Mortality Prediction of Patients with Heart Failure

AN6003 Team6

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Executive Summary

Heart failure is a clinical syndrome, which is become a major public concern in recent decades due to its increasing severity. Since the market of medical services for patients with heart failure becomes larger and larger, the diagnosis and treatment process of heart failure should be improved, especially for National Heart Centre Singapore (NHCS), the pioneer specializing in cardiovascular diseases. Opportunities for NHCS can be found in optimizing the process to provide a better service, thus achieving its goal of reducing re-hospitalization and death, gaining more business, and winning a higher reputation.

The current diagnosis and treatment process has several pain points: (1) Negligence of Prevention; (2) Limited Medical Resources (Labor & Materials); (3) Shortage of Timely Communication of Medical Plans with Patients and Their Families. To solve these pain points, we deliver a two-part solution:

- **Determining the main factors leading to heart failure death to help diagnose potential heart failure at an early stage when the patients are taking a physical examination**
- **Predicting the death risk to (1) determine the priority among the patients with heart failure to optimize resource allocation and (2) help discuss the medical plan with patients and their family**

After benchmarking the current solution, our model will focus more on the business problems of NHCS by choosing a more practical dataset, selecting fewer features, applying more understandable evaluation metrics, and better results models.

We applied random forest as the model to deliver the two-part solution. For the feature selection, it is found that time, serum creatinine, and ejection fraction seem to be the three top variables to consider when making predictions, which means hospitals can pay more attention to those values of patients during the physical examination and investigate the potential of having heart failure. When it comes to the death event prediction, we figure out that the random forest model trained by 80% of the dataset appears to have the best performance with 87.93% accuracy and 86.67% recall. Both two parts of our solution reach our success criteria well.

Detailed implementation and extension plan of our solution is also given. The model can be used in many scenarios and can be quite helpful for NHCS to optimize its diagnosis and treatment process of heart failure.

Contents

1 Introduction

1.1 Background

Heart failure is a serious chronic cardiovascular disease with a high prevalence in Singapore but can be prevented and controlled. More attention should be paid to this specific sector of heart disease to improve the diagnosis and treatment process.

- **Heart failure is a serious disease with a high mortality rate; the market of medical services for heart failure shows strong growth potential.**

  Heart failure means that the heart is unable to pump blood as well as it should, which will bring a lot of inconvenience to daily life with a high death risk. For example, fatigue and shortage of breath, and even daily activities such as running, and climbing are life-threatening to the patients. According to the American Heart Association, about half of heart failure patients die within five years [1]. Based on the data from CDC, about 697,000 people in the United States died from heart disease in 2020, that's 1 in every 5 deaths [2]. This is not only the case for the US but is for the global. Cardiovascular diseases have been the top 1 cause of death, which leads to deaths nearly twice the one led by cancer, the second biggest cause (see Figure 1). Besides, it can be also observed from the figure that the deaths caused by cardiovascular diseases have grown stably at a compound annual growth rate (CAGR) of 1.9% from 1990 to 2019, which implies a larger and larger market for medical services for heart diseases.

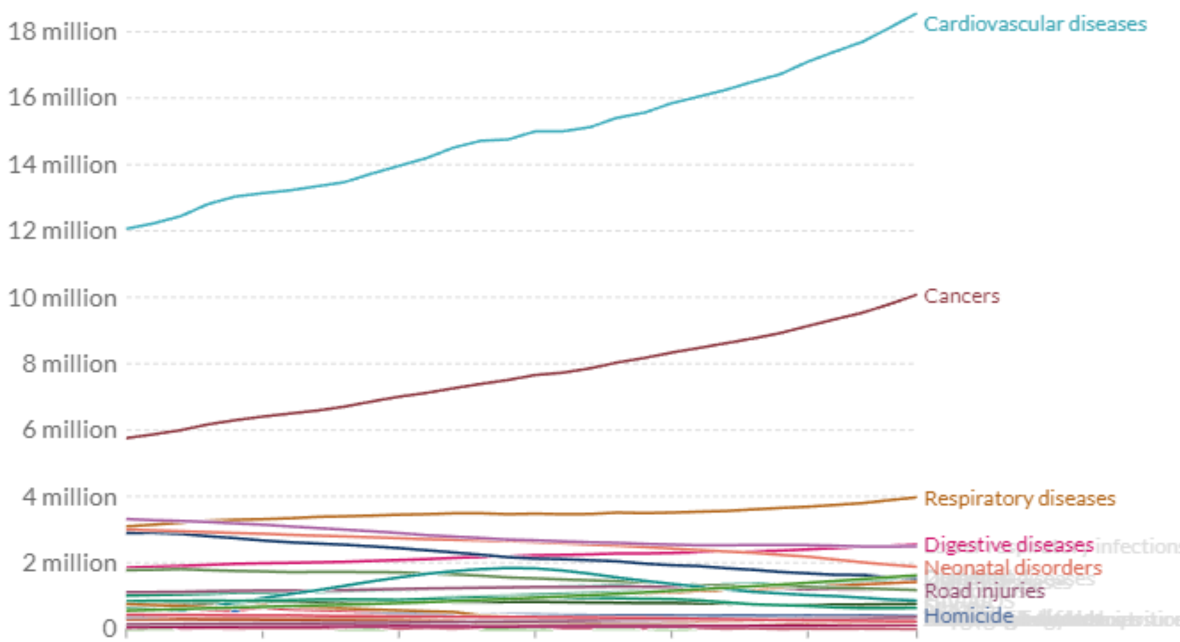

Figure 1. Number of Death by Cause, World, 1990 to 2019 [3].

Since heart failure usually results from other chronic cardiovascular diseases, it's a major disease among all types of heart diseases. From Figure 2, we can figure out that the death rate among all populations caused by heart failure reached over half the rate caused by heart disease, indicating that more attention should be paid to heart failure.

