heartdetect

Seminar Group 7 Team 6

Heart Detect

A two-stage, analytics-based approach to heart disease prevention

Bryan Lim Kai Wei (U2121763H)
Gerald Ong Jon Kai (U2122864K)
Hong Zhi Hao (U2121820G)
Jiang Lei (U2121557B)
Toh Jing Qiang (U2121442H)
Zainab Zuvairiyah D/O V M Saifudeen (U2010049J)

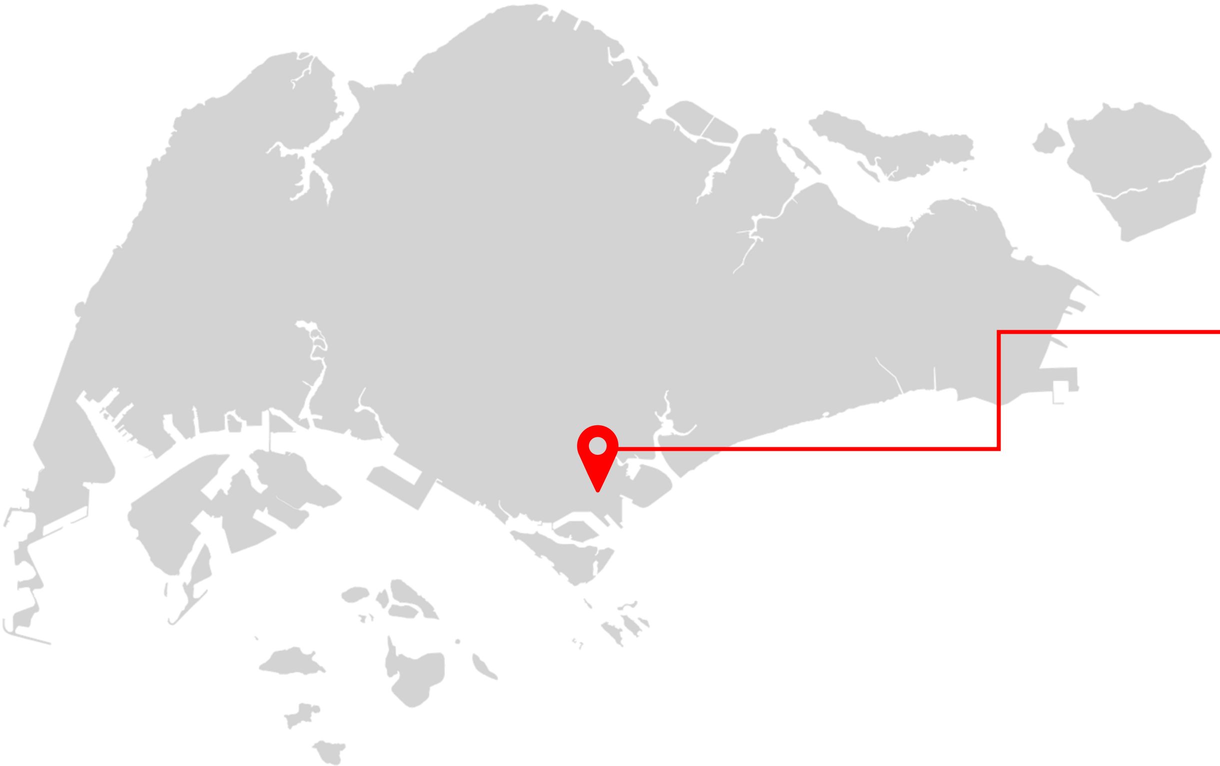
Introduction to Cardiovascular Diseases (CVD) in Singapore

Zhi Hao

Top 3 causes of hospitalization and death

1 in 5 Singaporeans have 1 or more risk factors

1 in 3 Singaporeans die due to CVD



More than 1/3 Singaporeans are not aware of risks factors

National Heart Centre Singapore
SingHealth

NCHS handling more than **120,000** outpatients
Manual assessment of CVD risk levels wastes manpower

Early Intervention of CVD

Zhi Hao

Reduce deaths	Prevention rather than treatment
80% of CVD can be prevented with the elimination of health risk behaviours *(Piepoli, et al., 2016)*	**Slow onset** of CVD and **long incubation periods** = **large window of opportunity** for intervention Symptoms are generally more serious upon diagnosis *(Qian, et al., 2022)*

→

Early intervention is critical in **preventing the onset of CVDs** and hence **increase the life expectancy** of Singaporeans

→

Business Problem

Creating a prediction tool using data analytics models:

- To aid in the early detection and intervention of CVDs
- To be utilized by medical professionals at the primary care level (GPs, polyclinics)

Sources: Piepoli, et al. (2016), Qian, et al. (2022)

Proposed Solution: HeartDetect

Zhi Hao

Latest solution

Predictive Risk Score for CAD In Southeast Asians with Chest Pain (PRECISE)

- Singapore's 1st CAD risk calculator
- Estimates likelihood of patient with no known history using variables such as age, gender, smoking status, ECG changes etc.
- Particularly helpful for patients with chest pain to monitor their health status

Limitations

- Only targets people presenting with chest pain
- Only addresses CAD (Cardiovascular Artery Disease)

Our proposed solution

heartdetect

HeartDetect – a 2 step preventive approach employing data analytical models

Stage 1: Individual Empowerment

Individuals can monitor their heart health by answering questions about their biological, medical, behavioral, genetic and environmental information.

Stage 2: Primary Medical Care

Individuals in high-risk category can visit a primary care physician (GP, polyclinic) for screening, where a data analytics model is used a support tool for physicians during decision making

- Extend coverage of preventive measures for heart disease
- Raise awareness of risk factors
- Maximize medical resource allocation

Stage 1: *Individual Empowerment* – Overview

Jiang Lei

1

Data Collection
From Kaggle
[315252 rows & 18 columns]

2

Data Preprocessing
Data Cleaning
One-hot Encoding

3

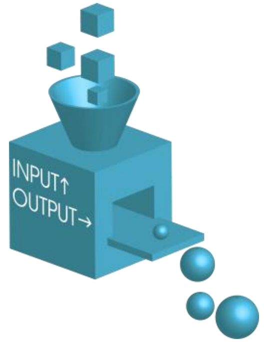
Data Exploration
Feature Engineering
Recursive Feature Elimination

4

Model Training
Optimize each model
&
Select best model
with predefined metrics

5

Model Explainer
Understand black-box algorithm
Interpret Prediction



Stage 1: *Individual Empowerment* – Data Overview

Jiang Lei

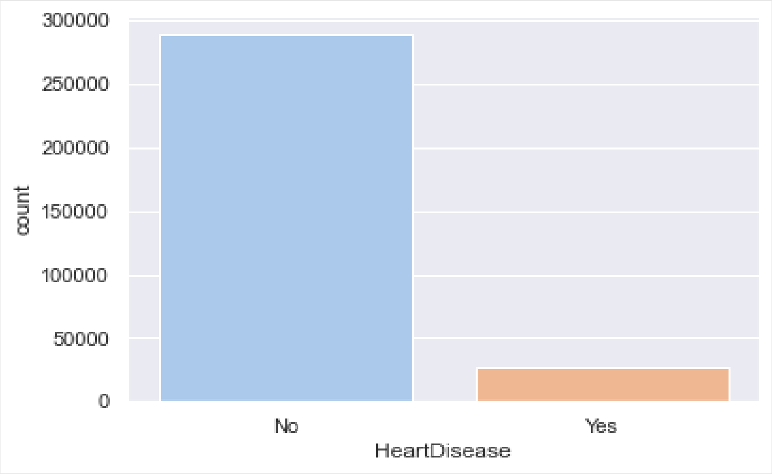
Singapore Residents → Personal Information → Monitor Heart Health

Demographical Variables	Medical History	Lifestyle	Recent Health Condition
Age **Gender** **Race** **BMI**	**Stroke** **Diabetic** **Asthma** **Kidney Disease** **Skin Cancer** * *(Ever told) (you had) a disease above?*	**Smoking** *have you smoked at least 100 cigarettes in your entire life?* **Alcohol Drinking** *adult men > 14 drinks / week* *adult women > 7 drinks / week* **Physical Activity** *whether exercise during the past 30 days other than regular job* **Sleep Time** *how many hours of sleep get in a 24-hour period on average*	**Difficulty in Walking** **General Health** *Rate it with **Very Good** / **Good** / **Excellent** / **Fair** / **Poor*** **Physical Health** *how many days during the past 30 was physical health **not good?*** **Mental Health** *how many days during the past 30 was mental health **not good?***

Stage 1: *Individual Empowerment* – Data Exploration

Jiang Lei

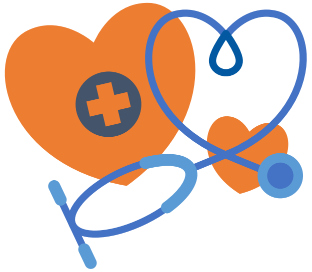
Distribution of Heart Disease



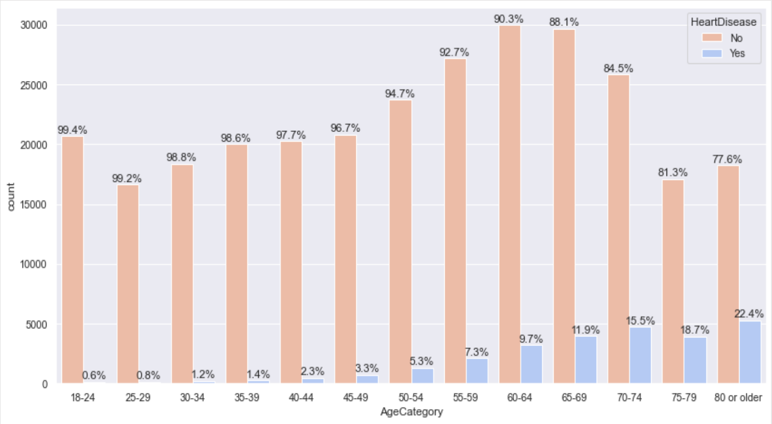
Unbalanced Predictor Variable

91% of rows – Low risk
9% of rows – High risk

- **Algorithm-based Sampling Required**
- **Be Alert of Overfitting of Models**

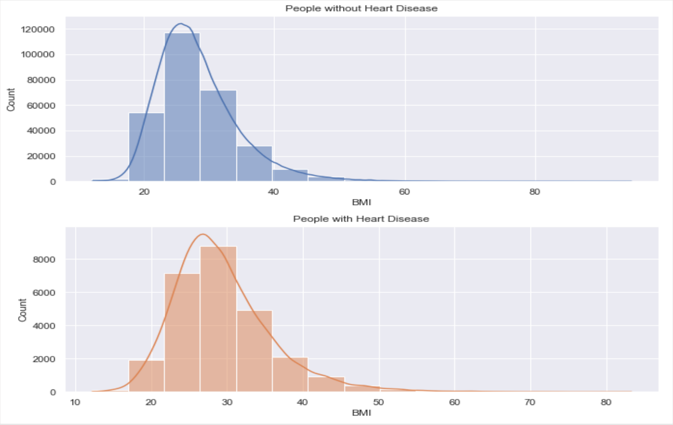


Demographical Variable(s)



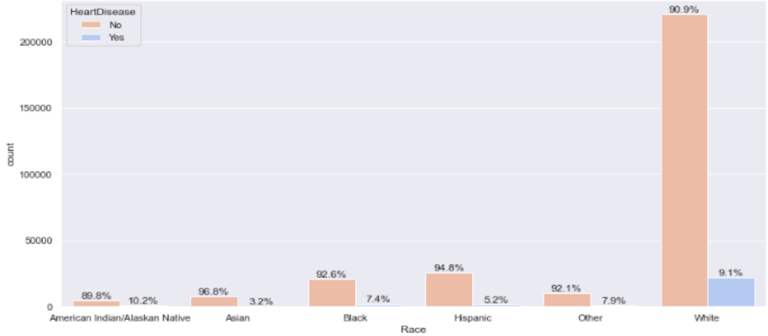
Age VS Heart Disease

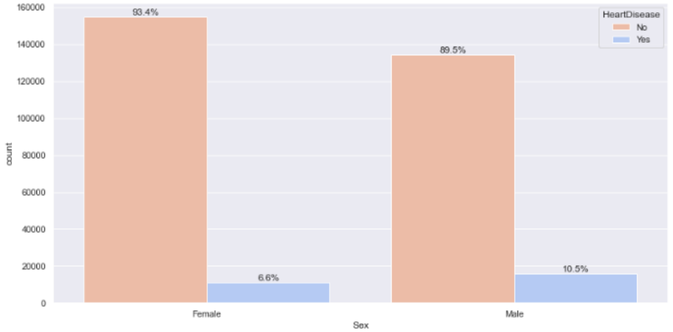
age increases, % of HD patients increases
> 10% HD patients among 65+ people



BMI VS Heart Disease

The distribution of BMI was very similar in cardiac patients and non-patients.





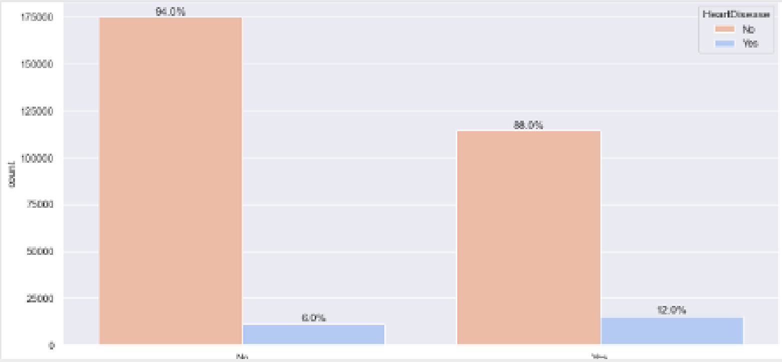
Race / Gender VS Heart Disease

The proportion of people with heart disease is very similar across gender and race.

Stage 1: *Individual Empowerment* – Data Exploration

Jiang Lei

Lifestyle Variable(s)

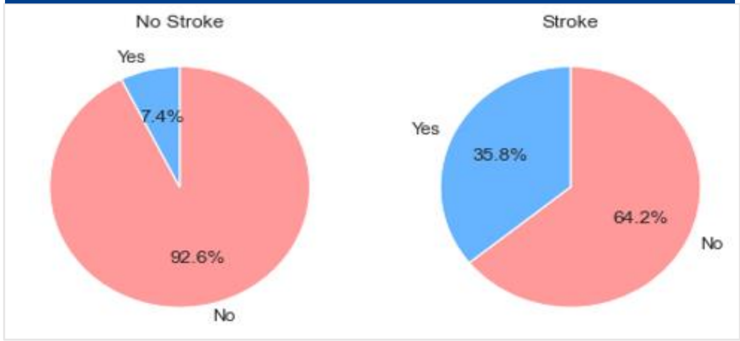


Smoker VS Heart Disease

12% of smokers are heart patients, 2 times of the non-smokers.

Smoking damages blood vessels, reduces the amount of oxygen in the blood, worsens heart conditions. (Health Hub, 2022)

Medical History Variable(s)



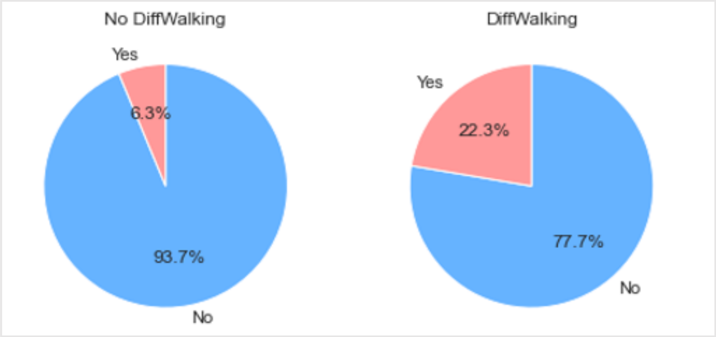
Stroke VS Heart Disease

35.8% of stroke patients also have heart disease, 5 times of the non-stroke patients.

Similarly, for people have been diagnosed with **diabetes** or **kidney disease**

High blood sugar caused by **diabetes** can damage blood vessels in the heart. (Singapore Heart Foundation, 2022)

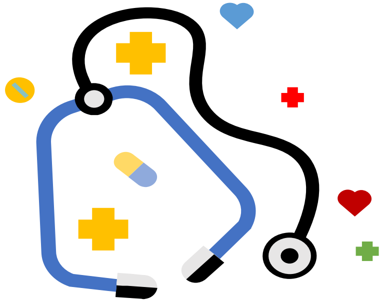
Current Health Variable(s)



Difficulty in Walking VS Heart Disease

22% of HD patients with difficulty in walking, 3.5 times of non-HD patients

People walk fast always show better cardiac status. (Yates, et al., 2017)



Sources: HealthHub (2022), Singapore Heart Foundation (2022), Yates, et.al. (2017)

Stage 1: *Individual Empowerment* – Pre-Modelling

Jiang Lei

Train-Test Split

The data set is randomly divided into training and test sets in a ratio of 7:3.

Sampling was required due to the disease-:non-disease imbalance distribution of 1:10.

Oversampling by SMOTE

Synthetic Minority Oversampling Technique (SMOTE) employed to **oversample** the trainset

Generates synthetic samples for “Heart Disease - Yes” group using other variables

Overcomes the overfitting problem

Performance Metric

Classification Accuracy
Percentage of correct prediction
(>80%)

ROC AUC score
Evaluate the performance of single model at different thresholds
(>70%)

False Negative Rate
Error of misclassifying high-risk populations as low risk (prediction 0, truth 1)
(<20%)

Stage 1: *Individual Empowerment* – Models

Jiang Lei

	Logistic Regression Model	Gradient Boosting Classifier	Random Forest Model
Model Optimization	Efficient machine learning **classification** algorithms	A more robust model **learns iteratively from each weak learner**	an ensemble of decision trees randomly selects variables and averages the prediction results
	3 Models Trained with **Recursive Feature Elimination** Cleaned dataset contains up to 50 one-hot-encoding variables	Model trained with **Hyperparameter Tuning** *Conducted on 2 parameters n_estimators, learning_rate*	Mitigate overfitting issue Highly stable Training time longer due to complexity
	Optimal Model uses **21** variables (7 features)	**11** Important features are highlighted	**All 17** features are used

Finding the best model based on 3 predetermined metrics

Stage 1: *Individual Empowerment* – Model Evaluation & Selection

Jiang Lei

	Logistic Regression	Gradient Boosting Classifier	Random Forest
Overall Accuracy	74.22%	87.54%	**99.62%**
False Negative Rate	78.46%	72.28%	**1.70%**
ROC-AUC Score	0.75	0.63	**0.99**
	Lowest Accuracy Worst FNR & Fair Score	Poor FNR High Accuracy & Lowest Score	Best FNR Highest Accuracy & Score

Important Features used in Random Forest

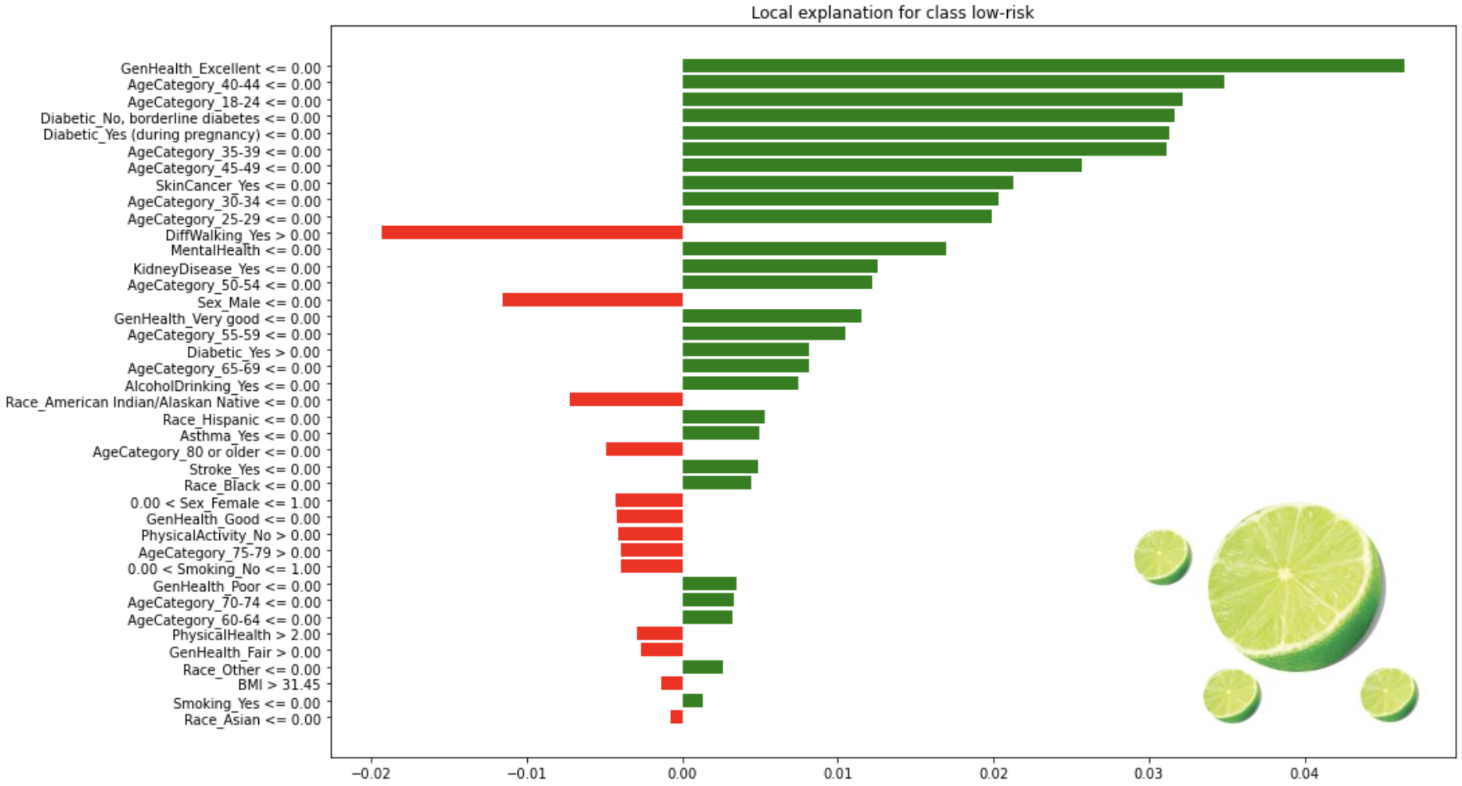
1. BMI
2. Age
3. Sleep Time
4. Diabetic
5. Race
6. Difficulty in Walking
7. General Health Status
8. Gender
9. Physical Health
10. Mental Health
11. Smoking
12. Stroke
13. Physical Activity
14. Skin Cancer
15. Asthma
16. Kidney Disease
17. Alcohol Drinking

How to build trust among end users (individuals) when interpreting predicted results (high risk/low risk)?

