Machine Learning Applied to Hepatocellular Carcinoma

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Section 1

Background HCC

HepatoCellular Carcinoma (HCC)

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- Data mining approach to tailor evaluation and treatment for HCC are limited in the literature.
- Using the HCC dataset, we undertook the data mining approach to evaluate the patient level factors to identify those who are at risk of one year mortality.

Section 2

Data Summary

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- Clinical data of 165 pts with HCC (demographic, risk factors, lab data, and survival features)
- 49 features from HCC clinical practice guidelines (Table 1)
- About 80
- Missing data represents 10.22
- The target variable is the survival at 1 year, coded as 0 (dies) and 1 (lives).

Data Summary Table

Table 1: HCC Data Summary of Selected Variables

	Overall (N=165)
gender	
female	32 (19.4%)
male	133 (80.6%)
symptom	
no	53 (36.1%)
yes	94 (63.9%)
N-Miss	18
alc	
no	43 (26.1%)
yes	122 (73.9%)

Section 3

Random Forest Model

Description

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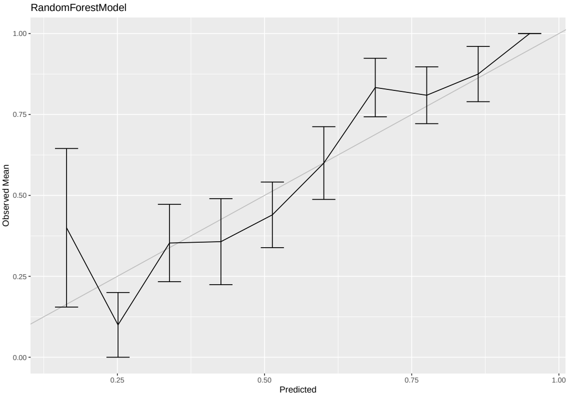
- 10 fold CV
- Tuned Hyperparameter Parameters with Bayesian Optimization
- Applied and tuned KNN imputation and Correlation Filter

Estimated Performance

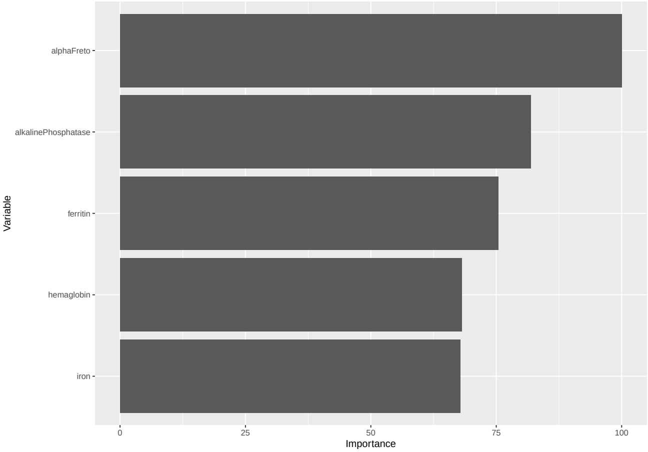
Table 2: RF results with knn imputation and corr filter

Metric	Mean	Median	SD	Min	Max	NA
Brier	0.175	0.175	0.046	0.115	0.245	0
Accuracy	0.720	0.719	0.103	0.562	0.875	0
Kappa	0.390	0.383	0.220	0.143	0.714	0
ROC AUC	0.799	0.808	0.137	0.608	0.983	0
Sensitivity	0.824	0.800	0.146	0.500	1.000	0
Specificity	0.555	0.619	0.184	0.333	0.833	0

