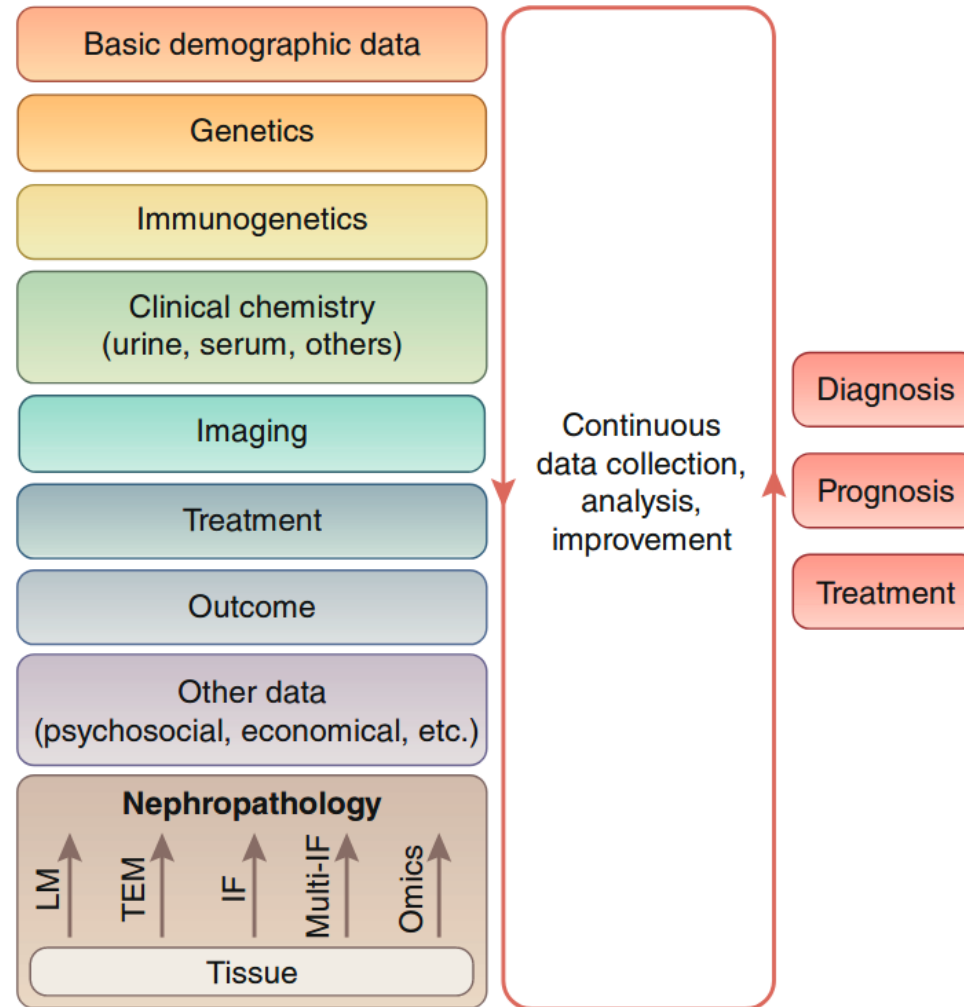


# Prognostication and Theranostics in Nephrology on Multimodal Datasets

Jan U. Becker  
Cologne, Germany

# Nephropathology big data und precision medicine

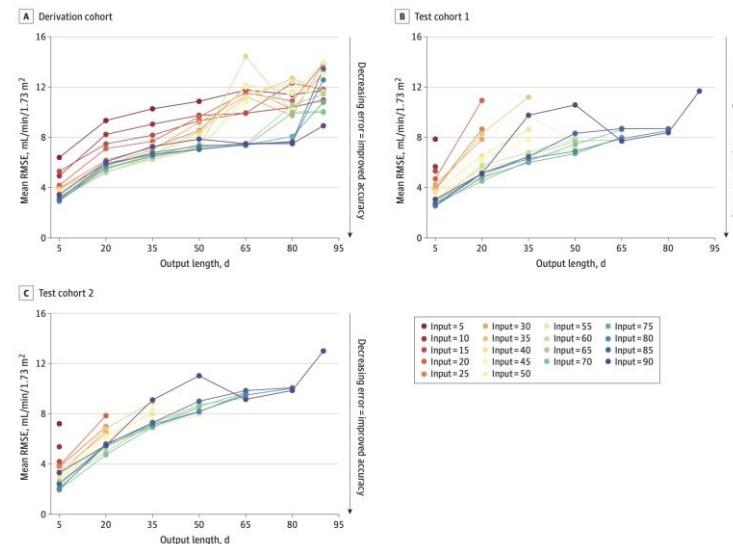


# Prognostic ML in Transplant Nephrology

- Renal transplant study
- First three months
- Training set: 100,867 values
- 2 test sets: 39,999
- Input: Sequence of eGFR
- Output: future eGFR
- Architecture: Sequence-to-Sequence Deep Learning vs. Autoregressive integrated moving average (ARIMA)

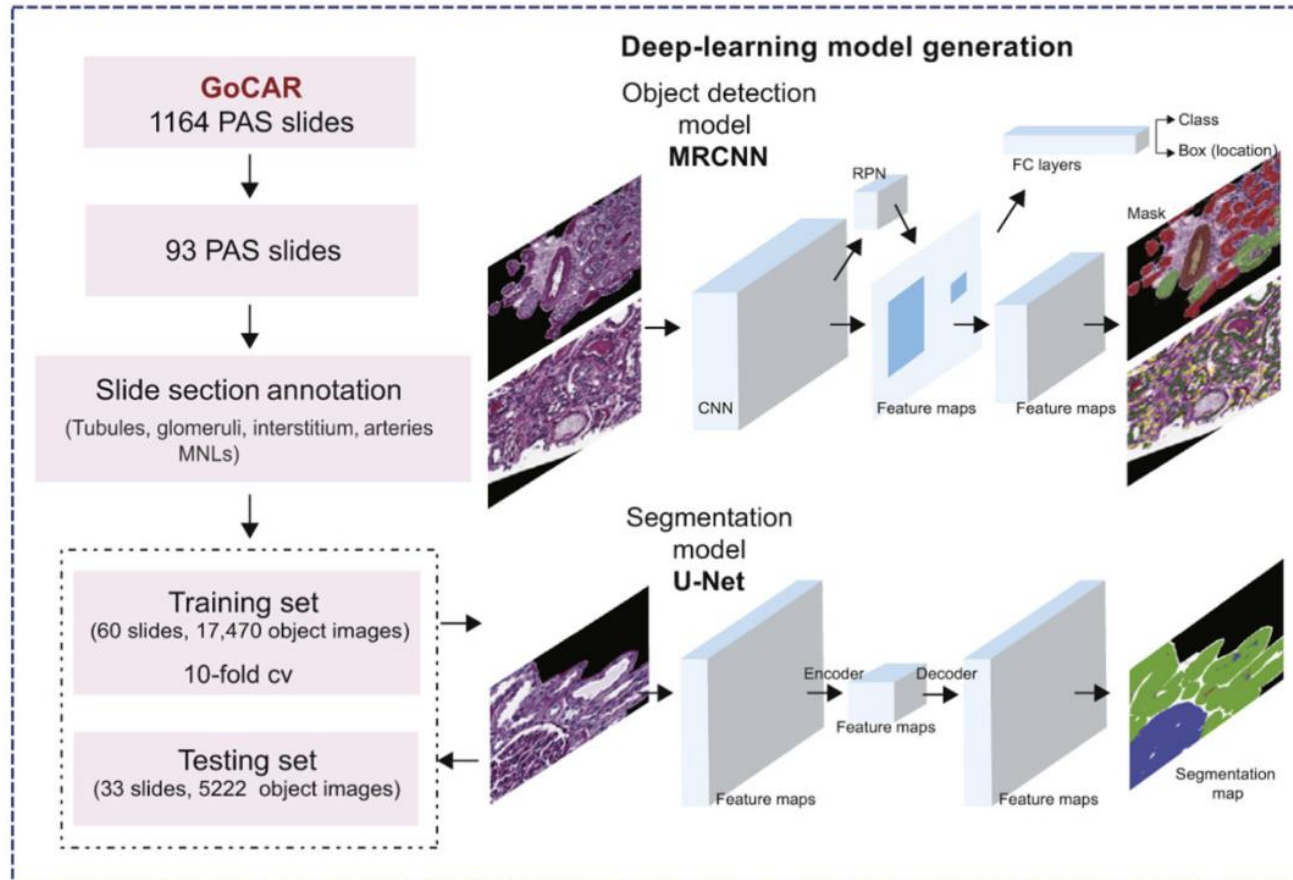
Table 2. Performance of ARIMA and Sequence-to-Sequence Models in the Derivation Cohort<sup>a</sup>

| Sequence       | RMSE (mL/min/1.73 m <sup>2</sup> ) |                      |
|----------------|------------------------------------|----------------------|
|                | Derivation cohort                  |                      |
|                | ARIMA                              | Sequence-to-sequence |
| IN: 5/OUT: 5   | 11.38                              | 6.40                 |
| IN: 5/OUT: 15  | 9.25                               | 6.92                 |
| IN: 30/OUT: 30 | 7.62                               | 6.59                 |
| IN: 45/OUT: 45 | 7.48                               | 6.94                 |
| IN: 90/OUT: 90 | 10.20                              | 8.90                 |

