Supervised Learning Diabetes report

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Project Goals

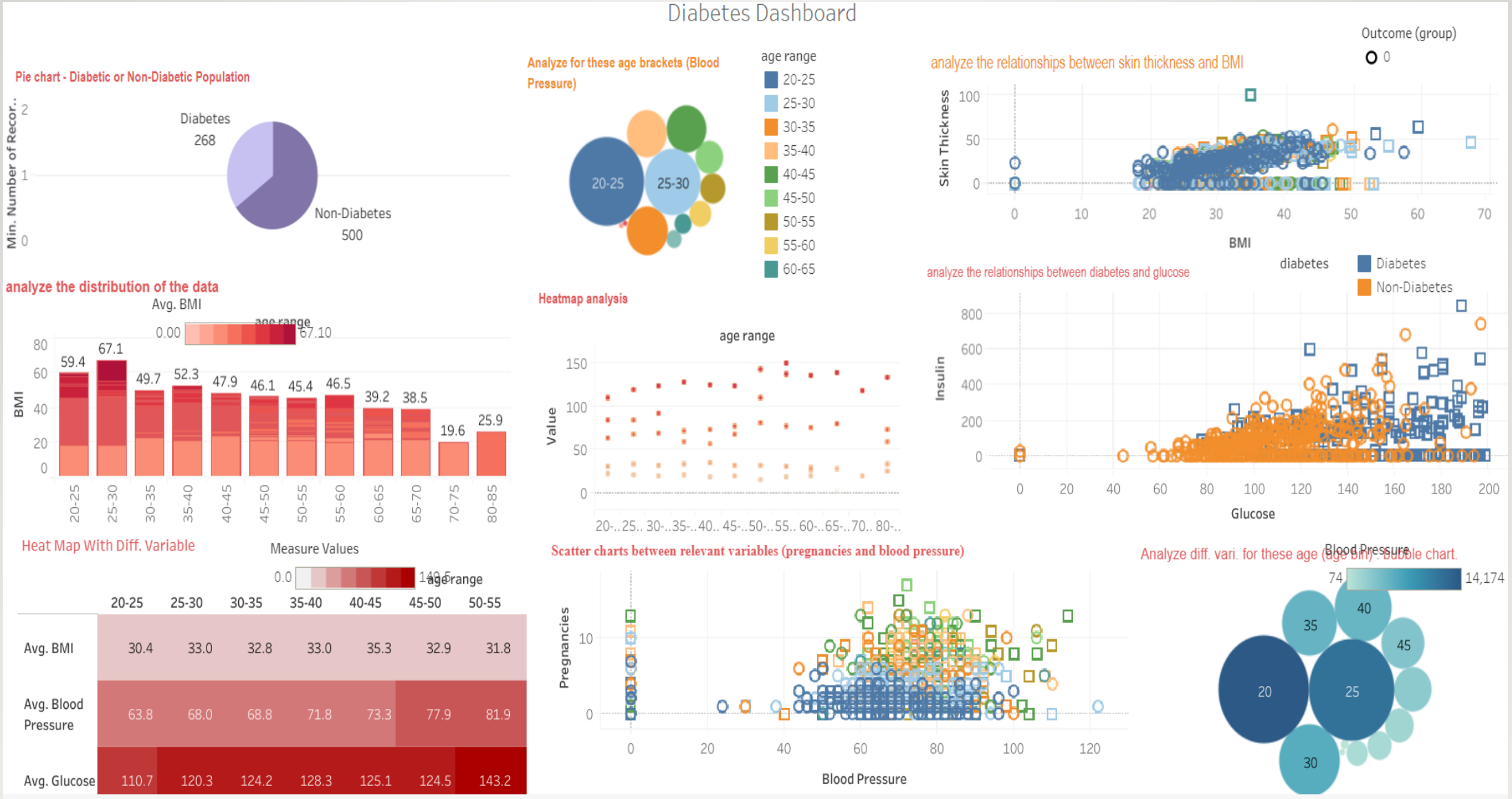
Use supervised learning techniques to build a machine learning model that can predict whether a patient has diabetes or not, based on certain diagnostic measurements.

