

How to evaluate Machine Learning models in Laboratory Medicine?

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IFCC

*International Federation
of Clinical Chemistry
and Laboratory Medicine*

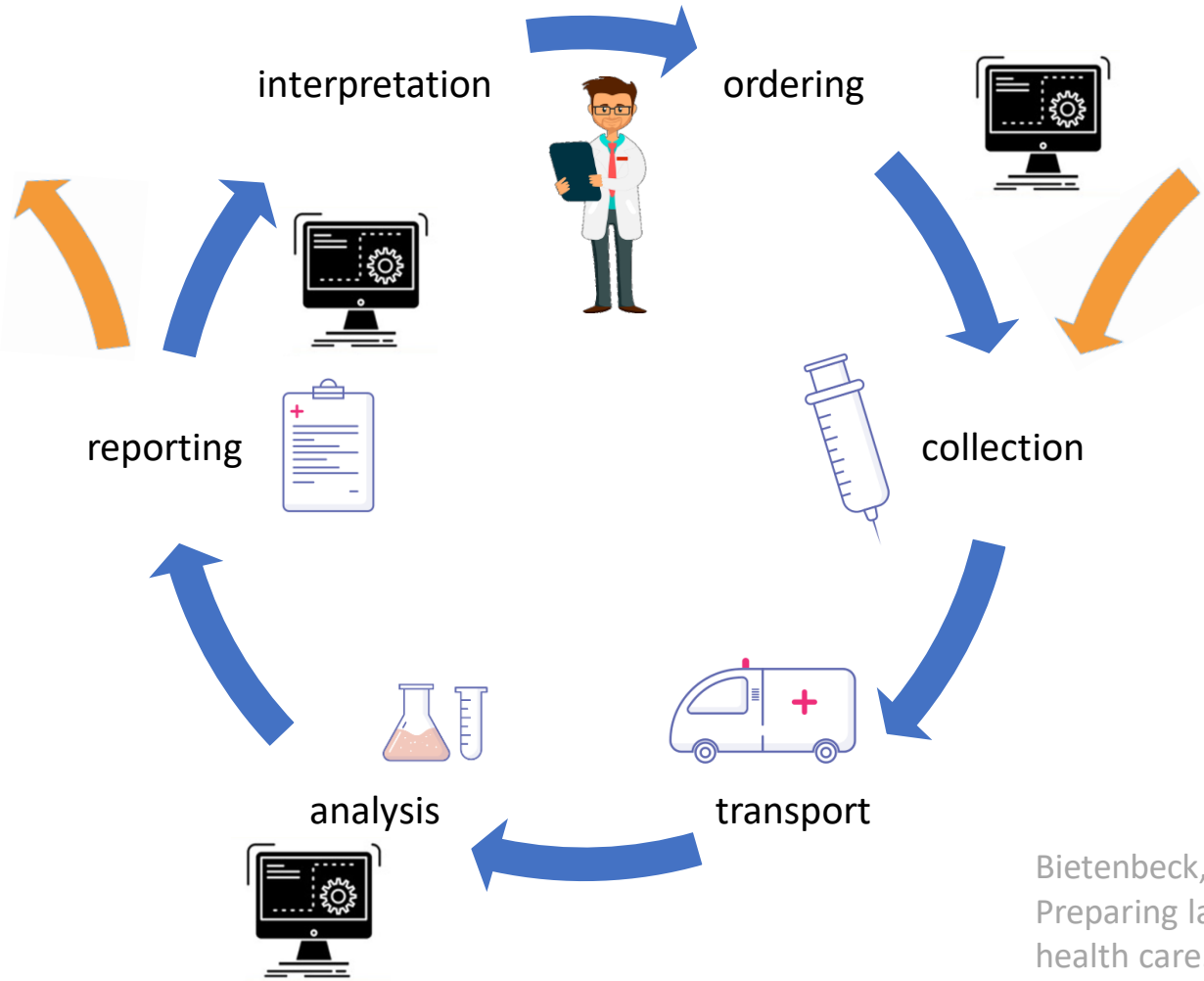
**Advancing
excellence in
laboratory medicine
for better healthcare
worldwide**

