# AI IN LIVER TRANSPLANTATION: CURRENT STATUS AND FUTURE PROSPECTS

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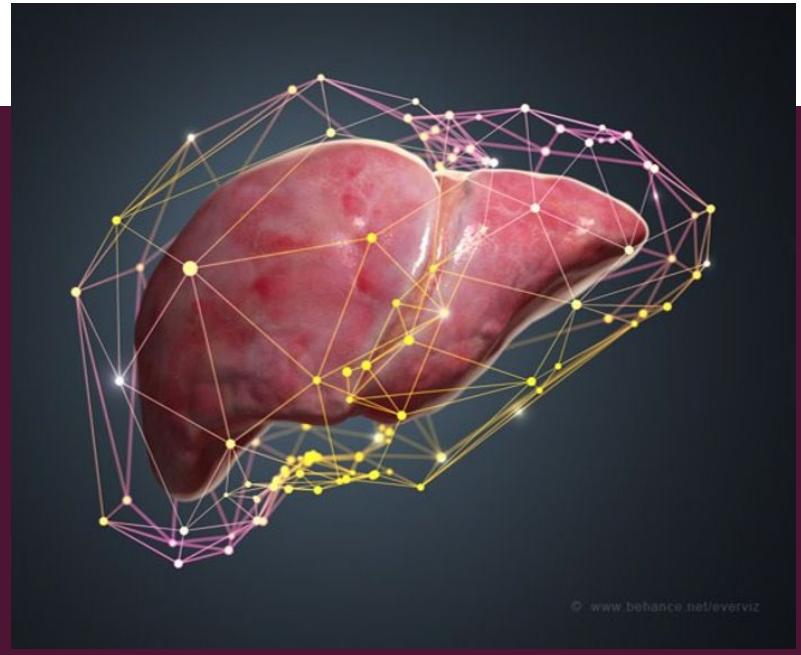
Transplant Rounds
February 1st, 2023



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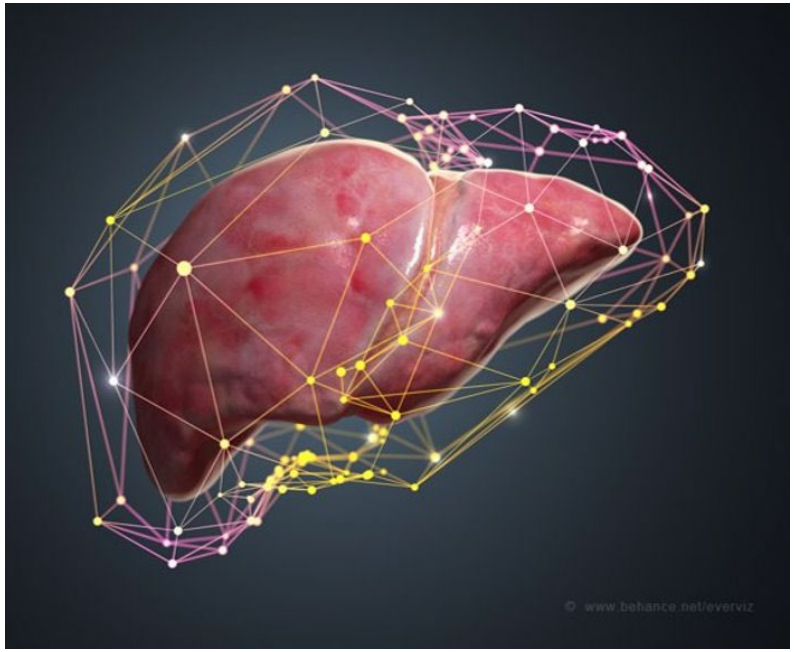
# OUTLINE

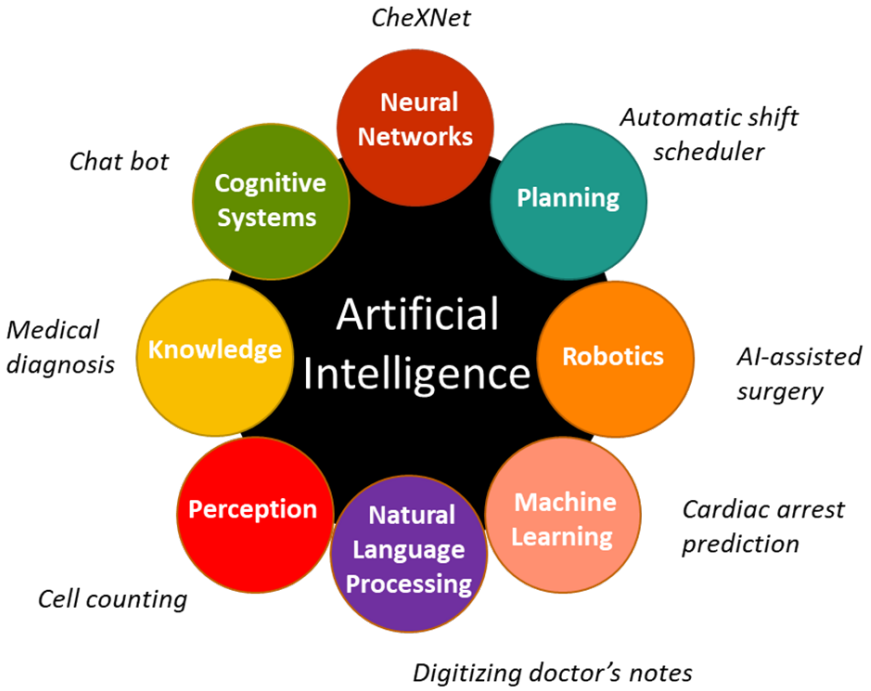
- What is Machine Learning? Tools, Applications & Limitations
- Why ML in Liver Transplantation?
- Case Studies in Liver Transplantation: Pre, Post-Transplant
- How about Fine-tuning with Molecular Data?
- Steps towards Clinical Deployment!



# WHAT IS ARTIFICIAL INTELLIGENCE?
# WHAT IS MACHINE LEARNING?

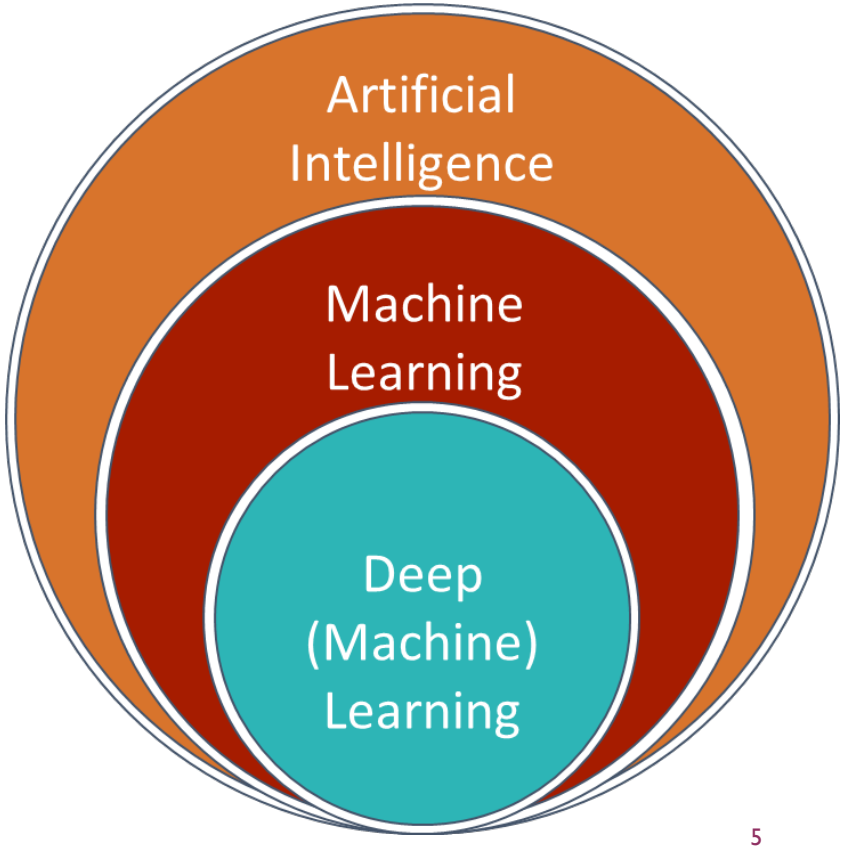
# WHAT IS ARTIFICIAL INTELLIGENCE?

- Intelligence combines many traits: learning, reasoning, problem solving, etc
- **Basically Intelligence demonstrated by machines**
- Many valid definitions
  - Technology that behaves intelligently using skills associated with human intelligence
  - Systems that act rationally
  - **Computer systems that use information and "act" in a goal-directed manner**



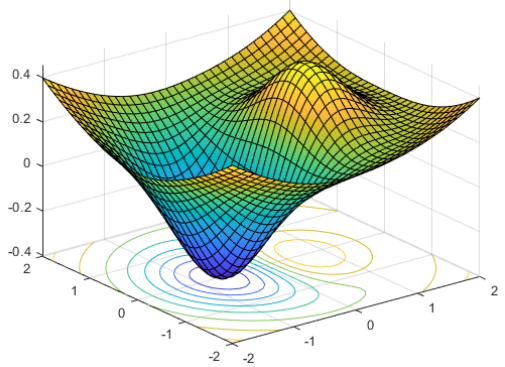
# WHAT IS MACHINE LEARNING?

- When many people say "AI" they are referring to machine learning (ML)
- ML is a subset of AI
  - *Field of AI that allows software applications to become more accurate at generating predictive models without being explicitly programmed*
- Detects hidden patterns and interrelationships within large datasets
- Deep learning (DL)/Neural networks (NNs) are a type of ML algorithms

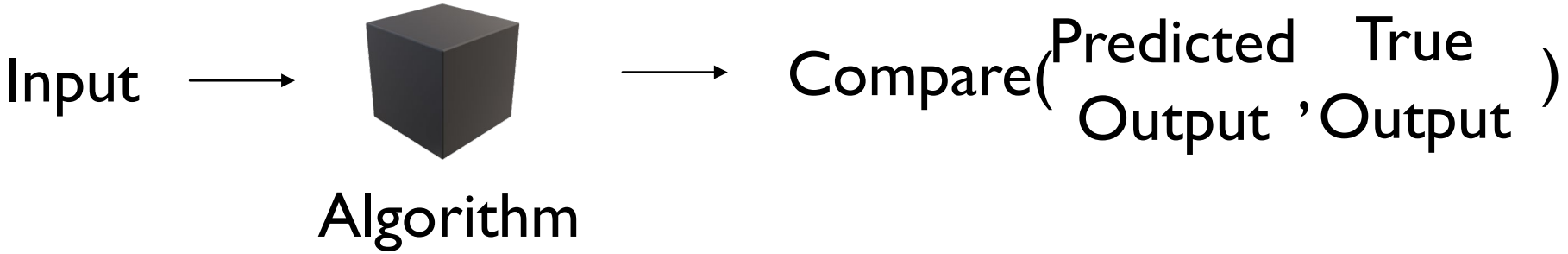


# MACHINE LEARNING PIPELINE

- Collect and process **inputs**
- Choose **algorithm** that can map input to output
- Collect and process **outputs**
- **Train** (optimize) algorithm until predicted and true outputs are similar

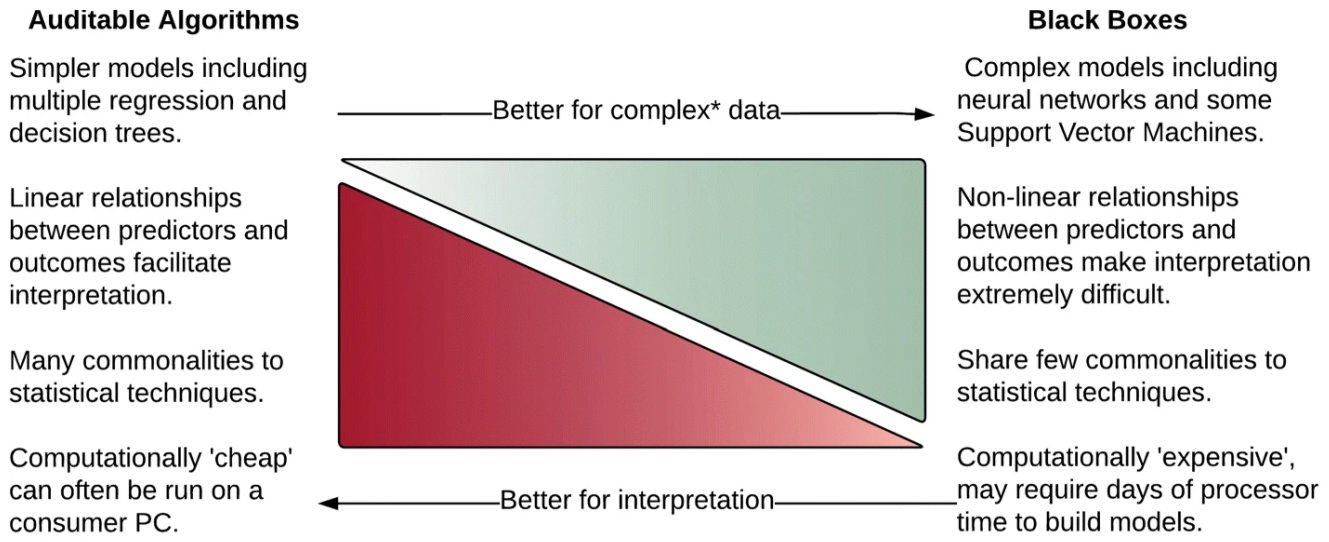



*Optimization*



# ML VS TRADITIONAL BIOSTATISTICS

- Standard clinical risk assessment models assume risk factor related in linear fashion to clinical outcomes
- ML can better incorporate multiple risk factors and identify more nuanced relationships between risk factors and outcomes
- ML Algorithms learn from existing data to find novel patterns




* 'Complex' data could refer to data which do not have a linear relationship with the outcome, such as a pixel in an image, the frequency of a wave in a sound bite, or movement data captured by a smart phone.

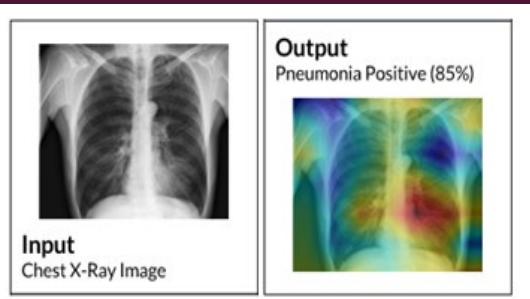

Spann A, Wang B, Goldenberg A, Bhat M. **Applying Machine Learning in Liver Disease & Transplantation: A Comprehensive Review,** Hepatology 2020

Sidney-Gibbons et al, BMC Medical Research Methodology 2019

# DIFFERENT MACHINE LEARNING TOOLS, APPLICATIONS & LIMITATIONS

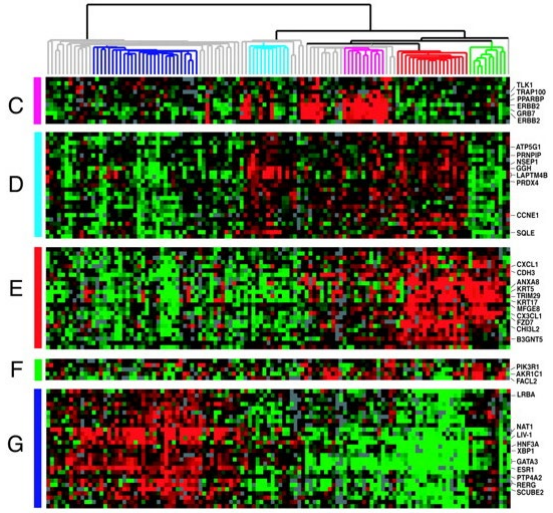
# THREE MAIN PARADIGMS OF ML

- Supervised learning (*predicting labels from data*)
- Unsupervised learning (*learning representations of the data*)
- Reinforcement learning (*dynamic decision making using data*)




*Predicting pneumonia from chest X-rays*

**Supervised Learning**



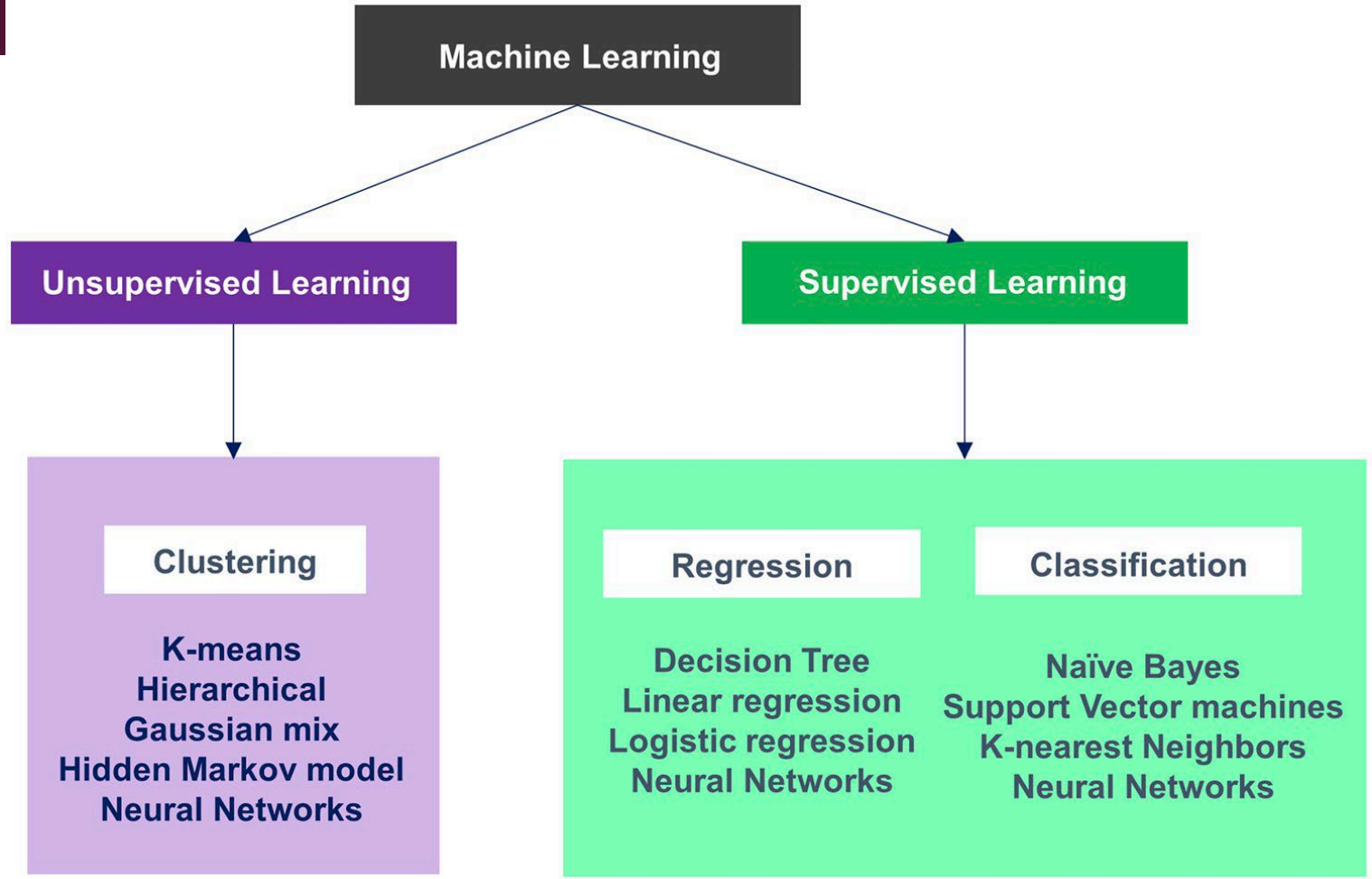

*Discovering breast cancer subtypes from gene expression arrays*

**Unsupervised Learning**

*Real-time drug dosing practices to understand optimal treatment course*

**Reinforcement Learning**

# ML MODELS FOR SPECIFIC TASKS

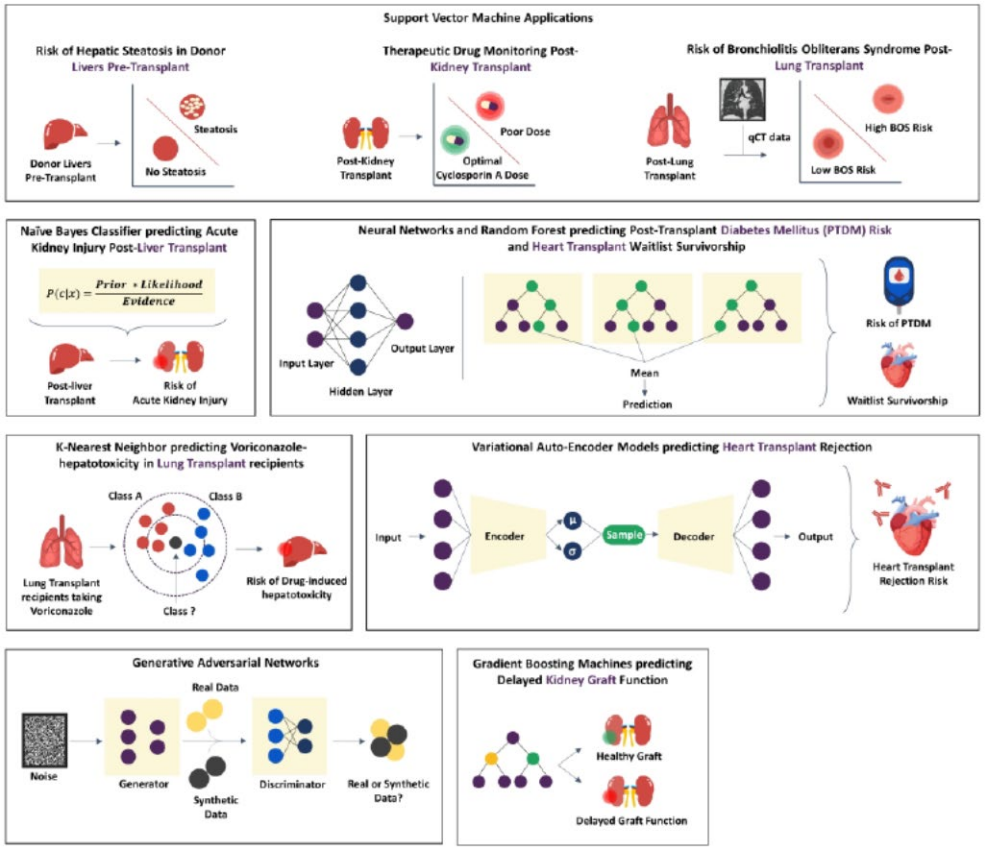



Tran J, Bhat M. Application of machine learning in liver transplantation: a review. Hepatology International 2022

# WHY ML IN TRANSPLANTATION?

# WHY ML IN TRANSPLANTATION?

- Various factors affect transplant pathology & outcomes: sex, ethnicity, genetics, environmental exposures, lifestyle, BMI, diabetes, immunosuppression
- Complex, non-linear patterns in liver enzymes, liver function tests, platelets, creatinine, sodium
- Electronic health record data, imaging technologies, histology, clinical sensors, wearables, molecular data
- **Applications in Donor-recipient matching**
- **Waitlist prioritization**
- **Prediction of Outcomes**