- Perform exploratory data analysis,
- Preprocessing and feature engineering, and
- Training machine learning model.
- Testing machine learning model.
- Validating machine learning model.

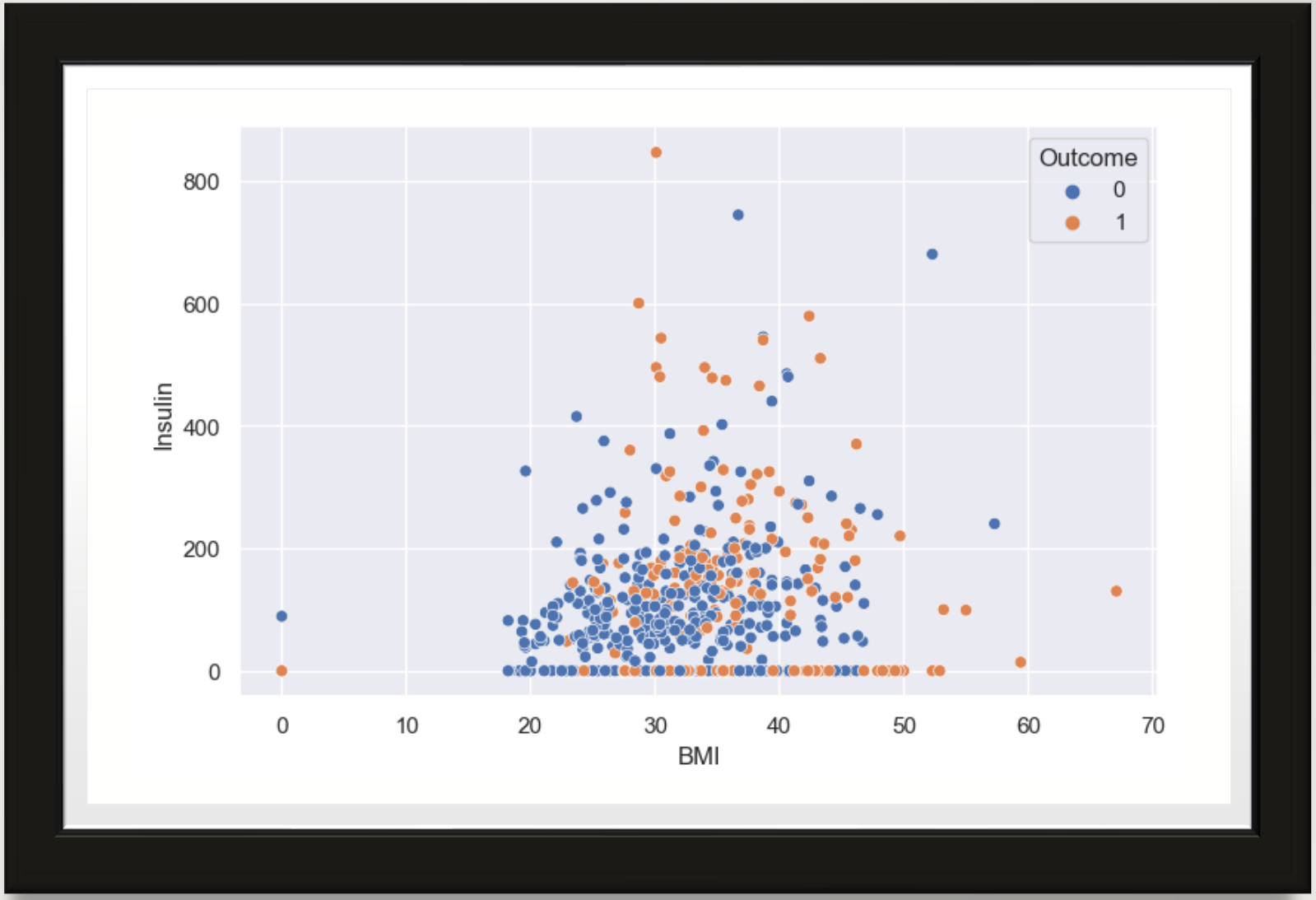
Process

- **Step 1:** Import libraries and load dataset
- **Step 2:** Explorative Data Analysis to understand the dataset.
- **Step 3:** Check for missing information in the dataset.
- **Step 4:** Clean dataset by identifying and treating outliers, and filling missing values.
- **Step 5:** Apply various machine learning algorithms
- **Step 6:** Validate the ML algorithms to ascertain the best.
- Step 7: Interpret and summary findings

