BC2406 Analytics I:
Visual and Predictive Analytics

Seminar 7 Group 3

Say NO to Myocardial Infarction Complications with NoMyocardial ⛔

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Executive Summary

National Heart Centre Singapore (NCHS), the regional leading centre for cardiovascular disease care and treatment, has always been focusing their efforts on the diagnostics of Acute Myocardial Infarction (AMI), yet little effort has been made to address the more prevalent issue regarding AMI-related complications. Tackling this issue is paramount as not only does it raise the chances of survivability, it also improves a patient's post-AMI lifestyle.

Complications associated with AMI are time-sensitive and potentially life threatening in nature. Pre-diagnosis of these complications at the time of a patient's hospital admission can enable doctors to perform timely preventive measures, which can be beneficial during a patient's emergency and post-recovery phase.

This report aims to provide insights on indicative risk factors for AMI-related complications that NHCS can utilise to enhance their current treatment protocols. Our solution, NoMyocardial, is designed to assist doctors in the early detection of possible MI-related complications and pave the way for doctors to reduce the further development of these complications, thereby improving patient quality of life even after AMI.

The predictive models we employed were Classification and Regression Tree (CART), to obtain important variables (general risk indicators) for AMI-related complications, and logistic regression to further analyse each variable by their levels (key risk indicators). During the training of the CART models, we found that using a minimum split value of 2 results in a rather sizable decision tree, which is inefficient in the real world. Therefore, to accommodate our large data size, we changed the minimum split value to 10.

Based on our preliminary CART analysis, we observed that in general, certain historical medical conditions, such as duration of arterial hypertension, essential hypertension and external heart pain, together with ECG readings relating to left ventricular MI, resulted in a higher likelihood of AMI-related complications. Delving into the specifics of each variable, we also discovered that the sets of risk factors responsible for the development of complications differed depending on the complication. For instance, key indicative risk factors for Atrial Fibrillation (AF) include History of Chronic Heart Failure, ECG readings (Qr & QS complex), and sudden AF ECG rhythms.

Subsequent to our risk factor analysis, we recognised the value proposition of targeting AMI-related complications as apart from driving early prevention for patients, it also creates new opportunities related to post-AMI care and treatment that can streamline time-consuming diagnostic processes, saving costs for NHCS and its patients.

Hence, in line with NHCS' goal of serving its patients with passion and innovation in cardiovascular care, this report also aims to shed light on the unexplored domain of AMI complications by proposing new methodologies that can complement existing efforts and improve the overall effectiveness of AMI treatments. Overall, we believe that these insights have vast potential to enhance the general well-being of AMI patients and allow NHCS to serve them better.

1. Background

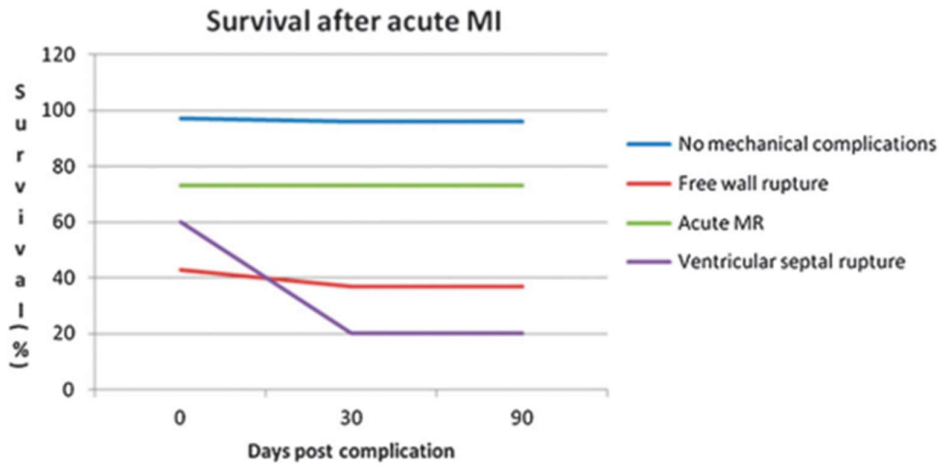
1.1. Problem Statement

Complications associated with acute myocardial infarction (AMI) are life-threatening and time-sensitive by nature. The lack of a pre-diagnosis process at the time of hospital admission hinders the opportunity for timely preventive measures and could result in further adverse developments of these complications (Hanifi, 2021). Additionally, due to the insufficient insights regarding AMI complications, doctors are unable to provide appropriate and timely post-AMI rehabilitation treatments, which could result in adverse complication developments (Chen, 2015).

1.2. Prevalence of Problem Statement

A study by the American Federation for Medical Research in 2015 highlighted the high morbidity and mortality of AMI complications (Bajaj et al., 2015). Figure 1 below illustrates the average survival rate of patients with various mechanical complications over a 90-day period.

Figure 1: Survival Rate after AMI



Another recent study during the Covid-19 pandemic[1] found that complications of AMI, such as out-of-hospital cardiac arrest and cardiogenic shock, were observed in a greater proportion of patients and led to increased mortality rates (Pourasghari et al., 2022). One reason cited for this increase was due to the fact that services supporting AMI and post-AMI care, such as respiratory therapy, were swamped during Covid-19 surges. As new variants and waves of Covid-19 emerge, complication rates are expected to increase accordingly, and doctors will need to react promptly to curb this rise. Hence,

[1] The study was conducted in 15 countries across North America, Europe and Asia and showed an increase in morbidity and mortality rates of post Covid-19 outbreak AMI patients.

there exists a dire need to gain deeper understanding about AMI-related complications which can assist doctors during their treatment.

Today, appropriate management of AMI complications remains a key consideration for heart attack centres (Wang & Cheung, 2018). In Singapore, NHCS's approach towards post-AMI monitoring and treatment involves a structured preventive cardiovascular programme with a standard course spanning approximately 16 sessions which consumes both time and resources (Chandra, n.d.). Furthermore, NHCS efforts in cardiac cases have always been narrowly focused towards predicting and preventing AMI. However, little emphasis has been placed in the analysis of AMI complications and post-AMI care services, presenting a huge business opportunity for our proposal.

1.3. National Heart Centre Singapore (NHCS) Existing Methods

NHCS is the region's leading centre for cardiovascular diseases, with a mission to serve patients through passion and innovation in cardiovascular care, research, and education. In 2021, NHCS had over 120,000 outpatient visits and performed approximately 17,000 cardiovascular scans (National Heart Centre Singapore, 2022).

Recognizing the importance of the vast amount of readily-available information from cardiac imaging, NHCS recently established an AI-driven Cardiac Imaging research laboratory to enhance prediction and detection of cardiovascular diseases, the first of its kind in Singapore and Southeast Asia (National Heart Centre Singapore, 2022).

The goals of the CSV.AI research laboratory are threefold: (1) to provide AI techniques for capturing and interpreting cardiac images to detect and predict cardiovascular disease, (2) to conduct in-depth assessments of cardiovascular disease among Singapore's at-risk populations, and (3) to enable the discovery of complex patterns of cardiovascular disease. NHCS's commitment to innovative ideas, growth and technological transformations is extremely evident.

1.4. Main Objective & Business Opportunity

Our proposal, NoMyocardial's primary objective is to assist doctors in understanding the key risk factors surrounding AMI complications and assist doctors with their decision making during the emergency phase of AMI. Our secondary objective is to improve the lives of AMI patients post emergency phase, by utilising our knowledge regarding complications to complement and improve existing treatment methods.

Our team proposes the use of machine learning models in predictive analytics to identify key indicative risk factors related to AMI complications (e.g. Atrial Fibrillation, Cardiogenic Shock), which are observable at hospital admission (e.g. ECG Readings, Past Medical Conditions). These data-driven insights serve as valuable takeaways for NHCS to achieve the aforementioned objectives.

Our group's insights, focused on the early detection of complications, are beneficial in driving timely intervention and saving lives (Khando, 2011). This aligns with NHCS's mission to wholeheartedly serve their patients. Furthermore, integrating them with the

objectives of the CSV.AI lab will also boost NHCS's overall reputation and cement its position as the region's leading cardiac care centre.

2. Data Selection

2.1. Myocardial Infarction Complications Dataset

The dataset we have chosen is the Myocardial Infarction Complications Dataset from the UCI Machine Learning Repository. The dataset consists of 1700 patients' information with a total of 124 variables (112 independent variables and 12 dependent variables). Given the large dataset, it is paramount that we apply domain knowledge to filter only relevant variables which support our main objectives. A detailed description of the dataset is provided by the University of Leicester[2].

2.2. Variable Selection

Selection of Independent Variables

After exploring the dataset, we noticed that the 112 independent variables can be decomposed into a variety of broad categories *(Refer to Table 1 & Appendix B)*. Subsequently, we extracted important categories which can be directly evaluated by doctors upon hospital admission.

Table 1: Breakdown of Categories for Independent Variables

Category	Abbreviation	Relevance to Proposal
Patient's Information	INFO	Not Important
Patient's Medical History	HISTORY	Important
Emergency Contact Team (ECT) Readings at Time of Admission	ECT TOA	Important
Intensive Care Unit (ICU) Readings at Time of Admission	ICU TOA	Important
Electrocardiogram (ECG) Readings at Time of Admission	ECG TOA	Important
On-site Treatment (ECT/ ICU)	ON SITE	Not Important
Post Emergency Treatment	POST TREATMENT	Not Important
Patient's Blood Content	BLOOD	Not Important[3]

[2] The dataset can be obtained from https://leicester.figshare.com/articles/dataset/Myocardial_infarction_complications_Database/12045261?file=22803572

[3] Given that our business proposal aims at identifying risk factors upon admission and prior to any long duration testing or treatment, we classified Blood Content as a non-key factor in our analysis.

Selection of Dependent Variables

The 12 dependent variables in the dataset correspond to the possible complications and outcomes (Lethal Outcome) of acute myocardial infarction. Out of the 11 possible complications, we decided to focus on the 3 most prevalent ones, namely Atrial Fibrillation (Target_AF), Chronic Heart Failure (Target_CN_HF) and Relapse of Myocardial Infarction (Target_Relapse_MI) *(Refer to Figure 2)*.

Figure 2: Breakdown of Complication Prevalence

Complication	With complication	
	#Cases	Fraction
Atrial fibrillation (Target_AF)	170	10.00%
Supraventricular tachycardia (Target_ST)	20	1.18*
Ventricular tachycardia (Target_VT)	42	2.47%
Ventricular fibrillation (Target_VF)	71	4.18%
Third-degree AV block (Target_3DG_AVB)	57	3.35%
Pulmonary edema (Target_PUM_ED)	159	9.35%
Myocardial rupture (Target_Myocardial_Rupture)	54	3.18%
Dressler syndrome (Target_Dressler)	75	4.41%
Chronic heart failure (Target_CN_HF)	394	23.18%
Relapse of myocardial infarction (Target_Relapse_MI)	159	9.35%
Post-infarction angina (Target_Post_HeartPain)	148	9.71%

For each of the 3 identified complications, our goal was to build models using the same set of independent variables for standardisation, and to evaluate and analyse the results of these models.

Description of Selected Dependent Variables

1) **Atrial fibrillation (Target_AF)**: Irregular and often rapid heart rhythm that can lead to blood clots in the heart.

2) **Chronic heart failure (Target_CN_AF)**: Failure of heart muscles to pump blood as well as it should. Blood backs up to the heart and fluids build up in the lungs, resulting in shortness of breath.

3) **Relapse of myocardial infarction (Target_Relapse_MI)**: Recurrent incidence of acute myocardial infarction.

2.3. Statistical Models

Given that our dependent variables are categorical in nature, we decided to employ both CART and logistic regression models.

Classification and Regression Tree (CART)

CART utilises decision tree algorithms for classification or regression predictive modelling problems. These algorithms work by recursively partitioning a dependent variable into sub-spaces based on its relationships with independent variables, until maximal homogeneity of the final sub-space.

Logistic Regression

Logistic regression belongs under the family of the Generalised Linear Model (GLM). It is a regression analysis technique used to show the relationship between independent variables and predict a qualitative response. The outcome is modelled as a linear combination of the independent variables.

Since CART does not require data to be linearly separable in space, it is able to automatically handle non-linear relationships between independent variables. Also, CART is a higher performance model when predicting on categorical dependent variables.

Our Approach

Given the characteristics of each model, we decided to train our CART model to obtain the important independent variables using variable importance. Subsequently, we ran the significant variables through logistic regression to further extract vital information. This will be elaborated in section 5 of our report.

3. Methodology

3.1. Data Cleaning & Preparation

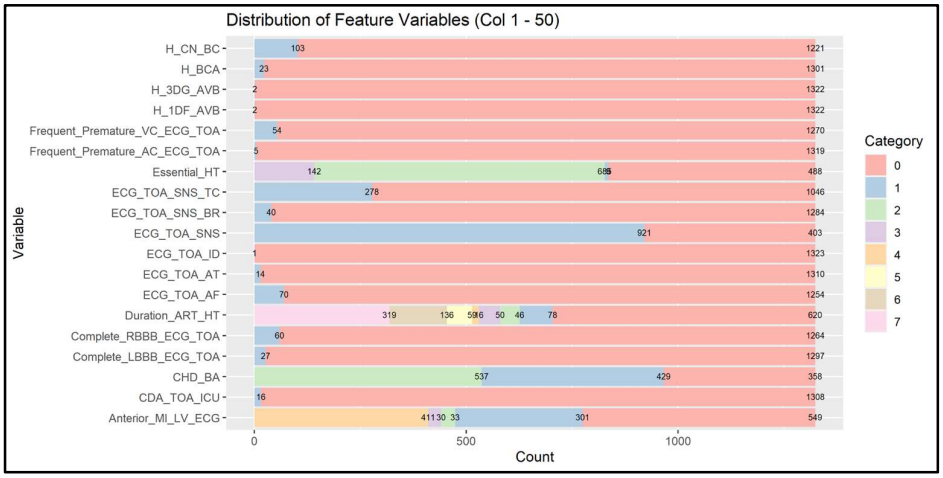
Based on the selection criteria detailed in Section 2.2, we filtered the dataset to include only those significant dependent and independent variables that were aligned with our main objective. We then handled missing values by either dropping them or replacing them with 0, with the aim of retaining as much information as possible while maintaining accuracy. The rationale of how we handled the missing values can be found in Appendix B.

3.2. Exploratory Data Analysis (EDA)

To better understand our data, our team performed EDA on the dataset. We plotted the distribution of our variables and found them to be severely imbalanced. (Refer to Figures 3,4 and Appendix C)

Figure 3: Distribution of Target Variables

Figure 4: Distribution of Feature Variables (Columns 1 to 50)



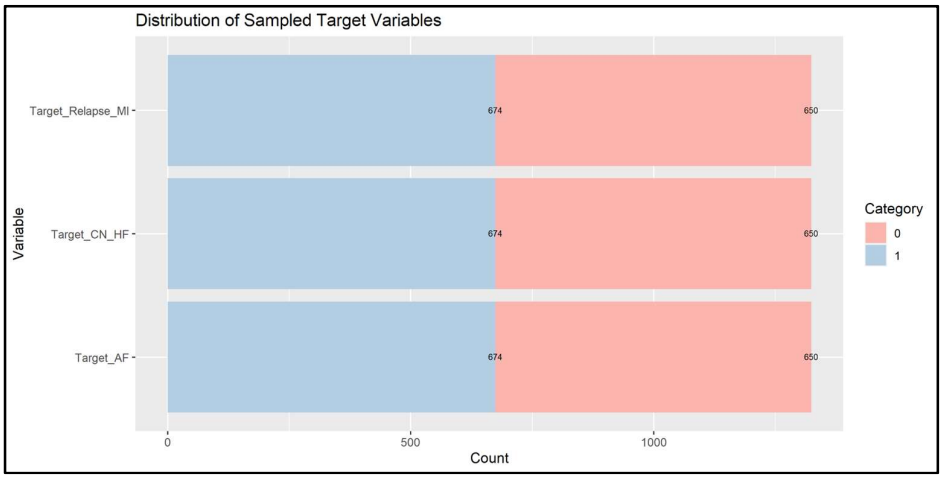
3.3. Balancing the Imbalanced Data

To address the problem of imbalanced dataset, we utilised the Random Over-Sampling Examples (ROSE) technique to over sample our minority classes and under sample our majority classes. ROSE "produces a synthetic, possibly balanced, sample of data simulated according to a smoothed-bootstrap approach" (ROSE Function - RDocumentation, n.d.).

For the independent variables, we established a 5% baseline below which the independent variables are dropped.

