Heart Failure Prediction Project

# Introduction

The purpose of this project is to explore and analyze heart failure data to develop and evaluate machine learning models capable of delivering accurate predictions.

The first section of the project will focus on data preparation and exploratory data analysis (EDA), starting with a concise explanation of the dataset and its variables. The second section will involve fitting three different machine learning models — Logistic Regression, SVM, Random Forest, and Decision Tree Boosting — and optimizing them to identify variants capable of delivering the most accurate predictions.

Finally, all models will be compared to determine which type performs best, not only in terms of prediction accuracy but also in interpretability and overall stability.

# Exploratory Data Analysis (EDA)

## Data description

The dataset analyzed in this project focuses on heart failure, specifically on determining whether a patient has heart disease based on various demographic characteristics and biomarkers. The dataset, originally titled *Heart Failure Prediction*, was sourced from *Kaggle*[[1]](#footnote-1).

According to *World Health Organization*, the cardiovascular diseases (CVDs) are the leading cause of death globally, representing 32% of all global deaths in 2019 – nearly 85% of those were due to a heart attack, or a stroke. There are many different variants of cardiovascular diseases, however nearly all of them are manageable if detected early. There are many proven behavioral (i.e.: unhealthy diet) and environmental (i.e.: air pollution) risk factors, which effects influence biomarkers, such as blood pressure. Those immediate risk factors can be measured in healthcare facilities, and thus it is possible to predict whether certain individual is in danger of developing a heart disease[[2]](#footnote-2).

There have been many attempts to model risks of developing a heart disease, with the notable one being the sex-specified algorithm - *Framingham Risk Score*. Its’ basic form is used to estimate the 10-year risk of developing a CVDs[[3]](#footnote-3).

## Data structure

This dataset was created by combining different datasets already available independently but not combined before – thus resulting in 918 observations of one outcome column (heart disease) and 11 predictors. To achieve a didactic purpose, the **original dataset has been modified to slightly imbalance the data** – the positive class was randomly undersampled.

The variables included in the dataset are as follows:

* *HeartDisease* [binary] – outcome column,
* *Age* [years],
* *Sex* [M/F],
* *RestingBP* [mm/Hg] – resting blood pressure,
  + High values suggest hypertension, a significant risk factor for heart disease.
* *Cholesterol* [mm/dl] - serum cholesterol,
  + Elevated cholesterol, particularly LDL ("bad" cholesterol), is associated with atherosclerosis and heart disease.
* *MaxHR* [beats/min] - maximum heart rate achieved,
  + A lower-than-expected maximum heart rate may indicate impaired cardiac function.
* *FastingBS* [binary, if > 120 mg/dl: 1] - fasting blood sugar,
  + A fasting blood sugar level above 120 mg/dl is indicative of hyperglycemia, a marker of diabetes or insulin resistance, which increases cardiovascular risk.
* *ChestPainType* [TA, ATA, NAP, ASY] - chest pain type,
  + TA (Typical Angina): Chest pain triggered by exertion, relieved by rest,
  + ATA (Atypical Angina): Less predictable or associated with other factors,
  + NAP (Non-Anginal Pain): Chest pain unrelated to heart disease,
  + ASY (Asymptomatic): No chest pain, common in silent ischemia[[4]](#footnote-4).
* *ExerciseAngina* [Y/N] - exercise-induced angina,
* *RestingECG* [Normal, ST, LVH] - resting electrocardiogram results,
  + Normal: No abnormalities detected,
  + ST: Indicates ST-T wave abnormalities, a sign of ischemia or previous heart attack,
  + LVH: Suggests left ventricular hypertrophy, a thickened heart muscle wall often due to chronic hypertension.
* *Oldpeak* - ST depression on the ECG during stress tests,
  + Indicates the severity of ischemia; higher values suggest worse outcomes.
* *ST\_Slope* [Up, Flat, Down] - the slope of the peak exercise ST segment.
  + Flat and Down indicates ischemia.

## Data Analysis

The exploratory data analysis (EDA) began with a review of **summary statistics (Table 1)** to gain an initial understanding of the dataset's overall structure and detect any potential anomalies or inconsistencies. This provided valuable insights into central tendencies, variability, and possible irregularities within both numerical and categorical features.

Table 1 Summary Statistics for numeric variables

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Age | RestingBP | Cholesterol | MaxHR | Oldpeak |
| **count** | 522.000000 | 522.000000 | 522.000000 | 522.000000 | 522.000000 |
| **mean** | 51.660920 | 131.197318 | 216.691571 | 143.622605 | 0.591762 |
| **std** | 9.497245 | 17.357076 | 88.244897 | 25.364167 | 0.899450 |
| **min** | 28.000000 | 80.000000 | 0.000000 | 63.000000 | -1.500000 |
| **25%** | 44.000000 | 120.000000 | 195.000000 | 126.250000 | 0.000000 |
| **50%** | 52.000000 | 130.000000 | 226.000000 | 145.000000 | 0.000000 |
| **75%** | 58.000000 | 140.000000 | 264.000000 | 162.000000 | 1.000000 |
| **max** | 76.000000 | 200.000000 | 564.000000 | 202.000000 | 5.000000 |

**A graph of a box plot

Description automatically generatedFor numerical variables, distributions were assessed to identify outliers, and appropriate corrections were applied when necessary to mitigate their impact.** This ensured the data remained representative and minimized distortions that could affect model performance. In the end, **only *cholesterol* was adjusted**, as observations at 0 must be a numerical mistake, and values above 500 are highly improbable. Observations at 0 were replaced using KNN Imputation later during data preparation process – for now, they are treated as NAN values), and observations over 500 were omitted, thus reducing the number of overall observations.

