5114-ai-in-hc-lp-diabpredict

March 2, 2024

[13]:
```
IMPORTING LIBRARIES:
```

[19]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import classification_report
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

[ ]:
```
DATASET UPLOAD:
```

[6]:
```python
diabetes_df = pd.read_csv('C:\\Users\\HP\\Downloads\\archive (1)\\diabetes.csv')
diabetes_df.head()
```

[6]:
```
   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
```

[ ]:
```
EXPLORATORY DATA ANALYSIS:
```

[7]:
```
diabetes_df.columns
```

[7]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

[ ]:
```
INFORMATION ABOUT DATASET:
```

[15]:
```
diabetes_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

[ ]:
```
CHECKING THE NULL VALUES IN DATASET:
```

[11]:
```
diabetes_df.isnull().head(10)
```

[11]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin    BMI  \
0        False    False          False          False    False  False
1        False    False          False          False    False  False
2        False    False          False          False    False  False
3        False    False          False          False    False  False
4        False    False          False          False    False  False
5        False    False          False          False    False  False
6        False    False          False          False    False  False
7        False    False          False          False    False  False
8        False    False          False          False    False  False
9        False    False          False          False    False  False

   DiabetesPedigreeFunction    Age  Outcome
0                     False  False    False
1                     False  False    False
2                     False  False    False
```

```
3                        False  False    False
4                        False  False    False
5                        False  False    False
6                        False  False    False
7                        False  False    False
8                        False  False    False
9                        False  False    False
```

[22]:
```
diabetes_df.isnull().sum()
```

[22]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

[ ]:
```
n the provided code snippet, the initial step involves checking for null values␣
↪using the isnull() function, followed by calculating the sum of those␣
↪missing values using the sum() function. However, this analysis may not␣
↪accurately reflect the presence of missing data in the dataset. In reality,␣
↪the dataset contains missing values represented by 0. To address this issue␣
↪and ensure the dataset's authenticity, the subsequent step involves␣
↪replacing these 0 values with NaN before initiating the imputation process.
```

[23]:
```
columns_to_replace = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',␣
↪'BMI']
diabetes_df_copy = diabetes_df.copy(deep=True)

# Replace 0 with NaN in specified columns
diabetes_df_copy[columns_to_replace] = diabetes_df_copy[columns_to_replace].
↪replace(0, np.NaN)

# Showing the Count of NANs
print(diabetes_df_copy.isnull().sum())
```

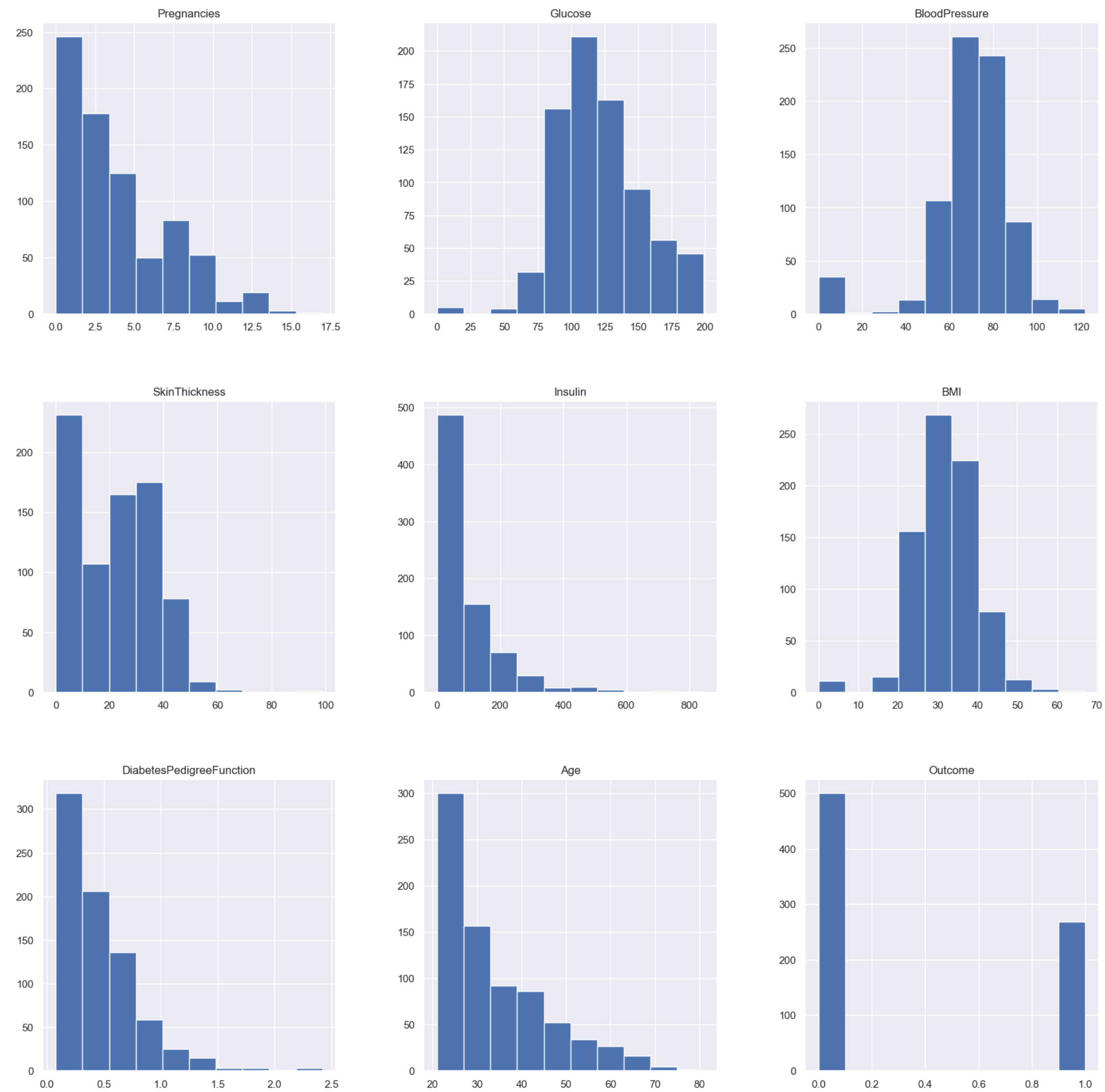
```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
```

```
Age                         0
Outcome                     0
dtype: int64
```