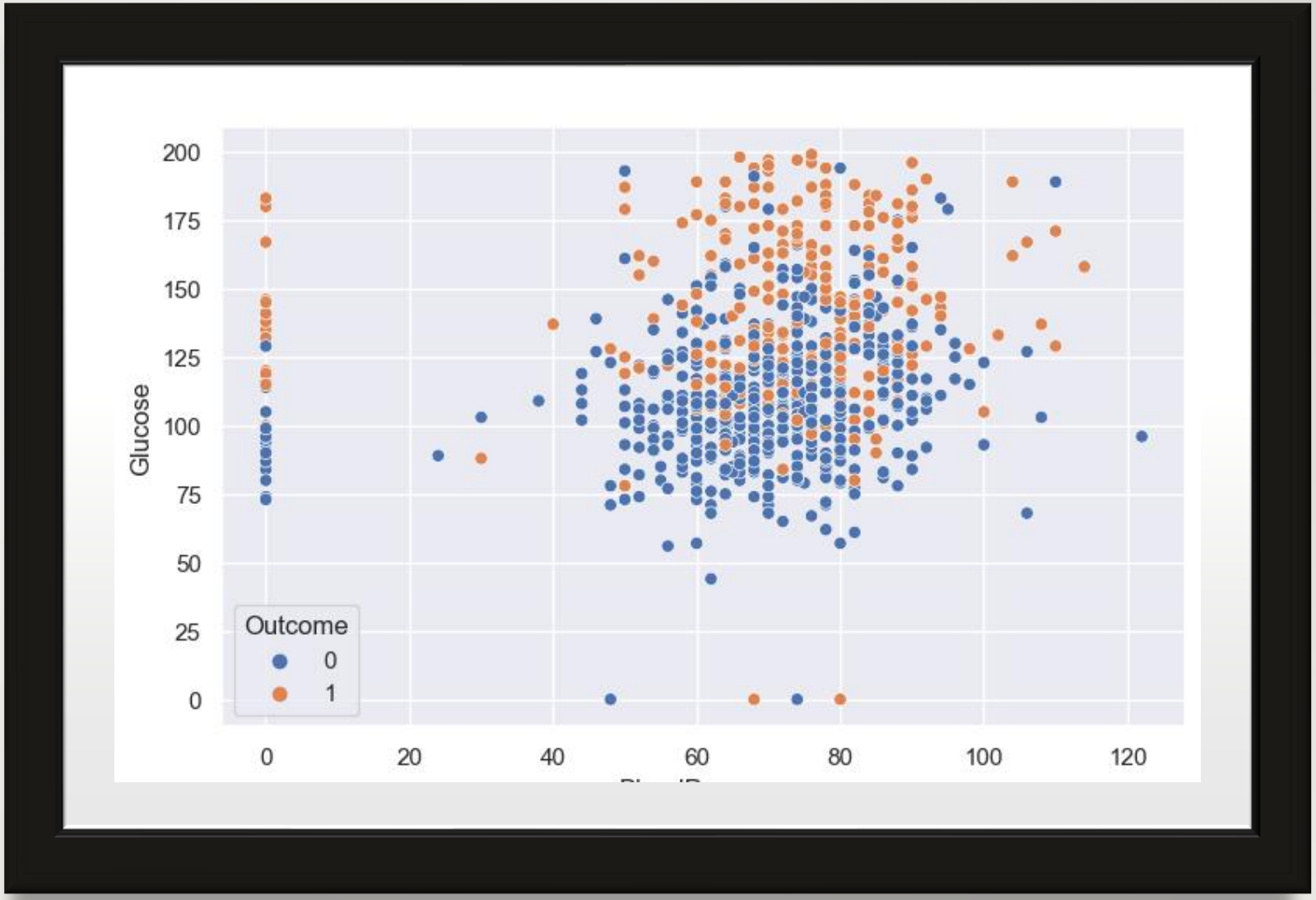
Data visualization dashboard



Insulin and BMI chart



Blood Pressure and glucose



Correlation Matrix

Dataset findings

After analyzing the histogram we can identify that there are some outliers in some columns.

