

# Project HeartBeat Heart Disease — — — — — Prevention

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# **Objectives**



# Significance of Cardiovascular Disease

18 million global deaths



1 in 3 deaths



**23** lives lost daily



#### **Barriers to CVD treatment**

Individual

+

**Healthcare** 



Perceived high check up costs



Fear of receiving a diagnosis



Lengthy waiting times for diagnostic tests

#### **Effects on CVD outcomes**



Missed opportunities to prevent CVD



**Increased treatment costs** 



Worse health outcomes



# Business Problem & Opportunity

Lack of strategies for early detection of CVD



Create comprehensive predictive model to detect CVD

By utilizing analytical tools,

**successful** forecasts of chronic illnesses can reach up to





# Business Problem & Opportunity

Leverage on Data Analytics



Gain insights on patient demographics, risk factors that may indicate risk of CVD

**Facilitate targeted preventive interventions** 

Enhance operational efficiency and costeffectiveness for healthcare and individuals

### **Project HeartBeat**

#### **Objectives**



Predictive tool that relies on non-medical data



Free & easily accessible for everyone



Empowers individuals to be proactive towards their cardiovascular health

#### **Benefits**



No need to wait and queue in hospitals



**Removes financial barriers** 



Reduce overall CVD mortality rates through early prevention

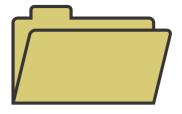
Joleen

# 02

# Data Sourcing & Exploration



### **Data Sourcing**

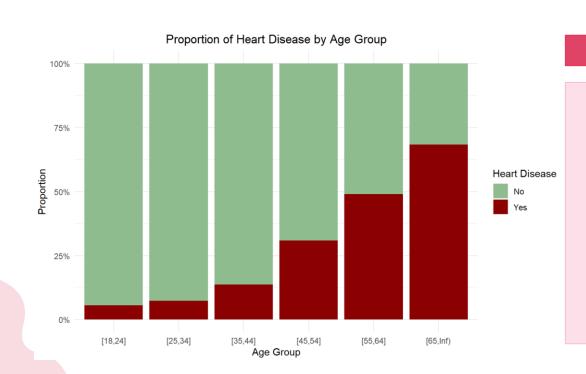


2022 Behavioural Risk Factor Surveillance System Survey Data (CDC) Categorized into

#### **Factors** related to CVD

- 1. Personal Particulars
- 2. Physical Characteristics
- 3. General Health Status
- 4. Health Habits & Behaviours
- 5. Health Issues & Illness History

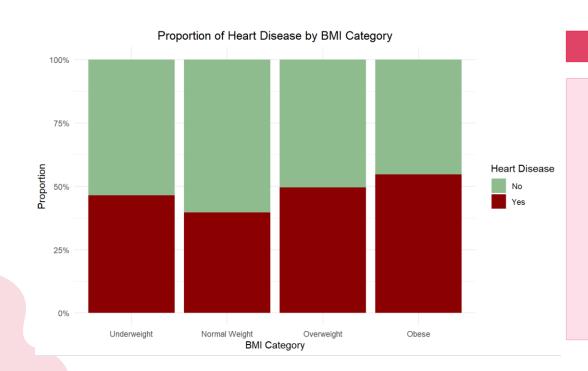
### **Heart Disease by Personal Factors**



#### **Data Exploration**

- Age is a significant risk factor that compromises on cardiovascular system
- Myriad physiological changes such as increased oxidative stress

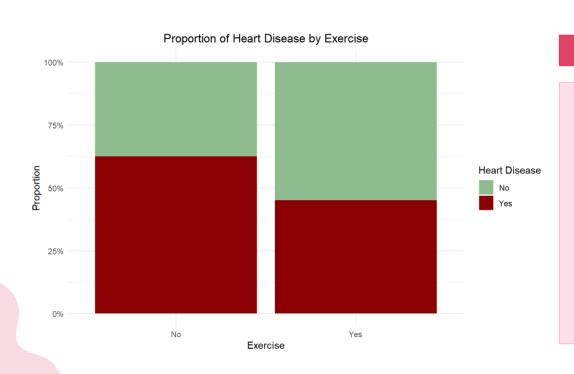
### **Heart Disease by Physical Characteristics**



#### **Data Exploration**

- Obesity contributes to various physiological mechanisms
- Haemoglobin deficiency is more prevalent among underweight individuals

