



# Framingham Heart Study

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## Executive Summary

Our team selected a dataset of health characteristics for nearly 4000 patients from the Framingham Heart Study in 2019. Characteristics included: sex, age, current smoker (yes/no), cigarettes smoked per day, blood pressure medication (yes/no), prior history of stroke (yes/no), prevalent to hypertension (yes/no), diabetes (yes/no), total cholesterol, systolic and diastolic blood pressure, body mass index, heart rate, glucose levels, and our target variable, risk of heart disease (yes/no). Our research is critical to help doctors predict if a particular patient is at risk of heart disease due to certain common characteristics within health records.

Our main findings based on the models are that our dataset is incredibly valuable for predicting if a patient is not at risk for heart disease, whereas it is incredibly weak at predicting a patient that is at risk. Within our supervised learning methods, we discovered that the biggest contributing factors to the risk of heart disease are record of prior stroke, cigarettes smoked per day, age and systolic blood pressure. Through unsupervised learning we discovered and reaffirmed that diabetes, prior stroke, and cigarettes smoked per day are the highest contributing factors to the risk of heart disease. Based on these findings, we first recommend that medical professionals take precaution when trying to predict the risk of heart disease, as the models we fit to the data vary in prediction accuracy. As humans get older, the intensity of care from medical professionals increases, so we have no recommendations to combat age as a significant predictor. We recommend that health professionals issue more blood pressure medication, as high systolic blood pressure is a significant contributor to risk of heart disease and there were many observations in the data with systolic blood pressure over 130 (Stage 1 Hypertension) that do not receive medication. Diabetes and prior stroke are uncontrollable, our only recommendations for

health professionals is to focus more on other contributing factors for patients with these characteristics, as they are at risk for heart disease by default. Lastly, cigarettes per day is a big contributing factor, but this study was completed in 2019 and the younger generations are now turning towards vaping. Because of this we recommend that health professionals roll out widespread research on vaping as opposed to smoking, as we do not know the implications it could have on risk for heart disease, as well as many other health issues.

## **Analysis:**

### **Supervised Learning**

In preparation of the data for the various models we transformed male, currentSmoker, BPMeds, prevalentStroke, prevalentHyp, diabetes, and TenYearCHD to factors, however for kNN we only converted TenYearCHD to a factor and kept the predictors as numerical, and for clustering we only converted TenYearCHD to a number as a character. We decided to take out the Education variable completely because our focus is on health related metrics to predict the risk of 10 year heart disease. Total cholesterol was also taken out; the information gained from the variable could typically be inferred through the diabetes variable, but also because there are many factors impacting cholesterol that are not in the dataset, so we did not have a reasonable way of replacing the missing data with accuracy. The NAs in CigsPerDay were replaced with 20, the average smoker in our dataset smoked ~18 cigarettes, but we decided to round to 20 given that a typical smoker in the dataset smoked in denominations of packs, or 20s. BPMeds describes whether or not the patient takes blood pressure meds. Because we had the systolic and diastolic blood pressure, we were able to replace missing values based on the rule that if systolic blood pressure is above 120 and diastolic is above 80, the patient is on blood pressure medication. There were also various missing values in the BMI, heartRate, and glucose categories, for which we decided to drop similar to cholesterol, because we had no way of meaningfully predicting these variables based on the other information about the observation. Also, it is important to note that we felt comfortable dropping observations because our dataset was large, containing 3825 observations still after our processing. After we had prepped the data, we dove into the analysis portion of the project.

Logistic Regression is a useful test to run when considering a situation with binary outcomes. In order to run the logistic regression, the appropriate categorical variables had to be converted into factors, and the data had to be randomly split into a training and a test set. While the overall accuracy of 85.29% may suggest the model has strong predicting capabilities, diving into the specificity and sensitivity uncovers a more nuanced conclusion. The sensitivity is 9.62%, meaning 9.62% of at-risk patients were correctly predicted to be at risk for heart disease, whereas the specificity of 99.3% means 99.3% of patients not at risk were predicted correctly by the model. These two metrics show a severe imbalance in strength of the model, it is extremely strong at predicting a patient not at risk for heart disease and extremely weak at predicting those who are at risk. A lift chart for the model shows a fairly flat curve that is close in proximity to the 45° line, as well as an AUC of .736. This shows that: while the model is a stronger predictor than random selection, it is not significantly stronger. This was to be expected however based on the difference between the sensitivity and specificity of the model. Taking a look at the coefficients of the model was interesting, as the coefficient for prior stroke had a coefficient of 3.3016320807, suggesting that is the most influential predictor variable. Another important coefficient was the coefficient of 1.0215558560 for cigarettes smoked per day, meaning for every one cigarette increase per day, the odds of a patient being at risk for heart disease increase by 2.16%, holding all else constant. This is a very significant number as we mentioned smokers typically smoke in denominations of packs, so an increase of one cigarette per day is a realistic possibility for many smokers. We then ran a best subset exhaustive search, which concluded that the best model for logistic regression would exclude variables diabetes, cholesterol, heart rate, and BMI. The first three variables chosen by the exhaustive search were age, cigarettes per day,

and systolic blood pressure, implying that they are heavily influential on risk of heart disease, and reaffirming the significance of cigarettes per day. See **Appendix Section E**.

