In [1]:

```
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix,
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
from sklearn.neural_network import MLPClassifier
import pyswarms as ps
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier, GradientBoostingClassifier
from sklearn.metrics import roc_curve, auc
```

```
C:\Users\HP\anaconda3\lib\site-packages\pandas\core\computation\expressions.py:21: UserWarning: Pandas requires ver
sion '2.8.4' or newer of 'numexpr' (version '2.8.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
C:\Users\HP\anaconda3\lib\site-packages\pandas\core\arrays\masked.py:60: UserWarning: Pandas requires version '1.3.
6' or newer of 'bottleneck' (version '1.3.4' currently installed).
  from pandas.core import (
C:\Users\HP\anaconda3\lib\site-packages\scipy\__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is
required for this version of SciPy (detected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [2]:
```
# Load the dataset
df = pd.read_csv("Heart_disease_cleveland_new.csv")
print(df)
```

```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0     63    1   0       145   233    1        2      150      0      2.3   
1     67    1   3       160   286    0        2      108      1      1.5   
2     67    1   3       120   229    0        2      129      1      2.6   
3     37    1   2       130   250    0        0      187      0      3.5   
4     41    0   1       130   204    0        2      172      0      1.4   
..   ...  ...  ..       ...   ...  ...      ...      ...    ...      ...   
298   45    1   0       110   264    0        0      132      0      1.2   
299   68    1   3       144   193    1        0      141      0      3.4   
300   57    1   3       130   131    0        0      115      1      1.2   
301   57    0   1       130   236    0        2      174      0      0.0   
302   38    1   2       138   175    0        0      173      0      0.0   

     slope  ca  thal  target  
0        2   0     2       0  
1        1   3     1       1  
2        1   2     3       1  
3        2   0     1       0  
4        0   0     1       0  
..     ...  ..   ...     ...  
298      1   0     3       1  
299      1   2     3       1  
300      1   1     3       1  
301      1   1     1       1  
302      0   0     1       0  

[303 rows x 14 columns]
```

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       303 non-null    int64  
 1   sex       303 non-null    int64  
 2   cp        303 non-null    int64  
 3   trestbps  303 non-null    int64  
 4   chol      303 non-null    int64  
 5   fbs       303 non-null    int64  
 6   restecg   303 non-null    int64  
 7   thalach   303 non-null    int64  
 8   exang     303 non-null    int64  
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64  
 11  ca        303 non-null    int64  
 12  thal      303 non-null    int64  
 13  target    303 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

In [4]:
```
#managing missing values
missing_values=df.isnull().sum()
print(missing_values)
```

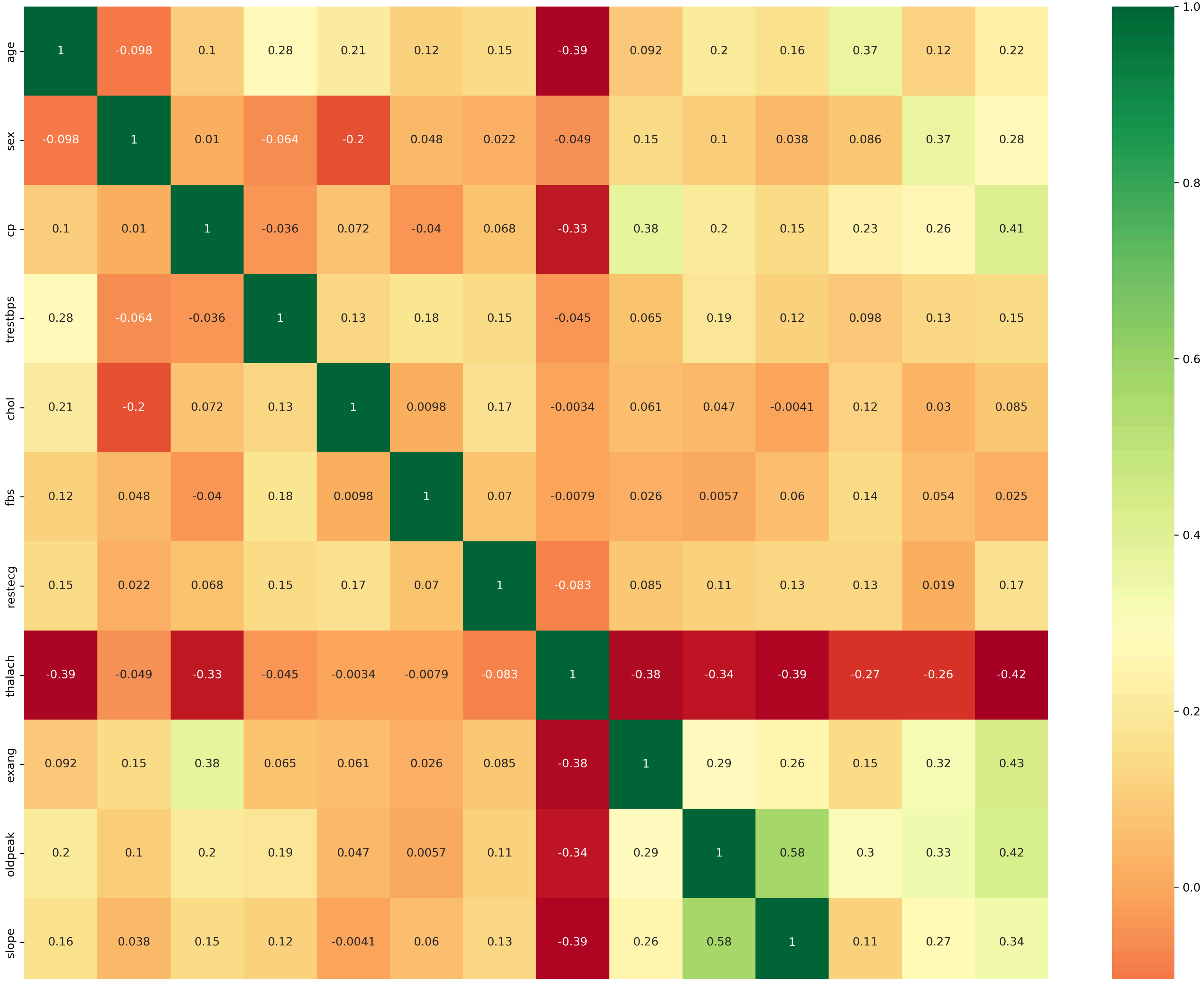
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

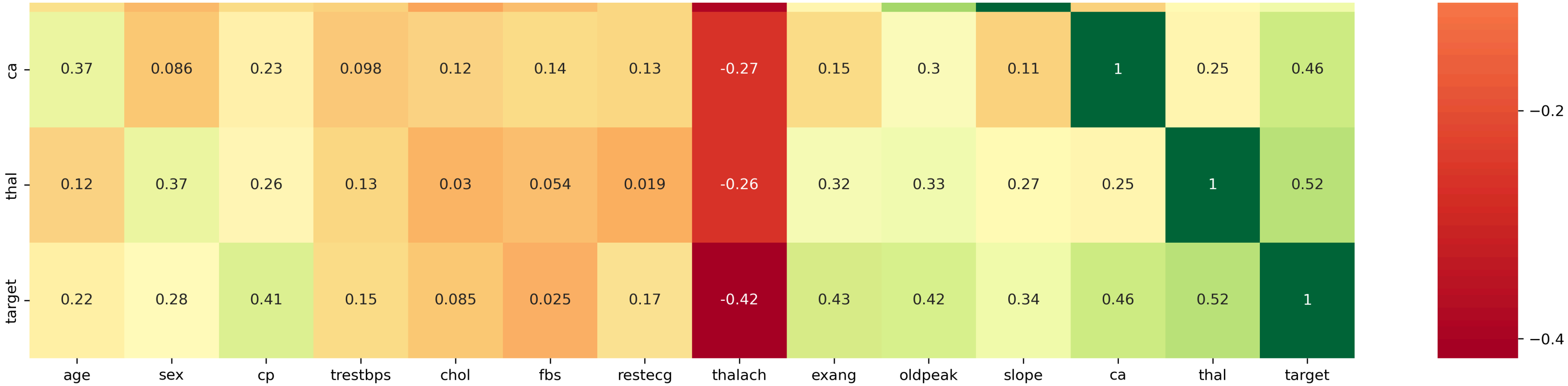
In [5]:
```
df.describe()
```

Out[5]:

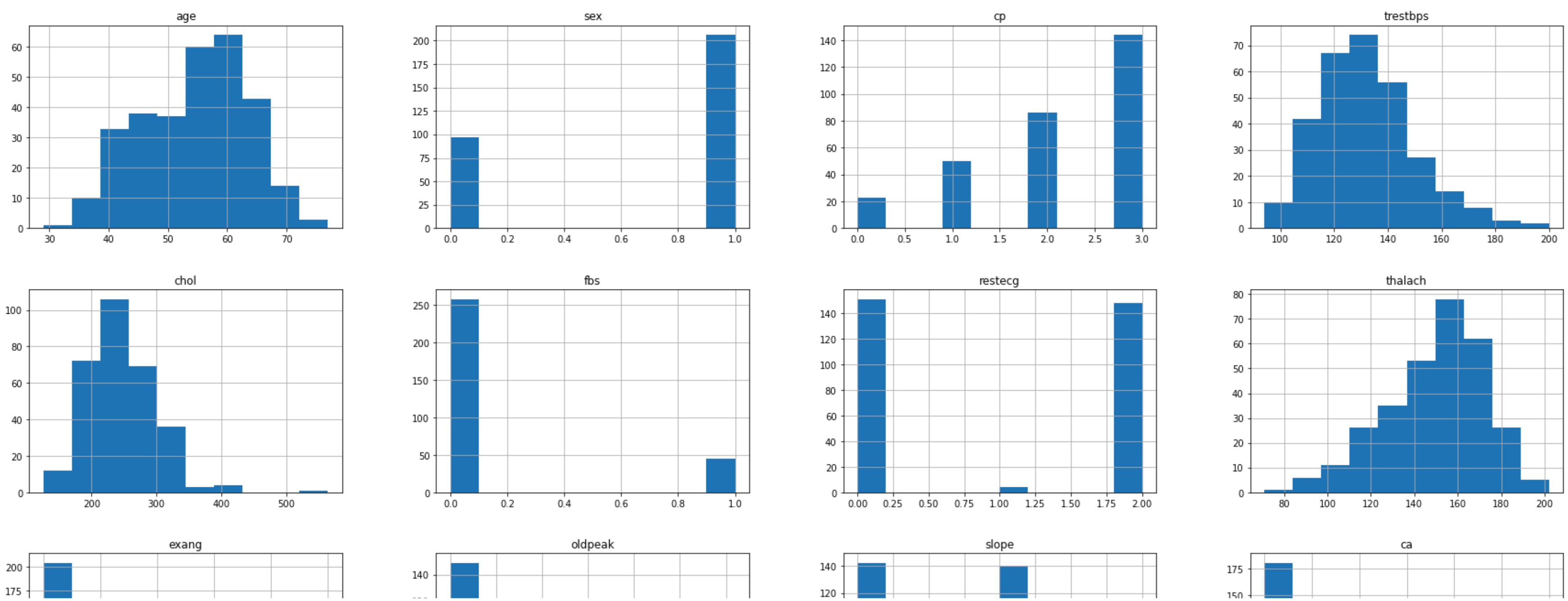
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303
mean	54.438944	0.679868	2.158416	131.689769	246.693069	0.148515	0.990099	149.607261	0.326733	1.039604	0.600660	[illegible]
std	9.038662	0.467299	0.960126	17.599748	51.776918	0.356198	0.994971	22.875003	0.469794	1.161075	0.616226	[illegible]
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	[illegible]
25%	48.000000	0.000000	2.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	0.000000	[illegible]
50%	56.000000	1.000000	2.000000	130.000000	241.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	[illegible]
75%	61.000000	1.000000	3.000000	140.000000	275.000000	0.000000	2.000000	166.000000	1.000000	1.600000	1.000000	1
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	[illegible]

In [6]:
```
import seaborn as sns
#get correlations of each features in dataset
corrmat = df.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20),dpi=300)
#plot heat map
g=sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```


age 1 -0.098 0.1 0.28 0.21 0.12 0.15 -0.39 0.092 0.2 0.16 0.37 0.12 0.22
sex -0.098 1 0.01 -0.064 -0.2 0.048 0.022 -0.049 0.15 0.1 0.038 0.086 0.37 0.28
cp 0.1 0.01 1 -0.036 0.072 -0.04 0.068 -0.33 0.38 0.2 0.15 0.23 0.26 0.41
trestbps 0.28 -0.064 -0.036 1 0.13 0.18 0.15 -0.045 0.065 0.19 0.12 0.098 0.13 0.15
chol 0.21 -0.2 0.072 0.13 1 0.0098 0.17 -0.0034 0.061 0.047 -0.0041 0.12 0.03 0.085
fbs 0.12 0.048 -0.04 0.18 0.0098 1 0.07 -0.0079 0.026 0.0057 0.06 0.14 0.054 0.025
restecg 0.15 0.022 0.068 0.15 0.17 0.07 1 -0.083 0.085 0.11 0.13 0.13 0.019 0.17
thalach -0.39 -0.049 -0.33 -0.045 -0.0034 -0.0079 -0.083 1 -0.38 -0.34 -0.39 -0.27 -0.26 -0.42
exang 0.092 0.15 0.38 0.065 0.061 0.026 0.085 -0.38 1 0.29 0.26 0.15 0.32 0.43
oldpeak 0.2 0.1 0.2 0.19 0.047 0.0057 0.11 -0.34 0.29 1 0.58 0.3 0.33 0.42
slope 0.16 0.038 0.15 0.12 -0.0041 0.06 0.13 -0.39 0.26 0.58 1 0.11 0.27 0.34
1.0
0.8
0.6
0.4
0.2
0.0

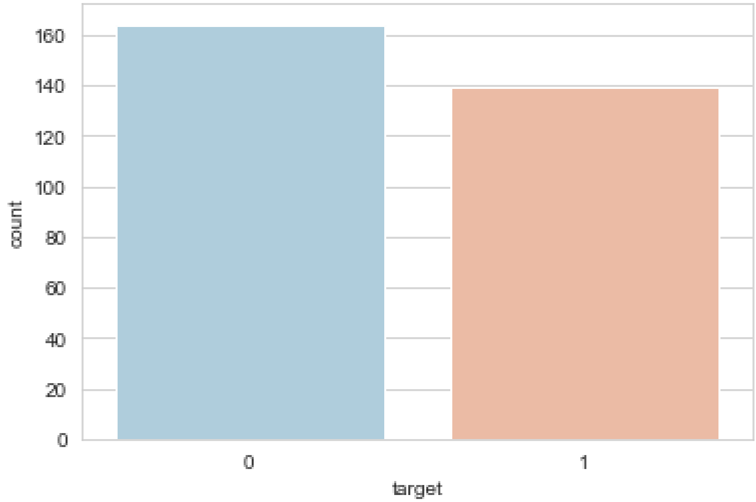


In [7]:
```
df.hist(figsize=(30, 20))
plt.savefig("histogram.png", dpi=300)
plt.show()
```



