

Machine Learning and Computational Medicine for Clinical development, Patients, and Regulators

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Disclosures: none

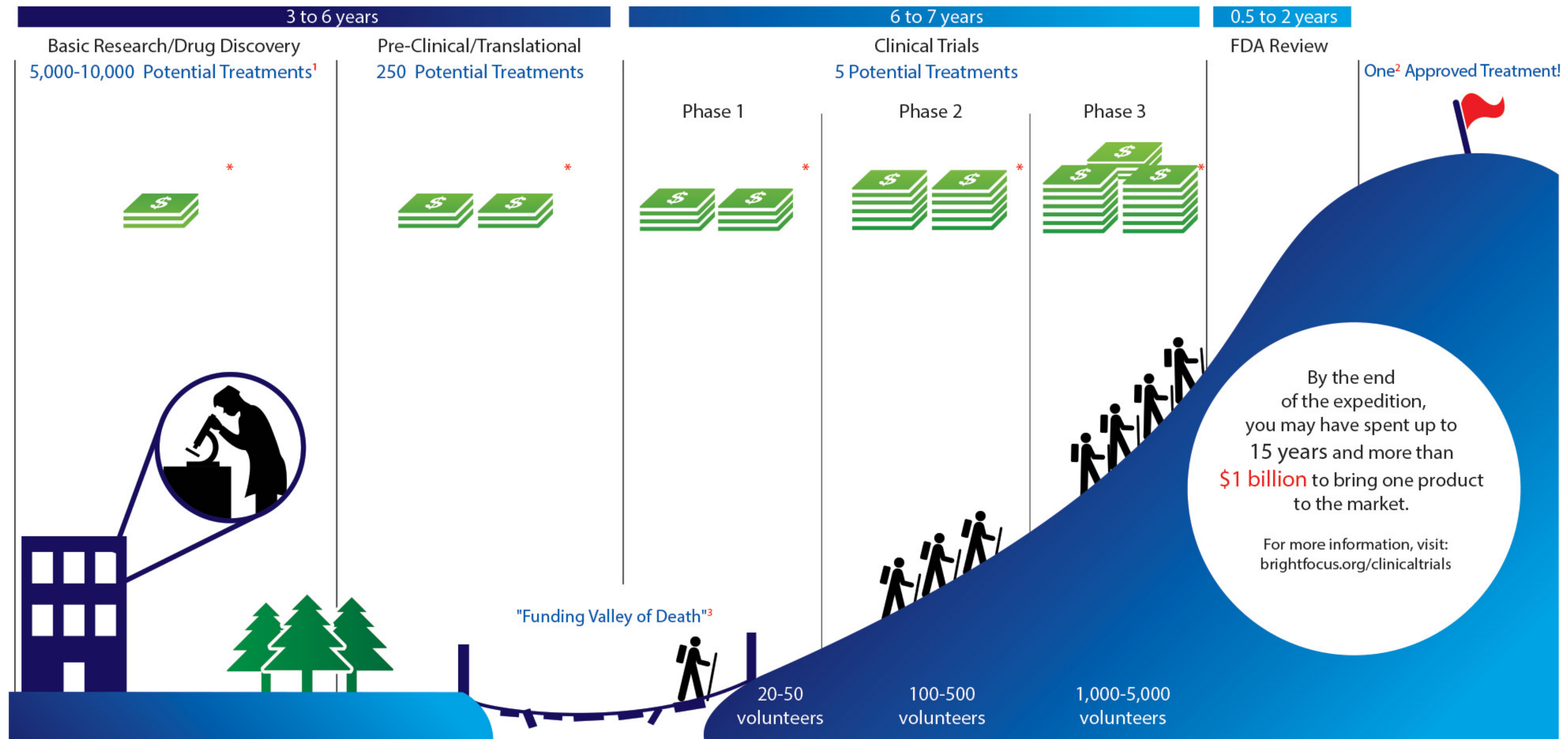


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Current Drug Development Paradigm

An Uphill Battle Imagine leading an expedition where every step is more difficult than the last...

The long journey begins in the lab, where scientists spend years testing thousands of ideas. Next, crossing the so-called "Funding Valley of Death" requires the resources and time needed to complete clinical trials, testing safety and effectiveness among what could end up being thousands of volunteers. At the end of this steep financial and scientific climb: Food and Drug Administration approval for a new treatment. Ultimately, it may have taken up to 15 years and more than \$1 billion to bring this treatment to the market.



¹ Although we are using the word "treatment," clinical trials also involve medical research studies in which people participate as volunteers to test new methods of prevention, screening, and diagnosis of disease.

² After approval, the product is manufactured for sale on the market, and the process enters Phase 4 (Post-Marketing Monitoring/Clinical Trials). At this point, the FDA monitors for public safety and adverse events, and the sponsor company may begin Phase 4 Clinical Trials to obtain information about long-term effects or to test the product in special patient populations.

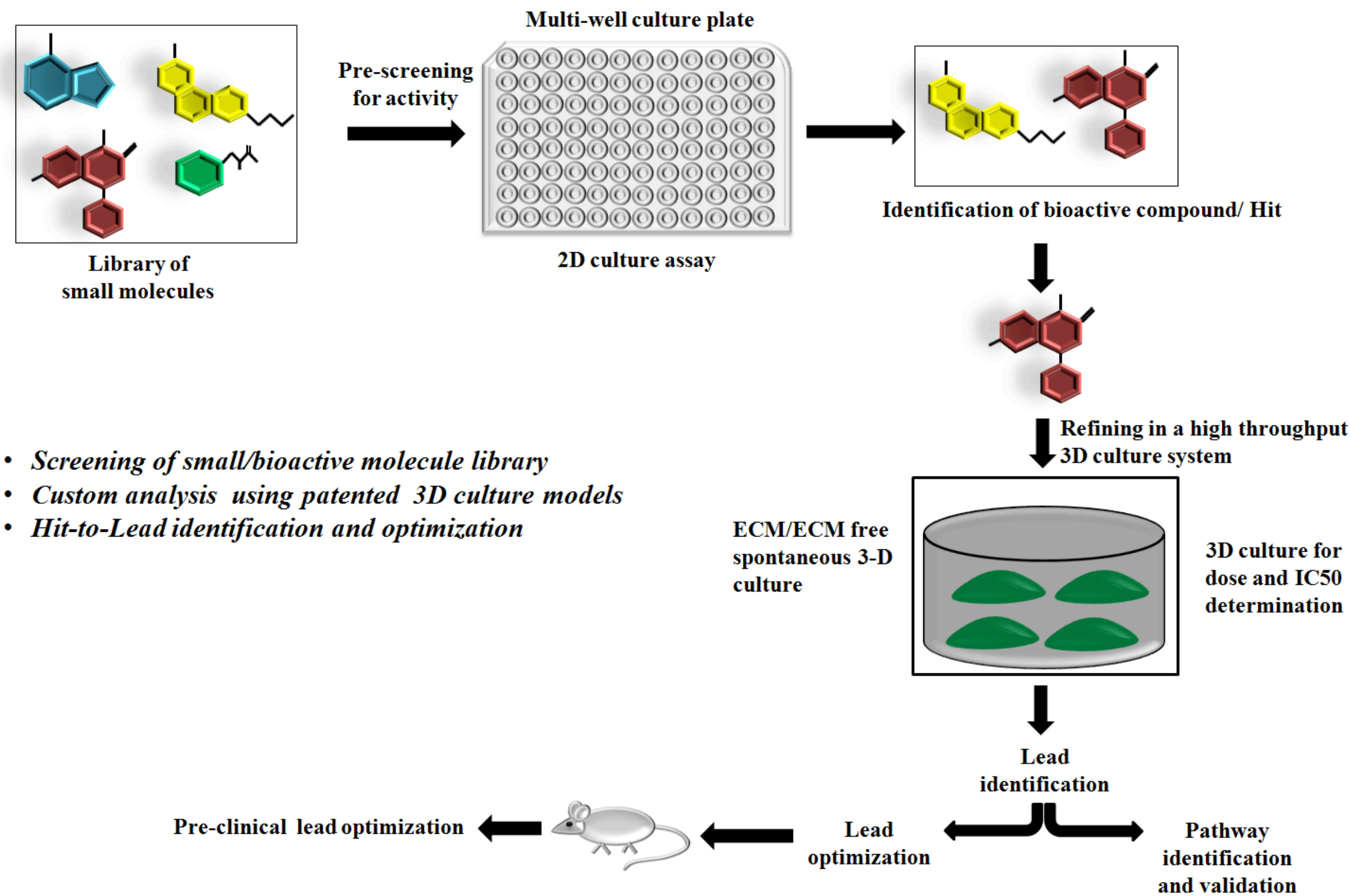
³ The "Funding Valley of Death" is the financial challenge many promising treatments face in having the opportunity to be scientifically tested in a clinical trial. In many cases, further financial support or partnerships are necessary to proceed.

* The cost of bringing a drug to market depends on a number of variables, but could be more than \$1 billion, including approximately \$50-840 million for Basic Research/Drug Development and Pre-Clinical/Translational research, and approximately \$50-970 million to complete all three Phases of the Clinical Trials.

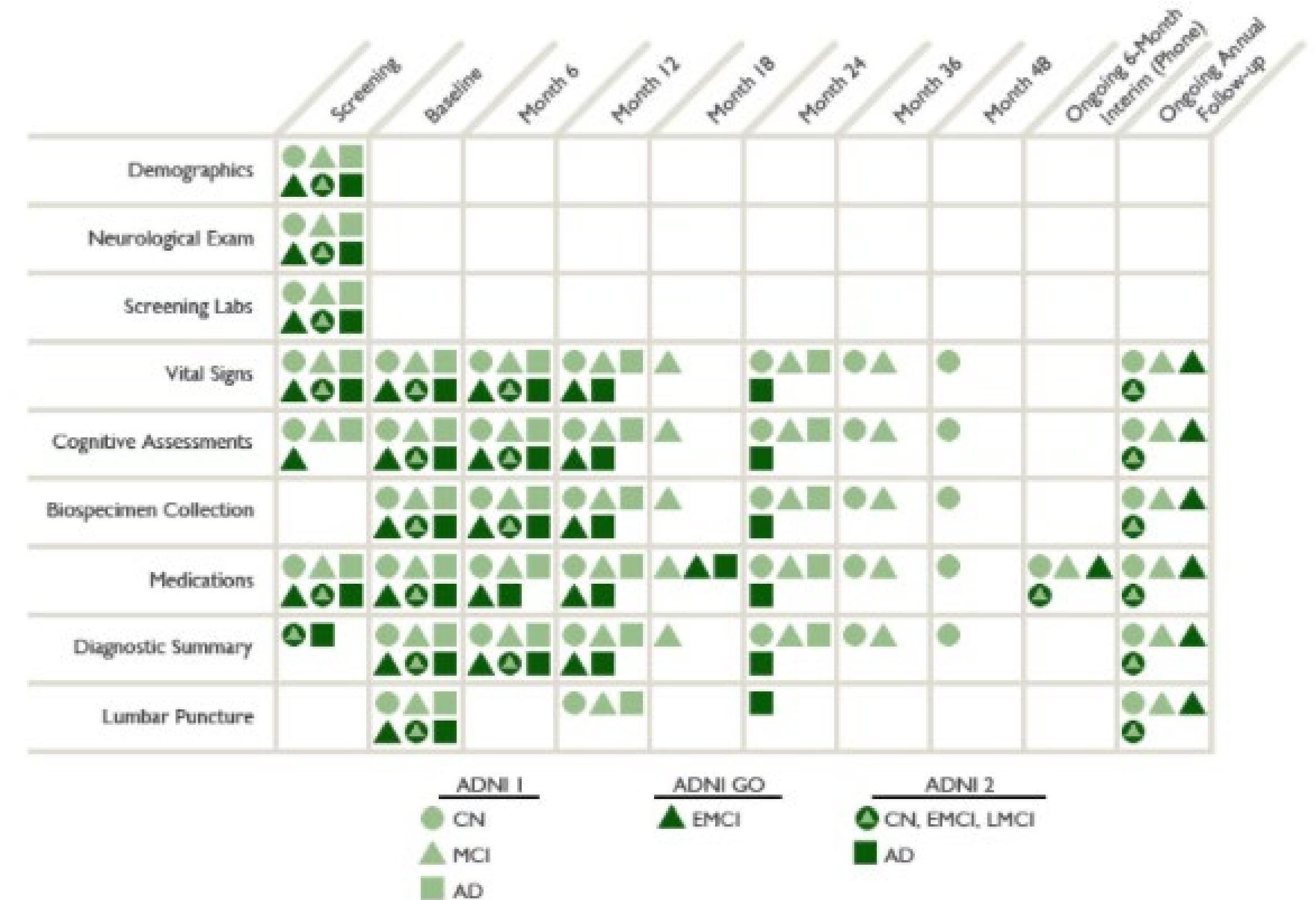


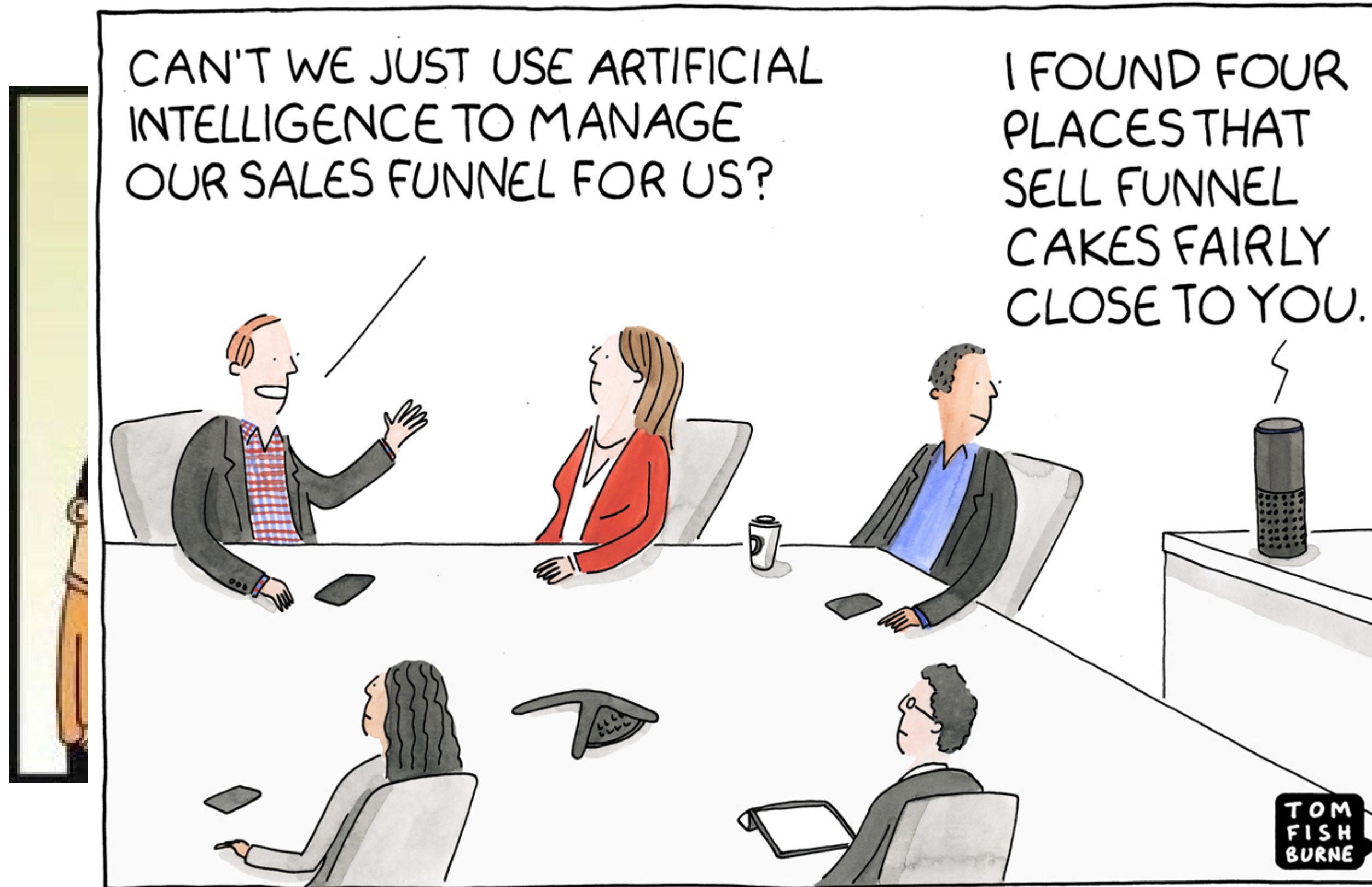
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Advanced Analytics for Clinical Datasets are Challenging



- Screening of small/bioactive molecule library
- Custom analysis using patented 3D culture models
- Hit-to-Lead identification and optimization