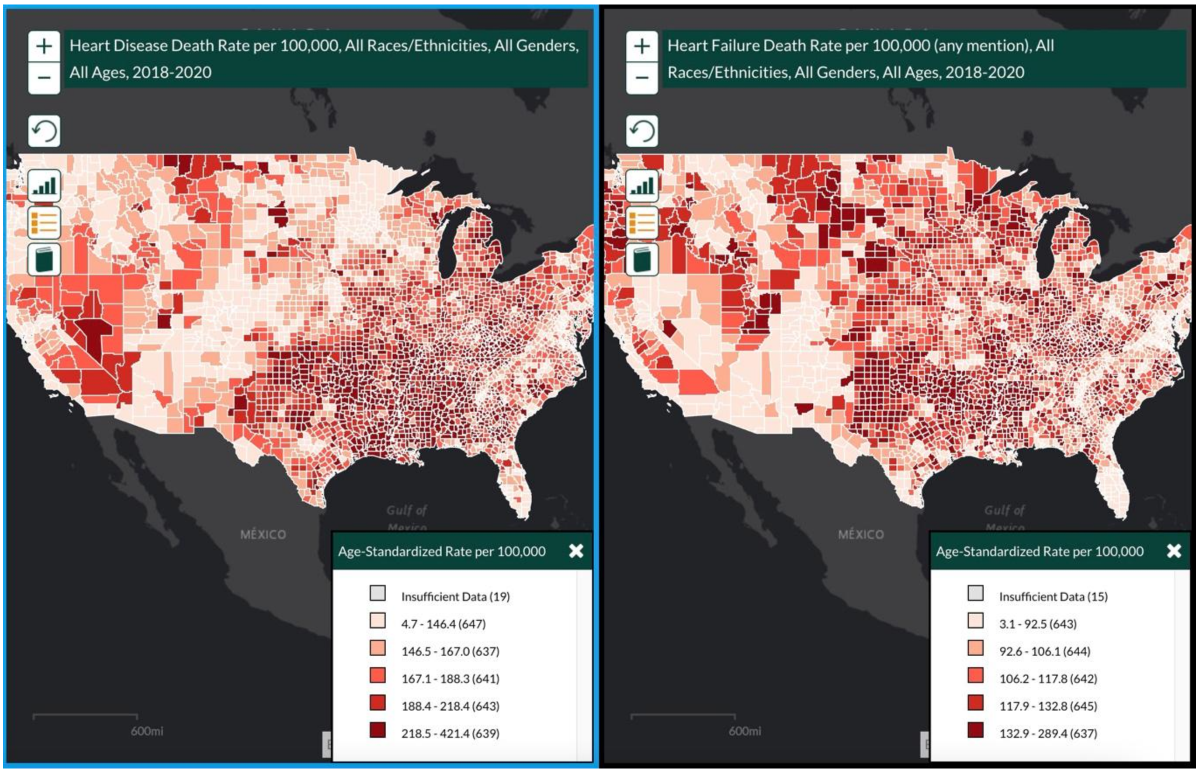

Figure 2. Death Rate per 100,000 in US 2018-2020: Heart Disease (Left); Heart Failure (Right) [4].

- **Heart failure is extremely prevalent in Singapore.**

  Among Singaporeans, there are 4.5% of them suffer from heart failure, while only 1%-2% have the disease in the United States and Europe [5]. Due to its high prevalence, heart failure has been identified as a priority area for disease management in Singapore. As per the recent number cited by National Heart Centre Singapore (NHCS), Singapore sees at least 5000 hospital admissions due to heart failure.

- **Heart failure is a chronic disease that can be prevented by early diagnosis and controlled through timely and long-time treatment.**

  In most cases, heart failure has no cure but can be controlled by timely and long-time medical attention. Early diagnosis and aggressive early treatment can change the trajectory of the disease. It is an incredibly crucial issue. Earlier treatment of a patient with angiotensin-converting enzyme inhibitors might help decrease mortality levels and reduce overall symptoms of heart failure. Earlier treatment for heart failure with ACE inhibitors may also prevent the patient's heart from increasing in size due to the condition [6].

1.2 Pain Points

As mentioned in the background, the diagnosis and treatment process of heart failure should be improved, especially for NHCS, the pioneer specializing in cardiovascular diseases. Since the market of medical services for patients with heart failure becomes larger and larger, optimizing the process to provide better service will be quite helpful for NHCS. However, the current diagnosis and treatment existing the following pain points:

- **Negligence of Prevention**

  Most patients are diagnosed with heart failure only when they have symptoms and come to the hospital. However, they are already at the middle and end-stage when they proactively seek treatment, which is hard for doctors to prevent the situation from getting worse. Heart failure can be easily controlled at an early stage. The negligence of prevention from heart failure is a crucial pain point, which can save a lot of lives if it is solved.

- **Limited Medical Resources (Labor & Materials)**

  NHCS has 10000 inpatients each year, sometimes it is hard for nurses/doctors to analyze the condition of all the inpatients carefully and give appropriate treatment. Improving the efficiency of diagnosis is important for NHCS to provide in-time care for these. Also, since the medical resources are limited, resource allocation should be given more attention thus all the patients can be given proper treatment in the big picture.

- **Shortage of Timely Communication of Medical Plans with Patients and Their Families**

  Communication is a crucial component in all steps of the healthcare process. Patients and their families can be up to date on their health condition and decide their future medical plans through effective discussions with doctors. Furthermore, suppose a patient suffers from advanced heart failure (a disease process that carries a high burden of symptoms, suffering, and death), NHCS may consider providing palliative care, which can complement traditional care to improve symptom amelioration, patient-caregiver communication, emotional support, and medical decision making. Both the timely health condition communication and the suggestion of providing palliative care requires efficient and accurate prediction of whether there will be a fatal risk for the patients.

2 Business Problem

2.1 Opportunity Statement

NHCS accounts for more than 100 of the hospital admission cases due to heart failure. With this level of consultation, NHCS has conceded that heart failure management is one of the key areas they target. To help NHCS to optimize the diagnosis and treatment process for heart failure and achieve its goal of reducing re-hospitalization and death, we find opportunities in

- **Determining the main factors leading to heart failure death to help diagnose potential heart failure at an early stage when the patients are taking a physical examination**

  To prevent heart failure at an early stage, it will be a great help if we can detect the key factors related to heart failure during regular physical examinations. In this case, early treatment can be given, and heart failure can be easily controlled.