K Nearest Neighbors (kNN) is a numerical data driven approach to classification, which uses the “nearest neighbors” in the data to classify observations by Euclidean distance calculation. Prior to application of the model, the predictor variables all had to be set to numerical values, the target variable had to be set to a factor of two, and the predictor variables had to be normalized. With application of the model, it is evident that a model with 7 nearest neighbors is applied, which generates the highest accuracy. The model has a fairly high accuracy of 84.64%, a very high specificity value of 96.79%, and a fairly high negative predictive value of 86.81%. The model is extremely better at predicting negative values than positive ones, as the sensitivity and positive predictive values are 11.47% and 37.31%, respectively. K Nearest Neighbors suggested the model as beneficial for predicting only whether a patient is not at risk for heart disease. See **Appendix Section A**.

Naive Bayes appears at first to be a good model for predicting whether or not one is at risk for heart disease based on their medical information, but is only beneficial for predicting whether someone is not at risk for heart disease. The overall accuracy of the model is 80.92%, which is much better than random selection, but a look at sensitivity and specificity shows us that the model is only 25.94% accurate when trying to predict whether one is at risk for heart disease, while the model is 91.09% accurate when predicting whether one is not at risk for heart disease. The precision of the model is 35.03%, meaning of the observations the model predicted as at risk for heart disease, 35.03% were actually at risk. The negative predictive value of the model is 86.92%, meaning of the observations the model predicted as not at risk for heart

disease, 86.92% were correctly identified. Naive Bayes suggests that the dataset is better used to predict if a patient is not at risk for heart disease. See **Appendix Section B**.

Classification trees are intended to help classify an outcome based on a set of predictors. We intended to classify the variable that contributes the most in causing a ten year risk of heart disease. From our tree we are able to learn that the two leading predictors influencing risk of heart disease, as age is the first classifier in our tree and systolic blood pressure is the second classifier. The tree indicates those most likely to have a ten year risk of heart disease are a person above 47 years old and a person with a systolic blood pressure above 155. We analyzed a confusion matrix to help us better understand our results because our target variable is categorical. From our confusion matrix we were able to learn that 958 of actual at-risk patients were correctly predicted by the algorithm, 145 at-risk patients were incorrectly predicted as not at risk by the algorithm, 25 non risk patients were predicted as at risk by the algorithm, and 20 observations were correctly identified as at risk for heart disease. This model has an accuracy of 85.19% with a sensitivity of 12.12% and a specificity of 97.46%. This sensitivity value tells us that our model is only 12.12% accurate when trying to predict whether one is at risk for heart disease, while the specificity value tells us that the model is 97.46% accurate when predicting whether one is not at risk for heart disease. As with our other supervised learning models, the classification tree is much more accurate in predicting patients not at risk compared to those at risk. See **Appendix Section C**.

## Unsupervised Learning

Clustering is an exploratory technique used to discover structure within a set of data and to summarize the properties of each cluster. We ran a hierarchical clustering with 3 clusters. Each cluster had its own profile, cluster 1 is the heavy smokers, who do not have diabetes or a previous stroke, cluster 2 is those who have had a previous stroke and do not have diabetes, cluster 3 is those who have never had a stroke before, but do have diabetes. Cluster three represents only patients who have not had a stroke before, but do have diabetes, and has a mean value for risk of heart disease equal to .61, suggesting patients with diabetes are at the highest risk for heart disease. Cluster two has a mean diabetes value of 0.05, meaning the cluster represents mostly patients without diabetes, as well as a prevalentStroke mean value of 1.00, meaning it represents only patients who have previously had a stroke. Cluster two also has the highest average for ten year risk of heart disease with a value of 0.41, suggesting patients without diabetes who have had a stroke are at high risk for heart disease. Cluster one represents patients who have never had a stroke, do not have diabetes, and do not take blood pressure medication. Cluster one has the highest cigs per day average at 9.04 as well as the highest average for current smokers at 0.49. Cluster one has a mean value for risk of heart disease equaling .15. This suggests that smoking is a factor contributing to heart disease, but not the biggest contributor. Based on our model, these are the biggest differentiating factors between each cluster, making diabetes, then previous stroke, then cigarettes per day the three biggest contributing factors to risk of heart disease. See **Appendix Section D**.



