Predicting Heart Disease with Personal Health Indicators

By: James Makanas

Background Information

- 2020 CDC Health Status Survey of 401,958 adults for the Behavioral Risk Factor Surveillance System (BRFSS)
 □ Originally had 279 columns
- Dataset trimmed to 391,795 rows with 18 columns potentially related to heart disease

Data Description

Dependent variable: Reported having coronary heart disease or myocardial infarction
 Binary
 Categorical

- Independent variables
 □ BMI (continuous)
 - ☐ Smoking (categorical)
 - ☐ Alcohol Drinking (categorical)
 - ☐ Stroke (categorical)
 - ☐ Physical Health (continuous)
 - ☐ Mental Health (continuous)
 - ☐ Difficulty Walking (categorical)
 - ☐ Sex (categorical)
 - ☐ Age Category (categorical)

- ☐ Diabetic (categorical)
- ☐ Physical Activity (categorical)
- ☐ General Health (categorical)
- ☐ Sleep Time (continuous)
- ☐ Asthma (categorical)
- ☐ Kidney Disease (categorical)
- ☐ Skin Cancer (categorical)

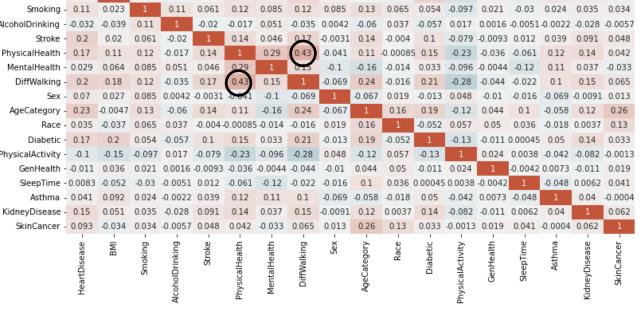
Primary Objectives

- ☐ Utilize the relevant health status indicators to create a binary classification model that predicts heart disease
- ☐ Go through the necessary preprocessing steps to prepare the data and then the model selection, tuning, and validation process

Methodology: Data Preprocessing

- No missing values
- No near-zero variance predictors out of numerical variables
- No collinearity
 - ☐ Highest correlation coefficient: .43





Correlation Heatmap

0.064 0.18 0.027 -0.0047 -0.037 0.2

0.052 0.11 -0.032 0.2 0.17 0.029 0.2 0.07 0.23 0.035 0.17 -0.1 -0.011 0.0083 0.041 0.15 0.093

- 0.75

- 0.50

- 0.25

- 0.00

- -0.25

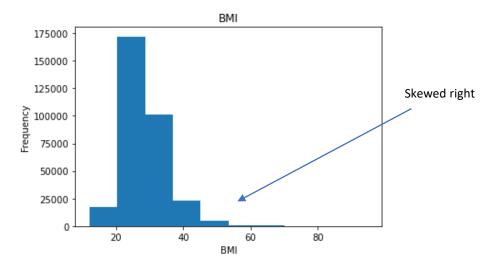
- -0.50

- -0.75

Methodology: Transforming Skewed Numerical Variables

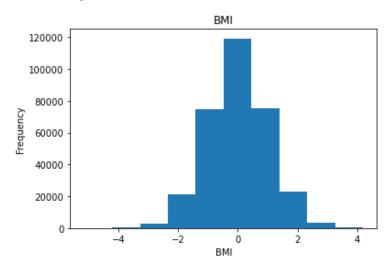
Before Yeo-Johnson

Variable	Skewness
	Coefficient
BMI:	<mark>1.33</mark>
PhysicalHealth:	<mark>2.60</mark>
MentalHealth:	<mark>2.33</mark>
SleepTime:	0.68



After Yeo-Johnson

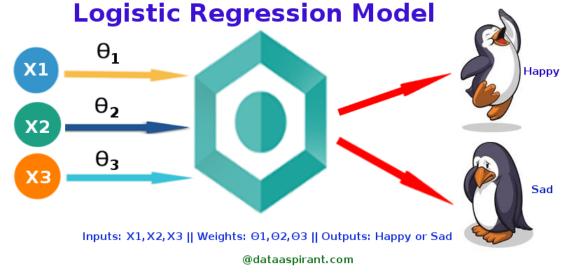
Variable	Skewness
	Coefficient
BMI:	<mark>-0.01</mark>
PhysicalHealth:	<mark>1.00</mark>
MentalHealth:	<mark>0.72</mark>
SleepTime:	0.68



