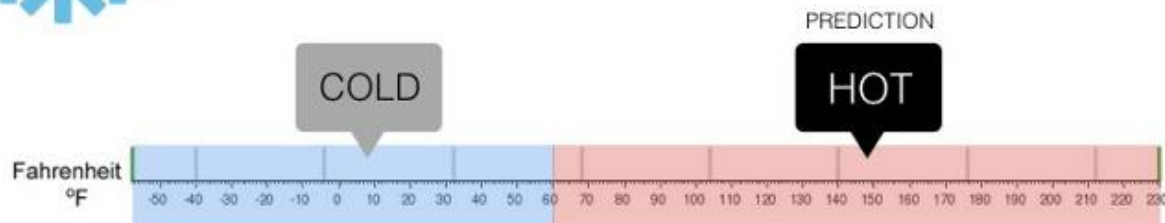
## Regression

What is the temperature going to be tomorrow?

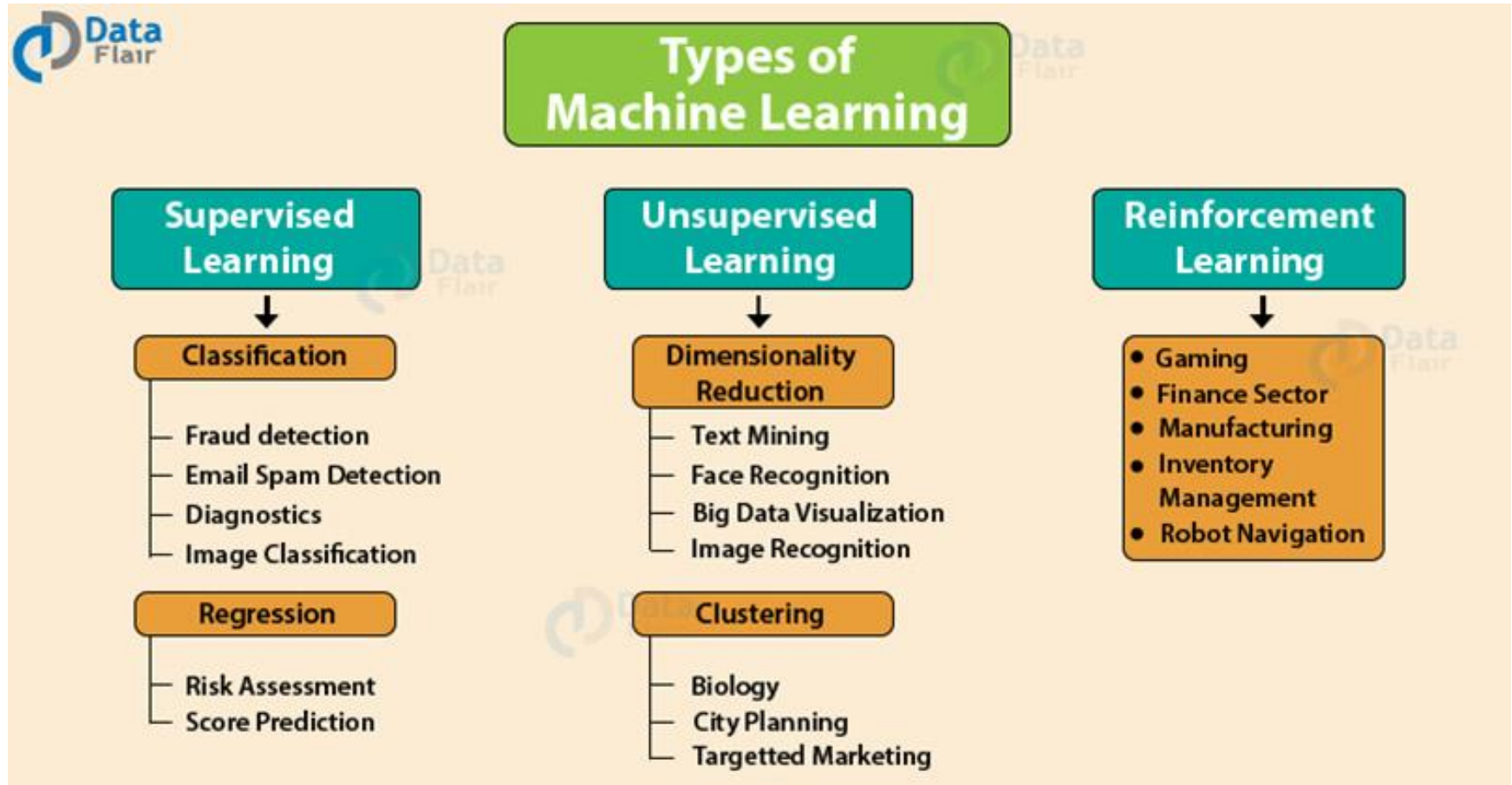


## Classification

Will it be Cold or Hot tomorrow?