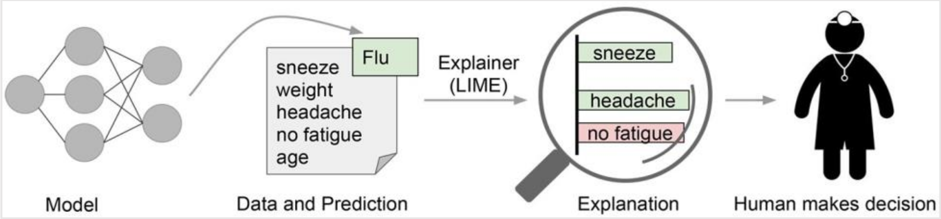
Stage 1: *Individual Empowerment* – Model Explainer

Sample Analytic Report for An Individual

Congratulations! You are at **low-risk** for heart disease.
However, please take note of the following factors (in red) that **negatively contribute** to your heart health.



Local Interpretable Model-Agnostic (LIME)



Trust in Model Using Accuracy Metrics

Test-set to measure model performance,
but still different from real-world data

Trust in Personal Predictions

Use positive & negative drivers (variables)
to explain prediction results and gain user trust

Ensure Local fidelity

Globally important features may not be significant
in the local context

Only a handful of variables directly relate to
an individual prediction

Stage 2: *Primary Care Prediction* – Overview

Jing Qiang

1

Data Collection
From Kaggle
[303 rows & 14 columns]

2

Data Preprocessing
Data Cleaning
Label Encoding & Encoding
to Meaningful Strings

3

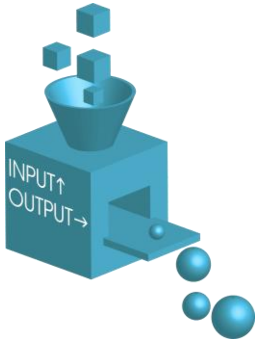
Data Exploration
Feature Insights

4

Model Training
Optimize each model
&
Select best model
with predefined metrics

5

Model Explainer
Understand black-box
algorithm
Interpret Prediction



Stage 2: *Primary Care Prediction* – Data Overview

Jing Qiang

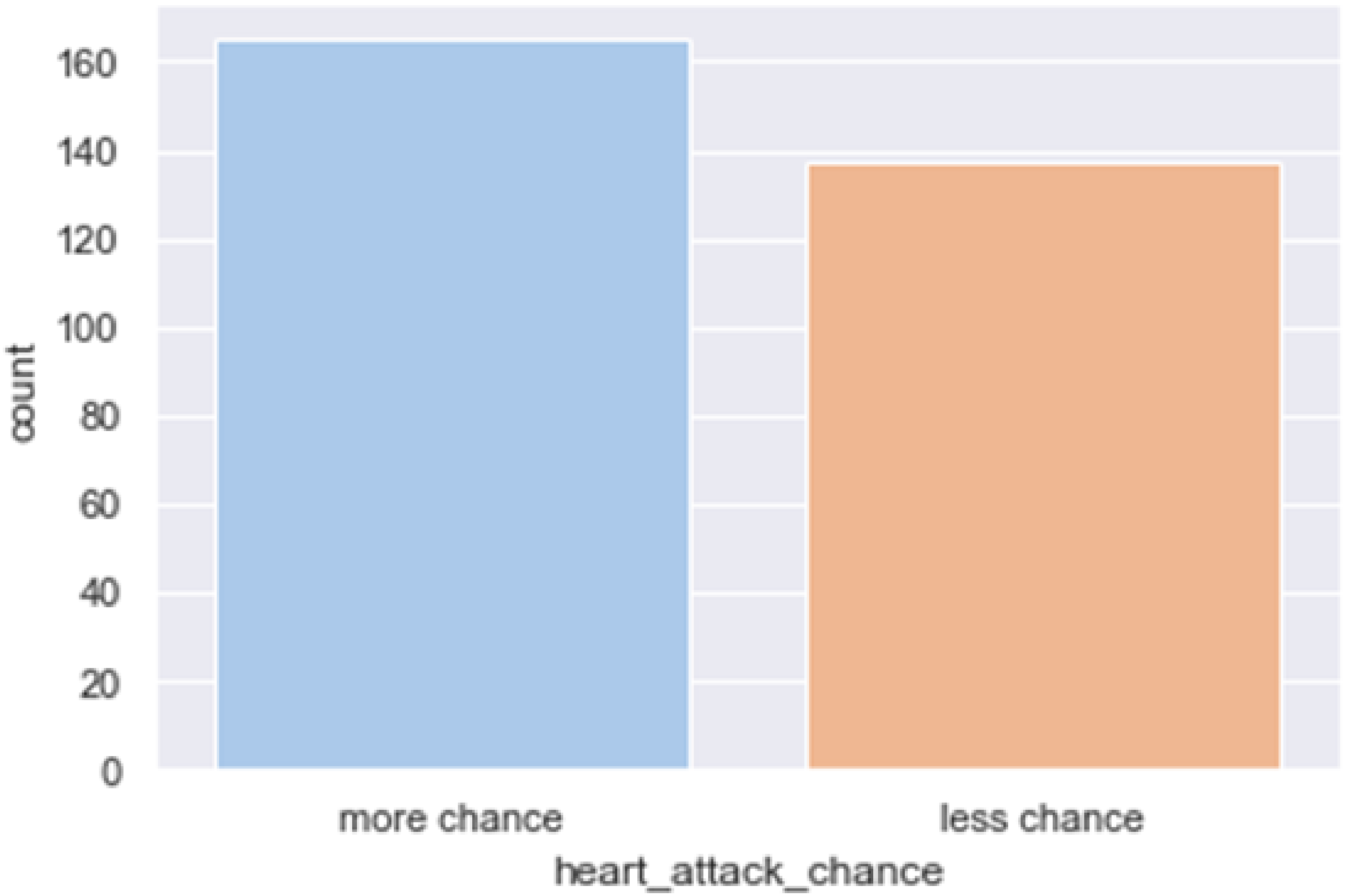
Patients → **Personal** + **Medical** Information → Doctor's Evaluation on Heart Health

Personal Variables	Electrocardiogram Variables	Blood-related Variables	Other Medical Variables
Age **Sex** **Chest Pain** ** Are you experiencing chest pain?*	**Heart Rate** **O2 Saturation** **Rest ECG** ** Resting ECG Results (0-2)*	**Resting Blood Pressure** **Fasting Blood Sugar** **Cholesterol**	**Exercise Induced Angina** **Number of major vessels** ** NOT blocked or interrupted by a build-up of fatty substances*

Stage 2: *Primary Care Prediction* – Data Exploration

Jing Qiang

Distribution of Heart Attack

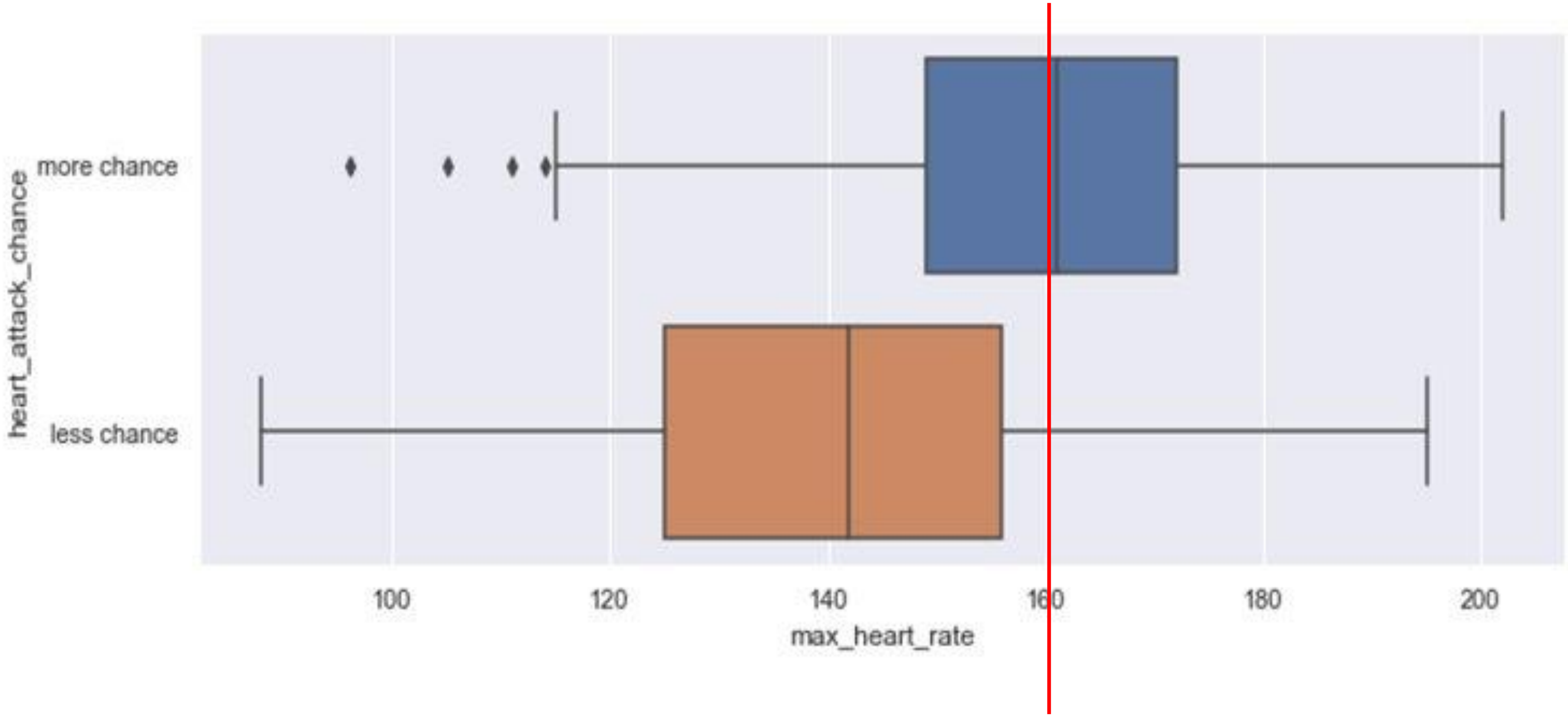


Balanced Predictor Variable

Stage 2: *Primary Care Prediction* – Data Exploration

Jing Qiang

Variable(s) - In-Line With Academic Research



Max Heart Rate VS Heart Attack

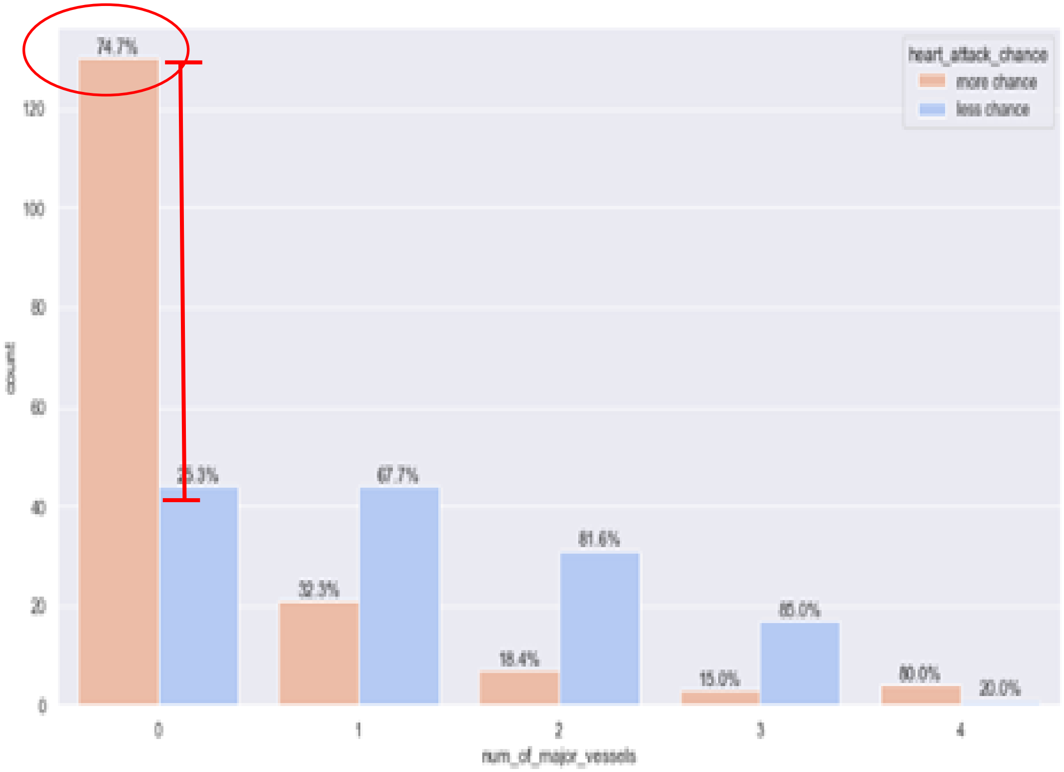
The chances of heart disease **increases** when one has a **higher max heart rate** *(~160bpm vs ~140bpm)* *(Perret-Guillaume, Joly, & Benetos, 2009)*

Sources: Perret-Guillaume, Joly, & Benetos (2009)

Stage 2: *Primary Care Prediction* – Data Exploration

Jing Qiang

Variable(s) - In-Line With Academic Research



Number of major vessel VS Heart Attack

The more **blood vessels detected** *(not blocked or interrupted by fatty substances)* **by fluoroscopy**, the **lower** the **chance** of having a high risk of heart disease.

Gender VS Heart Attack

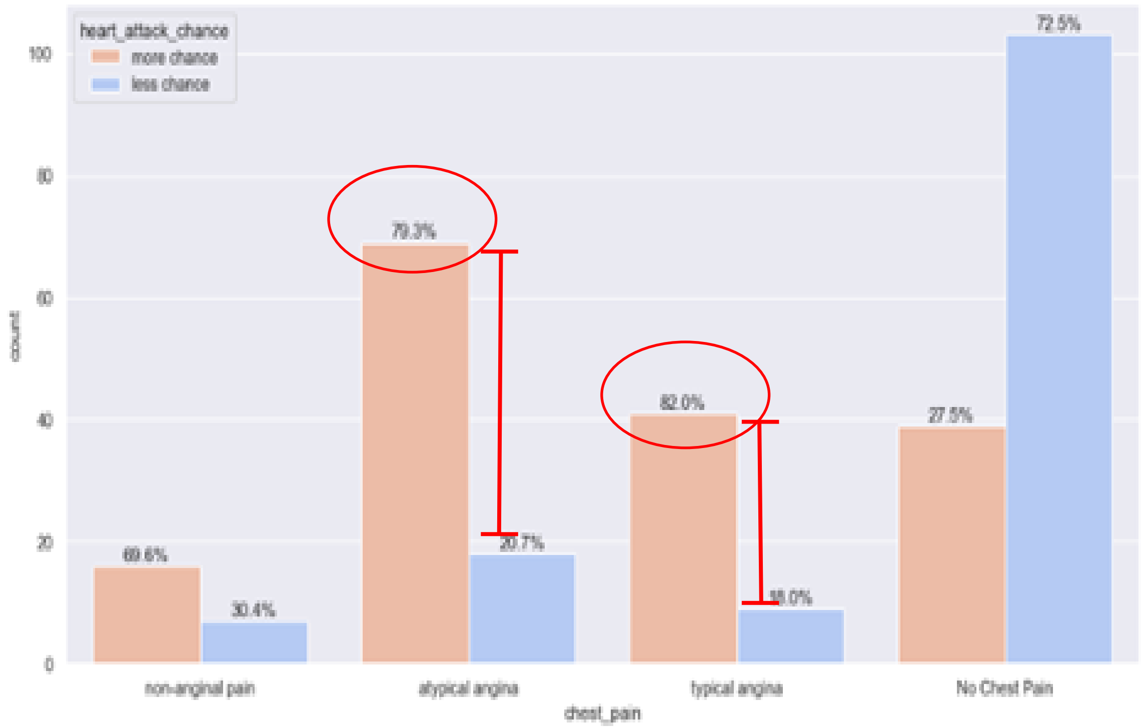
Females are shown to be at a **higher risk** of a heart attack *(females' 75% vs males' 45.1%)* *(Carauna, 2018)*

Sources: Carauana (2018)

Stage 2: *Primary Care Prediction* – Data Exploration

Jing Qiang

Variable(s) - In-Line With Academic Research



Chest Pain VS Heart Attack

Those with **chest pain** has a **greater than 69.6%** of having a higher chance of heart attack *(Singapore General Hospital, n.d.)*

Rest ECG VS Heart Attack

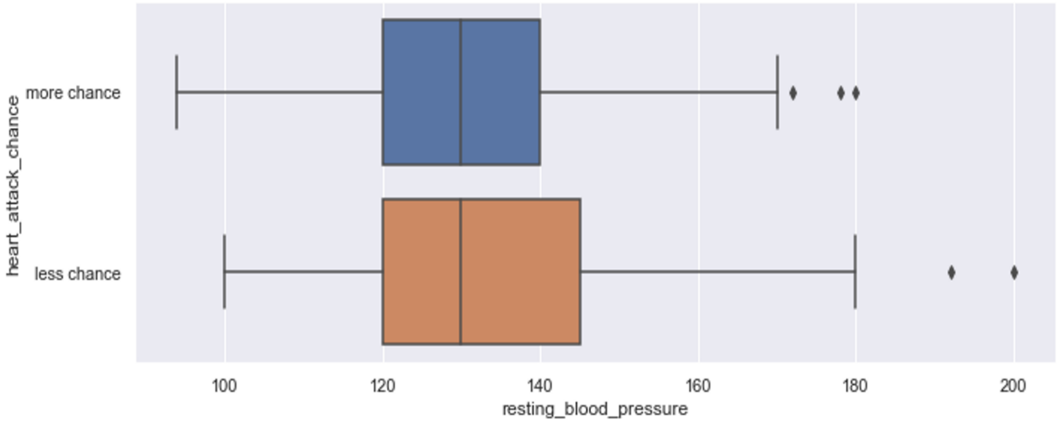
Those with **ST-T wave abnormality** has **17.3% more chance** of higher risk of heart attack *(Beckerman, et al., 2005)*

Sources: Singapore General Hospital (n.d.), Beckerman, et al. (2005)

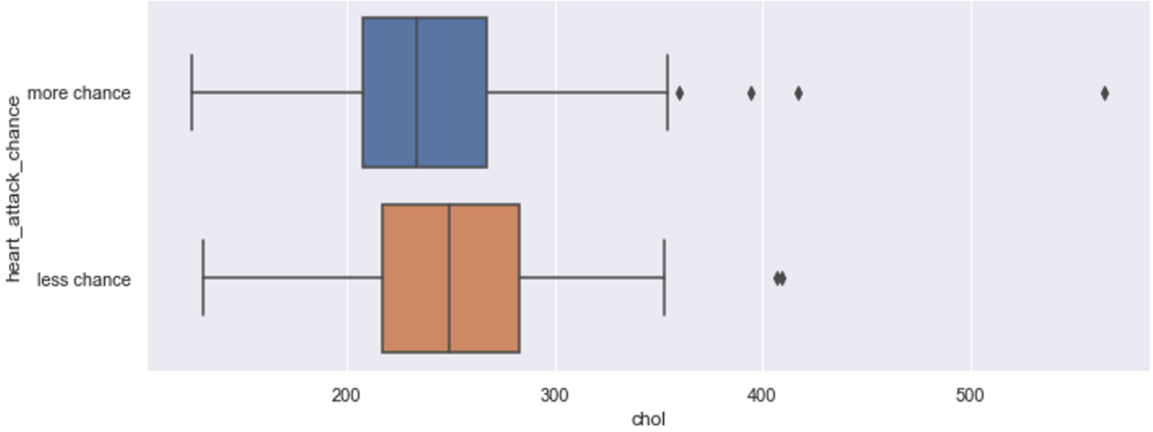
Stage 2: *Primary Care Prediction* – Data Exploration

