Data Science Capstone- 'HealthCare Project'

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Task: Week 1

Data Exploration

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('health care diabetes.csv')
df.head()
```

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

```
df.tail()
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0
```

```
df.shape
```

```
(768, 9)
```

```
df.isna().apply(pd.value_counts).T
```

```
                          False
Pregnancies                 768
Glucose                     768
```

```
BloodPressure               768
SkinThickness               768
Insulin                     768
BMI                         768
DiabetesPedigreeFunction    768
Age                         768
Outcome                     768
```

```
#df.info()

df.describe()
```

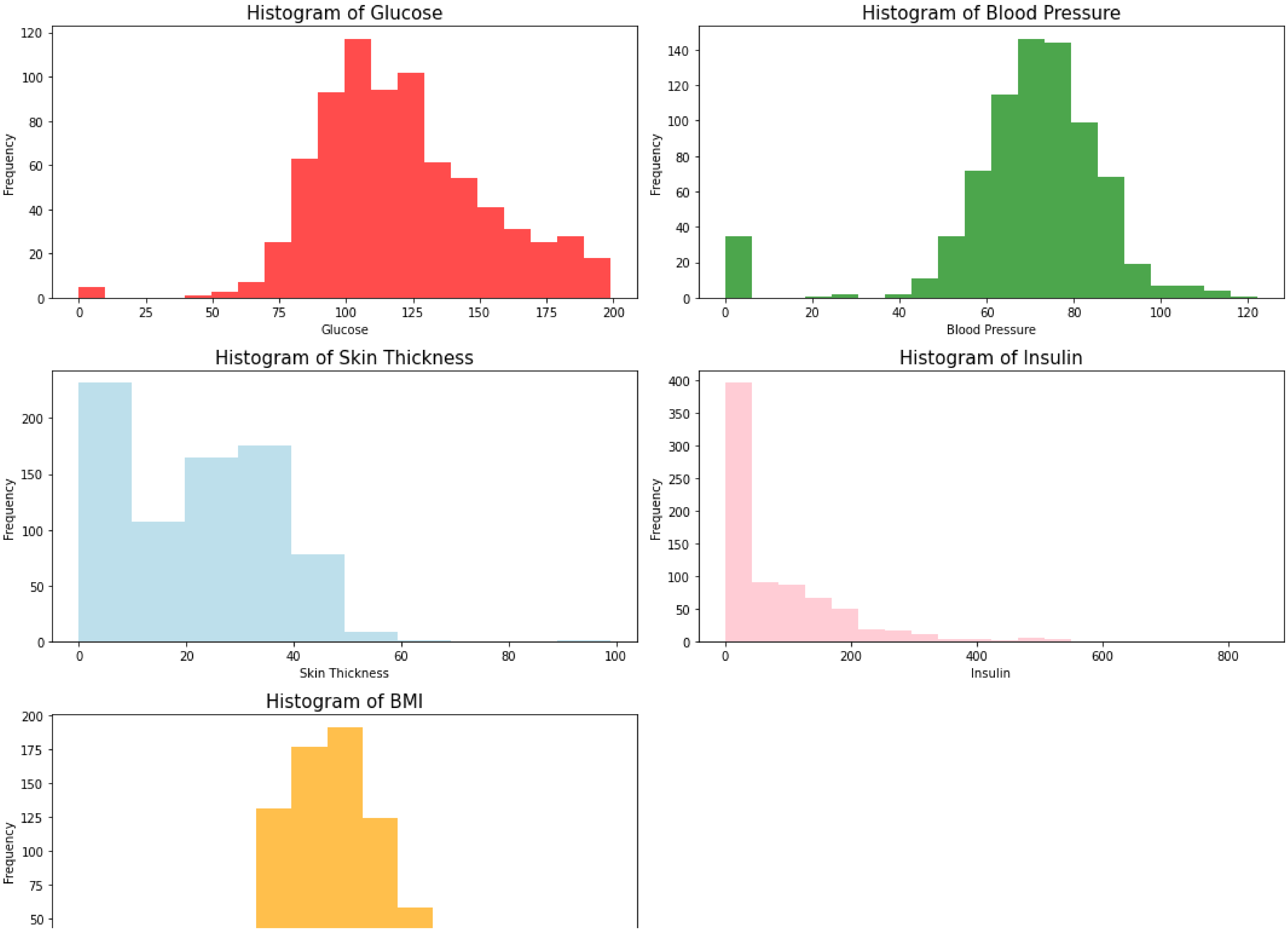
```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

Observations:

- There are instances where some of the measurements (e.g., glucose, blood pressure, skin thickness, insulin, BMI) have minimum values of 0, which might be indicative of missing or erroneous data and should be investigated.
- The dataset seems to have a wide range of values, with some features having a notable standard deviation (higher standard deviation indicates that the values are spread out over a larger range from the mean).
- The mean of the outcome is 0.35, suggesting that the dataset might be imbalanced toward non-diabetic cases.
- Consideration should be given to handling missing or zero values and standardizing or normalizing the data before analysis or modeling.

```
# Exploring the variables using histograms.

fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(15,12))
# Histogram of Glucose
axes[0][0].hist(df['Glucose'], bins=20, alpha=0.7, color='red')
axes[0][0].set_title('Histogram of Glucose', fontsize=15)
axes[0][0].set_xlabel('Glucose')
axes[0][0].set_ylabel('Frequency')

# Histogram of Blood Pressure
axes[0][1].hist(df['BloodPressure'], bins=20, alpha=0.7, color='green')
axes[0][1].set_title('Histogram of Blood Pressure', fontsize=15)
axes[0][1].set_xlabel('Blood Pressure')
axes[0][1].set_ylabel('Frequency')

# Histogram of Skin Thickness
axes[1][0].hist(df['SkinThickness'], bins=10, alpha=0.8, color='lightblue')
axes[1][0].set_title('Histogram of Skin Thickness', fontsize=15)
axes[1][0].set_xlabel('Skin Thickness')
axes[1][0].set_ylabel('Frequency')

# Histogram of Insulin
```

```python
axes[1][1].hist(df['Insulin'], bins=20, alpha=0.8, color='pink')
axes[1][1].set_title('Histogram of Insulin', fontsize=15)
axes[1][1].set_xlabel('Insulin')
axes[1][1].set_ylabel('Frequency')

# Histogram of BMI
axes[2][0].hist(df['BMI'], bins=15, alpha=0.7, color='orange')
axes[2][0].set_title('Histogram of BMI', fontsize=15)
axes[2][0].set_xlabel('BMI')
axes[2][0].set_ylabel('Frequency')

fig.delaxes(axes[2][1])  # remove the last empty subplot.

plt.tight_layout()
plt.show()
```



Histogram of Glucose
Frequency
Glucose
0
20
40
60
80
100
120
0
25
50
75
100
125
150
175
200
Histogram of Blood Pressure
Frequency
Blood Pressure
0
20
40
60
80
100
120
140
Histogram of Skin Thickness
Frequency
Skin Thickness
0
50
100
150
200
0
20
40
60
80
100
Histogram of Insulin
Frequency
Insulin
0
50
100
150
200
250
300
350
400
0
200
400
600
800
Histogram of BMI
Frequency
50
75
100
125
150
175
200

```
zero_count = (df[['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI']]==0).sum()
zero_count

# Observations:
# From the below outcome, you can see counts of 0 values for each variable:
    # Glucose        ---> 5
    # Blood Pressure ---> 35
    # Skin Thickness ---> 227
    # Insulin        ---> 374
    # BMI            ---> 11

# We will replace these zero values with the median of each variable.
```

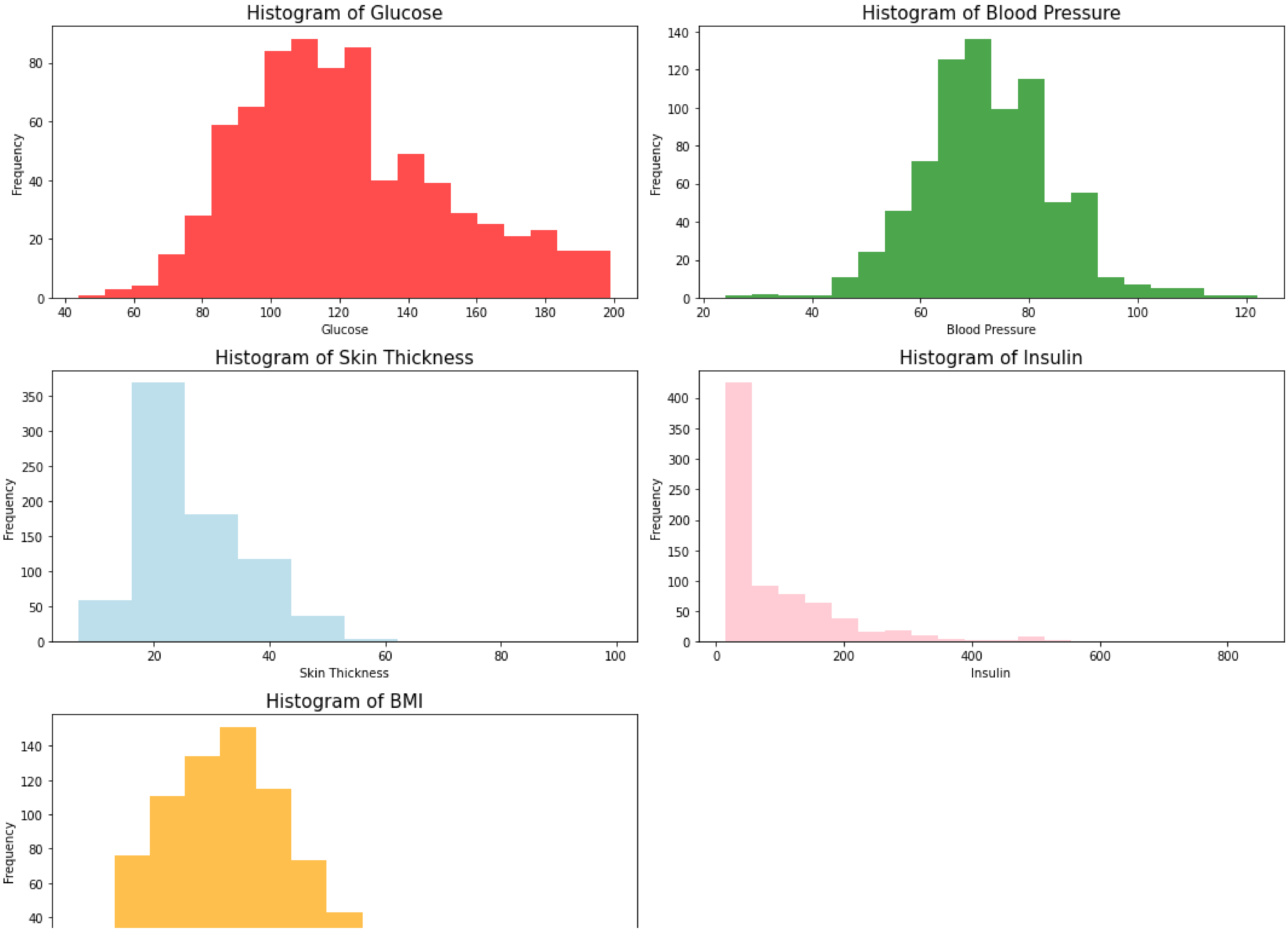
```
Glucose            5
BloodPressure     35
SkinThickness    227
Insulin          374
BMI               11
dtype: int64
```

```
# replace 0 with median in specified column.
df['Glucose'].replace(0, df['Glucose'].median(), inplace=True)
df['BloodPressure'].replace(0, df['BloodPressure'].median(), inplace=True)
df['SkinThickness'].replace(0, df['SkinThickness'].median(), inplace=True)
df['Insulin'].replace(0, df['Insulin'].median(), inplace=True)
df['BMI'].replace(0, df['BMI'].median(), inplace=True)

# checking descriptive analysis after handling missing values.
df.describe()
```

```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000   
mean      3.845052  121.656250      72.386719      27.334635   94.652344   
std       3.369578   30.438286      12.096642       9.229014  105.547598   
min       0.000000   44.000000      24.000000       7.000000   14.000000   
25%       1.000000   99.750000      64.000000      23.000000   30.500000   
50%       3.000000  117.000000      72.000000      23.000000   31.250000   
75%       6.000000  140.250000      80.000000      32.000000  127.250000   
max      17.000000  199.000000     122.000000      99.000000  846.000000   

              BMI  DiabetesPedigreeFunction         Age     Outcome  
count  768.000000                768.000000  768.000000  768.000000  
mean    32.450911                  0.471876   33.240885    0.348958  
std      6.875366                  0.331329   11.760232    0.476951  
min     18.200000                  0.078000   21.000000    0.000000  
25%     27.500000                  0.243750   24.000000    0.000000  
50%     32.000000                  0.372500   29.000000    0.000000  
75%     36.600000                  0.626250   41.000000    1.000000  
max     67.100000                  2.420000   81.000000    1.000000  
```

