



# Smart Healthcare Expense & Disease Prediction System

# Problem Statement



This project aims to build a Smart Healthcare Prediction System that can predict diseases and estimate healthcare expenses using patient data and improve lifestyle by giving suggestions.

# Data Overview

**Dataset Shape:** (1338, 7)

Rows: Number of patient records – 1338.

**Columns:**

Age, Sex, BMI, Children, Smoker, Region, Charges.

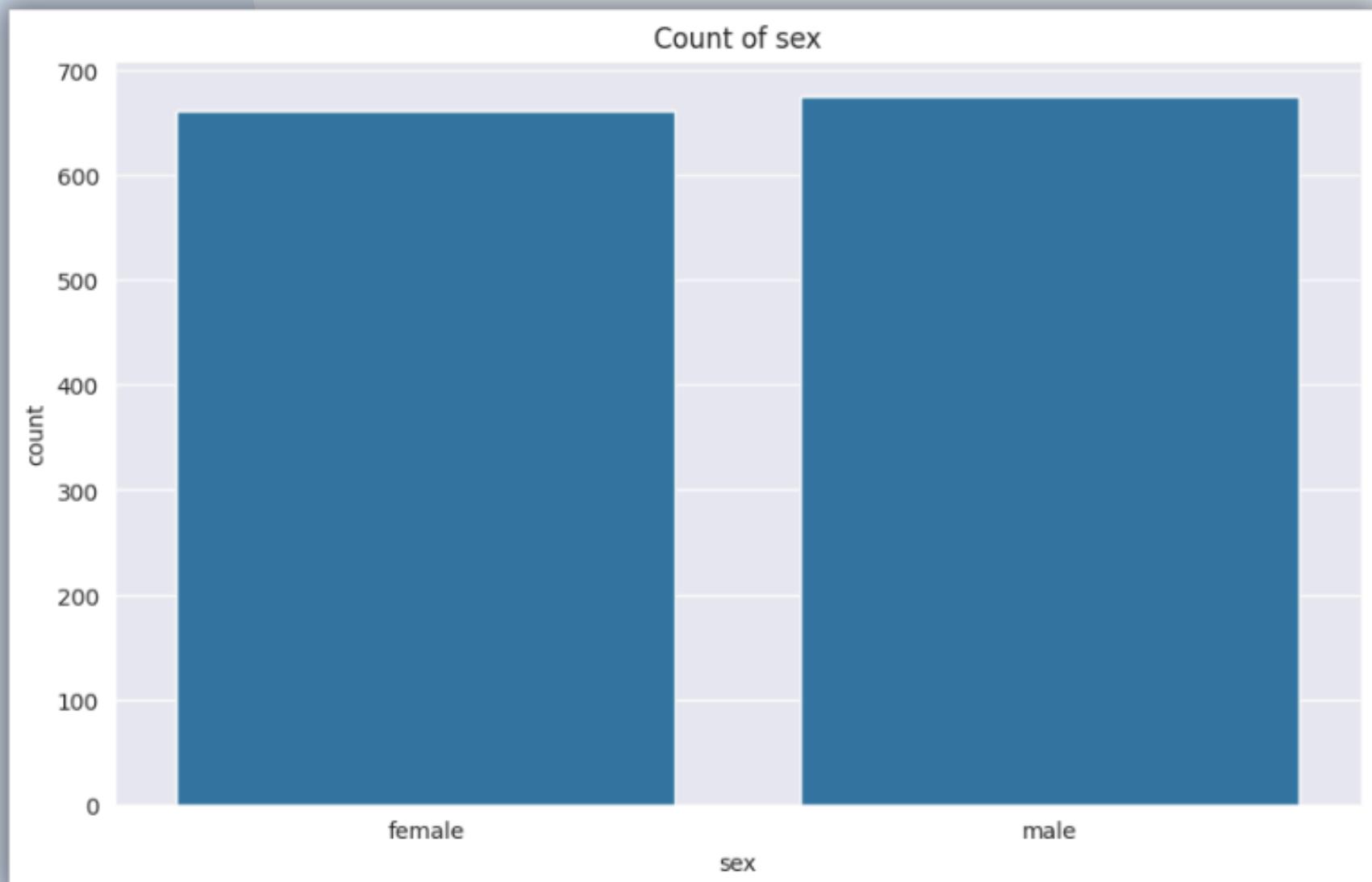
**Purpose:**

To analyze patient health data for predicting disease likelihood and estimating medical expenses, helping in early diagnosis and effective financial planning.