For Example:-

Blood Pressure - A living person cannot have a diastolic blood pressure of zero.

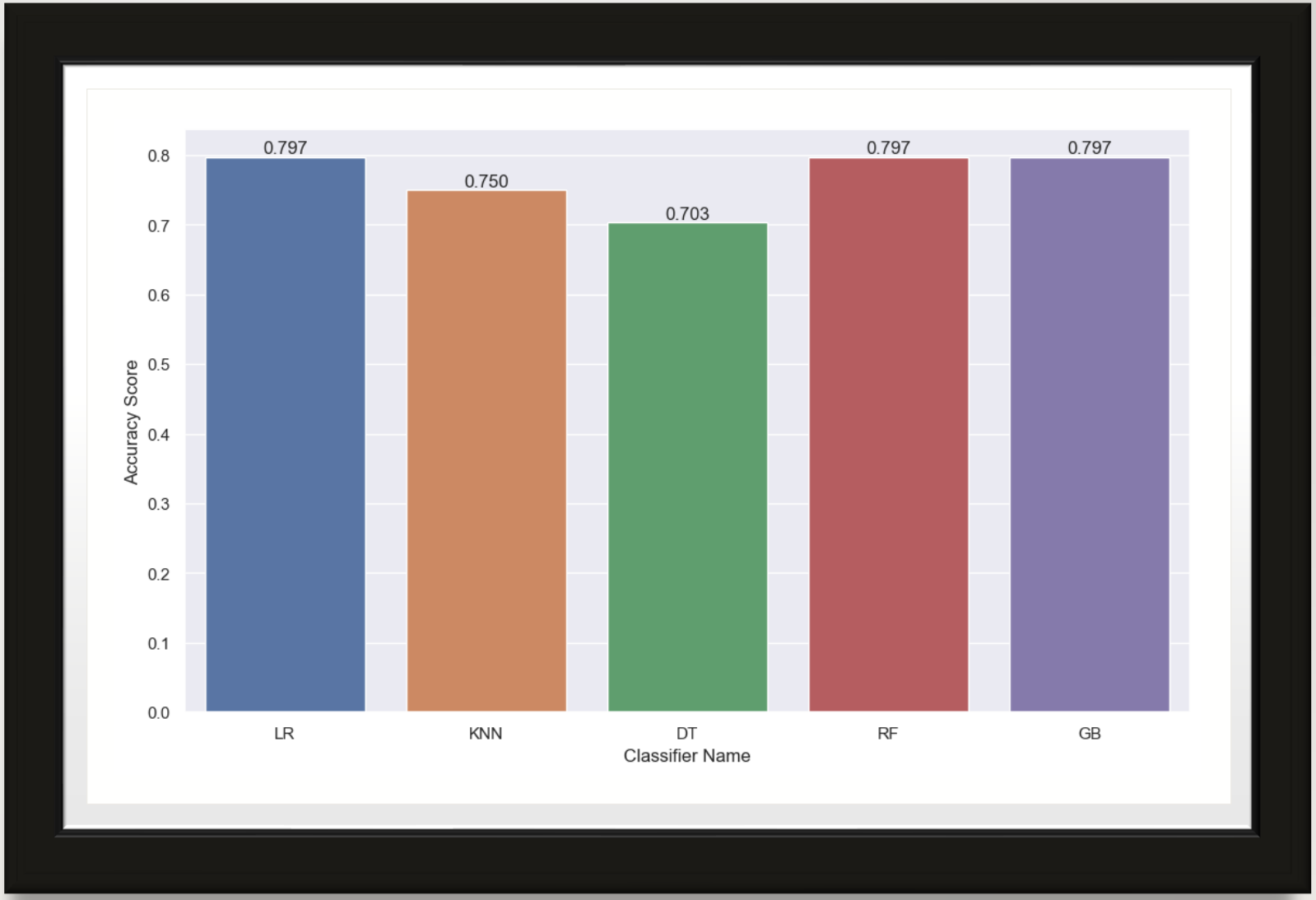
Plasma glucose levels - Zero is invalid number as fasting glucose level would never be as low as zero.