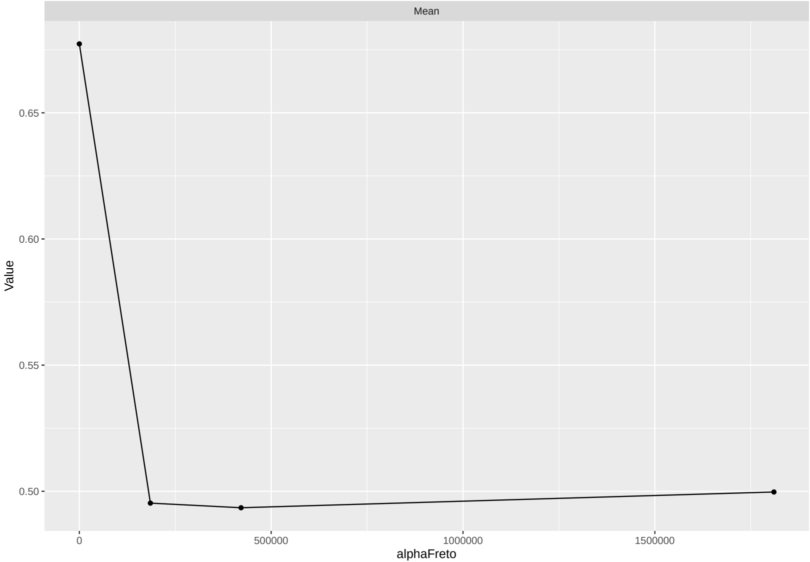
Calibration Plots



Variable Importance



Partial Dependence



Section 4

XGBoost Model

Description

{Input: training set $\{(x_i, y_i)\}_{i=1}^{N}$, a differentiable loss function $L(y, F(x))$, a number of weak learners M and a learning rate α. }

1. Initialize model with a constant value: $\hat{f}_{(0)}(x) = argmin_\theta \sum_{i=1}^{N} L(y_i, \theta)$.
2. For $m = 1, ..., M$:
   a Compute gradients and hessians:
   $\hat{g}_m(x_i) = \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x)=\hat{f}_{m-1}(x)}$
   $\hat{h}_m(x_i) = \left[\frac{\partial^2 L(y_i, f(x_i))}{\partial f(x_i)^2}\right]_{f(x)=\hat{f}_{m-1}(x)}$.

   b Fit a base learner using the training set $\left\{x_i, -\frac{\hat{g}_m(x_i)}{\hat{h}_m(x_i)}\right\}_{i=1}^{N}$ by solving the optimization problem below:
   $\hat{\phi}_m = argmin_{\phi\in\Phi} \sum_{i=1}^{N} \frac{1}{2}\hat{h}_m(x_i)\left[-\frac{\hat{g}_m(x_i)}{\hat{h}_m(x_i)} - \phi(x_i)\right]^2$.

   c Update the model: $\hat{f}_m(x) = \hat{f}_{(m-1)}(x) + \alpha\hat{\phi}_m$.
3. Output $\hat{f}(x) = \hat{f}_{(M)}(x)$.

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- Tuning inputs: KNN with the number of neighbors, correlation among variables, principal component analysis proportion of variance to be retained.
- XGBoost includes different regularization penalties to prevent overfitting. It can be run on multiple CPU cores and servers to save training time.

Estimated Performance

Table 3: XGBoost results with knn imputation and feature selection using correlation

Metric	Mean	Median	SD	Min	Max	NA
Brier	0.221	0.219	0.086	0.081	0.344	0
Accuracy	0.701	0.688	0.096	0.562	0.889	0
Kappa	0.360	0.353	0.210	0.097	0.766	0
ROC AUC	0.768	0.775	0.116	0.584	0.961	0
Sensitivity	0.774	0.800	0.116	0.600	0.909	0
Specificity	0.586	0.619	0.187	0.333	0.857	0