## Appendix

- Section A (KNN)

Confusion Matrix and Statistics

	Reference	
Prediction	0	1
0	1270	193
1	42	25

Accuracy : 0.8464  
95% CI : (0.8273, 0.8641)  
No Information Rate : 0.8575  
P-Value [Acc > NIR] : 0.8988

Kappa : 0.1162

Mcnemar's Test P-Value : <2e-16

Sensitivity : 0.11468  
Specificity : 0.96799  
Pos Pred Value : 0.37313  
Neg Pred Value : 0.86808  
Prevalence : 0.14248  
Detection Rate : 0.01634  
Detection Prevalence : 0.04379  
Balanced Accuracy : 0.54133

'Positive' Class : 1

- Section B (Naive Bayes)

Confusion Matrix and Statistics

	Reference	
Prediction	0	1
0	1176	177
1	115	62

Accuracy : 0.8092  
95% CI : (0.7885, 0.8286)  
No Information Rate : 0.8438  
P-Value [Acc > NIR] : 0.9998791

Kappa : 0.1905

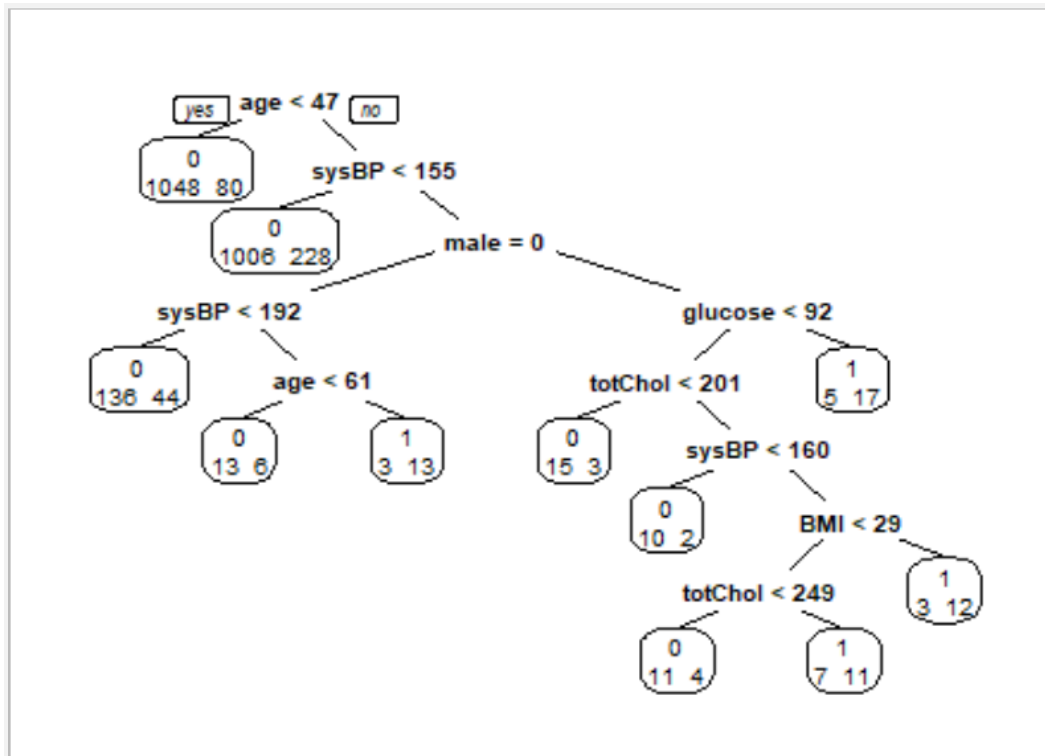
Mcnemar's Test P-Value : 0.0003573

Sensitivity : 0.25941  
Specificity : 0.91092  
Pos Pred Value : 0.35028  
Neg Pred Value : 0.86918  
Prevalence : 0.15621  
Detection Rate : 0.04052  
Detection Prevalence : 0.11569  
Balanced Accuracy : 0.58517

'Positive' Class : 1

- Section C (Classification Tree)

Classification Tree:



#### Confusion Matrix and Statistics

	Reference	
Prediction	0	1
0	958	145
1	25	20

Accuracy : 0.8519  
 95% CI : (0.83, 0.872)  
 No Information Rate : 0.8563  
 P-value [Acc > NIR] : 0.681

