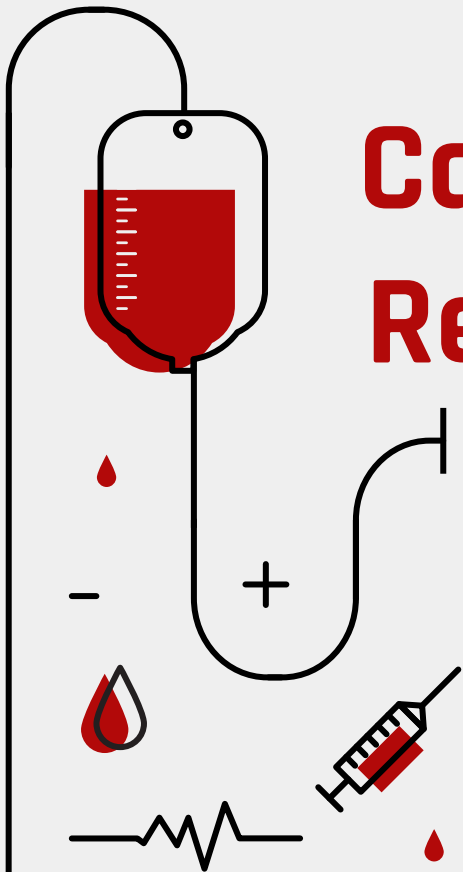


# Can Machine Learning Revolutionize Anemia Diagnosis?

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# Table of contents



## Introduction



## ML Models

Models with/without pre-processing

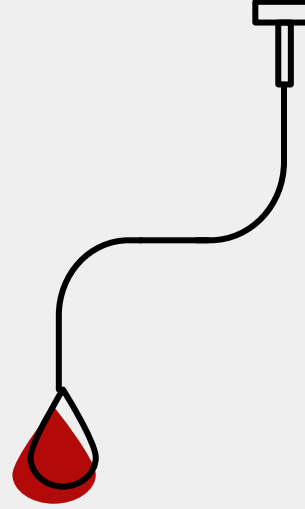


## Data Analysis

Data analysis and overview



## Summary and Takeaways



# Introduction

# Introduction

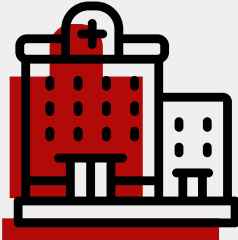
Anemia is a widespread health challenge that often goes undiagnosed, potentially impacting millions of individuals worldwide. By leveraging data-driven insights and understanding key risk factors, we can develop more effective strategies for early detection and treatment. Our research aims to shed light on this critical health issue and contribute to improved public health outcomes.





# Data Analysis

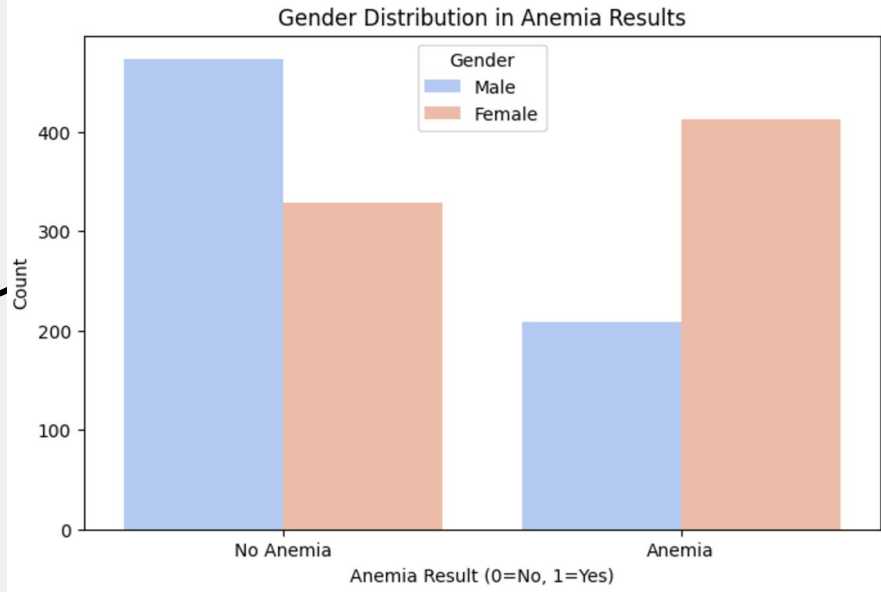
# Data Analysis



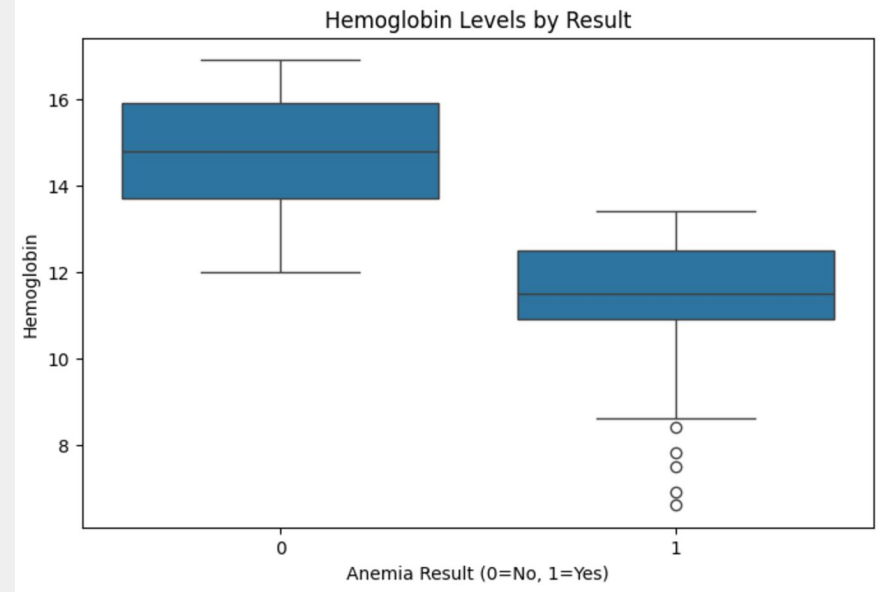
## Data Overview:

This dataset contains 1421 