- **Predicting the death risk to (1) determine the priority among the patients with heart failure to optimize resource allocation and (2) help discuss the medical plan with patients and their family**

  Since medical resources including labor and materials are limited and sometimes costly, resource allocation is important to improve efficiency and overall performance. Predicting mortality in patients hospitalized is crucial for assessing the severity of illness and adjudicating the value of novel treatments, interventions, and healthcare policies. Also, timely discussion of the future health condition and future medical plan including whether to provide palliative care to patients and their families can be provided.

2.2 Success Criteria

Based on the problems to solve, success criteria can be established to evaluate our final delivery:

- **Determining the main factors indicating the heart failure death**
  - **Requirements**

    (1) convenient to collect during the physical examination

    (2) minimum number of factors that is sufficient to indicate the heart failure death
  - **Specifications: 3-6 factors that are easy to collect**

- **Predicting the death event of patients with heart failure**
  - **Requirements: Develop a predictive model with**

(1) High accuracy: Accuracy represents the ratio of correct predictions out of all predictions. Thus, high accuracy can help to determine the priority among all the patients to implement the resource allocation.

(2) High recall: Recall means the ratio of correct prediction out of the predictions for positive outcomes. In our case, it means that the model can predict as many positive death events as positive. High recall can support NHCS to discuss future health conditions and suggesting medical plans with the patients and families.

- **Specifications:** In general, there exists a precision-recall tradeoff when optimizing the models. Since the predictive model will be used to solve the problems with a different focus, relatively high accuracy and recall rate is expected.

  (1) Accuracy: ≥ 80%

  (2) Recall: ≥ 80%

3 Benchmark & Concept Generation

3.1 Benchmark

In recent years, machine learning and deep learning have developed rapidly and are widely used in the medical and bioengineering field. Compared with traditional prediction models for heart disease patients, machine learning and deep learning methods have a major advantage in predicting mortality in cardiac patients in studies that can synthesize all aspects of patient information.

Some prediction models are built to design targeted care management for hospitalized patients who are at higher risk for post-discharge mortality. Mark Stampehl et al. [7] used categorical regression trees, full logistic regression, and stepwise logistic regression methods and assessed the effect of patient characteristics on patient mortality. The stepwise logistic regression they built performed best in predicting mortality within 30 days to 1 year with an AUC of 0.74-0.75. Applying this model hospitals may identify patients with reduced or preserved ejection fraction and provide them with more advanced health care. And with the constant development of medical databases, the data of cardiac patients are becoming more and more perfect and comprehensive, and the volume and dimension of data are gradually increasing.

Many scholars have used deep learning methods in addition to machine learning algorithms to evaluate and predict mortality assessment models for cardiac patients. Joon-Kwon et al. [8] established a deep neural network (DNN) to predict mortality in patients with acute heart failure. And by comparing their model with the scoring system for in-hospital mortality of patients with acute heart failure (specified by the American Heart Association) (Get with the Guidelines-Heart Failure, GWTG-HF), the deep learning model had a better AUC of 0.880. They use this DNN model to improve the decision-making of hospitals on high-risk patients.

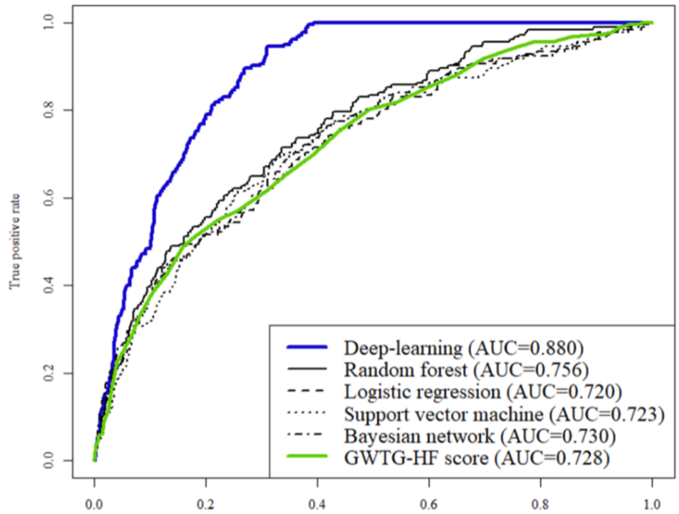

Figure 3. The ROC Curve of the Model by Joon-Kwon [8].

Advanced heart failure patients not only suffer from shortness of breath and fatigue as a result of their disease process, but also have a high burden of somatic complaints, including pain, nausea, anxiety, and depression, leading to a significant decrease in the life quality for both patients and their caregivers. In this case, some heart failure models are built to predict the mortality of patients, so that palliative care can be provided if their probability of death is high. Sho Suzuki et al. [9] used multiple logistic regression analysis with stepwise variable selection to select mortality predictor variables and determine weighted scores. The study also identified five factors such as whether the patient was hospitalized and body mass as the most critical factors affecting patient mortality.

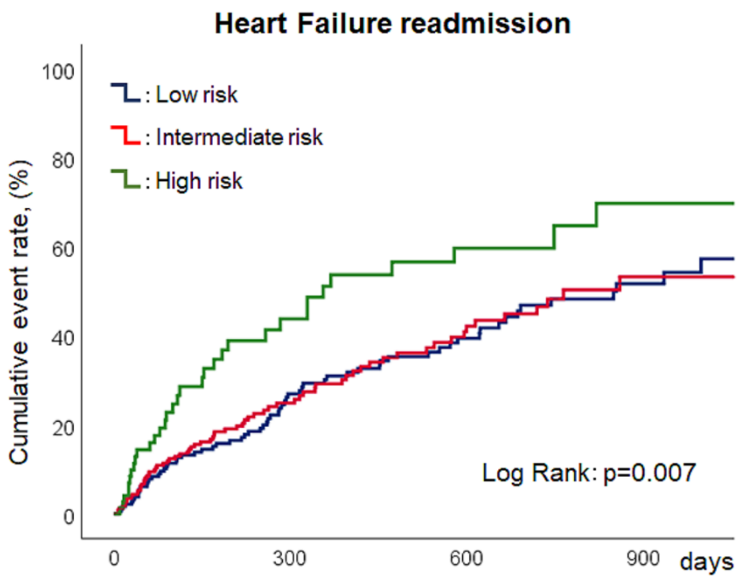

Figure 4. Kaplan-Meier Plots of HF Readmission according to Risk Score Index [9].