[ ]:
```
DATA VISUALIZATION:
```

[ ]:
```
DATA DISTRIBUTION PLOTS BEFORE REMOVING THE NULL VALUES :
```

[26]:
```
p = diabetes_df.hist(figsize = (20,20))
```

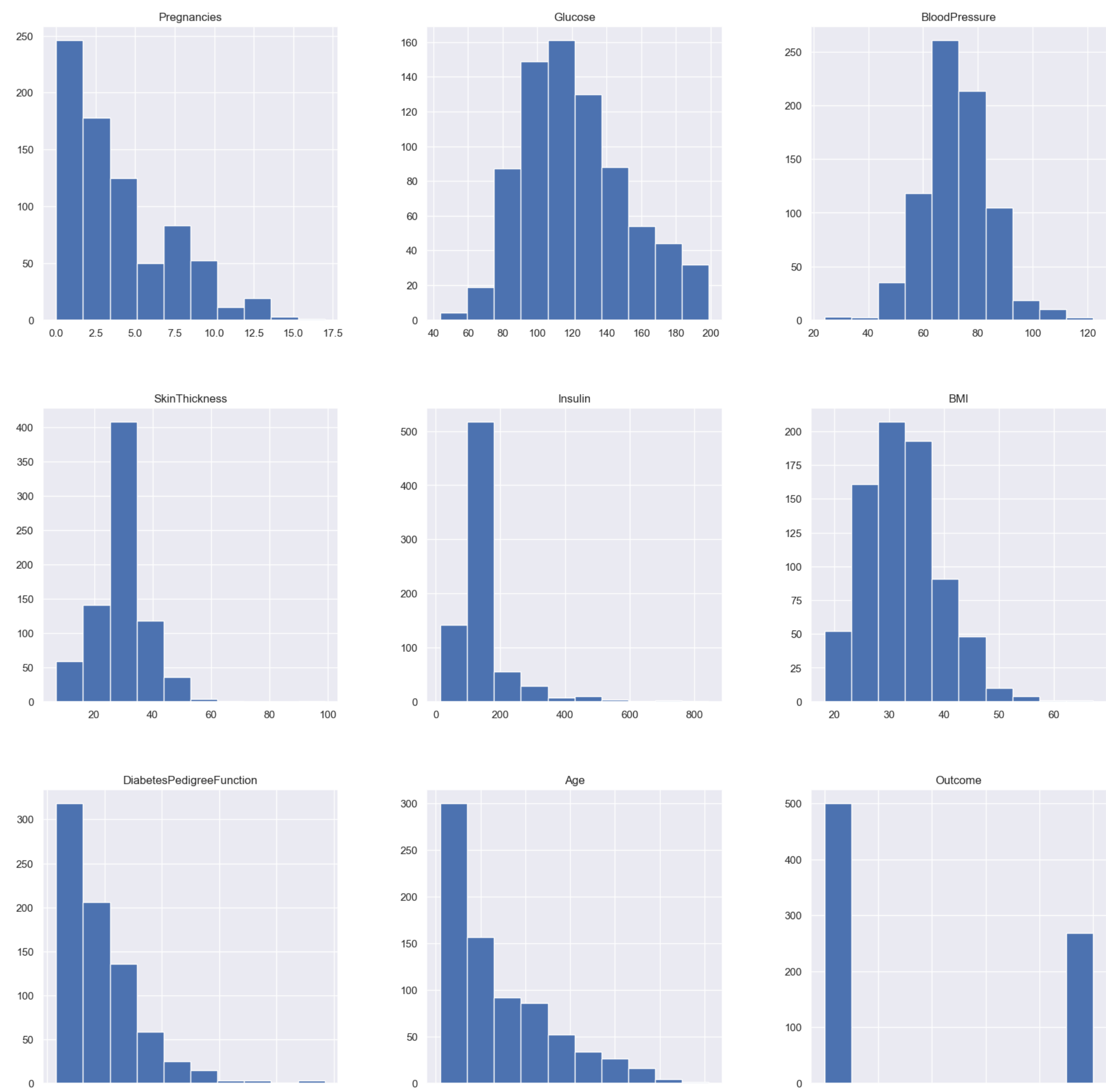


[ ]:
```
Now we will be imputing the mean value of the column to each missing value of␣
 ↪that particular column.
```

[27]:
```python
diabetes_df_copy['Glucose'].fillna(diabetes_df_copy['Glucose'].mean(), inplace = True)