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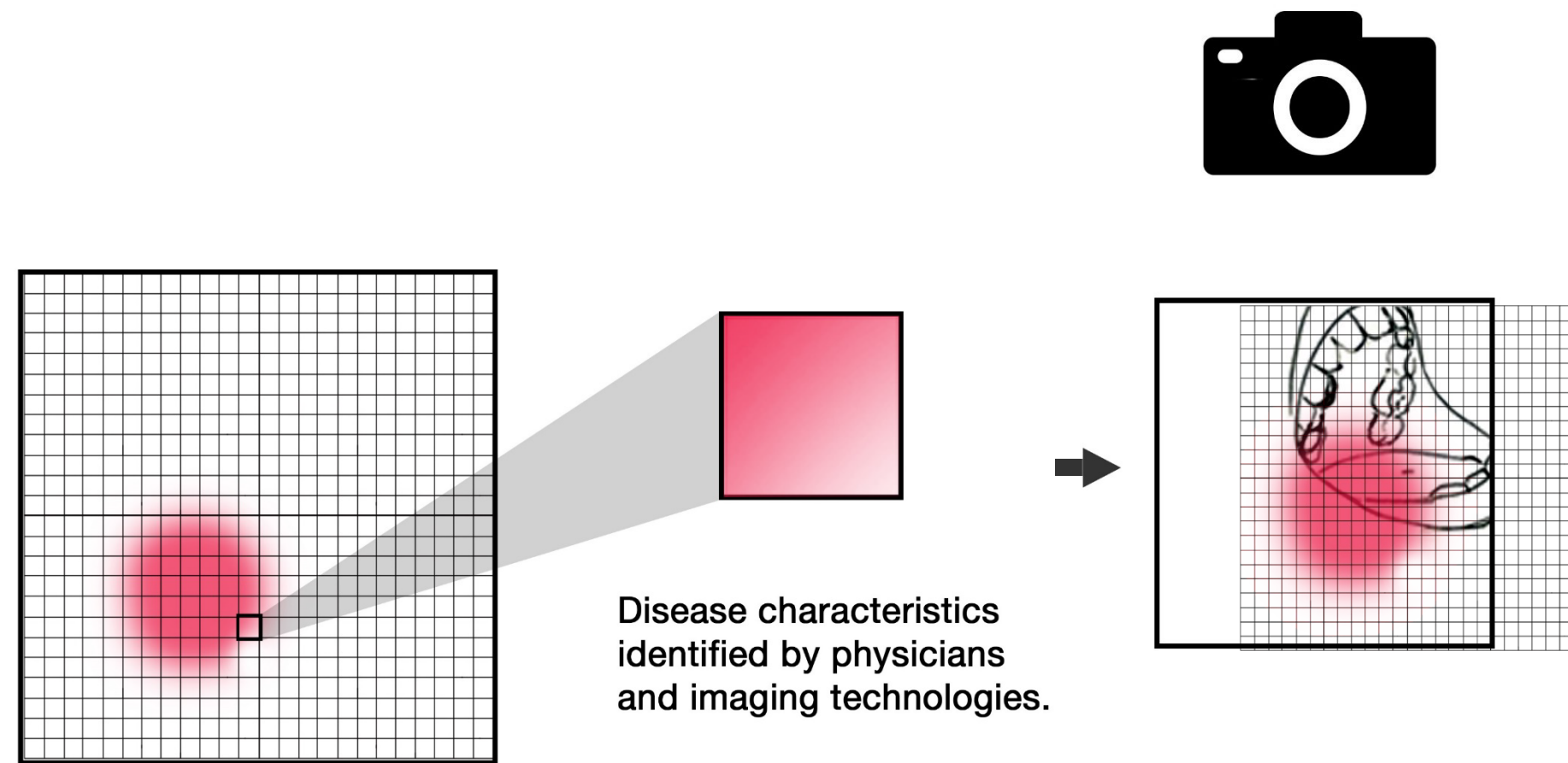
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Limitations and applications of machine learning (and AI)

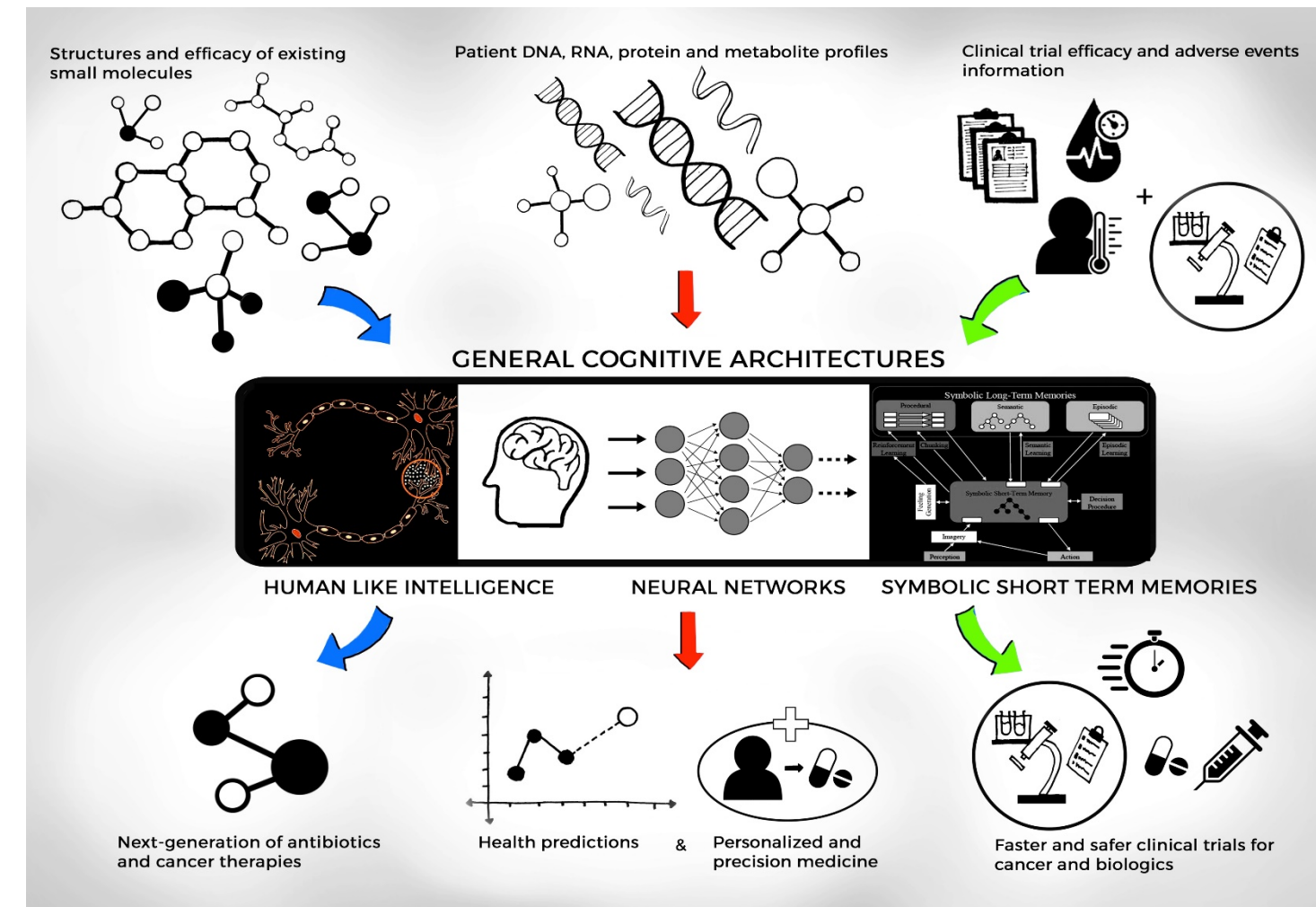
(Automation vs. Knowledge vs. Intelligence)



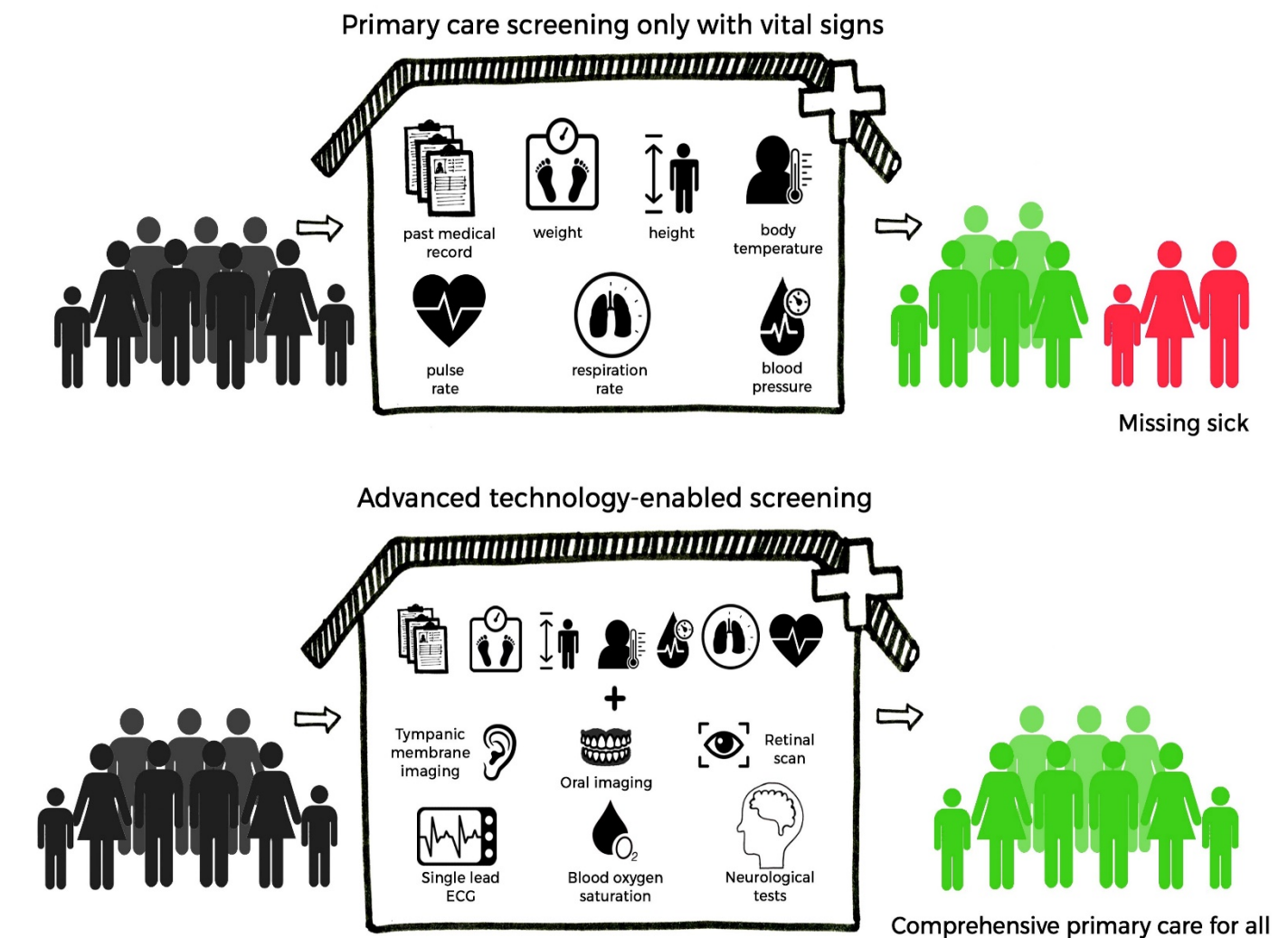
Research Areas



Medical imaging technologies using unorthodox artificial intelligence for early disease diagnoses

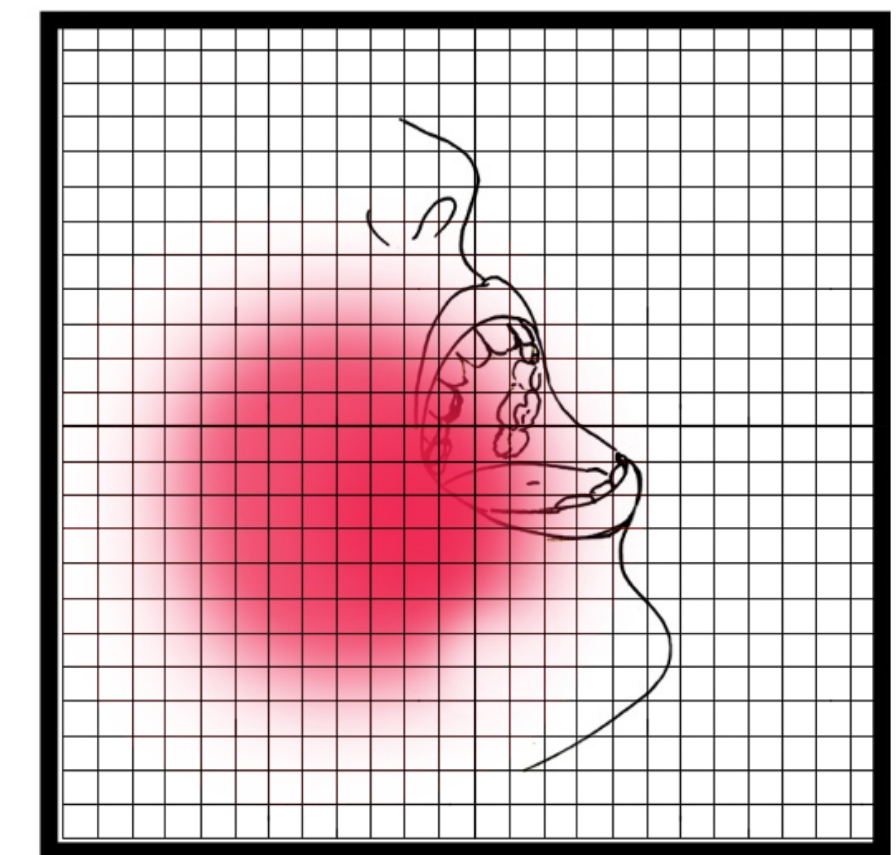
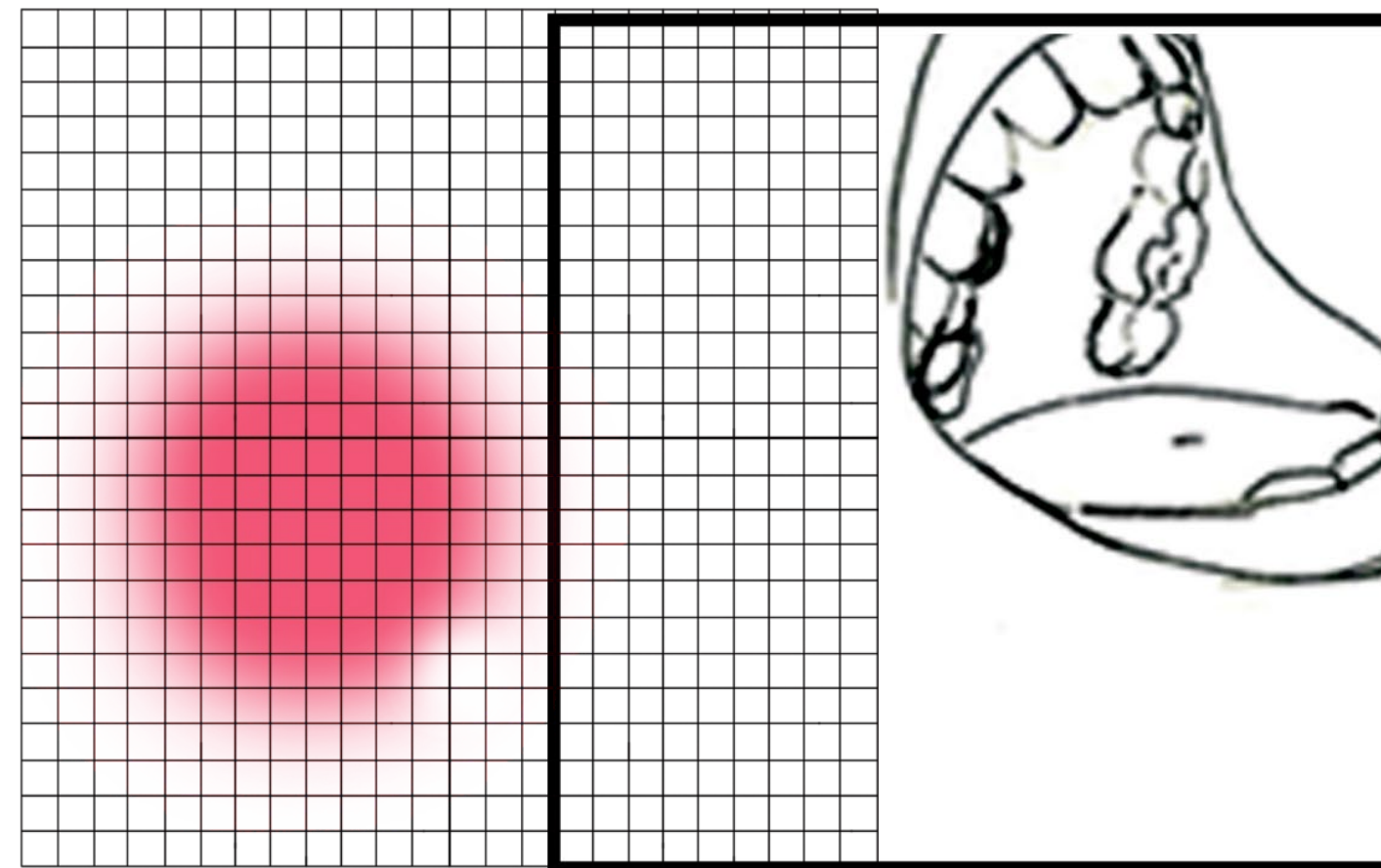