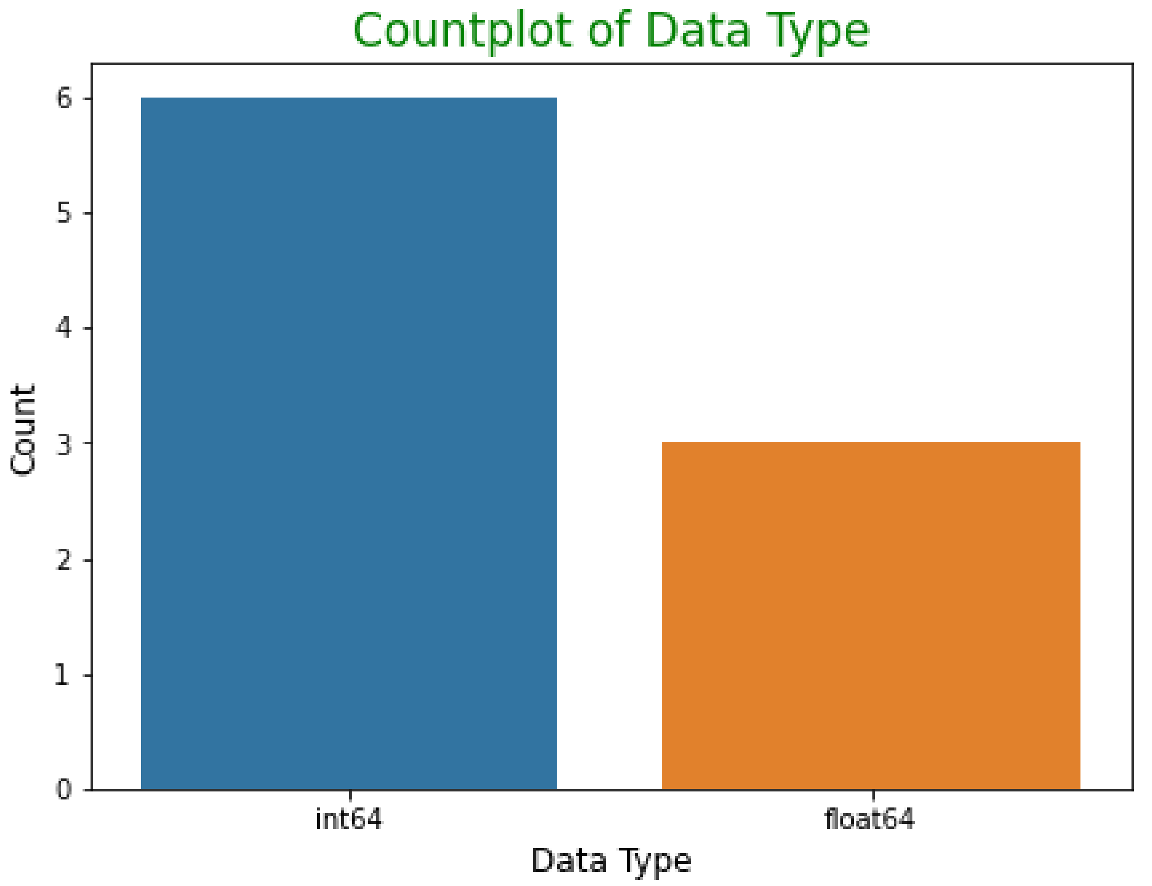
```
# Exploring data distribution after handling missing values

fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(15,12))
# Histogram of Glucose
axes[0][0].hist(df['Glucose'], bins=20, alpha=0.7, color='red')
axes[0][0].set_title('Histogram of Glucose', fontsize=15)
axes[0][0].set_xlabel('Glucose')
axes[0][0].set_ylabel('Frequency')

# Histogram of Blood Pressure
```

```python
axes[0][1].hist(df['BloodPressure'], bins=20, alpha=0.7, color='green')
axes[0][1].set_title('Histogram of Blood Pressure', fontsize=15)
axes[0][1].set_xlabel('Blood Pressure')
axes[0][1].set_ylabel('Frequency')

# Histogram of Skin Thickness
axes[1][0].hist(df['SkinThickness'], bins=10, alpha=0.8, color='lightblue')
axes[1][0].set_title('Histogram of Skin Thickness', fontsize=15)
axes[1][0].set_xlabel('Skin Thickness')
axes[1][0].set_ylabel('Frequency')

# Histogram of Insulin
axes[1][1].hist(df['Insulin'], bins=20, alpha=0.8, color='pink')
axes[1][1].set_title('Histogram of Insulin', fontsize=15)
axes[1][1].set_xlabel('Insulin')
axes[1][1].set_ylabel('Frequency')

# Histogram of BMI
axes[2][0].hist(df['BMI'], bins=15, alpha=0.7, color='orange')
axes[2][0].set_title('Histogram of BMI', fontsize=15)
axes[2][0].set_xlabel('BMI')
axes[2][0].set_ylabel('Frequency')

fig.delaxes(axes[2][1])  # remove the last empty subplot.

plt.tight_layout()
plt.show()
```


Histogram of Glucose
Frequency
0 20 40 60 80
40 60 80 100 120 140 160 180 200
Glucose
Histogram of Blood Pressure
Frequency
0 20 40 60 80 100 120 140
20 40 60 80 100 120
Blood Pressure
Histogram of Skin Thickness
Frequency
0 50 100 150 200 250 300 350
20 40 60 80 100
Skin Thickness
Histogram of Insulin
Frequency
0 50 100 150 200 250 300 350 400
0 200 400 600 800
Insulin
Histogram of BMI
Frequency
40 60 80 100 120 140

```python
data_type = pd.DataFrame(df.dtypes, columns=['Dtype'])
print(data_type)

# potting the countplot of data_type
plt.figure(figsize=(7,5))
sns.countplot(data=data_type, x='Dtype')
plt.title('Countplot of Data Type', fontsize=17, color='green')
plt.xlabel('Data Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.show()
```

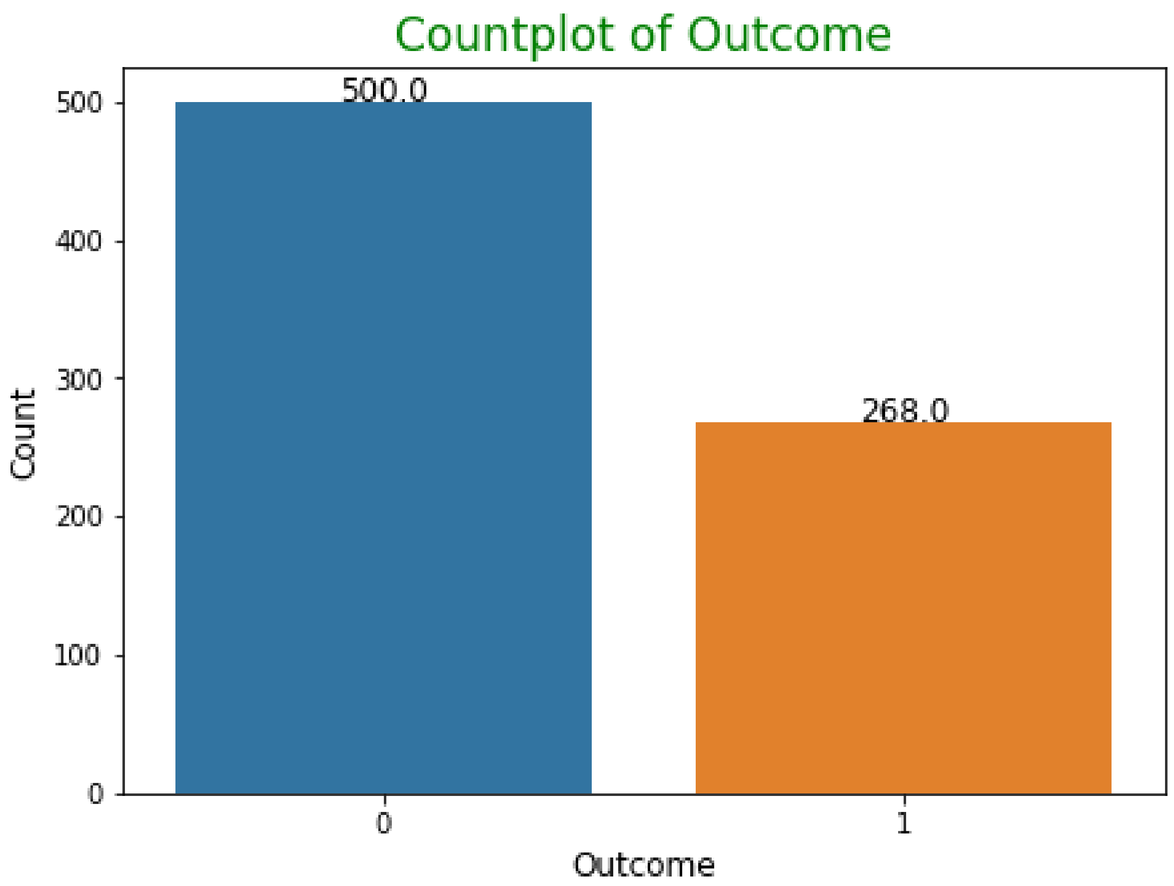
```
                            Dtype
Pregnancies                 int64
Glucose                     int64
BloodPressure               int64
SkinThickness               int64
Insulin                   float64
BMI                       float64
DiabetesPedigreeFunction  float64
Age                         int64
Outcome                     int64
```




```python
#value count of Outcome.
print(df.Outcome.value_counts())

#visualize the Outcome by plotting Countplot().
plt.figure(figsize=(7,5))
plot = sns.countplot(x = df['Outcome'])
for p in plot.patches:    # Display the count number on the bars
    plot.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', xytext=(0, 4),
                  textcoords='offset points', fontsize=12)
```

```
plt.title('Countplot of Outcome', fontsize=17, color='green')
plt.xlabel('Outcome', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.show()
```

```
0    500
1    268
Name: Outcome, dtype: int64
```



The outcome variable in the dataset represents whether an individual has diabetes or not, with values 0 and 1.

