An ensemble model accurately predicts blood transfusion after instrumented spinal fusion

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INTRODUCTION:

Allogeneic blood transfusion after spinal fusion is associated with increased rate of post-operative complications and length of stay. Additionally, the cost of stay for a patient who receives blood transfusion after spinal fusion is significantly higher than for those who do not receive transfusion. It would be of utility to pre-operatively determine which patients are at increased risk of requiring blood transfusion after instrumented spinal fusion. We aim to develop a machine learning-driven ensemble model for prediction of blood transfusion after instrumented spinal fusion. Additionally, we aim to identify novel features important for model performance.

METHODS:

Adult patients who underwent instrumented spinal fusion at a tertiary care academic medical center between 2013-2020 were included. The primary outcome was post-operative packed red blood cell transfusion during the index hospitalization. We developed an ensemble machine learning model predicting complication risk using AutoPrognosis, an automated machine learning framework that configures the optimally performing ensemble of machine learning-based prognostic models. We compared this model with logistic regression and four standard machine learning models (XGBoost, gradient boosting, AdaBoost, random forest). Discrimination was assessed using area under the receiver operating characteristic curve (AUROC). Calibration was assessed using calibration slope, calibration intercept, and Brier scores. We also ranked importance of each included feature for model performance utilizing a partial dependence function. This was repeated for cervical and lumbar fusion subgroups.

RESULTS:

A total of 2,053 patients met inclusion criteria; 1,024 patients underwent cervical fusion and 836 patients underwent lumbar fusion. Two hundred and four (9.9%) patients required post-operative blood transfusion; 4.1% and 9.6% of patients required transfusion in the cervical and lumbar cohorts, respectively. When trained on the entire cohort, the ensemble model was the best performing model (AUROC: 0.909). This model was well-calibrated with a calibration slope of 1.11, calibration intercept of -0.02, and Brier score of 0.059. The following features were important for the ensemble model: spinopelvic fixation, spinal deformity, spinal malignancy, fusion spanning $\geq$2 junctions, thoracic fusion, posterior instrumentation, corpectomy, psychiatric comorbidity (Table 1). The ensemble model resulted in AUROC of 0.890 and 0.789 when retrained on the cervical and lumbar fusion subgroups, respectively. The most important features for the cervical cohort included spinal infection, posterior fusion, spinal trauma, and spinal deformity (Table 2). The most important features for the lumbar subgroup included spinal infection, posterior fusion, thoracic fusion, and male sex (Table 3). Number of fused levels and pre-operative hemoglobin were the most important continuous features for the overall cohort and the cervical/lumbar subgroups.

DISCUSSION AND CONCLUSION:

We report a well-calibrated ensemble machine learning algorithm for prediction of post-operative blood transfusion after instrumented fusion. This model has excellent discrimination with an AUROC of 0.909; it similarly performs well for cervical and lumbar fusion. We additionally identify novel features important for model performance for each subgroup. Accurate pre-operative prediction of transfusion requirement may allow for pre-operative optimization and improved resource utilization. Furthermore, intra-operative measures can be taken to reduce risk of transfusion (e.g. tranexamic acid administration).

Table 1. Relative feature importance for transfusion after instrumented spinal fusion

Feature	Rank in ensemble model	Change to risk prediction
Binary features		
Spinopelvic fixation	1	0.0706
Fusion across ≥3 sections	2	0.0598
Cervical fusion	3	-0.0430
Posterior instrumentation	4	0.0313
Thoracic fusion	5	0.0289
Psychiatric comorbidity	6	0.0227
Indication: degenerative disease	7	-0.0225
Corpectomy	8	0.0146
Indication: deformity	9	0.0145
Indication: malignancy	10	0.0107
Continuous features		
Number of levels fused	1	0.1341
Pre-operative hemoglobin	2	-0.0980
Pre-operative WBC count	3	0.0170
Body mass index	4	-0.0112
Age	5	-0.0071

WBC: white blood cell

Table 2. Relative feature importance for transfusion after instrumented cervical fusion

Feature	Rank in ensemble model	Change to risk prediction
Binary features		
Indication: infection	1	0.0354
Combined anterior-posterior approach	2	0.0220
Pre-operative non-motor neurologic symptoms	3	-0.0130
Posterior instrumentation	4	0.0087
Indication: deformity	5	0.0078
Active malignancy	6	0.0070
Pre-operative motor deficit	7	0.0051
Indication: trauma	8	0.0044
Male sex	9	0.0044
Fixation for spinal fracture	10	0.0044
Continuous features		
Pre-operative hemoglobin	1	-0.0377
Pre-operative WBC count	2	0.0147
Number of levels fused	3	0.0064
Age	4	0.0063
Charlson comorbidity index	5	0.0043

WBC: white blood cell

Table 3. Relative feature importance for transfusion after instrumented lumbar fusion

Feature	Rank in ensemble model	Change to risk prediction
Binary features		
Indication: infection	1	0.0380
Combined anterior-posterior approach	2	0.0288
Indication: deformity	3	0.0131
Posterior instrumentation	4	0.0107
Corpectomy	5	0.0102
Interbody fusion	6	0.0068
Thoracic fusion	7	0.0062
Junctional fusion	8	0.0052
Active malignancy	9	0.0050
Male sex	10	0.0049
Continuous features		
Pre-operative WBC count	1	0.0355
Number of levels fused	2	0.0206
Pre-operative hemoglobin	3	-0.0162
Age	4	0.0147
Charlson comorbidity index	5	0.0038

WBC: white blood cell