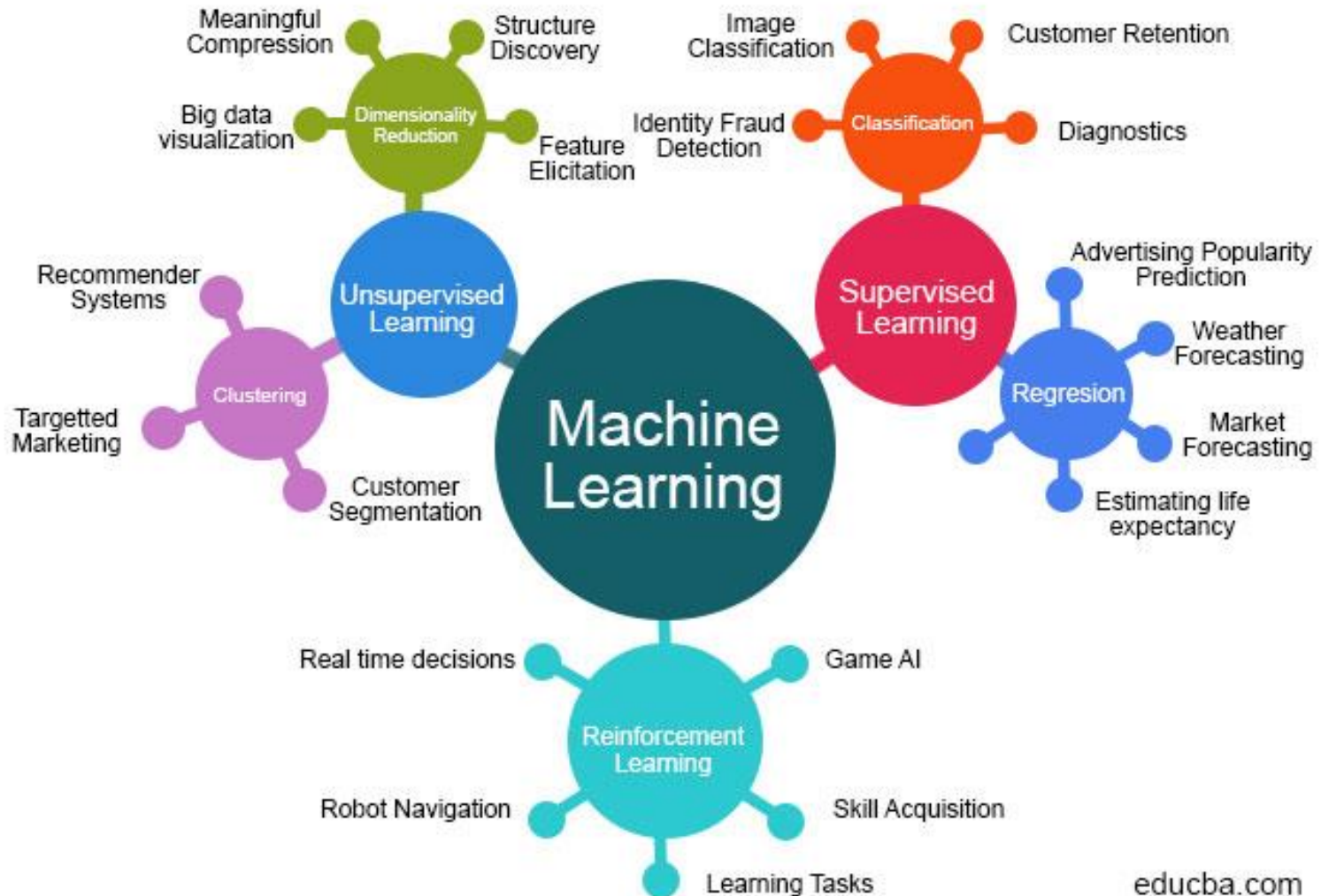
# Main types of machine learning





# Algorithms are proliferating...

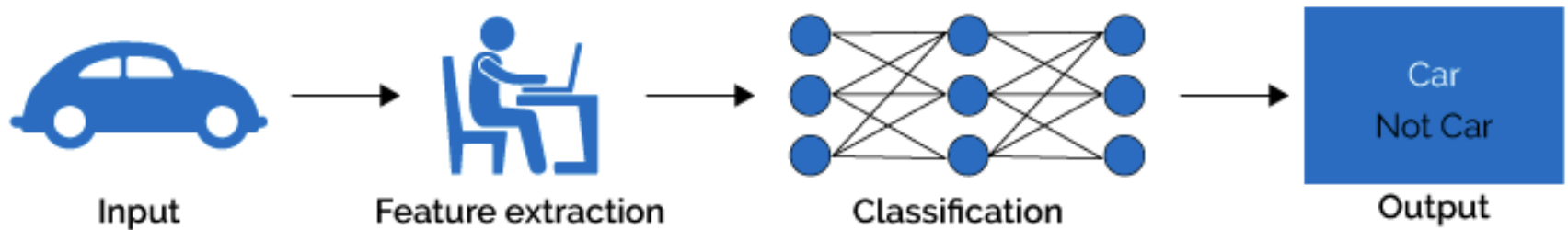
## Machine Learning Algorithms



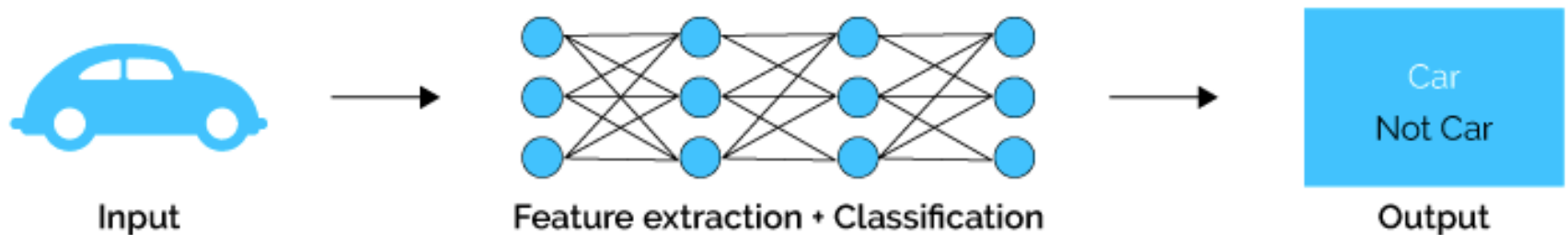
educba.com

# Machine learning vs deep learning

## Machine Learning



## Deep Learning



# What algorithms are eating: « Big data »

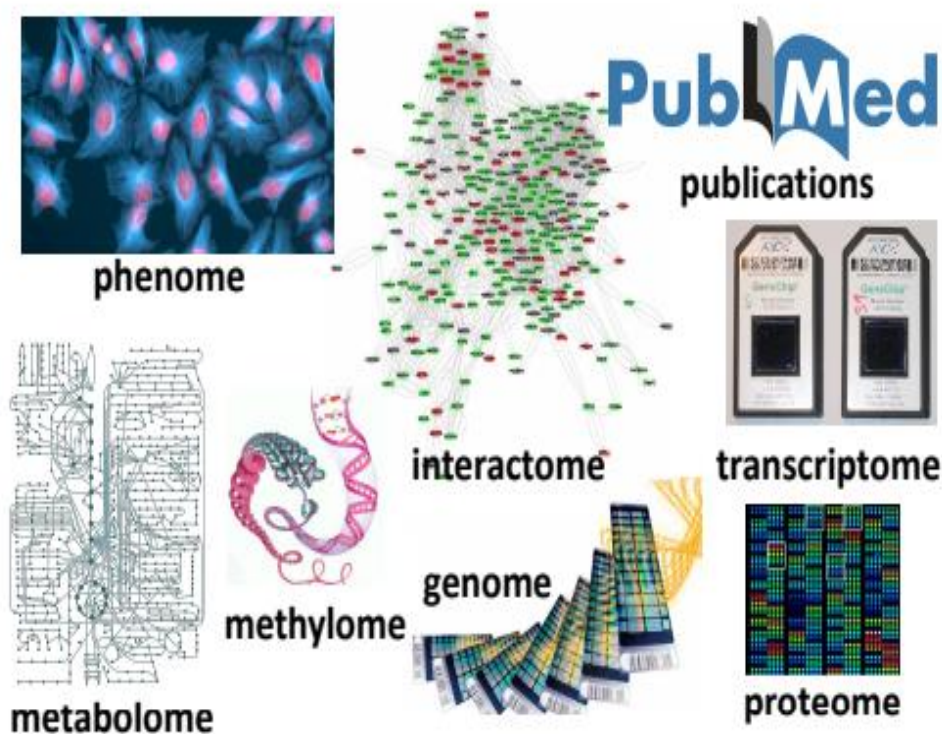
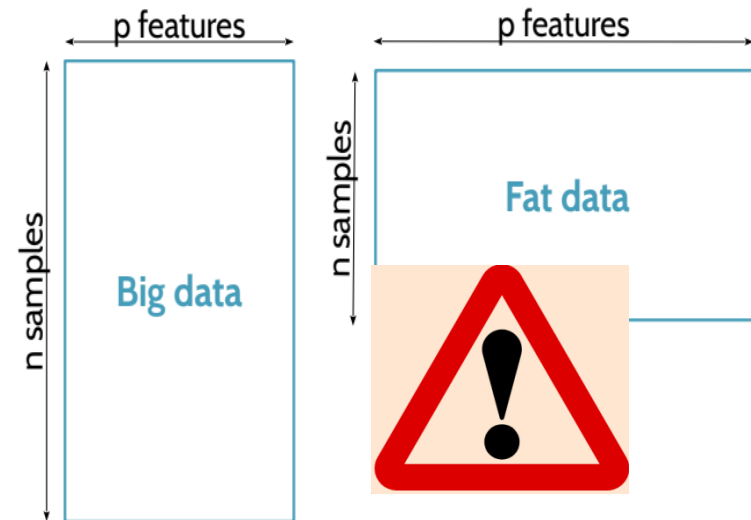


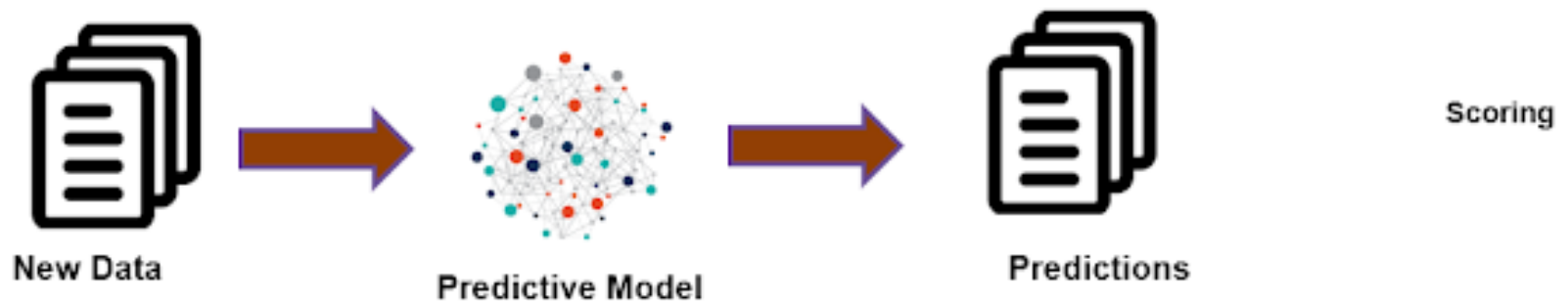
Image sources: ajc1@ flickr; Zlir'a@wikimedia



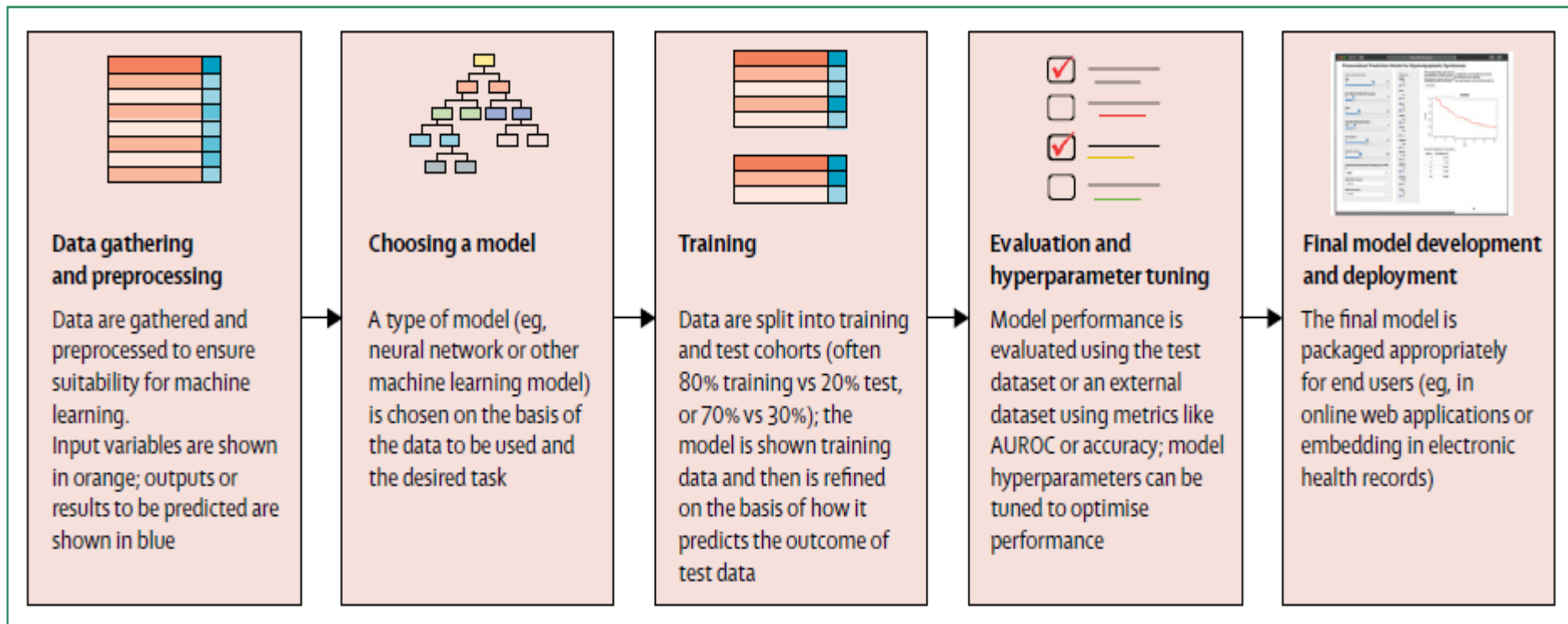
E.g. **Genome-Wide Association Studies (GWAS)**:

- ▶  $p = 10^5 - 10^7$  **S**ingle **N**ucleotide **P**olymorphisms (SNPs)
- ▶  $n = 10^2 - 10^4$  samples.

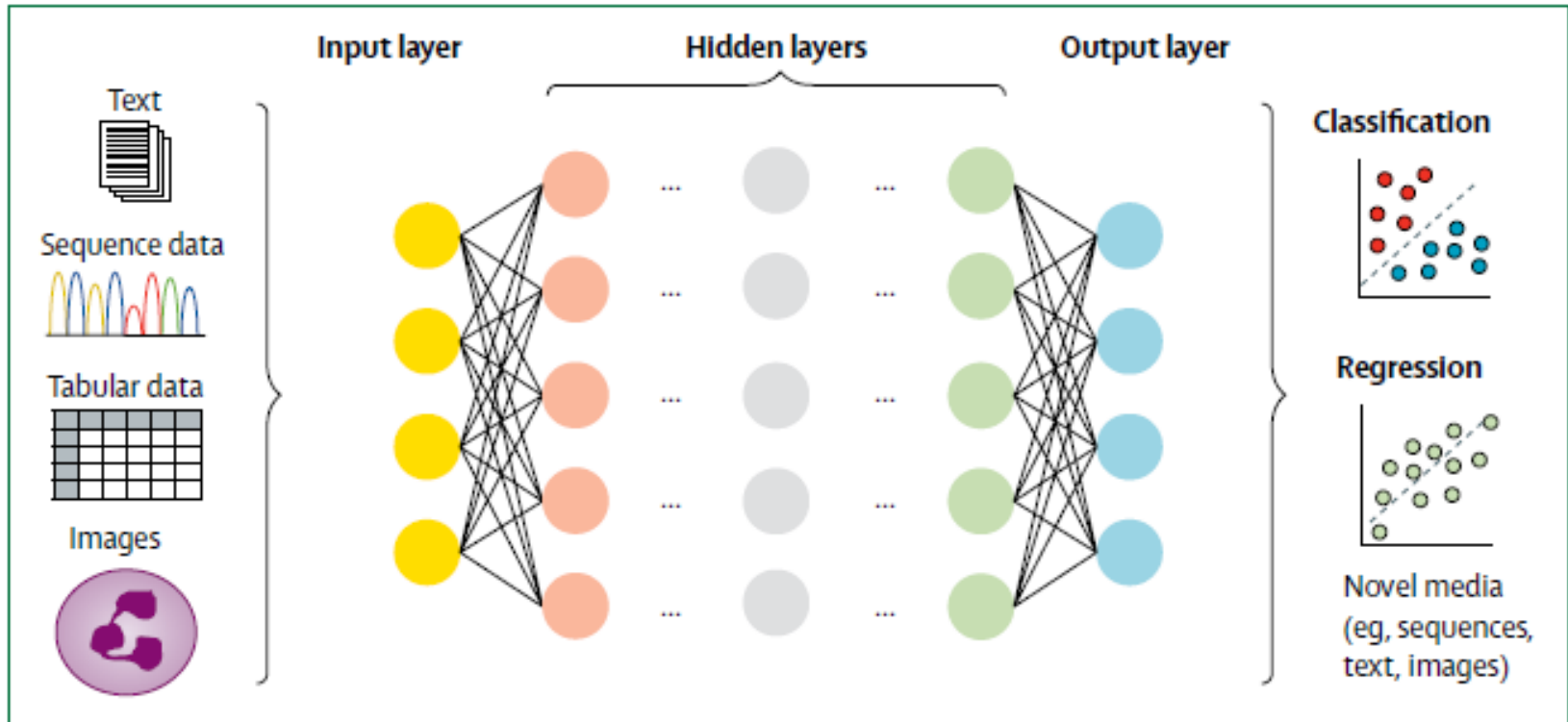
# Typical machine learning workflow



# Typical machine learning workflow (2)



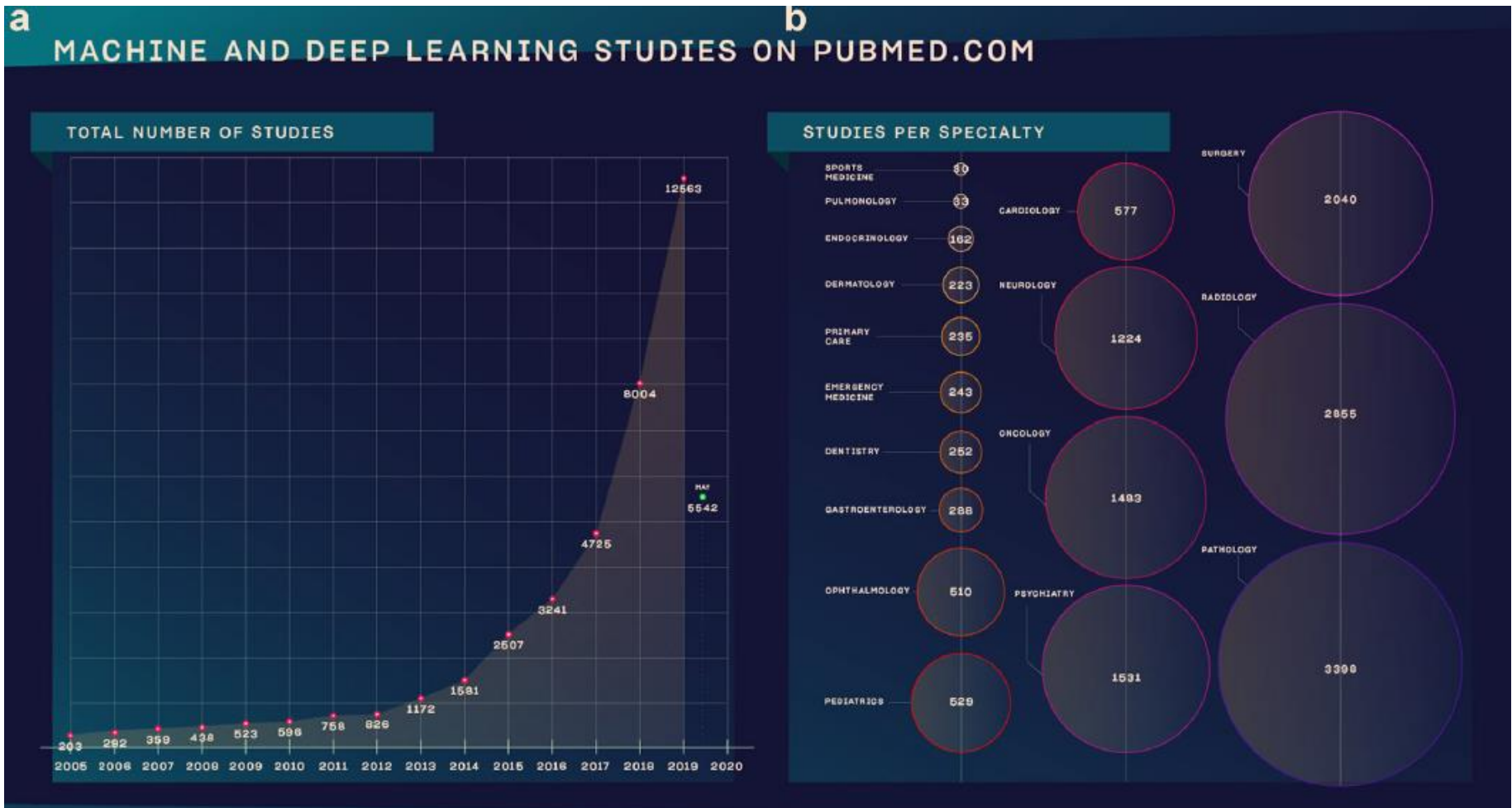
# Typical scheme of deep learning



AI in medicine:  
what, why, how?



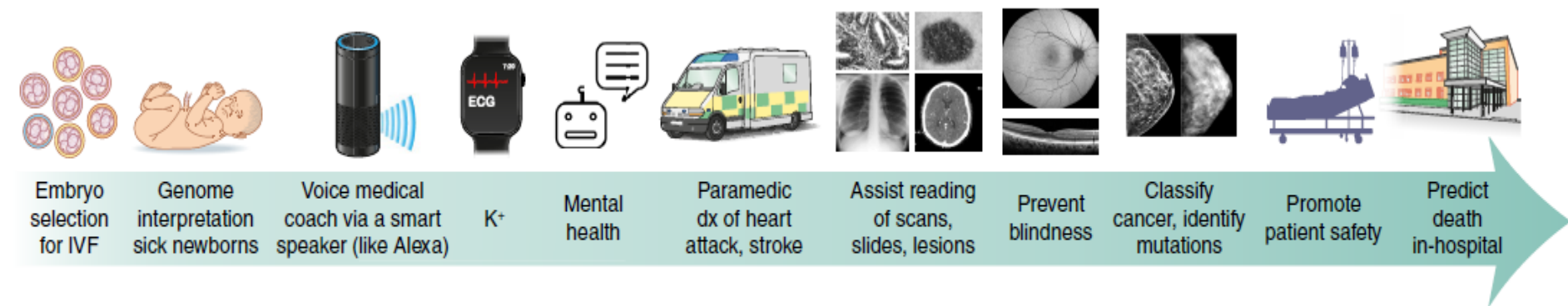
# AI and medicine: articles are proliferating...



Mesko et al., Npj Digital Med, 2020

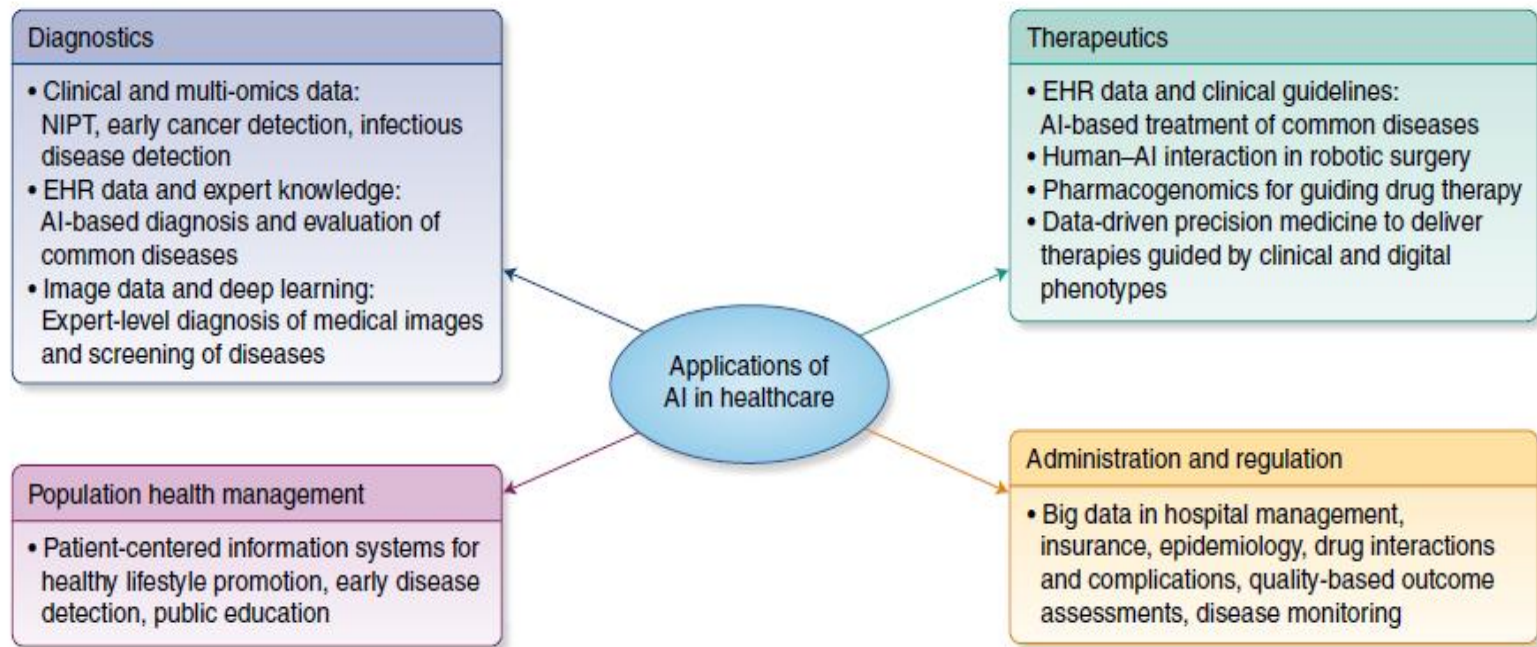


# Potential applications in medicine (non-exhaustive list)



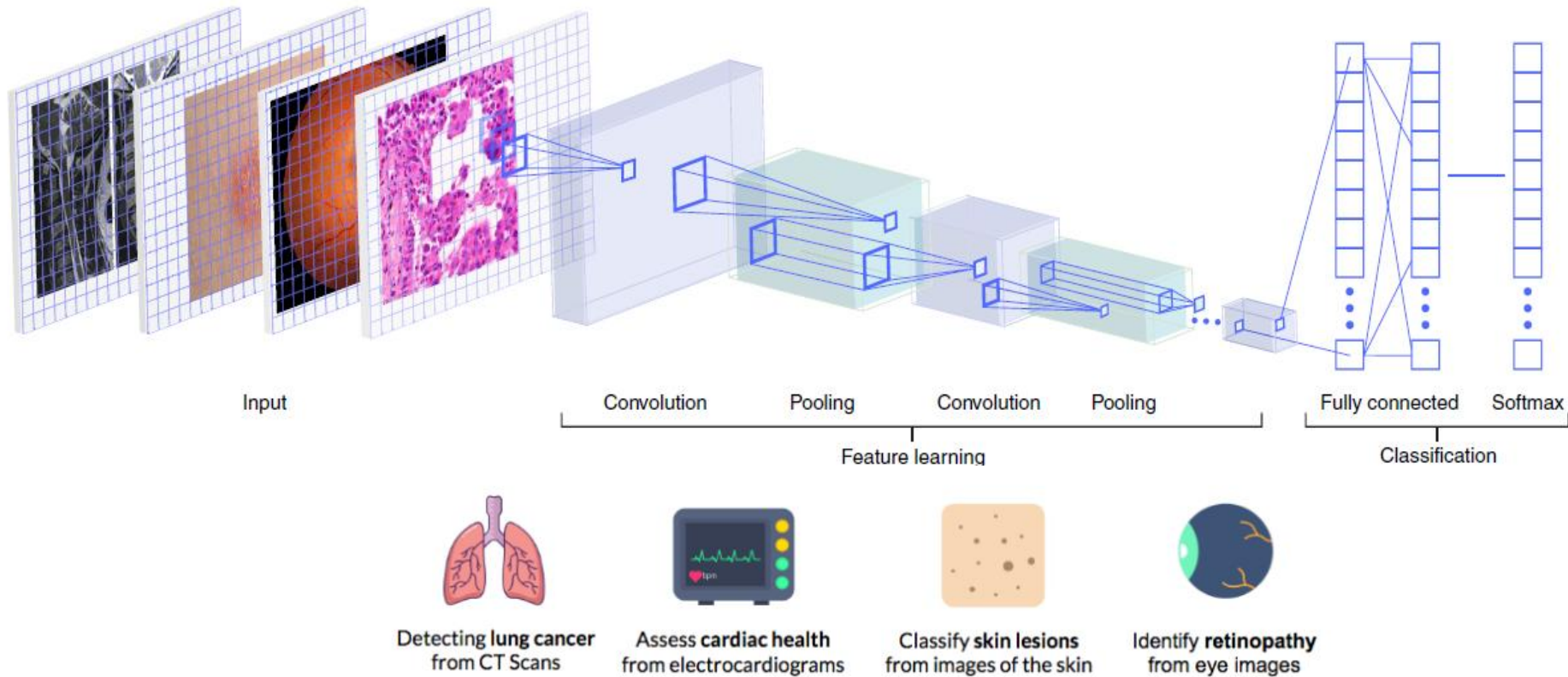
**Fig. 2 | Examples of AI applications across the human lifespan.** dx, diagnosis; IVF, in vitro fertilization K<sup>+</sup>, potassium blood level. Credit: Debbie Maizels/  
Springer Nature

# Potential applications in medicine



**Fig. 1 | Potential roles of AI-based technologies in healthcare.** In the healthcare space, AI is poised to play major roles across a spectrum of application domains, including diagnostics, therapeutics, population health management, administration, and regulation. NIPT, noninvasive prenatal test. Credit: Debbie Maizels/Springer Nature

# Pioneer applications: medical image analysis



<https://www.datarevenue.com/en-blog/artificial-intelligence-in-medicine>

# Some AI tools are already used in clinical practice

**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

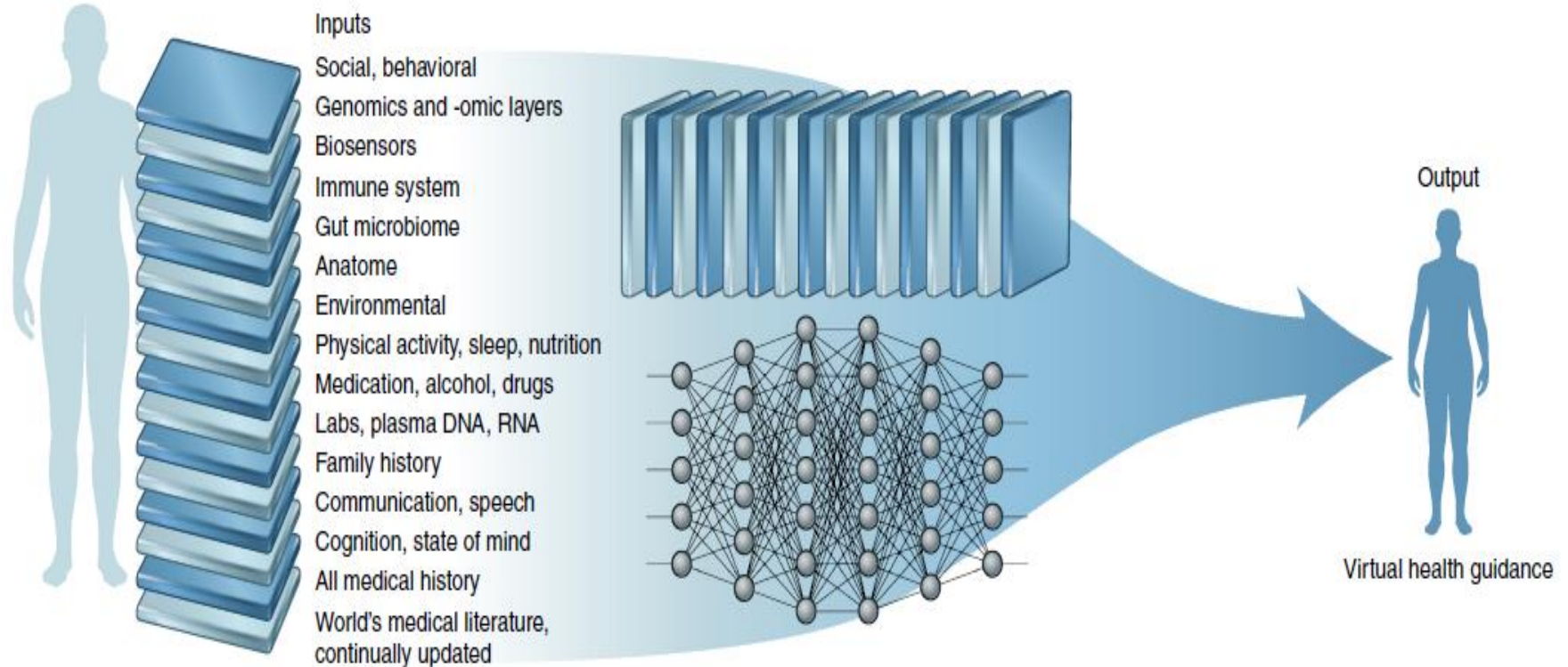
Topol, Nat Med 2019

# Screening for diabetic retinopathy





# Perspective: the « virtual medical coach »



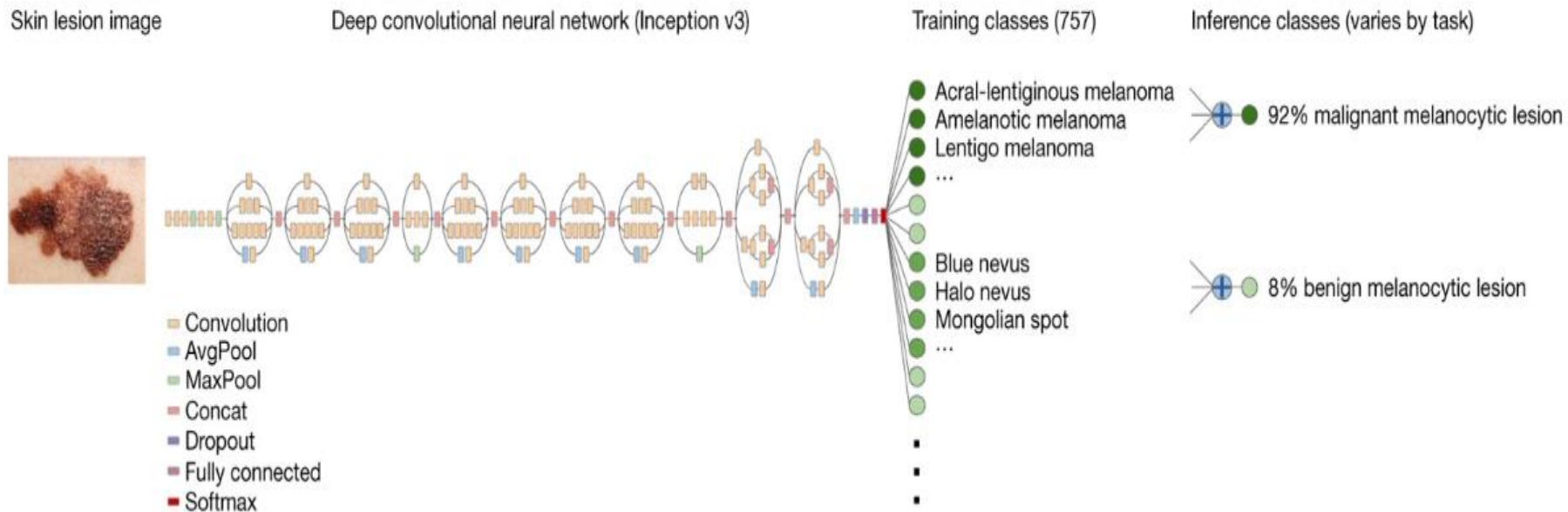
**Fig. 3 |** The virtual medical coach model with multi-modal data inputs and algorithms to provide individualized guidance. A virtual medical coach that uses comprehensive input from an individual that is deep learned to provide recommendations for preserving the person's health. Credit: Debbie Maizels/ Springer Nature

# AI in oncology: some applications

# Skin cancer classification



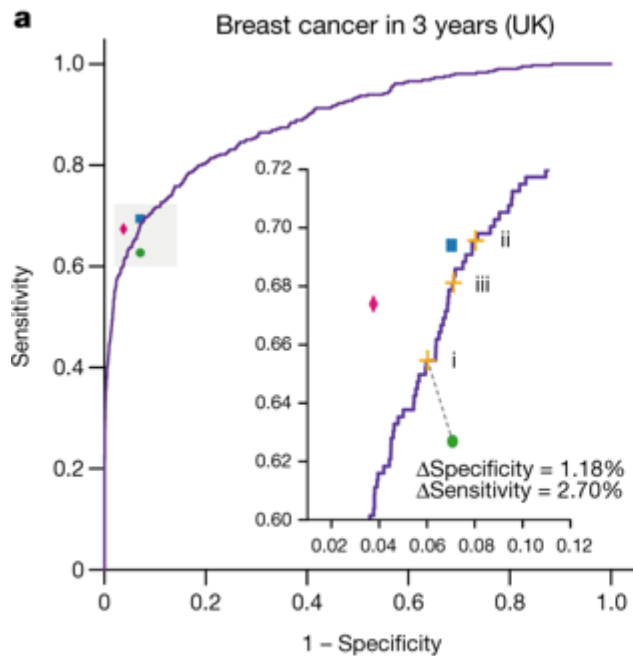
From: Dermatologist-level classification of skin cancer with deep neural networks