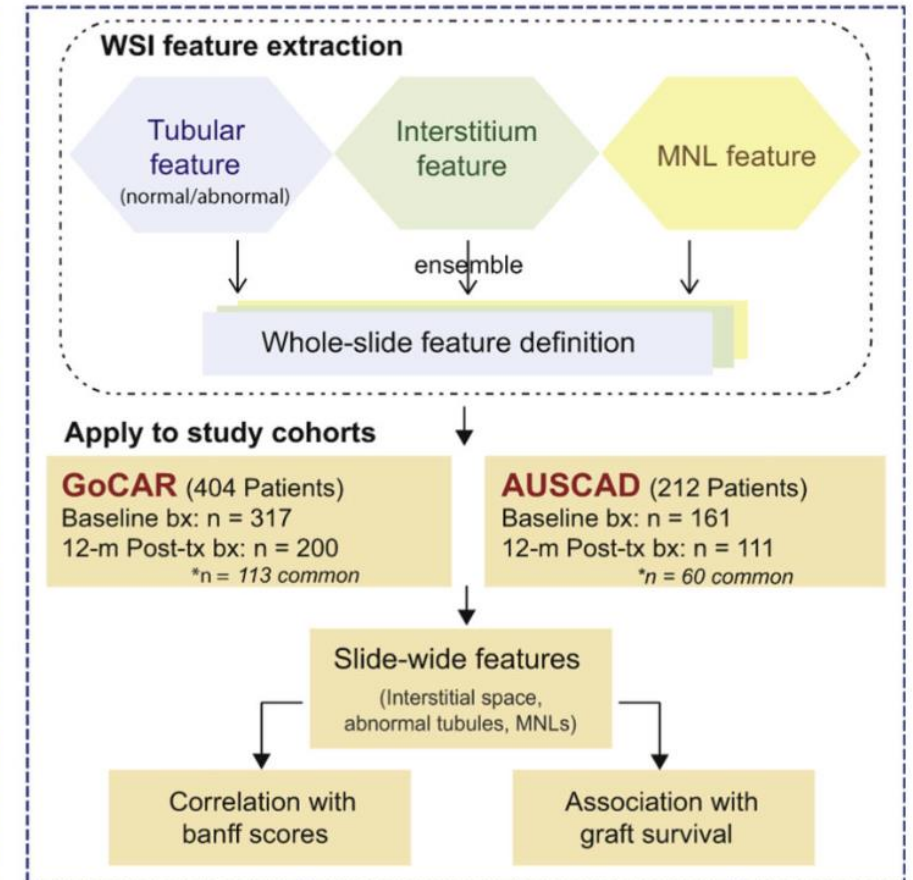


# Prognostic ML in Transplant Nephropathology

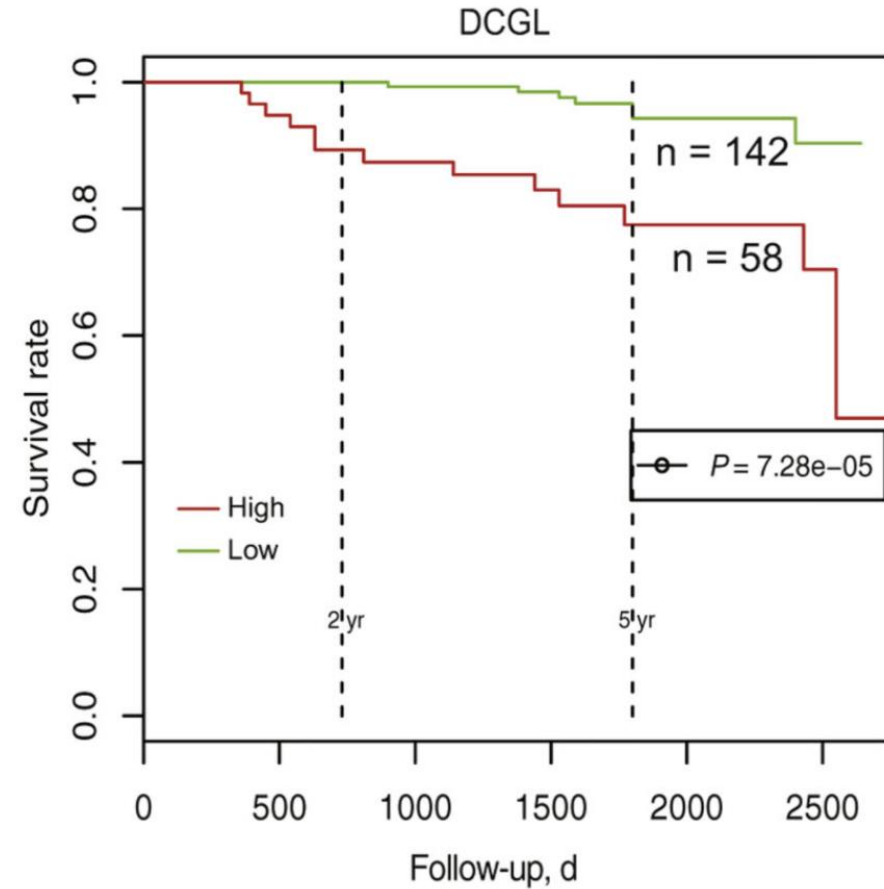
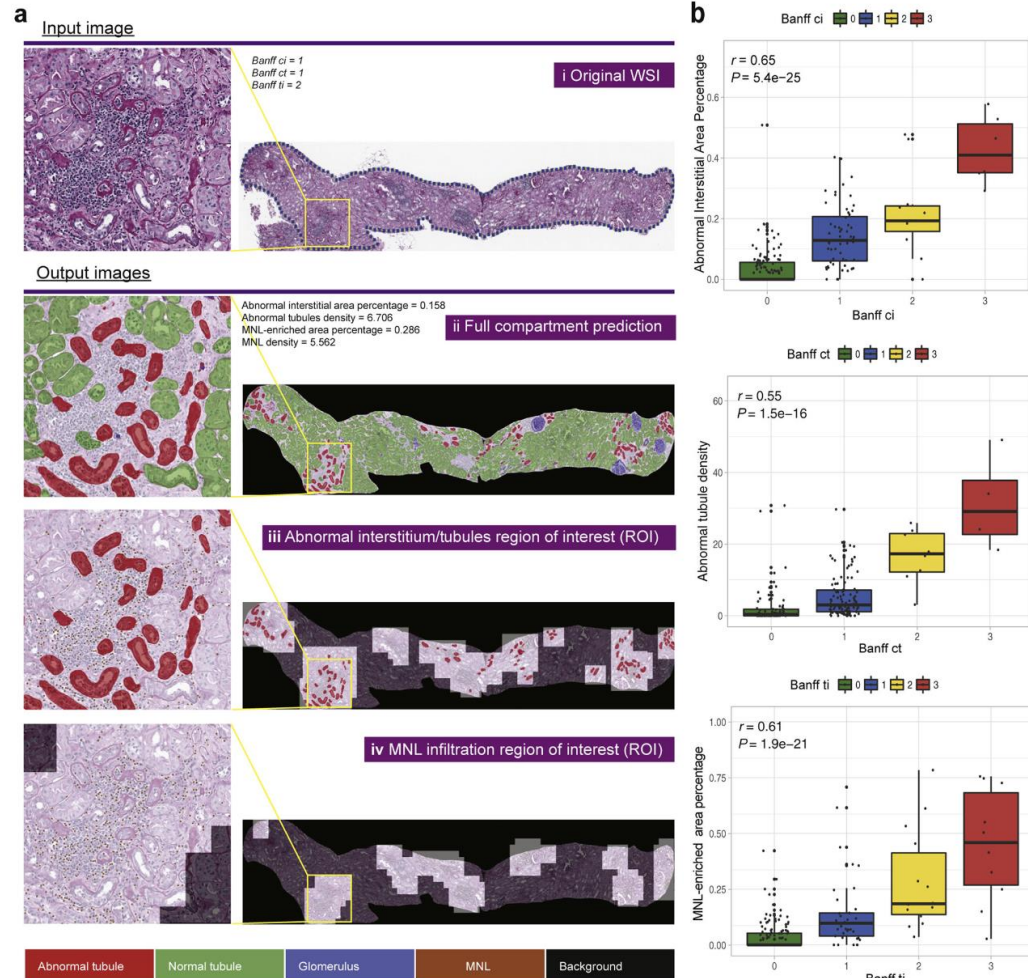
## Tissue compartment recognition (stage I)



