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Optimizing Sensitivity in Machine Learning Models for Pediatric Post-operative Kyphosis Prediction

Raja Ayu Mahessya[1], Dian Eka Putra[2], Rostam Ahmad Efendi[3], Rayendra[4], Rozi Meri[5], Riyan Ikhbal Salam[6], Dedi Mardianto[7], Ikhsan[8*], Ismael[9], Arif Rizki Marsa[10]

[1]Department of Computer Engineering, Universitas Putra Indonesia 'YPTK' Padang, Padang, Indonesia

[2,3,4,5,6,7,8,9,10]Department of Information Technology, Politeknik Negeri Padang, Padang, Indonesia

[1]ayumahessya@upiyptk.ac.id, [2]dianekaputra@pnp.ac.id, [3]rostamahmadefendi@pnp.ac.id, [4]rayendra@pnp.ac.id, [5]rozimeri@pnp.ac.id, [6]riyan@pnp.ac.id, [7]dedimardianto@pnp.ac.id, [8]ikhsan85@pnp.ac.id, [9]ismael@pnp.ac.id, [10]arifrizkimarsa@pnp.ac.id

Abstract

Post-operative kyphosis represents a significant complication following pediatric spinal corrective surgery, necessitating sophisticated prediction methods to identify high-risk patients. This study developed and evaluated machine learning models for kyphosis prediction using a dataset of 81 pediatric patients by comparing the logistic regression and decision tree approaches. Despite achieving a higher overall accuracy (82%), the logistic regression model failed to identify any kyphosis cases, rendering it clinically ineffective. Conversely, the decision tree model demonstrated superior clinical utility by successfully identifying 33% of kyphosis cases while maintaining 71% accuracy. Feature importance analysis established starting vertebral position as the dominant predictor (importance=0.554), followed by patient age (0.416), with vertebrae count contributing minimally (0.030). The decision tree identified critical thresholds for risk stratification: operations beginning at or above T8-T9, particularly in children aged 5-9 years, carried a substantially elevated kyphosis risk. Our methodological approach emphasizes sensitivity over conventional accuracy metrics, recognizing that missing high-risk patients have greater clinical consequences than unnecessary monitoring. This study demonstrates the capacity of decision tree models to extract clinically meaningful patterns from small, imbalanced surgical datasets that elude conventional statistical approaches.

Keywords: decision trees; imbalanced classification; pediatric spinal surgery; post-operative kyphosis; machine learning

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1. Introduction

Machine learning approaches have increasingly transformed healthcare decision-making by enhancing diagnostic accuracy [1], [2], improving prognostic capabilities [3], and informing personalized treatment strategies. Within surgical specialties [4], these computational techniques offer particular promise for identifying complex patterns of risk that may not be apparent through traditional statistical methods or clinical heuristics [5].

Integrating machine learning with clinical expertise represents a powerful approach to addressing challenging medical problems [6], including predicting post-operative complications where multiple interacting factors may influence outcomes [7]-[9].

Spinal deformity surgery in pediatric populations presents a domain whe re such advanced analytical approaches could significantly impact clinical care [10], [11]. Kyphosis, an abnormal forward curvature of the spine, can develop or progress following corrective spinal surgery [12], potentially compromising both functional outcomes and patient quality of life [13].

Despite its clinical significance, current approaches to risk assessment for post-operative kyphosis remain predominantly based on univariate analyses [14], subjective clinical judgment, or simplified risk categorizations that may not adequately capture the complex interplay of contributing factors [15].

The etiology of post-operative kyphosis is multifactorial, with potential contributions from patient age, skeletal maturity, extent of the surgical intervention, anatomical location of the procedure, fixation techniques, and underlying pathophysiology [16], [17]. The intricate interactions between these variables create a prediction challenge well-suited to machine learning techniques, which excel at identifying non-linear relationships and complex patterns within multidimensional data.

Developing more sophisticated predictive models for post-operative kyphosis carries significant implications for clinical practice [18]. Enhanced prognostic capabilities could guide surgical planning, including decisions regarding the extent of fusion, selection of instrumentation strategies, and implementation of preventive measures for high-risk patients [19]. Improved risk assessment would facilitate more informed consent discussions, allowing patients and families to understand better procedure-specific risks rather than relying on population-level statistics.

This study aims to develop and evaluate a machine learning model for predicting the occurrence of kyphosis following corrective spinal surgery in pediatric patients, based on readily available pre-operative and intra-operative variables. Specifically, we seek to identify the key predictors of post-operative kyphosis from among patient age, number of vertebrae involved in the operation, and the location of the first vertebra operated on. Beyond merely developing a predictive model, we endeavor to interpret the resulting patterns to extract clinically meaningful insights regarding risk thresholds and variable interactions.

Ultimately, we aim to translate these findings into a practical clinical decision-support framework that can guide surgical planning and post-operative management strategies, demonstrating the potential for machine learning to enhance clinical decision-making in pediatric spinal surgery.

2. Methods

This study utilized the kyphosis dataset derived from clinical observations of 81 pediatric patients who underwent corrective spinal surgery [20]. The predictor variables include patient age at time of operation (measured in months, ranging from 1 to 206), the number of vertebrae involved in the operation (ranging from 2 to 10), and the index of the first (topmost) vertebra operated on (ranging from 1 to 18). The outcome variable indicates the presence or absence of kyphosis following the surgical intervention.

Initial examination of the dataset revealed noteworthy characteristics that influenced our subsequent analytical approach. The age distribution exhibited a bimodal pattern, suggesting distinct pediatric and adolescent subpopulations within the cohort. The median age was 87 months (approximately 7.25 years), with a substantial standard deviation of 58.1 months reflecting the wide age range.

The operations typically involved four vertebrae (median), while the topmost vertebra operated on was most commonly at position 12 (median). A critical observation was the class imbalance in the outcome variable, with 79% of patients showing no evidence of post-operative kyphosis, while 21% developed the condition. Table 1 summarizes these dataset characteristics, including the distributions of all variables.

Table 1. Dataset Characteristics

Feature	Type	Range/Values	Mean	Median	Standard Deviation
Age	Numeric	1-206 months	83.7	87	58.1
Number	Numeric	2-10 vertebrae	4.3	4	1.7
Start	Numeric	1-18 (vertebra index)	10.3	12	4.5
Kyphosis	Categorical	"absent" (n=64, 79%), "present" (n=17, 21%)	-	-	-

Prior to model development, we preprocessed the data through several sequential steps. The categorical outcome variable "Kyphosis" was encoded to binary values using scikit-learn's LabelEncoder [21], [22], transforming "absent" to 0 and "present" to 1. We then separated the dataset into feature and target components, with the feature matrix containing the Age, Number, and Start variables, while the target vector contained the encoded Kyphosis variable.

To facilitate model training and evaluation, we partitioned the dataset using a stratified train-test split methodology, allocating 80% of observations to the training set and reserving 20% for testing. Stratification ensured that both subsets maintained the original class distribution while setting a random state of 42 guaranteed reproducibility. Though we considered feature standardization, we ultimately determined it unnecessary given that decision trees are invariant to monotonic transformations of input features.

The decision tree classifier was selected as our primary modeling approach after carefully considering multiple factors relevant to statistical performance and clinical utility [23], [24]. Decision trees offer exceptional interpretability, producing rule-based classifications that can be directly translated into clinical guidelines. Figure 1 provides a comprehensive visualization of our data preprocessing and modeling pipeline, illustrating the sequential workflow from initial data loading to clinical framework development.

Given the relatively modest dataset size (81 observations) and the clinical context where interpretability was prioritized over marginal performance improvements. While hyperparameter tuning might potentially enhance model performance, we maintained the default configuration to mitigate overfitting risk given the limited sample size and to preserve the interpretability of the resulting tree structure.

The model was trained on the 80% partition of the dataset (65 patients) designated for training. Figure 2 illustrates the architecture of the trained decision tree, revealing the hierarchical decision rules derived from the data. The tree's primary split occurred on the Start variable at a threshold of 8.5, reinforcing the critical importance of vertebral level in predicting surgical outcomes. Secondary splits involved Age, with different thresholds in different branches (30.5 months in the high-risk branch and 174.5 months in the lower-risk branch), suggesting that age-related effects are contextual and depend on the vertebral level of the operation.

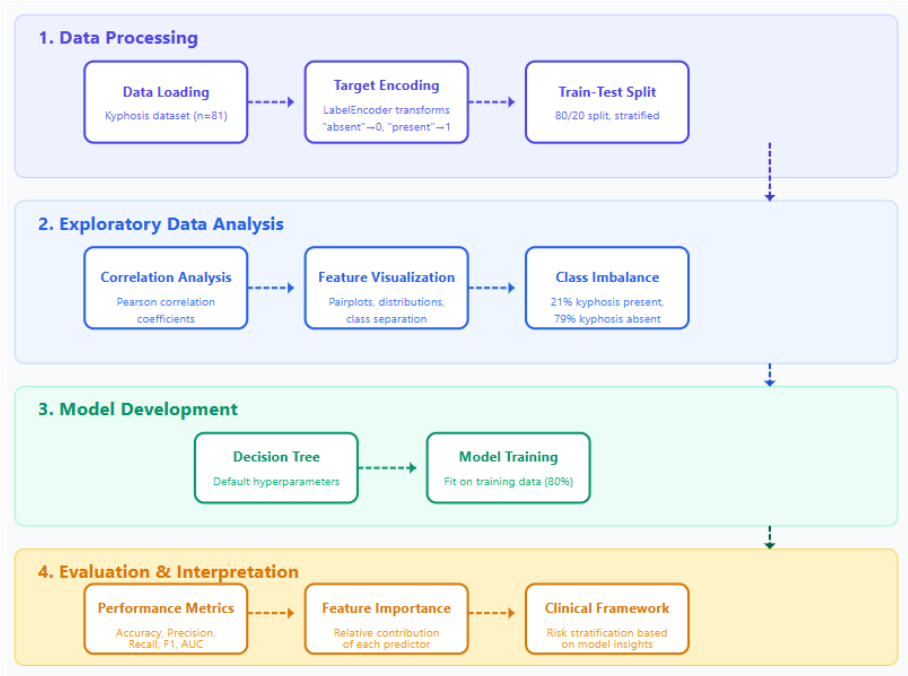

Figure 1. Data Processing and Modeling Pipeline

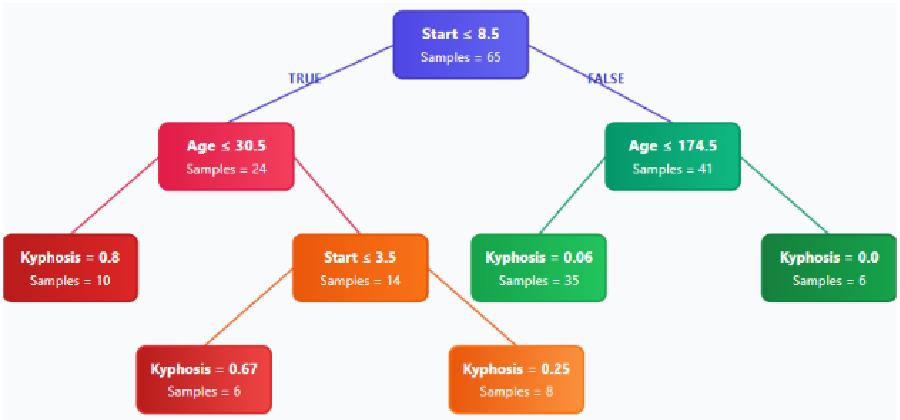

Figure 2. Decision Tree Architecture

3. Results and Discussions

The present study investigated the prediction of post-operative kyphosis in patients who underwent corrective spinal surgery using a machine learning approach. Our dataset comprised 81 patients with three predictor variables (Age in months, Number of vertebrae involved, and Start vertebra) and a binary outcome indicating the presence or absence of kyphosis following surgery.

Initial data exploration revealed that approximately 21% of patients (n=17) developed kyphosis post-operatively, while 79% (n=64) did not, highlighting a notable class imbalance that influenced subsequent modeling considerations. The predictor variables demonstrated substantial variability: patient age ranged from 1 to 206 months (median = 87 months) with a distinctive bimodal distribution suggesting separate pediatric and adolescent subpopulations; the number of vertebrae involved ranged from 2 to 10 (median = 4);

and the starting vertebra ranged from 1 to 18 (median = 12).

The correlation analysis (Figure 3) revealed important relationships between predictors and surgical outcomes. Most notably, the "Start" variable exhibited a strong negative correlation with kyphosis presence ($r = -0.45$, $p < 0.001$), indicating that operations beginning on vertebrae higher in the spine (lower numbers) were associated with a significantly increased risk of post-operative kyphosis.

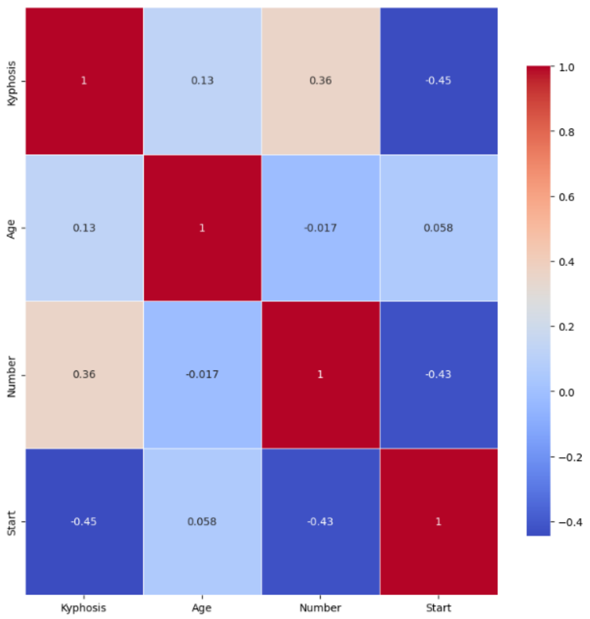

Figure 3. Correlation Analysis

The "Number" variable showed a moderate positive correlation ($r = 0.36$, $p < 0.01$), suggesting that more extensive operations carried elevated risk. Interestingly, in univariate analysis, patient age demonstrated only a weak positive correlation ($r = 0.13$, $p = 0.24$) with kyphosis outcomes. This finding would later prove misleading when examined through more sophisticated analytical approaches.

The pairwise relationships between variables further illuminated patterns in the data. Most notably, operations beginning on vertebrae 1-9 showed substantially higher kyphosis risk than those beginning at vertebra 10 or higher. Additionally, we observed that younger patients with operations involving more vertebrae appeared to have elevated kyphosis risk, suggesting potential interaction effects that simple correlation analysis might not capture.

3.1 Model Training and Evaluation

Using an 80/20 train-test split, we trained the model on 65 patients and evaluated performance on 16 patients. The model's performance on the test set is summarized in Table 2, presenting class-specific and overall metrics.

The model achieved moderate performance with an overall accuracy of 71% and a weighted F1-score of 0.71. As visualized in the confusion matrix (Figure 4), of the 14 patients without kyphosis, 11 were correctly classified (true negatives), and three were incorrectly predicted to develop kyphosis (false positives).

Among the three patients with kyphosis, one was correctly identified (true positive), while two were misclassified as kyphosis-absent (false negative). The resulting performance metrics demonstrated notable asymmetry between the classes: precision and recall for the negative class were 0.85 and 0.79, respectively, while for the positive class, they were significantly lower at 0.25 and 0.33.

Table 2. Classification Performance Metrics

Class	Precision	Recall	F1-Score	Specificity	Support
0 (Absent)	0.85	0.79	0.81	0.33	14
1 (Present)	0.25	0.33	0.29	0.79	3
Accuracy			0.71		17
Macro avg	0.55	0.56	0.55	0.56	17
Weighted Avg	0.74	0.71	0.71	0.43	17

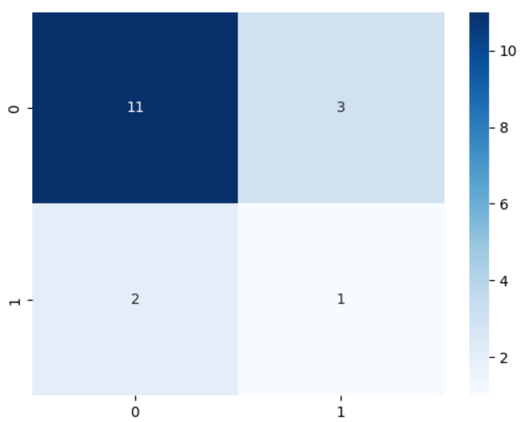

Figure 4. Confusion Matrix

This discrepancy in performance among the classes can be partially attributed to the underlying class imbalance. However, it also suggests fundamental challenges in identifying the complex pattern of risk factors for kyphosis development. From a clinical perspective, the low recall for kyphosis presence (0.33) is particularly concerning, as the model fails to identify two-thirds of patients who will develop post-operative kyphosis.

The findings suggest that the model exhibits modest discriminative ability. While it performs better than random guessing, it does not reach the performance level typically necessary for clinical decision-support.

3.2 Feature Importance Analysis

The feature importance analysis emerged as a key strength of this study, revealing that vertebral position (55.4%) and patient age (41.5%) are the primary drivers of postoperative kyphosis risk, while the number of vertebrae involved plays a minimal role (3.0%). This finding is particularly valuable from a clinical perspective, as it aligns with surgical intuition and offers concrete guidance for risk stratification. The identification of vertebral position as the dominant predictor, with a critical threshold around T8-T9, suggests that surgeries beginning at or above this level warrant heightened caution.

The partial dependence plots (Figure 5) further elucidated the nature of these relationships by illustrating how predicted kyphosis probability changes as a function of each feature while averaging the effects of others. These plots revealed a precipitous decline in kyphosis risk as the number of starting vertebrae increased beyond the 8-9 threshold identified by the model. For Age, the relationship was distinctly non-monotonic, with an elevated risk observed in very young patients (under 30 months) and adolescents (120-180 months), while children in middle childhood demonstrated relative resilience.

The model's identification of a threshold around vertebrae 8-9 represents a clinically actionable finding, suggesting that operations beginning above this level may benefit from modified surgical approaches or enhanced stabilization techniques to mitigate the elevated kyphosis risk.

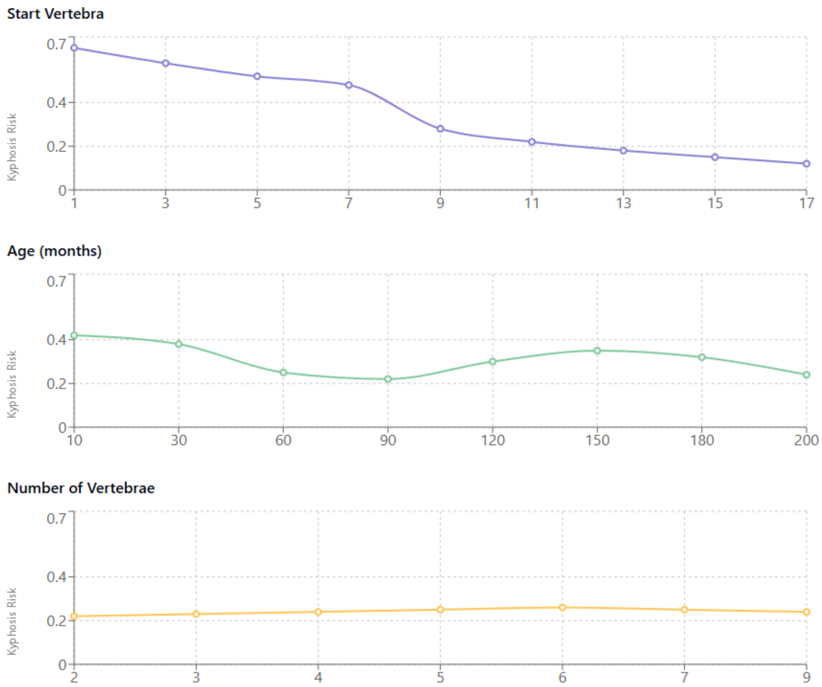

Figure 5. Partial Dependence Plots

While the dataset provided sufficient variability to train the model and extract meaningful patterns, its modest size and single-institution origin constrained the generalizability of the findings. The risk thresholds and predictor importance identified here may be influenced by institution-specific surgical practices, patient demographics, or data collection methods, potentially limiting their applicability to broader populations.

3.3 Clinical Decision Support Tool and Future Directions

Based on our findings, we developed a clinical decision support framework (Figure 6) that integrates the primary risk factors into a stratified risk assessment tool. This framework identifies four risk categories based on the interaction of vertebral level and patient age, with corresponding clinical recommendations for each risk stratum.

The highest risk is assigned to operations on vertebrae 1-8 in either very young patients (<30 months) or adolescents (120-180 months), for whom enhanced stabilization techniques and more frequent monitoring are recommended. Conversely, the lowest risk category comprises operations on vertebrae 9-18 in middle childhood patients (30-120 months), where standard surgical protocols may be sufficient.

While our model demonstrates only moderate predictive performance, the insights generated regarding the relative importance and interaction of risk factors represent a valuable contribution to surgical planning for kyphosis prevention. Identifying specific risk thresholds for vertebral level and age categories provides a more nuanced understanding of kyphosis risk than previously available.

The partial dependence analysis further refines this understanding by characterizing the relationships between predictors and outcomes. It particularly highlights the non-linear effects of age that may have been missed in previous research using simpler analytical approaches.

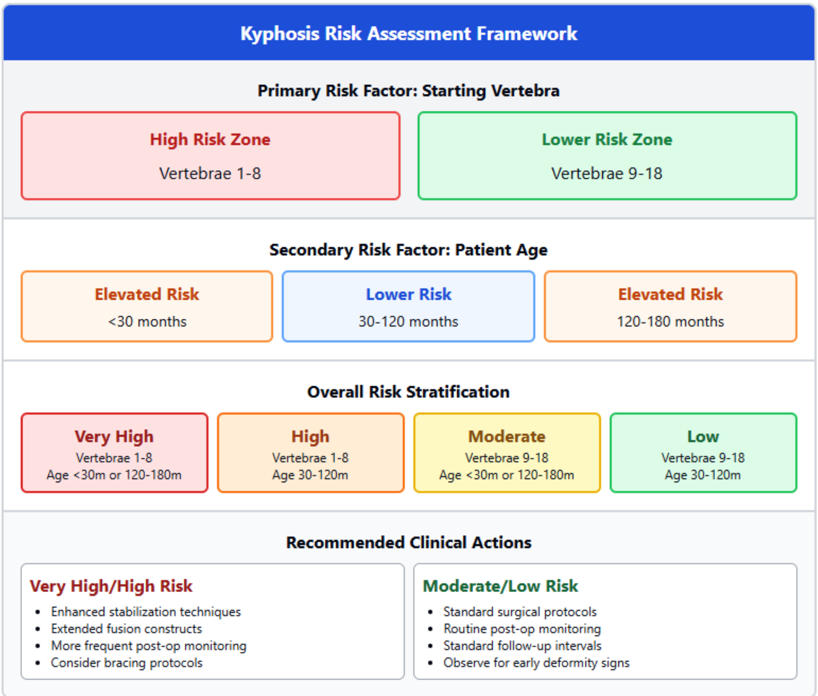

Figure 6. Clinical Decision Support Framework

Figure 6 is the clinical decision support framework for post-operative Kyphosis Risk Stratification. The framework categorizes patients into four risk levels, with recommendations: high-risk patients require enhanced stabilization (e.g., extra screws, dual-rod systems, bone grafts) and more frequent monitoring (e.g., 3-month visits, MRI/CT); low-risk patients follow standard protocols and routine 6-month X-ray follow-ups

This study demonstrates the potential value of machine learning approaches in extracting clinically relevant patterns from surgical outcomes data, even with modest sample sizes. While the resulting model may not achieve the performance necessary for autonomous clinical decision-making, it validates and quantifies clinical observations regarding risk factors and suggests specific thresholds that can inform surgical planning and post-operative monitoring protocols.

The finding that vertebral level and patient age interact to determine kyphosis risk, while the extent of the operation plays a minimal role, challenges conventional wisdom and suggests opportunities for more targeted risk mitigation strategies in pediatric spinal surgery.

3.4 Clinical Implications and Real-World Impact

The decision tree model developed to predict postoperative kyphosis in pediatric spinal surgery patients achieved an accuracy of 71%, correctly identifying the presence or absence of this condition in roughly seven out of every ten cases. At first glance, this performance might appear encouraging, suggesting a reasonable ability to distinguish between patients who will and will not develop kyphosis after surgery.

However, accuracy alone provides an incomplete picture, particularly in a dataset where only 21% of patients ultimately develop the condition. A more telling metric in this clinical context is the model's sensitivity, which is 33%. This indicates that the model identifies just one-third of the patients who will actually develop kyphosis, leaving the majority of high-risk cases undetected. This low sensitivity carries significant clinical significance, as the failure to flag these patients, known as false negatives, could have profound consequences for patient outcomes.

In pediatric spinal surgery, missing a case of kyphosis is not trivial. Postoperative kyphosis can set in motion a cascade of complications, including progressive spinal deformity, persistent pain, and compromised mobility, all of which can disrupt a child's physical development and overall well-being.

Despite its limitations, the decision tree model offers insights that hold promise for clinical applications, particularly through the identification of the starting vertebral level as a pivotal risk factor. The model pinpoints a threshold around vertebrae 8–9 (T8–T9), suggesting that surgery beginning at or above this level is associated with an increased risk of kyphosis. This finding could guide surgeons in stratifying patients based on the operative site, enabling tailored approaches to mitigate risk.

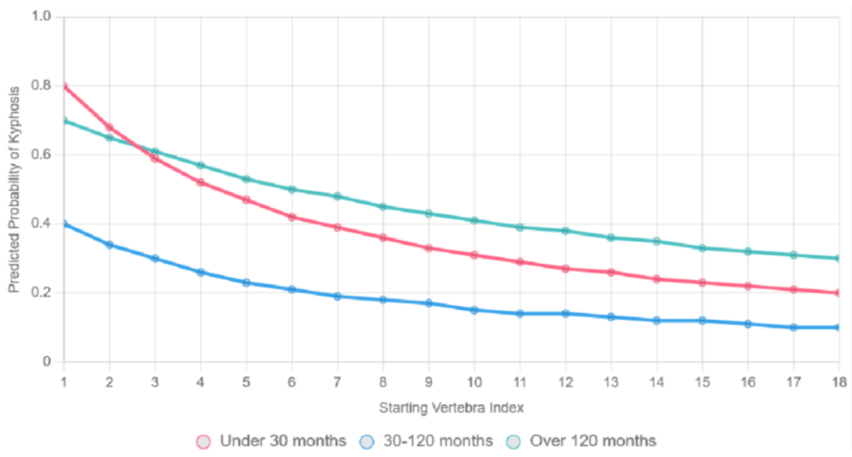

Figure 7. Predicted Probability of Kyphosis by Starting Vertebra and Age Group

To illustrate how these findings might translate into practice, we considered a visual representation of the model's risk stratification capabilities. Figure 7 depicts the predicted probability of kyphosis as a function of the starting vertebral level and patient age group. This chart reveals a clear gradient: operations at higher vertebral levels (lower indices) correspond to greater risk, with the effect most pronounced in the youngest and oldest patients.

For instance, a child under 30 months of age undergoing surgery at vertebra 1 faces a markedly higher probability of kyphosis than a child of middle age (30–120 months) undergoing surgery at a lower vertebral level. Such a tool could serve as a practical reference for clinicians, offering a quick visual aid to assess risks and guide discussions with families regarding the potential outcomes of surgery.

Compared to current clinical practices, the decision tree model introduces a structured, data-driven alternative to the often intuitive and experience-based approaches that dominate risk assessment in pediatric spinal surgery. Traditionally, surgeons rely on their expertise, supplemented by basic statistical tools or heuristic guidelines, to gauge the likelihood of complications, such as kyphosis.

In contrast, the decision tree systematically evaluates these variables and distills them into actionable decision rules, such as the T8–T9 threshold. Although its current sensitivity limits its standalone reliability, the model provides a transparent framework that can augment clinical judgment and offer a reproducible basis for identifying at-risk patients. With further development—perhaps through larger datasets or advanced techniques to improve the detection of true positives—this approach could evolve into a more definitive tool, bridging the gap between empirical knowledge and computational precision.

4. Conclusions

This study utilized machine learning techniques to predict post-operative kyphosis following corrective spinal surgery, yielding several clinically relevant insights despite the model's moderate performance. The decision tree classifier achieved an overall accuracy of 71%, with a specificity of 79%, although it exhibited a lower sensitivity of 33% in detecting kyphosis cases.

Our analysis identified the vertebral level as the primary predictor of postoperative kyphosis, accounting for 55.4% of the model's predictive power, with a critical threshold around vertebrae 8-9. This finding quantifies clinical observations, indicating that surgeries initiated above this level are associated with a significantly higher risk, independent of other variables. Patient age emerged as the second most influential predictor (41.5%), despite its weak univariate correlation, demonstrating the decision tree's capacity to detect non-linear effects.

Building upon these findings, we propose a clinical decision support framework that stratifies risk by examining the interaction between vertebral level and patient age. This tool has the potential to enhance surgical decision-making, improve the quality of informed consent discussions, and guide the development of personalized post-operative care plans.

To address the limitations of the study and enhance its clinical applicability, we propose the following targeted research directions. Collaborating with multiple institutions to expand the dataset would facilitate a larger and more diverse sample, incorporating additional variables such as pre-operative Cobb angle and surgical techniques to improve model accuracy. Investigating advanced machine learning methodologies—such as random forests, gradient boosting (e.g., XGBoost), or neural networks—could augment predictive performance, with comparisons to the current decision tree elucidating trade-offs between accuracy and interpretability. These steps delineate a comprehensive approach to refining the model and maximizing its impact on surgical practice.

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