Findings:

- **Class 0** (indicating individuals without diabetes) has a **count of 500.**
- **Class 1** (indicating individuals with diabetes) has a **count of 268.**

Observations:

- The data appears to be imbalanced, as there are more instances of Class 0(non-diabetic) than Class 1(diabetic).
- Imbalanced datasets can pose challenges for machine learning models because they may become biased towards the majority class (class 0 in this case).

Future Course of action:

1. Resampling: You can consider resampling techniques to balance the dataset. There are two main approaches:

- **Oversampling:** Create additional samples for the minority class (class 1) to balance the class distribution.
- **Undersampling:** Remove some samples from the majority class (class 0) to balance the class distribution.

2. Synthetic Data Generation: Techniques like Synthetic Minority Over-sampling Technique **(SMOTE)** can be used to generate synthetic samples for the minority class.

3. Model Selection: Choose machine learning algorithms that are less sensitive to class imbalance. Some algorithms can be adjusted with class weights to give more importance to the minority class.

4. Consider using ensemble methods like Random Forest or Gradient Boosting, which can handle class imbalance better than individual classifiers.

5. When evaluating the model, avoid accuracy as the primary metric. Instead, use metrics like precision, recall, F1-score, or the area under the Receiver Operating Characteristic (ROC-AUC) curve, which are more informative for imbalanced datasets.

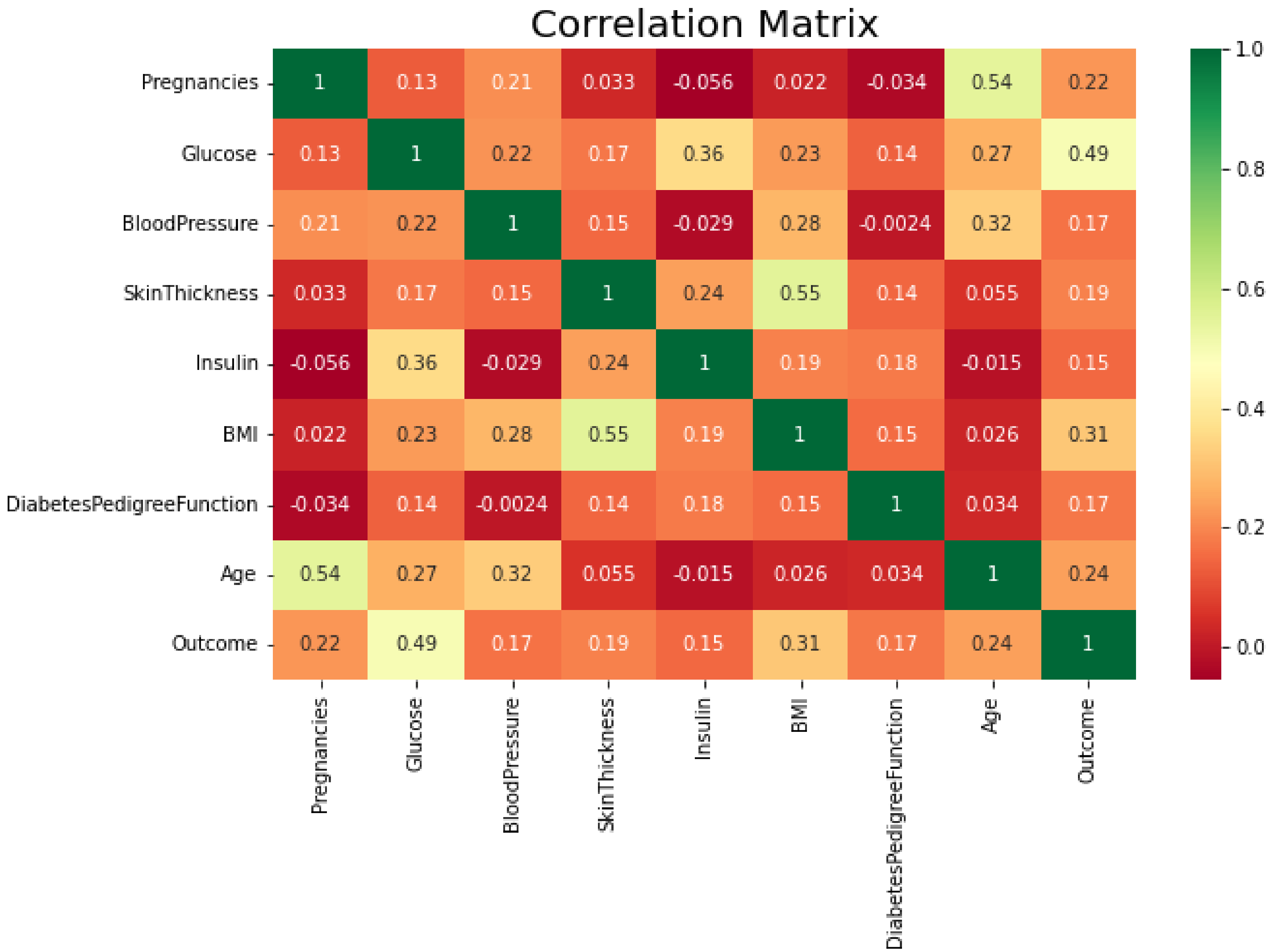
```
sns.pairplot(df[['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'Outcome']], hue='Outcome')
plt.show()
```

Glucose
BloodPressure
SkinThickness
Insulin
Outcome
0
1

```python
# Correlation

corr = df.corr()
corr
```

```
                          Pregnancies   Glucose  BloodPressure  SkinThickness  \
Pregnancies                  1.000000  0.128213       0.208615       0.032568   
Glucose                      0.128213  1.000000       0.218937       0.172143   
BloodPressure                0.208615  0.218937       1.000000       0.147809   
SkinThickness                0.032568  0.172143       0.147809       1.000000   
Insulin                     -0.055697  0.357573      -0.028721       0.238188   
BMI                          0.021546  0.231400       0.281132       0.546951   
DiabetesPedigreeFunction    -0.033523  0.137327      -0.002378       0.142977   
Age                          0.544341  0.266909       0.324915       0.054514   
Outcome                      0.221898  0.492782       0.165723       0.189065   

                           Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies              -0.055697  0.021546                 -0.033523   
Glucose                   0.357573  0.231400                  0.137327   
BloodPressure            -0.028721  0.281132                 -0.002378   
SkinThickness             0.238188  0.546951                  0.142977   
Insulin                   1.000000  0.189022                  0.178029   
BMI                       0.189022  1.000000                  0.153506   
DiabetesPedigreeFunction  0.178029  0.153506                  1.000000   
Age                      -0.015413  0.025744                  0.033561   
Outcome                   0.148457  0.312249                  0.173844   

                               Age   Outcome  
Pregnancies               0.544341  0.221898  
Glucose                   0.266909  0.492782  
BloodPressure             0.324915  0.165723  
SkinThickness             0.054514  0.189065  
Insulin                  -0.015413  0.148457  
BMI                       0.025744  0.312249  
DiabetesPedigreeFunction  0.033561  0.173844  
Age                       1.000000  0.238356  
Outcome                   0.238356  1.000000  
```

```python
# visulaize the correlation using heatmap.

plt.figure(figsize=(10,6))
sns.heatmap(corr, annot=True, cmap='RdYlGn')
plt.title('Correlation Matrix', fontsize=20)
plt.show()
```



	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
Pregnancies	1	0.13	0.21	0.033	-0.056	0.022	-0.034	0.54	0.22
Glucose	0.13	1	0.22	0.17	0.36	0.23	0.14	0.27	0.49
BloodPressure	0.21	0.22	1	0.15	-0.029	0.28	-0.0024	0.32	0.17
SkinThickness	0.033	0.17	0.15	1	0.24	0.55	0.14	0.055	0.19
Insulin	-0.056	0.36	-0.029	0.24	1	0.19	0.18	-0.015	0.15
BMI	0.022	0.23	0.28	0.55	0.19	1	0.15	0.026	0.31
DiabetesPedigreeFunction	-0.034	0.14	-0.0024	0.14	0.18	0.15	1	0.034	0.17
Age	0.54	0.27	0.32	0.055	-0.015	0.026	0.034	1	0.24
Outcome	0.22	0.49	0.17	0.19	0.15	0.31	0.17	0.24	1

Observations:

- There is a positive correlation between the number of Pregnancies and Age (0.54). This is expected, as older individuals are likely to have a higher number of pregnancies.
- Glucose level is positively correlated with Outcome (0.49), indicating that higher glucose levels are associated with a higher likelihood of having diabetes.
- Age is positively correlated with Outcome (0.24), suggesting that older individuals are more likely to have diabetes.
- The Diabetes Pedigree Function has weak correlations with most other features.
- Features like Glucose, BMI, and Age have relatively higher positive correlations with the Outcome, indicating their potential importance in predicting diabetes.

Task: Week 2

Data Modeling

```
# Extract the features and target variable from data.

X = df.iloc[:,0:8].values
y = df.iloc[:,-1].values
```

```
# As we know target vaiable i.e Outcome is imbalaced.
# So, we will handle the imbalanced data with SMOTE technique using over_sampling.

from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=0)

# resample the data
X_res, y_res = sm.fit_resample(X, y)

#X_res.shape, y_res.shape, y_res.value_counts()

# Split the data into training and testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.20, random_state=0)

#X_train.shape, y_train.shape, y_train.value_counts()
```

Performing Model Training and checking its performance

We use different algorithm to train the model and its performance and compare with KNN Algorithm.