people with categories of Gender Hemoglobin MCH MCHC MCV and Results

# Data Analysis

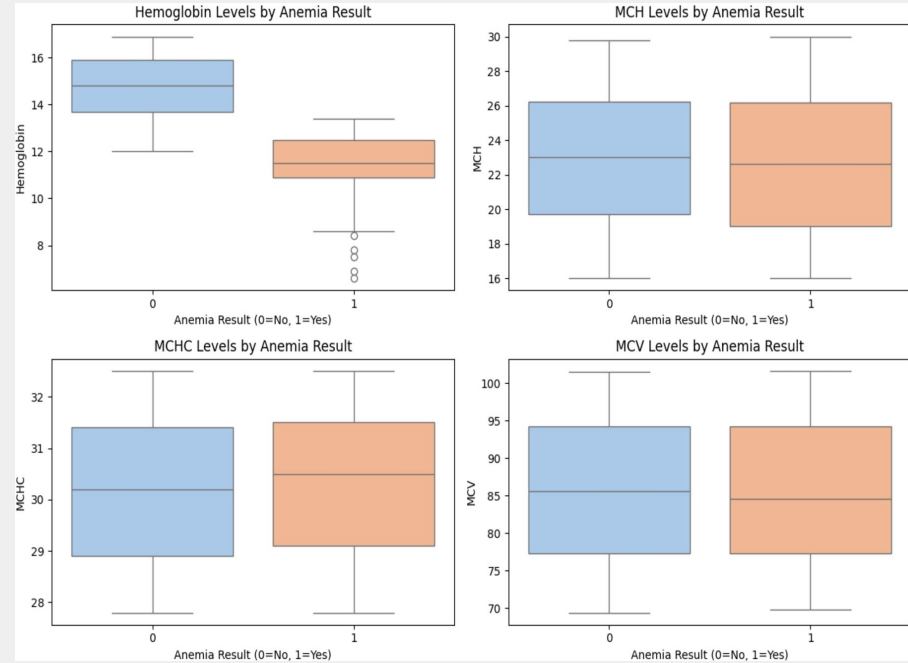
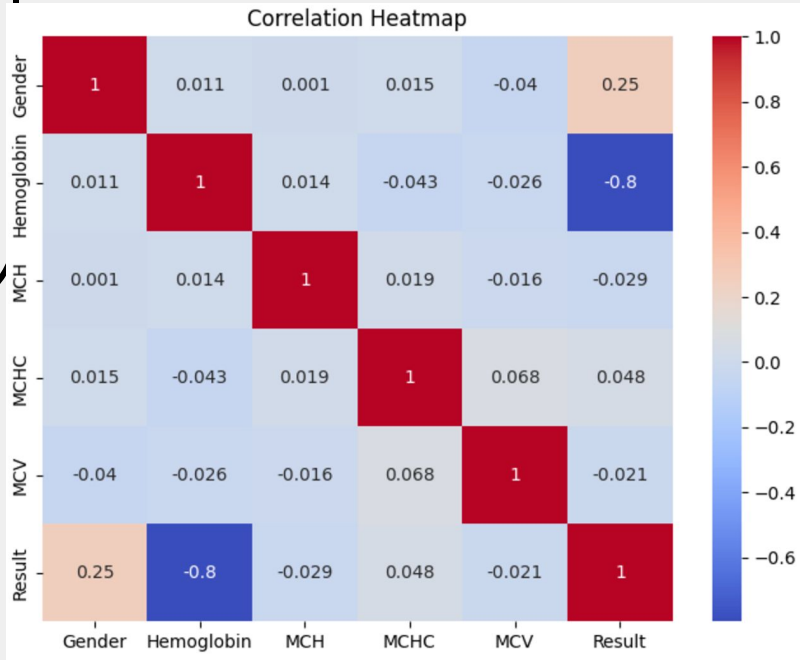