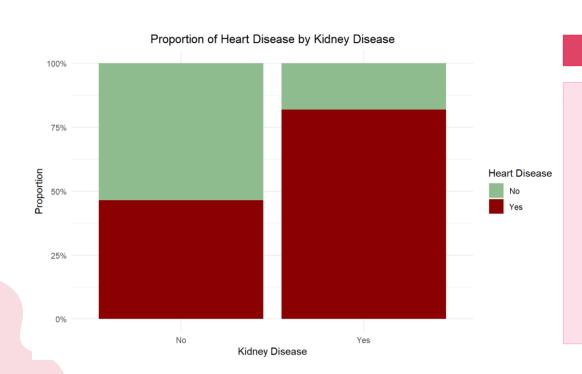
### **Heart Disease by Health Habits & Behaviours**



#### **Data Exploration**

 Physical inactivity can lead to other risk factors of heart disease such as diabetes, obesity etc.

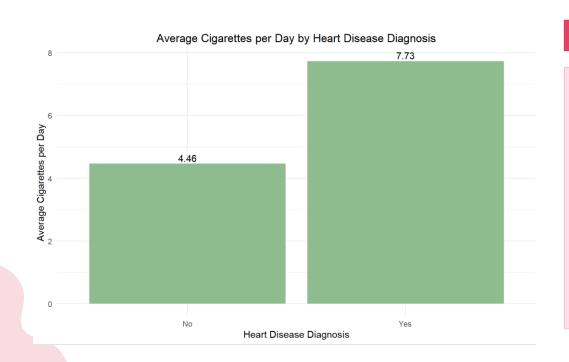
### **Heart Disease by Heart Issues & Illness History**



#### **Data Exploration**

- Strain placed on the heart due to kidney dysfunction
- More effort required to circulate blood to kidney
- Presence of high blood pressure exacerbates the strain

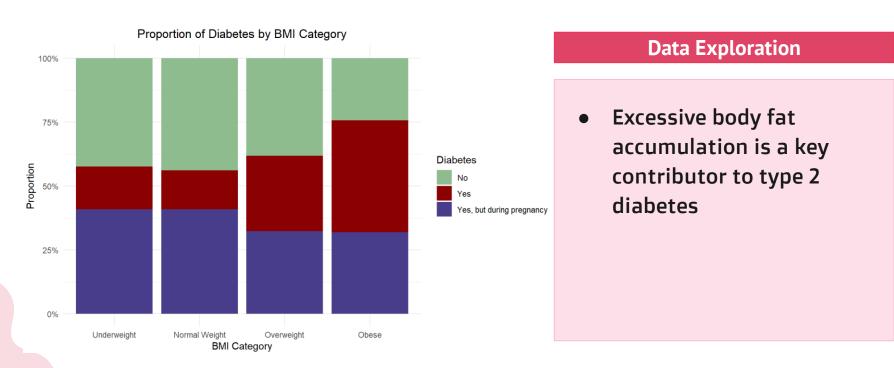
### **Average Cigarettes Per Day**



#### **Data Exploration**

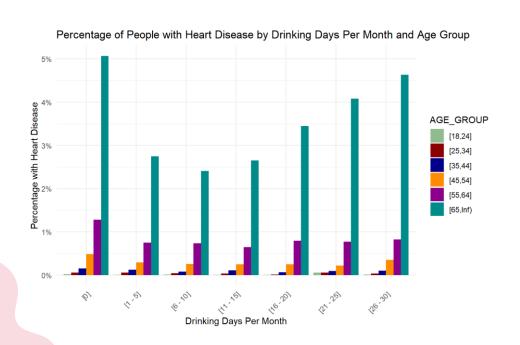
- Compounds present in cigarette promote the accumulation of plaque in blood vessels
- Elevate heart rate and induce inflammation