In [8]:
```
sns.set_style('whitegrid')
sns.countplot(x='target',data=df,palette='RdBu_r')
```

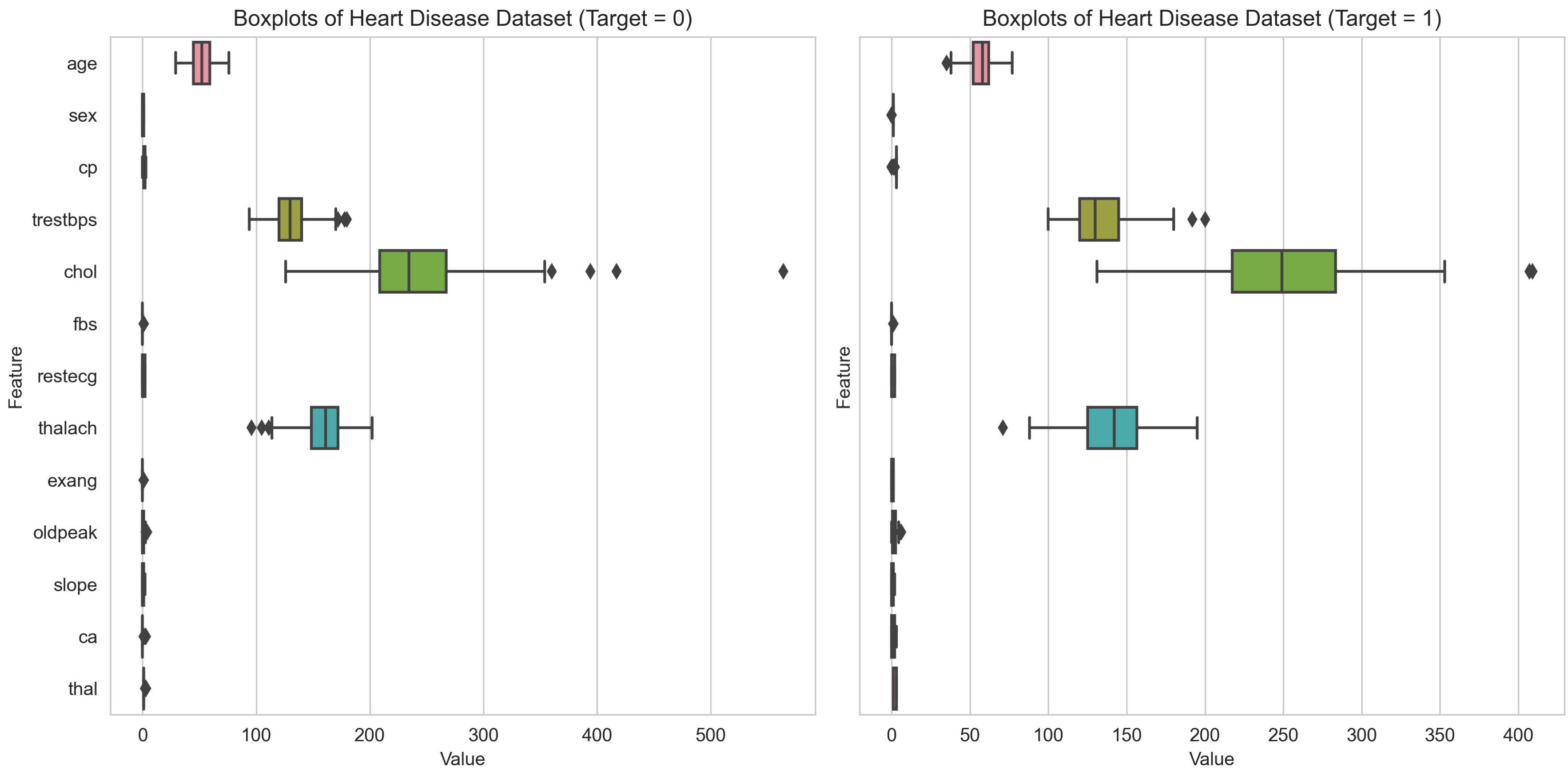
Out[8]: <AxesSubplot:xlabel='target', ylabel='count'>



In [9]:
```
# Define the target column
target_column='target'
```

In [10]:

```
# Separate the dataset based on target values
df_healthy = df[df[target_column] == 0]  # No heart disease
df_disease = df[df[target_column] == 1]  # Heart disease

# Features to plot (excluding the target column)
features = [col for col in df.columns if col != target_column]

# Create subplots
fig, axes = plt.subplots(1, 2, figsize=(12, 6),dpi=300, sharey=True)

# Convert DataFrame to long format for Seaborn
df_healthy_melted = df_healthy.melt(value_vars=features, var_name="Feature", value_name="Value")
df_disease_melted = df_disease.melt(value_vars=features, var_name="Feature", value_name="Value")

# Boxplot for target = 0 (No heart disease)
sns.boxplot(y="Feature", x="Value", data=df_healthy_melted, ax=axes[0])
axes[0].set_title("Boxplots of Heart Disease Dataset (Target = 0)")

# Boxplot for target = 1 (Heart disease)
sns.boxplot(y="Feature", x="Value", data=df_disease_melted, ax=axes[1])
axes[1].set_title("Boxplots of Heart Disease Dataset (Target = 1)")

# Adjust layout
plt.tight_layout()
plt.show()
```



In [11]:
```
# Extract features and target variable
X = df.drop(columns=["target"]).values
y = df["target"].values
```

In [12]:
```
# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
```

In [13]:

```
# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [14]:

```
# Define the MLPGAN class
class MLPGAN:
    def __init__(self, n_inputs, n_hidden=64, n_outputs=1, population_size=200, generations=100, mutation_rate=0.05,
        self.n_inputs = n_inputs
        self.n_hidden = n_hidden
        self.n_outputs = n_outputs
        self.dim = (n_inputs * n_hidden) + (n_hidden * n_outputs) + n_hidden + n_outputs
        self.population_size = population_size
        self.generations = generations
        self.mutation_rate = mutation_rate
        self.crossover_rate = crossover_rate
        self.population = np.random.randn(self.population_size, self.dim) * 0.01

    def forward_prop(self, params, X):
        input_hidden_weights = params[:self.n_inputs * self.n_hidden].reshape(self.n_inputs, self.n_hidden)
        hidden_output_weights = params[self.n_inputs * self.n_hidden:self.n_inputs * self.n_hidden + self.n_hidden *
        hidden_bias = params[self.n_inputs * self.n_hidden + self.n_hidden * self.n_outputs:self.n_inputs * self.n_hi
        output_bias = params[-self.n_outputs:]

        hidden_layer = np.maximum(0.01 * (np.dot(X, input_hidden_weights) + hidden_bias), np.dot(X, input_hidden_weig
        output_layer = 1 / (1 + np.exp(-(np.dot(hidden_layer, hidden_output_weights) + output_bias)))
        return output_layer

    def fitness_function(self, params, X, y):
        y_pred = self.forward_prop(params, X)
        accuracy = accuracy_score(y, (y_pred >= 0.5).astype(int))
        mse = np.mean((y_pred - y.reshape(-1, 1))**2)
        return accuracy - (0.4 * mse)

    def select_parents(self):
        fitness = np.array([self.fitness_function(ind, X_train_scaled, y_train) for ind in self.population])
        fitness = np.maximum(fitness - fitness.min(), 1e-10)
        probabilities = fitness / fitness.sum()
        selected_indices = np.random.choice(len(probabilities), self.population_size // 2, p=probabilities)
        return self.population[selected_indices]

    def crossover(self, parents):
        offspring = []
        for _ in range(self.population_size - len(parents)):
            if random.random() < self.crossover_rate:
                p1, p2 = random.sample(list(parents), 2)
```

```
                point = random.randint(1, self.dim - 1)
                child = np.concatenate((p1[:point], p2[point:]))
                offspring.append(child)
        return np.array(offspring)

    def mutate(self, offspring):
        for i in range(len(offspring)):
            if random.random() < self.mutation_rate:
                mutation_point = random.randint(0, self.dim - 1)
                offspring[i][mutation_point] += np.random.randn() * 0.01
        return offspring

    def train(self, X_train, y_train):
        for _ in range(self.generations):
            parents = self.select_parents()
            offspring = self.crossover(parents)
            offspring = self.mutate(offspring)
            self.population = np.vstack((parents, offspring))
        self.best_params = self.select_parents()[-1]

    def predict(self, X):
        y_pred = self.forward_prop(self.best_params, X)
        return (y_pred >= 0.5).astype(int)
```

In [15]:

```
# Train the genetic algorithm-based MLP model
mlp_ga = MLPGAN(n_inputs=X.shape[1])
mlp_ga.train(X_train_scaled, y_train)
```

In [16]:

```
# Generate predictions from MLPGAN
y_pred_mlp_ga = mlp_ga.predict(X_train_scaled)
y_pred_mlp_ga_test = mlp_ga.predict(X_test_scaled)
```

In [17]:
```
# Append MLP-GA predictions as additional features
X_train_combined = np.column_stack((X_train_scaled, y_pred_mlp_ga))
X_test_combined = np.column_stack((X_test_scaled, y_pred_mlp_ga_test))
```

In [18]:
```
# Train the Random Forest Classifier with tuned parameters
rf = RandomForestClassifier(n_estimators=200, max_depth=10, min_samples_split=4, min_samples_leaf=2, random_state=42)
rf.fit(X_train_combined, y_train)
```

Out[18]:
```
RandomForestClassifier(max_depth=10, min_samples_leaf=2, min_samples_split=4,
                       n_estimators=200, random_state=42)
```

In [19]:
```
# Make final predictions
y_pred_rf = rf.predict(X_test_combined)
```

In [20]:
```
# Compute evaluation metrics
accuracy_rf = accuracy_score(y_test, y_pred_rf)
precision_rf = precision_score(y_test, y_pred_rf)
recall_rf = recall_score(y_test, y_pred_rf)
f1_rf = f1_score(y_test, y_pred_rf)
auc_rf = roc_auc_score(y_test, y_pred_rf)
```

In [21]:
```
models = {
    "Logistic Regression": LogisticRegression(C=1.5, penalty='l2'),
    "SVM": SVC(C=1, gamma=0.1, kernel='rbf'),
    "KNN": KNeighborsClassifier(n_neighbors=5),
    "Decision Tree": DecisionTreeClassifier(criterion='gini'),
    "Random Forest": RandomForestClassifier(n_estimators=1000, criterion='gini'),
    "Extra Trees": ExtraTreesClassifier(n_estimators=100),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100, max_depth=3),
    "GaussianNB": GaussianNB(),
    "XGBoost": XGBClassifier(n_estimators=300, max_depth=15),
    "MLP-BP": MLPClassifier(hidden_layer_sizes=(30,), activation='relu', solver='adam')
}
```

In [22]:

```
results = []
for name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)

    if hasattr(model, "predict_proba"):
        y_proba = model.predict_proba(X_test_scaled)[:,1]
    else:
        y_proba = model.decision_function(X_test_scaled)

    results.append({
        'Model': name,
        'Accuracy': accuracy_score(y_test, y_pred),
        'Precision': precision_score(y_test, y_pred),
        'Recall': recall_score(y_test, y_pred),
        'F1 Score': f1_score(y_test, y_pred),
        'AUC': roc_auc_score(y_test, y_proba)
    })
```

```
C:\Users\HP\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:692: ConvergenceWarning: S
tochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
```

In [23]:

```
results.append({
    'Model': 'MLP-GA-RF',
    'Accuracy': accuracy_rf,
    'Precision': precision_rf,
    'Recall': recall_rf,
    'F1 Score': f1_rf,
    'AUC': auc_rf
})
```

In [24]:

```
# Print the results
print("MLP+GA+RF Model Metrics:")
print(f"Accuracy: {accuracy_rf:.4f}")
print(f"Precision: {precision_rf:.4f}")
print(f"Recall: {recall_rf:.4f}")
print(f"F1 Score: {f1_rf:.4f}")
print(f"AUC: {auc_rf:.4f}")
```

```
MLP+GA+RF Model Metrics:
Accuracy: 0.9672
Precision: 0.9643
Recall: 0.9643
F1 Score: 0.9643
AUC: 0.9670
```

In [25]:

