```python
import numpy as np
import pandas as pd
import os
for dirname, _, filenames in os.walk('D:/Dataset/parkinson'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
D:/Dataset/parkinson\parkinsons.data
```

```python
from PIL import Image
from IPython.display import display

# Provide the full path to the image
img = Image.open("D:/Header.jpg")  # Adjust the filename if needed
display(img)
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from termcolor import colored
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, GridSearchCV,
cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, f1_score, recall_score,
precision_score, confusion_matrix, roc_curve, auc


data = pd.read_csv(r'D:\Dataset\Parkinson\parkinsons.data')

data.head()

             name  MDVP:Fo(Hz)  MDVP:Fhi(Hz)  MDVP:Flo(Hz)
MDVP:Jitter(%)  \
0  phon_R01_S01_1      119.992       157.302        74.997
0.00784
1  phon_R01_S01_2      122.400       148.650       113.819
0.00968
2  phon_R01_S01_3      116.682       131.111       111.555
0.01050
3  phon_R01_S01_4      116.676       137.871       111.366
0.00997
4  phon_R01_S01_5      116.014       141.781       110.655
0.01284

   MDVP:Jitter(Abs)  MDVP:RAP  MDVP:PPQ  Jitter:DDP  MDVP:Shimmer  ...
\
0           0.00007   0.00370   0.00554     0.01109       0.04374  ...

1           0.00008   0.00465   0.00696     0.01394       0.06134  ...

2           0.00009   0.00544   0.00781     0.01633       0.05233  ...

3           0.00009   0.00502   0.00698     0.01505       0.05492  ...

4           0.00011   0.00655   0.00908     0.01966       0.06425  ...


   Shimmer:DDA      NHR     HNR  status      RPDE       DFA   spread1
\
0      0.06545  0.02211  21.033       1  0.414783  0.815285 -4.813031

1      0.09403  0.01929  19.085       1  0.458359  0.819521 -4.075192

2      0.08270  0.01309  20.651       1  0.429895  0.825288 -4.443179

3      0.08771  0.01353  20.644       1  0.434969  0.819235 -4.117501

4      0.10470  0.01767  19.649       1  0.417356  0.823484 -3.747787


    spread2        D2       PPE
```

```
0  0.266482  2.301442  0.284654
1  0.335590  2.486855  0.368674
2  0.311173  2.342259  0.332634
3  0.334147  2.405554  0.368975
4  0.234513  2.332180  0.410335

[5 rows x 24 columns]
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Data columns (total 24 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   name              195 non-null    object
 1   MDVP:Fo(Hz)       195 non-null    float64
 2   MDVP:Fhi(Hz)      195 non-null    float64
 3   MDVP:Flo(Hz)      195 non-null    float64
 4   MDVP:Jitter(%)    195 non-null    float64
 5   MDVP:Jitter(Abs)  195 non-null    float64
 6   MDVP:RAP          195 non-null    float64
 7   MDVP:PPQ          195 non-null    float64
 8   Jitter:DDP        195 non-null    float64
 9   MDVP:Shimmer      195 non-null    float64
 10  MDVP:Shimmer(dB)  195 non-null    float64
 11  Shimmer:APQ3      195 non-null    float64
 12  Shimmer:APQ5      195 non-null    float64
 13  MDVP:APQ          195 non-null    float64
 14  Shimmer:DDA       195 non-null    float64
 15  NHR               195 non-null    float64
 16  HNR               195 non-null    float64
 17  status            195 non-null    int64
 18  RPDE              195 non-null    float64
 19  DFA               195 non-null    float64
 20  spread1           195 non-null    float64
 21  spread2           195 non-null    float64
 22  D2                195 non-null    float64
 23  PPE               195 non-null    float64
dtypes: float64(22), int64(1), object(1)
memory usage: 36.7+ KB
```

```
data.describe()
```

```
       MDVP:Fo(Hz)  MDVP:Fhi(Hz)  MDVP:Flo(Hz)  MDVP:Jitter(%)  \
count   195.000000    195.000000    195.000000      195.000000
mean    154.228641    197.104918    116.324631        0.006220
std      41.390065     91.491548     43.521413        0.004848
min      88.333000    102.145000     65.476000        0.001680
25%     117.572000    134.862500     84.291000        0.003460
```

```
50%     148.790000    175.829000    104.315000        0.004940
75%     182.769000    224.205500    140.018500        0.007365
max     260.105000    592.030000    239.170000        0.033160

       MDVP:Jitter(Abs)    MDVP:RAP    MDVP:PPQ  Jitter:DDP
MDVP:Shimmer  \
count        195.000000  195.000000  195.000000  195.000000
195.000000
mean           0.000044    0.003306    0.003446    0.009920
0.029709
std            0.000035    0.002968    0.002759    0.008903
0.018857
min            0.000007    0.000680    0.000920    0.002040
0.009540
25%            0.000020    0.001660    0.001860    0.004985
0.016505
50%            0.000030    0.002500    0.002690    0.007490
0.022970
75%            0.000060    0.003835    0.003955    0.011505
0.037885
max            0.000260    0.021440    0.019580    0.064330
0.119080

       MDVP:Shimmer(dB)  ...  Shimmer:DDA         NHR         HNR
status  \
count        195.000000  ...   195.000000  195.000000  195.000000
195.000000
mean           0.282251  ...     0.046993    0.024847   21.885974
0.753846
std            0.194877  ...     0.030459    0.040418    4.425764
0.431878
min            0.085000  ...     0.013640    0.000650    8.441000
0.000000
25%            0.148500  ...     0.024735    0.005925   19.198000
1.000000
50%            0.221000  ...     0.038360    0.011660   22.085000
1.000000
75%            0.350000  ...     0.060795    0.025640   25.075500
1.000000
max            1.302000  ...     0.169420    0.314820   33.047000
1.000000

             RPDE         DFA     spread1     spread2          D2
PPE
count  195.000000  195.000000  195.000000  195.000000  195.000000
195.000000
mean     0.498536    0.718099   -5.684397    0.226510    2.381826
0.206552
std      0.103942    0.055336    1.090208    0.083406    0.382799
0.090119
```

```
min      0.256570    0.574282   -7.964984    0.006274    1.423287
0.044539
25%      0.421306    0.674758   -6.450096    0.174351    2.099125
0.137451
50%      0.495954    0.722254   -5.720868    0.218885    2.361532
0.194052
75%      0.587562    0.761881   -5.046192    0.279234    2.636456
0.252980
max      0.685151    0.825288   -2.434031    0.450493    3.671155
0.527367

[8 rows x 23 columns]
```

```
data.isna().sum()
```

```
name                0
MDVP:Fo(Hz)         0
MDVP:Fhi(Hz)        0
MDVP:Flo(Hz)        0
MDVP:Jitter(%)      0
MDVP:Jitter(Abs)    0
MDVP:RAP            0
MDVP:PPQ            0
Jitter:DDP          0
MDVP:Shimmer        0
MDVP:Shimmer(dB)    0
Shimmer:APQ3        0
Shimmer:APQ5        0
MDVP:APQ            0
Shimmer:DDA         0
NHR                 0
HNR                 0
status              0
RPDE                0
DFA                 0
spread1             0
spread2             0
D2                  0
PPE                 0
dtype: int64
```

```
data.columns
```

```
Index(['name', 'MDVP:Fo(Hz)', 'MDVP:Fhi(Hz)', 'MDVP:Flo(Hz)',
'MDVP:Jitter(%)',
       'MDVP:Jitter(Abs)', 'MDVP:RAP', 'MDVP:PPQ', 'Jitter:DDP',
       'MDVP:Shimmer', 'MDVP:Shimmer(dB)', 'Shimmer:APQ3',
'Shimmer:APQ5',
       'MDVP:APQ', 'Shimmer:DDA', 'NHR', 'HNR', 'status', 'RPDE',
'DFA',
       'spread1', 'spread2', 'D2', 'PPE'],
      dtype='object')
```

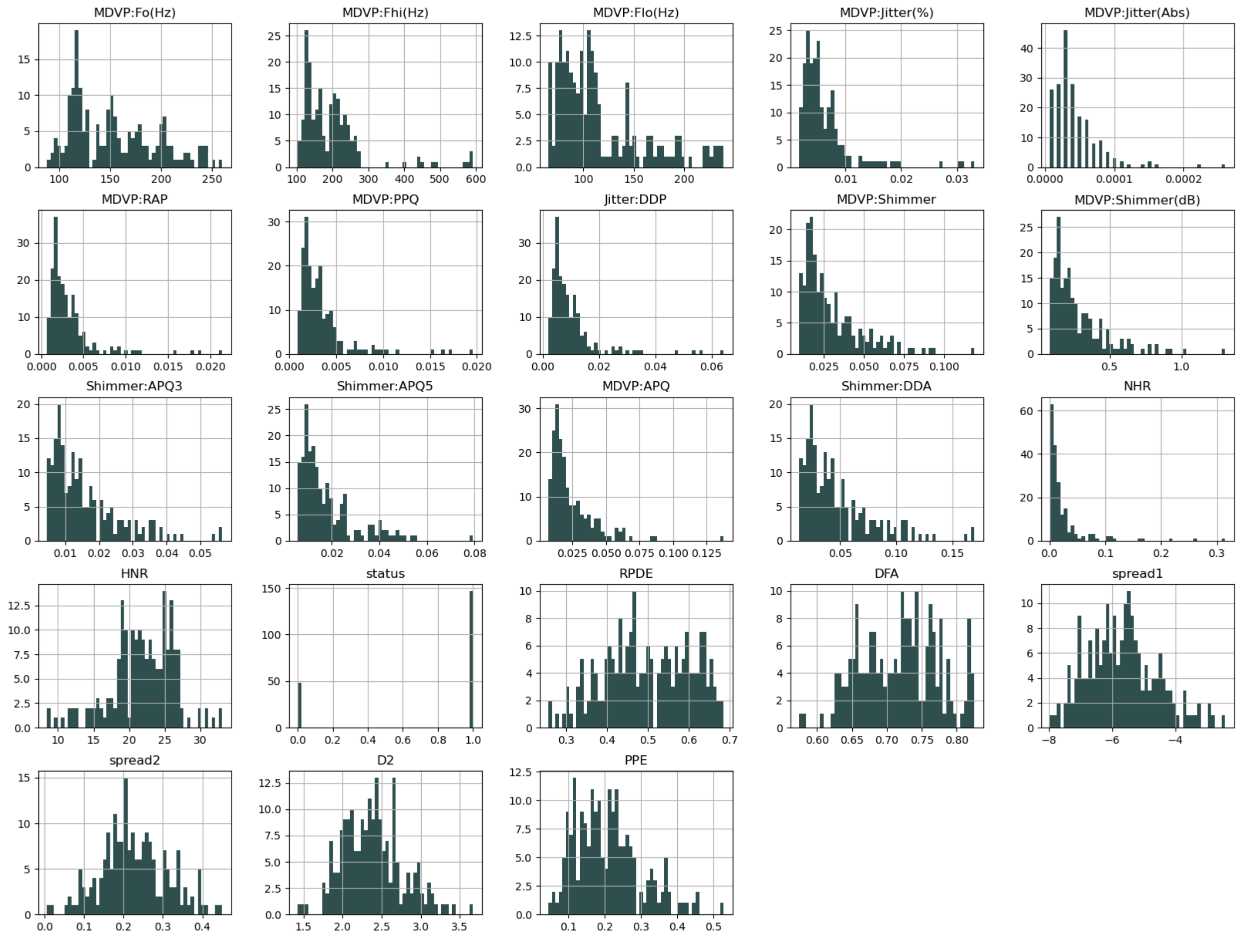
```
data.duplicated().sum()
```

```
0
```

```
data["status"].value_counts()
```

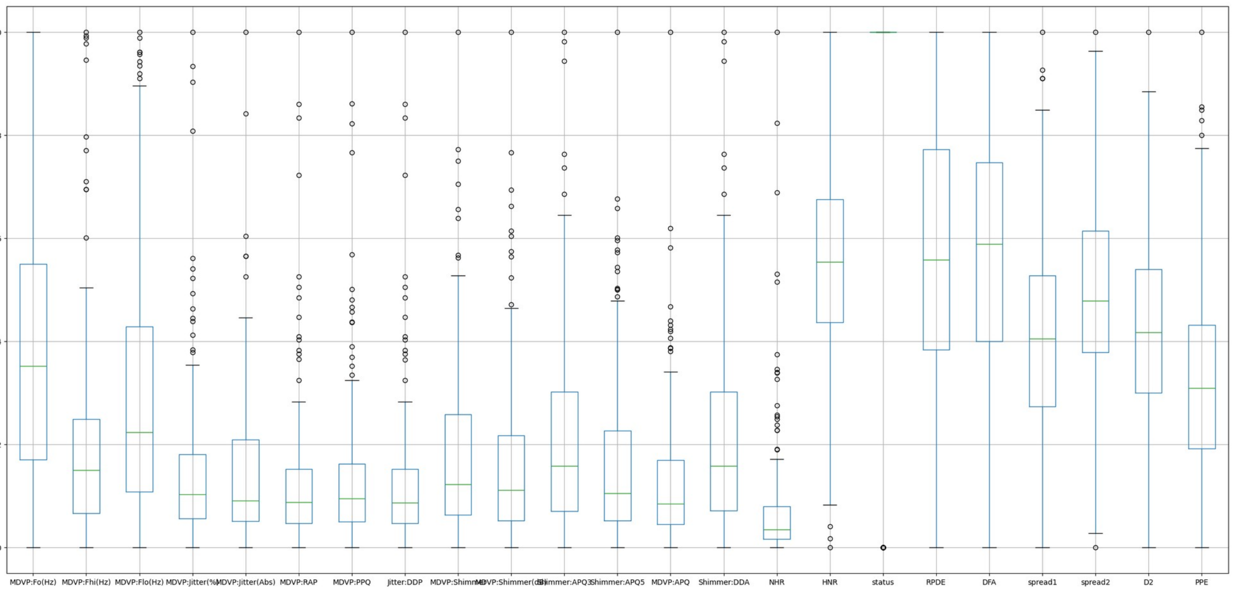
```
status
1    147
0     48
Name: count, dtype: int64
```

```
data.hist(bins=50, figsize =(20,15), color = 'darkslategrey')
plt.show(block=False)
```

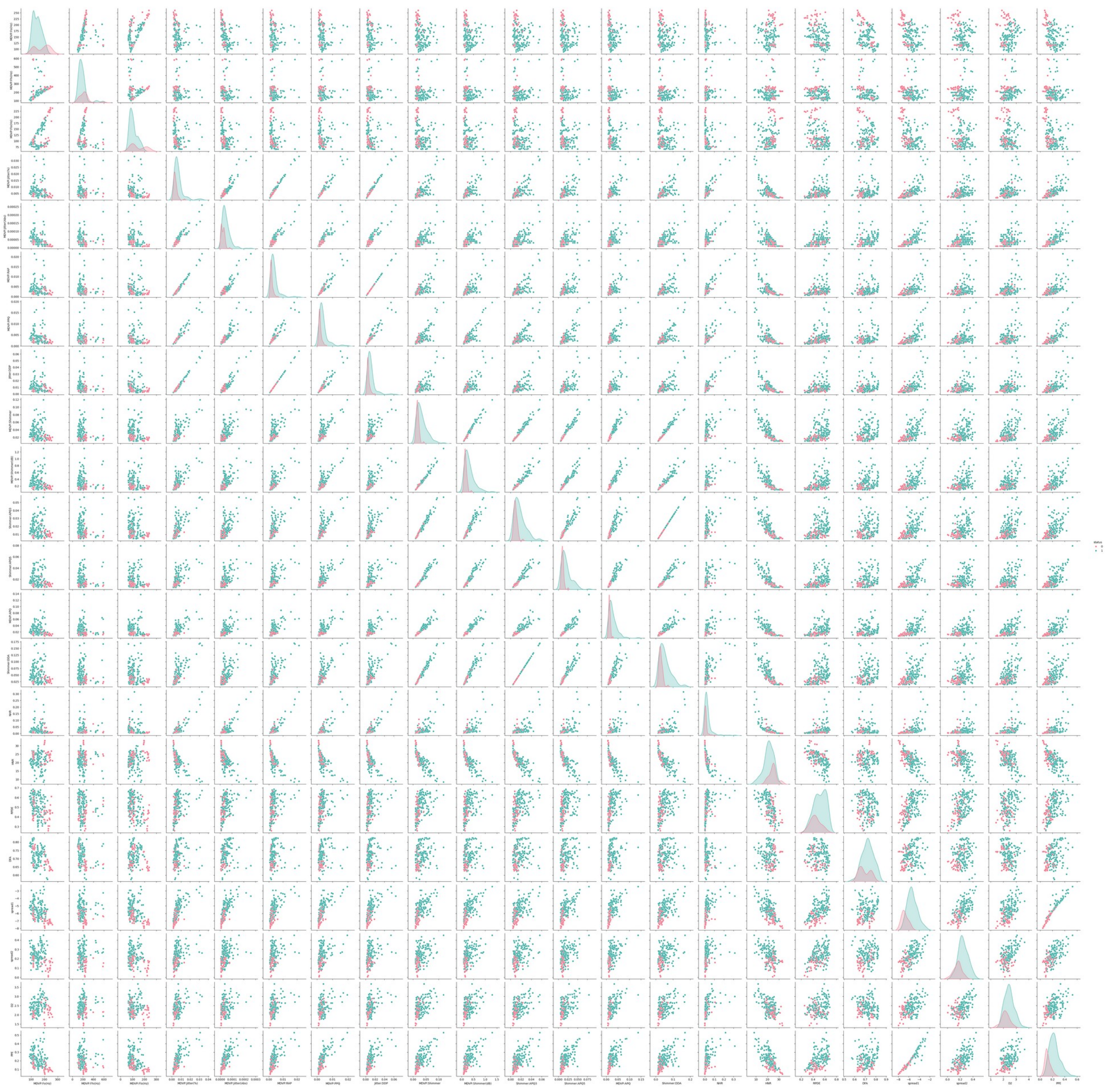


```
minmax = MinMaxScaler()
data_boxplot = data.drop(['name'],axis=1)
data_boxplot = minmax.fit_transform(data_boxplot)
boxplot = pd.DataFrame(data_boxplot, columns =
data.drop(['name'],axis=1).columns)
```

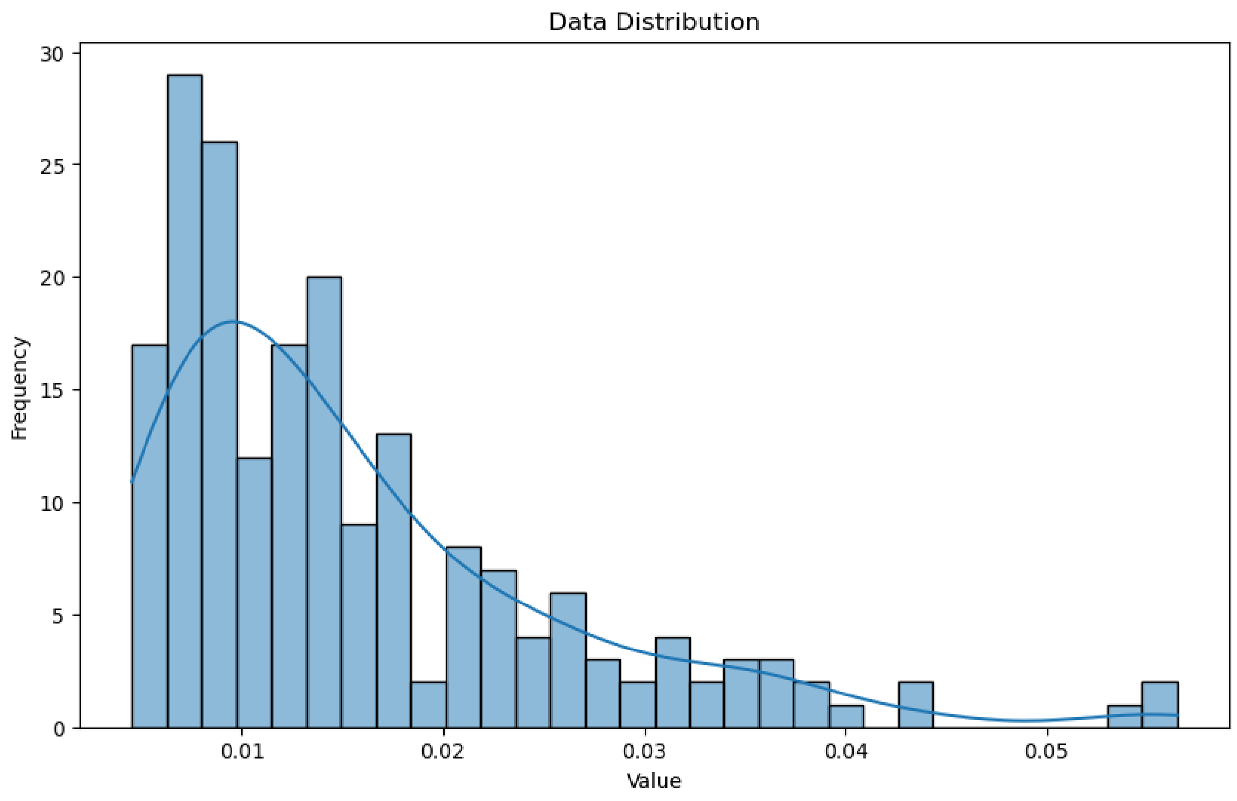
```python
boxplot.boxplot(figsize=(30,14))
plt.show(block=False)
```



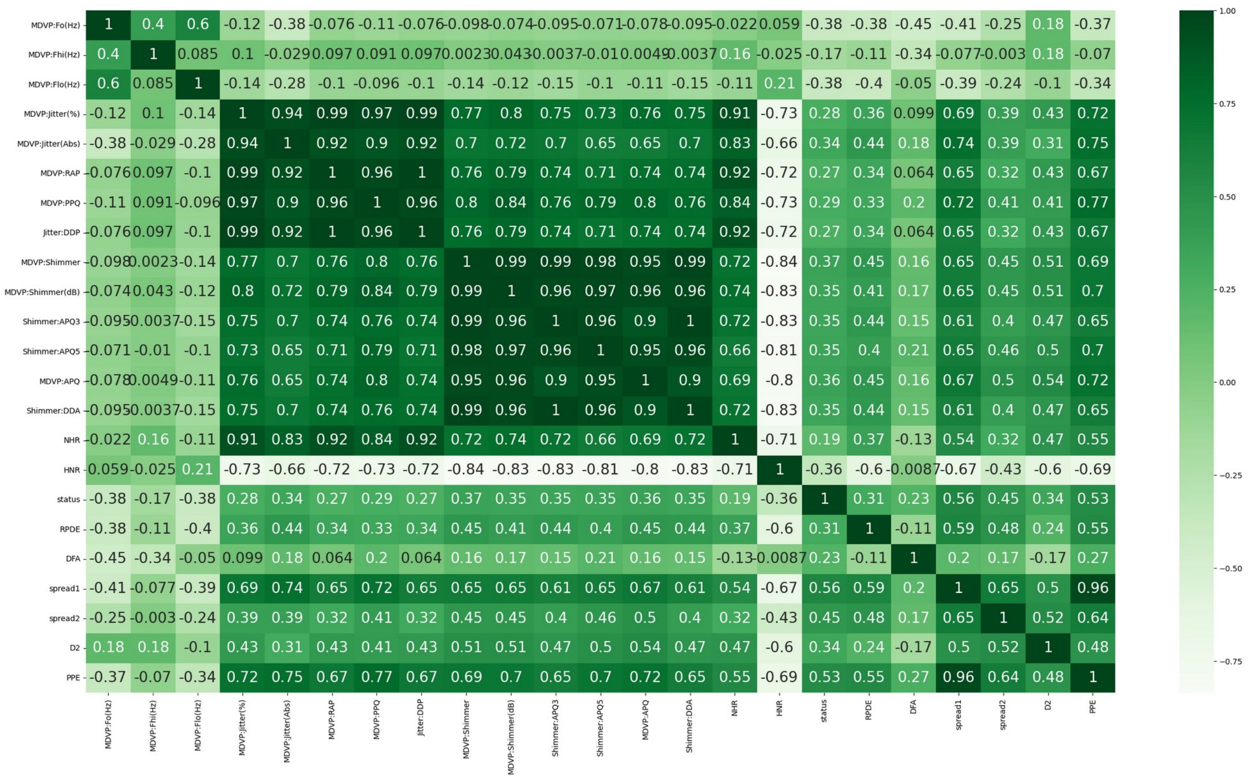
```python
sns.pairplot(data, hue='status', palette='husl')  # 'status' (0 =
Healthy, 1 = Parkinson's)
plt.show()
```



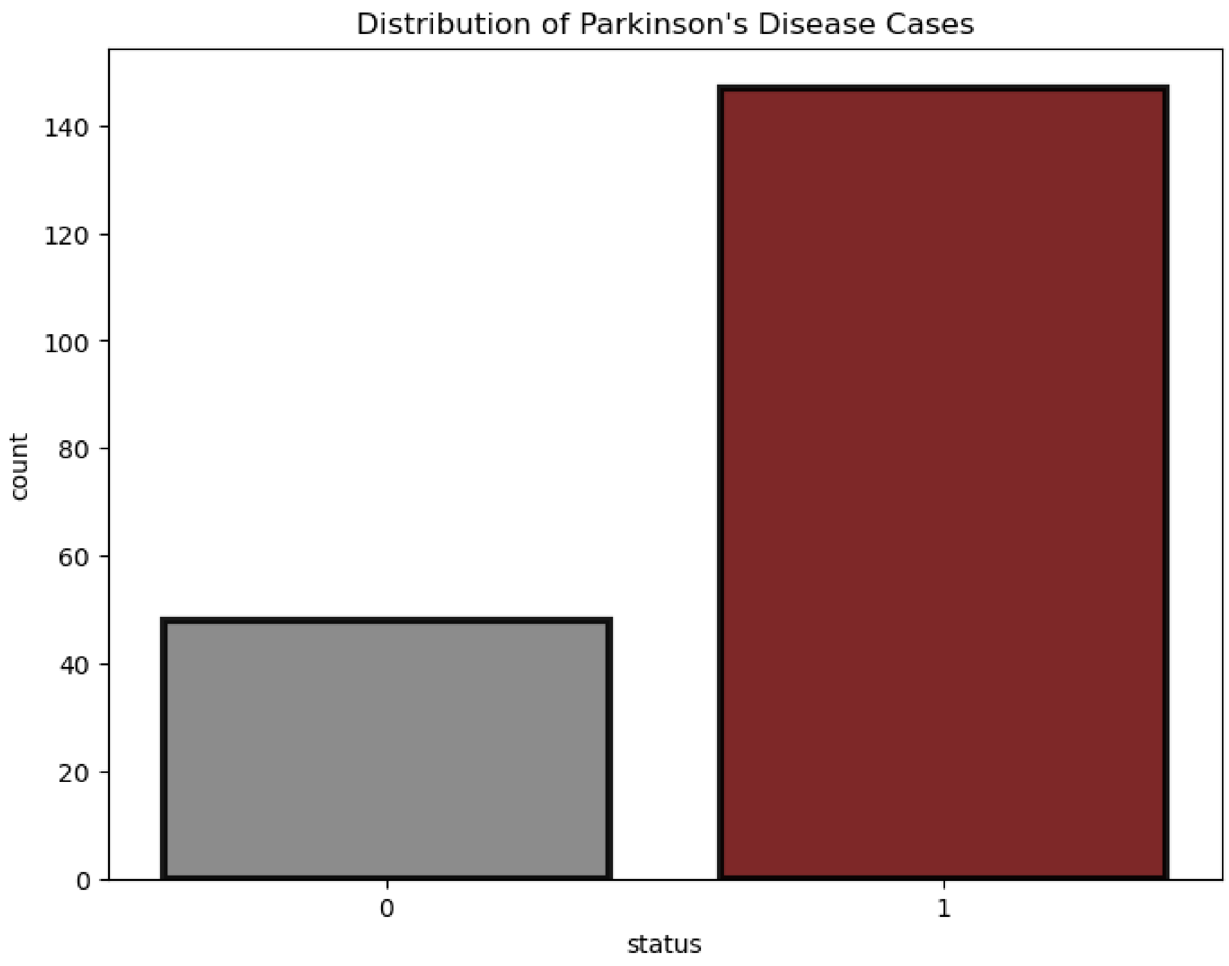
```python
data.dropna(inplace=True)
data.replace([np.inf, -np.inf], np.nan, inplace=True)
plt.figure(figsize=(10, 6))
sns.histplot(data['Shimmer:APQ3'], kde=True, bins=30)
plt.title('Data Distribution')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.show()
```



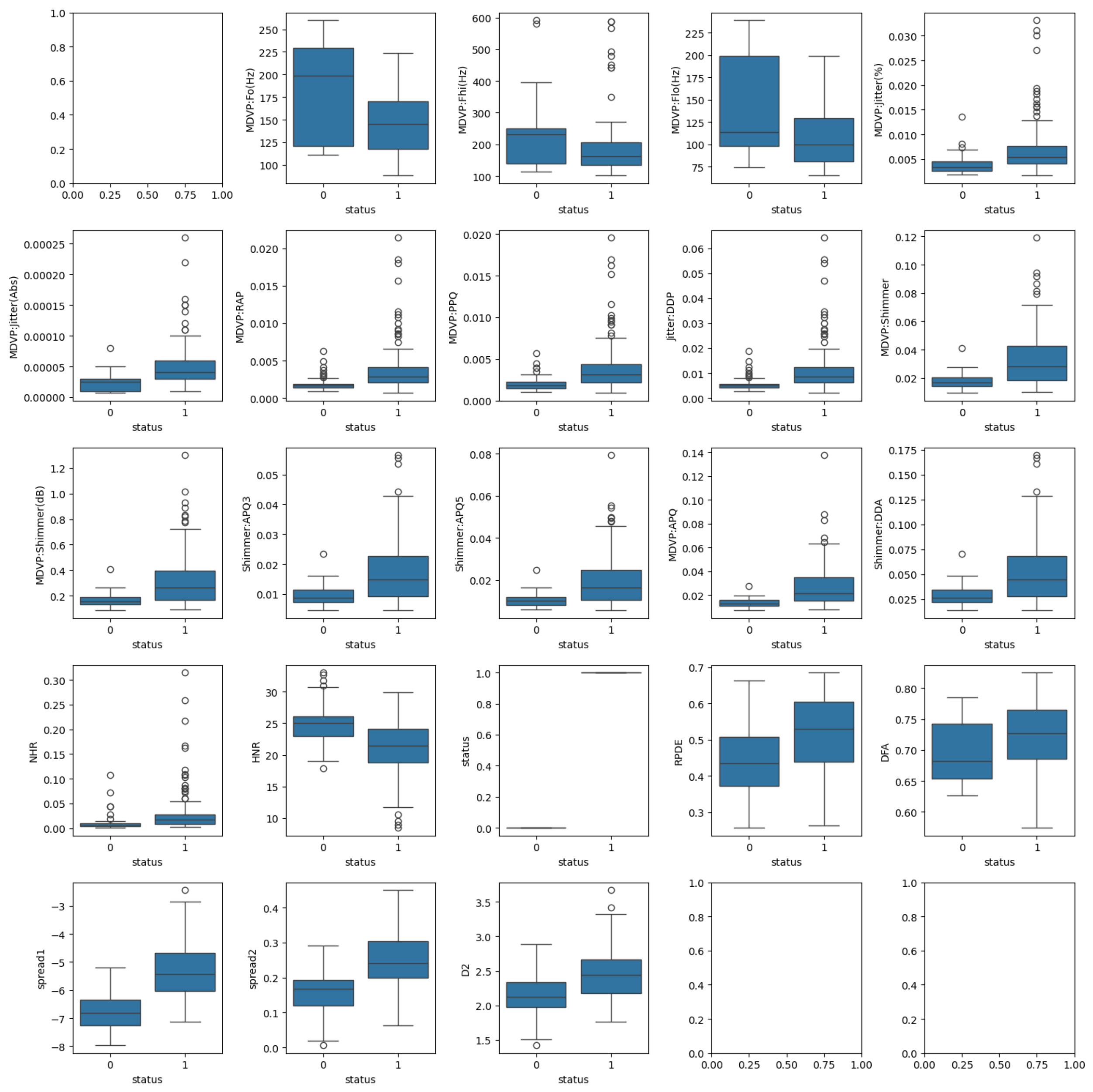
```
import seaborn as sns
import matplotlib.pyplot as plt

# Select only numeric columns for correlation calculation
numeric_data = data.select_dtypes(include=['number'])

plt.figure(figsize=(30,16))
sns.heatmap(numeric_data.corr(), annot=True, cmap='Greens',
annot_kws={'size':19})
plt.show()
```



```python
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8,6))
sns.countplot(data=data, x='status', hue='status', palette=['grey',
'maroon'], edgecolor='black', linewidth=3, alpha=0.9)
plt.legend([],[], frameon=False)  # Hide legend if not needed
plt.title("Distribution of Parkinson's Disease Cases")
plt.show()
```



```
fig,axes=plt.subplots(5,5,figsize=(15,15))
axes=axes.flatten()

for i in range(1,len(data.columns)-1):

sns.boxplot(x='status',y=data.iloc[:,i],data=data,orient='v',ax=axes[i
])
plt.tight_layout()
plt.show()
```



