

Supervised Learning Project

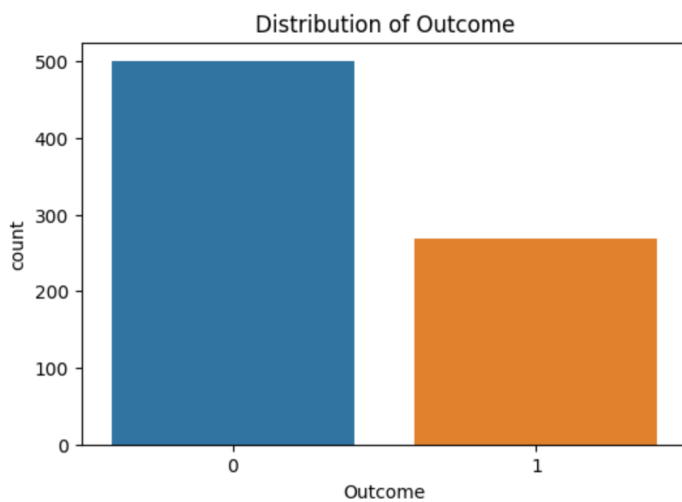
— based on the “Diabetes” dataset

Part1: Exploratory Data Analysis

1. Get some basic information about the dataset, including shape, columns, data types, null values.
2. Visualize the relationships between the different variables.