Novel ethical and explainable artificial intelligence based digital medicines and treatments

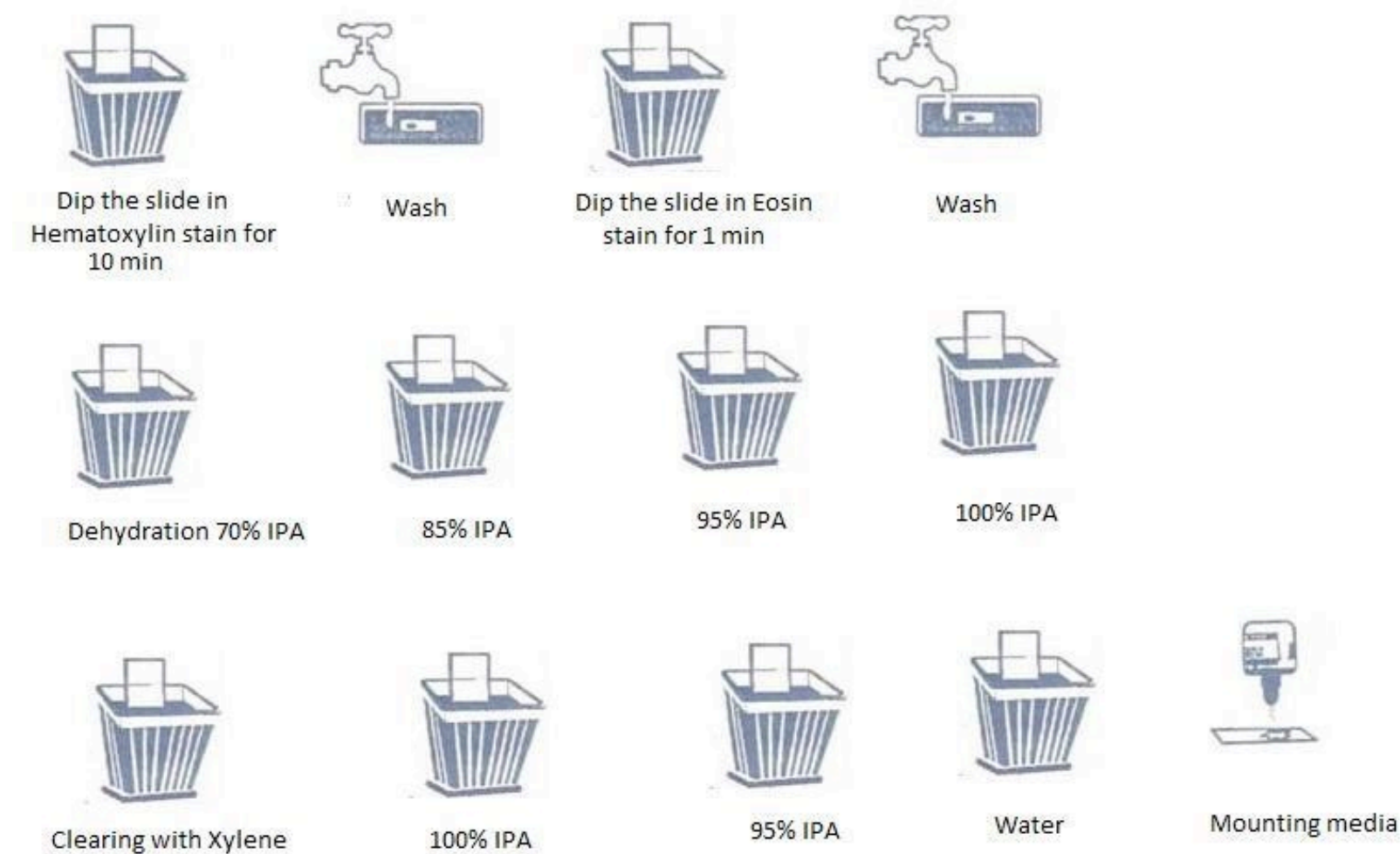


Point-of-care medical technologies for real world data and evidence generation

Unorthodox Image Processing and Biomarker Generation



Computational Histological Staining and Destaining of Prostate Core Biopsy RGB Images with Generative Adversarial Neural Networks



Collaboration with Brigham and Womens Hospital

Computational histological staining and destaining of prostate core biopsy RGB images with generative adversarial neural networks

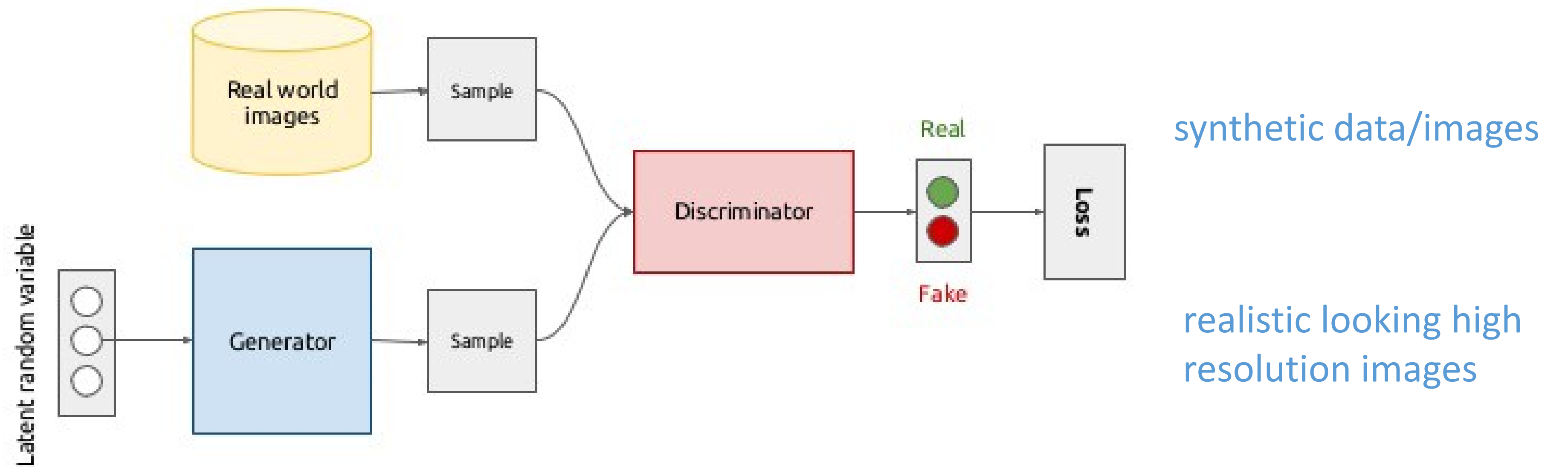
A. Rana, G. Yauney, A. Lowe and Pratik Shah

2018 17th IEEE International Conference of Machine Learning and Applications, DOI: 10.1109/ICMLA.2018.00133



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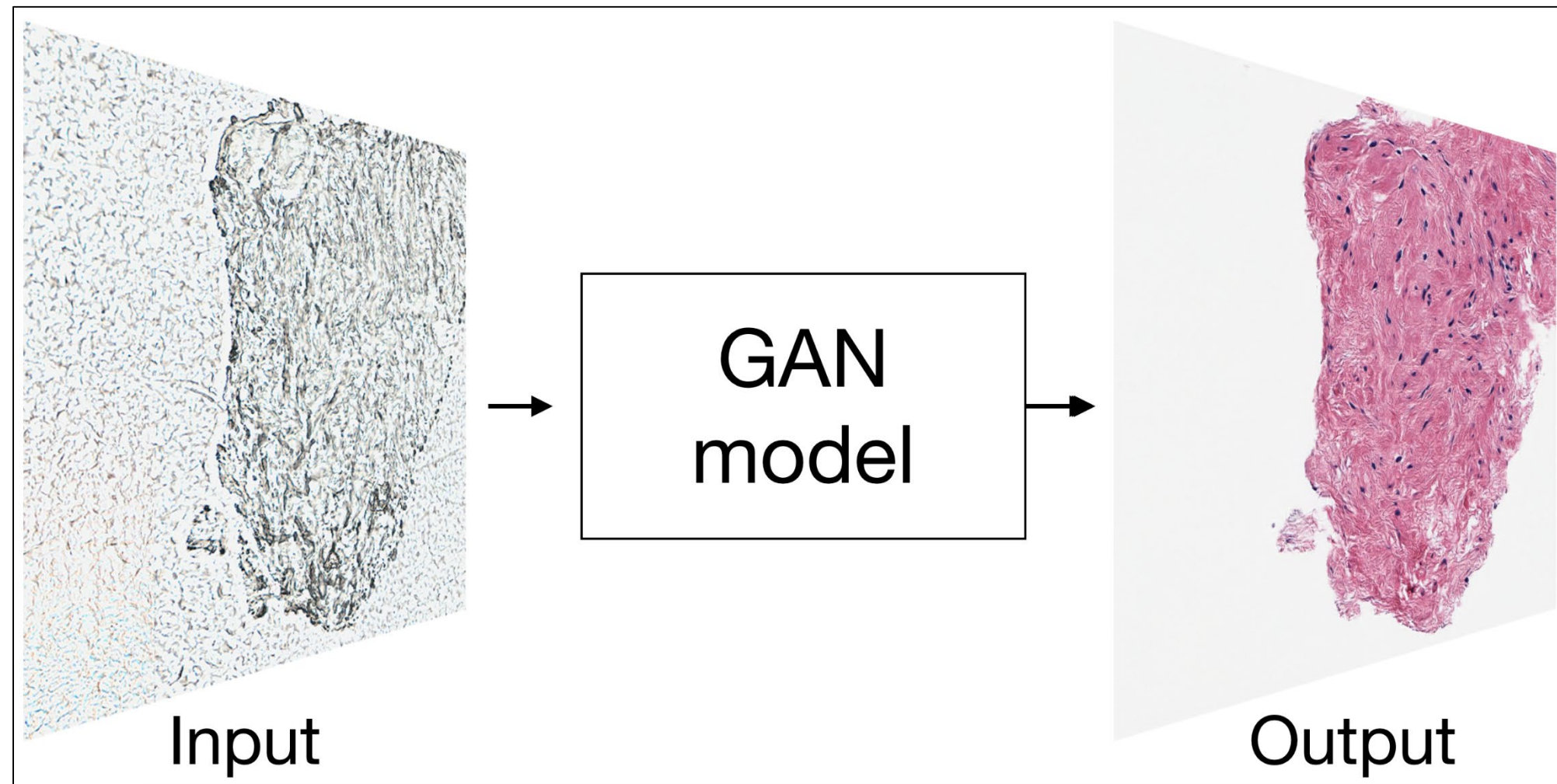
Generative Adversarial Neural Networks for New Medical Knowledge



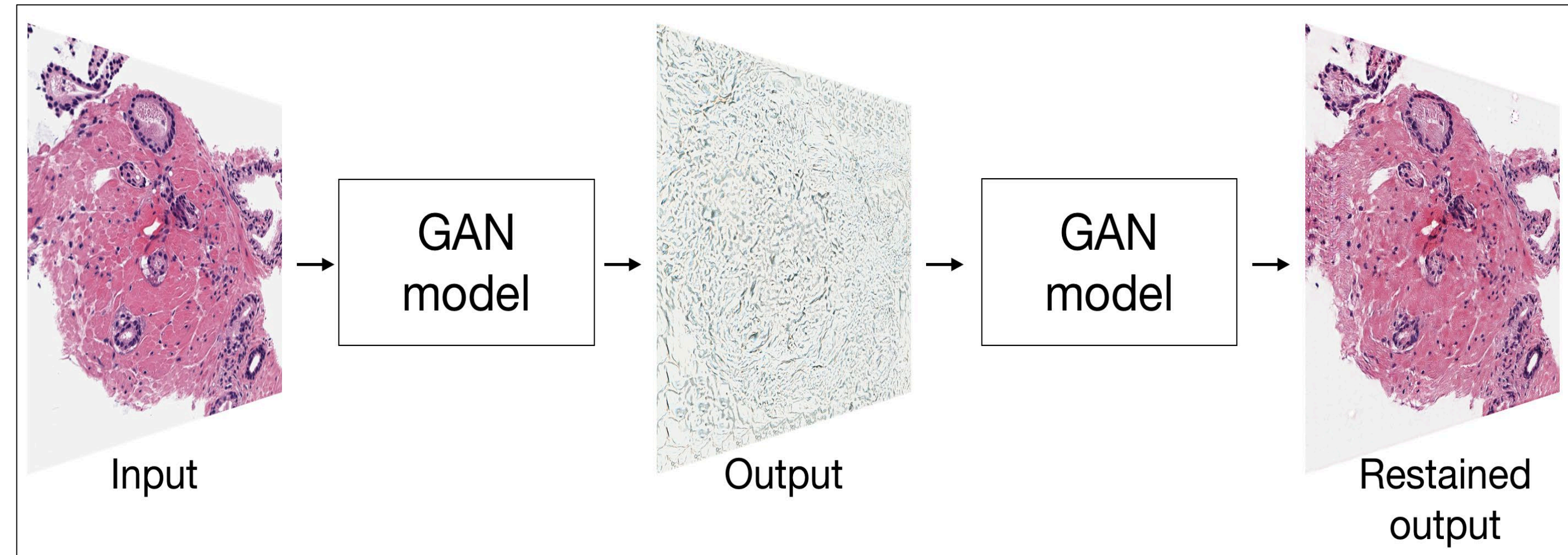
$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$



H & E Staining and Destaining of Prostate Core Biopsy Images



Computational staining



Computational destaining



Collaboration with [Brigham and Womens Hospital](#)

Computational histological staining and destaining of prostate core biopsy RGB images with generative adversarial neural networks

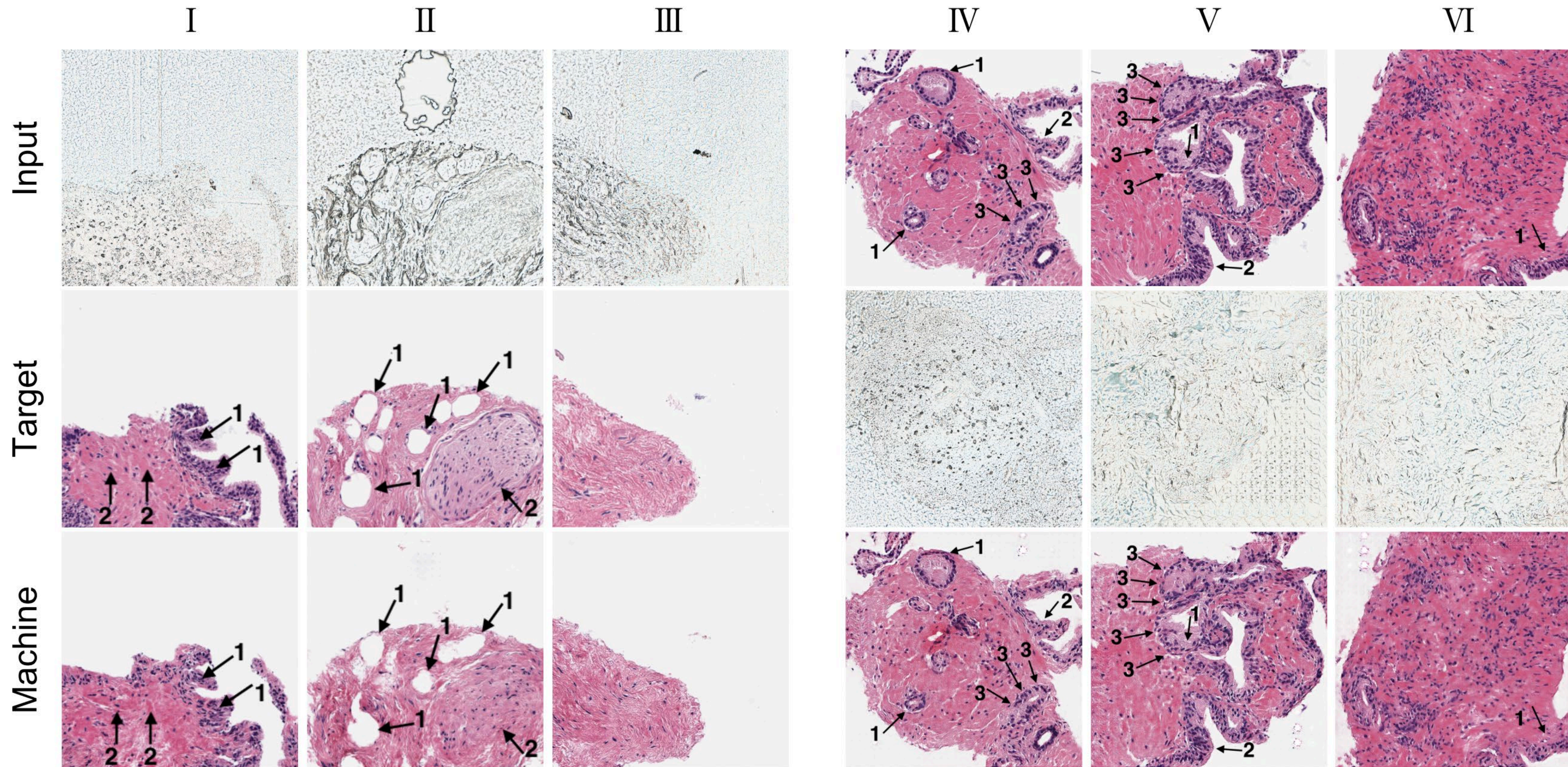
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Computational Staining and Destaining of Prostate Cancer Biopsy