- a. Logistic Regression
- a. Random Forest Classifier
- a. Gradient Boosting Classifier
- a. Support Vector Machine
- a. Decision Tree Classifier
- a. KNN Classifier

1. **Logistic Regression Algorithm:**

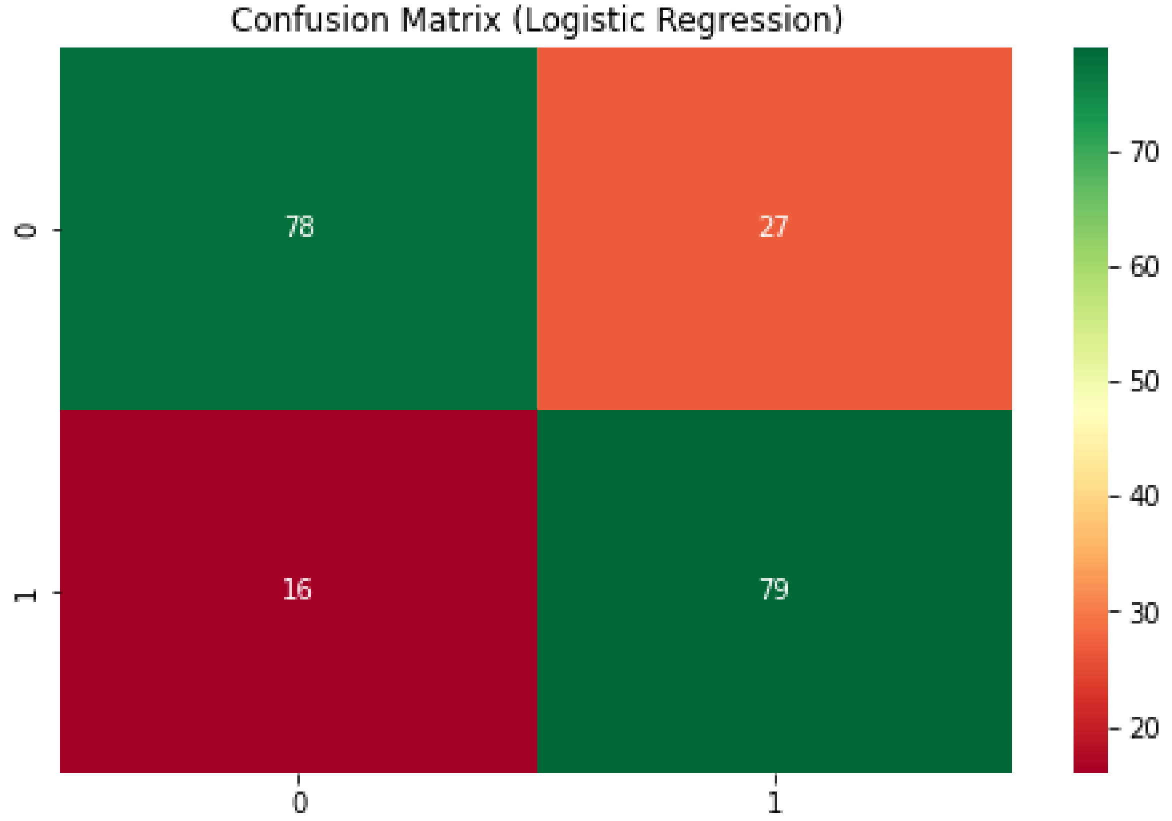
```
# Using Logistic Regression Algorithm.
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X_train, y_train)
lr

# predicting the model(lr)
lr_pred = lr.predict(X_test)

# checking accuracy
acc_lr = lr.score(X_test, y_test)
print('Accuracy: {:.2f}'.format(acc_lr*100),'%')
```

```
Accuracy: 78.50 %
```

```
from sklearn.metrics import confusion_matrix, classification_report
cm_lr = confusion_matrix(y_test, lr_pred)
print('Confusion Matrix:\n', cm_lr)

# plotting heatmap of confusion matrix
plt.figure(figsize=(8,5))
sns.heatmap(cm_lr, annot=True, fmt='g', cmap='RdYlGn')
plt.title('Confusion Matrix (Logistic Regression)', fontsize=12)
```

```
plt.show()

print('Classification Report of Logistic Regression:\n', classification_report(y_test, lr_pred))
```

```
Confusion Matrix:
 [[78 27]
 [16 79]]
```

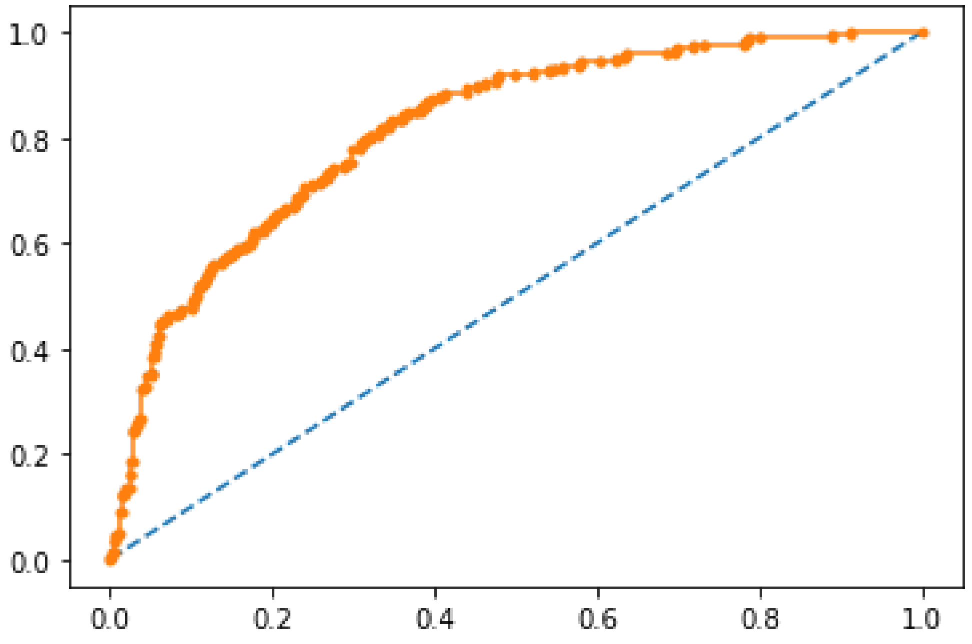



```
Classification Report of Logistic Regression:
               precision    recall  f1-score   support

           0       0.83      0.74      0.78       105
           1       0.75      0.83      0.79        95

    accuracy                           0.79       200
   macro avg       0.79      0.79      0.78       200
weighted avg       0.79      0.79      0.78       200
```

```
# Preparing ROC (Receiver Operating Characteristic) & AUC score (Area Under the Curve)
from sklearn.metrics import roc_curve, roc_auc_score

# predict probabilities
prob = lr.predict_proba(X)
# Keep probabilities for the positive outcomes only
prob = prob[:,1]
# Calculate AUC
auc = roc_auc_score(y, prob)
print('AUC: %.3f' % auc)
# Calculate ROC Curve
fpr, tpr, thresholds = roc_curve(y, prob)
# plot no skill
plt.plot([0,1],[0,1], linestyle='--')
```

```
# plot the roc curve for the model
plt.plot(fpr, tpr, marker='.')

plt.show()
```

```
AUC: 0.818
```



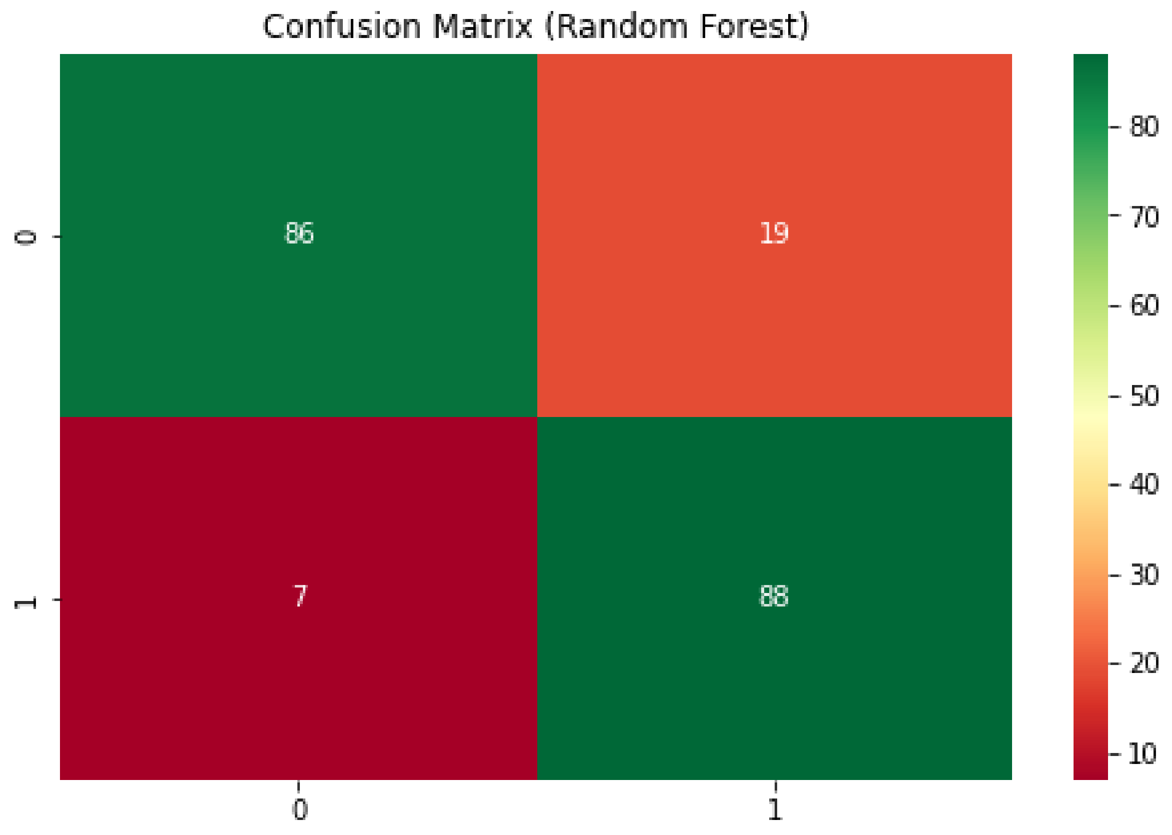
2. **Random Forest Classifier Algorithm:**

```
# Using Random Forest Algorithm.
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(random_state=0, max_depth=10)
rfc.fit(X_train, y_train)
rfc

# predicting the model(rfc)
rfc_pred = rfc.predict(X_test)

# checking accuracy
acc_rfc = rfc.score(X_test, y_test)
print('Accuracy: {:.2f}'.format(acc_rfc*100),'%')
```

```
Accuracy: 87.00 %
```

```
from sklearn.metrics import confusion_matrix, classification_report
cm_rfc = confusion_matrix(y_test, rfc_pred)
print('Confusion Matrix:\n', cm_rfc)

# plotting heatmap of confusion matrix
plt.figure(figsize=(8,5))
sns.heatmap(cm_rfc, annot=True, fmt='g', cmap='RdYlGn')
plt.title('Confusion Matrix (Random Forest)', fontsize=12)
plt.show()

print('Classification Report of Random Forest:\n', classification_report(y_test, rfc_pred))
```

```
Confusion Matrix:
 [[86 19]
 [ 7 88]]
```