Skin Fold Thickness - For normal people, skin fold thickness can’t be less than 10 mm better yet zero.

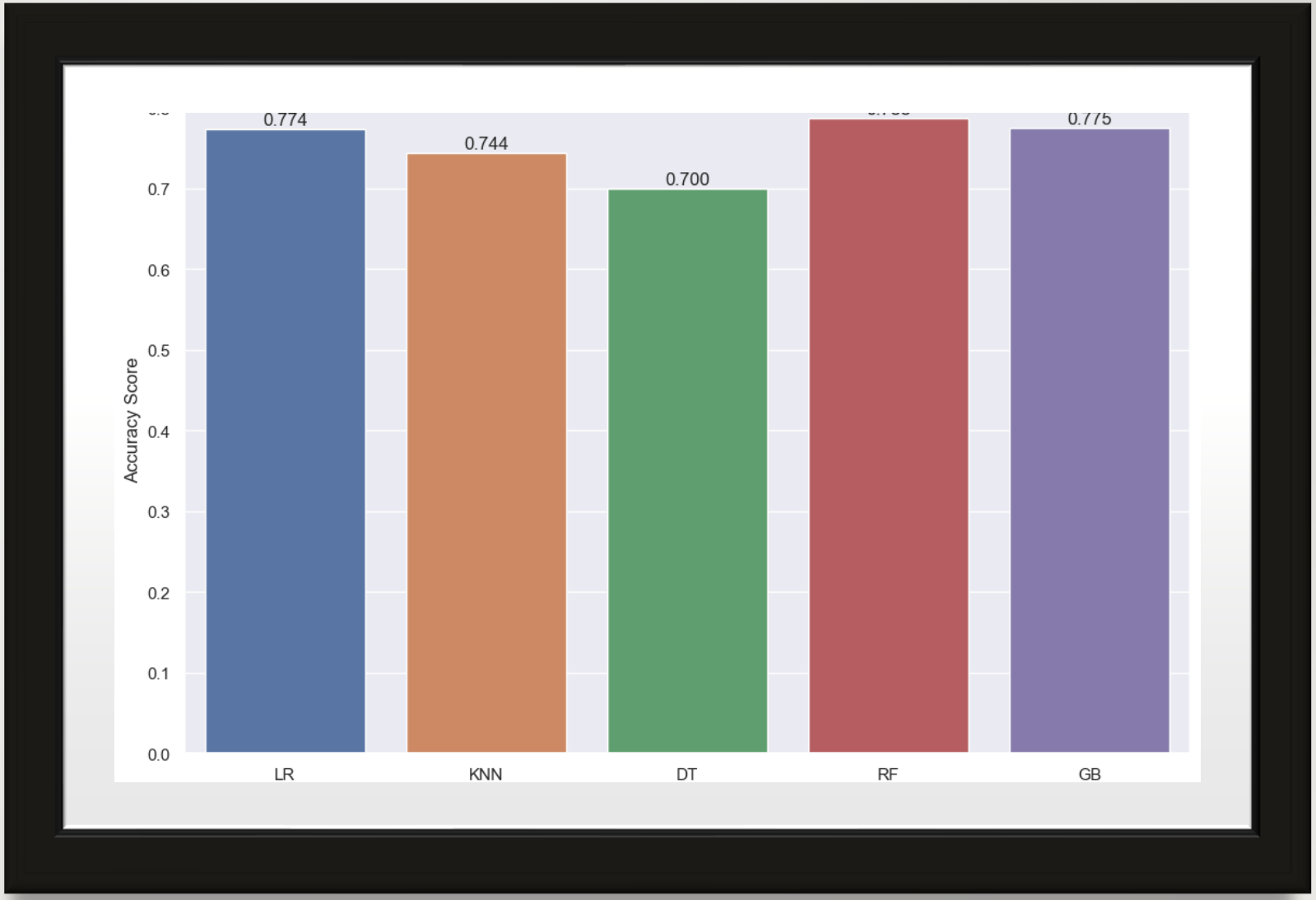
BMI: Should not be 0 or close to zero unless the person is really underweight which could be life-threatening.

