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KENTUCKY

Roadmap to AI Integration: A Smarter Future for Cancer Care

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AI In Precision Oncology Journal, Editorial Board

Member



Disclosures

- Tempus AI
- xCures
- BMS
- Merck
- AstraZeneca & DSI
- Quest / Haystack
- Gilead
- L'Oreal / La Roche-Posay Oncology

What is the first action one takes after processing the need for treatment of a cancer diagnosis?

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"We want someone with *experience*."

What about *experience* makes it so desirable?

1

2

What about *experience* makes it so desirable?

1

Adequate number of cases (high power)
to best optimize **pattern recognition**.

2

What about *experience* makes it so desirable?

1

Adequate number of cases (high power) to best optimize **pattern recognition**.

2

To appreciate the number of variables—whether from the chosen intervention, or specific patient characteristics—to **achieve the desired outcome**.

What are two functions of AI?

1

2

What are two functions of AI?

1

Enormous capability for large data processing and pattern recognition.

2

What are two functions of AI?

1

Enormous capability for large data processing and **pattern recognition**.

2

To best **predict** outcome. Both in those hoped to achieve, as well as those to avoid.

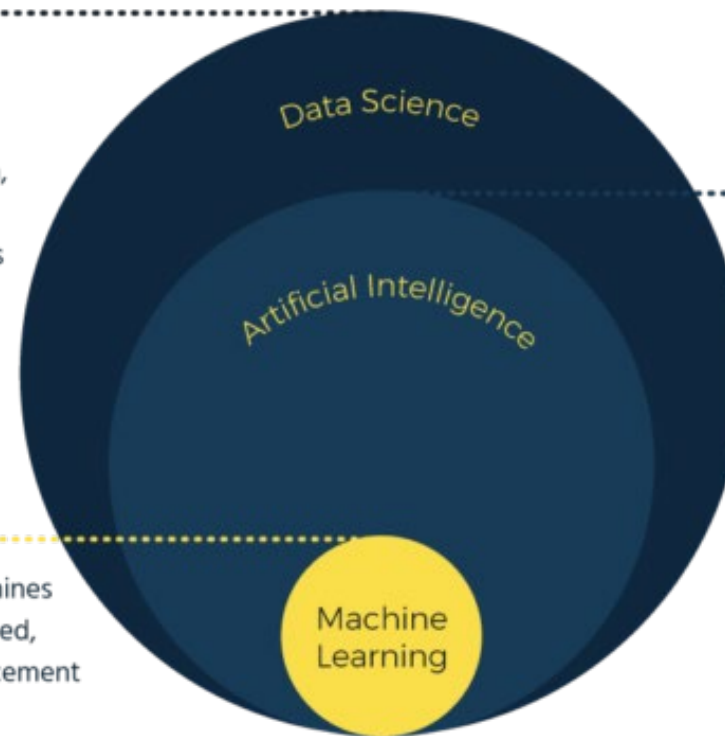
AI vs. Data Science vs. Machine Learning

Data Science

- Collection, preparation, and analysis of data
- Leverages AI/ML, research, industry expertise, and statistics to make business decisions

Machine Learning

- Algorithms that help machines improve through supervised, unsupervised, and reinforcement learning
- Subset of AI and Data Science tool



Artificial Intelligence

- Technology for machines to understand/interpret, learn, and make 'intelligent' decisions
- Includes Machine Learning among many other fields

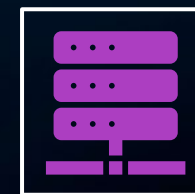
Deep Learning



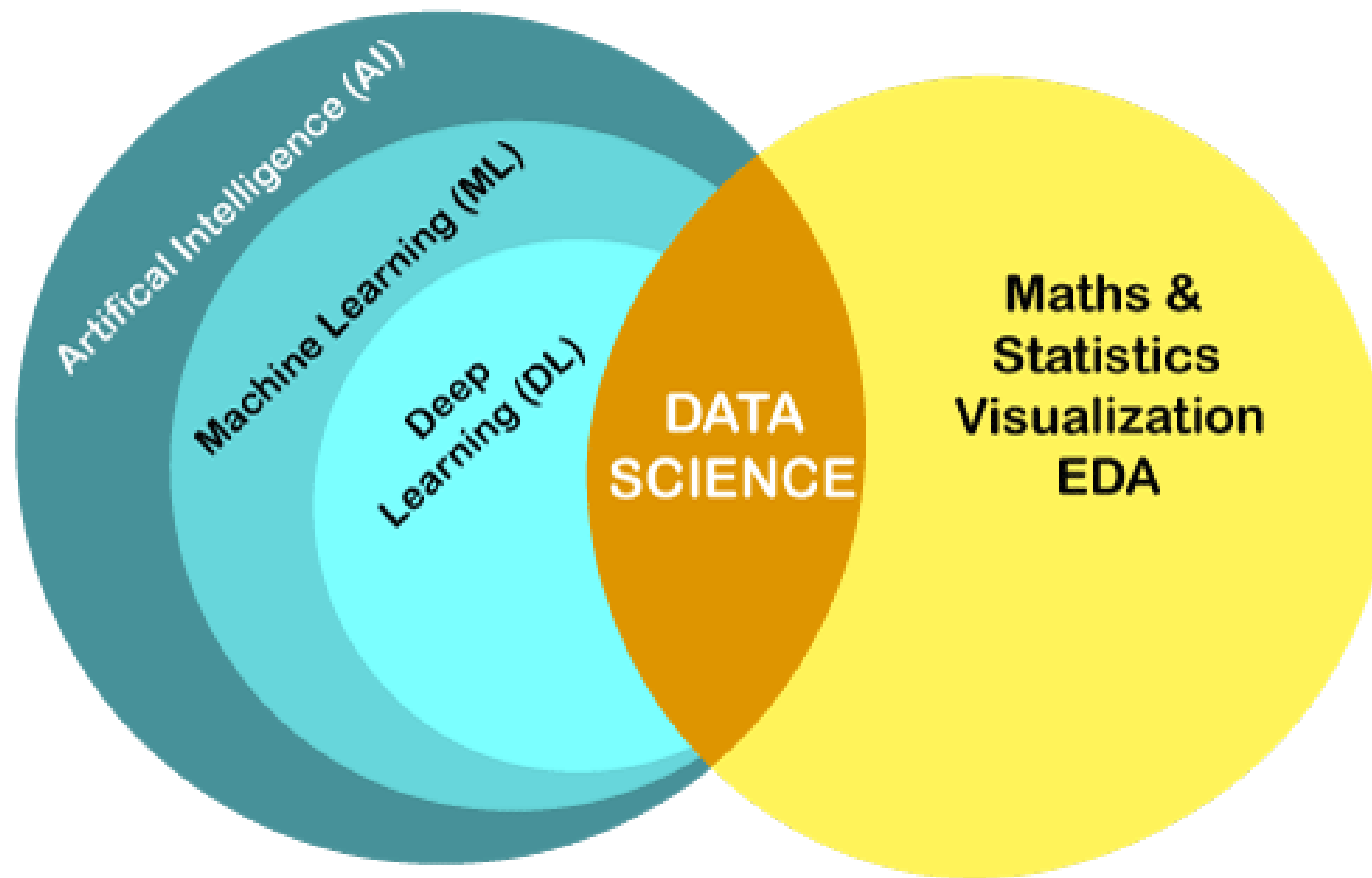
Whereas older machine learning algorithms classically *plateaued* as data sets grow larger, with *deep learning*, algorithms continue to *improve* with the more data they receive.



le. Self driving cars, language translation, image captions



Multiple layers of processing—generated outputs get handed off as new inputs, etc



The Infamous “Move 37”

Historic match of Go in 2016 between
AlphaGo and legend Lee Sedol

AlphaGo makes a move so unconventional
the entire crowd of onlookers gasp,
suspecting it surely made an error.

Later became known as ‘Move 37’, so far
removed from any human player’s intuition,
demonstrating AI’s ability to recognize
patterns and predict in a manner simply out
of the box of the *aggregate* of human
ability.