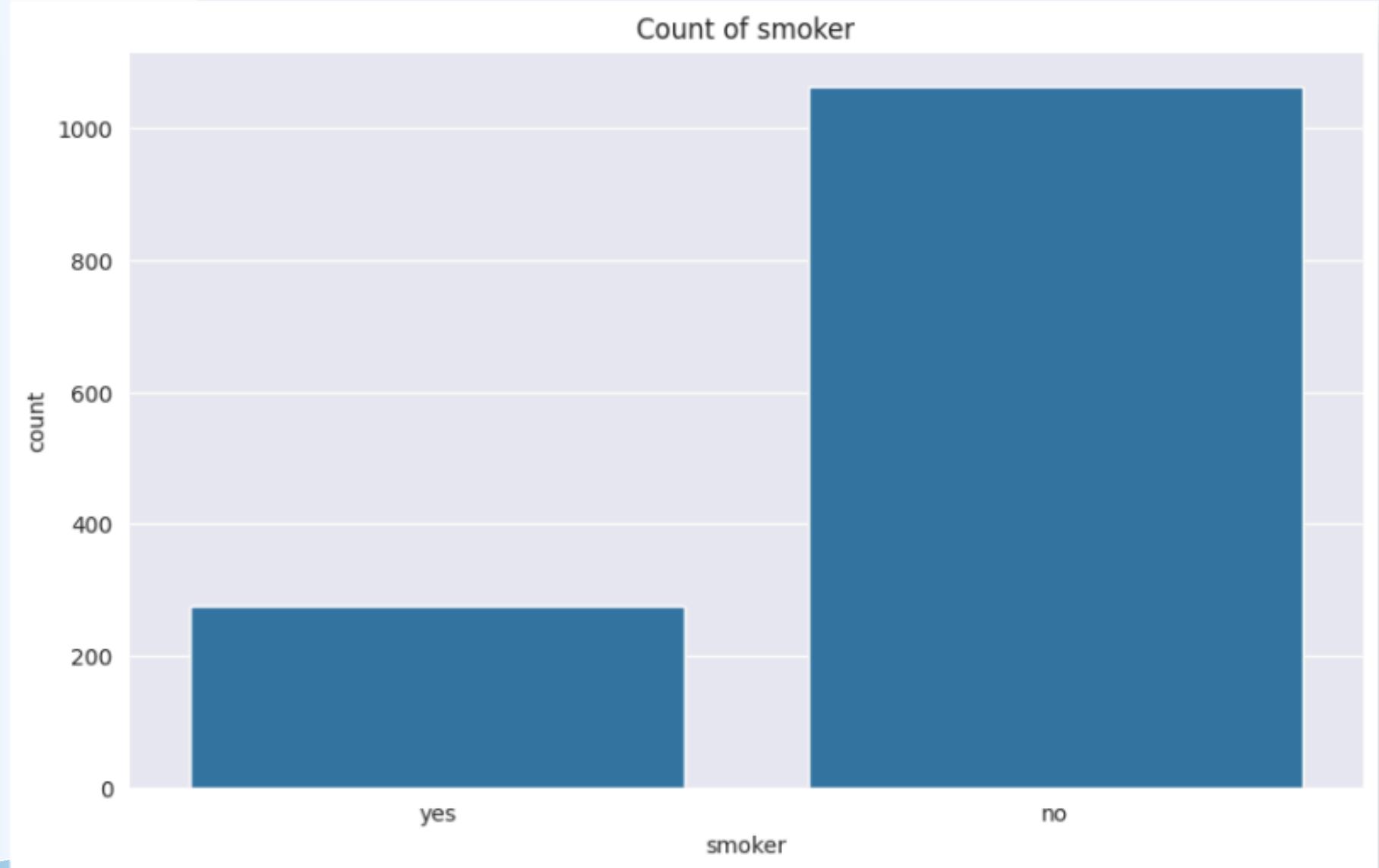


# EDA Visuals

Countplot- Gender Distribution



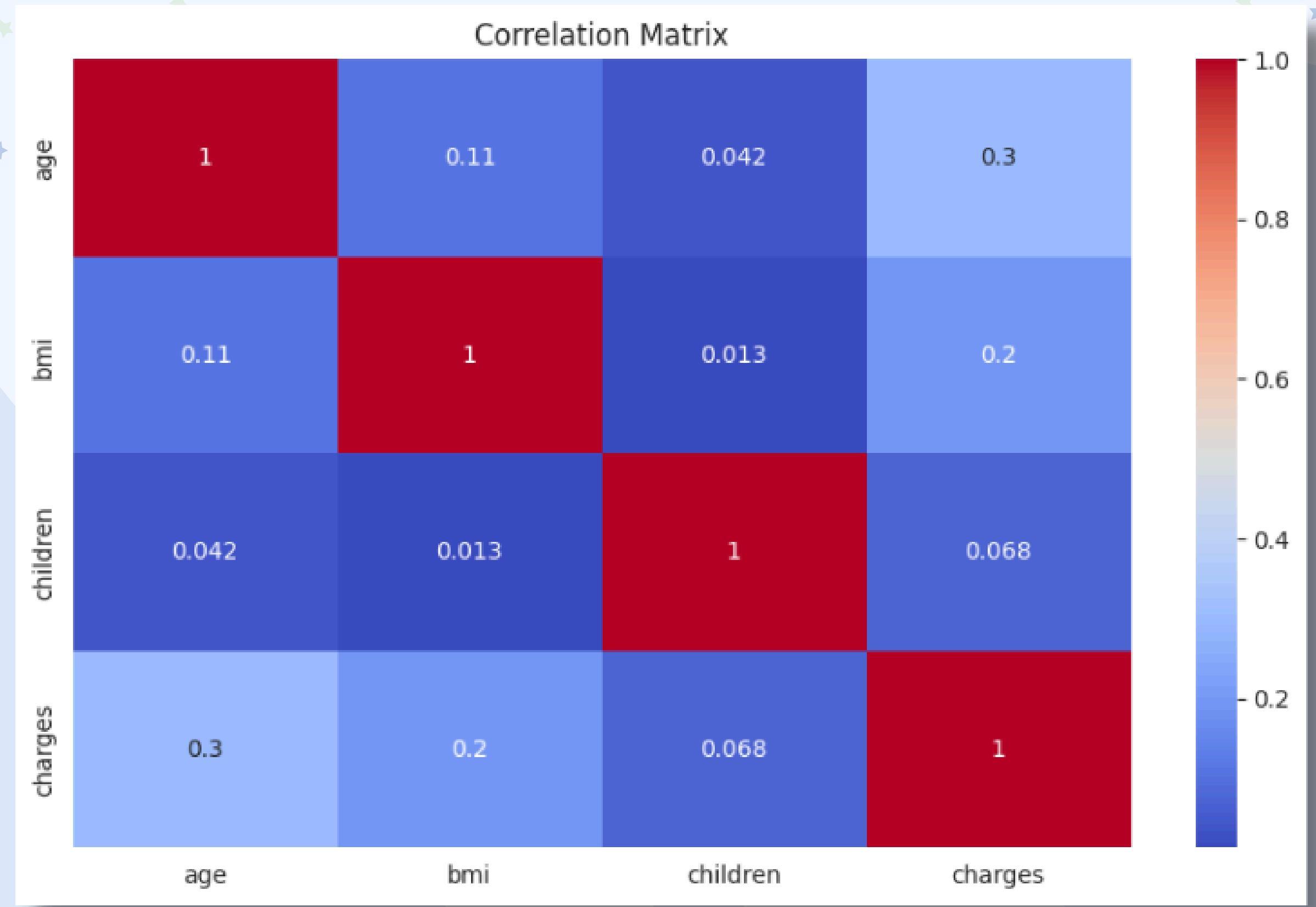
Countplot- Smokers Distribution



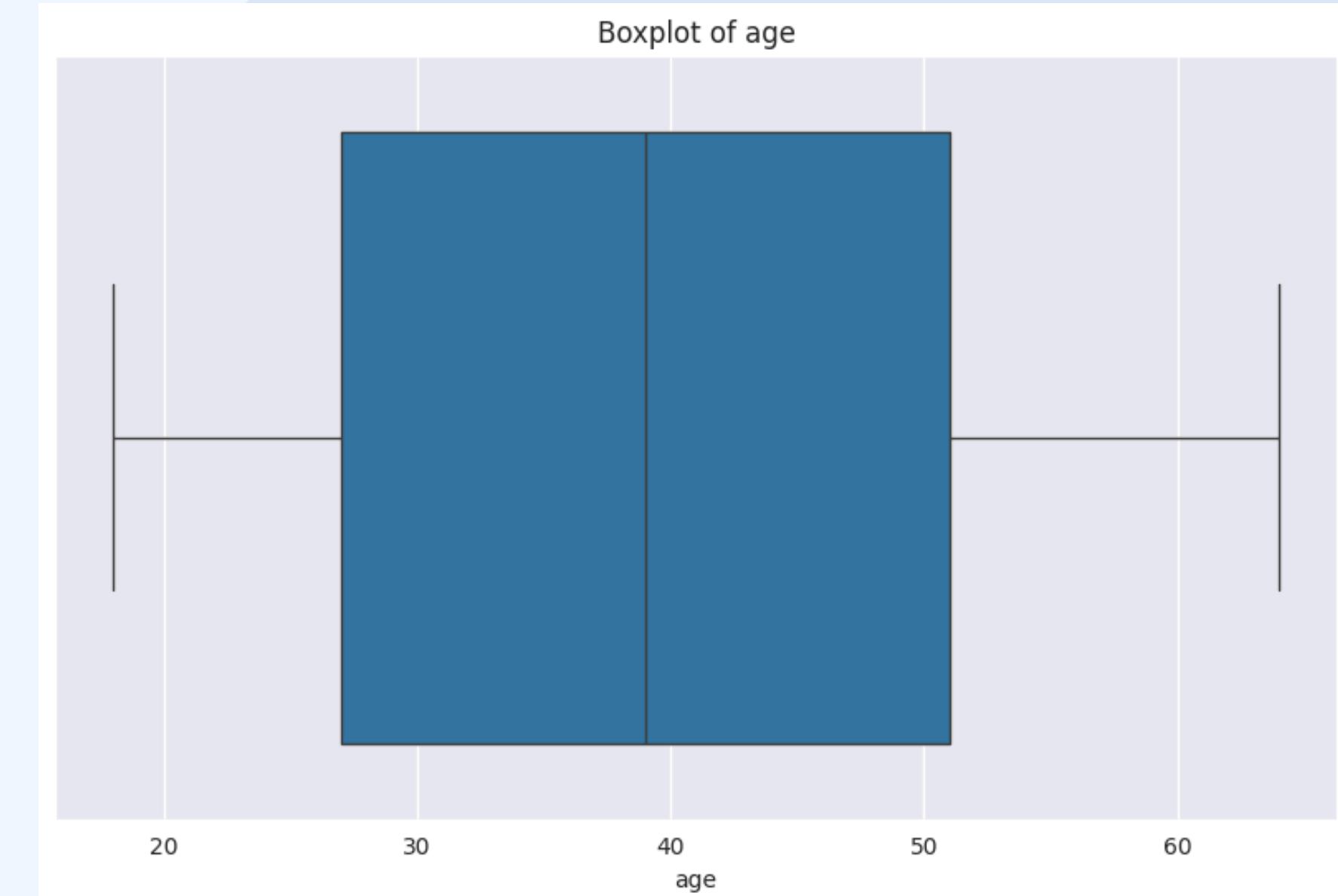
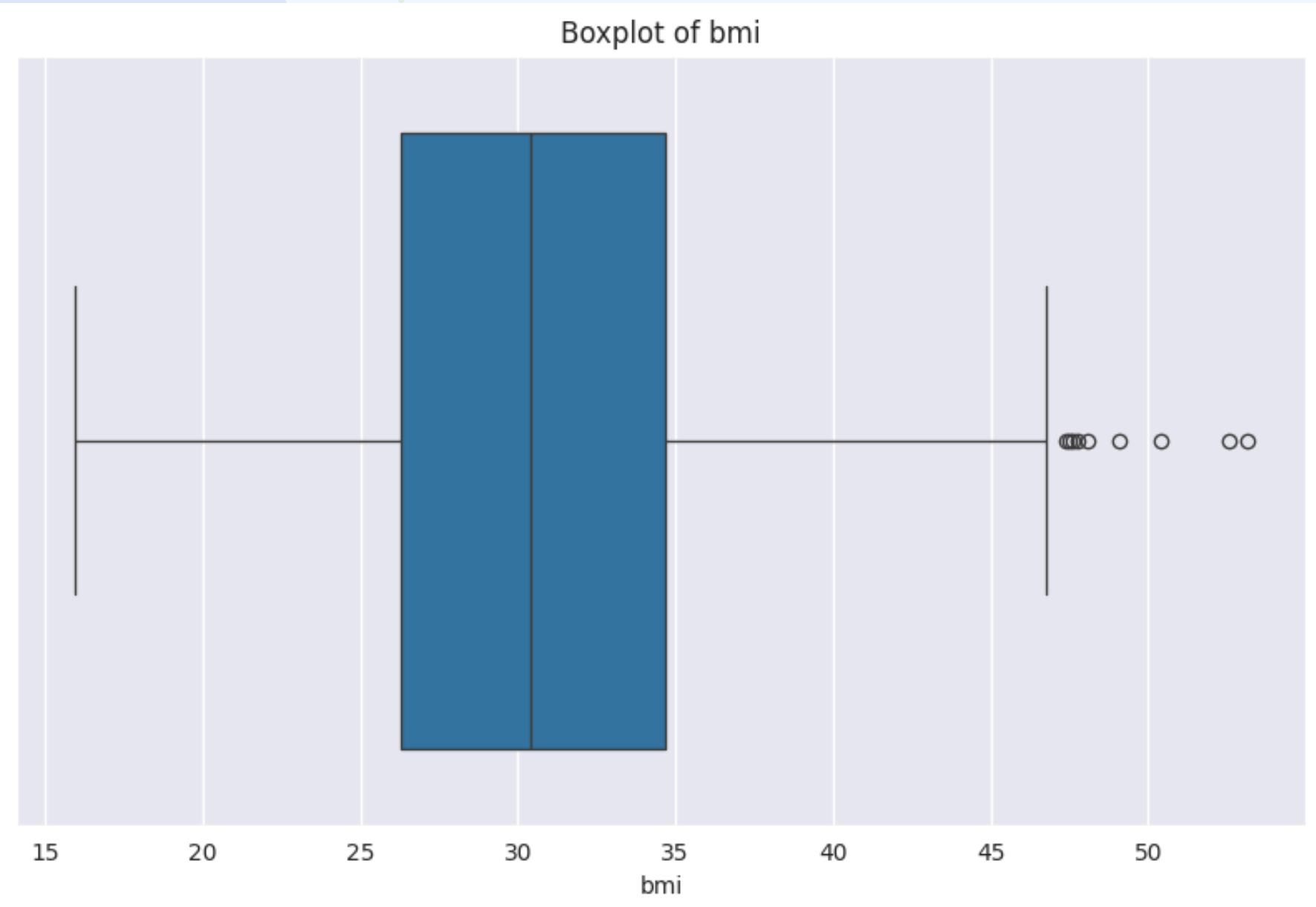
# Pairplot : relations and clusters by smoker status



# Heatmap : Feature Correlations



# Boxplot: Outliers



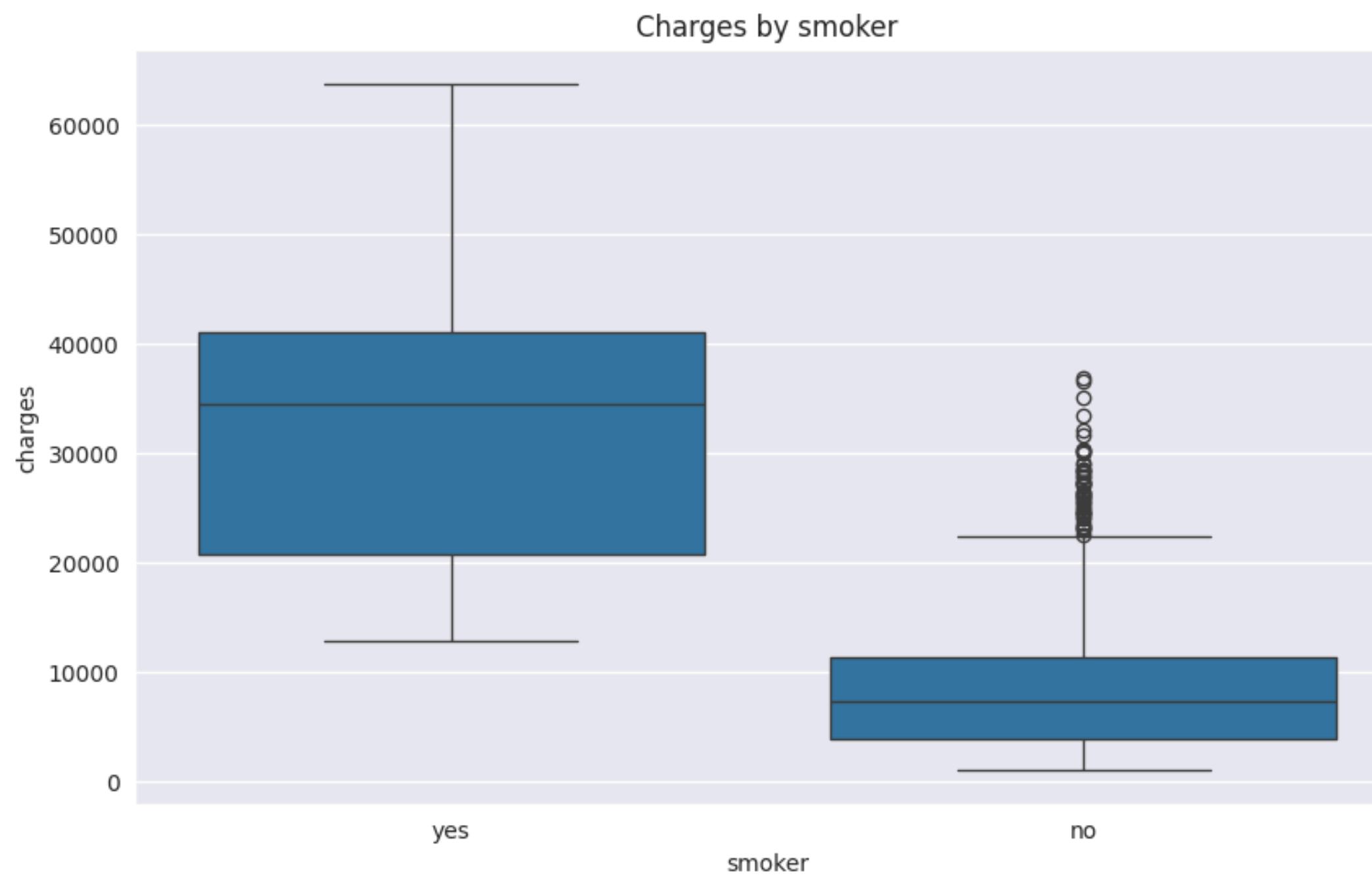
**Data Info:**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   age         1338 non-null    int64  
 1   sex         1338 non-null    object  
 2   bmi         1338 non-null    float64 
 3   children    1338 non-null    int64  
 4   smoker      1338 non-null    object  
 5   region      1338 non-null    object  
 6   charges     1338 non-null    float64 
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

**Statistical Summary:**

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

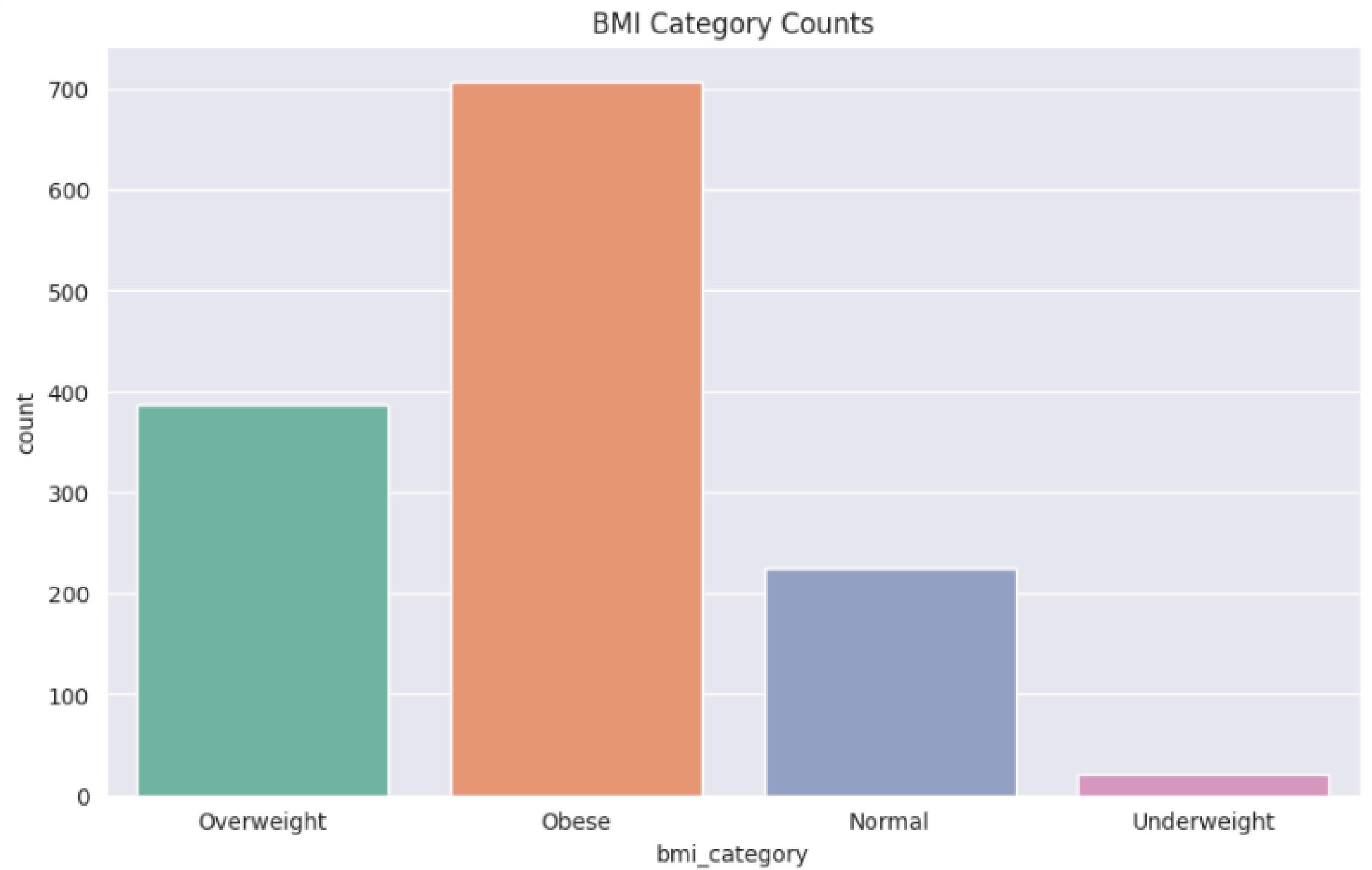
## Boxplot: Outliers



Number of outliers in charges: 139

# Feature Engineering

- A new feature `bmi_category` was created to classify patients based on their Body Mass Index (BMI).
- BMI values were grouped into four categories – Underweight, Normal, Overweight, and Obese
- Label encoding `bmi_category`

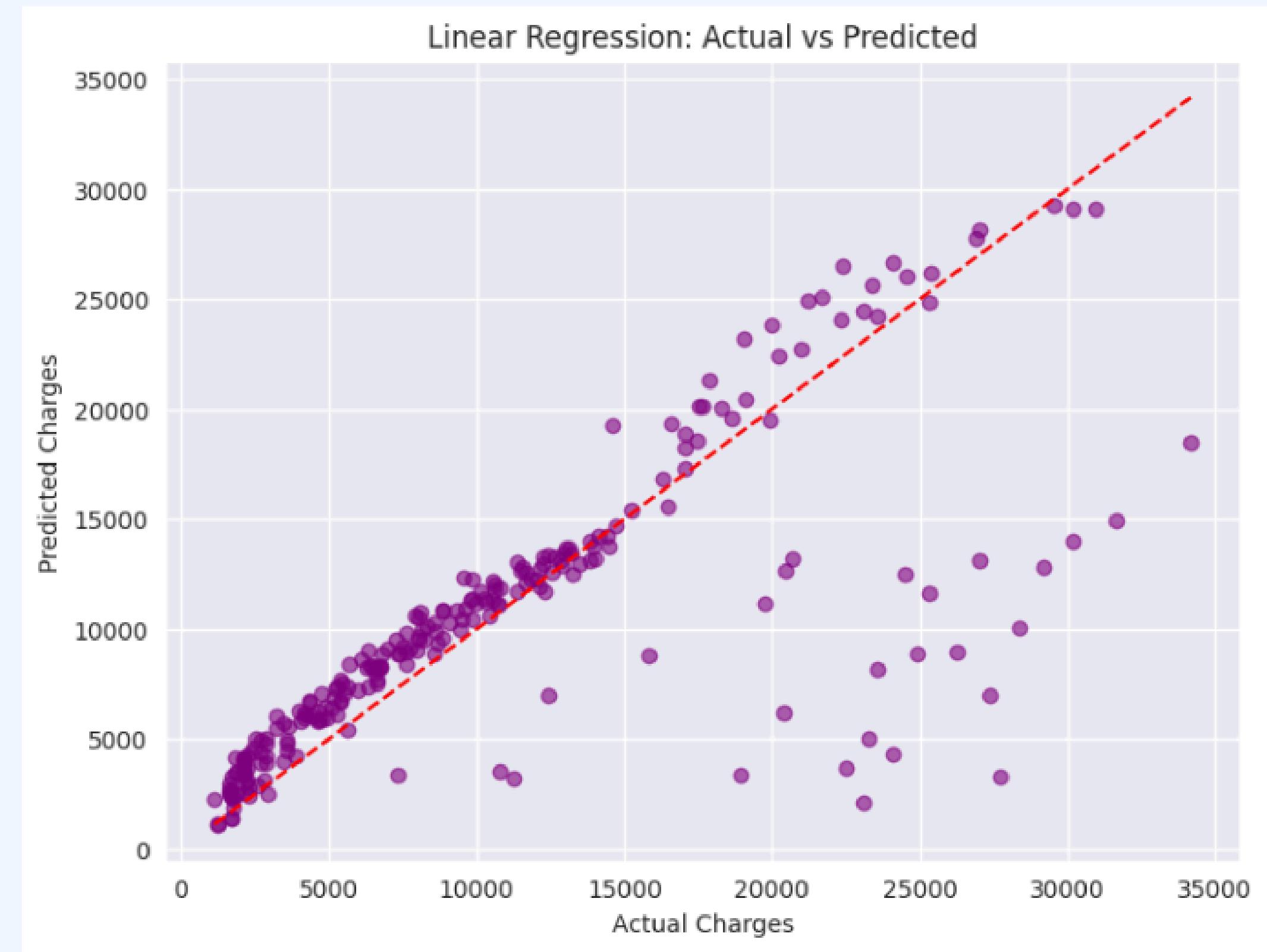


# Models Implemented

## Linear Regression

### Model Performance:

- R<sup>2</sup>. Score: 0.5568.
- MSE: 27647351.6858.
- RMSE: 5258.0749.
- MAE: 2797.0320.

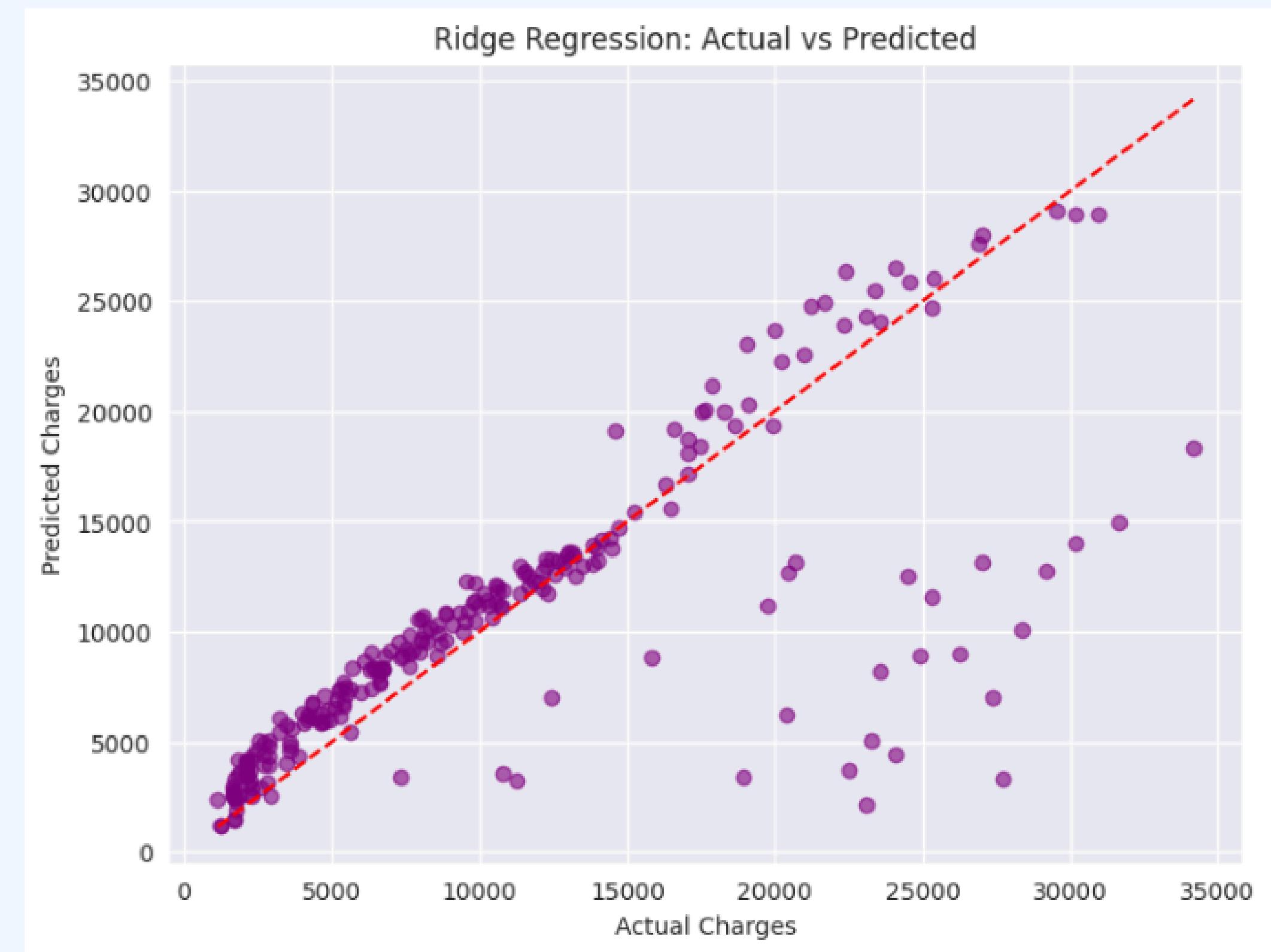


# Models Implemented

## Ridge Regression

### Ridge Regression Performance:

- R<sup>2</sup> Score: 0.5579
- MSE: 27575547.8138
- RMSE: 5251.2425
- MAE: 2791.5766

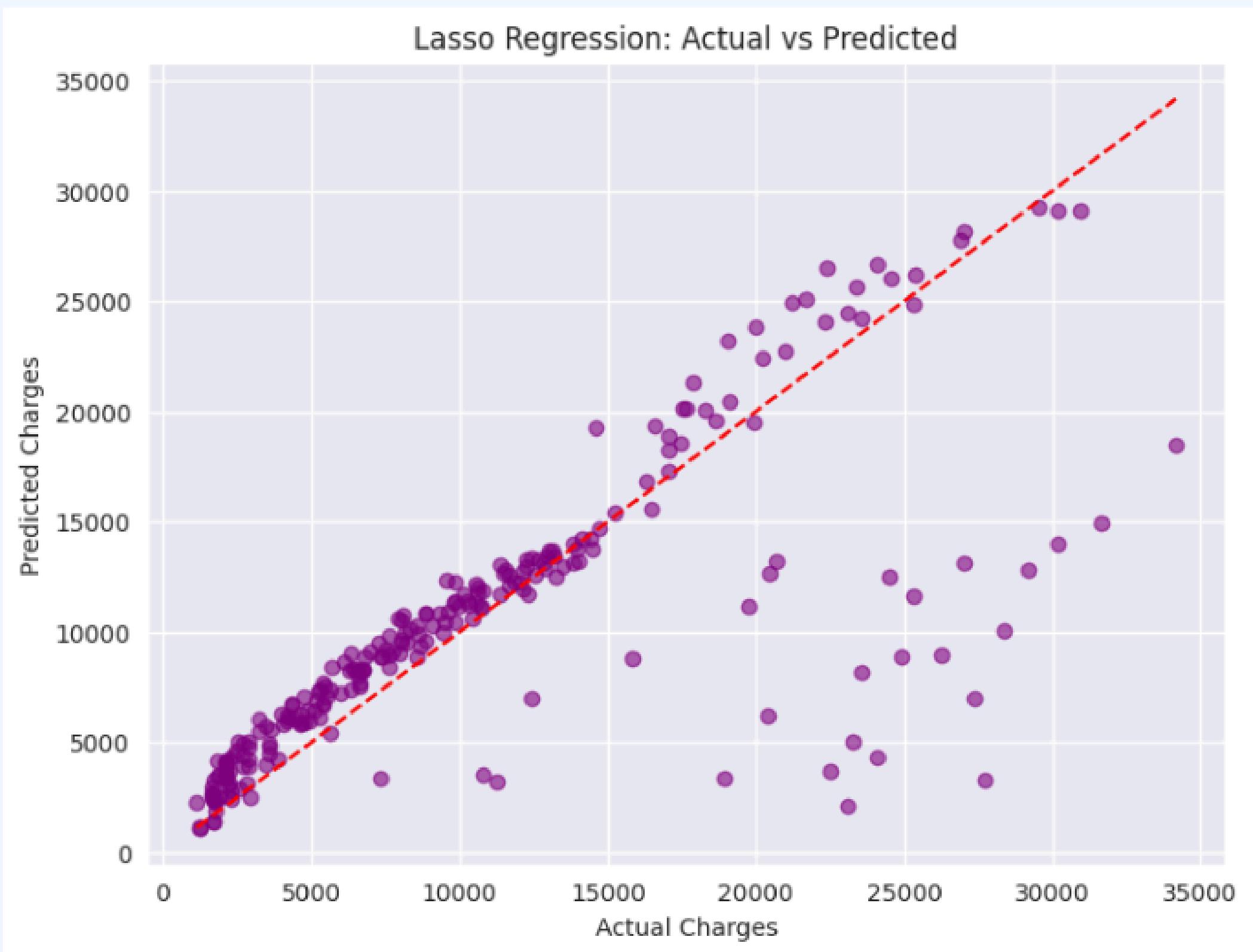


# Models Implemented

## Lasso Regression

### Lasso Regression Performance:

- R<sup>2</sup> Score: 0.5568
- MSE: 27647317.0629
- RMSE: 5258.0716
- MAE: 2797.024

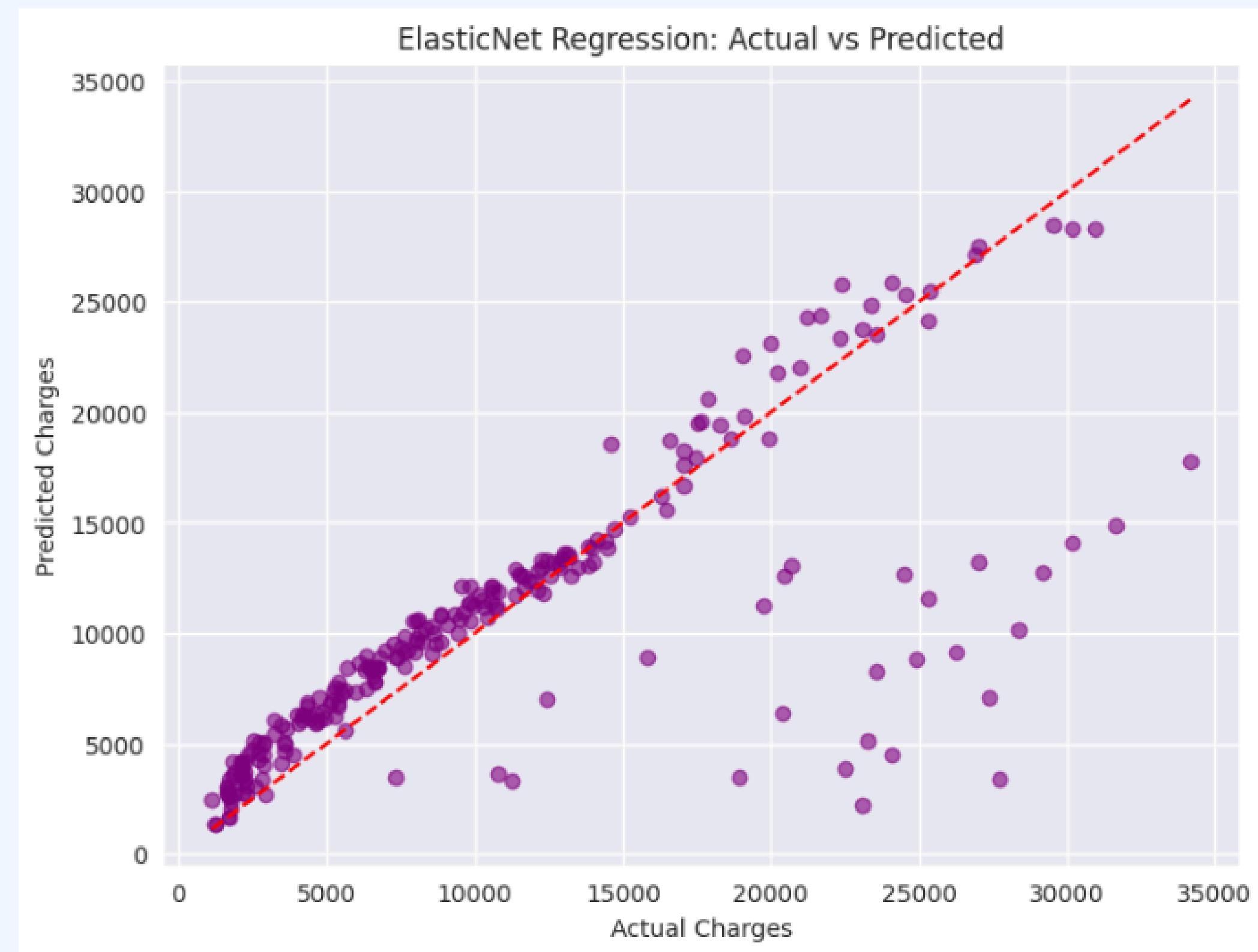


# Models Implemented

## ElasticNet Regression

### ElasticNet Regression Performance:

- R<sup>2</sup> Score: 0.5611
- MSE: 27380338.4948
- RMSE: 5232.6225
- MAE: 2778.8538



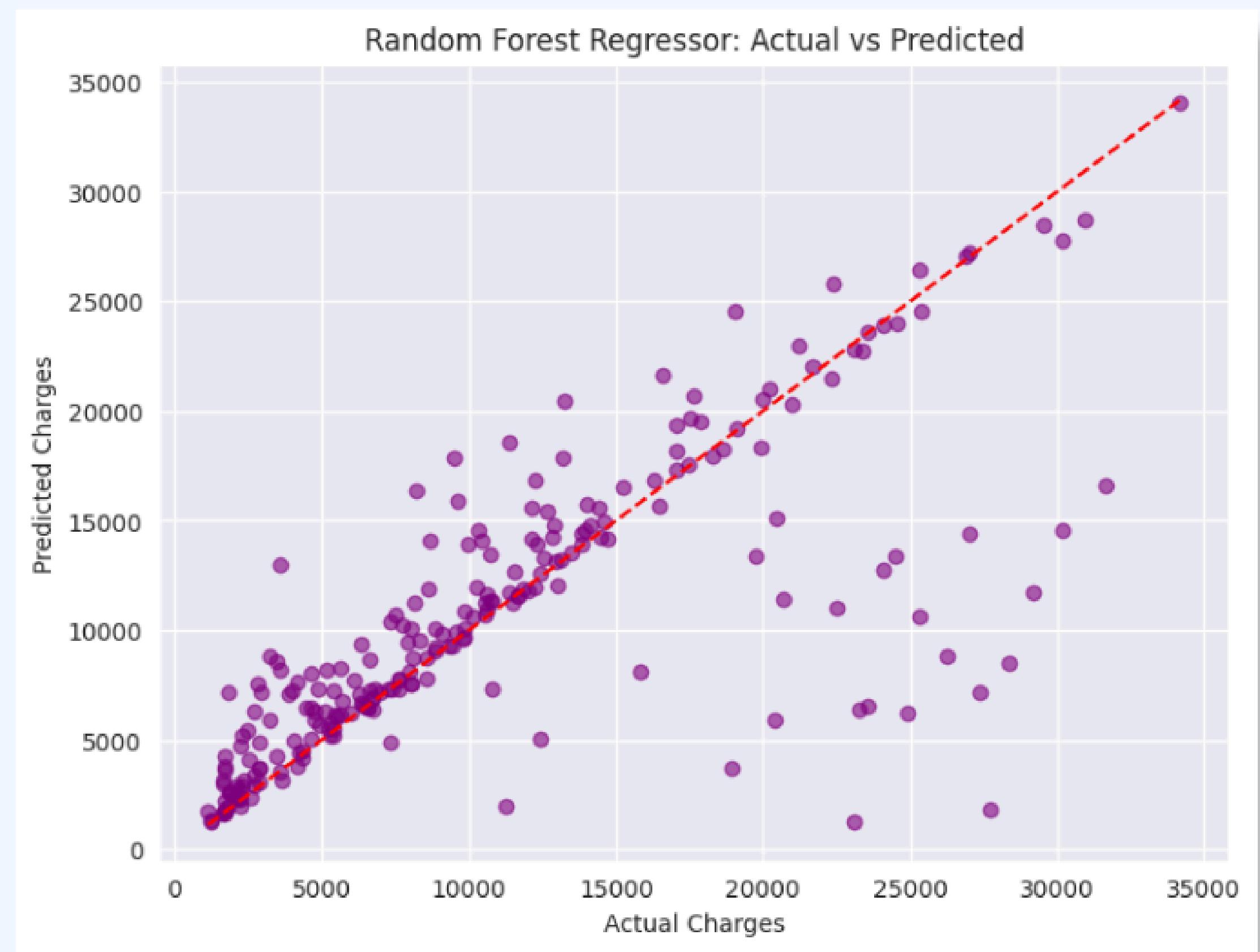
# Models Implemented

## Random Forest Regression

### Random Forest Regressor

#### Performance:

- R<sup>2</sup> Score: 0.5607
- MSE: 27403463.4422
- RMSE: 5234.8317
- MAE: 2689.3716

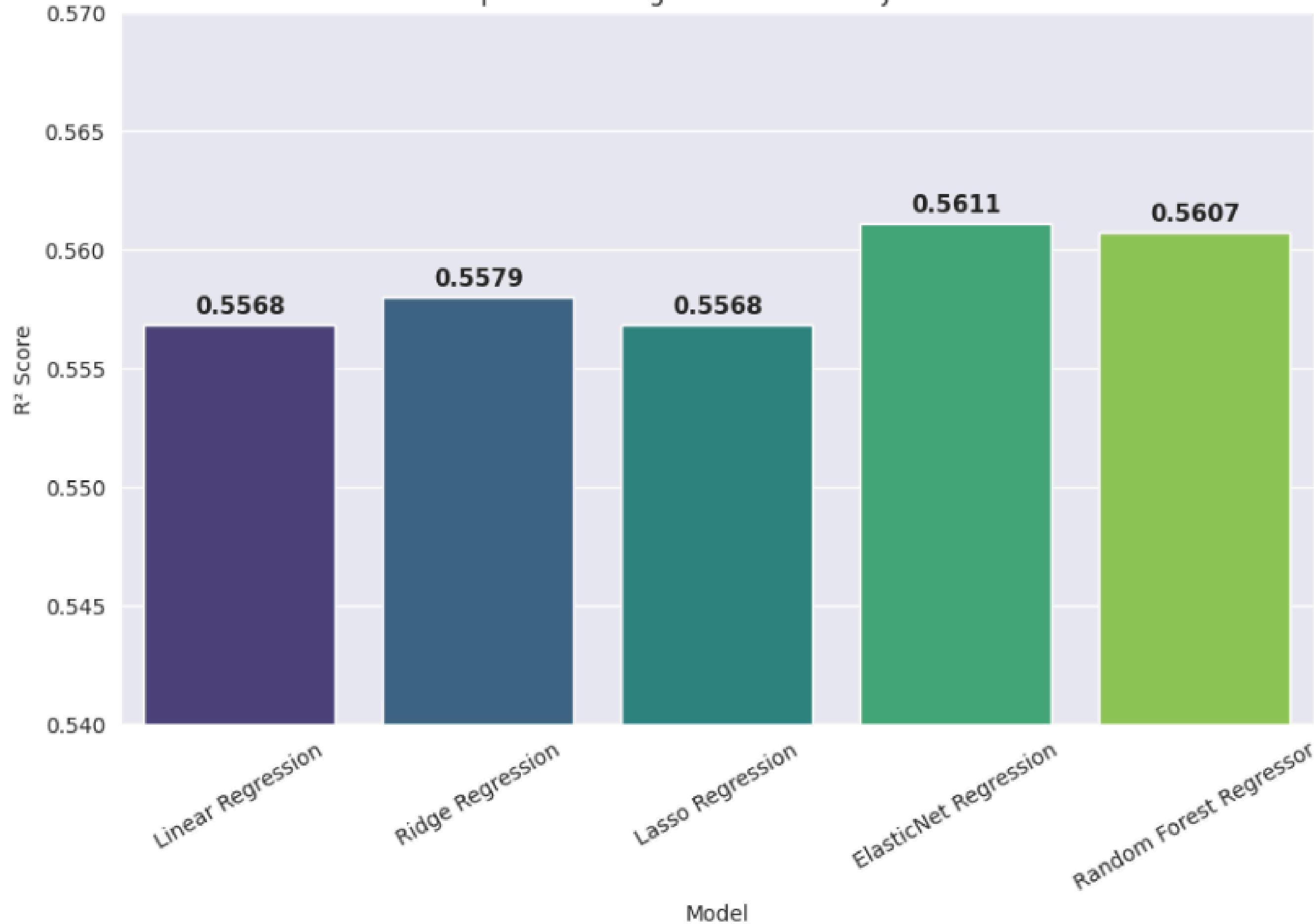


# Model Comparison Table

Model Comparison Table:

	Model	R2 Score	MSE	RMSE	MAE
3	ElasticNet Regression	0.561074	2.738034e+07	5232.622526	2778.853821
4	Random Forest Regressor	0.560703	2.740346e+07	5234.831749	2689.371620
1	Ridge Regression	0.557945	2.757555e+07	5251.242502	2791.576617
2	Lasso Regression	0.556794	2.764732e+07	5258.071611	2797.024703
0	Linear Regression	0.556794	2.764735e+07	5258.074903	2797.031953

### Comparison of Regression Models by R<sup>2</sup> Score



# Feature Engineering

- The charges column was divided into three categories – Low Risk, Medium Risk, and High Risk – based on medical expense ranges.
- These categories were label encoded into numbers so the model can process them easily.

```
Class distribution in full data:
```

```
risk
```

```
Low Risk      712
```

```
Medium Risk   464
```

```
High Risk     23
```

```
Name: count, dtype: int64
```

```
Class distribution in test set:
```

```
risk_label
```

```
1      142
```

```
2      93
```

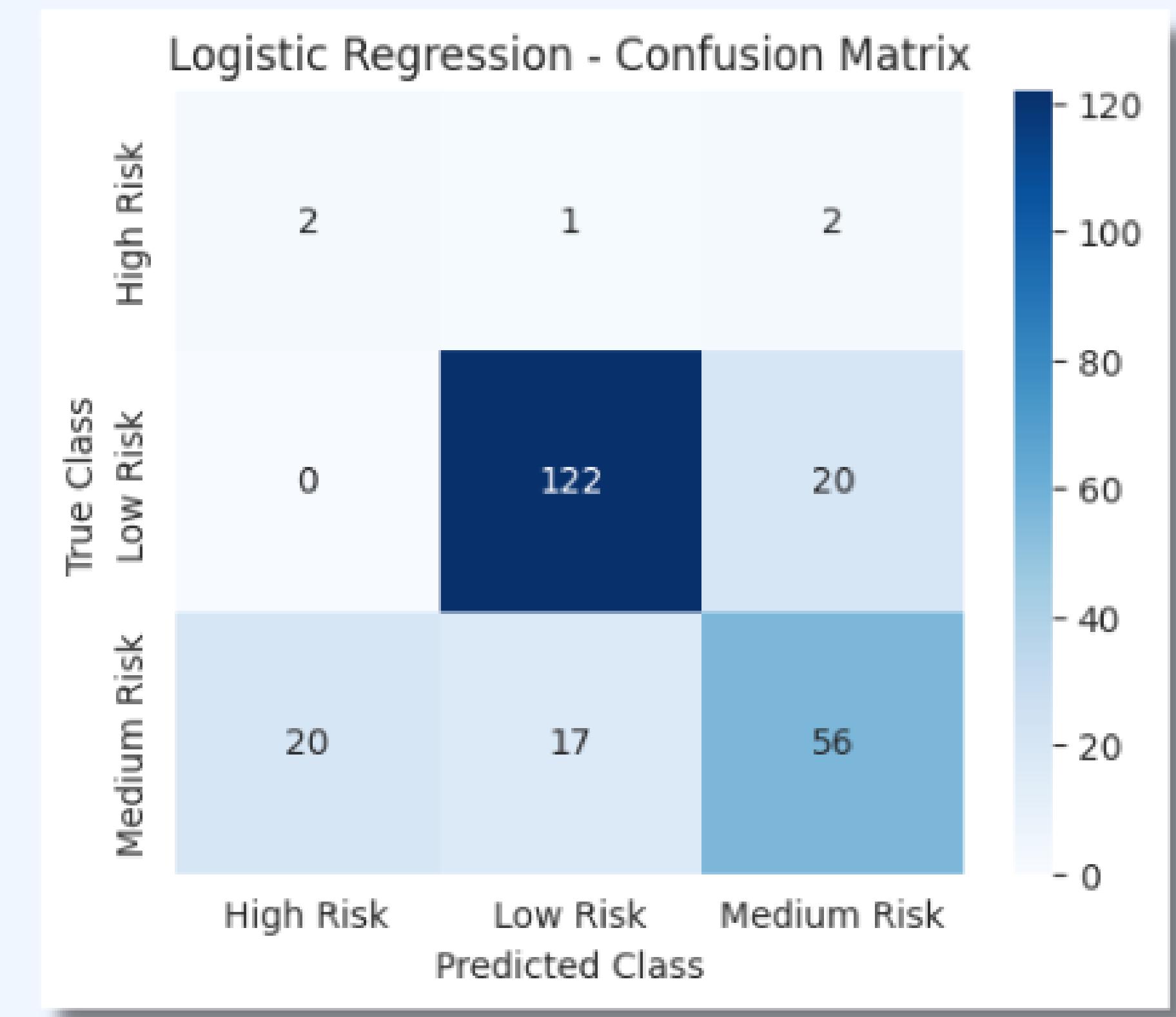
```
0       5
```

```
Name: count, dtype: int64
```

# Models Implemented

## Logistic Regression

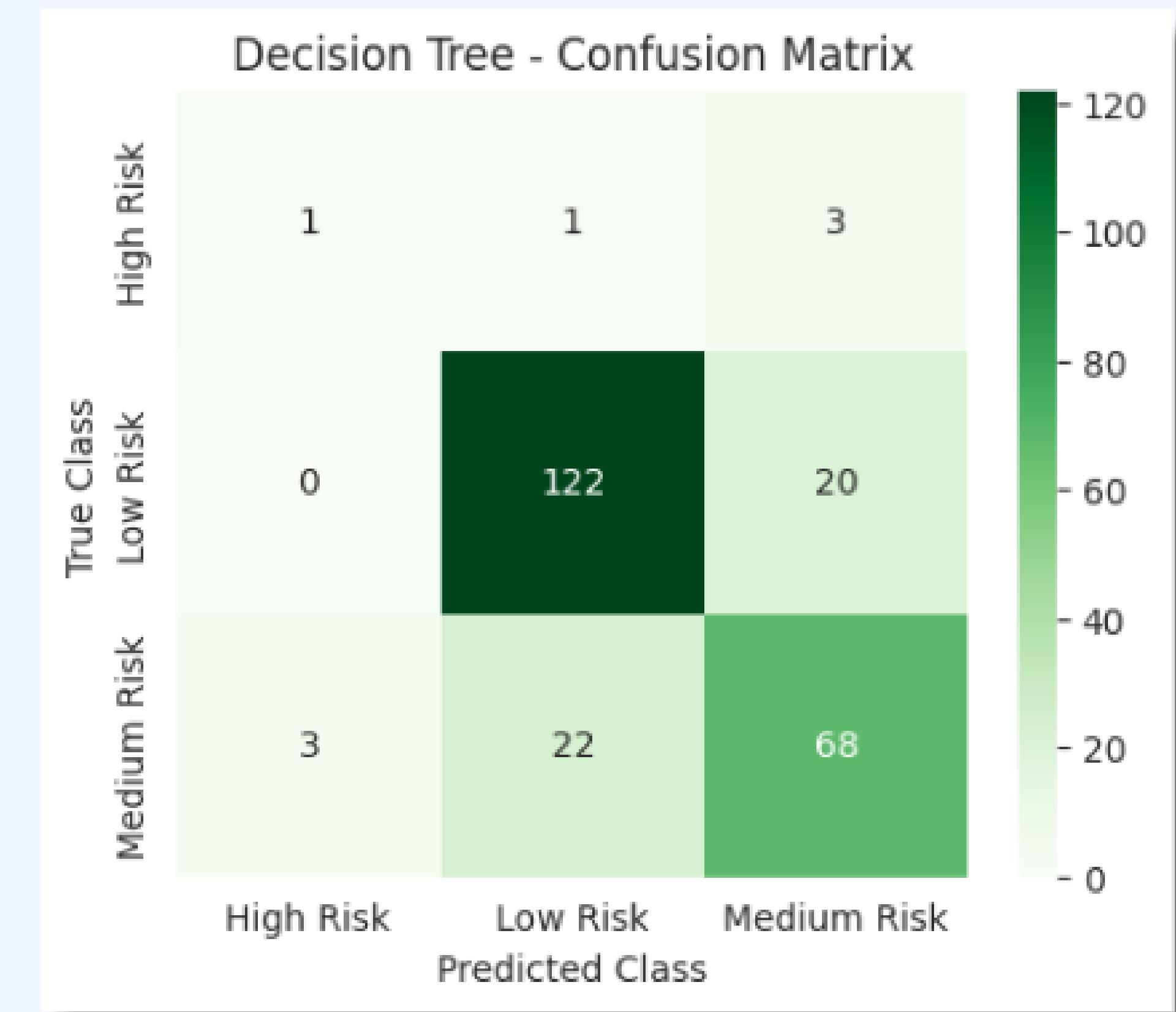
**Accuracy:** 0.7500,  
**Precision:** 0.7957



# Models Implemented

**Accuracy:** 0.7958,  
**Precision:** 0.7926

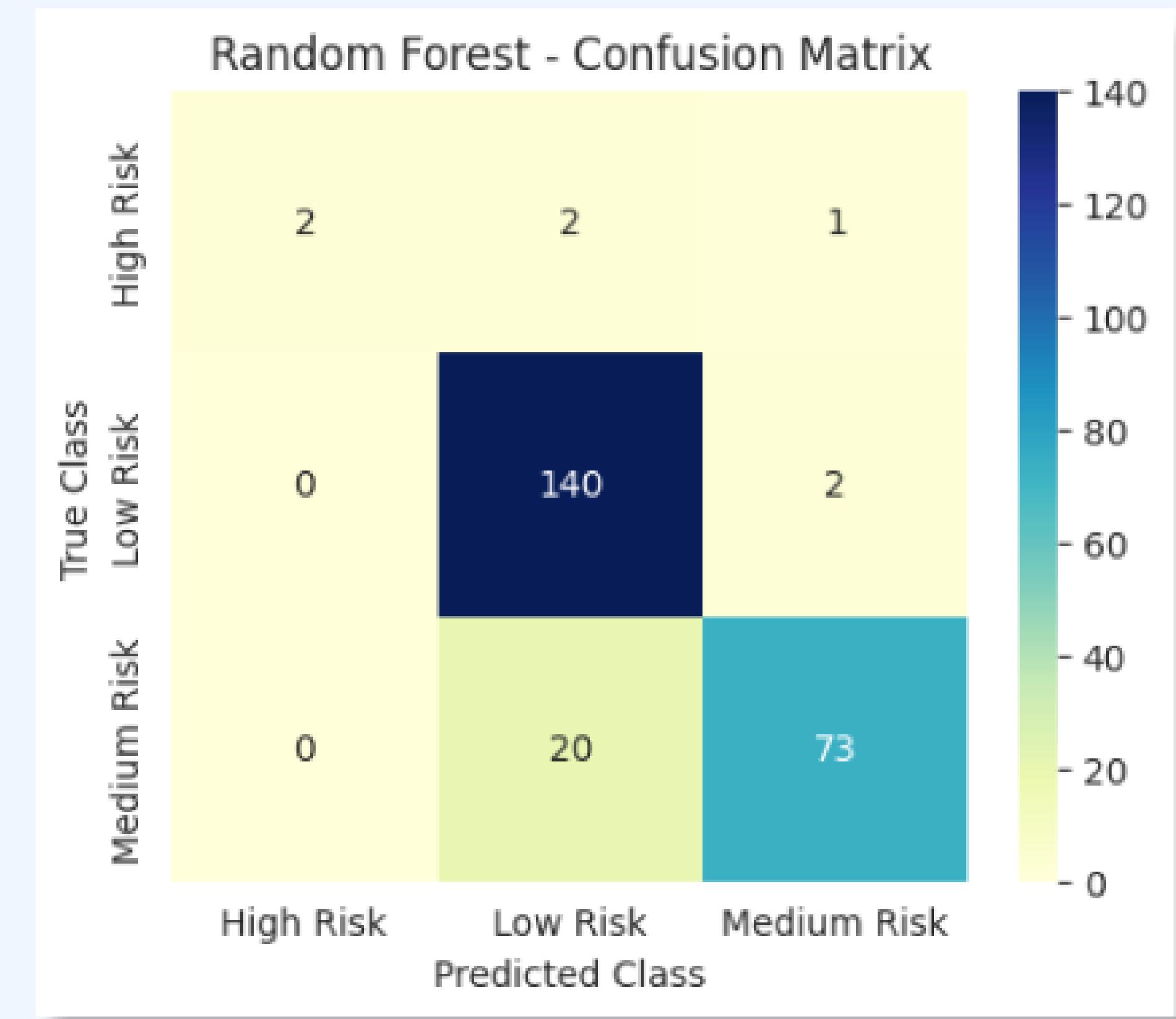
## Decision Tree



# Models Implemented

**Accuracy:** 0.8958,  
**Precision:** 0.9044

## Random Forest



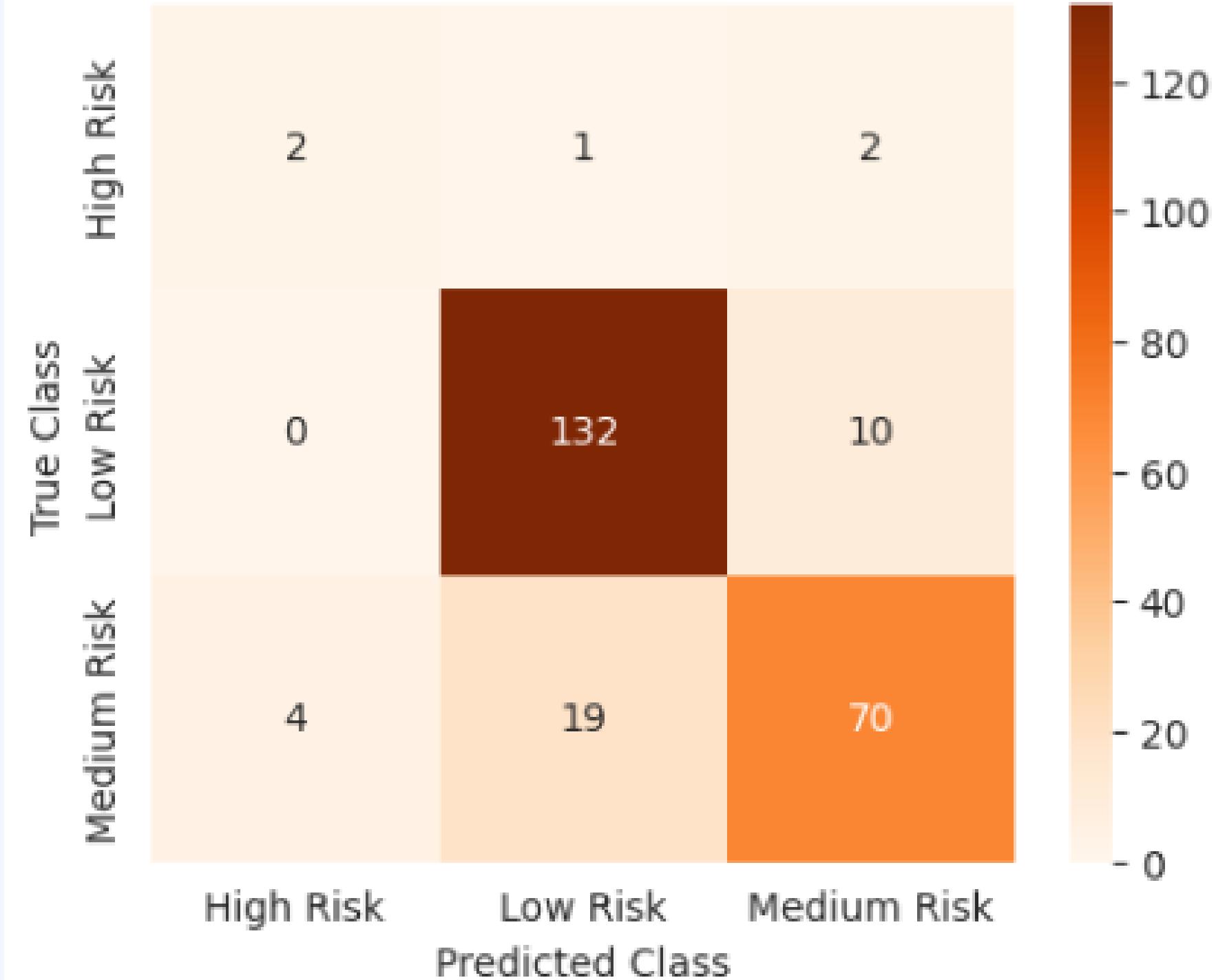
# Models Implemented

## SVM

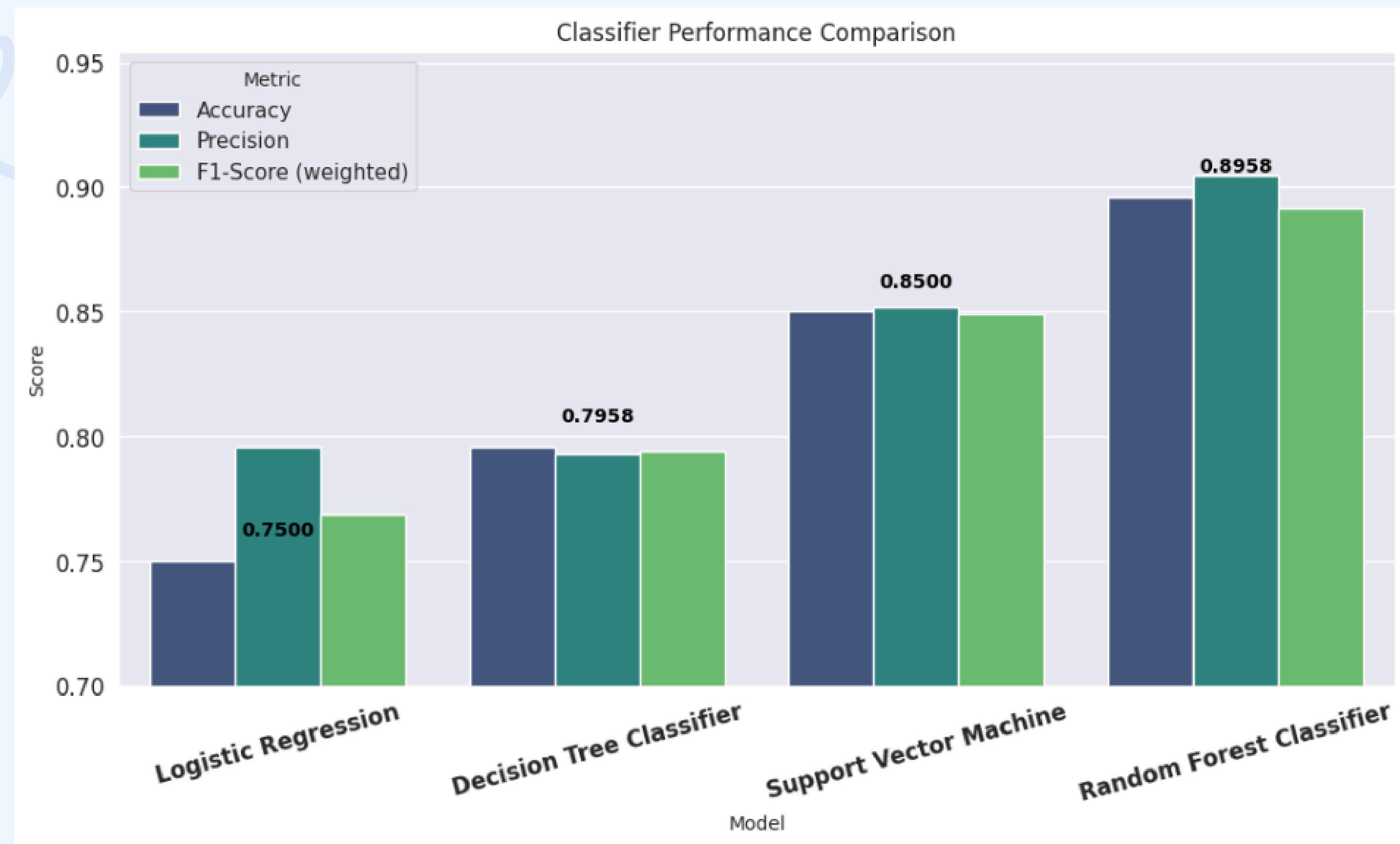
**Accuracy:** 0.8500

**Precision:** 0.8516

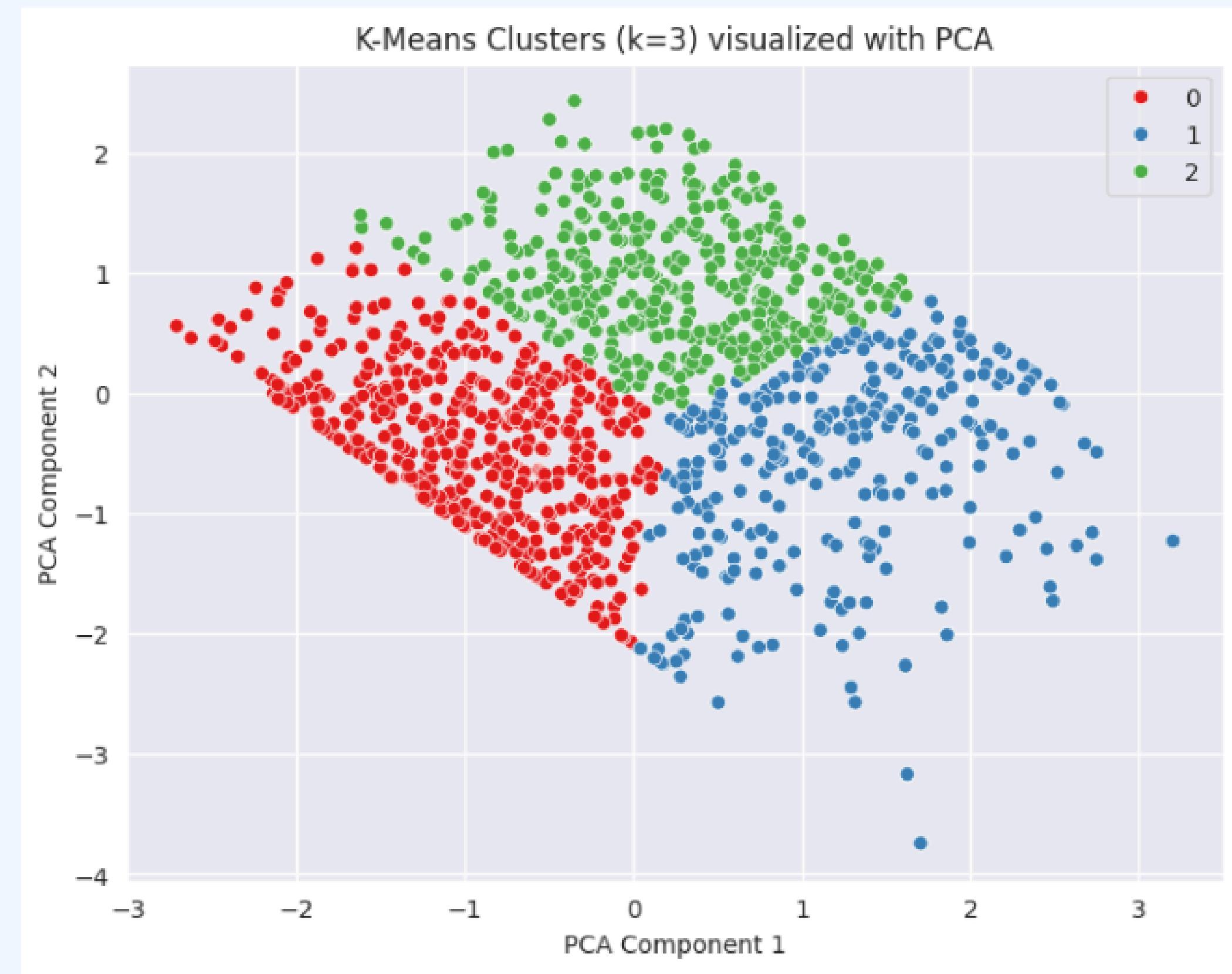
SVM - Confusion Matrix



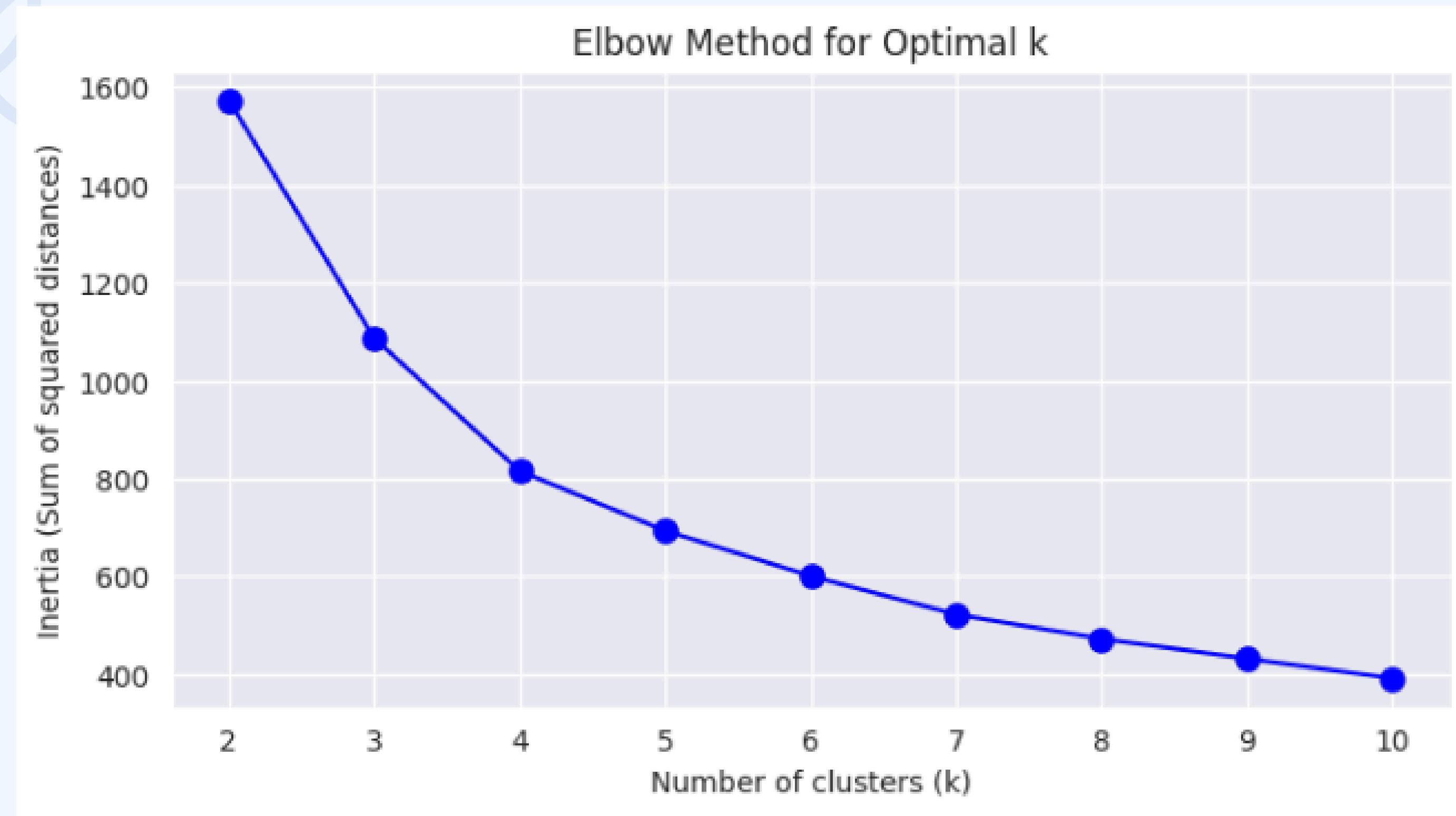
# Model Comparison Table



# K-Means Clustering



# K-Means Clustering



- The K-Means clustering algorithm grouped individuals into meaningful lifestyle or risk-based categories.
- Evaluation using Silhouette Score confirmed good cluster quality and separation.
- Overall, this approach provides valuable insights for health risk prediction and personalized insurance planning.





# Conclusion

- For classification, the Random Forest Classifier gave the highest accuracy and stability among all models.
- For regression, the Linear Regression model achieved the best  $R^2$  score and lowest mean squared error (MSE).
- Hence, Random Forest is best suited for disease risk prediction, while Linear Regression is most effective for medical expense prediction.



# Thank You