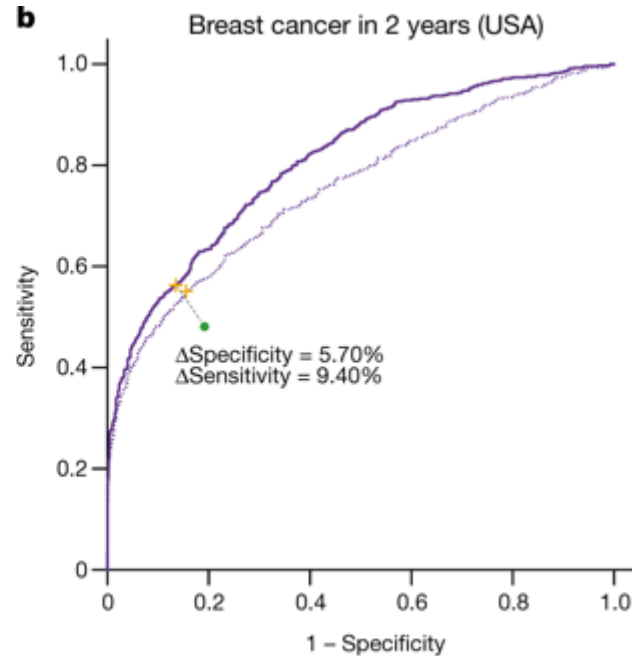
Esteva et al., Nature 2017



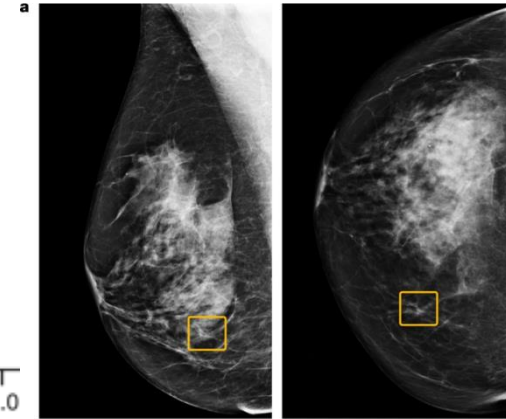
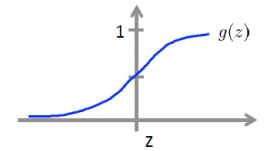
# Breast cancer screening



— AI system  
+ AI operating point  
• Mean first reader  
■ Mean second reader  
◆ Consensus

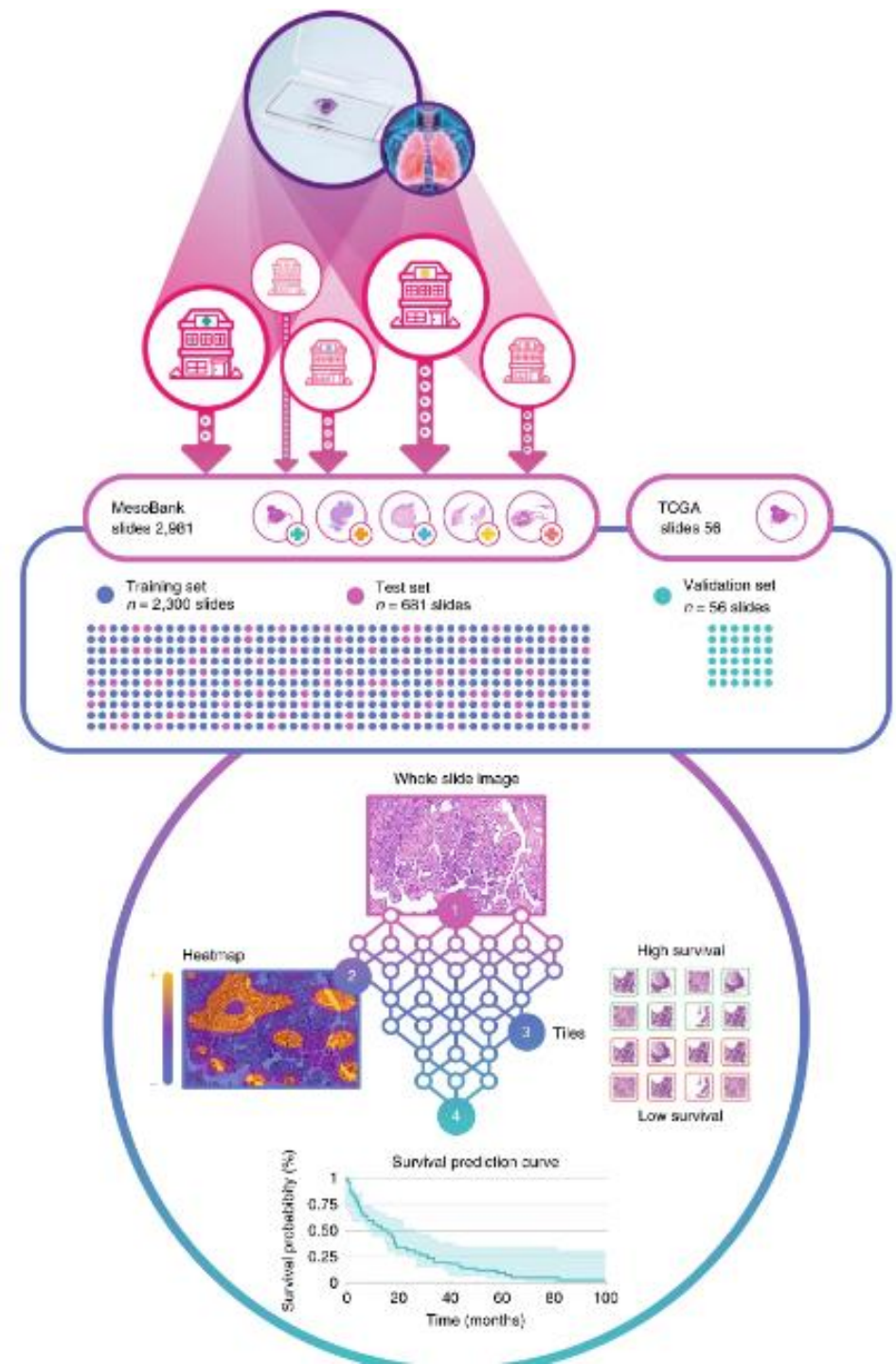


— AI system  
+ AI operating point  
• Mean human reader  
..... AI system (UK training only)



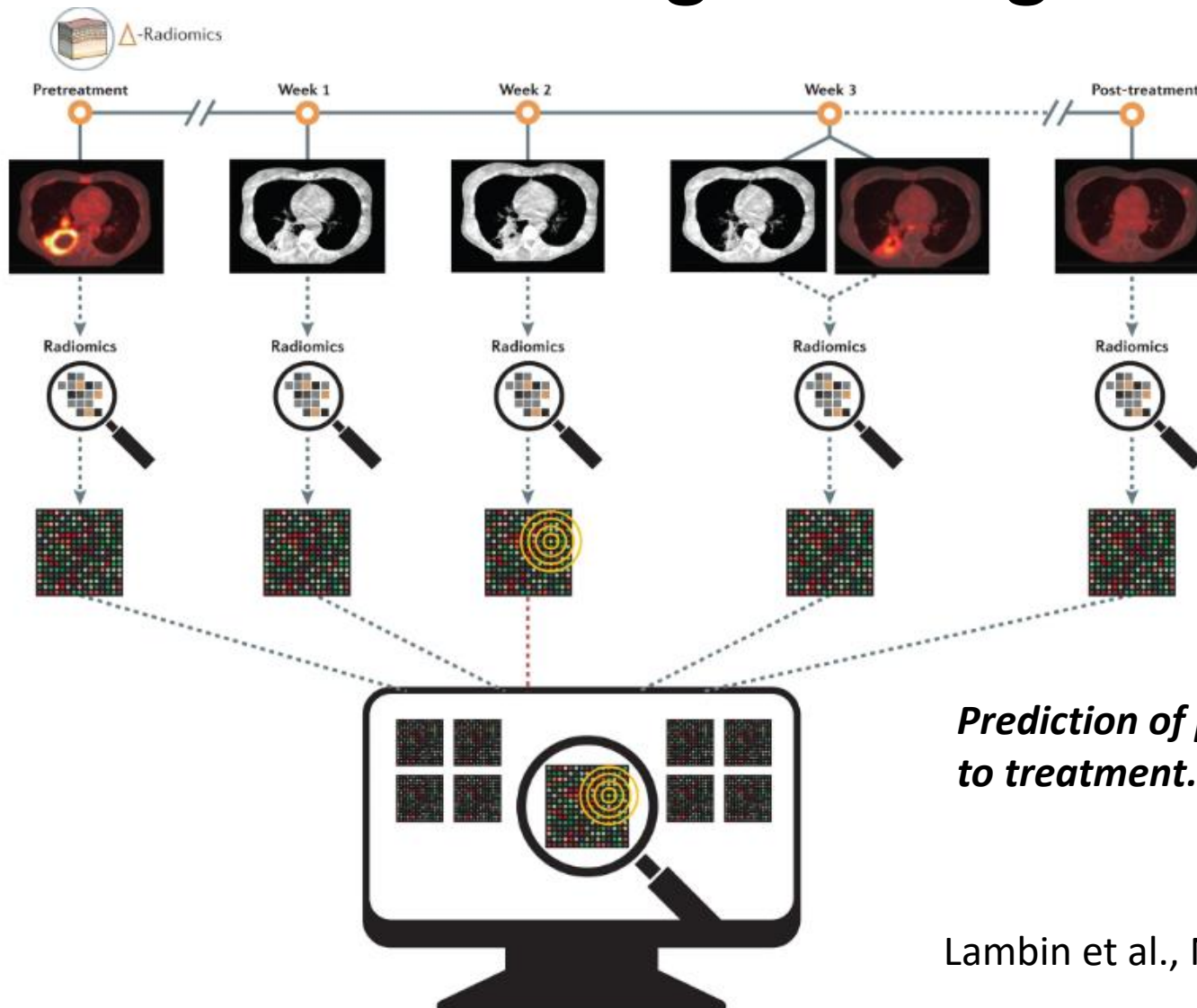
*International evaluation of an AI system for breast cancer screening, Scott Mayer McKinney, Marcin Sieniek, [...]Shravya Shetty, Nature volume 577, pages89–94(2020)*