Visualization

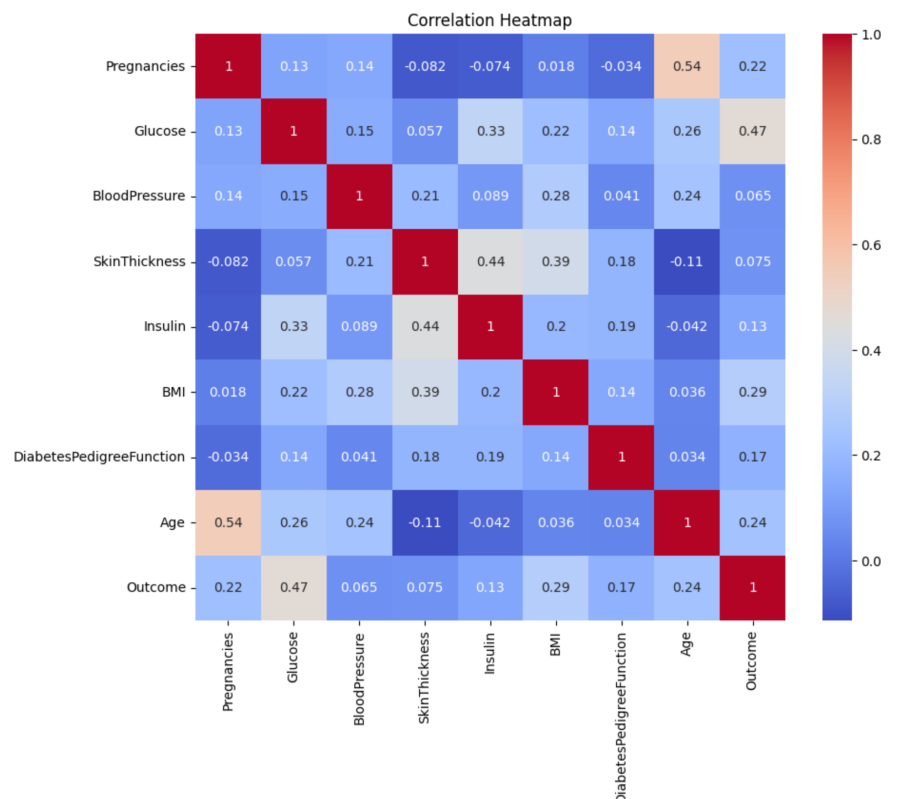
2.1 Outcome Distribution



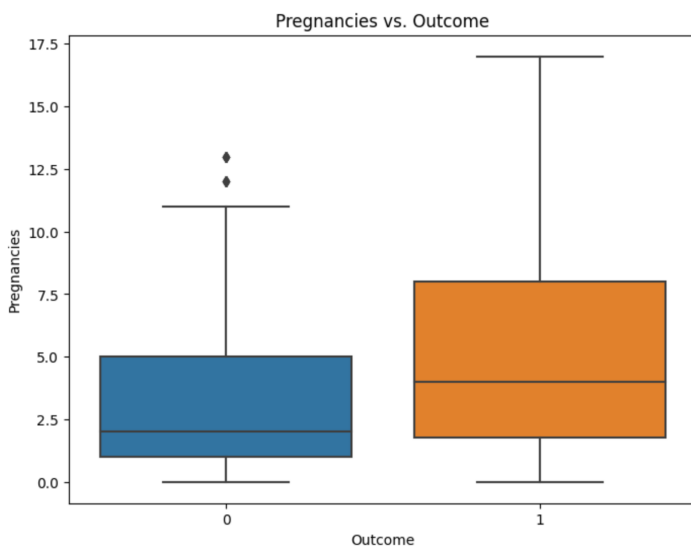
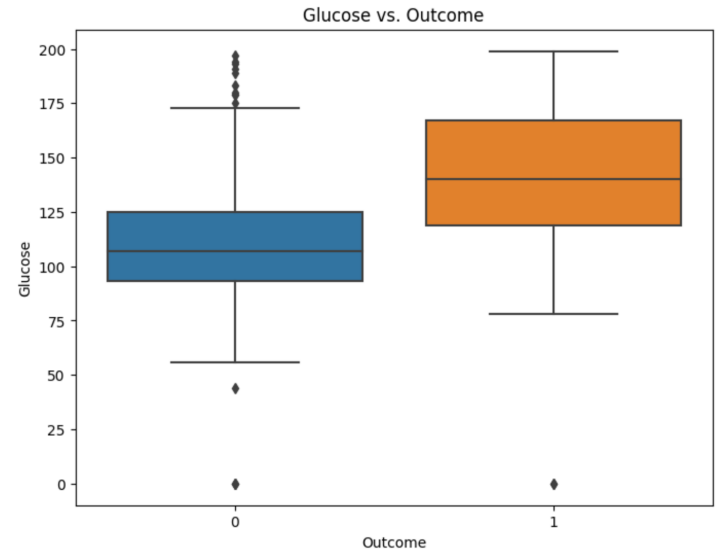
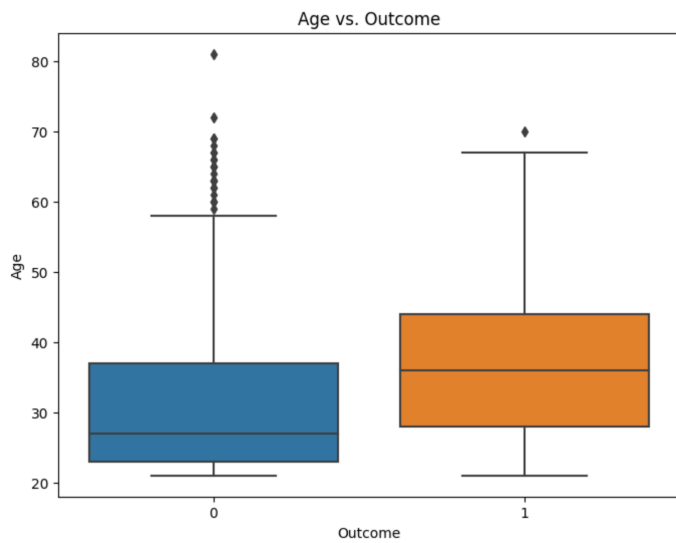
Attention: imbalanced data

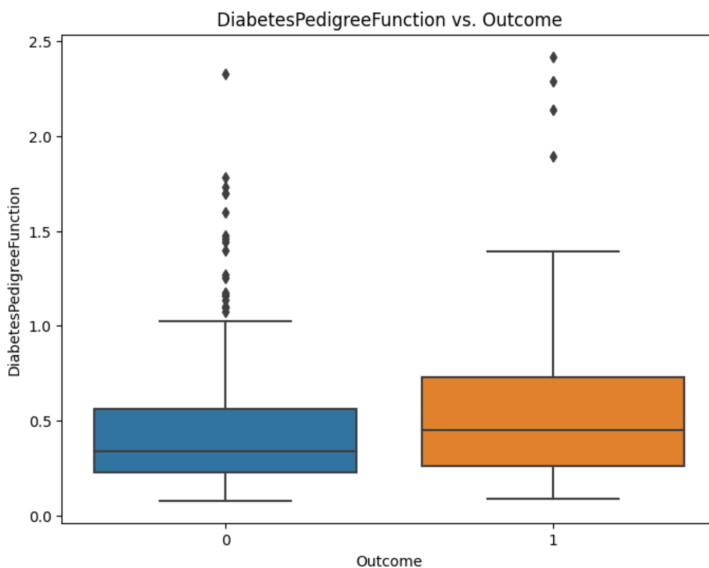
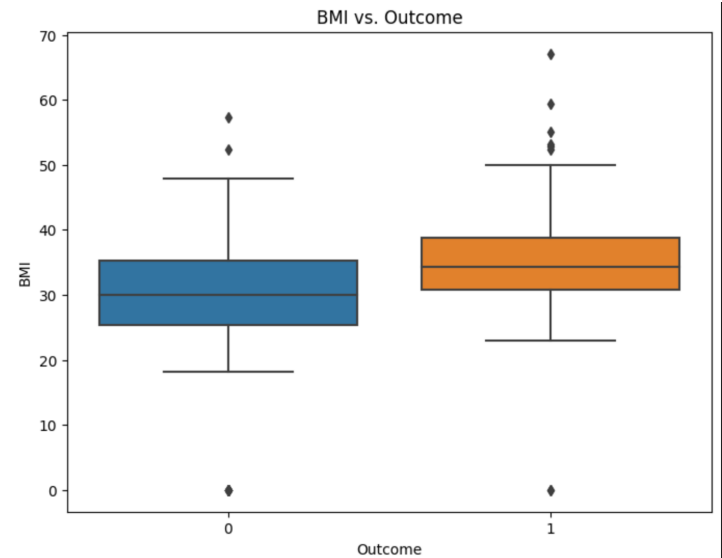
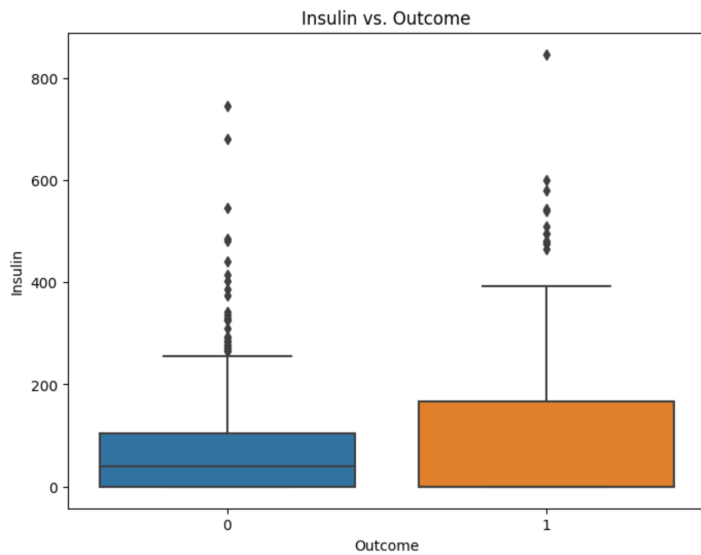
2.2 Correlation Heatmap

