## Cardiovascular Diseases Risk Prediction

Kevin Shi & Rithvik Sukumaran

## **Presentation Roadmap**

- 1. Introduction and Problem
- 2. Overview of EDA
- 3. Models and Results
- 4. Conclusion

#### Introduction

- Cardiovascular diseases (CVDs) are a significant health issue for millions around the world.
- Existing health conditions and lifestyle factors play a crucial role in determining an individual's vulnerability to CVDs.
- Objective:
  - Develop an understanding of the risk factors associated with CVDs
  - Create predictive models that can assess an individual's vulnerability to CVDs
- Our project highlights the significance of the application of AI in medicine
  - Support understanding, knowledge, & new findings
  - Inform data driven decisions

#### **Our Dataset**

- The Behavioral Risk Factor Surveillance System (BRFSS) collects comprehensive health-related data from U.S. residents through telephone surveys conducted by various state health departments in collaboration with the Centers for Disease Control and Prevention (CDC).
- Our dataset contains 308854 rows (records) and 19 columns (features)
  - Of the 19 features, 7 are numerical, 9 are categorical, and 3 are ordinal
- Features in the dataset are related to lifestyle factors that have commonly been associated with an increased risk of various CVDs

### **Details of Our Methodology**

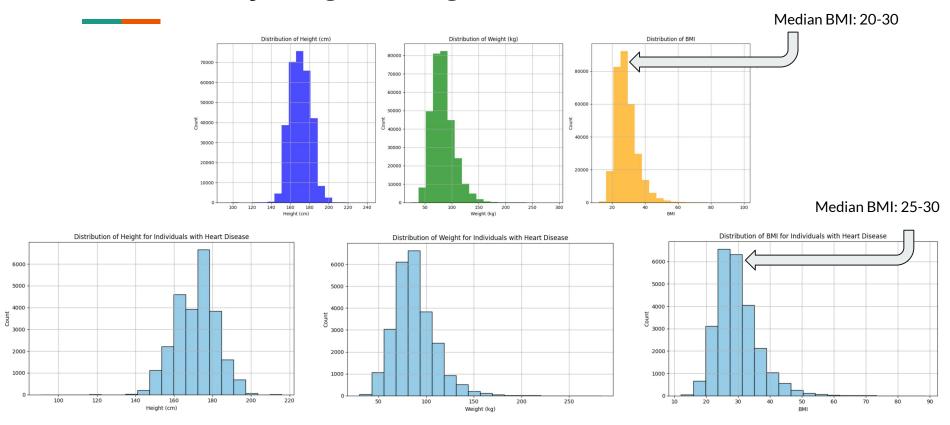
Task:

Predict CVD from a few select risk factors and identify which risk factors are the most significant Solution:

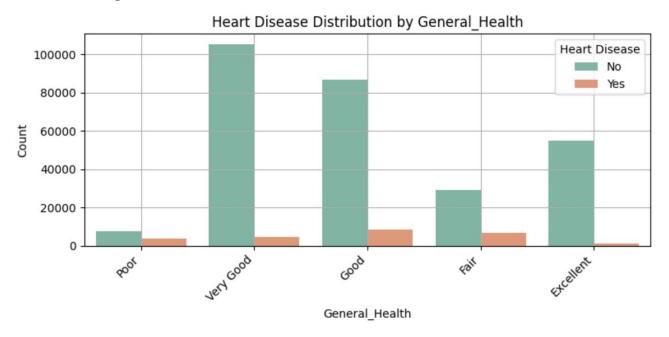
Data Analysis and Machine Learning

Tools:
Python, sklearn, pandas, matplotlib,
Google colab

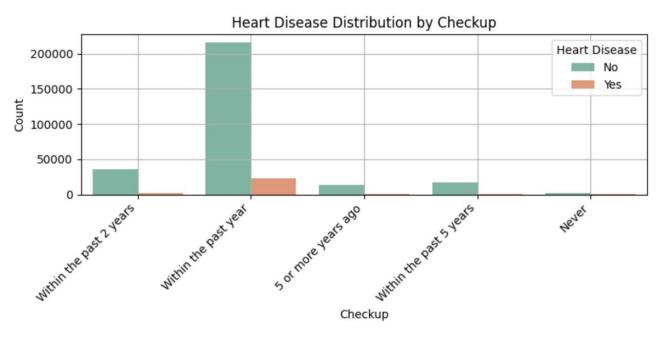
## EDA: CVD by Height, Weight, & BMI



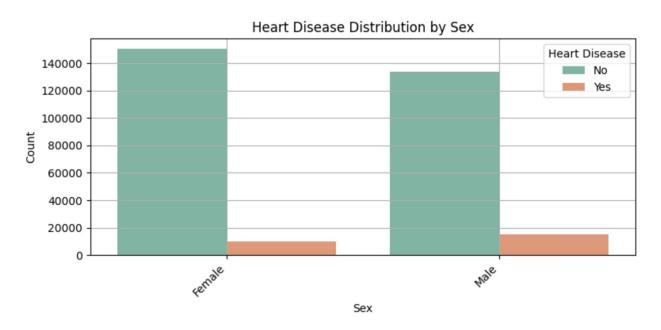
## **EDA: CVD by General Health**



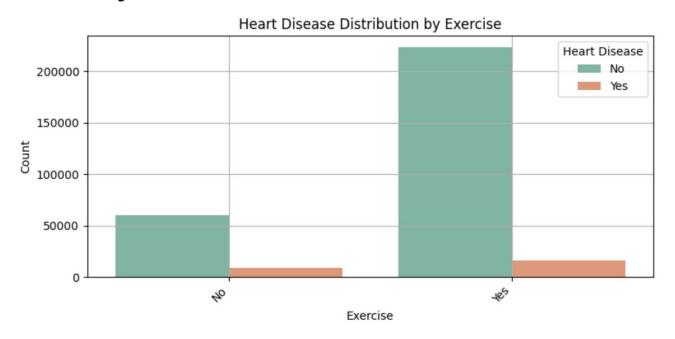
## **EDA: CVD by Checkup Frequency**



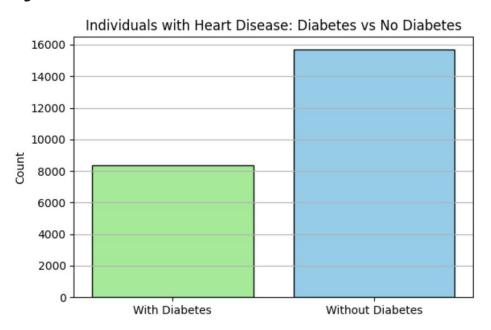
## **EDA: CVD by Sex**



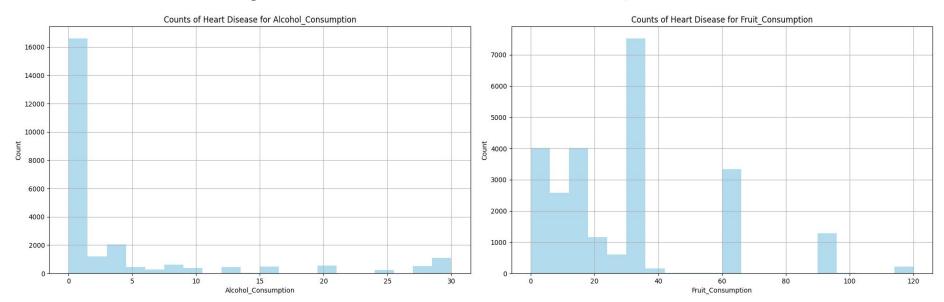
## **EDA: CVD by Exercise**



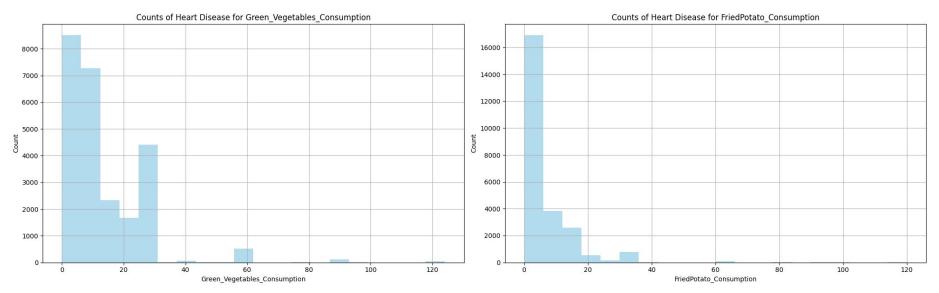
## **EDA: CVD by Diabetes**



## **EDA: CVD by Alcohol & Fruit Consumption**



## **EDA: CVD by Vegetable & Fried Potato Consumption**



## **Preprocessing for Modeling**

```
ohedf.columns
Index(['Exercise', 'Heart Disease', 'Skin Cancer', 'Other Cancer',
       'Depression', 'Diabetes', 'Arthritis', 'Sex', 'Height (cm)',
       'Weight (kg)', 'BMI', 'Smoking History', 'Alcohol Consumption',
       'Fruit Consumption', 'Green Vegetables Consumption',
       'FriedPotato Consumption', 'General Health Excellent',
       'General Health Fair', 'General Health Good', 'General Health Poor',
       'General Health Very Good', 'Checkup 5 or more years ago',
       'Checkup Never', 'Checkup Within the past 2 years',
       'Checkup Within the past 5 years', 'Checkup Within the past year',
       'Age Category 18-24', 'Age Category 25-29', 'Age Category 30-34',
       'Age Category 35-39', 'Age Category 40-44', 'Age Category 45-49',
       'Age Category 50-54', 'Age Category 55-59', 'Age Category 60-64',
       'Age Category 65-69', 'Age Category 70-74', 'Age Category 75-79',
       'Age Category 80+'],
      dtvpe='object')
```