FINDING MORE “MOVE 37”S

- **How?**
 - Real world data—lots of it
 - GenerativeAI is what has let us FIND, and make SENSE OF IT. Use it.
- Longitudinal / continuous / outcome data
 - Takes into account the variables, the choices, and the outcome
 - Helps us potentially unravel/uncover the ‘why’s
- Not just longitudinal thought. What else?
 - **Cross-Sectional**
 - Helps benchmark / vet / reassess: PD1/PDL1 *quality*, decipher outcome from misread path or radiology, clinical *relevance* (VUSs, concurrent meds, ESR/CRP relevance)
- Multi-modal, multi-dimensional, multi-variable cataloguing and interrogation

► [Cancers \(Basel\)](#). 2024 Mar 12;16(6):1130. doi: [10.3390/cancers16061130](https://doi.org/10.3390/cancers16061130) [↗](#)

Deep-Learning-Based Predictive Imaging Biomarker Model for EGFR Mutation Status in Non-Small Cell Lung Cancer from CT Imaging

[Abhishek Mahajan](#)^{1,2,*}, [Vatsal Kania](#)³, [Ujjwal Agarwal](#)³, [Renuka Ashtekar](#)³, [Shreya Shukla](#)³, [Vijay Maruti Patil](#)⁴,
[Vanita Noronha](#)⁴, [Amit Joshi](#)⁴, [Nandini Menon](#)⁴, [Rajiv Kumar Kaushal](#)⁵, [Swapnil Rane](#)⁵, [Anuradha Chougule](#)⁴,
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PMCID: PMC10968632 PMID: [38539465](#)

- **88% accuracy in predicting EGFR mutations from CT scans alone!**

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<https://www.mdpi.com/2072-6694/16/6/1130>

- **88% accuracy** in predicting EGFR mutations from CT scans alone
- **990 patients from two NSCLC trials**
 - employed an end-to-end pipeline analyzing CT images without precise segmentation
 - Two 3D convolutional neural networks segmented lung masses and nodules
- **Semantic features**
 - pure solid tumours with no associated ground glass component ($p < 0.03$)
 - the absence of peripheral emphysema ($p < 0.03$)
 - presence of pleural retraction ($p = 0.004$)
 - presence of fissure attachment ($p = 0.001$)
 - presence of metastatic nodules in both tumour-containing & non-tumour-containing lobes ($p = 0.001$)
 - the presence of ipsilateral pleural effusion ($p = 0.04$)
 - average enhancement of the tumour mass above 54 HU ($p < 0.001$)



Expert Review of Molecular Diagnostics >

Volume 24, 2024 - Issue 5

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Review

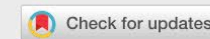
Artificial intelligence in digital histopathology for predicting patient prognosis and treatment efficacy in breast cancer

Christine McCaffrey, Chowdhury Jahangir, Clodagh Murphy, Caoimbhe Burke, [William M. Gallagher](#) & Arman Rahman

Pages 363-377 | Received 07 Dec 2023, Accepted 19 Apr 2024, Published online: 09 May 2024

Cite this article

<https://doi.org/10.1080/14737159.2024.2346545>



Tumor-Infiltrating Lymphocytes (TILs):

- **Quantification and Spatial Analysis**
 - AI algorithms excelled at accurately quantifying TILs within the tumor microenvironment (TME) from digitized H&E images.
 - Went beyond simple counting: AI could analyze the spatial distribution and density of TILs, which proved crucial for predicting response to both chemotherapy and immunotherapy.
- **TIL Subsets:**
 - Some studies explored the prognostic and predictive value of different TIL subsets (e.g., CD8+ T cells, CD4+ T cells). AI could potentially identify these subsets based on morphological features or by integrating data from multiplex IHC staining.




