# Predicting mechanical complications after adult spinal deformity surgery using a machine learning approach

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**Research Article**

**Keywords:** machine learning, adult spinal deformity, mechanical complication, body mass index, bone mineral density, random forest

**Posted Date:** February 7th, 2022

**DOI:** https://doi.org/10.21203/rs.3.rs-1300769/v1

# Abstract

Several methods have been developed to prevent mechanical complications after adult spinal deformity (ASD) surgery, but mechanical complications remain frequent in ASD surgery. A modified Global Alignment and Proportion (GAP) scoring system in addition to body mass index (BMI) and bone mineral density (BMD; the GAPB system), was developed to predict mechanical complications after ASD surgery. This study aimed to create an ideal machine learning model to predict mechanical complications in ASD surgery based on GAPB factors. Between January 2009 and December 2018, 238 consecutive patients with ASD, who received at least four-level fusions and were followed-up for ≥2 years, were included in the study. Data collection included demographic and radiological examinations. The data were stratified into training (n=167, 70%) and test (n=71, 30%) sets and input to machine learning algorithms, including logistic regression, random forest gradient boosting system, and deep neural network. The patients' average age and follow-up period were 67.1±6.17 years and 28.54±4.25 months, respectively. BMI, BMD, the relative pelvic version score, the relative lumbar lordosis score, and the relative sagittal alignment score of the GAP score were significantly different in the training and test sets ($p<0.05$) between the complication and no complication groups. In the training set, the AUCs for logistic regression, gradient boosting, random forest, and deep neural network were 0.871 (0.817–0.925), 0.942 (0.911–0.974), 1.000 (1.000–1.000), and 0.947 (0.915–0.980), respectively, and the accuracies were 0.784 (0.722–0.847), 0.868 (0.817–0.920), 1.000 (1.000–1.000), and 0.856 (0.803–0.909), respectively. In the test set, the AUCs were 0.785 (0.678–0.893), 0.808 (0.702–0.914), 0.810 (0.710–0.910), and 0.730 (0.610–0.850), respectively, and the accuracies were 0.732 (0.629–0.835), 0.718 (0.614–0.823), 0.732 (0.629–0.835), and 0.620 (0.507–0.733), respectively. The random forest achieved the best predictive performance on the training and test dataset. This study created a comprehensive model to predict mechanical complications after ASD surgery, and the random forest showed the best predictive ability. This information can be used to prevent mechanical complications during ASD surgery.


# Introduction

Adult spinal deformity (ASD) is a disorder that is globally prevalent. (1) It is characterized by significant low back/leg pain, stooping, and poor health-related quality of life (HRQOL) in patients with ASD compared with the general population. Although spinal surgery for correcting ASD is invasive, it is effective in symptomatic cases where conservative treatment is often unsuccessful. (2) However, the surgical correction of ASD is a difficult procedure that is known to have a high risk of complications during the surgery and postoperative period. (3) The estimated incidence of morbidity and mortality due to surgical correction is 31.3% and 0.5%, respectively. (3) Since there are many complications of ASD surgery, there are some ideal surgical target parameters such as SRS-Schwab classification and age-adjusted alignment goals. (4, 5) There are also formulas, such as the Global Alignment and Proportion (GAP) score, which predict mechanical complications after ASD surgery, and the GAPB system, which combines body mass index (BMI) and bone mineral density (BMD) with the GAP score. (6, 7)

Most studies have been performed using simple statistical techniques. such as linear regression and logistic regression, and in practice, they provide information on mean values that do not properly reflect the characteristics of the population. However, in the past few years, the medical field has increasingly adopted

computational techniques that allow the processing of large amounts of data and the creation of complex mathematical models that describe the relationships between different variables. The idea behind artificial intelligence is to create a system that mimics the natural ability of humans to continuously learn as they access new data and apply it to new situations in the future. Our research team reported that GAPB predicts mechanical complications better than other systems related to ASD. (6) This study aimed to create an ideal machine learning model to predict mechanical complications in ASD surgery based on the GAPB system.

## Materials And Methods

# Patient population

This was a retrospective analysis of surgically treated patients with ASD enrolled from 2009 to 2017. This study was approved by the institutional review board of the hospital. Written informed consent was obtained from all participants. The inclusion criteria were as follows: patients who underwent ASD surgery to correct sagittal imbalance; the presence of one of the following radiological criteria, including coronal Cobb angle >20°, sagittal vertical axis >5 cm, pelvic tilt (PT) >25°, and/or thoracic kyphosis > 60°, and/or pelvic incidence minus lumbar lordosis (PI-LL) >10°; use of posterior spinal fixation and instruments with ASD surgery at ≥level 4; and patients with a follow-up period of ≥2 years. The exclusion criteria were patients with ASD due to syndrome, autoimmune disease, infection, tumor, or other pathological conditions. Between January 2009 and December 2017, 491 patients with ASD underwent ASD surgery at our hospital. Among them, 253 patients with a follow-up period of <2 years, patients without corrective surgery for ASD, and those with a surgical level of ≤3 were excluded. Between January 2009 and December 2017, 238 consecutive patients with sagittal imbalance who underwent ASD surgery were ultimately included in the study. All methods were carried out in accordance with relevant guidelines and regulations.

# Data collection

Demographic data, radiologic parameters, surgical characteristics, HRQOL data were collected for all 238 patients included in the electronic medical records. Demographic data included age, sex, BMI, and BMD. Surgical features included blood loss during the surgery, operation time, duration of hospitalization, number of levels fused, upper and lower instrumented vertebrae (UIV and LIV), number of osteotomy vertebrae, and presence of interbody fusion. The following sagittal alignment parameters were measured: PI, PT, lumbar vertebral lordosis (LL [L1–S1]), PI-LL, C7 sagittal vertical axis, and global tilt. Radiographic measures included preoperative, postoperative, and final follow-up alignment parameters. The incidence of proximal junctional kyphosis, proximal junctional failure, distal junctional failure, distal junctional kyphosis, rod fracture, implant-related complications, and need for revision surgery were assessed. Proximal junctional kyphosis was defined as a ≥10° increase in kyphosis between UIV and UIV + 2 between the early postoperative and 2-year follow-up radiographs. Proximal junctional failure was defined as a fracture of UIV or UIV + 1, withdrawal of the instrument in UIV, and/or sagittal subluxation. Distal junctional kyphosis/failure referred to a ≥10° increase in kyphosis angle between LIV and LIV-1, and/or withdrawal of the apparatus from the LIV. Rod breakage referred to single or double rod breakage. Implant-related complications included other radiographic implant-related complications such as screw loosening, breakage, pullout, or interbody

graft, hook, or screw leave. HRQOL was measured using the Oswestry Disability Index, the Spinal Research Society-22 Spinal Malformation Questionnaire, and ShortForm-36.

# Prediction models and evaluation

The patients were randomly divided into training (n=167, 70%) and test (n=71, 30%) datasets (Figure 1). The training set was used to develop the model, and the test set was used to evaluate the model. We performed four analyses to classify the occurrence of complications. First, univariable and multivariable logistic regressions were used. Variables with $p<0.05$ in the univariable analysis were entered in the multivariable analysis. The final multivariable model was determined using a stepwise variable selection method. Second, the gradient boosting model was created with the R package "xgboost," and variable importance was visualized. For this analysis, a maximum tree depth of 2, learning rate of 0.3, and number of boosting of 20 were considered. Third, random forest classification was performed using the R package "random forest." For this analysis, the number of trees was set to 500, and the number of variables used in each tree was set to five, which had the largest Kappa value. Fourth, a deep neural network was used via the R package "nnet." For this analysis, a hidden layer of 10 was employed.

Diagnostic performance was evaluated using the receiver operating characteristic (ROC) curve, area under the curve (AUC), accuracy, sensitivity, and specificity for each dataset. To calculate the accuracy, sensitivity, and specificity, the optimal cutoff points were computed using Youden's index. ROC curves and AUC comparisons were performed using DeLong's method. Comparisons of accuracy, sensitivity, and specificity were performed using generalized estimating equations.

# Statistical analysis

Descriptive statistics are presented as frequencies and percentages for categorical variables and as means and standard deviations for continuous variables. To compare the characteristics of patients in the complication and no complication groups, the chi-square test (or Fisher's exact test) was used for categorical variables and an independent two-sample t-test was used for continuous variables. All statistical analyses were performed using SAS, version 9.4 (SAS Institute, Cary, NC, USA). Statistical significance was set at $p<0.05$.

## Results

# Patient demographics

Two hundred thirty-eight patients underwent ASD surgery (204 female [86%], 34 male [14%]); their demographic data are shown in Table 1. Of those patients, 167 (70.2%) were assigned to the training set and 71 (29.8%) to the test set. The patients' average age and follow-up period were 67.1±6.17 years and 28.54±4.25 months, respectively. The mean ages of patients in the training and test sets were 67.80±7.49 years and 66.94±6.98 years, respectively. When comparing the groups with and without complications in the training set, BMI, BMD, the relative pelvic version score, the relative lumbar lordosis score, and the relative sagittal alignment score were statistically significant. When comparing the groups with and without complications in the test set, BMI, BMD, the relative pelvic version score, the relative lumbar lordosis score,

and the relative sagittal alignment score were statistically significant. When comparing the group with and without complications in the test set, BMI, BMD, the relative pelvic version score, the relative lumbar lordosis score, the lordosis distribution index score, and the relative sagittal alignment score were statistically significant.

Table 1
Patient demographics

| | Training set (n=167) | | | Test set (n=71) | | |
|---|---|---|---|---|---|---|
| | Complication | | P-value | Complication | | P-value |
| | No Yes | | | No Yes | | |
| | (n=96) (n=71) | | | (n=42) (n=29) | | |
| Age | 67.18±7.07 | 68.63±7.99 | 0.2148 | 66.40±6.64 | 67.72±7.49 | 0.4376 |
| Gender | 12 | 9 | 0.9729 | 8 | 5 | 0.8466 |
| Male | 84 | 62 | | 34 | 24 | |
| Female | | | | | | |
| BMI (kg/m$^2$) | 23.54±2.92 | 24.70±3.05 | 0.0131* | 23.39±2.53 | 25.02±2.79 | 0.0127* |
| BMD (T-score) | -1.57±0.85 | -2.60±0.98 | <.0001* | -1.85±0.83 | -2.41±0.86 | 0.0070* |
| GAP score | | | | | | |
| Relative pelvic version score | | | 0.0025* | | | 0.0015* |
| 0 | 41 | 17 | | 24 | 5 | |
| 1 | 10 | 6 | | 4 | 3 | |
| 2 | 35 | 25 | | 11 | 11 | |
| 3 | 10 | 23 | | 3 | 10 | |
| Relative lumbar lordosis score | 42 | 13 | <0.001* | 19 | 5 | 0.0008* |
| 0 | 45 | 21 | | 18 | 9 | |
| 2 | 9 | 37 | | 5 | 15 | |
| 3 | | | | | | |
| Lordosis distribution index score | 54 | 33 | 0.5471 | 26 | 13 | 0.0448 |
| 0 | 9 | 6 | | 3 | 5 | |
| 1 | 15 | 16 | | 7 | 1 | |
| 2 | 18 | 16 | | 6 | 10 | |
| 3 | | | | | | |

GAP, Global Alignment and Proportion; BMI, body mass index; BMD, bone mineral density

*Statistically significant

| | Training set (n=167) | | | Test set (n=71) | | |
|---|---|---|---|---|---|---|
| **Relative spinopelvic alignment score** | **35** | **15** | **0.0003*** | **19** | **4** | **0.0003*** |
| **0** | **51** | **31** | | **17** | **8** | |
| **1** | **10** | **25** | | **6** | **17** | |
| **3** | | | | | | |
| GAP, Global Alignment and Proportion; BMI, body mass index; BMD, bone mineral density | | | | | | |
| ***Statistically significant** | | | | | | |

# Logistic regression model

The results of the univariate and multivariate logistic regression analyses are presented in Table 2. The following variables were significantly related to mechanical complications of ASD surgery in univariate logistic regression: BMI, BMD, relative pelvic version score, relative lumbar lordosis score, and relative sagittal alignment score. In the multivariate logistic regression, BMD and relative lumbar lordosis score were significantly related to mechanical complications of ASD surgery.

Table 2
Logistic regression

| Variable | Univariable model | | Multivariable model 3 | | Multivariable model 4 | |
|---|---|---|---|---|---|---|
| | OR (95% CI) | P-value | OR (95% CI) | P-value | OR (95% CI) | P-value |
| Age | 1.03 (0.98-1.07) | 0.2148 | 1.284 (1.073-1.536) | 0.0063* | 1.284 1.073-1.536 | 0.0063* |
| Gender<br>Male<br>Female | reference<br>0.98(0.39-2.48) | 0.9729 | | | | |
| BMI (kg/m$^2$) | 1.14(1.03-1.27) | 0.0151* | 1.13(0.99-1.30) | 0.0797 | | |
| BMD (T-score) | 0.26(0.16-0.41) | <.0001* | 0.28(0.16-0.46) | <.0001* | 0.28(0.17-0.47) | <.0001* |
| Relative pelvic version score<br>0<br>1<br>2<br>3 | reference<br>1.45(0.45-4.61)<br>1.72(0.80-3.70)<br>5.55(2.18-14.10) | 0.5321<br>0.1627<br>0.0003* | reference<br>1.42(0.35-5.73)<br>0.87(0.29-2.58)<br>0.22(0.04-1.26) | 0.6195<br>0.7981<br>0.0899 | | |
| Relative lumbar lordosis score<br>0<br>2<br>3 | reference<br>1.51(0.67-3.39)<br>13.28(5.10-34.62) | 0.3202<br><.0001* | reference<br>1.71(0.54-5.38)<br>28.81(4.77-174.05) | 0.3601<br>0.0003* | reference<br>1.43(0.57-3.55<br>11.02(3.80-31.98) | 0.4442<br><.0001* |
| Lordosis distribution index<br>0<br>1<br>2<br>3 | reference<br>1.09(0.36-3.34)<br>1.75(0.76-3.99)<br>1.45(0.65-3.24) | 0.8790<br>0.1867<br>0.3590 | | | | |

GAP, Global Alignment and Proportion; BMI, body mass index; BMD, bone mineral density

*Statistically significant

| Variable | Univariable model | | Multivariable model 3 | | Multivariable model 4 | |
|---|---|---|---|---|---|---|
| | OR (95% CI) | P-value | OR (95% CI) | P-value | OR (95% CI) | P-value |
| Relative sagittal alignment score | reference | 0.3625 | reference | 0.9059 | | |
| 0 | 1.42(0.67-3.01) | 0.0003* | 0.94(0.33-2.65) | 0.8126 | | |
| 1 | 5.83(2.25-15.08) | | 1.22(0.24-6.11) | | | |
| 3 | | | | | | |
| GAP, Global Alignment and Proportion; BMI, body mass index; BMD, bone mineral density | | | | | | |
| *Statistically significant | | | | | | |

# Gradient boosting model

The results of the gradient boosting analysis are shown in Figure 2. BMI, BMD, and relative lumbar lordosis score were the most important variables in the gradient boosting model.

# Random forest model

The results of the random forest analyses are shown in Figure 3. BMI, BMD, and relative lumbar lordosis score were the most important variables in the random forest model.

# Deep neural network model

The results of the deep neural network analyses are shown in Figure 4. The most important variables in this model were the lordosis distribution index score and relative sagittal alignment score.

# Diagnostic performance of the machine learning models

The AUCs for the four machine learning models are presented in Table 3. In the training set, the AUCs for logistic regression, gradient boosting, random forest, and deep neural network model were 0.871 (0.817–0.925), 0.942 (0.911–0.974), 1.000 (1.000–1.000), and 0.947 (0.915–0.980), respectively, and the accuracies were 0.784 (0.722–0.847), 0.868 (0.817–0.920), 1.000 (1.000–1.000), and 0.856 (0.803–0.909), respectively. In the test set, the AUCs for the same models were 0.785 (0.678–0.893), 0.808 (0.702–0.914), 0.810 (0.710–0.910), and 0.730 (0.610–0.850), respectively, and the accuracies were 0.732 (0.629–0.835), 0.718 (0.614–0.823), 0.732 (0.629–0.835), and 0.620 (0.507–0.733), respectively. The random forest achieved the best

predictive performance on the training and test dataset. Figure 5 shows the ROC curve of each model in the training and test sets.

Table 3
Diagnostic performance between machine learning model

| Training set | | | | | |
|---|---|---|---|---|---|
| Model | Cut off point | AUC (95%CI) | Accuracy(95%CI) | Sensitivity(95%CI) | Specificity(95%CI) |
| Logistic regression | >0.3108393 | 0.871(0.817-0.925) | 0.784(0.722-0.847) | 0.873(0.796-0.951) | 0.719(0.629-0.809) |
| Gradient boosting | >0.4046899 | 0.942(0.911-0.974) | 0.868(0.817-0.920) | 0.915(0.851-0.980) | 0.833(0.759-0.908) |
| Random forest | >0.483 | 1.000(1.000-1.000) | 1.000(1.000-1.000) | 1.000(1.000-1.000) | 1.000(1.000-1.000) |
| Deep neural network | >0.4064502 | 0.947(0.915-0.980) | 0.856(0.803-0.909) | 0.972(0.933-1.000) | 0.771(0.687-0.855) |

| Test set | | | | | |
|---|---|---|---|---|---|
| Model | Cut off point | AUC (95%CI) | Accuracy(95%CI) | Sensitivity(95%CI) | Specificity(95%CI) |
| Logistic regression | >0.3108393 | 0.785(0.678-0.893) | 0.732(0.629-0.835) | 0.759(0.603-0.914) | 0.714(0.578-0.851) |
| Gradient boosting | >0.4046899 | 0.808(0.702-0.914) | 0.718(0.614-0.823) | 0.828(0.690-0.965) | 0.643(0.498-0.788) |
| Random forest | >0.483 | 0.810(0.710-0.910) | 0.732(0.629-0.835) | 0.759(0.603-0.914) | 0.714(0.578-0.851) |
| Deep neural network | >0.4064502 | 0.730(0.610-0.850) | 0.620(0.507-0.733) | 0.897(0.786-1.000) | 0.429(0.279-0.578) |

# Discussion

The prevalence of mechanical complications, with radiologic and clinical manifestations, after surgery for adult spinal deformities is reported to be 30%, and more than 50% of these patients undergo revision surgery for treatment. (8) Soroceanu et al. reported that radiographic and implant-related complications accounted for 31.7%, and in 52.6% of these complications, reoperation for mechanical correction was required. (9) There are many aspects of ASD surgery with notable variability, including the occurrence of complications and outcomes. (10) GAPB is a system that is used to predict mechanical complications that occur after ASD

surgery, including both patient-specific and radiological factors. (6) In this study, we constructed a model to predict mechanical complications after ASD surgery using GAPB factors.

Recently, several studies using deep learning algorithms, such as random forest, gradient boosting, and neural networks, have been conducted for the spine. (11) Yagi et al. created a post-surgical complication prediction model for ASD surgery in adults using spinal alignment, demographic data, and surgical invasiveness; 170 participants were enrolled in this study. A decision tree for 2-year postoperative complications was constructed and confirmed by splitting data in a 7:3 ratio for training and testing, (12) with the external validation of 25 ASD patients who underwent surgery at different hospitals. (12) For the test sample, the predictive model was 92% accurate, the AUC was 0.963, and the external validation was 84% accurate.

Lafage created a machine learning model to determine the upper vertebra in ASD surgery. (13) The samples were stratified into three groups: 70% for training, 15% for validation, and 15% for performance testing. A neural network model was used, and the results showed an accuracy of 81.0%, precision of 87.5%, and recall of 87.5%.

Pellise et al. created a model to predict the incidence of adverse events after ASD surgery using a random forest model. (14) The model was trained using 80% of the data for the training set and 20% for the test set and showed adequate predictive accuracy, with AUCs ranging from 0.67 to 0.92. (14) Durand et al. created a model for predicting blood transfusion following surgery for adult spinal deformities. (15) A total of 1029 patients were analyzed and divided into datasets for training (n = 824) and validation (n = 205). The random forest model showed an AUC of 0.85 (95% confidence interval 0.80–0.90) and was reported to show better predictive ability than single-decision tree models. (15) Ames et al. created a model to predict the cost of surgery for ASD. The regression tree and random forest models were used to predict the occurrence of treatment costs exceeding $100,000. (16) The results of the regression tree analysis using CTREE resulted in an adjusted $R^2$ value of 56% at 90 days and 35.6% at 2 years of direct cost forecasting. Random C-forest regression analysis showed an adjusted $R^2$ value of 57.4% at 90 days and 28.8% at 2 years of direct cost forecasts. Peng et al. created a model to predict proximal junctional kyphosis after surgery in adolescent patients with idiopathic scoliosis. (17) The random forest has great value for predicting the individual risk of developing proximal junctional kyphosis after long instrumentation and fusion surgery in patients with Lenke 5 adolescent idiopathic scoliosis. Jain created a model to predict discharge delay, medical complications, and readmission within 90 days after long-segment posterior lumbar spine fusion surgery (18) using logistic regression, random forest, and elastic net.

In our study, we created a model to predict the mechanical complications that occur after ASD surgery. We used logistic regression, gradient boosting, random forest, and deep neural networks. Important factors were BMD, BMI, relative lumbar lordosis score, lordosis distribution index score, and relative sagittal alignment score. The patients were randomly divided into training (70%) and test (30%) datasets. In the training set, the AUC for random forest was 1.000 and the accuracy was 1.000. In the test set, the AUC for random forest was 0.81 and the accuracy was 0.732. Random forest achieved the best predictive performance on the training and test dataset.

# Limitations

This study has several limitations. Because our models were built using retrospective data, future efforts to update these models are required. Additionally, the reasons for mechanical complications after ASD correction are multifactorial. Many factors affect the outcome of surgery, including the surgical method, upper level instrumentation, muscle mass, and various underlying conditions. These factors were excluded when the model was created.

However, the GAPB system is helpful in predicting mechanical complications after ASD surgery. (6) Noh et al. reported that the GAPB system was more meaningful in the moderately disproportioned and severely disproportioned GAP groups. We believe that it will be helpful to develop models that predict mechanical complications through machine learning.

## Conclusions

This study created a comprehensive model to predict mechanical complications after ASD surgery. The random forest was found to be the most appropriate model for predicting mechanical complications after ASD surgery. This information can be used to prevent mechanical complications during ASD surgery.

## Declaration

# Data availability

The datasets generated and analysed during the current study are not publicly available due hospital policy but are available from the corresponding author on reasonable request.

# Conflict of Interest and Source of funding

The authors report no conflict of interest concerning the materials or methods used in this study or the fundings specified in this paper

## References

1. Grabel ZJ, Hart RA, Clark AJ, Park SH, Shaffrey CI, Scheer JK, et al. Adult spinal deformity knowledge in orthopedic spine surgeons: Impact of fellowship training, experience, and practice characteristics. Spine deformity. 2018 Jan;6(1):60.
2. Soroceanu A, Burton D, Oren J, Smith J, Hostin R, Shaffrey C, et al. Medical complications after adult spinal deformity surgery: Incidence, risk factors, and clinical impact. Spine (Philadelphia, Pa. 1976). 2016 Nov 15,;41(22):1718–23.
3. Lee NJ, Kothari P, Kim JS, Shin JI, Phan K, Di Capua J, et al. Early complications and outcomes in adult spinal deformity surgery: An NSQIP study based on 5803 patients. Global spine journal. 2017 Aug;7(5):432–40.

4. SCHWAB F, PATEL A, UNGAR B, FARCY J, LAFAGE V. In: Adult spinal deformity-postoperative standing imbalance: How much can you tolerate? an overview of key parameters in assessing alignment and planning corrective surgery. Hagerstown, MD: Lippincott Williams & Wilkins; 2010. p. 2224–31.
5. Lafage R, Schwab F, Challier V, Henry J, Gum J, Smith J, et al. Defining spino-pelvic alignment thresholds: Should operative goals in adult spinal deformity surgery account for age? Spine (Philadelphia, Pa. 1976). 2016 Jan;41(1):62-8.
6. Noh SH, Ha Y, Obeid I, Park JY, Kuh SU, Chin DK, et al. Modified global alignment and proportion scoring with body mass index and bone mineral density (GAPB) for improving predictions of mechanical complications after adult spinal deformity surgery. The spine journal. 2020 May;20(5):776–84.
7. Yilgor C, Sogunmez N, Boissiere L, Yavuz Y, Obeid I, Kleinstück F, et al. Global alignment and proportion (GAP) score: Development and validation of a new method of analyzing spinopelvic alignment to predict mechanical complications after adult spinal deformity surgery. Journal of bone and joint surgery. American volume. 2017 Oct 4,;99A(19):1661–72.
8. Kwan KYH, Lenke LG, Shaffrey CI, Carreon LY, Dahl BT, Fehlings MG, et al. Are higher global alignment and proportion scores associated with increased risks of mechanical complications after adult spinal deformity surgery? an external validation. Clinical orthopaedics and related research. 2021 Feb 1,;479(2):312–20.
9. Soroceanu A, Diebo BG, Burton D, Smith JS, Deviren V, Shaffrey C, et al. Radiographical and implant-related complications in adult spinal deformity surgery: Incidence, patient risk factors, and impact on health-related quality of life. Spine (Philadelphia, Pa. 1976). 2015 Sep 15,;40(18):1414-21.
10. Ames CP, Smith JS, Pellisé F, Kelly M, Alanay A, Acaroğlu E, et al. Artificial intelligence based hierarchical clustering of patient types and intervention categories in adult spinal deformity surgery: Towards a new classification scheme that predicts quality and value. Spine (Philadelphia, Pa. 1976). 2019 Jul 1,;44(13):915.
11. Joshi RS, Haddad AF, Lau D, Ames CP. Artificial intelligence for adult spinal deformity. Neurospine. 2019 Dec;16(4):686–94.
12. Yagi M, Hosogane N, Fujita N, Okada E, Tsuji O, Nagoshi N, et al. Predictive model for major complications 2 years after corrective spine surgery for adult spinal deformity. European spine journal. 2019 Jan;28(1):180–7.
13. Lafage R, Ang B, Alshabab BS, Elysee J, Lovecchio F, Weissman K, et al. Predictive model for selection of upper treated vertebra using a machine learning approach. World neurosurgery. 2021 Feb;146:e225-32.
14. Pellisé F, Serra-Burriel M, Smith JS, Haddad S, Kelly MP, Vila-Casademunt A, et al. Development and validation of risk stratification models for adult spinal deformity surgery. Journal of neurosurgery. Spine. 2019 Jun 28,;31(4):1–599.
15. Durand W, DePasse J, Daniels A. Predictive modeling for blood transfusion after adult spinal deformity surgery: A tree-based machine learning approach. Spine (Philadelphia, Pa. 1976). 2018 Aug 1,;43(15):1058–66.
16. Ames C, Smith J, Gum J, Kelly M, Vila-Casademunt A, Burton D, et al. Utilization of predictive modeling to determine episode of care costs and to accurately identify catastrophic cost nonwarranty outlier patients

in adult spinal deformity surgery: A step toward bundled payments and risk sharing. Spine (Philadelphia, Pa. 1976). 2020 Mar 1,;45(5):E252-65.

17. Peng L, Lan L, Xiu P, Zhang G, Hu B, Yang X, et al. Prediction of proximal junctional kyphosis after posterior scoliosis surgery with machine learning in the lenke 5 adolescent idiopathic scoliosis patient. Frontiers in bioengineering and biotechnology. 2020 Jan 1,;8:559387.
18. Jain D, Durand W, Burch S, Daniels A, Berven S. Machine learning for predictive modeling of 90-day readmission, major medical complication, and discharge to a facility in patients undergoing long segment posterior lumbar spine fusion. Spine (Philadelphia, Pa. 1976). 2020 Aug 15,;45(16):1151–60.

## Figures

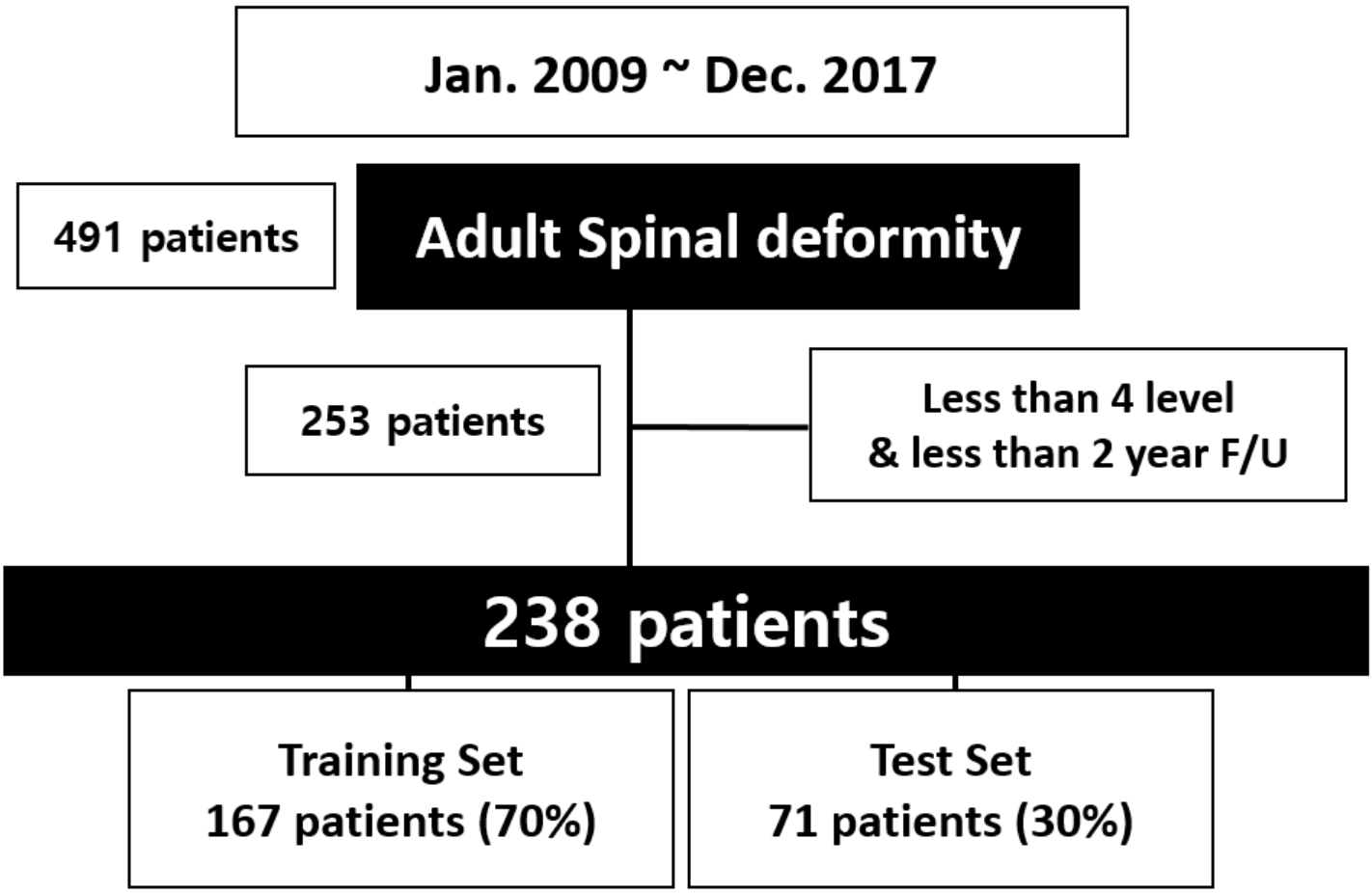


**Figure 1**

Flowchart of the patients in our study.

F/U, follow-up

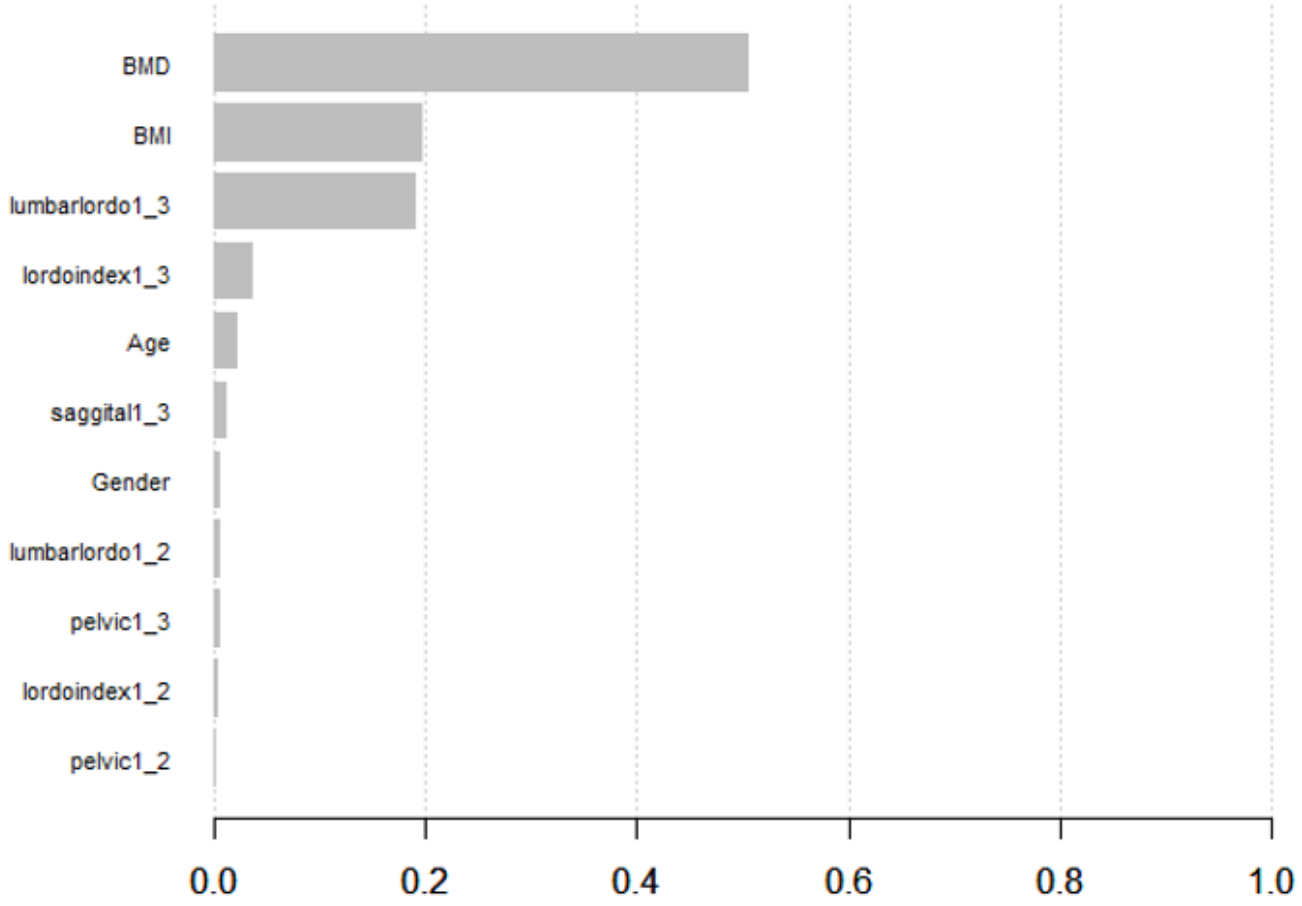


**Figure 2**

Results of the gradient boosting model. The most important variables in the model were BMI, BMD, and relative lumbar lordosis score

BMD, bone mineral density; BMI, body mass index

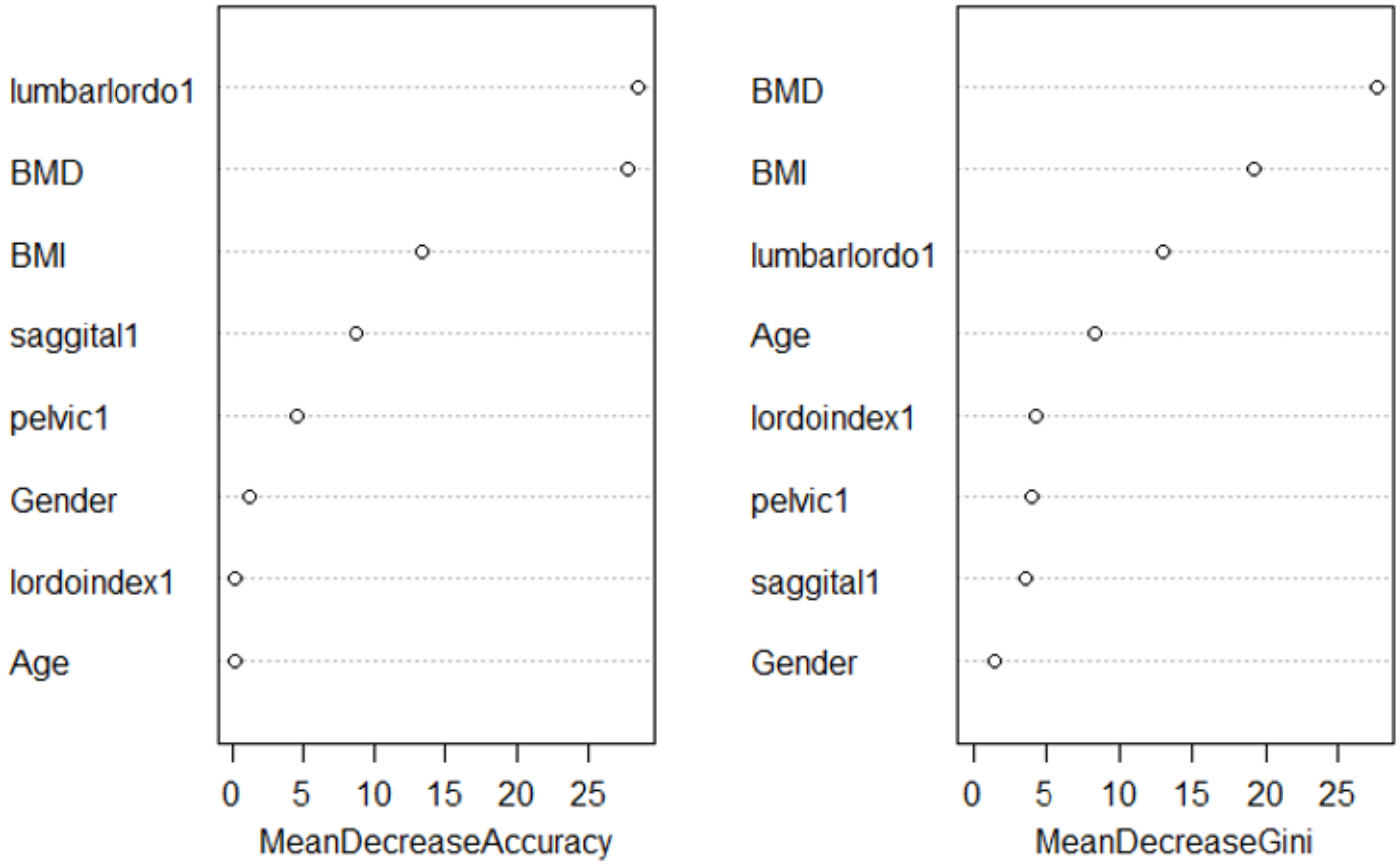


**Figure 3**

Results of the random forest model. The most important variables in this model were BMI, BMD, and relative lumbar lordosis score

BMD, bone mineral density; BMI, body mass index

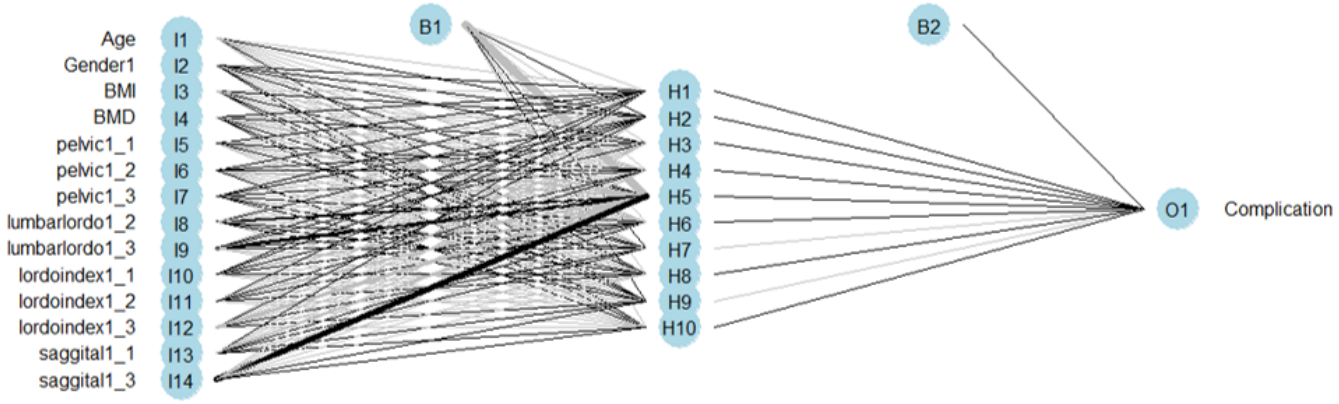


**Figure 4**

Results of the gradient boosting model. The most important variables in this model were lordosis distribution index score and relative sagittal alignment score.

BMD, bone mineral density; BMI, body mass index

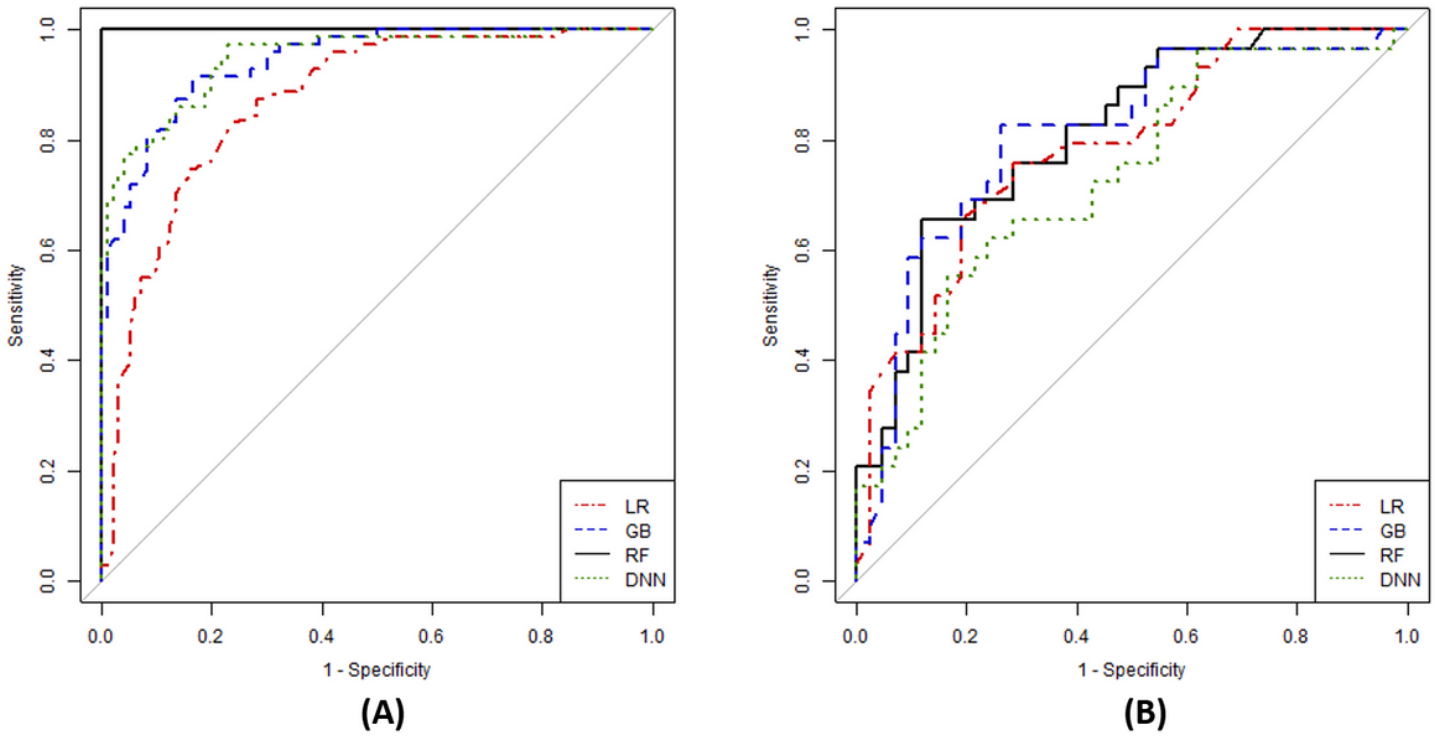


**Figure 5**

ROC curve of each model in the training set (A) and test set (B).

DNN, deep neural network; GB, gradient boosting; LR, logistic regression; RF, random forest