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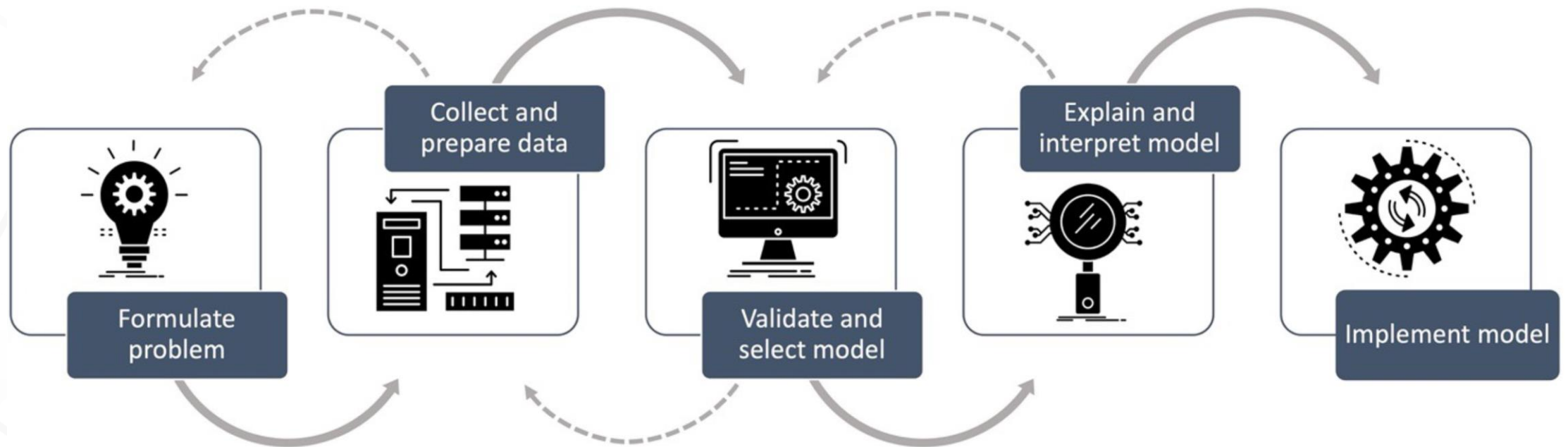
Machine Learning applications can facilitate in all phases of Laboratory Medicine

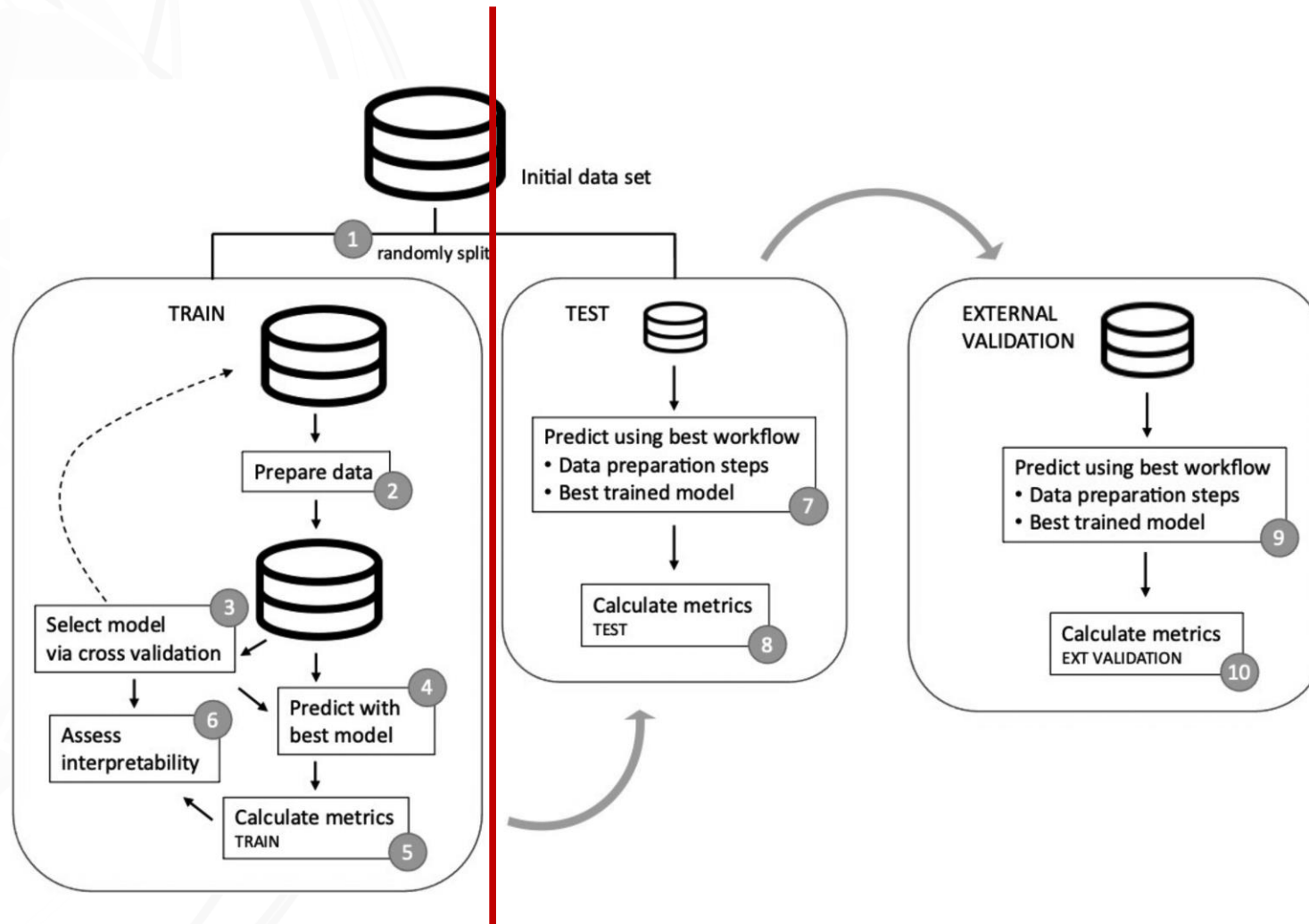
- Electronic Health Records
- patient
- Clinical decision support systems
- research
- ...