Other Histological Features:

- **Nuclear Features:** AI algorithms to analyze size, shape, texture, and chromatin organization—reflecting the genetic instability and aggressiveness of the tumor, which can influence treatment response.
- **Tumor-Stroma Ratio (TSR):** The ratio of tumor cells to stromal cells in the TME was also found to be predictive of treatment response. AI could accurately quantify the TSR, which provided insights into the tumor's microenvironment and its potential to respond to therapy.
- **Mitotic Count:** AI algorithms could identify and count mitotic figures, which are indicative of cell proliferation and tumor aggressiveness. This information could be used to predict response to chemotherapy.
- **Large-Scale DNA Organization (LDO):** AI could analyze the organization of DNA within the nucleus, which can be correlated with disease states and used to predict prognosis and potentially treatment response.



Integration of Multi- Modal Data

- **Combining Histological and Clinical Data**
 - Some studies demonstrated the potential of integrating histological features extracted by AI with clinical data (e.g., age, tumor stage, hormone receptor status) to improve the accuracy of treatment response prediction.
- **Inferring Genomic and Proteomic Data:**
 - Emerging research suggests that AI algorithms may be able to infer genomic and proteomic information directly from H&E images. This could provide a more comprehensive understanding of the tumor's molecular profile and its potential response to targeted therapies.

▶ [Eur Radiol. 2021 Oct 15;32\(5\):3131–3141. doi: 10.1007/s00330-021-08306-w](#) 

Analysis of mammograms using artificial intelligence to predict response to neoadjuvant chemotherapy in breast cancer patients: proof of concept

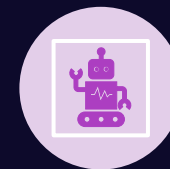
[I Skarping](#)^{1,2,✉}, [M Larsson](#)³, [D Förnvik](#)⁴

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PMCID: PMC9038782 PMID: [34652522](#)



For training and validation, 1485 images obtained from 400 patients were used, and the model was ultimately applied to a test set consisting of 53 patients.



The artificial intelligence (AI) model predicted the pCR as represented by the area under the curve of 0.71 (95% confidence interval 0.53–0.90; $p = 0.035$). The sensitivity was 46% at a fixed **specificity of 90%**.

