Dysphagia Risk Prediction in Hospitalized Patients

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Multivariable Risk Prediction of Dysphagia in Hospitalized Patients Using Machine Learning

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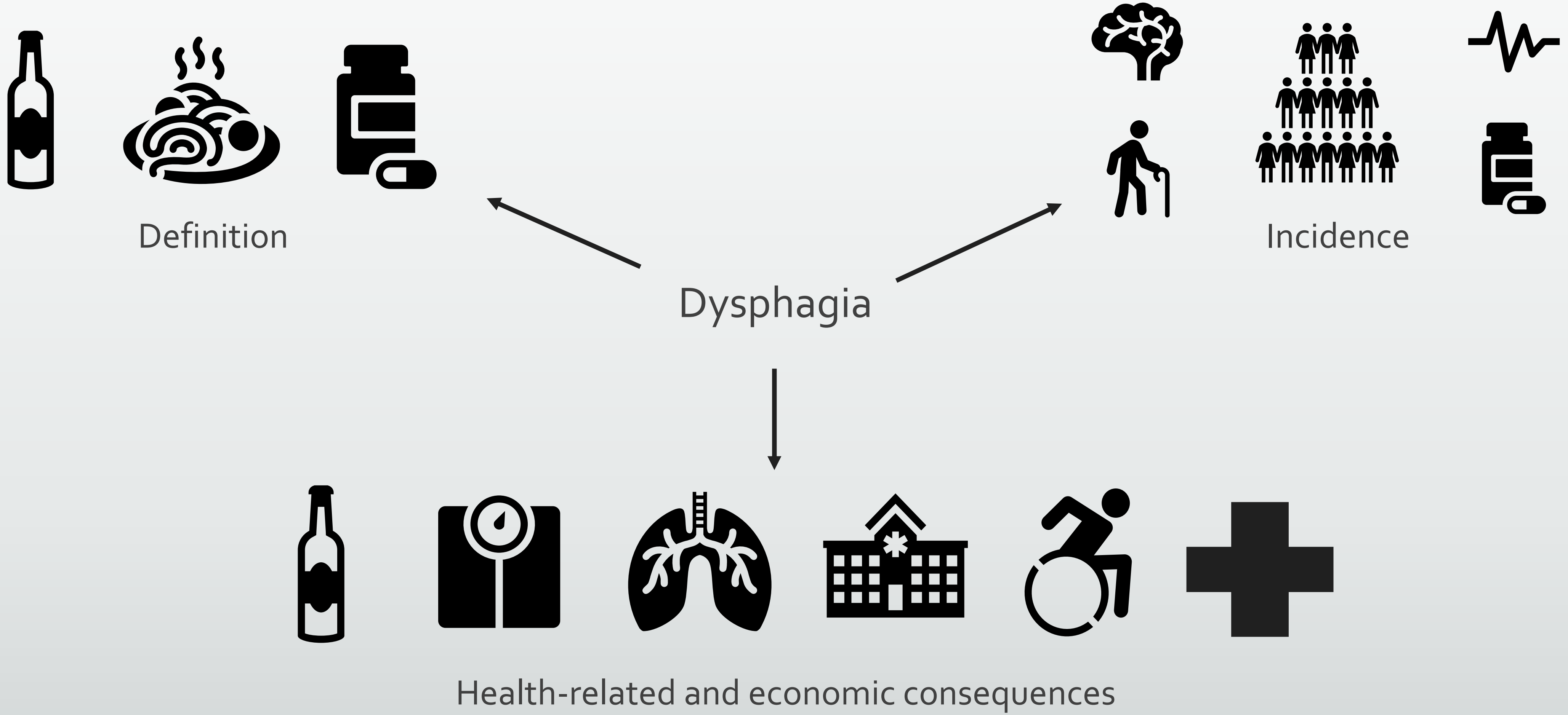
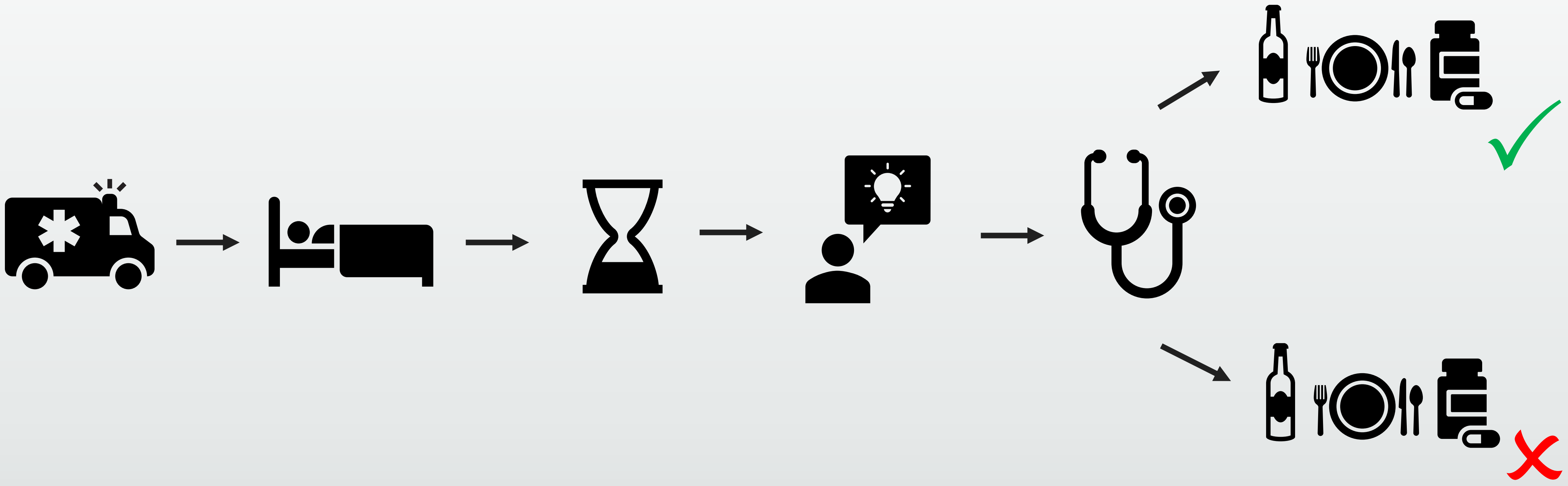
The development and implementation of the study received approval from the Ethics Committee of the Medical University of Graz (30-146 ex 17/18).
We used the TRIPOD statement [1] as guideline for developing, validating and reporting the models.

Medical Background – Dysphagia is the difficulty or total incapability of swallowing liquids, food or medication.



Status Quo – Various screening tools, scales and scores are used to detect and diagnose swallowing disorders.



Literature - Previous prediction models did not use machine learning methods and are commonly based on *additional* clinical examinations

State-of-the-art of dysphagia prediction

- Zhou et al. [2], 2019
  - Sensitivity of 68.5 %
  - Specificity of 89.0 %
- Gandolfo et al. [3], 2019
  - Sensitivity of 67.0 %
  - Specificity of 95.7 %
  - Area under the receiver operating characteristic curve (AUROC) of 0.79
- Grimm et al. [4], 2015
  - AUROC of 0.75

Objective

- Development of a predictive model that identifies patients with an increased risk for dysphagia
- Identification at an early stage of hospitalization to enable diagnostic, preventive and therapeutic steps
- Use of routinely documented electronic health records for prediction

Material & Methods I

- Data set
  - Routine longitudinal clinical data of the hospital information system (openMEDOCS) of the Styrian Hospitals Limited Liability Company (KAGes)
- Outcome definition
  - ICD-10 coded diagnosis for dysphagia (R13) or aspiration pneumonia (J69)
  - Nursing diagnosis of swallowing disorder
- Study cohort
  - 12,068 patients with dysphagia
  - 21,716 patients without dysphagia

Material & Methods II

- Feature set (n = 886)

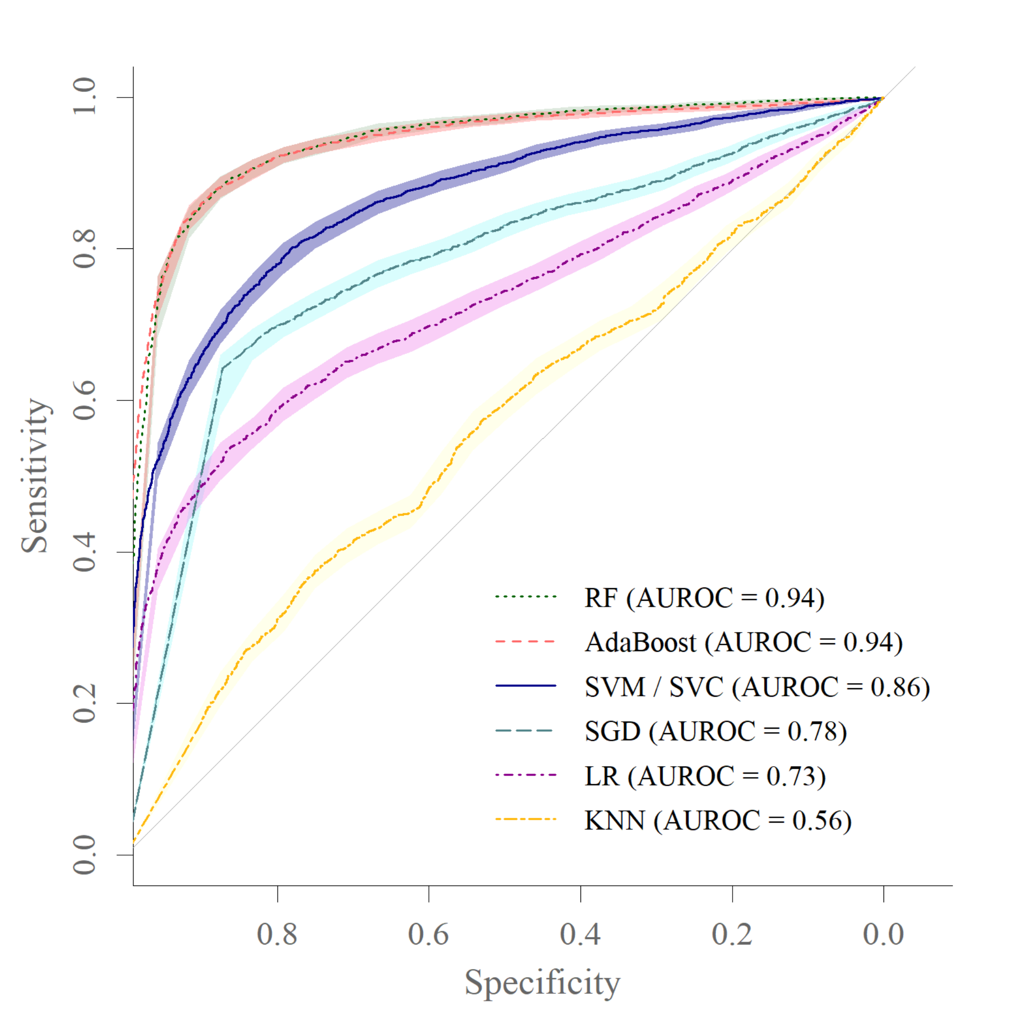
Data type	Description	n
Demographic Data	e. g. age, gender	28
Diagnosis Codes	ICD-10 Codes e. g. malignant neoplasm of hypopharynx, Groups of ICD-10 Codes e.g. cerebrovascular diseases	286
Procedures Codes	e. g. spine surgery, magnetic resonance imaging	103
Laboratory Data	e. g. thrombocytes, creatine	190
Nursing Protocols	e. g. body mass index, movement disorders	92
Administrative Data, Indices	e. g. Charlson Comorbitity Index, number of hospital stays	25
Medication Data	e. g. calcium, antipsychotics	162

Material & Methods III

- Data set split
  - Training data set – 80% of the cases (n = 27,027)
  - Test data set – 20% of the cases (n = 6,757)
- Methods
  - Random Forest (RF)
  - Adaboost Classifier (AdaBoost)
  - Support Vector Machine (SVM)
  - Linear Model with Stochastic Gradient Descent (SGD)
  - Logistic Regression (LR)
  - K-Nearest Neighbour (KNN)

- Training via 10-fold cross-validation, preserving the relative class distributions
- Sensitivity and specificity were selected using the closest topleft method

Results I – Comparing the models, the tree-based methods RF and AdaBoost achieved the highest AUROC of 0.94



Results II – Performances of the different machine learning models on the held-out test data; RF and AdaBoost outperformed previous prediction models from literature

Model (Python module)	AUROC	Acc.	Sens.	Spec.	Prec.
RF[1] (ensemble)	**0.94**	0.88	0.88	0.88	0.80
AdaBoost[1] (ensemble)	**0.94**	0.88	0.88	0.89	0.81
SVM[2] (svm)	0.86	0.79	0.80	0.78	0.68
SGD[2] (linear_model)	0.78	0.77	0.70	0.81	0.67
LR[2] (linear_model)	0.73	0.71	0.62	0.76	0.59
KNN[2] (neighbors)	0.56	0.55	0.55	0.55	0.41

[1] RF and AdaBoost were trained and tested on the data set with 886 features. [2] SVM, SGD, LR and KNN were trained and tested on the scaled and encoded data set with 1,783 features

Next steps

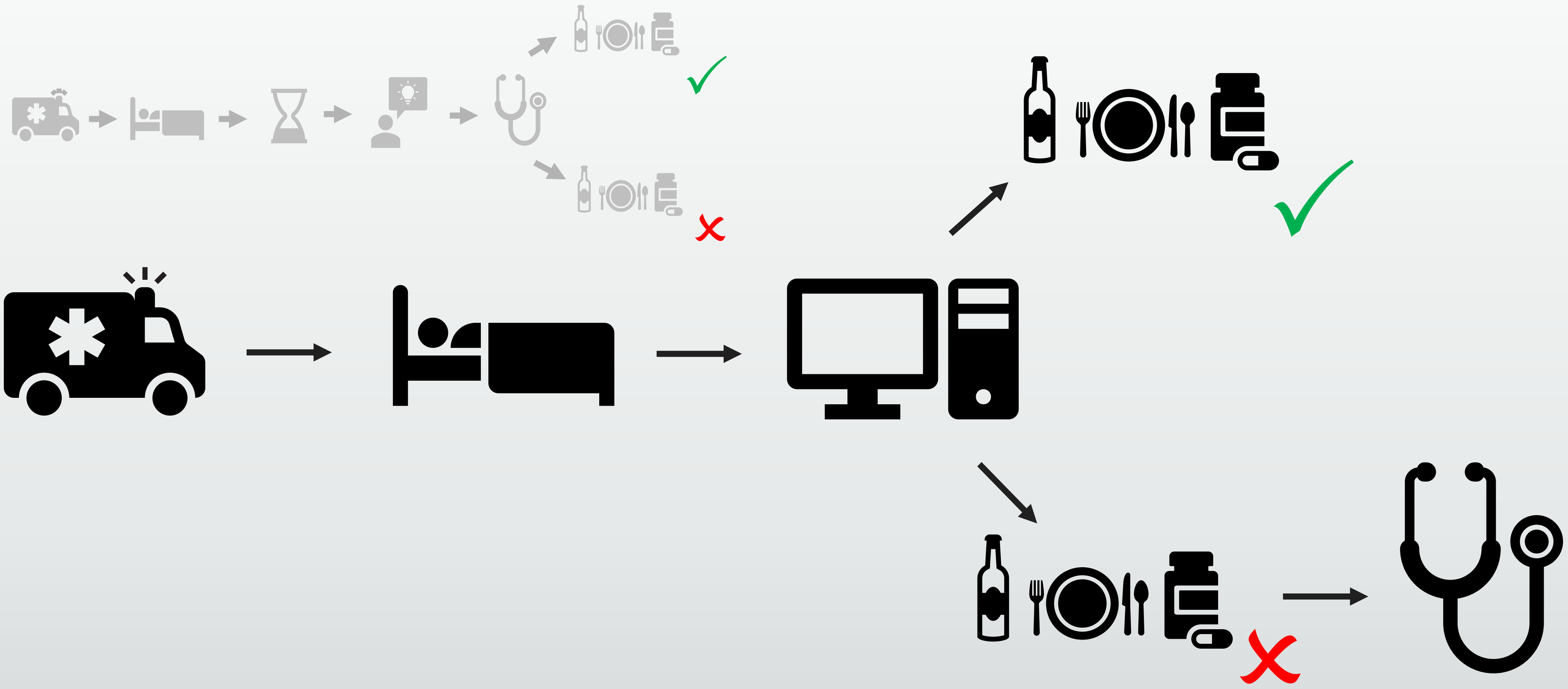
Limitations

- Missing data
- Misdiagnosed patients in the control group

Future work

- Deep learning methods
- Feature extraction and selection
- Real-time prediction
- Model evaluation

Vision – A real-time dysphagia risk prediction to provide a reliable support at the time the patient needs it



Literature

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