diabetes_df_copy['BloodPressure'].fillna(diabetes_df_copy['BloodPressure'].mean(), inplace = True)
diabetes_df_copy['SkinThickness'].fillna(diabetes_df_copy['SkinThickness'].median(), inplace = True)
diabetes_df_copy['Insulin'].fillna(diabetes_df_copy['Insulin'].median(), inplace = True)
diabetes_df_copy['BMI'].fillna(diabetes_df_copy['BMI'].median(), inplace = True)
```

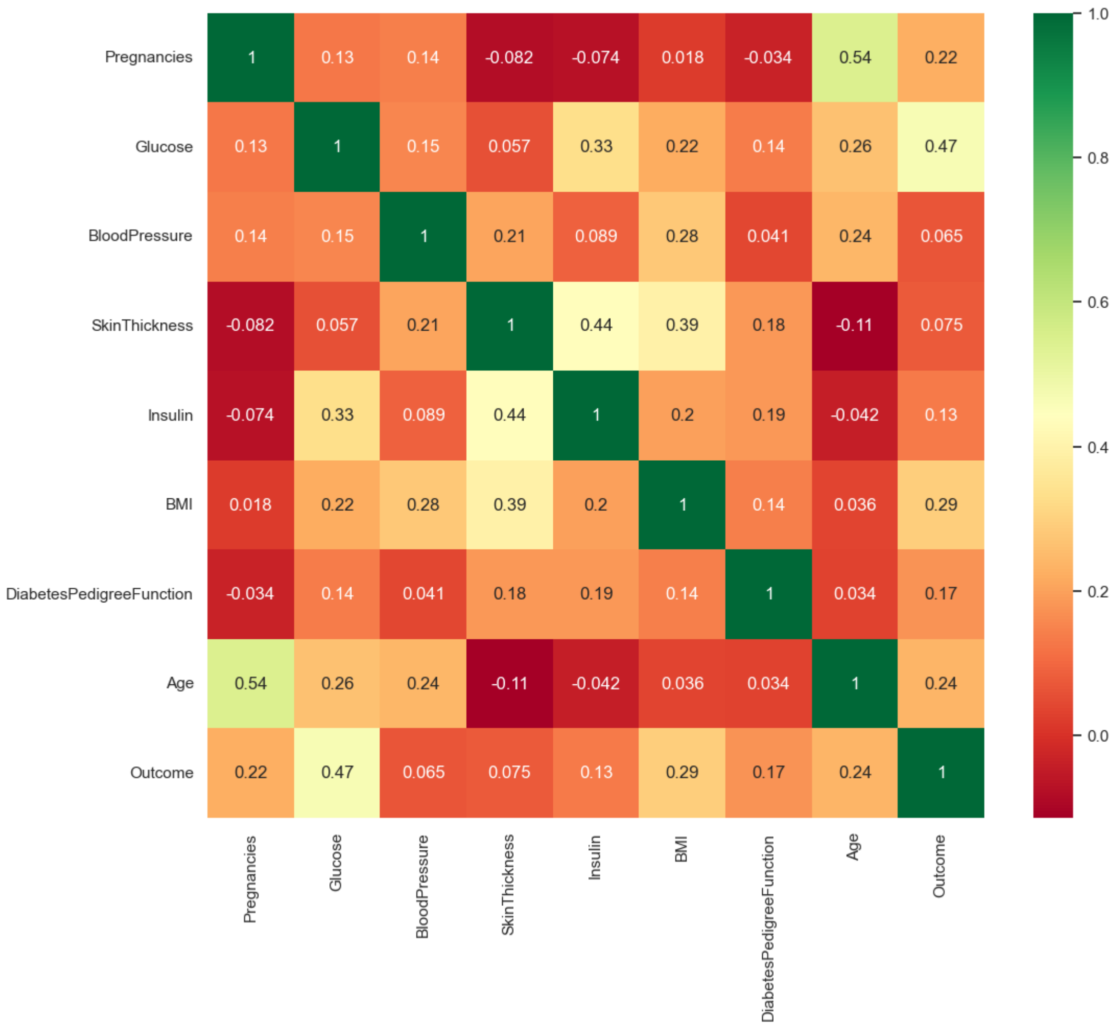
[ ]:
```
DATA DISTRIBUTION PLOTS AFTER REMOVING THE NULL VALUES:
```