Computational staining

Computational destaining



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Images and Machine learning

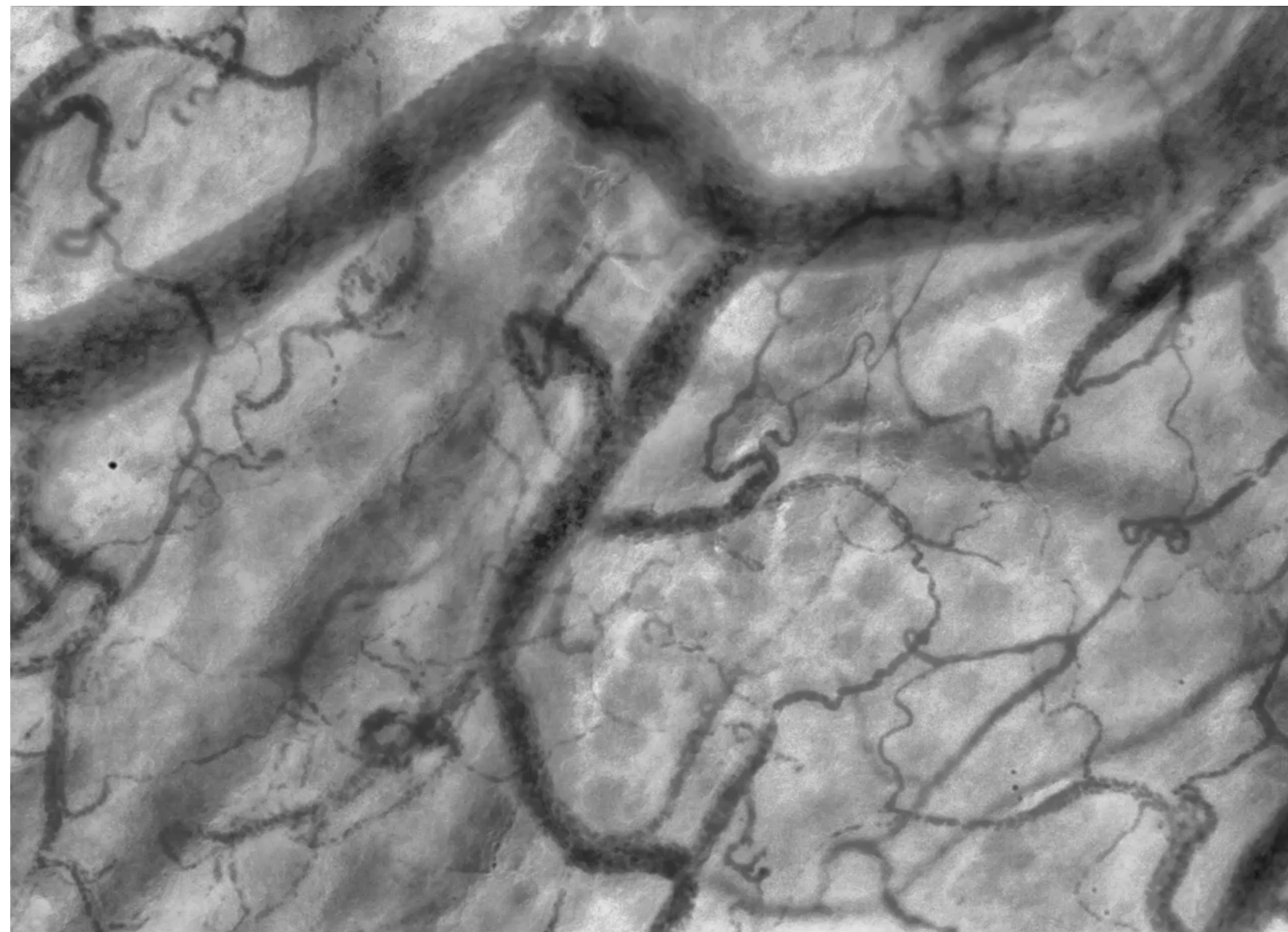
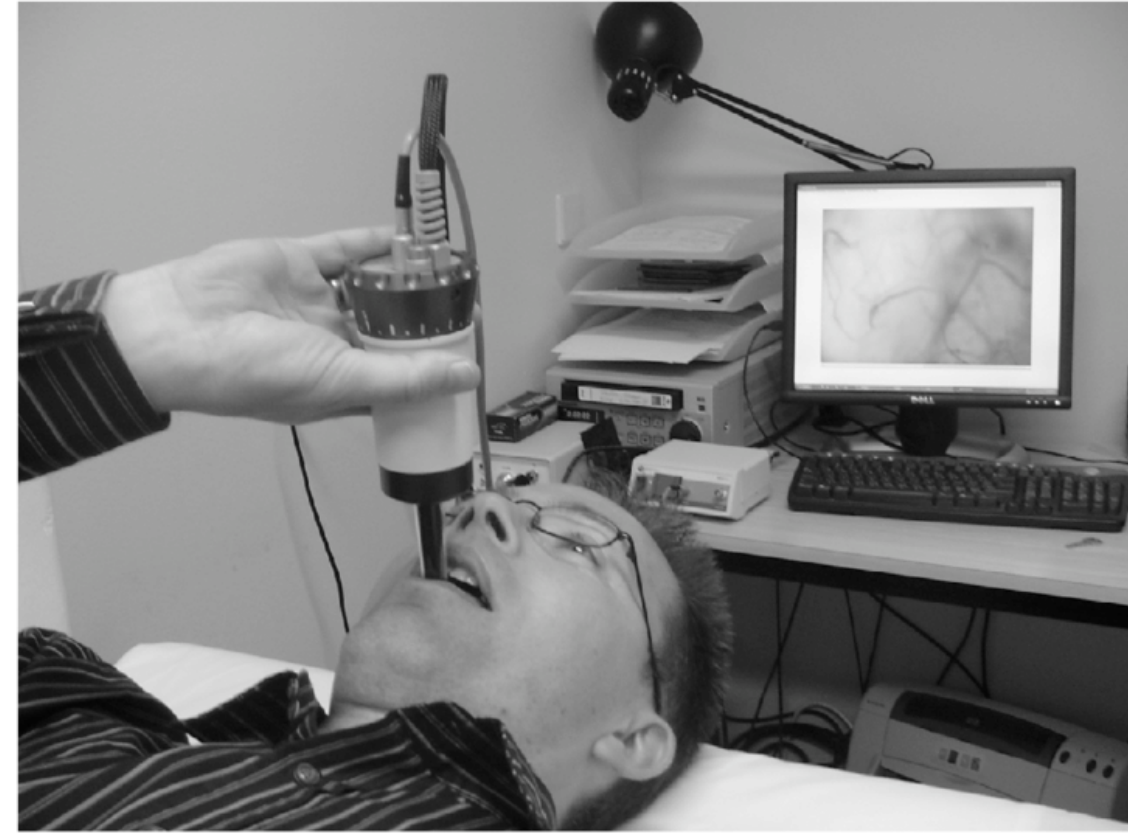
- **Data standards and generalization**
- **Detailed validation studies with physician raters**
- **Deployment and testing: New clinical trials for algorithms, software as medical device and integration at point of care (need based)**
- **Regulation and communication with physician and patients**
- **Case studies with other hospitals and data for generalization**

“Explainable” Machine Saliency for Medical Knowledge

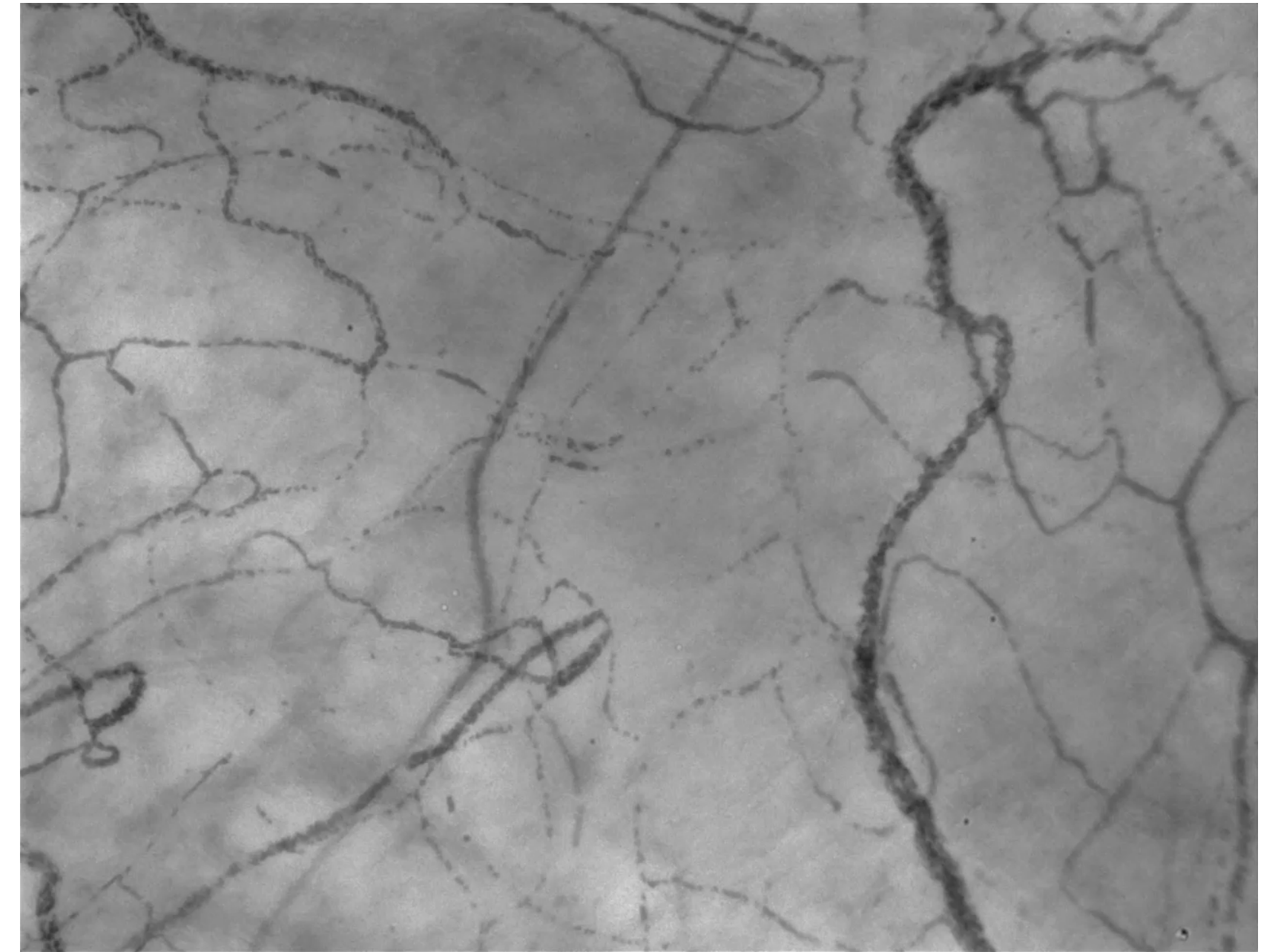
Collaboration with Beth Israel Deaconess Medical Center



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Healthy Patient



Septic Patient

Machine learning algorithms for classification of microcirculation images from septic and non-septic patients

P. Javia, Rana A and Pratik Shah

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Collaboration with Beth Israel Deaconess Medical Center

Neural Network based Learning from Microcirculation Videos

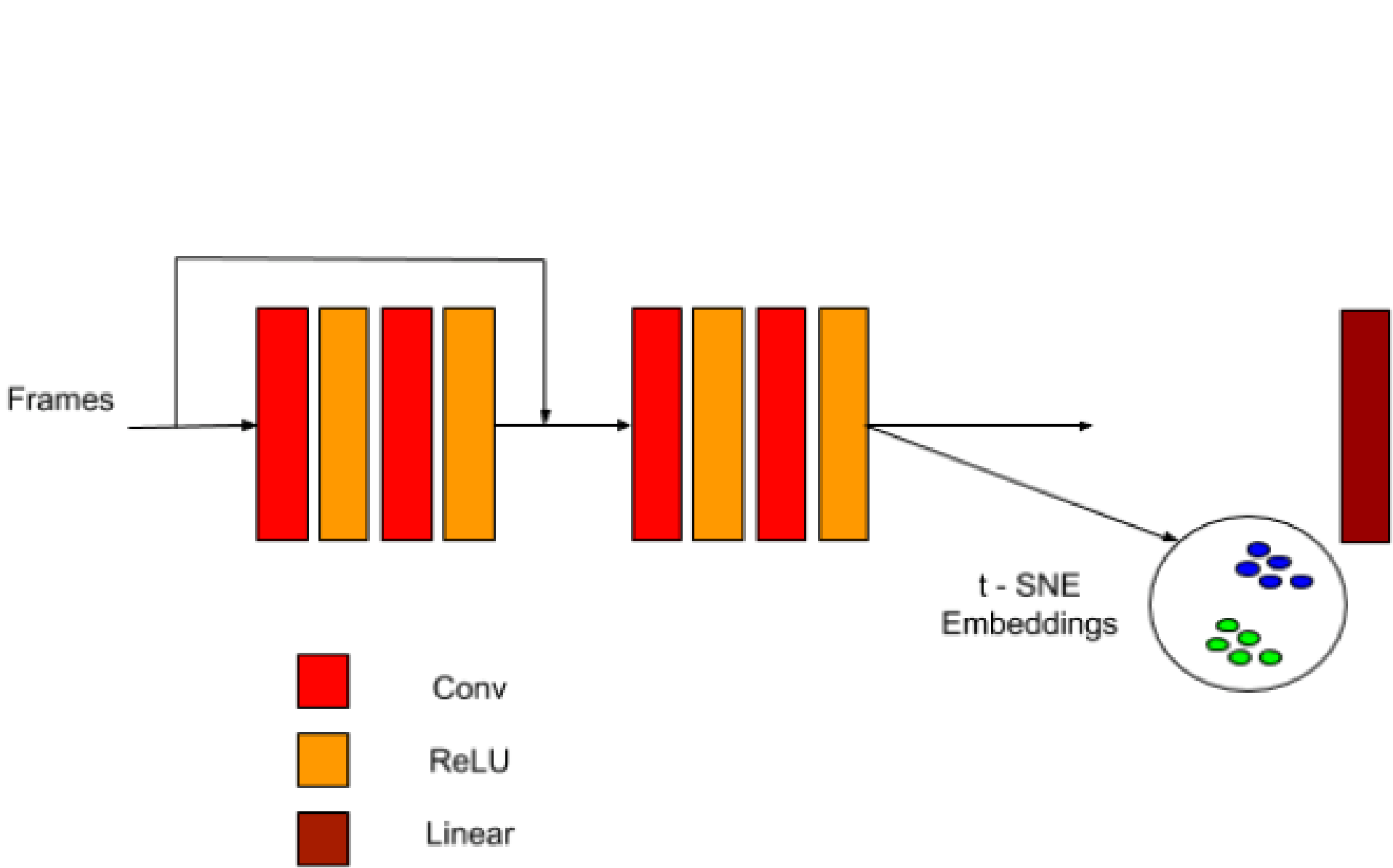


Fig. 2: The last convolutional layer used for visualization of t-SNE embedding.

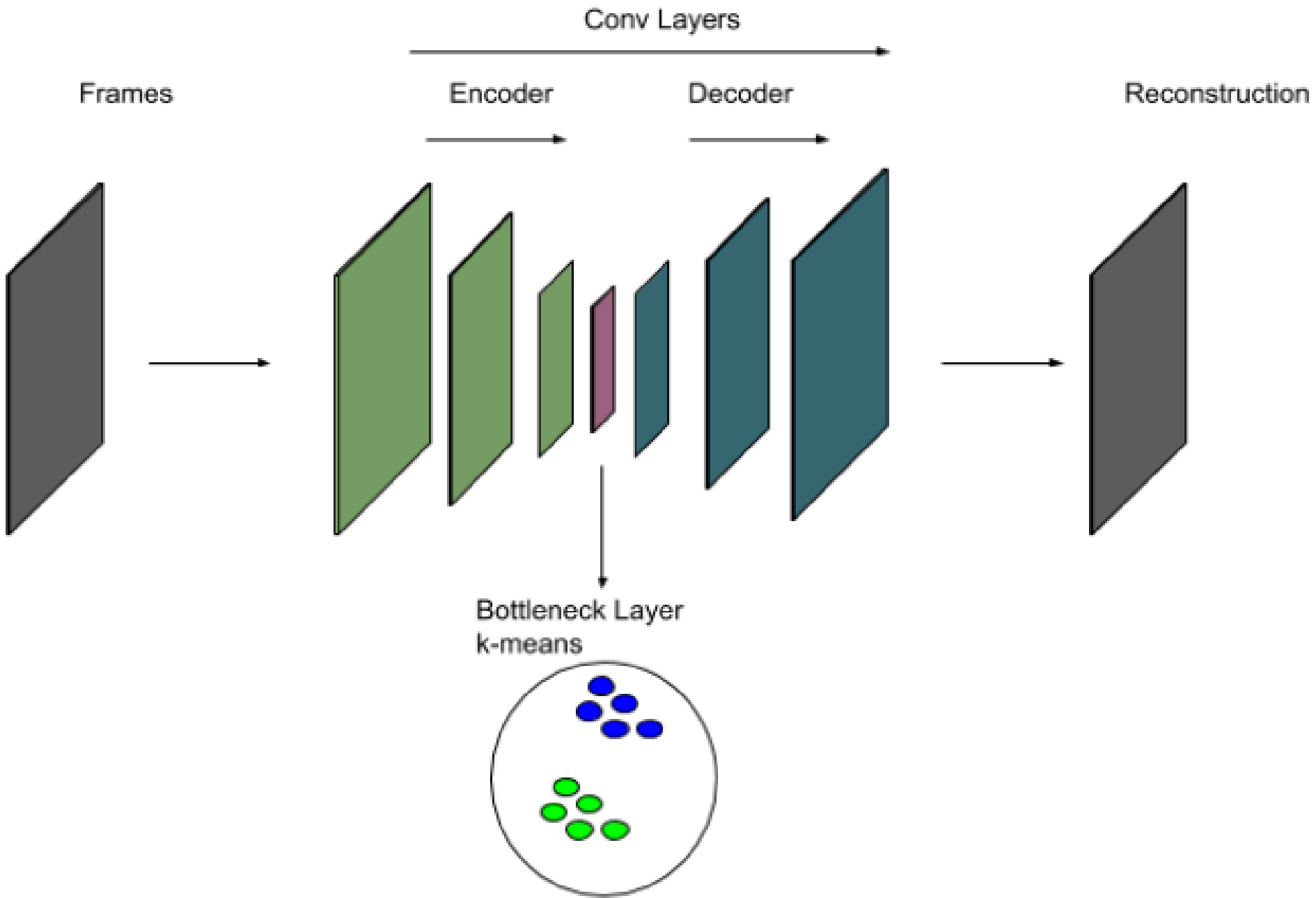


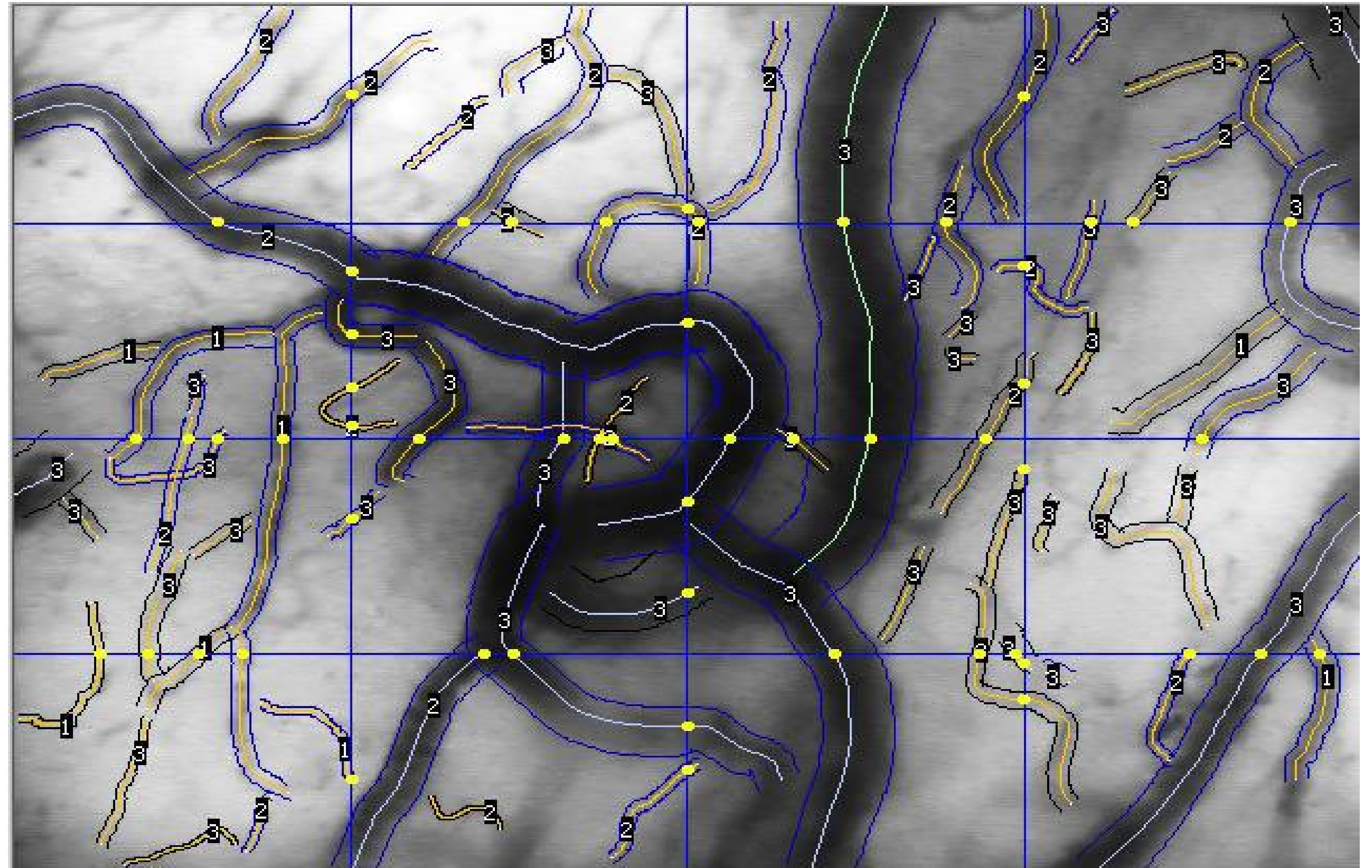
Fig. 3: Feature vector from the trained autoencoder used for k-means clustering and visualization.

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Image and Clinical Analysis by Human Experts vs. Algorithms

- Frame Average
- Vessel Segmentation
- Blood Flow Analysis
 - Microvascular Flow Index (MFI)
 - Portion of Perfused Vessels (PPV)
 - Perfused Vessel Density (PVD)
 - Heterogeneity Index
 - Total Vessel Density



Collaboration with Beth Israel Deaconess Medical Center

Machine learning algorithms for classification of microcirculation images from septic and non-septic patients

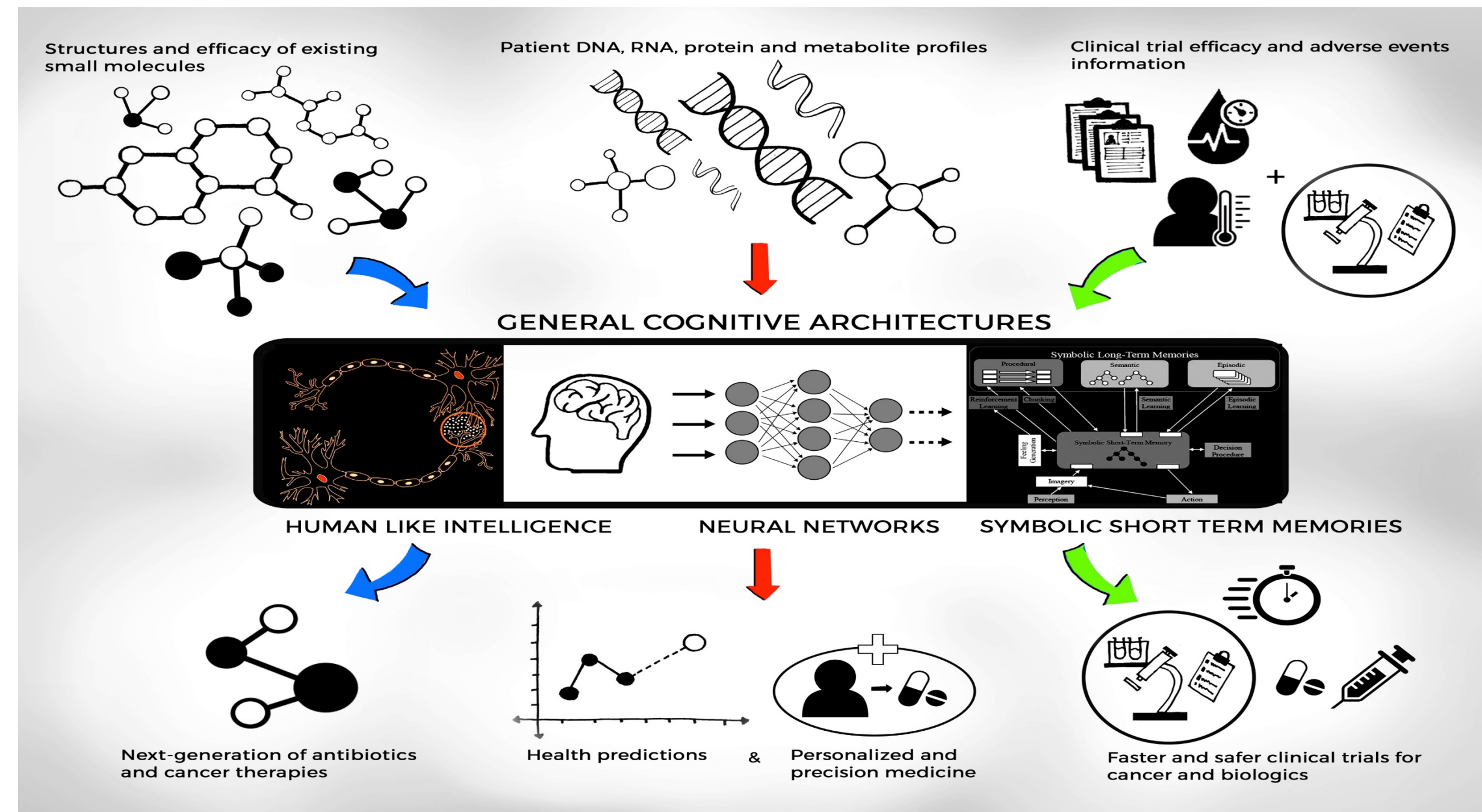
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Machine Learning and AI for Clinical Trial Design

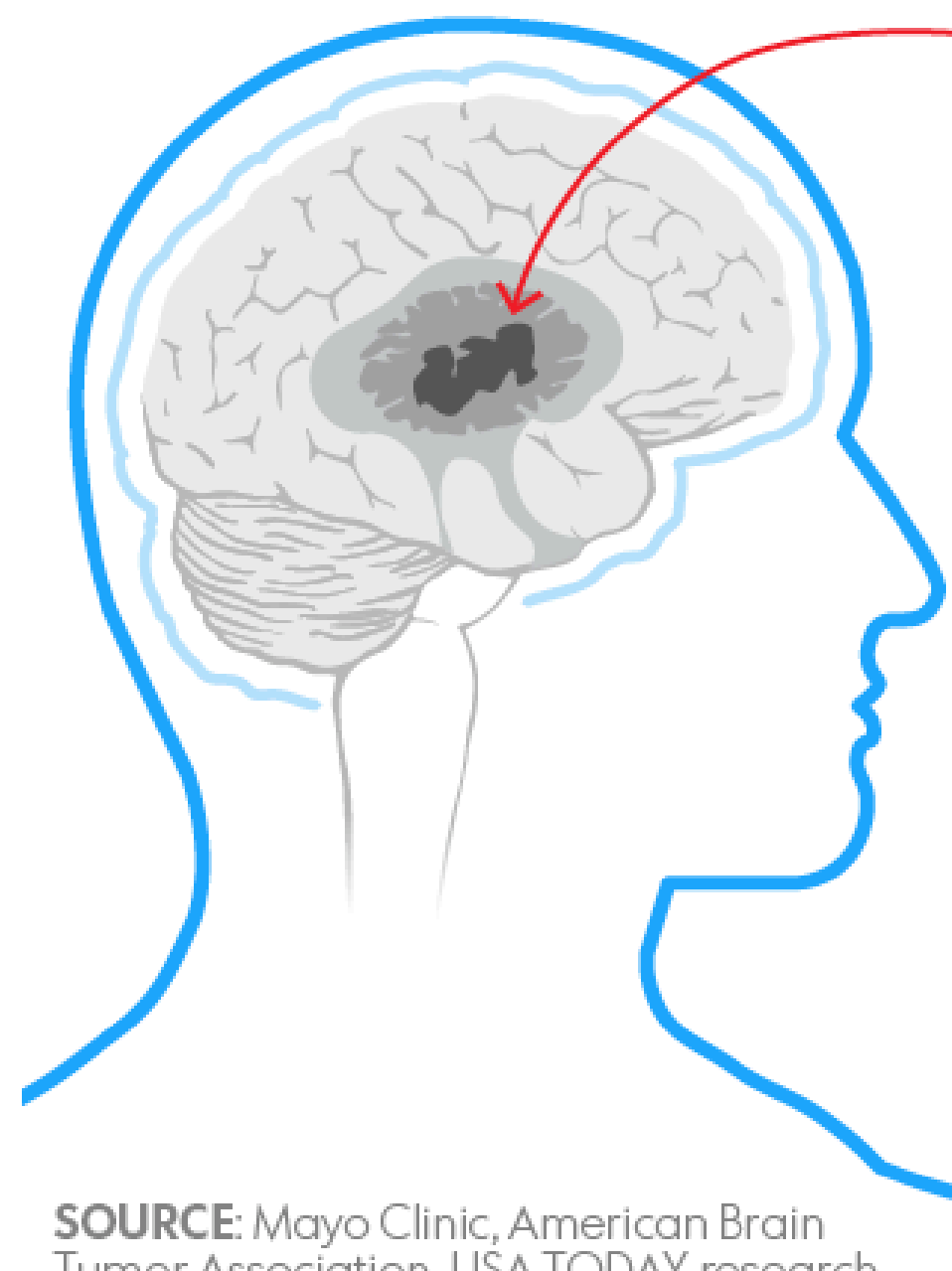


Novel ethical and explainable artificial intelligence based digital medicines and treatments

Glioblastoma Treatment and Toxicity with Chemo-and-Radiotherapy

GLIOBLASTOMA

WHAT IT IS: An aggressive type of brain cancer that starts in the glial cells of the brain and spreads rapidly throughout the brain.



SYMPTOMS:
Headache, nausea, drowsiness, impaired vision

TREATMENT:
Chemotherapy, radiation, and surgery

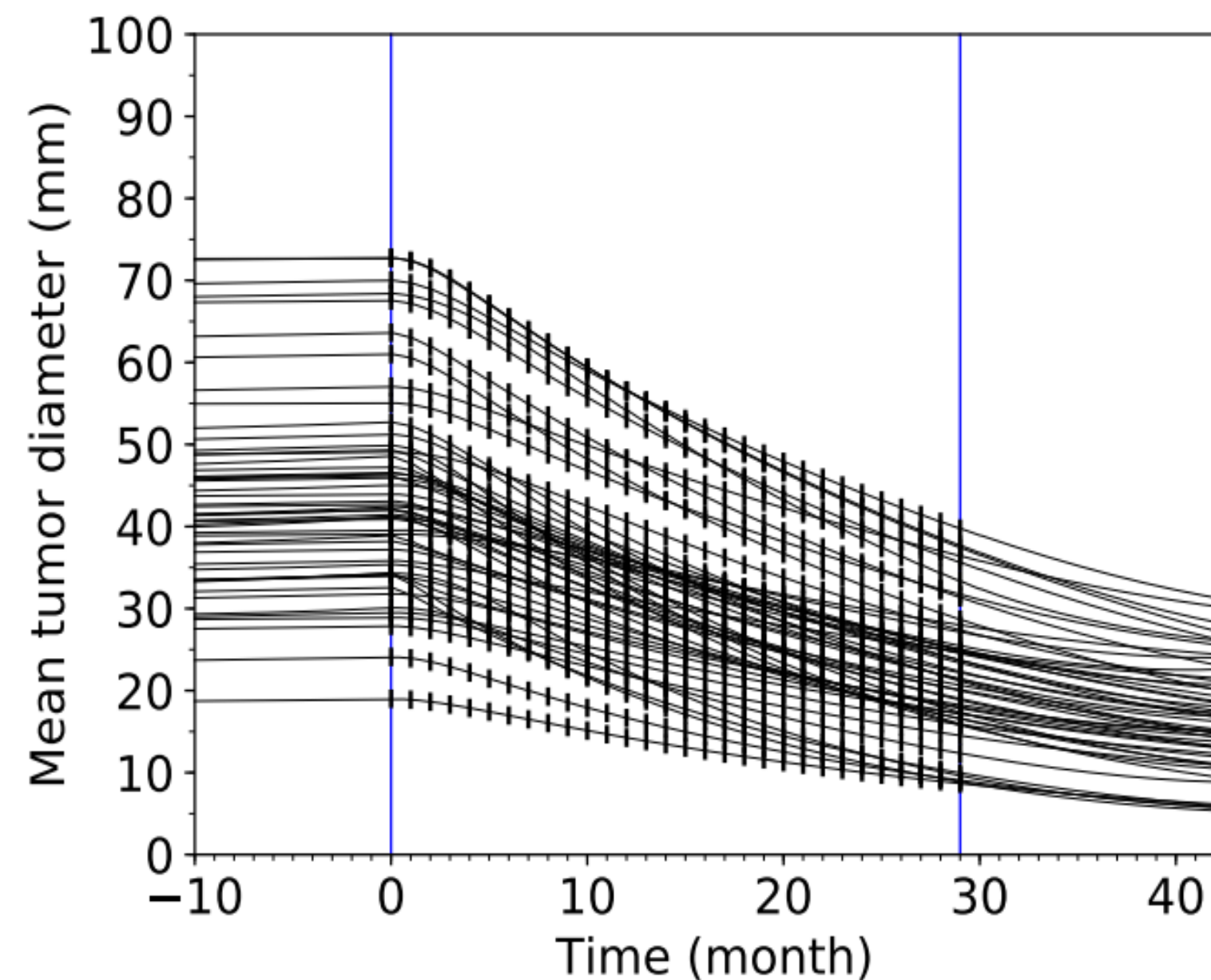
HOW COMMON IS IT?
About 12,390 cases projected in 2017

MEDIAN SURVIVAL RATE:
14-15 months

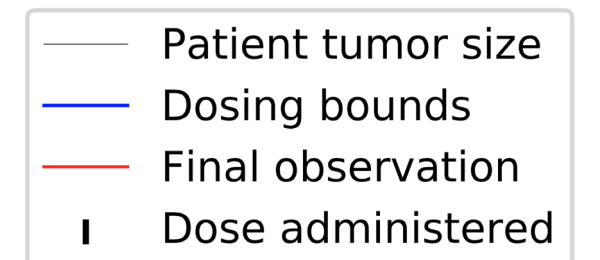
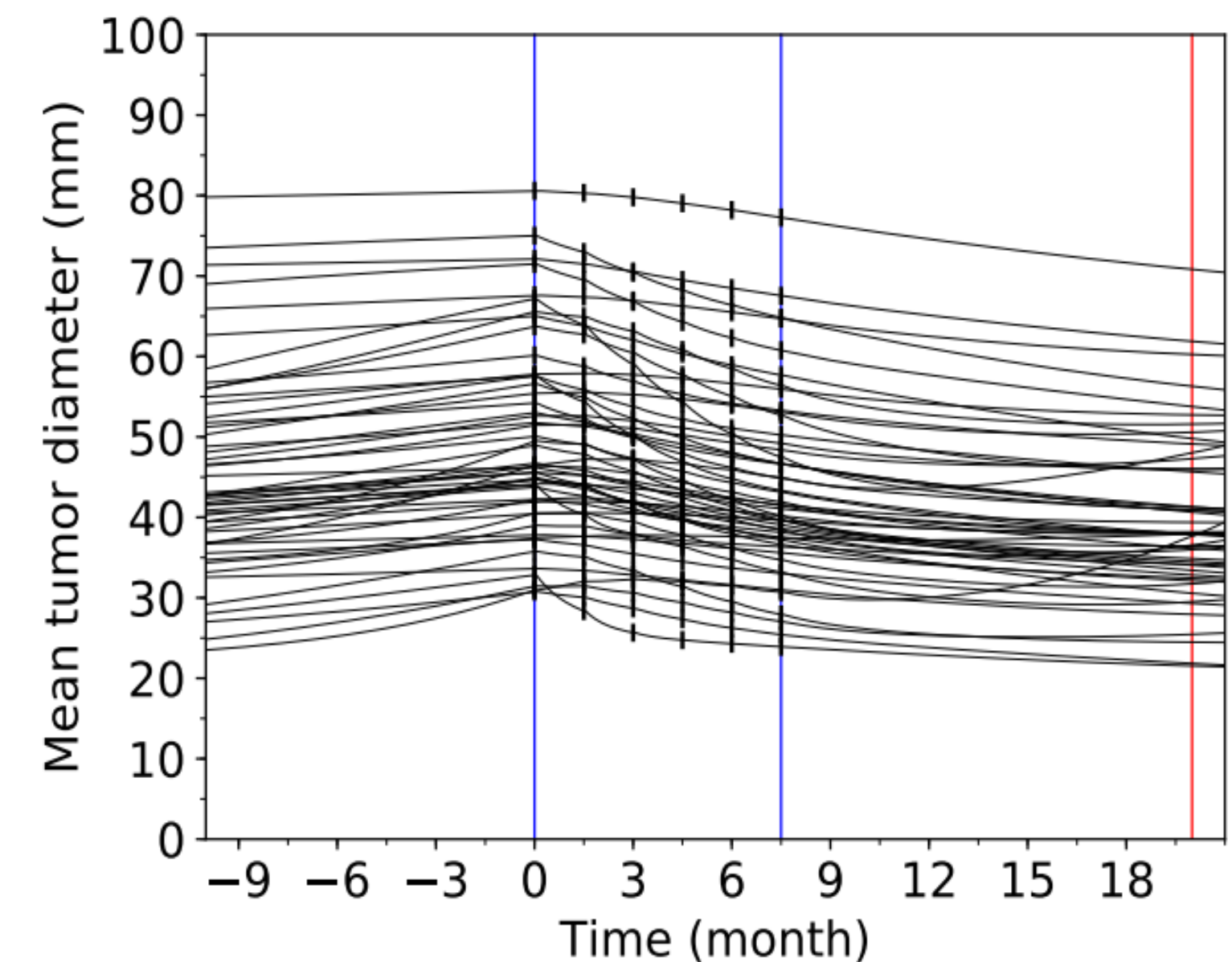
SOURCE: Mayo Clinic, American Brain Tumor Association, USA TODAY research
Janet Loehrke and George Petras, USA TODAY



Human expert Temozolomide dosing regimen



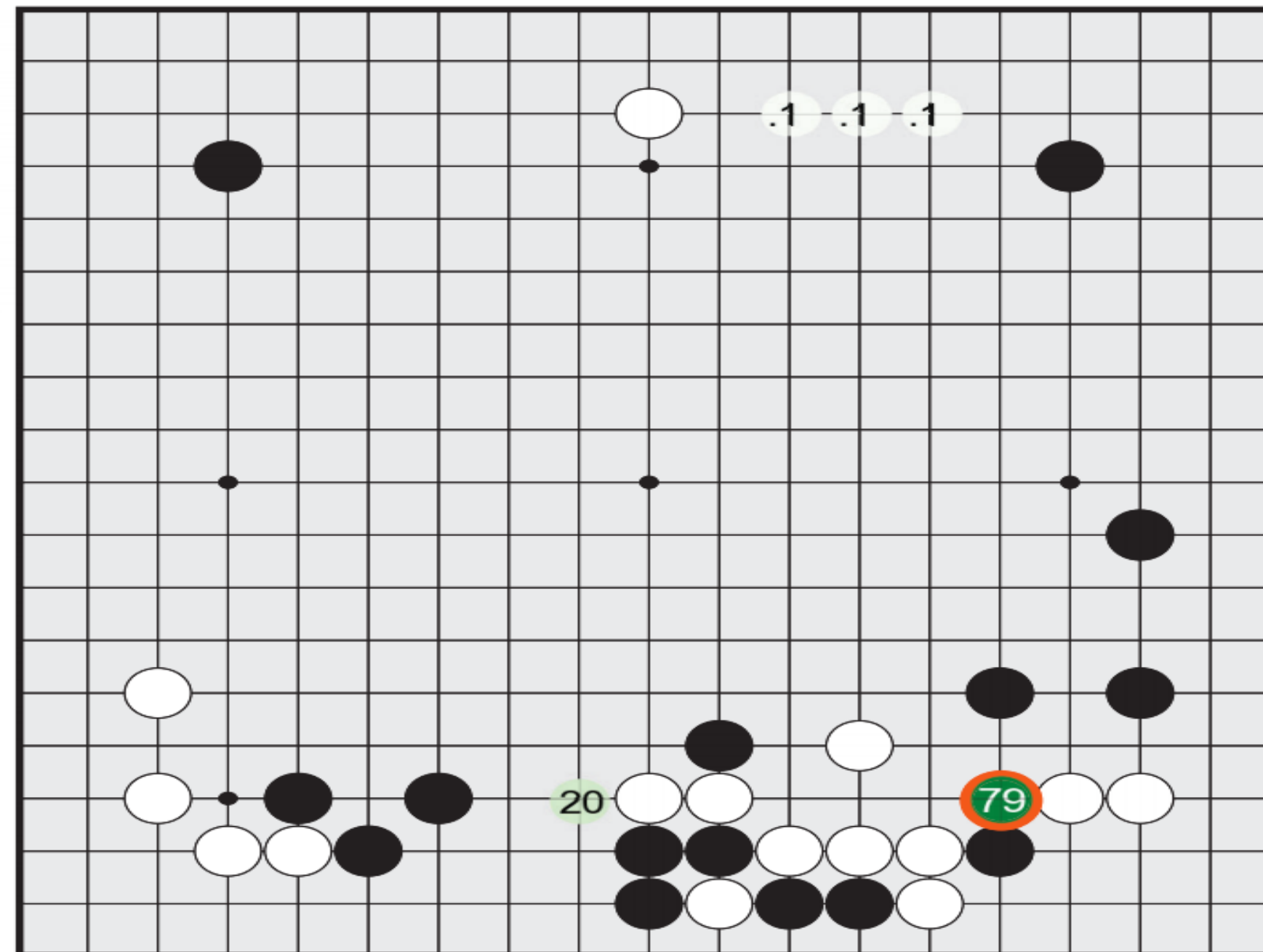
Human expert PCV dosing regimen



Reinforcement Learning

Formal definition:

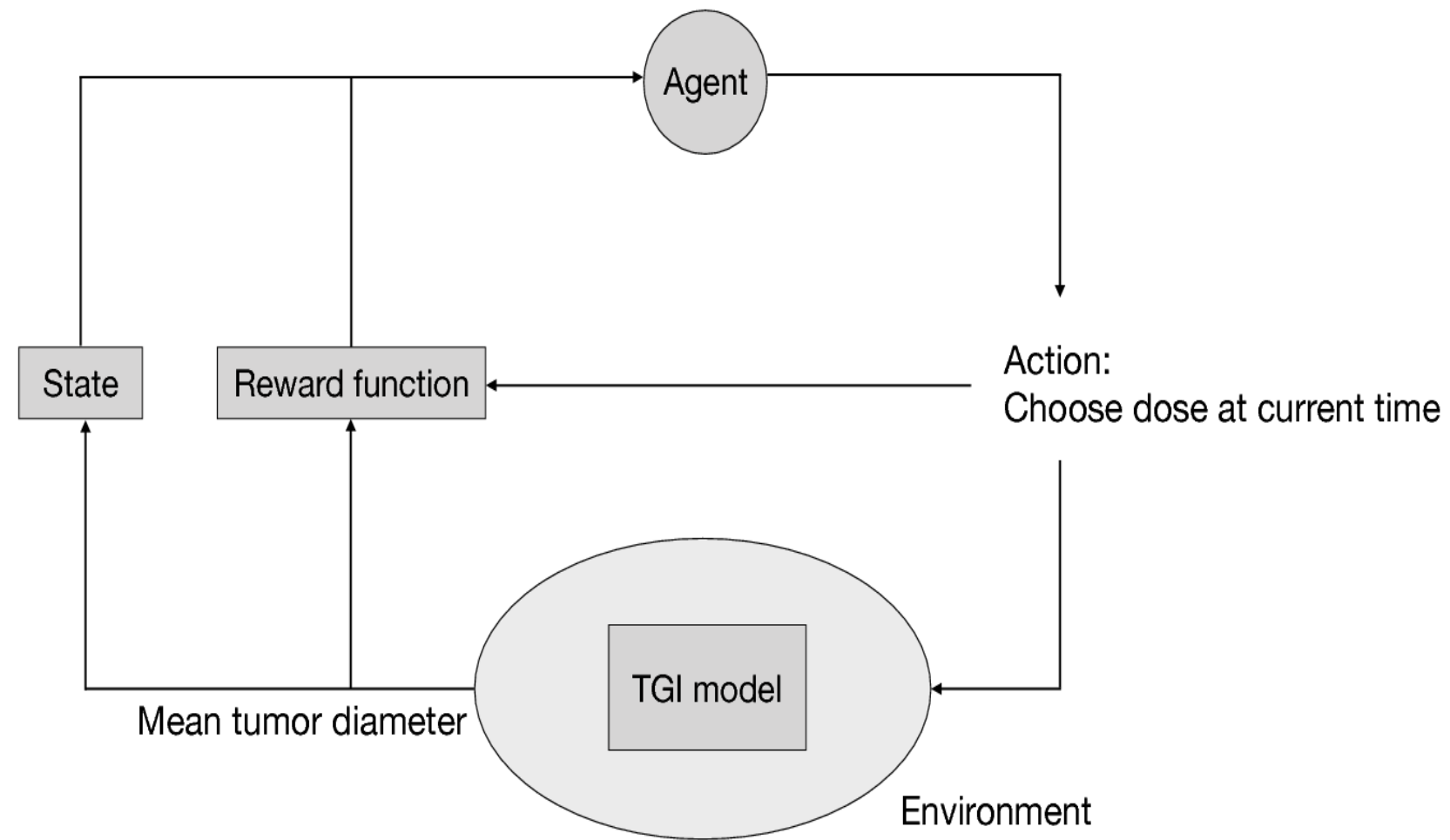
- States
- Actions
- Transition
- Reward
- Discount factor



Silver, David, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser et al.
"Mastering the game of Go with deep neural networks and tree search." *Nature* 529, no. 7587 (2016): 484-489.



Learning environment, rewards and penalties



The reinforcement learning agent interacts with an environment containing a tumor growth inhibition (TGI) model. The reward is determined in part by the values used for the reinforcement learning model's state and the agent's most recent action.