Insulin: In a rare situation a person can have zero insulin but by observing

Models performance- Accuracy score metrics



Model performance – Kfold Cross validation



Model summary – Logistic Regression

OLS Regression Results

Dep. Variable:	Outcome	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	1.450e+29
Date:	Tue, 25 Jul 2023	Prob (F-statistic):	0.00
Time:	10:03:47	Log-Likelihood:	19403.
No. Observations:	636	AIC:	-3.879e+04
Df Residuals:	630	BIC:	-3.877e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.013e-15	3.66e-15	0.277	0.782	-6.18e-15	8.2e-15
Pregnancies	4.195e-15	1.72e-16	24.345	0.000	3.86e-15	4.53e-15
Glucose	-7.581e-17	2.16e-17	-3.505	0.000	-1.18e-16	-3.33e-17
BMI	-2.151e-16	8.92e-17	-2.412	0.016	-3.9e-16	-4e-17
DiabetesPedigreeFunction	5.135e-16	2.27e-15	0.226	0.821	-3.94e-15	4.97e-15
Outcome	1.0000	1.42e-15	7.03e+14	0.000	1.000	1.000

Omnibus:	53.377	Durbin-Watson:	1.916
Prob(Omnibus):	0.000	Jarque-Bera (JB):	65.689
Skew:	-0.787	Prob(JB):	5.44e-15
Kurtosis:	3.035	Cond. No.	875.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