[28]:
```python
p = diabetes_df_copy.hist(figsize = (20,20))
```



[ ]:
```
FEATURES CORRELATION:
```

[30]:
```
plt.figure(figsize=(12, 10))
correlation_matrix = diabetes_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='RdYlGn')
plt.show()
```



[ ]:
```
DATA SCALING:
```

[ ]:
```
Let's check the data before scaling it
```

[31]:
```
diabetes_df_copy.head()
```

[31]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6    148.0           72.0           35.0    125.0  33.6
1            1     85.0           66.0           29.0    125.0  26.6
2            8    183.0           64.0           29.0    125.0  23.3
3            1     89.0           66.0           23.0     94.0  28.1
4            0    137.0           40.0           35.0    168.0  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
```

[ ]:
```
AFTER STANDARD SCALING:
```

[32]:
```python
columns_to_scale = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']

sc_X = StandardScaler()
X = pd.DataFrame(sc_X.fit_transform(diabetes_df_copy[columns_to_scale]), columns=columns_to_scale)
X.head()
```

[32]:
```
   Pregnancies   Glucose  BloodPressure  SkinThickness   Insulin       BMI  \
0     0.639947  0.865108      -0.033518       0.670643 -0.181541  0.166619
1    -0.844885 -1.206162      -0.529859      -0.012301 -0.181541 -0.852200
2     1.233880  2.015813      -0.695306      -0.012301 -0.181541 -1.332500
3    -0.844885 -1.074652      -0.529859      -0.695245 -0.540642 -0.633881
4    -1.141852  0.503458      -2.680669       0.670643  0.316566  1.549303

   DiabetesPedigreeFunction       Age
0                  0.468492  1.425995
1                 -0.365061 -0.190672
2                  0.604397 -0.105584
3                 -0.920763 -1.041549
4                  5.484909 -0.020496
```

[ ]:
```
DATA SPLITTING:
```

[34]:
```python
# Specify the features and target variable
X = diabetes_df.drop('Outcome', axis=1)
y = diabetes_df['Outcome']

# Perform the train-test split
random_state_value = 7  # You can change this value if needed
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,
 ↪random_state=random_state_value)
```

[ ]: MODEL BUILDING USING ML ALGORITHMS:

[ ]: RANDOM FOREST:

[35]:
```python
from sklearn.ensemble import RandomForestClassifier

# Specify the number of estimators
n_estimators_value = 200

# Create and train the RandomForestClassifier
rfc = RandomForestClassifier(n_estimators=n_estimators_value)
rfc.fit(X_train, y_train)
```

[35]: RandomForestClassifier(n_estimators=200)

[ ]: CHECKING THE ACCURACY SCORE ON TRAINING SET:

[36]:
```python
# Predict on the training set
rfc_train = rfc.predict(X_train)

# Calculate and print the accuracy score
accuracy_score_train = metrics.accuracy_score(y_train, rfc_train)
print("Accuracy_Score =", format(accuracy_score_train))
```