#### **Models**

- KNN
  - 10-Fold Cross Validation
  - Tested with 5, 10, 15, 20, 25, and 30 Neighbors
- Random Forest
  - O Tested with 5-Fold, 10-Fold, 15-Fold, and 20-Fold Cross Validation
- Naive Bayes
  - O Tested with 5-Fold, 10-Fold, 15-Fold, and 20-Fold Cross Validation

#### Naive Bayes

# Precision Recall f1 Accuracy num\_folds 0 0.197206 0.471347 0.277879 0.801757 5 1 0.197510 0.472109 0.278205 0.801991 10 2 0.198835 0.471428 0.278534 0.801900 15 3 0.198219 0.471789 0.278480 0.802000 20

## **Experimental Results**

		Precision	Recall	f1	Accuracy	num_neighbors
	0	0.174976	0.013135	0.024428	0.915206	
	1	0.375000	0.000761	0.001518	0.919111	10
KNN	2	0.486667	0.000561	0.001120	0.919162	15
	3	0.000000	0.000000	0.000000	0.919146	20
	4	0.000000	0.000000	0.000000	0.919146	25
	5	0.000000	0.000000	0.000000	0.919150	30

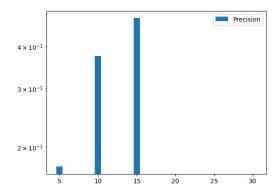
Random Forest

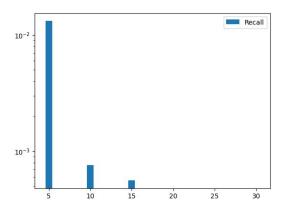
	Precision	Recall	f1	Accuracy	num_folds
0	0.441357	0.044211	0.080358	0.918194	5
1	0.443334	0.045613	0.082675	0.918188	10
2	0.439369	0.044972	0.081411	0.918104	15
3	0.444500	0.045173	0.081898	0.918211	20

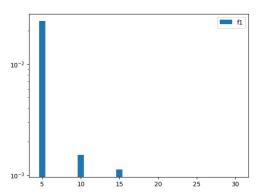
	Model	F1
1	Logistic Regression	0.32564
2	Naive Bayes	0.26982
3	Decision Tree Classifier	0.22237
4	K Neighbors Classifier	0.27350
5	Random Forest Classifier	0.17830

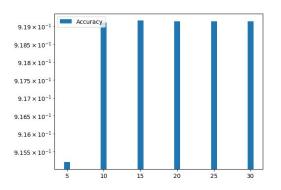
Lupague R.M.J.M., Mabborang R.C., Bansii A.G., Lupague M.M. (2023) Integrated Machine Learning Moderfor Comprehensive Heart Disease Risk Assessment Based on Multi-Dimensional Health Factors





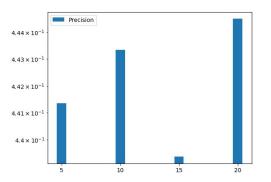


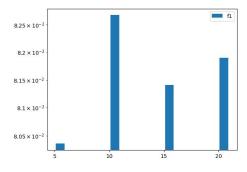


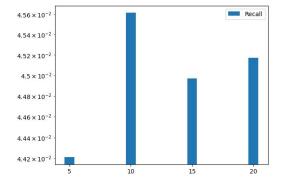


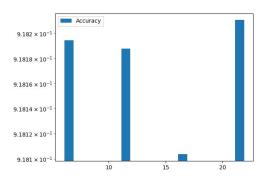
#### **Random Forest**

```
array([0.01960809, 0.01427426, 0.01579944, 0.0187046, 0.02144972, 0.01837596, 0.01548138, 0.09530568, 0.1258011, 0.14161415, 0.01630808, 0.06008439, 0.09162513, 0.09413556, 0.08859432, 0.00640482, 0.01449094, 0.00771149, 0.02193178, 0.0079308, 0.00238815, 0.00068243, 0.00562183, 0.00299067, 0.00818475, 0.00140625, 0.0014288, 0.00206393, 0.00270284, 0.00331855, 0.00410394, 0.00517215, 0.00681821, 0.00837412, 0.00927102, 0.01075815, 0.01135102, 0.01773149])
```