Kappa : 0.1373

Mcnemar's Test P-Value : <2e-16

Sensitivity : 0.12121  
 Specificity : 0.97457  
 Pos Pred Value : 0.44444  
 Neg Pred Value : 0.86854  
 Prevalence : 0.14373  
 Detection Rate : 0.01742  
 Detection Prevalence : 0.03920  
 Balanced Accuracy : 0.54789

'Positive' class : 1

- Section D (Clustering)

Descriptive statistics by group

group: 1

	vars	n	mean	sd	median	trimmed	mad	min
male	1	3785	0.44	0.50	0.00	0.43	0.00	0.00
age	2	3785	49.56	8.57	49.00	49.29	10.38	32.00
currentSmoker	3	3785	0.49	0.50	0.00	0.49	0.00	0.00
cigsPerDay	4	3760	9.04	11.95	0.00	6.94	0.00	0.00
BPMeds	5	3785	0.03	0.18	0.00	0.00	0.00	0.00
prevalentstroke	6	3785	0.00	0.00	0.00	0.00	0.00	0.00
prevalentHyp	7	3785	0.31	0.46	0.00	0.26	0.00	0.00
diabetes	8	3785	0.02	0.15	0.00	0.00	0.00	0.00
totchol	9	3785	236.94	44.74	234.00	234.86	43.00	113.00
sysBP	10	3785	132.25	21.93	128.00	130.01	19.27	83.50
diaBP	11	3785	82.89	11.93	82.00	82.18	10.38	48.00
BMI	12	3785	25.79	4.03	25.38	25.53	3.66	15.54
heartRate	13	3785	75.74	11.94	75.00	75.07	10.38	44.00
glucose	14	3785	80.78	17.33	78.00	78.84	11.86	40.00
TenYearCHD	15	3785	0.15	0.36	0.00	0.06	0.00	0.00
heart	16	3785	1.00	0.00	1.00	1.00	0.00	1.00

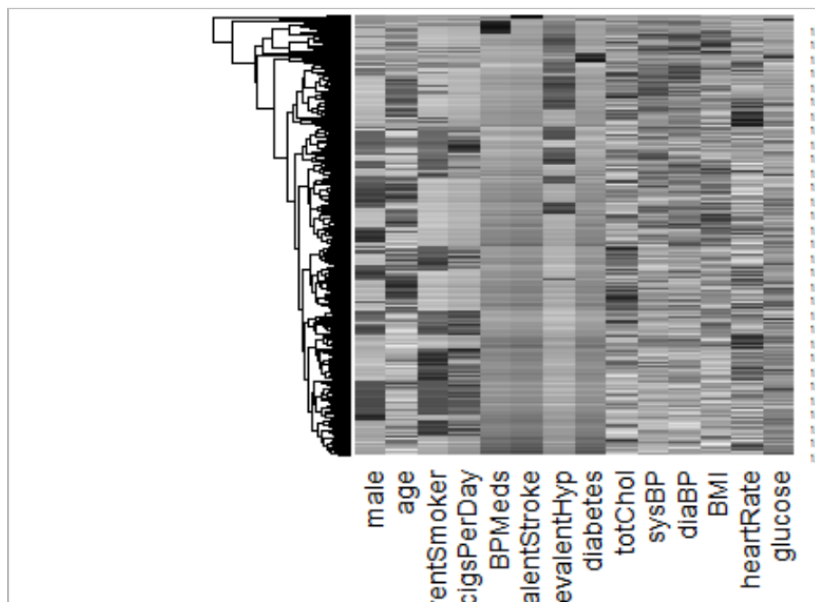
group: 2

	vars	n	mean	sd	median	trimmed	mad	min
male	1	22	0.41	0.50	0.00	0.39	0.00	0.00
age	2	22	55.73	7.25	57.00	56.33	6.67	38.00
currentSmoker	3	22	0.23	0.43	0.00	0.17	0.00	0.00
cigsPerDay	4	22	3.18	6.46	0.00	1.94	0.00	0.00
BPMeds	5	22	0.27	0.46	0.00	0.22	0.00	0.00
prevalentStroke	6	22	1.00	0.00	1.00	1.00	0.00	1.00
prevalentHyp	7	22	0.73	0.46	1.00	0.78	0.00	0.00
diabetes	8	22	0.05	0.21	0.00	0.00	0.00	0.00
totchol	9	22	246.32	39.73	253.00	246.89	48.18	161.00
sysBP	10	22	149.84	22.16	151.00	149.81	17.79	101.00
diaBP	11	22	90.45	12.93	93.50	90.83	10.38	64.00
BMI	12	22	27.45	7.43	28.11	26.40	6.60	18.73
heartRate	13	22	72.36	10.90	74.50	72.17	9.64	54.00
glucose	14	22	89.55	32.68	80.00	83.28	9.64	54.00
TenYearCHD	15	22	0.41	0.50	0.00	0.39	0.00	0.00
heart	16	22	2.00	0.00	2.00	2.00	0.00	2.00