## WSI clinical investigation (stage II)

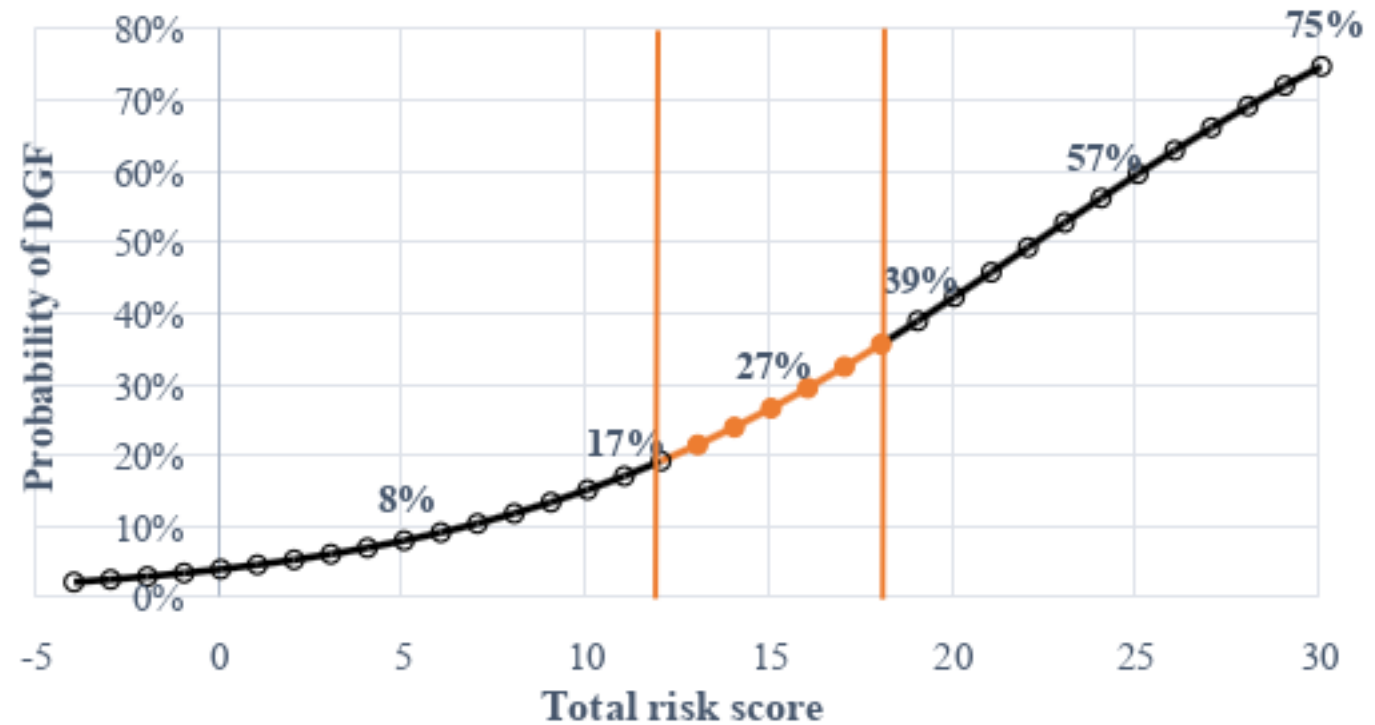


# Prognostic ML in Transplant Nephropathology



# 2-Step-Score for the Prognostication of Delayed Graft Function

| Risk factor  | Addition to risk score |              |  |            |                 |       | Risk score |
|--|------------------------|--------------|--|------------|-----------------|-------|------------|
| <i>Donor BMI<br/>(kg/m<sup>2</sup>)</i>            | < 18.5                 | 18.5 to < 25 |  | 25 to < 30 |                 | >= 30 |            |
|  | -2                     | 0            |  | +3         |                 | +6    |            |
| <i>Recipient BMI<br/>(kg/m<sup>2</sup>)</i>        | < 18.5                 | 18.5 to < 25 |  | 25 to < 30 |                 | >= 30 |            |
|  | -2                     | 0            |  | +2         |                 | +3    |            |
| <i>Recipient CVM IgG</i>                           | Negative               |              |  | Positive   |                 |       |            |
|  | 0                      |              |  | +5         |                 |       |            |
| <i>Number of HLA-DR mismatches</i>                 | Less than two          |              |  | Two        |                 |       |            |
|  | 0                      |              |  | +6         |                 |       |            |
| <i>Dialysis vintage in years</i>                   | < 1                    | 1 to < 3     | 3 to < 4                                     |            | 4 to < 6        | >= 6  |            |
|  | 0                      | +1           | +2   |            | +3              | +5    |            |
| <i>Cold ischaemia time in hours</i>                | < 2                    | 2 to <6      | 6 to <10                                     | 10 to < 14 | 14 to < 18      | >= 18 |            |
|  | 0                      | +1           | +2   | +3         | +4              | +5    |            |
| <b>Total score without histological assessment</b> | - 4 to 11 points       |              | 12 to 18 points<br>(18% to 36% risk)         |            | 19 to 30 points |       |            |
|  | Low risk               |              | Medium risk: histological assessment advised |            | Increased risk  |       |            |
| <i>Number of glomeruli</i>                         | < 20                   |              | 20 to < 30                                   |            | 30 to < 40      | >= 40 |            |
|  | 0                      |              | -2   |            | -4              | -7    |            |
| <i>Banff cv</i>                                    | cv0, cv1 or cv2        |              |  | cv3        |                 |       |            |
|  | 0                      |              |  | +5         |                 |       |            |
|  | <b>Total score =</b>   |              |  |            |                 |       |            |

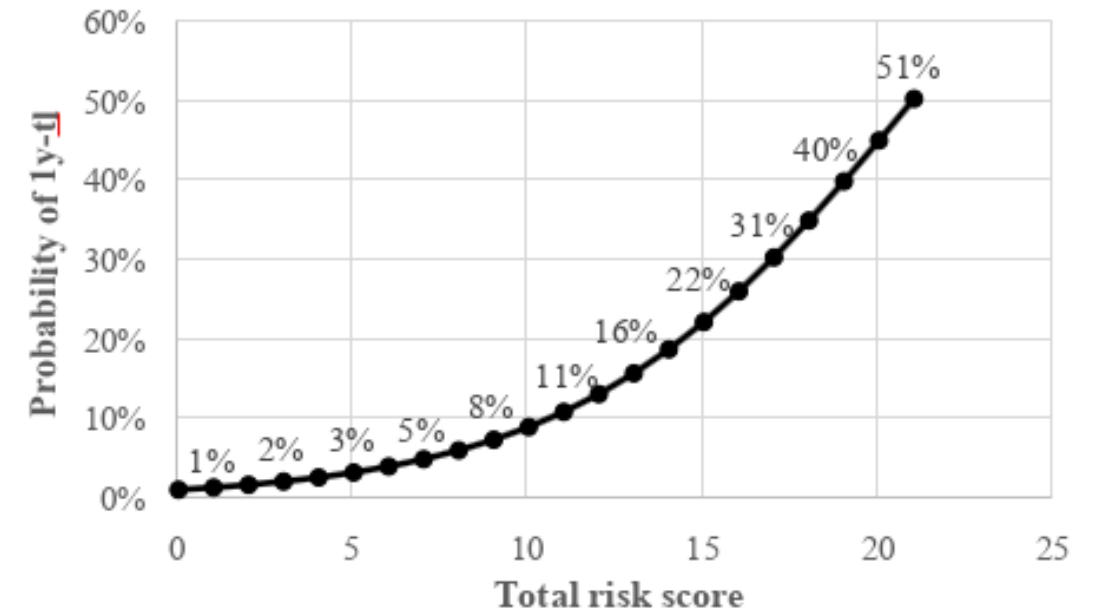


Ernst, NCT, in press

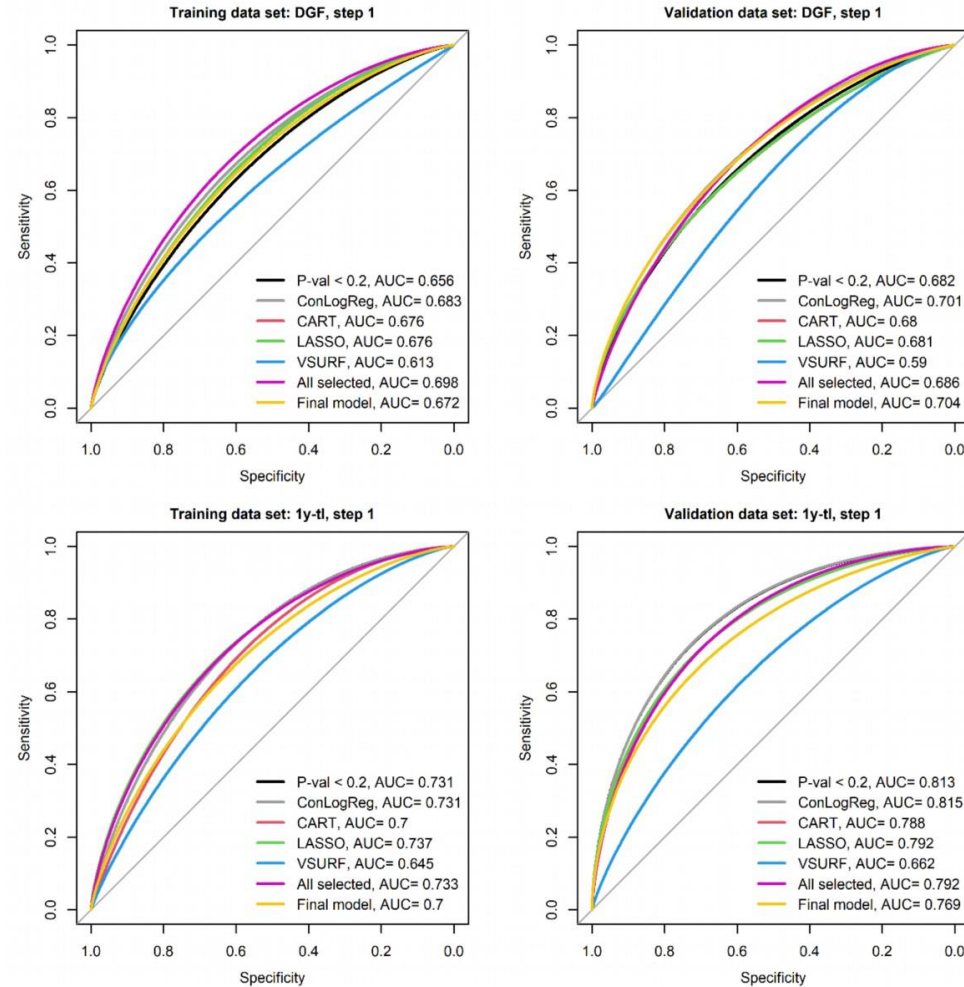


# 2-Step-Score for the Prediction of 1-Year Transplant Survival

| Risk factor  | Addition to risk score |            |            |            |  |            | Risk score |  |
|--|------------------------|------------|------------|------------|--|------------|------------|--|
| <i>Donor age in years</i>                          | < 30                   | 30 to < 40 | 40 to < 50 | 50 to < 60 |  | >= 60      |            |  |
|  | 0                      | +1         | +3         | +4         |  | +6         |            |  |
| <i>Sum of HLA-A, -B and -DR mismatches</i>         | 0                      | 1          | 2          | 3          |  | 4 or 5     | 6          |  |
|  | 0                      | +1         | +2         | +3         |  | +4         | +5         |  |
| <i>Cold ischaemia time in hours</i>                | < 2                    | 2 to <6    | 6 to <10   | 10 to < 14 |  | 14 to < 18 | >= 18      |  |
|  | 0                      | +1         | +2         | +3         |  | +4         | +5         |  |
| <b>Total score without histological assessment</b> |                        |            |            |            |  |            |            |  |
| <i>Banff ct</i>                                    | ct0 or ct1             |            |            | ct2 or ct3 |  |            |            |  |
|  | 0                      |            |            | +6         |  |            |            |  |
|  | <b>Total score =</b>   |            |            |            |  |            |            |  |
|  |                        |            |            |            |  |            |            |  |



# LogReg superior to ML in 2-Step-Score Development

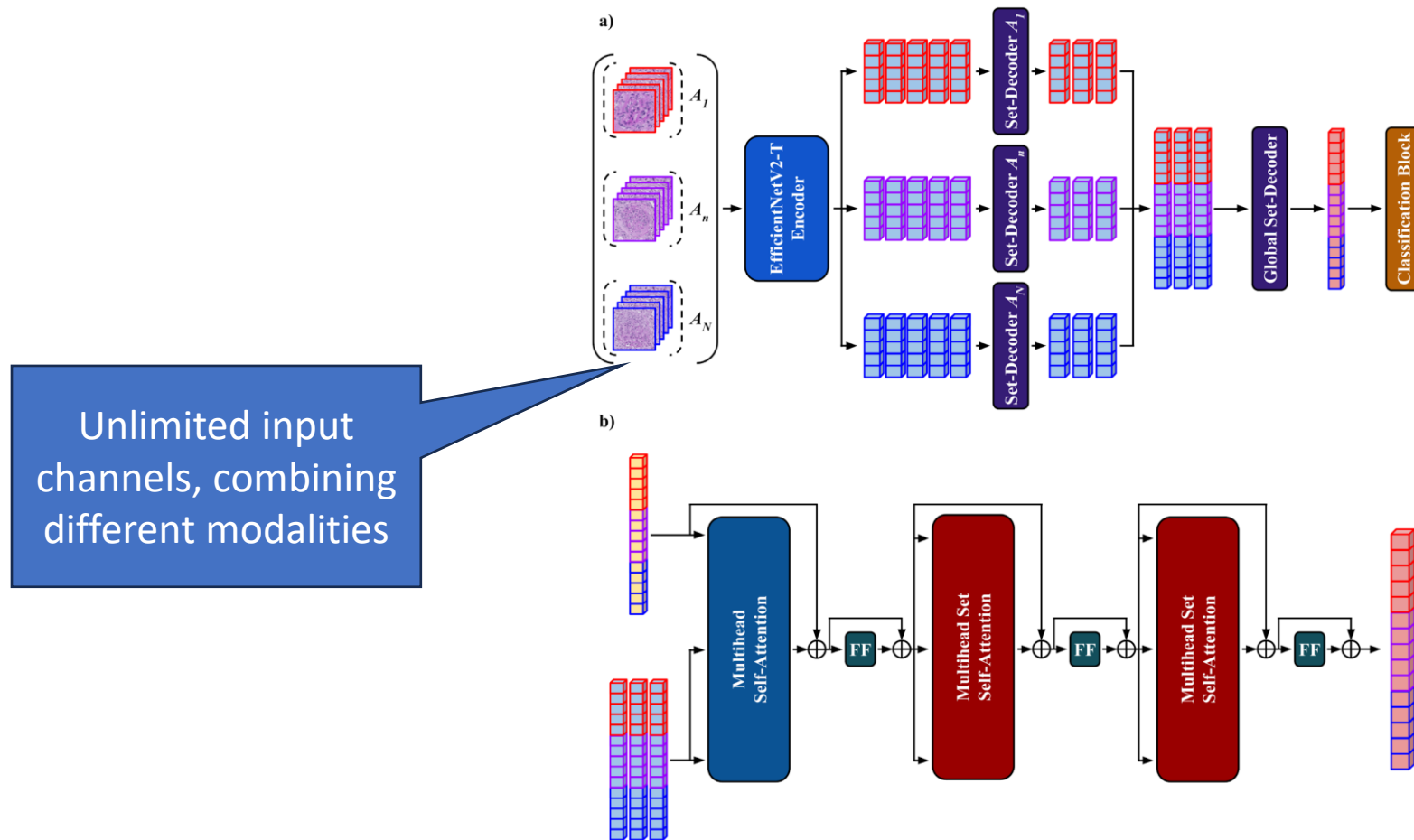




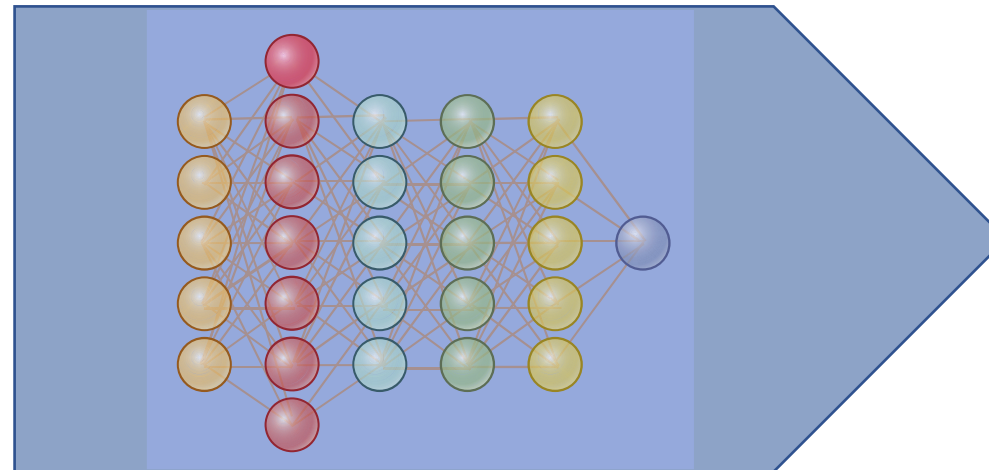
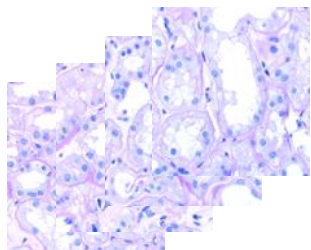
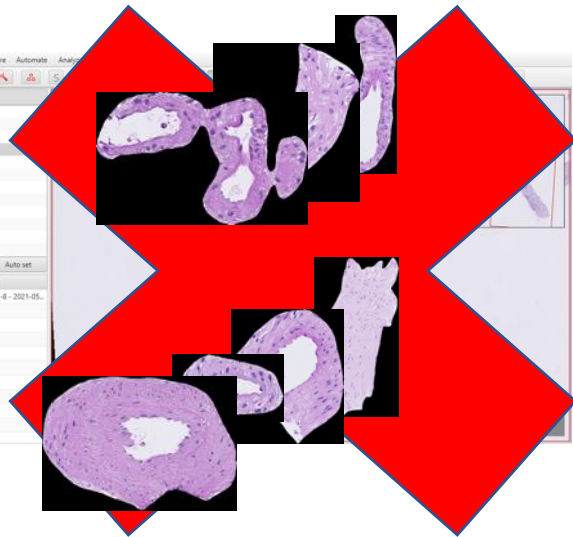
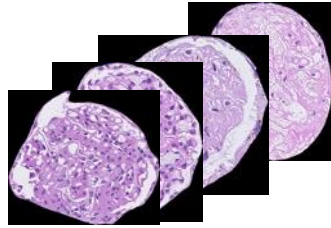
# Multimodal Machine Learning

- Use every source of information available for the task
- Not just histology images
  - Paraffin histology
  - Immunohistology
  - Electron microscopy
- But also clinical parameters
- Including e.g. immunogenetic data for transplants
- Parametrisation of such data?

# MILxFormer Architecture



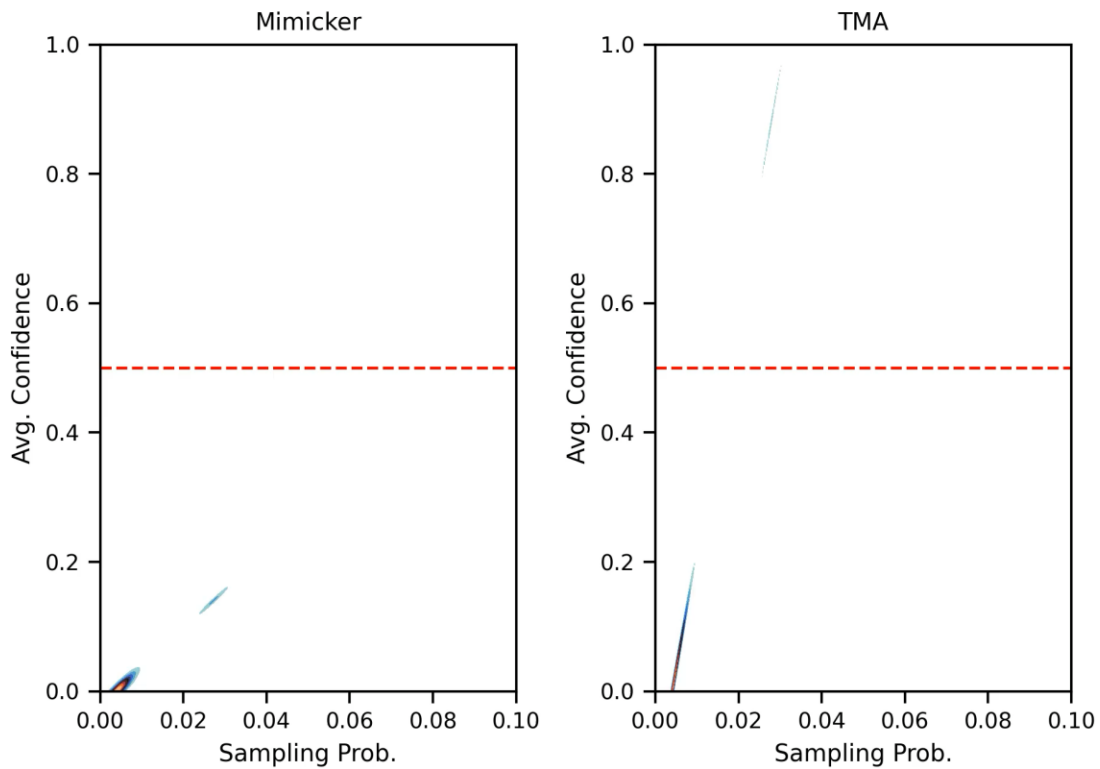
# ML as Multiple-Instance Learning



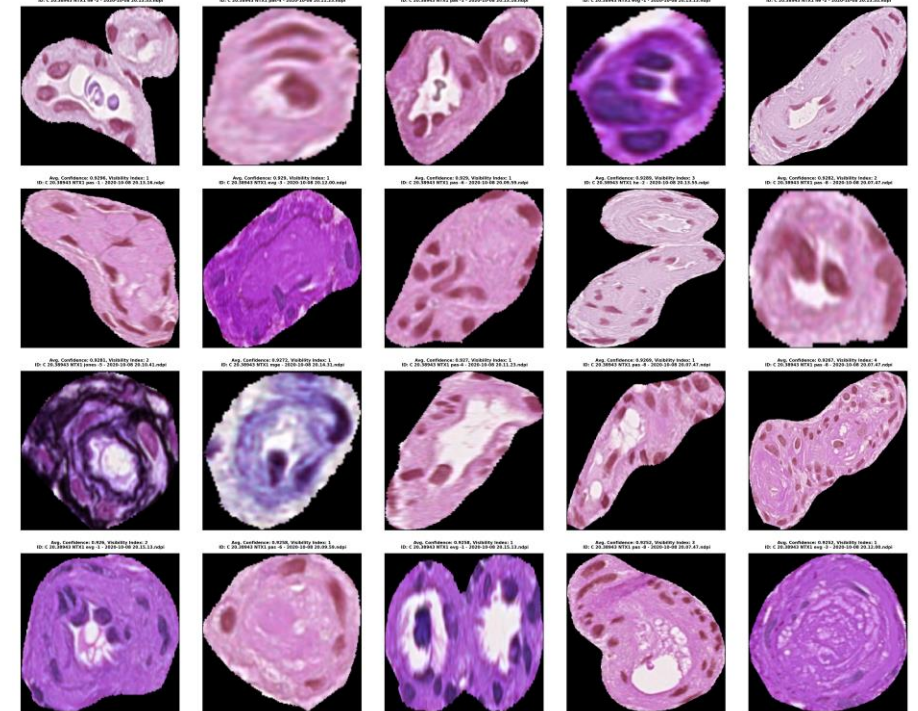
Meaningful output

# Soft Markov Chain Monte Carlo Sampling

Avg. Confidence vs. MCMC Compartment Sampling Probability, Case WCM\_TMA\_2, Compartment ID: ARTERIOLE, Validation Iter.: 1



Top 20 (of total 861) ARTERIOLE compartment crops, class TMA, case C 20.38943



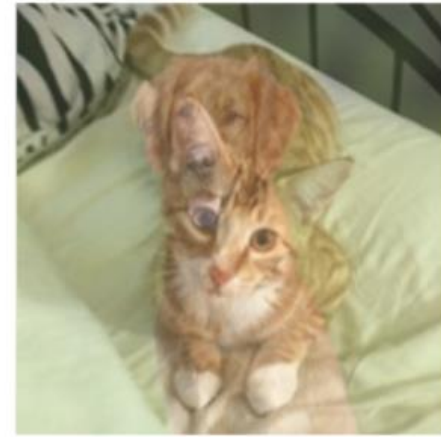
# Advanced Methods of Sample Size Augmentation for MILxFormer: MixUp



$[1.0, 0.0]$   
cat dog



$[0.0, 1.0]$   
cat dog

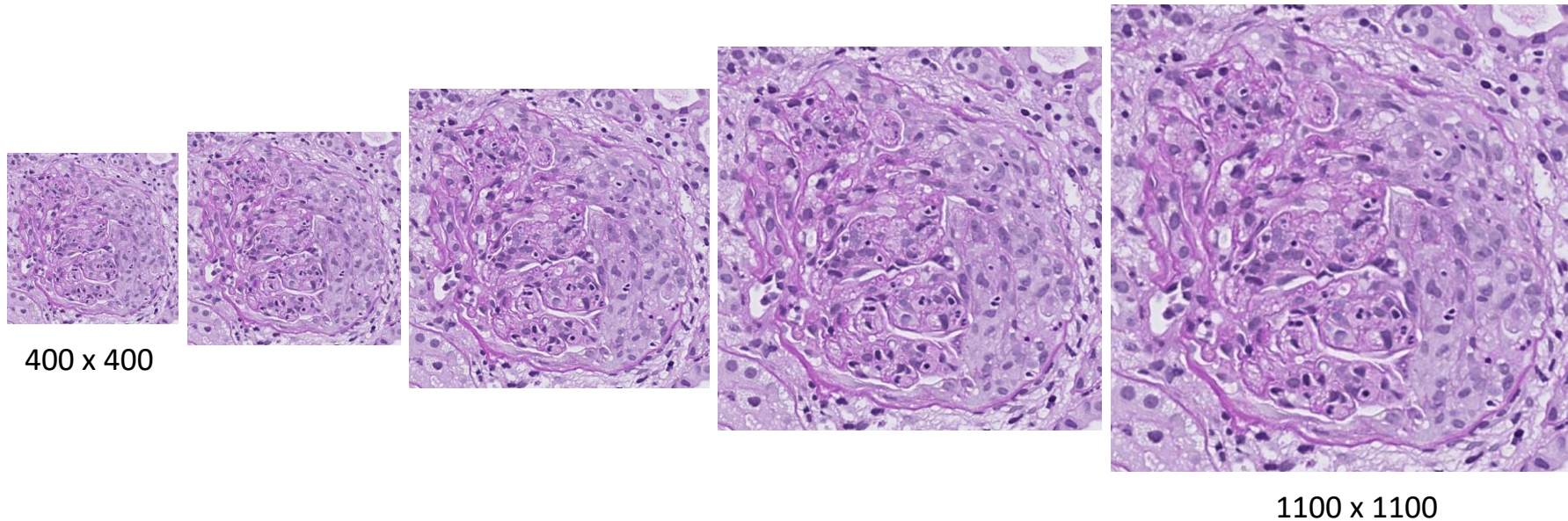


$[0.7, 0.3]$   
cat dog



# Advanced Methods of Sample Size Augmentation for MILxFormer: MILxScale

4 different resolutions from to 1100 x 1100



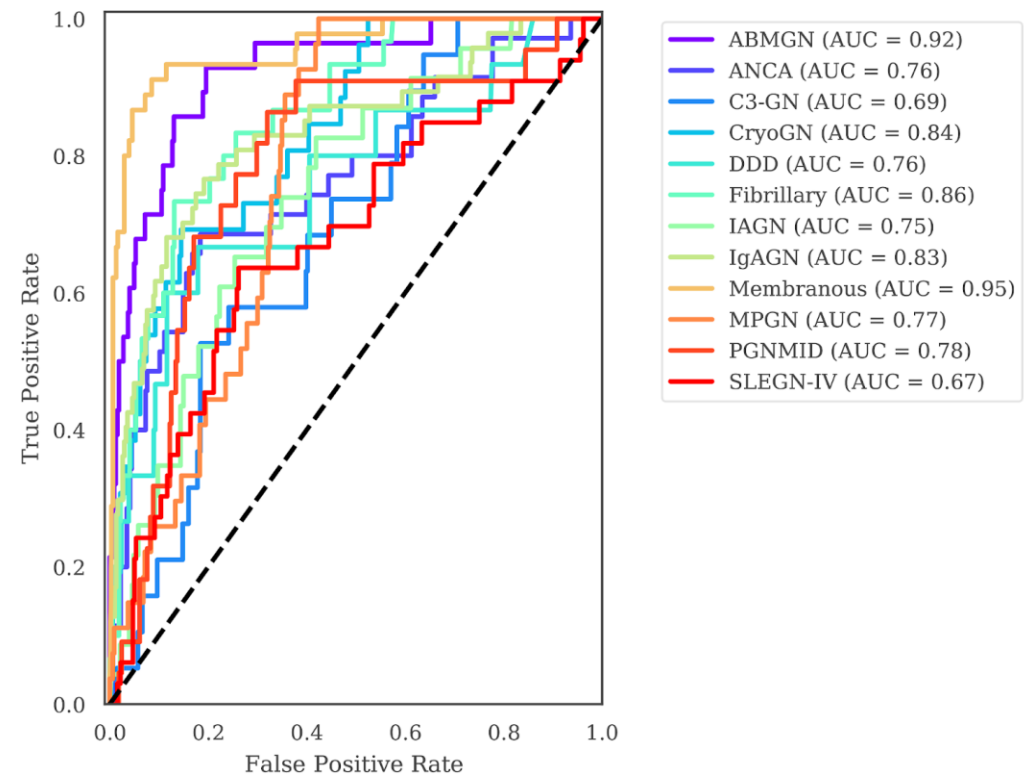


# Development of MILxFormer from MorphSet

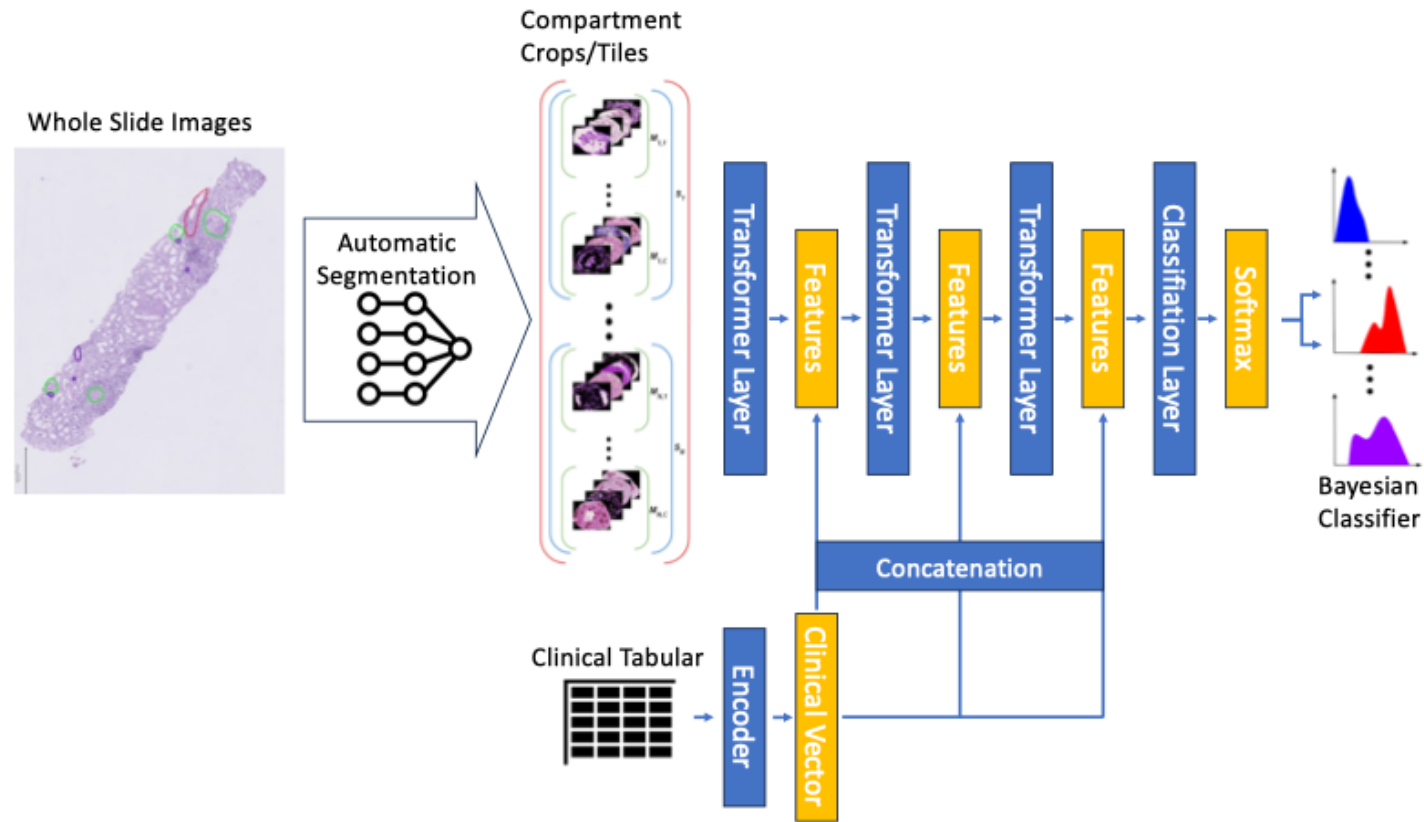
- Soft Markov Chain Monte Carlo Sampling instead of MC Sampling
- MILxUp: implementation of MixUp Zhang et al arXiv 2020 sample size augmentation
- MILxScale: 4 different resolutions from 400 x 400 to 1100 x 1100 as sample size augmentation
- MILxDrop: dropout (removal of corrupted filter nodes) in order to improve generalisation

# MILxFormer Architecture for Advanced Classification tasks

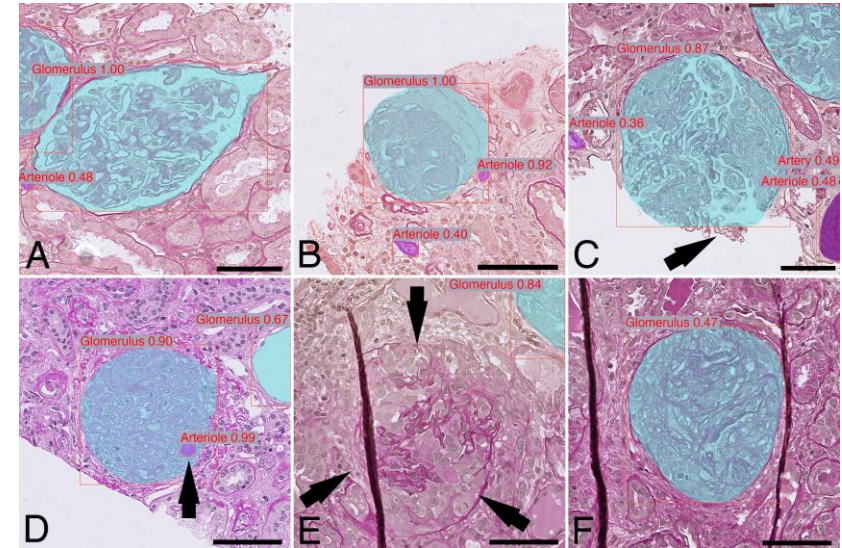
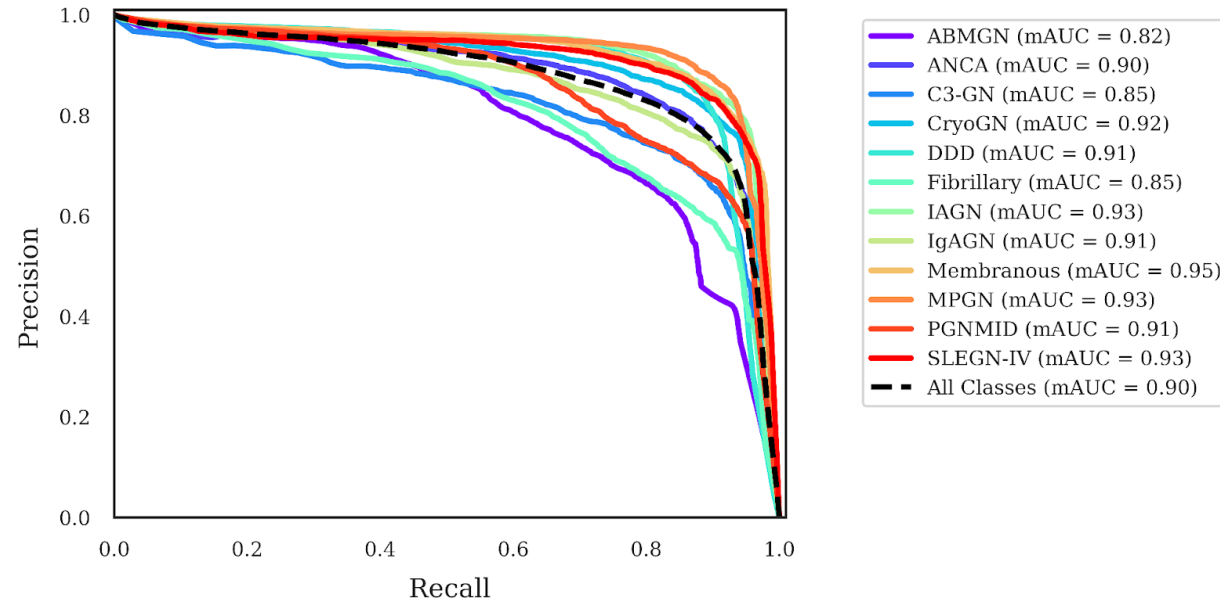
- Input: PAS glomerular transections (crops)
- Output: 12 classes of GN
- Training set: glomerular crops from 350 biopsies
- Weakly supervised training
- MILxFormer architecture
- Internal cross-validation



# MILxFormer+ for Multimodal Data

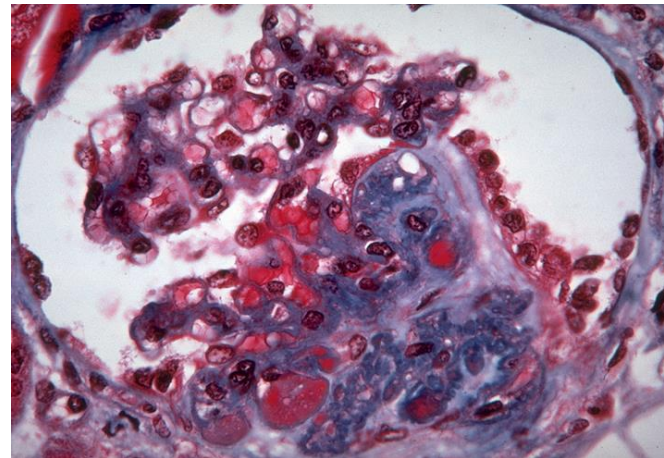
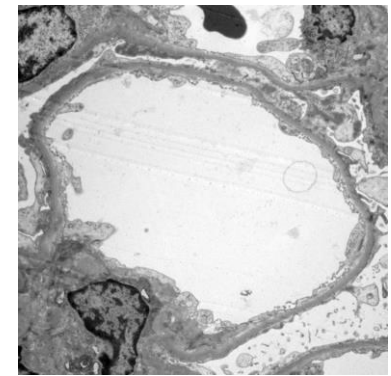
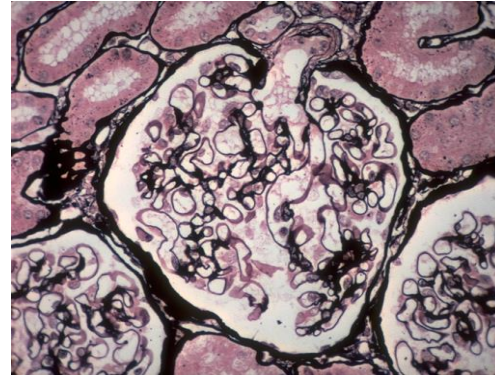


# Automatic Segmentation



# Integration of clinical tabulation with histology: Treatment response with SRNS

- Steroid resistant nephrotic syndrome: podocytopathy predominantly in children
- Cause: defect in podocyte-relevant genes or unknown circulating factor (T cell-secreted?)
- Histology: minimal change-nephropathy, FSGS, diffuse mesangial sclerosis (DMS)

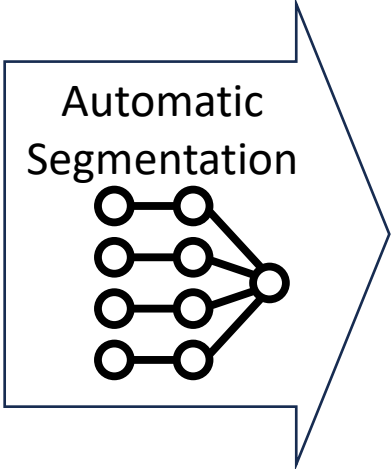


# Steroid Resistant Nephrotic Syndrome

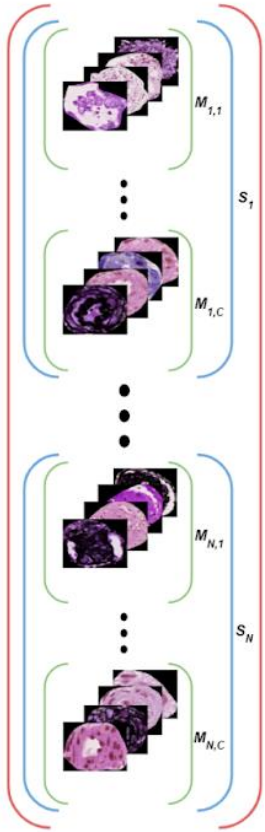
- Steroid resistance: max. 14 weeks without response to immunosuppression
- Then „intensified immunosuppression“ with e.g. CNIs
- Current paradigm: conventional histology inferior for prognosis and theranostic compared to genetics
- PodoNet cohort, 14 centres (Izmir to Vilnius), very large domain shifts
- n=201 biopsies, n=114 no remission, n=42 partial remission, n=45 complete remission



