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Predicting ICU Admission for Patients with Elective Surgery

Development of a Machine Learning Model and its Prospective Validation in Clinical Practice

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Why is it crucial to predict an ICU admission?

- increasing population size +
  higher life expectancy +
  „civilisation diseases“ =
  more patients in need of intensive care units (ICU) (Rhodes et al., 2012)
- Frequent utilization of ICU beds
  - associated with higher costs
  - decreases access for patients who may profit more (Kose et al., 2015)

→ Identify patients most likely to benefit from ICU admission!

Current Way of Risk Assessment

- **Preoperative assessment** prior to elective surgery
- Assessment of physical condition prior to surgery
  American **S**ociety of **A**naesthesiologists (ASA) – Physical Status tool
  - Six categories: 1-healthy person; 6- brain-dead person
  - Helps estimating anaesthetic complications
  - Very subjective → moderate interrater reliability (Kose et al., 2015)

- Risk estimation is **crucial** for ICU bed and anaesthetic management
- Need for more **objective methods** with higher sensitivity than ASA
- Need for **implementation**!

Research on Prediction of ICU Admission

- ICU Admission
  - CARES model (Chan et al., 2018)
    AUROC (area under the ROC curve): 0.84
- Several machine learning based risk prediction models, but only few made their way to clinical practice!
  - MySurgeryRisk (Bihorac et al., 2018)
    - Predicts ICU stay (> 48 hours)
    - Machine learning based model
    - AUROC: 0.88
- Results may differ between **retrospectively collected test data**, and **prospective validation** data with real-time prediction!

Data Set and Feature Selection

- Routine data of a **KAGes** (regional healthcare provider Austria) hospital
  - 330 inpatient beds
  - 20 ICU beds (12 with mechanical ventilation)

- Outcome: admission to ICU within five days after surgery
  Prediction Time: last preoperative assessment

Feature group	Examples	n
Demographic Data	Age, sex	30
Disease Codes	ICD-10 codes	345
Procedure Codes	X-ray, MRI	103
Laboratory Data	CRP, gamma-GT	46
Nursing Protocols	sleeping disorder	96
Administrative Data	Transfers, hospital admissions	10