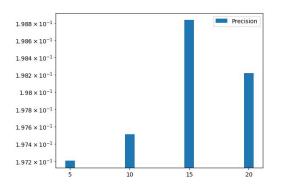


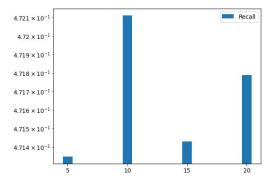
## Random Forest Feature Importance

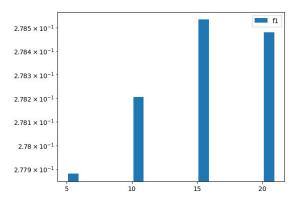
index	feature	importance
9	BMI	0.1416141488530385
8	Weight_(kg)	0.12580110206974682
7	Height_(cm)	0.095305677169544
13	Green_Vegetables_Consumption	0.09413555643070755
12	Fruit_Consumption	0.09162513491299387
14	FriedPotato_Consumption	0.08859432127399156
11	Alcohol_Consumption	0.060084390002987556
18	General_Health_Poor	0.02193178433355509
4	Diabetes	0.021449720928456668
0	Exercise	0.019608088628981078

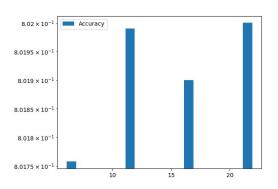
## **Naive Bayes**

```
nb.feature log prob
F⇒ array([[ -6.08105346, -8.26327604, -8.25710757, -7.46889393,
             -7.79044706, -7.02852677, -6.59639476, -0.7033811,
             -1.41998473, -2.49091597, -6.78556852, -4.19645163,
             -2.44098568, -3.11874165, -3.999295 , -7.48790398,
             -8.12422024, -7.02536255, -9.45128236, -6.83266903,
             -8.93068506, -11.18605692, -7.91817557, -8.65699069,
             -6.11133183, -8.56378528, -8.76798576, -8.59306486,
             -8.47787562, -8.43051283, -8.48194761, -8.3249523,
             -8.22672143, -8.10991895, -8.10656749, -8.20688181,
             -8.65276599, -8.63781085],
           [ -6.29246387, -7.5243825 , -7.5212606 , -7.25970316,
             -6.838367 , -6.41156422, -6.34918824, -0.70440368,
            -1.3818661 , -2.4600255 , -6.38747557 ,-4.43902832,
             -2.51125458, -3.21842546, -4.03897913, -8.9625987,
             -7.1495114 , -6.91247497, -7.77358756, -7.48864447,
           -10.09531904, -11.83988282, -8.67881643, -9.80115246,
            -5.94659426, -11.39957098, -11.27118981, -10.6595925,
           -10.36702044, -9.89701681, -9.46944025, -8.88652516,
             -8.36224988, -7.95328674, -7.73110393, -7.53898548,
             -7.75337027, -7.48727404]])
```









## **Naive Bayes Probabilities**

index	feature	0	1
7	Height_(cm)	-0.7033811003828951	-0.7044036810446599
8	Weight_(kg)	-1.4199847296416799	-1.3818661026698766
9	BMI	-2.4909159741193534	-2.460025500146795
12	Fruit_Consumption	-2.440985680117972	-2.511254575254359
13	Green_Vegetables_Consumption	-3.1187416486812864	-3.218425458348131
14	FriedPotato_Consumption	-3.999294997234893	-4.038979134662814
11	Alcohol_Consumption	-4.196451627305674	-4.439028318393484
24	Checkup_Within the past year	-6.111331828951377	-5.9465942572964
0	Exercise	-6.081053458858651	-6.29246387358071
6	Sex	-6.59639476163049	-6.349188241643962

#### **Bonus: Neural Network**

```
Epoch 1/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 10/10
<keras.callbacks.History at 0x7e99774aeda0>
```

## **Conclusion Main Idea - Contributing Factors to CVDs**

- Our Feature Importance
  - o Height, weight, BMI
  - Fruit, Green Vegetable, Fried Potato, Alcohol Consumption
  - General health
  - Checkup Frequency
  - Diabetes
  - Sex
  - Exercise
- Research Paper's Feature Importance
  - Sex
  - Diabetes
  - General Health

## Summary

- We have achieved high accuracy with a variety of different models
- Contrary to one of our initial hypotheses, the neural network proved surprisingly effective for this simple task
- Challenges we faced:
  - Training the models on large volumes of data
  - Learning the tensorflow APi
- Moving forward:
  - Create a more specialized neural network
  - Tune more hyperparameters
  - Address the severe overfitting issues (possibly with data augmentation)

## References

Lupague R.M.J.M., Mabborang R.C., Bansil A.G., Lupague M.M. (2023) Integrated Machine Learning Model for Comprehensive Heart Disease Risk Assessment Based on Multi-Dimensional Health Factors, European Journal of Computer Science and Information Technology, 11 (3), 44-58