Glucose - Outcome: 0.47
BMI - Outcome: 0.29
Pregancies - Outcome: 0.22
Age - Outcome: 0.24



2.3 Boxplot for outliers





Part2: Preprocessing & Feature Engineering

1. Handling missing values
Filled the missing values with medium of each column.
2. Handling outliers
Using IQR-based approach.
3. Feature engineering
Create a new feature named 'BMI_Category' with labels: Underweight, Normal, Overweight, Obese and applied label encoding.
4. Handling imbalanced data
Apply random undersampling to balance the classes.

Part3: Train ML Model

Select **Logistic Regression** and **Random Forest** models.

3.1 Base model result

```
Type 1 Error (False Positive Rate):
Logistic Regression: 0.2222222222222222
Random Forest: 0.1717171717171717
```

```
Type 2 Error (False Negative Rate):
Logistic Regression: 0.32727272727272727
Random Forest: 0.2909090909090909
```

```
Classification Report logreg:
              precision    recall  f1-score   support

      0       0.81      0.78      0.79        99
      1       0.63      0.67      0.65        55

   accuracy          0.74        154
  macro avg       0.72      0.73      0.72        154
 weighted avg       0.75      0.74      0.74        154
```

```
Classification Report rf:
              precision    recall  f1-score   support

      0       0.84      0.83      0.83        99
      1       0.70      0.71      0.70        55

   accuracy          0.79        154
  macro avg       0.77      0.77      0.77        154
 weighted avg       0.79      0.79      0.79        154
```

Random Forest has less Type1 and type2 errors and a higher F1 score.

3.2 Tuned model result

```
Type 1 Error (False Positive Rate):
Logistic Regression: 0.2222222222222222
Random Forest: 0.18181818181818182
```

```
Type 2 Error (False Negative Rate):
Logistic Regression: 0.34545454545454546
Random Forest: 0.2909090909090909
```

```
Classification Report logreg:
              precision    recall  f1-score   support

      0       0.80      0.78      0.79        99
      1       0.62      0.65      0.64        55

   accuracy          0.73        154
  macro avg       0.71      0.72      0.71        154
 weighted avg       0.74      0.73      0.74        154
```

```
Classification Report rf:
              precision    recall  f1-score   support

      0       0.84      0.82      0.83        99
      1       0.68      0.71      0.70        55

   accuracy          0.78        154
  macro avg       0.76      0.76      0.76        154
 weighted avg       0.78      0.78      0.78        154
```

Random Forest has less Type1 and type2 errors and a higher F1 score.

Part4: Conclusion

From the machine learning models developed and the exploratory data analysis (EDA) conducted, there are my findings:

1. Logistic Regression and Random Forest were developed as predictive models for diabetes outcome. The base Random Forest model shows a better F1 score with less Type1 and Type2 errors. I tried to tune both the model and the F1 scores and Type1, Type2 error are worse than the original model, so the original Random Forest model is the best model for predicting diabetes in my analysis.
2. Based on the correlation heatmap, Glucose is the most significant predictor of diabetes outcome. Also, age, BMI and pregnancy play important roles.
3. Proper preprocessing steps, including feature scaling, one-hot-encoding significantly improved the model's performance in this case.
4. The dataset shows an imbalanced distribution, with a higher number of non-diabetic cases compared to diabetic cases.