```

metrics = {
    "Accuracy": accuracy_rf,
    "Precision": precision_rf,
    "Recall": recall_rf,
    "F1 Score": f1_rf,
    "AUC": auc_rf
}
```

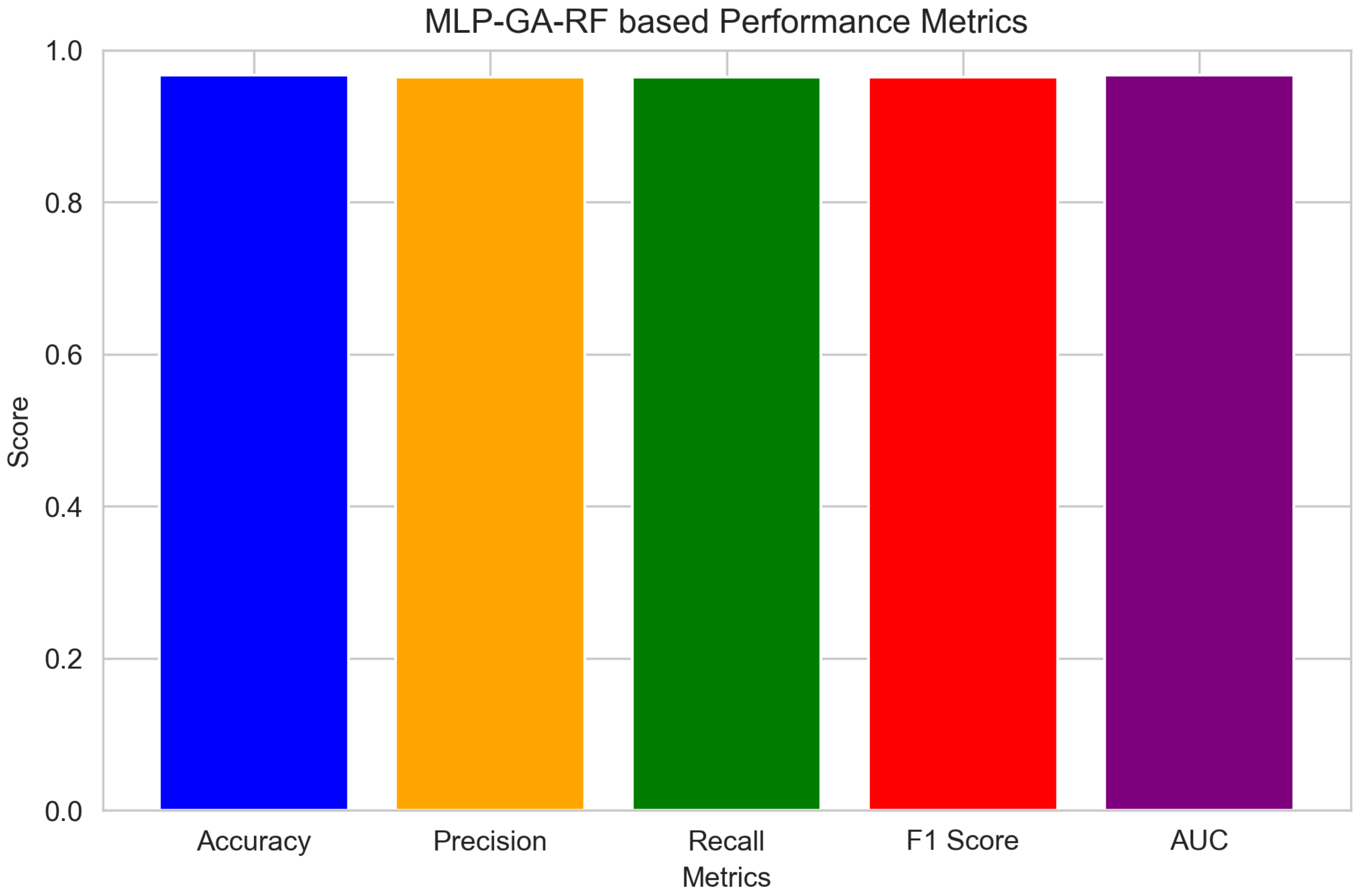
In [26]:

```
results_df = pd.DataFrame(results)
print(results_df.sort_values(by='Accuracy', ascending=False))
```

```
                  Model  Accuracy  Precision    Recall  F1 Score       AUC
10            MLP-GA-RF  0.967213   0.964286  0.964286  0.964286  0.966991
2                   KNN  0.901639   0.823529  1.000000  0.903226  0.924242
4         Random Forest  0.901639   0.843750  0.964286  0.900000  0.952381
0   Logistic Regression  0.868852   0.812500  0.928571  0.866667  0.952381
7            GaussianNB  0.868852   0.794118  0.964286  0.870968  0.949134
8               XGBoost  0.868852   0.812500  0.928571  0.866667  0.906926
9                MLP-BP  0.868852   0.794118  0.964286  0.870968  0.957792
1                   SVM  0.852459   0.806452  0.892857  0.847458  0.944805
6     Gradient Boosting  0.852459   0.787879  0.928571  0.852459  0.945887
5           Extra Trees  0.836066   0.764706  0.928571  0.838710  0.935065
3         Decision Tree  0.786885   0.714286  0.892857  0.793651  0.794913
```

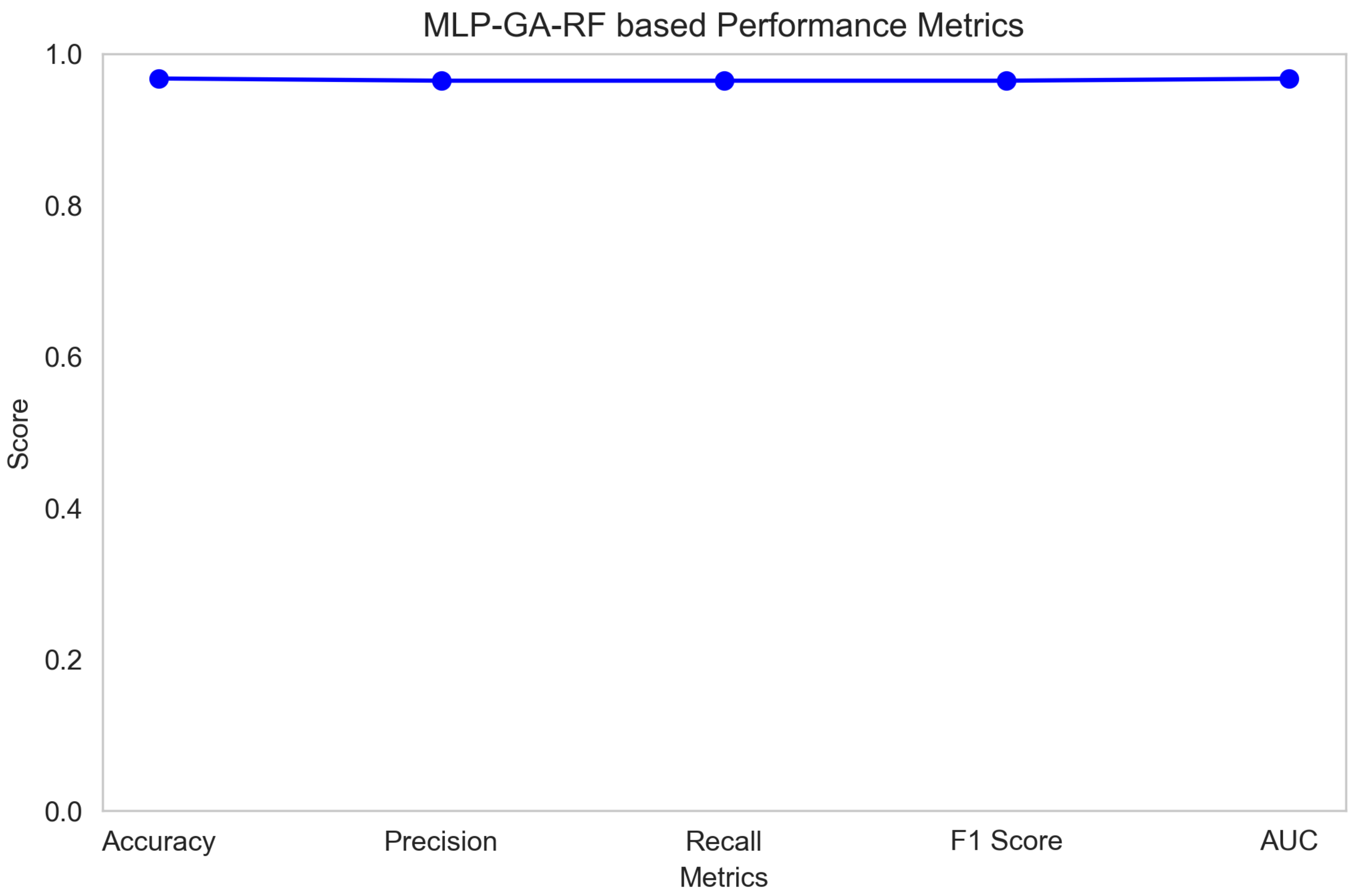
In [27]:

```
plt.figure(figsize=(8, 5),dpi=300)
plt.bar(metrics.keys(), metrics.values(), color=['blue', 'orange', 'green', 'red', 'purple'])
plt.xlabel("Metrics")
plt.ylabel("Score")
plt.ylim(0, 1)
plt.title("MLP-GA-RF based Performance Metrics")
plt.show()
```


MLP-GA-RF based Performance Metrics
1.0
0.8
0.6
0.4
0.2
0.0
Score
Accuracy
Precision
Recall
F1 Score
AUC
Metrics

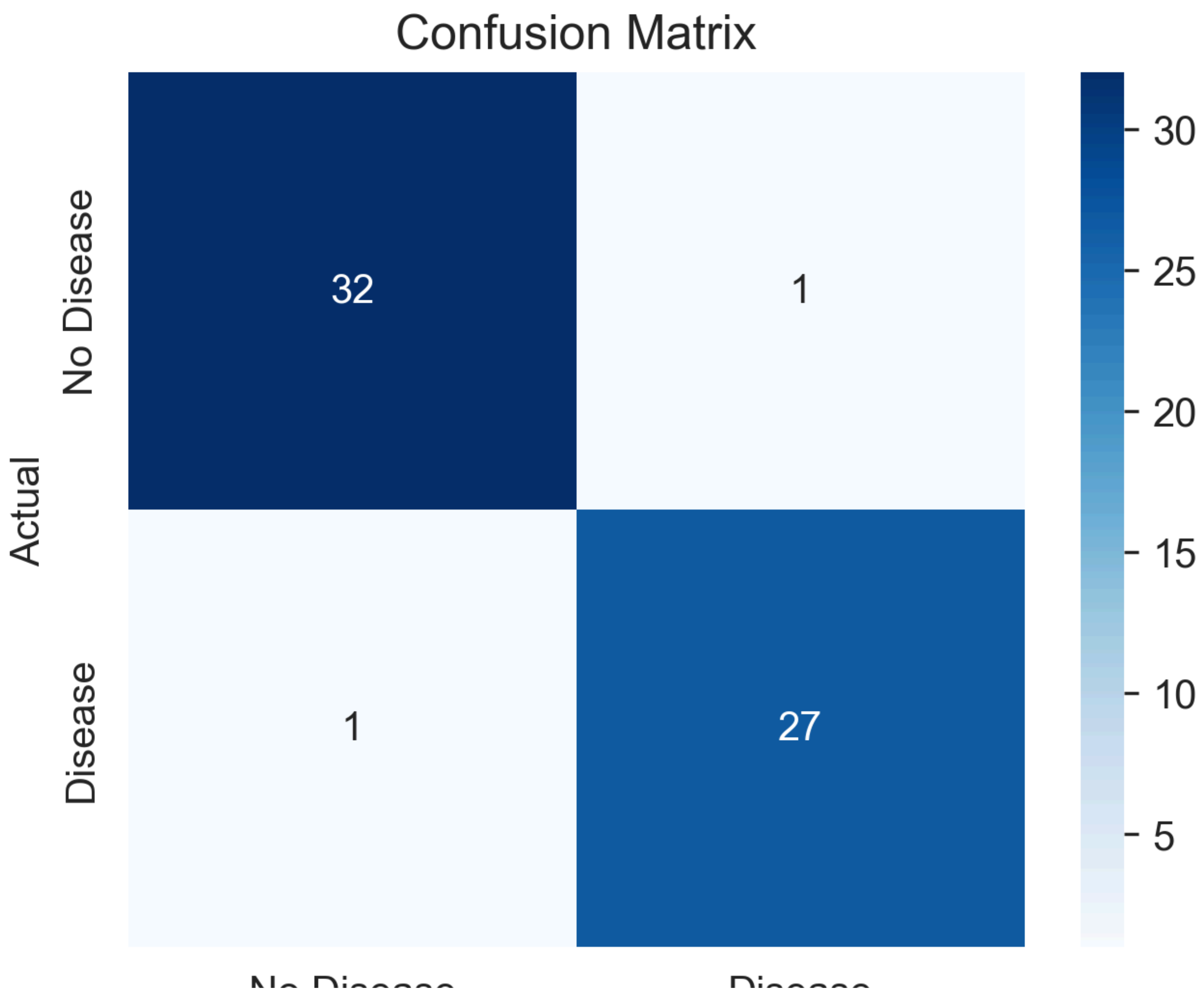
In [28]:

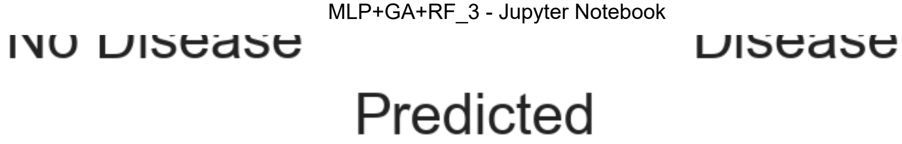
```
plt.figure(figsize=(8, 5),dpi=300)
plt.plot(list(metrics.keys()), list(metrics.values()), marker='o', linestyle='-', color='b')
plt.xlabel("Metrics")
plt.ylabel("Score")
plt.ylim(0, 1)
plt.title("MLP-GA-RF based Performance Metrics")
plt.grid()
plt.show()
```


MLP-GA-RF based Performance Metrics
1.0
0.8
0.6
0.4
0.2
0.0
Score
Accuracy
Precision
Recall
F1 Score
AUC
Metrics

In [29]:

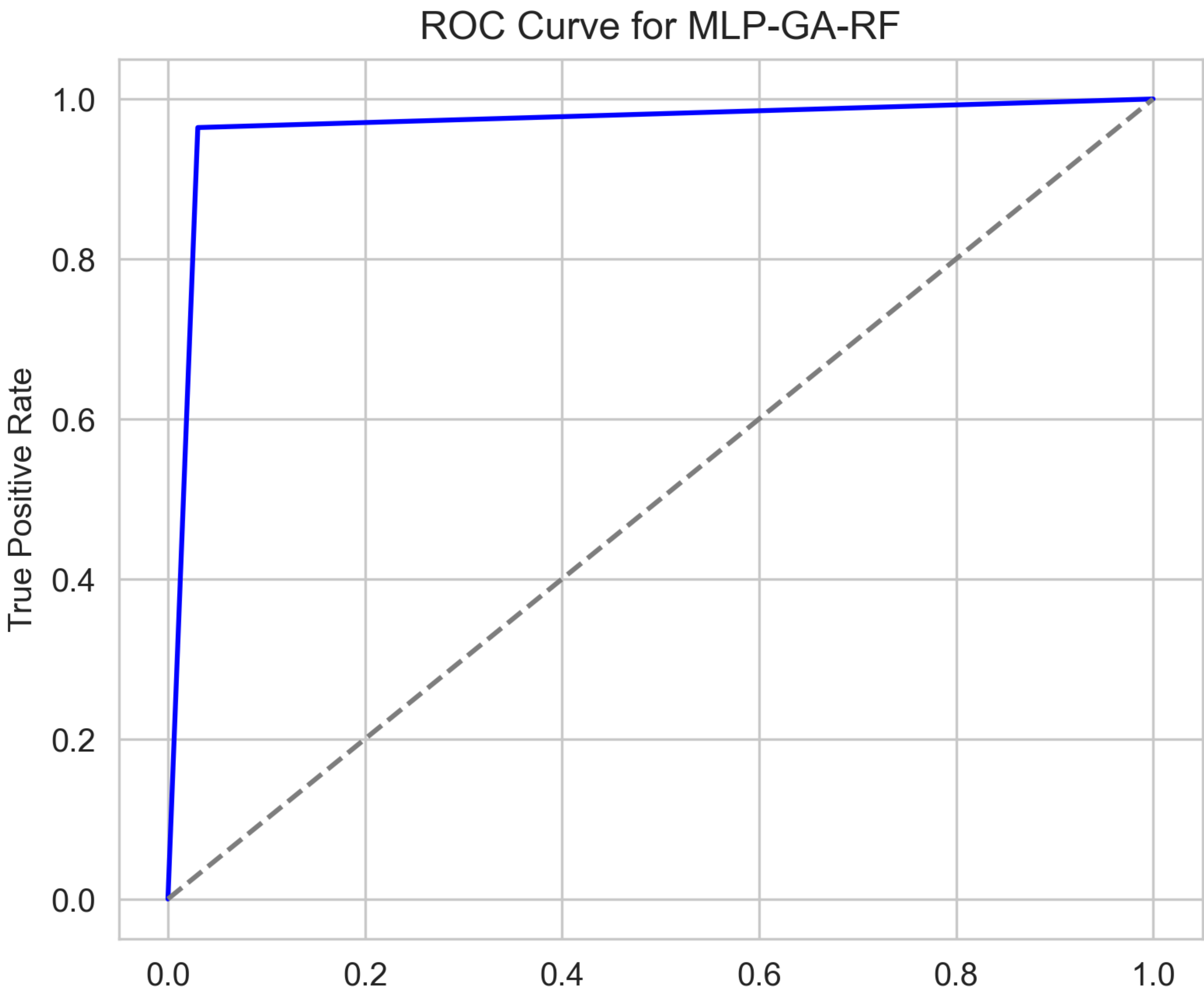
```
# Confusion matrix visualization
cm = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(5, 4),dpi=300)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No Disease", "Disease"], yticklabels=["No Disease",
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```


Confusion Matrix
Actual
No Disease
Disease
32
1
1
27
30
25
20
15
10
5


No Disease
Disease
Predicted

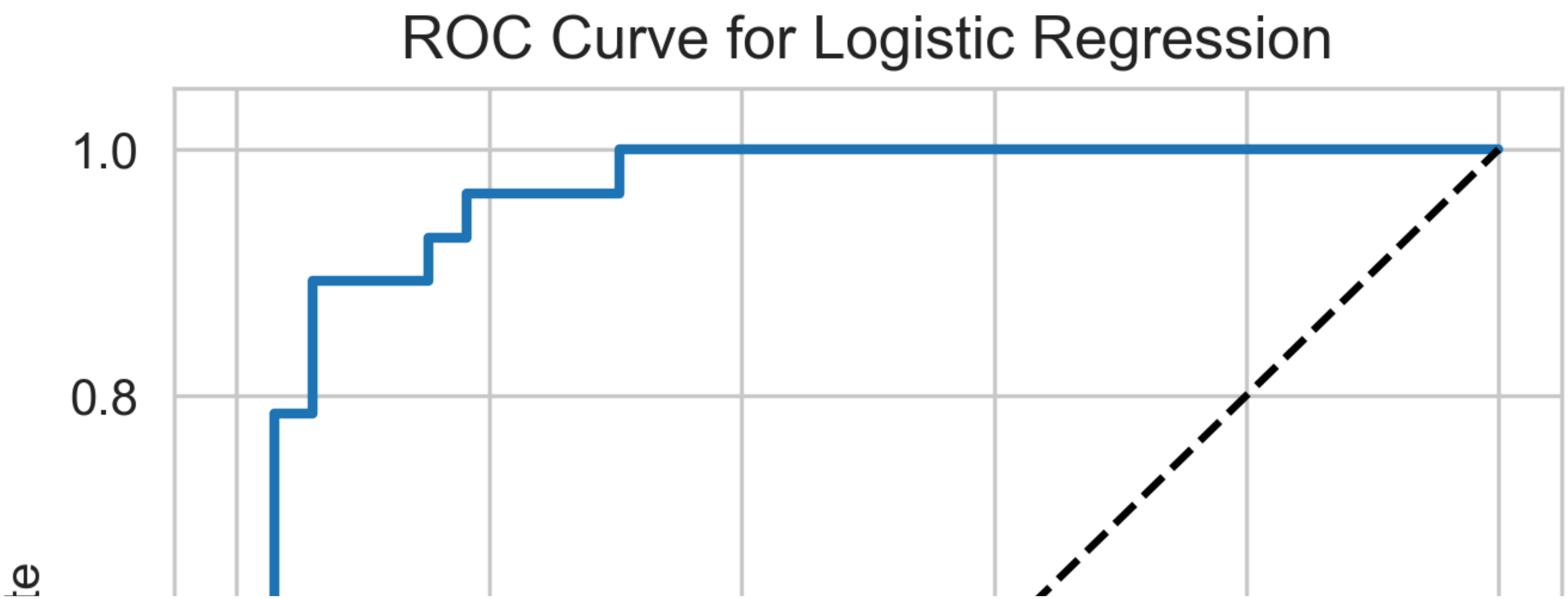
In [30]:

```
# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_rf)
plt.figure(figsize=(6, 5),dpi=300)
plt.plot(fpr, tpr, color='blue', label=f'ROC curve (AUC = {auc_rf:.2f})')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve for MLP-GA-RF")
#plt.legend()
plt.show()
```

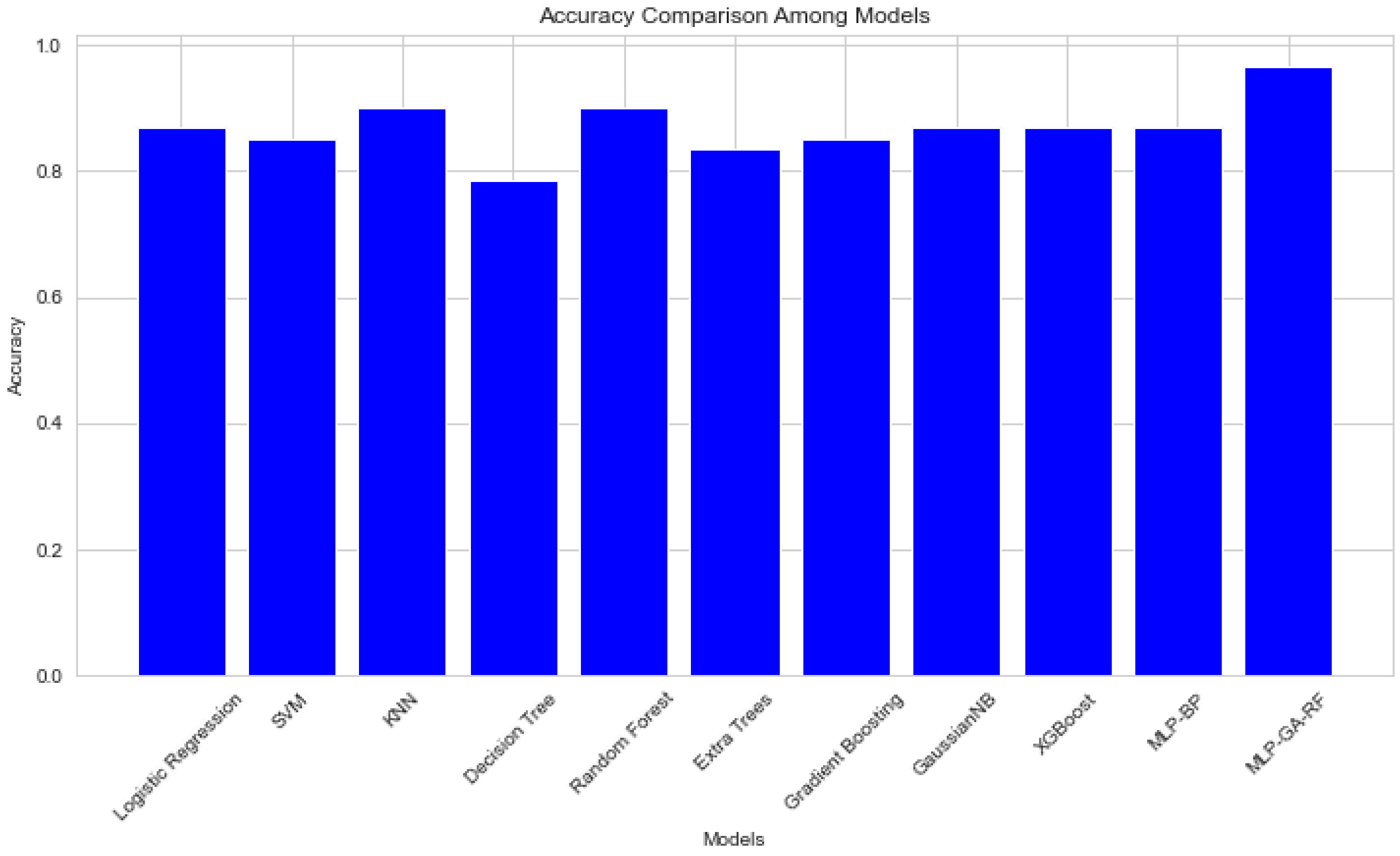

ROC Curve for MLP-GA-RF
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

False Positive Rate

In [31]:
```
# Plot individual ROC curves for each model without AUC and with dpi=300
for name, model in models.items():
    plt.figure(figsize=(5, 5), dpi=300)  # High-resolution figure
    model.fit(X_train_scaled, y_train)
    if hasattr(model, "predict_proba"):
        y_probs = model.predict_proba(X_test_scaled)[:, 1]  # Get probability scores
    else:
        y_probs = model.decision_function(X_test_scaled)  # Use decision_function if predict_proba is unavailable
    fpr, tpr, _ = roc_curve(y_test, y_probs)

    plt.plot(fpr, tpr, linewidth=2, label=f'{name}')
    plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC Curve for {name}')
    plt.legend(loc='lower right')
    plt.show()
```

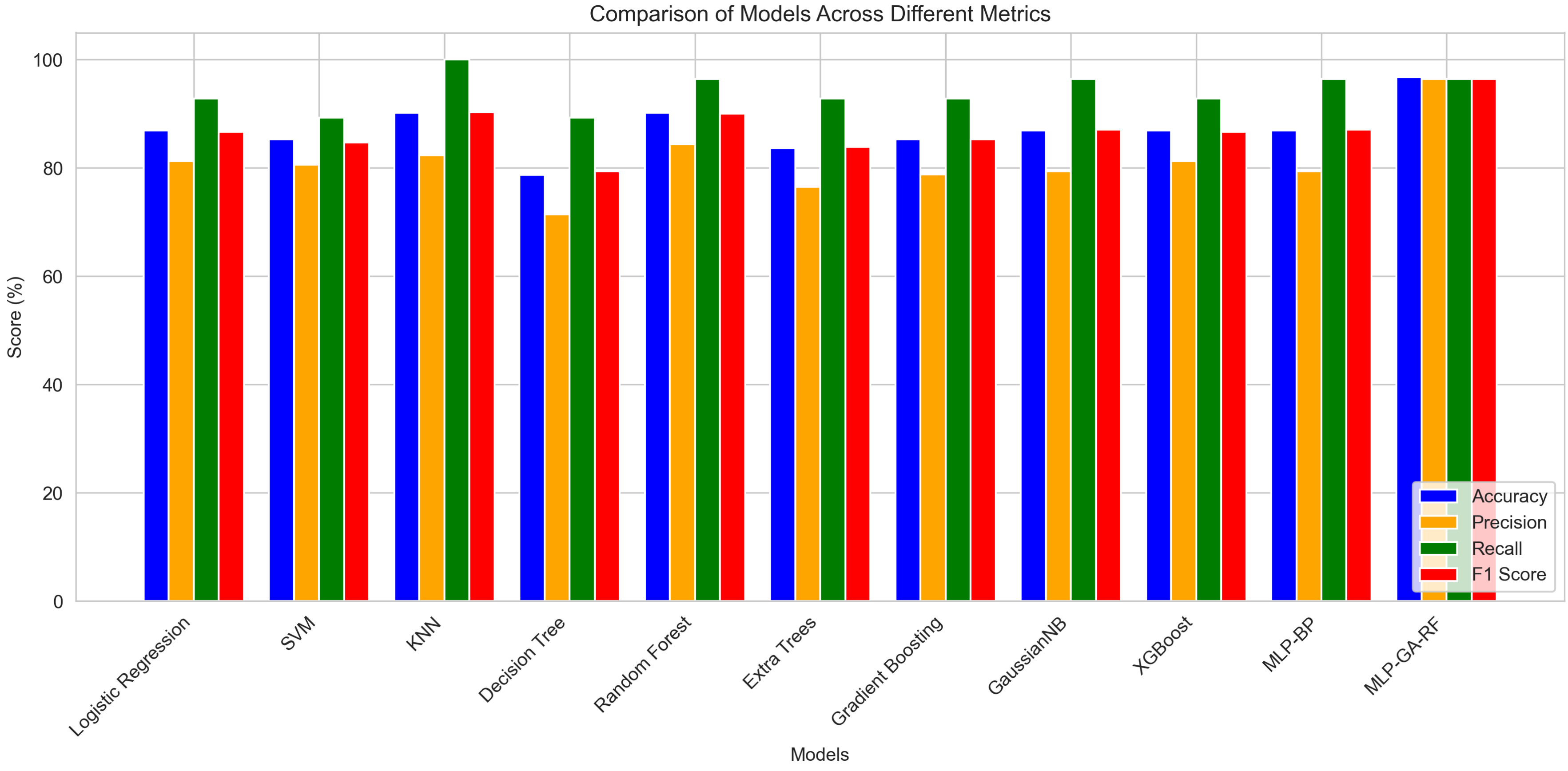


In [32]:
```
# Bar Plot for Accuracy Comparison
plt.figure(figsize=(12, 6))
plt.bar(results_df['Model'], results_df['Accuracy'], color='blue')
plt.xlabel("Models")
plt.ylabel("Accuracy")
plt.title("Accuracy Comparison Among Models")
plt.xticks(rotation=45)
plt.show()
```