NEURAL NETWORKS

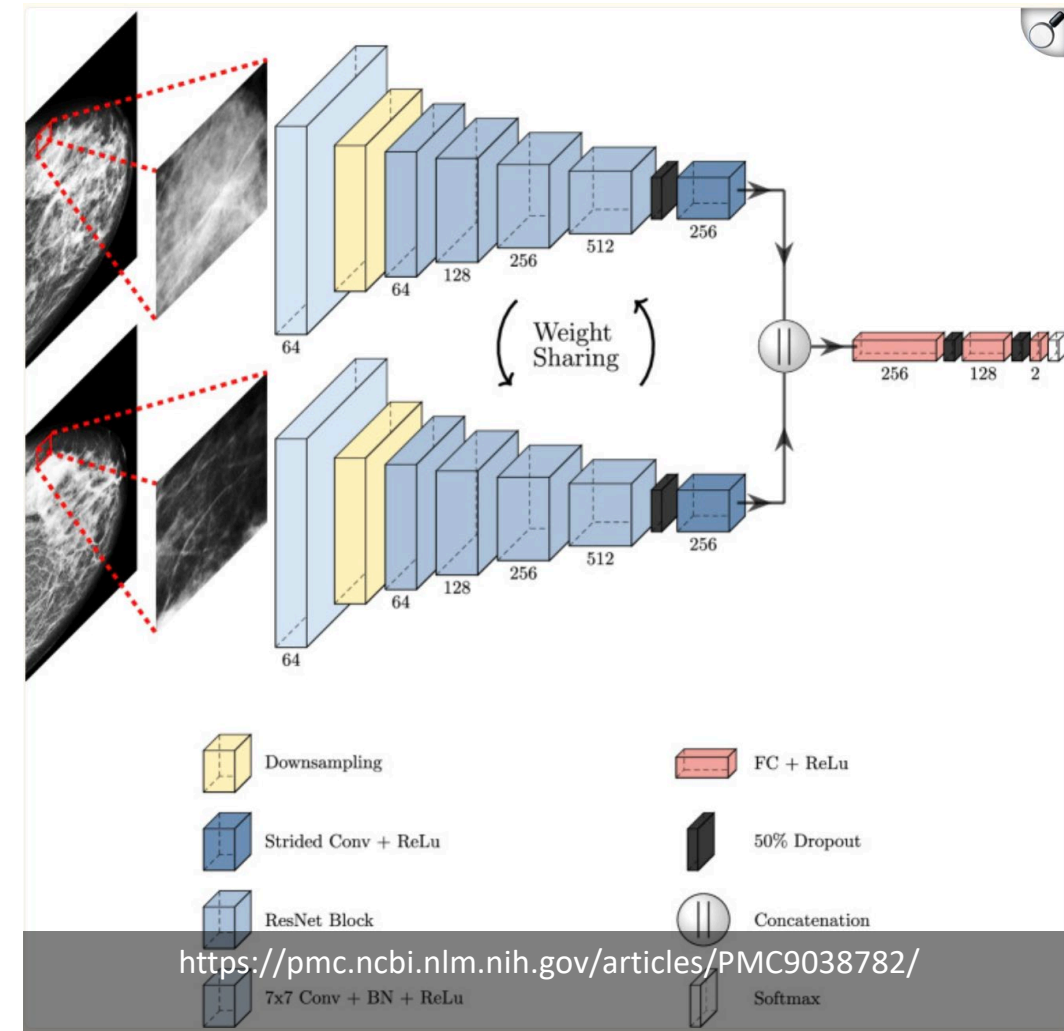
THE DEEP LEARNING SYSTEM USED TO PREDICT PCR IN DM CONSISTS OF TWO MAIN STEPS

(1) A NETWORK FOR DETECTION TUMORS IS FIRST APPLIED TO THE DM

(2) IMAGE PATCHES ARE EXTRACTED AROUND THE DETECTED TUMOR IN ADDITION TO THE SAME POSITION IN THE REFERENCE IMAGE (CONTRALATERAL CANCER-FREE BREAST).

THE TWO IMAGE PATCHES ARE FED INTO A CLASSIFICATION NETWORK THAT PREDICTED PCR.

BY EXTRACTING SMALLER IMAGE PATCHES OF INTEREST, THE CLASSIFICATION NETWORK IS FORCED TO MAKE PREDICTIONS BASED ON WHAT WAS HYPOTHESED TO BE RELEVANT INFORMATION INSTEAD OF OVERFITTING THE INFORMATION TO IRRELEVANT INPUT.



Conceive:

AI-Powered Oncology - A Fully Enabled Workflow of the Future



Personalized Risk Stratification

Comprehensive Data

AI algorithms analyze a vast array of patient-specific data, including biologic age, metabolic markers (ESR, CRP, A1c), and cardiovascular reserve from wearables.

Wearable Insights

Wearables provide continuous monitoring of physiological duress through skin dilatatory and perspiration assessments and REM sleep analysis.

Holistic Assessment

Family history, environmental exposures, and lifestyle factors are integrated for a complete risk profile. AI identifies high-risk individuals for early intervention.

AI-Enhanced Radiologic Screening

1

Intelligent Mammograms

AI/ML algorithms trained on massive datasets analyze mammograms with exceptional accuracy, automatically ordering MRIs or biopsies for suspicious cases.