```
Accuracy_Score = 1.0
```

[ ]: CHECKING THE ACCURACY SCORE ON TESTING SET:

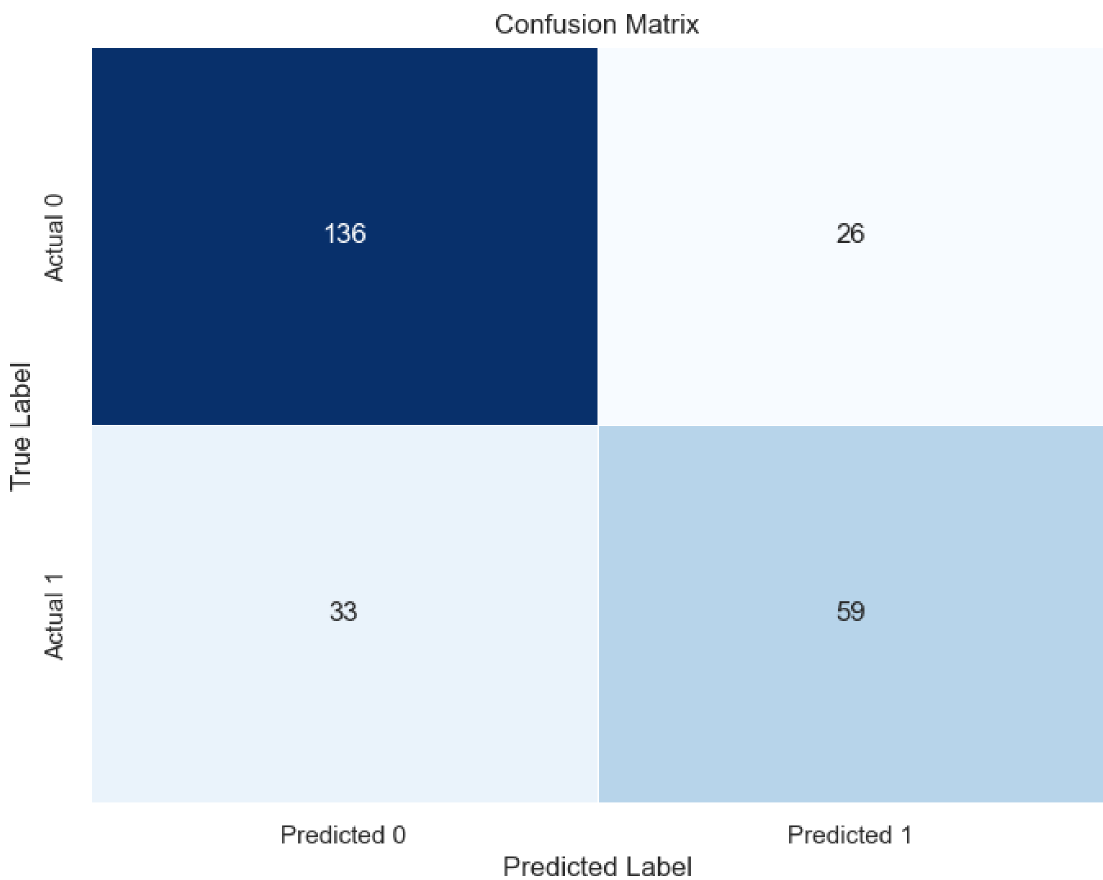
[37]:
```python
# Predict on the test set
predictions = rfc.predict(X_test)

# Calculate and print the accuracy score
accuracy_score_test = metrics.accuracy_score(y_test, predictions)
print("Accuracy_Score =", format(accuracy_score_test))
```

```
Accuracy_Score = 0.7677165354330708
```

[ ]: CLASSIFICATION REPORT & CONFUSION MATRIX:

[40]:
```python
# Assuming 'y_test' contains the true labels and 'predictions' contains the
 ↪predicted labels
cm = confusion_matrix(y_test, predictions)

# Create a heatmap for the confusion matrix
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', linewidths=.5, cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'], yticklabels=['Actual␣
 ↪0', 'Actual 1'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```



[41]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.80      0.84      0.82       162
           1       0.69      0.64      0.67        92

    accuracy                           0.77       254
   macro avg       0.75      0.74      0.74       254
```

```
weighted avg       0.76      0.77      0.77       254
```

[ ]:
```
DECISION TREE:
```

[42]:
```python
from sklearn.tree import DecisionTreeClassifier

