Using the National Health Interview Survey Linked Mortality Files to Train and Assess the Performance of Machine Learning Prediction Models to Predict All-Cause Mortality and Interpret Model Predictions using Explainable Al

Orlando Davy, MPH; Frances McCarty, PhD; Yulei He, PhD; Cordell Golden, MPS

Background

- NCHS Data Linkage Program produces high-quality linked data files that can be used for a wide-range of health-related research topics and data science applications
- Machine learning (ML) prediction models can be used to predict outcomes with high predictive accuracy, but require quality and accurate data for training
- Explainable AI (XAI) involves visual global and local methods used to enhance the understanding of complex ML models overall and make model predictions interpretable

Objectives

- Evaluate selected ML prediction models using linked data as the training data and validation source to assess model performance for predicting all-cause mortality
- Use XAI to interpret model results

Methods

Data Source

- Public-use 2000 2001 National Health Interview Survey (NHIS) Linked Mortality Files (LMF) with mortality information through 2019
- IPUMS NHIS harmonized data used for the analysis
- Linkage eligible NHIS sample adult respondents with complete information for selected predictor variables (n = 46,949)

Data Analysis

- Analysis performed using R v 4.3.1, package included: caret v6.0-94, pdp v0.8.1, lime v0.5.3, and yardstick v1.2.0
- Selected ML prediction models: Random Forest (RF), Gradient Boosting Machine (GBM), Support Vector Machine (SVM), Naïve Bayes (NB)
- XAI methods used: Variable Importance Plots (VIP); Partial dependence plots (PDP), LIME Local Features Plot
- Initial feature set included 20 predictor variables plus one target (outcome) variable
- Only records with complete information for all predictor variables were included Training set: 2000 NHIS LMF (n = 23,210)
- Validation set: 2001 NHIS LMF (n = 23,739)

Steps:

- 1. VIP used to identify ten most important variables (2000 NHIS LMF)
- 2. ML models trained using most important variables (2000 NHIS LMF)
- 3. Trained models were re-run using 2001 NHIS LMF
- 4. Model results compared to outcome from 2001 NHIS LMF
- 5. Precision-Recall curves (PR-AUC) used to visually assess model performance
- 6. Additional metrics evaluated to assess performance: Misclassification Error, Precision, Recall, Balanced Accuracy, F1-Score, and Processing Time

Results

- Older age (70+ years), hypertension, diabetes, widow/divorced/separated, and inactivity were consistent top 10 predictors for all-cause mortality across all models
- The GBM model had the lowest error rate, highest F1-score and PR-AUC estimate
- SVM precision was greater compared to the other models, but had the lowest recall
- Processing time was reasonable across models, the NB model was the most efficient
- Partial dependence shows older age groups tend to have a more positive impact on predicting the correct class (Mortality = "Yes")

CONCLUSIONS

 The ML models performed reasonably well when predicting all-cause mortality when trained with high-quality data

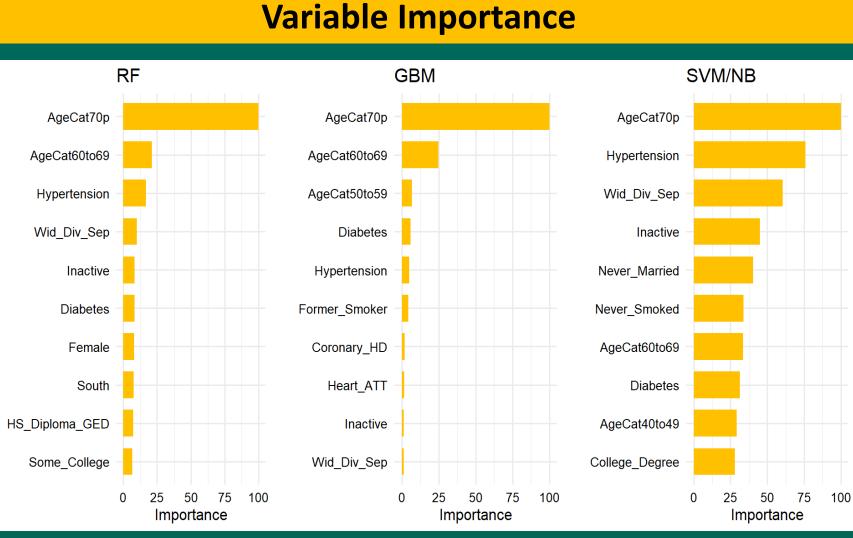
Limitations

- Only complete cases used for analysis
- Information for predictor variables derived from self-reports

Target Variable* and Feature Set

1. Age	12. Hy
2. Sex	13 . Dia
3. Race and Ethnicity	14. Co
4. Education	15. He
5. Marital Status	16. He
6. Poverty to Income Ratio	17. Pla
7. Health Insurance	18 . Ba
8. Inactivity	19. Ps
9. Smoking Status	20. Re
10. Excessive Alcohol Consumption	21. Mo

11. Body Mass Index

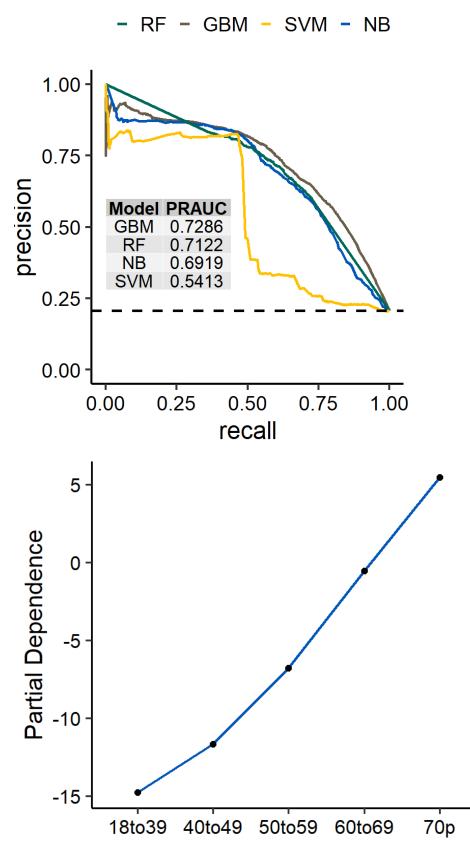


Performance Measures

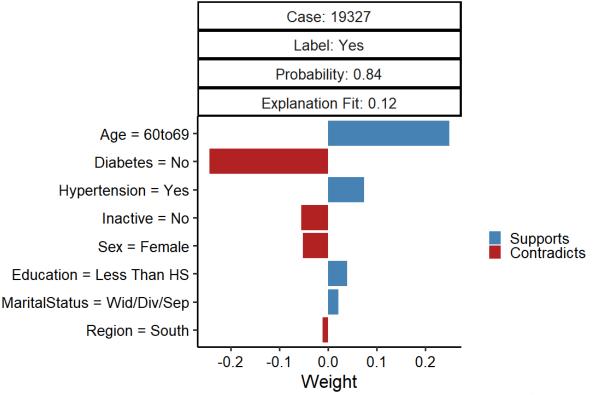
	RF	GBM	SVM	NB
Misclassification Error	0.1305	0.1239	0.1320	0.1560
Precision	0.7304	0.7752	0.8262	0.6044
Recall	0.5826	0.5957	0.4562	0.7051
Balanced Accuracy	0.7633	0.7723	0.7156	0.7926
F1-Score	0.6481	0.6648	0.5878	0.6509
Process Time(min)	3.20	0.58	1.00	0.02

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- /lortality*

Global Procedures



An Example of a Local Procedure



CONTACT INFO: odavy@cdc.gov