Jing Qiang

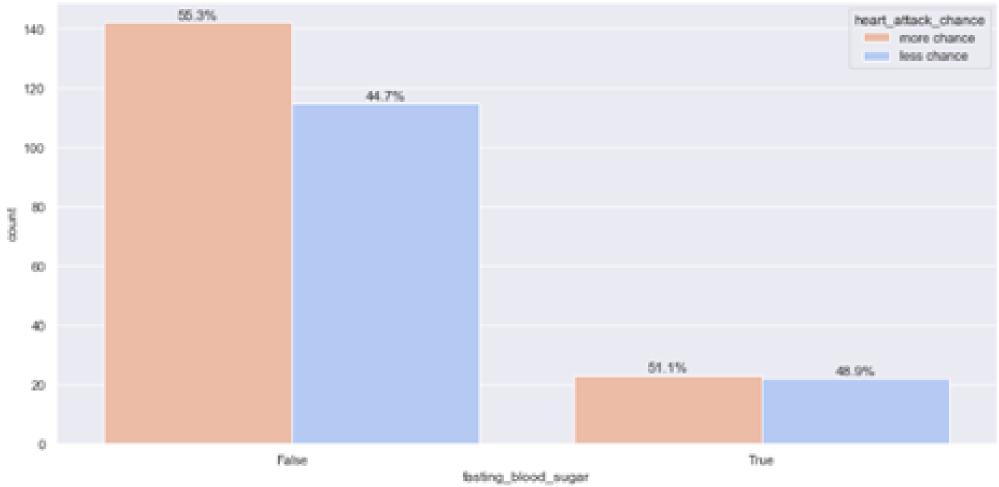
Variable(s) - No Significant Impact



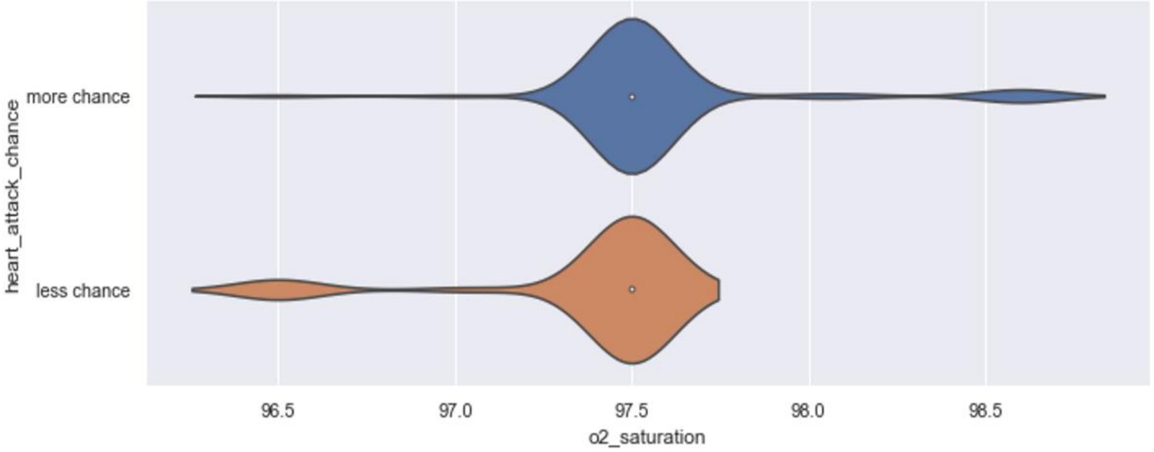
Heart Attack Chance VS Heart Attack



Cholesterol VS Heart Attack



Fasting Blood Sugar VS Heart Attack

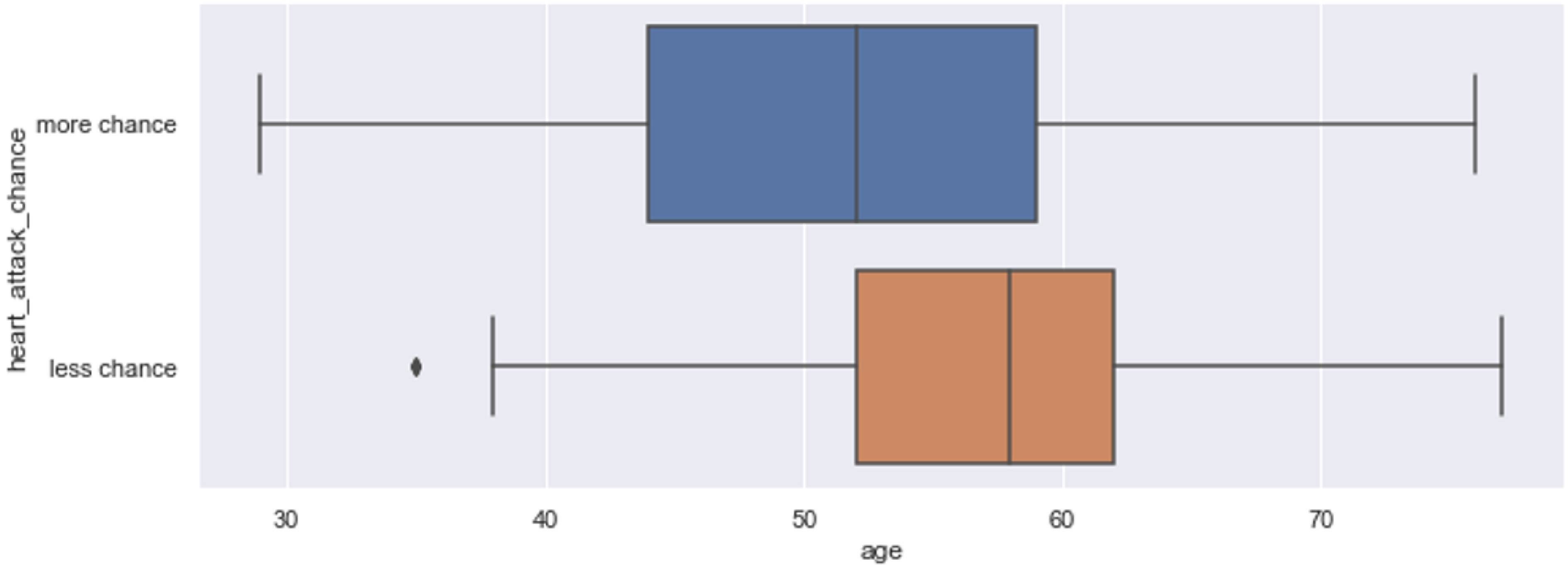


O2 Saturation VS Heart Attack

Stage 2: *Primary Care Prediction* – Data Exploration

Jing Qiang

Variable(s) - Contradicts Current Research



Age VS Heart Attack

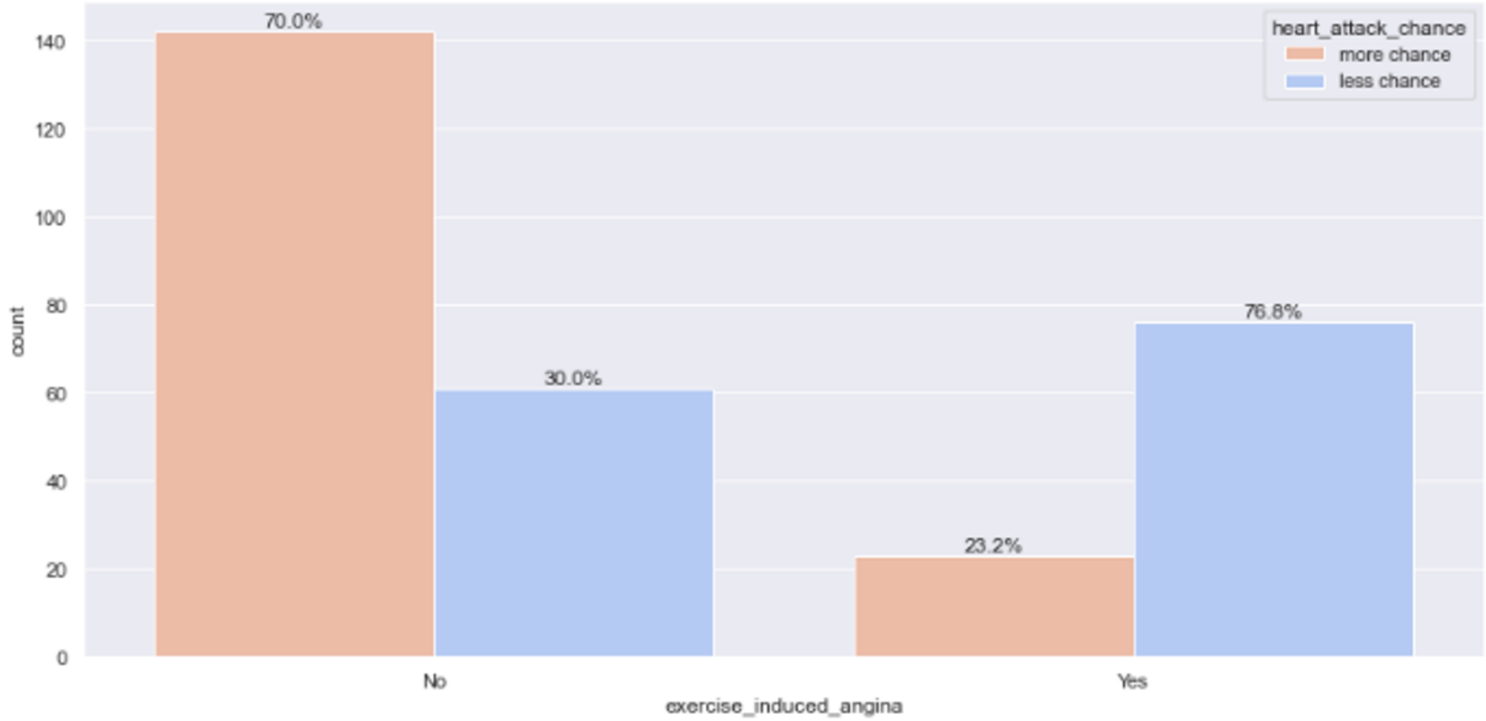
The **younger** you are, the **higher** the **risk** of you getting a heart disease, which contradicts existing research (Rodgers, et al., 2019)

Source: Rodgers, et al. *(2019)*

Stage 2: *Primary Care Prediction* – Data Exploration

Jing Qiang

Variable(s) - Contradicts Current Research



Exercised Induced Angina VS Heart Attack

Having exercise-induced angina is a common complaint of cardiac patients (Brown & Oldridge, 1985), but our exploration shows **not having exercise-induced angina** means one have is at a **higher risk** of heart disease.

Source: Brown & Oldridge. (1985)

Stage 2: *Primary Care Prediction* – Pre-Modelling

Train-Test Split

The data set is randomly divided into training and test sets in a ratio of 7:3.

Cross Validation was required due to the small size of the dataset.

Cross Validation (5-fold)

5-fold Cross Validation is employed to **evaluate** analytical models on the limited train dataset sample.

It splits the train dataset into **5 groups**, using 4 groups to train the model and 1 group to validate the model. This is repeated for all possible combinations of the 5 groups.

Overcomes the limited dataset problem.

Performance Metric

Classification Accuracy
Percentage of correct prediction
(>80%)

ROC AUC score
Evaluate the performance of single model at different thresholds
(>70%)

False Negative Rate
Error of misclassifying high-risk populations as low risk (prediction 0, truth 1)
(<=20%)

Stage 2: *Primary Care Prediction* – Models

Jing Qiang

Model Optimization

Classification & Regression Tree (CART) Model	**Random Forest Model**
Efficient machine learning **classification** algorithms	An ensemble of many CART that randomly selects variables and averages the prediction results
Growing Tree to the **Maximum** using default hyperparameters	**Feature Importance** Dropping features with importance value of 0
Prune tree using cp value chosen from tree with the **minimum** cross validation error	**Hyperparameter Tuning** using GridSearchCV

Finding the best model based on 3 predetermined metrics

Stage 2: *Primary Care Prediction* – Model Evaluation & Selection

Jing Qiang

	Logistic Regression	Random Forest
Overall Accuracy	74.41%	**85.06%**
False Negative Rate	30.43%	**20.93%**
ROC-AUC Score	0.78	**0.84**

Poor Accuracy
Undesirable FNR & ROC-AUC Score

Best FNR
Highest Accuracy & ROC AUC Score

Important Features used in Random Forest

1. Max Heart Rate
2. Number of major vessels
3. Chest Pain
4. Age
5. Exercise Induced Angina
6. Cholesterol
7. Resting Blood Pressure
8. Sex
9. O2 Saturation
10. Rest ECG
11. Fasting Blood Sugar

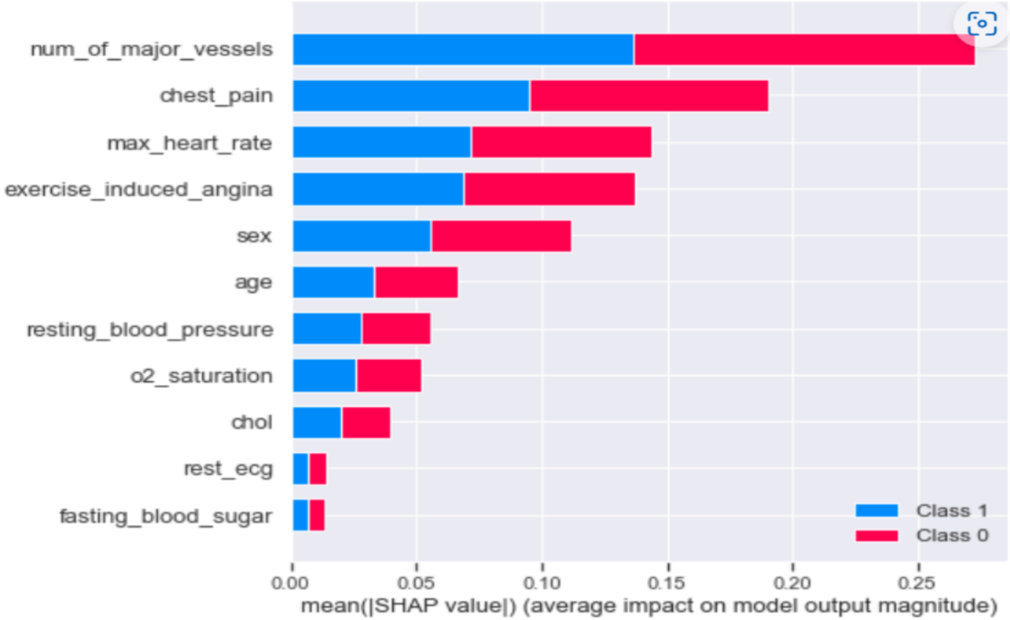
How can end-user (doctors) interpret prediction result – high risk / low risk, and proceed from this result?

Stage 2: *Primary Care Prediction* – Model Explainer

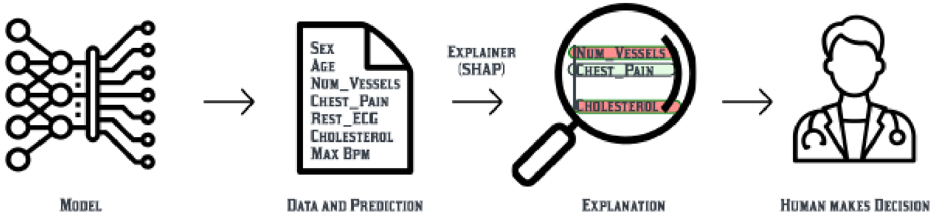
Jing Qiang

Sample Analytic Report about a Patient for A Doctor

Danger! The patient is at **high-risk** for heart disease.
The following factors (in blue) **contribute** to the patient's high risk heart health. Conduct a more **detailed medical test / administer treatments** in those areas.



SHapley Additive exPlanations (SHAP)



Enables Global Interpretability

The collective SHAP values can show **how much** each predictor contributes, either **positively** or **negatively**, to the target variable.

Enables Local Interpretability

Each prediction has its own set of SHAP values, increasing transparency as it enables doctors to **pinpoint** and **contrast** the impacts of different features on the prediction

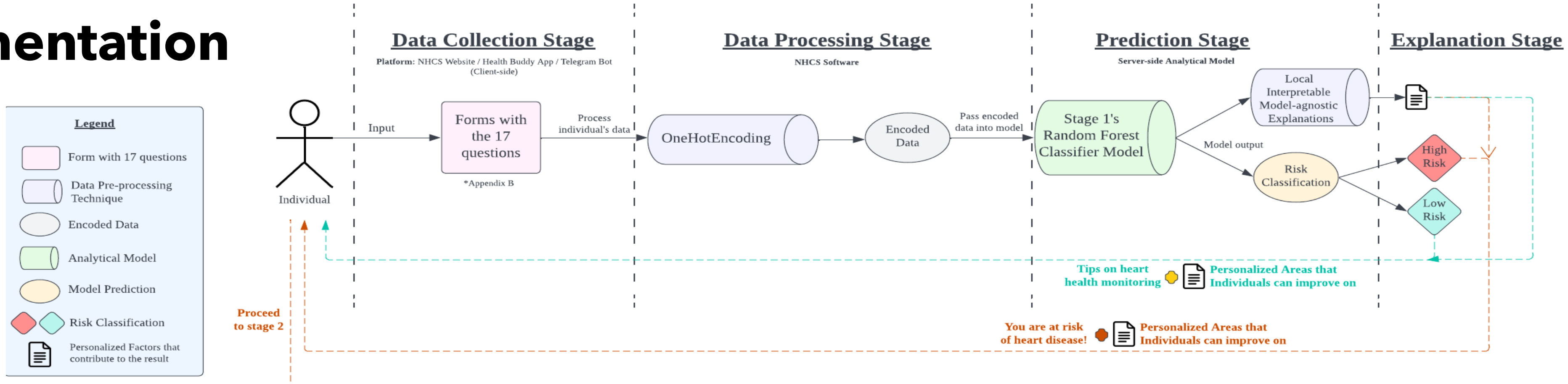
Trust in Heart Predictions

Use positive & negative drivers (variables) to explain prediction results and gain doctors and patients' **trust**

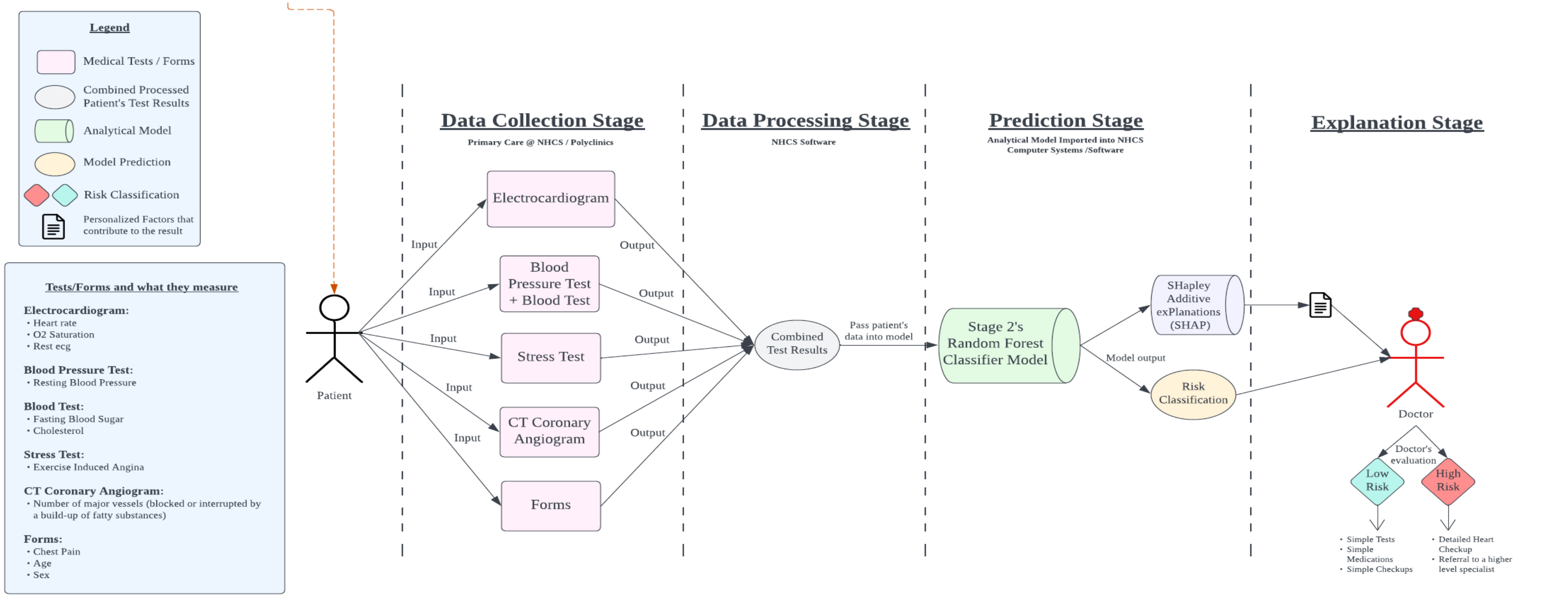
Business Implementation

Zainab

Stage 1 (Home)

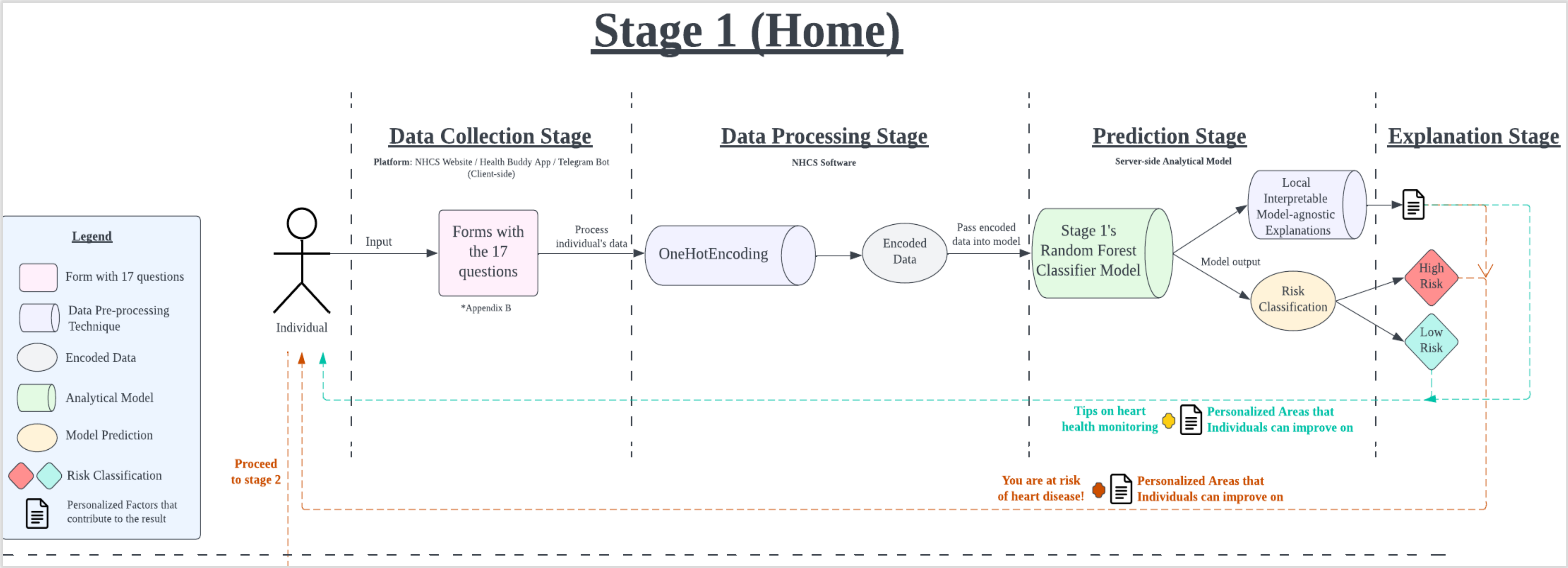


Stage 2 (NHCS)



Business Implementation: *Stage 1* – Technical Flowchart

Zainab



Business Implementation: *Stage 1* – End Users

Zainab

Potential End Users

General Public
Who is aware of monitoring his/her heart health

Jolin, 23
NTU Student

Visitors of NHCS
Found to have symptoms of heart attack

Amy, 40
Have chest pain

Patients with Relevant Medical History
Diabetes, Stroke, etc.

Jay, 65
Stroke Patient

Accessible Methods

General Public: Proactively use prediction tool through online platforms e.g., SingHealth Website, HealthBuddy App, Telegram Bot

SingHealth – Defining Tomorrow's Medicine | National Heart Centre Singapore SingHealth

Visitors of NHCS / Patients with Relevant Medical History: An invitation link to online risk prediction will be sent to their phones periodically as a reminder for regular heart health monitoring

Work with Active Ageing Hub / Eldercare Centre to provide manual data collection and automated risk prediction for seniors who have difficulty accessing the Internet

HEALTH MONITORING | ntuc Health | United Medicare Centre 爱心康复中心 Trusted Care. Quality Life.

Business Implementation: *Stage 1* – User Journey Map

Zainab

Jay, 65
Stroke Patient

1 **Answer Simple Questionnaire**

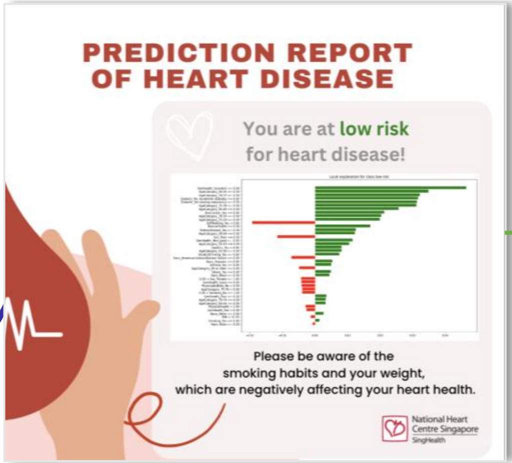
17 non-medical indicators will be used as inputs for the questionnaire

SingHealth
Defining Tomorrow's Medicine

National Heart Centre Singapore
SingHealth

17 Questions Individuals Can Answer

1. What is your BMI?
2. (Ever told) (you had) a stroke?
3. What is your gender?
4. Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 are you in good physical condition?
5. Now thinking about your mental health, for how many days during the past 30 was your mental health not good?
6. Would you say that in general your health is excellent, very good, good, fair, or poor?
7. Have you smoked at least 100 cigarettes in your entire life? [Note: 5 packs = 100 cigarettes]
8. Have more than 7 drinks per week?
9. (Ever told) (you had) skin cancer?
10. What is your race?
11. (Ever told) (you had) diabetes?
12. (Ever told) (you had) asthma?
13. Do you have serious difficulty walking or climbing stairs?
14. Which of the fourteen-level age category do you fall into?
15. Would you say that in general your health is good?
16. On average, how many hours of sleep do you get in a 24-hour period?
17. Not including kidney stones, bladder infection or incontinence, were you ever told you had kidney disease?

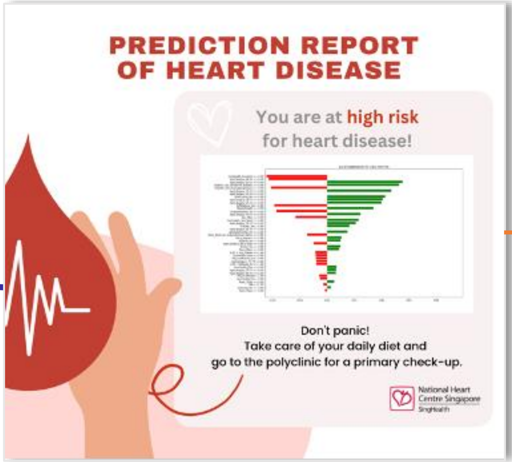


Low Risk

instructed to maintain heart health

2 **Receive Risk Prediction Result & Analytics Report**

3 **Decision Making**



High Risk

guide users to primary care @ NHCS for primary heart checkup

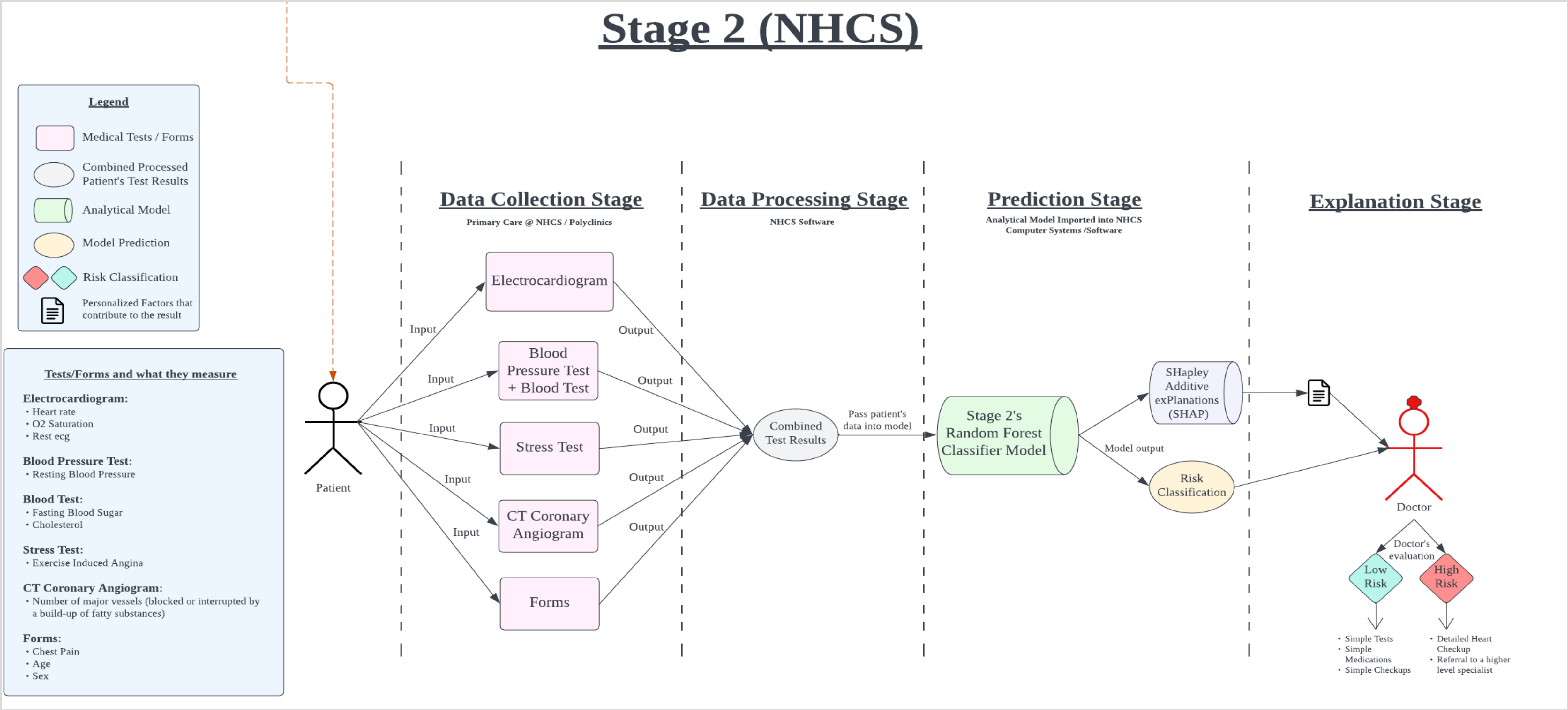
National Heart Centre Singapore
SingHealth

Stage 2

Prediction of Heart Disease Risk using medical attributes

Business Implementation: *Stage 2* – Technical Flowchart

Zainab



Business Implementation: *Stage 2 – Implementation Scenario*

Who?

High Risk Individuals
identified in stage 1

Regular individuals
with appointment for heart related issues

Where?

Primary Care Facilities
such as NHCS and Polyclinics

SingHealth
Defining Tomorrow's Medicine

National Heart Centre Singapore
SingHealth

How?

- Analytical model pre-trained and saved to the system
- Can be exported for import in other systems and hospitals

Business Implementation: *Stage 2* – User Journey Map

Zainab

Amy, 40
Self-checked High-risk Patient

1 Primary Tests
5 basic tests conducted at primary care

ECG

Blood Test

Blood Pressure

Stress Test

CT Coronary Angiography

2 Received Risk Prediction Result
With analytics report

Low Risk
Analyze reports to understand the patient's heart health and make recommendations accordingly

High Risk
Report reveals which factors contribute significantly to the patient's high risk, such as chest pain, and takes the next relevant detailed tests (e.g., screening for coronary artery disease).

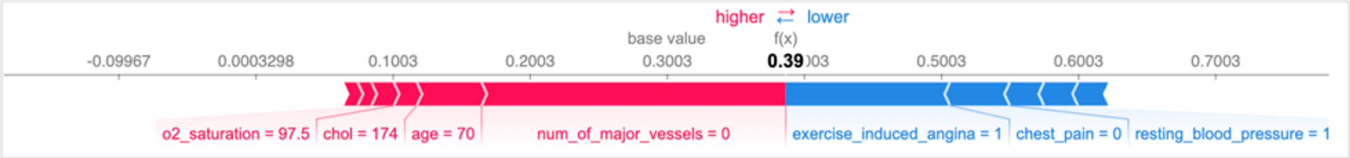
3 Decision Making
Based on Risk Prediction Level & Analytics Report & Expertise

Given simple testing with **medications** and screening

Advised to use stage 1 **self-prediction tool** to monitor heart health closely

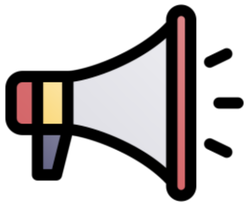
Determine the next course of action according to significant contributing factor

e.g., detailed **cardiac examinations** and **referrals to heart center** / specialist consultant



Expected Outcomes

Bryan



Raise Public Awareness

By **answering the questions** required for stage 1, **individuals** gain awareness of the risk factors for heart disease

Provide Timely Alert

From the **prediction result,** individuals can seek timely intervention before the heart disease materialises.

Optimise Medical Procedures

- **Individuals** would **know** if they need go for a heart check-up
- **Doctors** would be able to **optimise** the next course of action for patient

Comparison with Latest Solution

Bryan

	heartdetect Stage 1	heartdetect Stage 2	PRECISE
Purpose	Allow **people** to **self-detect** their risk of having **heart disease**	Allow **doctors** to **detect** the risk of having **heart disease**	Allow **patients/doctors** to **self-detect/detect** the risk of having **coronary artery disease**
Variables	17	11	7
Model Used	Random Forest	Random Forest	Logistic Regression
Explainer Model	LIME	SHAP	-
Output	High Risk (1) or Low Risk (0) (Categorical) with Explanation of factors	High Risk (1) or Low Risk (0) (Categorical) with Explanation of factors	Probability of having CAD (Continuous)

Comparison Analysis: By offering a more personalised approach with clearer explanations for our model, we are better than PRECISE

Bryan

Purpose

heartdetect vs PRECISE

Detect **heart diseases** for **everyone**

Detect **CAD** for people with **chest pain above 30 years**

Variables

heartdetect vs PRECISE

Different Variables for **each stage** to offer a more **personalised** output

Same Variables whether for clinical usage or nonclinical usage

Output

heartdetect vs PRECISE

Gives users a **categorical output** of whether they are high or low risk

Explains to them why they obtained the given result

Provide a **percentage** to users to interpret whether they are high or low risk

No explanation of how the percentage is derived

Limitations, and our strategies to get mitigate them

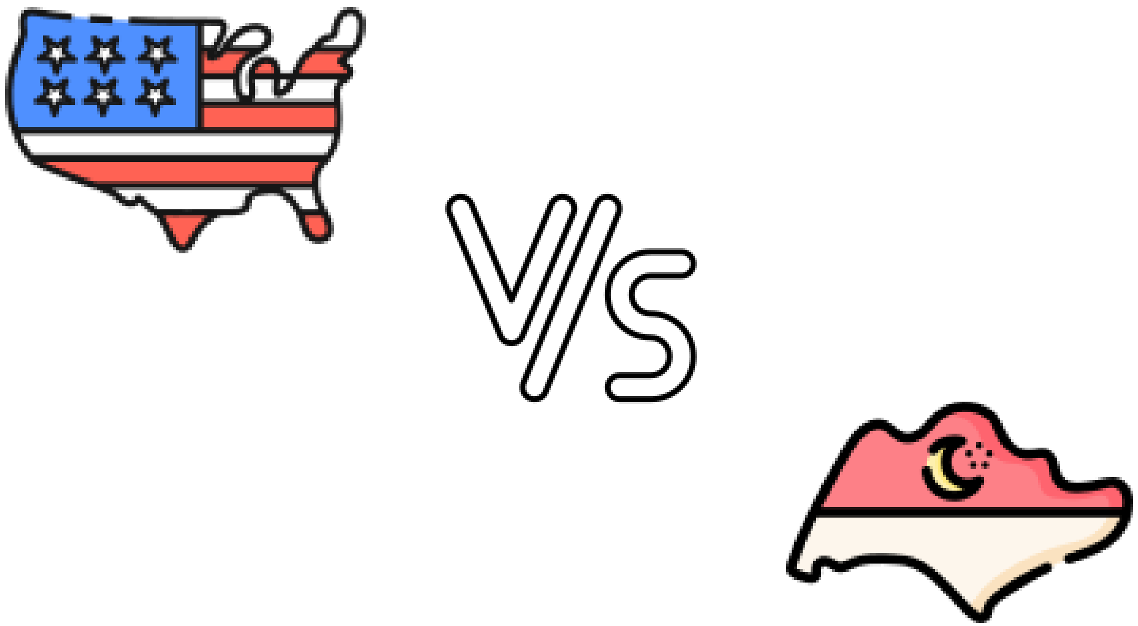
Gerald

Dataset Limitations

1

Data Origin

Dataset used is based on **American** individual data, which may **lose accuracy** in local implementation



Limitations, and our strategies to get mitigate them

Gerald

Dataset Limitations

1

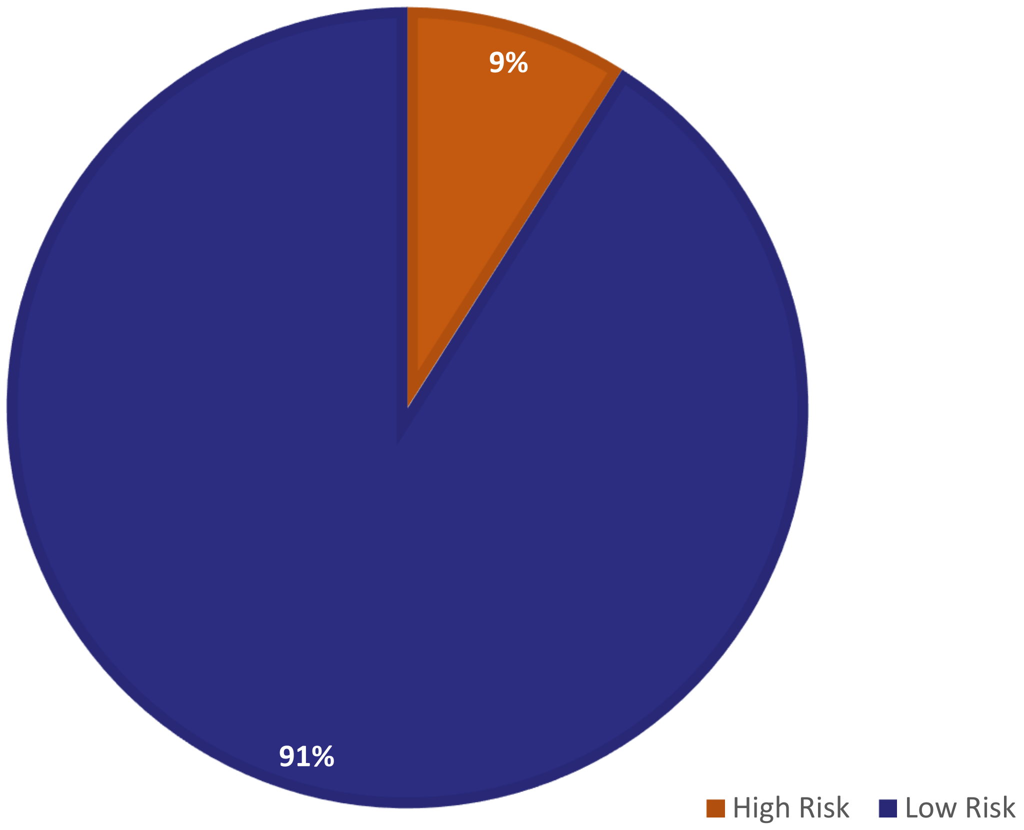
Data Origin

Dataset used is based on **American** individual data, which may **lose accuracy** in local implementation

2

Data Imbalance

Dataset used is **imbalanced** in terms of individuals with low and high risk of heart disease



Limitations, and our strategies to get mitigate them

Gerald

Dataset Limitations

1

Data Origin

Dataset used is based on **American** individual data, which may **lose accuracy** in local implementation

2

Data Imbalance

Dataset used is **imbalanced** in terms of individuals with low and high risk of heart disease

	2021	2020	2019
Total No. of Deaths	24,292	22,054	21,446
Ischaemic Heart Diseases	20.1%	20.5%	18.8%
Cerebrovascular Diseases (including stroke)	6.1%	6.0%	5.8%
Hypertensive Diseases (including hypertensive heart disease)	3.4%	2.9%	2.6%
Other Heart Diseases	2.3%	2.1%	2.0%
Atherosclerosis	0.2%	0.2%	0.1%
Total % of Deaths from Cardiovascular Disease	32.0%	31.7%	29.3%
Total No. of Deaths from Cardiovascular Disease	7,762	6,990	6,291

Limitations, and our strategies to get mitigate them

Gerald

Dataset Limitations

1

Data Origin

Dataset used is based on **American** individual data, which may **lose accuracy** in local implementation

2

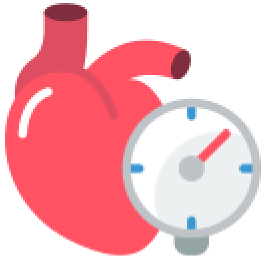
Data Imbalance

Dataset used is **imbalanced** in terms of individuals with low and high risk of heart disease

3

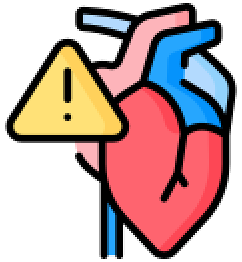
Other factors

Other risk factors such as **genetics**, were not considered though research has shown its role in risk prediction



High Blood Pressure

High Cholesterol



History of Heart Disease

Limitations, and our strategies to get mitigate them

Gerald

Dataset Limitations

1

Data Origin
Dataset used is based on **American** individual data, which may **lose accuracy** in local implementation

2

Data Imbalance
Dataset used is **imbalanced** in terms of individuals with low and high risk of heart disease

3

Other factors
Other risk factors such as **genetics**, were not considered though research has shown its role in risk prediction

Mitigating Strategies

1 2

Collecting more cardiovascular disease data from **Singaporeans**

3

Research or consult experts to determine which genetic indicators are valuable

Conclusion

Gerald

Stages

1

Stage 1

Individual Empowerment
Convenient self-predicting & monitoring tool

2

Stage 2

Prediction @ Primary Care
A decision support tool for physicians to make decisions based on analytics result

Increase involvement of individuals and primary care sector

Reduce life-threatening impacts of Heart Disease through early detection, timely intervention and optimal treatment

Shift the focus from post-diagnosis treatment to prevention

Conclusion

heartdetect

THANKS!

If you have any question, feel free to contact us at:

- Email: Jlei002@e.ntu.edu.sg
- GitHub: https://github.com/xJQx/bc2406-project

References

Carauna, C. (2018 , December 14). SciDev.Net. Retrieved from Lifestyle diseases swamp Asia's healthcare systems : https://www.scidev.net/asia-pacific/news/lifestyle-diseases-swamp-asia-s-healthcare-systems/

Perret-Guillaume, C., Joly, L., & Benetos, A. (2009). Heart rate as a risk factor for cardiovascular disease . Prog Cardiovasc Dis. , 6-10.

Heart failure - alcohol and smoking. HealthHub. (n.d.). Retrieved October 29, 2022, from https://www.healthhub.sg/a-z/diseases-and-conditions/716/Heart-Failure-Alcohol-and-Smoking#:~:text=Smoking%20damages%20the%20blood%20vessels,lung%20diseases%20and%20stomach%20ulcers.

Piepoli, M. F., Hoes, A. W., Agewall, S., Albus, C., Brotons, C., Catapano, A. L., . . . Løchen, M.-L. (2016). 2016 European Guidelines on cardiovascular disease prevention in clinical practice . EAS Updates, 207-274.

Qian, X., Li, Y., Zhang, X., Guo, H., He, J., & Wang, X. (2022). A Cardiovascular Disease Prediction Model Based on Routine Physical Examination Indicators Using Machine Learning Methods: A Cohort Study . Front. Cardiovasc. Med. .

Singapore Heart Foundation. (2022). Singapore Heart Foundation. Retrieved from Heart Disease Statistics: https://www.myheart.org.sg/health/heart-disease-statistics/

Yates, T., Zaccardi, F., Dhalwani, N. N., Davies, M. J., Bakrania, K., Celis-Morales, C. A., . . . Khunti, K. (2017). Association of walking pace and handgrip strength with all-cause, cardiovascular, and cancer mortality: a UK Biobank observational study . European Heart Journal, 3232-3240.