Methodology: Model Selection

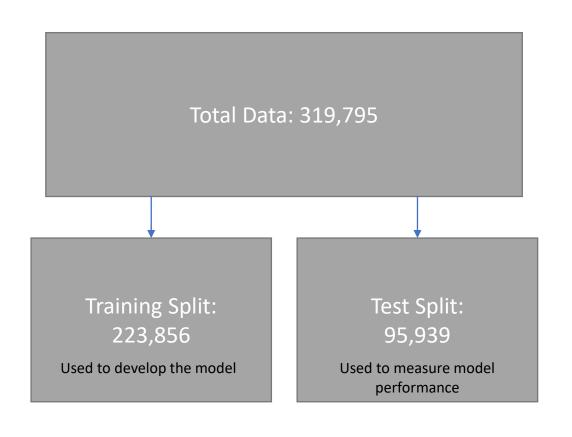
Model Type Selected: Logistic Regression

- Good for binary classification
 - ☐ 1: Heart disease present
 - ☐ 0: No heart disease present
- Estimates the relationship between the binary dependent variable and the independent features selected



(Source: http://dataaspirant.com/2017/03/02/how-logistic-regression-model-works/)

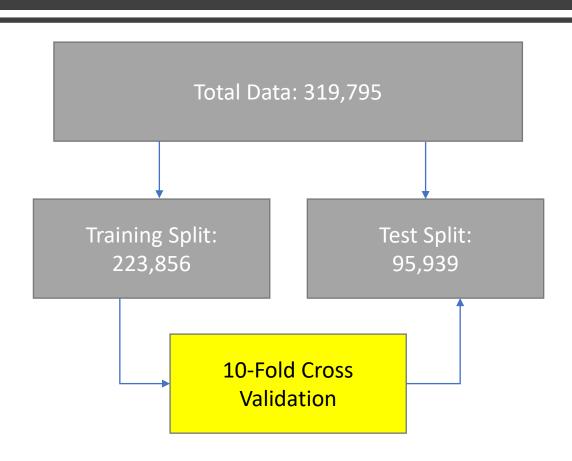
Methodology: Model Training and Validation



Data Split

- 70% of the data will be used within model development.
- 30% of the data will be used to measure model performance after the model was developed.
- Data split allows for a large sample for both training and testing. This also allows for additional model validation prior to evaluating model performance on test data.

Methodology: Model Training and Validation



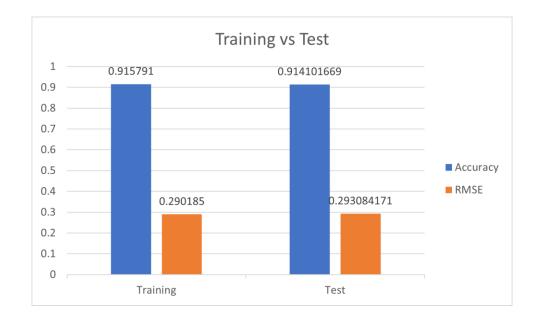
Model Validation

- Prior to testing, the model was validated with 10-fold cross validation on a portion of the training split not used to develop the model.
- Accuracy: 91.58%

Results: Model Performance

Model Validation

- After validating the model with a portion of the training data not used in developing the model, the model was then evaluated on the test split data.
- Training Model Validation
 - ☐ Accuracy: 91.58%
 - ☐ Root Mean Squared Error: .2901
- Test Model Performance
 - ☐ Accuracy: 91.41%
 - ☐ RMSE: .2931
- Strong performance in predicting different samples of the data shows that the model will perform well on brand new data



Potential Uses

- With this logistic regression model, we can potentially predict the presence of coronary heart disease or myocardial infarction at a large scale given that the people provide their health status indicators related to heart disease
- Health organizations
- At home use

References

https://www.kaggle.com/datasets/kamilpytlak/personal-key-indicators-of-heart-disease https://dataaspirant.com/how-logistic-regression-model-works/