# Create and train the DecisionTreeClassifier
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
```

[42]:
```
DecisionTreeClassifier()
```

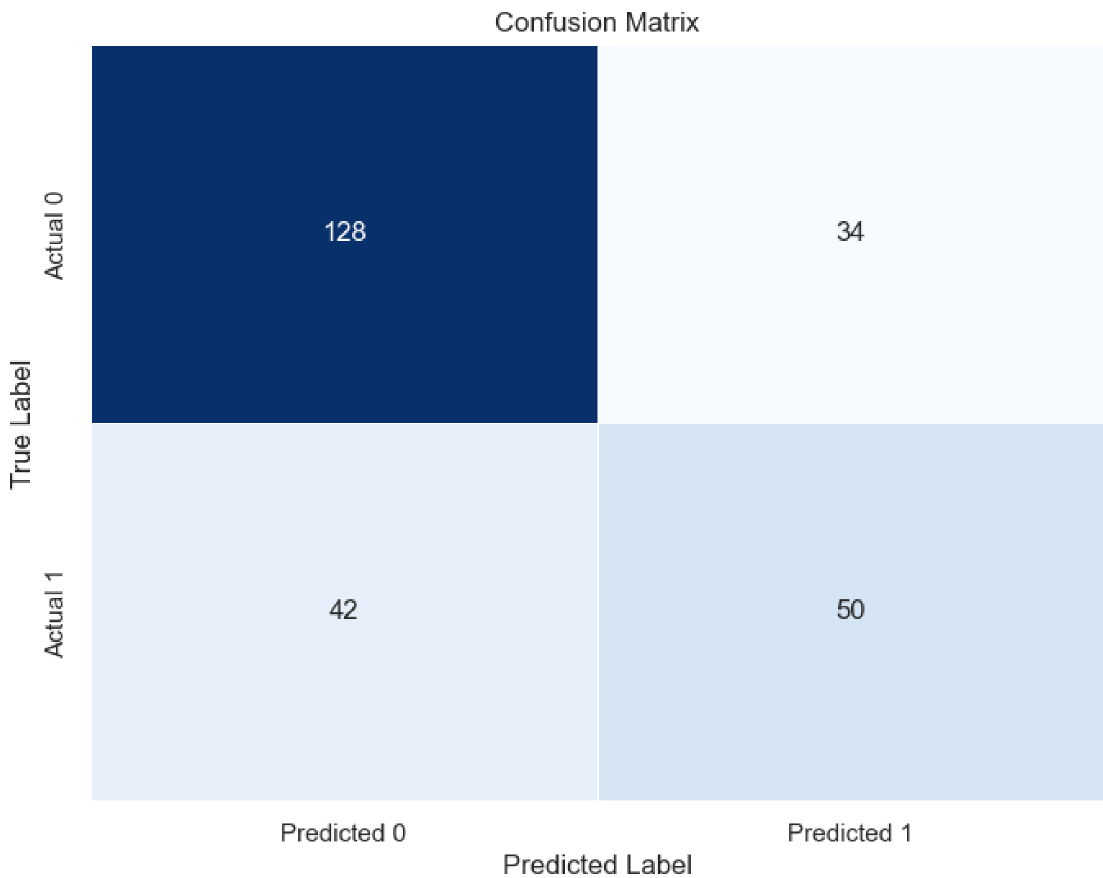
[ ]:
```
CHECKING THE ACCURACY SCORE ON TESTING SET:
```

[43]:
```python
# Predict on the test set
predictions = dtree.predict(X_test)

# Calculate and print the accuracy score
accuracy_score_test = metrics.accuracy_score(y_test, predictions)
print("Accuracy Score =", format(accuracy_score_test))
```

```
Accuracy Score = 0.7007874015748031
```

[ ]:
```
CLASSIFICATION REPORT & CONFUSION MATRIX:
```

[44]:
```python
# Assuming 'y_test' contains the true labels and 'predictions' contains the␣
↪predicted labels
cm = confusion_matrix(y_test, predictions)

# Create a heatmap for the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', linewidths=.5, cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'], yticklabels=['Actual␣
↪0', 'Actual 1'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```



[45]:
```python
from sklearn.metrics import classification_report

# Assuming 'y_test' contains the true labels and 'predictions' contains the␣
 ↪predicted labels
print("Classification Report:\n", classification_report(y_test, predictions))
```