In [33]:

```
# Extracting performance metrics for visualization
models_list = results_df['Model'].values
accuracy = results_df['Accuracy'].values * 100
precision = results_df['Precision'].values * 100
recall = results_df['Recall'].values * 100
f1_score_values = results_df['F1 Score'].values * 100

# Set width and positions for bars
x = np.arange(len(models_list))
width = 0.2

# Create a grouped bar chart
fig, ax = plt.subplots(figsize=(12, 6),dpi=300)
ax.bar(x - 1.5 * width, accuracy, width, label="Accuracy", color='blue')
ax.bar(x - 0.5 * width, precision, width, label="Precision", color='orange')
ax.bar(x + 0.5 * width, recall, width, label="Recall", color='green')
ax.bar(x + 1.5 * width, f1_score_values, width, label="F1 Score", color='red')

# Labels and formatting
ax.set_ylabel("Score (%)")
ax.set_xlabel("Models")
ax.set_xticks(x)
ax.set_xticklabels(models_list, rotation=45, ha='right')
ax.set_title("Comparison of Models Across Different Metrics")
ax.legend(loc="lower right")

# Display the plot
plt.tight_layout()
plt.show()
```


Comparison of Models Across Different Metrics
Score (%)
0
20
40
60
80
100
Accuracy
Precision
Recall
F1 Score
Logistic Regression
SVM
KNN
Decision Tree
Random Forest
Extra Trees
Gradient Boosting
GaussianNB
XGBoost
MLP-BP
MLP-GA-RF
Models

In [ ]:

In [ ]:

In [ ]:

In [1]:

```
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix,
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
from sklearn.neural_network import MLPClassifier
import pyswarms as ps
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier, GradientBoostingClassifier
from sklearn.metrics import roc_curve, auc
```

```
C:\Users\HP\anaconda3\lib\site-packages\pandas\core\computation\expressions.py:21: UserWarning: Pandas requires ver
sion '2.8.4' or newer of 'numexpr' (version '2.8.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
C:\Users\HP\anaconda3\lib\site-packages\pandas\core\arrays\masked.py:60: UserWarning: Pandas requires version '1.3.
6' or newer of 'bottleneck' (version '1.3.4' currently installed).
  from pandas.core import (
C:\Users\HP\anaconda3\lib\site-packages\scipy\__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is
required for this version of SciPy (detected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [2]:
```
# Load the dataset
df = pd.read_csv("Heart_disease_cleveland_new.csv")
print(df)
```

```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0     63    1   0       145   233    1        2      150      0      2.3   
1     67    1   3       160   286    0        2      108      1      1.5   
2     67    1   3       120   229    0        2      129      1      2.6   
3     37    1   2       130   250    0        0      187      0      3.5   
4     41    0   1       130   204    0        2      172      0      1.4   
..   ...  ...  ..       ...   ...  ...      ...      ...    ...      ...   
298   45    1   0       110   264    0        0      132      0      1.2   
299   68    1   3       144   193    1        0      141      0      3.4   
300   57    1   3       130   131    0        0      115      1      1.2   
301   57    0   1       130   236    0        2      174      0      0.0   
302   38    1   2       138   175    0        0      173      0      0.0   

     slope  ca  thal  target  
0        2   0     2       0  
1        1   3     1       1  
2        1   2     3       1  
3        2   0     1       0  
4        0   0     1       0  
..     ...  ..   ...     ...  
298      1   0     3       1  
299      1   2     3       1  
300      1   1     3       1  
301      1   1     1       1  
302      0   0     1       0  

[303 rows x 14 columns]
```

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       303 non-null    int64  
 1   sex       303 non-null    int64  
 2   cp        303 non-null    int64  
 3   trestbps  303 non-null    int64  
 4   chol      303 non-null    int64  
 5   fbs       303 non-null    int64  
 6   restecg   303 non-null    int64  
 7   thalach   303 non-null    int64  
 8   exang     303 non-null    int64  
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64  
 11  ca        303 non-null    int64  
 12  thal      303 non-null    int64  
 13  target    303 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

In [4]:

```
#managing missing values
missing_values=df.isnull().sum()
print(missing_values)
```

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

In [5]:

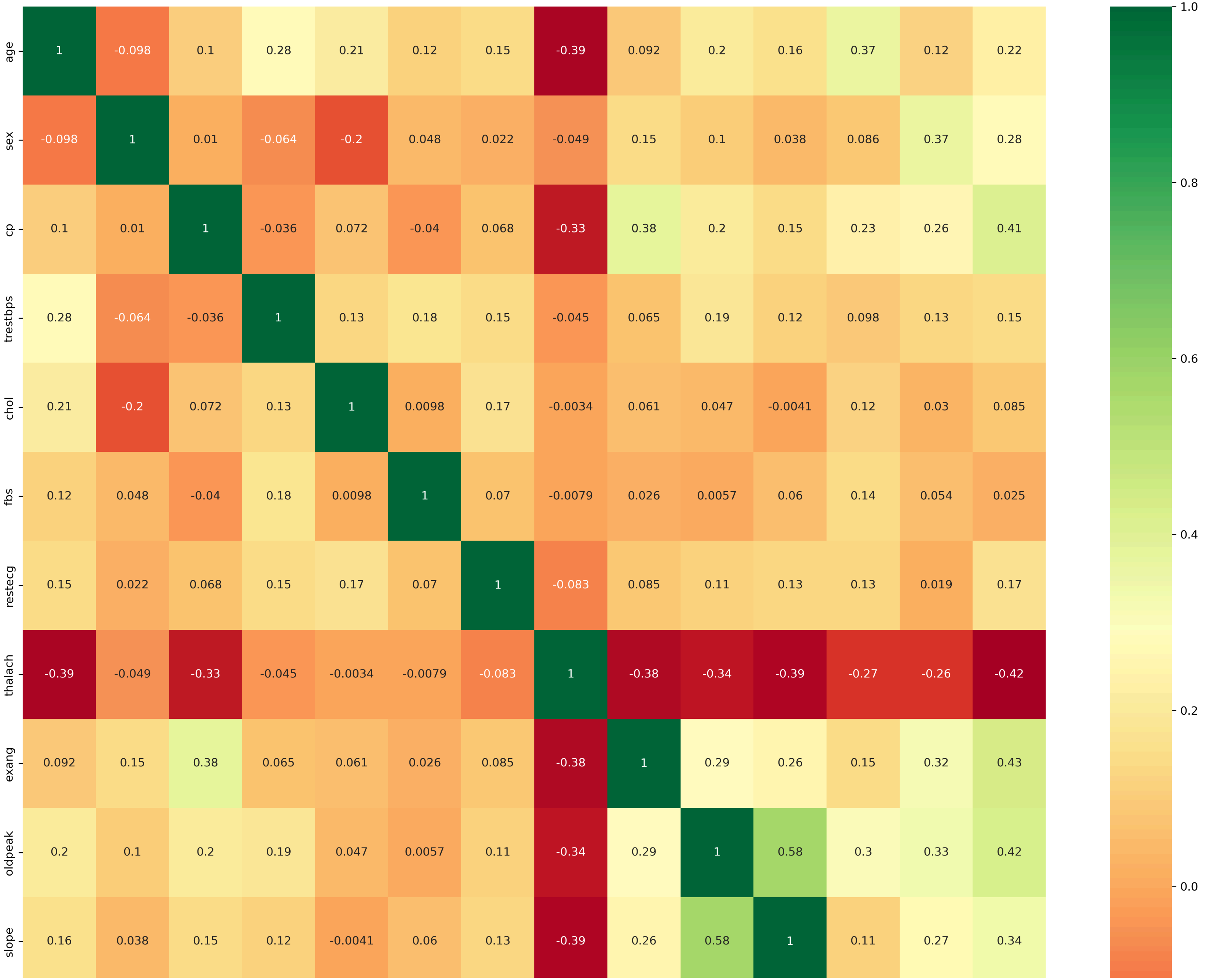
```
df.describe()
```

Out[5]:

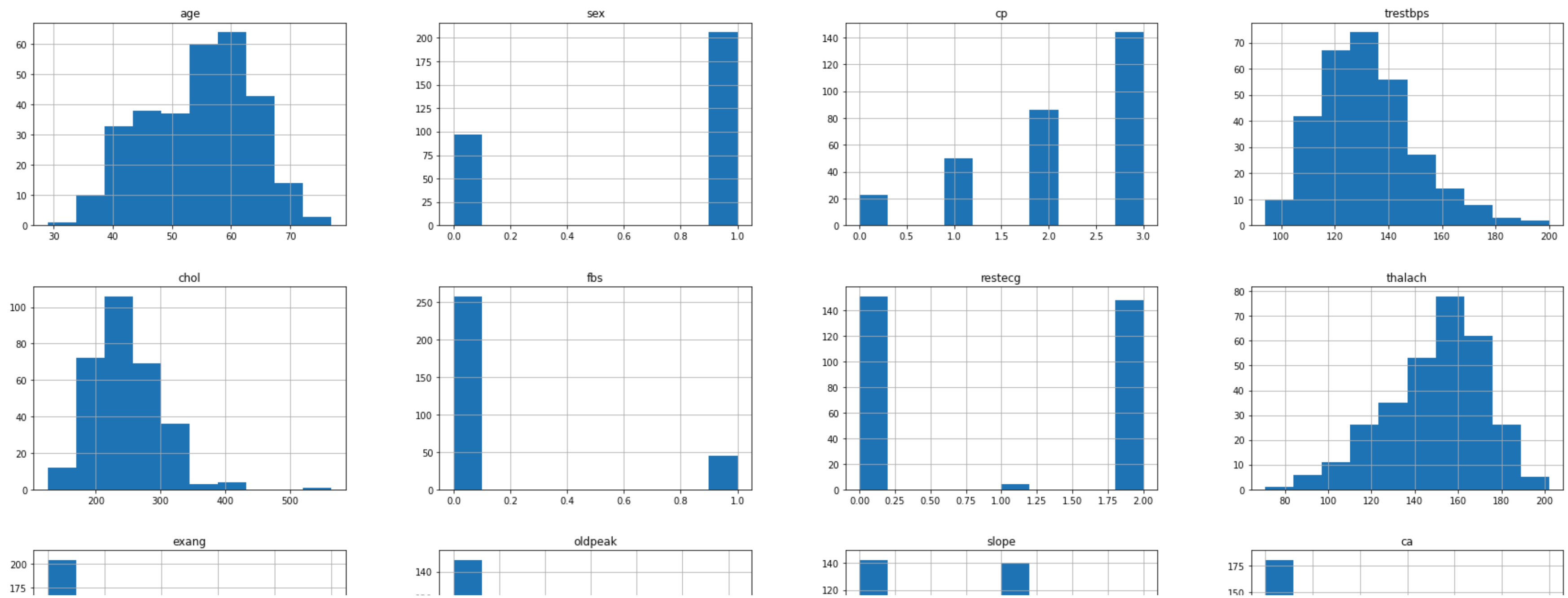
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.438944	0.679868	2.158416	131.689769	246.693069	0.148515	0.990099	149.607261	0.326733	1.039604	0.600660
std	9.038662	0.467299	0.960126	17.599748	51.776918	0.356198	0.994971	22.875003	0.469794	1.161075	0.616226
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000
25%	48.000000	0.000000	2.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	0.000000
50%	56.000000	1.000000	2.000000	130.000000	241.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000
75%	61.000000	1.000000	3.000000	140.000000	275.000000	0.000000	2.000000	166.000000	1.000000	1.600000	1.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000

In [6]:

```
import seaborn as sns
#get correlations of each features in dataset
corrmat = df.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20),dpi=300)
#plot heat map
g=sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```

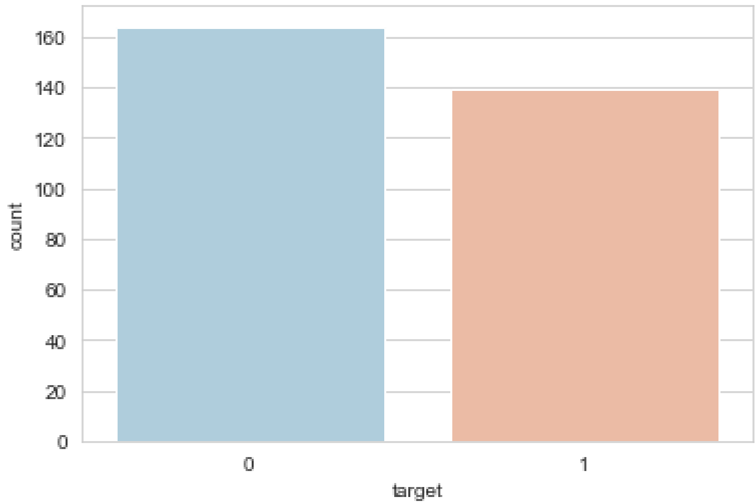

age 1 -0.098 0.1 0.28 0.21 0.12 0.15 -0.39 0.092 0.2 0.16 0.37 0.12 0.22
sex -0.098 1 0.01 -0.064 -0.2 0.048 0.022 -0.049 0.15 0.1 0.038 0.086 0.37 0.28
cp 0.1 0.01 1 -0.036 0.072 -0.04 0.068 -0.33 0.38 0.2 0.15 0.23 0.26 0.41
trestbps 0.28 -0.064 -0.036 1 0.13 0.18 0.15 -0.045 0.065 0.19 0.12 0.098 0.13 0.15
chol 0.21 -0.2 0.072 0.13 1 0.0098 0.17 -0.0034 0.061 0.047 -0.0041 0.12 0.03 0.085
fbs 0.12 0.048 -0.04 0.18 0.0098 1 0.07 -0.0079 0.026 0.0057 0.06 0.14 0.054 0.025
restecg 0.15 0.022 0.068 0.15 0.17 0.07 1 -0.083 0.085 0.11 0.13 0.13 0.019 0.17
thalach -0.39 -0.049 -0.33 -0.045 -0.0034 -0.0079 -0.083 1 -0.38 -0.34 -0.39 -0.27 -0.26 -0.42
exang 0.092 0.15 0.38 0.065 0.061 0.026 0.085 -0.38 1 0.29 0.26 0.15 0.32 0.43
oldpeak 0.2 0.1 0.2 0.19 0.047 0.0057 0.11 -0.34 0.29 1 0.58 0.3 0.33 0.42
slope 0.16 0.038 0.15 0.12 -0.0041 0.06 0.13 -0.39 0.26 0.58 1 0.11 0.27 0.34
1.0
0.8
0.6
0.4
0.2
0.0

In [7]:
```
df.hist(figsize=(30, 20))
plt.savefig("histogram.png", dpi=300)
plt.show()
```



In [8]:
```
sns.set_style('whitegrid')
sns.countplot(x='target',data=df,palette='RdBu_r')
```