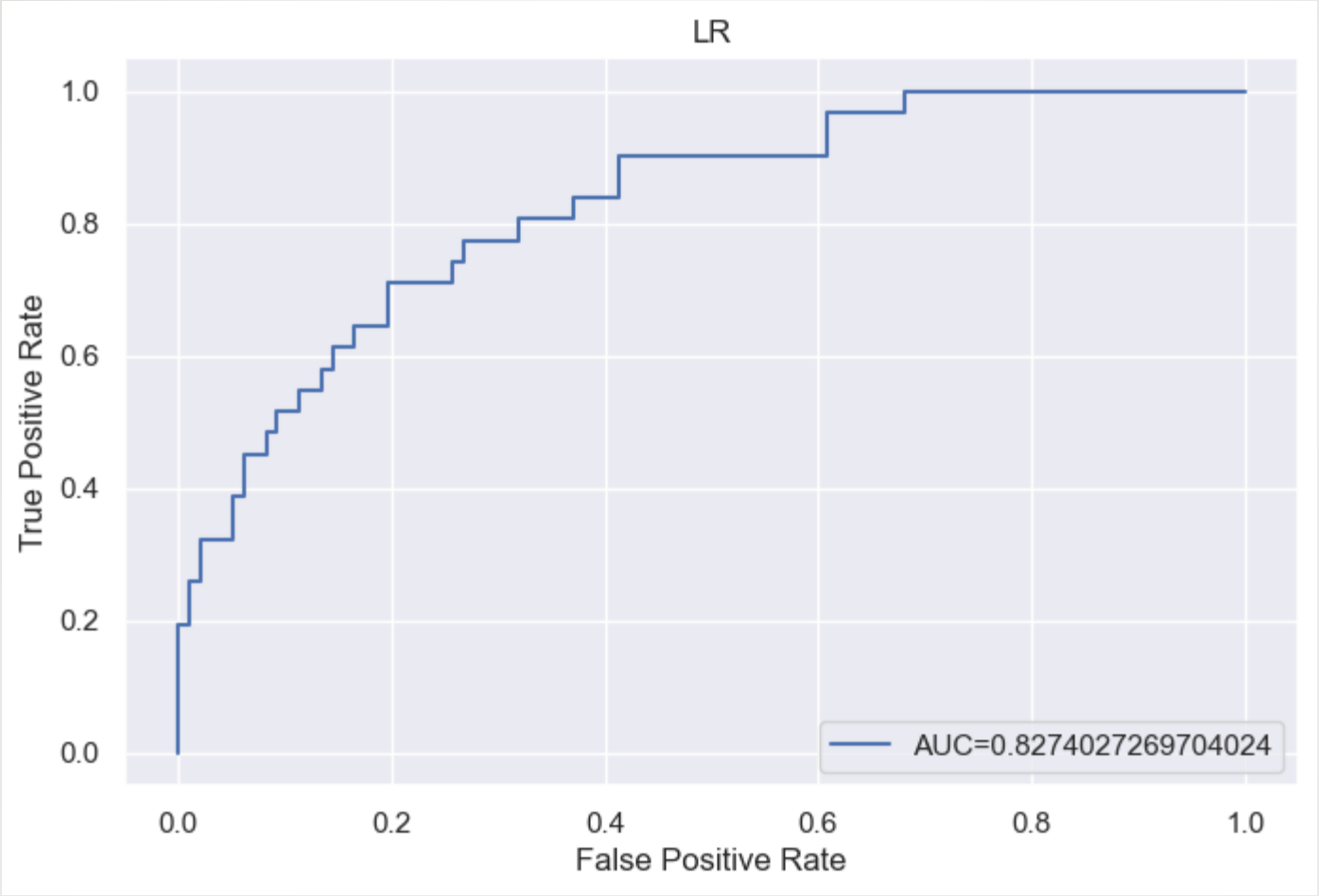
Model classification report-recall, precision, f1-score

LR	precision	recall	f1-score	support
0	0.80	0.90	0.85	439
1	0.69	0.50	0.58	197
accuracy			0.77	636
macro avg	0.74	0.70	0.71	636
weighted avg	0.76	0.77	0.76	636