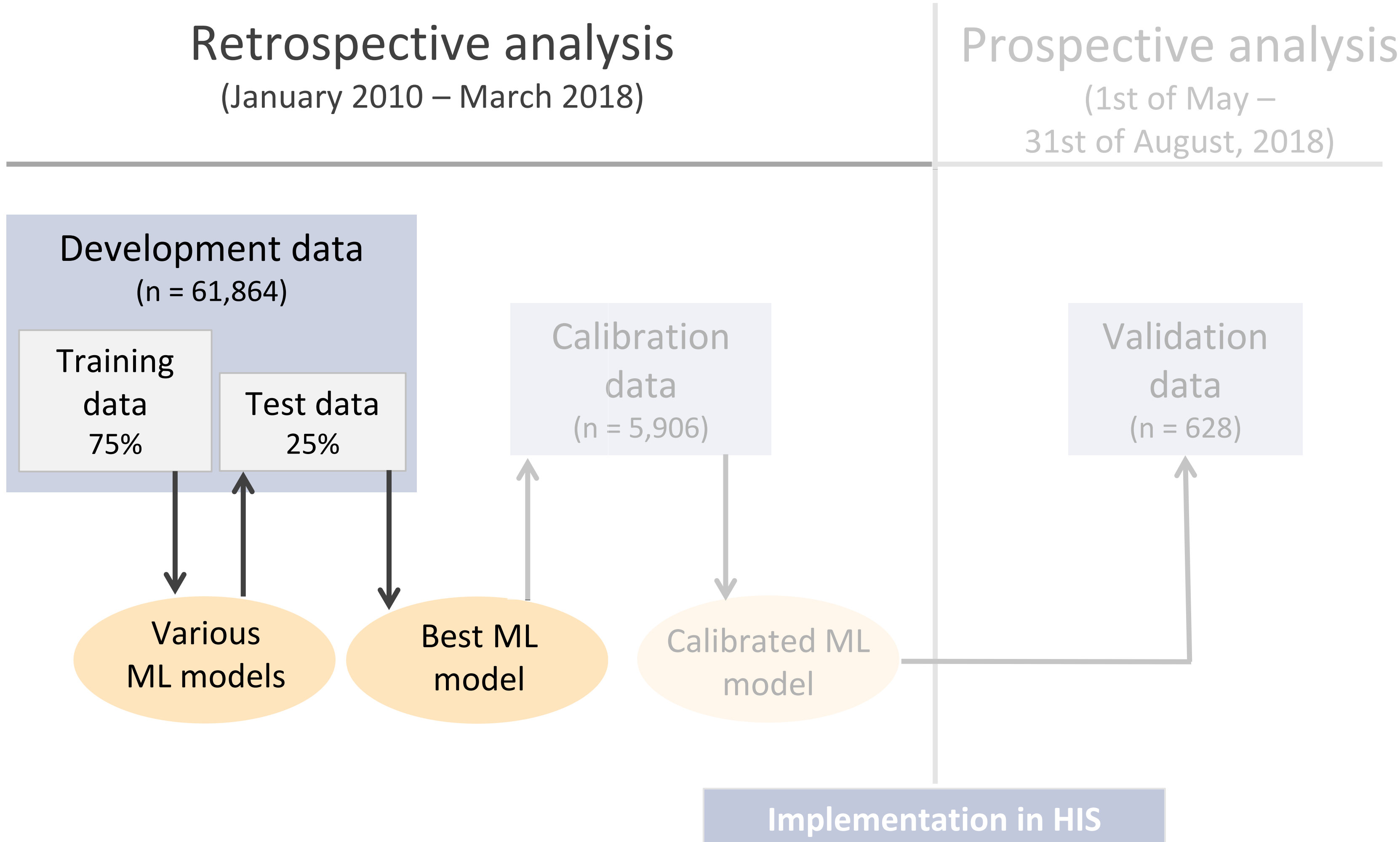
N = 630

Selection:

Frequency based approach

(0.1% -2.0% of patients to avoid rare values)

1. Training and Identification of the best ML (machine learning) model



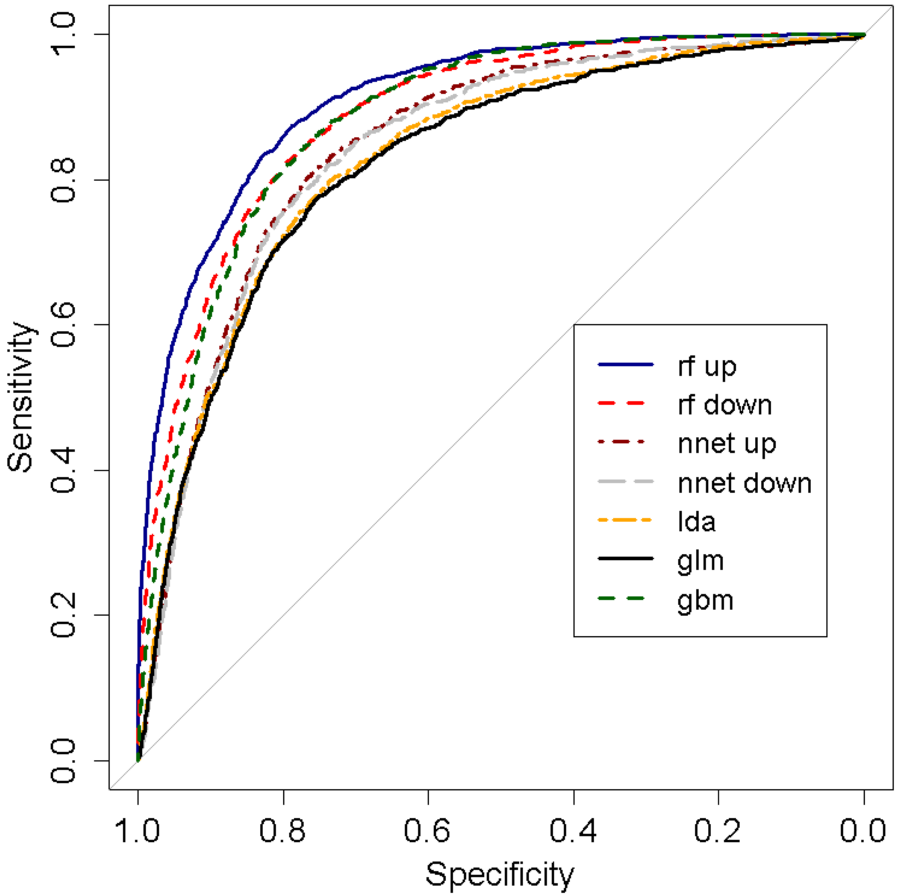
Results of Various ML Methods on Test Data

- R, *caret* package
  5-times repeated 10-fold cross validation

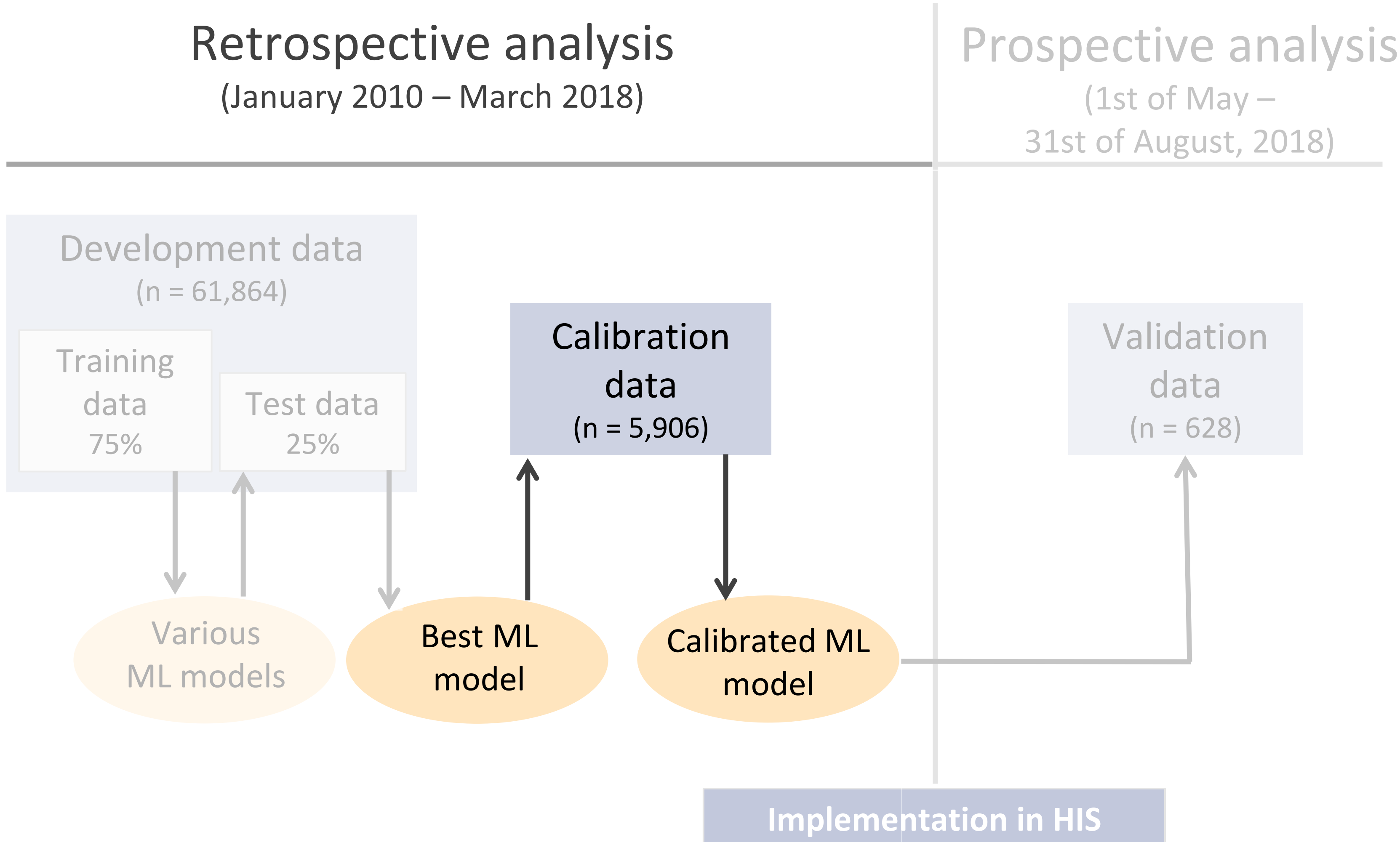
- Methods:
  - Random Forest *(rf up/down)*
  - Neural Net *(nnet up/down)*
    feed-forward, one hidden layer
  - Linear Discriminant Analysis *(lda)*
  - Logistic Regression *(glm)*
  - Stochastic Gradient Boosting *(gbm)*

- Random Forest with upsampling

AUROC:	0.91 [0.90-0.92]
Accuracy:	82.8 %
Sensitivity:	83.3 %
Specificity:	82.7 %



2. Calibration of the Best Performing ML model



Calibration & Implementation in the Hospital Information System(HIS)

- Set two thresholds for three risk classes
- Distribution depending on availability of ICU beds

	NO	Y
976	0.152	0.848
741	0.172	0.828
1123	0.192	0.808
929	0.264	0.736
4470	0.372	0.628
3422	0.378	0.622
830	0.422	0.578
173	0.446	0.554
2025	0.456	0.544

Very high risk (7%)

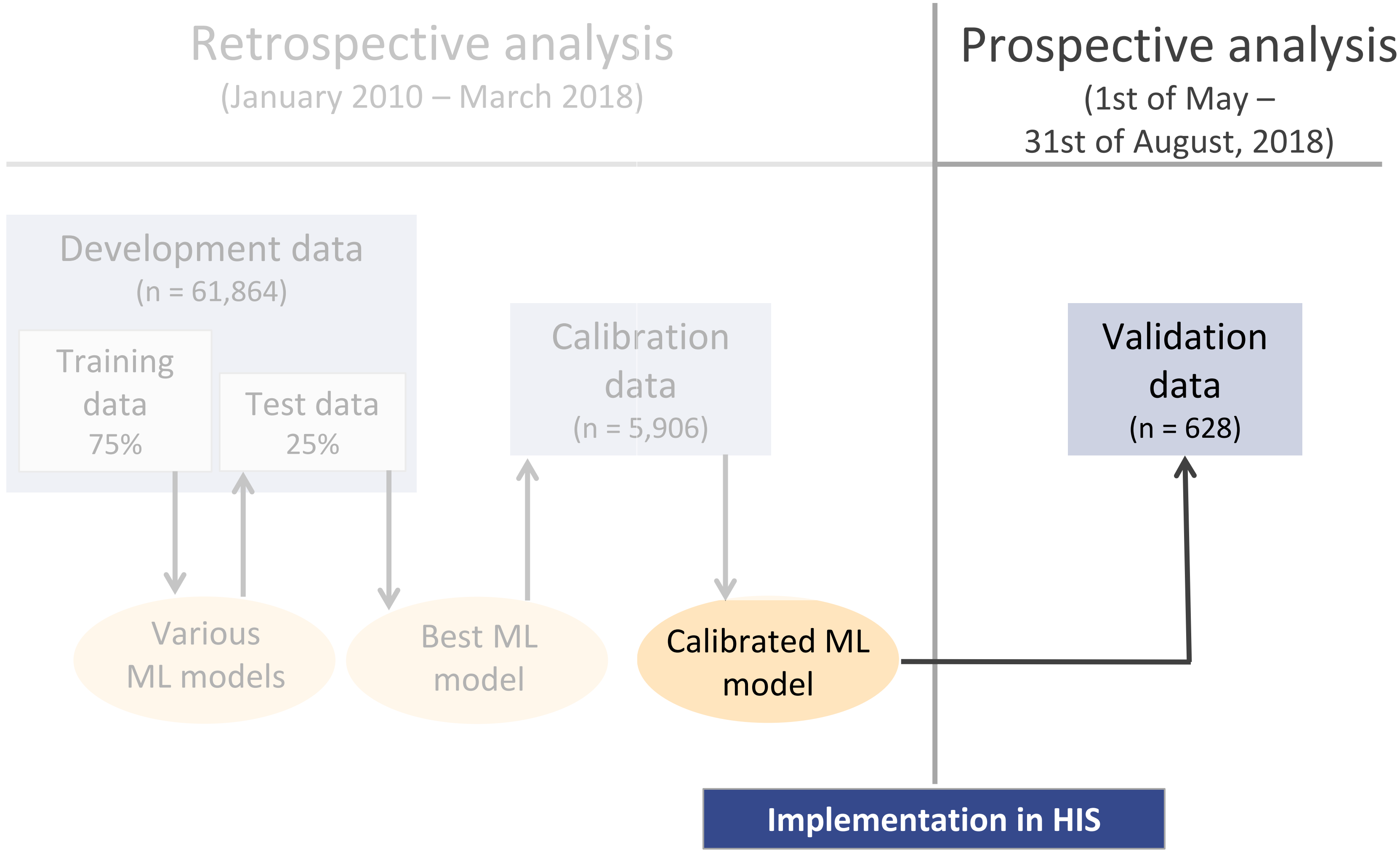
High risk (11%)