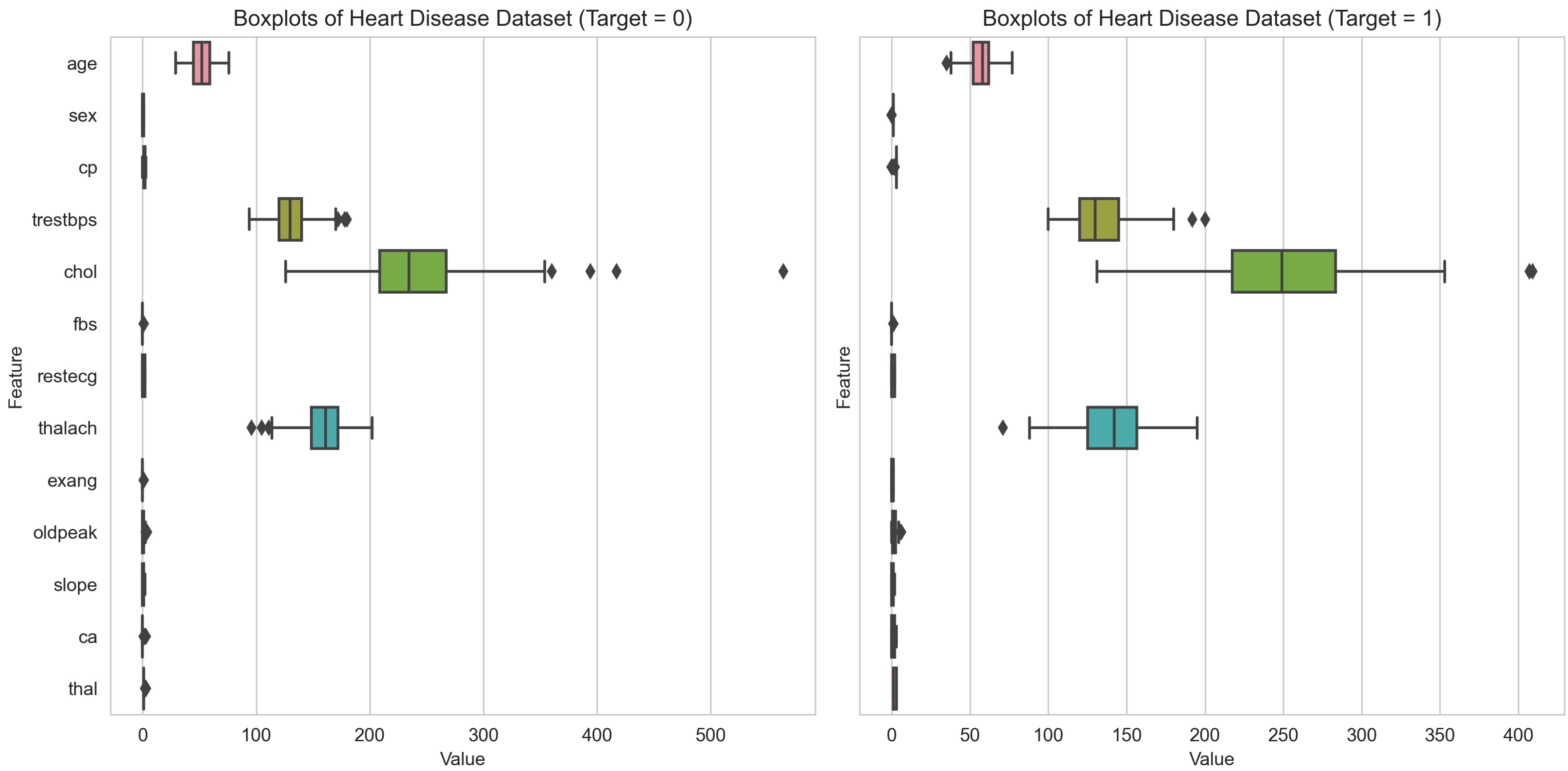
Out[8]: <AxesSubplot:xlabel='target', ylabel='count'>



In [9]:
```
# Define the target column
target_column='target'
```

In [10]:

```
# Separate the dataset based on target values
df_healthy = df[df[target_column] == 0]  # No heart disease
df_disease = df[df[target_column] == 1]  # Heart disease

# Features to plot (excluding the target column)
features = [col for col in df.columns if col != target_column]

# Create subplots
fig, axes = plt.subplots(1, 2, figsize=(12, 6),dpi=300, sharey=True)

# Convert DataFrame to long format for Seaborn
df_healthy_melted = df_healthy.melt(value_vars=features, var_name="Feature", value_name="Value")
df_disease_melted = df_disease.melt(value_vars=features, var_name="Feature", value_name="Value")

# Boxplot for target = 0 (No heart disease)
sns.boxplot(y="Feature", x="Value", data=df_healthy_melted, ax=axes[0])
axes[0].set_title("Boxplots of Heart Disease Dataset (Target = 0)")

# Boxplot for target = 1 (Heart disease)
sns.boxplot(y="Feature", x="Value", data=df_disease_melted, ax=axes[1])
axes[1].set_title("Boxplots of Heart Disease Dataset (Target = 1)")

# Adjust layout
plt.tight_layout()
plt.show()
```



In [11]:
```
# Extract features and target variable
X = df.drop(columns=["target"]).values
y = df["target"].values
```

In [12]:
```
# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
```

In [13]:
```
# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [14]:

```
# Define the MLPGAN class
class MLPGAN:
    def __init__(self, n_inputs, n_hidden=64, n_outputs=1, population_size=200, generations=100, mutation_rate=0.05,
        self.n_inputs = n_inputs
        self.n_hidden = n_hidden
        self.n_outputs = n_outputs
        self.dim = (n_inputs * n_hidden) + (n_hidden * n_outputs) + n_hidden + n_outputs
        self.population_size = population_size
        self.generations = generations
        self.mutation_rate = mutation_rate
        self.crossover_rate = crossover_rate
        self.population = np.random.randn(self.population_size, self.dim) * 0.01

    def forward_prop(self, params, X):
        input_hidden_weights = params[:self.n_inputs * self.n_hidden].reshape(self.n_inputs, self.n_hidden)
        hidden_output_weights = params[self.n_inputs * self.n_hidden:self.n_inputs * self.n_hidden + self.n_hidden *
        hidden_bias = params[self.n_inputs * self.n_hidden + self.n_hidden * self.n_outputs:self.n_inputs * self.n_hi
        output_bias = params[-self.n_outputs:]

        hidden_layer = np.maximum(0.01 * (np.dot(X, input_hidden_weights) + hidden_bias), np.dot(X, input_hidden_weig
        output_layer = 1 / (1 + np.exp(-(np.dot(hidden_layer, hidden_output_weights) + output_bias)))
        return output_layer

    def fitness_function(self, params, X, y):
        y_pred = self.forward_prop(params, X)
        accuracy = accuracy_score(y, (y_pred >= 0.5).astype(int))
        mse = np.mean((y_pred - y.reshape(-1, 1))**2)
        return accuracy - (0.4 * mse)

    def select_parents(self):
        fitness = np.array([self.fitness_function(ind, X_train_scaled, y_train) for ind in self.population])
        fitness = np.maximum(fitness - fitness.min(), 1e-10)
        probabilities = fitness / fitness.sum()
        selected_indices = np.random.choice(len(probabilities), self.population_size // 2, p=probabilities)
        return self.population[selected_indices]

    def crossover(self, parents):
        offspring = []
        for _ in range(self.population_size - len(parents)):
            if random.random() < self.crossover_rate:
                p1, p2 = random.sample(list(parents), 2)
```

```
                point = random.randint(1, self.dim - 1)
                child = np.concatenate((p1[:point], p2[point:]))
                offspring.append(child)
        return np.array(offspring)

    def mutate(self, offspring):
        for i in range(len(offspring)):
            if random.random() < self.mutation_rate:
                mutation_point = random.randint(0, self.dim - 1)
                offspring[i][mutation_point] += np.random.randn() * 0.01
        return offspring

    def train(self, X_train, y_train):
        for _ in range(self.generations):
            parents = self.select_parents()
            offspring = self.crossover(parents)
            offspring = self.mutate(offspring)
            self.population = np.vstack((parents, offspring))
        self.best_params = self.select_parents()[-1]

    def predict(self, X):
        y_pred = self.forward_prop(self.best_params, X)
        return (y_pred >= 0.5).astype(int)
```

In [15]:

```
# Train the genetic algorithm-based MLP model
mlp_ga = MLPGAN(n_inputs=X.shape[1])
mlp_ga.train(X_train_scaled, y_train)
```

In [16]:

```
# Generate predictions from MLPGAN
y_pred_mlp_ga = mlp_ga.predict(X_train_scaled)
y_pred_mlp_ga_test = mlp_ga.predict(X_test_scaled)
```

In [17]:
```
# Append MLP-GA predictions as additional features
X_train_combined = np.column_stack((X_train_scaled, y_pred_mlp_ga))
X_test_combined = np.column_stack((X_test_scaled, y_pred_mlp_ga_test))
```

In [18]:
```
# Train the Random Forest Classifier with tuned parameters
rf = RandomForestClassifier(n_estimators=200, max_depth=10, min_samples_split=4, min_samples_leaf=2, random_state=42)
rf.fit(X_train_combined, y_train)
```

Out[18]:
```
RandomForestClassifier(max_depth=10, min_samples_leaf=2, min_samples_split=4,
                       n_estimators=200, random_state=42)
```

In [19]:
```
# Make final predictions
y_pred_rf = rf.predict(X_test_combined)
```

In [20]:
```
# Compute evaluation metrics
accuracy_rf = accuracy_score(y_test, y_pred_rf)
precision_rf = precision_score(y_test, y_pred_rf)
recall_rf = recall_score(y_test, y_pred_rf)
f1_rf = f1_score(y_test, y_pred_rf)
auc_rf = roc_auc_score(y_test, y_pred_rf)
```

In [21]:
```
models = {
    "Logistic Regression": LogisticRegression(C=1.5, penalty='l2'),
    "SVM": SVC(C=1, gamma=0.1, kernel='rbf'),
    "KNN": KNeighborsClassifier(n_neighbors=5),
    "Decision Tree": DecisionTreeClassifier(criterion='gini'),
    "Random Forest": RandomForestClassifier(n_estimators=1000, criterion='gini'),
    "Extra Trees": ExtraTreesClassifier(n_estimators=100),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100, max_depth=3),
    "GaussianNB": GaussianNB(),
    "XGBoost": XGBClassifier(n_estimators=300, max_depth=15),
    "MLP-BP": MLPClassifier(hidden_layer_sizes=(30,), activation='relu', solver='adam')
}
```

In [22]:

```
results = []
for name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)

    if hasattr(model, "predict_proba"):
        y_proba = model.predict_proba(X_test_scaled)[:,1]
    else:
        y_proba = model.decision_function(X_test_scaled)

    results.append({
        'Model': name,
        'Accuracy': accuracy_score(y_test, y_pred),
        'Precision': precision_score(y_test, y_pred),
        'Recall': recall_score(y_test, y_pred),
        'F1 Score': f1_score(y_test, y_pred),
        'AUC': roc_auc_score(y_test, y_proba)
    })
```

```
C:\Users\HP\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:692: ConvergenceWarning: S
tochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
```

In [23]:

```
results.append({
    'Model': 'MLP-GA-RF',
    'Accuracy': accuracy_rf,
    'Precision': precision_rf,
    'Recall': recall_rf,
    'F1 Score': f1_rf,
    'AUC': auc_rf
})
```

In [24]:

```
# Print the results
print("MLP+GA+RF Model Metrics:")
print(f"Accuracy: {accuracy_rf:.4f}")
print(f"Precision: {precision_rf:.4f}")
print(f"Recall: {recall_rf:.4f}")
print(f"F1 Score: {f1_rf:.4f}")
print(f"AUC: {auc_rf:.4f}")
```

```
MLP+GA+RF Model Metrics:
Accuracy: 0.9672
Precision: 0.9643
Recall: 0.9643
F1 Score: 0.9643
AUC: 0.9670
```

In [25]:

```

metrics = {
    "Accuracy": accuracy_rf,
    "Precision": precision_rf,
    "Recall": recall_rf,
    "F1 Score": f1_rf,
    "AUC": auc_rf
}
```

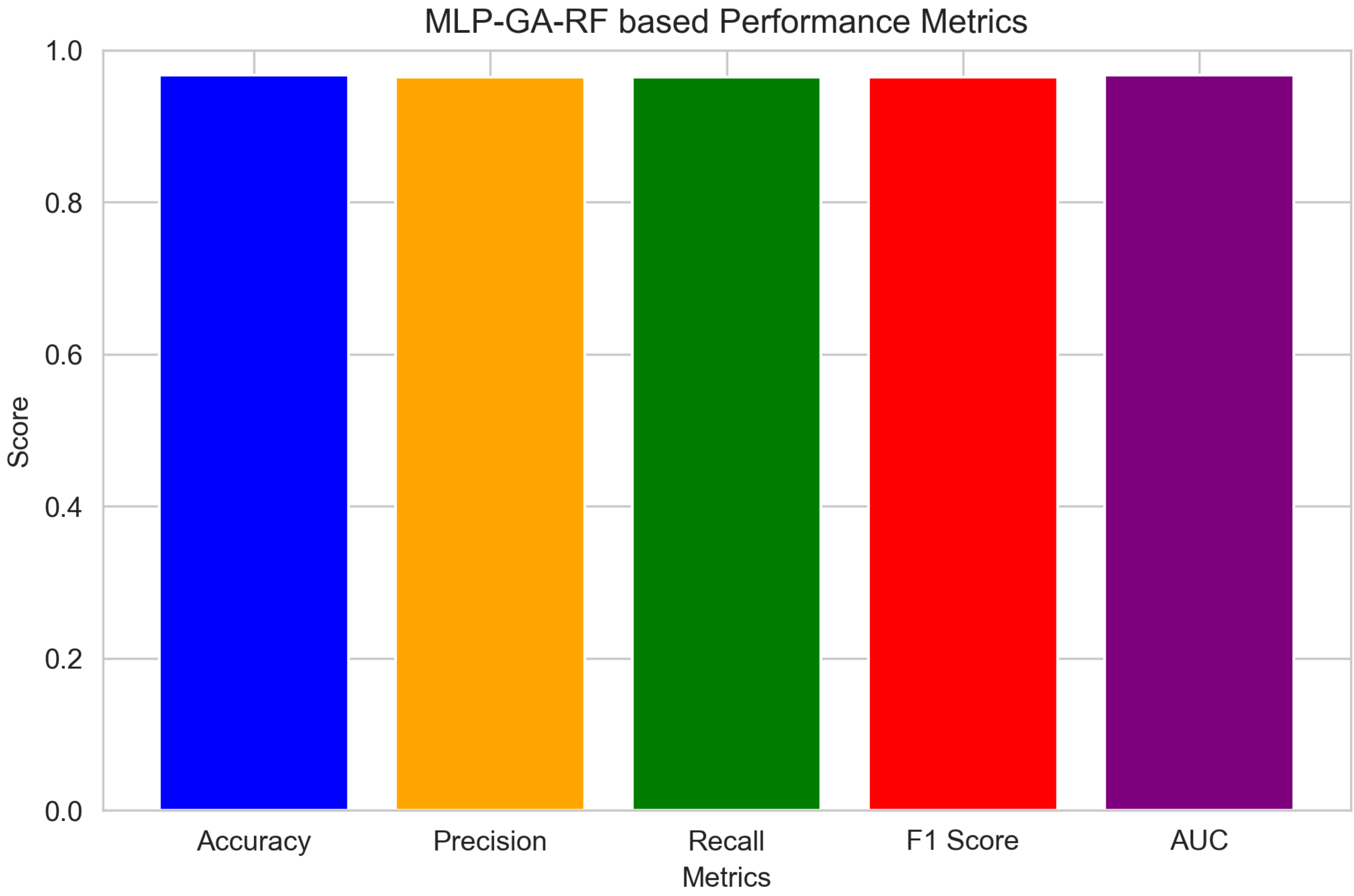
In [26]:

```
results_df = pd.DataFrame(results)
print(results_df.sort_values(by='Accuracy', ascending=False))
```

```
                  Model  Accuracy  Precision    Recall  F1 Score       AUC
10            MLP-GA-RF  0.967213   0.964286  0.964286  0.964286  0.966991
2                   KNN  0.901639   0.823529  1.000000  0.903226  0.924242
4         Random Forest  0.901639   0.843750  0.964286  0.900000  0.952381
0   Logistic Regression  0.868852   0.812500  0.928571  0.866667  0.952381
7            GaussianNB  0.868852   0.794118  0.964286  0.870968  0.949134
8               XGBoost  0.868852   0.812500  0.928571  0.866667  0.906926
9                MLP-BP  0.868852   0.794118  0.964286  0.870968  0.957792
1                   SVM  0.852459   0.806452  0.892857  0.847458  0.944805
6     Gradient Boosting  0.852459   0.787879  0.928571  0.852459  0.945887
5           Extra Trees  0.836066   0.764706  0.928571  0.838710  0.935065
3         Decision Tree  0.786885   0.714286  0.892857  0.793651  0.794913
```

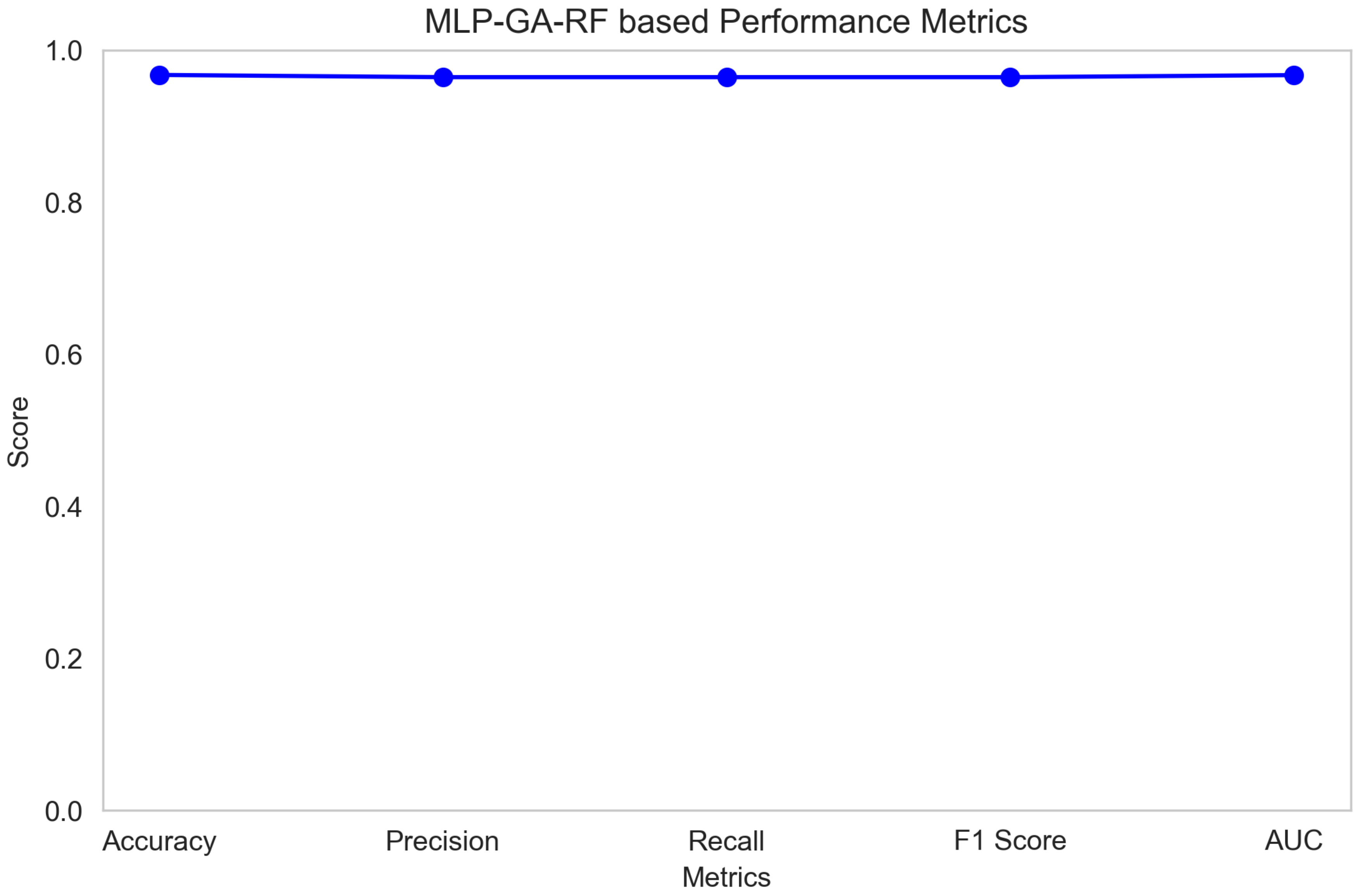
In [27]:

```
plt.figure(figsize=(8, 5),dpi=300)
plt.bar(metrics.keys(), metrics.values(), color=['blue', 'orange', 'green', 'red', 'purple'])
plt.xlabel("Metrics")
plt.ylabel("Score")
plt.ylim(0, 1)
plt.title("MLP-GA-RF based Performance Metrics")
plt.show()
```


MLP-GA-RF based Performance Metrics
1.0
0.8
0.6
0.4
0.2
0.0
Score
Accuracy
Precision
Recall
F1 Score
AUC
Metrics

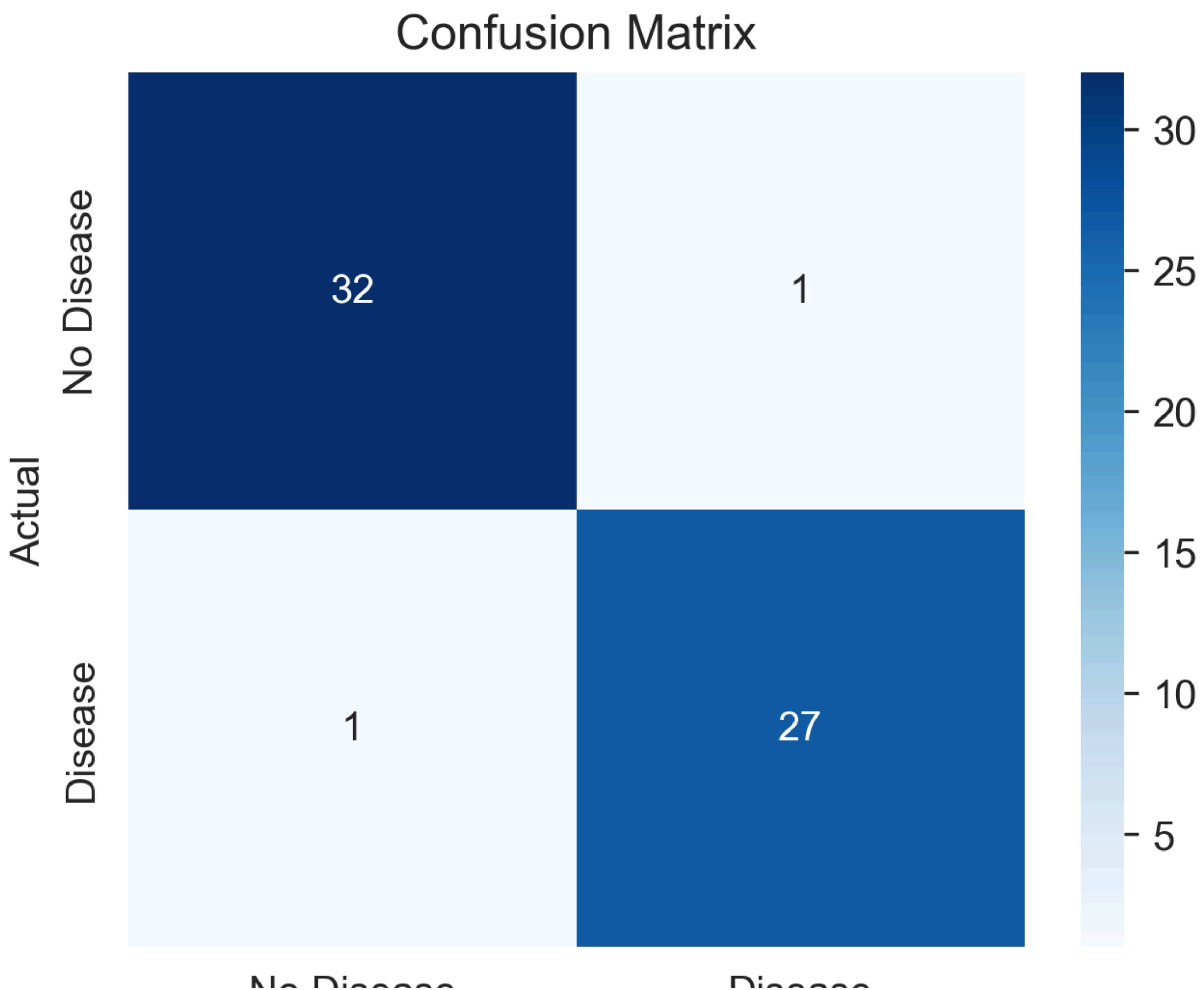
In [28]:

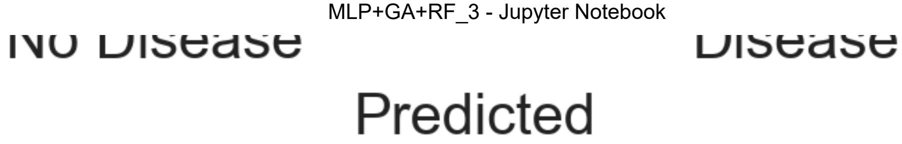
```
plt.figure(figsize=(8, 5),dpi=300)
plt.plot(list(metrics.keys()), list(metrics.values()), marker='o', linestyle='-', color='b')
plt.xlabel("Metrics")
plt.ylabel("Score")
plt.ylim(0, 1)
plt.title("MLP-GA-RF based Performance Metrics")
plt.grid()
plt.show()
```


MLP-GA-RF based Performance Metrics
1.0
0.8
0.6
0.4
0.2
0.0
Score
Accuracy
Precision
Recall
F1 Score
AUC
Metrics

In [29]:

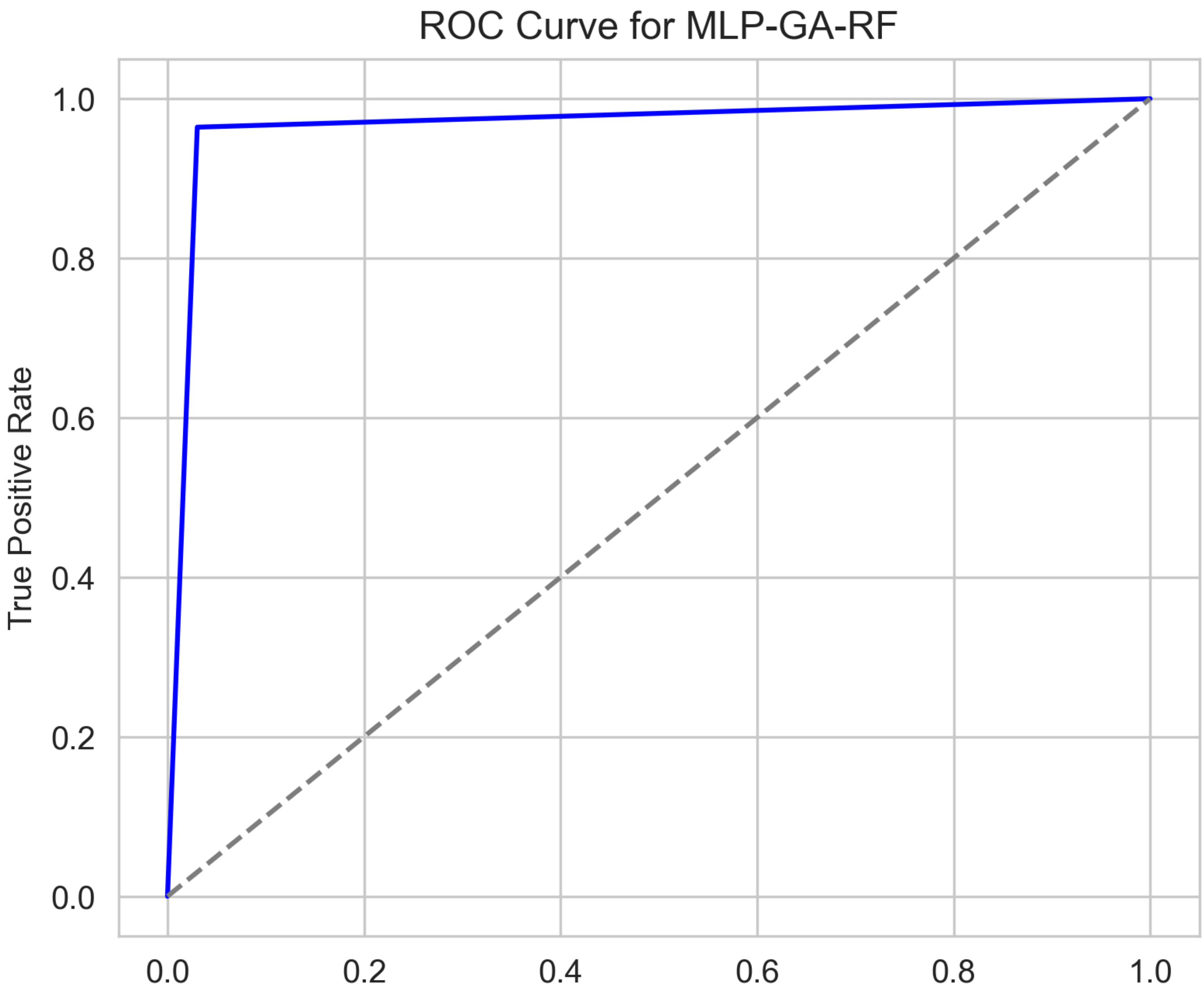
```
# Confusion matrix visualization
cm = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(5, 4),dpi=300)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No Disease", "Disease"], yticklabels=["No Disease",
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```