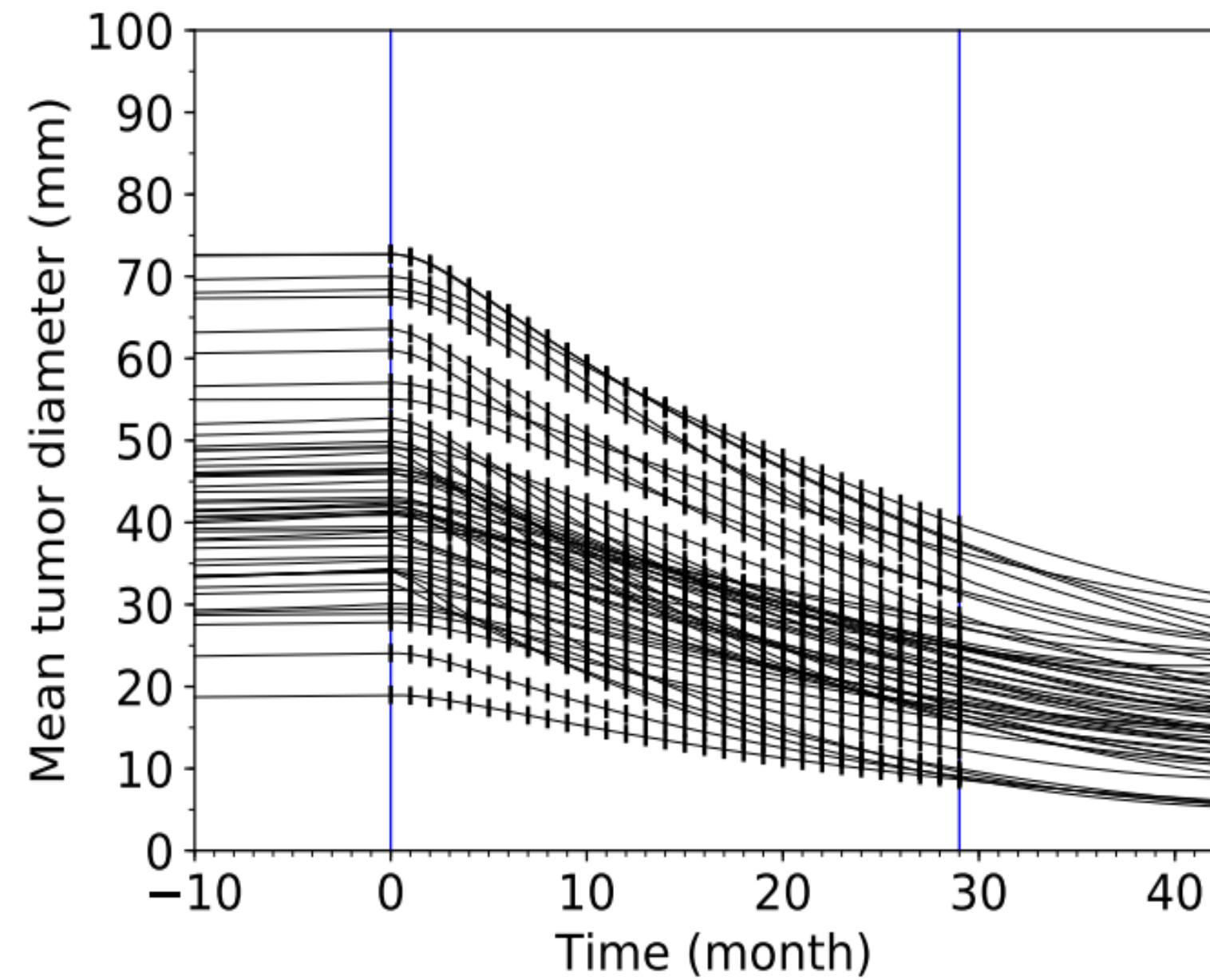
Off-Policy deep Q learning

$$Q^*(s, a) = R(s, a, s') + \gamma \sum_{s' \in S} T(s, a, s') \max_{a'} Q^*(s', a')$$

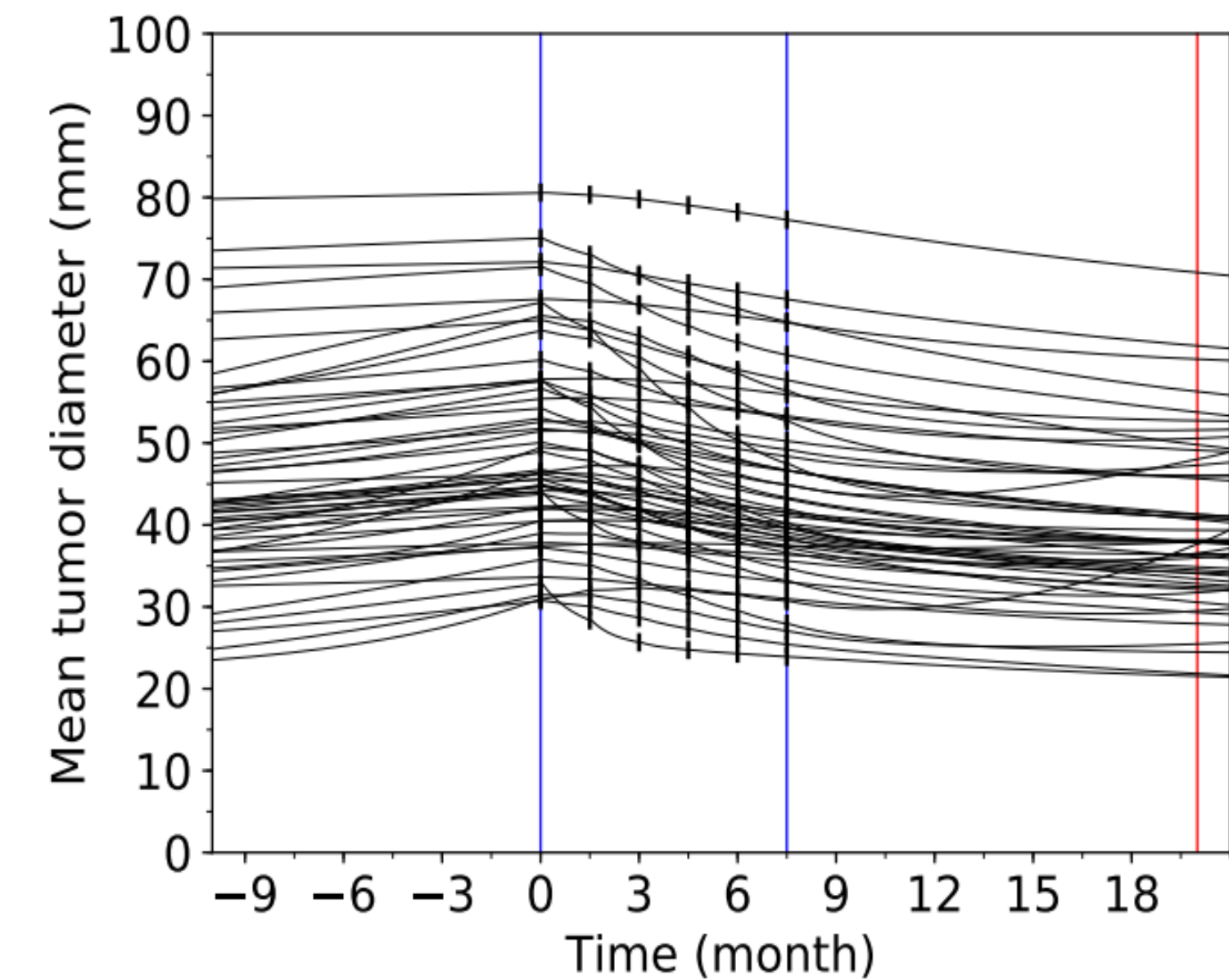
Actions are sampled according to an epsilon-greedy strategy, after which the optimal action from each state can be found:

$$\pi^*(s) = \operatorname{argmax}_a Q^*(s, a)$$

Human expert Temozolomide dosing regimen



Human expert PCV dosing regimen



$$R = c (MTD_t - MTD_{t'}) - \text{penalty} \cdot \text{concentration}$$

$$R_{\text{final}} = c_{\text{final}} (MTD_{\text{initial}} - MTD_{\text{final}})$$

$$C = 1, C_{\text{final}} = 10$$

TMZ penalties = 1 and 5

PCV penalties = 1 and 10

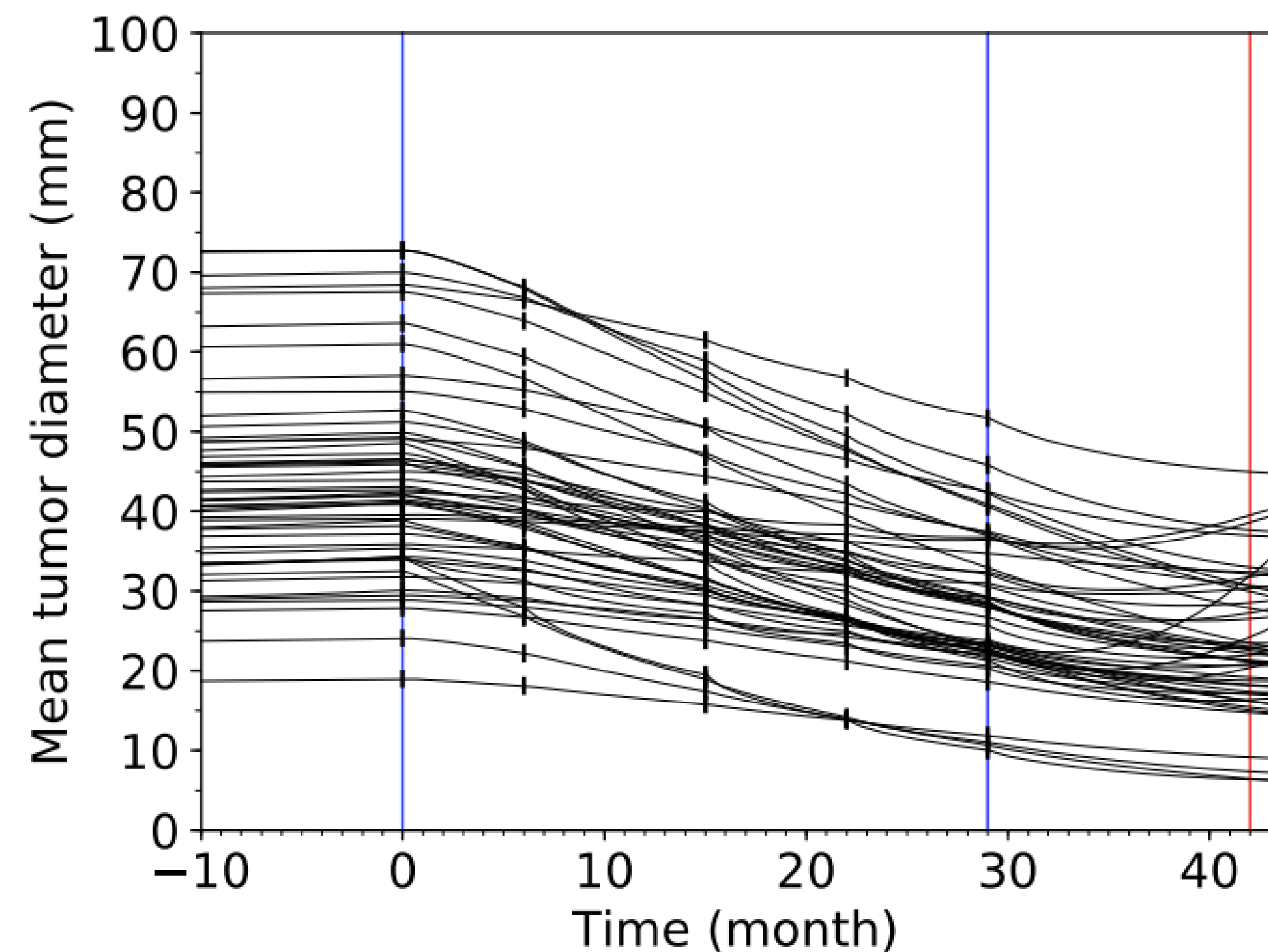
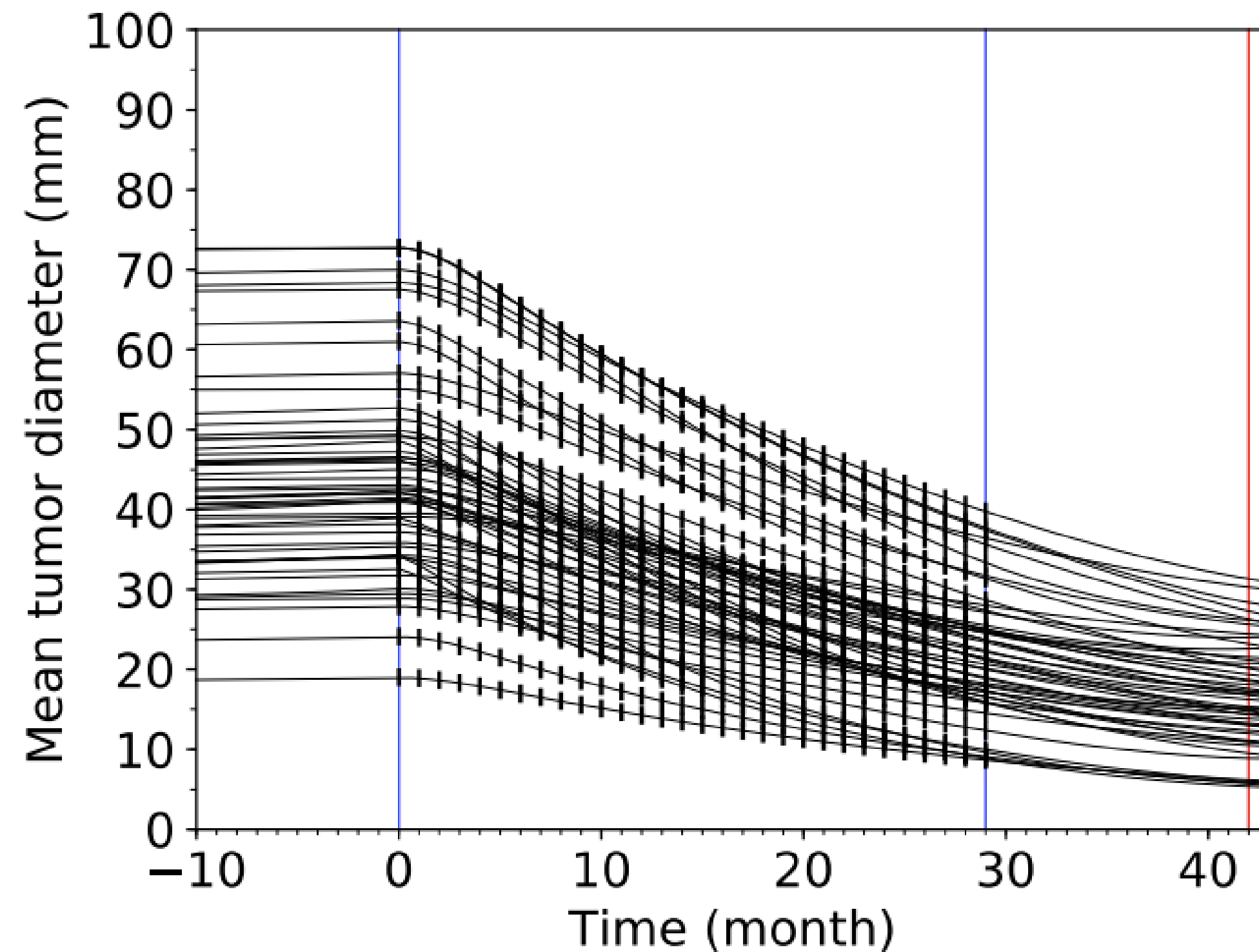
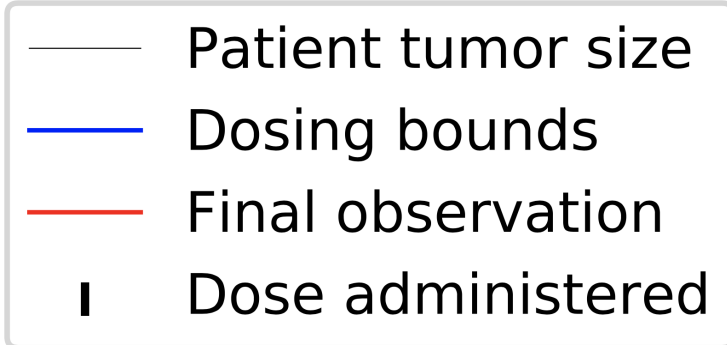


Digital Therapeutics and Algorithmic Design of Clinical Trials

Goal: Reduce number of doses for all patients

Human experts

Machine policy



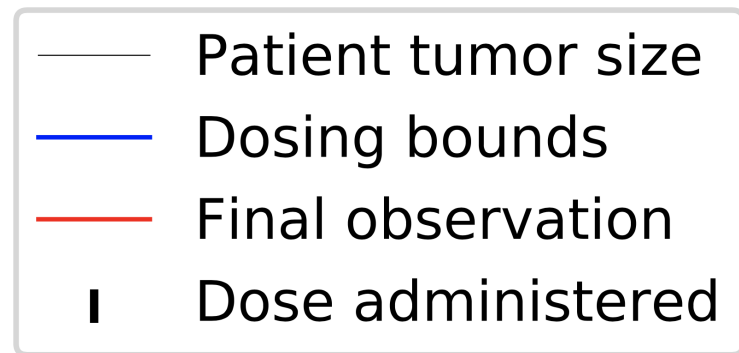
Digital Therapeutics and Algorithmic Design of Clinical Trials

