Dysphagia Risk Prediction in Hospitalized Patients

Speaker: Anna Maria Lienhart, BSc
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Multivariable Risk Prediction of Dysphagia in Hospitalized Patients Using Machine Learning

Anna Maria LIENHART\textsuperscript{a,1}, Diether KRAMER\textsuperscript{a}, Stefanie JAUK\textsuperscript{a}, Markus GUGATSCHKA\textsuperscript{b}, Werner LEODOLTER\textsuperscript{a} and Thomas SCHLEGL\textsuperscript{c}

\textsuperscript{a} Styrian Hospitals Limited Liability Company (KAGes), Graz, Austria
\textsuperscript{b} Division of Phoniatics, Medical University of Graz, Austria
\textsuperscript{c} University of Applied Sciences St. Pölten, Austria

\textsuperscript{1} Corresponding Author: Anna Maria Lienhart, KAGes-Management, Informations- und Prozessmanagement, A-8010 Graz, Billrothgasse 18a, E-Mail: AnnaMaria.Lienhart2@klinikum-graz.at

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)

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

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<thead>
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<tbody>
<tr>
<td>RF¹ (ensemble)</td>
<td>0.94</td>
<td>0.88</td>
<td>0.88</td>
<td>0.88</td>
<td>0.80</td>
</tr>
<tr>
<td>AdaBoost¹ (ensemble)</td>
<td>0.94</td>
<td>0.88</td>
<td>0.88</td>
<td>0.89</td>
<td>0.81</td>
</tr>
<tr>
<td>SVM² (svm)</td>
<td>0.86</td>
<td>0.79</td>
<td>0.80</td>
<td>0.78</td>
<td>0.68</td>
</tr>
<tr>
<td>SGD² (linear_model)</td>
<td>0.78</td>
<td>0.77</td>
<td>0.70</td>
<td>0.81</td>
<td>0.67</td>
</tr>
<tr>
<td>LR² (linear_model)</td>
<td>0.73</td>
<td>0.71</td>
<td>0.62</td>
<td>0.76</td>
<td>0.59</td>
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<tr>
<td>KNN² (neighbors)</td>
<td>0.56</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.41</td>
</tr>
</tbody>
</table>

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