# Prediction of mesothelioma prognosis based on pathological slides



Courtiol et al.,  
Nature Med 2019

# Radiomics: « texture » analysis of radiological images



***Prediction of prognosis, response to treatment...***

# AI in hematology

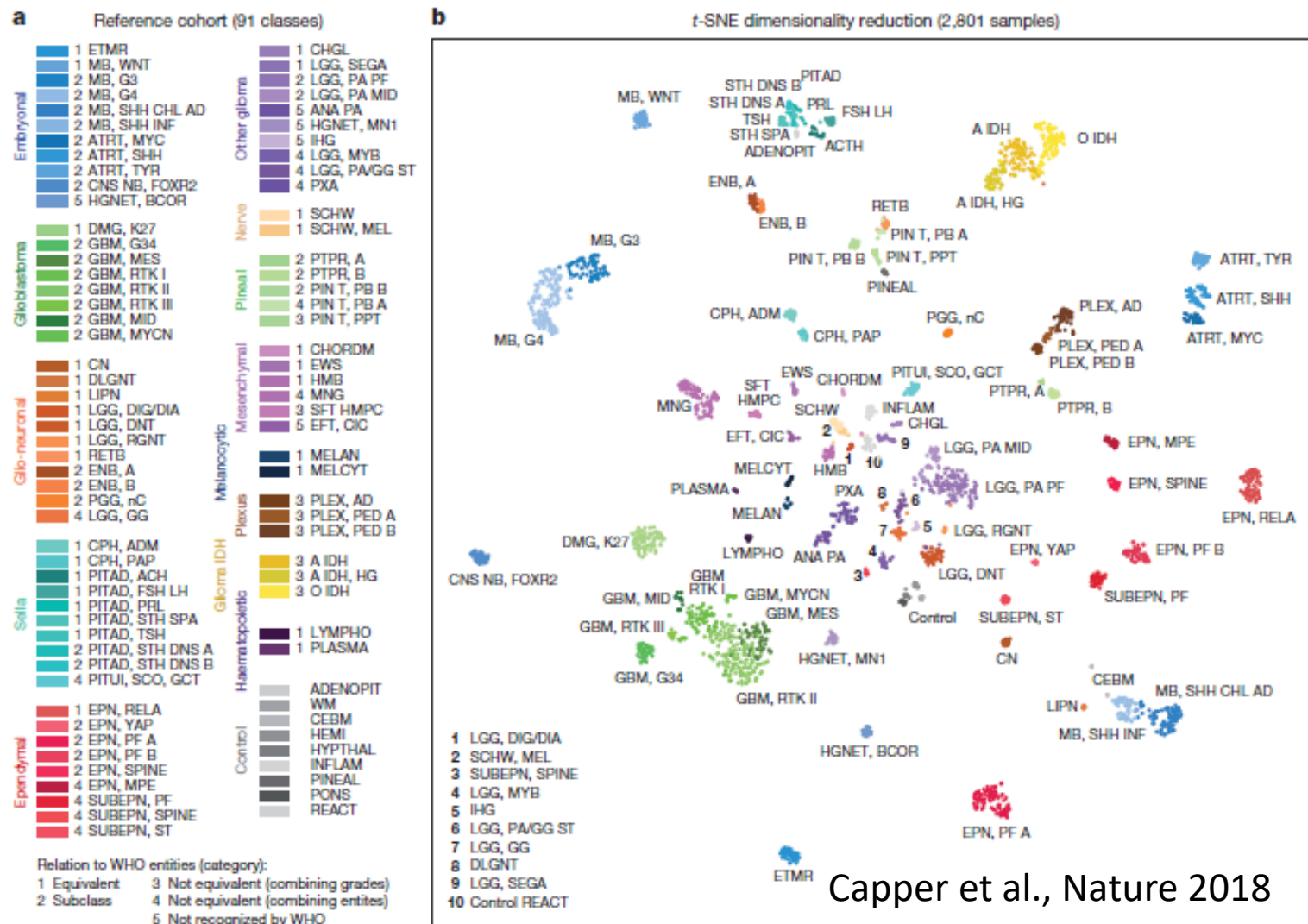
	Sample size	Application	Method	Results
Kimura et al (2019) <sup>23</sup>	3261 peripheral smears	Leucocyte classification; distinguishing aplastic anaemia and myelodysplastic syndrome	CNN, gradient boosting	Sensitivity vs specificity was 93.5% vs 96.0% for leucocyte detection, and 96.2% vs 100% for aplastic anaemia vs myelodysplastic syndrome differentiation
Achi et al (2019) <sup>22</sup>	128 patients	Differentiating diffuse large B-cell lymphoma, small lymphocytic lymphoma, Burkitt lymphoma, and normal lymph nodes	CNN	95% accuracy per slide; 100% accuracy per patient
Li (2019) <sup>23</sup>	41 patients	Detection of acute myeloid leukaemia bone marrow involvement via PET-CT	Manual feature engineering (PyRadiomics)	Sensitivity vs specificity was 87.5% vs 89.5% for bone marrow involvement; outperformed visual inspection of scans
Milgrom et al (2019) <sup>24</sup>	251 patients	Predicting refractory Hodgkin lymphoma from PET-CT	CNN	AUROC of 0.95 for model vs 0.78 for tumour volume; 0.65 for standardised uptake value
Moraes et al (2019) <sup>25</sup>	283 patients	Differential diagnosis of chronic lymphocytic leukaemia and B cell lymphomas via flow cytometry	Decision tree	95% inclusion of correct diagnosis in differential diagnosis; 66% definitive diagnosis
Ni et al (2016) <sup>26</sup>	51 patients	Detection of MRD in acute myeloid leukaemia via flow cytometry	Support vector machine	Similar performance with manual flow analysis (concordance=0.986)
Fuse (2019) <sup>27</sup>	217 patients	Prediction of acute leukaemia relapse after allogeneic stem cell transplantation	Decision tree	0.75 AUROC for relapse after transplantation
Goswami et al (2019) <sup>28</sup>	347 patients	Risk stratification for autologous stem cell transplantation in multiple myeloma	Decision tree	Significant risk-stratification and identification of high-risk features
Nazha (2019) <sup>29</sup>	433 and 113 patients	Predicting resistance to hypomethylating agents in patients with myelodysplastic syndrome on the basis of NGS myeloid malignancy panel	Recommender algorithm	Improved stratification of patients by risk of resistance to a hypomethylating agent
Gal et al (2019) <sup>30</sup>	493 patients	Response to induction therapy in paediatric acute myeloid leukaemia	K-nearest neighbours	0.84 AUROC for response to induction
Candia (2015) <sup>31</sup>	60 patients	Unsupervised analysis of microRNA expression signatures in acute myeloid leukaemia and acute lymphocytic leukaemia	Dimension reduction, network analysis	Identification of novel microRNA signatures in acute myeloid leukaemia and acute lymphocytic leukaemia

AUROC=area under the receiver operating characteristic curve. CNN=convolutional neural network. MRD=minimal residual disease. NGS=next-generation sequencing.

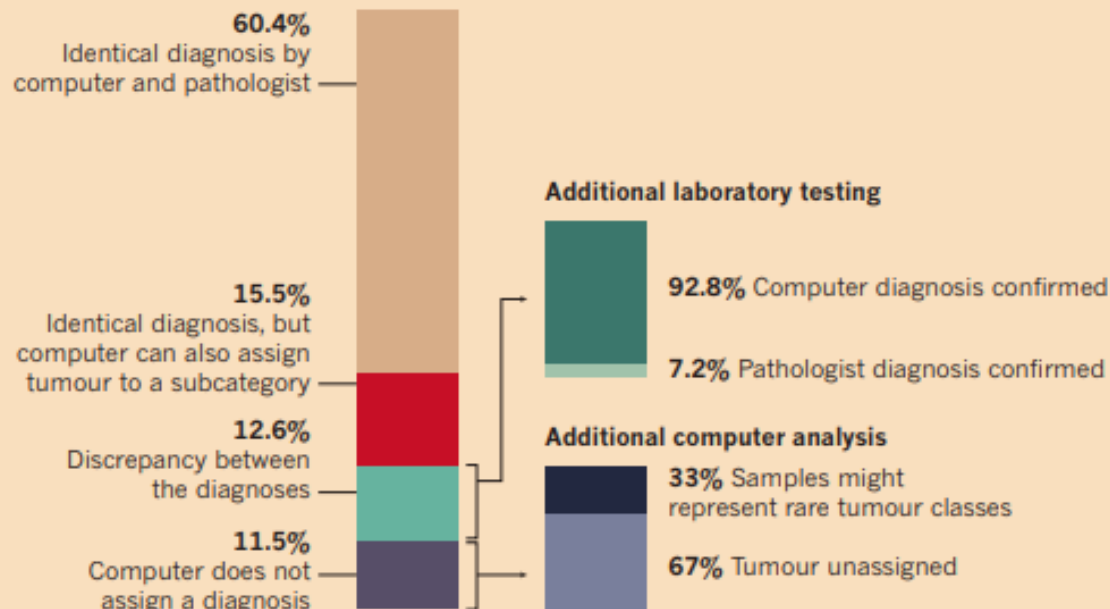
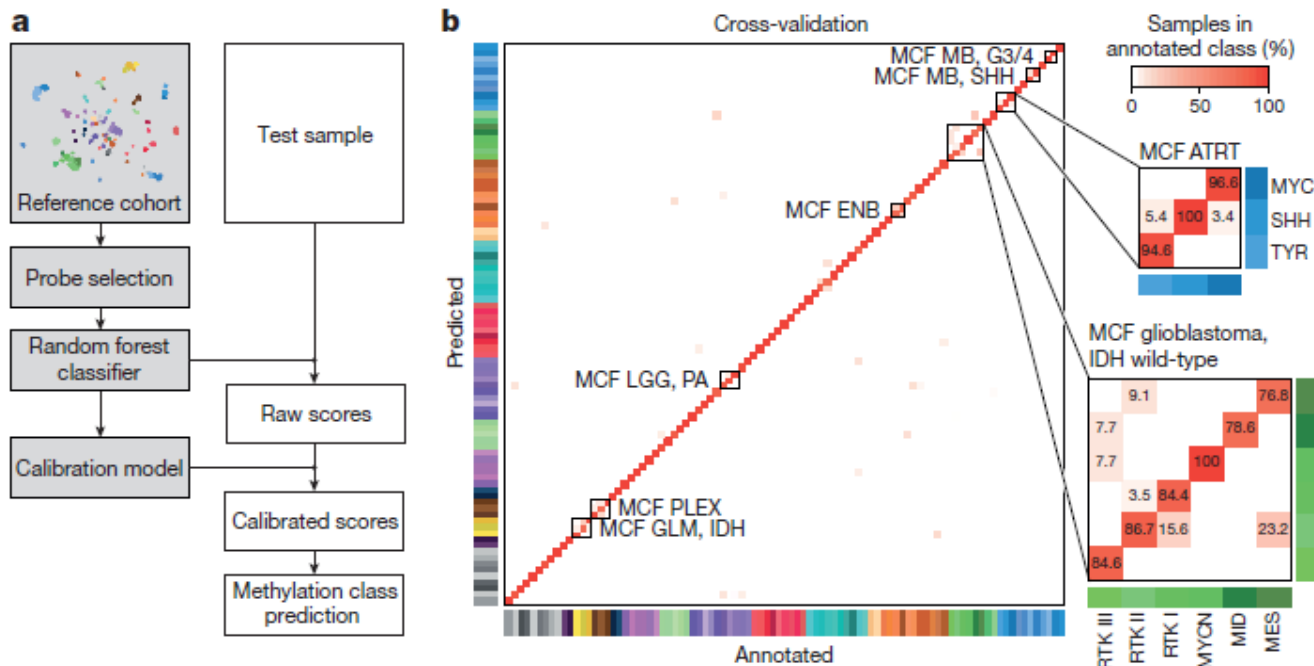
**Table: Representative artificial intelligence in malignant haematology publications**