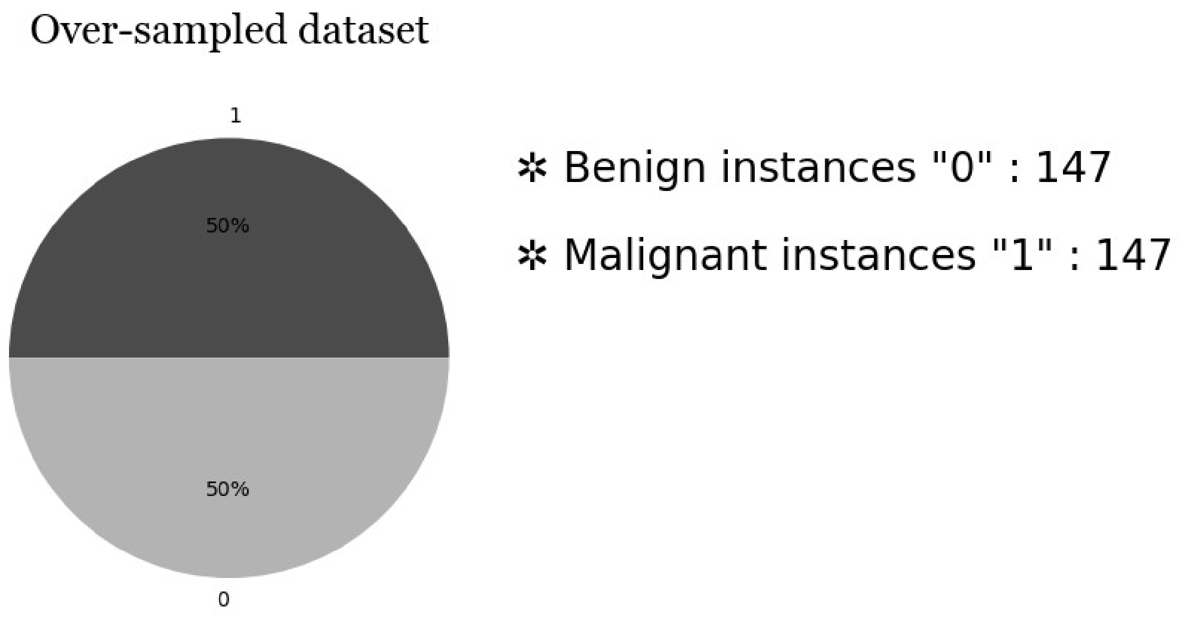
```python
X=data.drop(['name','status'],axis=1)
y=data["status"]

smote_sampler = SMOTE(random_state=42)
X_smote, y_smote = smote_sampler.fit_resample(X, y)
smote_data = pd.concat([X_smote, y_smote], axis=1)
smote_data.shape
```

```
(294, 23)
```

```python
len(smote_data[smote_data.status==1].value_counts())
```

```
147
```

```
num_status=smote_data['status'].value_counts()
over_counts = num_status.values
plt.pie(num_status, labels=num_status.index.values,
colors=[ (0.29296875,0.29296875,0.29296875),
(0.703125,0.703125,0.703125)]
        , autopct='%d%%')
plt.title('Over-sampled dataset', y=1.05, fontsize=20,
fontfamily='Georgia')
plt.text(x=1.3, y=0.8, s=f'✲ Benign instances "0" :
{len(smote_data[smote_data.status==0].value_counts())}', fontsize=20)
plt.text(x=1.3, y=0.4, s=f'✲ Malignant instances "1" :
{len(smote_data[smote_data.status==1].value_counts())}', fontsize=20)
plt.show(block=False)
```

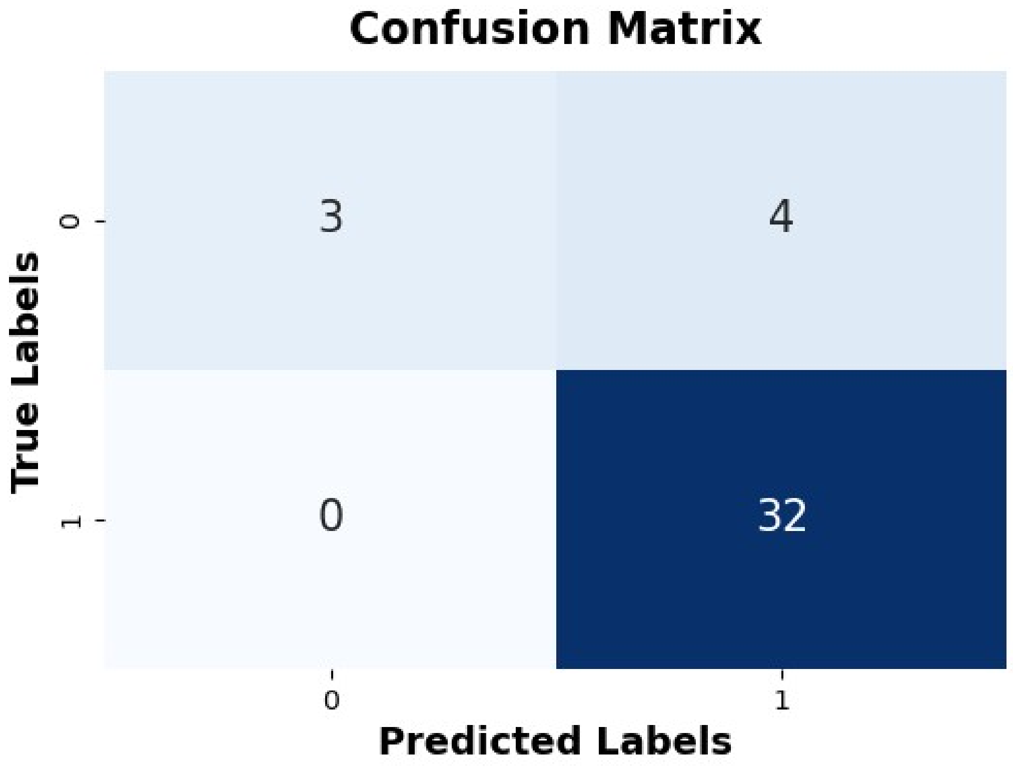


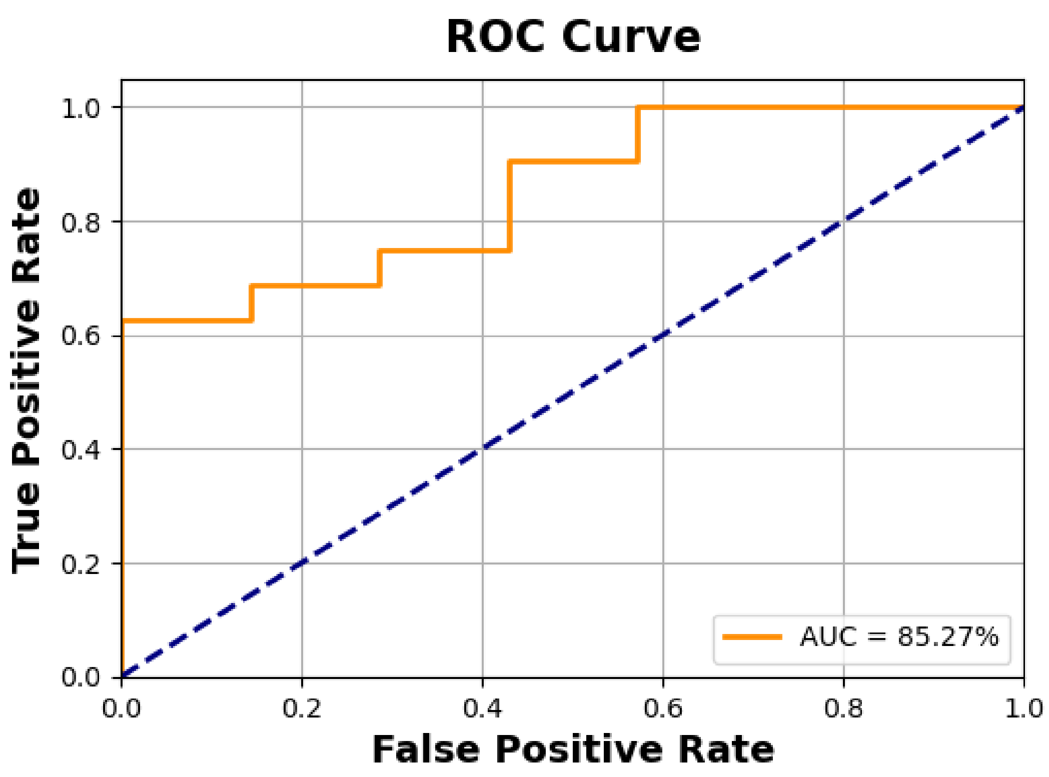
```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

X_smote_train, X_smote_test, y_smote_train, y_smote_test =
train_test_split(X_smote, y_smote, train_size=0.8, random_state=42)

minmax = MinMaxScaler()

X_train_scaled = minmax.fit_transform(X_train)
X_test_scaled = minmax.transform(X_test)

X_smote_train_scaled = minmax.fit_transform(X_smote_train)
X_smote_test_scaled = minmax.transform(X_smote_test)

def Evaluate_Performance(Model, Xtrain, Xtest, Ytrain, Ytest):
    """Evaluate model performance with detailed metrics and
```

```
visualization."""
    from sklearn.metrics import classification_report, roc_auc_score

    # Train the model
    Model.fit(Xtrain, Ytrain)

    # Cross-validation score
    overall_score = cross_val_score(Model, Xtrain, Ytrain, cv=10,
scoring='accuracy')
    model_score = np.average(overall_score)

    # Predictions
    Ypredicted = Model.predict(Xtest)
    Ypred_proba = Model.predict_proba(Xtest)[:, 1] if hasattr(Model,
"predict_proba") else None

    # Accuracy Metrics
    training_acc = round(Model.score(Xtrain, Ytrain) * 100, 2)
    testing_acc = round(accuracy_score(Ytest, Ypredicted) * 100, 2)
    precision = round(precision_score(Ytest, Ypredicted) * 100, 2)
    recall = round(recall_score(Ytest, Ypredicted) * 100, 2)
    f1 = round(f1_score(Ytest, Ypredicted) * 100, 2)
    auc_roc = round(roc_auc_score(Ytest, Ypred_proba) * 100, 2) if
Ypred_proba is not None else "N/A"

    # Print Model Evaluation Metrics
    print("\n□ MODEL PERFORMANCE SUMMARY")
    print("=" * 50)
    print(f" □ Training Accuracy  : {training_acc}%")
    print(f" □ Cross-Validation   : {round(model_score * 100, 2)}%")
    print(f" □ Testing Accuracy   : {testing_acc}%")
    print(f" □ Precision Score    : {precision}%")
    print(f" □ Recall Score       : {recall}%")
    print(f" □ F1 Score           : {f1}%")
    print(f" □ AUC-ROC Score      : {auc_roc}%")
    print("=" * 50)

    # Classification Report
    print("\n□ Classification Report:\n")
    print(classification_report(Ytest, Ypredicted))

    # Confusion Matrix
    conf_matrix = confusion_matrix(Ytest, Ypredicted)
    plt.figure(figsize=(6, 4))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="Blues",
annot_kws={"size": 16}, cbar=False)
    plt.xlabel("Predicted Labels", fontsize=14, fontweight="bold")
    plt.ylabel("True Labels", fontsize=14, fontweight="bold")
    plt.title("Confusion Matrix", fontsize=16, fontweight="bold",
pad=10)
```

```
    plt.show()

    # AUC-ROC Curve
    if Ypred_proba is not None:
        fpr, tpr, _ = roc_curve(Ytest, Ypred_proba)
        plt.figure(figsize=(6, 4))
        plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'AUC =
{auc_roc}%')
        plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
        plt.xlim([0.0, 1.0])
        plt.ylim([0.0, 1.05])
        plt.xlabel('False Positive Rate', fontsize=14,
fontweight="bold")
        plt.ylabel('True Positive Rate', fontsize=14,
fontweight="bold")
        plt.title('ROC Curve', fontsize=16, fontweight="bold", pad=10)
        plt.legend(loc="lower right")
        plt.grid()
        plt.show()

LR = LogisticRegression()
LR.fit(X_train_scaled,y_train)
y_pred_LR = LR.predict(X_test_scaled)
print('-'*80)
print("Logistic Regression :")
print("-"*16)
Evaluate_Performance(LR, X_train_scaled, X_test_scaled, y_train,
y_test)
```

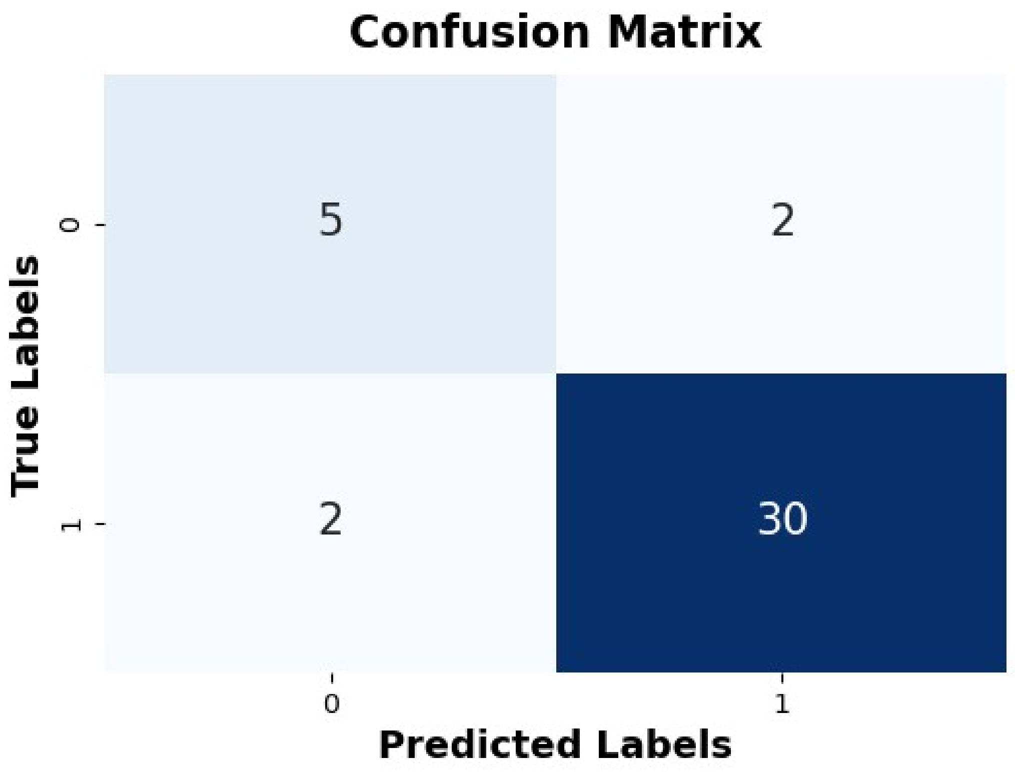
```
----------------------------------------------------------------------
----------
Logistic Regression :
----------------

 MODEL PERFORMANCE SUMMARY
==================================================
  Training Accuracy  : 85.26%
  Cross-Validation   : 83.87%
  Testing Accuracy   : 89.74%
  Precision Score    : 88.89%
  Recall Score       : 100.0%
  F1 Score           : 94.12%
  AUC-ROC Score      : 85.27%
==================================================

 Classification Report:

              precision    recall  f1-score   support

           0       1.00      0.43      0.60         7
           1       0.89      1.00      0.94        32

    accuracy                           0.90        39
   macro avg       0.94      0.71      0.77        39
weighted avg       0.91      0.90      0.88        39
```