2

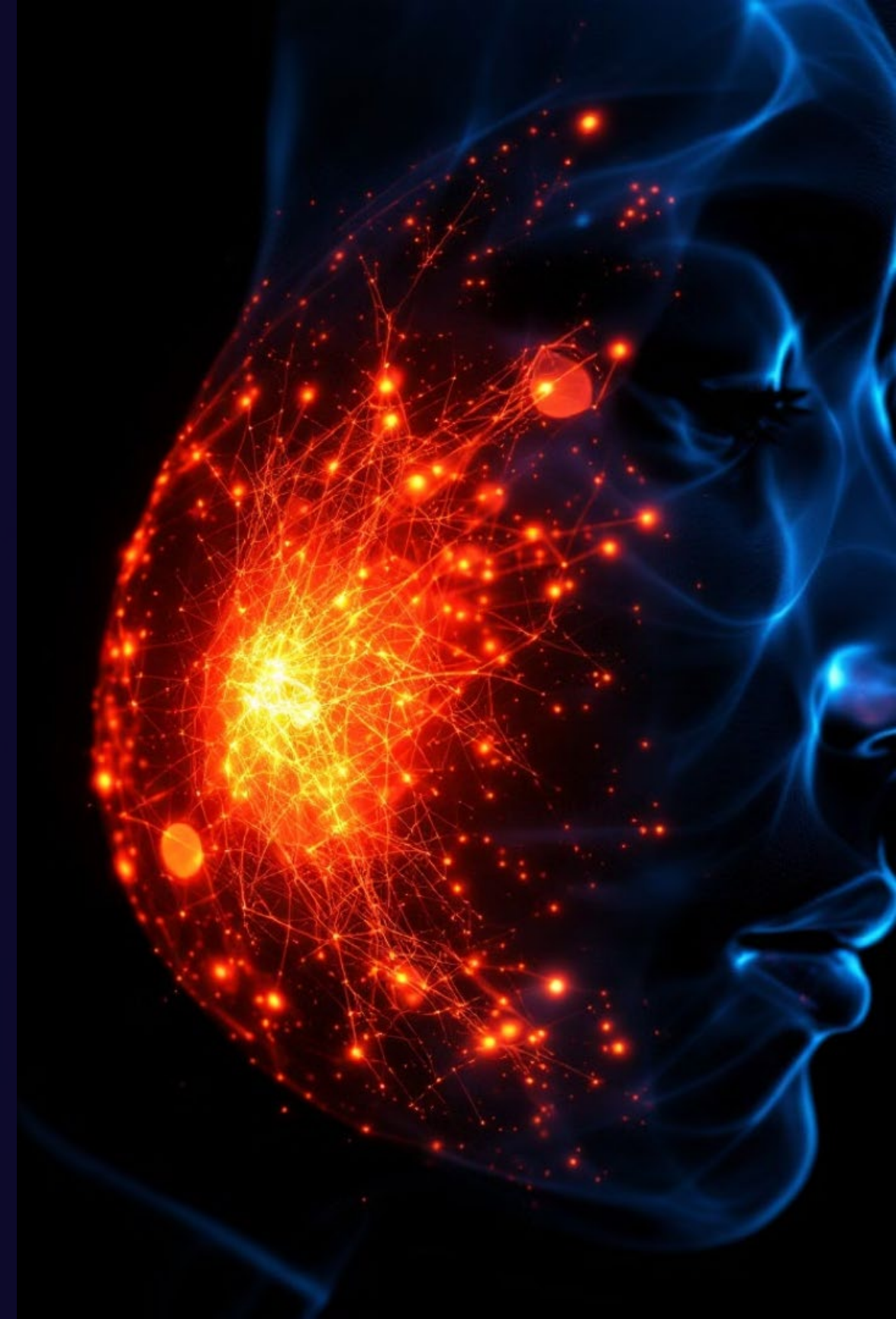
Predictive PET/CT Scans

AI/ML characterizes PET/CT scans in real-time, predicting the likelihood of EGFR positivity in lung cancer or HER2 in breast cancer, guiding targeted therapy decisions.

3

Streamlined Workflow

By automating the detection and characterization of potential cancers, AI accelerates the diagnostic process, reducing delays in treatment initiation.



Intelligent Follow-Up Triage

Prioritized Scheduling

AI triages follow-up appointments based on immediate need and risk assessment. Negative mammograms are automatically scheduled, while suspected cancers are prioritized.

Proactive Molecular Testing

Molecular testing is automatically ordered based on AI-predicted likelihood from staging and radiomics, even before follow-up, expediting personalized treatment planning.

Digital Pathology Analysis

AI-driven digital pathology provides specific characterization of aggressiveness and microenvironment analysis, optimizing immunotherapy considerations.