Females diagnosed with Anemia is greater.



Patients diagnosed with Anemia appears with a lower medium Hemoglobin

# Data Analysis

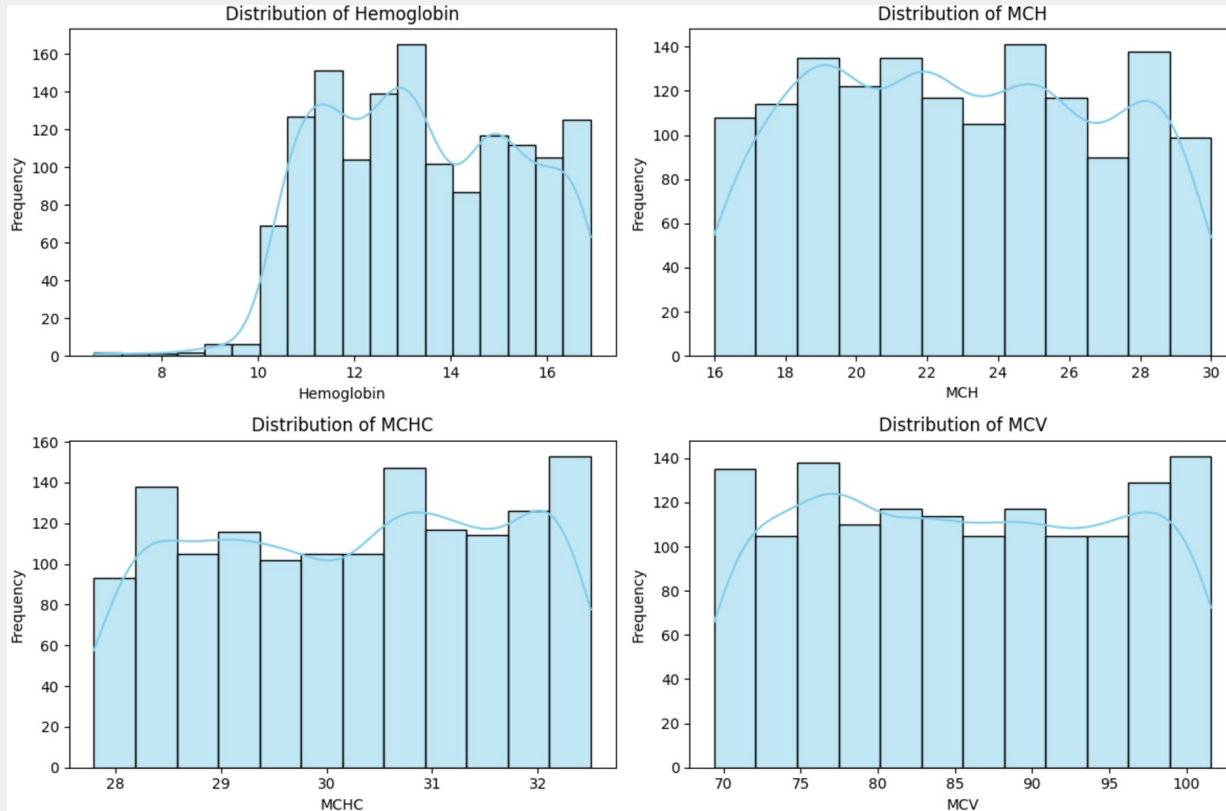


Correlation heatmap showcase the correlation between different variables

Boxplots of all variable



# Distribution



# The proportions of the class variable

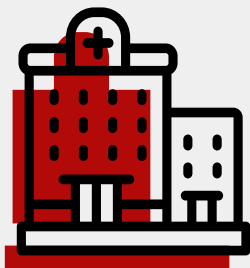
- 0 (not anemic): 56%
- 1 (anemic): 44%



# Machine Learning Models

\*Without Pre-processing

# Machine Learning Models

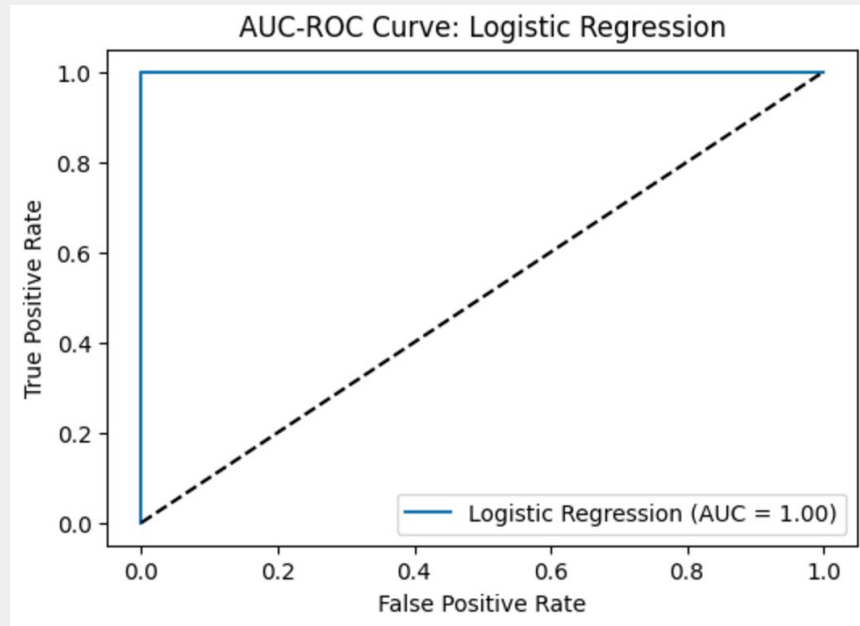
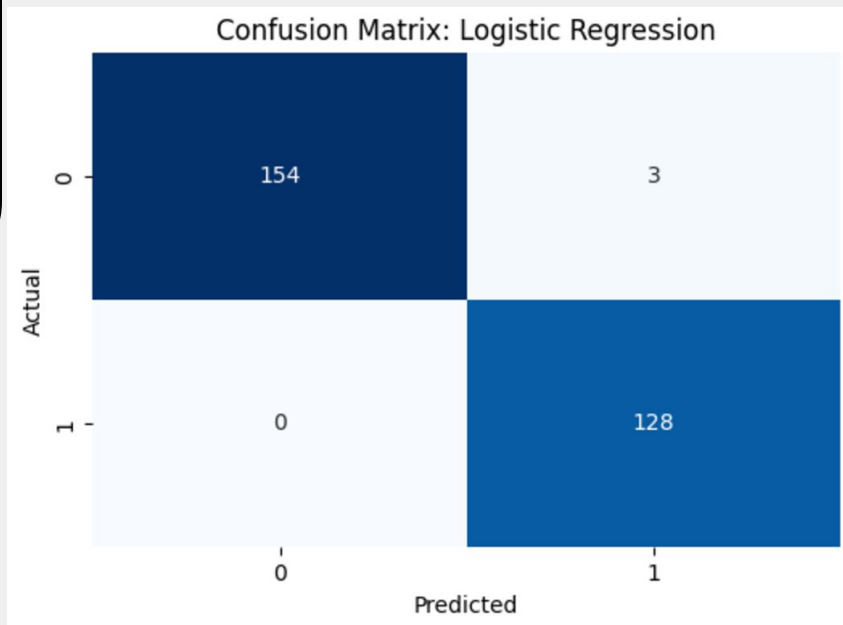


Models used in this projects:

1. Logistic Regression
2. Gaussian Naive Bayes
3. Decision Trees

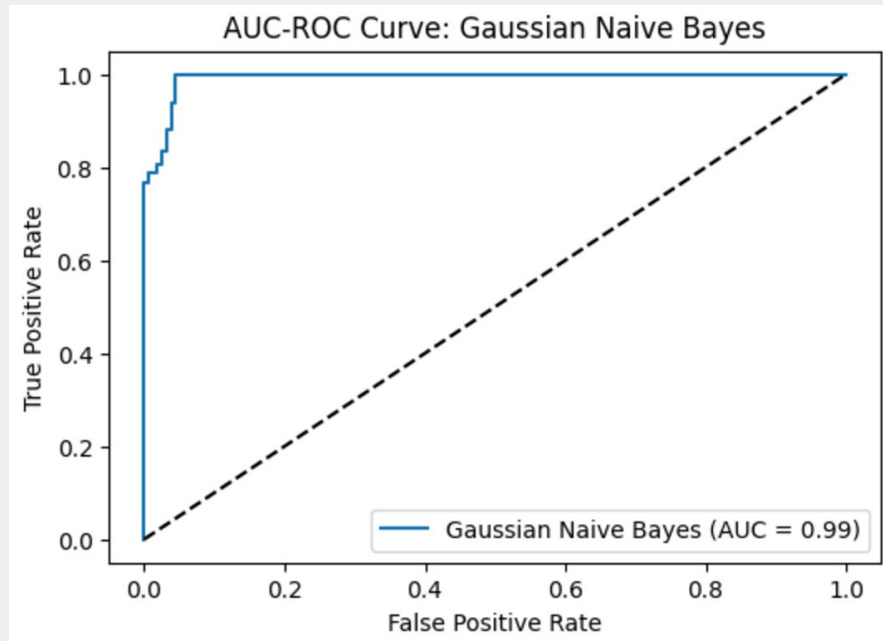
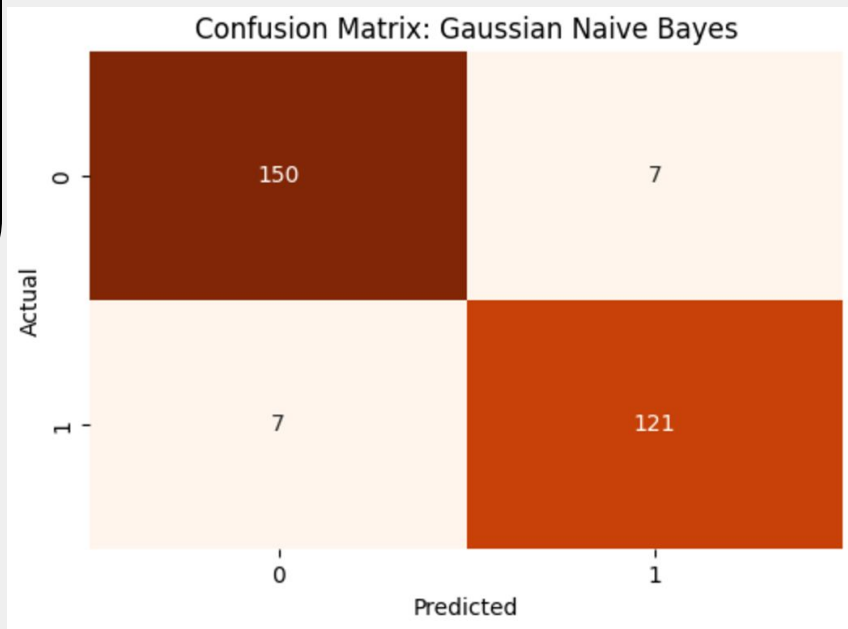
70/30 split was adopted in this project

# Logistic Regression



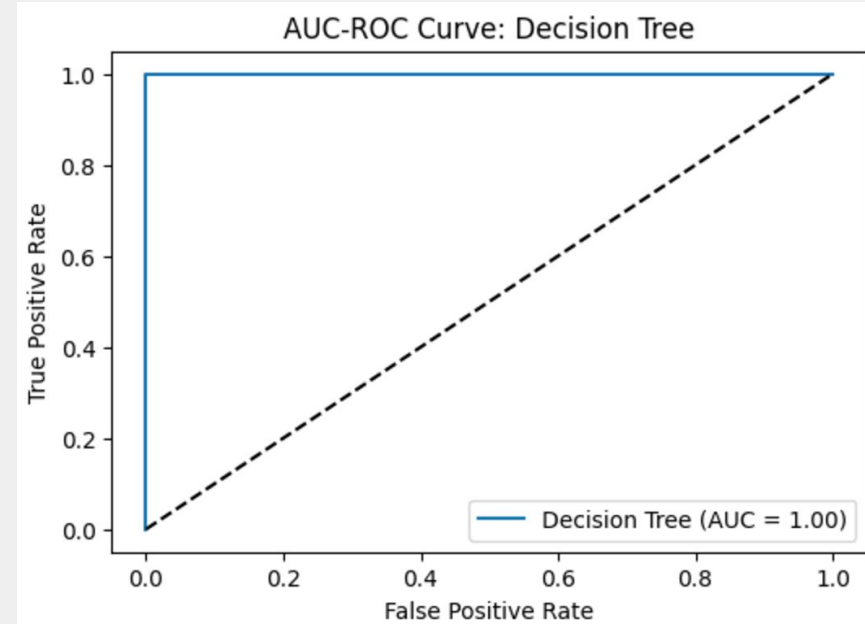
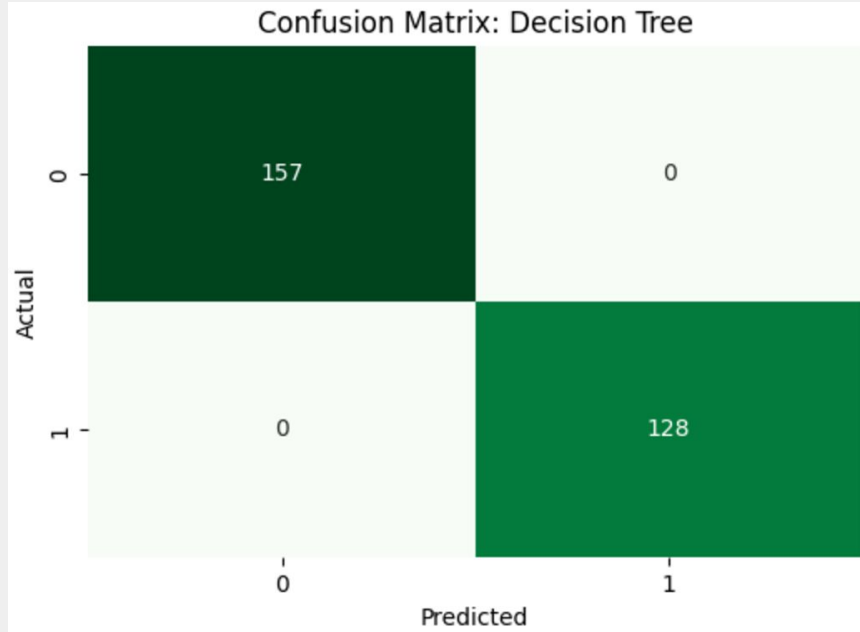
Accuracy: 0.99 F1 Score: 0.99 Recall: 1.00 AUC-ROC; 1.00

# Gaussian Naive Bayes



Accuracy: 0.95 F1 Score: 0.95 Recall: 0.95 AUC-ROC: 0.99

# Decision Tree



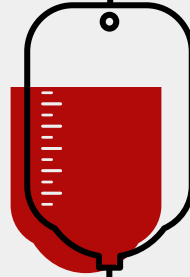
Accuracy: 1.00 F1 Score: 1.00 Recall: 1.00 AUC-ROC: 1.00

# Overfitting?



## Method 1

**Adopt an 80/20 split  
to 70/30**



## Method 2

**Cross-validation**





**Adopt an 80/20  
split to 70/30**

## Method 1:

<i>Split</i>	<i>80/20 Split</i>	<i>70/30 Split</i>
<b><i>Logistic Regression</i></b>	<i>Accuracy: 0.99</i> <i>F1 Score: 0.99</i> <i>Recall: 1.00</i> <i>AUC-ROC: 1.00</i>	<i>Accuracy: 0.99</i> <i>F1 Score: 0.99</i> <i>Recall: 1.00</i> <i>AUC-ROC: 1.00</i>
<b><i>Gaussian Naive Bayes</i></b>	<i>Accuracy: 0.97</i>  <i>F1 Score: 0.96</i>  <i>Recall: 0.98</i>  <i>AUC-ROC: 0.99</i>	<i>Accuracy: 0.95</i>  <i>F1 Score: 0.95</i>  <i>Recall: 0.95</i>  <i>AUC-ROC: 0.99</i>
<b><i>Decision Trees</i></b>	<i>Accuracy: 1</i>  <i>F1 Score: 1</i>  <i>Recall: 1</i>  <i>AUC-ROC: 1</i>	<i>Accuracy: 1</i>  <i>F1 Score: 1</i>  <i>Recall: 1</i>  <i>AUC-ROC: 1</i>



# Cross-validation

## Method 2:

<b>Logistic Regression</b>	<p>Cross-Validation Metrics (5-Fold):</p> <p>Accuracy Scores: [0.99497487 0.97487437 0.98492462 1. 0.98989899]</p> <p>Mean Accuracy: 0.99</p> <p>F1 Scores: [0.99435028 0.9726776 0.98342541 1. 0.98876404]</p> <p>Mean F1 Score: 0.99</p> <p>ROC-AUC Scores: [0.99979525 0.99948927 0.99938713 1. 1.]</p> <p>Mean ROC-AUC: 1.00</p>
<b>Gaussian Naive Bayes</b>	<p>Cross-validation Accuracy Scores: [0.89949749 0.96482412 0.92462312 0.94974874 0.93939394]</p> <p>Mean Cross-validation Accuracy: 0.9356174813461247</p> <p>Cross-validation AUC Scores: [0.97583948 0.99775281 0.98508682 0.98947906 0.98904959]</p> <p>Mean Cross-validation AUC: 0.9874415510319494</p>
<b>Decision Trees</b>	<p>Cross-validation Accuracy Scores: [1. 1. 1. 1. 1.]</p> <p>Mean Cross-validation Accuracy: 1.0</p> <p>Cross-validation AUC Scores: [1. 1. 1. 1. 1.]</p> <p>Mean Cross-validation AUC: 1.0</p>

**If there is no overfitting, why does this set of data perform so well?**

# Improvement

<i>Method</i>	<i>Accuracy</i>	<i>F1-score</i>	<i>Recall</i>	<i>AUC-ROC</i>
<i>Logistic Regression(No pre-processing)</i>	0.99	0.99	1	1
<i>Logistic Regression (SMOTE)</i>	0.99	0.99	1	1

<i>Method</i>	<i>Accuracy</i>	<i>F1-score</i>	<i>Recall</i>	<i>AUC-ROC</i>
<i>Gaussian Naive Bayes (No pre-processing)</i>	0.95	0.95	0.95	0.99
<i>Gaussian Naive Bayes (SMOTE)</i>	0.97	0.97	0.98	0.99

<i>Method</i>	<i>Accuracy</i>	<i>F1-score</i>	<i>Recall</i>	<i>AUC-ROC</i>
<i>Decision Trees (No pre-processing)</i>	1	1	1	1
<i>Decision Trees (SMOTE)</i>	1	1	1	1



## Standardization

The data did not follow a normal distribution



## SMOTE

The potential class imbalances in the dataset

### What happens after improvement?

The Naive Bayes model's accuracy increased from 95% to 97%, F1-score from 95% to 97%, and recall from 95% to 98%

# Feature Selection

## Feature Selection with the most relevant features (Hemoglobin and Gender)

Method	Accuracy	F1-score	Recall	AUC--ROC
Logistic Regression(No pre-processing)	0.99	0.99	1	1
Logistic Regression (Feature Selection)	0.99	0.99	1	1

Method	Accuracy	F1-score	Recall	AUC--ROC
Gaussian Naive Bayes (No pre-processing)	0.95	0.95	0.95	0.99
Gaussian Naive Bayes (Feature Selection)	0.97	0.97	0.98	0.99

Method	Accuracy	F1-score	Recall	AUC--ROC
Decision Trees (No pre-processing)	1	1	1	1
Decision Trees (Feature Selection)	1	1	1	1

## Feature Selection with the least relevant features (MCH, MCHC, and MCV)

Method	Accuracy	F1-score	Recall	AUC--ROC
Logistic Regression(No pre-processing)	0.99	0.99	1	1
Logistic Regression (Feature Selection with the most relevant features)	0.99	0.99	1	1
Logistic Regression (Feature Selection with the least relevant features)	0.55	0.00	0.00	0.51

Method	Accuracy	F1-score	Recall	AUC--ROC
Gaussian Naive Bayes (No pre-processing)	0.95	0.95	0.95	0.99
Gaussian Naive Bayes (Feature Selection with the most relevant features)	0.97	0.97	0.98	0.99
Gaussian Naive Bayes (Feature Selection with the least relevant features)	0.57	0.08	0.04	0.56

Method	Accuracy	F1-score	Recall	AUC--ROC
Decision Trees (No pre-processing)	1	1	1	1
Decision Trees (Feature Selection with the most relevant features)	1	1	1	1
Decision Trees (Feature Selection with the least relevant features)	0.96	0.96	0.93	0.96

# Summary

## Logistic Regression model performance:

<i>Method</i>	<i>Accuracy</i>	<i>F1-score</i>	<i>Recall</i>	<i>AUC-ROC</i>
<i>Logistic Regression(No pre-processing)</i>	0.99	0.99	1	1
<i>Logistic Regression (SMOTE)</i>	0.99	0.99	1	1
<i>Logistic Regression (Feature Selection with the most relevant features)</i>	0.99	0.99	1	1
<i>Logistic Regression (Feature Selection with the least relevant features)</i>	0.55	0.00	0.00	0.51

## Gaussian Naive Bayes model performance:

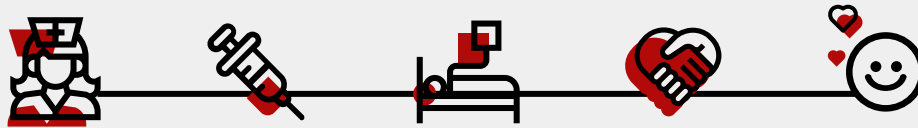
<i>Method</i>	<i>Accuracy</i>	<i>F1-score</i>	<i>Recall</i>	<i>AUC-ROC</i>
<i>Gaussian Naive Bayes (No pre-processing)</i>	0.95	0.95	0.95	0.99
<i>Gaussian Naive Bayes (SMOTE)</i>	0.97	0.97	0.98	0.99
<i>Gaussian Naive Bayes (Feature Selection with the most relevant features)</i>	0.97	0.97	0.98	0.99
<i>Gaussian Naive Bayes (Feature Selection with the least relevant features)</i>	0.57	0.08	0.04	0.56

## Decision Tree model performance:

<i>Method</i>	<i>Accuracy</i>	<i>F1-score</i>	<i>Recall</i>	<i>AUC-ROC</i>
<i>Decision Trees (No pre-processing)</i>	1	1	1	1
<i>Decision Trees (SMOTE)</i>	1	1	1	1
<i>Decision Trees (Feature Selection with the most relevant features)</i>	1	1	1	1
<i>Decision Trees (Feature Selection with the least relevant features)</i>	0.96	0.96	0.93	0.96

# Real - World Applications

- Decision Tree model
- Logistic Regression model
- SMOTE and feature selection



# Key Takeaways



**Decision  
Trees**



**Logistic  
Regression**



**Naive  
Bayes**



# Thanks!

Do you have any questions?