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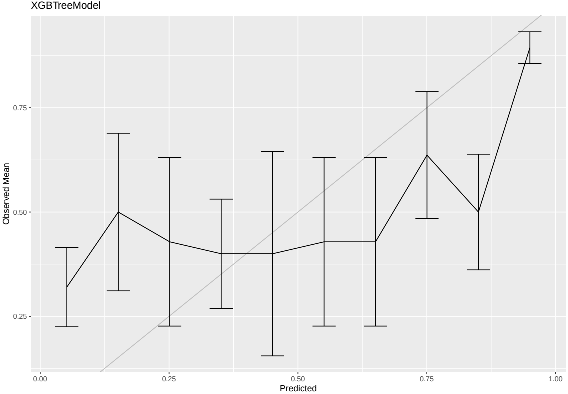
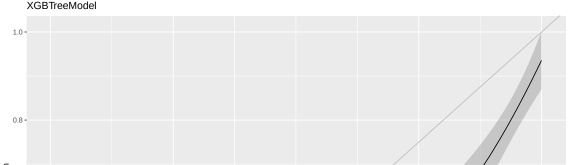
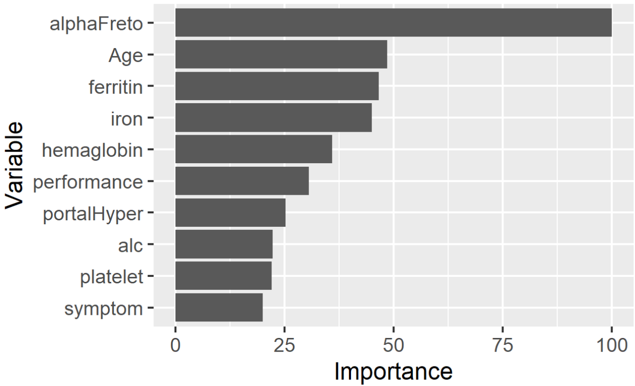
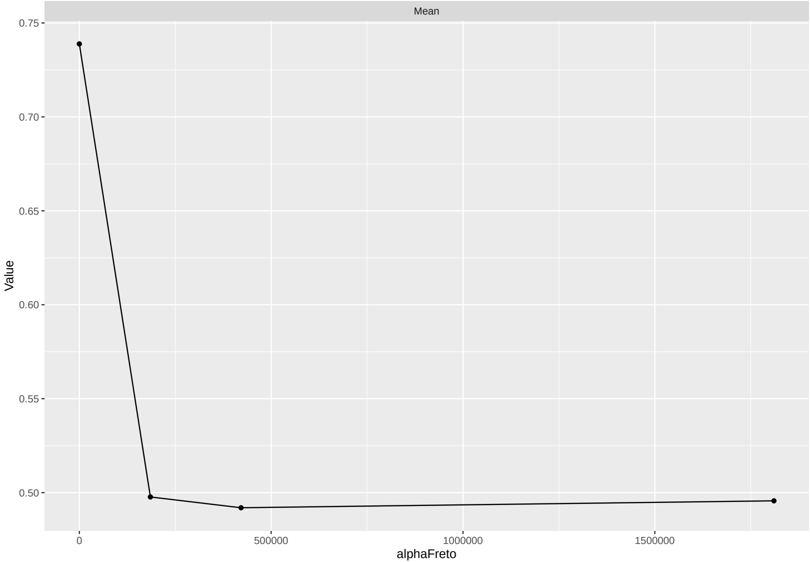




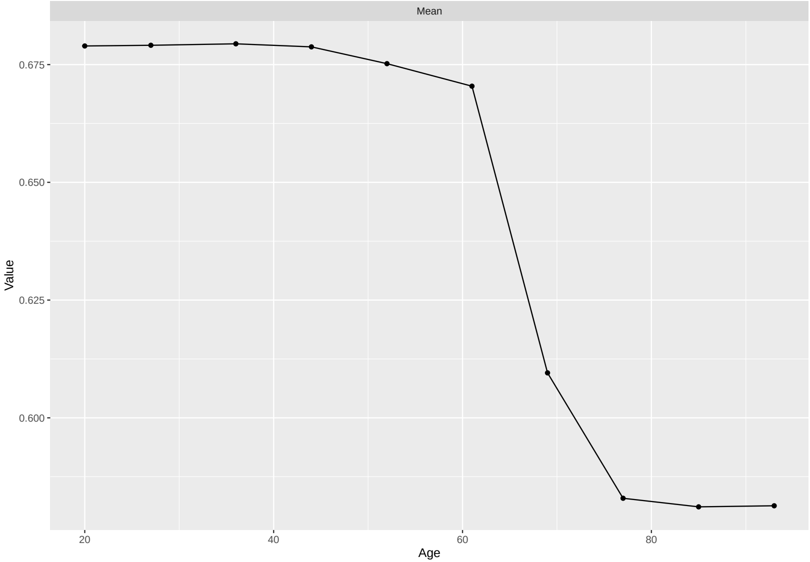
Variable Importance



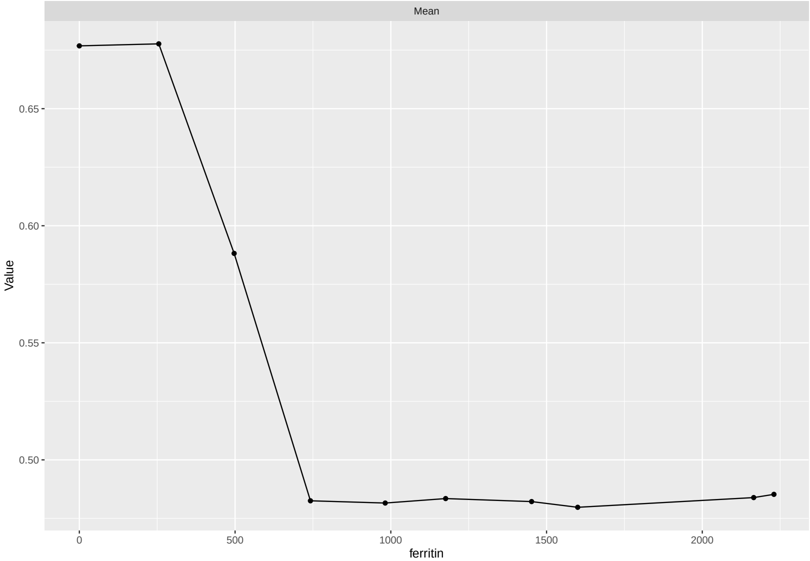
Partial Dependence: alphaFreto



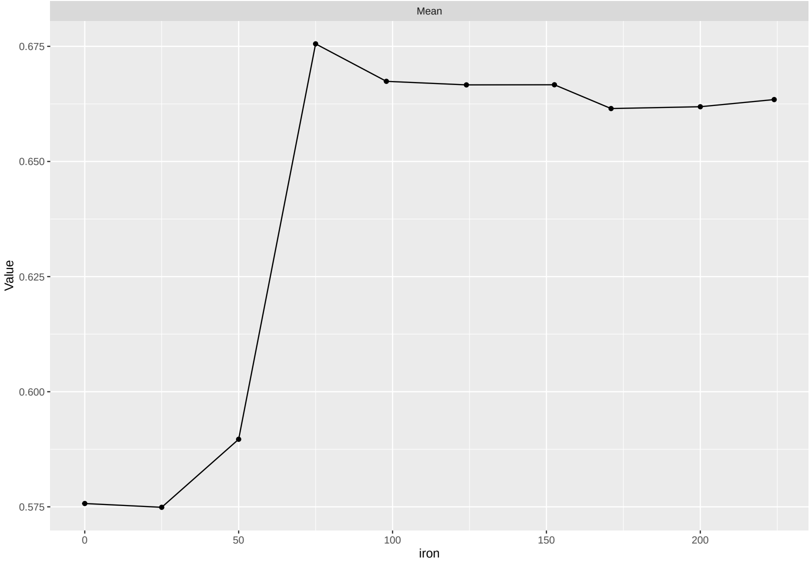
Partial Dependence: Age



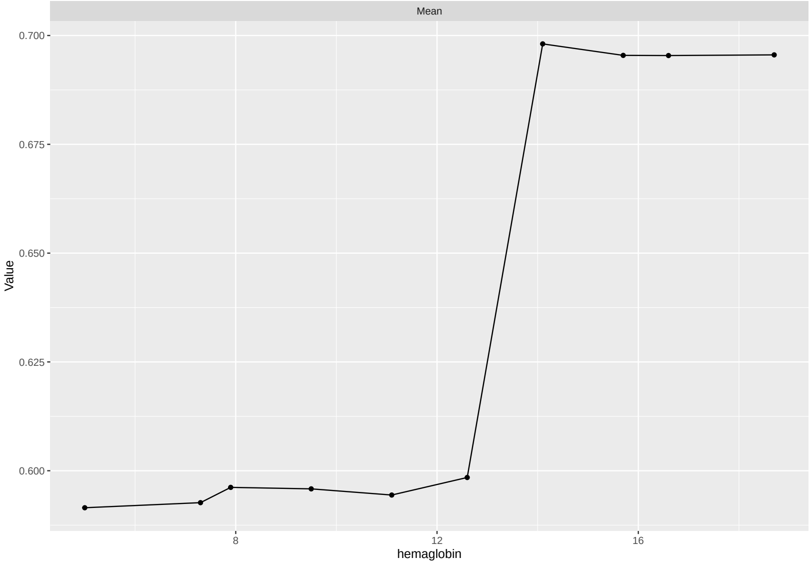
Partial Dependence: ferritin



Partial Dependence: iron



Partial Dependence: hemaglobin



Section 5

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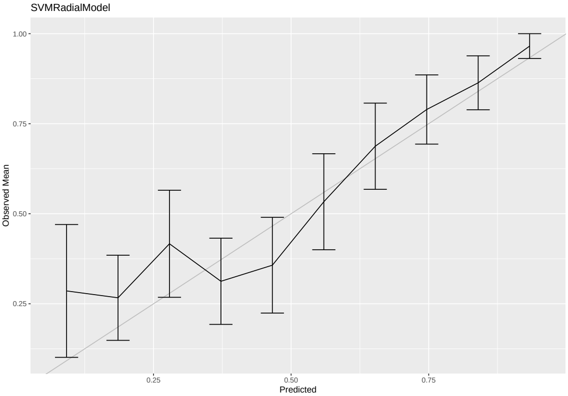
- Radial Basis kernel function: $\exp(-\sigma^2 \|x - x'\|^2)$; $\sigma = 0.0123873$
- Cost of misclassification C $=$0.8956493
- imputation using KNN with neighbors $= 4$

Estimated Performance

Table 4: SVMRad results with knn imputation

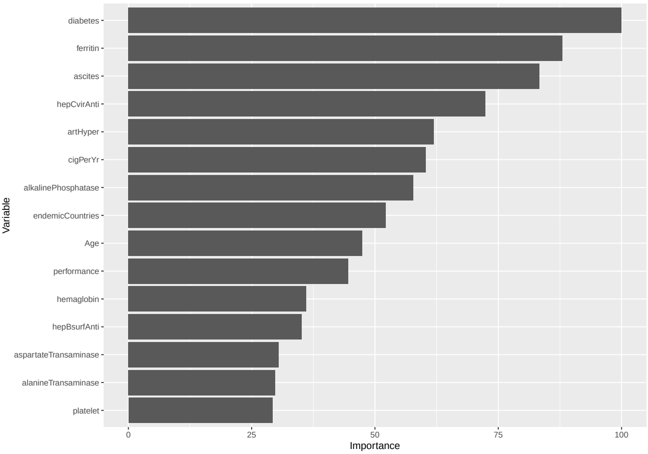
Metric	Mean	Median	SD	Min	Max	NA
Brier	0.176	0.166	0.057	0.101	0.287	0
Accuracy	0.756	0.764	0.119	0.562	0.938	0
Kappa	0.482	0.503	0.254	0.097	0.871	0
ROC AUC	0.818	0.829	0.101	0.600	0.967	0
Sensitivity	0.803	0.809	0.107	0.600	0.909	0
Specificity	0.681	0.643	0.190	0.500	1.000	0

Calibration Plots



- Decently calibrated. Low probabilities have many false negatives.

