MACHINE LEARNING APPROACHES TO PREDICT INTRAOPERATIVE TRANSFUSION

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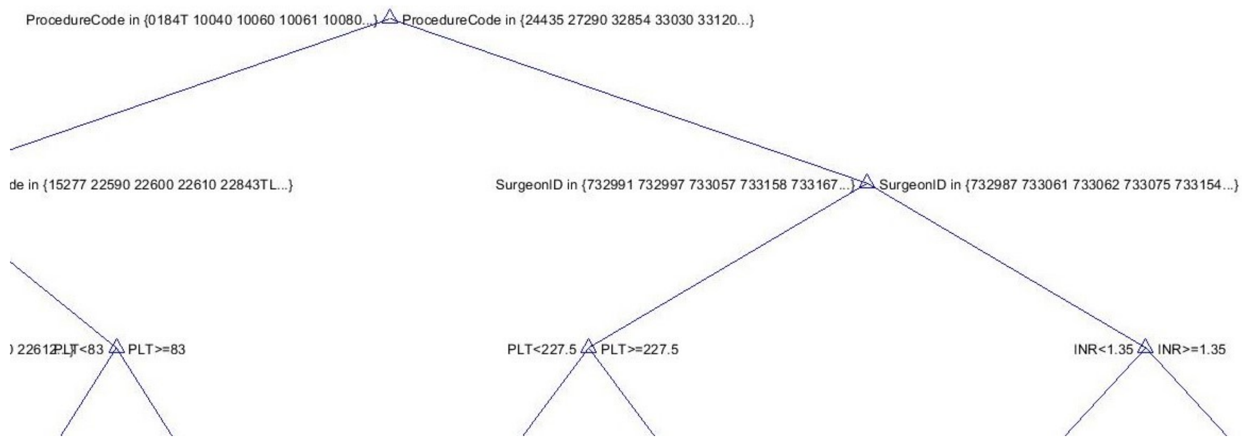
Background: Unnecessary laboratory tests are a source of significant cost and are a burden to health systems. Obtaining a preoperative type and screen expedites matched blood administration in the OR, however, obtaining type and screens for patients who are very unlikely to require blood administration represents an unnecessary expense. Currently, the maximum surgical blood ordering schedule (MSBOS) provides guidelines regarding preoperative pre-transfusion testing and blood product ordering. With the advent of machine learning approaches, opportunities exist to mine the vast amount of perioperative data and develop computationally optimized approaches to predict preoperative pretransfusion testing.

Methods: Data were retrieved from Vanderbilt University Medical Center's Perioperative Data Warehouse and included patients >18 years old, who underwent surgery at Vanderbilt's main operating rooms. Demographics, comorbidities, preoperative labs, medications, surgeon, procedure code and urgency of operation were collected. The response variable was intraoperative transfusion of any blood product.
The performance of the following machine learning algorithms were compared: logistic regression, decision tree, support vector machines, and Naïve Bayes classifiers. K-folds validation was used. RUSBoosting was used to compensate for class imbalance. F-score, precision, sensitivity, accuracy, and area under the receiver operating characteristic (AUROC) curve were assessed.

Results: The AUROC for the following models was logistic regression (0.66), support vector machines (0.88), Naïve Bayes classifiers (0.94), and decision tree (0.92). Class imbalance represented a challenge in this dataset as cases with transfusion represented only 2.3% of total OR cases. Decision trees with medium number of splits had the highest F1 score (0.52), which represents a balanced metric between positive predictive value and sensitivity. A RUSBoosted decision trees model was used with an improvement in sensitivity from 47% to 85%. Most important to the RUSBoosted decision tree model were primary procedure code, surgeon ID and laboratory results (e.g. Platelets < 83×10^9/L).

Conclusion: Machine learning approaches are a feasible way to predict preoperative pretransfusion testing needs. Optimizing machine learning models to specific test performance metrics can provide helpful models which may be incorporated in decision support.

Image: Root and Partial Nodes of Decision Tree Classifier Model.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PLT>=83
PLT<227.5
PLT>=227.5
INR<1.35
INR>=1.35