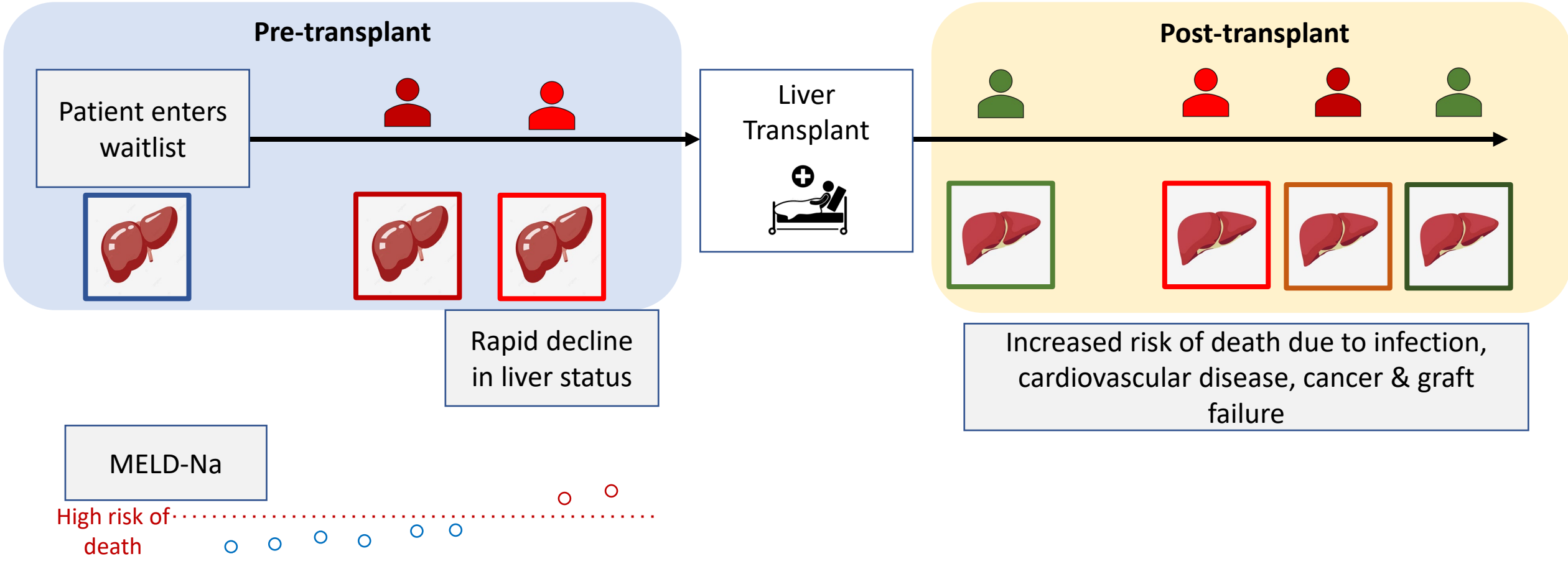


[1]Spann A, Wang B, Goldenberg A, Bhat M. Applying Machine Learning in Liver Disease & Transplantation: A Comprehensive Review, Hepatology 2020

[2]Gotlieb N, Spann A, Wang B, Bhat M. Applying Machine Learning in Solid Organ Transplantation. NPJ Digital Medicine, 2022

**[3]Bhat M, Rabindranath M, Sordid-Chara B, Simonetto D. In Press, Journal of Hepatology 2023**

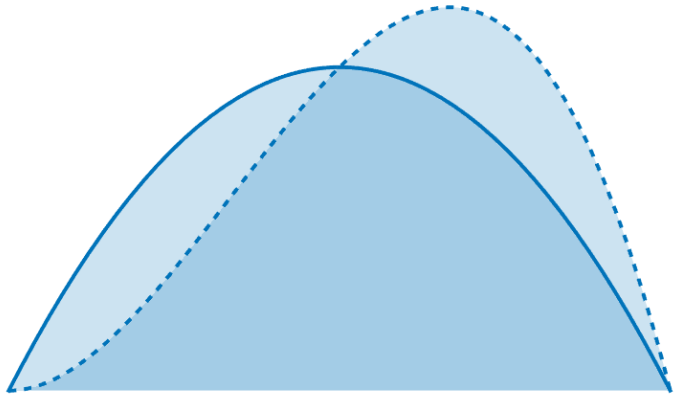
# OPPORTUNITY FOR AI IN LIVER TRANSPLANT



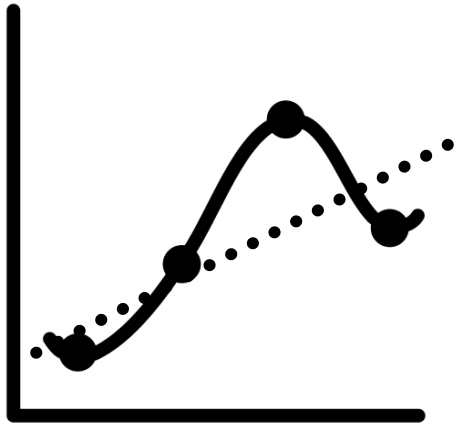
# CASE STUDIES IN LIVER TRANSPLANTATION

# MELD NA

**MELD-Na= MELD + 1.32 x (137 - Na) - [0.033 x MELD*(137 - Na)]**
**MELD = 3.78×ln[serum bilirubin (mg/dL)] + 11.2×ln[INR] + 9.57×ln[serum creatinine (mg/dL)] + 6.43**



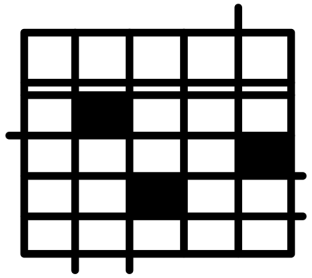
Shift in Underlying Patient Cohort



Linear Functional Form

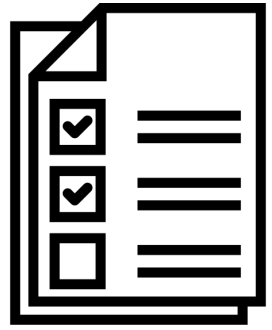
Disadvantages Female Patients (Locke et al., 2020; Karnam R et al, JAMA Surgery, 2021)

# AI METHOD: DYNAMELD



121,647 Patients Listed for Transplant in U.S. Between 2002 and 2021

Adult Patients with Decompensated Cirrhosis

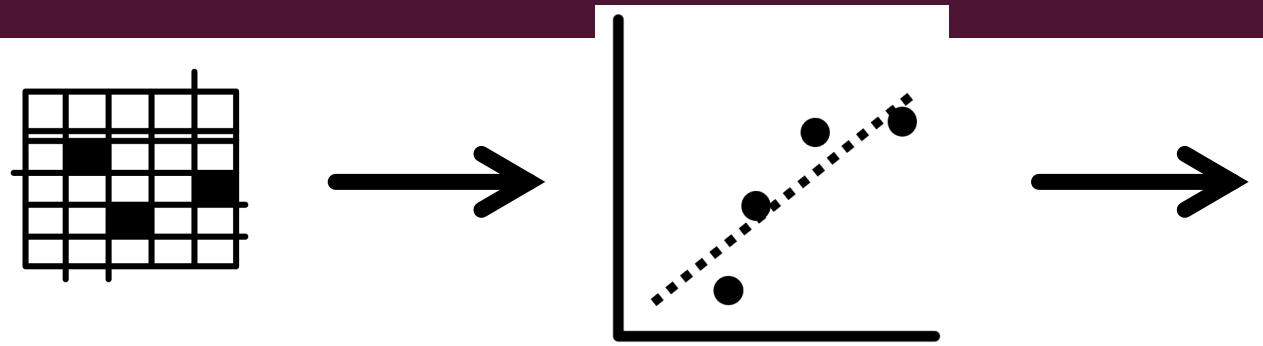


342 Static and Time-Varying Features per Patient

Cooper M, Brudno M, Krishnan R, Bhat M. Oral, AASLD Liver Meeting Nov 2022

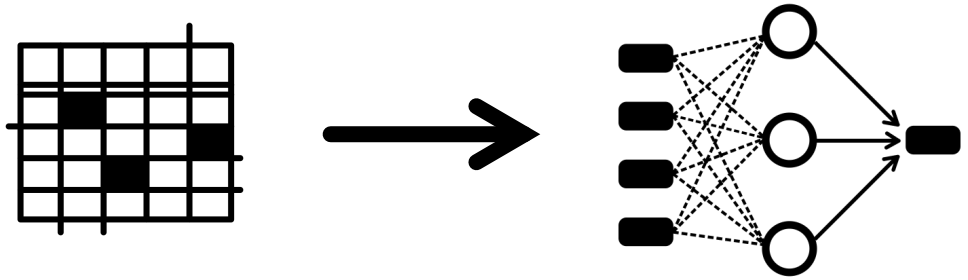
# DYNAMELD

CoxPH:
(Linear Survival Analysis)



Patient Risk Score

DeepSurv:
(Nonlinear Survival Analysis)



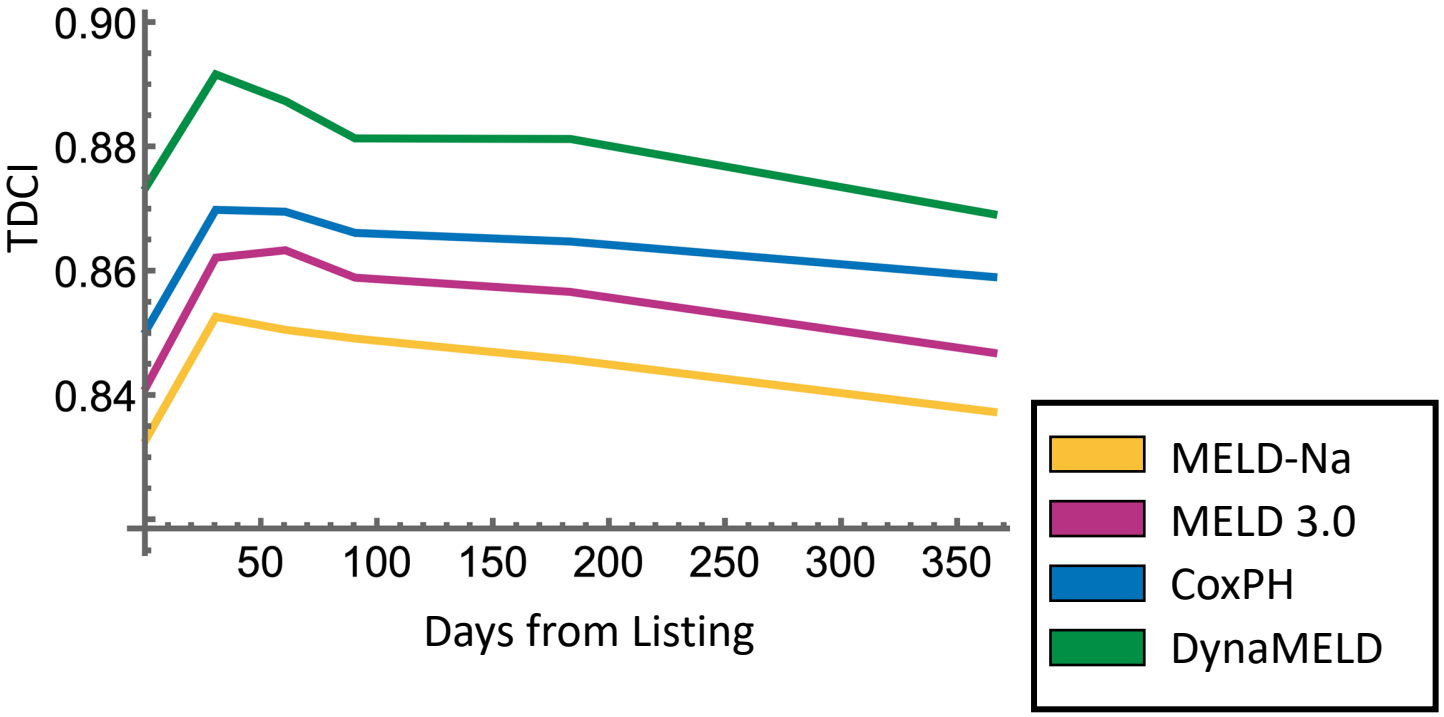
Patient Risk Score



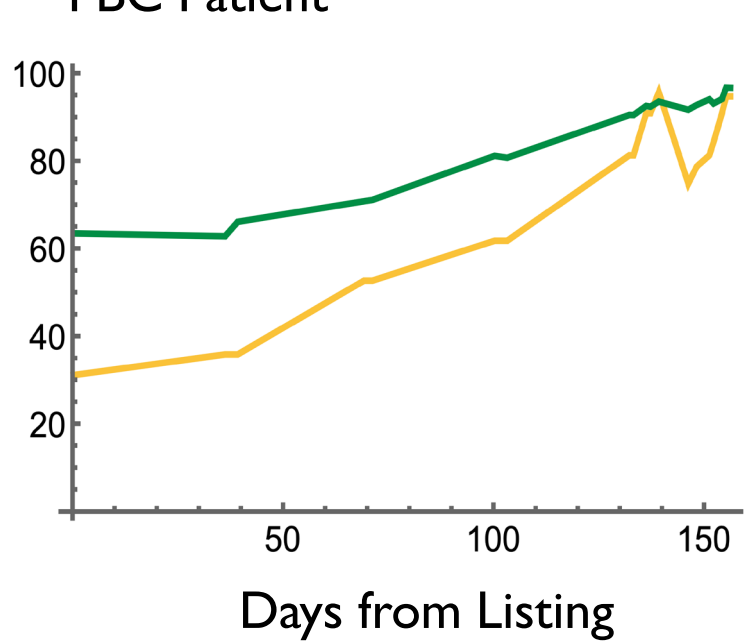
DynaMELD: **DeepSurv** model, but modified to add covariates to each patient/time-point instance that correspond to ***rate-of-change of time varying covariates***