Low risk (82%)

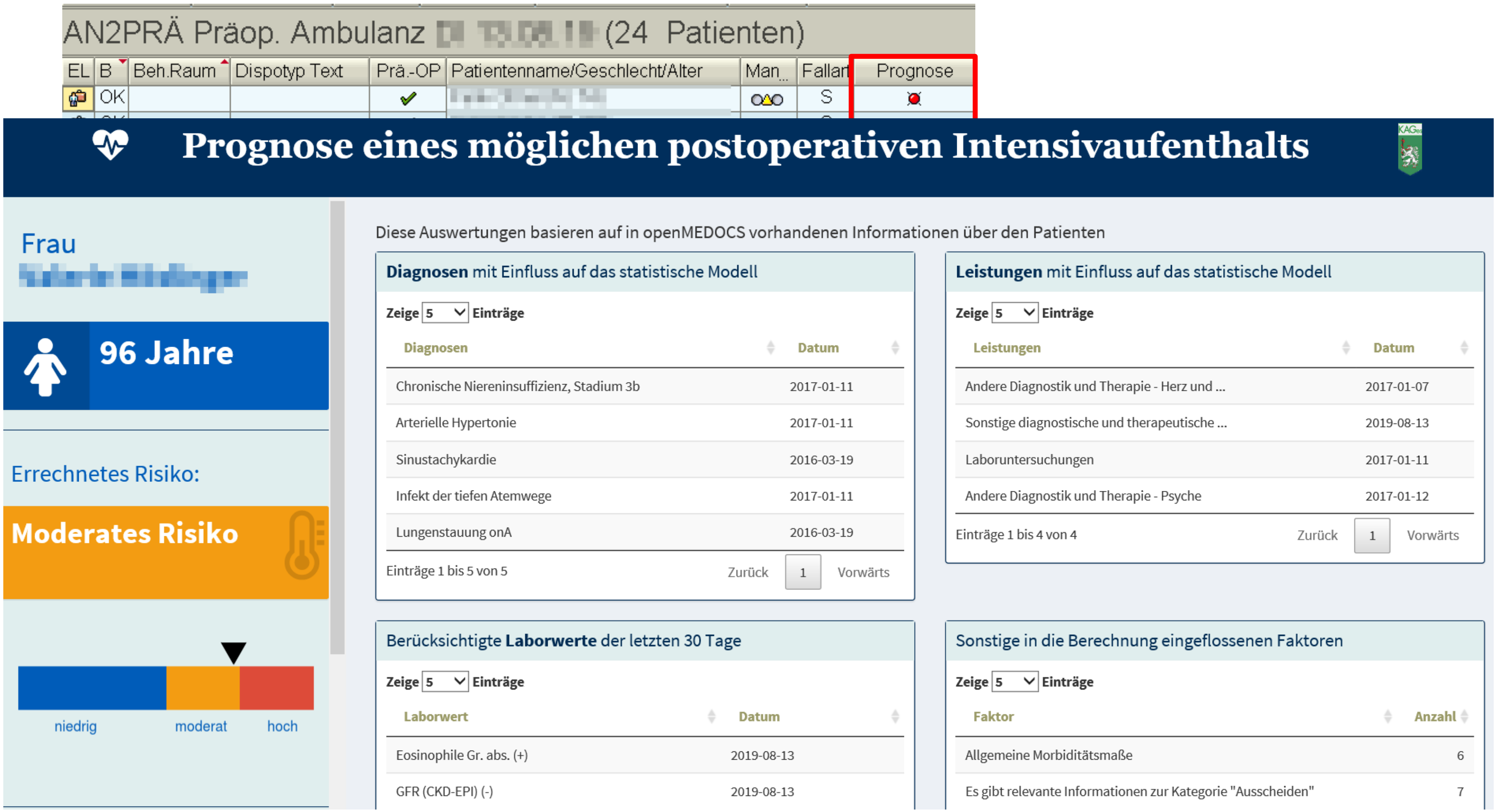
→ **Implementation in HIS**

- Visible for three anaesthesiologists
- Risk prediction for every patient with a preoperative assessment

3. Implementation and Prospective Validation



Visualization of Risk Score and Patient Specific Features



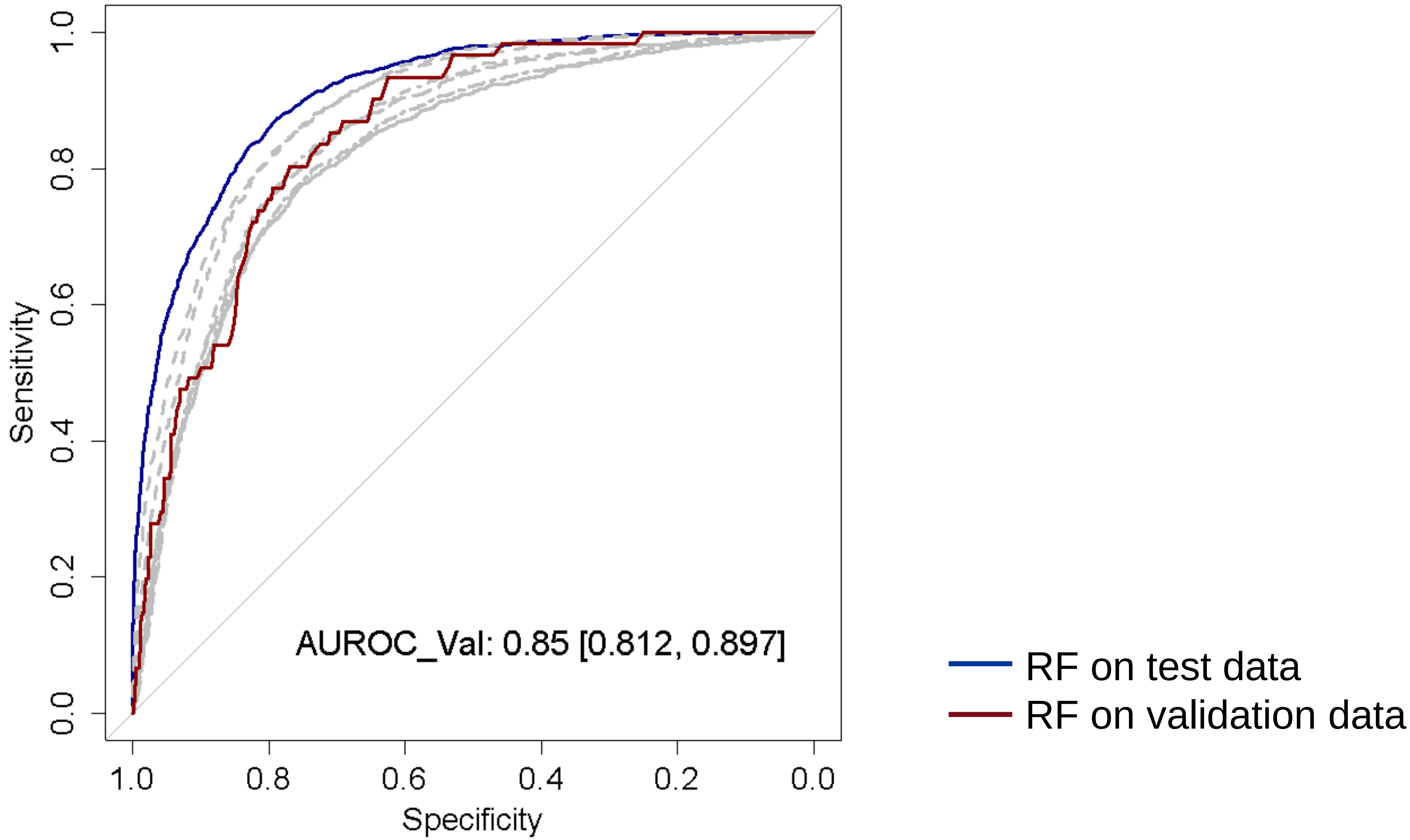
Real-Time Validation on 628 Patients with Preoperative Assessment (May – August 2018)