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

           0       0.75      0.79      0.77       162
           1       0.60      0.54      0.57        92

    accuracy                           0.70       254
   macro avg       0.67      0.67      0.67       254
weighted avg       0.70      0.70      0.70       254
```

[ ]:
```
SUPPORT VECTOR MACHINE (SVM):
```

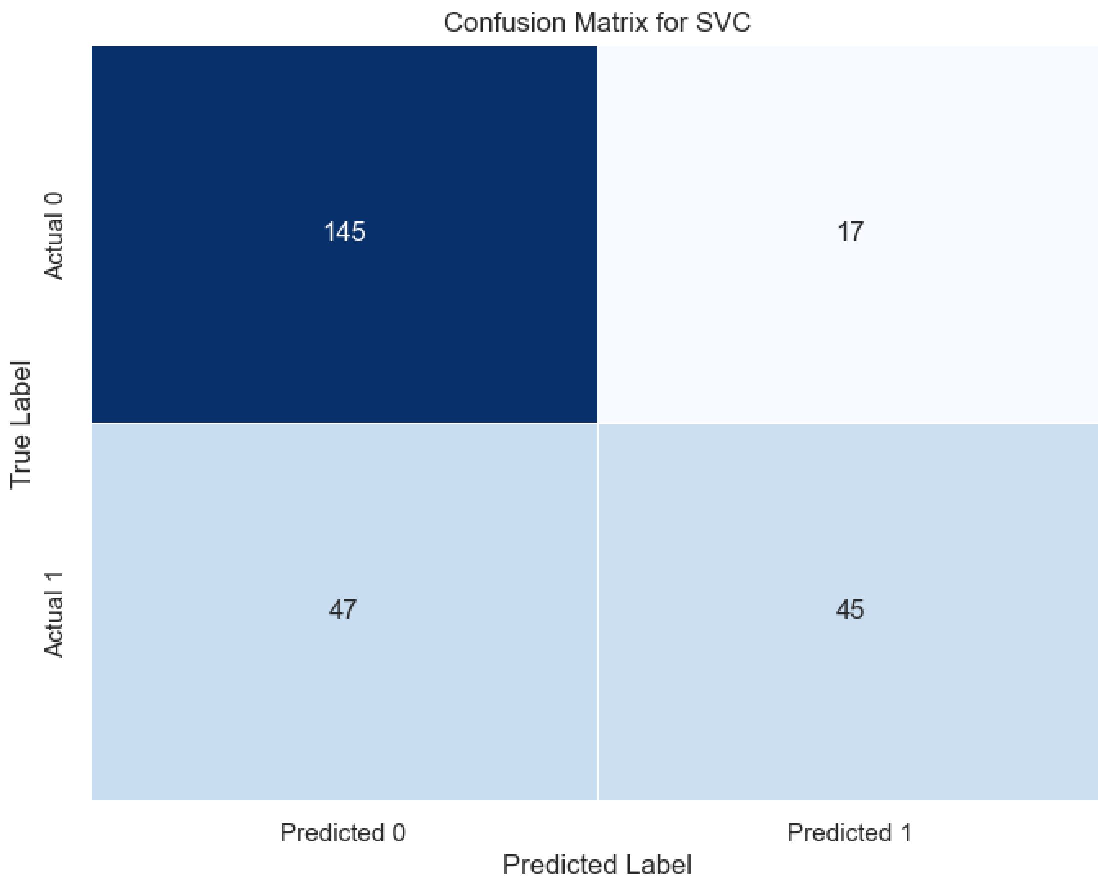
[49]:
```python
from sklearn.svm import SVC
from sklearn import metrics

# Assuming 'X_test' contains the testing features
svc_model = SVC()
svc_model.fit(X_train, y_train)
```

[49]:
```
SVC()
```

[50]:
```python
# Predict on the test set
svc_pred = svc_model.predict(X_test)

# Calculate and print the accuracy score
accuracy_score_svc = metrics.accuracy_score(y_test, svc_pred)
print("Accuracy Score =", format(accuracy_score_svc))
```