Goal: Reduce number of doses for all patients

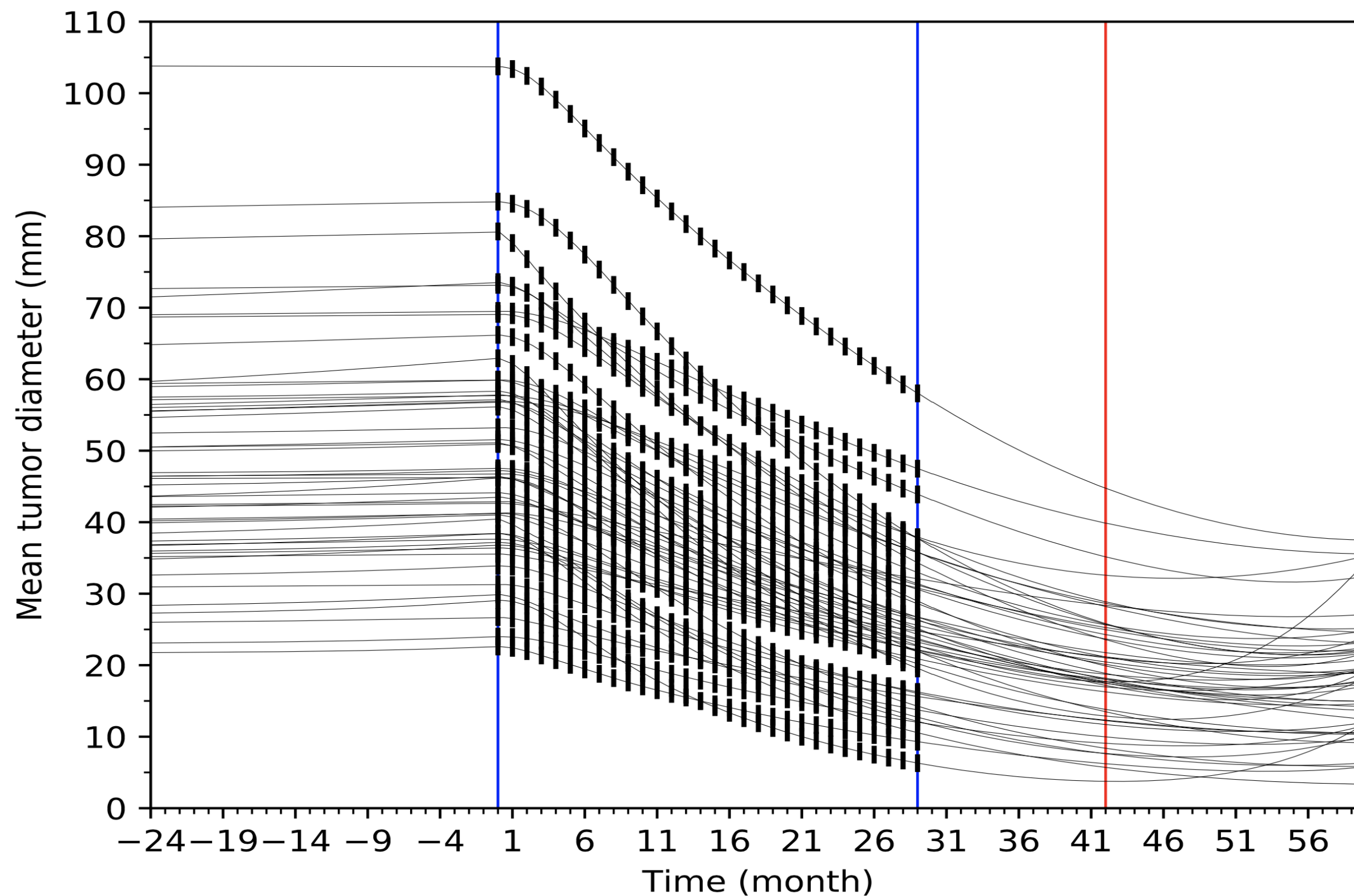
	Month of trial																													
Dosing regimen	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Expert	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Machines	✓	✓	✓	.	✓	✓	.	.	.	✓	.	.	.	✓	✓	.	.	.	✓	.	.	.

Digital Therapeutics and Algorithmic Design of Clinical Trials

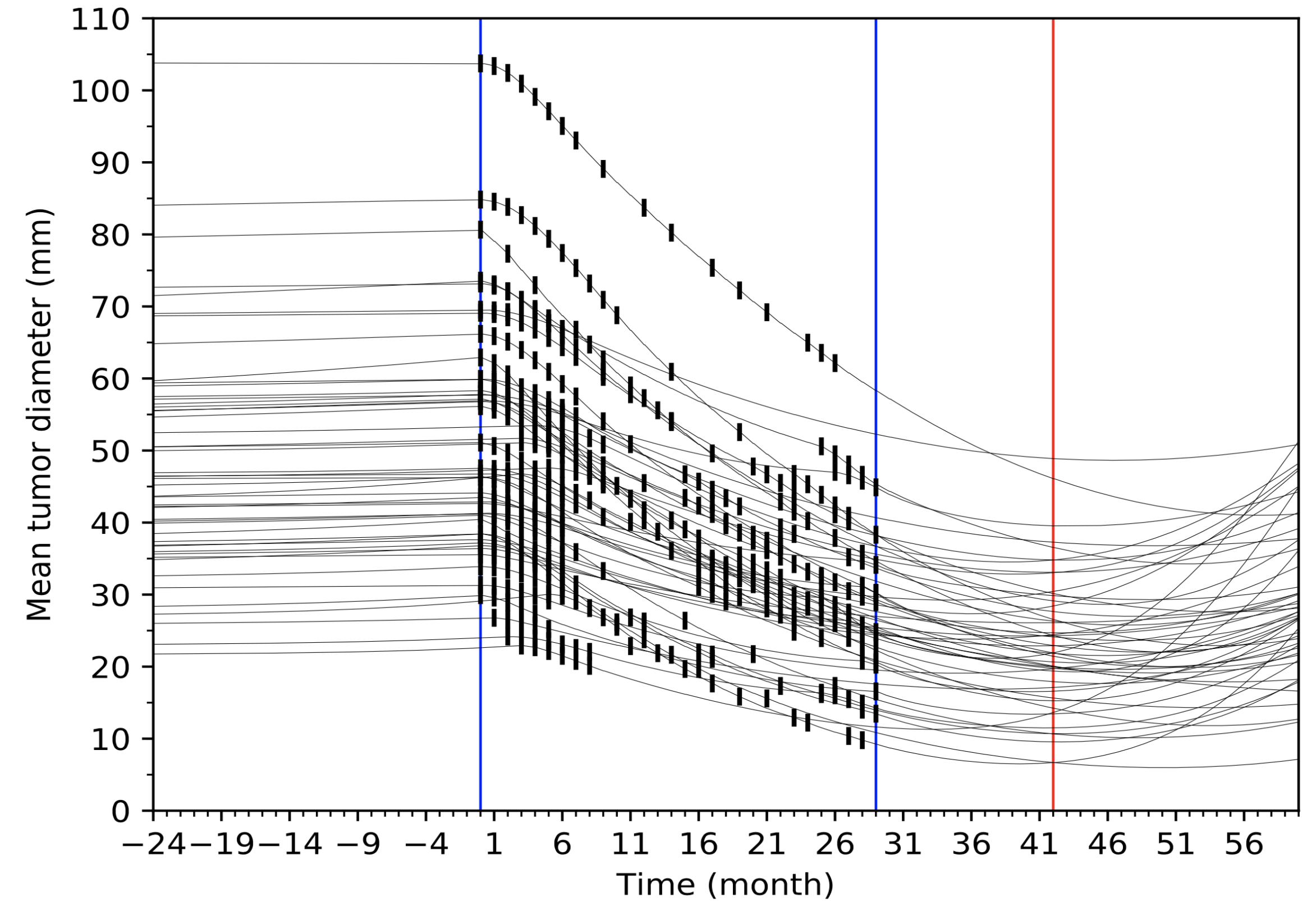
Goal: Reduce numbers of interventions for individual patients



Human experts



Machine policy



Learned policies with penalties and MTD reductions in TMZ cohort trials

Conc.	Penalty	Month of trial																													
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
A	Fixed	None	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
B	Fixed	Small	1	1	1	0	1	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
C	Fixed	Large	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1
D	Variable	None	1	1	1	1	.25	.75	1	1	.75	.75	.75	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
E	Variable	Small	1	1	.75	.75	0	0	.25	.5	0	.5	0	0	.5	0	0	.5	0	0	.5	0	.5	0	0	.25	.5	0	0	.5	
F	Variable	Large	1	.5	0	0	0	0	0	0	.25	.25	0	.25	.25	0	.25	0	.25	.25	0	.25	0	.25	.25	0	.25	.25	0	.25	

Table 2: Learned policies for trial-based TMZ experiments where all simulated patients received the same dose each month. Agents with a fixed concentration could give a unit dose, whereas agents with a variable concentration could give doses at 25%, 50%, 75%, and 100% of the unit dose’s concentration. Penalty: size of the dose penalty the agent tried to minimize while maximizing mean tumor diameter reduction. Conc: concentration.

	Trial parameters			Average MTD change			
	Treatment	Conc.	Type	Expert policy	No penalty	Small penalty	Large penalty
A	TMZ	Fixed	Patient	-61.04% ± 11.63%	-60.95% ± 11.64%	-51.89% ± 15.31%	-35.97% ± 17.05%
B	TMZ	Fixed	Trial	-62.18% ± 10.50%	-62.17% ± 10.51%	-54.09% ± 14.05%	-46.27% ± 17.93%
C	TMZ	Variable	Patient	-60.51% ± 10.68%	-60.23% ± 10.80%	-39.35% ± 46.02%	-7.15% ± 40.80%
D	TMZ	Variable	Trial	-62.86% ± 11.41%	-62.72% ± 11.43%	-54.03% ± 15.21%	-45.69% ± 18.06%

Language, Literacy and Vocabulary of Machine Learning Research for Improving Health outcomes

- **Inclusion and diversity in datasets are key to engender a fair clinical development process driven by algorithms**
- **Causal inferences and data standards should be implemented**
- **Machine learning and humans: synergy not competition**
- **Black box: Saliency, explicability and explainability is important but not rate-limiting**
- **Deployment and testing: New clinical trials for algorithms to be piloted**
- **Regulation and communication with patients and physicians to de-risk technology**
- **Automation vs. Knowledge vs. Intelligence**
- **It is a new field. We can do it right together vs. operating in silos**

Artificial Intelligence in Clinical Development to Improve Public Health:

Key recommendations



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FLATIRON HEALTH

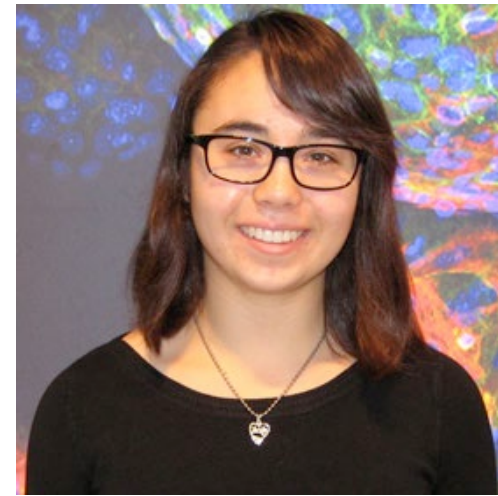


- New models and technologies for health research: digitally empowered researchers, physicians, regulators, patients and citizens
- Addressing current and near-term artificial intelligence (AI), machine learning (ML), medical imaging and neural network capabilities as they pertain to digital medicines and improving health
- Safer, faster and effective real world evidence driven clinical trials and novel digital endpoints
- Developing a sustainable model to bridge the gap between AI and data science experts, life sciences communities and physicians
- Encrypted ML, AI and other data sharing platforms to protect confidential information; and
- Collaborations with leaders and experts from within MIT, government, foundations, life sciences, universities, patient advocacy groups and technology corporations.

Research Staff & Students



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Sharon Wu



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Keith Angelino



Perikumar Javia



Gaurav Bhatia



Alicia Chong



Judy Chang

Collaborators



Dr. Francis Kendall



Dr. Nate Shapiro



Dr. Ali Muftu



Dr. SV Subramanian



Dr. Ali Lowe

Institutions and Funding



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Peer-Reviewed Medical Technology Research

- Gregory Yauney, Keith Angelino, David A. Edlund, **Pratik Shah**★ “**Convolutional Neural Network for Combined Classification of Fluorescent Biomarkers and Expert Annotations using White Light Images**” 2017 17th International Conference on Bioinformatics and Bioengineering, DOI: 10.1109/BIBE.2017.00-37
- **Pratik Shah**★, Gregory Yauney, Otkrist Gupta, Vincent Patalano II, Mrinal Mohit, Rikin Merchant, S. V. Subramanian. “**Technology-Enabled Non-Invasive Examinations Augment Primary Care.**” 2018 *BMJ Open* , 8 (4) e018774; DOI: 10.1136/bmjopen-2017-018774
- Aman Rana, Gregory Yauney, Lawrence Wong, Ali Muftu, and **Pratik Shah**★ “**Automated Segmentation of Gingival Diseases from Oral Images**” 2017 National Institutes of Health Special Topics Conference on Healthcare Innovations and Point-of-Care Technologies, DOI: 10.1109/HIC.2017.8227605
- Aman Rana, Gregory Yauney, Ali Lowe, **Pratik Shah**★ “**Computational Histological Staining and Destaining of Prostate Core Biopsy Images**” 2018 IEEE International Conference on Machine Learning and Applications. DOI: 10.1109/ICMLA.2018.00133
- Emma Yee, Shefali Lathwal, **Pratik Shah**, and Hadley Sikes. “**Detection of a Biomarker of Periodontal Disease in Human Saliva Using Stabilized, Vertical Flow Immunoassays**” 2018 ACS Sensors. DOI: 10.1021/acssensors.7b00745
- Gregory Yauney, Aman Rana, Perikumar Javia, Lawrence Wong, Ali Muftu, **Pratik Shah**★ “**Automated Process Incorporating Machine Learning Segmentation and Correlation of Oral Diseases with Systemic Health**” 2019 41st IEEE International Engineering in Medicine and Biology Conference-(Under Review)
- **Pratik Shah**★, Francis Kendall, Sean Khozin, Ryan Goosen, Amy Abernethy, Jiaying Hu, Jason Laramie, Michael Ringel, and Nicholas Schork. “**Machine learning and Artificial Intelligence in clinical development: a translational perspective**” 2019, Nature Digital Medicine (Under review)



Peer-Reviewed Medical Technology Research

- Gregory Yauney, **Pratik Shah**★ “**Reinforcement learning with action-derived rewards for chemotherapy and clinical trial dosing regimen selection**” Proceedings of the 3rd Machine Learning for Healthcare Conference, PMLR 85:161-226
- Perikumar Javia, Aman Rana, Nate Shapiro, **Pratik Shah**★ “**Machine learning algorithms for classification of microcirculation images from septic and non-septic patients**”. 17th IEEE International Conference of Machine Learning and Applications, DOI: 10.1109/ICMLA.2018.00097
- Keith Angelino, David A. Edlund, and **Pratik Shah**★ “**Near-Infrared Imaging for Detecting Caries and Structural Deformities in Teeth**” 2017 Journal of Translational Engineering in Health and Medicine. DOI: 10.1109/JTEHM.2017.2695194
- Keith Angelino, David A. Edlund, Gaurav Bhatia, Sharon Wu, and **Pratik Shah**★ “**Near-infrared transillumination guides administration of dental 2D radiography and CBCT imaging**” 2017 17th International Conference on Bioinformatics and Bioengineering. DOI: 10.1109/BIBE.2017.00-33
- **Pratik Shah**★, Keith Angelino, David A. Edlund, Mrinal Mohit, and Gregory Yauney “**Clinical Validation and Assessment of a Modular Fluorescent Imaging System and Algorithm for Rapid Detection and Quantification of Dental Plaque.**” 2017 BMC Oral. DOI: 10.1186/s12903-017-0472-4.
- Puri RS, Athanassiadis AG, Gill N, Sathya SS, Rathod G, Wahi A, Satat G, MajmudarM, **Shah P**★. **Design and Preliminary Evaluation of a Wearable Device for Mass-Screening of Sleep Apnea.** 2016 Proceedings of Annual International Conference of the IEEE Engineering in Medicine and Biology Society. DOI:10.1109/EMBC.2016.7591085.

★ = Senior Supervising Author



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