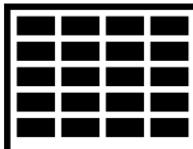
Whole Slide Images



Compartment  
Crops/Tiles



Clinical Tabular



Encoder

Clinical Vector

Transformer Layer

Features

Transformer Layer

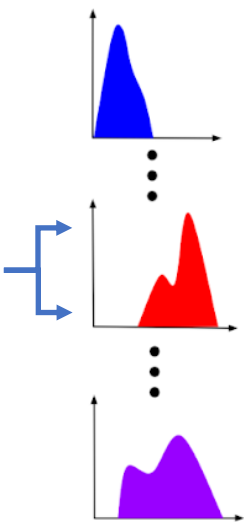
Features

Transformer Layer

Features

Classification Layer

Softmax

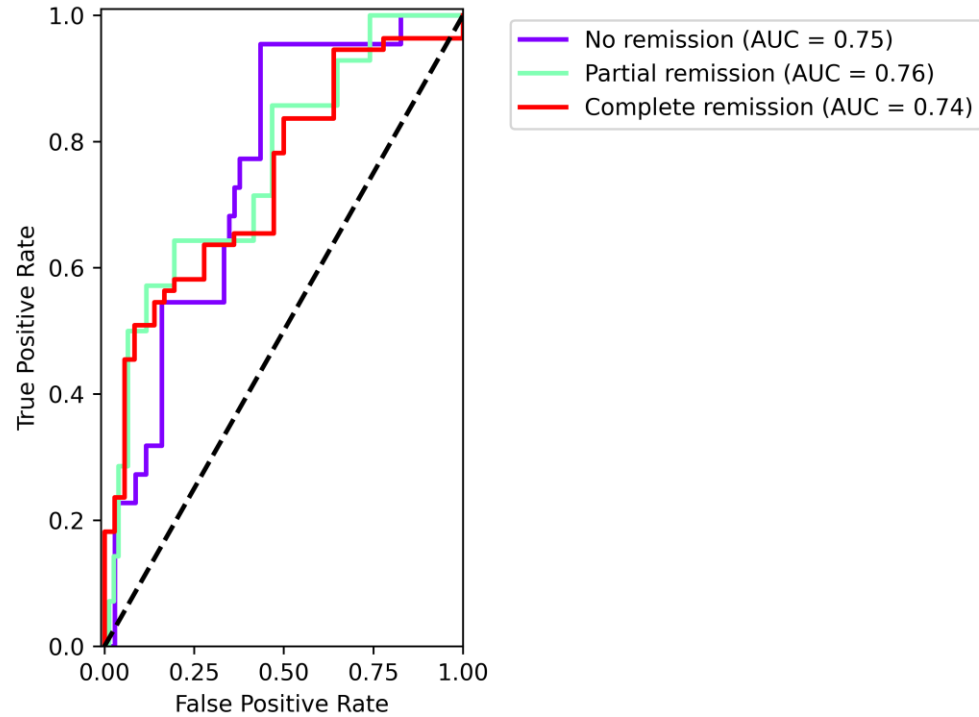


Bayesian Classifier

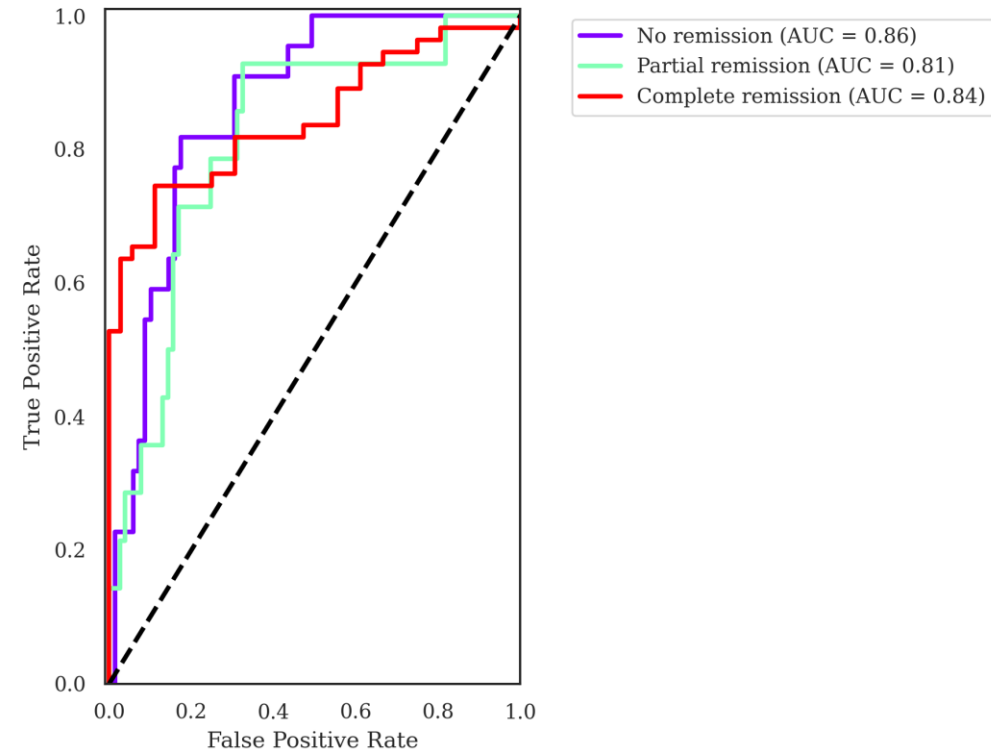
Concatenation

# Theranostics for SRNS with MILxFormer

Classwise ROC Curves, Task: Podonet



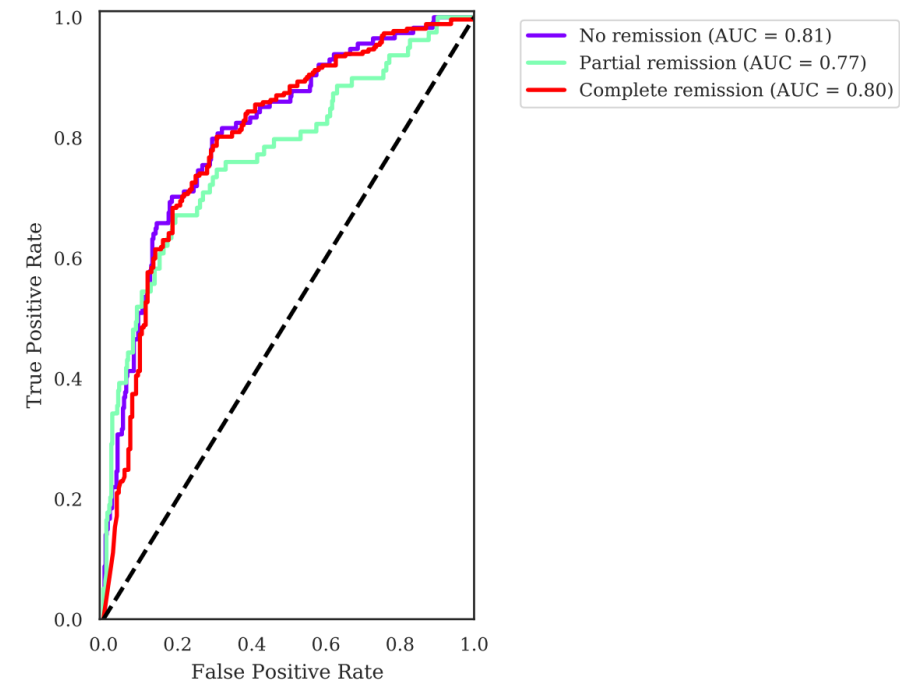
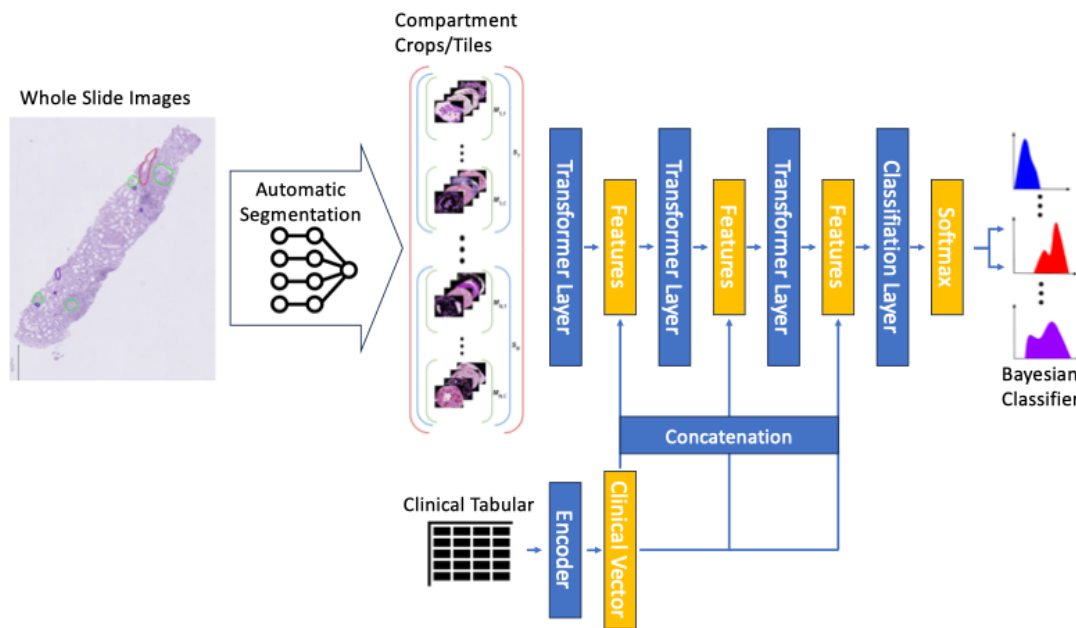
Gaussian naive Bayes classifier  
Only clinical data at biopsy (incl. binary Mutation)



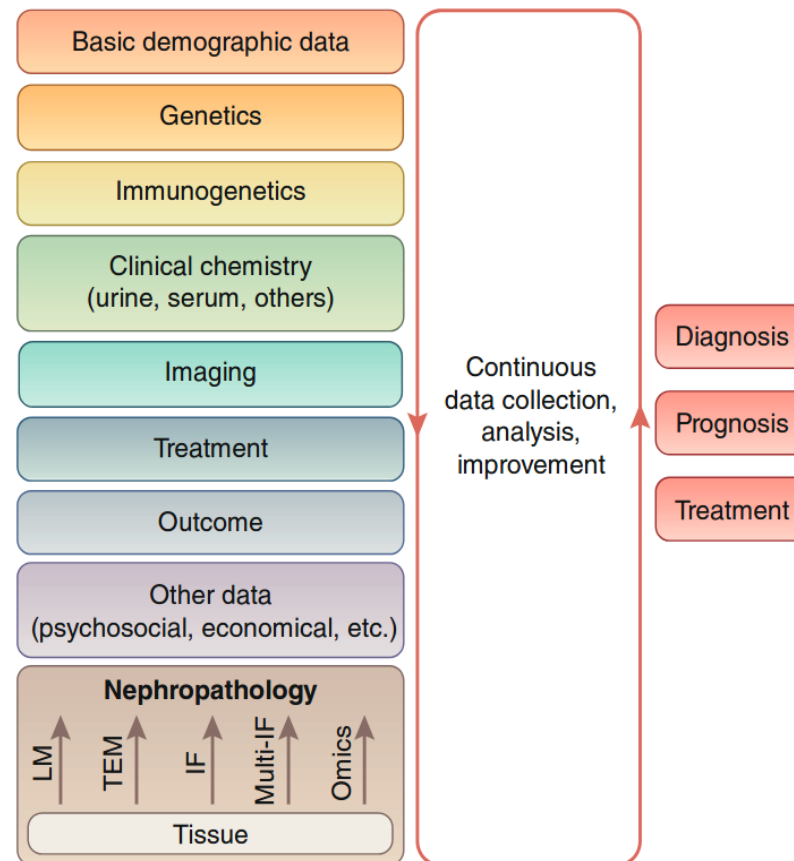
MILxFormer  
Only histology

# Theranostics for SRNS with MILxFormer

Response to intensified IS in SRNS  
(5-fold internal cross-validation)



# Nephropathology, Big Data and Precision Medicine



# Summary/Outlook

- Weakly supervised ML is currently the only realistic option for the evaluation of large clinico-pathological datasets for diagnostics, prognostication and theranostics
- A framework of segmentation followed by classification allows for rapid and efficient, training, upscaling and expansion with large datasets from trusted institutions
- We need large reference datasets with ERKNet's ERKReg, CERTAIN/CTS as go-to platforms for native and transplant nephrology
- Integration of (multimodal) foundation models next frontier

Datasets with (treatment)  
outcome needed



# Thank you!

- Houston: Hien V. Nguyen, Pietro A. Cicalese, Syed Rizvi, Chandra Mohan, Badri Roysam
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- Amsterdam: Joris Roelofs, Jesper Kers
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- Rotterdam: Marian Clahsen-van Groningen
- London: Candice Roufosse
- Szeged: Béla Ivanyi, Sándor Turkevi-Nagy
- New York: Surya Seshan, Ibrahim Batal
- Baltimore: Avi Rosenberg
- ERKNet, PodoNet (F. Schäfer), CERTAIN (B. Tönshoff)
- DFG and Köln Fortune