# AI in cancer genomics and transcriptomics

# DNA methylation-based classification of central nervous system tumours



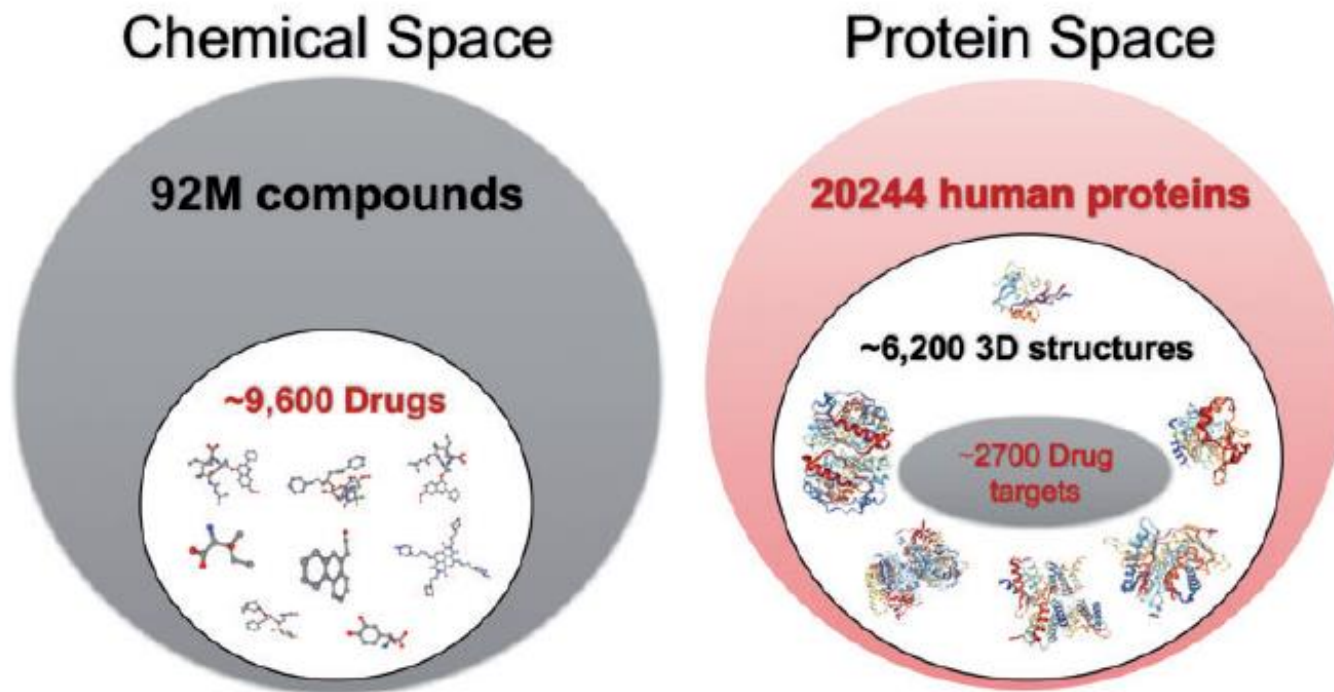




- *Cf later session: prediction of primary tumor using transcriptomics*

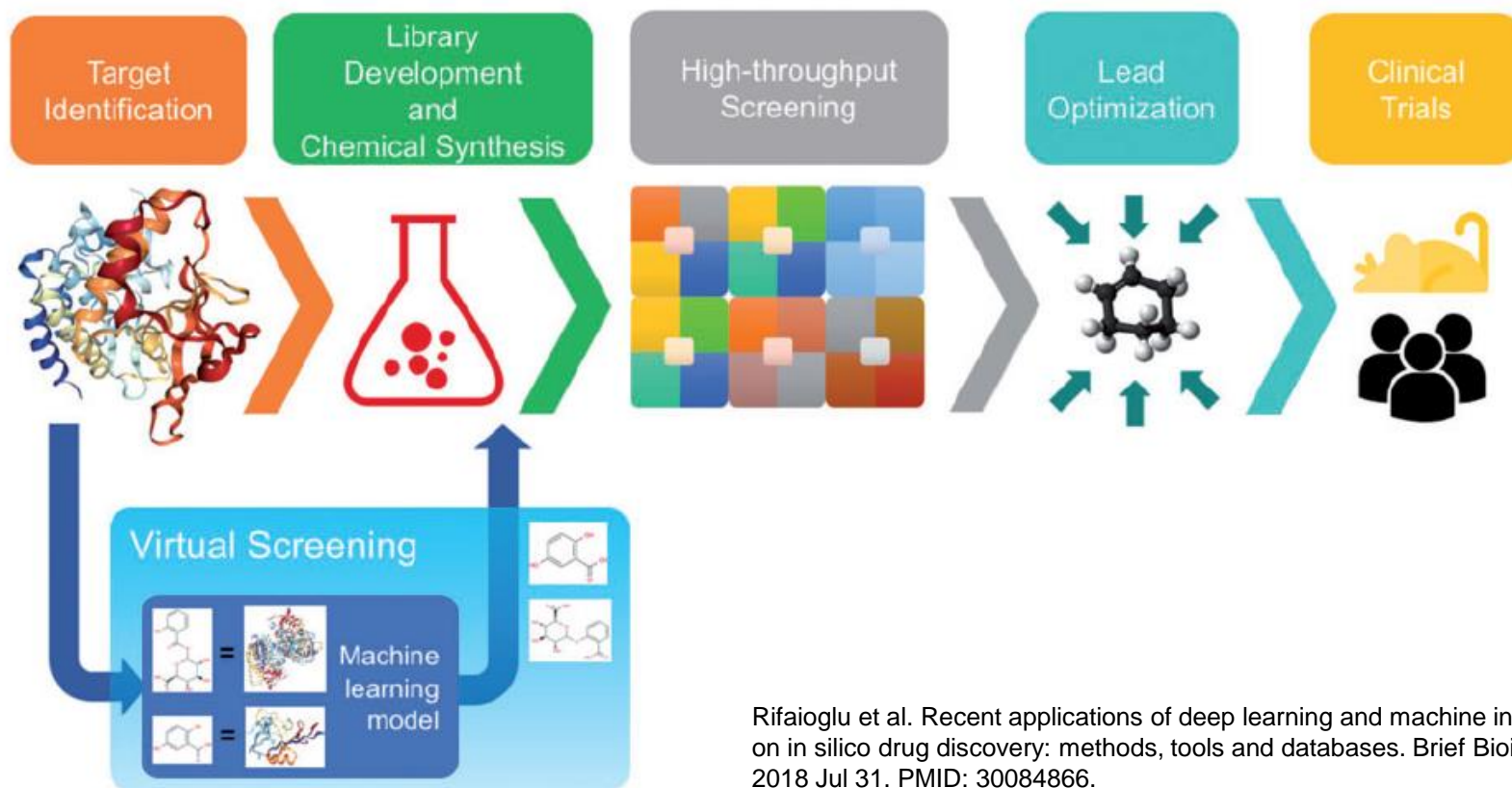


# Drug development



Rifaioglu et al. Recent applications of deep learning and machine intelligence on in silico drug discovery: methods, tools and databases. Brief Bioinform. 2018 Jul 31. PMID: 30084866.

# Drug discovery in details



Rifaioğlu et al. Recent applications of deep learning and machine intelligence on in silico drug discovery: methods, tools and databases. Brief Bioinform. 2018 Jul 31. PMID: 30084866.

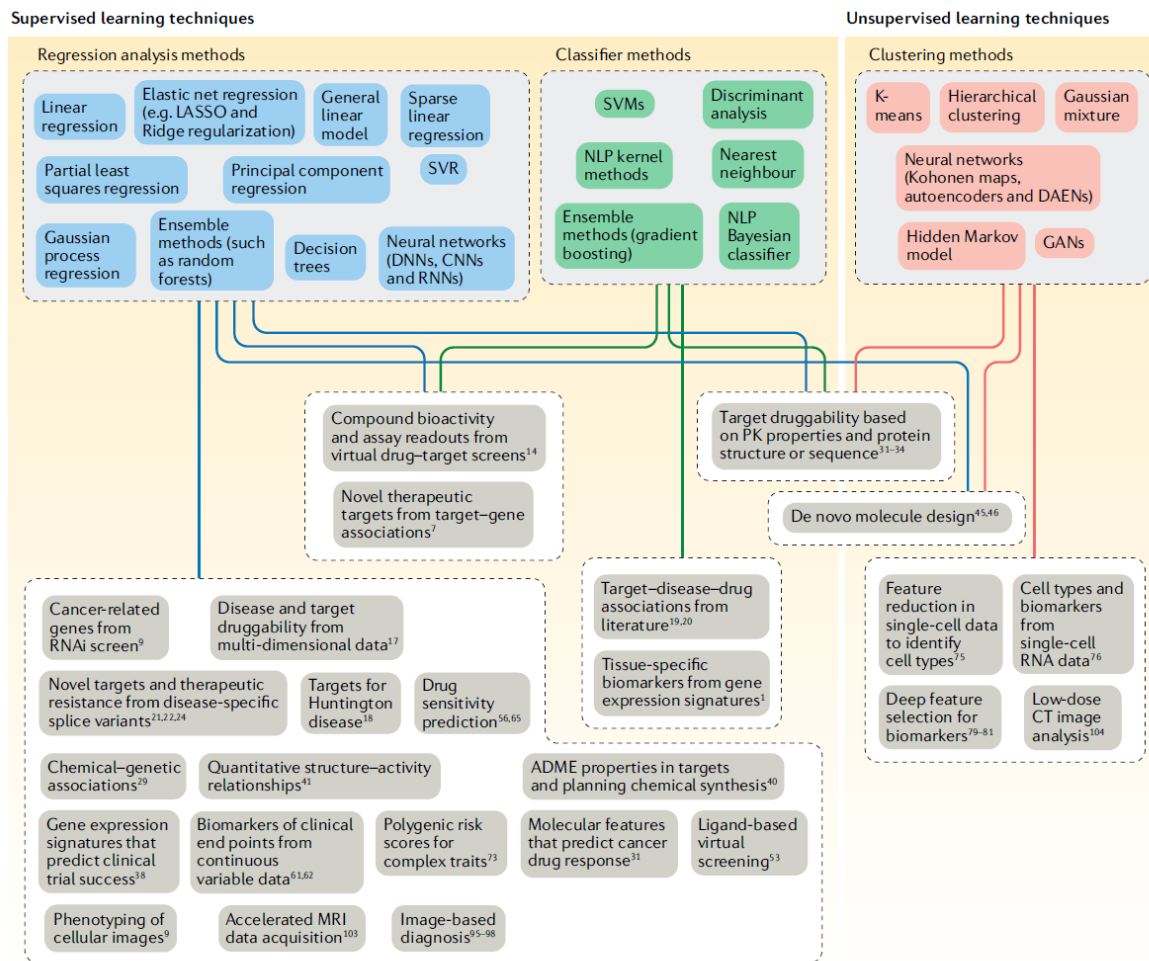
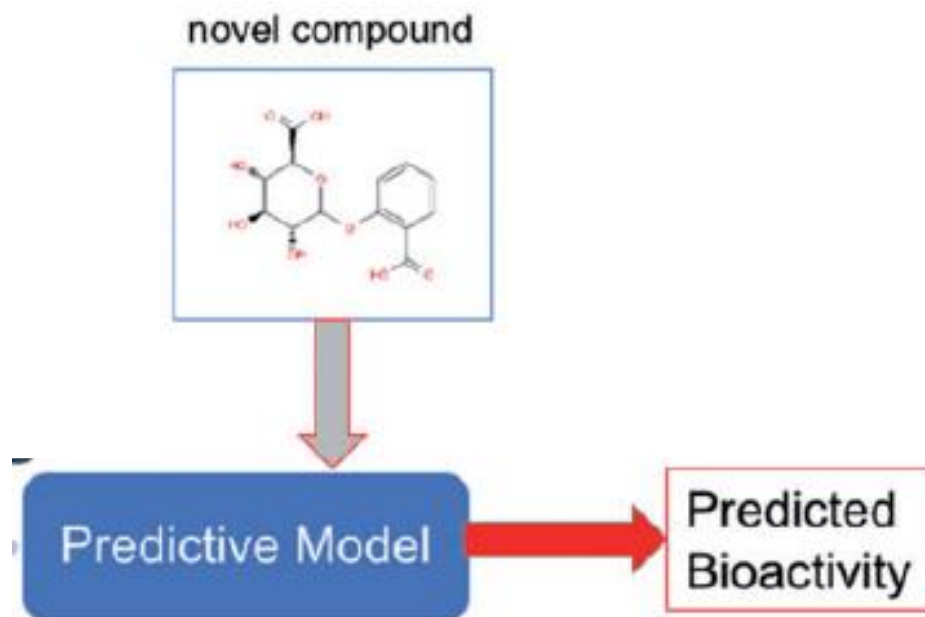


