SDS 322E Project: Myocardial Infarction Complications

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Introduction

Myocardial infarction (MI), more commonly known as heart attack, is a condition that afflicts a large subset of the population. It is defined as the end of blood flow to a certain heart tissue, leading to a loss of function. The cause of MI, coronary artery disease, is the leading cause of death in the United States, furthering the susceptibility of the population (Ojha & Dhamoon, 2022). The disease can also lead to a plethora of complications, which were the focus of this study.

The overall question our study focused on was, "What specific patient attributes contribute to development of selected MI complications?" It was inspired by different classification studies done by Golovenkin et al. (2020) in, "Trajectories, bifurcations, and pseudo-time in large clinical datasets: applications to myocardial infarction and diabetes data." This study used a dataset from The University of California at Irvine's (UCI) Machine Learning Repository originally sourced from the University of Leicester. The motivation and rationale was to create a system or guidelines for designing a system based on specific complications and input features to predict future complications based on current patient attributes. This is vital as it is a non-trivial task for specialists to predict the development of complications due to MI. By accurately predicting complications due to MI, specialists can appropriately intervene, improve and optimize treatment on a patient-by-patient basis, focusing on preventative measures as opposed to reactive measures.

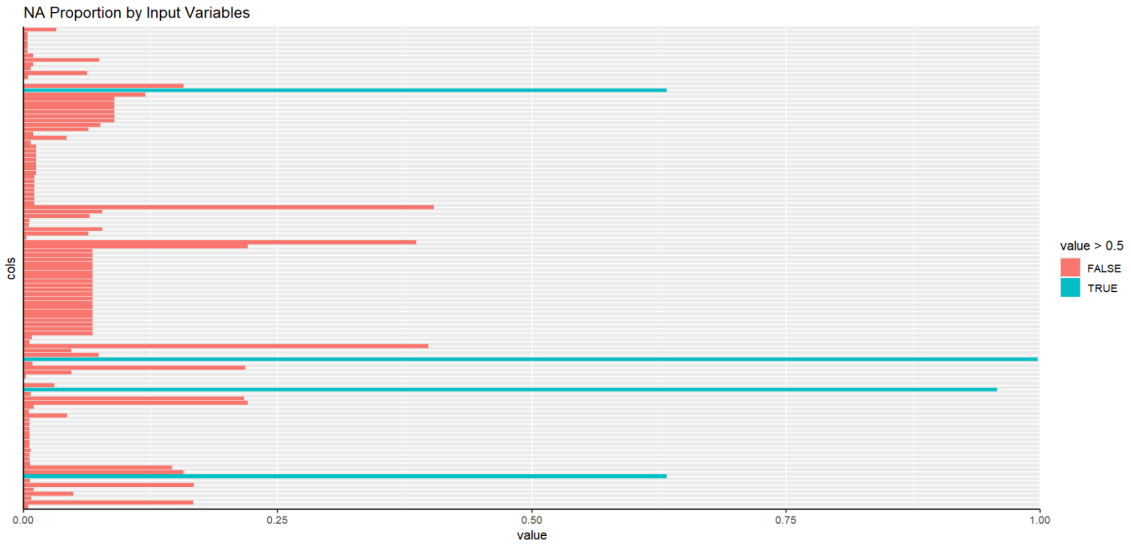
The main goals of this project were 1) to understand relationships between patient attributes at any time in their hospital stay and specific prevalent complications of MI *(exploratory data analysis)* and 2) to classify patients for each individual complication based on a patient's data (*classification task).* The specific complications used in our analysis were selected as they were the four most prevalent. Those complications were: chronic heart failure (ZSN), atrial fibrillation (FIBR_PREDS), pulmonary edema (OTEK_LANC), and the relapse of the myocardial infarction (REC_IM). We compared the accuracy of classifications for every complication in relation to each other.

Dataset & Cleaning Procedures

The dataset used for analysis in this project was donated by the School of Mathematics and Actuarial science at the University of Leicester to the Machine Learning Repository of University of California, Irvine's (UCI) Center for Machine Learning and Intelligent Systems. The data was collected at the Krasnoyarsk Interdistrict Clinical Hospital No. 20 named after I. S. Berzon (Russia) in the years 1992-1995 (Golovenkin et al., 2020). The structure of the dataset includes 1700 observations of 124 distinct attributes. Within these attributes, 111 (columns 2-112) were input attributes, 12 (columns 113-124) were complications. The input attributes included four different moments in time for complication prediction: (1) at the time of admission, (2) 24 hours post-admission, (3) 48 hours post-admission, and (4) 72 hours post-admission.

Among each attribute column, there were three different types of data stored within each observation: (1) real or continuous data, (2) nominal categorical data (either stored as a '0' or '1'), and (3) ordinal categorical data. Note, the scales for which the ordinal categorical data was ranked differed across various attribute columns. In total, there were 15974 missing observations across each column, which corresponded to roughly 7.57% of the total data. Firstly, frequency of missing observations (NA's) were compared across columns to obtain the columns where more than 50% of observations were missing as shown in **Figure 1**.

Figure 1: Proportion of NA's by Input Attribute Columns



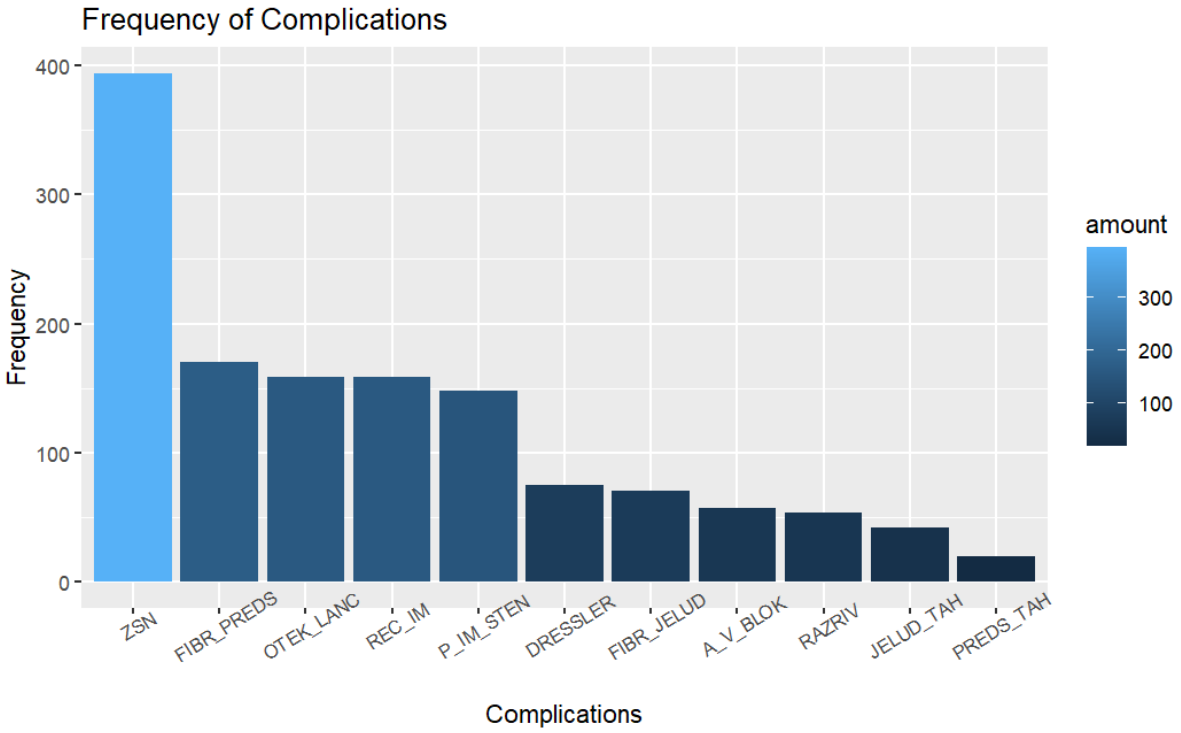
From **Figure 1**, it is evident that there are exactly 4 columns of which more than 50% of observations are missing. These columns were labeled IBS_NASL (corresponding to heredity on CHD or heredity on coronary heart disease), S_AD_KBRIG (corresponding to the systolic blood pressure according to the emergency cardiology team), D_AD_KBRIG (corresponding to the diastolic blood pressure according to the emergency cardiology team), and KFK_BLOOD (corresponding to serum CPK content or serum creatine phosphokinase contain). As these columns had more than 50% missing values, we decided to remove them entirely. Additionally, we removed the first column which corresponds to the ID number of the patient as it could not be related to the patient nor would it indicate any specific difference in the development of a patient's complications due to MI. After removing the four columns with more than 50% missing observations and the first column corresponding to ID, there were 10498 missing values remaining, representing about 5.19% of the remaining data.