- Clinical information
- Results from other laboratories



Bietenbeck, A., & Streichert, T. (2021). Preparing laboratories for interconnected health care. *Diagnostics*, 11(8), 1487.





In the manuscript:

- 30.000 features from novel Omics method
- 60 samples (30 healthy, 30 ill)
- Principal component analysis
- Support vector machine for classification
- Leave-one-out cross validation
- No external validation
- Code available
- AUC: .69



Insufficient cases for number of features



Weak validation

What might have happened...

- Nobody understands the data so let's do machine learning
- First approach (e.g. removal of correlated features, random forest): AUC .56
- Next approaches: try out other pre-processing pipelines, algorithms... (> 100 permutations ...)
- Report only the best result

1. New cases not similar enough to any of the training examples – failure to generalize
2. Similar inputs associated with different outputs
3. Defined outcomes are controversial because of an ill-defined gold standard
4. Insufficient infrastructure or resources (data scientists) for machine learning
5. Unreliable outcome labelling, lack of in-house expertise to provide training diagnoses.
6. No clear strategy or understanding of the operational context
7. Traditional rule-based software methods are equivalent/better (simple or well-characterized problem)
8. Insufficient data (quantity or quality)

Features:

MCV

HB

Ferritin

Reticulocytes

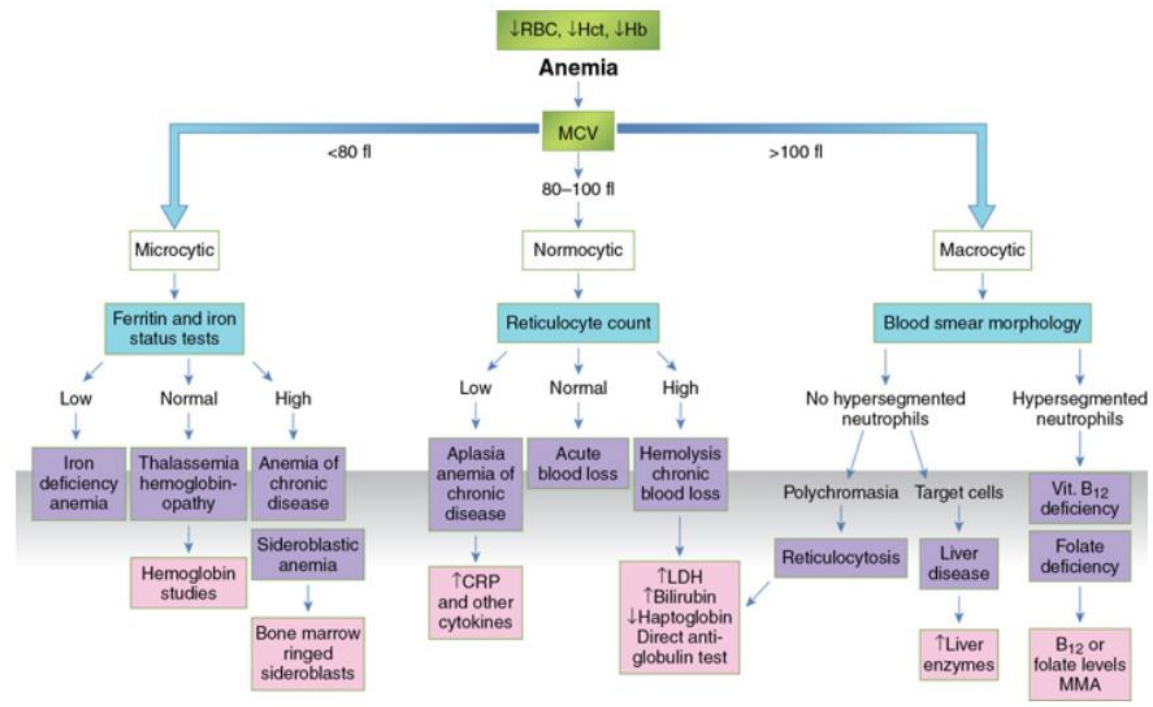
Haptoglobin



Outcome:

- Iron deficiency anemia
- Renal anemia
- Hemolytic anemia
- Other forms of anemia