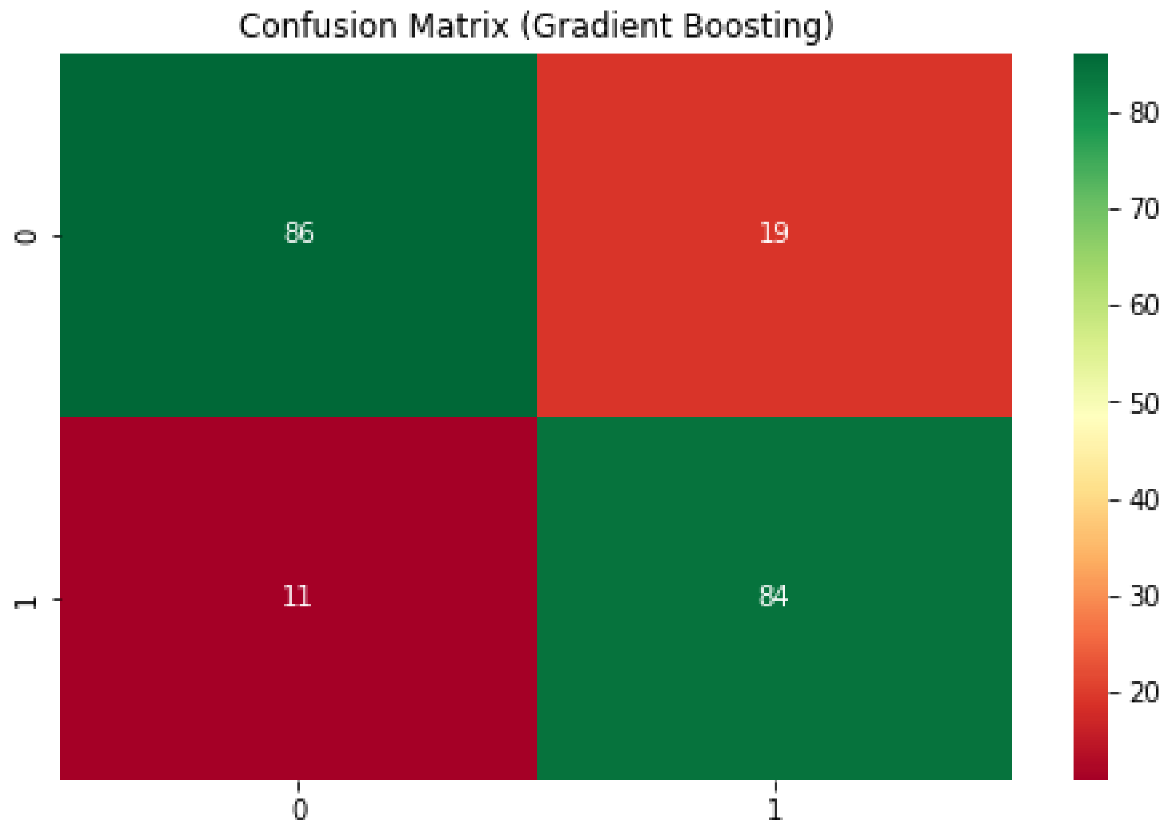

```
Classification Report of Random Forest:
              precision    recall  f1-score   support

           0       0.92      0.82      0.87       105
           1       0.82      0.93      0.87        95

    accuracy                           0.87       200
   macro avg       0.87      0.87      0.87       200
weighted avg       0.88      0.87      0.87       200
```

3. **Gradient Boosting Classifier Algorithm:**

```
# Using Gradient Boosting Algorithm.
from sklearn.ensemble import GradientBoostingClassifier
gbc = GradientBoostingClassifier(n_estimators=50, random_state=1)
gbc.fit(X_train, y_train)
gbc

# predicting the model(gbc)
gbc_pred = gbc.predict(X_test)

# checking accuracy
acc_gbc = gbc.score(X_test, y_test)
print('Accuracy: {:.2f}'.format(acc_gbc*100),'%')

Accuracy: 85.00 %

from sklearn.metrics import confusion_matrix, classification_report
cm_gbc = confusion_matrix(y_test, gbc_pred)
print('Confusion Matrix:\n', cm_gbc)

# plotting heatmap of confusion matrix
plt.figure(figsize=(8,5))
```

```
sns.heatmap(cm_gbc, annot=True, fmt='g', cmap='RdYlGn')
plt.title('Confusion Matrix (Gradient Boosting)', fontsize=12)
plt.show()

print('Classification Report of Gradient Boosting:\n', classification_report(y_test, gbc_pred))
```

```
Confusion Matrix:
 [[86 19]
 [11 84]]
```




```
Classification Report of Gradient Boosting:
               precision    recall  f1-score   support

           0       0.89      0.82      0.85       105
           1       0.82      0.88      0.85        95

    accuracy                           0.85       200
   macro avg       0.85      0.85      0.85       200
weighted avg       0.85      0.85      0.85       200
```

4. **Support Vector Machine Algorithm:**

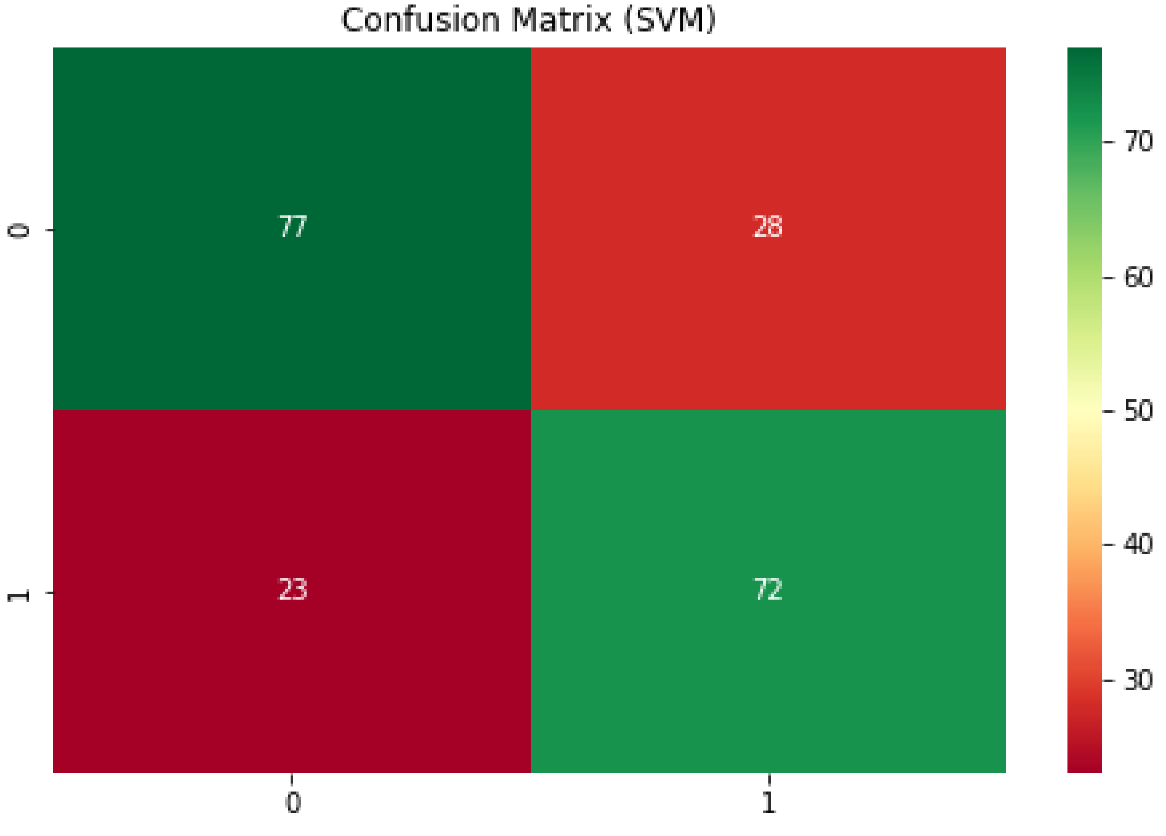
```
# Using SVM Algorithm.
from sklearn.svm import SVC
svc = SVC(kernel='rbf', gamma='scale', probability=True)
svc.fit(X_train, y_train)
svc

# predicting the model(svc)
svc_pred = svc.predict(X_test)

# checking accuracy
```

```
acc_svc = svc.score(X_test, y_test)
print('Accuracy: {:.2f}'.format(acc_svc*100),'%')
```

```
Accuracy: 74.50 %
```

```
from sklearn.metrics import confusion_matrix, classification_report
cm_svc = confusion_matrix(y_test, svc_pred)
print('Confusion Matrix:\n', cm_svc)

# plotting heatmap of confusion matrix
plt.figure(figsize=(8,5))
sns.heatmap(cm_svc, annot=True, fmt='g', cmap='RdYlGn')
plt.title('Confusion Matrix (SVM)', fontsize=12)
plt.show()

print('Classification Report of SVM:\n', classification_report(y_test, svc_pred))
```

```
Confusion Matrix:
 [[77 28]
 [23 72]]
```

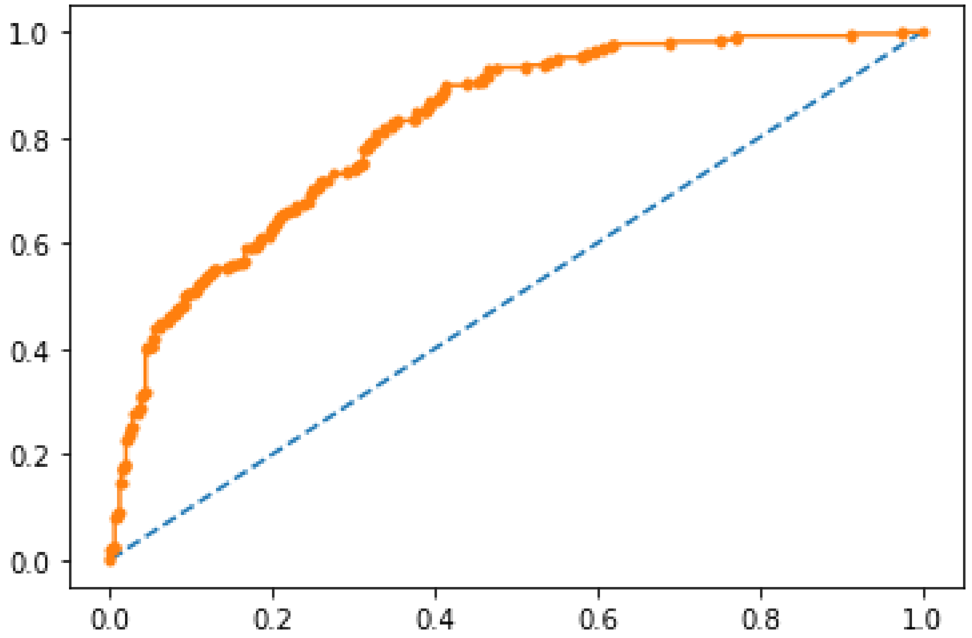



```
Classification Report of SVM:
              precision    recall  f1-score   support

           0       0.77      0.73      0.75       105
           1       0.72      0.76      0.74        95

    accuracy                           0.74       200
   macro avg       0.74      0.75      0.74       200
weighted avg       0.75      0.74      0.75       200
```

```
# Preparing ROC (Receiver Operating Characteristic) & AUC score (Area Under the Curve)
from sklearn.metrics import roc_curve, roc_auc_score
```

```
# predict probabilities
svm_prob = svc.predict_proba(X)
# Keep probabilities for the positive outcomes only
svm_prob = svm_prob[:,1]
# Calculate AUC
svm_auc = roc_auc_score(y, svm_prob)
print('AUC: %.3f' % svm_auc)
# Calculate ROC Curve
fpr, tpr, thresholds = roc_curve(y, svm_prob)
# plot no skill
plt.plot([0,1],[0,1], linestyle='--')
# plot the roc curve for the model
plt.plot(fpr, tpr, marker='.')

plt.show()
```

```
AUC: 0.822
```