```
Accuracy Score = 0.7480314960629921
```

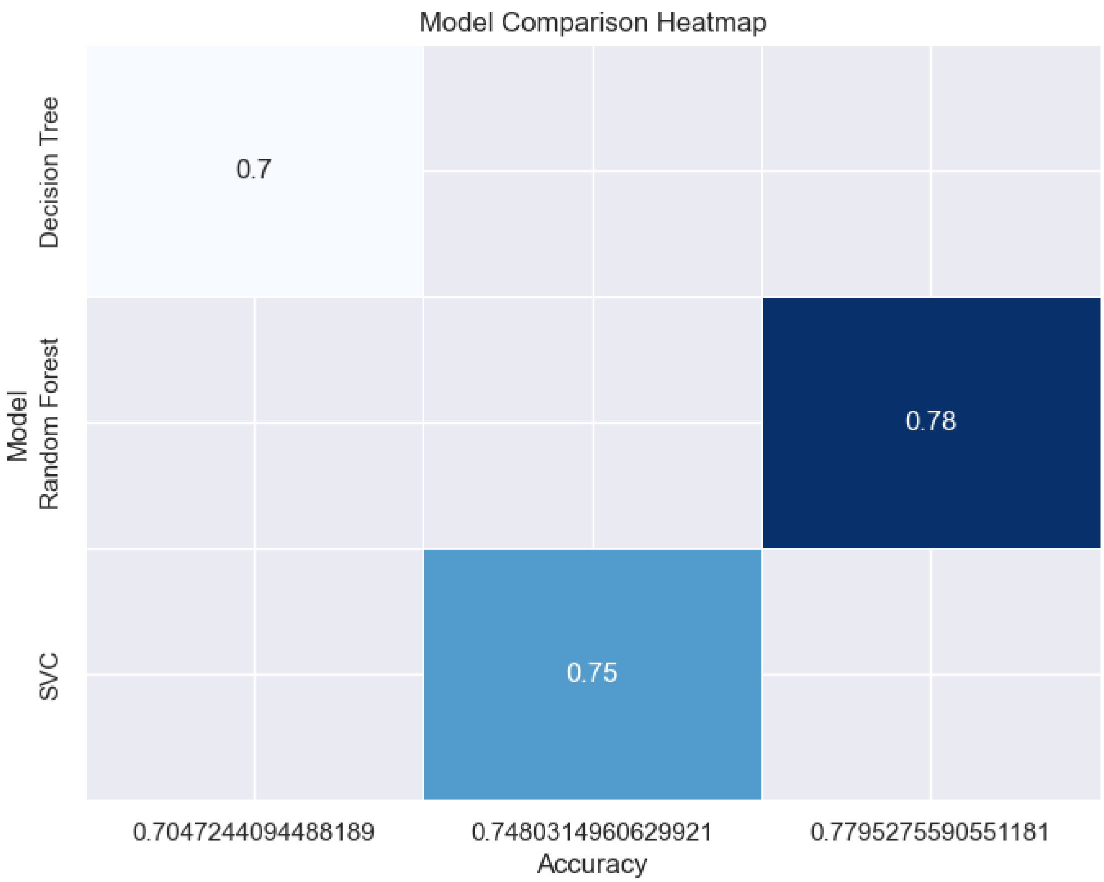
[51]:
```python
# Assuming 'y_test' contains the true labels and 'svc_pred' contains the␣
↪predicted labels
cm_svc = confusion_matrix(y_test, svc_pred)

# Create a heatmap for the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm_svc, annot=True, fmt='d', cmap='Blues', linewidths=.5,␣
↪cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'], yticklabels=['Actual␣
↪0', 'Actual 1'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for SVC')
plt.show()
```



[52]:
```
from sklearn.metrics import classification_report

# Assuming 'y_test' contains the true labels and 'svc_pred' contains the
↪predicted labels
print("Classification Report for SVC:\n", classification_report(y_test,
↪svc_pred))
```

```
Classification Report for SVC:
               precision    recall  f1-score   support

           0       0.76      0.90      0.82       162
           1       0.73      0.49      0.58        92

    accuracy                           0.75       254
   macro avg       0.74      0.69      0.70       254
weighted avg       0.74      0.75      0.73       254
```

[56]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Assuming 'X' contains features and 'y' contains the target variable
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,
 ↪random_state=7)

# Train Random Forest Classifier
rfc = RandomForestClassifier(n_estimators=200)
rfc.fit(X_train, y_train)
predictions_rfc = rfc.predict(X_test)
accuracy_rfc = accuracy_score(y_test, predictions_rfc)

# Train Decision Tree Classifier
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
predictions_dtree = dtree.predict(X_test)
accuracy_dtree = accuracy_score(y_test, predictions_dtree)

# Train Support Vector Classifier
svc_model = SVC()
svc_model.fit(X_train, y_train)
predictions_svc = svc_model.predict(X_test)
accuracy_svc = accuracy_score(y_test, predictions_svc)

# Create a dataframe for model comparison
model_comparison = pd.DataFrame({
    'Model': ['Random Forest', 'Decision Tree', 'SVC'],
    'Accuracy': [accuracy_rfc, accuracy_dtree, accuracy_svc]
})

# Plot a heatmap for model comparison
plt.figure(figsize=(8, 6))
sns.heatmap(model_comparison.pivot(index='Model', columns='Accuracy',
 ↪values='Accuracy'),
            annot=True, cmap='Blues', linewidths=.5, cbar=False)
plt.xlabel('Accuracy')
plt.ylabel('Model')
plt.title('Model Comparison Heatmap')
plt.show()
```


Model Comparison Heatmap
Decision Tree
Random Forest
SVC
Model
0.7
0.78
0.75
0.7047244094488189
0.7480314960629921
0.7795275590551181
Accuracy