group: 3

	vars	n	mean	sd	median	trimmed	mad	min
male	1	18	0.44	0.51	0.00	0.44	0.00	0.00
age	2	18	54.78	7.20	54.50	54.75	11.12	43.00
currentSmoker	3	18	0.33	0.49	0.00	0.31	0.00	0.00
cigsPerDay	4	18	6.44	11.58	0.00	4.75	0.00	0.00
BPMeds	5	18	0.11	0.32	0.00	0.06	0.00	0.00
prevalentStroke	6	18	0.00	0.00	0.00	0.00	0.00	0.00
prevalentHyp	7	18	0.56	0.51	1.00	0.56	0.00	0.00
diabetes	8	18	1.00	0.00	1.00	1.00	0.00	1.00
totchol	9	18	249.89	54.45	233.00	248.75	34.84	160.00
sysBP	10	18	152.39	34.85	152.75	151.59	37.06	102.50
diaBP	11	18	87.17	15.11	84.75	87.38	15.94	60.00
BMI	12	18	27.43	5.65	27.58	27.43	6.03	17.17
heartRate	13	18	77.89	12.89	76.50	77.50	12.60	52.00
glucose	14	18	310.22	57.16	307.00	310.44	77.84	223.00
TenYearCHD	15	18	0.61	0.50	1.00	0.62	0.00	0.00
heart	16	18	3.00	0.00	3.00	3.00	0.00	3.00

	Group.1	male	age	currentSmoker	cigsPerDay	BPMeds
1	1	0.4435931	49.56486	0.4929987	NA	0.0343461
2	2	0.4090909	55.72727	0.2272727	3.181818	0.2727273
3	3	0.4444444	54.77778	0.3333333	6.444444	0.1111111
		prevalentStroke	prevalentHyp	diabetes	totChol	sysBP
1		0	0.3093791	0.02245707	236.9369	132.2485
2		1	0.7272727	0.04545455	246.3182	149.8409
3		0	0.5555556	1.00000000	249.8889	152.3889
		diaBP	BMI	heartRate	glucose	TenYearCHD
1		82.89062	25.79132	75.74055	80.78283	0.1492734
2		90.45455	27.44773	72.36364	89.54545	0.4090909
3		87.16667	27.42611	77.88889	310.22222	0.6111111



- Appendix Section E:

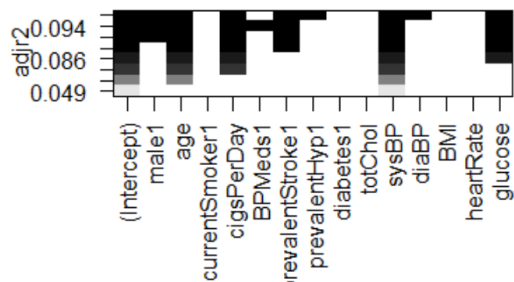
```
> exp(coef(logRegrModelInc))
```

(Intercept)	male1	age	currentSmoker1
0.0003573511	1.6375859236	1.0572016126	1.0181001110
cigsPerDay	BPMeds1	prevalentStroke1	prevalentHyp1
1.0215558560	1.4924171107	3.3016320807	1.4013679300
diabetes1	totChol	sysBP	diaBP
1.1000748841	1.0030675327	1.0182524808	0.9865161819
BMI	heartRate	glucose	
1.0069321378	0.9987087492	1.0068194466	

```
> pROCData[9]
```

```
$auc
```

```
Area under the curve: 0.736
```



Confusion Matrix and Statistics

Prediction	Reference	
	0	1
0	1282	216
1	9	23

Accuracy : 0.8529  
 95% CI : (0.8342, 0.8703)  
 No Information Rate : 0.8438  
 P-value [Acc > NIR] : 0.1711

Kappa : 0.1379

Mcnemar's Test P-value : <2e-16

Sensitivity : 0.09623  
 Specificity : 0.99303  
 Pos Pred Value : 0.71875  
 Neg Pred Value : 0.85581  
 Prevalence : 0.15621  
 Detection Rate : 0.01503  
 Detection Prevalence : 0.02092  
 Balanced Accuracy : 0.54463

'Positive' class : 1