### **Diabetes by BMI Category**



Joleen

# Heart Disease by Drinking Days Per Month and Age Group



#### **Data Exploration**

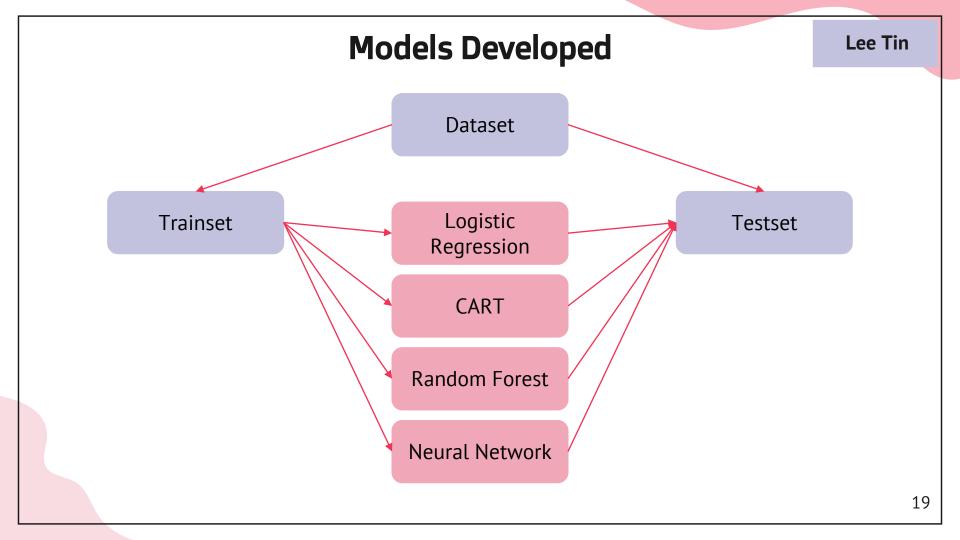
- Excessive alcohol consumption can increase risk of high blood pressure
- Dependent on the frequency and amount of alcohol consumed

Lee Tin

# 03 MODELS







Lee Tin

### **Logistic Regression**

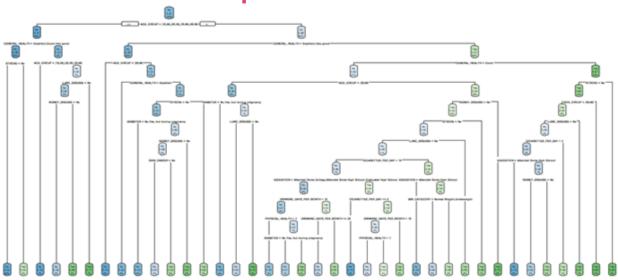
#### call:

```
glm(formula = HEART_DISEASE ~ AGE_GROUP + EDUCATION + UNABLE_TO_AFFORD_MED +
BMI_CATEGORY + GENERAL_HEALTH + PHYSICAL_HEALTH + CIGARETTES_PER_DAY +
STROKE + SKIN_CANCER + OTHER_CANCER + LUNG_DISEASE + KIDNEY_DISEASE +
ARTHRITIS + DIABETES, family = binomial, data = trainData,
na.action = na.omit)
```

- Model built based on <u>insights derived from EDA</u>
- <u>Backward stepwise selection</u> was employed
- Checked for <u>multicollinearity</u>
- Variables with <u>high p-values removed</u>, due to <u>lack of statistically</u> <u>significant impact</u> on the target variable, resulting in the <u>optimal</u> <u>logistic regression model</u>

#### **CART - Classification Tree**

#### **Optimal Prune**



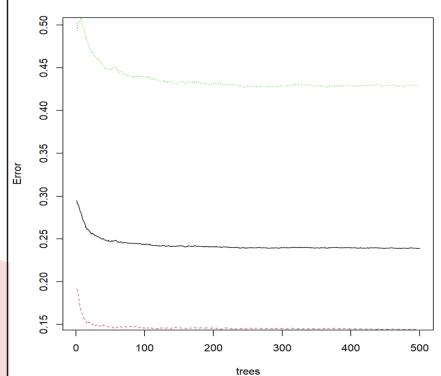
- Optimal complexity parameter determined based on <u>cross-validation</u> results
- Tree is <u>pruned</u> using this optimal CP of 0.00118497 to <u>38 terminal nodes</u>

#### Lee Tin

#### **Random Forest**

#### **OOB Error against Number of Trees**





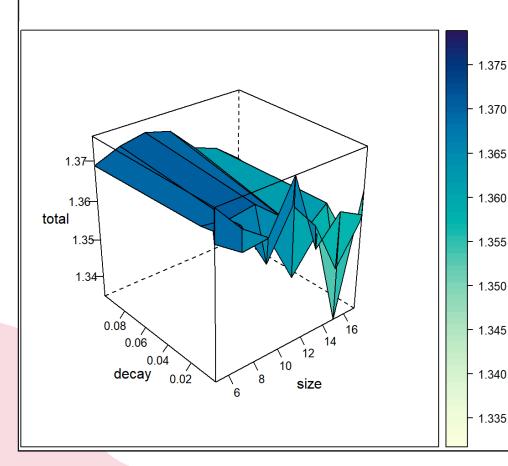
#### **Model Evaluation**

- Optimal model determined by minimising and stabilising the Out-of-bag (OOB) error
- Stabilized after <u>100 to 150</u> trees
- OOB error <u>23.92%</u>

#### Lee Tin

#### **Neural Network**

1.350



#### **Model Evaluation**

Through grid search, optimal size of 17 nodes and weight decay of 1e-05, gives the best model accuracy and the optimal Neural Network model

### **Confusion Matrix Results**

Logistic Regression		Predicted		
		No	Yes	
Actual No		TN 8345	FP 2837	
	Yes	FN 1319	TP 4282	

Random Forest		Predicted		
		No	Yes	
Actual	No	TN 22254	FP 3882	
	Yes	FN 5742	TP 7326	

CART		Predicted		
		No	Yes	
Actual No		TN 9524	FP 1678	
	Yes	FN 2261	TP 3340	

Neural Network		Predicted		
		No	Yes	
Actual	No	TN 10823	FP 379	
	Yes	FN 4168	TP 1433	

# **Model Employed**

Models	TPR (%)	FNR (%)	FPR (%)	TNR (%)	Accuracy (%)
Logistic Regression	76.5	23.5	25.3	74.7	75.3
CART	59.6	40.4	15.0	85.0	76.6
Random Forest	56.1	43.9	14.9	85.1	75.5
Neural Network	25.6	74.4	3.4	96.6	72.9

#### **Final Decision**

- <u>Logistic regression model</u>
   has been selected as the
   <u>most optimal</u> model
- All 4 models have <u>similar</u> <u>accuracy</u>
- Logistic regression has the <u>highest TPR of 76.5%</u>



Lee Tin

# **Business Insights from Models**

#### **VARIABLE IMPORTANCE**

Variable	Importance
AGE_GROUP [above 65]	18.815
GENERAL HEALTH [fair & poor]	26.030 25.663
STROKE	18.665

#### **Insights**

- These variables appear to have notable impacts on the likelihood of developing CVD
- Understanding the importance of these variables can <u>enable</u> <u>more targeted</u> and <u>effective</u> <u>preventive strategies</u>

Lee Tin

# **Business Insights from Models**

# ODDS RATIO FOR LOGISTIC REGRESSION

Variable	Odds Ratio
AGE_GROUP [above 65]	14.729
GENERAL HEALTH [poor]	7.600
STROKE	2.453

#### **Insights**

#### Higher odds ratio:

- 1) in AGE\_GROUP for individual aged above 65
- 2) poor GENERAL\_HEALTH
- 3) for individual with stroke signifies a <u>heightened risk of CVD</u>

Prioritize interventions aimed at improving these variables can help with resource allocation and reduce the risk of CVD, ultimately improve patient outcomes and cost efficiency

Sally

# NHCS' Current Measures



### **Current Reactive Measures**

#### **Cardiac Tests**

#### Supplemented with

#### Al Tool

- Echocardiogram (ECG),
- Cardiac Computed Tomography (CT) Scan,
- Exercise Stress Test (Treadmill Exercise) and more







- Gabor-Convolutional Neural Network (Gabor-CNN) algorithm
- Recognise ECG patterns to diagnose CVD
- 98.5% Accuracy





# Limitations

# Limited Improvement in Efficiency and Cost

Al tool still requires ECG to be conducted

Costly and time-consuming



Lack of Early Prevention
Measures

- Current focus on **reactive measures**
- Potential delayed diagnosis for those at risk only when they show CVD symptoms



Limited Predictive Variables

- Al tool only analyses ECG signals
- Non-medical factors also play a part in determining risk



Sally



# 05

# Proposed Solution

# **Proposed Solution**

**Current Measures** 



**Supplemented with** 

Our Solution





Cardiac Health Monitoring and Prediction (CHAMP)

# **Overview of CHAMP App: 3Ps**







Predictive Analytics Models Personalised Preventive Measures

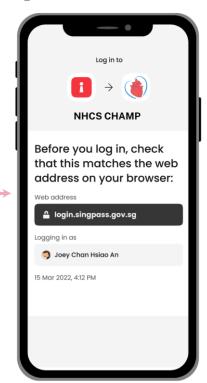
Public Education

Sally

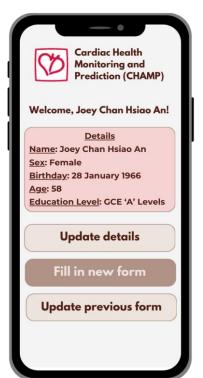
# Predictive Feature 1: Retrieval of Input Factors



Biometric Login



Automatic Retrieval of Details & Form History



# Predictive Feature 2: Risk Assessment Sally Form

Categorical Variables

Select category from dropdown

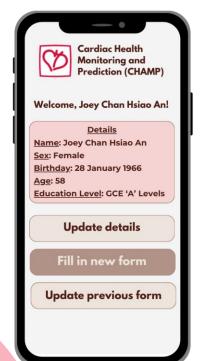


Continuous Variables

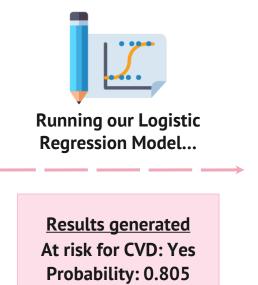
Fill in numerical value

Sally

# Predictive Feature 3: Utilisation of Logistic Regression Model

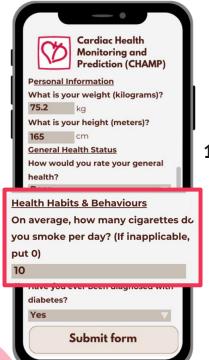






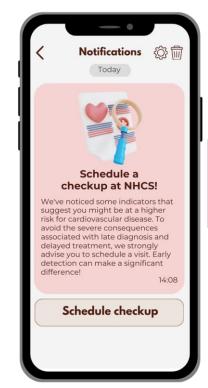


### **Preventive Features: At risk for CVD**



1. Personalised Health Advice

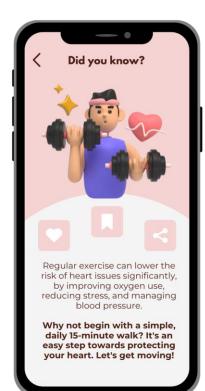




2. Scheduled Check-up Notifications

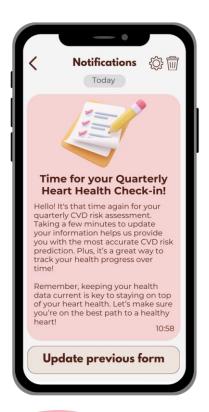
### **Preventive Features: Not at risk**

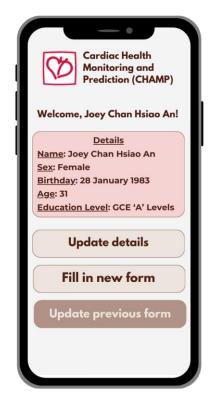




- Educational information about CVD
- Raise awareness even if they are not at risk

### Preventive Features: For everyone





Quarterly reminders to update Risk
Assessment Form

- Continuous monitoring to track improvements
- Dynamic adjustments in health advice

## **Review of CHAMP App**







Personalised Preventive Measures



Public Education

### **Value Proposition**



User-Friendly Interface



Simplified Registration



Freely Available



**Preventive Approach** 



**Risk Prediction** 



**Lifestyle Integration** 

### **Feasibility**



Initial Investment

Software Development and Singpass integration



users

Free Accessibility





Financial Empowerment

Enabling proactive preventive measures without cost burdens.



Facilitates early detection of CVD

Early Detection





Long-Term Cost Saving

Long-term benefits outweigh short-term costs

### **Feasibility**





Indicates effectiveness in reducing Cardiovascular Disease (CVD) mortality



**Cost of Treatment** 

Assess the app's effectiveness in reducing healthcare expenses for users

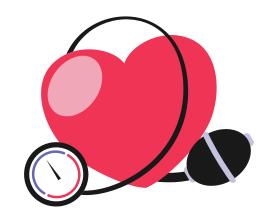


**Waiting Time** 

Evaluate improvements in healthcare accessibility facilitated by CHAMP

# 06

# Improvements & Conclusion





### **Limitations & Improvements**

	Limitation	Improvement
Inaccurate Information	Accuracy reliant on completeness of user-provided data.	Integrate wearable devices for real-time health data and schedule periodic checkups for validation.
Subjectivity of Self- Assessment	User input introduces variability in predictions.	Provide structured prompts for classification, reducing subjectivity and improving accuracy.
Limited Comprehensiveness of Risk Factors	Current dataset <b>lacks crucial factors</b> like dietary habits.	Access local datasets with broader factors and utilize user data for enhanced predictive ability.

### **Conclusion**

**Enhance Clinical Capabilities** 

**Optimal Patient Care** 

**Cost-Efficiency and Sustainability** 

Reputable Leader in Cardiovascular Care



# PowerBl Demonstration

# Thank You!

Do you have any questions?