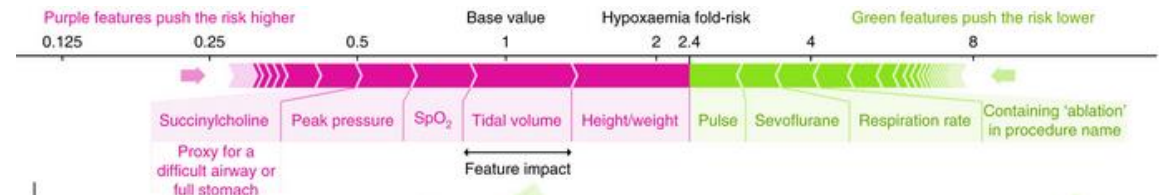
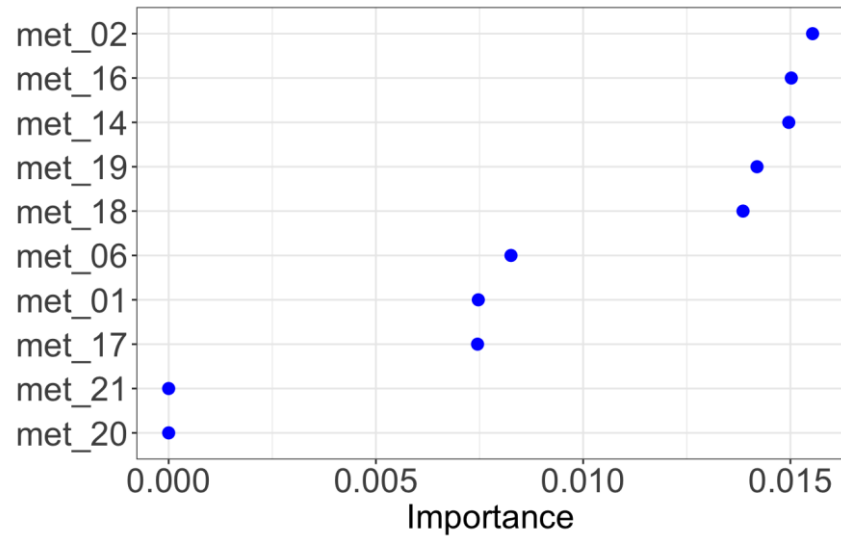
“deep neural
network”



Rifai, Nader. Tietz textbook of clinical chemistry and molecular diagnostics-e-book. Elsevier Health Sciences, 2017.

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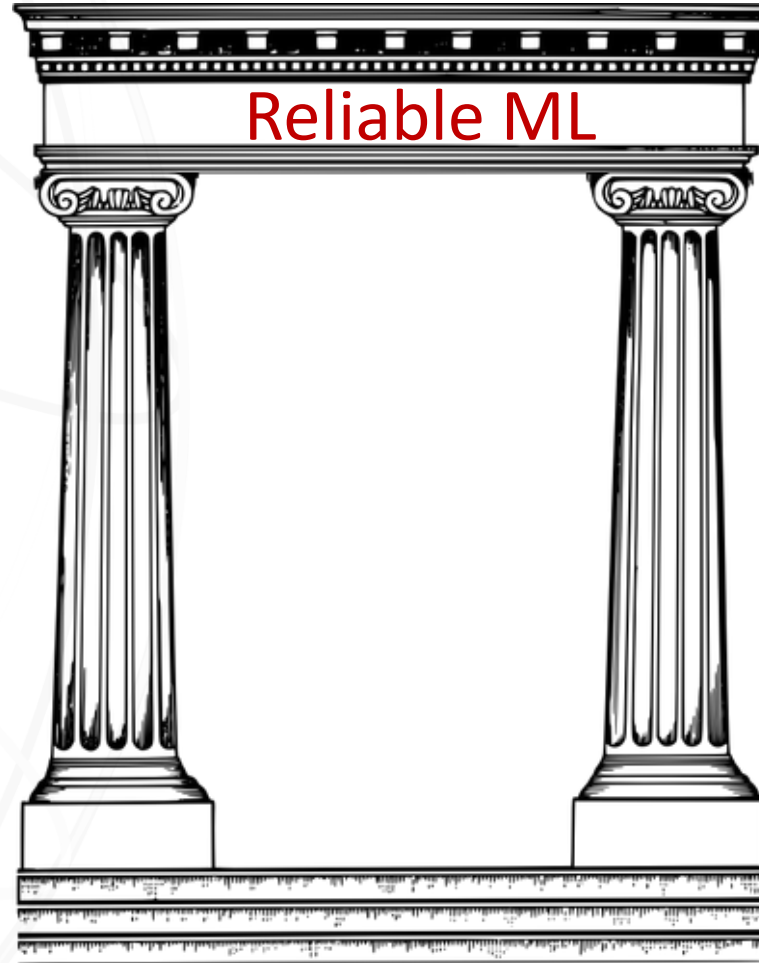
Feature importance analysis