# DynaMELD: AUC of 0.92 vs MELD Na AUC of 0.85

Time-Dependent Concordance Index(TDCI), 90-Day-Mortality




Risk Percentile, 54y/o Female PBC Patient




Initial MELD-Na Score: **17**
Died after **156** Days Waitlisted

<u>Significance testing</u>: At listing, $\text{TDCI}_{\text{MELD-Na}} < \text{TDCI}_{\text{DynaMELD}}$, $(p = 9.7e^{-55})$

# LIVSIM: SIMULATING ALLOCATION OUTCOMES

Dataset: Cohort of 16,210 (9339 M, 6871 F) patients listed since the introduction of the MELD-Na.

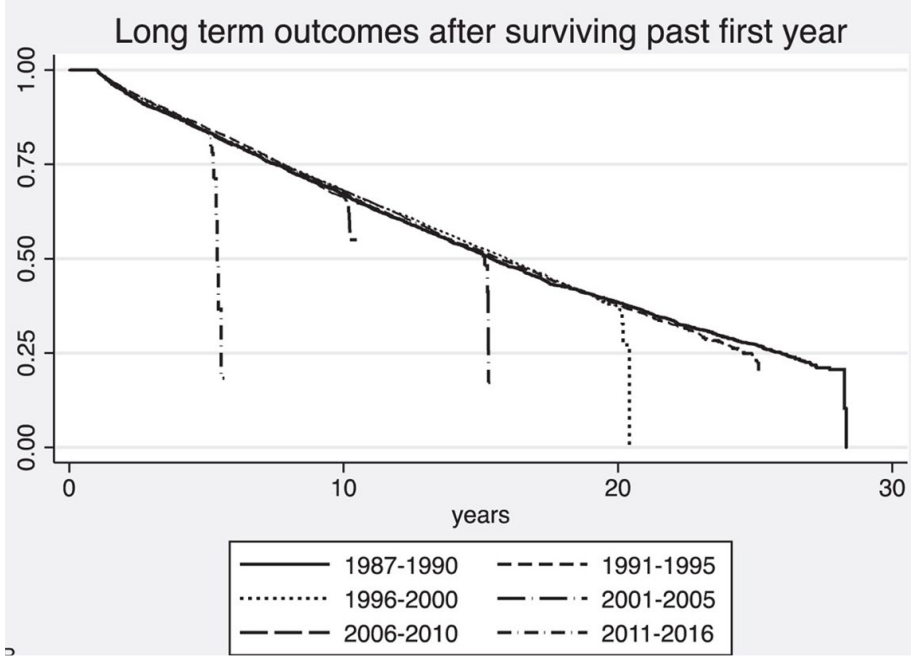
Simulation Results:

| Model Class | Pre-Transplant Mortality | Pre-Transplant Mortality (Women) |
|---|---|---|
| MELD-Na | 1,282 (7.9%) | 550 (8.1%) |
| MELD 3.0 | 1,249 (7.7%) | 553 (8.2%) |
| DynaMELD | 1,119 (6.9%) | 468 (6.9%) |

# POST-TRANSPLANT

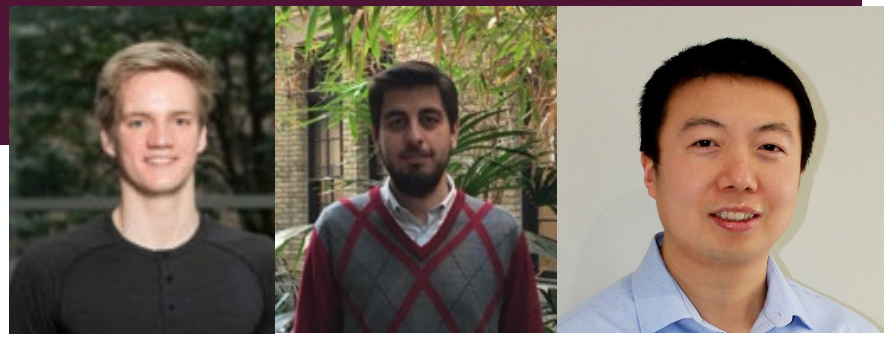
- Median survival of LT recipients 20 years less than Canadian life expectancy*
- Existing comorbidities, lifelong immunosuppression
- Compromised by heightened incidence of cancer, cardiometabolic disease, and infection
- Care of LT recipients based on limited evidence

- **How can we change this and turn Transplant into a Cure?**




Rana A, et al, Annals of Surgery 2019

Bera C, et al, 2023



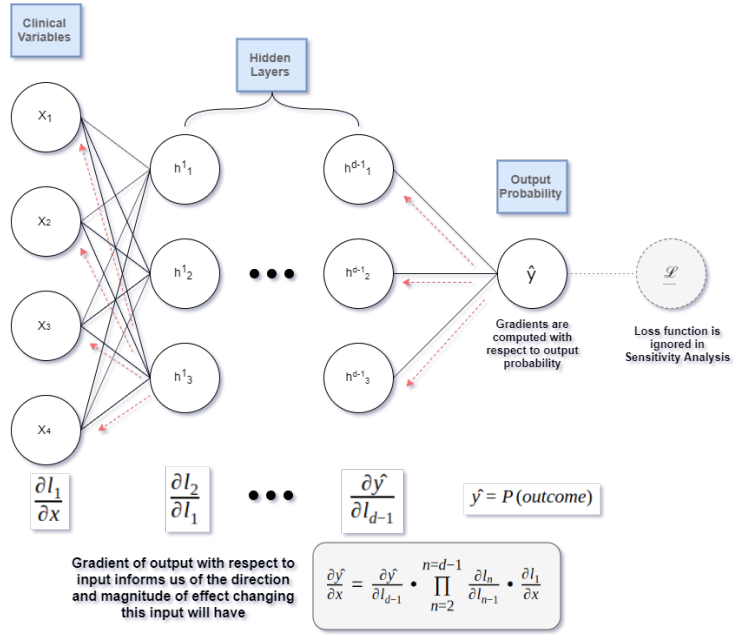
# Predicting mortality due to long-term complications after LT

## Long-term mortality risk stratification of liver transplant recipients: real-time application of deep learning algorithms on longitudinal data

*Osvald Nitski*, Amirhossein Azhie*, Fakhar Ali Qazi-Arisar, Xueqi Wang, Shihao Ma, Leslie Lilly, Kymberly D Watt, Josh Levitsky, Sumeet K Asrani, Douglas S Lee, Barry B Rubin, Mamatha Bhat†, Bo Wang†*

# PREDICTING MORTALITY DUE TO LONG-TERM COMPLICATIONS AFTER LT

- Evaluated various Deep ML algorithms to predict mortality
- Incorporate **longitudinal** data
- Classify patients into **major** risk categories
- Make a more '**personalized**' risk calculator for managing long term transplant care that can be used at each follow up




**Nitski O, Azhie A, Qazi F, Bhat M*, Wang B*, Lancet Digital Health May 2021**

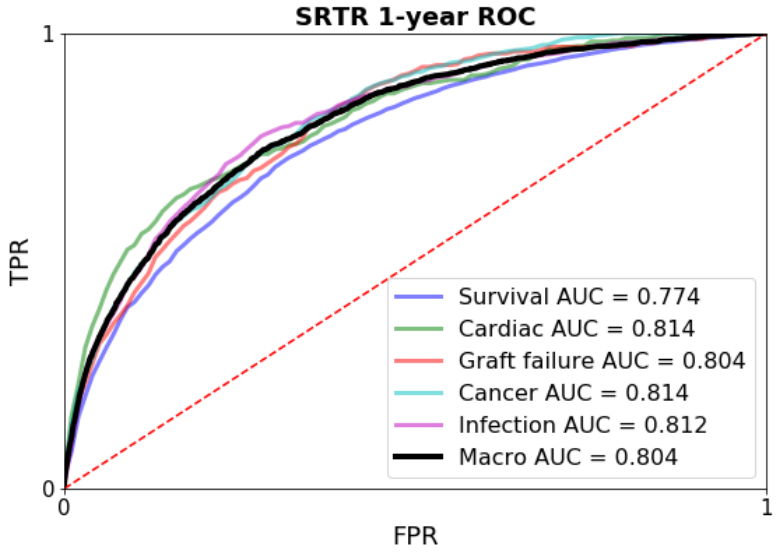
- **65,732** U.S. liver transplant recipients between 2002-2014
- **Annual** follow-ups
- **267** clinical variables used
- **5 outcomes** predicted
  - Survival
  - Death by Graft Failure
  - Death by Infection
  - Death by Cardiac event
  - Death by Cancer
- **1 year** & **5 year** outlooks predicted