5. **Decision Tree Classifier Algorithm:**

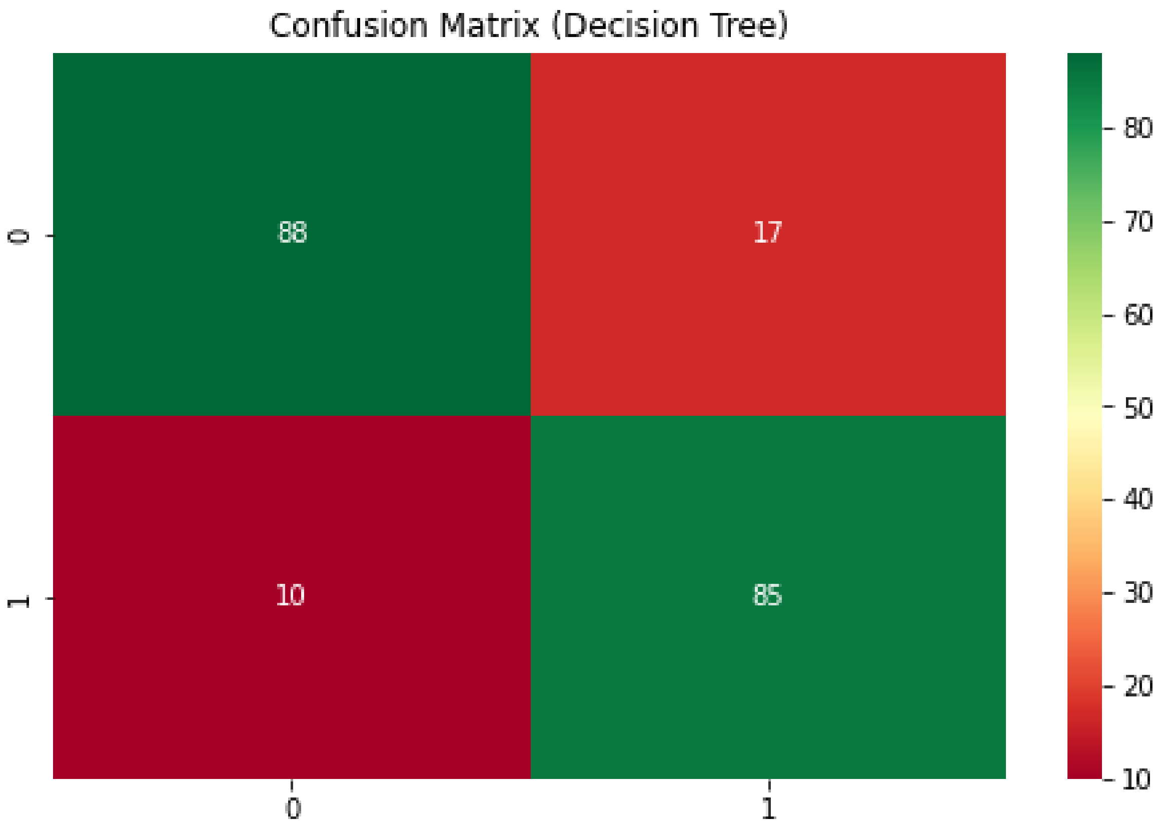
```
# Using Gradient Boosting Algorithm.
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier(max_depth=10, criterion='gini', random_state=1)
dtc.fit(X_train, y_train)
dtc

# predicting the model(dtc)
dtc_pred = dtc.predict(X_test)

# checking accuracy
acc_dtc = dtc.score(X_test, y_test)
print('Accuracy: {:.2f}'.format(acc_dtc*100),'%')
```

```
Accuracy: 86.50 %
```

```
from sklearn.metrics import confusion_matrix, classification_report
cm_dtc = confusion_matrix(y_test, dtc_pred)
print('Confusion Matrix:\n', cm_dtc)
```

```
# plotting heatmap of confusion matrix
plt.figure(figsize=(8,5))
sns.heatmap(cm_dtc, annot=True, fmt='g', cmap='RdYlGn')
plt.title('Confusion Matrix (Decision Tree)', fontsize=12)
plt.show()

print('Classification Report of Decision Tree:\n', classification_report(y_test, dtc_pred))
```

```
Confusion Matrix:
 [[88 17]
 [10 85]]
```




```
Classification Report of Decision Tree:
               precision    recall  f1-score   support

           0       0.90      0.84      0.87       105
           1       0.83      0.89      0.86        95

    accuracy                           0.86       200
   macro avg       0.87      0.87      0.86       200
weighted avg       0.87      0.86      0.87       200
```

6. **KNearest Neighbor(KNN) Classifier Algorithm:**

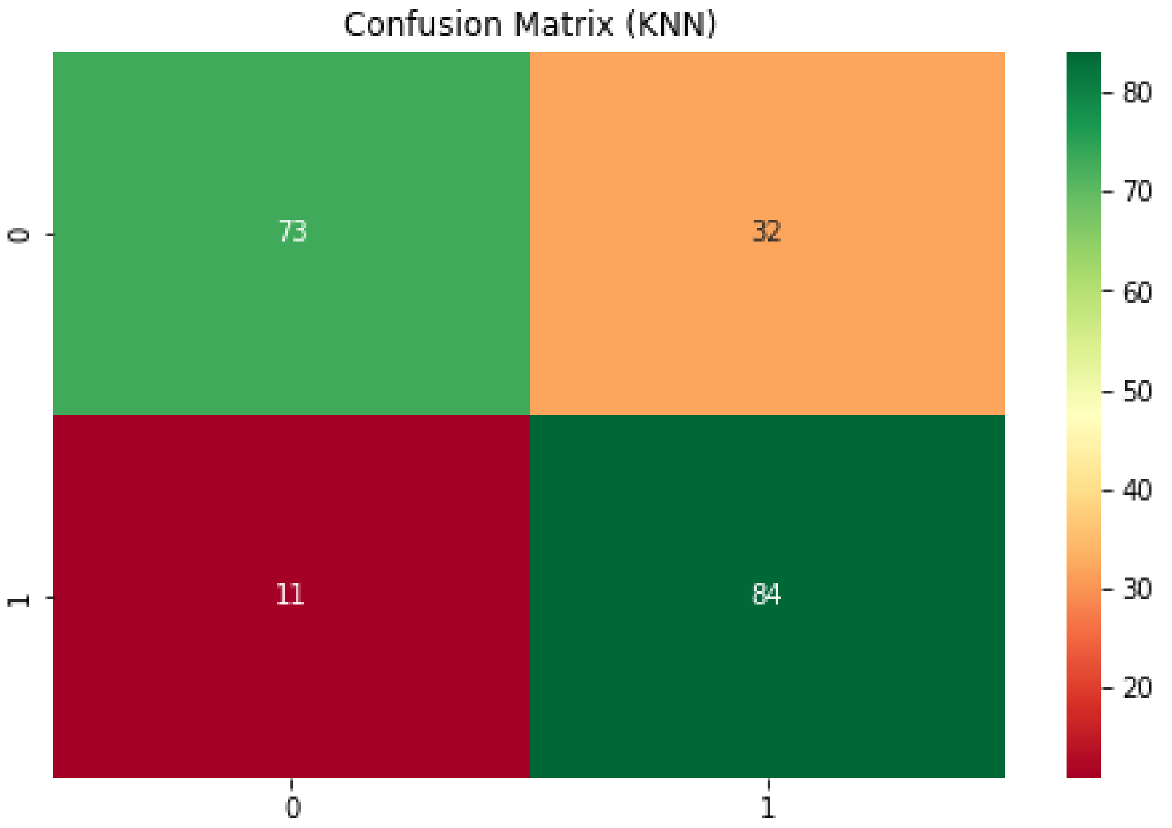
```
# Using KNN Algorithm.
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7, metric='minkowski')
knn.fit(X_train, y_train)
knn

# predicting the model(KNN)
knn_pred = knn.predict(X_test)
```

```python
# checking accuracy
acc_knn = knn.score(X_test, y_test)
print('Accuracy: {:.2f}'.format(acc_knn*100),'%')
```

```
Accuracy: 78.50 %
```

```python
from sklearn.metrics import confusion_matrix, classification_report
cm_knn = confusion_matrix(y_test, knn_pred)
print('Confusion Matrix:\n', cm_knn)

# plotting heatmap of confusion matrix
plt.figure(figsize=(8,5))
sns.heatmap(cm_knn, annot=True, fmt='g', cmap='RdYlGn')
plt.title('Confusion Matrix (KNN)', fontsize=12)
plt.show()

print('Classification Report of KNN:\n', classification_report(y_test, knn_pred))
```

```
Confusion Matrix:
 [[73 32]
 [11 84]]
```



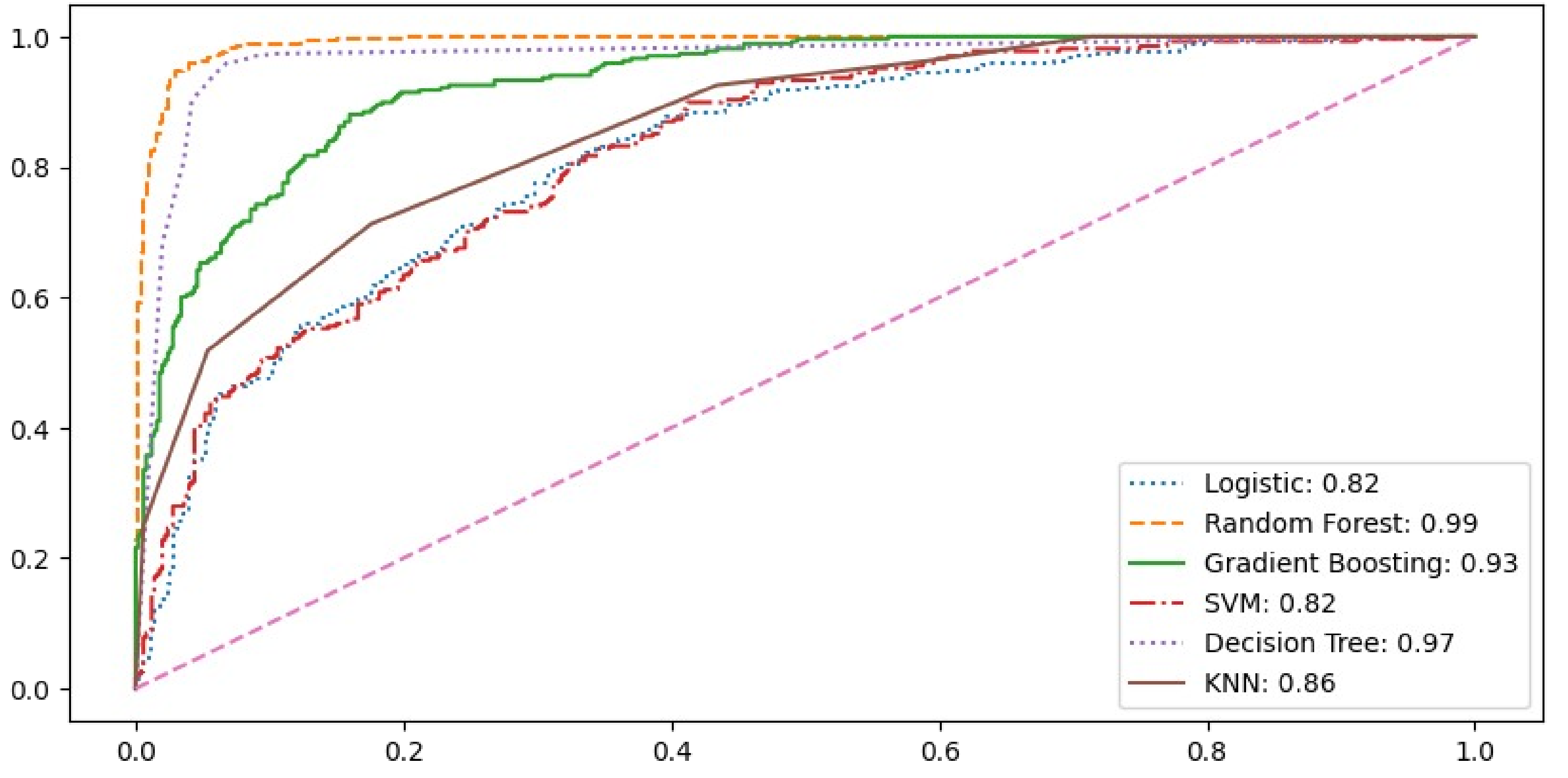

```
Classification Report of KNN:
               precision    recall  f1-score   support

           0       0.87      0.70      0.77       105
           1       0.72      0.88      0.80        95

    accuracy                           0.79       200
   macro avg       0.80      0.79      0.78       200
weighted avg       0.80      0.79      0.78       200
```

```python
# Preparing ROC (Receiver Operating Characteristic) & AUC score (Area Under the Curve)

from sklearn.metrics import roc_curve, roc_auc_score

# predicting the probability of all the model.
prob_Logistic = lr.predict_proba(X)
prob_rfc = rfc.predict_proba(X)
prob_gbc = gbc.predict_proba(X)
prob_svm = svc.predict_proba(X)
prob_dtc = dtc.predict_proba(X)
prob_knn = knn.predict_proba(X)

# Keep probabilities for the positive outcomes only.
# [:,1]---> taking all the rows of positive classes. ROC_curve works only for positive classes.
prob_Logistic = prob_Logistic[:,1]
prob_rfc = prob_rfc[:,1]
prob_gbc = prob_gbc[:,1]
prob_svm = prob_svm[:,1]
prob_dtc = prob_dtc[:,1]
prob_knn = prob_knn[:,1]

# Calculate AUC (Area Under the curve)
auc_logistic = roc_auc_score(y, prob_Logistic)
auc_rfc = roc_auc_score(y, prob_rfc)
auc_gbc = roc_auc_score(y, prob_gbc)
auc_svm = roc_auc_score(y, prob_svm)
auc_dtc = roc_auc_score(y, prob_dtc)
auc_knn = roc_auc_score(y, prob_knn)

#showing & compare AUC_score and Accuracy_Score.
score = pd.DataFrame({'Model': ['Logistic Regression', 'Random forest Classifier', 'Gradient Boosting Classifier',
                                    'Support Vector Machine', 'Decision Tree Classifier', 'KNearest Neighbor Classifier'],
                         'AUC_Score': [auc_logistic, auc_rfc, auc_gbc, auc_svm, auc_dtc, auc_knn],
                         'Accuracy_Score': [acc_lr, acc_rfc, acc_gbc, acc_svc, acc_dtc, acc_knn]}).sort_values(by='AUC_Score', ascending=False)
score
```

	Model	AUC_Score	Accuracy_Score
1	Random forest Classifier	0.991030	0.870
4	Decision Tree Classifier	0.967201	0.865
2	Gradient Boosting Classifier	0.929597	0.850
5	KNearest Neighbor Classifier	0.860410	0.785
3	Support Vector Machine	0.822325	0.745
0	Logistic Regression	0.818149	0.785

```python
# Calculate fpr, tpr for ROC Curve
lr_fpr, lr_tpr, lr_threshold = roc_curve(y, prob_Logistic)
rfc_fpr, rfc_tpr, rfc_threshold = roc_curve(y, prob_rfc)
gbc_fpr, gbc_tpr, gbc_threshold = roc_curve(y, prob_gbc)
svm_fpr, svm_tpr, svm_threshold = roc_curve(y, prob_svm)
dtc_fpr, dtc_tpr, dtc_threshold = roc_curve(y, prob_dtc)
knn_fpr, knn_tpr, knn_threshold = roc_curve(y, prob_knn)

# Plotting ROC Curve for the model
plt.figure(figsize=(10,5), dpi=100)

plt.plot(lr_fpr, lr_tpr, linestyle='dotted', label= ('Logistic: %.2f'% auc_logistic))
plt.plot(rfc_fpr, rfc_tpr, linestyle='--', label= ('Random Forest: %.2f'% auc_rfc))
plt.plot(gbc_fpr, gbc_tpr, linestyle='-', label= ('Gradient Boosting: %.2f'% auc_gbc))
plt.plot(svm_fpr, svm_tpr, linestyle='-.', label= ('SVM: %.2f'% auc_svm))
plt.plot(dtc_fpr, dtc_tpr, linestyle=':', label= ('Decision Tree: %.2f'% auc_dtc))
```

```
plt.plot(knn_fpr, knn_tpr, linestyle='-', label= ('KNN: %.2f'% auc_knn))

plt.plot([0,1],[0,1], linestyle='--')

plt.legend()
plt.show()
```



Observations:

- The Random Forest Classifier stands out with the highest AUC score and good accuracy.
- Decision Tree and Gradient Boosting also perform well, following closely behind Random Forest.
- KNearest Neighbor and Logistic Regression show decent performance but are not leading in terms of AUC or accuracy.
- Support Vector Machine(SVM) lags behind the other models in both AUC and accuracy. It might require tuning or feature engineering to improve its performance.

Compare all model with KNN(KNearest Neighbor):

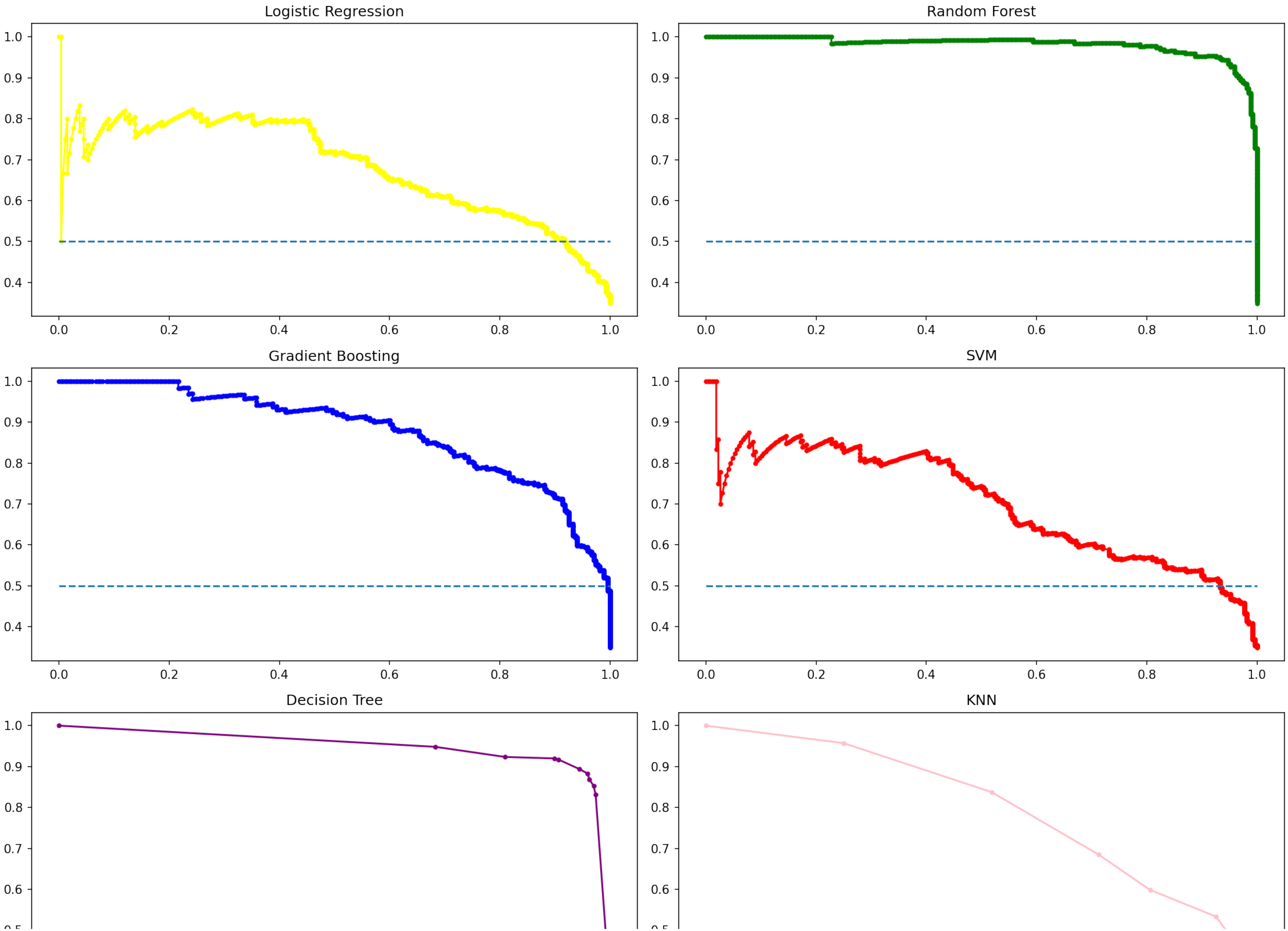
- Random Forest, Decision Tree, and Gradient Boosting models outperform KNN in terms of AUC and accuracy.
- KNN has lower AUC and accuracy compared to the top-performing models.
- Support Vector Machine and Logistic Regression have lower AUC and accuracy compared to KNN.

```
#Precision Recall Curve for all models.

from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from sklearn.metrics import average_precision_score
# predict probabilities
prob_Logistic = lr.predict_proba(X)
prob_rfc = rfc.predict_proba(X)
prob_gbc = gbc.predict_proba(X)
prob_svm = svc.predict_proba(X)
prob_dtc = dtc.predict_proba(X)
prob_knn = knn.predict_proba(X)

# keep probabilities for the positive outcome only
```