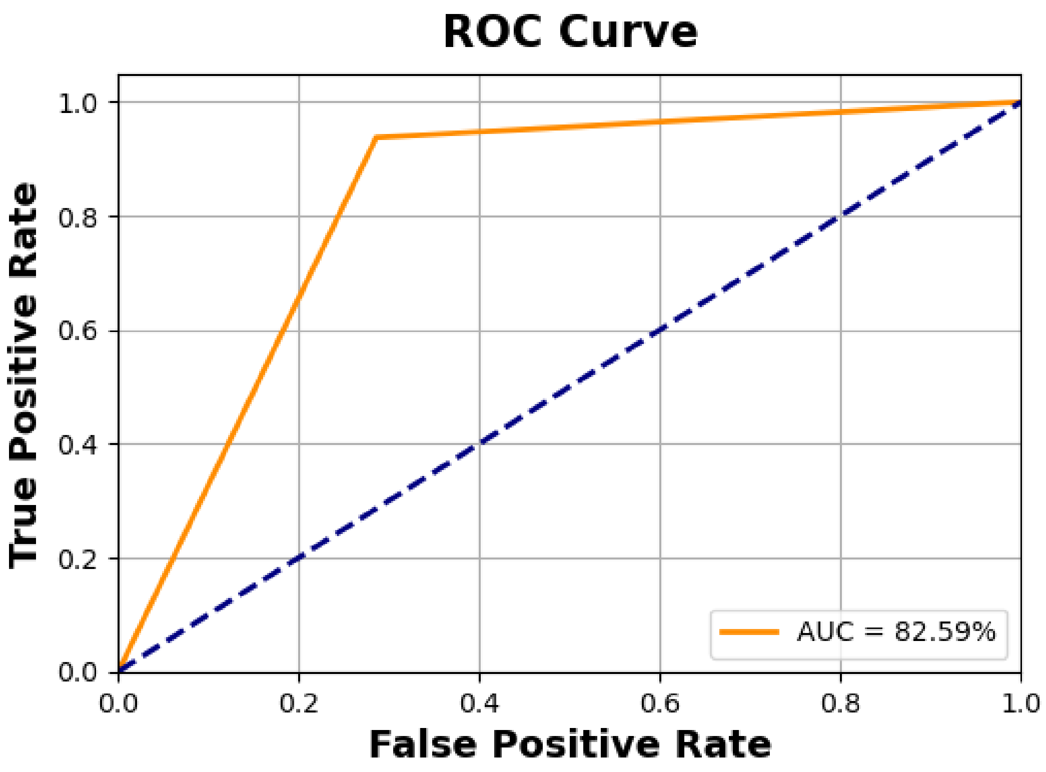




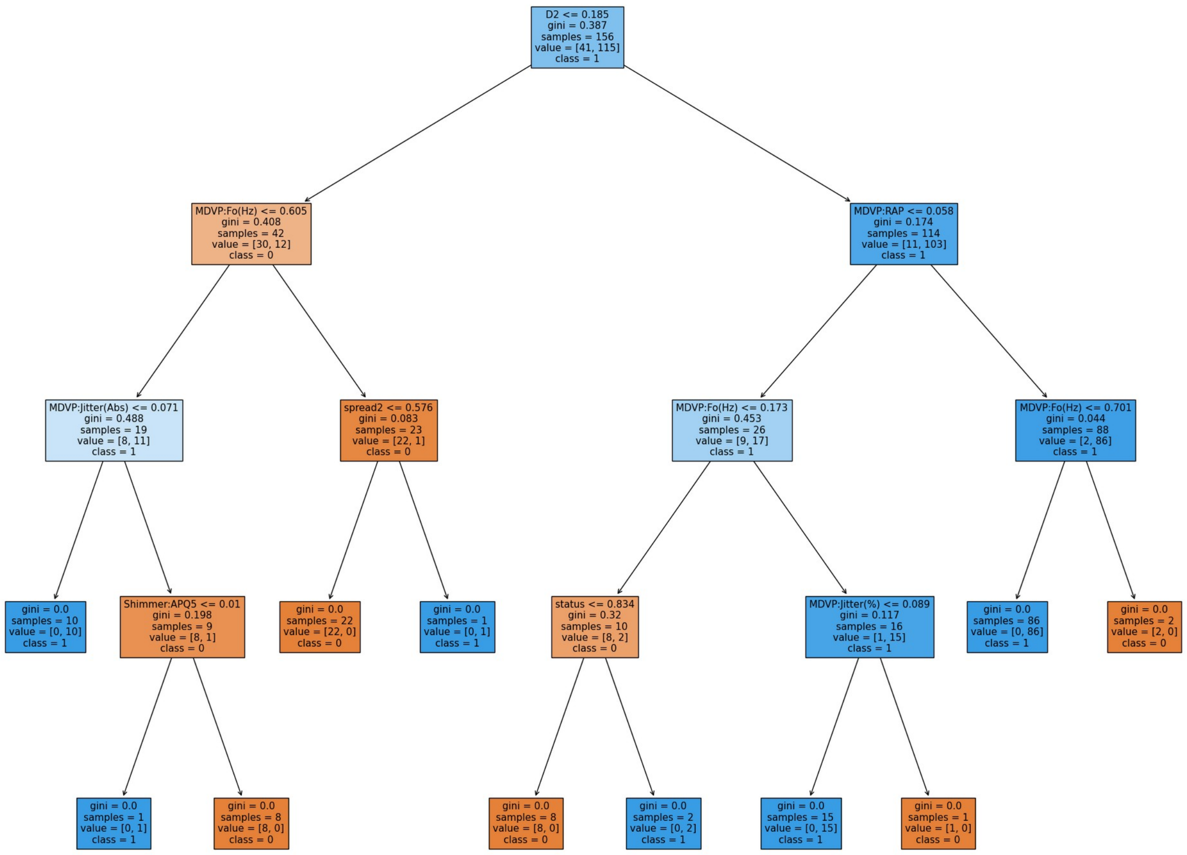
```
DTC=DecisionTreeClassifier()
DTC.fit(X_train_scaled, y_train)
y_pred_DTC = DTC.predict(X_test_scaled)
print('-'*80)
print('Decision Tree Classifier :')
print("-"*16)
Evaluate_Performance(DTC, X_train_scaled, X_test_scaled, y_train,
y_test)
print('\n')
print("DECISION TREE :")
fig = plt.figure(figsize=(25,20))
tree = plot_tree(DTC, feature_names = [ c for c in
data.drop(['name'],axis=1).columns], class_names=['0','1'],
filled=True)
```

```
----------------------------------------------------------------------
----------
Decision Tree Classifier :
----------------

 MODEL PERFORMANCE SUMMARY
==================================================
  Training Accuracy   : 100.0%
  Cross-Validation    : 88.46%
  Testing Accuracy    : 89.74%
  Precision Score     : 93.75%
 □ Recall Score       : 93.75%
 □ F1 Score           : 93.75%
 □ AUC-ROC Score      : 82.59%
==================================================

□ Classification Report:

              precision    recall  f1-score   support

           0       0.71      0.71      0.71         7
           1       0.94      0.94      0.94        32

    accuracy                           0.90        39
   macro avg       0.83      0.83      0.83        39
weighted avg       0.90      0.90      0.90        39
```



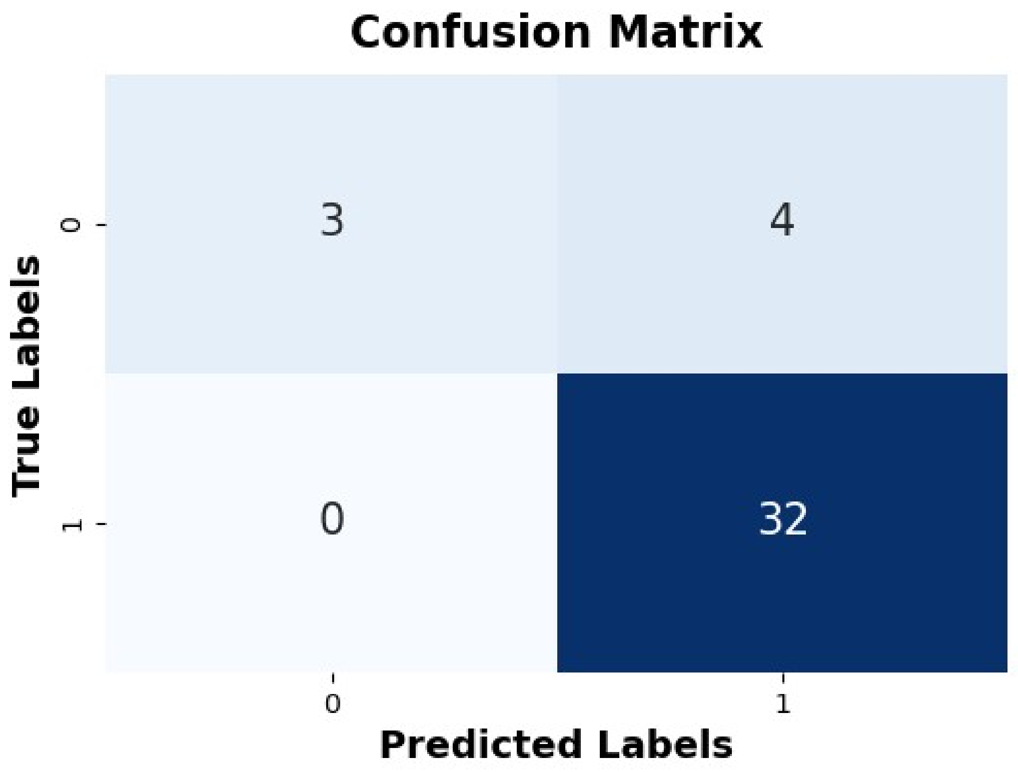


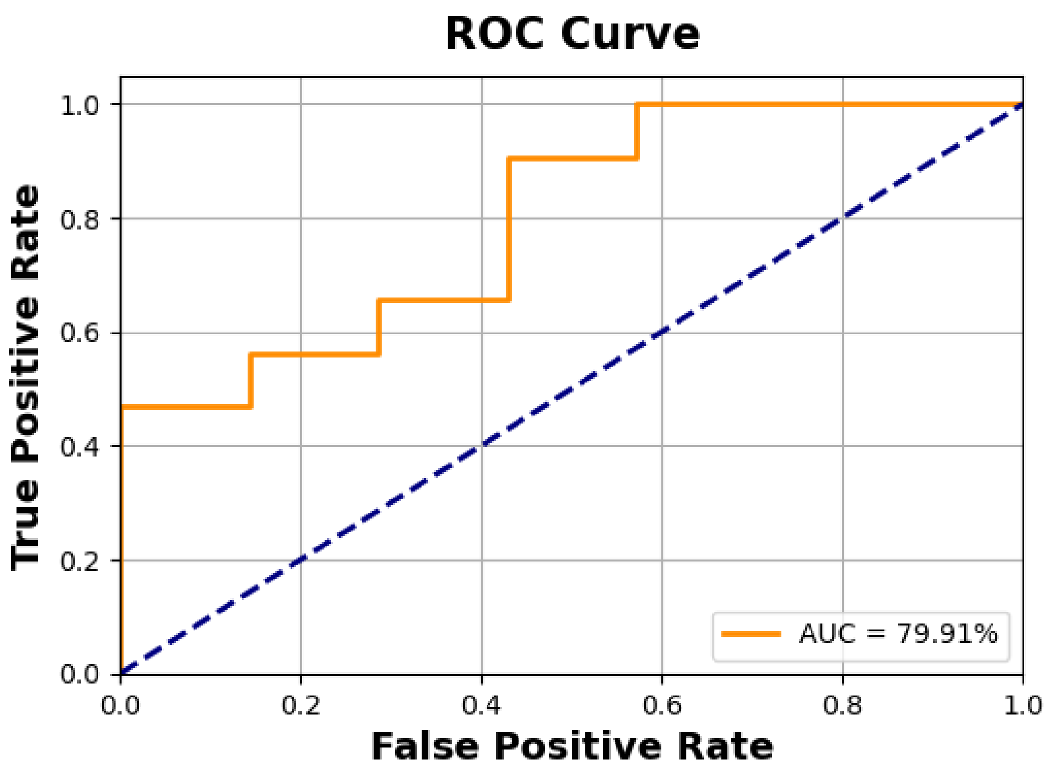
```
DECISION TREE :
```



```python
SVM = SVC(probability=True, kernel = 'linear')
SVM.fit(X_train_scaled,y_train)
y_pred_SVM = SVM.predict(X_test_scaled)
print('-'*80)
print("Support Vector Machine:")
print("-"*16)
Evaluate_Performance(SVM, X_train_scaled, X_test_scaled, y_train, 
y_test)
```

```
----------------------------------------------------------------------
----------
Support Vector Machine:
----------------

□ MODEL PERFORMANCE SUMMARY
==================================================
 □ Training Accuracy  : 88.46%
 □ Cross-Validation   : 87.67%
 □ Testing Accuracy   : 89.74%
 □ Precision Score    : 88.89%
 □ Recall Score       : 100.0%
 □ F1 Score           : 94.12%
 □ AUC-ROC Score      : 79.91%
==================================================

□ Classification Report:

              precision    recall  f1-score   support

           0       1.00      0.43      0.60         7
           1       0.89      1.00      0.94        32

    accuracy                           0.90        39
   macro avg       0.94      0.71      0.77        39
weighted avg       0.91      0.90      0.88        39
```

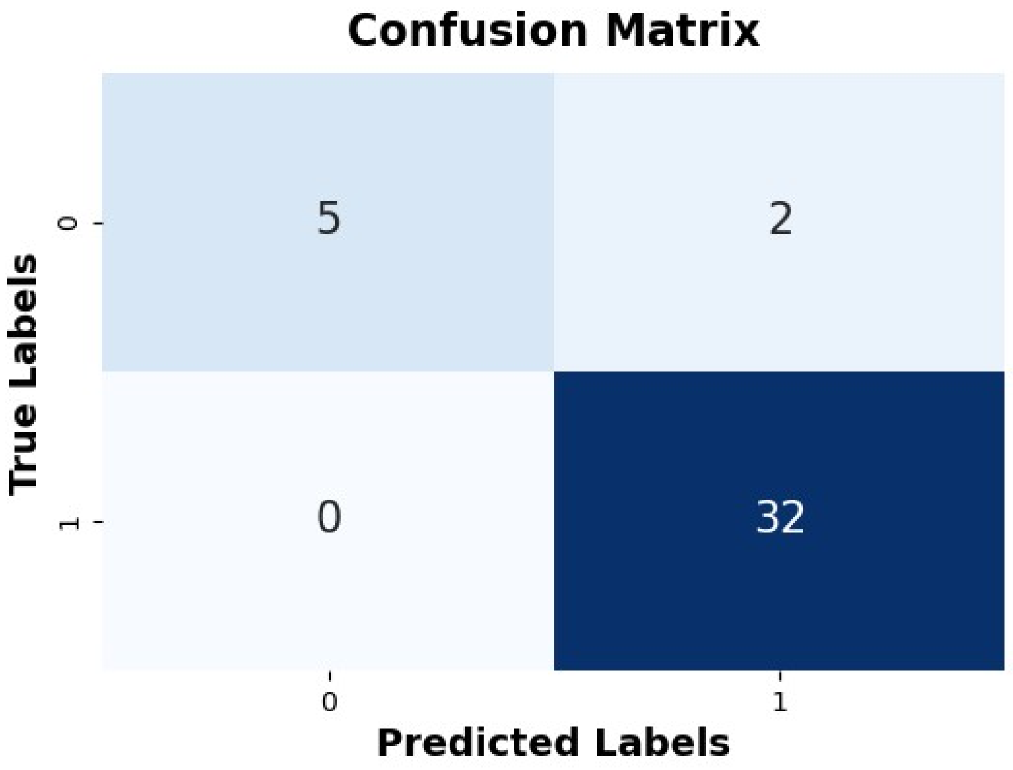


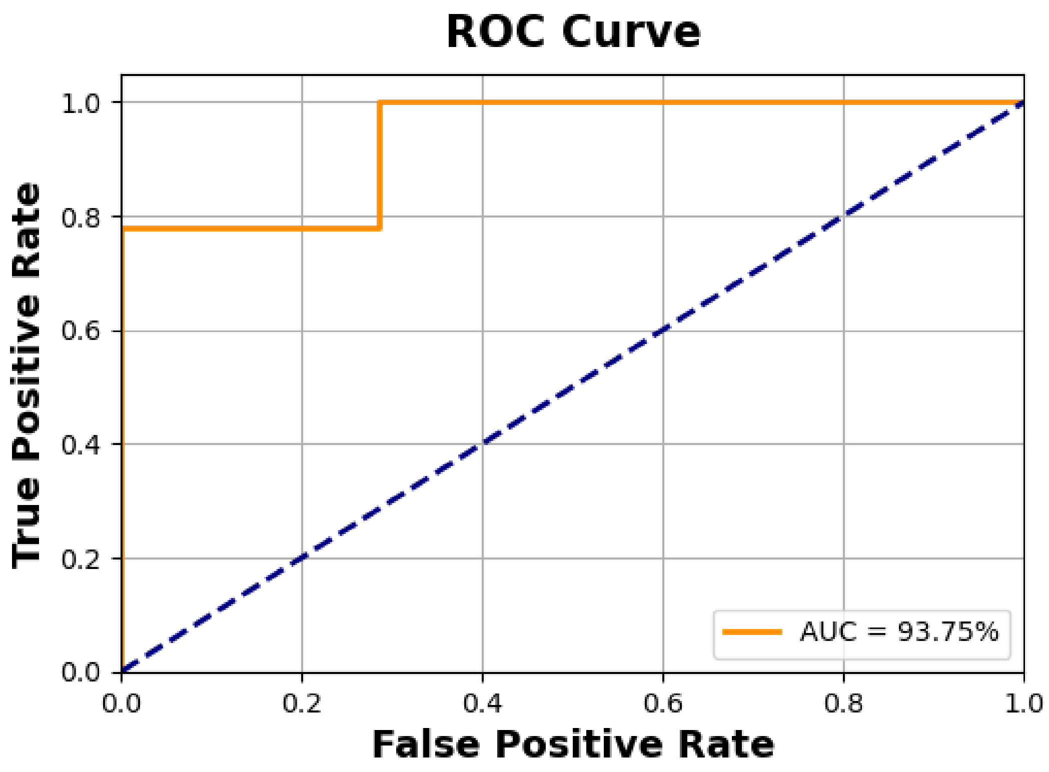


```
RFC=RandomForestClassifier(n_estimators=150)
RFC.fit(X_train_scaled, y_train)
y_pred_RFC = RFC.predict(X_test_scaled)
print('-'*80)
print('Random Forest Classifier')
print("-"*16)
Evaluate_Performance(RFC, X_train_scaled, X_test_scaled, y_train,
y_test)
```

```
--------------------------------------------------------------------------------
Random Forest Classifier
----------------

□ MODEL PERFORMANCE SUMMARY
==================================================
 □ Training Accuracy  : 100.0%
 □ Cross-Validation   : 89.67%
 □ Testing Accuracy   : 94.87%
 □ Precision Score    : 94.12%
 □ Recall Score       : 100.0%
 □ F1 Score           : 96.97%
 □ AUC-ROC Score      : 93.75%
==================================================

□ Classification Report:
```

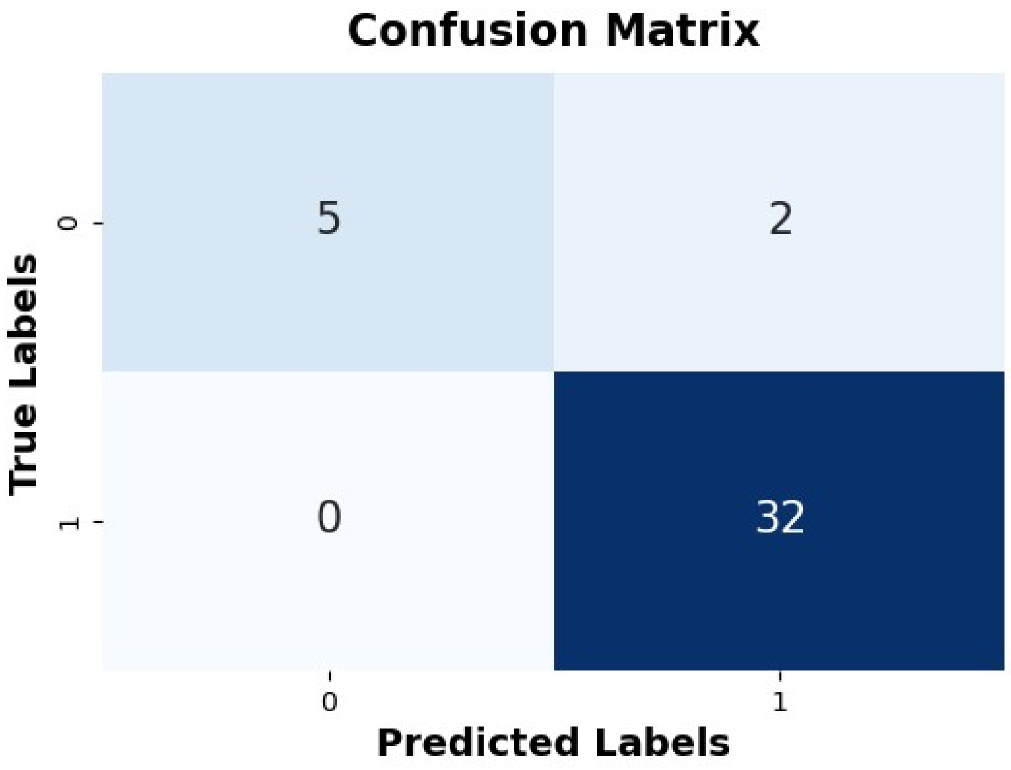
```
              precision    recall  f1-score   support

           0       1.00      0.71      0.83         7
           1       0.94      1.00      0.97        32

    accuracy                           0.95        39
   macro avg       0.97      0.86      0.90        39
weighted avg       0.95      0.95      0.95        39
```