For the dependent variables, we utilised ROSE's ovum.sample method to oversample the minority class and under sample the majority class to create a more balanced distribution. *(Refer to Figure 5)*

Figure 5: Distribution of Sampled Target Variables



4. Analytics Models

4.1. Model Training

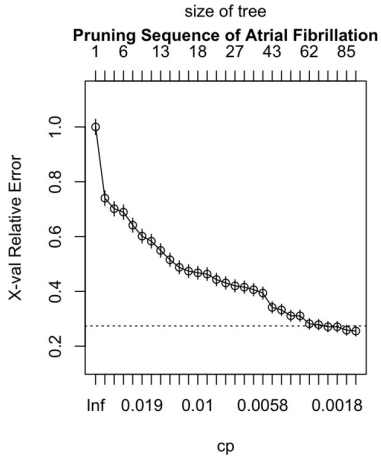
For each of the 3 complications identified, we split the data into train set and test set at a 7:3 ratio to use for model training and allow checking of accuracy of our model.

Using the train data set, we use the CART model with method 'class' since all our dependent variables are categorical. We set the minimum split value to be 2 and the CP value to be 0 to expand the decision tree to the maximum.

4.2. Model Fine-tuning

We realised that by expanding the tree to the maximum, the tree size will become too large and the model will become too complex, causing the model to overfit the training data *(Refer to Figure 6 and Appendix D for pruning sequences)*. Hence, we changed the minimum split value to 10 to accommodate our large data size.

Figure 6: Pruning Sequence of Atrial Fibrillation



By checking the CP graph for each complication's model, we extracted the lowest CP value and added one standard error (1 SE) to it. We then determined the optimal CP value by calculating the geometric mean of the first 2 CP values below the determined level or directly using the CP value given by the CP graph plotted. Using these optimal CP values, we trained new CART models to check the variable importance of each complication.

After fine-tuning our models, we achieved high predictive accuracy across all models and evaluated their respective confusion matrix *(Refer to Figure 7 for Prediction Accuracy and Appendix D for Confusion Matrix)*.

Figure 7: Table showing Predictive Accuracy for each model

	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI
Accuracy (%)	93.95	90.68	94.71

5. Results

5.1. Brief Summary

We broke down our findings into two broad sectors, firstly general risk indicators of AMI complications which we utilised for early recognition of complications and assisting doctors in their decision-making during AMI emergency phase, and secondly diving into specific risk factors to provide valuable insights into AMI complications, which NHCS can act on to improve post-AMI recovery phase.

5.2. Variable Importance

After running each CART model, we ran variable importance using **2% as our baseline** for significant variables. Our justification for this baseline is as follows:

1) Dataset comprised of multiple variables which could have diluted the significance levels for each variable
2) Imbalanced distribution of these feature variables could have resulted in minority classes being rare instances, despite having relevance.

General Risk Indicators

Based on our CART variable importance, we observed the following commonly-sighted variables across all complications, which we classified as general risk indicators for AMI-related complications *(Refer to Table 2)*. These factors serve as primary indicators to alert doctors about potential complications which could arise.

Table 2: General Risk Indicators of MI Complications

S/N	Risk Factors	Abbreviation
1	History of External Heart Pain	H_EXT_HeartPain
2	Duration of Arterial Hypertension	Duration_ART_HT
3	Presence of Essential Hypertension	Essential_HT
4	Quantity of Myocardial Infarction in the past	H_QTY_MI
5	ECG readings Left Ventricle MI	MI_LV_ECG

5.3. Deeper Dive into Key Risk Indicators

Subsequently, we conducted feature selection using our CART important features and ran logistic regression to further analyse each variable by their levels, retrieving key risk indicators for each complication *(Refer to Appendix E)*.

For our Logistics Regression analysis, we obtained the statistically significant variables based on z-test probability < 0.05 and Odds Ratio > 1. Odds ratio > 1 implies that the variable class increases the odds of having AMI complication. We also analysed the odds ratio confidence interval to ascertain the statistical significance. If the odds ratio

confidence interval excludes one, it indicates statistical significance and we can include the variable as a key risk indicator.

Atrial Fibrillation (AF)

Our Logistic Regression consists of the following important variables derived from our CART feature selection *(Refer to Figure 8)*. We also analysed the odds ratio and corresponding confidence intervals *(Refer to Table 3 and 4)*.

Our key findings associated with increased risk of AF:

1) Patients with abnormally fast/ normal ECG rhythms upon admission.
2) Patients with historical medical conditions, particularly Chronic Heart Failure, Hypertension & Diabetes Mellitus.
3) Sudden occurrence of AF or AF-related ECG readings.
4) ECG readings of Lateral Left Ventricular MI (QR & Qs complex).

Figure 8: Variable Importance for Atrial Fibrillation

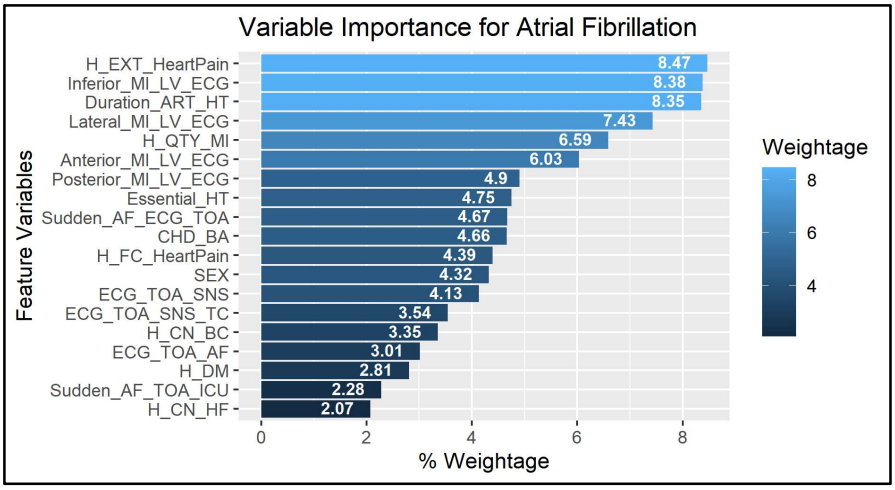


Table 3: Odds Ratio Analysis for Atrial Fibrillation

```
> AF_summary
                 term  estimate std.error statistic      p.value Odds Ratio  CI_2.5%  CI_97.5%
1:        (Intercept) 1.0370560 0.4688092  2.212107 2.695928e-02   2.820900 1.686554  7.128874
2:          H_CN_HF1 1.2652048 0.3006380  4.208399 2.571864e-05   3.543819 2.556608  4.934556
3: Lateral_MI_LV_ECG1 0.6013830 0.2185406  2.751813 5.926628e-03   1.824641 1.193937  2.815637
4: Lateral_MI_LV_ECG2 0.8573375 0.3217053  2.664978 7.699327e-03   2.356877 1.258829  3.678164
5: Lateral_MI_LV_ECG3 1.1866467 0.3967890  2.990624 2.784083e-03   3.276077 1.520131  7.225653
6: Lateral_MI_LV_ECG4 1.7812125 0.4611950  3.862168 1.123852e-04   5.937051 2.446113 15.029940
7: Sudden_AF_ECG_TOA1 2.6619058 0.4750960  5.602880 2.108192e-08  14.323561 8.548505 37.772949
8: Sudden_AF_TOA_ICU1 1.7202595 0.4486497  3.834304 1.259202e-04   5.585978 2.360097 13.828068
```

Table 4: Key Indicative Risk Factors (Statistically Significant)

Risk Factors	Abbreviation	OR
History of Chronic Heart Failure	H_CN_HF1	**3.54**
ECG Readings - Lateral MI LV (QRS no change)	Lateral_MI_LV_ECG1	**1.82**
ECG Readings - Lateral MI LV (QR-complex)	Lateral_MI_LV_ECG2	**2.36**

ECG Readings - Lateral MI LV (Qr-complex)	Lateral_MI_LV_ECG3	**3.28**
ECG Readings - Lateral MI LV (QS-complex)	Lateral_MI_LV_ECG4	**5.94**
Sudden AF ECG Rhythm (Admission)	Sudden_AF_ECG_TOA1	**14.32**
Sudden AF ICU (Admission)	Sudden_AF_TOA_ICU1	**5.59**

** Highlighted cells have greater significance (CI excludes 1 & large Odds Ratio)*

Chronic Heart Failure

Our Logistic Regression consists of the following important variables derived from our CART feature selection *(Refer to Figure 9)*. We also analysed the odds ratio and corresponding confidence intervals *(Refer to Table 5 and 6)*.

Our key findings associated with increased risk of Chronic Heart Failure:

1) Patients with history of External and Functional Heart Pain
2) Patients with historical medical conditions particularly chronic heart failure, hypertension, coronary heart disease, obstructive bronchitis & diabetes mellitus
3) Patients with obstructive bronchitis is more likely than bronchitis
4) Patients with Stage 3 of Essential Hypertension are more likely than Stage 2.
5) ECG readings for Lateral Left Ventricular MI (QR & QS complex) are more likely than (Qr complex)

Figure 9: Variable Importance for Chronic Heart Failure

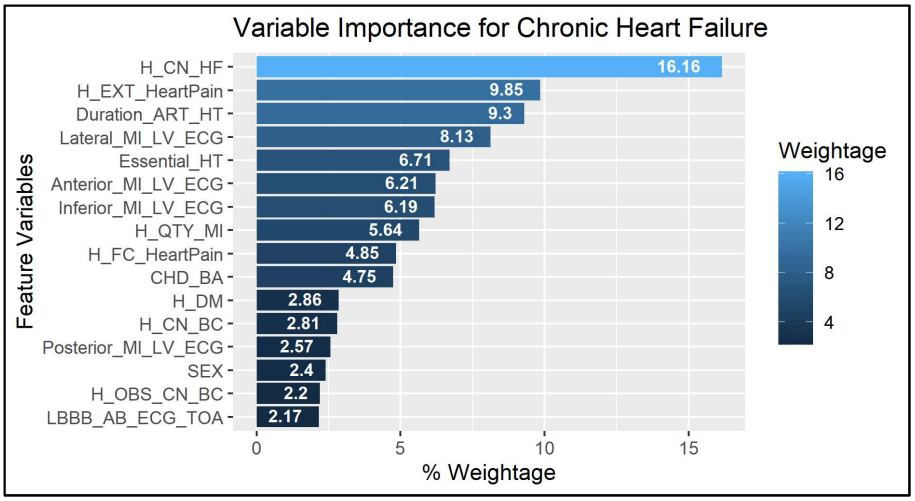


Table 5: Odds Ratio Analysis for Chronic Heart Failure

```
> CNHF_summary
                term  estimate std.error statistic      p.value Odds Ratio    CI_2.5%    CI_97.5%
1:      Essential_HT2 0.5038318 0.1934326  2.604689 9.195773e-03   1.655051   1.134297   2.422957
2:      Essential_HT3 1.0613646 0.2600180  4.081889 4.467122e-05   2.890313   1.741311   4.831437
3:          H_CN_BC1 0.4869306 0.2426002  2.007132 4.473564e-02   1.627314   1.010829   2.621482
4:          H_CN_HF1 4.1922620 0.4766578  8.795119 1.428961e-18  66.172306  28.718817 193.029747
5:       H_OBS_CN_BC1 0.6016398 0.2748750  2.188776 2.861313e-02   1.825109   1.064914   3.138868
6:          H_QTY_MI3 1.3003425 0.3444793  3.774806 1.601322e-04   3.670553   1.897310   7.366780
7: Lateral_MI_LV_ECG2 1.1021741 0.3092888  3.563576 3.658361e-04   3.010705   1.652016   5.564282
8: Lateral_MI_LV_ECG3 0.6867091 0.3484702  1.970639 4.876513e-02   1.987165   1.005315   3.949062
9: Lateral_MI_LV_ECG4 1.3215499 0.4335942  3.047896 2.304497e-03   3.749228   1.613932   8.914156
```

Table 6: Key Indicative Risk Factors (Statistically Significant)

Risk Factors	Abbreviation	OR
Stage 2 Essential Hypertension	Essential_HT2	**1.66**
Stage 3 Essential Hypertension	Essential_HT3	**2.89**
History of Chronic Bronchitis	H_CN_BC1	**1.63**
History of Heart Failure	H_CN_HF1	**66.17**
History of Obstructive Chronic Bronchitis	H_OBS_CN_BC1	**1.83**
History of 3 counts of Myocardial Infarction	H_QTY_MI3	**3.67**
ECG Readings - Lateral MI LV (QR-complex)	Lateral_MI_LV_ECG2	**3.01**
ECG Readings - Lateral MI LV (Qr-complex)	Lateral_MI_LV_ECG3	**1.99**
ECG Readings - Lateral MI LV (QS-complex)	Lateral_MI_LV_ECG4	**3.75**

** Highlighted cells have greater significance (CI excludes 1 & large Odds Ratio)*

Relapse of Myocardial Infarction

Our Logistic Regression consists of the following important variables derived from our CART feature selection *(Refer to Figure 10)*. We also analysed the odds ratio and corresponding confidence intervals *(Refer to Table 7 and 8)*.

Our key findings associated with increased risk of Relapse of MI:

1) Patients with history of External and Functional Heart Pain, and Diabetes Mellitus
2) ECG readings for Lateral Left Ventricular MI (QRS no change & QR-complex) and Anterior Left Ventricular MI (Qr-complex)
3) Analysing ECG readings is critical in identifying potential relapses in MI in comparison to the other two complications

Figure 10: Variable Importance for Relapse of MI

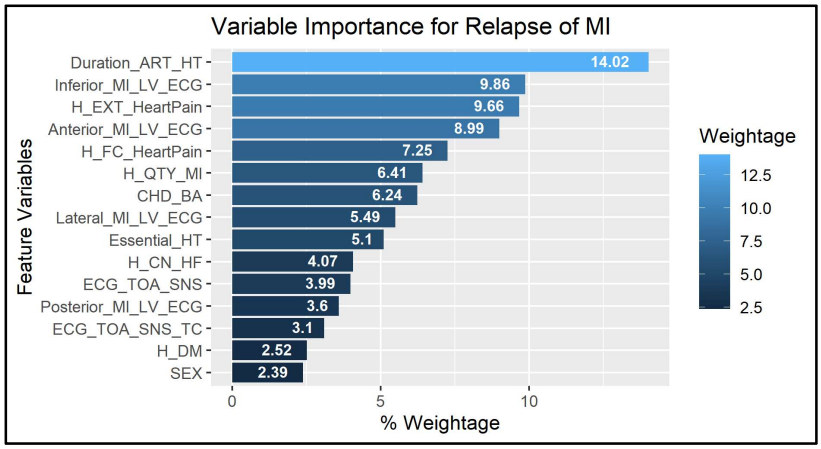


Table 7: Odds Ratio Analysis for Relapse of MI

```
> RMI_summary
                  term  estimate std.error statistic      p.value Odds Ratio  CI_2.5% CI_97.5%
1: Anterior_MI_LV_ECG3 1.0919682 0.4990063  2.188286 0.0286488069   2.980134 1.129049 5.887957
2:        ECG_TOA_SNS1 0.5231454 0.2474226  2.114380 0.0344827967   1.687327 1.043153 2.757075
3:     ECG_TOA_SNS_TC1 0.8985405 0.2710498  3.315039 0.0009163043   2.456016 1.449629 4.201707
4:              H_DM1 0.6143486 0.1904078  3.226488 0.0012531941   1.848452 1.276484 2.695261
5:  Lateral_MI_LV_ECG1 0.5229470 0.1954450  2.675674 0.0074579126   1.686992 1.152662 2.482002
6:  Lateral_MI_LV_ECG2 0.9489937 0.3099535  3.061729 0.0022006226   2.583109 1.413267 4.771429
```

Table 8: Key Indicative Risk Factors (Statistically Significant)

Risk Factors	Abbreviation	OR
ECG Readings - Anterior MI LV (Qr-Complex)	Anterior_MI_LV_ECG3	**2.98**
ECG Readings - Normal Rhythm (TOA)	ECG_TOA_SNS1	**1.69**
ECG Readings - Abnormally Fast Rhythm (TOA)	ECG_TOA_SNS_TC1	**2.46**
History of Diabetes Mellitus	H_DM1	**1.85**
ECG Readings - Lateral MI LV (QRS no change)	Lateral_MI_LV_ECG1	**1.69**
ECG Readings - Lateral MI LV (QR-complex)	Lateral_MI_LV_ECG2	**2.58**

** Highlighted cells have greater significance (CI excludes 1 & large Odds Ratio)*

6. Way Forward for NHCS

6.1. Data-driven Insights

In this paper, we have conducted a thorough analysis of the selected dataset, allowing us to understand the risk indicators that may lead to potential complications for AMI patients. These insights can bridge the knowledge gap for AMI complications and allow doctors to respond timely upon admission to the hospital.

This valuable information can also be brought forward during the post recovery phase, allowing doctors to analyse their patient's susceptibility to development of AMI complications and improve on existing care and treatment methods.

6.2. Existing Methods are Time-consuming

Cardiovascular Diagnostic Testing

NHCS has previously followed an adequate protocol in performing cardiac tests and medical evaluations on patients. Patients are first required to undergo a preparticipation cardiac test, which assists doctors in diagnosing potential heart issues or cardiovascular disorders that a patient may have. Before proceeding with further treatment, the doctor or cardiologist may perform any of the following cardiac tests, depending on the clinical circumstances.:

1. *Electrocardiogram (ECG):* This monitors the heart's electrical activity, including heart rate and rhythm, as well as any structural cardiac problems.
2. *Echocardiogram:* This monitors the heart's electrical activity, including heart rate and rhythm, as well as any structural cardiac problems.
3. *Advanced functional cardiac imaging:* These are second-line scans that are exclusively available in hospitals, which combine stress testing with an imaging modality (ultrasound / CT scan / MRI) to assess for suspected ischemic heart disease.
4. *CT coronary angiogram:* This is a non-invasive imaging technique that uses a CT scanner and an intravenous dye to detect any blockages in the cardiac arteries.
5. *Cardiopulmonary Exercise Test:* This is comparable to the ETT, but with additional components to assess overall cardiopulmonary health and fitness by measuring both heart and lung functions.

If a patient's heart scan indicates a serious blockage, coronary angioplasty and stenting, or perhaps coronary artery bypass surgery, will be performed immediately. A specialist may then recommend whether it is safe or whether further clinical intervention is required, depending on the findings of the data.

Cardiac Rehabilitation Programme

After the emergency phase of AMI, doctors may recommend a cardiac rehabilitation programme, which normally spans across 16 sessions. These sessions include diet modifications and medications to help the patient gradually resume a normal lifestyle

and reduce the risk of another heart attack. Existing programmes comprises a multidisciplinary approach which involves a team of cardiac specialists to monitor the patient's health (Guide, 2022). However, we believe that there is opportunity to improve this programme by tailoring recommendations of healthcare specialists based on the type of AMI-complication and its likelihood of occurrence. By leveraging on our data-driven insights, we believe that NoMyocardial can complement the implementation of these existing programmes.

6.3. Follow-up actions

Fast response to the complications of AMI

Upon the admission of the patient, we are able to determine possible complications using NoMyocardial. Doctors can pre-prepare medications required for the specific complications before admission. In the event of complications occurring, the doctors are more likely to quickly identify the complication with the aid of the data provided. They can also quickly administer the medication prepared beforehand. With these measures, patients are treated quickly which will reduce the fatality rate.

Tailored Cardiac Rehabilitation Programmes

NoMyocardial can offer insights into a patient's likelihood of developing a certain AMI complication during their post recovery period through analysing the patient's medical history and on-site medical readings. NHCS can leverage this information to structure their rehabilitation programme towards reducing further development of these complications.

For instance, depending on the type of complication, NHCS can also refer its patients to their respective cardiac specialists for further diagnosis and treatment. This includes administering medication such as corticosteroids to reduce the likelihood of atrial fibrillation. Having more specialised teams can also significantly reduce the overhead requirement (costs incurred) of an extensive healthcare team, while allowing patients to undergo the required treatment.

Opportunity for Enhancement of Monitoring Tools

NoMyocardial insights serve as a stepping-stone to spearhead new diagnostic developments. Subsequent to our analysis, more accurate analytics tools can be developed and made available to existing patients with a history of cardiac diseases. For instance, we can utilise our CART model to complement existing/new remote AI-driven heart monitoring systems to collect data, identify and flag out the key risk factors concerning AMI complications.

These essential data collected can also help streamline the process of patients having to go through multiple rounds of screening. So this would help healthcare professionals in mitigating the immediate complications upon the patient's admission to the hospital. It would enable them to make more educated decisions to enhance clinical and operational outcomes.

Greater Clarity and Awareness towards AMI-complications Symptoms

Our solution, NoMyocardial, provides doctors with more clarity on the type of complication that can occur in AMI patients. Consequently, doctors can place greater emphasis on advising patients about the more prevalent symptoms that lead to the complication. In turn, patients can gain more awareness and pay closer attention to these symptoms, coming back for follow-up screenings if their symptoms worsen. For instance, if a patient is predicted to have Atrial Fibrillation, their doctors can advise them to look out for signs of chest pain, dizziness and shortness of breath.

7. Conclusion

In conclusion, our report sheds light on key risk indicators associated with AMI complications, which can pave the way for future developments and enhancements of existing treatments methods for AMI complications. By leveraging on our proof of concept, we are optimistic that our solution, NoMyocardial can assist NHCS better serve its patients holistically, both during emergency as well as post recovery phases. Furthermore, it presents us with an opportunity for more efficient resource allocation. We have progressed far in terms of predicting and preventing AMI. Now, let's redirect our approach towards improving the post recovery lives of AMI patients, resolve this vital problem at hand and cement NHCS reputation as the best regional hub for cardiovascular care.

8. References

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9. Appendices

Appendix A: Abbreviation Dictionary[4]

Abbreviation	Meaning	Abbreviation	Meaning
“AB”	Anterior Branch	"HF"	Heart Failure
“AF”	Atrial Fibrillation	"HT"	Hypertension
"ART"	Arterial	“ICU”	Intensive Care Unit
“AT”	Atrial	“ID”	Idioventricular
“AVB”	AV block	"Irregular_HB"	Arrhythmia (Irregular Heartbeat)
“BA”	Before Admission	“K”	Potassium
"BB"	Beta-blockers	"LV"	Left Ventricular
“BC”	Bronchitis	“NA”	Sodium
“BCA”	Bronchial Asthma	“OB”	Obesity
“BP”	Blood Pressure	“OBS”	Obstructive
“BR”	Bradycardia	“PB”	Posterior Branch
“CDS”	Cardiogenic Shock	“PN”	Pneumonia
“CHD”	Coronary Heart Disease	“PUM”	Pulmonary
“ChestPain”	Angina pectoris	“QTY”	Quantity
“CN”	Chronic	"RV"	Right Ventricular
“CP”	Complete	“S”	Streptase
“DG”	Degree	“SB”	Sinoatrial Block
“DIA”	Diastolic	“SNS”	Sinus
“DM”	Diabetes Mellitus	“ST”	Supraventricular Tachycardia
“ECG”	Electrocardiogram	“Sudden”	Paroxysms
“ECT”	Emergency Cardiology Team	“SYS”	Systolic
“ED”	Edema	“TB”	Tuberculosis
“ESR	Erythrocyte sedimentation rate	“TC”	Tachycardia
“EXT”	External_	“TOA”	Time of Admission
“FC”	Functional Class	“TX”	Thyrotoxicosis
“FT”	Fibrinolytic Therapy	“VF”	Ventricular Fibrillation
“H_”	Anamnesis (History of)	“VT”	Ventricular Tachycardia

[4] The dataset can be obtained from https://leicester.figshare.com/articles/dataset/Myocardial_infarction_complications_Database/12045261?file=22803572

Appendix B: Data Cleaning

Columns 1 - 40

S/N	Column	Category	Missing Data	S/N	Column	Category	Missing Data
1	ID	INFO	No missing data	21	H_3DG_AVB	HISTORY	Replace with 0
2	AGE	INFO	8 missing values ~ Drop	22	H_LBBB	HISTORY	Replace with 0
3	SEX	INFO	No missing data	23	H_ICC_LBBB	HISTORY	Replace with 0
4	H_QTY_MI	HISTORY	4 missing values ~ Drop	24	H_CP_LBBB	HISTORY	Replace with 0
5	H_EXT_HeartPain	HISTORY	106 missing values ~ Drop	25	H_ICC_RBBB	HISTORY	Replace with 0
6	H_FC_HeartPain	HISTORY	73 missing values ~ Drop	26	H_CP_RBBB	HISTORY	Replace with 0
7	CHD_BA	HISTORY	51 missing values ~ Drop	27	H_DM	HISTORY	Replace with 0
8	Heredity_CHD	HISTORY	Replace with 0	28	H_OB	HISTORY	Replace with 0
9	Essential_HT	HISTORY	Replace with 0	29	H_TX	HISTORY	Replace with 0
10	Symptomatic_HT	HISTORY	Replace with 0	30	H_CN_BC	HISTORY	Replace with 0
11	Duration_ART_HT	HISTORY	248 Missing Values - Replace with 0	31	H_OBS_CN_BC	HISTORY	Replace with 0
12	H_CN_HF	HISTORY	54 missing values ~ Drop	32	H_BCA	HISTORY	Replace with 0
13	H_Irregular_HB	HISTORY	Replace with 0	33	H_CN_PN	HISTORY	Replace with 0
14	H_Premature_AC	HISTORY	Replace with 0	34	H_PUM_TB	HISTORY	Replace with 0

15	H_Premature_VC	HISTORY	Replace with 0	35	SYS_BP_ECT	ECT TOA	Replace with 0
16	H_Sudden_AF	HISTORY	Replace with 0	36	DIA_BP_ECT	ECT TOA	Replace with 0
17	H_Persistent_AF	HISTORY	Replace with 0	37	SYS_BP_ICU	ICU TOA	Replace with 0
18	H_VF	HISTORY	Replace with 0	38	DIA_BP_ICU	ICU TOA	Replace with 0
19	H_Sudden_VT	HISTORY	Replace with 0	39	PUM_ED_TOA_ICU	ICU TOA	Replace with 0
20	H_1DF_AVB	HISTORY	Replace with 0	40	CDA_TOA_ICU	ICU TOA	Replace with 0

Columns 41 - 80

S/N	Column	Category	Missing Data	S/N	Column	Category	Missing Data
41	Sudden_AF_TOA_ICU	ICU TOA	Replace with 0	61	Persistent_AF_ECG_TOA	ECG TOA	Drop Cases without ECG
42	Sudden_ST_TOA_ICU	ICU TOA	Replace with 0	62	Sudden_ST_ECG_TOA	ECG TOA	Drop Cases without ECG
43	Sudden_VT_TOA_ICU	ICU TOA	Replace with 0	63	Sudden_VT_ECG_TOA	ECG TOA	Drop Cases without ECG
44	VF_TOA_ICU	ICU TOA	Replace with 0	64	VF_ECG_TOA	ECG TOA	Drop Cases without ECG
45	Anterior_MI_LV_ECG	ECG TOA	Drop Cases without ECG	65	SB_ECG_TOA	ECG TOA	Drop Cases without ECG
46	Lateral_MI_LV_ECG	ECG TOA	Drop Cases without ECG	66	1DG_AVB_ECG_TOA	ECG TOA	Drop Cases without ECG
47	Inferior_MI_LV_ECG	ECG TOA	Drop Cases without ECG	67	Type1_2DG_AVB_ECG_TOA	ECG TOA	Drop Cases without ECG
48	Posterior_MI_LV_ECG	ECG TOA	Drop Cases without ECG	68	Type2_2DF_AVB_ECG_TOA	ECG TOA	Drop Cases without ECG
49	MI_VR	ECG TOA	Drop Cases without ECG	69	3DF_AVB_ECG_TOA	ECG TOA	Drop Cases without ECG

50	ECG_TOA_SNS	ECG TOA	Drop Cases without ECG	70	LBBB_AB_ECG_TOA	ECG TOA	Drop Cases without ECG
51	ECG_TOA_AF	ECG TOA	Drop Cases without ECG	71	LBBB_PB_ECG_TOA	ECG TOA	Drop Cases without ECG
52	ECG_TOA_AT	ECG TOA	Drop Cases without ECG	72	Incomplete_LBBB_ECG_TOA	ECG TOA	Drop Cases without ECG
53	ECG_TOA_ID	ECG TOA	Drop Cases without ECG	73	Complete_LBBB_ECG_TOA	ECG TOA	Drop Cases without ECG
54	ECG_TOA_SNS_TC	ECG TOA	Drop Cases without ECG	74	Incomplete_RBBB_ECG_TOA	ECG TOA	Drop Cases without ECG
55	ECG_TOA_SNS_BR	ECG TOA	Drop Cases without ECG	75	Complete_RBBB_ECG_TOA	ECG TOA	Drop Cases without ECG
56	Premature_AC_ECG_TOA	ECG TOA	Drop Cases without ECG	76	FT_C750k	ON SITE	Replace with 0 (No Treatment)
57	Frequent_Premature_AC_ECG_TOA	ECG TOA	Drop Cases without ECG	77	FT_C1M	ON SITE	Replace with 0 (No Treatment)
58	Premature_VC_ECG_TOA	ECG TOA	Drop Cases without ECG	78	FT_C3M	ON SITE	Replace with 0 (No Treatment)
59	Frequent_Premature_VC_ECG_TOA	ECG TOA	Drop Cases without ECG	79	FT_S	ON SITE	Replace with 0 (No Treatment)
60	Sudden_AF_ECG_TOA	ECG TOA	Drop Cases without ECG	80	FT_C500k	ON SITE	Replace with 0 (No Treatment)

Columns 81 - 120

S/N	Column	Category	Missing Data	S/N	Column	Category	Missing Data
81	FT_C250k	ON SITE	Replace with 0 (No Treatment)	101	OPIOID_2D	POST TREATMENT	Drop all cases
82	FT_S1.5m	ON SITE	Replace with 0 (No	102	OPIOID_3D	POST	Drop all cases

			Treatment)			TREATMENT	
83	Hypokalemia	BLOOD	Drop missing value	103	NSAID_1H	POST TREATMENT	Drop all cases
84	K_BLOOD	BLOOD	Drop missing value	104	NSAID_2D	POST TREATMENT	Drop all cases
85	Increase_NA	BLOOD	Drop missing value	105	NSAID_3D	POST TREATMENT	Drop all cases
86	NA_BLOOD	BLOOD	Drop missing value	106	LIDOCAINE_ICU	ON SITE (ICU)	Replace with 0
87	ALT_BLOOD	BLOOD	Drop missing value	107	BB_ICU	ON SITE (ICU)	Replace with 0
88	AST_BLOOD	BLOOD	Drop missing value	108	CAB_ICU	ON SITE (ICU)	Replace with 0
89	KFK_BLOOD	BLOOD	Drop column	109	HERAPIN_ICU	ON SITE (ICU)	Replace with 0
90	L_BLOOD	BLOOD	Drop missing value	110	A_ACID_ICU	ON SITE (ICU)	Replace with 0
91	ESR	BLOOD	Drop missing value	111	TICLID_ICU	ON SITE (ICU)	Replace with 0
92	HOSPITAL_TIME	TOA	Drop missing value	112	TRENTAL_ICU	ON SITE (ICU)	Replace with 0
93	RELAPSE_1H	POST TREATMENT	Drop all cases	113	**Target_AF**	Response Y	No Missing
94	RELAPSE_2D	POST TREATMENT	Drop all cases	114	Target_ST	Response Y	No Missing
95	RELAPSE_3D	POST TREATMENT	Drop all cases	115	Target_VT	Response Y	No Missing
96	OPIOID_ECT	ON SITE (ECT)	Replace with 0	116	Target_VF	Response Y	No Missing

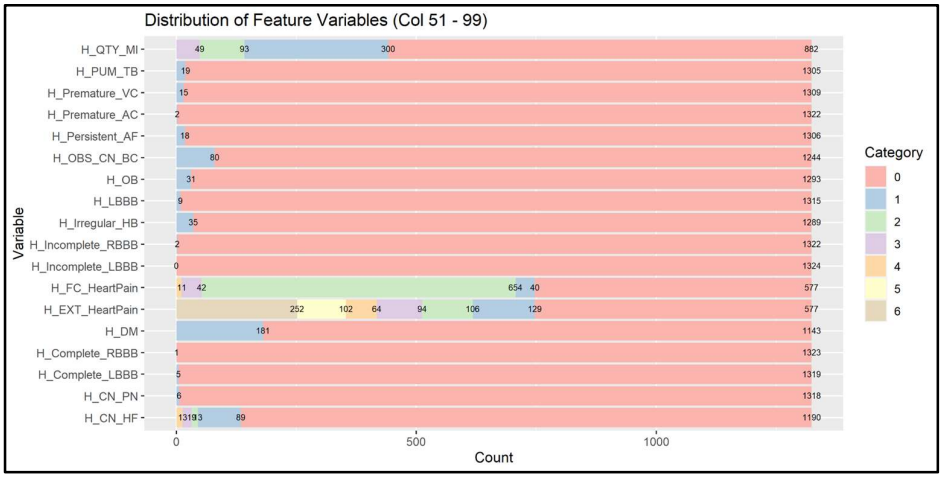
97	NSAID_ECT	ON SITE (ECT)	Replace with 0	117	Target_3DG_AVB	Response Y	No Missing
98	LIDOCAINE_ECT	ON SITE (ECT)	Replace with 0	118	Target_PUM_ED	Response Y	No Missing
99	NITRATE_ECT	ON SITE (ECT)	Replace with 0	119	Target_Myocardial_Rupture	Response Y	No Missing
100	OPIOID_1H	POST TREATMENT	Drop all cases	120	Target_Dressler	Response Y	No Missing

Columns 121 - 124

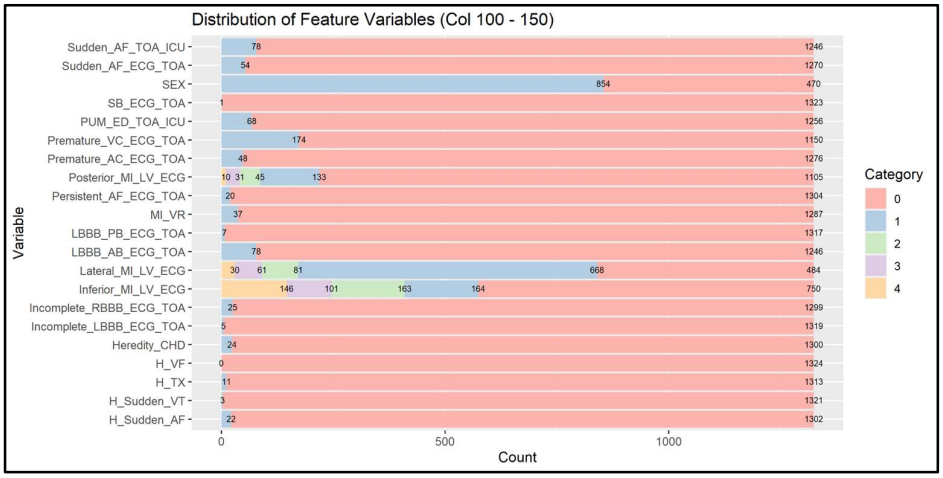
S/N	Column	Category	Missing Data	S/N	Column	Category	Missing Data
121	**Target_CN_HF**	Response Y	No Missing	123	Target_Post_HeartPain	Response Y	No Missing
122	**Target_Relapse_MI**	Response Y	No Missing	124	Target_Lethal	Response Y	No Missing

Appendix C: Exploratory Data Analysis

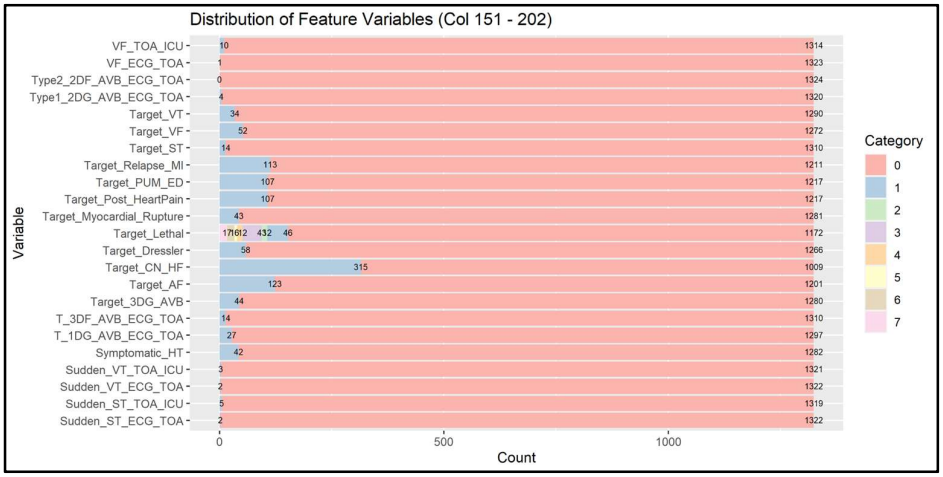
Distribution of Feature Variables (Columns 51 to 99)



Distribution of Feature Variables (Columns 100 to 150)

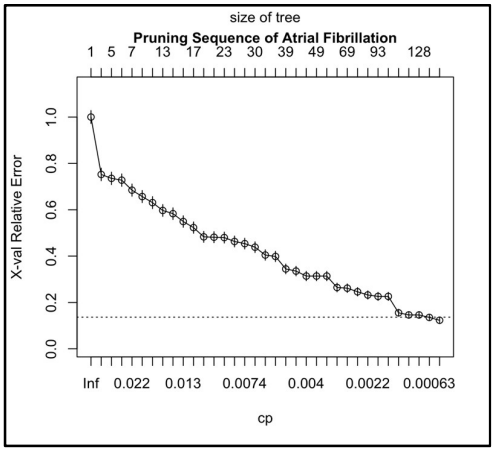


Distribution of Feature Variables (Columns 151 to 202)

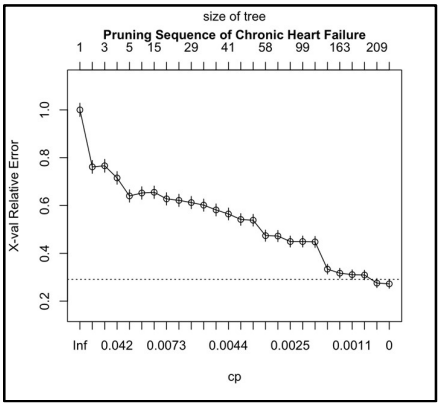


Appendix D: Model Training Diagrams

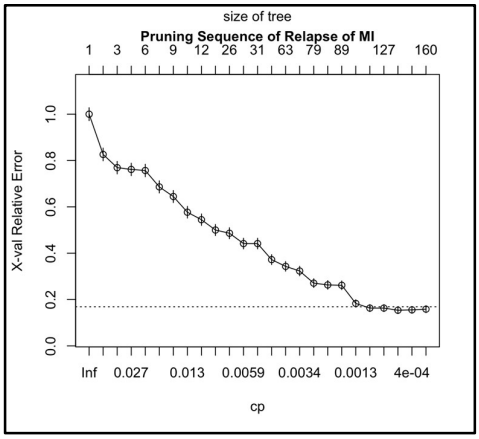
Pruning Sequence of Atrial Fibrillation



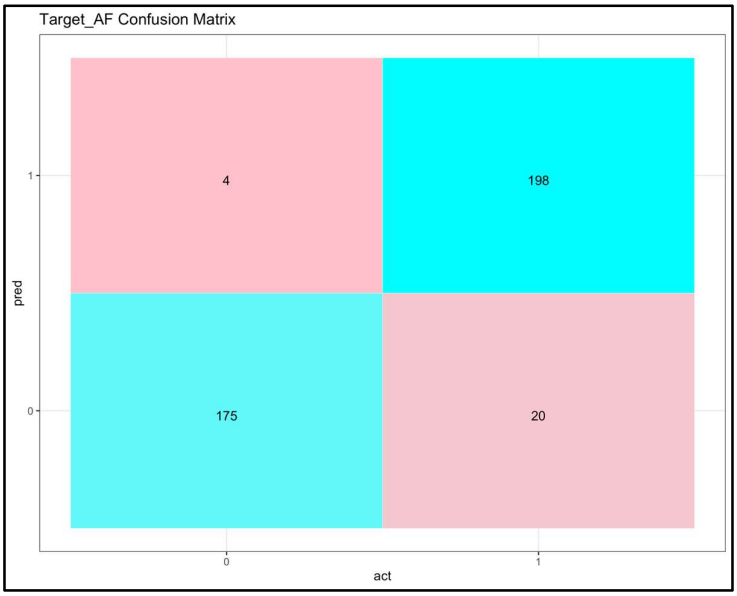
Pruning Sequence of Chronic Heart Failure



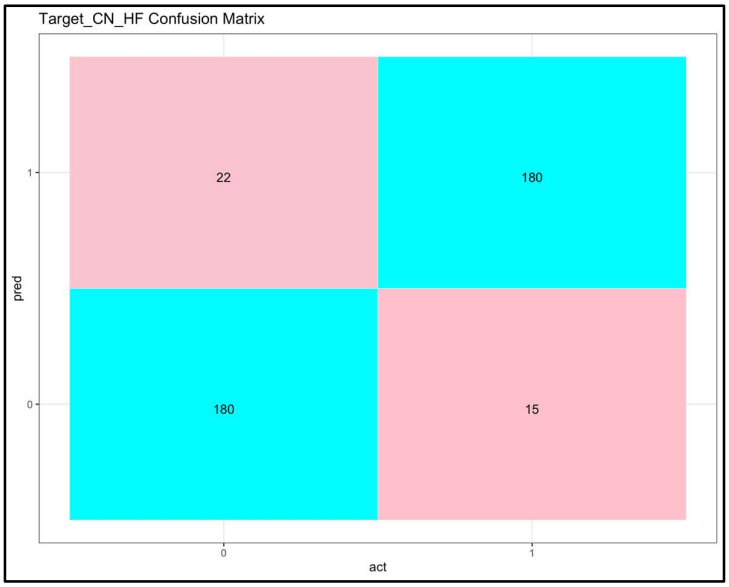
Pruning Sequence of Chronic Heart Failure