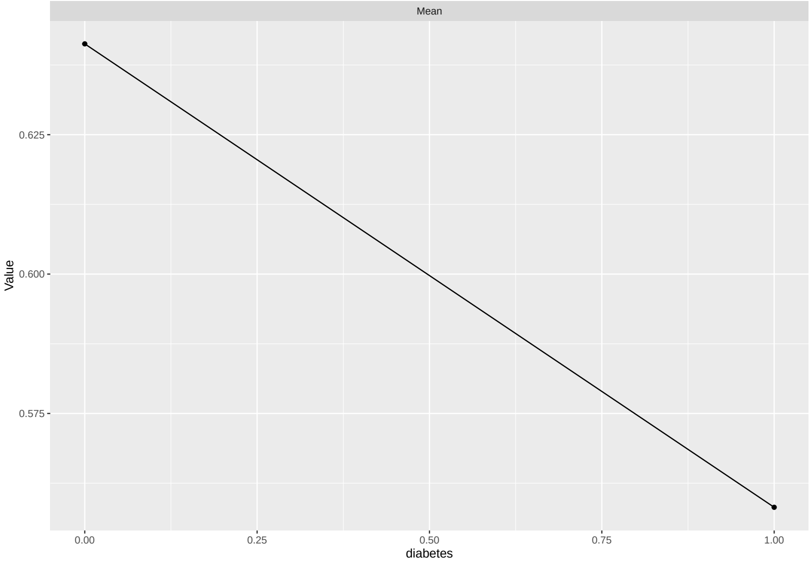
Variable Importance



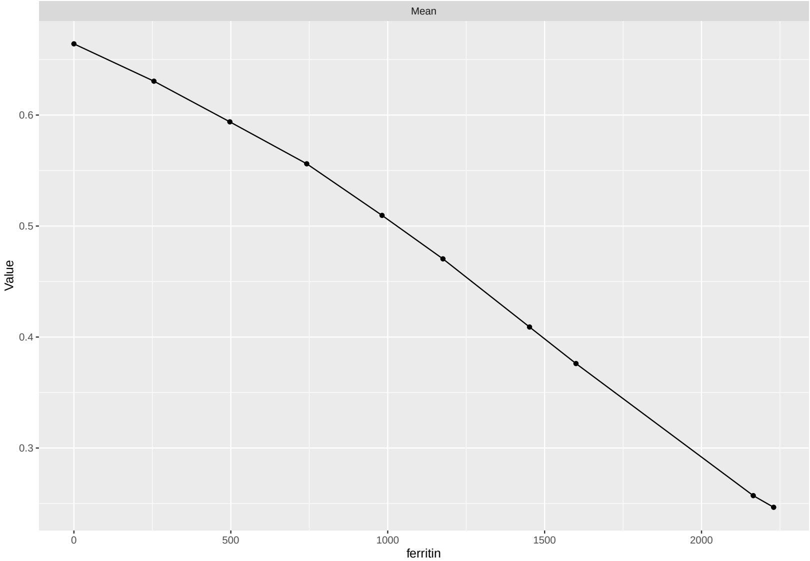
Variable Importance

- Symptoms (performance)
- Indicators of liver injury/disease/infection (hepBsurfAnti, hepCvirAnti,aspartateTransaminase, alkalinePhosphatase, ferritin, totalProteins, ascites, hemoglobin)
- Biological Characteristics (age, portalVeinThromb)
- Risk factors (diabetes, artHyper)
- behavioral/demographic (endemicCountries, cigPerYr)

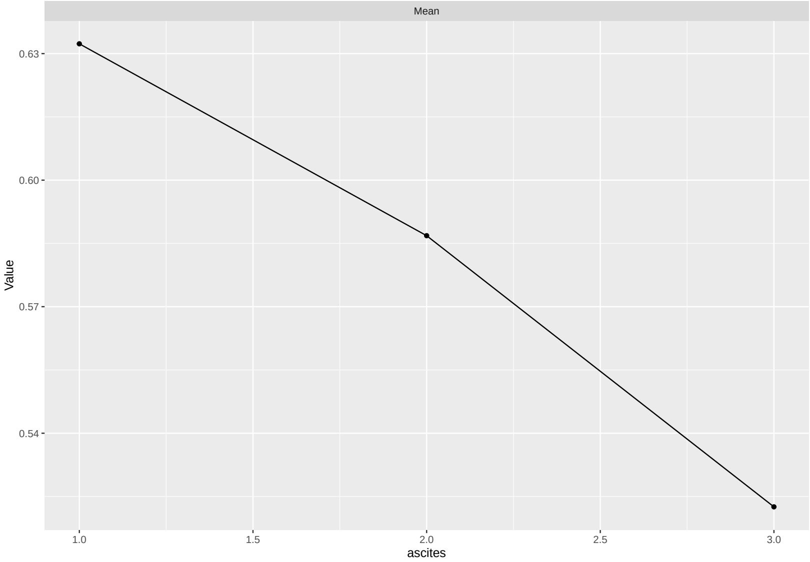
Partial Dependence: diabetes



Partial Dependence: ferritin



Partial Dependence ascites



Section 6

Final Model choice

Criteria

- Final model was chosen by the model with the highest Sensitivity

Table 5: Comparison of Sensitivity

	Metric	Mean	Median	SD	Min	Max
RandomForest	Sensitivity	0.824	0.800	0.146	0.5	1.000
XGBTree	Sensitivity	0.774	0.800	0.116	0.6	0.909
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- Minimizes incorrectly telling a patient they will die

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Section 7

References

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