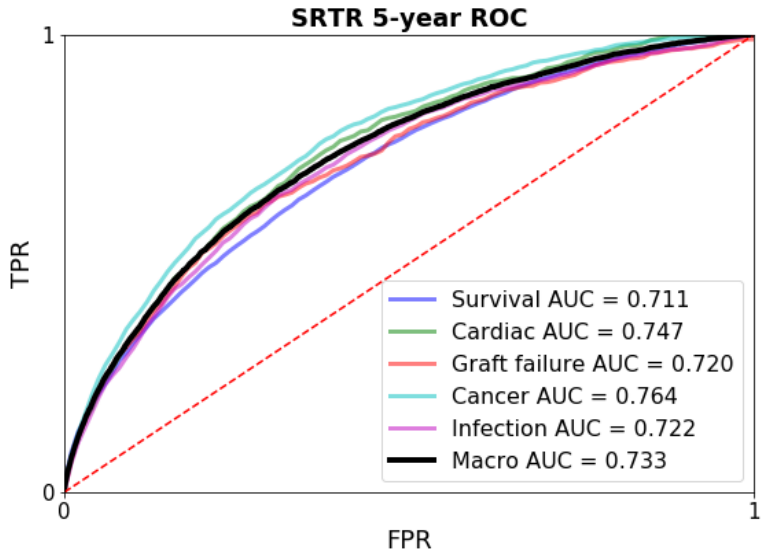

SCIENTIFIC REGISTRY OF TRANSPLANT RECIPIENTS

**Nitski O, Azhie A, Qazi F, Bhat M*, Wang B*, Lancet Digital Health May 2021**

# SRTR Test Set Performance (AUROC)

- Best performing model is Transformer



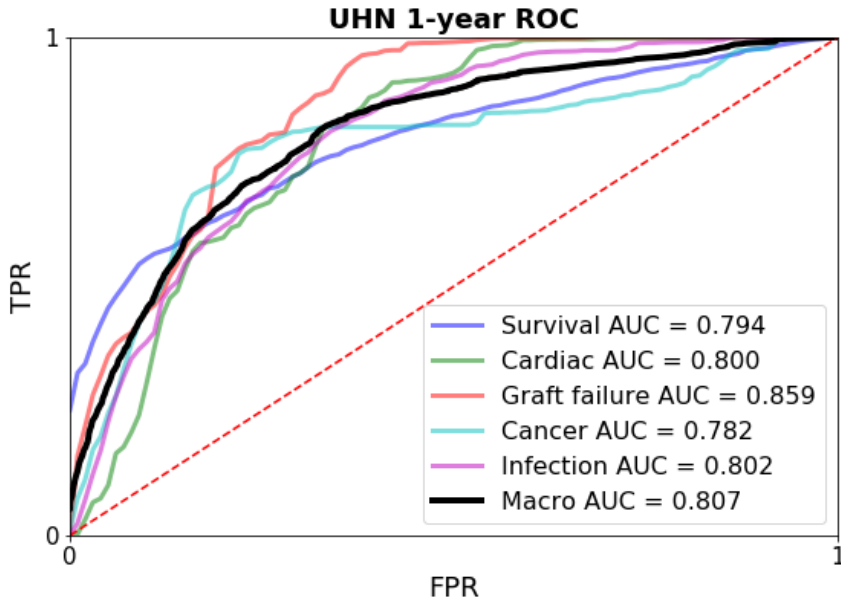



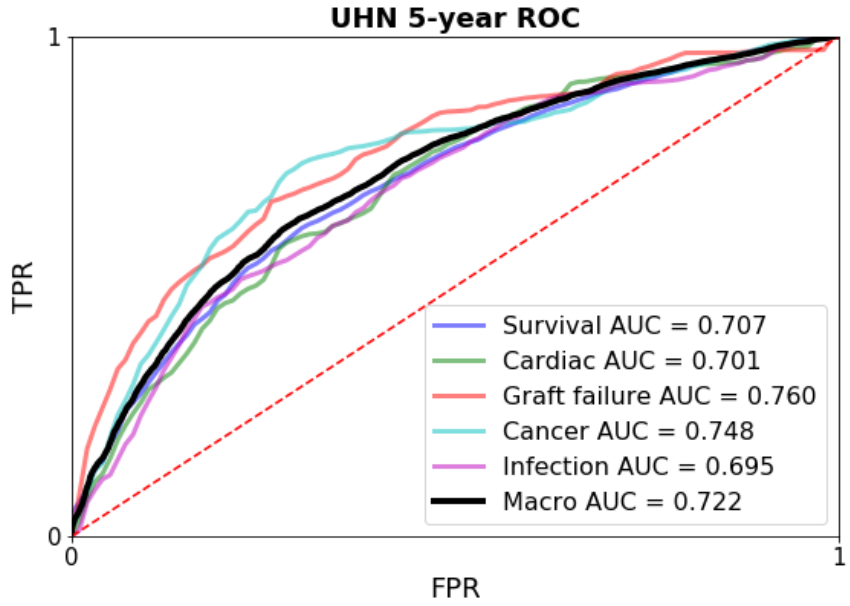

- **Logistic Regression AUC is 0.714 (1 year) and 0.648 (5 year)**



**Nitski O, Azhie A, Qazi F, Bhat M*, Wang B*, Lancet Digital Health May 2021**

# UHN Cross-Validation




**Nitski O, Azhie A, Qazi F, Bhat M*, Wang B*, Lancet Digital Health May 2021**

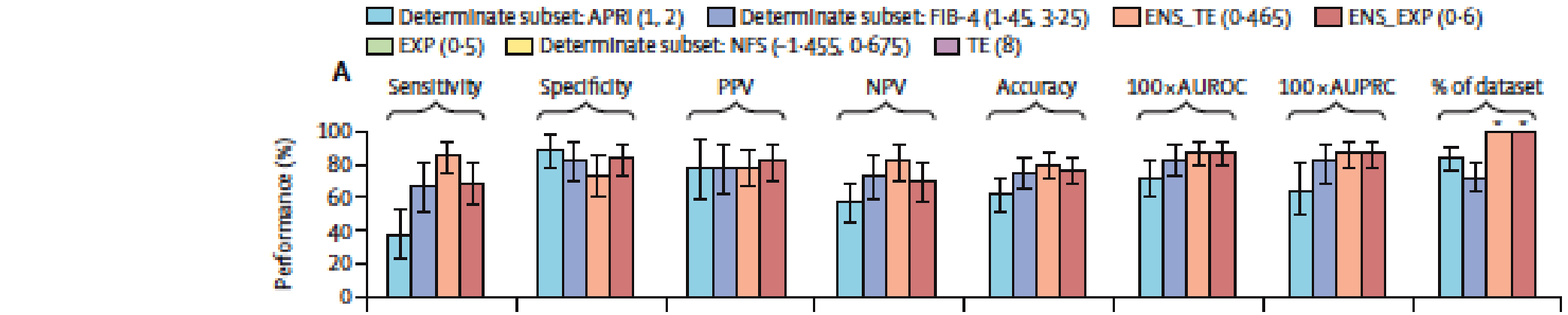
# RANKED FEATURES

| Top 10 in SRTR | Top 10 in UHN |
|---|---|
| Time since transplant | Donor age |
| Donor Age | MELD score |
| Candidate Age | Patient carried over from pediatric to adult LT clinic |
| Recipient Age at Transplant | Sirolimus trough level |
| Number of hospitalizations after LT | Cyclosporine 2 hours post-dose level |
| Candidate last serum Sodium | Hepatocellular carcinoma (primary indication for LT) |
| Serum Total Bilirubin (at follow up) | Recipient age at transplant |
| Serum Alkaline Phosphatase (at follow up) | Graft Failure |
| Number of rejection episodes after LT | Recurrent HCC |
| Serum SGOT (AST) at follow up | Tacrolimus trough level |



**Nitski O, Azhie A, Qazi F, Bhat M*, Wang B*, Lancet Digital Health May 2021**

# EFFECTIVE DETECTION OF ADVANCED FIBROSIS WITH ENSEMBLE ML



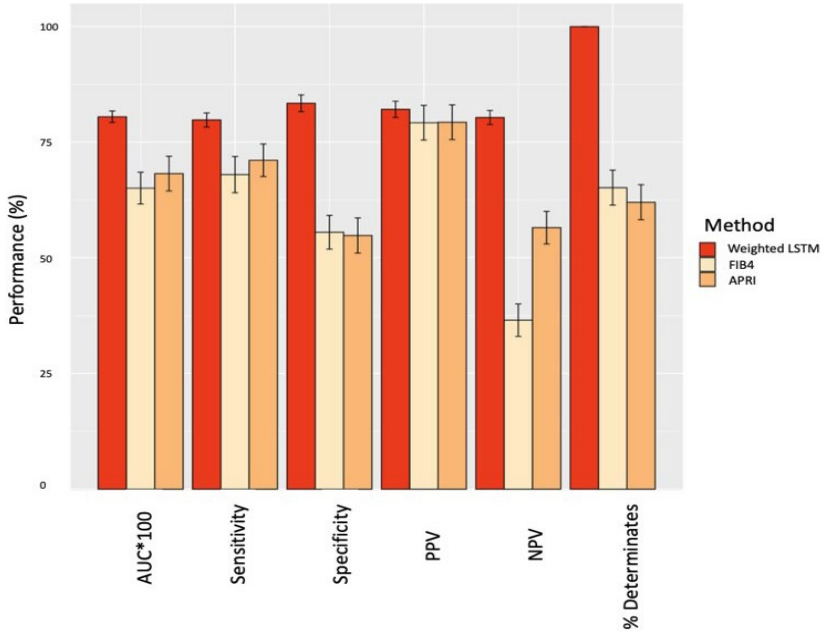

| | Sensitivity | Specificity | PPV | NPV | Accuracy | 100 x AUROC | 100 x AUPRC | % of dataset |
|---|---|---|---|---|---|---|---|---|
| Determinate subset: APRI (1, 2) | 37·8 | 88·1 | 77·3 | 56·9 | 62·1 | 71·9 | 64·3 | 83·7 |
| Determinate subset: FIB-4 (1·45, 3·25) | 66·7 | 82·1 | 77·4 | 72·7 | 74·7 | 82·5 | 82·2 | 72·1 |
| ENS_TE (0·465) | 85·5 | 73·5 | 78·3 | 81·8 | 79·8 | 87·0 | 87·8 | 100·0 |
| ENS_EXP (0·6) | 69·1 | 83·7 | 82·6 | 70·7 | 76·0 | 87·0 | 87·8 | 100·0 |
| APRI vs ENS_TE p value | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 |
| FIB-4 vs ENS_TE p value | <0·0001 | <0·0001 | 0·0003 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 |
| APRI vs ENS_EXP p value | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 |
| FIB-4 vs ENS_EXP p value | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 | <0·0001 |

THE LANCET
Digital Health

Development and validation of an ensemble machine learning framework for detection of all-cause advanced hepatic fibrosis: a retrospective cohort study

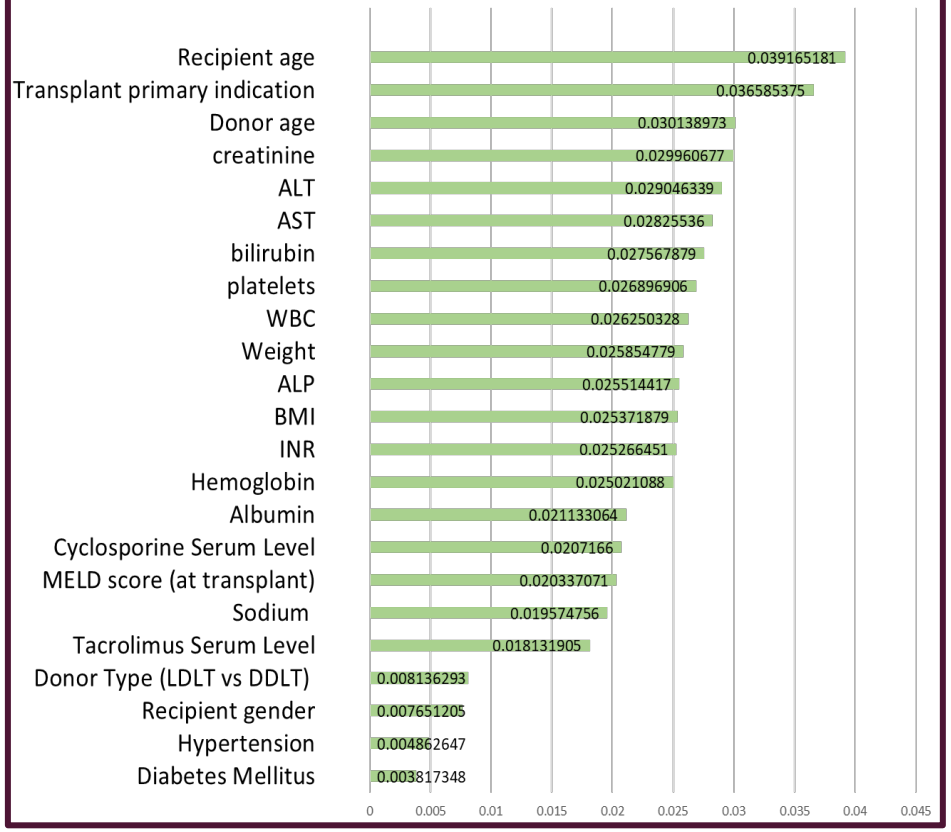
Soren Sabet Sarvestany, Jeffrey C Kwong, Amirhossein Azhie, Victor Dong, Orlando Cerocchi, Ahmed Fuad Ali, Ravikiran S Karnam, Hadi Kuriry, Mohamed Shengir, Elisa Candido, Raquel Duchen, Giada Sebastiani, Keyur Patel, Anna Goldenberg*, Mamatha Bhat*

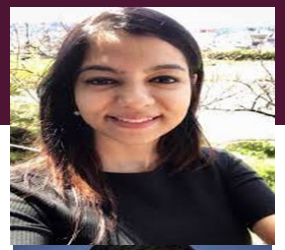
# Deep Learning Framework for Dynamic Diagnosis of Graft Fibrosis after Liver Transplantation using Longitudinal Data




| Parameters | Weighted LSTM | FIB4 | APRI |
|---|---|---|---|
| AUC | 0.798 [0.790, 0.810] | 0.650 [0.636, 0.663] | 0.682 [0.671, 0.694] |
| Sensitivity | 0.788 | 0.68 | 0.711 |
| Specificity | 0.814 | 0.555 | 0.548 |
| Positive predictive value | 0.821 | 0.792 | 0.793 |
| Negative predictive value | 0.803 | 0.365 | 0.565 |
| % Determinates | 100 | 65.17 | 62.01 |

## Top Ranked Features



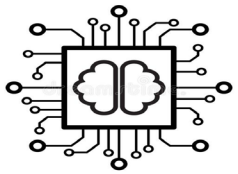



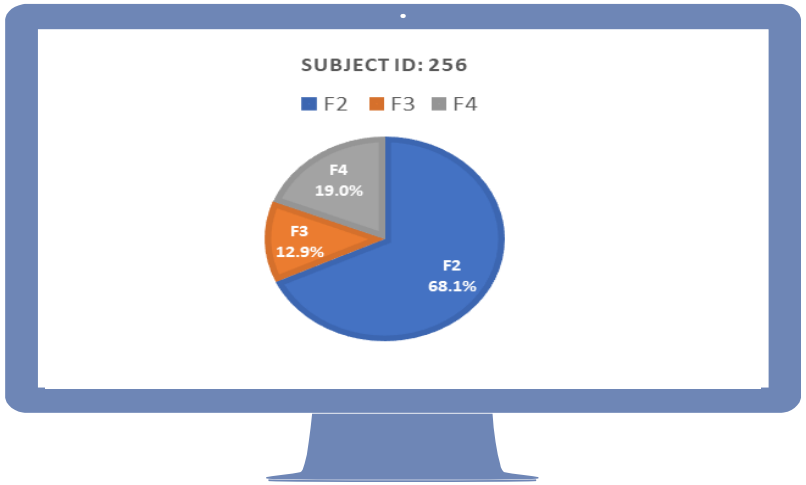
Azhie A*, Sharma D*, Xu W, **Bhat M,** Lancet digital health, 2023

# WHAT WOULD A CLINICIAN SEE?

Input variables for 1 sample patient at 279 days after transplant

| Variables | Subject ID 256 | |
|---|---|---|
| Timepoint | Transplant | Liver biopsy |
| Days after transplant | ----- | 279 |
| Fibrosis stage (biopsy) | ----- | F2 |
| Recipient gender | Female | Female |
| Recipient age | 47.93 | ----- |
| WBC | 2 | 1.2 |
| Platelets | 30 | 43 |
| Creatinine | 20 | 132 |
| INR | 1.36 | 1.44 |
| Albumin | 33 | 31 |
| Sodium | 134 | 142 |
| TACROLIMUS | ----- | 18.2 |
| Cyclosporine | ----- | ----- |
| Sirolimus | ----- | ----- |
| Hemoglobin | 78 | 86 |
| Total bilirubin | 18 | 93 |
| AST | 63 | 44 |
| ALT | 50 | 37 |
| ALP | 22 | 106 |
| MELD | 12 | 12 |
| Donor age | 63 | ----- |
| Transplant primary indication | Hepatitis C | Hepatitis C |
| Donor Type | DDLT | DDLT |
| Weight(kg) | 53.6 | 55.5 |
| BMI | 22.02 | 22.80 |
| Diabetes mellitus (Y/N) | 0 | 0 |
| Hypertension (Y/N) | 0 | 0 |
| Dyslipidemia (Y/N) | 0 | 0 |



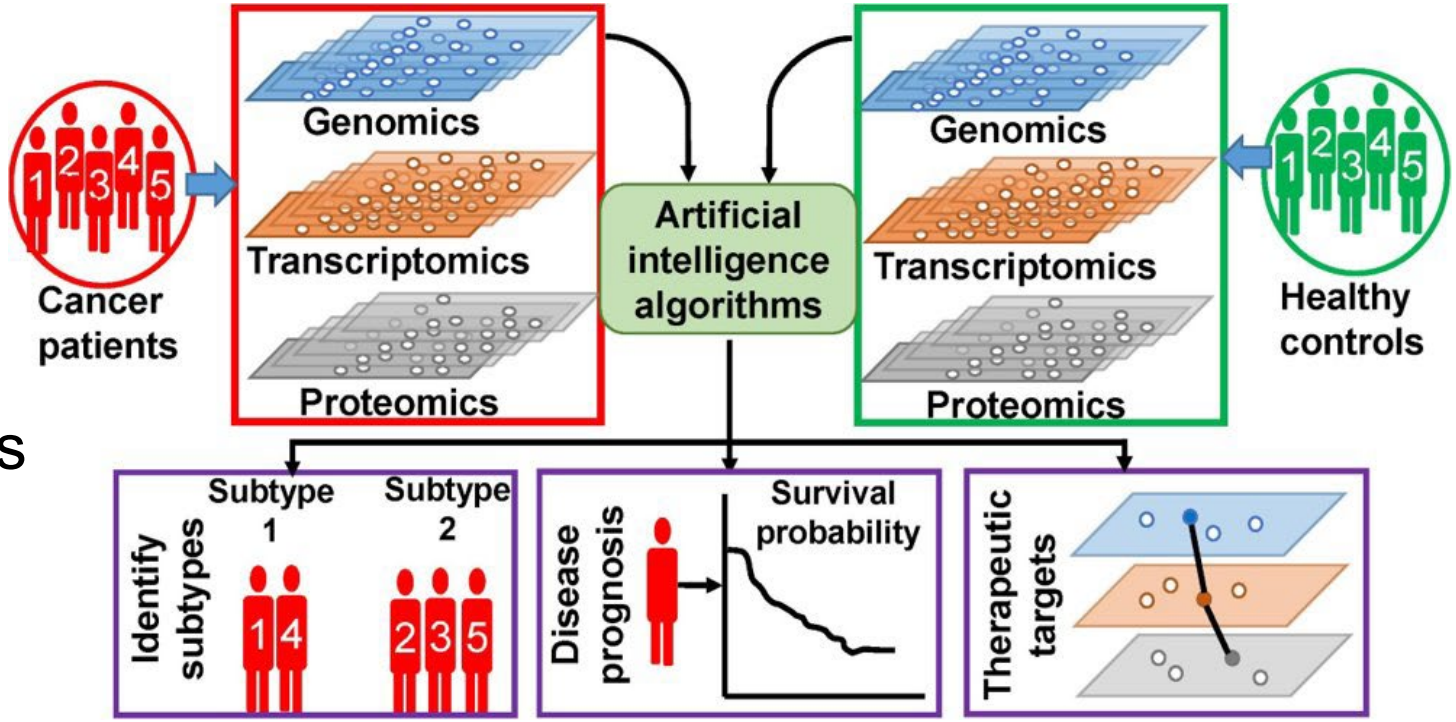



This patient is at high risk of F2 fibrosis at this follow up visit
→ May benefit from more strict management

# HOW ABOUT FINE-TUNING PREDICTIONS WITH MOLECULAR DATA?

# INTEGRATION OF MULTI-OMICS & CLINICAL DATA

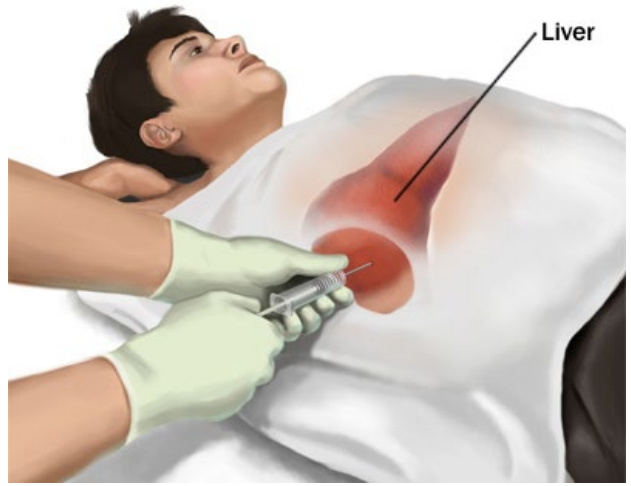
- **Supervised:** for Prognostic prediction
- **Unsupervised:** for Clustering into patient disease subgroups




Nayak et al, Frontiers in Oncology, 2021

# LIVER GRAFT INJURY IN OVER 50%

- 25% of post-LT mortality is due to graft failure
- Over 50% of LT will have increased Liver enzymes
- Rejection, NASH, viral, biliary
- Ultrasound with Doppler followed by
- Liver biopsy as gold standard for diagnosis
- **BUT Invasive (multiple risks)**
- **<u>Often Delayed</u>**



# DIAGNOSTIC PUZZLE

- Physician has a hunch based on patient profile and test patterns
- Example:
- Young LT recipient
- Elevated LEs (100-200 range)
- ALT>AST and elevated ALP  while tapering IS
- Most likely to be Acute rejection

# HOWEVER, PUZZLE MAY FALL APART!

- Biopsy not readily available
- Treatment empirically initiated before biopsy
- Inappropriate therapy may be administered,

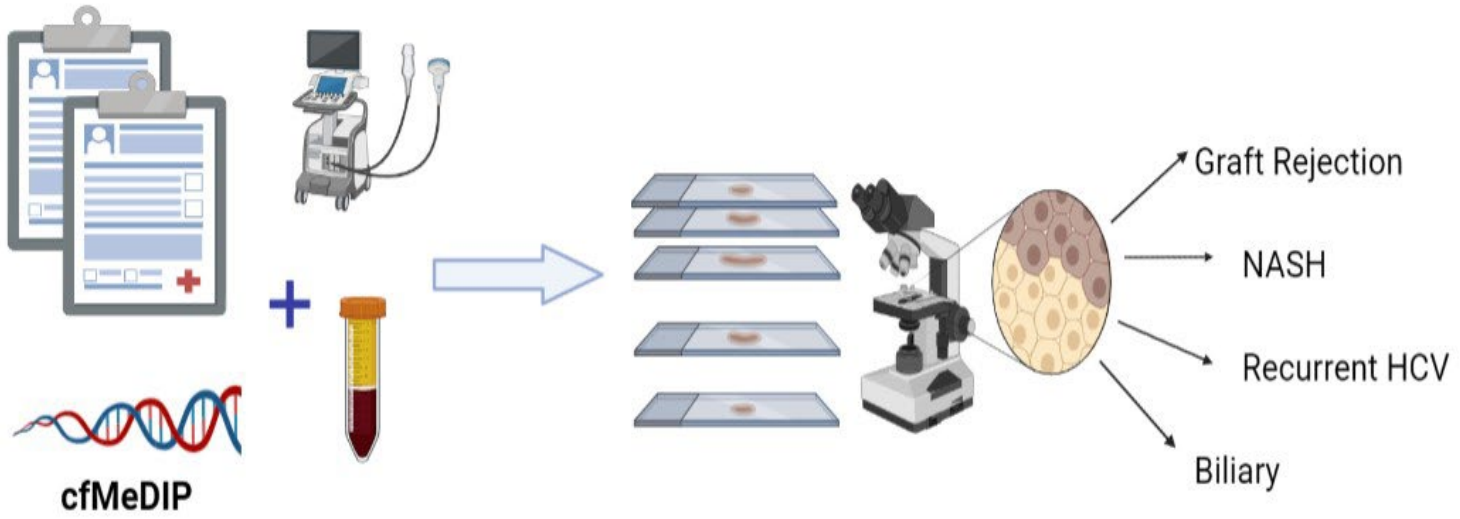
  i.e. steroids when it is a viral infection

  =>Unsafe, risk of adverse outcomes

**ALGORITHMIC DECISION SUPPORT NEEDED!**

# OBJECTIVE:

- **Develop a Machine Learning Algorithm** trained on Clinical, Laboratory, and Radiomic data to identify graft pathology
- Methylation patterns on circulating dd-cfDNA to further refine

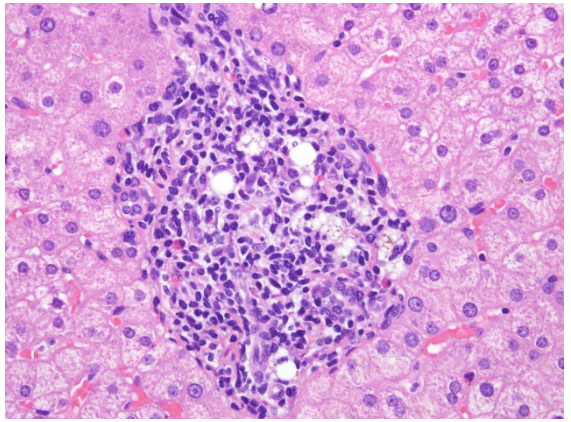


# STUDY POPULATION

- Over 7,000 liver graft biopsies performed at UHN 1987-2020

- **Longitudinal Clinical, Laboratory,** and **Radiomic features on ultrasound** over the week preceding biopsy

- Recipients divided based on histologic diagnosis:
  - Graft rejection
  - NASH
  - Recurrent HCV
  - Biliary complications



# ML RESULTS

| Category | Sensitivity | Specificity | PPV | NPV | AUC |
|---|---|---|---|---|---|
| Acute Cellular Rejection | 0.8139 | 0.7366 | 0.6449 | 0.8707 | 0.7752 |
| Alloimmune hepatitis | 0.8923 | 0.9325 | 0.8021 | 0.9598 | 0.9123 |
| Biliary complications | 0.9024 | 0.9112 | 0.8263 | 0.9153 | 0.9021 |
| Vascular Congestion | 0.8823 | 0.9254 | 0.8155 | 0.9221 | 0.9054 |
| Recurrent HCV | 0.8630 | 0.7427 | 0.7143 | 0.8791 | 0.8028 |
| NASH | 0.8766 | 0.8923 | 0.8119 | 0.9234 | 0.9003 |
| Averaged AUC over all the classes : **0.866** | | | | | |

Performance of ANN in detecting different graft pathologies as well as the overall AUC

Comparison of ANN with other ML algorithms and logistic regression

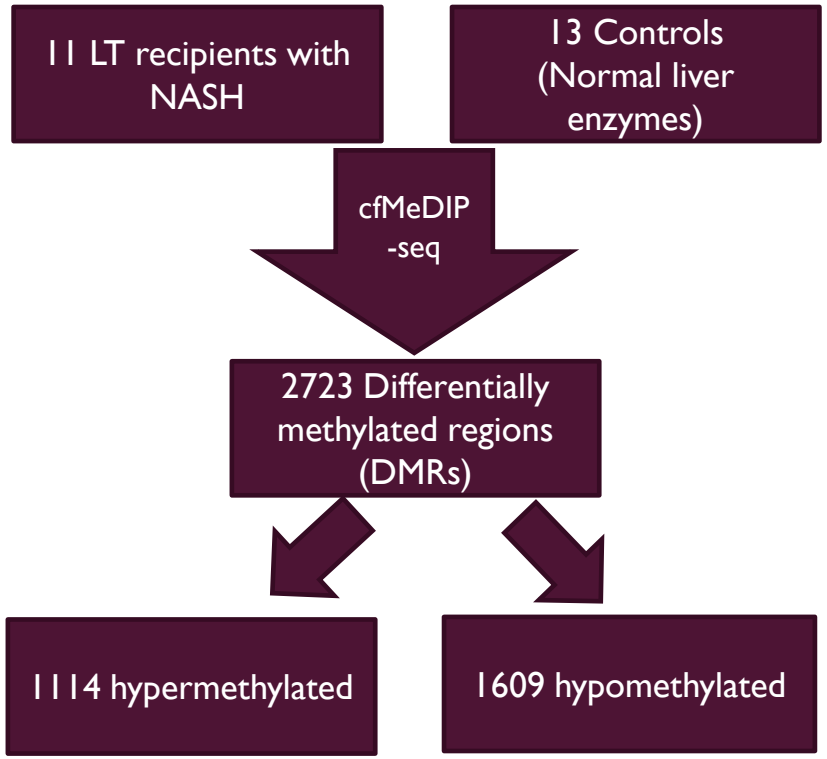
| Methods | Primary diagnosis AUC, [95% CI] |
|---|---|
| Neural Network (ANN- Best performing model) | **0.866 [0.844, 0.891]** |
| Random Forest (RF) | 0.823, [0.812, 0.839] |
| Logistic Regression | 0.767, [0.626, 0.796] |
| Lasso Regression | 0.783, [0.769, 0.802] |
| Ridge Regression | 0.781, [0.771, 0.811] |

# Top Predictive Variables for Graft Pathologies (Using ANN)

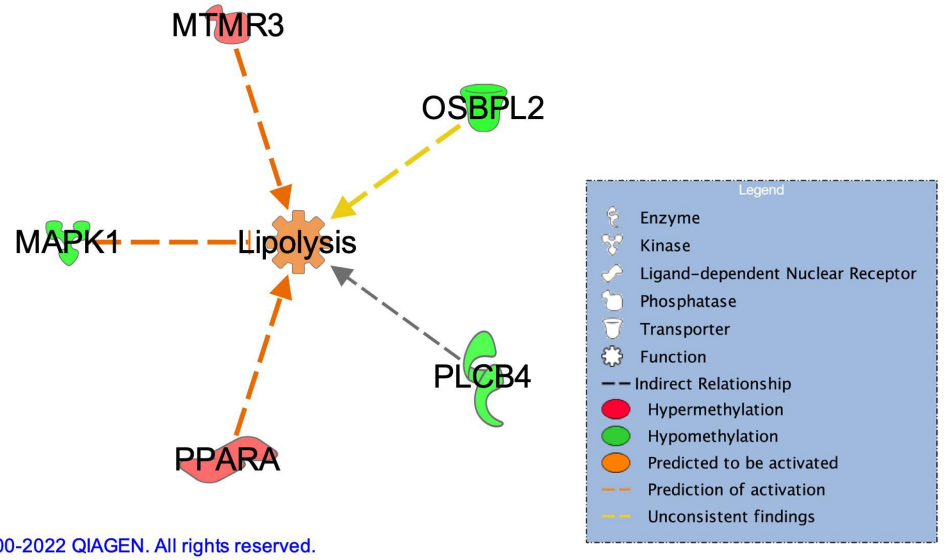
| Top 10 Predictive Variables | Acute cellular Rejection | Alloimmune Hepatitis | Biliary Complications | Congestion | Recurrent HCV | NASH |
|---|---|---|---|---|---|---|
| 1 | **ALT** | **Recipient Age** | **ALP** | **ALP** | **ALP** | **Hgb** |
| 2 | **ALP** | **Cyclosporine serum level** | **Total Bilirubin** | **Platelets** | **Total Bilirubin** | **ALP** |
| 3 | **Hgb** | **AST** | **Recipient Age** | **Total Bilirubin** | **Hgb** | **Recipient Age** |
| 4 | **WBC** | **Hgb** | **ALT** | **Recipient Age** | **WBC** | **ALT** |
| 5 | **Recipient Age** | **Platelets** | **WBC** | **ALT** | **Recipient Age** | **Creatinine** |
| 6 | Total Bilirubin | Donor age | Hgb | Cyclosporine Serum level | ALT | AST |
| 7 | Creatinine | Total Bilirubin | AST | AST | Creatinine | Platelets |
| 8 | AST | Tacrolimus Serum level | Platelets | Donor Age | Albumin | Cyclosporine Serum level |
| 9 | Albumin | WBC | Creatinine | WBC | AST | Albumin |

# CFMEDIP-SEQ: DNA METHYLATION PATTERNS ON CIRCULATING DNA

- ddcfDNA tells us there is graft injury, but **not the cause**
- Methylation patterns on cfDNA could help




Lipid metabolism with lipolysis function particularly upregulated in LT recipients with NASH versus Controls

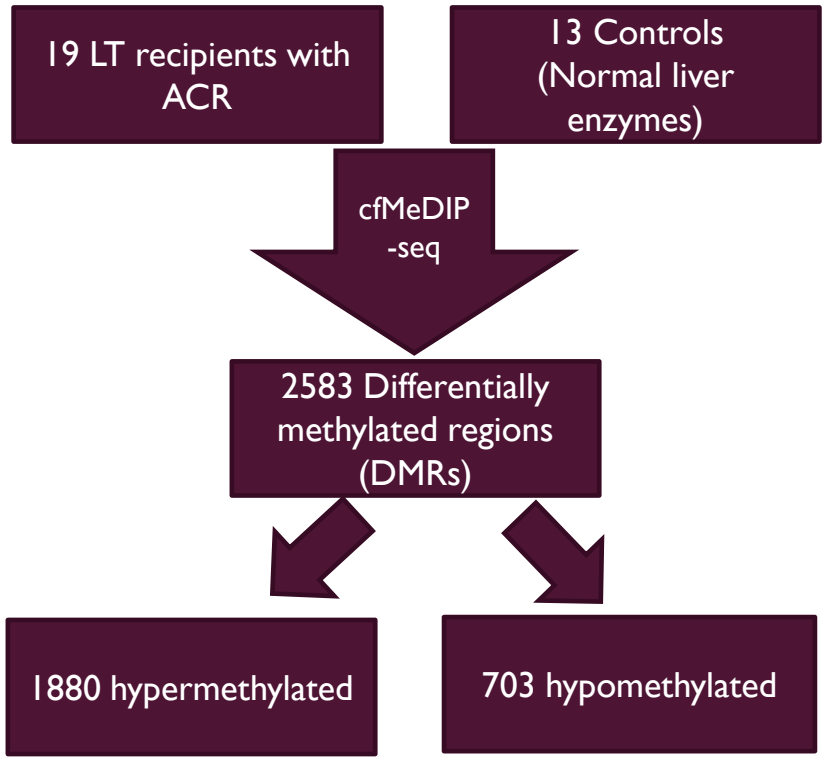




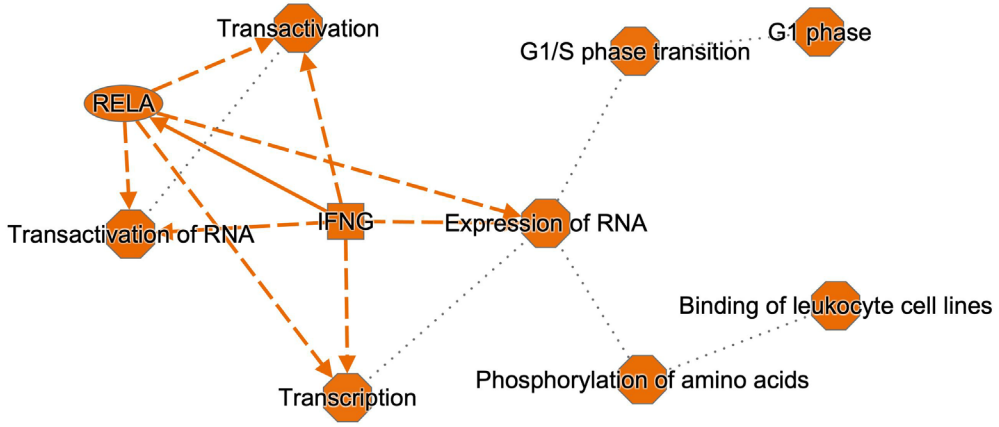

cfMeDIP-seq assay: Shen R, D. De Carvalho, Nature 2018

# METHYLATION PATTERNS SPECIFIC FOR REJECTION

- Methylation patterns on cfDNA could distinguish ACR patients from Controls



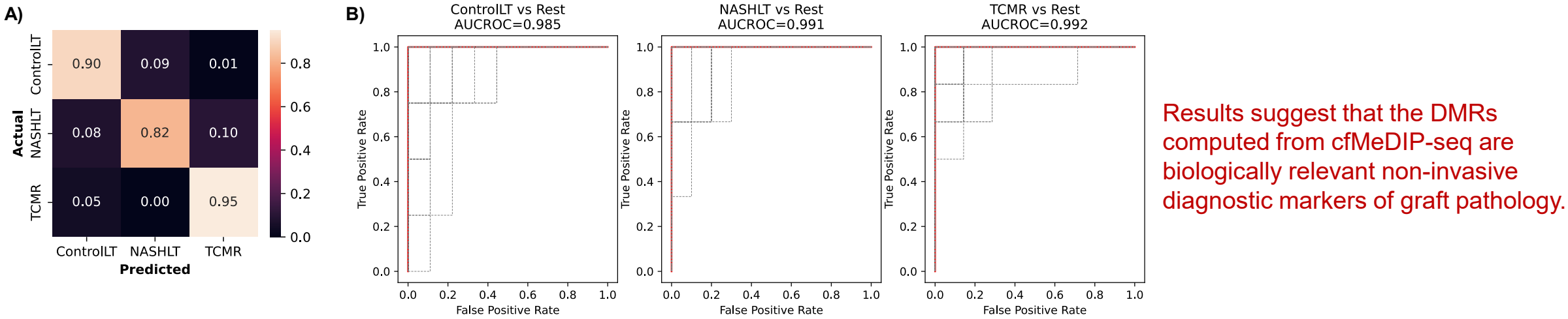

- Platelet derived graft factors (PDGFs) pathway is activated in LT recipients with ACR versus Controls
- ACR triggers activation of several processes:



# INTEGRATIVE ML TOOL TO CLASSIFY LIVER PATHOLOGY: COMBINED CLINICAL VARIABLES + CFMEDIP-SEQ

| | |
|---|---|
| Model | Multiclass Logistic Regression with L2 regularization<br>Models were trained with class weights to deal with class imbalances |
| Features | Methylation enrichment levels of top 1000 differentially methylated regions (DMRs)<br>+ Clinical and Laboratory Variables |
| Samples | 43 patients; NASH-LT (n=11), Acute Rejection (n=19), Control LTRs (n=13) |

**Results from 101 stratified bootstrapped models, each with a different 70-30 train-test split**

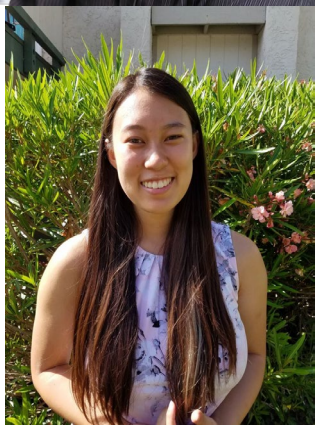



Results suggest that the DMRs computed from cfMeDIP-seq are biologically relevant non-invasive diagnostic markers of graft pathology.

- Models achieved relatively good classification for Control LT and Acute Rejection (with **94% and 98% TPR** (recall/sensitivity) respectively

# STEPS TOWARDS CLINICAL DEPLOYMENT!

# DASHBOARD EXAMPLES



DATA | PREDICTIONS

## Emily Johnson

| | | | | | |
|---|---|---|---|---|---|
| **Age:** | 54 | **DOB:** | 01-Jun-1969 | **Status:** | Outpatient |
| **Transplants:** | LIV: DD: 17-NOV-2017 | **Duct:** | Duct-to-duct | **Dx:** | Primary biliary cholangitis |
| **Primary care:** | Mamatha Bhat | **Primary coord:** | G. Yarranton | **Phone:** | H: (123) 456-3213 W: (314) 159-2223 |
| **Allergies:** | 0 | **Alerts:** | OHIP | **TGLN ID:** | 8222575 |

Filter by Date | Display Columns | Search

| Date | Weight | MELD | Hemoglobin (Hgb) | White Blood Cell (WBC) | Platelets (PLT) | International Normalized Ratio (INR) | P |
|---|---|---|---|---|---|---|---|
| 2022-05-01 | 77.7 | | | | | | |
| 2022-03-21 | | 9 | 134 | 3.2 | 151 | 0.9 | |
| 2022-02-08 | | 8 | 135 | 4.4 | 164 | 0.8 | |
| 2022-01-09 | | 11 | 119 | 3.5 | 143 | 0.9 | |
| 2021-11-12 | | 7 | 128 | 3.1 | 143 | 0.9 | |
| 2021-11-02 | 70.5 | | | | | | |
| 2021-10-28 | | 6 | 129 | 3.9 | 144 | 0.9 | 28 |
| 2021-10-14 | | 7 | 132 | 3.5 | 165 | 0.9 | |


DATA
PREDICTIONS
Predictions After 1 Year
40%
60%
39%
2%
0%
19%
Survival
Mortality
Cancer
Cardiac Events
Graft Failure
Infection
Mortality
Predictions After 5 Years
24%
76%
58%
2%
1%
15%
Survival
Mortality
EDIT DATA
LOAD
SAVE
Feature importance for:
Survival
1 Year
Outcome probability: 40 Baseline: 86
Increasing Probability
Bilirubin 16%
Cholesterol 16%
HCO3 15%
Decreasing Probability
Sirolimus -16%
Tacrolimus -15%
K -15%

Data | Results

| Imp. rank | Patient Data | Value | Add |
|---|---|---|---|
| 1 | Donor age | 54 | + |
| 2 | MELD score | 21 pts | + |
| 3 | Patient transferred from paediatri... | Yes | + |
| 4 | Sirolimus trough level | 2 ng/mL | + |
| 5 | Ciclosporin 2-h post-dose level | 712.7 n... | + |
| 6 | Hepatocellular carcinoma as a pri... | No | + |
| 7 | Recipient age at transplantation | 24 | + |
| 8 | Graft failure | No | + |
| 9 | Recurrent hepatocellular carcinoma | No | + |
| 10 | Tacrolimus trough level | 4 ng/mL | + |
| 11 | HCV-induced cirrhosis as a prima... | No | + |
| 12 | Primary sclerosing cholangitis as ... | Yes | + |
| 13 | Donor type | Living | + |
| 14 | MELD-Na score | 20 pts | + |
| 15 | Time since liver transplantation | 3 mo. | + |
| 16 | Diabetes (at follow-up) | No | + |
| 17 | NASH cirrhosis as a primary indicat... | No | + |

## Interventions

Reset All | Run

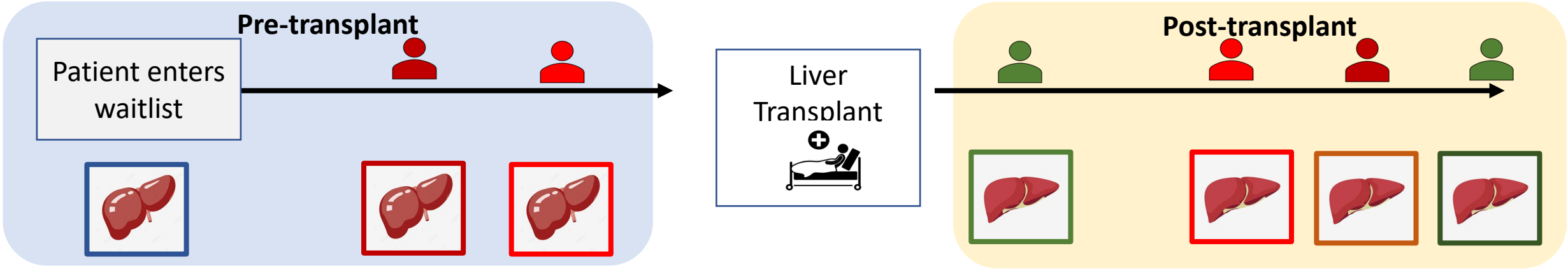
# DYNACOMP DEPLOYMENT GOALS

- Integrate DynaCOMP into LT clinic to Optimize Patient Outcomes
- **SHAPley values** to obtain modifiable ranked features
- Evaluate impact by **patient outcomes** and number of relevant referrals made by physicians supported by AI tool
- Evaluate **patient comfort** with AI-guided care in clinic
- Conduct **qualitative interviews** of physicians and refine dashboards to prepare for deployment beyond UHN

# CURRENT STATE

- **Endorsement from UHN Ajmera Center: Transplant AI Initiative**
- QA/QI approval for deployment of ML model
- AI-LTP front end fully designed and validated with clinicians
  - ML models were validated by UHN DATA ML Engineers
- Direct access to Epic (new) and OTTR (historic) data established
- National efforts through CDTRP

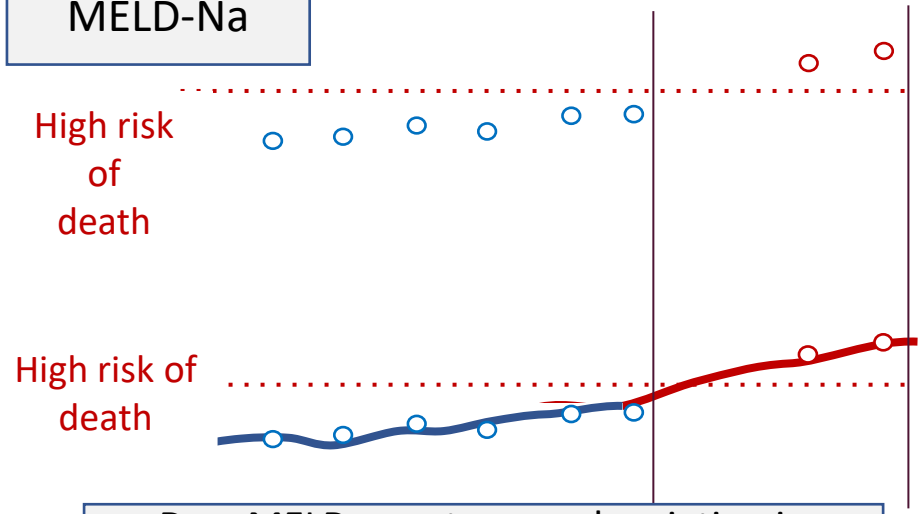
# Vision for the Future of AI in Liver Transplantation



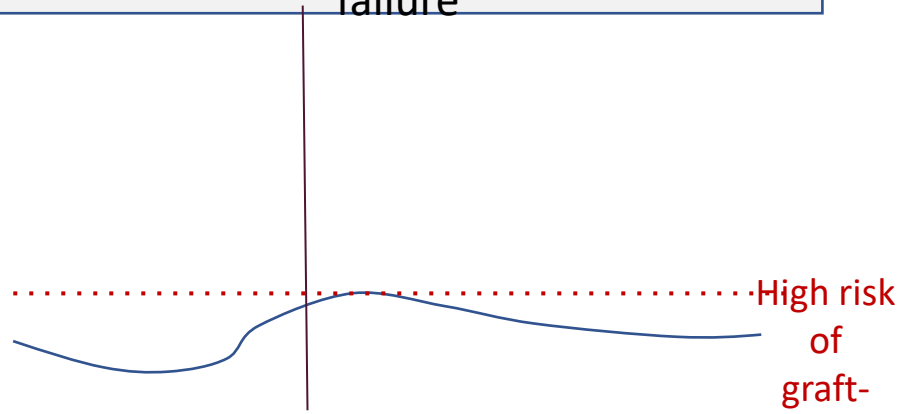

Rapid decline in liver status

Increased risk of death due to infection, cardiovascular disease, cancer & graft failure

MELD-Na




DynaMELD uses temporal variation in biomarkers to *accurately forecast* the onset of future liver status decline




Modifications in care to decrease risk

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