In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, co
```

In [2]:
```python
#Load the dataset
data=pd.read_csv("gender.csv")
```

In [3]:
```python
data.head()
```

Out[3]:

	long_hair	forehead_width_cm	forehead_height_cm	nose_wide	nose_long	lips_thin	distanc
0	1	11.8	6.1	1	0	1	
1	0	14.0	5.4	0	0	1	
2	0	11.8	6.3	1	1	1	
3	0	14.4	6.1	0	1	1	
4	1	13.5	5.9	0	0	0	

In [4]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5001 entries, 0 to 5000
Data columns (total 8 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   long_hair                  5001 non-null   int64  
 1   forehead_width_cm          5001 non-null   float64
 2   forehead_height_cm         5001 non-null   float64
 3   nose_wide                  5001 non-null   int64  
 4   nose_long                  5001 non-null   int64  
 5   lips_thin                  5001 non-null   int64  
 6   distance_nose_to_lip_long  5001 non-null   int64  
 7   gender                     5001 non-null   object 
dtypes: float64(2), int64(5), object(1)
memory usage: 312.7+ KB
```

In [5]:
```
data.shape
```

Out[5]:
```
(5001, 8)
```

Convert categorical data ('gender') to numerical values.

In [6]:
```
data['gender'] = data['gender'].map({'Male': 0, 'Female': 1})
```

In [7]:
```
data['gender']
```

Out[7]:
```
0       0
1       1
2       0
3       0
4       1
       ..
4996    1
4997    1
4998    1
4999    1
5000    0
Name: gender, Length: 5001, dtype: int64
```

Split the dataset into features (X) and target variable (y)

In [8]:
```
X = data.drop('gender', axis=1)
y = data['gender']
```

In [9]:
```
X
```

Out[9]:

	long_hair	forehead_width_cm	forehead_height_cm	nose_wide	nose_long	lips_thin	dista
0	1	11.8	6.1	1	0	1	
1	0	14.0	5.4	0	0	1	
2	0	11.8	6.3	1	1	1	
3	0	14.4	6.1	0	1	1	
4	1	13.5	5.9	0	0	0	
...	...	...	...	...	...	...	
4996	1	13.6	5.1	0	0	0	
4997	1	11.9	5.4	0	0	0	
4998	1	12.9	5.7	0	0	0	
4999	1	13.2	6.2	0	0	0	
5000	1	15.4	5.4	1	1	1	

5001 rows × 7 columns

In [10]:
```
y
```

Out[10]:
```
0       0
1       1
2       0
3       0
4       1
       ..
4996    1
4997    1
4998    1
4999    1
5000    0
Name: gender, Length: 5001, dtype: int64
```

```
Train-Test Split
Split the data into training and testing sets
```

In [11]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rand
```

In [12]:
```
X_train
```

Out[12]:

	long_hair	forehead_width_cm	forehead_height_cm	nose_wide	nose_long	lips_thin	dist
4677	1	15.4	6.6	0	1	1	
800	1	12.2	5.2	0	0	0	
3671	0	11.5	5.8	0	0	0	
4193	1	12.7	5.1	0	0	0	
2968	1	15.1	5.6	1	1	1	
...	...	...	...	...	...	...	
4426	1	13.0	6.5	0	0	0	
466	1	13.1	5.5	0	0	0	
3092	1	12.0	5.9	0	0	0	
3772	1	12.8	5.4	0	0	0	
860	1	11.4	5.5	0	0	0	

4000 rows × 7 columns

In [13]:
```
X_test
```

Out[13]:

	long_hair	forehead_width_cm	forehead_height_cm	nose_wide	nose_long	lips_thin	dist
1501	1	13.2	5.7	1	1	1	
2586	1	13.7	6.0	0	0	0	
2653	0	12.9	5.3	0	0	0	
1055	1	13.2	5.9	1	1	1	
705	0	15.2	5.6	1	1	1	
...	...	...	...	...	...	...	
2313	1	13.5	5.8	0	0	0	
3214	1	12.6	5.5	1	1	1	
2732	1	14.3	5.7	0	0	0	
1926	1	13.9	6.3	1	1	1	
4227	1	13.0	5.4	0	1	0	

1001 rows × 7 columns

In [14]:
```python
y_train
```

Out[14]:
```
4677    0
800     1
3671    1
4193    1
2968    0
       ..
4426    1
466     1
3092    1
3772    1
860     1
Name: gender, Length: 4000, dtype: int64
```

In [15]:
```python
y_test
```

Out[15]:
```
1501    0
2586    1
2653    1
1055    0
705     0
       ..
2313    1
3214    0
2732    1
1926    0
4227    1
Name: gender, Length: 1001, dtype: int64
```

Print the lengths of the training and testing sets

In [16]:
```python
print(f"Training set length of X: {len(X_train)}")
print(f"Testing set lengthof X: {len(X_test)}")
```

```
Training set length of X: 4000
Testing set lengthof X: 1001
```

Scaling Data
Standardize the features

In [17]:
```python
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [18]:
```
X_train
```

Out[18]:
```
array([[ 0.38484494,  1.99684971,  1.2022527 , ...,  0.98708341,
         1.01867434,  0.9965061 ],
       [ 0.38484494, -0.8848672 , -1.38383285, ..., -1.01308561,
        -0.981668  , -1.00350615],
       [-2.59844915, -1.51524277, -0.27551047, ..., -1.01308561,
        -0.981668  , -1.00350615],
       ...,
       [ 0.38484494, -1.06497451, -0.09079008, ..., -1.01308561,
        -0.981668  , -1.00350615],
       [ 0.38484494, -0.34454528, -1.01439206, ..., -1.01308561,
        -0.981668  , -1.00350615],
       [ 0.38484494, -1.60529643, -0.82967166, ..., -1.01308561,
        -0.981668  , -1.00350615]])
```

In [19]:
```
X_test
```

Out[19]:
```
array([[ 0.38484494,  0.01566934, -0.46023087, ...,  0.98708341,
         1.01867434,  0.9965061 ],
       [ 0.38484494,  0.4659376 ,  0.09393032, ..., -1.01308561,
        -0.981668  , -1.00350615],
       [-2.59844915, -0.25449162, -1.19911246, ..., -1.01308561,
        -0.981668  ,  0.9965061 ],
       ...,
       [ 0.38484494,  1.00625952, -0.46023087, ..., -1.01308561,
        -0.981668  , -1.00350615],
       [ 0.38484494,  0.64604491,  0.64809151, ...,  0.98708341,
         1.01867434,  0.9965061 ],
       [ 0.38484494, -0.16443797, -1.01439206, ...,  0.98708341,
        -0.981668  ,  0.9965061 ]])
```

In [20]:
```
# Print the first five rows of the scaled features
print("Scaled Features (First 5 rows):\n", X_train[:5])
```

```
Scaled Features (First 5 rows):
 [[ 0.38484494  1.99684971  1.2022527  -0.98807114  0.98708341  1.01867434
   0.9965061 ]
 [ 0.38484494 -0.8848672  -1.38383285 -0.98807114 -1.01308561 -0.981668
  -1.00350615]
 [-2.59844915 -1.51524277 -0.27551047 -0.98807114 -1.01308561 -0.981668
  -1.00350615]
 [ 0.38484494 -0.43459893 -1.56855325 -0.98807114 -1.01308561 -0.981668
  -1.00350615]
 [ 0.38484494  1.72668875 -0.64495127  1.01207287  0.98708341  1.01867434
   0.9965061 ]]
```

Decision Tree Model
Implement Decision Tree classifier

In [21]:
```
dt_classifier = DecisionTreeClassifier()
```

In [22]:
```
# Hyperparameter Optimization using GridSearchCV
dt_params = {'criterion': ['gini', 'entropy'], 'max_depth': [None, 10, 20, 30]
dt_grid = GridSearchCV(dt_classifier, dt_params, cv=5)
dt_grid.fit(X_train, y_train)
```

Out[22]:

GridSearchCV (https://scikit-learn.org/1.4/modules/generated/sklearn.model_selec

estimator: DecisionTreeClassifier

DecisionTreeClassifier (https://scikit-learn.org/1.4/modules/generated/sklearn.tree.DecisionTre

In [23]:
```
# Print the best parameters and corresponding cross-validation accuracy
print("Best Decision Tree Parameters:", dt_grid.best_params_)
print("Decision Tree Cross-Validation Accuracy:", dt_grid.best_score_)
```

```
Best Decision Tree Parameters: {'criterion': 'gini', 'max_depth': 10, 'min_s
amples_leaf': 1, 'min_samples_split': 10}
Decision Tree Cross-Validation Accuracy: 0.9710000000000001
```

In [24]:
```
# Train the Decision Tree model
best_dt_model = dt_grid.best_estimator_
best_dt_model.fit(X_train, y_train)
```

Out[24]:

DecisionTreeClassifier (https://scikit-learn.org/1.4/modules/gen

DecisionTreeClassifier(max_depth=10, min_samples_split=10)

In [25]:
```
# Make predictions on the testing set
dt_predictions = best_dt_model.predict(X_test)
dt_predictions
```

Out[25]:
```
array([0, 1, 1, ..., 1, 0, 0], dtype=int64)
```

Evaluate performance

In [26]:
```
dt_accuracy = accuracy_score(y_test, dt_predictions)
dt_accuracy
```

Out[26]:
```
0.961038961038961
```

In [27]:
```
dt_precision = precision_score(y_test, dt_predictions)
dt_precision
```

Out[27]: 0.9639278557114228

In [28]:
```
dt_recall = recall_score(y_test, dt_predictions)
dt_recall
```

Out[28]: 0.9581673306772909

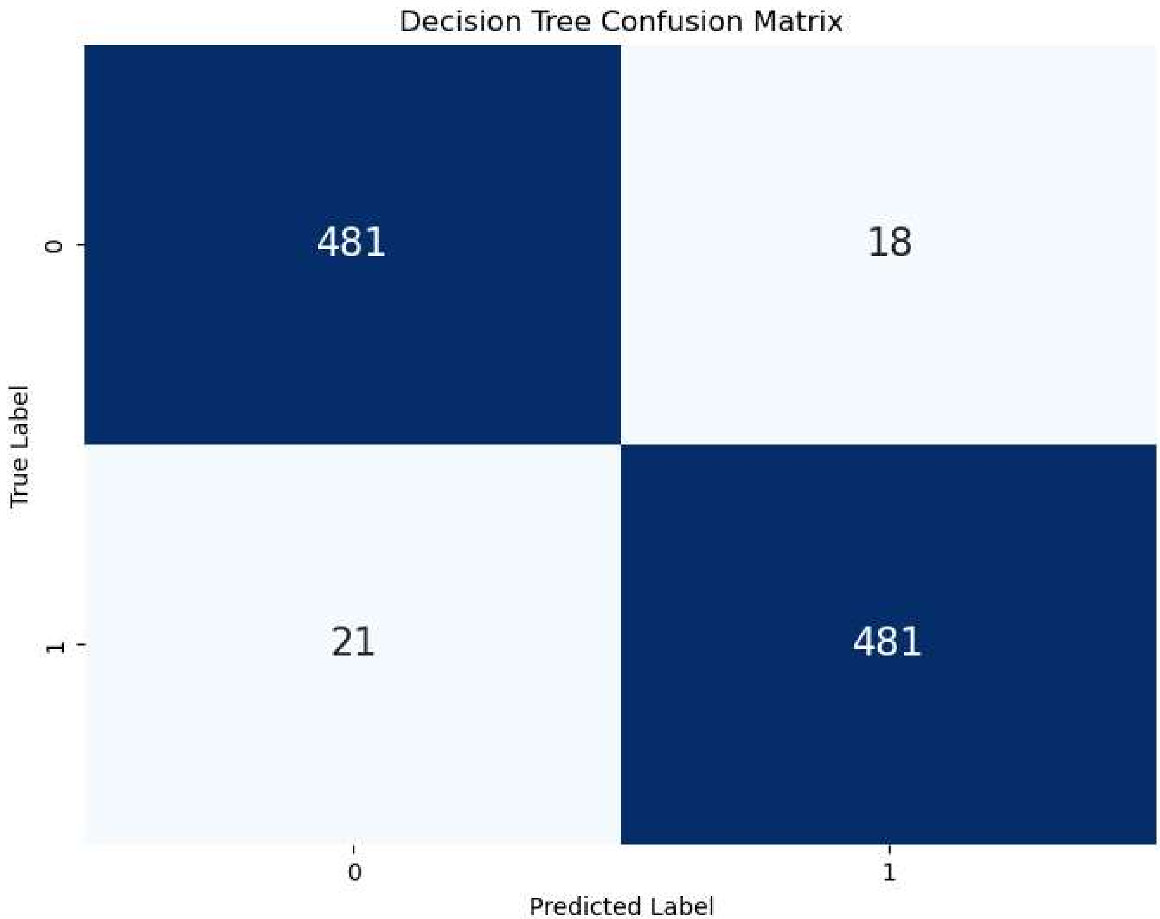
In [29]:
```
dt_f1_score = f1_score(y_test, dt_predictions)
dt_f1_score
```

Out[29]: 0.961038961038961

In [30]:
```
dt_conf_matrix = confusion_matrix(y_test, dt_predictions)
dt_conf_matrix
```

Out[30]:
```
array([[481,  18],
       [ 21, 481]], dtype=int64)
```

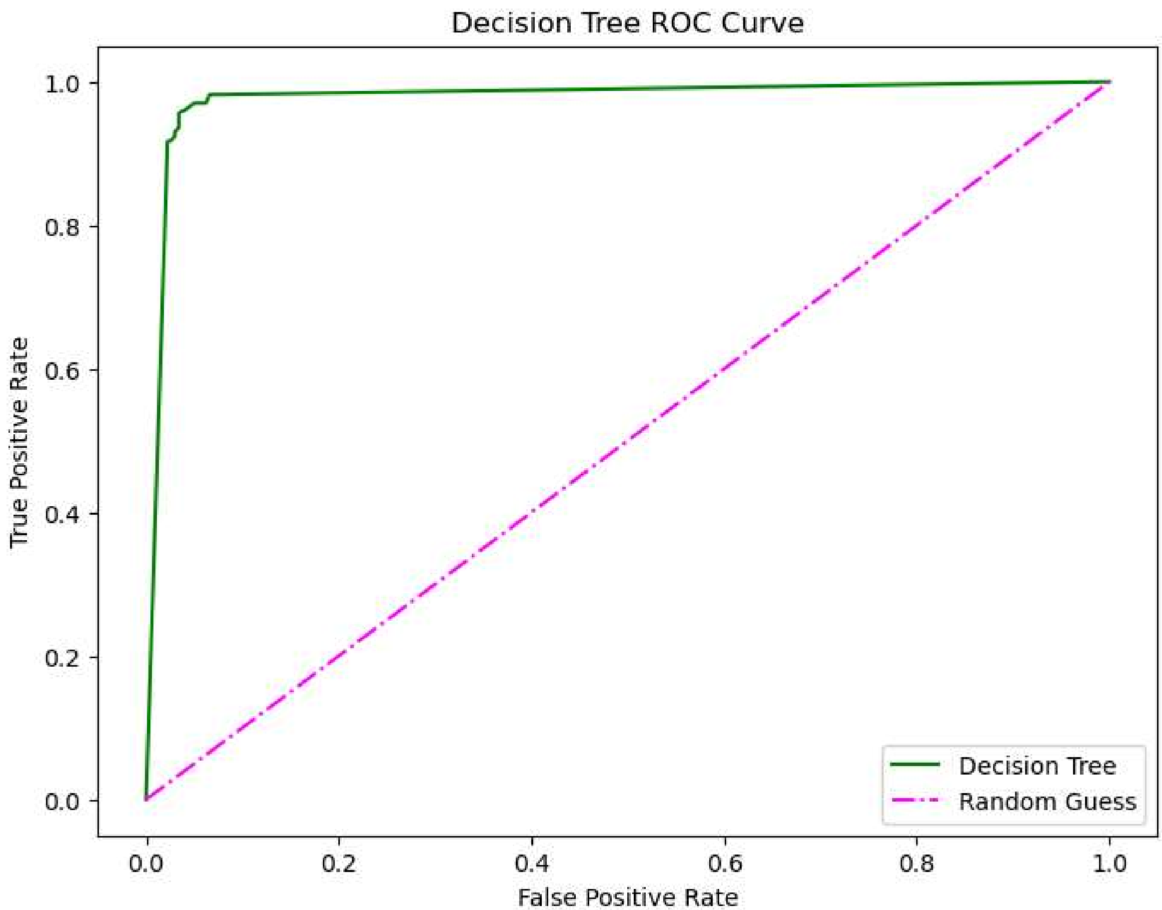
In [31]:
```
# Visualize confusion matrix using Seaborn
plt.figure(figsize=(8, 6))
sns.heatmap(dt_conf_matrix, annot=True, fmt='d', cmap="Blues", cbar=False, an
plt.title("Decision Tree Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [32]:
```
dt_roc_auc = roc_auc_score(y_test, best_dt_model.predict_proba(X_test)[:, 1])
dt_roc_auc
```

Out[32]:
```
0.9775307587286126
```

In [33]:
```
# Visualization: ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, best_dt_model.predict_proba(X_test)[
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label='Decision Tree',color="green")
plt.plot([0, 1], [0, 1], linestyle='-.', color='magenta', label='Random Guess
plt.title('Decision Tree ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```




```
Random Forest Model
Implement Random Forest classifier
```

In [34]:
```
rf_classifier = RandomForestClassifier()
```

In [35]:
```
# Hyperparameter Optimization using GridSearchCV
rf_params = {'n_estimators': [50, 100, 150], 'max_depth': [None, 10, 20, 30],
rf_grid = GridSearchCV(rf_classifier, rf_params, cv=5,scoring="accuracy")
rf_grid.fit(X_train, y_train)
```

Out[35]:

```
GridSearchCV
(https://scikit-learn.org/1.4/modules/generated/sklearn.model_selec
estimator: RandomForestClassifier
RandomForestClassifier
(https://scikit-learn.org/1.4/modules/generated/sklearn.ensemble.RandomF
```

In [36]:
```
# Print the best parameters and corresponding cross-validation accuracy
print("Best Random Forest Parameters:", rf_grid.best_params_)
print("Random Forest Cross-Validation Accuracy:", rf_grid.best_score_)
```

```
Best Random Forest Parameters: {'max_depth': None, 'min_samples_leaf': 2, 'm
in_samples_split': 10, 'n_estimators': 150}
Random Forest Cross-Validation Accuracy: 0.9772500000000001
```

In [37]:
```
# Train the Random Forest model
best_rf_model = rf_grid.best_estimator_
best_rf_model.fit(X_train, y_train)
```

Out[37]:

```
RandomForestClassifier
(https://scikit-learn.org/1.4/modu
RandomForestClassifier(min_samples_leaf=2, min_samples_split=10,
n_estimators=150)
```

In [38]:
```
# Make predictions on the testing set
rf_predictions = best_rf_model.predict(X_test)
```

Evaluate performance

In [39]:
```
rf_accuracy = accuracy_score(y_test, rf_predictions)
rf_accuracy
```

Out[39]: 0.9660339660339661

In [40]:
```
rf_precision = precision_score(y_test, rf_predictions)
rf_precision
```

Out[40]: 0.95703125

In [41]:
```
rf_recall = recall_score(y_test, rf_predictions)
rf_recall
```

Out[41]: 0.9760956175298805

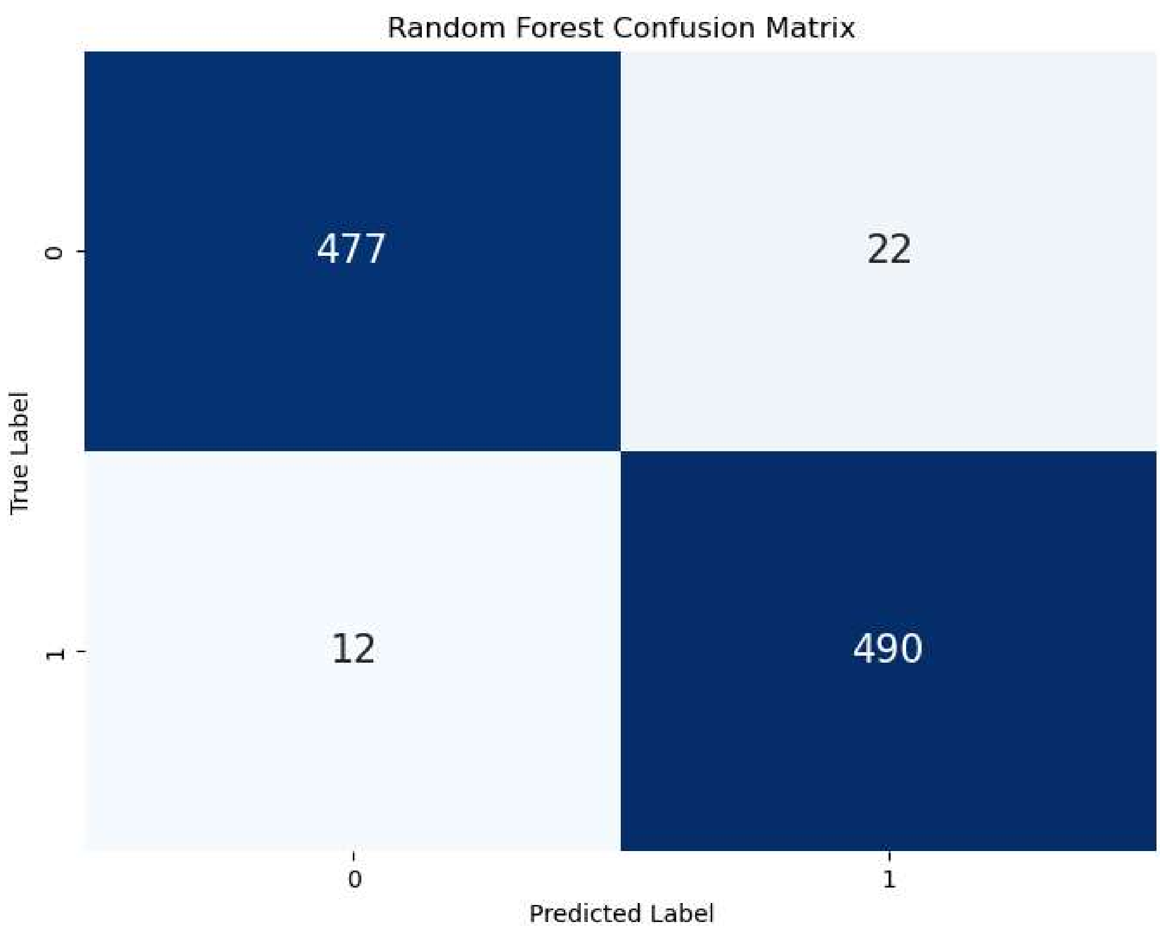
In [42]:
```
rf_f1_score = f1_score(y_test, rf_predictions)
rf_f1_score
```

Out[42]: 0.9664694280078896

In [43]:
```
rf_conf_matrix = confusion_matrix(y_test, rf_predictions)
rf_conf_matrix
```

Out[43]:
```
array([[477,  22],
       [ 12, 490]], dtype=int64)
```

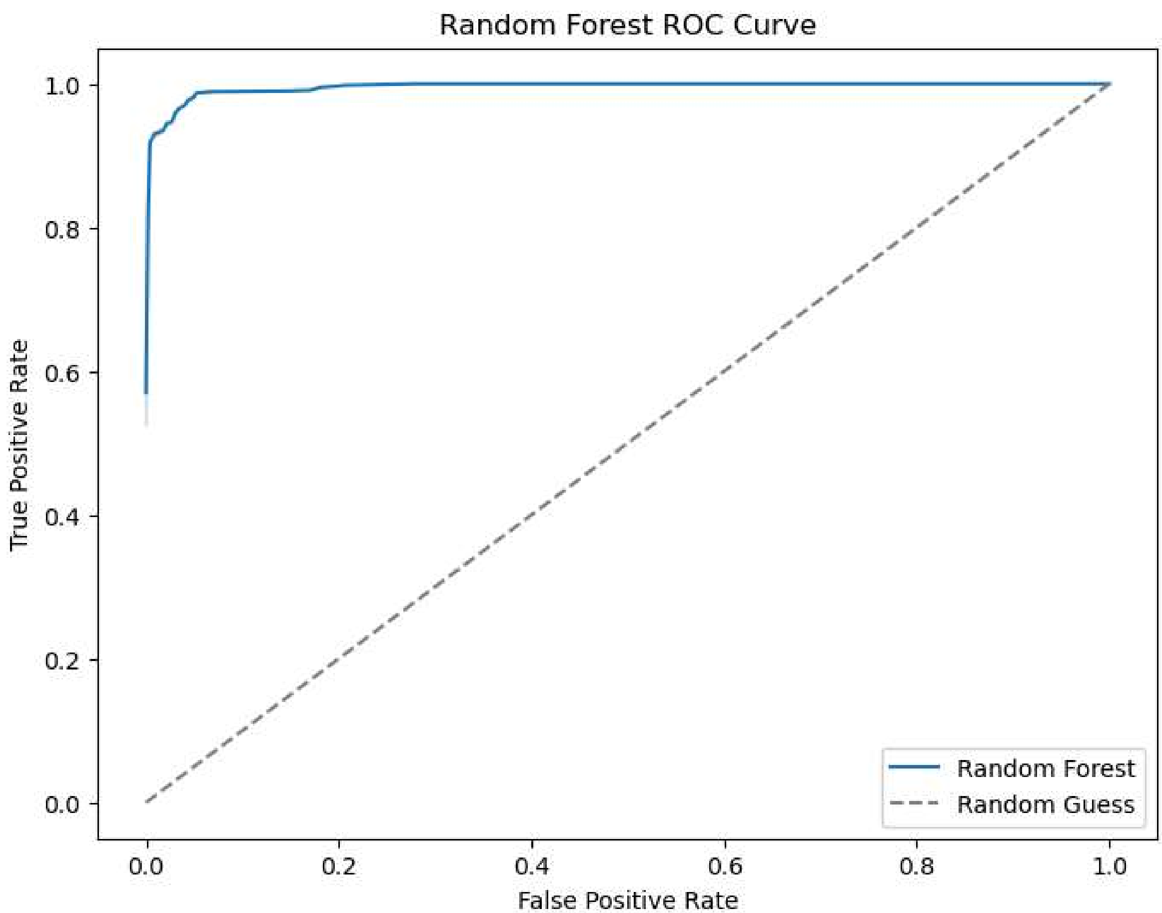
In [44]:
```
# Visualize confusion matrix using Seaborn
plt.figure(figsize=(8, 6))
sns.heatmap(rf_conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False, ann
plt.title("Random Forest Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [45]:
```
rf_roc_auc = roc_auc_score(y_test, best_rf_model.predict_proba(X_test)[:, 1])
rf_roc_auc
```

Out[45]: 0.9956167314709099

In [46]:
```
# Visualization: ROC Curve using Seaborn
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, best_rf_model.predict_proba
plt.figure(figsize=(8, 6))
sns.lineplot(x=fpr_rf, y=tpr_rf, label='Random Forest')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray', label='Random Guess')
plt.title('Random Forest ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Task 6: Comparison and Analysis

In [47]:
```python
# Compare the performance of Decision Tree and Random Forest models
print("\nDecision Tree Performance:")
print(f"Accuracy: {dt_accuracy:.4f}")
print(f"Precision: {dt_precision:.4f}")
print(f"Recall: {dt_recall:.4f}")
print(f"F1 Score: {dt_f1_score:.4f}")
print(f"AUC-ROC Score: {dt_roc_auc:.4f}")
print("Confusion Matrix:\n", dt_conf_matrix)

print("\nRandom Forest Performance:")
print(f"Accuracy: {rf_accuracy:.4f}")
print(f"Precision: {rf_precision:.4f}")
print(f"Recall: {rf_recall:.4f}")
print(f"F1 Score: {rf_f1_score:.4f}")
print(f"AUC-ROC Score: {rf_roc_auc:.4f}")
print("Confusion Matrix:\n", rf_conf_matrix)
```

```
Decision Tree Performance:
Accuracy: 0.9610
Precision: 0.9639
Recall: 0.9582
F1 Score: 0.9610
AUC-ROC Score: 0.9775
Confusion Matrix:
 [[481  18]
 [ 21 481]]

Random Forest Performance:
Accuracy: 0.9660
Precision: 0.9570
Recall: 0.9761
F1 Score: 0.9665
AUC-ROC Score: 0.9956
Confusion Matrix:
 [[477  22]
 [ 12 490]]
```

In [48]:
```python
# Provide insights into the advantages and disadvantages of each model
print("\nAdvantages and Disadvantages:")
print("Decision Tree:")
print("Advantages: Simple, interpretable, requires less data preprocessing.")
print("Disadvantages: Prone to overfitting, may not generalize well.")

print("\nRandom Forest:")
print("Advantages: Handles overfitting by combining multiple trees, often prov
print("Disadvantages: Complexity, harder to interpret compared to a single dec
```

```
Advantages and Disadvantages:
Decision Tree:
Advantages: Simple, interpretable, requires less data preprocessing.
Disadvantages: Prone to overfitting, may not generalize well.

Random Forest:
Advantages: Handles overfitting by combining multiple trees, often provides
better generalization.
Disadvantages: Complexity, harder to interpret compared to a single decision
tree.
```

In [ ]: