Methods

Four modeling approaches are considered here:

1. Logistic Regression (LR): fits a conventional logistic regression model using the same 9 parsimonious variables as included in the McNamara et al. study.

2. Logistic Regression with Lasso (Lasso): couples a conventional logistic regression approach with a cost function (Lasso), which results in a parsimonious set of variables that maximizes predictive capabilities.

3. Gradient Descent Boosting (XGBoost): leverages the creation of many weak decision trees to produce a final, accurate prediction via weighted majority vote (“boosting”); unlike logistic regression, XGBoost is able to account for nonlinear, higher-order interactions among variables.


Results

Table 1: Summary of model performance for LR, Lasso, XGBoost, and Meta models

| Model   | ROC AUC (C-statistic) | PR AUC | Sensitivity | Specificity | PPV | NPV | Brier Score
|---------|-----------------------|--------|-------------|-------------|-----|-----|-------------
| LR      | 0.872                 | 0.900  | 0.55        | 0.55        | 0.55| 0.55| 0.044
| Lasso   | 0.41                  | 0.45   | 0.53        | 0.93        | 0.53| 0.53| 0.044
| XGBoost | 0.929                 | 0.929  | 0.93        | 0.93        | 0.93| 0.93| 0.044
| Meta    | 0.930                 | 0.930  | 0.93        | 0.93        | 0.93| 0.93| 0.044

Table 2: Shift table comparison of individual risk estimates from Lasso and XGBoost/Meta models

<table>
<thead>
<tr>
<th>Lasso risk</th>
<th>XGBoost/Meta risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low (&lt; 1%)</td>
<td>0.2% (88.777)</td>
</tr>
<tr>
<td>Moderate (1-5%)</td>
<td>1.8% (1.233)</td>
</tr>
<tr>
<td>High (&gt; 5%)</td>
<td>9.5% (258)</td>
</tr>
</tbody>
</table>

Table 2. Each cell represents a cohort of patients whose individual Lasso risk falls within the Lasso range and whose individual XGBoost/Meta classifier risk falls within the given XGBoost/Meta risk range. Event rate is given as a percentage for each cohort, and the sample size is shown in parentheses.