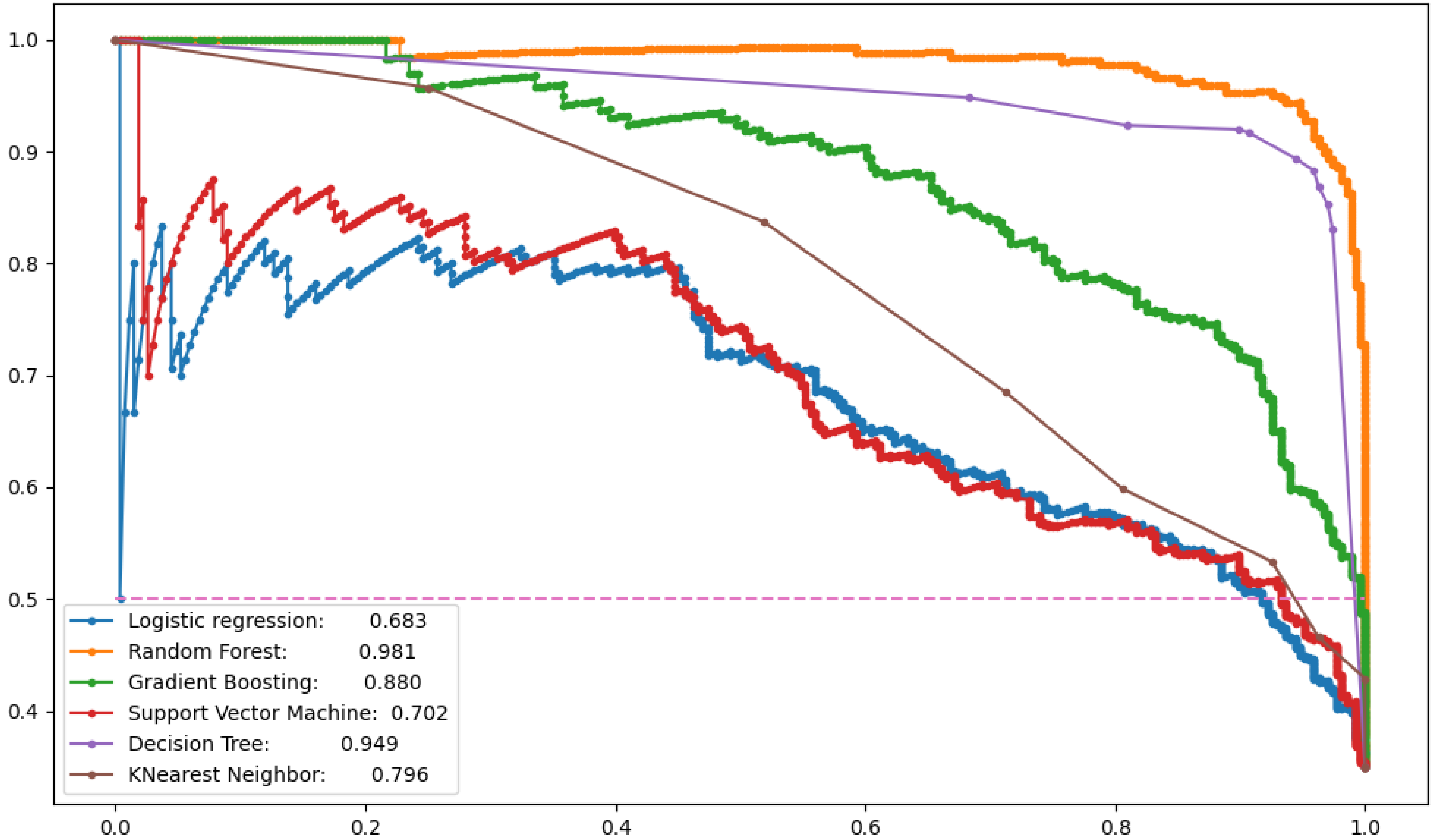
```python
prob_Logistic = prob_Logistic[:,1]
prob_rfc = prob_rfc[:,1]
prob_gbc = prob_gbc[:,1]
prob_svm = prob_svm[:,1]
prob_dtc = prob_dtc[:,1]
prob_knn = prob_knn[:,1]

# predict class values
yhat_logistic = lr.predict(X)
yhat_rfc = rfc.predict(X)
yhat_gbc = gbc.predict(X)
yhat_svm = svc.predict(X)
yhat_dtc = dtc.predict(X)
yhat_knn = knn.predict(X)

# calculate precision-recall curve
lr_precision, lr_recall, lr_thresholds = precision_recall_curve(y, prob_Logistic)
rfc_precision, rfc_recall, rfc_thresholds = precision_recall_curve(y, prob_rfc)
gbc_precision, gbc_recall, gbc_thresholds = precision_recall_curve(y, prob_gbc)
svm_precision, svm_recall, svm_thresholds = precision_recall_curve(y, prob_svm)
dtc_precision, dtc_recall, dtc_thresholds = precision_recall_curve(y, prob_dtc)
knn_precision, knn_recall, knn_thresholds = precision_recall_curve(y, prob_knn)

# calculate F1 score
lr_f1 = f1_score(y, yhat_logistic)
rfc_f1 = f1_score(y, yhat_rfc)
gbc_f1 = f1_score(y, yhat_gbc)
svm_f1 = f1_score(y, yhat_svm)
dtc_f1 = f1_score(y, yhat_dtc)
knn_f1 = f1_score(y, yhat_knn)

# calculate precision-recall AUC
lr_auc = auc(lr_recall, lr_precision)
rfc_auc = auc(rfc_recall, rfc_precision)
gbc_auc = auc(gbc_recall, gbc_precision)
svm_auc = auc(svm_recall, svm_precision)
dtc_auc = auc(dtc_recall, dtc_precision)
knn_auc = auc(knn_recall, knn_precision)

# calculate average precision score
lr_avg_precision = average_precision_score(y, prob_Logistic)
rfc_avg_precision = average_precision_score(y, prob_rfc)
gbc_avg_precision = average_precision_score(y, prob_gbc)
svm_avg_precision = average_precision_score(y, prob_svm)
dtc_avg_precision = average_precision_score(y, prob_dtc)
knn_avg_precision = average_precision_score(y, prob_knn)
print('Logistic Regression:          f1_score= %.3f; auc= %.3f; avg_precision= %.3f' % (lr_f1, lr_auc, lr_avg_precision))
print('Random forest Classifier:     f1_score= %.3f; auc= %.3f; avg_precision= %.3f' % (rfc_f1, rfc_auc, rfc_avg_precision))
print('Gradient Boosting Classifier: f1_score= %.3f; auc= %.3f; avg_precision= %.3f' % (gbc_f1, gbc_auc, gbc_avg_precision))
print('Support Vector Machine:       f1_score= %.3f; auc= %.3f; avg_precision= %.3f' % (svm_f1, svm_auc, svm_avg_precision))
print('Decision Tree Classifier:     f1_score= %.3f; auc= %.3f; avg_precision= %.3f' % (dtc_f1, dtc_auc, dtc_avg_precision))
print('KNearest Neighbor Classifier: f1_score= %.3f; auc= %.3f; avg_precision= %.3f' % (knn_f1, knn_auc, knn_avg_precision))


# plot the precision-recall curve for the models
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(15,12), dpi=150)

axes[0][0].plot(lr_recall, lr_precision, marker='.', color='yellow')
axes[0][0].plot([0,1],[0.5,0.5], linestyle='--')
axes[0][0].set_title('Logistic Regression')
```

```python
axes[0][1].plot(rfc_recall, rfc_precision, marker='.', color='green')
axes[0][1].plot([0,1],[0.5,0.5], linestyle='--')
axes[0][1].set_title('Random Forest')

axes[1][0].plot(gbc_recall, gbc_precision, marker='.', color='blue')
axes[1][0].plot([0,1],[0.5,0.5], linestyle='--')
axes[1][0].set_title('Gradient Boosting')

axes[1][1].plot(svm_recall, svm_precision, marker='.', color='red')
axes[1][1].plot([0,1],[0.5,0.5], linestyle='--')
axes[1][1].set_title('SVM')

axes[2][0].plot(dtc_recall, dtc_precision, marker='.', color='purple')
axes[2][0].plot([0,1],[0.5,0.5], linestyle='--')
axes[2][0].set_title('Decision Tree')

axes[2][1].plot(knn_recall, knn_precision, marker='.', color='pink')
axes[2][1].plot([0,1],[0.5,0.5], linestyle='--')
axes[2][1].set_title('KNN')

plt.tight_layout()
plt.show()
```

```
Logistic Regression:          f1_score= 0.651; auc= 0.683; avg_precision= 0.685
Random forest Classifier:     f1_score= 0.924; auc= 0.981; avg_precision= 0.981
Gradient Boosting Classifier: f1_score= 0.801; auc= 0.880; avg_precision= 0.880
Support Vector Machine:       f1_score= 0.651; auc= 0.702; avg_precision= 0.703
Decision Tree Classifier:     f1_score= 0.919; auc= 0.949; avg_precision= 0.922
KNearest Neighbor Classifier: f1_score= 0.687; auc= 0.796; avg_precision= 0.750
```


Logistic Regression
Random Forest
Gradient Boosting
SVM
Decision Tree
KNN
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.0
0.2
0.4
0.6
0.8
1.0

```
# plotting Precision- recall curve for all model in single Graph
plt.figure(figsize=(10,6), dpi=100)
plt.plot(lr_recall, lr_precision, marker='.', label=('Logistic regression:      % .3f'% lr_auc))
plt.plot(rfc_recall, rfc_precision, marker='.', label=('Random Forest:           % .3f'% rfc_auc))
plt.plot(gbc_recall, gbc_precision, marker='.', label=('Gradient Boosting:       % .3f'% gbc_auc))
plt.plot(svm_recall, svm_precision, marker='.', label=('Support Vector Machine: % .3f'% svm_auc))
plt.plot(dtc_recall, dtc_precision, marker='.', label=('Decision Tree:           % .3f'% dtc_auc))
plt.plot(knn_recall, knn_precision, marker='.', label=('KNearest Neighbor:       % .3f'% knn_auc))

plt.plot([0,1],[0.5,0.5], linestyle='--')

plt.legend()
plt.tight_layout()
plt.show()
```



Observations:

- Random Forest and Decision Tree models perform excellent with high scores across all metrics.
- Gradient Boosting also performs well but not as high as Random Forest and Decision Tree.
- KNearest Neighbor has moderate performance, and its scores are lower than Random Forest and Decision Tree.
- Logistic Regression and Support Vector Machine show relatively lower performance compared to the ensemble models.

END.