Empowered Patient Experience



Real-Time Updates

Patients receive parallel updates on their own app, staying informed about their plan and next steps. Doctors reinforce the course of action, ensuring alignment.



Personalized Treatment Plans

Treatment plans consider real-world evidence (RWE), known relationships to therapy responses and toxicities, and patient-specific pharmacogenomics and SNPs.



Automated Approvals

Prior authorizations are automatically generated with full justification of the personalized regimen, streamlining the approval process and minimizing delays.

Real-Time Treatment Monitoring

1

Wearable-Driven Alerts

Wearables monitor REM cycles and cardiac variability, alerting for potential complications like PE, anemia, or early infection, prompting timely toxicity checks.

2

Toxicity Management

AI assesses skin turgor to manage diarrhea in real-time, prompting both management and treatment adjustments to minimize patient discomfort and complications.

3

Dynamic Dosing

Dosing adjustments are based on assessments of tissue turnover and inflammatory markers, optimizing treatment effectiveness while reducing potential toxicities.



Immediate Insight on Treatment Response



AI algorithms analyze tumor shedding trends and metabolomics data, providing immediate insights on treatment response. This enables rapid adaptation of treatment plans for better outcomes.

By understanding the immediate effect of a drug, doctors can quickly react and improve the treatment and outcome for the patient.



Key Takeaways & Next Steps

1

AI-Driven Transformation

AI is poised to revolutionize oncology, enabling personalized risk stratification, streamlined screening, and proactive treatment monitoring for improved patient outcomes.

2

Integration Imperative

Integrating AI into existing workflows requires collaboration between healthcare professionals, researchers, and investors to unlock its full potential.

3

Future Vision

Embracing AI in oncology will lead to earlier detection, more effective treatments, and a better quality of life for cancer patients, paving the way for a healthier future.

Developing an AI Model:

Step 1 – Training

- AI system needs to be fed data.
- You can do a **feasibility** study (test accuracy with x amount of data—then extrapolate what more data would do / how it would perform) to see if the data is enough and adequate.
 - **Features** are / is the data you want it to analyze.
 - **Labels**, aka the ‘answers’—what you want it to know / come to the conclusion of, from said features
- *Tabular data, because it is already structured, make it less suited to maximize deep learning techniques. Deep learning leverages inherent structure in data—ie resonance in a pixel, and its relation to the pixels around it.*

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- Evaluating a model’s performance during training is done using **proxy metrics**.
 - These are **context-dependent** without any universal definition of ‘good’, or ‘health’. (ie, no defined confidence interval or p value)
 - Classification accuracy
 - Sensitivity & specificity
 - Area under the receiver operating characteristic (ROC) curve (True positive over false positive)
 - One problem can be **overfitness**—the process was over-complicated and too ‘fit’ to knock the training data out of the park, but given its so contingent on that, its not as good with *additional* data that vary from that which it was trained on

Quantity *and* quality / quality labeling is crucial in training an AI model well

Developing an AI Model:

Step 2 – Validation

- Tests model in a live environment, with pre-registered endpoints
 - Of note, learning / development of the model is ***paused*** during this process of demonstrating model's effectiveness in real-world scenarios.
- Generalizability, of which can be an issue due to:
 - biases in training data, overfittness, and mismatch between the training environment vs the training one.
- **NOTE: most** AI studies have not undergone a prospective validation study. In other words, most are stage one only. This is a **huge gap** as it has not been tested for *real-world performance*.
 - This is the only way we go from theory, to a *practical* application.