Sindhu Avula et al. [10] combined CART with PRISM scores to predict mortality in heart disease patients within one year after the disease, the discriminatory ability of PRISM categorical score (AUC

= 0.701) was not significantly different than the discriminatory ability of modified CART (AUC = 0.686) but improved significantly with the combination of PRISM (categorical) score + modified CART (AUC = 0.740).

3.2 Concept Generation

Based on the current studies, we figure out that there exist some gaps in the existing model, and improvement can be done by our solution in four aspects: **dataset**, **feature selections**, **evaluation metrics,** and **the result of the model**.

- **Dataset**

  We find the common limitations in the current studies:

  1) the data of patients are difficult to collect leading to a very small dataset, and there is no way to further improve the accuracy and generalizability of the model
  2) the follow-up time is too short, many studies choose 180 days as the monitoring period. There might not be enough possible death, leading to an imbalance of data between death and non-death cases.

  Thus, we pay attention to these potential issues while selecting the dataset for model training. Our dataset has a total of 299 data, which is considered a medium-sized dataset compared to the currently available studies. 35.5% of the follow-up days of patients in our dataset are over 180 days, which is much longer than those of existing studies.

- **Feature Selection**

  Many current studies applied more than 20 input variables for model construction, including atrial fibrillation, cancer, and the presence of respiratory failure. During our model-building process, we find that inputting more variables contributes very little to the accuracy and recall of our prediction. Considering the cost, efficiency, and level of convenience associated with information collection, we decide to choose the top 3-6 important features only. Feature selection helps to reproduce the model easily by focusing on the data that would most impact the prediction while maintaining high accuracy and recall. In our models, we apply features such as medical history, regular blood, and urine tests, etc., the data for which is available in the physical examination and can be gathered efficiently without any usage of extra resources.

- **Evaluation Metrics**

  Almost all existing models on heart failure mortality prediction use AUC/ROC as an evaluation metric, our solution differs in that we use accuracy and recall as the evaluation metrics. Accuracy and recall are commonly used metrics, while in opposition, the AUC is used only when it's about classification problems with probabilities in order to analyze the prediction more deeply. As a result, accuracy and recall are more understandable and intuitive even to a non-technical person, thus can be easily and widely used by all the medical staff.

Besides, by using these two metrics, we can apply our model to different business scenarios. The higher accuracy would imply that the organization can segment the patients into different groups and can further optimize resource allocation. Since there is a huge gap in demand and supply, a judicious use that minimizes the death event can be focused on with the highest accuracy our model can derive from limited features and cost. And recall refers to the rate quantifying the number of correct positive predictions made out of all positive predictions that could have been made. Recall in this case plays as a warning for people who might have a higher risk to die from heart failure. A correct prediction helps both the doctor and patient become conscious of the condition and plan ahead in terms of treatment and financial support.

- **Result**

  Our model shows better results than the above models. Since the first study was conducted by Mark Stampehl as an example, the AUC of their model is around 0.75, while our model has a higher AUC which is around 0.83. However, we focus more on recall and accuracy, which is a more understandable metric to NHCS, our model has both recall and accuracy that is higher than 0.85 on the test set, which is strong evidence that our prediction model has good discriminatory ability. Higher accuracy and recall enable the hospital make right decisions on the medical plan and avoid future conflicts caused by false predictions between doctors and patients.

In conclusion, our solution is better than the existing solution mentioned above in the way that we focus more on the business problems of NHCS, while others focus more on the technical side. The metrics used and the dataset selected present in an understandable and practical way. In addition, our model can target different business scenarios based on the needs of NHCS.

4 Solution

4.1 Dataset

The data set selected is "Machine Learning + Survival for Heart Failure" from Kaggle by FangYang which was initially posted in October, 2021. There are 299 observations and 13 features in which the target variable is **DEATH_EVENT**. Table 1 indicates the explanation of each feature.

Table 1. Variables and corresponding explanations in the dataset.

Variable	Explanation
Age	Age of the patient
Anaemia	Decrease of red blood cells or hemoglobin
Creatinine_phosphokinase	Level of the CPK enzyme in the blood (mcg/L)
Diabetes	Whether the patient has diabetes
Ejection_fraction	Percentage of blood leaving the heart at each contraction
High_blood_pressure	Whether the patient has hypertension
Platelets	Platelets in the blood (kiloplatelets/mL)
Serum_creatinine	Level of serum creatinine in the blood (mg/dL)
Serum_sodium	Level of serum sodium in the blood (mEq/L)
Sex	Gender of the patient
Smoking	Smoking status of the patient
Time	Follow-up period (days)
Death_Event	Whether the patient deceased during the follow-up period

4.2 Exploratory Data Analysis

Exploratory data analysis is the process of conducting preliminary research on data to obtain a general understanding while looking at the dataset. It does not only help with identifying obvious mismatched values or errors in the dataset but also finds relationships between variables to ensure the results finally produced are valid and respond to the business questions.

4.2.1 Data Overview

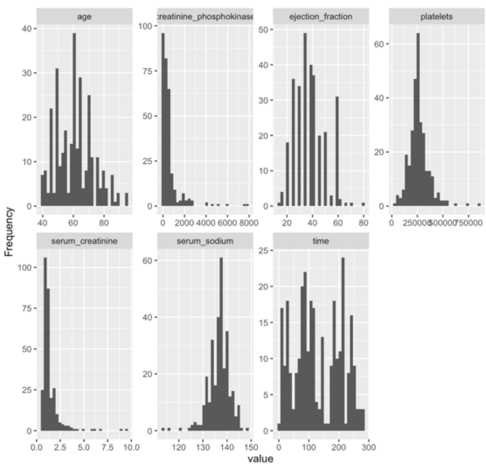

Figure 5. Histogram for Continuous Variables

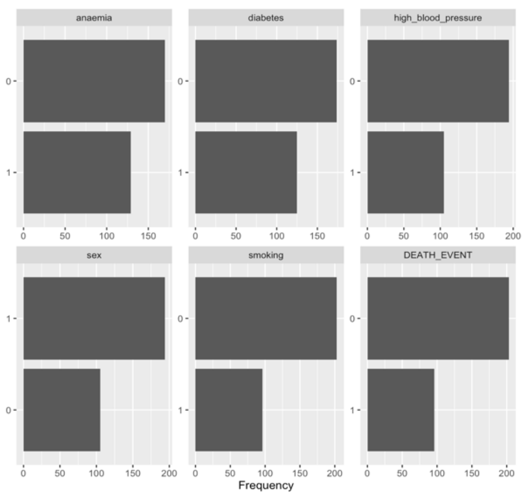

Figure 6. Bar Chart for Discrete Variables

Figure 5 shows a basic histogram for all 7 continuous variables, in which most of the continuous variables exhibit an obvious left skew or a right skew. Figure 6 provides the bar chart for all 6 discrete variables, and it is interesting to figure out which variables are the most effective to predict the death event. We then selected several continuous variables and look at more details.

4.2.2 Distribution Analysis for Single Variable

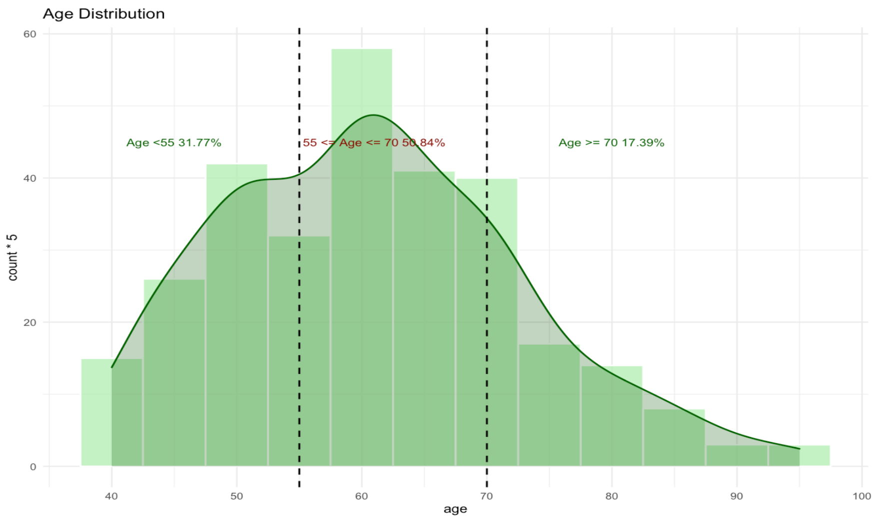

Figure 7. Distribution of *Age*

As shown in Figure 7, the distribution of patients' age is slightly right skewed, and nearly half of the population's age is in the range of 55 to 70, and around 33% of the population is between the age of 40 and 55. In that case, we would start our analysis later from the age and figure out how well the age is related to the death event.

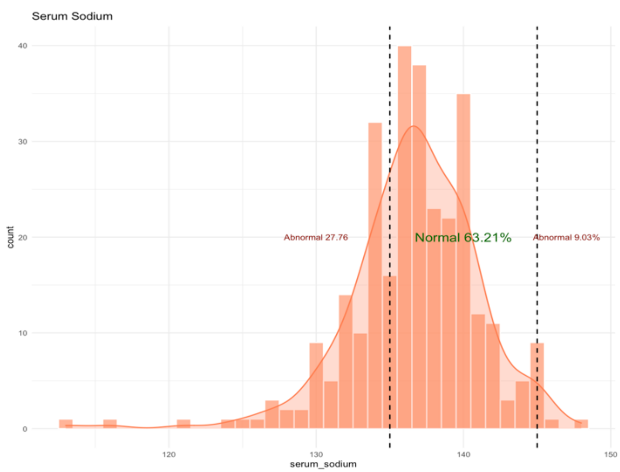

Figure 8. Distribution of *Serum Sodium Level*

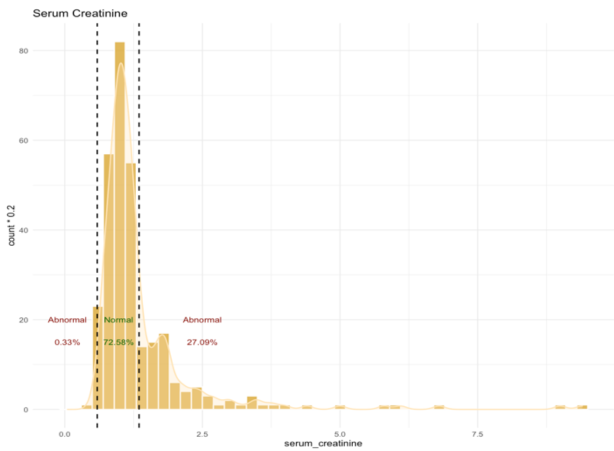

Figure 9. Distribution of *Serum Creatinine Level*

Regarding the normal range of serum sodium levels of 135 to 145 announced by UCSF Health, 63% of the patients in the dataset have a normal serum sodium level. In addition, the outliers on the left of the graph indicate the extremely low serum sodium level of several patients. Similarly, from Figure 9, approximately 73% of our population is within the normal serum creatinine, and there also exist several extreme values for the patients. We are interested in finding how those variables affect the prediction.

4.2.3 Correlation Analysis

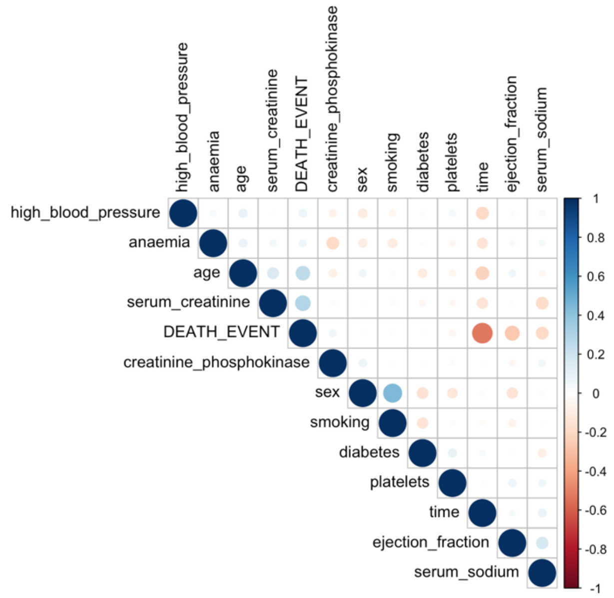

Figure 10. Correlation Between Variables

From Figure 10, the correlation between ***death event*** and ***time*** appears to have the highest correlation, and the ***death event*** also has a relatively strong correlation with ***serum creatinine***, ***serum sodium***, ***ejection fraction***, and ***age*** at first sight. We then list those variables as the first consideration for further analysis by doing feature engineering and modeling.

4.2.4 Density and Distribution Analysis on Variables by Death Event

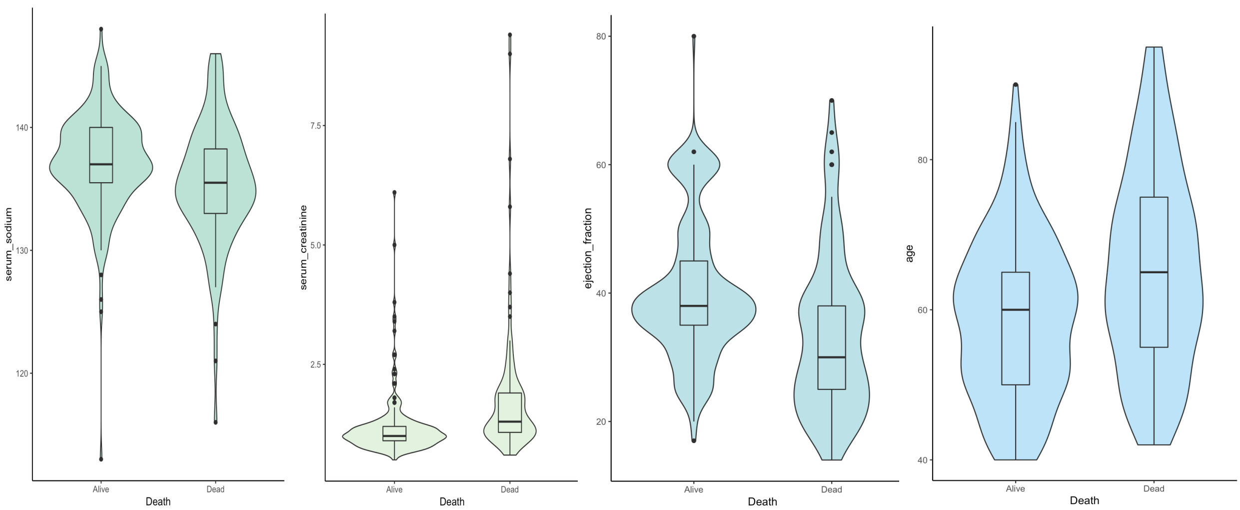

Figure 11. Violin Chart for *Death Event* and *Serum Sodium*, *Serum Creatinine*, *Ejection Fraction*, and *Age*

The figures above demonstrate the density, distribution, and peak of the level of serum sodium, the level of serum creatinine, the percentage of blood leaving the heart at each contraction, and the age of the patients who were dead or alive at the end respectively.

Figure 11 implies that the dead patients have a relatively lower serum sodium level than the live patients as the box plot for dead people has a lower median and quartile. Similarly, the higher interquartile range for dead patients and the higher median value suggest that the higher serum creatinine may be the cause of the death event to some extent. In addition, there is only one outlier for the age of alive and dead patients, and the median of dead patients is larger than alive patients. Thus, we assume age may be one of the causes of death caused by heart failure.

4.3 Modeling

4.3.1 Feature Selection

Modeling

Feature selection is the process of reducing the number of variables for a predictive model, which helps with improving the performance of the model as well as reducing the computational cost of modeling, saving the working memory, lowering the risk of multicollinearity, and so on. As a result, it can help with increasing the accuracy of the business model without considering other useless variables.

With this dataset, we chose Recursive Feature Elimination (RFE) to select the best combination of variables. Recursive Feature Elimination is an effective tool to find the most relevant variables that can make the prediction of the death event. In this process, Random Forest has been used as the function, and repeated k-fold cross-validation has been used as the method with 12 folds. In the meantime, the data has been split into train and test with 80% to 20%, which means, we select 80% of the dataset to build the model and predict the death event, and then test on another 20% of cases. Since the output is a categorical result, Accuracy and Kappa have been used as the evaluation metrics to evaluate the efficiency of the model.

Results

Figure 12 represents the accuracy and kappa value of different numbers of variables after feature elimination. Intuitively, when **the number of variables is 3, the accuracy and kappa reach the highest value**, and the result shows those three variables are ***ejection_fraction***, ***serum_creatinine***, and ***time***, which indicates that the model built by those variables can make the prediction of death event most accurate. Thus, those variables would be the first consideration for later interpretation and modeling.

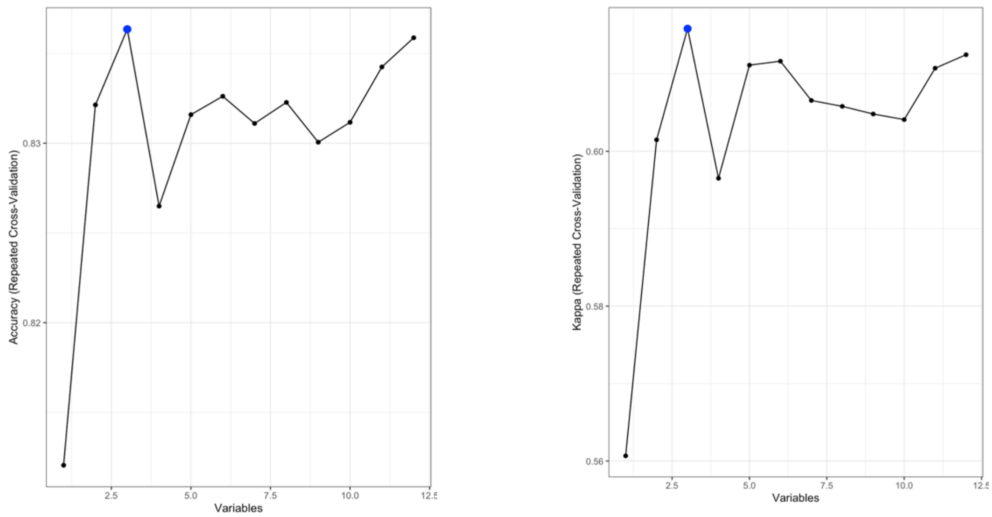

Figure 12. Accuracy and Kappa of models with different numbers of variables after RFE

4.3.2 Death Event Prediction Model

Modeling

After comparing the logistic regression, CART, and random forest models, we get the highest recall and accuracy from the **random forest** model trained on 80% of the dataset. A detailed comparison between different models can be found in the Appendix.

The random forest model applies the bagging method by creating many random sub-samples with replacements to avoid high variance, overfitting and build a stronger model for the prediction.

We tried 25, 100, and 500 separately as the number of the single tree included in our random forest model and 1, 3, and 12 as the number of variables randomly sampled as candidates at each split, and the out-of-bag error can be minimized when B = 500, RSF = 3. Based on the previous RFE feature selection result, we found that using 3, 6, and 12 features can provide the highest accuracy/recall and we applied the parameter to our model. The result shows that our model performs the best when 6 features are selected.

The model focuses on both accuracy and recall and makes a trade-off between these two indicators. Accuracy refers to the number of patients who are predicted right, whether they require the treatment or not, and recall refers to the number of predicted patients who truly need treatment over the total number of patients who truly need treatment. High accuracy can help the hospital to identify the patients who need the treatment and allocate the medical resources properly, and high recall can reduce the misdiagnose of those patients who truly need treatment. With both high accuracy and high recall, the hospital can offer palliative care or advanced treatment to those patients who are severe with relatively shorter life expectancy.

Results

The random forest model reached an accuracy of 87.93% and a recall of 86.67%, which meets our success criteria of both achieving 80% well and can be considered a satisfying outcome.

Based on the model we built, we also draw a graph to show the importance of each variable in the prediction of heart failure. Time, ejection fraction, and serum creatinine are considered the top 3 indicators of severe heart failure that may lead to death, so more attention should be paid to these factors while NHCS doing the mortality prediction.

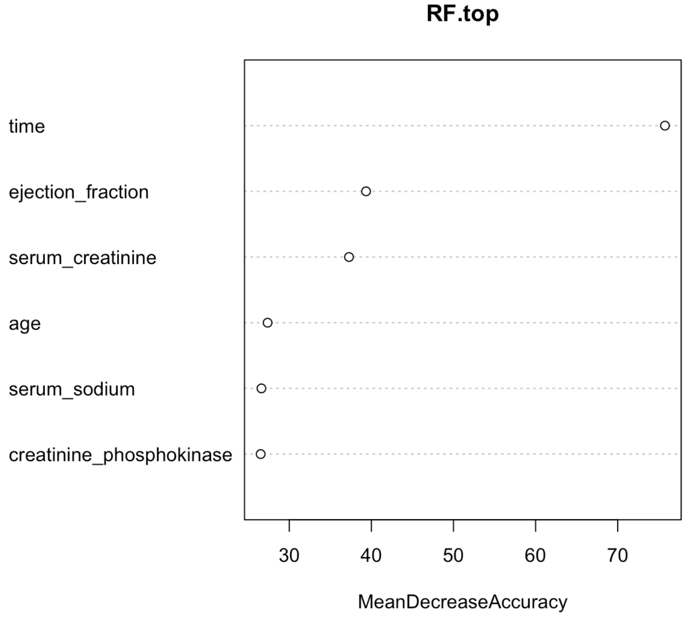

Figure 13. Importance of Variables in the Model

5 Business Outcomes

Regarding the mentioned indicators, doctors and nurses might pay closer attention to those indicators during the medical examination in order to recognize aberrant values in the examination report earlier and start treating patients at an early stage. In that case, the patients may feel that the hospital takes their health seriously, which would increase the reputation and trust of the hospital. As a result, more people may be willing to visit the hospital because they believe that they will receive thorough examinations that will benefit their way of life.

Additionally, with better prediction of the death event, the hospitals can allocate their resources, such as doctors, nurses, and wards more efficiently. For instance, placing those patients in the same ward who require the same level of medical attention or assigning less serious patients to the same nurse or doctor. In that way, doctors and nurses can improve their service by spending more time communicating with patients and their relatives. In that way, the hospital's quality of service can also be improved, and it will draw in more patients, which leads to a virtuous circle of attracting more brilliant doctors and providing better service.

Most importantly, with early intervention and in-time arrangement of medical plans for high-risk patients, NHCS may reduce the overall mortality rate. As hospital mortality has been usually used to assess the quality of care, a decreased rate can enhance a hospital's reputation and status in the medical field.

6 Suggestion

6.1 Implementation

With this study, we focus on deriving two-part solutions to accurately predict the death event given a patient is already diagnosed with heart failure and diagnosing the heart failure event when they had their physical examination. The main idea of our model thus targets detecting the heart failure condition very early on and mitigating any loss of life by timely treatment and better resource allocation.

As per the recent data published by Singapore Heart Foundation, 24 people die of heart disease in a single week, and heart failure stands predominant [11]. As pointed above, the pain points in heart failure management range from patient negligence to the lack of the right treatment plans. Somehow the supply of grievous patients has been hugely expanding when compared to the resources (in terms of cardiovascular professionals, prenatal care, medical schemes, etc.) available.

Following is the detailed implementation plan for our two-part solution:

- **Early diagnosis of heart failure post physical examination (not already diagnosed)**

  When it comes to the aspect of negligence in identifying and managing the situation of heart failure, early detection can solve both the former and latter. Because to identify the risks of heart failure, regular nature tests such as blood picture, KTF/LTF, sugar, and cholesterol levels can bring about results for patients who might be more prone to heart attack than others. If the occurrence of a heart attack is detected early in the cycle, the main impacting variables from our model such as serum creatinine and ejection fraction can be monitored urgently, and a subsequent treatment plan can be followed timely. The accurate categorization and highly prone predictions can therefore work towards the business problems stated above in terms of prioritizing the care for critical patients and optimizing the resources from case to case.

- **Predict the death event when the patient is already diagnosed with heart failure**

  - **Feature Selection**

    To target this, our model employs the best feature selection process. With regards to it, we focus on routine data collection of certain variables which would give the most accurate prediction of heart failure conditions. With our dataset, we find that serum creatinine and serum sodium have the highest correlation with the death event. As popularly known in the medical community, creatinine and sodium are both associated with waste extraction and thus validate kidney function and the prevalence of diabetes. Our model aims to collect data with respect to urine and blood pictures to identify the seriousness of the diseases from monthly regular checkups.

This gives the model its accuracy to predict the death event given the relevant feature with a high standard of accuracy.

- **Resource Allocation**

  During the study of this model, we see that people who are older than 50 years old seem to be at a higher risk for death from heart failure, so preemptive care can be authorized in these cases. In segmenting the patients into groups as per the risk and severity, the central resources including more senior doctors, extensive care units, and frequency of medical checkups can further be predicted through our models. Additionally, patients with a similar medical plan can be fixed on similar medical consultations given their condition of the heart is stable or urgent. The fact that 10 out of 15 people recommended to NHCS do not require immediate or specialized attention can be taken advantage of here for judiciously analyzing the current demand-supply gap i.e., by assigning stable patients to resident doctors for regular monitoring and serious ones to the specialists.

- **Medical Plan generation discussion**

  Once the disease is detected, the doctor-patient discussion would be around the medical plan which is most suitable to the health condition of the patient. Since heart failure is the cause of the prevalence of genetically impacting diseases such as diabetes and hypertension, a family plan to keep monitoring the health status of other family members should be promoted. Additionally, as per our model, if the patient had a negative death event but got a positive this time, clear decisions on how to modify the medical plans can be discussed and implemented. In other scenarios, when the patient's death event has been predicted positive for a long time, the suggestion of taking a new route to treatment or more palliative care can be advised.

6.2 Extension

Surprisingly, there is a lack of information available on the specialty field of practice called cardiology, and this is because Singaporeans often take action only when a cardiovascular disease strikes, which ultimately defines our business problem for this model. Discussing in the following points the extension of our model, to mitigate future and current issues: From 2017 to 2022, there has been an average of 300 cardiovascular professionals yearly, however, the NHCS alone sees around 160,000 patients a year, out of which 10% accounts to heart failure and 5% of latter require extensive surgeries. Now we see the huge demand-supply gap, which can only be catered to by careful analysis of current demand and optimizing all the resources that we have.

- **Demand forecasting to fill the gap between demand and supply**

  From 2017 to 2022, there has been an average of 300 cardiovascular professionals yearly, however, the NHCS alone sees around 160,000 patients a year, out of which 10% account for heart failure and 5% of the latter require extensive surgeries [12]. Now we see the huge demand-supply gap, which can only be catered to by careful analysis of current demand and optimizing all the resources that we have. First demand forecasting, wherein we gather relevant feature data and predict the demand for cardiologists. Major education institutions can become relevant partners and promote the agenda by optimizing the admits. Secondly, judiciously utilizing the current supply i.e., by assigning stable patients to resident doctors for regular monitoring [13].

- **Establishing a Medical Nudge System to help with resource allocation**

  Attaining efficiency in this part can be quite far-fetched, however using the data-built models, a comprehensive Medical Nudge System can be devised. This would require a field experiment with cardiologists, gathering the standardized initial treatment suggestion and plans as per the symptoms depicted by a stable person. This database would have the treatment plans, (for instance the standard course of Diuretics is given at the early stage of heart failure detection), which would be provided to the resident medical students when they undertake the stable patients. By this, we aim to save the specialized resource for our second category of patients – hypotensive patients.

- **Promoting awareness to encourage regular health checkups**

  Most of the Singapore population is not aware of the risk of heart failure due to the co-existence of diseases such as diabetes, hypertension, etc. Promoting awareness about heart failure and prone areas to the same becomes eminently important, especially post-COVID'19. As per the health ministry data, the deaths due to heart failure increased by 80% due to COVID'19 complications. The promotional measures can include designating a month for heart health awareness and the best practices to maintain good heart health, for instance

USA considers February the heart health awareness month and wears red to spread the cause. Installing CPR Kiosks in educational institutions and hospitals, helping youth to understand the eminence of heart disease so they can learn the basics where they spend most of their time. An introduction of inexpensive regular checkup medical plans can encourage people to have a health checkup regularly and take necessary actions immediately.

7 Conclusion & Future Work

Considering heart failure is a serious chronic cardiovascular disease with a high prevalence in Singapore with a market continuously growing at a constant rate, NHCS, as the pioneer, should pay more attention to improving its diagnosis and treatment process for heart failure. To help with the optimization, we aim at (1) determining the main factors leading to heart failure death to further help the hospital to diagnose the patients who have potential heart failure at an early stage ; (2) predicting the death risk to determine the priority among the patients with heart failure to optimize resource allocation and help discuss the medical plan with patients and their family.

To solve the problem, we develop a two-part solution employing the machine learning method. For the feature selection, it is found that time, serum creatinine, and ejection fraction seem to be the three top variables to consider when making predictions, which means hospitals can pay more attention to those values of patients during the physical examination and investigate the potential of having heart failure. When it comes to the death event prediction, we figure out that random forest model trained by 80% of the dataset appears to have the best performance with 87.93% accuracy and 86.67% recall. Both two parts of our solution reach our success criteria well.

In the future, A much more time-consuming and yet effective strategy would be using Machine Learning techniques would be developing CNN/RNN models for blood and urine picturing to identify the most common changes or risk factors of diseases such as diabetes, hypertension, or even heart failure. If any irregularity is detected, the patient can be made aware and the issue can be treated well in time before it reaches the heart. Because blood and urine are the most routine tests that are taken by people all over the world, data collection wouldn't be an issue and with each run of the model, the machine can track patterns and anomalies. Also, as we see most heart failure cases are diabetes or kidney malfunction, the effective usage of the above model can help manage the risk/proneness to heart failure at the very beginning.

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Appendix

	Accuracy	Recall
Random Forest	87.93%	86.67%
Logistic Regression	76.83%	64.52%
CART	82.22%	72.41%