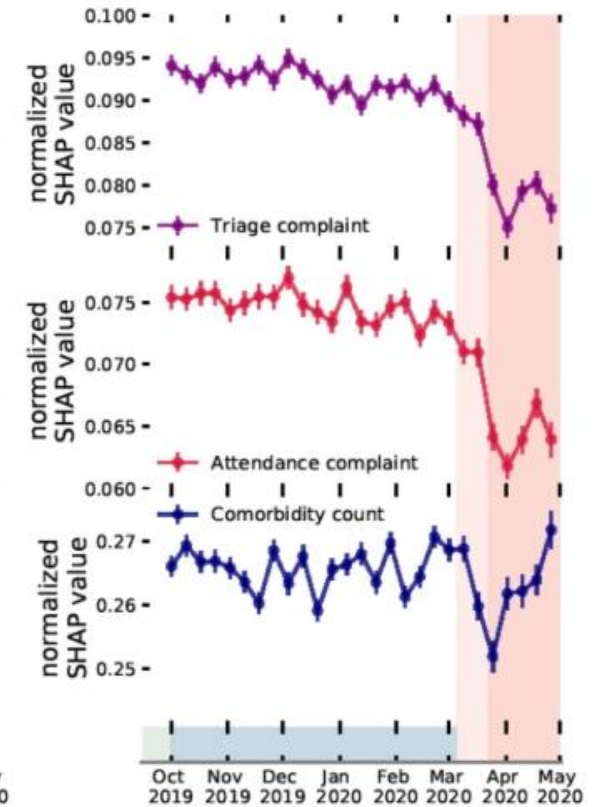
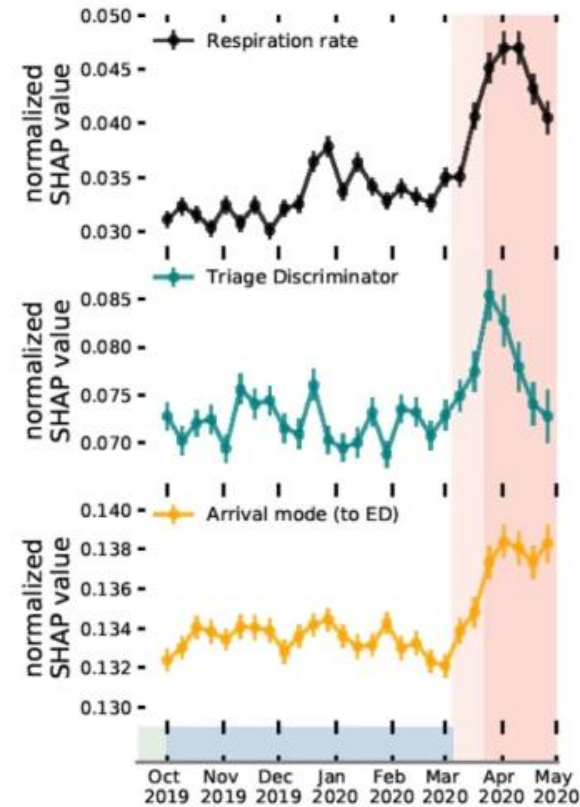
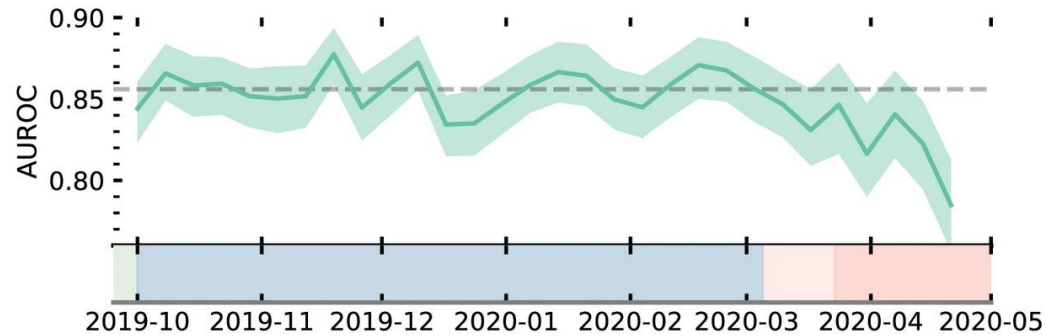
Lundberg, Scott M., et al. "Explainable machine-learning predictions for the prevention of hypoxaemia during surgery." *Nature biomedical engineering* 2.10 (2018): 749-760.

Recommendation 13: Interpret the results and performance of the selected model using suitable global and/or local interpretability methods. Address performance and potential harms in relevant subgroups and clinical scenarios.

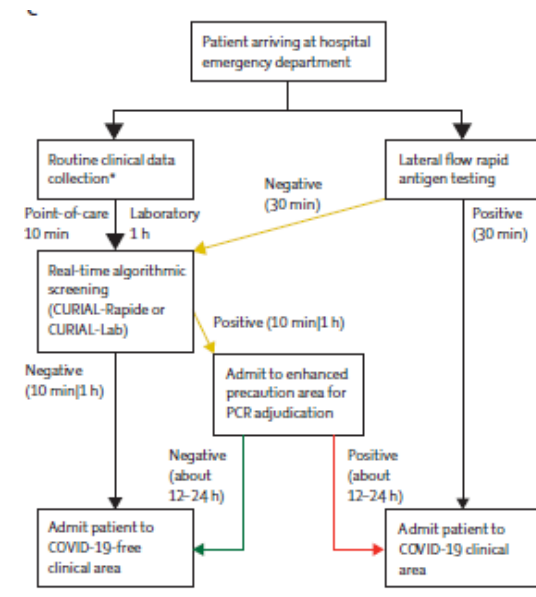
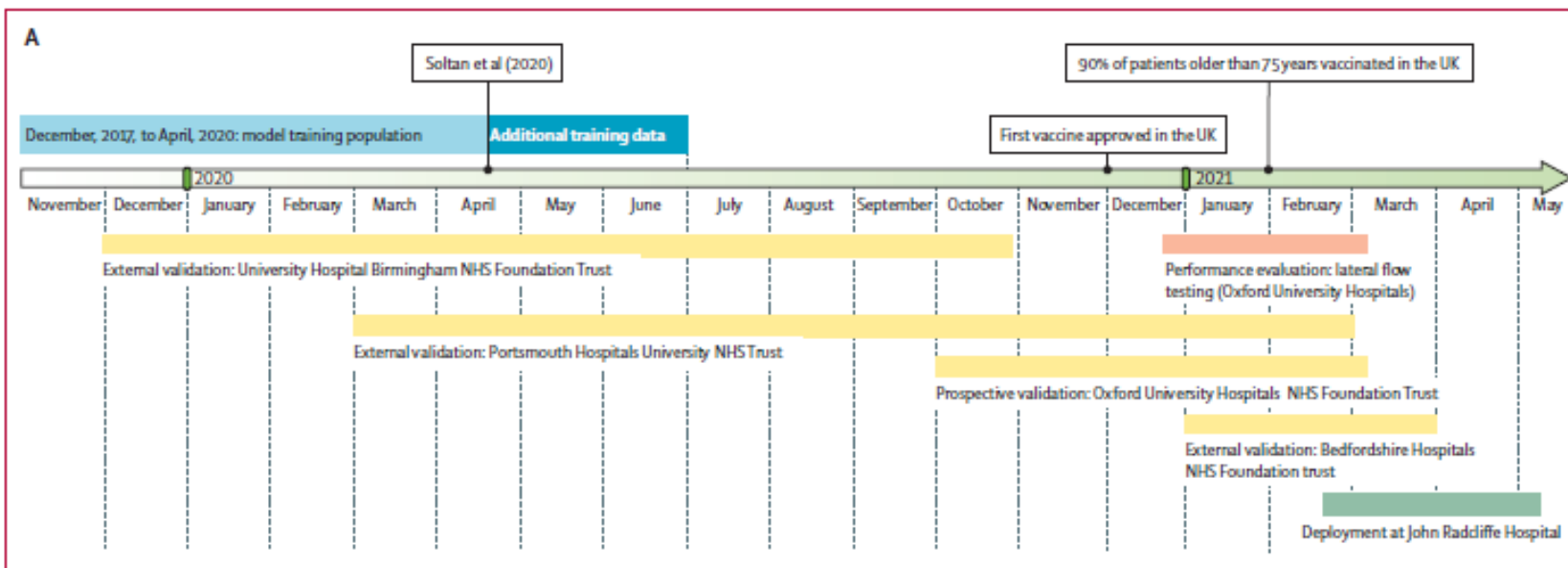
Data



Interpretability,
(knowledge)