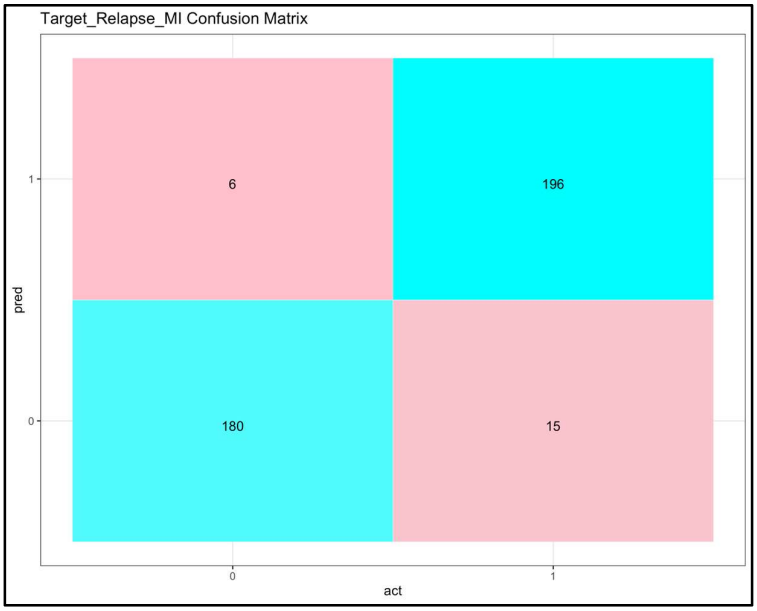
Confusion Matrix for Atrial Fibrillation



Confusion Matrix for Chronic Heart Failure



Confusion Matrix for Relapse of MI



Appendix E: Logistics Regression Results

Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI	Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI
(Intercept)	1.04 *	-0.18	-1.13 **	**H_EXT_HeartPain4**	-14.91	-10.50	14.12
	(0.47)	(0.35)	(0.44)		(3956.18)	(378.59)	(1455.40)
SEX1	-0.67 ***	-0.95 ***	-0.14	**H_EXT_HeartPain5**	-13.76	-10.56	15.07
	(0.15)	(0.15)	(0.15)		(3956.18)	(378.59)	(1455.40)
H_QTY_MI1	-0.81 ***	0.31	0.03	**H_EXT_HeartPain6**	-14.21	-10.19	15.18
	(0.20)	(0.18)	(0.17)		(3956.18)	(378.59)	(1455.40)
H_QTY_MI2	-0.11	0.42	-0.57 *	**H_FC_HeartPain1**	15.98	11.02	-13.20
	(0.29)	(0.30)	(0.26)		(3956.18)	(378.59)	(1455.40)
H_QTY_MI3	0.07	1.30 ***	-2.21 ***	**H_FC_HeartPain2**	15.22	10.47	-13.38
	(0.40)	(0.34)	(0.52)		(3956.18)	(378.59)	(1455.40)
H_EXT_HeartPain1	-15.08	-10.36	14.79	**H_FC_HeartPain3**	14.93	8.71	-13.39
	(3956.18)	(378.59)	(1455.40)		(3956.18)	(378.59)	(1455.40)
H_EXT_HeartPain2	-15.39	-10.96	14.62	**H_FC_HeartPain4**	*-2.03*	9.40	-28.32
	(3956.18)	(378.59)	(1455.40)		(4122.88)	(378.59)	(1529.94)

H_EXT_HeartPain3	-15.18	-10.98	14.47	**CHD_BA1**	0.33	0.47	-0.81 **
	(3956.18)	(378.59)	(1455.40)		(0.30)	(0.27)	(0.28)

Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI	Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI
CHD_BA2	-0.30	0.35	-0.26	**Duration_ART_HT5**	-0.63	-0.63	-0.10
	(0.24)	(0.21)	(0.21)		(0.36)	(0.38)	(0.38)
Essential_HT1	-16.13	0.72	-14.43	**Duration_ART_HT6**	-0.33	-0.85 **	0.50
	(2195.00)	(0.88)	(597.32)		(0.30)	(0.28)	(0.26)
Essential_HT2	-0.02	0.50 **	0.26	**Duration_ART_HT7**	-0.20	-0.95 ***	0.20
	(0.21)	(0.19)	(0.19)		(0.23)	(0.21)	(0.21)
Essential_HT3	-0.42	1.06 ***	-0.11	**H_CN_HF1**	1.27 ***	4.19 ***	-0.53
	(0.28)	(0.26)	(0.25)		(0.30)	(0.48)	(0.30)
Duration_ART_HT1	-0.62	-0.89 *	-2.08 ***	**H_CN_HF2**	-0.84	-0.79	0.20
	(0.37)	(0.35)	(0.47)		(0.80)	(0.60)	(0.66)
Duration_ART_HT2	-16.92	-0.50	0.50	**H_CN_HF3**	-0.17	0.24	-1.33 **
	(715.33)	(0.41)	(0.35)		(0.66)	(0.55)	(0.48)
Duration_ART_HT3	-0.37	-0.93 *	-0.83 *	**H_CN_HF4**	1.01	0.37	0.37
	(0.39)	(0.40)	(0.43)		(0.76)	(0.70)	(0.69)

Duration_ART_HT4	-0.03	-0.51	0.25	**H_DM1**	0.15	0.28	0.61 **
	(0.59)	(0.61)	(0.61)		(0.21)	(0.20)	(0.19)

Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI	Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI
H_CN_BC1	-1.13 ***	0.49 *		**Lateral_MI_LV_ECG3**	1.19 **	0.69 *	0.00
	(0.30)	(0.24)			(0.40)	(0.35)	(0.37)
Sudden_AF_TOA_ICU1	1.72 ***			**Lateral_MI_LV_ECG4**	1.78 ***	1.32 **	0.76
	(0.45)				(0.46)	(0.43)	(0.47)
Anterior_MI_LV_ECG1	-0.74 *	-0.97 **	-0.93 **	**Inferior_MI_LV_ECG1**	-0.42	-0.16	-0.42
	(0.34)	(0.30)	(0.32)		(0.32)	(0.30)	(0.31)
Anterior_MI_LV_ECG2	-17.91	-0.34	-2.43 ***	**Inferior_MI_LV_ECG2**	-0.49	-0.05	0.29
	(665.03)	(0.50)	(0.60)		(0.37)	(0.32)	(0.32)
Anterior_MI_LV_ECG3	-1.28 *	-0.25	1.09 *	**Inferior_MI_LV_ECG3**	0.55	0.18	0.29
	(0.58)	(0.54)	(0.50)		(0.37)	(0.34)	(0.35)
Anterior_MI_LV_ECG4	-0.37	-0.13	-0.14	**Inferior_MI_LV_ECG4**	-0.18	-0.23	-0.63 *
	(0.34)	(0.30)	(0.32)		(0.37)	(0.31)	(0.32)
Lateral_MI_LV_ECG1	0.60 **	0.28	0.52 **	**Posterior_MI_LV_ECG1**	0.02	-0.00	-0.29
	(0.22)	(0.19)	(0.20)		(0.26)	(0.26)	(0.24)

Lateral_MI_LV_ECG2	0.86 **	1.10 ***	0.95 **	**Posterior_MI_LV_ECG2**	-2.48 ***	-0.43	-0.20
	(0.32)	(0.31)	(0.31)		(0.67)	(0.40)	(0.36)

Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI	Variables	Atrial Fibrillation	Chronic Heart Failure	Relapse of MI
Posterior_MI_LV_ECG3	0.38	-0.33	-0.42	**ECG_TOA_SNS_TC1**	-1.12 ***		0.90 ***
	(0.40)	(0.43)	(0.47)		(0.32)		(0.27)
Posterior_MI_LV_ECG4	-1.37	-0.13	-0.45	**Sudden_AF_ECG_TOA1**	2.66 ***		
	(0.79)	(0.77)	(0.75)		(0.48)		
ECG_TOA_SNS1	-0.95 ***		0.52 *	**H_OBS_CN_BC1**		0.60 *	
	(0.29)		(0.25)			(0.27)	
ECG_TOA_AF1	-2.41 ***			**LBBB_AB_ECG_TOA1**		0.26	
	(0.62)					(0.27)	
N	*1324*	*1324*	*1324*				
AIC	1476.57	1505.99	1628.94				
BIC	1756.75	1770.60	1888.36				
Pseudo R2	0.40	0.37	0.28				

All continuous predictors are mean-centered and scaled by 1 standard deviation. *** p < 0.001; ** p < 0.01; * p < 0.05.