Confusion Matrix
Actual
No Disease
Disease
32
1
1
27
30
25
20
15
10
5


No Disease
Disease
Predicted

In [30]:

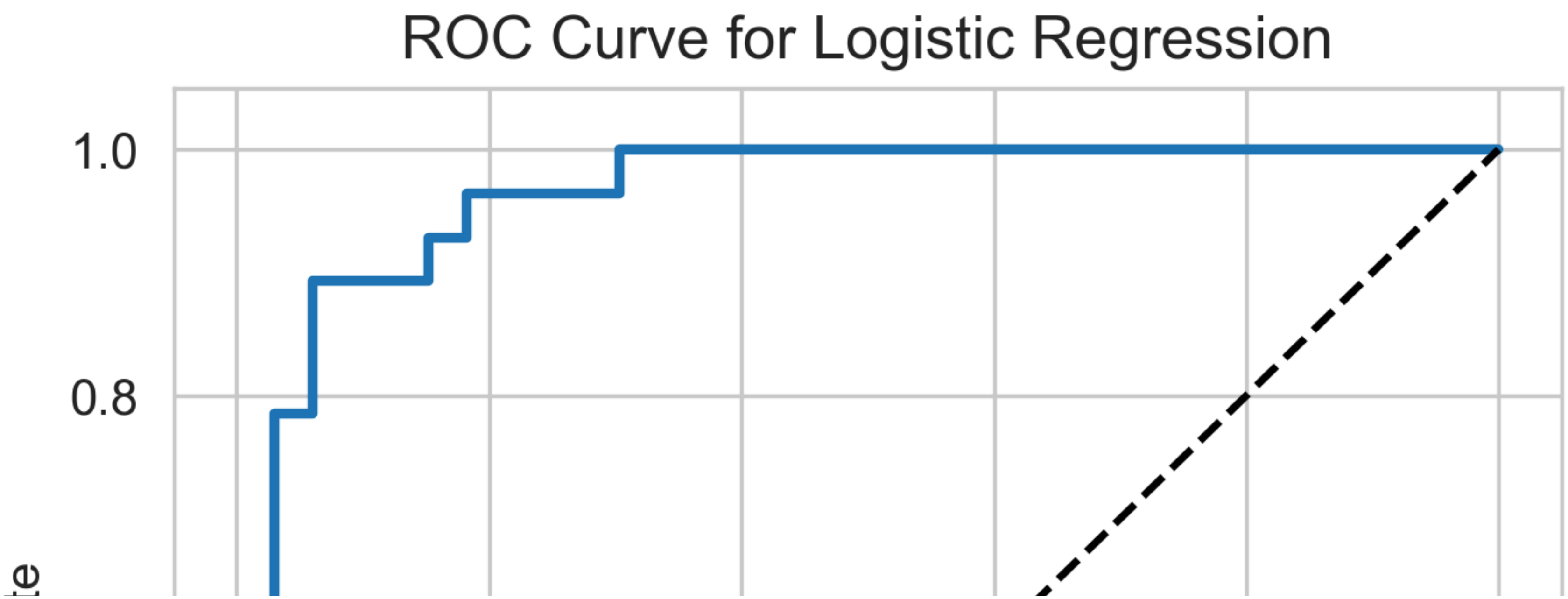
```
# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_rf)
plt.figure(figsize=(6, 5),dpi=300)
plt.plot(fpr, tpr, color='blue', label=f'ROC curve (AUC = {auc_rf:.2f})')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve for MLP-GA-RF")
#plt.legend()
plt.show()
```


ROC Curve for MLP-GA-RF
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

False Positive Rate

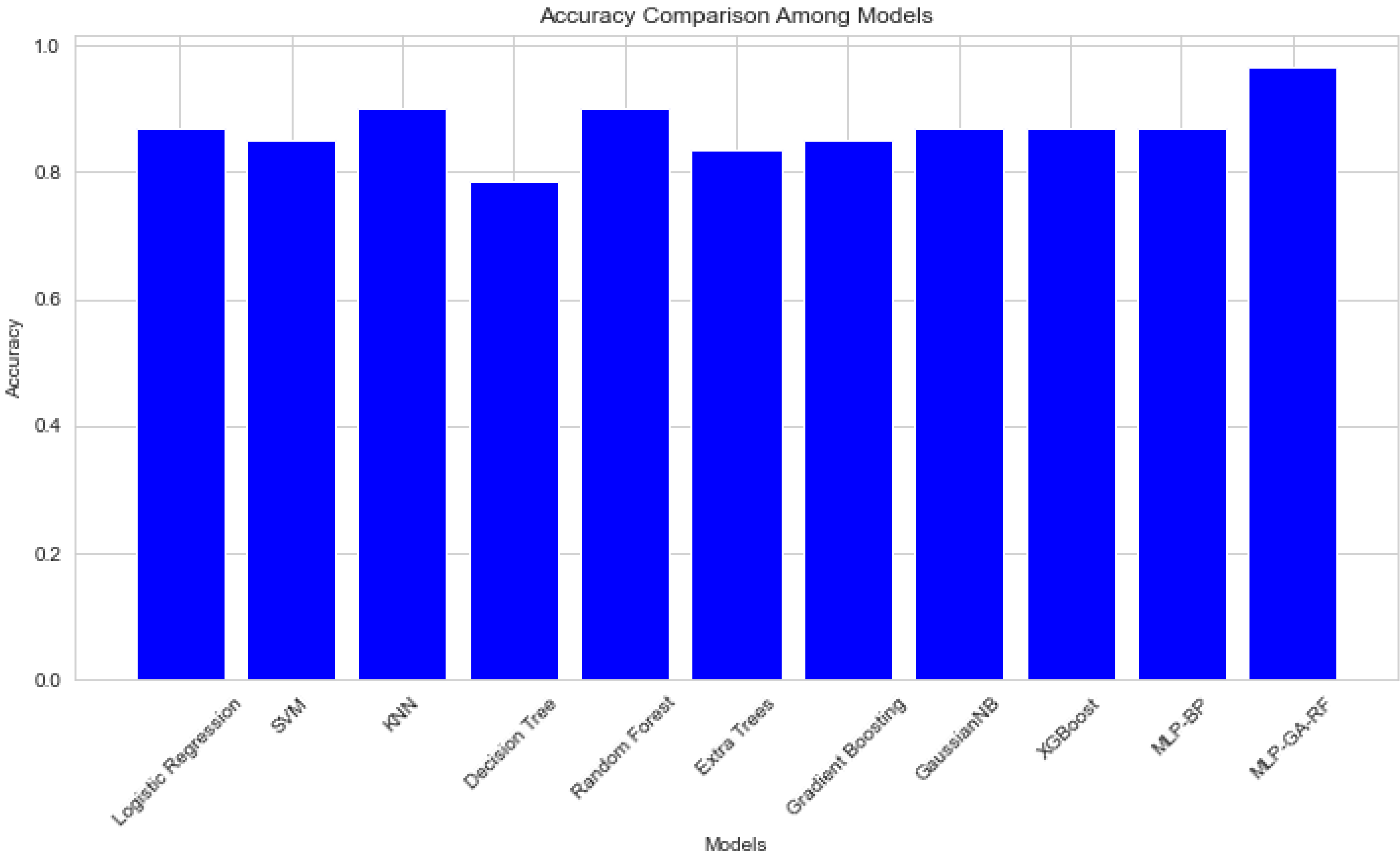
In [31]:

```
# Plot individual ROC curves for each model without AUC and with dpi=300
for name, model in models.items():
    plt.figure(figsize=(5, 5), dpi=300)  # High-resolution figure
    model.fit(X_train_scaled, y_train)
    if hasattr(model, "predict_proba"):
        y_probs = model.predict_proba(X_test_scaled)[:, 1]  # Get probability scores
    else:
        y_probs = model.decision_function(X_test_scaled)  # Use decision_function if predict_proba is unavailable
    fpr, tpr, _ = roc_curve(y_test, y_probs)

    plt.plot(fpr, tpr, linewidth=2, label=f'{name}')
    plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC Curve for {name}')
    plt.legend(loc='lower right')
    plt.show()
```



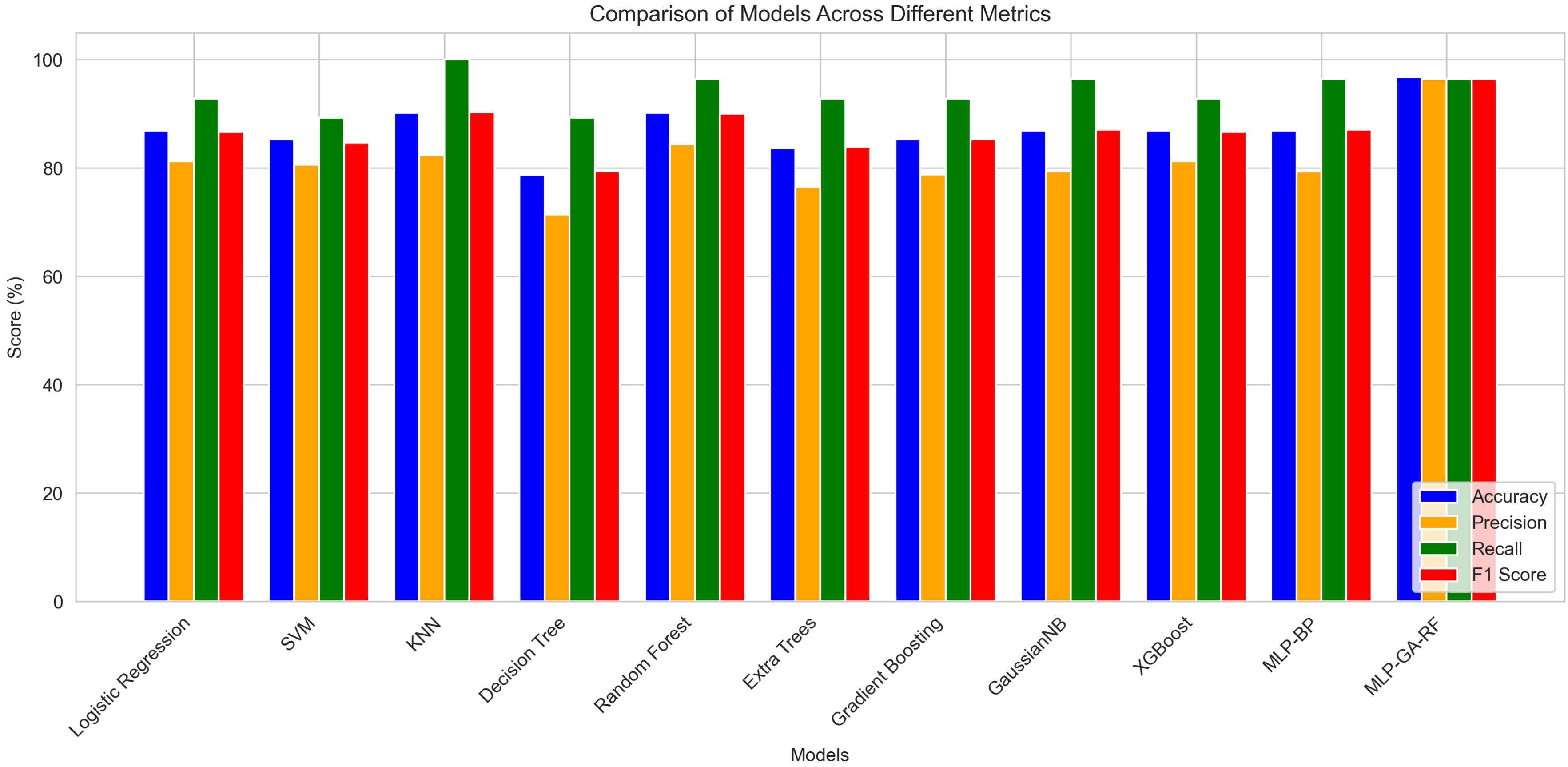
In [32]:

```
# Bar Plot for Accuracy Comparison
plt.figure(figsize=(12, 6))
plt.bar(results_df['Model'], results_df['Accuracy'], color='blue')
plt.xlabel("Models")
plt.ylabel("Accuracy")
plt.title("Accuracy Comparison Among Models")
plt.xticks(rotation=45)
plt.show()
```



In [33]:

```
# Extracting performance metrics for visualization
models_list = results_df['Model'].values
accuracy = results_df['Accuracy'].values * 100
precision = results_df['Precision'].values * 100
recall = results_df['Recall'].values * 100
f1_score_values = results_df['F1 Score'].values * 100

# Set width and positions for bars
x = np.arange(len(models_list))
width = 0.2

# Create a grouped bar chart
fig, ax = plt.subplots(figsize=(12, 6),dpi=300)
ax.bar(x - 1.5 * width, accuracy, width, label="Accuracy", color='blue')
ax.bar(x - 0.5 * width, precision, width, label="Precision", color='orange')
ax.bar(x + 0.5 * width, recall, width, label="Recall", color='green')
ax.bar(x + 1.5 * width, f1_score_values, width, label="F1 Score", color='red')

# Labels and formatting
ax.set_ylabel("Score (%)")
ax.set_xlabel("Models")
ax.set_xticks(x)
ax.set_xticklabels(models_list, rotation=45, ha='right')
ax.set_title("Comparison of Models Across Different Metrics")
ax.legend(loc="lower right")

# Display the plot
plt.tight_layout()
plt.show()
```


Comparison of Models Across Different Metrics
Score (%)
100
80
60
40
20
0
Accuracy
Precision
Recall
F1 Score
Logistic Regression
SVM
KNN
Decision Tree
Random Forest
Extra Trees
Gradient Boosting
GaussianNB
XGBoost
MLP-BP
MLP-GA-RF
Models

In [ ]:

In [ ]:

In [ ]: