Outcome Verbesserung durch Artificial Intelligence (AI)

Prof. Dr. Jens Meier

Klinik für Anästhesiologie und operative Intensivmedizin

Kepler Universitätsklinikum, Linz

Unsere Vorstellung?

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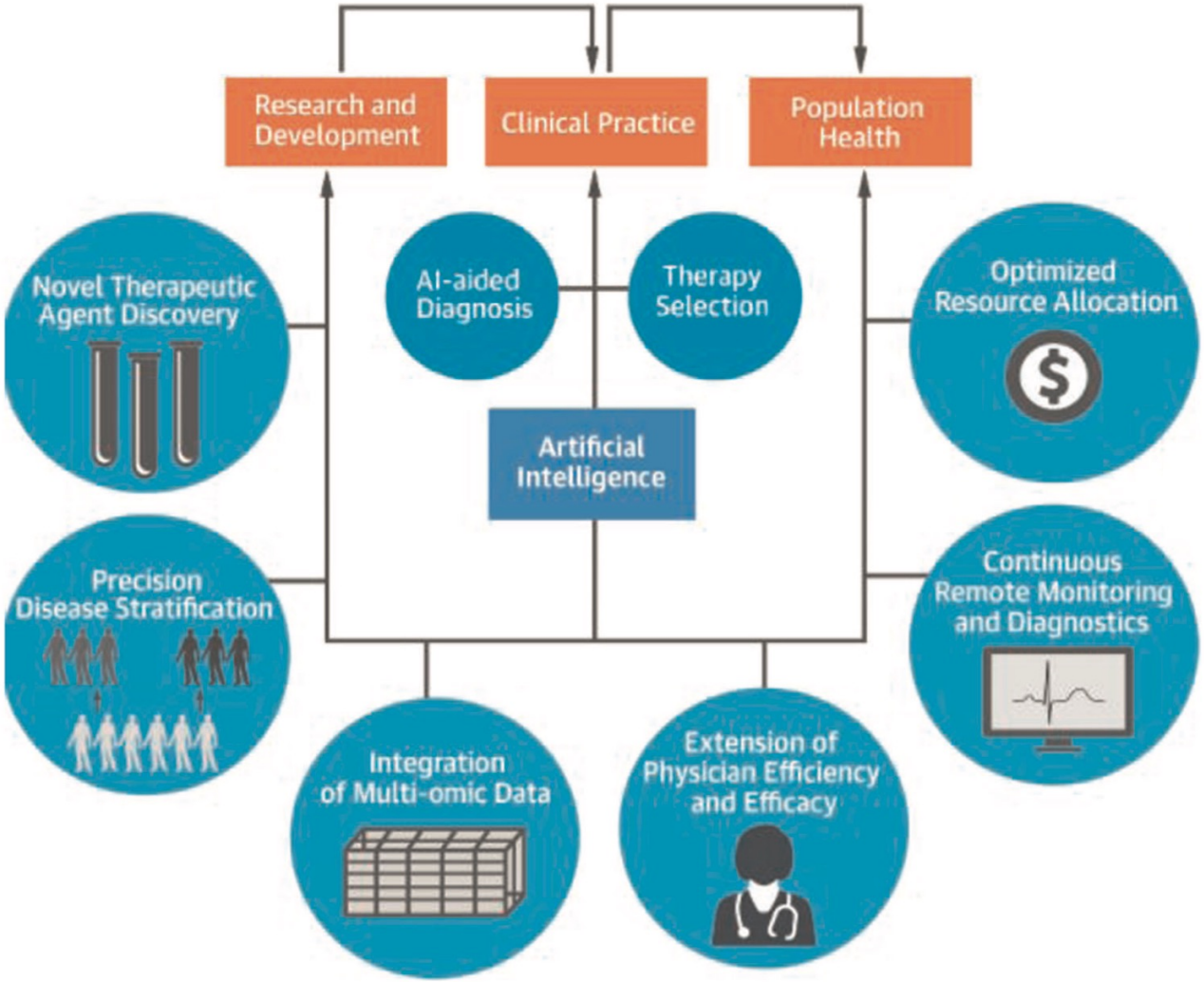
Einsatzmöglichkeiten von ML und KI



Khalsa, J Card Surg, 2020

Die Welt ist viel banaler....

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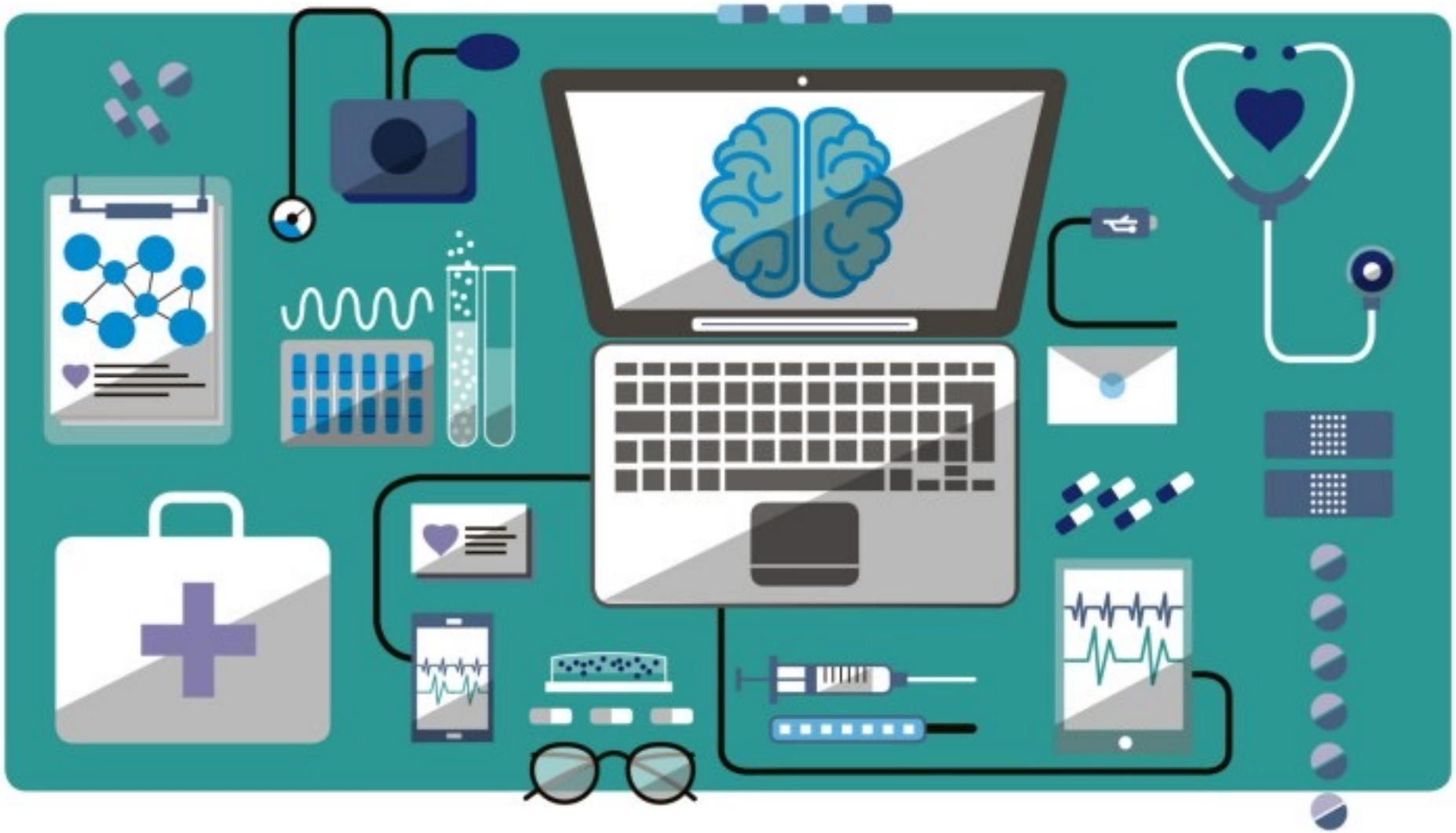

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Choosing Wisely® CELEBRATING 10 YEARS

An initiative of the ABIM Foundation

Choosing Wisely®

Promoting conversations between patients and clinicians

The *Choosing Wisely* initiative continues to help patients choose care that is supported by evidence and is truly necessary, however, ABIM Foundation's focus has evolved to include issues of trust in health care and how trust contributes to better health care outcomes, increased patient satisfaction, and greater physician well-being.

Datenschutzerklärung - Nutzungsbedingungen

Medizin ist multidimensional

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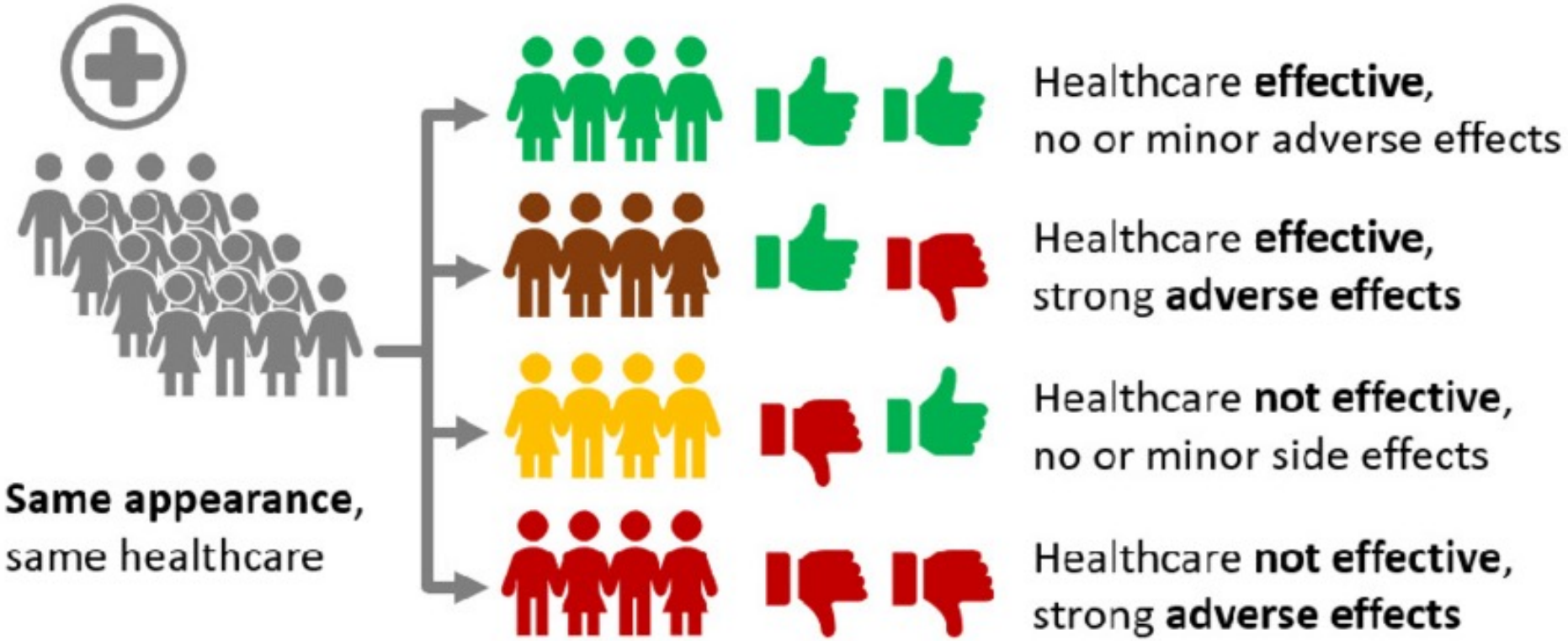

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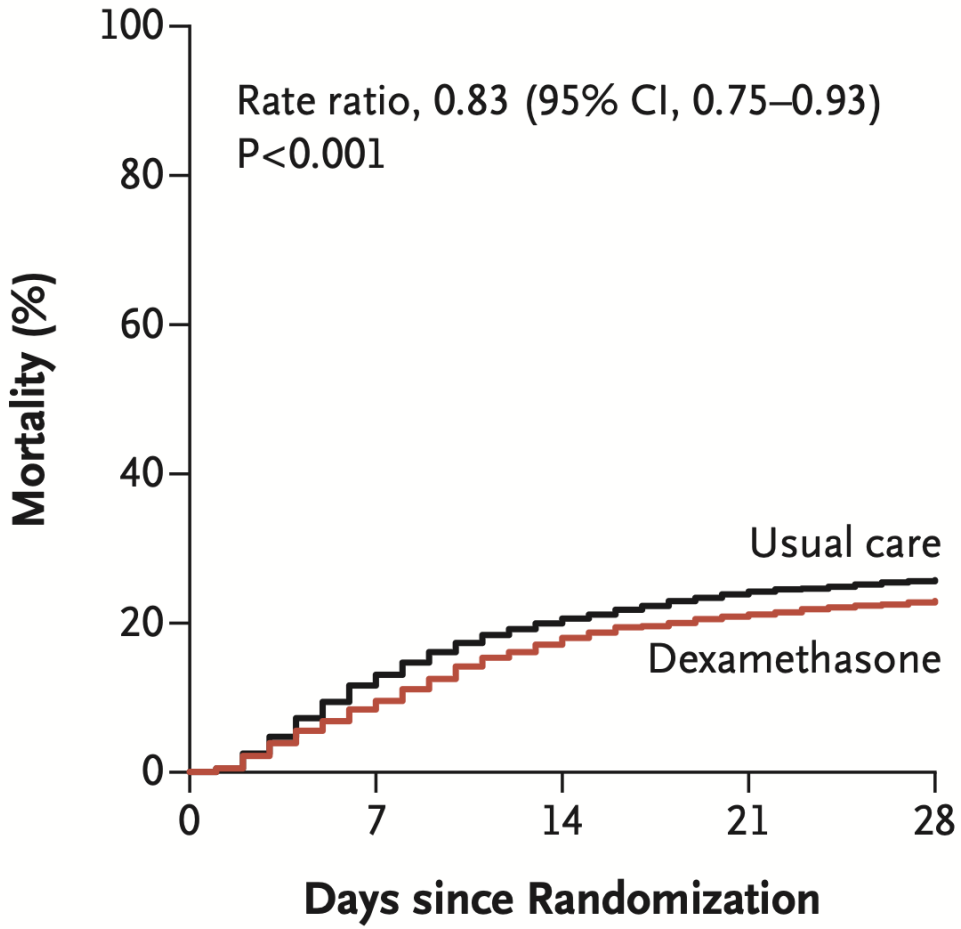
Dexamethasone in Hospitalized Patients with Covid-19

The RECOVERY Collaborative Group*



Wer hat profitiert?

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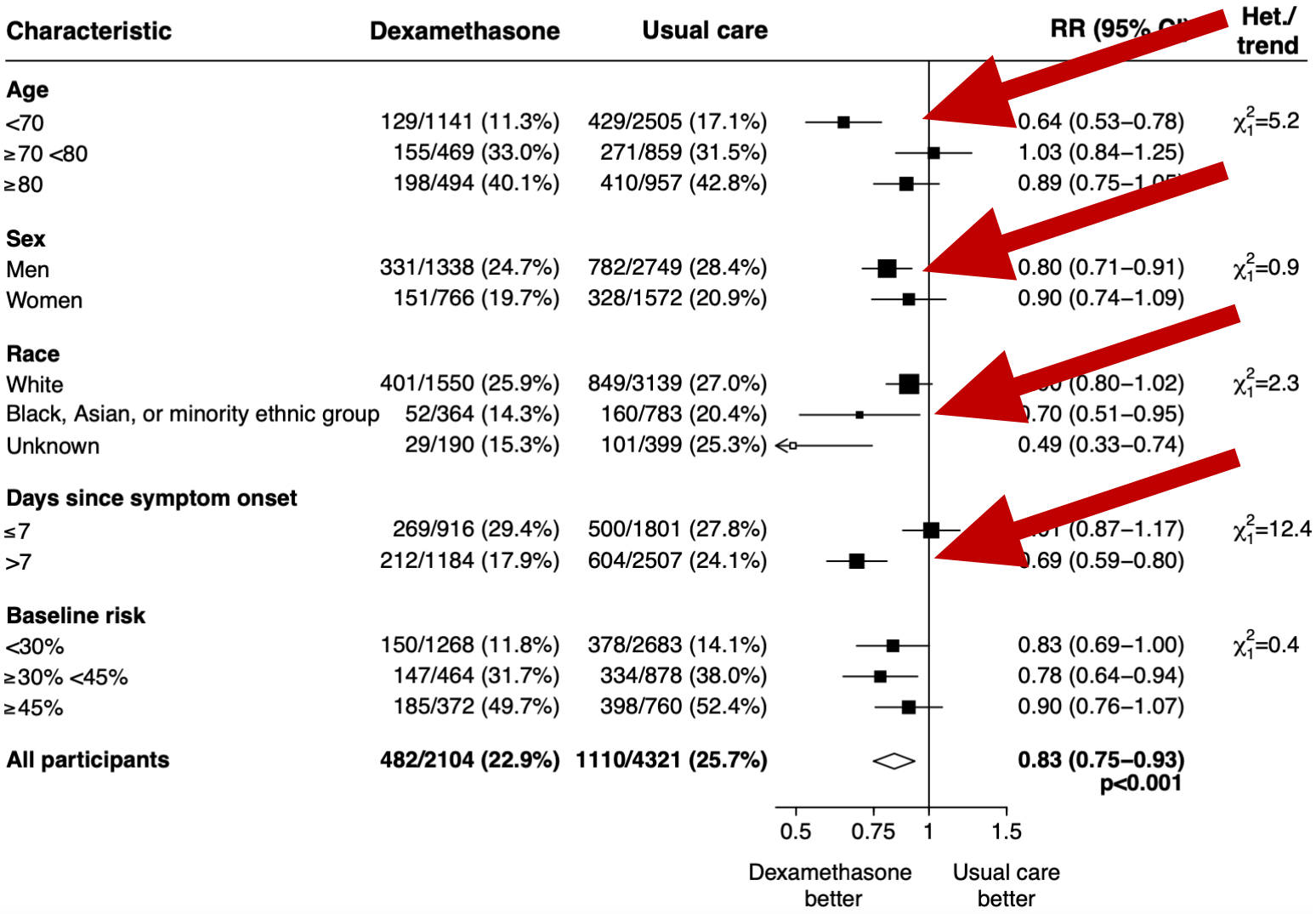
Figure S1: Effect of allocation to dexamethasone on 28–day mortality by other pre–specified baseline characteristics



Meine Patienten?

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Meine Patienten?

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Medizin ist multidimensional

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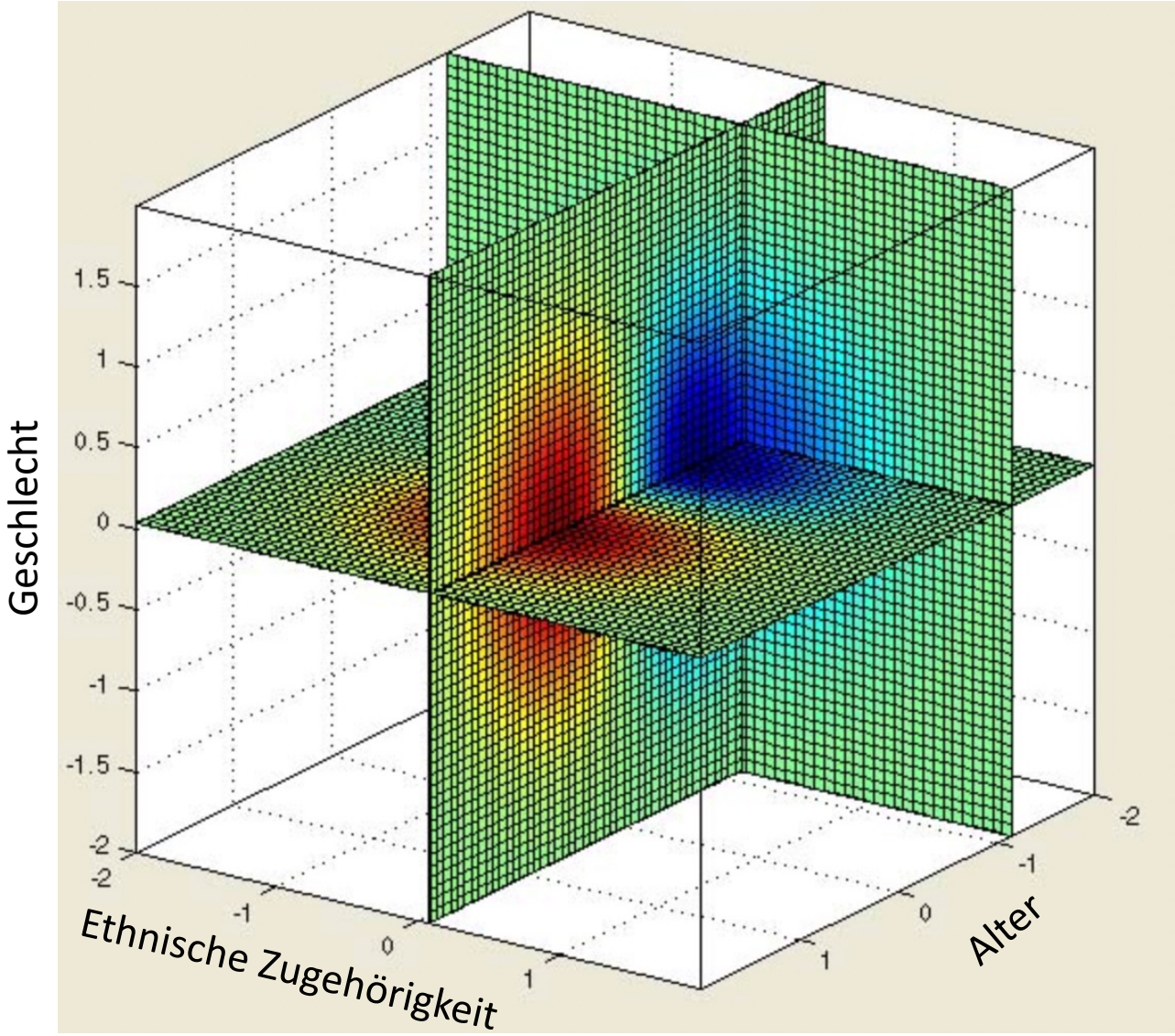

Wie heissen die typischen Methoden?

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Wie heissen die typischen Methoden?

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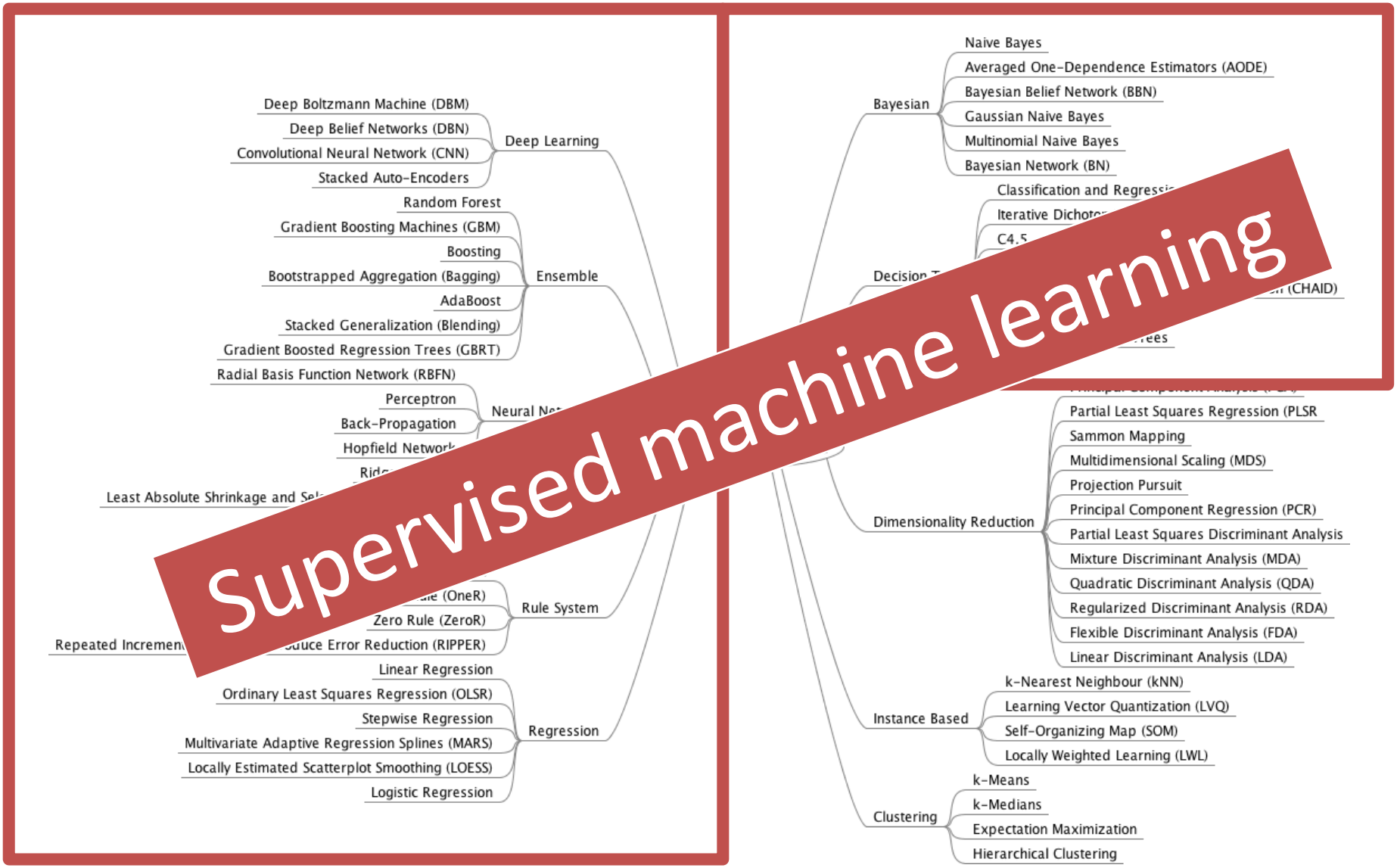
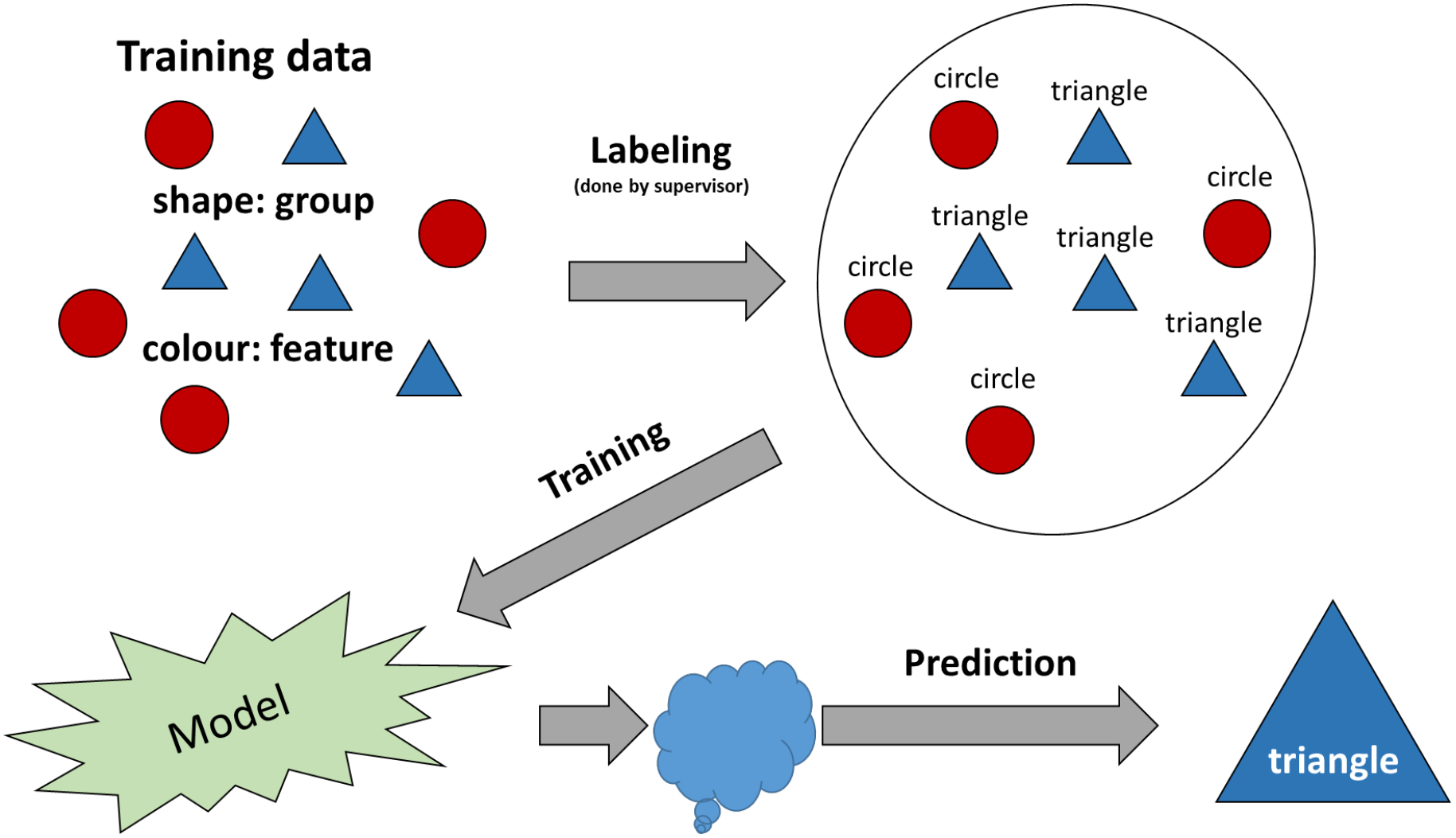


Supervised machine learning

Supervised machine learning



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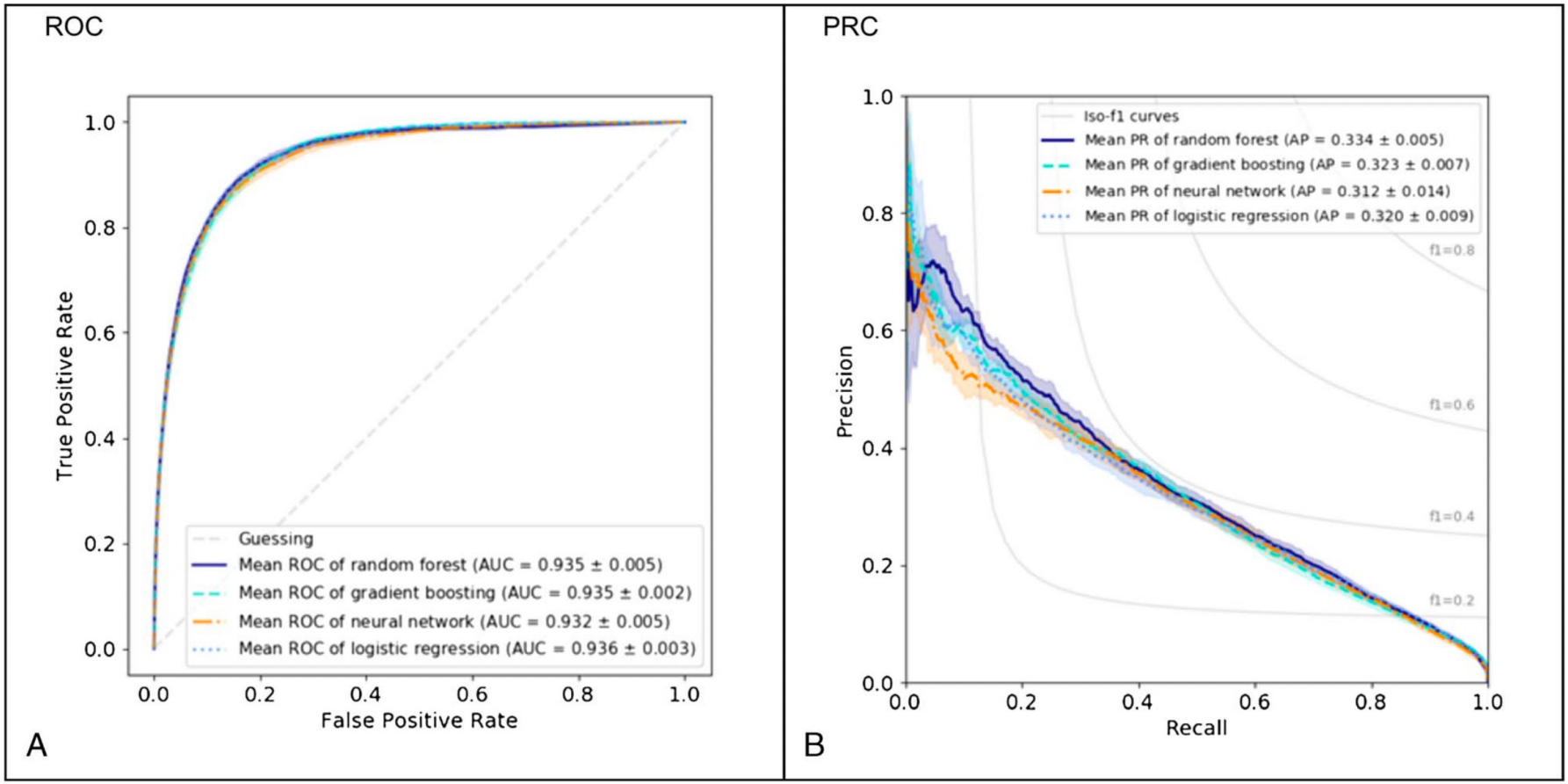
Machine Learning–Based Mortality Prediction of Patients at Risk During Hospital Admission

Kevin M. Trentino, MPH, Karin Schwarzbauer, MSc,† Andreas Mitterecker, MSc,†*
*Axel Hofmann, Dr. rer. medic,‡§|| Adam Lloyd, MBA,¶ Michael F. Leahy, MBChB,**††*
Thomas Tschoellitsch, MD,‡‡ Carl Böck, MSc,‡‡ Sepp Hochreiter, PhD,§§|||| and Jens Meier, MD¶¶



Trentino, J Pat Saf, 2022

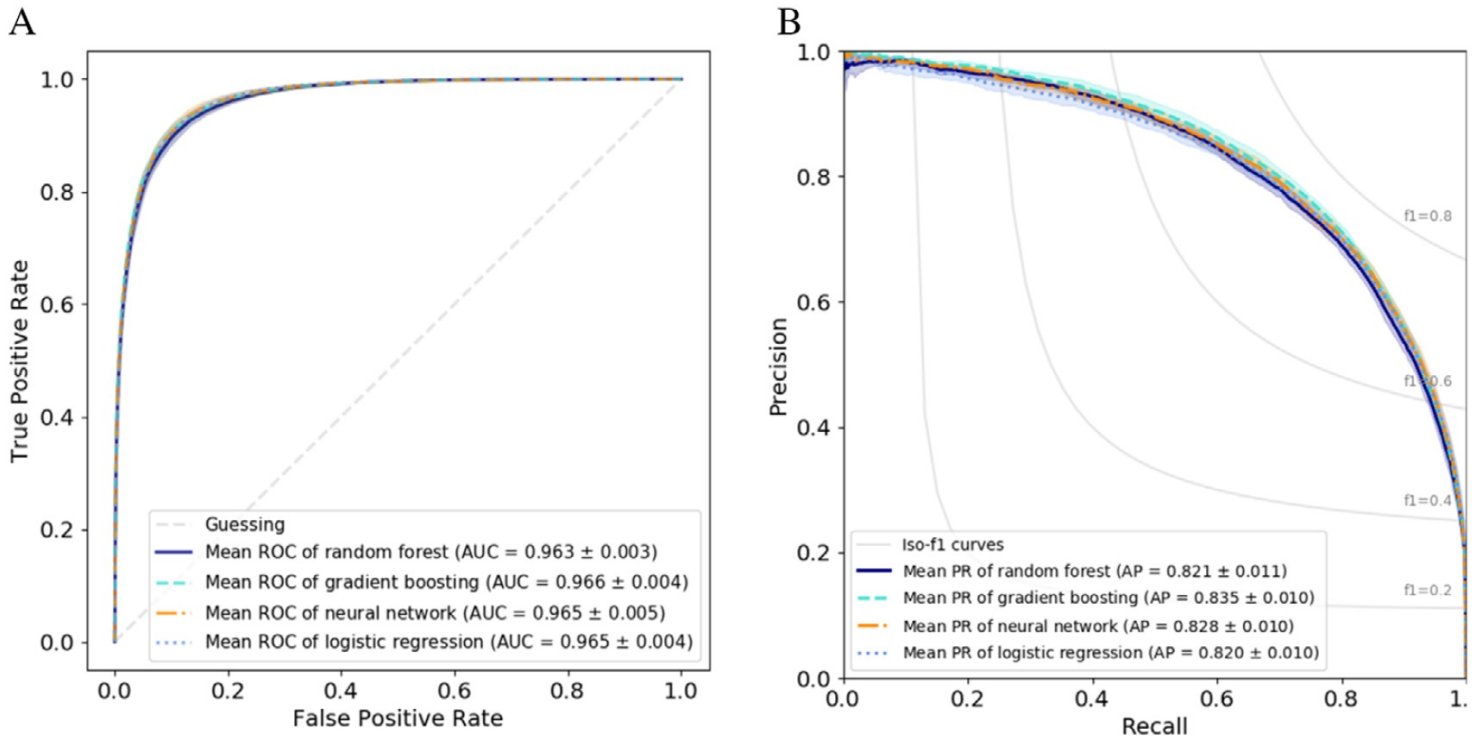
Received: 6 December 2019 | Revised: 10 May 2020 | Accepted: 15 May 2020
DOI: 10.1111/trf.15935

ORIGINAL RESEARCH

TRANSFUSION

Machine learning–based prediction of transfusion

Andreas Mitterecker[1] | Axel Hofmann[2] | Kevin M. Trentino[3] | Adam Lloyd[3] | Michael F. Leahy[4] | Karin Schwarzbauer[1] | Thomas Tschoellitsch[5] | Carl Böck[5] | Sepp Hochreiter[1] | Jens Meier[5]



Mitterecker, Transfusion, 2019

Erklärende Variablen

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TABLE 3 Feature importance for transfusion

Rank	Random forest		Gradient boosting		Logistic regression	
	Feature	**Importance**	**Feature**	**Importance**	**Feature**	**Importance**
1	Hb at admission	137.95	Hb at admission	157.49	Hb at admission	32.43
2	Secondary diagnosis code D64.9: Anemia, unspecified	49.09	Age	101.28	Secondary diagnosis code D64.9: Anemia, unspecified	14.50
3	Age	36.53	CCI	33.03	DRG F10B: Interventional coronary procedures	10.34
4	Secondary diagnosis code D50.0: Iron deficiency	26.04	Secondary diagnosis code D64.9: Anemia, unspecified	15.54	Secondary diagnosis code D50.0: Iron deficiency	9.32
5	CCI	18.31	Hb at admission grouped	12.82	Secondary diagnosis code D62: Acute posthemorrhagic anaemia	6.90
6	Secondary diagnosis code D62: Acute posthemorrhagic anaemia	16.62	Sex	11.53	DRG minor class	6.52
7	Sex	10.16	Secondary diagnosis code Y92.22: Health service area	10.88	DRG F41B: Circulatory disorders, Adm	5.69
8	Secondary diagnosis code D63.0: Anemia neuroplastic disease	7.36	Admission year 8	8.03	DRG I68B: Nonsurgical spinal disorders, minor complexity	5.67

Mitterecker, Transfusion, 2019

Massivtransfusionen in der Herzchirurgie

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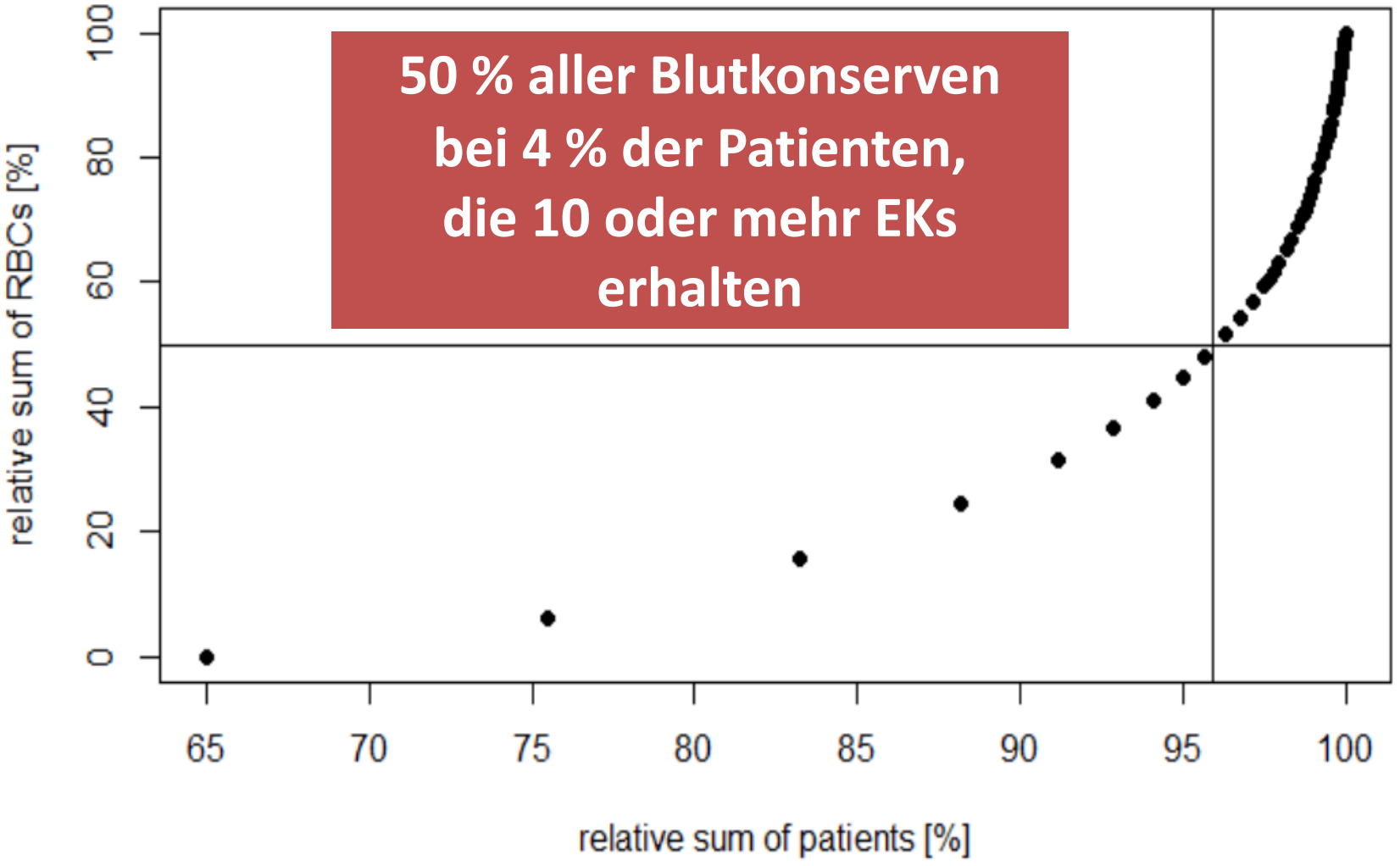

Tschoellitsch, EJA, 2022

Massivtransfusionen in der Herzchirurgie

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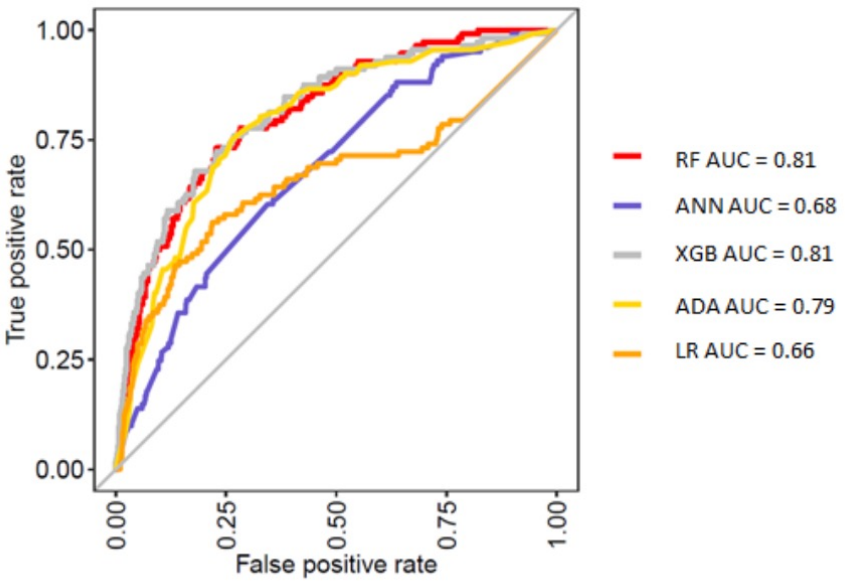

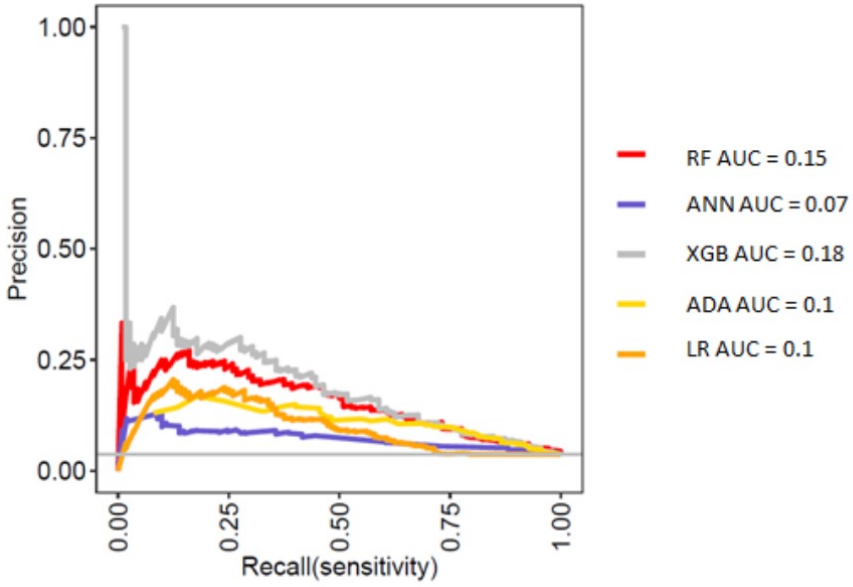

	PPV	NPV	AUC ROC	AUC F_1-score
all features				
RF	0.110 (0.09-0.13)	0.987 (0.98-0.99)	0.810 (0.76-0.86)	0.150
ANN	0.065 (0.05-0.08)	0.977 (0.97-0.98)	0.680 (0.62-0.74)	0.070
XGB	0.126 (0.1-0.16)	0.985 (0.98-0.99)	0.810 (0.76-0.86)	0.180
ADA	0.099 (0.08-0.12)	0.987 (0.98-0.99)	0.790 (0.74-0.84)	0.100
LR	0.090 (0.07-0.11)	0.979 (0.97-0.98)	0.660 (0.6-0.72)	0.100

Tschoellitsch, EJA, 2022

Massivtransfusionen in der Herzchirurgie die acht wichtigsten Features

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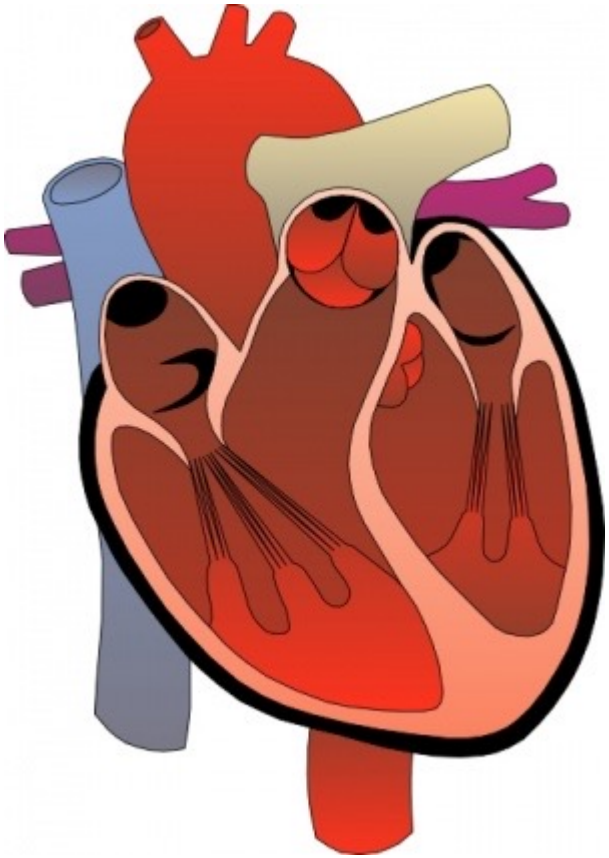
1. EuroSCORE II
2. urgency of surgery
3. ASA score
4. hemoglobin concentration
5. age
6. assist device surgery
7. creatinine level
8. glomerular filtration rate

Tschoellitsch, EJA, 2022

Mortalität bei Herzklappeneingriffen



2229 Patienten

129 präoperative Eigenschaften

Vorhersage der Mortalität

Evaluierte Prädiktionsmodelle:

random forests

neural network

support vector machine

Bodenhofer, EJCTS, 2021

Mortalität bei Herzklappeneingriffen

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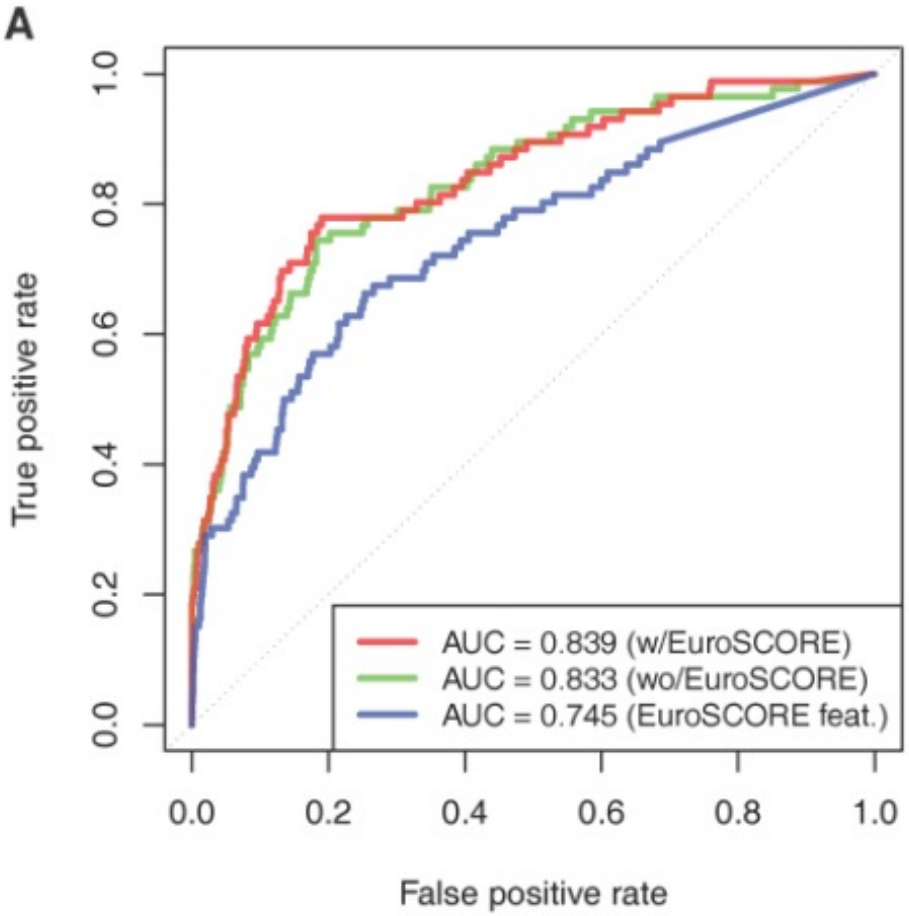

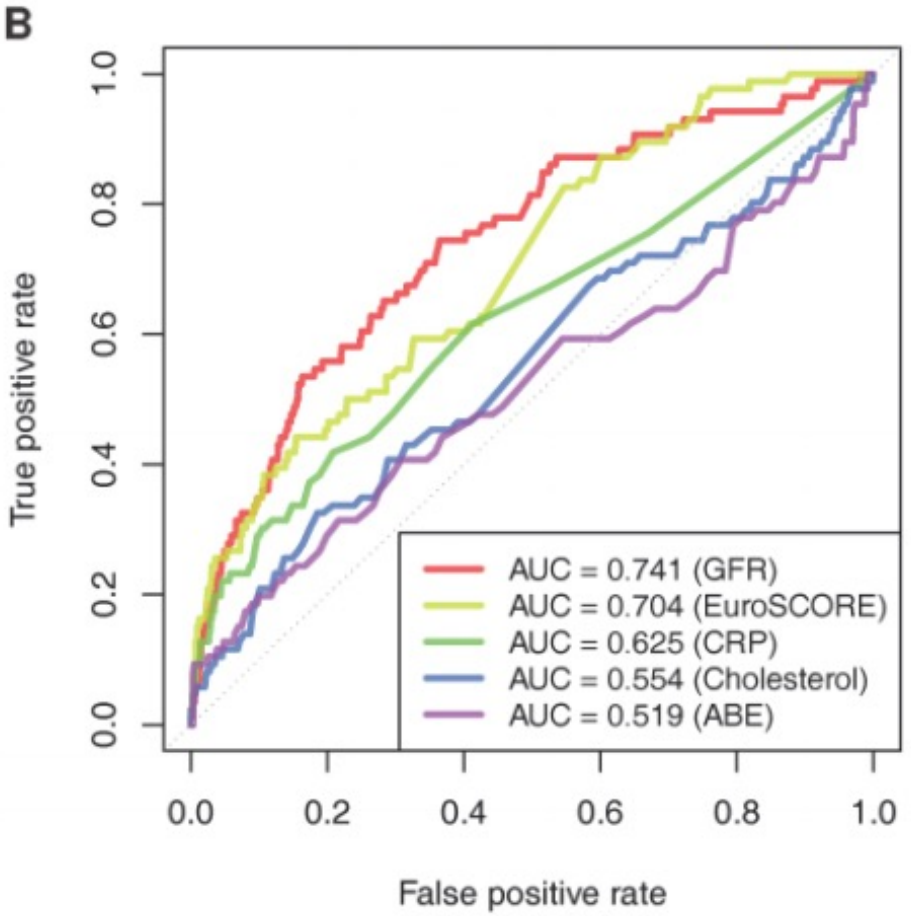

Bodenhofer, EJCTS, 2021

Vorhersage der Mortalität Kardiochirurgie

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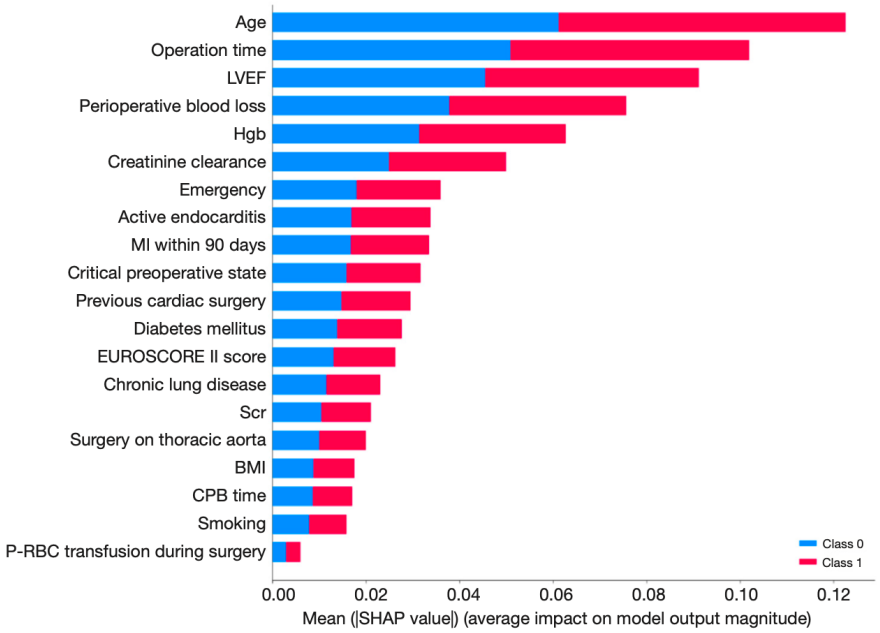
Table 3 The performance for each of the models

Models	Sensitivity	Specificity	Accuracy	AUC
EuroSCORE I	0.61	0.78	0.71	0.70*
EuroSCORE II	0.66	0.79	0.74	0.73*
STS model	0.62	0.79	0.73	0.71*
Logistic regression model	0.71	0.78	0.76	0.74*
Machine learning models with 10-fold cross validation				
Random forest	0.83	0.92	0.89	0.87
Neural network	0.69	0.85	0.80	0.79
Support vector machine	0.75	0.84	0.82	0.81
Gradient boosting machine	0.78	0.85	0.84	0.82

*, P value <0.001 compared to the random forest with 10-fold cross validation. AUC, area under the curve; STS, Society of Thoracic Surgeons.



Fan, Cardiovasc Diagn Ther, 2022

Mortalitätsprädiktion nach Aufnahme auf der kardiochirurgischen ICU

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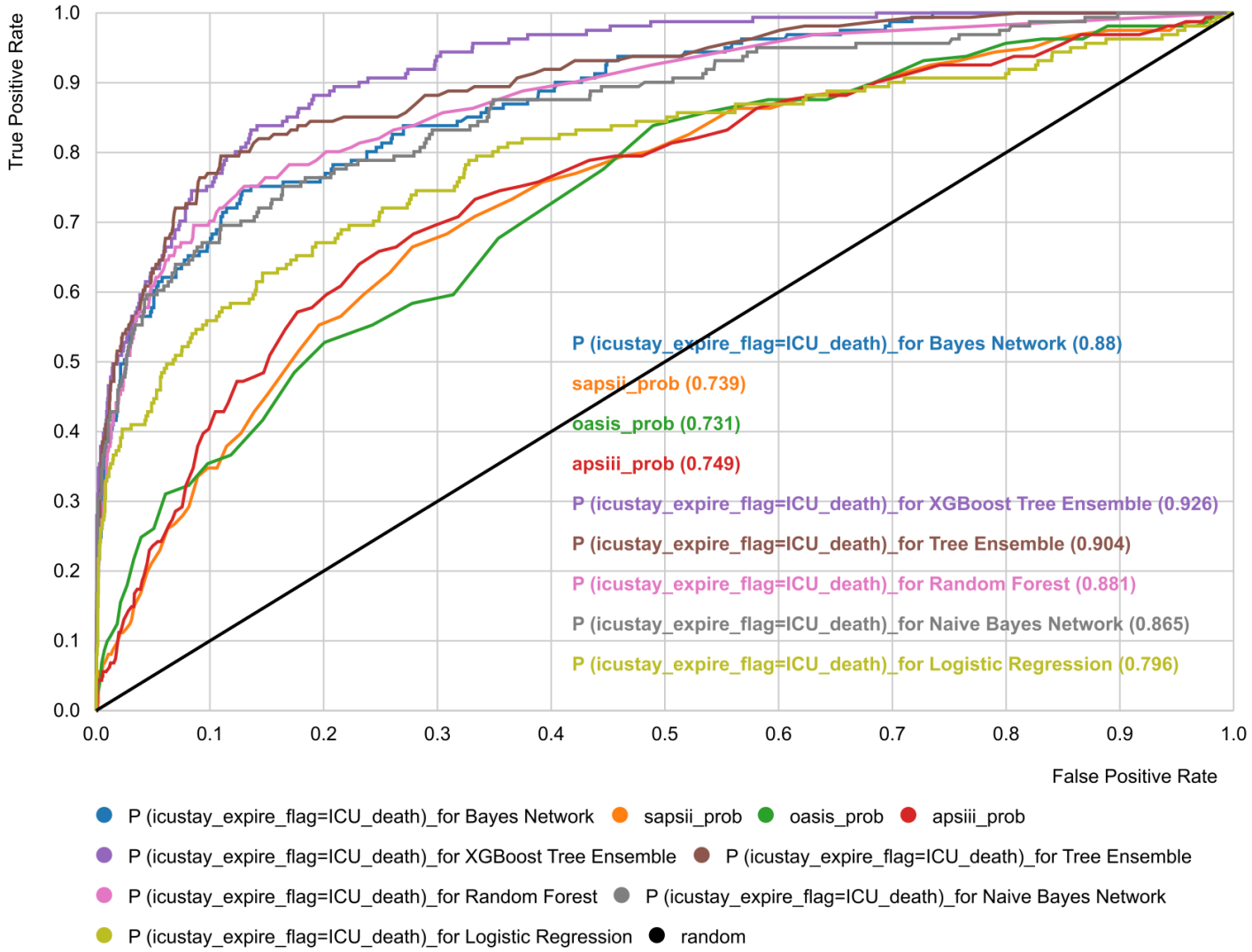
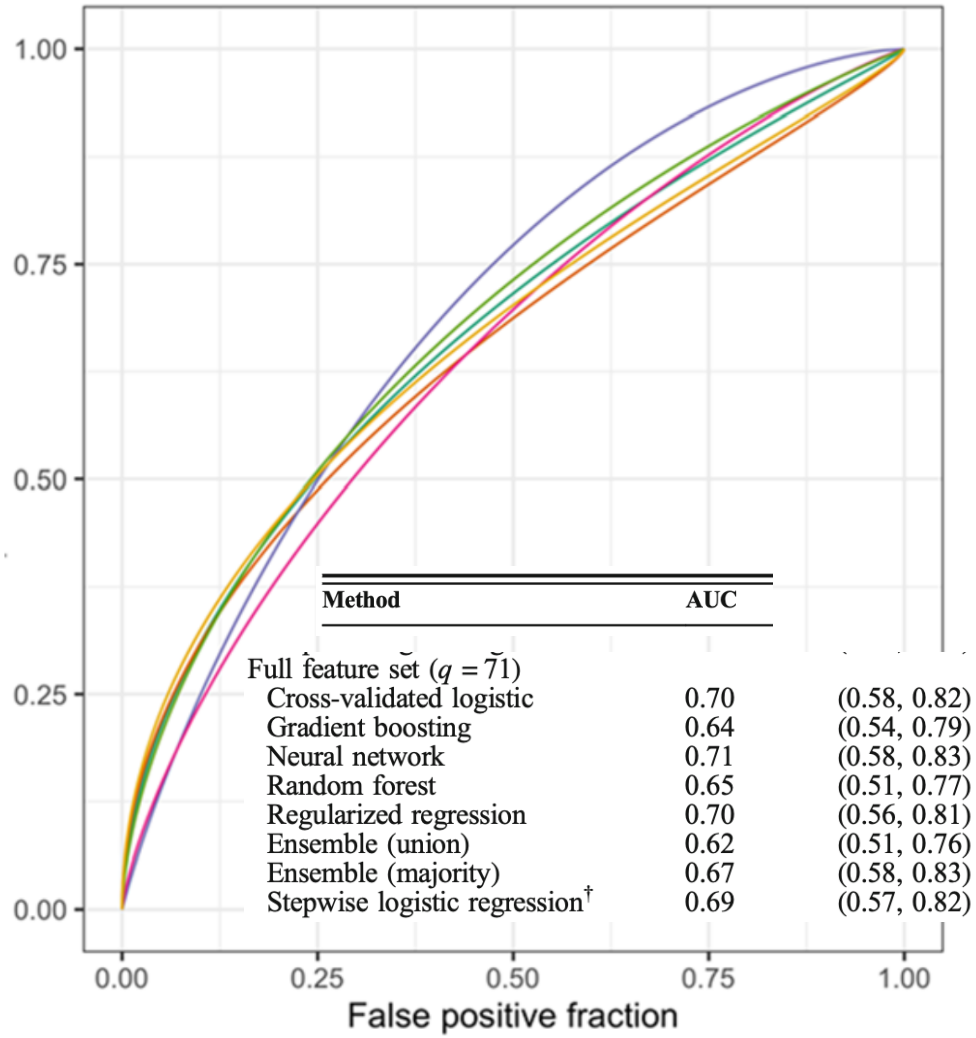


Nistal-Nuño, J Clin Mon Comp, 2022

Vorhersage eines postoperativen Delirs



Method	AUC	
Full feature set ($q = 71$)		
Cross-validated logistic	0.70	(0.58, 0.82)
Gradient boosting	0.64	(0.54, 0.79)
Neural network	0.71	(0.58, 0.83)
Random forest	0.65	(0.51, 0.77)
Regularized regression	0.70	(0.56, 0.81)
Ensemble (union)	0.62	(0.51, 0.76)
Ensemble (majority)	0.67	(0.58, 0.83)
Stepwise logistic regression†	0.69	(0.57, 0.82)

ML model
- Logistic regression
- Gradient boost
- Regularized regression
- Random forest
- Neural network
- Stepwise regression

Racine, JGIM, 2020

Diagnostik des Williams-Beuren Syndroms

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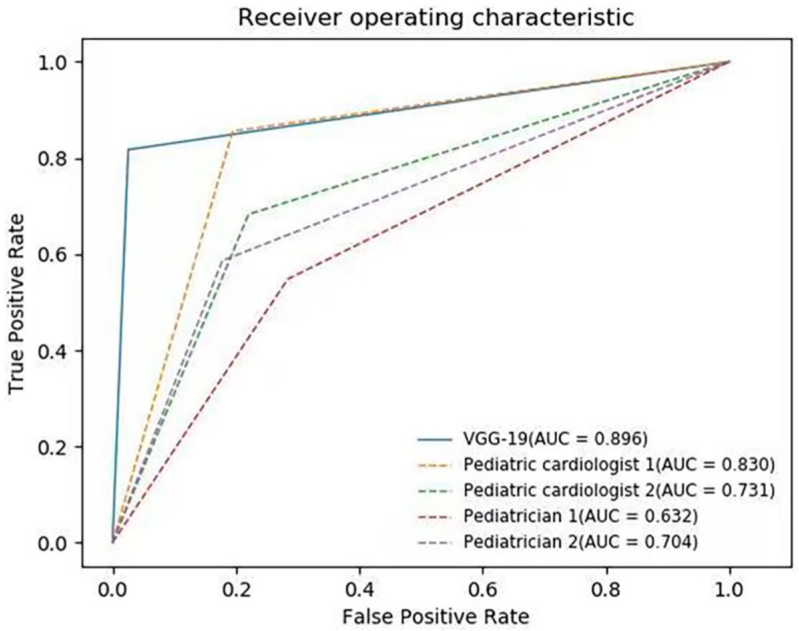
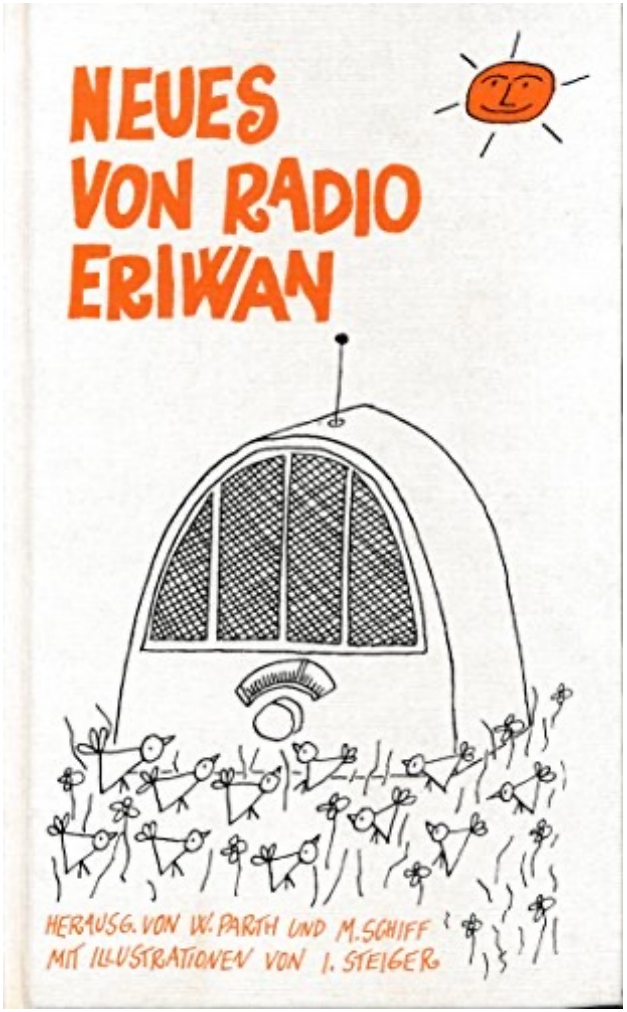
Mikrodeletionssyndromen (Chromosom-7q-Syndrom)



Liu, Frontiers in Ped, 2021

Und wird dadurch outcome verbessert?



Im Prinzip ja, aber wissen es noch nicht….

- alle Studien proof of principle
- kein prospektiver Beweis
- Modelle gelten streng nur für

  trainierte Grundgesamtheit

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