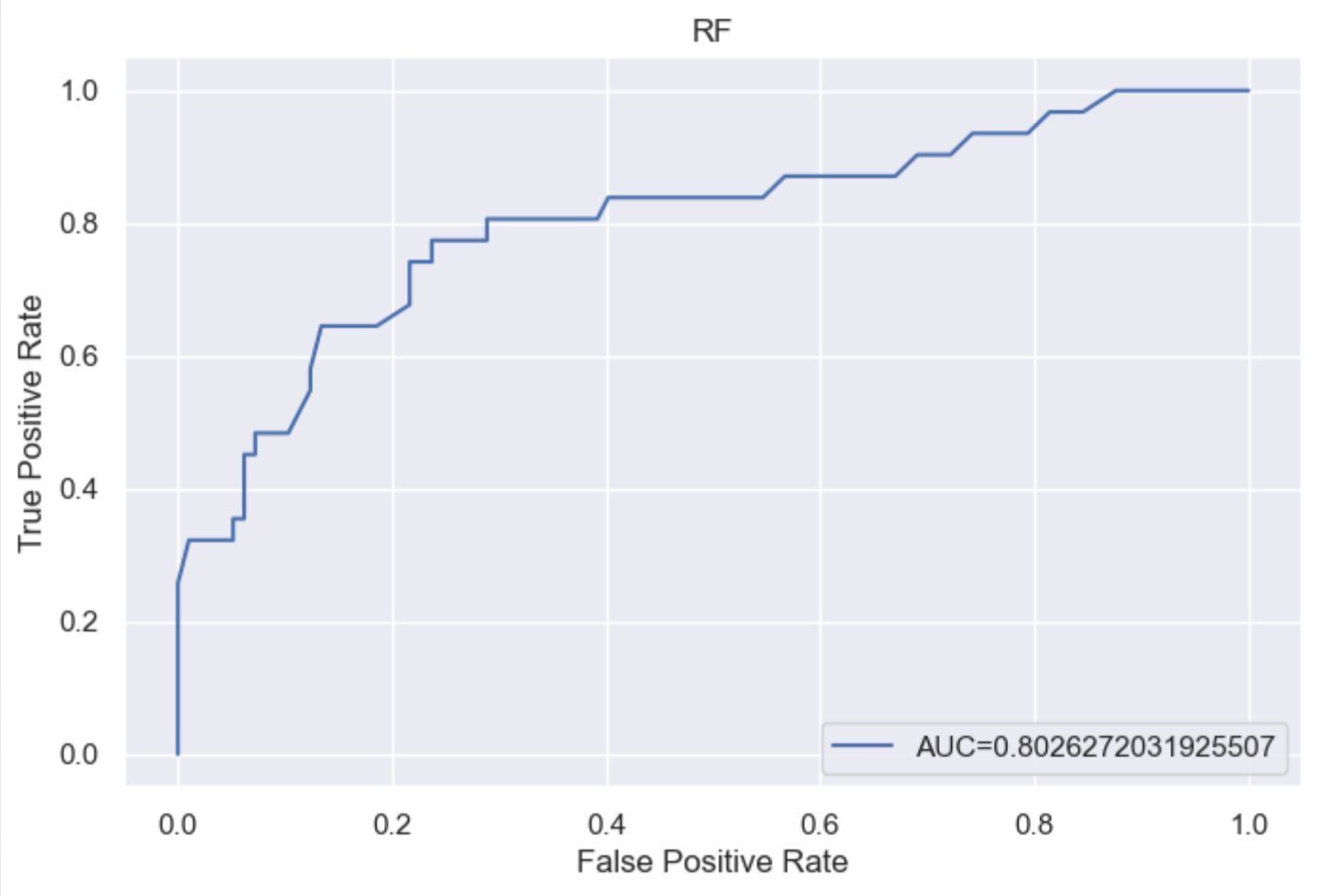
KNN	precision	recall	f1-score	support
0	0.84	0.88	0.86	439
1	0.70	0.62	0.66	197
accuracy			0.80	636
macro avg	0.77	0.75	0.76	636
weighted avg	0.80	0.80	0.80	636

DT	precision	recall	f1-score	support
0	0.97	0.95	0.96	439
1	0.88	0.93	0.91	197
accuracy			0.94	636
macro avg	0.93	0.94	0.93	636
...				
accuracy			0.92	636
macro avg	0.91	0.89	0.90	636
weighted avg	0.92	0.92	0.92	636

Roc-AUC curve for Logistic regression



Roc-AUC curve for Random Forest



Conclusion

We can see the Logistic Regression, Random Forest and Gradient Boosting have performed better than the rest.

Diabetic and non-diabetic groups shows similar distribution pattern.

Most variables shows relative positive relationship between themselves.

Skin thickness and Insulin shows a lot of outliers due to the numbers of zeros.

Pregnancies, glucose and BMI variables help to explain the outcome variables better.