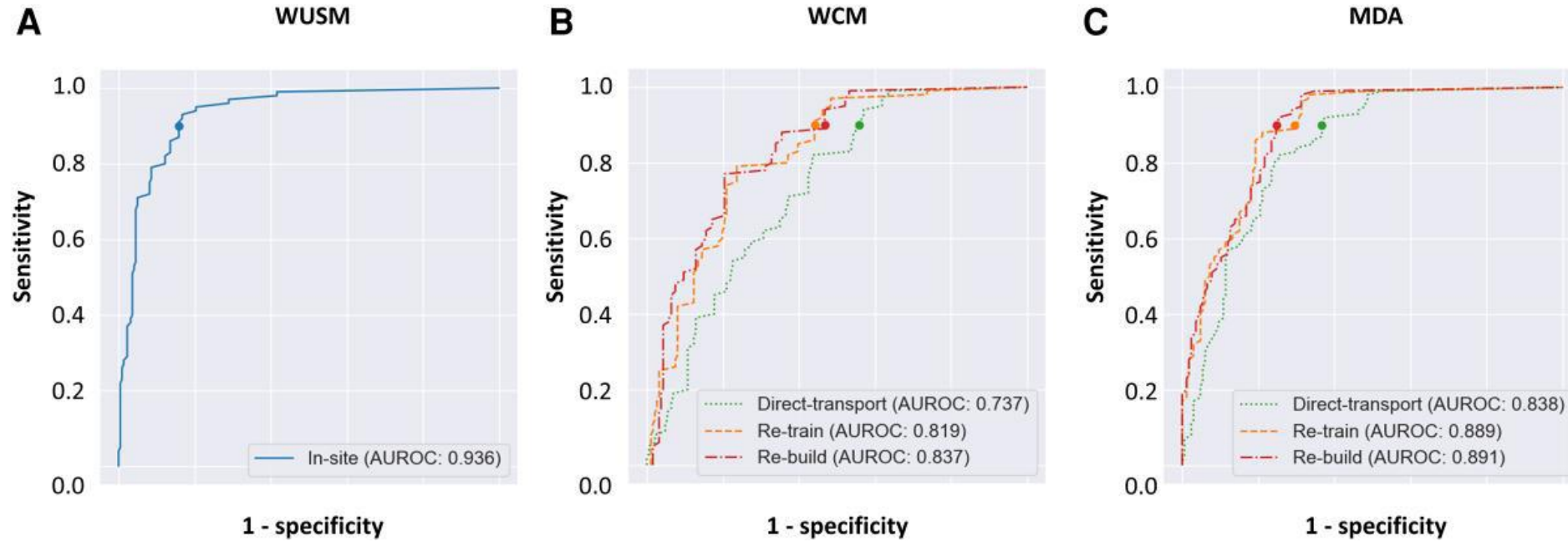
Duckworth, Christopher, et al. "Using explainable machine learning to characterise data drift and detect emergent health risks for emergency department admissions during COVID-19." *Scientific reports* 11.1 (2021): 23017.



Soltan, Andrew AS, et al. The Lancet Digital Health 2022

The screenshot displays the Stream.ML Marketplace interface. At the top, the Stream.ML logo and navigation menu are visible. The main header reads "Marketplace". Below this, there are filters for "Data Type", "Created Date", and "Descending", along with search and close buttons. The marketplace is filled with model cards, each featuring a representative image, a title, a brief description, and a "VIEW DETAILS" link. The models listed include:

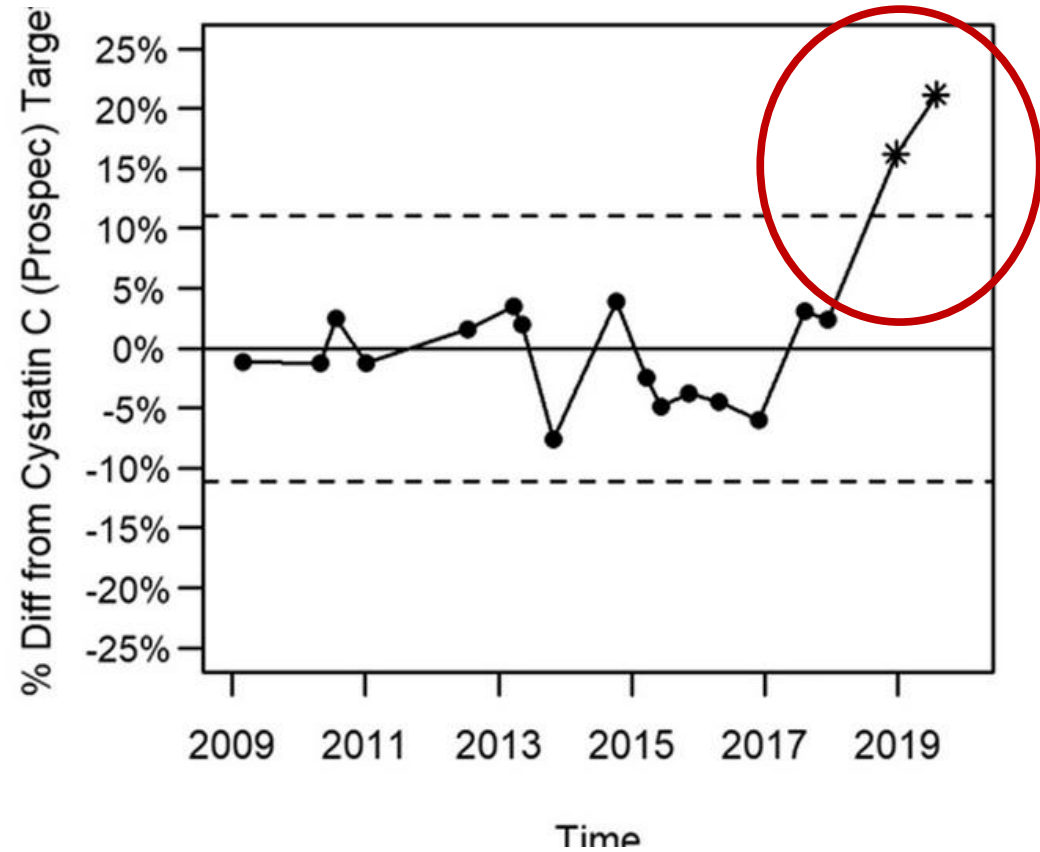
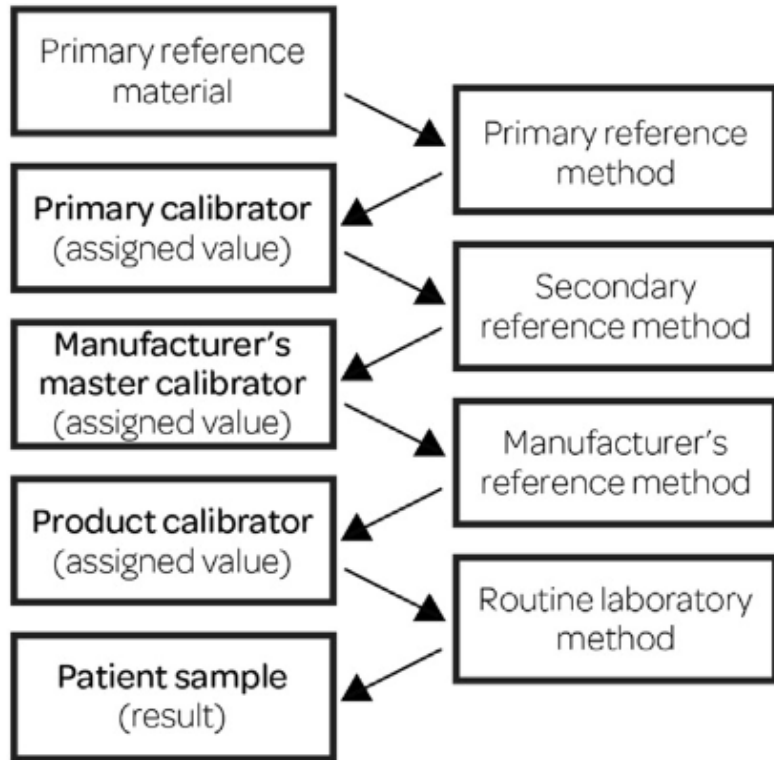
- Canari**: Cannabis plant health analysis based on leaf imagery.
- Rock Identification**: Model for identifying rock hand samples.
- VGG19**: Convolutional network for visual recognition.
- ResNet50**: Convolutional network for visual recognition.
- NASNetMobile**: Convolutional network for visual recognition.
- NASNetLarge**: Convolutional network for visual recognition.
- MobileNetV2**: Convolutional network for visual recognition.
- MobileNet**: Convolutional network for visual recognition.
- DenseNet201**: Convolutional network for visual recognition.
- InceptionV3**: Convolutional network for visual recognition.
- InceptionResNetV2**: Convolutional network for visual recognition.
- Xception**: Convolutional network for visual recognition.



“This difference could be partially attributed to the fact that both WUSM and MDA laboratories use the same analyzers to conduct routine chemistry tests [...]”

Yang, He S., et al. "Generalizability of a Machine Learning Model for Improving Utilization of Parathyroid Hormone-Related Peptide Testing across Multiple Clinical Centers." *Clinical chemistry* 69.11 (2023): 1260-1269.

Traceable and stable measurements prevent model deterioration



Karger, Amy B., et al. "Long-term longitudinal stability of kidney filtration marker measurements: Implications for epidemiological studies and clinical care." *Clinical chemistry* 67.2 (2021): 425-433.



- Keep it simple: Only use Machine Learning when you have to.
- Beware of data leakage!
- Machine Learning is no “magic bullet”: Insufficient data (quantity and quality) cannot lead to convincing results.
- Play to your strengths: Use interpretability methods to evaluate machine learning models.
- Only stable, traceable measurements can guarantee stable, transferable ML models.

Clinical Chemistry 69:7
690–698 (2023)

Special Report



Machine Learning in Laboratory Medicine: Recommendations of the IFCC Working Group

Stephen R. Master ^{a,b,*} Tony C. Badrick,^c Andreas Bietenbeck ^d and Shannon Haymond^{e,f,*}

- <https://area9lyceum.com/laboratorymedicine/>
- IFCC Webinar part 2
- lab@bietenbeck.net

NEJM
Knowledge+

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Learning Lab



MACHINE LEARNING (ADVANCED)

AACC Learning Lab Advanced

Author information
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Stephen R. Master, MD, PhD
Li Zhu, PhD

Learning objectives:

- ✓ Explain principles of machine learning
- ✓ Describe machine learning process

START LEARNING NOW



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www.ifcc.org | eacademy.ifcc.org