ICU admission	Predicted Risk Category: Low		High		Very high		Total
	n	%	n	%	n	%	n
No	**459**	**(80.8)**	83	(14.6)	26	(4.6)	568
Yes	16	(26.7)	**26**	**(43.3)**	**18**	**(30.0)**	60
Total	475	(75.6)	109	(17.4)	44	(7.0)	628

Sensitivity: 73.3%

Specificity: 80.8%

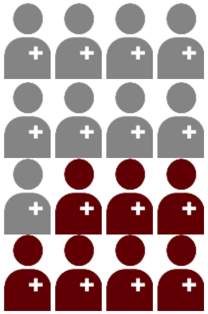
ROC of a Random Forest Model on Test Data Compared to Validation Data



Incorrect Classifications were analysed by a Clinical Expert

1. Patients with ICU stay + „low risk“ (n = 16)

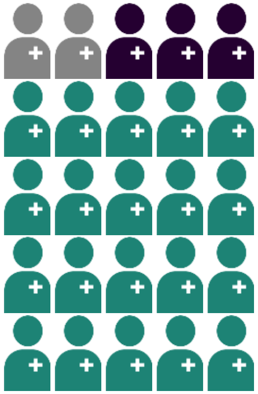
   - **little information** in the HIS (n=9), for some no ICD 10 codes yet



2. Patients without ICU stay + „(very) high risk“ (n = 26)

   - **non-severe surgeries** (n=26)
     percutaneous transluminal angioplasty (PTA), shunt procedures, cataract, lipoma

   - Due to type of surgery, highly unlikely for ICU admission
   - ASA 3 (n=21), ASA 4 (n=3)



Limitations

- Data from hospital information system
  - Availability (e.g. no coded diagnoses)
  - Non-structured data → NLP methods will be necessary

- All patients in false positive group had non-severe surgeries

Severe: 40%
Non-severe: 60%

→ more information on surgery is needed for prediction

Which will be the next steps?

1. Include features with information of elective surgery
   - Severity
   - Type of anaesthesia
2. Evaluate user perception and experience
3. Long-term evaluate the performance of the model

Short Summary

- Random forest based prediction model for **ICU admission** after elective surgery
  (within the **best performing** published models)

- **Prospectively** validated in a clinical setting:
  Real-time prediction **performance was high**

- Future research will focus on how the machine learning prediction is **perceived by health care professionals**.

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References

- A. Bihorac, T. Ozrazgat-Baslanti, A. Ebadi, A. Motaei, M. Madkour, P.M. Pardalos, G. Lipori, W.R. Hogan, P.A. Efron, F. Moore, L.L. Moldawer, D.Z. Wang, C.E. Hobson, P. Rashidi, X. Li, and P. Momcilovic, MySurgeryRisk: Development and Validation of a Machine-learning Risk Algorithm for Major Complications and Death After Surgery, *Annals of Surgery*. (2018) 1. doi:10.1097/SLA.0000000000002706.

- D.X.H. Chan, Y.E. Sim, Y.H. Chan, R. Poopalalingam, and H.R. Abdullah, Development of the Combined Assessment of Risk Encountered in Surgery (CARES) surgical risk calculator for prediction of postsurgical mortality and need for intensive care unit admission risk: a single-center retrospective study, *BMJ Open*. **8** (2018) e019427. doi:10.1136/bmjopen-2017-019427.

- I. Kose, C. Zİncircioglu, M. Çakmak, G. Cabbaroglu, N. Senoglu, and M. Gonullu, Postoperative patients in the intensive care unit: Identifying those who do not really need it, *Journal of Critical Care*. **30** (2015) 1295–1298. doi:10.1016/j.jcrc.2015.08.012.

- A. Rhodes, and R.P. Moreno, Intensive care provision: a global problem, *Revista Brasileira de Terapia Intensiva*. **24** (2012) 322–325. doi:10.1590/S0103-507X2012000400005.

Variable Importance for Random Forest UP

- Number of procedures
- CT
- Number of medical procedures
- Age
- Days since last stay
- Endoscopy
- Charlson Comorbidity Index
- Number of transfers
- Other Diagnostics and Therapie (Heart and circulatory system)
- Number of diagnosis
- Number of nursing procedures
- Sonography
- Longest hospital stay (days)
- Anaesthesia
- Glucose level
- Malignant neoplasms of digestive organs
- MRT
- …
- Disorientation (Nursing Assessment)
- Deficiency of other nutrient elements
- Hodgkin‘s lymphoma