Developing an AI Model:

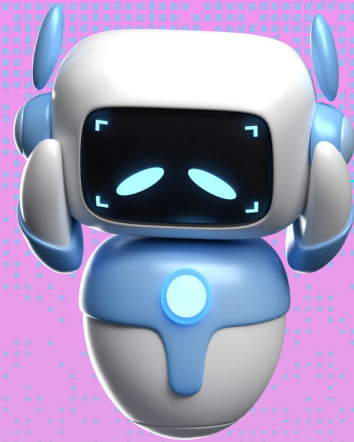
Step 3 – Deployment

- Integrate (on IT / tech level)
- Ensure regulations/compliance
 - Governance, monitoring, adapting/reassessing models
-and be productive, or actually ‘work’

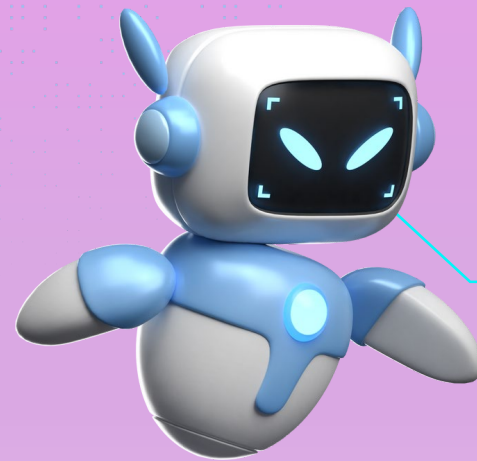
- AI fundamentally believes everything that happened yesterday, will happen tomorrow. That it is unchanging, and consistent.
 - Hence, not perpetuating inherent biases from, ie.:
 - *Ordering behavior (geographically / regionally)*
 - *Previously biased studies / cohorts*
 - *Features unique to a locoregional patient population (ie smoking, obesity, etc)*

--is important.

Potential problems



DEPENDENCE ON TECHNOLOGY



Trust Issues: Patient *and* Physician
Guideline vs AI assessment?

Is 'Dependence' Anything... New?

What would happen if
Google maps & Waze
disappeared?

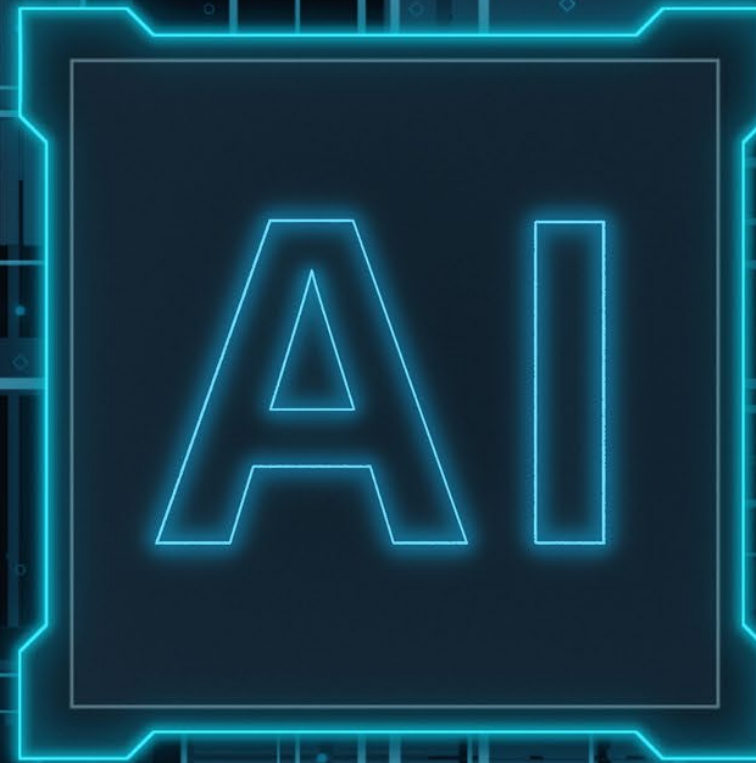
Google Search. Kayak. Uber.

Social Media. Email.

Weather apps.

Amazon.

Costco & Wal-Mart online.



Chemotherapy dosing
(kg, CrCl, mg/m²)

NCCN. NCBI. Package inserts.

Uptodate. Toxicity grading.

Holding parameters.

Medication interactions.

Cancer analysis.

Pharmacogenomics/SNPS

Guideline querying.

Radiology reads.

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- <https://mitsloanedtech.mit.edu/ai/basics/>
- <https://www.techtarget.com/searchenterpriseai/definition/unsupervised-learning>

Thank You.



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