Fig. 2 | **Machine learning tools and their drug discovery applications.** This figure gives an overview of the machine

Vamathevan J,. Applications of machine learning in drug discovery and development. Nat Rev Drug Discov. 2019 Apr 11. doi: 10.1038/s41573-019-0024-5. [Epub ahead of print] Review. PubMed PMID: 30976107

# Predictions



Rifaioğlu et al. Recent applications of deep learning and machine intelligence on in silico drug discovery: methods, tools and databases. Brief Bioinform. 2018 Jul 31. PMID: 30084866.

# Tasks with EHR

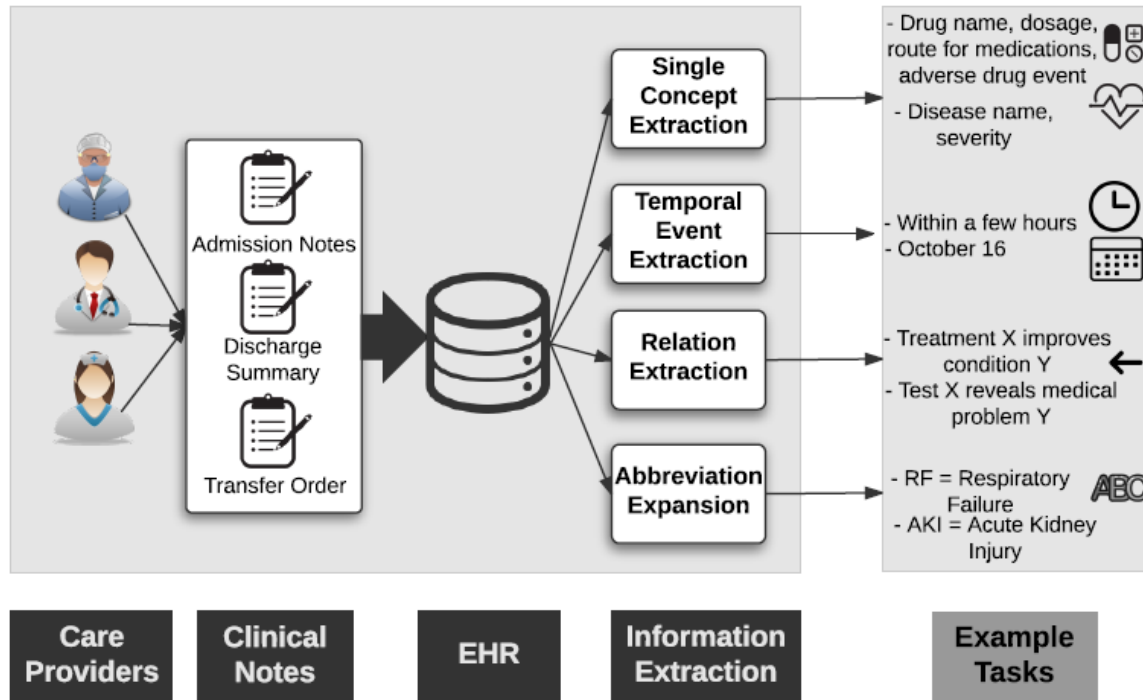


Fig. 7. EHR Information Extraction (IE) and example tasks.

Deep EHR: A Survey of Recent Advances in Deep Learning Techniques for Electronic Health Record (EHR) Analysis.  
Benjamin Shickel, Patrick J. Tighe, Azra Bihorac, and Parisa Rashidi. arXiv:1706.03446v2

# Some comments

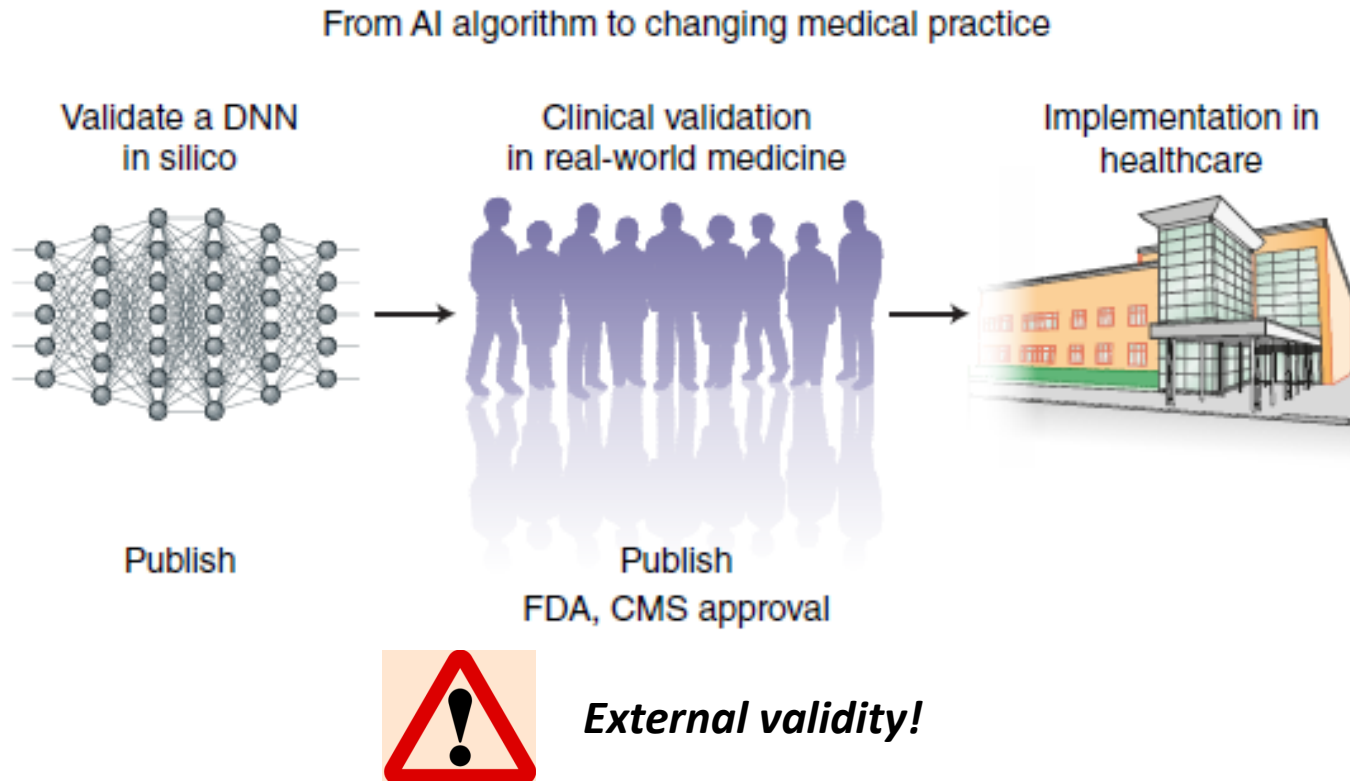
- AI can potentially be used in **every question in medicine that can be answered with data:** prediction of diagnosis, prognosis, response to treatment...
- As soon as there are **enough good data** to train an algorithm
- **Genomics and transcriptomics are well-suited to AI** (high number of features, « big data »), especially with recent techniques (**single-cell**)
- ***But may suffer from low number of samples (« fat data »)***

# Conclusions and perspectives

- AI is **essential** to help the human brain in dealing with « big data »
- It has the potential to change practice in almost **all areas of medicine**
- However **AI does not replace** the doctor
- Algorithms have to be validated and show benefit in **real life**
- **Interpretability** issue

*This subject is being updated every day...*

# Be careful not to skip steps before use in real life



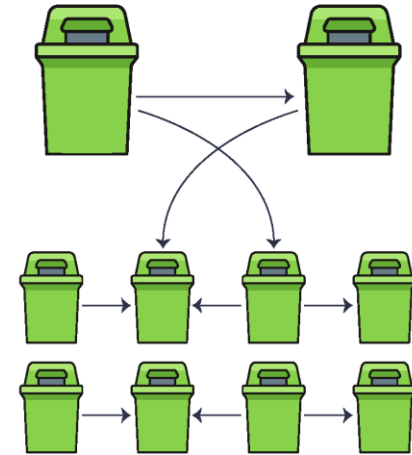




**POOR DATASET**



**PERFECT MODEL**



**POOR PREDICTION**

## What data scientists actually do



3%: Building training sets

4%: Refining algorithms

5%: Others

9%: Mining data for patterns

19%: Collecting data sets

60%: Cleaning and organizing data

# Acknowledgments



Dr Stéphane Champiat (DITEP)  
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**THANK YOU FOR YOUR ATTENTION!**