For handling the remaining missing observations, the continuous or real data had to be handled differently from the categorical nominal and ordinal data. The real variables that were present within the dataset were age (AGE), systolic blood pressure according to the intensive care unit (S_AD_ORIT), diastolic blood pressure according to the intensive care unit (D_AD_ORIT), serum potassium content (K_BLOOD), serum sodium content (NA_BLOOD), serum AlAT content or serum alanine aminotransferase content (ALT_BLOOD), serum AsAT content or serum aspartate aminotransferase content (AST_BLOOD), white blood cell count (L_Blood) and ESR or erythrocyte sedimentation rate (ROE). For these variables, we decided to replace any missing observation in each column with the mean of the respective column. Following this imputation, 8313 missing values remained, representing about 4.11% of the remaining data. For the nominal and ordinal categorical variables, we decided to replace any missing values in each value with the mode of each respective column. After this final imputation, there remained no missing values in our dataset and the original number of observations was maintained at 1700. In our cleaned dataset, columns 1-107 were able to be utilized as input features and columns 108-119 were complications.

Exploratory Analysis

Firstly, we decided which complications to analyze by visualizing the frequency of each complication as shown in **Figure 2**. As seen in the figure, the complications with the most amount of cases were chronic heart failure (ZSN) with 394 cases, atrial fibrillation (FIBR_PREDS) with 170 cases, pulmonary edema (OTEK_LANC) with 159 cases, and relapse of myocardial infarction (REC_IM) with 159 cases.

Figure 2: Frequency of Complications



After selecting a subset of the total complications to analyze, we created correlation heat maps for each of the input variables with the selected complications. The choice to use correlation heat maps was based upon the fact that each complication was a nominal categorical variable. The following heat maps show the highest correlated input variables with each selected complication in **Figures 3 - 6.**

Figure 3: Correlation Heat Map for Selected Complications and Columns 9-12

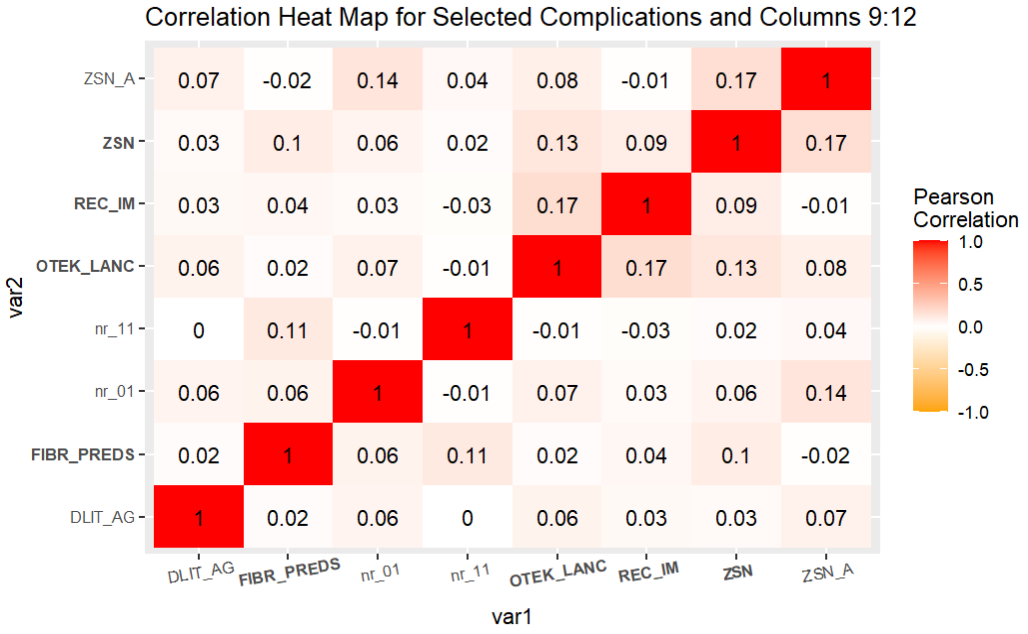


Figure 4: Correlation Heat Map for Selected Complications and Columns 53-56

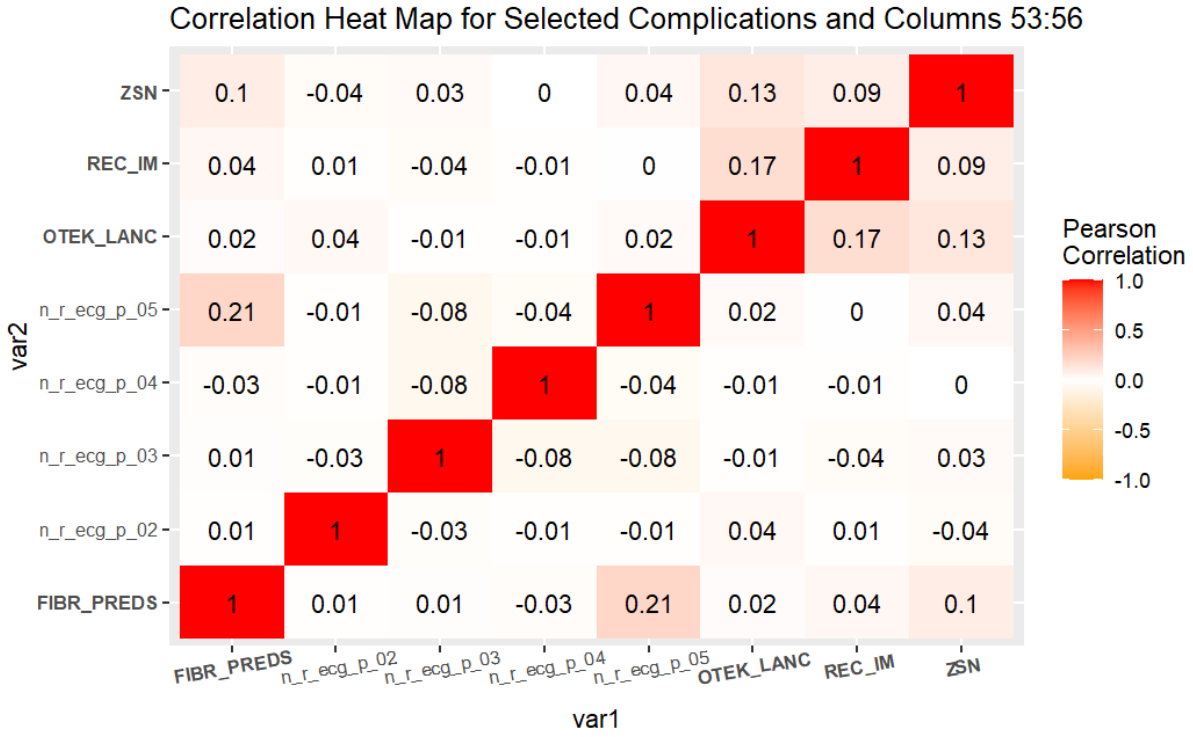


Figure 5: Correlation Heat Map for Selected Complications and Columns 93-96

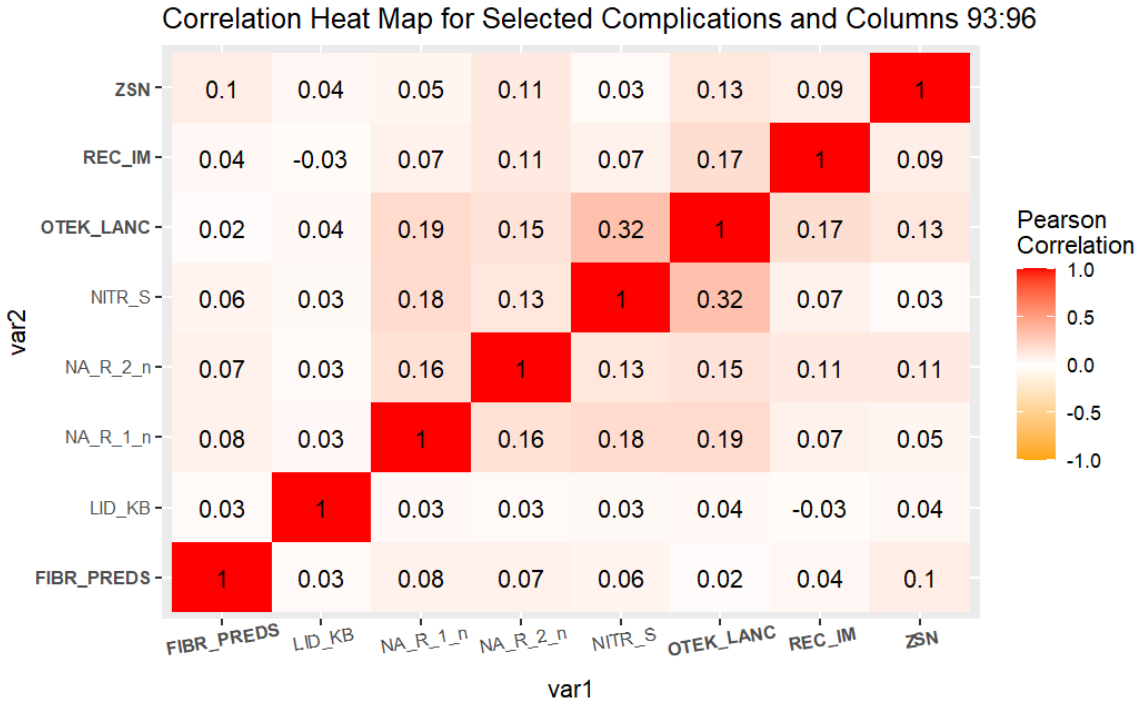
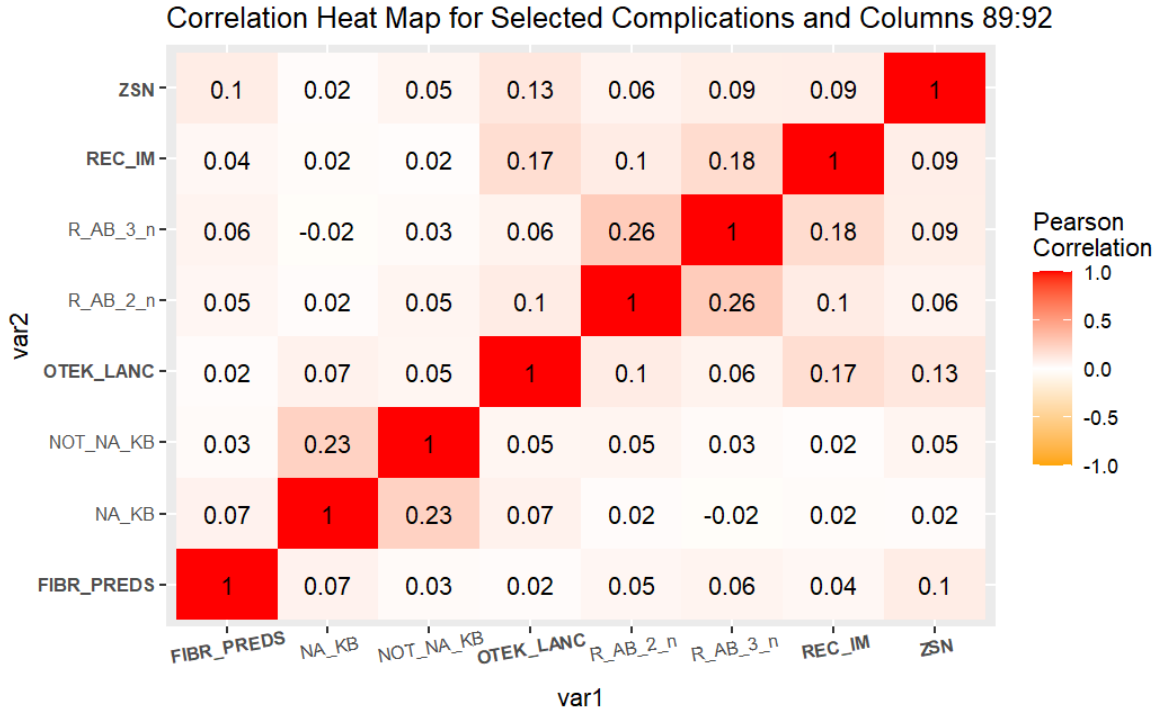


Figure 6: Correlation Heat Map for Selected Complications and Columns 89-92



From the following figures, the most correlated input variables to each selected complication was found. For chronic heart failure (ZSN), the input variable with the highest Pearson correlation coefficient was the presence of chronic heart failure in the anamnesis (ZSN_A) or the presence of chronic heart failure in the patient's medical history. Atrial fibrillation (FIBR_PREDS) was most highly correlated with whether or not the patient experienced paroxysms of atrial fibrillation on ECG at the time of admission to hospital (n_r_ecg_p_05). For pulmonary edema (OTEK_LANC), the input variable with the highest Pearson correlation coefficient was the use of liquid nitrates in the ICU (NITR_S). Relapse of MI (REC_IM) was most highly correlated with whether or not the patient experienced a relapse of the pain on the third day of the hospital period (R_AB_3_n). The results are summarized in **Table 1.**

Table 1: Summary of Pearson's Correlation Coefficient for Highest Correlated Input Variables for Each Selected Complication

Input Variable	**Selected Complication**	**Pearson's correlation coefficient (*Pearson's r*)**
Presence of chronic heart failure in the anamnesis (*ZSN_A*)	Chronic heart failure (*ZSN*)	0.1693715
Paroxysms of atrial fibrillation on ECG at the time of admission to the hospital (*n_r_ecg_p_05*)	Atrial Fibrillation (*FIBR_PREDS*)	0.2072312
Use of Liquid Nitrates in the ICU (*NITR_S*)	Pulmonary Edema (*OTEK_LANC*)	0.3218104895
Relapse of pain on the third day of the hospital period (*R_AB_3_n*)	Relapse of Myocardial Infarction (*REC_IM*)	0.1844414894

Based on these input variables and selected complications, the frequency and proportions of each input variable were plotted against their respective selected complication. **Figures 7 - 14** show these plots, with **Figures 7, 9, 11,** and **13** depicting the frequency of each input variable plotted against their respective selected complications and **Figures 8, 10, 12,** and **14** depicting the proportion of each input variable plotted against their respective selected complications.

Figure 7: Frequency of ZSN_A severity vs. Development of ZSN as a Complication of MI

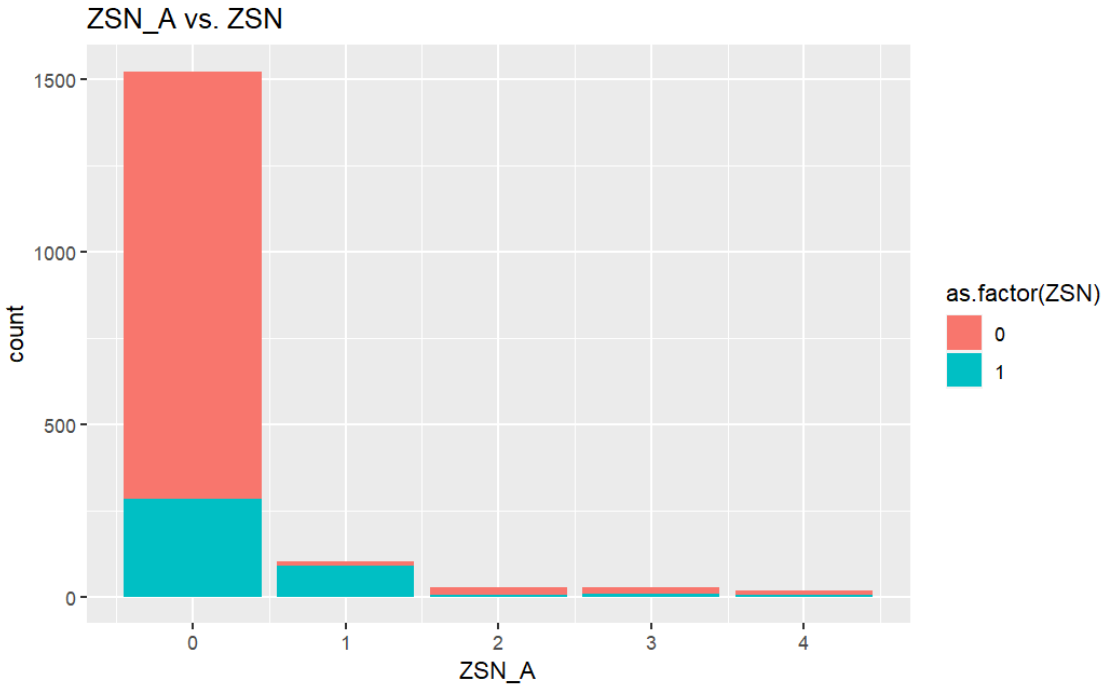


Figure 8: Proportion of ZSN_A severity vs. Development of ZSN as a Complication of MI

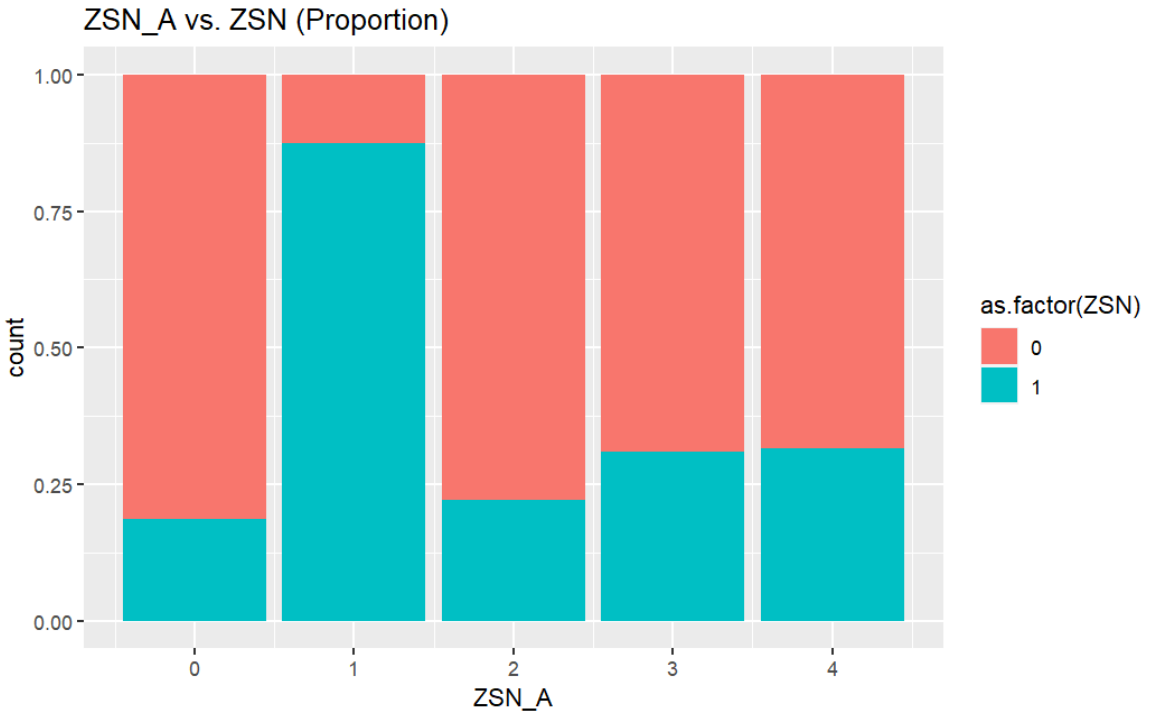


Figure 9: Frequency of n_r_ecg_p_05 vs. Development of FIBR_PREDS as a Complication of MI

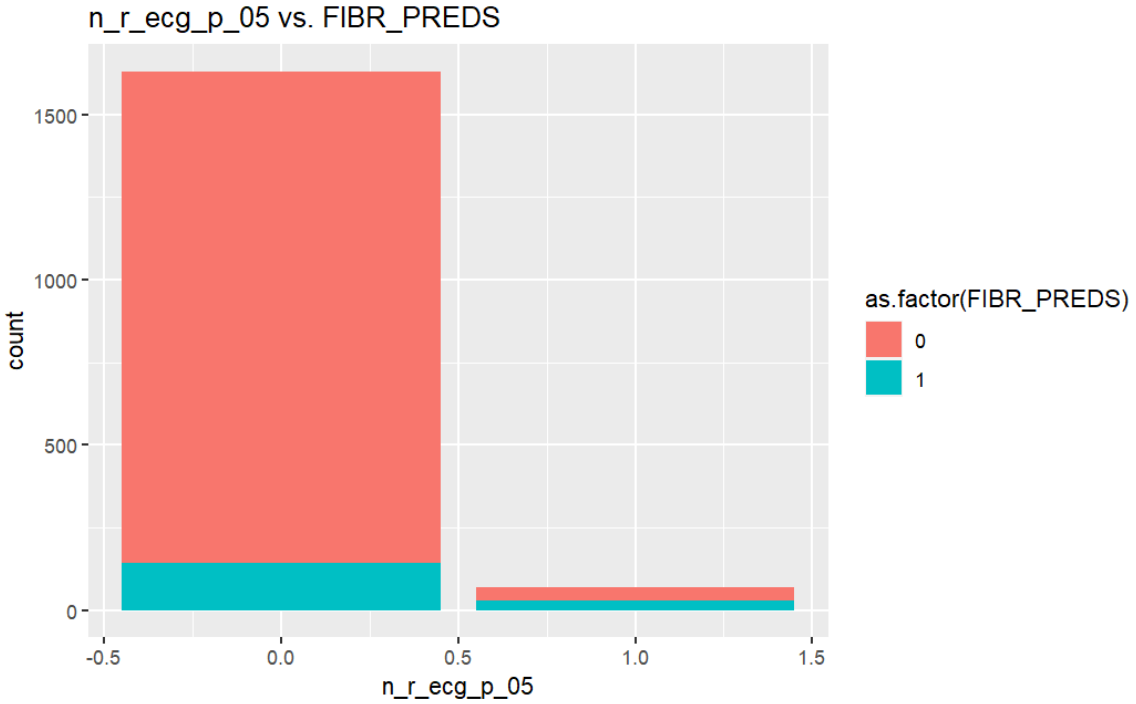


Figure 10: Proportion of n_r_ecg_p_05 vs. Development of FIBR_PREDS as a Complication of MI

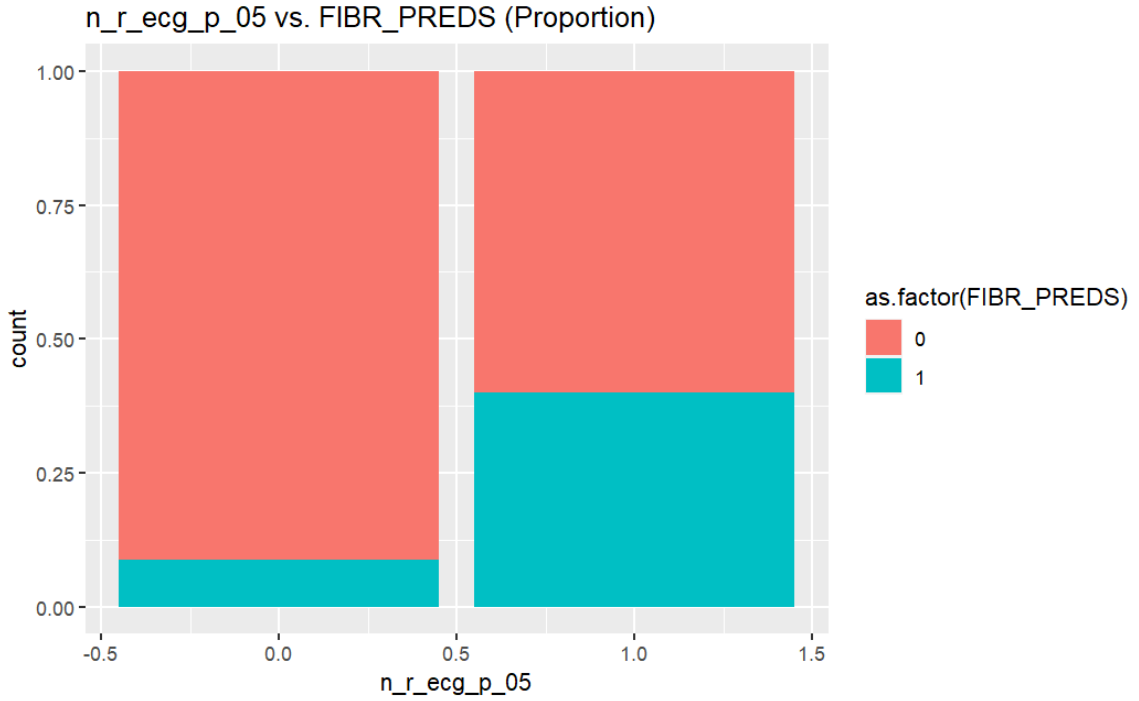


Figure 11: Frequency of NITR_S vs. Development of OTEK_LANC as a Complication of MI

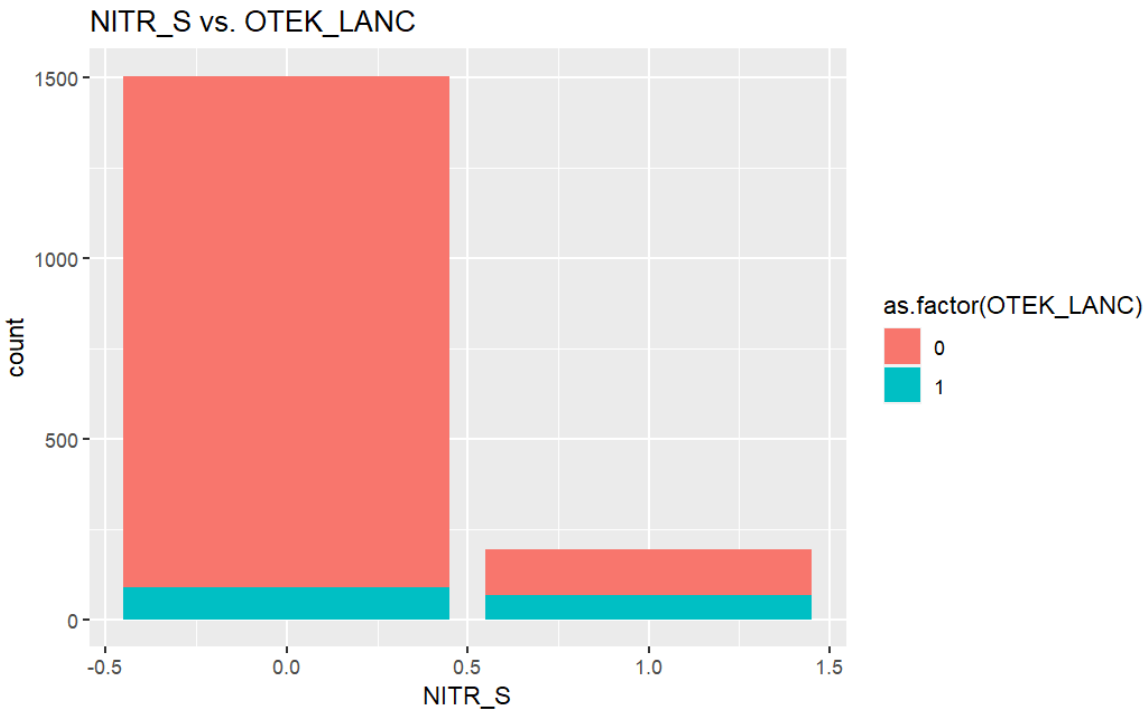


Figure 12: Proportion of NITR_S vs. Development of OTEK_LANC as a Complication of MI

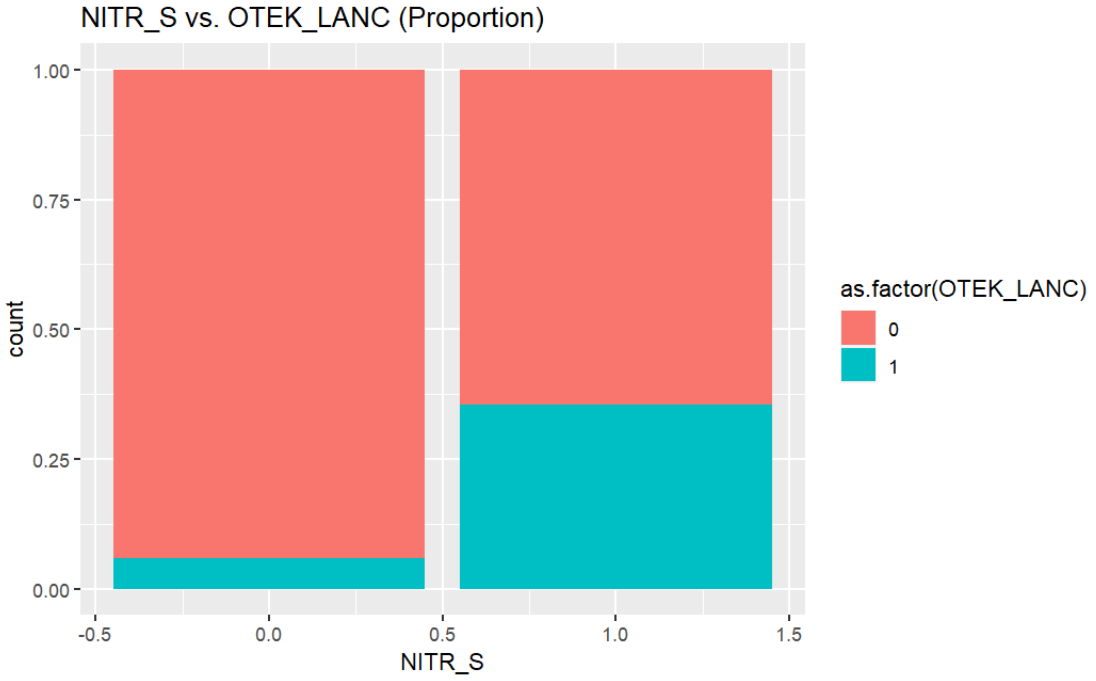


Figure 13: Frequency of R_AB_3_n severity vs. Development of REC_IM as a Complication of MI

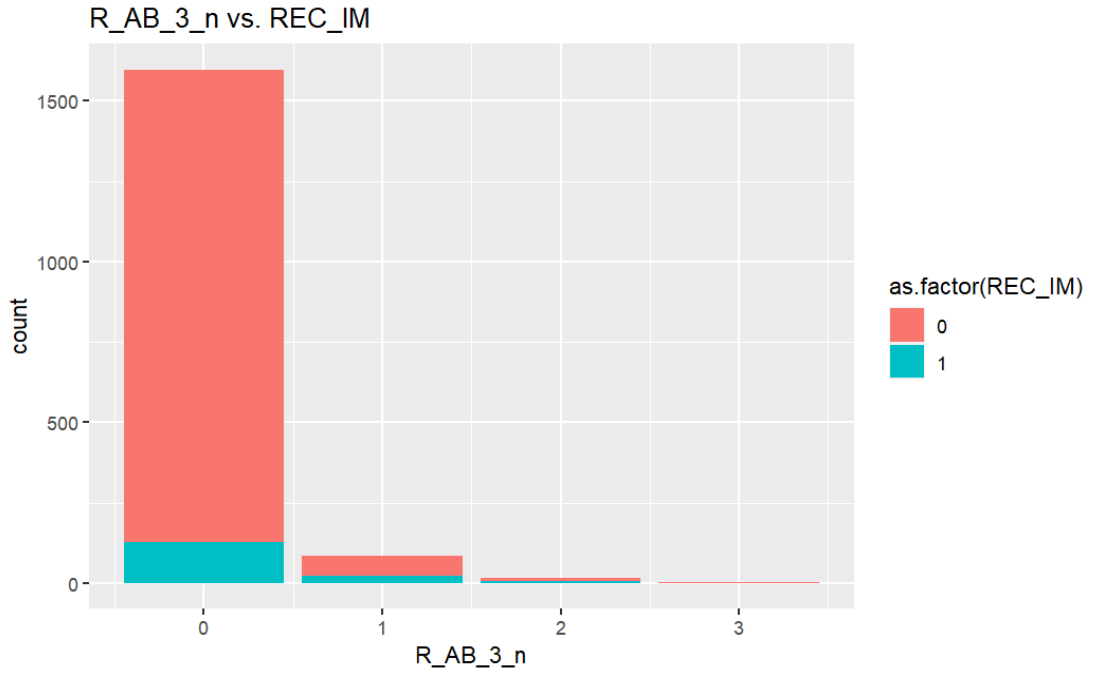
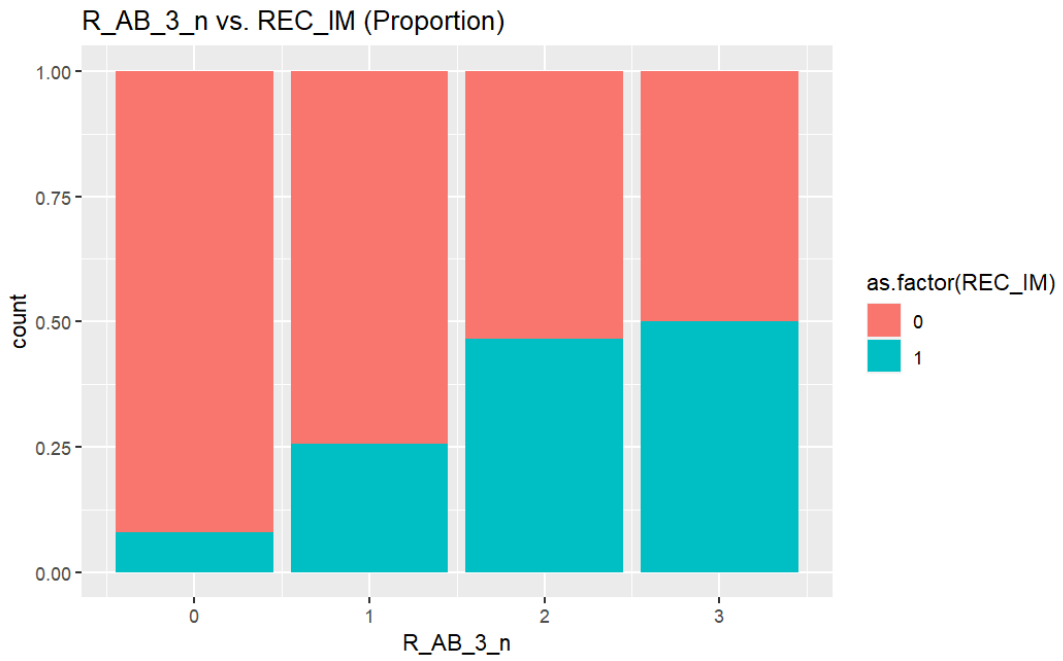


Figure 14: Proportion of R_AB_3_n severity vs. Development of REC_IM as a Complication of MI



Observing **Figure 8**, we see that a greater proportion of patients who have chronic heart failure present within their anamnesis (medical histories) with a severity level of 1, developed chronic heart failure as a complication of MI. Anamnesis describes the patient's memory of a certain incidence, so the data in the ZSN_A column is self-reported. A 2015 study conducted by Lala et al. provides that "patients hospitalized with acute decompensated heart failure (ADHF) are at high risk for readmission, morbidity, and mortality" (Lala et al., 2015). From their findings and **Figure 8**, we hypothesized that if an individual has presence of chronic heart failure at a severity level of 1 in their medical history, then the person is more likely to develop chronic heart failure as a complication of MI.

Figure 10 shows that a greater proportion of patients who have paroxysms of atrial fibrillation on their ECG's at the time of admission to the hospital tend to develop atrial fibrillation as a complication of MI. Here, paroxysms of atrial fibrillation refers to sudden signs of atrial fibrillation on a patient's ECG upon admission to the hospital. Pillarisetti et al. (2009) states, "AF [atrial fibrillation] frequently starts as paroxysmal atrial fibrillation (PAF) and gradually progresses to permanent atrial fibrillation in about 77% of patients over a time period of 14 years despite anti-arrhythmic therapy as shown in a study by Kato et al. Epidemiological studies and animal models suggest that AF begets AF since the fibrillating myocardium causes electrical remodeling that further perpetuates AF" (Pillarisetti et al., 2009). Thus, we hypothesized that if a patient experiences paroxysms of atrial fibrillation on their ECG at the time of admission, they are more likely to develop atrial fibrillation as a complication of MI.

We see by **Figure 12**, we see that a greater proportion of patients who have had liquid nitrates used in their treatments while in the ICU, developed pulmonary edema as a complication of MI. Organic nitrates are used as treatments for patients with "congestive heart failure, acute

coronary syndrome, or severe hypertension," and patients who had pulmonary edema when admitted to the hospital showed "[rapid] improv[ement] after treatment" (Hsieh et al., 2018). Pulmonary edema is a condition where the patient's lungs are filled with fluid to the point where they have trouble breathing. The improvement in this condition is due to the administration of nitrates, and the common practice of using them as a treatment led us to conclude that patients treated with nitrates are more likely to be those being treated for pulmonary edema. Thus we hypothesized that if a patient is treated with nitrates in the ICU, they are more likely to develop pulmonary edema as a complication of MI.

As made evident by **Figure 14**, a greater proportion of patients who have experienced a relapse of pain on the third day of a hospital stay, developed a relapse of MI as a complication of MI. In a study on recurrent myocardial infarction, Thune et al. (2011) state, "The strongest predictors of recurrent MI were reduced estimated glomerular filtration rate, unstable angina, diabetes, and age" (Thune et al., 2011). As listed, unstable angina or unstable chest pain, is a strong predictor of recurrence or relapse of MI. Thus, we hypothesized that if a patient experiences a relapse of pain (angina) on the third day of a hospital stay, then they are more likely to develop a relapse of MI as a complication of MI.

Modeling

Clustering was utilized to determine possible links between the input features or attributes and the outputs, which represented the possible complications of MI. In our cluster analysis, we used only the most highly correlated input columns for each of 4 chosen output columns. These included ZSN_A (presence of chronic heart failure in the anamnesis), n_r_ecg_p_05 (paroxysms of atrial fibrillation on the ECG at time of admission), NITR_S (use of liquid nitrates in the ICU), and R_AB_3_n (relapse of pain on the third day of the hospital stay). We used a hierarchical clustering algorithm on these columns to develop 10 clusters and compared their correlations to all 12 output columns. A cluster dendrogram is shown in **Figure 15**, and a correlation heat map is shown in **Figure 16** below.

Figure 15: Cluster Dendrogram

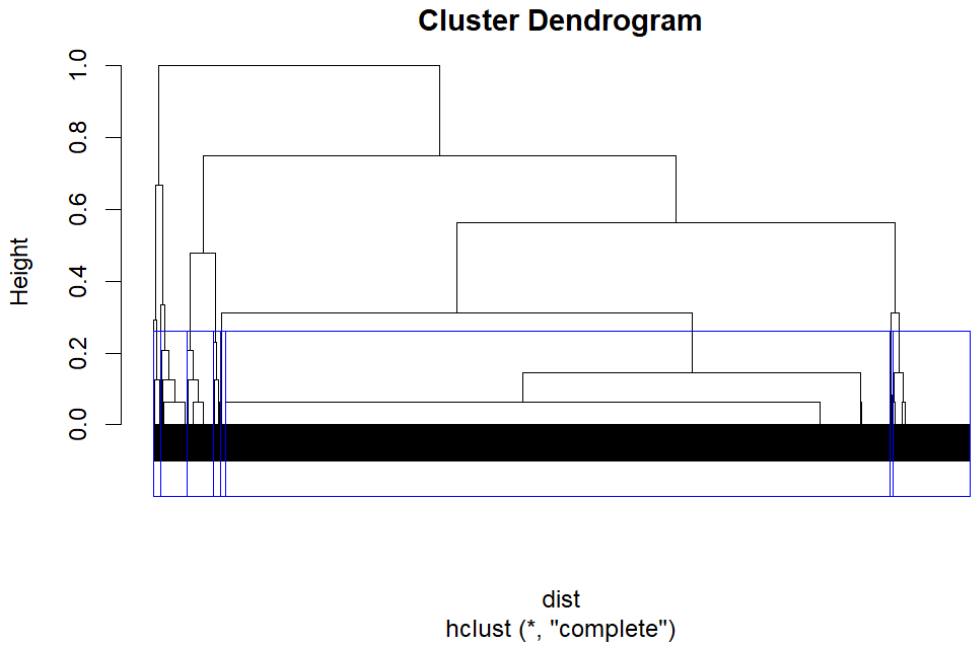
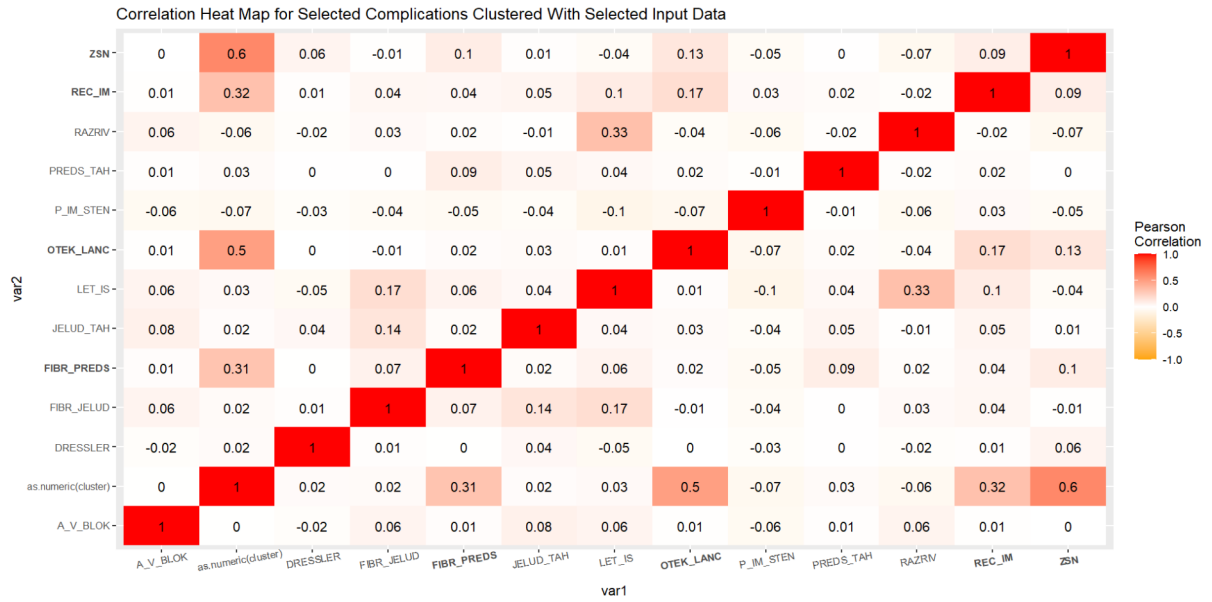


Figure 16: Correlation Heat Map for Selected Complications Clustered with Selected Input Data

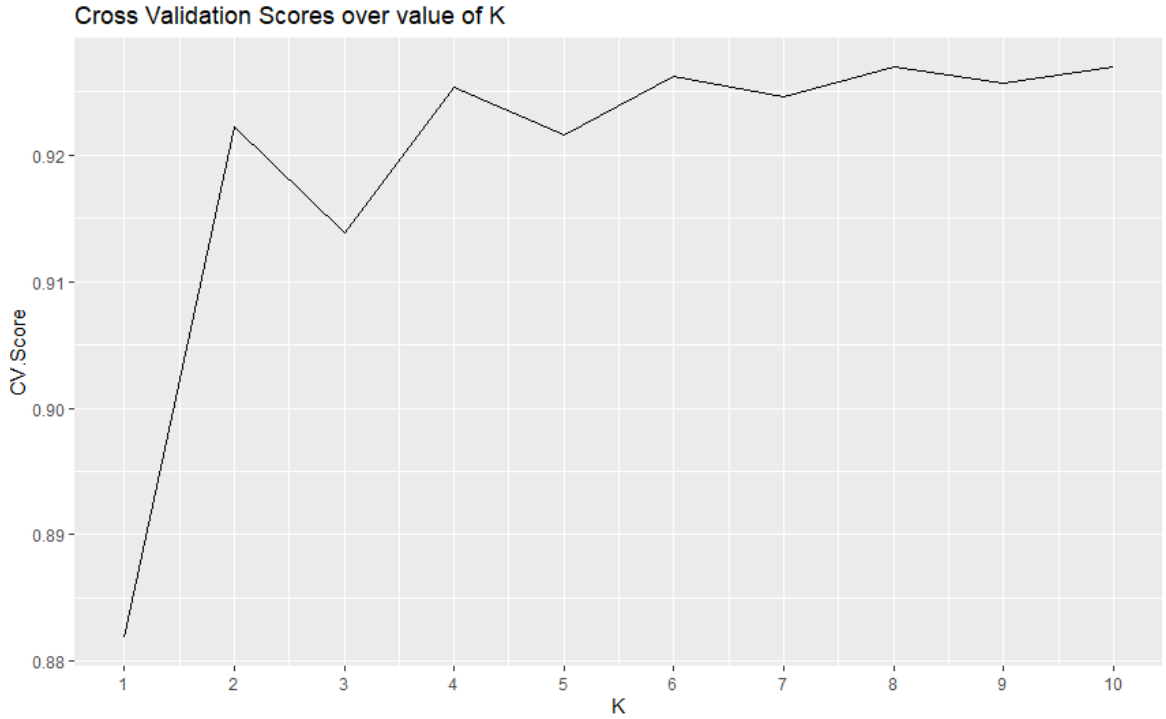


Observing **Figure 16,** we see that the correlations for ZSN (chronic heart failure), REC_IM (relapse of MI), OTEK_LANC (pulmonary edema), and FIBR_PREDS (atrial fibrillation) were significantly higher with the cluster values than with the individual input columns.

To complete the classification task, a series of classifiers using the k-nearest neighbors (k-NN) were used on input columns 2-112 to predict the potential complications (which are found in output columns 113-123). Note that column 124, containing the lethal outcome (LET_IS), was omitted from our classification set as to focus on specific complications of MI. The decision to use the k-NN algorithm was made for the reason of being able to adjust the value of k, representing the number of nearest neighbors to be compared. The motivation to use a single classifier for each complication was decided on as it ensured least information loss, or complete use of the information provided within the dataset. However, this could be limited to information for specific times such as time of admission, and the ends of the first, second, and third days of the hospital period. The idea of using a single classifier which could predict combinations of complications was considered. This was under consideration as complications were not mutually exclusive, as a patient could have more than one complication at once. However, we decided that individual classifiers would require less data to accurately predict than combinations. Additionally, not all combinations were represented in the data set. This comes from the fact that there are 11 complications or a set of complications containing elements, meaning all subsets of this set (or all combinations of these complications) would be 2^{11} or 2048 different combinations, but there are only 1700 observations.

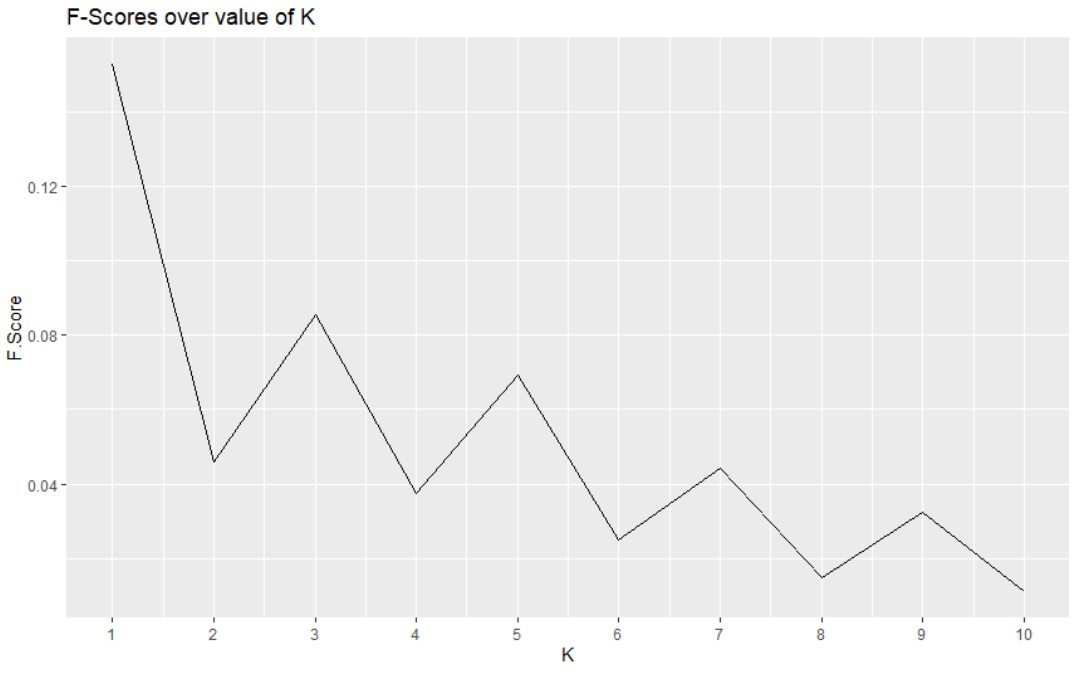
A 10-Fold Cross Validation algorithm was used on each classifier - meaning one classifier for each k-value and output pair - for k-values 1-10. To determine the best value of k, the average accuracy calculated by the cross validation of all outputs was compared for each k-value. The k-value with the best cross validation score was found to be 8, as shown in **Figure 17**.

Figure 17: Cross Validation Scores over value of K for K-Nearest Neighbors



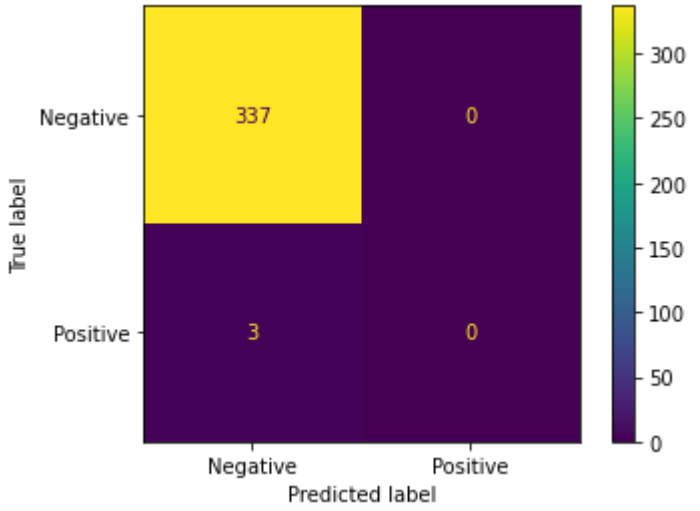
An alternative method for determining the best possible k-value was used but yielded poor results. Instead of using cross validation scores from the Sci-Kit Learn model selection library, an algorithm was constructed using similar 10-fold validation, using f-scores over accuracy scores. The reasoning behind this was that while the method described above yielded very high accuracy scores, the precision and recall scores were comparatively low. F-scores reliably combine precision and recall. However, when utilizing the previous k-values, the highest f-score yielded was 0.1527, at a k-value of 1. This is shown in **Figure 18**.

Figure 18: F-Scores over value of K for K-Nearest Neighbors



The final series of classifiers used k-NN with k-values set to 8. The average accuracy for these classifiers was 92.70%, and a random train/test sample of our data allowed us to explain the low precision and recall scores. For each of the complications we set out to predict, the dataset represents positive values (patients who did have a specific compilation) poorly. This is shown in **Figure 19** below. As seen in the figure, most observations in the dataset were negative values (most people did not have the specific complication). So, while the accuracy of our classifiers is high, this is most likely due to the majority of the data for each complication being negative values. In other words, any classifier that would predict most patients as negative would evaluate as having a high accuracy when tested on records in this dataset. Having a higher k-value for the k-NN models would have a higher probability of positive records being included in the classification decision, while having a low k-value could mean a very low chance of getting any reference of a positive record. We can see from **Figure 17** and **Figure 18** that as k increases, we get a slightly higher accuracy, but a slightly lower f-score.

Figure 19: Confusion Matrix for Supraventricular tachycardia



In **Figures 20, 21, 22** and **23**, we see the confusion matrices for each of our selected complications, with accuracy, precision and recall scores for each classifier based on complications reported in **Table 2.**

Figure 20: Confusion Matrix for Chronic Heart Failure (ZSN)

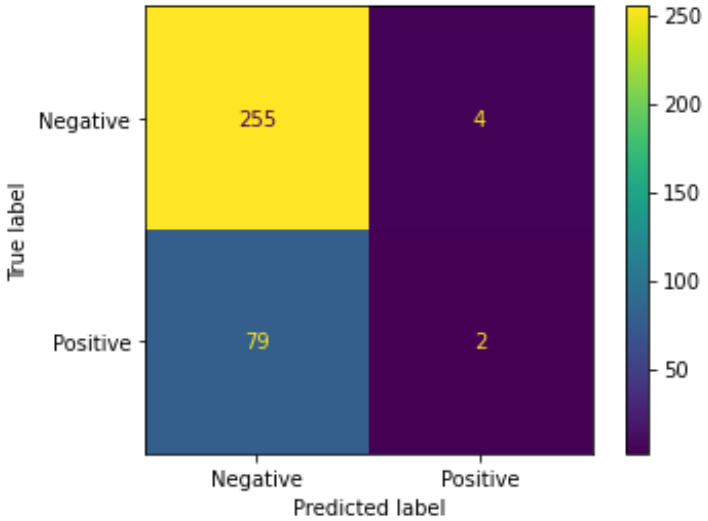


Figure 21: Confusion Matrix for Atrial Fibrillation (FIBR_PREDS)

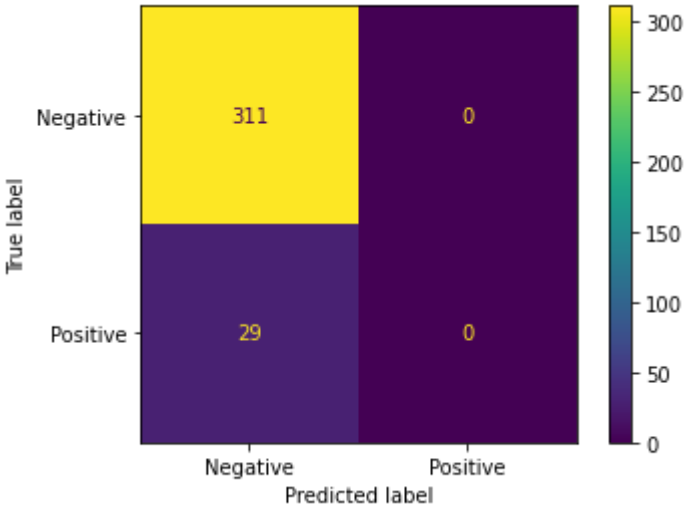


Figure 22: Confusion Matrix for Pulmonary Edema (OTEK_LANC)

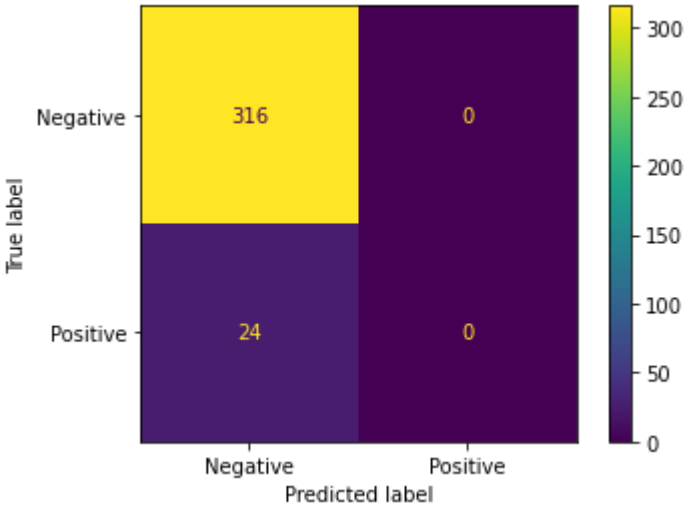


Figure 23: Confusion Matrix for Relapse of Myocardial Infarction (REC_IM)

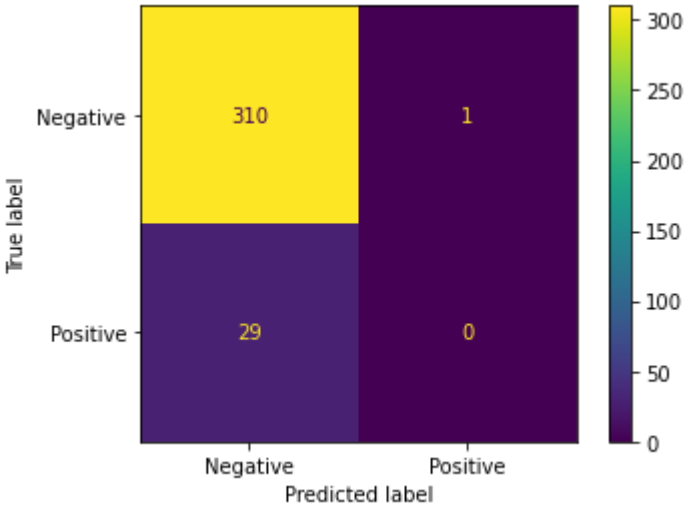


Table 2: Summary of Accuracy, Recall, and Precision Scores for Classifiers Based on Complication

Classifier Complication	Accuracy Score	Precision Score	Recall Score
Atrial Fibrillation (FIBR_PREDS)	0.9147058823529411	0.0	0.0
Supraventricular tachycardia (PREDS_TAH)	0.9911764705882353	0.0	0.0
Ventricular tachycardia (JELUD_TAH)	0.9735294117647059	0.0	0.0
Ventricular fibrillation (FIBR_JELUD)	0.95	0.0	0.0
Third-degree AV block (A_V_BLOK)	0.9647058823529412	0.0	0.0
Pulmonary edema (OTEK_LANC)	0.9294117647058824	0.0	0.0
Myocardial rupture (RAZRIV)	0.9764705882352941	0.0	0.0
Dressler syndrome (DRESSLER)	0.9647058823529412	0.0	0.0
Chronic heart failure (ZSN)	0.7558823529411764	0.3333333333333333	0.024691358024691357
Relapse of the myocardial infarction (REC_IM)	0.9117647058823529	0.0	0.0
Post-infarction angina (P_IM_STEN)	0.9	0.0	0.0

Discussion

Overall each classifier predicts negative cases well, however, in general is not efficient at predicting positive cases due to low overall recall scores. The only complication that had a precision score or recall score higher than zero was chronic heart failure (ZSN) with a precision score at 0.33 and 0.0247 respectively as seen in **Table 2**. This can also be seen by comparing **Figures 20-23** specifically looking at the true positive values. Observing accuracy scores for

each model, chronic heart failure (ZSN) has the lowest accuracy score of all the complications. In **Table 2** we note that the classifier for chronic heart failure (ZSN) has an accuracy score of roughly 0.75. From **Figure 21** and **Table 2**, the classifier for atrial fibrillation (FIBR_PREDS) has an accuracy score of 0.91. Furthermore, based on **Figure 22** and **Table 2**, the classifier for pulmonary edema (OTEK_LANC) has an accuracy score of 0.92. Additionally, from **Figure 23** and **Table 2**, we see that the classifier for relapse of MI (REC_IM) has an accuracy score of 0.90. The classifier which had the highest accuracy score from **Table 2** was supraventricular tachycardia (PREDS_TAH) with an accuracy score of roughly 0.99.

Across all of the classifiers, the mean accuracy score when classifying patients based on a specific complication of MI was roughly 0.930214. As all classifiers possess a proclivity to classify negative values, we note this as a limitation that can be ameliorated. Despite this limitation, we believe that for the types of patients present within this dataset, these models can be used to accurately classify and predict patients into various complication groups which is crucial to effective treatment.

Our classification task could have been improved in several ways. Firstly, testing each classifier over a wider range of k values for the K-Nearest Neighbors (k-NN) algorithm could have made a significant difference. For example, testing k values between 1 and 100, or even 1 and 500. Additionally, the classifiers based upon the K-Nearest Neighbors algorithm may have been outperformed by classifiers using the Naive-Bayes or a Decision Tree algorithms. The presence of continuous, nominal and ordinal data made it difficult to properly clean the dataset as continuous missing values were handled differently than nominal and ordinal missing values. Moreover, different imputation methods were used for missing continuous values and missing nominal and ordinal values. The large amount of input columns (124) made it difficult to understand how the different columns contributed to the presence of a specific complication as a result of MI. As there were 124 distinct variables, a principal component analysis (PCA) could have been conducted to reduce the dimensionality of the dataset. However, as various combinations of input features could have contributed to specific complications more than other input features individually, there is a need in further analysis to group the input columns based on literature and empirical evidence of treatments for each specific complication. This would involve finding the input features that specifically relate to the treatment of a complication of MI and creating a group of such variables. Furthermore, this created difficulties when performing a cluster analysis. As the dataset had many different types of input variables, in the future a SHAP analysis could be utilized to evaluate the importance and contribution of the specific input variables or the combination of the input variables based on the aforementioned groupings.

Conclusion

Using the Myocardial Infarctions dataset donated by the University of Leicester, we developed 11 different classifiers using the K-Nearest Neighbor algorithm to classify and predict the complications patients would experience as a complication of myocardial infarction (MI). For the complications we chose to analyze, the classifier for chronic heart failure (ZSN) had an accuracy score of 0.7558, the classifier for atrial fibrillation (FIBR_PREDS) had an accuracy score of 0.9147, the classifier for pulmonary edema (OTEK_LANC) had an accuracy score of 0.929 and the classifier for relapse of MI (REC_IM) had an accuracy score of 0.9. The average accuracy score among classifiers for all 11 complications was 0.930214. The motivation behind these models was to design a tool to help physicians and specialists catch the development of the complications of MI early and optimize treatment for their patients.

This study was subject to limitations, and for future analysis we recommend creating a systematic imputation technique to deal with missing continuous, nominal and ordinal variables. Secondly, conducting a principal component analysis (PCA) will reduce dimensions which will aid the overall analysis as there are a high number of features present within the dataset (124). Furthermore, we recommend grouping the input features based upon a literature analysis on the treatments of specific complications of MI to gain insight on current treatment techniques. Other classification models based on the Naive Bayes and Decision Tree algorithms could also be tested for any improvement in accuracy, recall and precision scores. Lastly, a SHAP analysis could be undertaken to understand how each feature contributes to the overall prediction of each model.

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