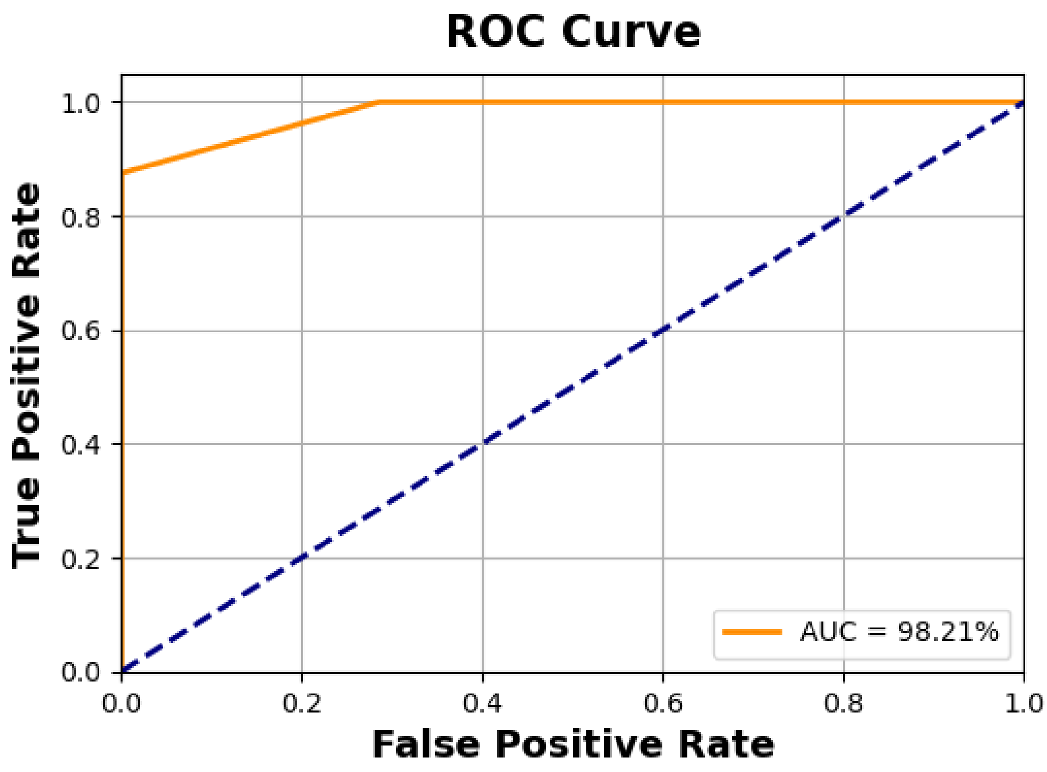




```
KNN = KNeighborsClassifier()
KNN.fit(X_train_scaled, y_train)
y_pred_KNN = KNN.predict(X_test_scaled)
print('-'*80)
print("Key- Nearest Neighbor :")
print("-"*16)
Evaluate_Performance(KNN, X_train_scaled, X_test_scaled, y_train,
y_test)

----------------------------------------------------------------------
----------
Key- Nearest Neighbor :
----------------

□ MODEL PERFORMANCE SUMMARY
==================================================
 □ Training Accuracy  : 96.79%
 □ Cross-Validation   : 89.79%
 □ Testing Accuracy   : 94.87%
 □ Precision Score    : 94.12%
 □ Recall Score       : 100.0%
 □ F1 Score           : 96.97%
 □ AUC-ROC Score      : 98.21%
==================================================

□ Classification Report:
```

```
              precision    recall  f1-score   support

           0       1.00      0.71      0.83         7
           1       0.94      1.00      0.97        32

    accuracy                           0.95        39
   macro avg       0.97      0.86      0.90        39
weighted avg       0.95      0.95      0.95        39
```





```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV

# Define parameter grid for tuning
param_grid = {
    'n_neighbors': [3, 5, 7, 9, 11],  # Testing different numbers of
neighbors
    'weights': ['uniform', 'distance'],  # Try both weighting methods
    'metric': ['euclidean', 'manhattan', 'minkowski']  # Different
distance metrics
}

# Initialize KNN model
knn = KNeighborsClassifier()

# GridSearchCV to find the best parameters
grid_search = GridSearchCV(knn, param_grid, cv=10, scoring='accuracy',
n_jobs=-1, verbose=1)
grid_search.fit(X_train_scaled, y_train)

# Get the best parameters
best_knn = grid_search.best_estimator_
print("\n� Best Parameters Found: ", grid_search.best_params_)

# Evaluate performance on test data
y_pred_best_knn = best_knn.predict(X_test_scaled)
```

```
# Print accuracy and classification report
from sklearn.metrics import classification_report, accuracy_score
print("\n□ Optimized KNN Accuracy: ", round(accuracy_score(y_test,
y_pred_best_knn) * 100, 2), "%")
print("\n□ Classification Report:\n", classification_report(y_test,
y_pred_best_knn))
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits

□ Best Parameters Found:  {'metric': 'manhattan', 'n_neighbors': 3,
'weights': 'distance'}

□ Optimized KNN Accuracy:  97.44 %

□ Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.86      0.92         7
           1       0.97      1.00      0.98        32

    accuracy                           0.97        39
   macro avg       0.98      0.93      0.95        39
weighted avg       0.98      0.97      0.97        39
```

```
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestClassifier

# Initialize a Random Forest model for feature selection
feature_selector = RFE(RandomForestClassifier(n_estimators=100,
random_state=42), n_features_to_select=10)
X_rfe = feature_selector.fit_transform(X_smote_train_scaled,
y_smote_train)

# Get selected features
selected_features = X.columns[feature_selector.support_]
print("\n□ Selected Features:\n", list(selected_features))
```

```
□ Selected Features:
 ['MDVP:Fo(Hz)', 'MDVP:Fhi(Hz)', 'MDVP:Flo(Hz)', 'MDVP:Shimmer',
'Shimmer:APQ5', 'MDVP:APQ', 'spread1', 'spread2', 'D2', 'PPE']
```

```
from xgboost import XGBClassifier

# Train XGBoost with optimal features
xgb_model = XGBClassifier(n_estimators=200, learning_rate=0.1,
max_depth=5, random_state=42)
xgb_model.fit(X_rfe, y_smote_train)
```

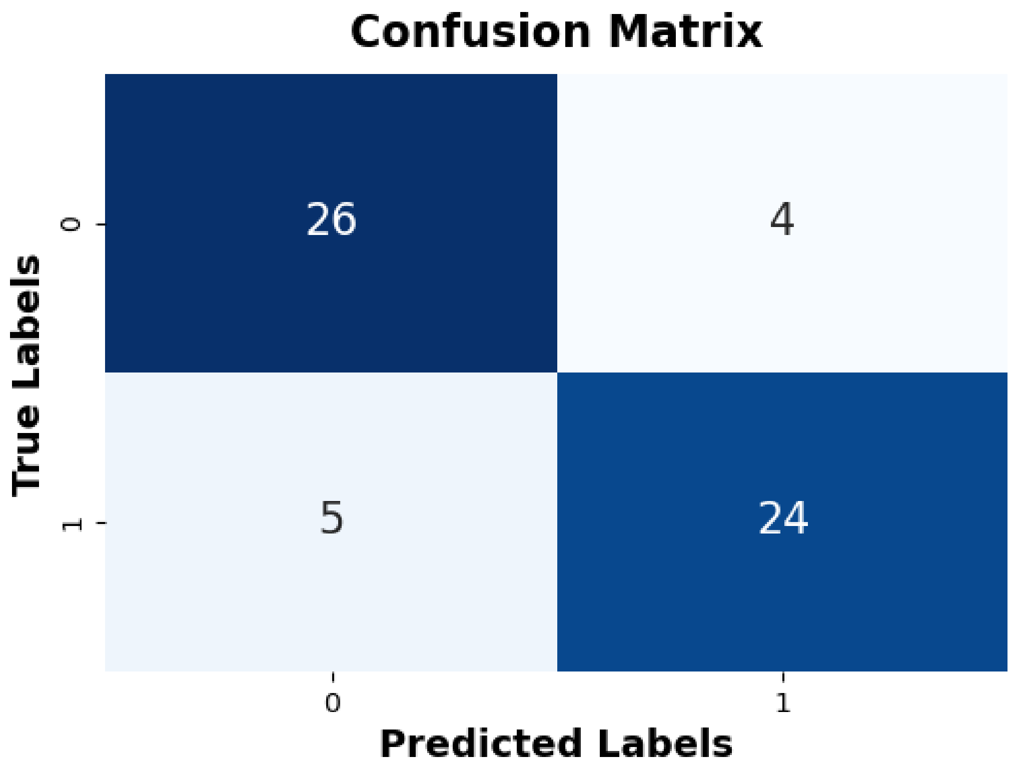
```
# Evaluate on test data (using the same selected features)
X_test_rfe = feature_selector.transform(X_smote_test_scaled)
y_pred_xgb = xgb_model.predict(X_test_rfe)

# Print performance metrics
from sklearn.metrics import classification_report, accuracy_score
print("\n XGBoost Accuracy:", round(accuracy_score(y_smote_test,
y_pred_xgb) * 100, 2), "%")
print("\n Classification Report:\n",
classification_report(y_smote_test, y_pred_xgb))
```

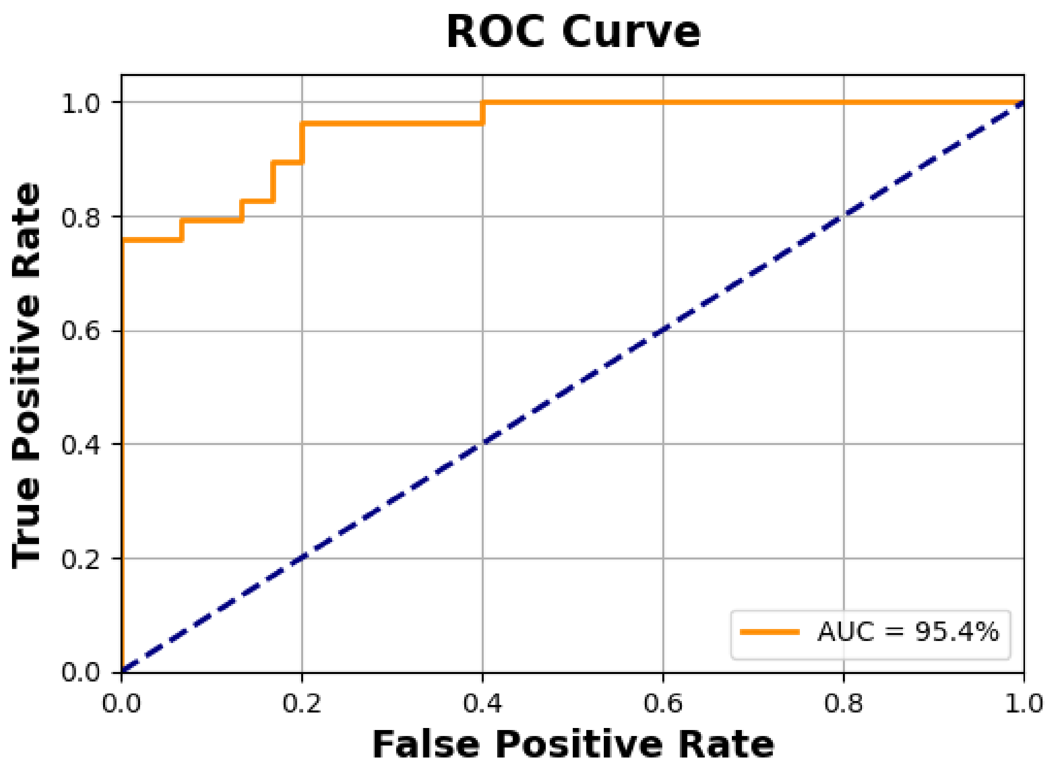
```
 XGBoost Accuracy: 98.31 %

 Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.97      0.98        30
           1       0.97      1.00      0.98        29

    accuracy                           0.98        59
   macro avg       0.98      0.98      0.98        59
weighted avg       0.98      0.98      0.98        59
```

```
LR.fit(X_smote_train_scaled,y_smote_train)
y_pred_LR_smote = LR.predict(X_smote_test_scaled)
print('-'*80)
print("Logistic Regression :")
print("-"*16)
Evaluate_Performance(LR, X_smote_train_scaled, X_smote_test_scaled,
y_smote_train, y_smote_test)
```

```
----------------------------------------------------------------------
----------
Logistic Regression :
----------------

 MODEL PERFORMANCE SUMMARY
==================================================
  Training Accuracy  : 79.57%
  Cross-Validation   : 77.46%
  Testing Accuracy   : 84.75%
  Precision Score    : 85.71%
  Recall Score       : 82.76%
  F1 Score           : 84.21%
  AUC-ROC Score      : 95.4%
==================================================

 Classification Report:
```

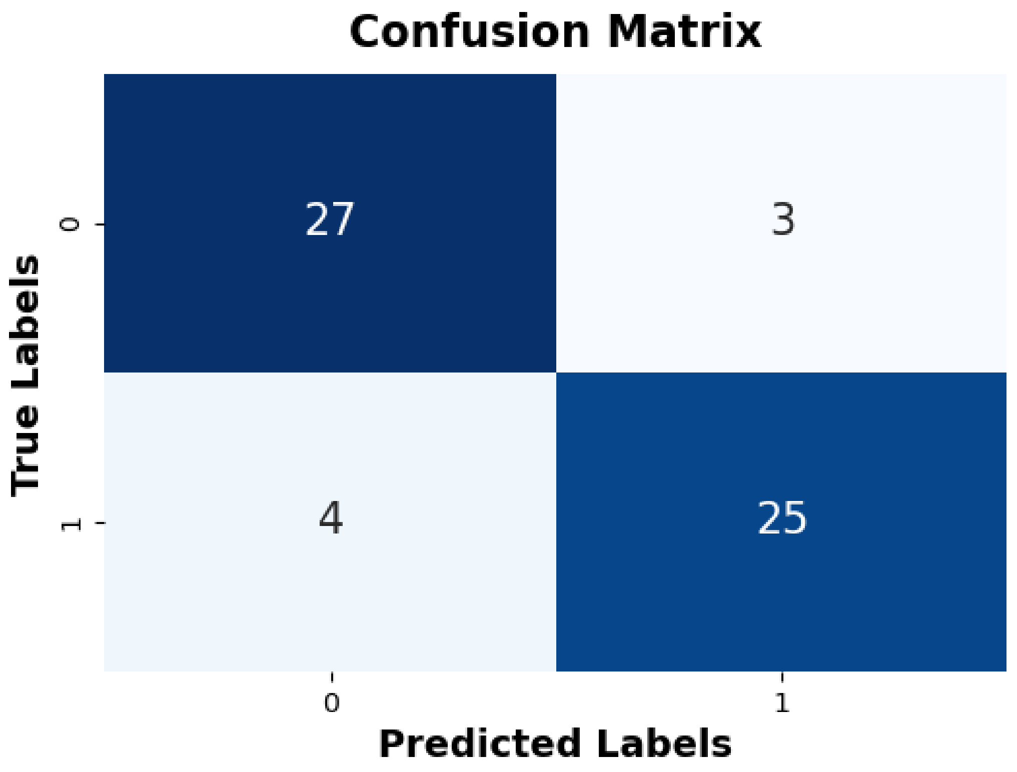
```
              precision    recall  f1-score   support

           0       0.84      0.87      0.85        30
           1       0.86      0.83      0.84        29

    accuracy                           0.85        59
   macro avg       0.85      0.85      0.85        59
weighted avg       0.85      0.85      0.85        59
```