Figure 1 Box plot of Cholesterol in training set after adjustments.

Additionally, to explore variable relationships, correlation analyses were conducted. **Linear relationships were assessed through *Pearsons’ correlation (Table 2)*, while *Spearman’s rho (Table 3)* was used to detect monotonic relationship between numerical features and the response variable.** This dual approach helped capture associations both among exogenous variables, and between exogenous and endogenous variables.

Table 2 Correlations among predictors

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Age | RestingBP | Cholesterol | MaxHR | Oldpeak |
| **Age** | 1.000000 | 0.235697 | 0.132970 | -0.391675 | 0.249109 |
| **RestingBP** | 0.235697 | 1.000000 | 0.125848 | -0.109799 | 0.190216 |
| **Cholesterol** | 0.132970 | 0.125848 | 1.000000 | -0.041538 | 0.112503 |
| **MaxHR** | -0.391675 | -0.109799 | -0.041538 | 1.000000 | -0.123762 |
| **Oldpeak** | 0.249109 | 0.190216 | 0.112503 | -0.123762 | 1.000000 |

**All correlations presented above seem to fall within an acceptable range, ensuring that the collinearity does not occur.** As for *Spearman’s rho* (Table 3), *Cholesterol* and *RestingBP* appear to have low correlation, however it may not imply them to be not significant in a machine learning model – it will be checked during model creation.

|  |  |
| --- | --- |
|  | Spearman’s rho |
| **Age** | 0.238759 |
| **RestingBP** | 0.098001 |
| **Cholesterol** | 0.061974 |
| **MaxHR** | -0.319722 |
| **Oldpeak** | 0.346148 |

Table 3 Correlations between numerical predictors and the response variable

**For categorical variables, *Cramer’s V (Table 4)* was employed to measure the strength of associations with the response variable**, highlighting potential dependencies and valuable predictive features. Additionally, the proportions of each class were examined to uncover any rare or underrepresented categories (assumed <1%) that could introduce bias or instability in the modeling. Most of these variables seem to have some predictive power, but a possible exception is *RestingECG*.

Table 4 Associations between categorical predictors and the response variable

|  |  |
| --- | --- |
|  | Cramer’s V |
| **Sex** | 0.241612 |
| **ChestPainType** | 0.442648 |
| **FastingBS** | 0.261378 |
| **RestingECG** | 0.056554 |
| **ExerciseAngina** | 0.479162 |
| **ST\_Slope** | 0.517812 |

**The overall response class imbalance is around 21.5% on the side of diagnosed with heart diseases.**

# Model Fitting

## Overview

The data has been split into a training and testing set using an 80/20 ratio, where 80% of the data is allocated to training and 20% to testing. As previously highlighted during the Exploratory Data Analysis (EDA) phase, cholesterol values recorded as 0 were initially treated as missing (NAN). For the modeling phase, these missing values have been inputted using K-Nearest Neighbors (KNN) imputation. This process was conducted separately for each dataset, with the KNN imputer trained solely on the training set to prevent data leakage.

After splitting, the summary statistics of the training and testing sets were compared to ensure they are not significantly different, reducing the risk of sampling bias. Fortunately, no major discrepancies were observed. However, the class distribution within the testing set reveals a ratio of 18 positive cases to 72 negative cases. This imbalance may introduce challenges during model evaluation and performance assessment.

To address this, we will employ Diagnostic Odds Ratio (DOR) for cross-validation. The following models will be tested, as outlined in the introduction:

1. **Logistic Regression** – A simple yet effective linear model used for binary classification problems. It estimates the probability of a given input belonging to the positive class by applying the logistic (sigmoid) function to a linear combination of the input features.
2. **Random Forest** – An ensemble learning method that constructs multiple decision trees during training. The model outputs the class that is the majority prediction of the individual trees, enhancing accuracy and reducing the risk of overfitting.
3. **Decision Tree Boosting** – A technique that builds decision trees sequentially, with each tree correcting errors made by the previous one. Popular boosting algorithms include XGBoost and LightGBM, known for their efficiency and strong performance.
4. **Support Vector Machine (SVM)** – A powerful algorithm that identifies a hyperplane in a high-dimensional space to separate classes. SVMs aim to maximize the margin between the closest data points (support vectors) and the hyperplane, leading to robust classification results, even for non-linearly separable data.

Initially, observation weighting will be applied to mitigate the class imbalance issue. Subsequently, undersampling and oversampling techniques will also be explored to further address the disparity between positive and negative cases in the dataset.

1. *Heart Failure Prediction Dataset*, Kaggle, <https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction?select=heart.csv> [06.12.2024] [↑](#footnote-ref-1)
2. *Cardiovascular Diseases (CVDs)*, WHO, <https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)> [06.12.2024] [↑](#footnote-ref-2)
3. *Framingham Risk Score*, Wikipedia, <https://en.wikipedia.org/wiki/Framingham_Risk_Score> [06.12.2024] [↑](#footnote-ref-3)
4. Ischemia here refers to cardiac ischemia, which is an insufficient blood flow to the heart muscle, often leading to chest pain (angina) or a heart attack. [↑](#footnote-ref-4)