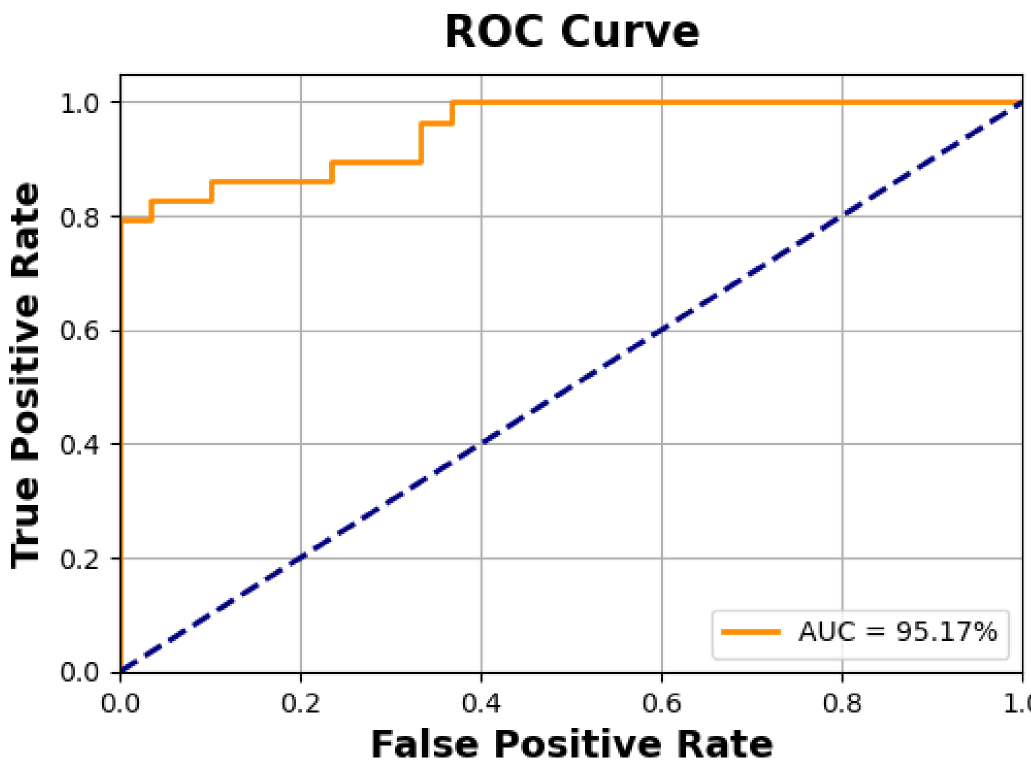




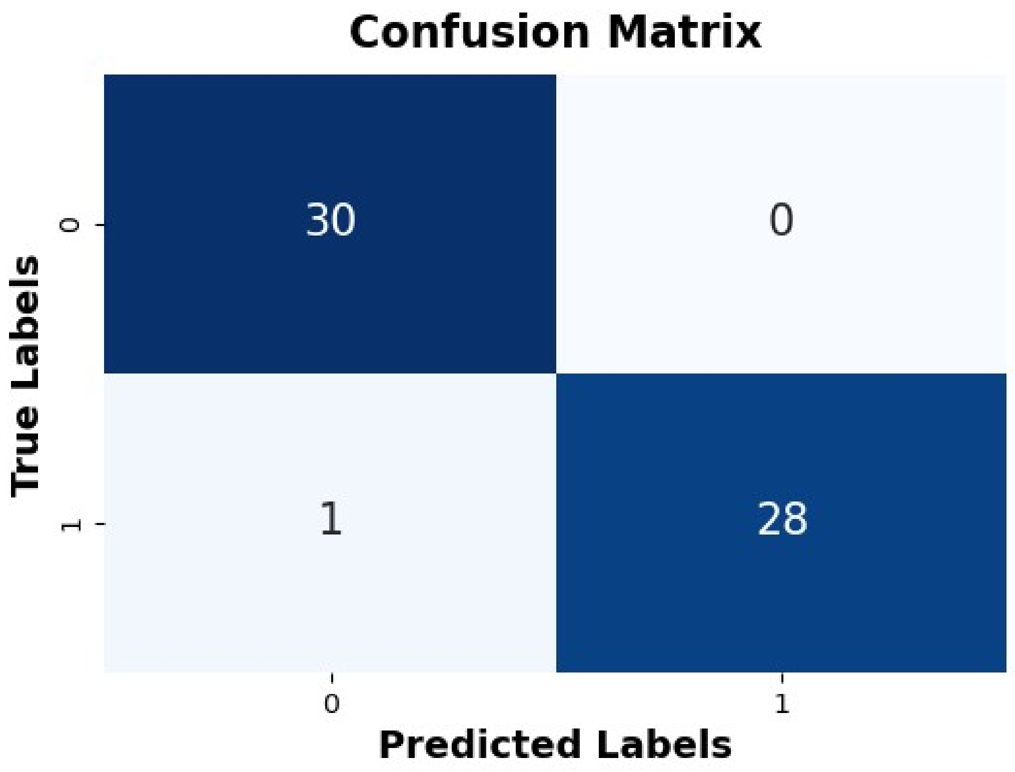
```
SVM.fit(X_smote_train_scaled,y_smote_train)
y_pred_SVM_smote = SVM.predict(X_smote_test_scaled)
print('-'*80)
print("Support vector machine :")
print("-"*16)
Evaluate_Performance(SVM, X_smote_train_scaled, X_smote_test_scaled,
y_smote_train, y_smote_test)

----------------------------------------------------------------------
----------
Support vector machine :
----------------

 MODEL PERFORMANCE SUMMARY
==================================================
  Training Accuracy   : 83.4%
  Cross-Validation    : 79.22%
  Testing Accuracy    : 88.14%
  Precision Score     : 89.29%
  Recall Score        : 86.21%
  F1 Score            : 87.72%
  AUC-ROC Score       : 95.17%
==================================================

 Classification Report:
```

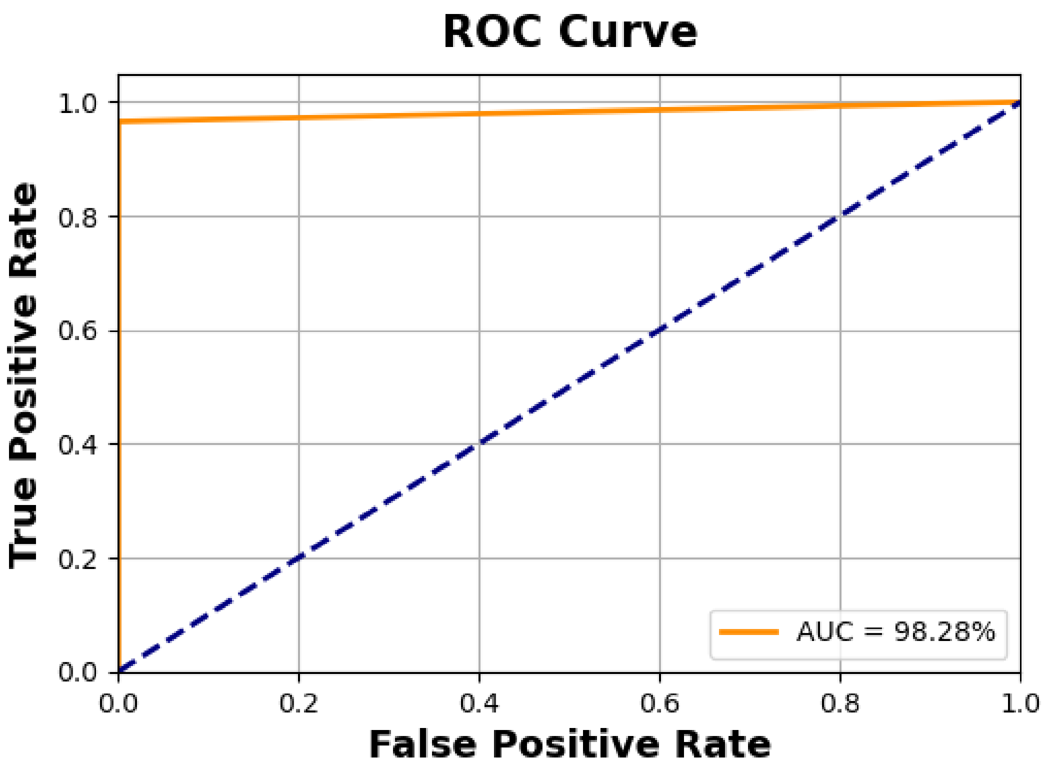
```
              precision    recall  f1-score   support

           0       0.87      0.90      0.89        30
           1       0.89      0.86      0.88        29

    accuracy                           0.88        59
   macro avg       0.88      0.88      0.88        59
weighted avg       0.88      0.88      0.88        59
```



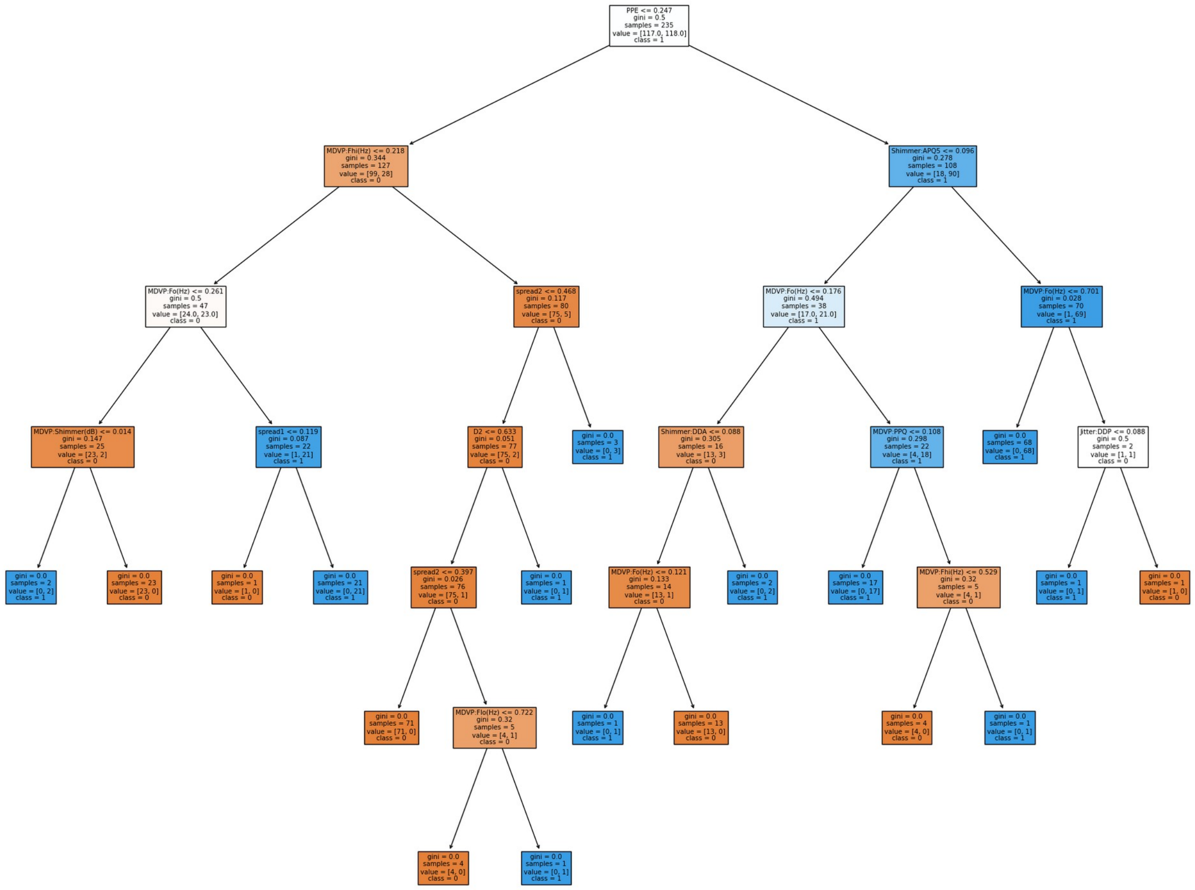


```
DTC = DecisionTreeClassifier(criterion='gini')
DTC.fit(X_smote_train_scaled,y_smote_train)
y_pred_DTC_smote = DTC.predict(X_smote_test_scaled)
print('-'*80)
print("Decision Tree Classifier :")
print("-"*16)
Evaluate_Performance(DTC, X_smote_train_scaled, X_smote_test_scaled,
y_smote_train, y_smote_test)
print( '--> Tree\'s Depth : ',DTC.tree_.max_depth,'\n')
print("DECISION TREE :")
fig = plt.figure(figsize=(25,20))
tree = plot_tree(DTC, feature_names = [ c for c in
smote_data.columns], class_names=['0','1'], filled=True)
plt.show()

----------------------------------------------------------------------
----------
Decision Tree Classifier :
----------------

□ MODEL PERFORMANCE SUMMARY
==================================================
 □ Training Accuracy  : 100.0%
 □ Cross-Validation   : 89.76%
 □ Testing Accuracy   : 98.31%
 □ Precision Score    : 100.0%
 □ Recall Score       : 96.55%
 □ F1 Score           : 98.25%
 □ AUC-ROC Score      : 98.28%
==================================================

□ Classification Report:

              precision    recall  f1-score   support

           0       0.97      1.00      0.98        30
           1       1.00      0.97      0.98        29

    accuracy                           0.98        59
   macro avg       0.98      0.98      0.98        59
weighted avg       0.98      0.98      0.98        59
```



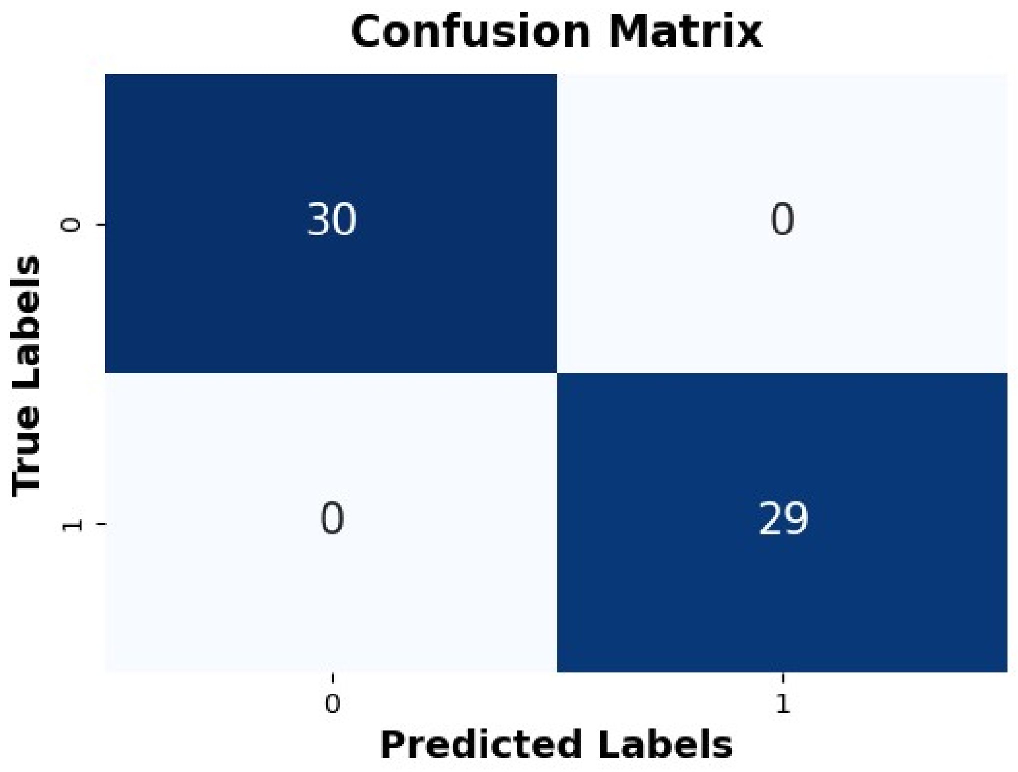


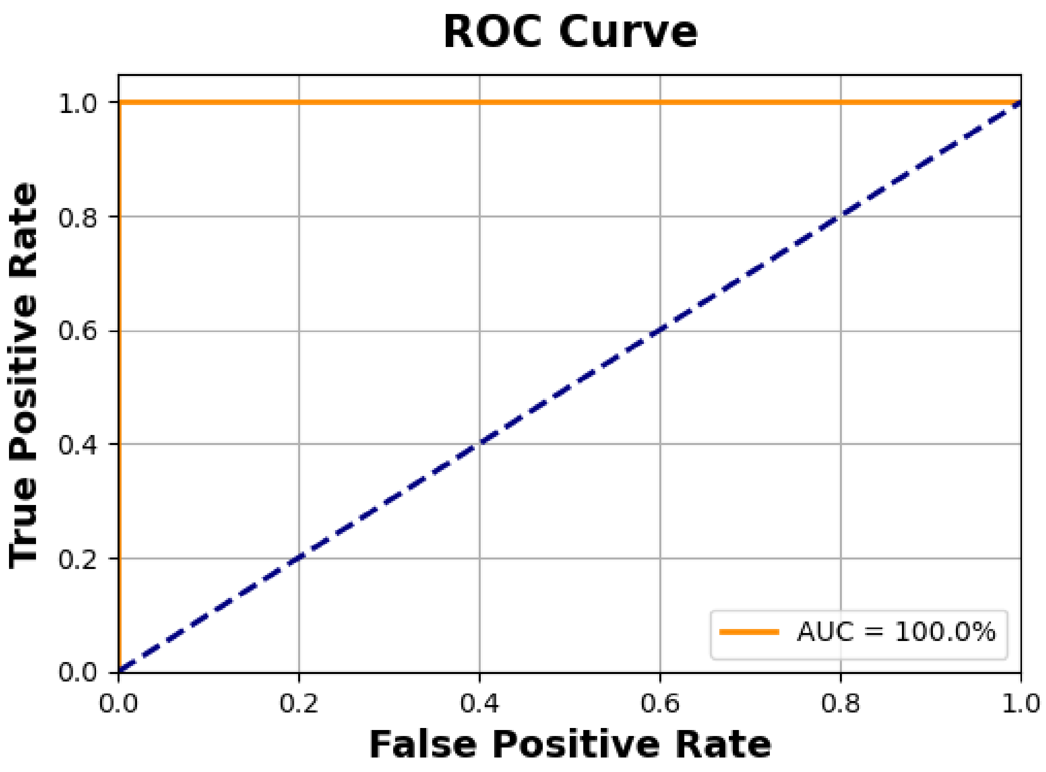
```
--> Tree's Depth :  6

DECISION TREE :
```


PPE <= 0.247 gini = 0.5 samples = 235 value = [117.0, 118.0] class = 1
MDVP:Fhi(Hz) <= 0.218 gini = 0.344 samples = 127 value = [99, 28] class = 0
Shimmer:APQ5 <= 0.096 gini = 0.278 samples = 108 value = [18, 90] class = 1
MDVP:Fo(Hz) <= 0.261 gini = 0.5 samples = 47 value = [24.0, 23.0] class = 0
spread2 <= 0.468 gini = 0.117 samples = 80 value = [75, 5] class = 0
MDVP:Fo(Hz) <= 0.176 gini = 0.494 samples = 38 value = [17.0, 21.0] class = 1
MDVP:Fo(Hz) <= 0.701 gini = 0.028 samples = 70 value = [1, 69] class = 1
MDVP:Shimmer(dB) <= 0.014 gini = 0.147 samples = 25 value = [23, 2] class = 0
spread1 <= 0.119 gini = 0.087 samples = 22 value = [1, 21] class = 1
D2 <= 0.633 gini = 0.051 samples = 77 value = [75, 2] class = 0
gini = 0.0 samples = 3 value = [0, 3] class = 1
Shimmer:DDA <= 0.088 gini = 0.305 samples = 16 value = [13, 3] class = 0
MDVP:PPQ <= 0.108 gini = 0.298 samples = 22 value = [4, 18] class = 1
gini = 0.0 samples = 68 value = [0, 68] class = 1
Jitter:DDP <= 0.088 gini = 0.5 samples = 2 value = [1, 1] class = 0
gini = 0.0 samples = 2 value = [0, 2] class = 1
gini = 0.0 samples = 23 value = [23, 0] class = 0
gini = 0.0 samples = 1 value = [1, 0] class = 0
gini = 0.0 samples = 21 value = [0, 21] class = 1
spread2 <= 0.397 gini = 0.026 samples = 76 value = [75, 1] class = 0
gini = 0.0 samples = 1 value = [0, 1] class = 1
MDVP:Fo(Hz) <= 0.121 gini = 0.133 samples = 14 value = [13, 1] class = 0
gini = 0.0 samples = 2 value = [0, 2] class = 1
gini = 0.0 samples = 17 value = [0, 17] class = 1
MDVP:Fhi(Hz) <= 0.529 gini = 0.32 samples = 5 value = [4, 1] class = 0
gini = 0.0 samples = 1 value = [0, 1] class = 1
gini = 0.0 samples = 1 value = [1, 0] class = 0
gini = 0.0 samples = 71 value = [71, 0] class = 0
MDVP:Flo(Hz) <= 0.722 gini = 0.32 samples = 5 value = [4, 1] class = 0
gini = 0.0 samples = 1 value = [0, 1] class = 1
gini = 0.0 samples = 13 value = [13, 0] class = 0
gini = 0.0 samples = 4 value = [4, 0] class = 0
gini = 0.0 samples = 1 value = [0, 1] class = 1
gini = 0.0 samples = 4 value = [4, 0] class = 0
gini = 0.0 samples = 1 value = [0, 1] class = 1

```python
RFC.fit(X_smote_train_scaled,y_smote_train)
y_pred_RFC_smote = RFC.predict(X_smote_test_scaled)
print('-'*80)
print("Random Forest Classifier :")
print("-"*16)
Evaluate_Performance(RFC, X_smote_train_scaled, X_smote_test_scaled,
y_smote_train, y_smote_test)
```

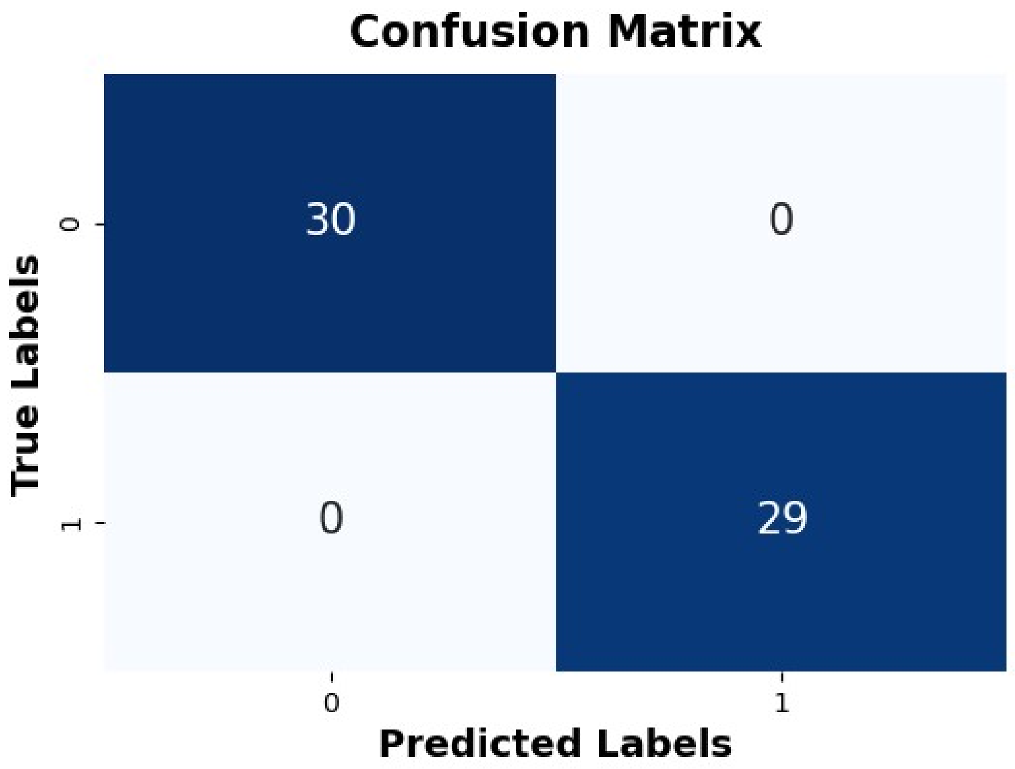
```
----------------------------------------------------------------------
----------
Random Forest Classifier :
----------------

□ MODEL PERFORMANCE SUMMARY
==================================================
 □ Training Accuracy  : 100.0%
 □ Cross-Validation   : 93.17%
 □ Testing Accuracy   : 100.0%
 □ Precision Score    : 100.0%
 □ Recall Score       : 100.0%
 □ F1 Score           : 100.0%
 □ AUC-ROC Score      : 100.0%
==================================================

□ Classification Report:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        30
           1       1.00      1.00      1.00        29

    accuracy                           1.00        59
   macro avg       1.00      1.00      1.00        59
weighted avg       1.00      1.00      1.00        59
```

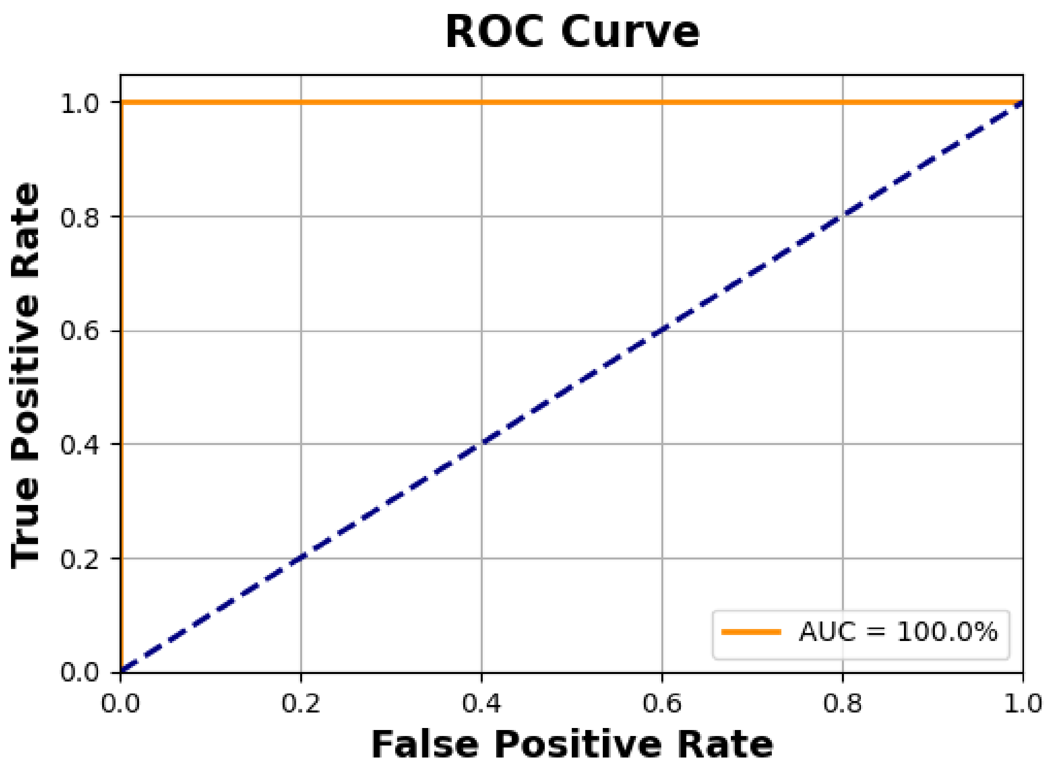




```
RFC.fit(X_smote_train_scaled,y_smote_train)
y_pred_RFC_smote = RFC.predict(X_smote_test_scaled)
print('-'*80)
print("Random Forest Classifier :")
print("-"*16)
Evaluate_Performance(RFC, X_smote_train_scaled, X_smote_test_scaled,
y_smote_train, y_smote_test)

-----------------------------------------------------------------------
---------
Random Forest Classifier :
----------------

□ MODEL PERFORMANCE SUMMARY
==================================================
 □ Training Accuracy  : 100.0%
 □ Cross-Validation   : 92.34%
 □ Testing Accuracy   : 100.0%
 □ Precision Score    : 100.0%
 □ Recall Score       : 100.0%
 □ F1 Score           : 100.0%
 □ AUC-ROC Score      : 100.0%
==================================================

□ Classification Report:
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        30
           1       1.00      1.00      1.00        29

    accuracy                           1.00        59
   macro avg       1.00      1.00      1.00        59
weighted avg       1.00      1.00      1.00        59
```

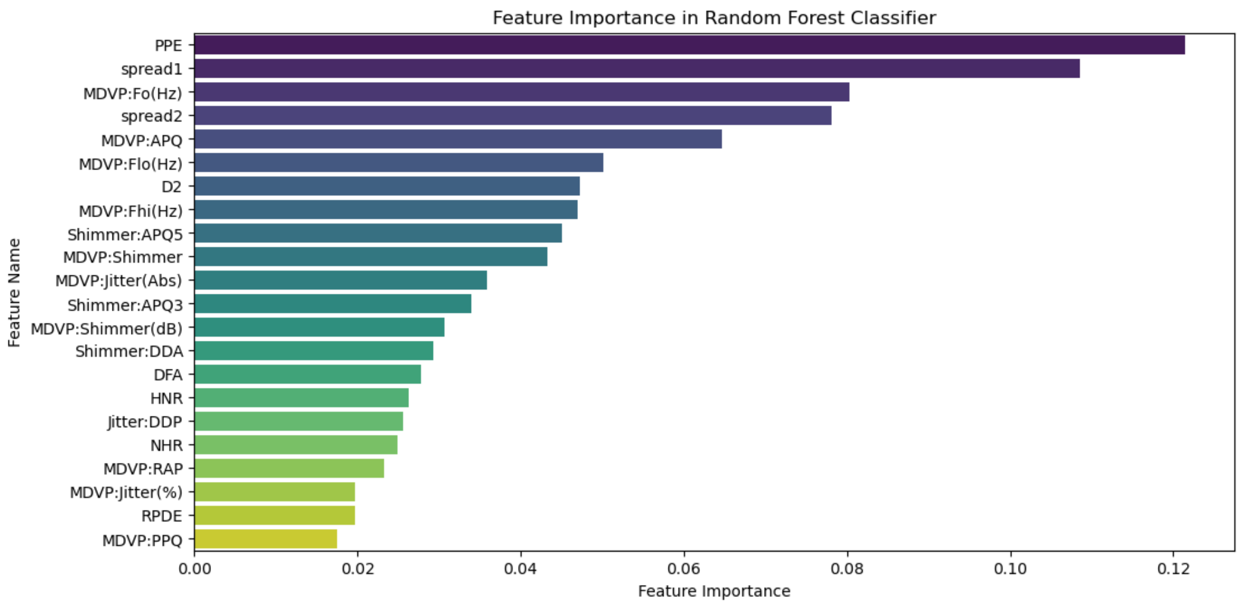




```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Get feature importances from the trained Random Forest model
feature_importances = RFC.feature_importances_

# Sort features by importance
sorted_indices = np.argsort(feature_importances)[::-1]

# Plot the feature importance
plt.figure(figsize=(12, 6))
sns.barplot(x=feature_importances[sorted_indices],
y=X.columns[sorted_indices], palette="viridis")
plt.xlabel("Feature Importance")
plt.ylabel("Feature Name")
plt.title("Feature Importance in Random Forest Classifier")
plt.show()
```

```
C:\Users\barat\AppData\Local\Temp\ipykernel_20900\1937795259.py:13:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.
```

```
  sns.barplot(x=feature_importances[sorted_indices],
y=X.columns[sorted_indices], palette="viridis")
```



```
     # Get feature importance scores
feature_importances = RFC.feature_importances_

# Convert to DataFrame for better readability
feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)

# Display the feature importance
print(feature_importance_df)
```

```
             Feature  Importance
21               PPE    0.121478
18           spread1    0.108541
0        MDVP:Fo(Hz)    0.080266
19           spread2    0.078083
12          MDVP:APQ    0.064637
2       MDVP:Flo(Hz)    0.050195
20                D2    0.047221
1       MDVP:Fhi(Hz)    0.046922
11      Shimmer:APQ5    0.045073
8       MDVP:Shimmer    0.043263
4   MDVP:Jitter(Abs)    0.035846
10      Shimmer:APQ3    0.033944
9   MDVP:Shimmer(dB)    0.030634
13       Shimmer:DDA    0.029274
17               DFA    0.027792
```

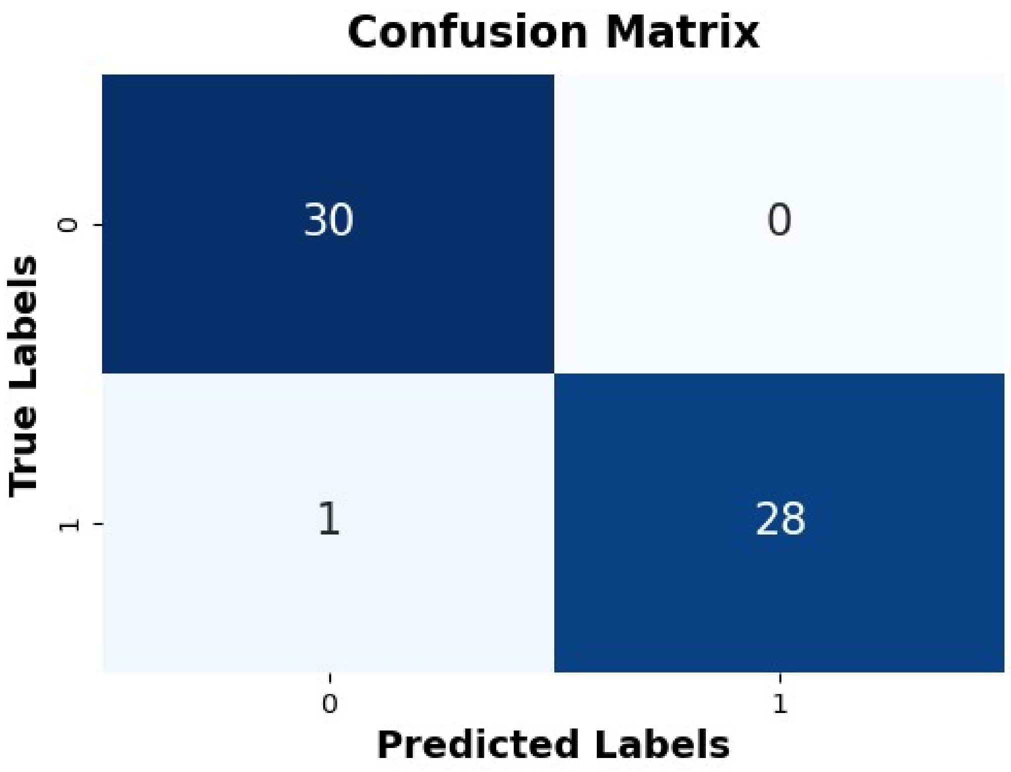
```
15                HNR    0.026215
7          Jitter:DDP    0.025583
14                NHR    0.024916
5            MDVP:RAP    0.023195
3     MDVP:Jitter(%)    0.019756
16               RPDE    0.019696
6            MDVP:PPQ    0.017469
```

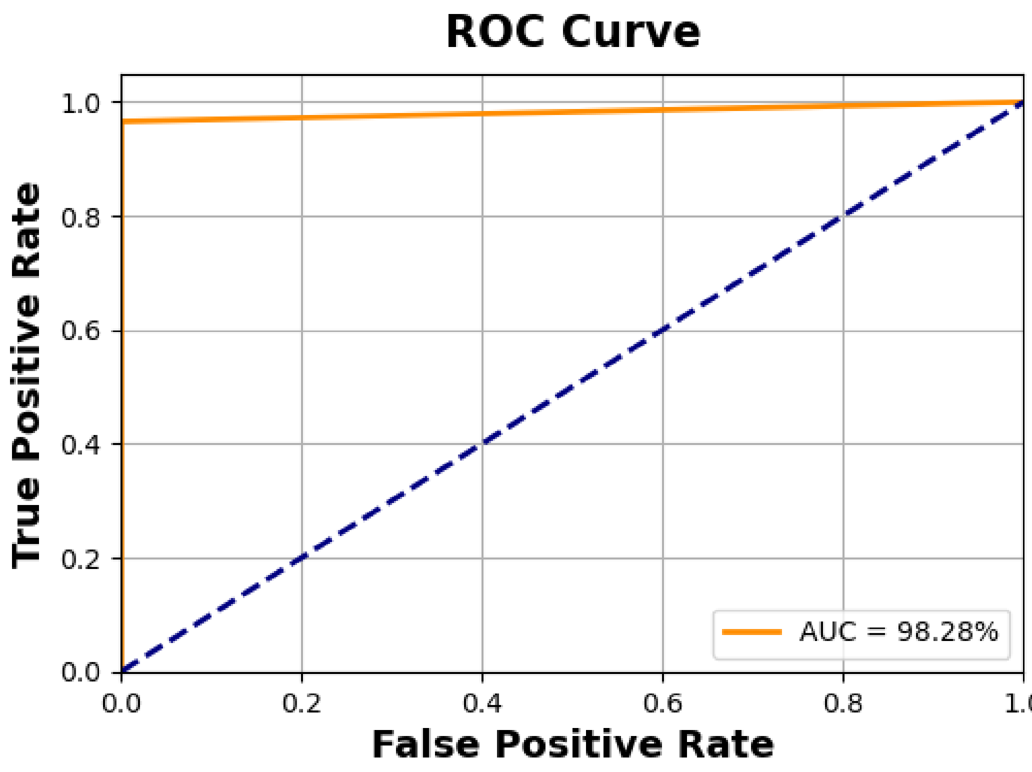
```
# Set a threshold for feature selection (e.g., keep only features with
importance > 0.02)
important_features =
feature_importance_df[feature_importance_df['Importance'] > 0.02]
['Feature'].tolist()

# Reduce dataset to important features only
X_selected = X[important_features]

# Re-split the dataset
X_train_sel, X_test_sel, y_train_sel, y_test_sel =
train_test_split(X_selected, y, test_size=0.2, random_state=42)

# Train the model
rf_model_selected = RandomForestClassifier(random_state=42)
rf_model_selected.fit(X_train_sel, y_train_sel)

# Evaluate the model
y_pred_selected = rf_model_selected.predict(X_test_sel)
print("New Accuracy after Feature Selection:",
accuracy_score(y_test_sel, y_pred_selected) * 100, "%")
```

```
New Accuracy after Feature Selection: 94.87179487179486 %
```

```
KNN = KNeighborsClassifier( n_neighbors = 1 )
KNN.fit(X_smote_train_scaled,y_smote_train)
y_pred_KNN_smote = KNN.predict(X_smote_test_scaled)
print('-'*80)
print("Key- Nearest Neighbor :")
print("-"*16)
Evaluate_Performance(KNN, X_smote_train_scaled, X_smote_test_scaled,
y_smote_train, y_smote_test)
```

```
----------------------------------------------------------------------------
----------
Key- Nearest Neighbor :
----------------

 MODEL PERFORMANCE SUMMARY
==================================================
  Training Accuracy  : 100.0%
  Cross-Validation   : 96.2%
  Testing Accuracy   : 98.31%
 □ Precision Score    : 100.0%
 □ Recall Score       : 96.55%
 □ F1 Score           : 98.25%
 □ AUC-ROC Score      : 98.28%
==================================================

□ Classification Report:

              precision    recall  f1-score   support

           0       0.97      1.00      0.98        30
           1       1.00      0.97      0.98        29

    accuracy                           0.98        59
   macro avg       0.98      0.98      0.98        59
weighted avg       0.98      0.98      0.98        59
```





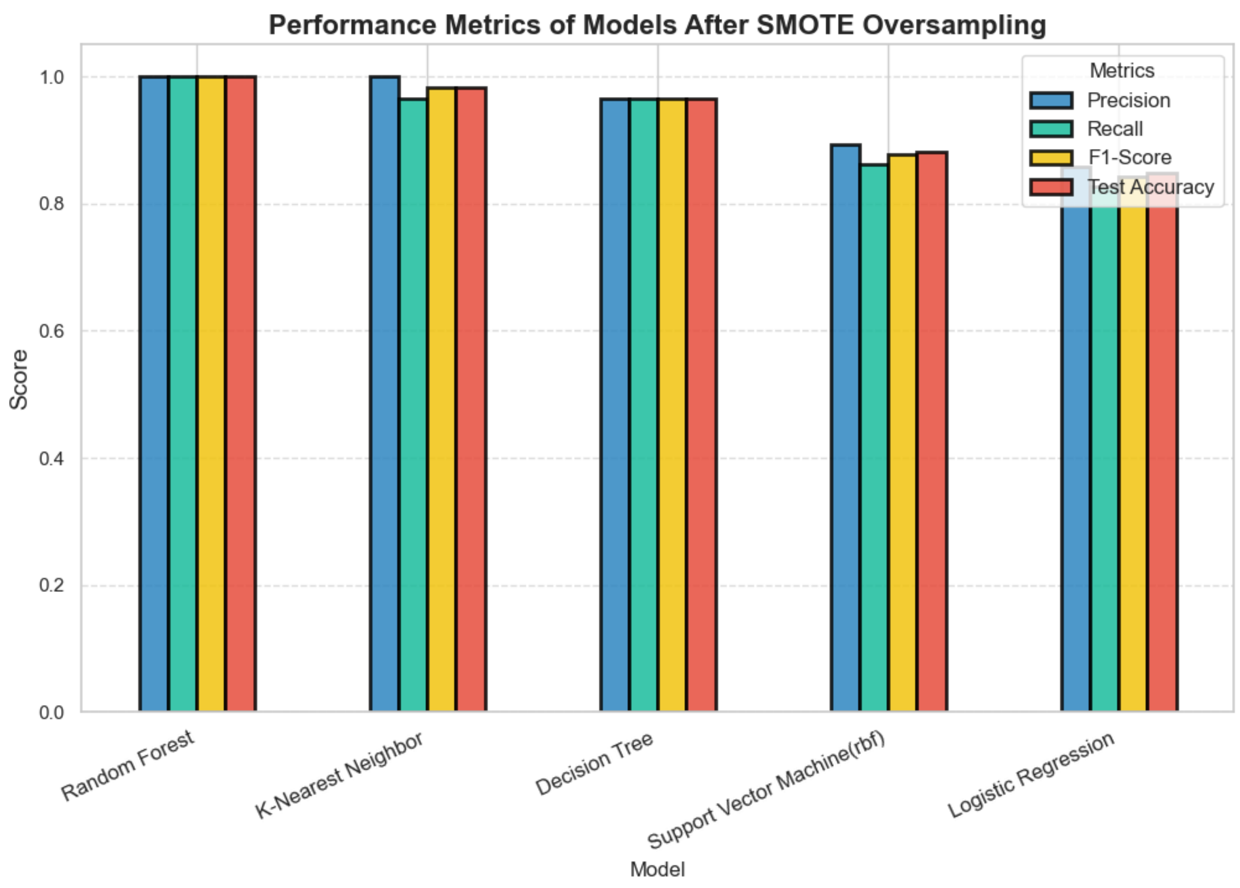
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
results = [
    {'Model': 'Logistic Regression', 'Precision':
precision_score(y_smote_test, y_pred_LR_smote) , 'Recall':
recall_score(y_smote_test, y_pred_LR_smote) ,
     'F1-Score': f1_score(y_smote_test, y_pred_LR_smote) ,'Training
Accuracy': LR.score(X_smote_train_scaled, y_smote_train), 'Test
Accuracy': accuracy_score(y_smote_test, y_pred_LR_smote)},

    {'Model': 'Support Vector Machine(rbf)', 'Precision':
precision_score(y_smote_test, y_pred_SVM_smote), 'Recall':
recall_score(y_smote_test, y_pred_SVM_smote),
     'F1-Score': f1_score(y_smote_test, y_pred_SVM_smote),'Training
Accuracy': SVM.score(X_smote_train_scaled, y_smote_train), 'Test
Accuracy': accuracy_score(y_smote_test, y_pred_SVM_smote)},

    {'Model': 'Decision Tree', 'Precision':
precision_score(y_smote_test, y_pred_DTC_smote), 'Recall':
recall_score(y_smote_test, y_pred_DTC_smote),
     'F1-Score': f1_score(y_smote_test, y_pred_DTC_smote),'Training
Accuracy': DTC.score(X_smote_train_scaled, y_smote_train), 'Test
Accuracy': accuracy_score(y_smote_test, y_pred_DTC_smote)},
    # □ Updated Random Forest Model (Feature Selection Applied)
    {'Model': 'Random Forest (Feature Selected)', 'Precision':
precision_score(y_test_sel, y_pred_selected),
     'Recall': recall_score(y_test_sel, y_pred_selected),
     'F1-Score': f1_score(y_test_sel, y_pred_selected),
     'Training Accuracy': rf_model_selected.score(X_train_sel,
y_train_sel),
     'Test Accuracy': accuracy_score(y_test_sel, y_pred_selected)},

    {'Model': 'K-Nearest Neighbor', 'Precision':
precision_score(y_smote_test, y_pred_KNN_smote), 'Recall':
recall_score(y_smote_test, y_pred_KNN_smote),
     'F1-Score': f1_score(y_smote_test, y_pred_KNN_smote),'Training
Accuracy': KNN.score(X_smote_train_scaled, y_smote_train), 'Test
Accuracy': accuracy_score(y_smote_test, y_pred_KNN_smote)},
]

# Convert to DataFrame
smote_results_df = pd.DataFrame(results)

# Sort models by Test Accuracy (for better visualization)
smote_results_df = smote_results_df.sort_values(by='Test Accuracy',
ascending=False)

# Display DataFrame
print("Results after balancing the dataset using SMOTE Over Sampler
technique : ")
print('-'*70)
display(smote_results_df)
```

```
Results after balancing the dataset using SMOTE Over Sampler technique
:
----------------------------------------------------------------------

                              Model  Precision    Recall  F1-Score  \
4                K-Nearest Neighbor   1.000000  0.965517  0.982456
2                     Decision Tree   0.965517  0.965517  0.965517
3  Random Forest (Feature Selected)   0.941176  1.000000  0.969697
1       Support Vector Machine(rbf)   0.892857  0.862069  0.877193
0               Logistic Regression   0.857143  0.827586  0.842105

   Training Accuracy  Test Accuracy
4           1.000000       0.983051
2           1.000000       0.966102
3           1.000000       0.948718
1           0.834043       0.881356
0           0.795745       0.847458
```

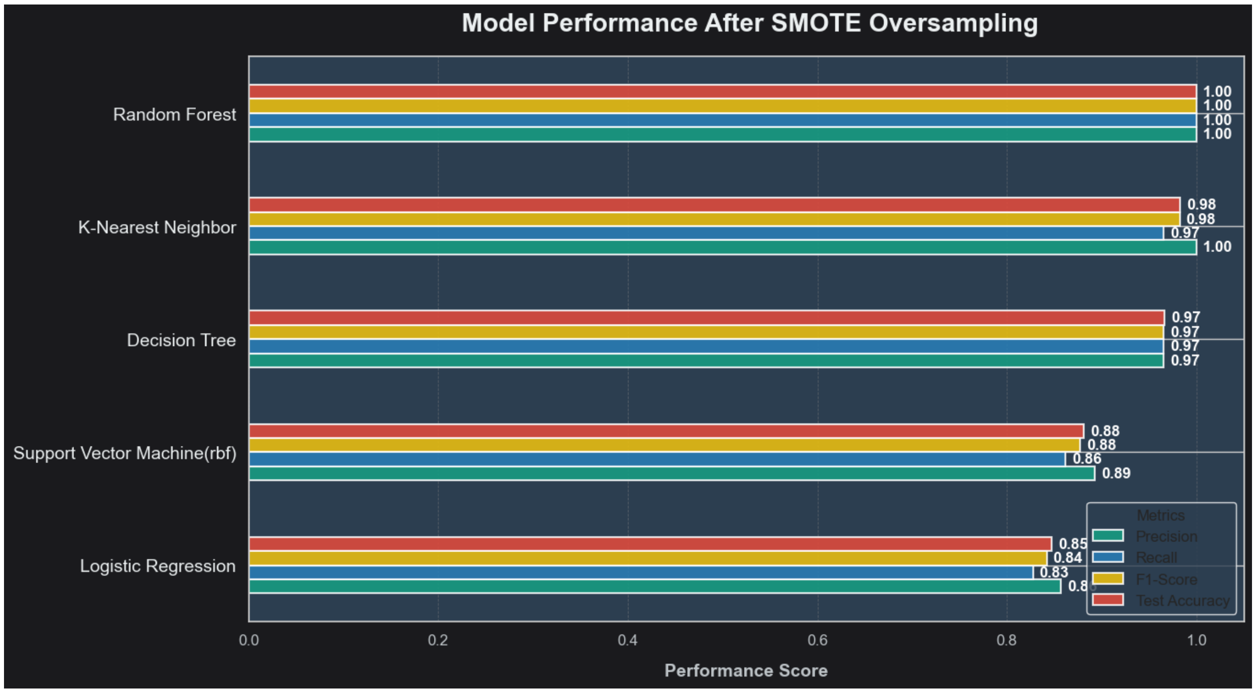
```
# Set seaborn style
sns.set_theme(style="whitegrid")
```

```
# Define colors for different metrics
colors = ['#2E86C1', '#1ABC9C', '#F1C40F', '#E74C3C']

# Plot the results
plt.figure(figsize=(12, 7))
smote_results_df.set_index('Model')[['Precision', 'Recall', 'F1-
Score', 'Test Accuracy']].plot(
    kind='bar', figsize=(12, 7), color=colors, edgecolor='black',
linewidth=2, alpha=0.85)

# Customizing the plot
plt.title('Performance Metrics of Models After SMOTE Oversampling',
fontsize=16, fontweight='bold')
plt.ylabel('Score', fontsize=14)
plt.xticks(rotation=25, fontsize=12, ha='right')
plt.legend(title="Metrics", fontsize=12)
plt.ylim(0, 1.05)  # Keep the range between 0 and 1 for better
readability

# Show grid for clarity
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Show the plot
plt.show()
```

```
<Figure size 1200x700 with 0 Axes>
```



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

# Set an elegant dark theme
plt.style.use("dark_background")
sns.set_theme(style="whitegrid")

# Convert results to DataFrame & sort
smote_results_df = pd.DataFrame(results).sort_values(by="Test
Accuracy", ascending=True)

# Define an eye-catching color palette with gradients
colors = ["#16A085", "#2980B9", "#F1C40F", "#E74C3C"]
gradient = np.linspace(0.2, 1, len(smote_results_df))

# Create figure and axes
fig, ax = plt.subplots(figsize=(14, 8))

# Plot stacked horizontal bars with transparency
bars = smote_results_df.set_index("Model")[["Precision", "Recall",
"F1-Score", "Test Accuracy"]].plot(
    kind="barh",
    ax=ax,
    color=colors,
    alpha=0.85,  # Subtle transparency
    edgecolor="white",
    linewidth=1.5
)

# Add annotations with a glow effect
for container in ax.containers:
    ax.bar_label(container, fmt="%.2f", label_type="edge",
fontsize=12, padding=5, color="white", fontweight="bold")

# Title & labels with better spacing
ax.set_title(" Model Performance After SMOTE Oversampling",
fontsize=20, fontweight="bold", color="#ECF0F1", pad=20)
ax.set_xlabel("Performance Score", fontsize=14, fontweight="bold",
color="#BDC3C7", labelpad=12)
ax.set_ylabel("")  # Remove y-label for a clean look

# Customize ticks and legend
ax.tick_params(axis="x", colors="#BDC3C7", labelsize=12)
ax.tick_params(axis="y", colors="#ECF0F1", labelsize=14)
ax.legend(title="Metrics", fontsize=12, loc="lower right",
facecolor="#2C3E50", edgecolor="white", framealpha=0.8)

# Add a background gradient to the entire figure
fig.patch.set_facecolor("#1A1A1D")
ax.set_facecolor("#2C3E50")

# Soft grid lines
ax.grid(axis="x", linestyle="--", linewidth=0.6, alpha=0.5,
color="gray")

# Show the improved visualization
plt.show()
```


Model Performance After SMOTE Oversampling
Random Forest
K-Nearest Neighbor
Decision Tree
Support Vector Machine(rbf)
Logistic Regression
1.00
1.00
1.00
1.00
0.98
0.98
0.97
1.00
0.97
0.97
0.97
0.97
0.88
0.88
0.86
0.89
0.85
0.84
0.83
0.86
Metrics
Precision
Recall
F1-Score
Test Accuracy
0.0
0.2
0.4
0.6
0.8
1.0
Performance Score