

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import OneHotEncoder
```

```
'''
### OLD FEATURES: Foot, Kick Direction, Keep

path = '/content/drive/MyDrive/IW_Seminar/IW_final/penalty_kick_old_features.csv'
penalty_kick_dataset = pd.read_csv(path, encoding = ('ISO-8859-1'), low_memory = False)
penalty_kick_dataset

'''

'\n### OLD FEATURES: Foot, Kick Direction, Keep\n\npath = '/content/drive/MyDrive/IW_Seminar/IW_final/penalty_kick_old_features.csv'\npenalty_kick_dataset = pd.read_csv(path, encoding = ('ISO-8859-1'), low_memory = False)\npenalty_kick_data
set'\n'

### JUST PLACEMENT
path = '/content/drive/MyDrive/IW_Seminar/IW_final/no_power_penalty_kick_new_features.csv'
penalty_kick_dataset = premier_dataset = pd.read_csv(path, encoding = ('ISO-8859-1'), low_memory = False)
penalty_kick_dataset
```

	Foot	Kick Direction	Keeper Direction	Placement	Goal
0	L	R	R	1	1
1	R	R	R	0	0
2	R	R	L	1	1
3	R	R	R	1	0
4	R	R	R	1	1
...	...	...	...	...	...
506	R	L	R	1	1
507	R	R	R	1	1
508	R	L	R	1	1
509	R	L	L	0	0
510	R	C	R	1	0

511 rows x 5 columns

```

penalty_kick_target = penalty_kick_dataset[['Goal']].copy()
# penalty_kick_features = pd.get_dummies(penalty_kick_dataset, columns = ['Foot', 'Kick Direction', 'Keeper
#penalty_kick_features = pd.get_dummies(penalty_kick_dataset, columns = ['Foot', 'Kick Direction', 'Keeper
# penalty_kick_features

ohe = OneHotEncoder(sparse_output = False)

dominant_foot = ohe.fit_transform(penalty_kick_dataset[['Foot']])
kick_direction = ohe.fit_transform(penalty_kick_dataset[['Kick Direction']])
keeper_direction = ohe.fit_transform(penalty_kick_dataset[['Keeper Direction']])

penalty_kick_np = np.zeros((len(penalty_kick_dataset),9))
penalty_kick_np[:,0:2] = dominant_foot
penalty_kick_np[:,2:5] = kick_direction
penalty_kick_np[:,5:8] = keeper_direction
penalty_kick_np[:,8:9] = penalty_kick_dataset[['Placement']].values
print(penalty_kick_np)

[[1. 0. 0. ... 0. 1. 1.]
 [0. 1. 0. ... 0. 1. 0.]
 [0. 1. 0. ... 1. 0. 1.]
 ...
 [0. 1. 0. ... 0. 1. 1.]
 [0. 1. 0. ... 1. 0. 0.]
 [0. 1. 1. ... 0. 1. 1.]]

...

### PLACEMENT AND POWER FEATURES
path = '/content/drive/MyDrive/IW_Seminar/IW_final/penalty_kick_new_features.csv'
penalty_kick_dataset = premier_dataset = pd.read_csv(path, encoding = ('ISO-8859-1'), low_memory = False)
penalty_kick_dataset

'''

\n### PLACEMENT AND POWER FEATURES\npath = '/content/drive/MyDrive/IW_Seminar/I
W_final/penalty_kick_new_features.csv'\npenalty_kick_dataset = premier_dataset =
pd.read_csv(path, encoding = ('ISO-8859-1'), low_memory = False)\npenalty_kick_d
ataset\n'

...

penalty_kick_target = penalty_kick_dataset[['Goal']].copy()
# penalty_kick_features = pd.get_dummies(penalty_kick_dataset, columns = ['Foot', 'Kick Direction', 'Keeper
#penalty_kick_features = pd.get_dummies(penalty_kick_dataset, columns = ['Foot', 'Kick Direction', 'Keeper
# penalty_kick_features

ohe = OneHotEncoder(sparse_output = False)

dominant_foot = ohe.fit_transform(penalty_kick_dataset[['Foot']])
kick_direction = ohe.fit_transform(penalty_kick_dataset[['Kick Direction']])
keeper_direction = ohe.fit_transform(penalty_kick_dataset[['Keeper Direction']])

penalty_kick_np = np.zeros((len(penalty_kick_dataset),8))
penalty_kick_np[:,0:2] = dominant_foot
penalty_kick_np[:,2:5] = kick_direction
penalty_kick_np[:,5:8] = keeper_direction
print(penalty_kick_np)
'''

```

```

'\npenalty_kick_target = penalty_kick_dataset[['Goal']].copy()\n# penalty_kick_f
eatures = pd.get_dummies(penalty_kick_dataset, columns = ['Foot', 'Kick Directio
n', 'Keeper Direction', 'Placement', 'Power'])\n#penalty_kick_features = pd.get_
dummies(penalty_kick_dataset, columns = ['Foot', 'Kick Direction', 'Keeper Direc
tion'])\n# penalty_kick_features\nnohe = OneHotEncoder(sparse_output = False)\n
\n\ndominant_foot = ohe.fit_transform(penalty_kick_dataset[['Foot']])\nkick_direc
tion = ohe.fit_transform(penalty_kick_dataset[['Kick Direction']])\nkeeper_direc
tion = ohe.fit_transform(penalty_kick_dataset[['Keeper Direction']])\n\npenalty
kick_np = np.zeros((len(penalty_kick_dataset).8))\npenalty_kick_np[:.0:2] = dom

```

```

penalty_kick_features_df = pd.DataFrame({'Left Footed': penalty_kick_np[:,0], 'Right Footed': penalty_kick
penalty_kick_features_df

```

	Left Footed	Right Footed	Kicked Left	Kicked Center	Kicked Right	Keeper Left	Keeper Center	Keeper Right	Placement
0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	1.0
1	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0
2	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	1.0
3	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	1.0
4	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	1.0
...	...	...	...	...	...	...	...	...	...
506	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0
507	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	1.0
508	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0
509	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0
510	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0

511 rows × 9 columns

```

penalty_kick_target

```

	Goal
0	1
1	0
2	1
3	0
4	1
...	...
506	1
507	1
508	1
509	0
510	0

511 rows × 1 columns

```

penalty_kick_target_np = penalty_kick_target.values.flatten()
print(penalty_kick_target_np)

```

```
[1 0 1 0 1 0 0 1 1 1 1 1 0 1 1 1 0 0 1 1 1 0 1 0 1 1 0 1 0 1 1 0 1 1 1
0 0 1 1 0 1 1 1 1 1 1 0 0 1 0 1 1 1 0 1 1 1 0 1 1 1 1 1 1 0 0 0 1 0 1
0 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 0 0 1 1 0 1 1 0 1 1 0 1 1 0 0 0 1 1 0 0
0 0 0 1 1 0 1 0 1 1 0 0 1 1 0 0 0 1 0 0 1 1 0 1 0 1 1 1 1 0 0 1 1 0 0 1 1
1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 0 1 1 0 0 0 1 1 1 1 0 1 1 0 0 1 1 1 1 0 1
1 1 1 0 1 1 0 1 0 1 1 1 0 1 1 0 0 1 1 0 0 1 0 1 1 1 0 1 1 0 1 1 0 0 1 1 1
0 1 0 1 0 0 1 1 1 1 1 1 1 0 0 0 0 1 1 0 0 0 1 1 0 1 1 1 0 1 0 0 1 0 1 1 0
1 0 0 0 1 1 1 1 0 0 1 0 1 0 1 1 1 1 1 0 1 0 1 0 1 1 0 0 1 1 0 1 1 1 0 1 1
0 1 1 1 1 0 1 0 1 1 1 1 0 0 1 1 0 1 1 0 1 0 0 0 0 1 0 1 0 0 0 1 1 1 1 1 1
1 1 1 1 0 0 1 1 0 0 1 1 0 1 1 0 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 1 0 0
0 0 1 0 1 1 1 0 1 0 0 1 0 1 0 0 0 0 1 1 1 1 1 1 1 0 0 1 1 0 1 1 0 1 0 0 1
0 1 0 1 1 1 0 1 0 1 0 0 1 0 1 0 1 0 0 1 1 0 1 0 1 1 1 0 0 1 1 1 1 1 0
1 1 1 0 0 0 0 0 1 1 1 1 1 1 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 1 1 0 1 0 0 0 1
0 1 0 0 0 1 1 1 1 1 1 0 0 1 1 0 1 1 0 1 1 1 0 1 1 1 0 0]
```

✓ In terms of how I will divide the training and testing data, what I have is training data, and my testing data will be data from an unseen event, such as Copa America penalty shootouts. Accuracy will be measured by how accurate the model predicted and comparing it to what actually happened.

But for now, I will split the data using the 80% train, 20% test rule

```
from sklearn.model_selection import train_test_split
x_main, x_test, y_main, y_test = train_test_split(penalty_kick_np, penalty_kick_target_np, test_size=0.20,
print('Length of x_main:', len(x_main))
print('Length of x_test:', len(x_test))
print('Length of y_main:', len(y_main))
print('Length of y_test:', len(y_test))

Length of x_main: 408
Length of x_test: 103
Length of y_main: 408
Length of y_test: 103
```

✓ Now I want to split train into validation and train

```
x_train, x_val, y_train, y_val = train_test_split(x_main, y_main, test_size = 0.2, random_state = 42, stratify=y_main)
print('Length of x_train:', len(x_train))
print('Length of x_val:', len(x_val))
print('Length of y_train:', len(y_train))
print('Length of y_val:', len(y_val))

Length of x_train: 326
Length of x_val: 82
Length of y_train: 326
Length of y_val: 82
```

✓ Training Data Below

```
x_train
```

```
array([[0., 1., 1., ..., 1., 0., 1.],
       [0., 1., 0., ..., 0., 0., 1.],
       [0., 1., 1., ..., 0., 1., 1.],
       ...,
       [0., 1., 0., ..., 0., 1., 1.],
       [0., 1., 1., ..., 0., 1., 1.],
       [0., 1., 0., ..., 1., 0., 1.]])
```

```
y_train
print(len(y_train))
print(np.sum(y_train))
```

```
326
199
```

## ✓ Performing EDA

### Imbalanced Dataset

```
# num_pens_missed = target_penalty_df['Target'].value_counts()[0.0]
# num_pens_scored = target_penalty_df['Target'].value_counts()[1.0]
num_pens_scored = np.sum(y_train)
num_pens_missed = len(y_train) - num_pens_scored
print("Number of penalties missed is:", num_pens_missed)
print("Number of penalties scored is:", num_pens_scored)
```

```
Number of penalties missed is: 127
Number of penalties scored is: 199
```

```
import matplotlib.pyplot as plt
```

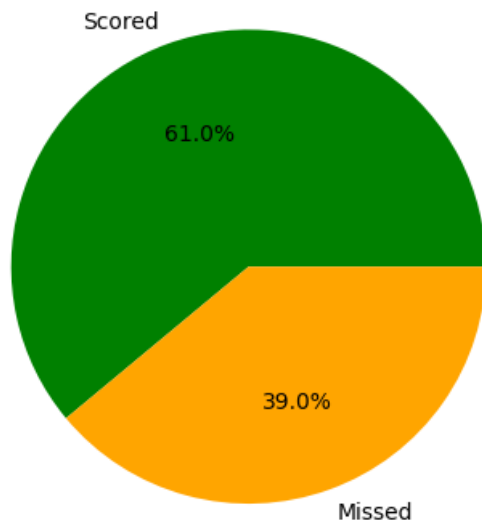
```
# Sample data
sizes = [num_pens_scored, num_pens_missed]
labels = ['Scored', 'Missed']
colors = ['green', 'orange']
```

```
# Create a pie chart
plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%')
```

```
# Add a title
plt.title('Frequency of Missed/Scored Penalties on Training')
```

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

## Frequency of Missed/Scored Penalties on Training



## NOW SHOW HOW IMBALANCED THE DATASET IS

### ✓ Will Now Implement Random Oversampling

```
from collections import Counter
from imblearn.over_sampling import RandomOverSampler

# features_penalty_dataset is the FEATURES (x_train) of the training set
print("Original dataset shape:", Counter(y_train))

Original dataset shape: Counter({1: 199, 0: 127})

oversample = RandomOverSampler(sampling_strategy='minority', random_state=42)
x_over, y_over = oversample.fit_resample(x_train, y_train)
x_train_final = np.vstack((x_over, x_val))
y_train_final = np.concatenate((y_over, y_val))
print("Oversampled dataset shape:", Counter(y_over))

Oversampled dataset shape: Counter({1: 199, 0: 199})
```

### ✓ TRAIN ON SOME MODELS

```
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error, accuracy_score, precision_scc
from sklearn.metrics import confusion_matrix, make_scorer
from sklearn import metrics
import matplotlib.pyplot as plt
import seaborn as sns
```

### ✓ RANDOM CLASSIFIER

## Declare Random Classifier Object

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(random_state=42)
```

### ▼ Base Model To Train & Test on Validation

```
#### TRAIN & PREDICT ON OVERSAMPLED DATA
rfc.fit(x_over,y_over)
y_rfc_base = rfc.predict(x_val)

### EVALUATION
f1_rfc_base = f1_score(y_val, y_rfc_base)
roc_rfc_base = roc_auc_score(y_val, y_rfc_base)
print('The AUC-ROC score for Base Random Forest is:', roc_rfc_base)
print('The F1 score for Base Random Forest is :', f1_rfc_base)

### CONFUSION MATRIX

cm = confusion_matrix(y_val, y_rfc_base)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True,cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Base Random Forest")

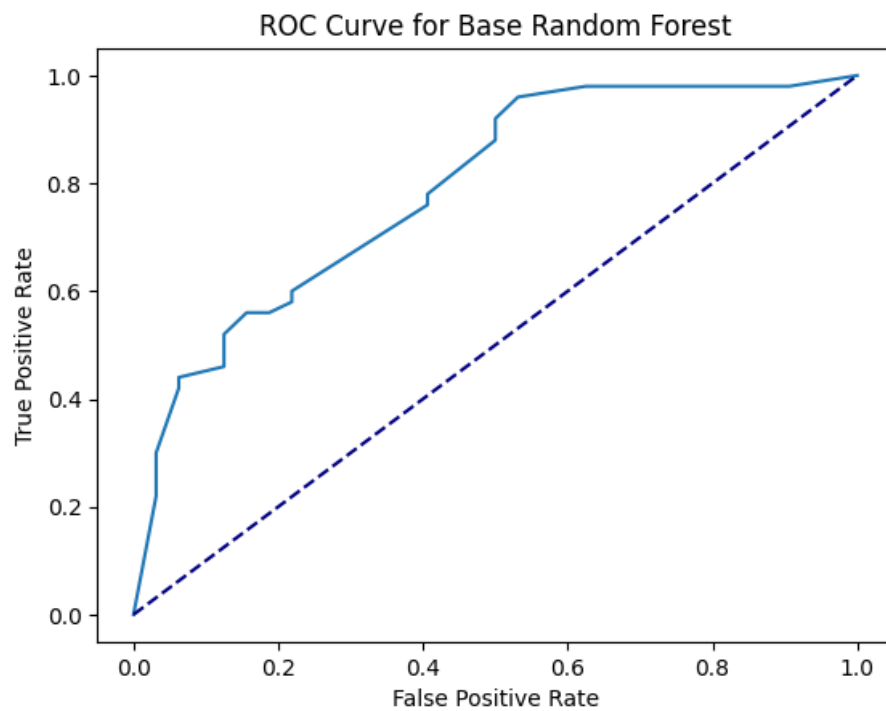
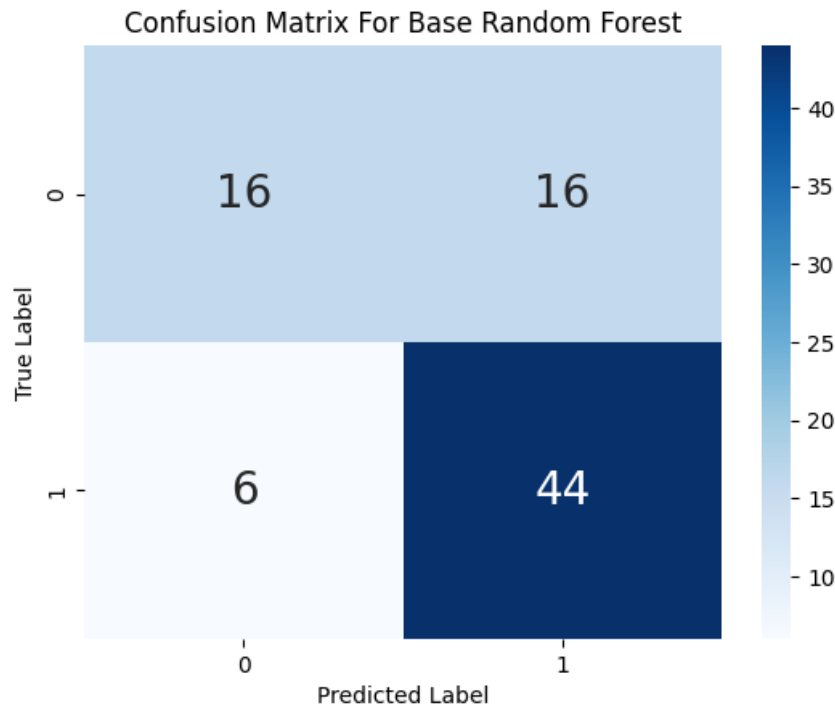
# Show the plot
plt.show()

### ROC CURVE
y_pred_rfc_base_proba = rfc.predict_proba(x_val)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_rfc_base_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Base Random Forest')
plt.show()
```

The AUC-ROC score for Base Random Forest is: 0.69

The F1 score for Base Random Forest is : 0.8



## ✓ HYPERPARAMETER TUNING

```
from sklearn.model_selection import GridSearchCV
```



```

# Define the parameter grid to search over
param_grid = {
    'n_estimators': [100, 500, 1000],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

grid_search = GridSearchCV(estimator=rfc, param_grid=param_grid, cv=5, scoring='f1', n_jobs=-1)
grid_search.fit(x_over, y_over)

### GET THE BEST PARAMS
best_params = grid_search.best_params_
print('The best parameters are:', best_params)

### FIT & PREDICT BASED ON THE NEW PARAMS
rfc.set_params(random_state = 42, **best_params)
print('rfc parameters:', rfc.get_params())
rfc.fit(x_over, y_over)
y_rfc_grid = rfc.predict(x_val)

### EVALUATION

f1_rfc_grid = f1_score(y_val, y_rfc_grid)
roc_rfc_grid = roc_auc_score(y_val, y_rfc_grid)
print('The AUC-ROC score for Random Forest After Tuning is:', roc_rfc_grid)
print('The F1 score for Random Forest Tree After Tuning is :', f1_rfc_grid)

### CONFUSION MATRIX

cm = confusion_matrix(y_val, y_rfc_grid)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Random Forest on Validation")

# Show the plot
plt.show()

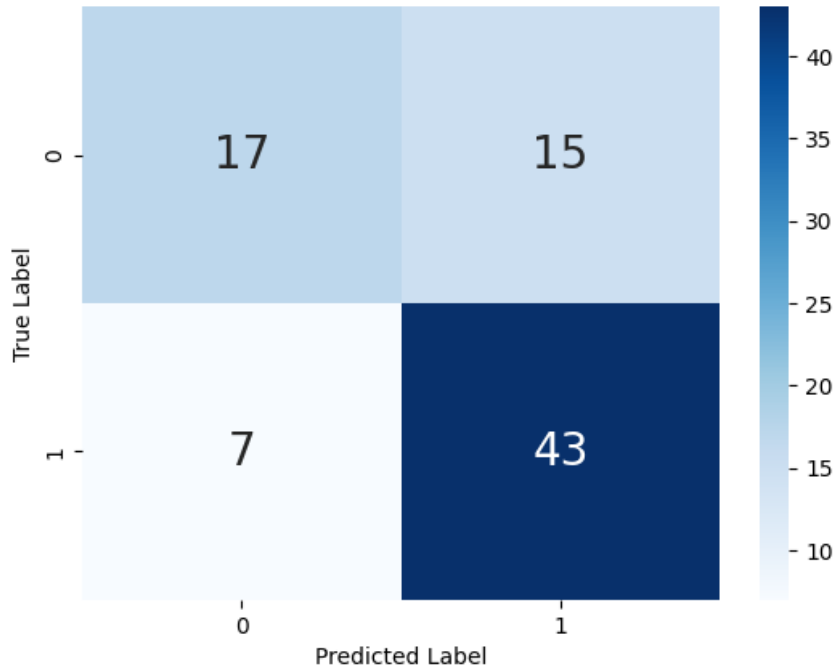
### ROC CURVE
y_pred_rfc_grid_proba = rfc.predict_proba(x_val)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_rfc_grid_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned Random Forest on Validation')
plt.show()

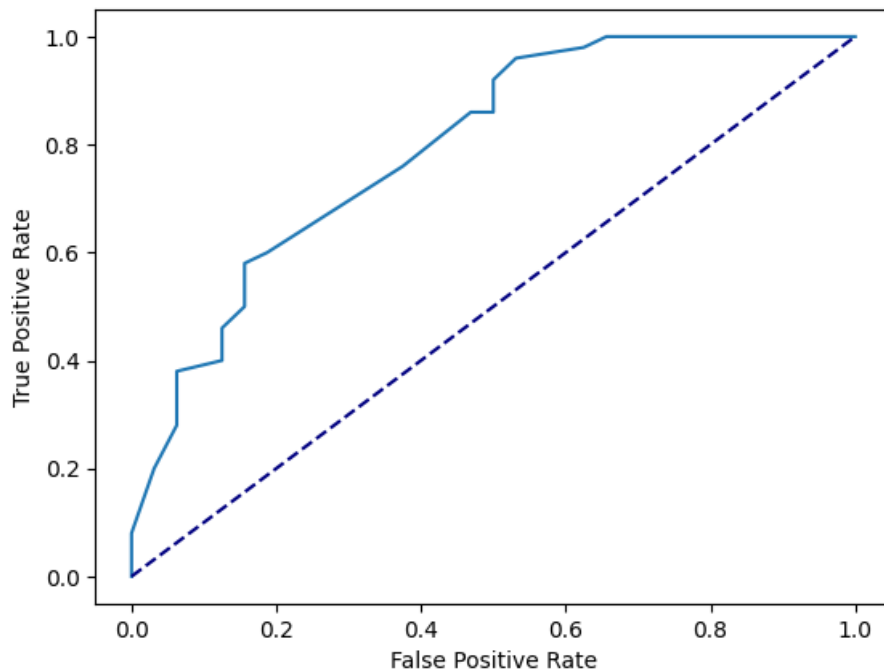
```

The best parameters are: {'max\_depth': None, 'min\_samples\_leaf': 4, 'min\_samples\_rfc parameters: {'bootstrap': True, 'ccp\_alpha': 0.0, 'class\_weight': None, 'cri The AUC-ROC score for Random Forest After Tuning is: 0.6956249999999999  
The F1 score for Random Forest Tree After Tuning is : 0.7962962962962963

### Confusion Matrix For Random Forest on Validation



### ROC Curve for Tuned Random Forest on Validation



✓ NOW USE THE TEST FOR FINAL EVALUATION

```
rfc.fit(x_train_final, y_train_final)
print('rfc parameters:', rfc.get_params())
y_rfc_final_preds = rfc.predict(x_test)

### TEST EVALUATION

f1_rfc_grid_test = f1_score(y_test, y_rfc_final_preds)
roc_rfc_grid_test = roc_auc_score(y_test, y_rfc_final_preds)
print('The AUC-ROC score for Random Forest After Tuning is:', roc_rfc_grid_test)
print('The F1 score for Random Forest Tree After Tuning is :', f1_rfc_grid_test)

### CONFUSION MATRIX

cm = confusion_matrix(y_test, y_rfc_final_preds)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned Random Forest on Test")

# Show the plot
plt.show()

### ROC CURVE
y_pred_rfc_grid_proba = rfc.predict_proba(x_test)[:,1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_rfc_grid_proba)

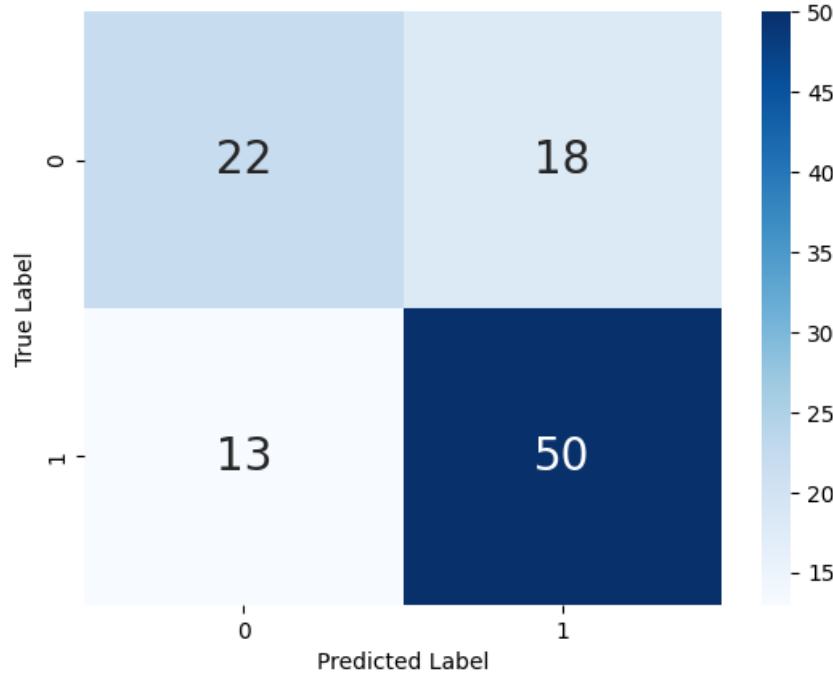
#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned Random Forest on Test')
plt.show()
```

rfc parameters: {'bootstrap': True, 'ccp\_alpha': 0.0, 'class\_weight': None, 'criterion': 'entropy', 'max\_depth': 10, 'max\_features': 'sqrt', 'max\_leaf\_nodes': 100, 'min\_samples\_leaf': 10, 'min\_samples\_split': 10, 'n\_estimators': 100, 'oob\_score': False, 'random\_state': 42, 'verbose': 0}

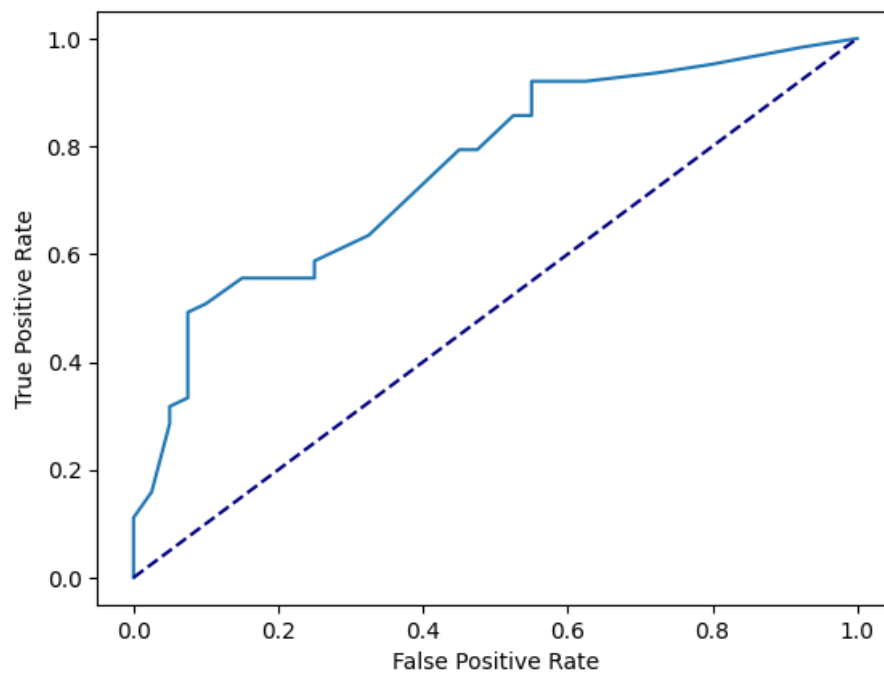
The AUC-ROC score for Random Forest After Tuning is: 0.6718253968253969

The F1 score for Random Forest Tree After Tuning is : 0.7633587786259542

Confusion Matrix For Tuned Random Forest on Test



ROC Curve for Tuned Random Forest on Test



## ▼ DECISION TREE MODEL

### ▼ Declare Decision Tree Object

```
from sklearn.tree import DecisionTreeClassifier
dtt = DecisionTreeClassifier(random_state = 42)
```

## ✓ NOW TRAIN ON MY BASE MODEL

```
### FIT AND MAKE PREDICTION
dtc.fit(x_over, y_over)
y_dtc_base = dtc.predict(x_val)

### EVALUATION
roc_dtc_base = roc_auc_score(y_val, y_dtc_base)
f1_dtc_base = f1_score(y_val, y_dtc_base)
print('The AUC-ROC score for Base Decision Tree is:', roc_dtc_base)
print('The F1 score for Base Decision Tree is :', f1_dtc_base)

### CONFUSION MATRIX
cm = confusion_matrix(y_val, y_dtc_base)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Base Decision Tree")

# Show the plot
plt.show()

### ROC CURVE PLOT

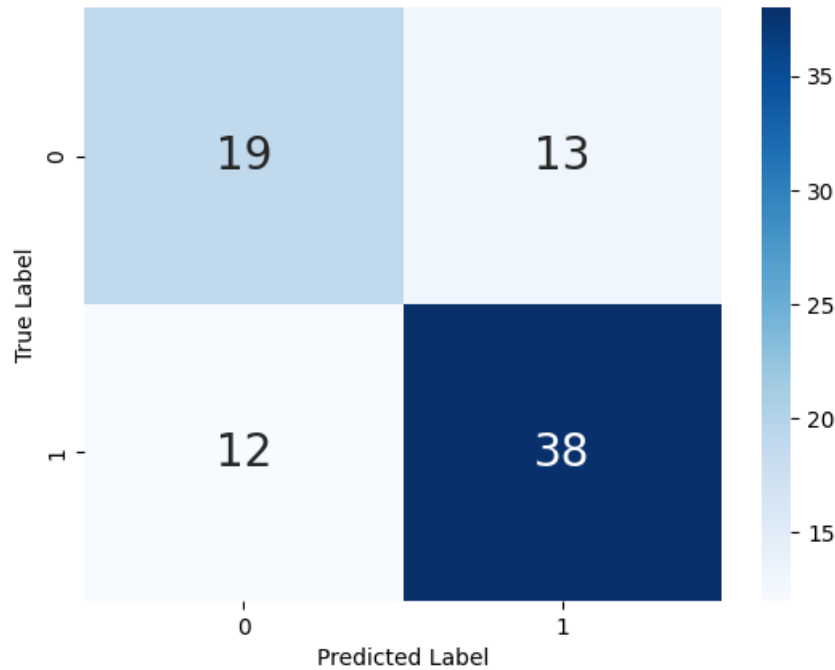
y_dtc_base_proba = dtc.predict_proba(x_val)[:,-1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_dtc_base_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC curve for Base Decision Tree')
plt.show()
```

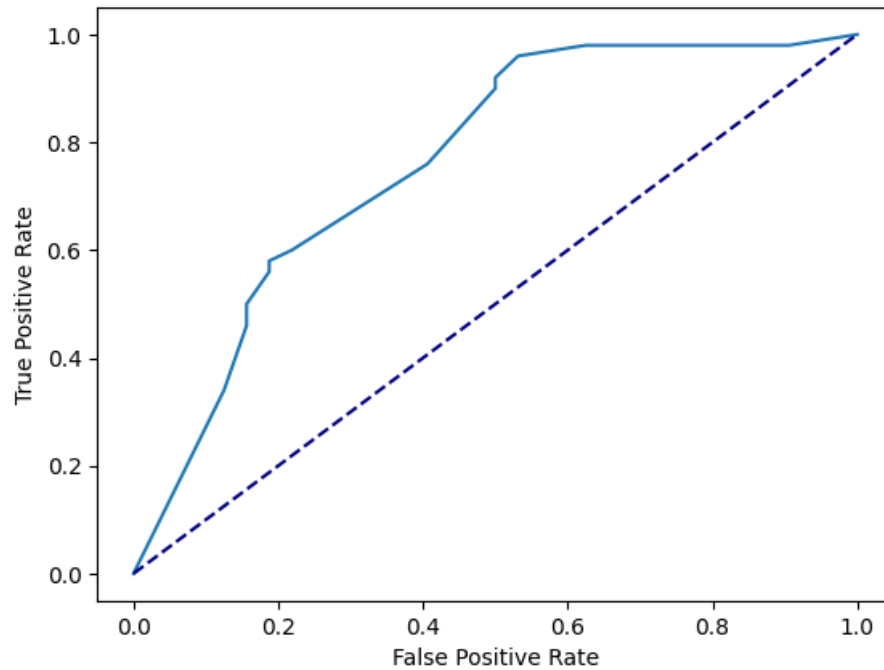
The AUC-ROC score for Base Decision Tree is: 0.676875

The F1 score for Base Decision Tree is : 0.7524752475247525

Confusion Matrix For Base Decision Tree



ROC curve for Base Decision Tree



✓ NOW TUNE HYPERPARAMETERS

```
# Define the parameter grid to search over
param_grid = {
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2', None]
}

# Create a grid search object and fit on the training data
grid_search = GridSearchCV(estimator=dtc, param_grid=param_grid, cv=5, scoring='f1', n_jobs=-1)
grid_search.fit(x_over, y_over)

### GET THE BEST PARAMS
best_params = grid_search.best_params_
print('The best parameters are:', best_params)

### FIT & PREDICT BASED ON THE NEW PARAMS
dtc.set_params(random_state = 42, **best_params)
print('The parameters are:', dtc.get_params())
dtc.fit(x_over, y_over)
y_dtc_grid = dtc.predict(x_val)

### EVALUATION

f1_dtc_grid = f1_score(y_val, y_dtc_grid)
roc_dtc_grid = roc_auc_score(y_val, y_dtc_grid)
print('The AUC-ROC score for Decision Tree After Tuning is:', roc_dtc_grid)
print('The F1 score for Decision Tree After Tuning is :', f1_dtc_grid)

### CONFUSION MATRIX

cm = confusion_matrix(y_val, y_dtc_grid)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned Decision Tree on Validation")

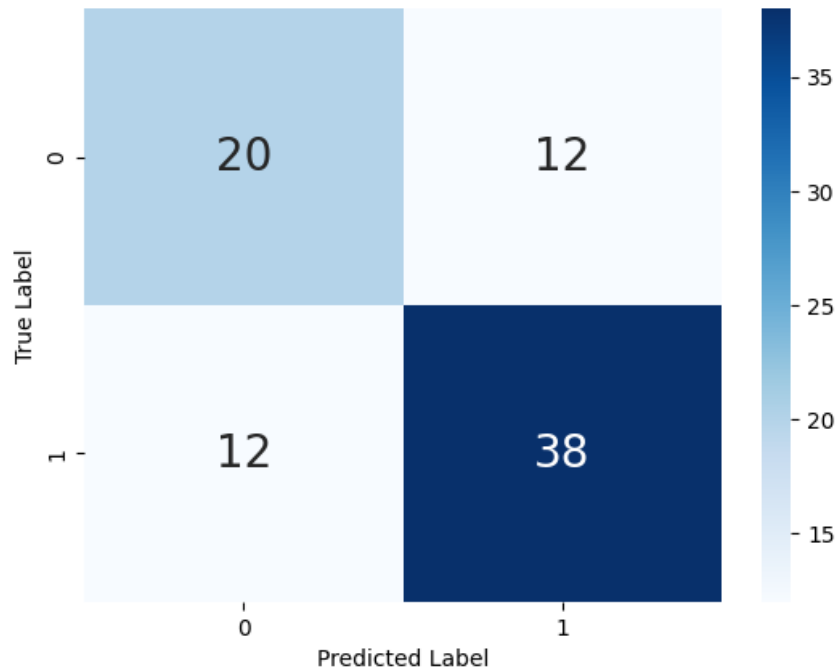
# Show the plot
plt.show()

### ROC CURVE
y_pred_dtc_grid_proba = dtc.predict_proba(x_val)[:,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_dtc_grid_proba)

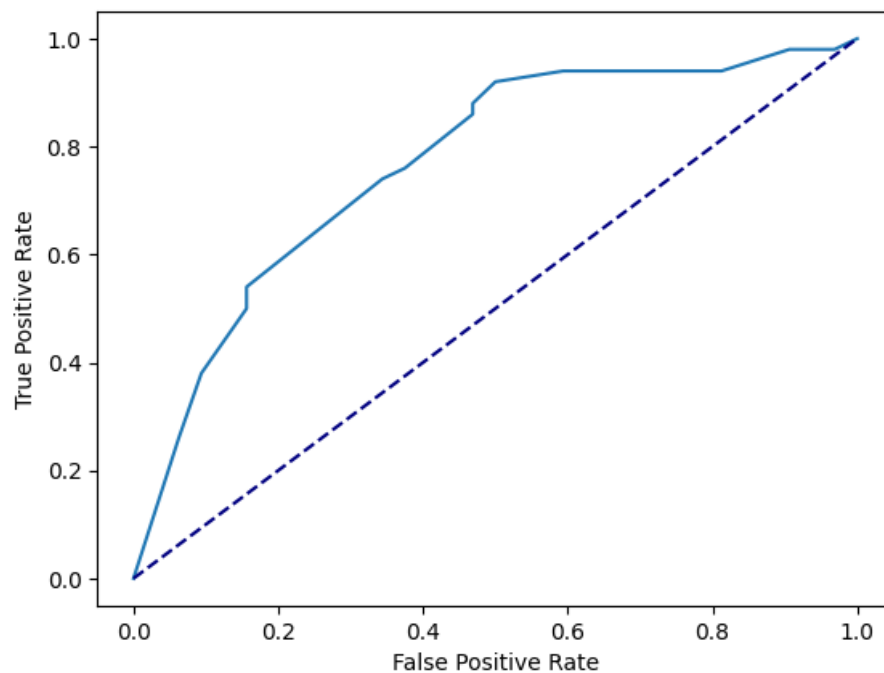
#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned Decision Tree on Validation')
plt.show()
```

The best parameters are: {'max\_depth': 5, 'max\_features': 'sqrt', 'min\_samples\_l  
The parameters are: {'ccp\_alpha': 0.0, 'class\_weight': None, 'criterion': 'gini'  
The AUC-ROC score for Decision Tree After Tuning is: 0.6925000000000001  
The F1 score for Decision Tree After Tuning is : 0.76

Confusion Matrix For Tuned Decision Tree on Validation



ROC Curve for Tuned Decision Tree on Validation



✖ NOW EVALUATE ON TEST DATASET



```
print('The parameters are:', dtc.get_params())
dtc.fit(x_train_final, y_train_final)
y_dtc_final_preds = dtc.predict(x_test)

### TEST EVALUATION

f1_dtc_grid_test = f1_score(y_test, y_dtc_final_preds)
roc_dtc_grid_test = roc_auc_score(y_test, y_dtc_final_preds)
print('The AUC-ROC score for Decision Tree on Test:', roc_dtc_grid_test)
print('The F1 score for Decision Tree on Test :', f1_dtc_grid_test)

### CONFUSION MATRIX

cm = confusion_matrix(y_test, y_dtc_final_preds)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned Decision Tree on Test")

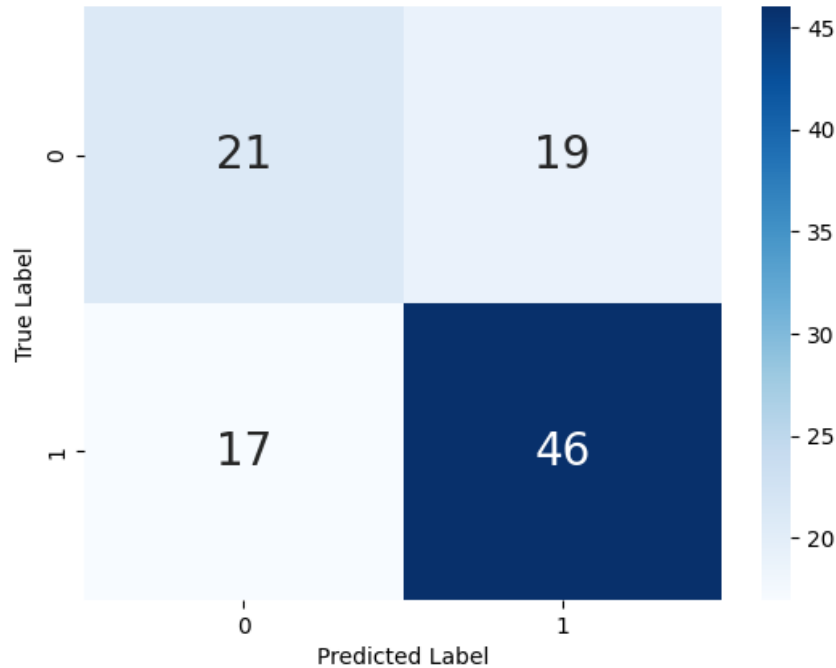
# Show the plot
plt.show()

### ROC CURVE
y_pred_dtc_grid_proba = dtc.predict_proba(x_test)[:,1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_dtc_grid_proba)

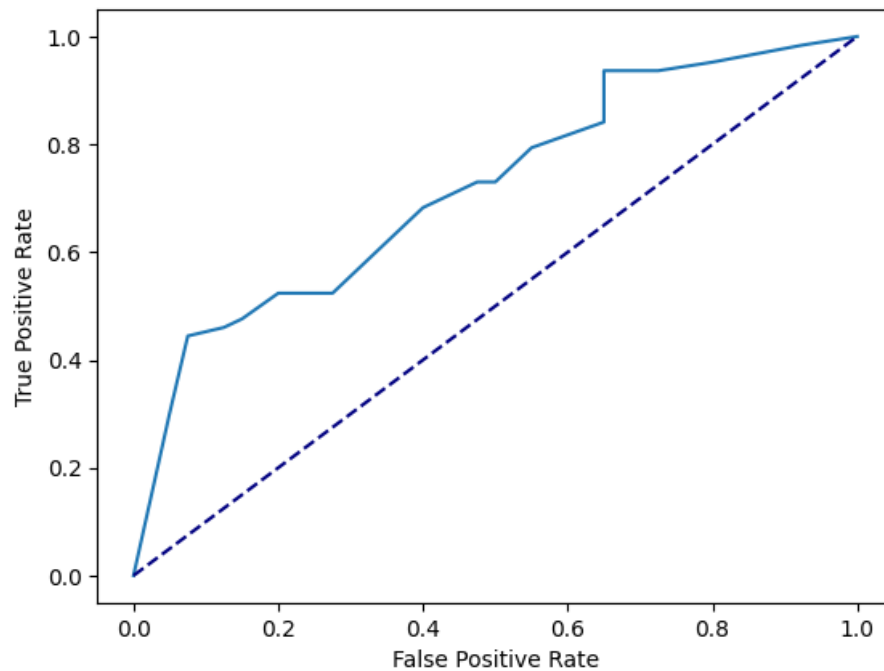
#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned Decision Tree on Test')
plt.show()
```

The parameters are: {'ccp\_alpha': 0.0, 'class\_weight': None, 'criterion': 'gini'  
The AUC-ROC score for Decision Tree on Test: 0.6275793650793651  
The F1 score for Decision Tree on Test : 0.7187500000000001

Confusion Matrix For Tuned Decision Tree on Test



ROC Curve for Tuned Decision Tree on Test



## ✓ LOGISTIC REGRESSION

### ✓ DECLARE LOGISTIC REGRESSION OBJECT

```
from sklearn.linear_model import LogisticRegression  
lr = LogisticRegression()
```

## ▼ BASE MODEL

```
### TRAIN & PREDICT
lr.fit(x_over, y_over)
y_lr_base = lr.predict(x_val)

### EVALUATE
roc_lr_base = roc_auc_score(y_val, y_lr_base)
f1_lr_base = f1_score(y_val, y_lr_base)
print('The AUC-ROC score for Base Logistic Regression is:', roc_lr_base)
print('The F1 score for Base Logistic Regression is:', f1_lr_base)

cm = confusion_matrix(y_val, y_lr_base)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues' ,fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Base Logistic Regression")

# Show the plot
plt.show()

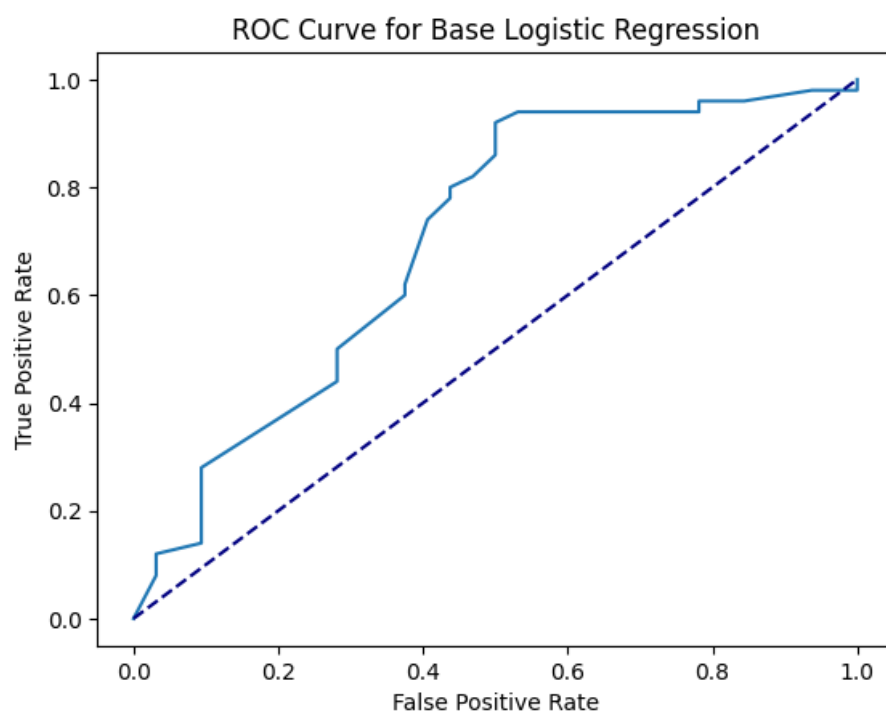
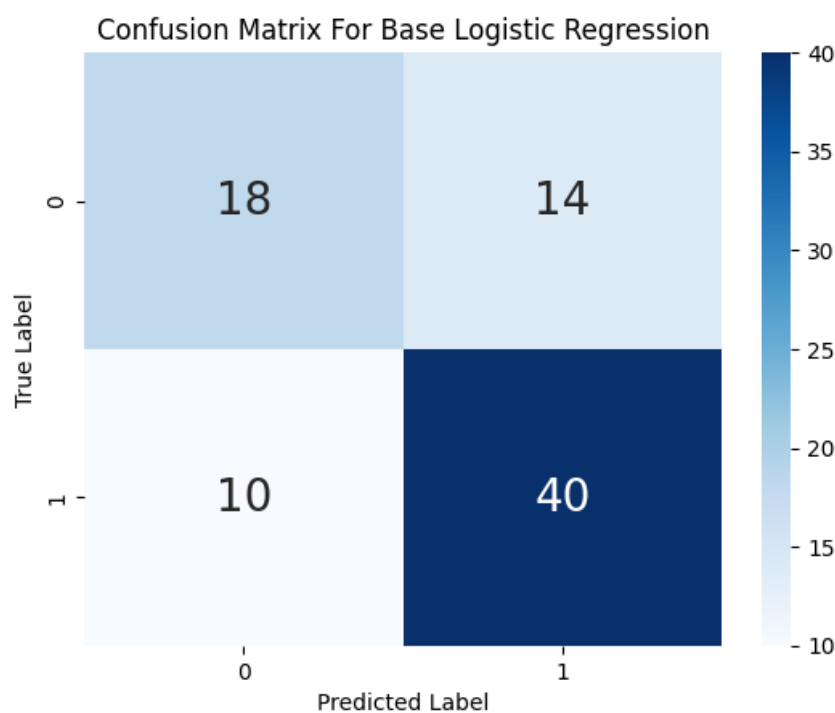
## ROC CURVE

y_lr_base_proba = lr.predict_proba(x_val)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_lr_base_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Base Logistic Regression')
plt.show()
```

The AUC-ROC score for Base Logistic Regression is: 0.68125

The F1 score for Base Logistic Regression is: 0.7692307692307692



## ▼ HYPERPARAMETER TUNING

```

# Define the parameter grid to search over
# Define the hyperparameters to search over
param_grid = {'penalty': ['l1', 'l2', 'elasticnet', 'none'],
              'C': [0.1, 1, 10, 100],
              'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']}

# Create a grid search object
# Create GridSearchCV object
grid_search = GridSearchCV(lr, param_grid=param_grid, cv=5, scoring='f1', n_jobs = -1)
# grid_search = GridSearchCV(lr, param_grid=param_grid, cv=5, scoring=['f1', 'roc_auc'], refit = 'f1', n_j

# Fit the grid search to the data
grid_search.fit(x_over, y_over)

### GET THE BEST PARAMS
best_params = grid_search.best_params_
print('The best parameters are:', best_params)

### FIT & PREDICT BASED ON THE NEW PARAMS
lr.set_params(random_state = 42, **best_params)
lr.fit(x_over, y_over)
y_lr_grid = lr.predict(x_val)

### EVALUATION

f1_lr_grid = f1_score(y_val, y_lr_grid)
roc_lr_grid = roc_auc_score(y_val, y_lr_grid)
print('The AUC-ROC score for Logistic Regression After Tuning is:', roc_lr_grid)
print('The F1 score for Logistic Regression After Tuning is :', f1_lr_grid)

### CONFUSION MATRIX

cm = confusion_matrix(y_val, y_lr_grid)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned Logistic Regression on Validation")

# Show the plot
plt.show()

### ROC CURVE
y_pred_lr_grid_proba = lr.predict_proba(x_val)[:,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_lr_grid_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned Logistic Regression on Validation')
plt.show()

```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py:3180 fits failed out of a total of 400.
```

The score on these train-test partitions for these parameters will be set to nan  
If these failures are not expected, you can try to debug them by setting error\_s

Below are more details about the failures:

-----  
20 fits failed with the following error:

Traceback (most recent call last):

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 3180, in _validate_estimator
    estimator.fit(X_train, y_train, **fit_params)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    solver = _check_solver(self.solver, self.penalty, self.dual)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    raise ValueError
```

ValueError: Solver newton-cg supports only 'l2' or 'none' penalties, got l1 pena

-----  
20 fits failed with the following error:

Traceback (most recent call last):

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 3180, in _validate_estimator
    estimator.fit(X_train, y_train, **fit_params)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    solver = _check_solver(self.solver, self.penalty, self.dual)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    raise ValueError
```

ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

-----  
20 fits failed with the following error:

Traceback (most recent call last):

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 3180, in _validate_estimator
    estimator.fit(X_train, y_train, **fit_params)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    solver = _check_solver(self.solver, self.penalty, self.dual)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    raise ValueError
```

ValueError: Solver sag supports only 'l2' or 'none' penalties, got l1 penalty.

-----  
20 fits failed with the following error:

Traceback (most recent call last):

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 3180, in _validate_estimator
    estimator.fit(X_train, y_train, **fit_params)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    solver = _check_solver(self.solver, self.penalty, self.dual)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    raise ValueError
```

ValueError: Solver newton-cg supports only 'l2' or 'none' penalties, got elastic

-----  
20 fits failed with the following error:

Traceback (most recent call last):

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 3180, in _validate_estimator
    estimator.fit(X_train, y_train, **fit_params)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    solver = _check_solver(self.solver, self.penalty, self.dual)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    raise ValueError
```

ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got elasticnet

-----  
20 fits failed with the following error:

Traceback (most recent call last):

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 3180, in _validate_estimator
    estimator.fit(X_train, y_train, **fit_params)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    solver = _check_solver(self.solver, self.penalty, self.dual)
```

```
File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1180, in _check_solver
    raise ValueError
```

ValueError: Only 'saga' solver supports elasticnet penalty, got solver=liblinear

20 fits failed with the following error:

Traceback (most recent call last):

File "/usr/local/lib/python3.10/dist-packages/sklearn/model\_selection/\_validation/estimator.fit(X\_train, y\_train, \*\*fit\_params)

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py solver = \_check\_solver(self.solver, self.penalty, self.dual)

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py raise ValueError(

ValueError: Solver sag supports only 'l2' or 'none' penalties, got elasticnet pe

20 fits failed with the following error:

Traceback (most recent call last):

File "/usr/local/lib/python3.10/dist-packages/sklearn/model\_selection/\_validation/estimator.fit(X\_train, y\_train, \*\*fit\_params)

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py fold\_coefs\_ = Parallel(n\_jobs=self.n\_jobs, verbose=self.verbose, prefer=pref

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py return super().\_\_call\_\_(iterable\_with\_config)

File "/usr/local/lib/python3.10/dist-packages/joblib/parallel.py", line 1085, if self.dispatch\_one\_batch(iterator):

File "/usr/local/lib/python3.10/dist-packages/joblib/parallel.py", line 901, i self.\_dispatch(tasks)

File "/usr/local/lib/python3.10/dist-packages/joblib/parallel.py", line 819, i job = self.\_backend.apply\_async(batch, callback=cb)

File "/usr/local/lib/python3.10/dist-packages/joblib/\_parallel\_backends.py", l result = ImmediateResult(func)

File "/usr/local/lib/python3.10/dist-packages/joblib/\_parallel\_backends.py", l self.results = batch()

File "/usr/local/lib/python3.10/dist-packages/joblib/parallel.py", line 288, i return [func(\*args, \*\*kwargs)

File "/usr/local/lib/python3.10/dist-packages/joblib/parallel.py", line 288, i return [func(\*args, \*\*kwargs)

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py return self.function(\*args, \*\*kwargs)

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py alpha = (1.0 / C) \* (1 - l1\_ratio)

TypeError: unsupported operand type(s) for -: 'int' and 'NoneType'

20 fits failed with the following error:

Traceback (most recent call last):

File "/usr/local/lib/python3.10/dist-packages/sklearn/model\_selection/\_validation/estimator.fit(X\_train, y\_train, \*\*fit\_params)

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py solver = \_check\_solver(self.solver, self.penalty, self.dual)

File "/usr/local/lib/python3.10/dist-packages/sklearn/linear\_model/\_logistic.py raise ValueError("penalty='none' is not supported for the liblinear solver")

ValueError: penalty='none' is not supported for the liblinear solver

warnings.warn(some\_fits\_failed\_message, FitFailedWarning)

/usr/local/lib/python3.10/dist-packages/sklearn/model\_selection/\_search.py:952:

```
0.71421112 0.71421112 0.71421112 0.71421112 nan nan
nan nan nan 0.71261312 0.71261312 nan
0.71261312 0.71261312 nan nan 0.71421112 nan
0.71421112 0.71421112 0.71421112 0.71421112 0.71421112 0.71421112
nan nan nan nan 0.71261312
0.71261312 nan 0.71261312 0.71261312 nan nan
0.71421112 nan 0.71421112 0.71261312 0.71261312 0.71261312
0.71261312 0.71261312 nan nan nan nan
nan 0.71261312 0.71261312 nan 0.71261312 0.71261312
nan nan 0.71261312 nan 0.71261312 0.71261312
0.71261312 0.71261312 0.71261312 0.71261312 nan nan
nan nan nan 0.71261312 0.71261312 nan
0.71261312 0.71261312]
```

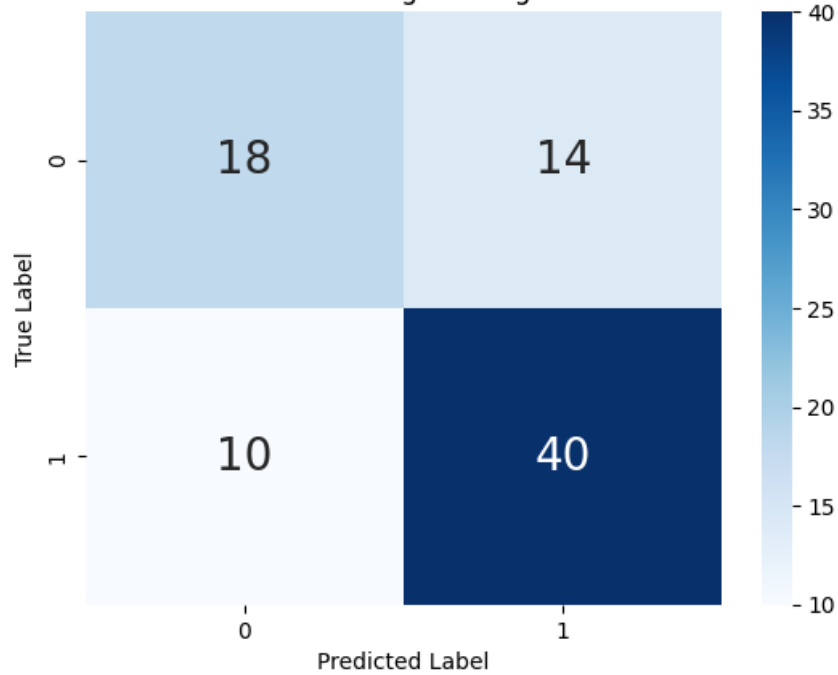
warnings.warn(

The best parameters are: {'C': 0.1, 'penalty': 'l1', 'solver': 'liblinear'}

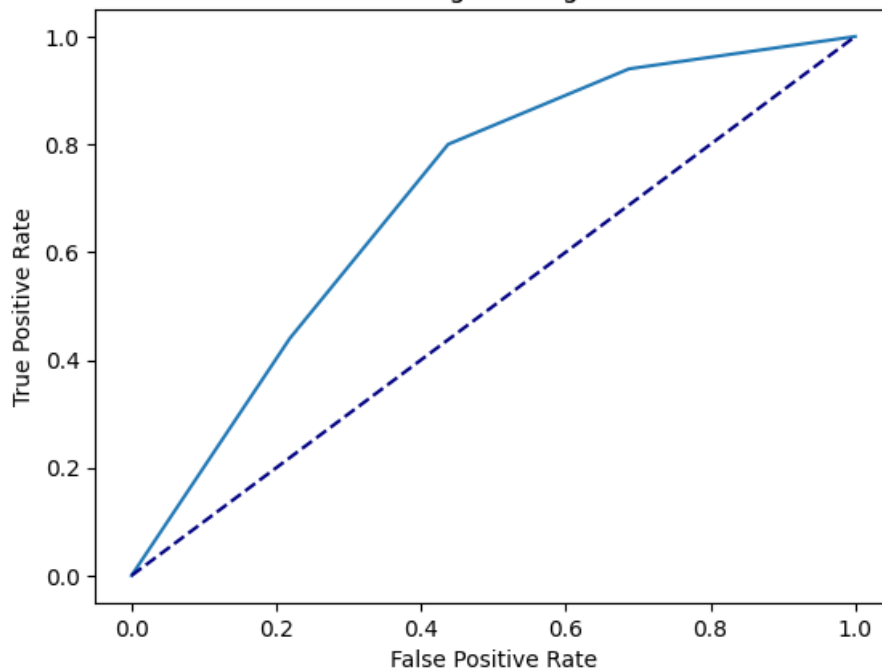
The AUC-ROC score for Logistic Regression After Tuning is: 0.68125

The F1 score for Logistic Regression After Tuning is : 0.7692307692307692

Confusion Matrix For Tuned Logistic Regression on Validation



ROC Curve for Tuned Logistic Regression on Validation



✓ NOW ON THE TEST DATASET



```
lr.fit(x_train_final, y_train_final)
y_lr_final_preds = lr.predict(x_test)

### TEST EVALUATION

f1_lr_grid_test = f1_score(y_test, y_lr_final_preds)
roc_lr_grid_test = roc_auc_score(y_test, y_lr_final_preds)
print('The AUC-ROC score for Logistic Regression on Test is:', roc_lr_grid_test)
print('The F1 score for Logistic Regression on Test is :', f1_lr_grid_test)

### CONFUSION MATRIX

cm = confusion_matrix(y_test, y_lr_final_preds)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

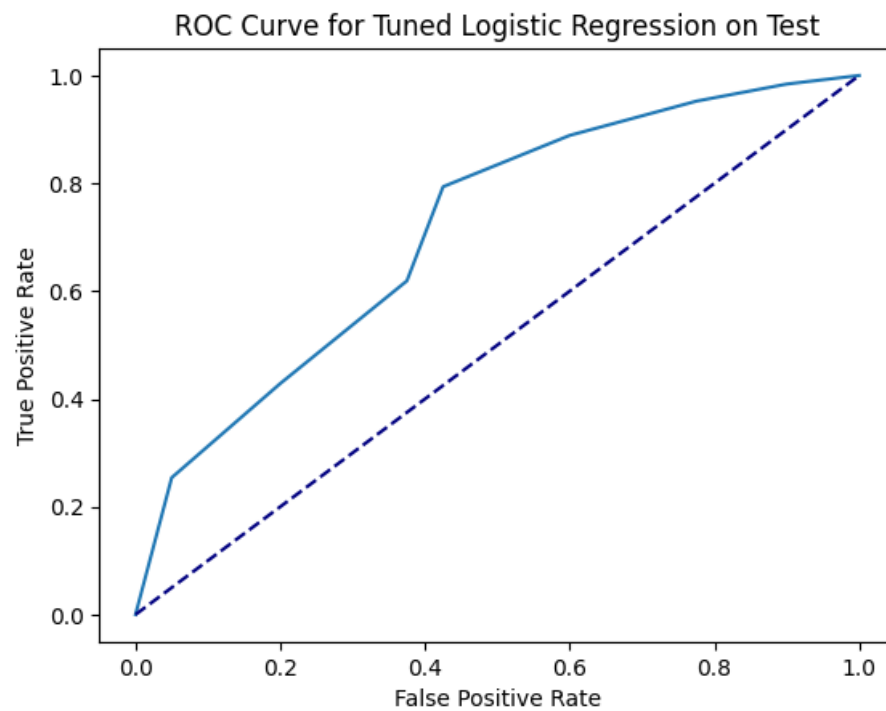
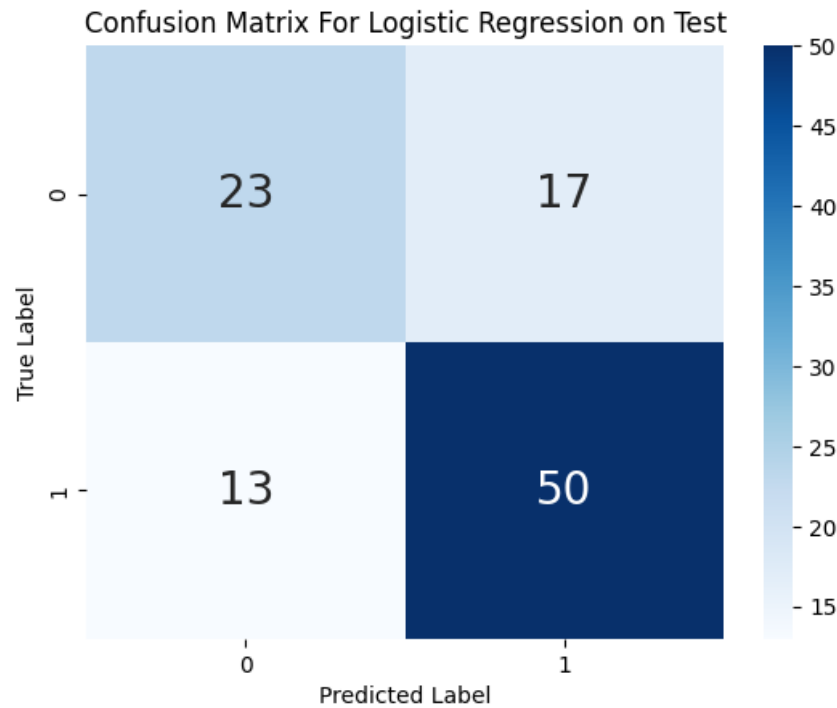
# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Logistic Regression on Test")

# Show the plot
plt.show()

### ROC CURVE
y_pred_lr_grid_proba = lr.predict_proba(x_test)[:,1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_lr_grid_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned Logistic Regression on Test')
plt.show()
```

The AUC-ROC score for Logistic Regression on Test is: 0.6843253968253967  
 The F1 score for Logistic Regression on Test is : 0.7692307692307693



## ✓ GRADIENT BOOSTING

### ✓ DECLARE GRADIENT BOOSTING OBJECT

```
from sklearn.ensemble import GradientBoostingClassifier
# create the Gradient Boosting model
gb = GradientBoostingClassifier(random_state=42)
```

## ✓ BASE MODEL

```
### TRAIN & PREDICT THE MODEL
gb.fit(x_over, y_over)
y_pred_gb = gb.predict(x_val)

### EVALUATION
roc_gb_base = roc_auc_score(y_val, y_pred_gb)
f1_gb_base = f1_score(y_val, y_pred_gb)
print('The AUC-ROC score for Base Gradient Boosting is:', roc_gb_base)
print('The F1 score for Base Gradient Boosting is:', f1_gb_base)

# print("Accuracy:", accuracy)
cm = confusion_matrix(y_val, y_pred_gb)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Base Gradient Boosting")

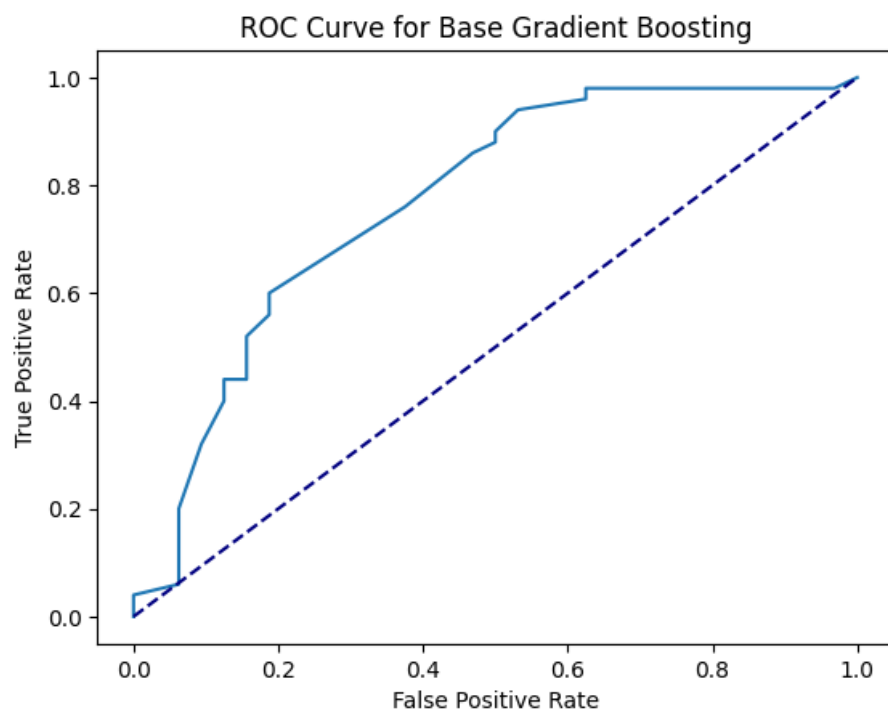
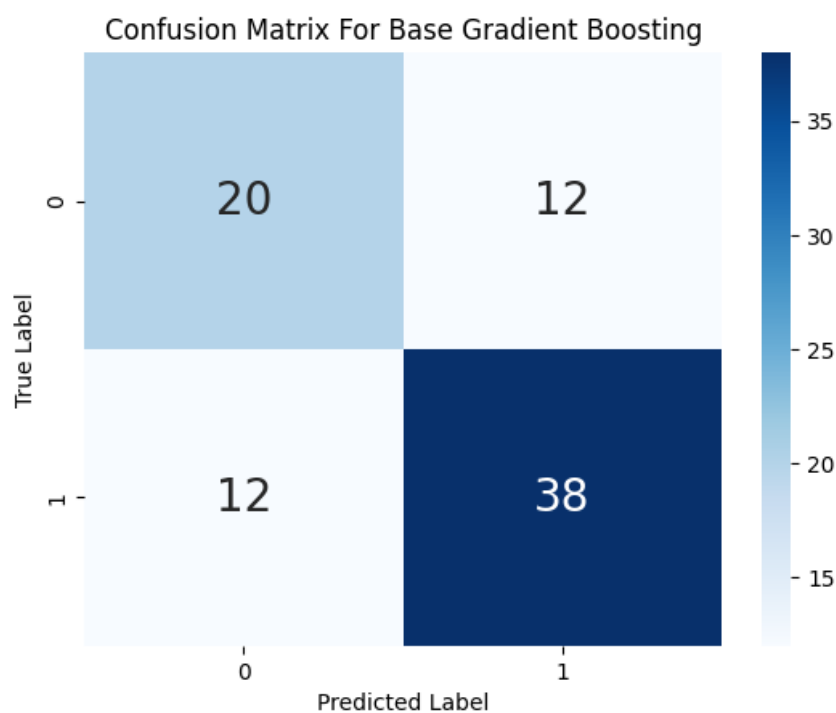
# Show the plot
plt.show()

### ROC CURVE
#define metrics
y_gb_base_proba = gb.predict_proba(x_val)[:,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_gb_base_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Base Gradient Boosting')
plt.show()
```

The AUC-ROC score for Base Gradient Boosting is: 0.6925000000000001

The F1 score for Base Gradient Boosting is: 0.76



## ✓ HYPERPARAMETER TUNING GRADIENT BOOSTING

```

# Define parameter grid for GridSearchCV
param_grid = {'learning_rate': [0.001, 0.01, 0.01, 0.1, 1], 'n_estimators': [50, 100, 200, 250, 300], 'max_de

# Define GridSearchCV object with Gradient Boosting model and parameter grid
grid_search = GridSearchCV(estimator=gb, param_grid=param_grid, cv=5, scoring = 'f1', n_jobs=-1)

# Fit the GridSearchCV object to the training data
grid_search.fit(x_over, y_over)

#### GET THE BEST PARAMS
best_params = grid_search.best_params_
print('The best parameters are:', best_params)

#### FIT & PREDICT BASED ON THE NEW PARAMS
gb.set_params(random_state = 42, **best_params)
gb.fit(x_over, y_over)
y_gb_grid = gb.predict(x_val)

#### EVALUATION

f1_gb_grid = f1_score(y_val, y_gb_grid)
roc_gb_grid = roc_auc_score(y_val, y_gb_grid)
print('The AUC-ROC score for Gradient Boosting After Tuning is:', roc_gb_grid)
print('The F1 score for Gradient Booting After Tuning is :', f1_gb_grid)

#### CONFUSION MATRIX

cm = confusion_matrix(y_val, y_gb_grid)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned Gradient Boosting on Validatio")

# Show the plot
plt.show()

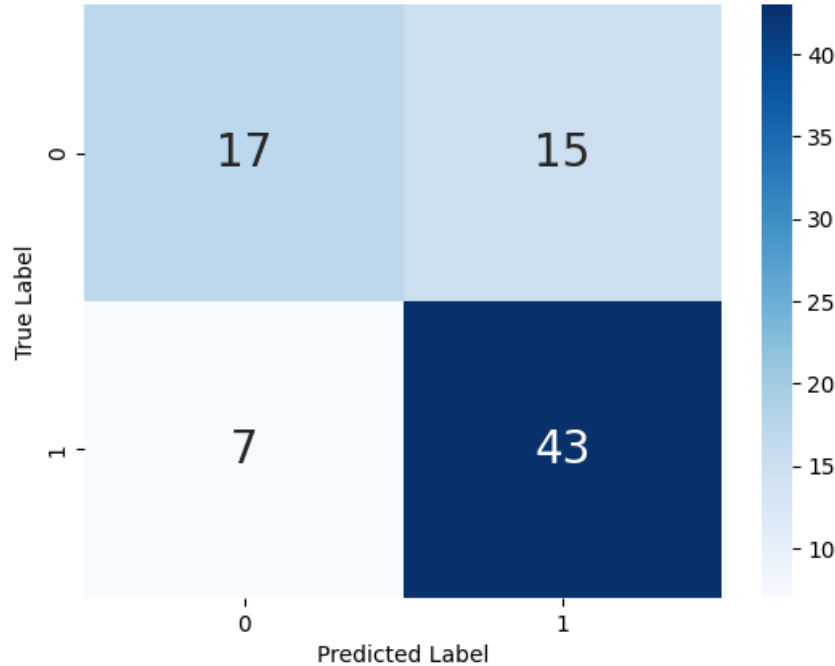
#### ROC CURVE
y_gb_grid_proba = gb.predict_proba(x_val)[:,:1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_gb_grid_proba)

#create ROC curve
plt.plot(fpr, tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Gradient Boosting on Validation')
plt.show()

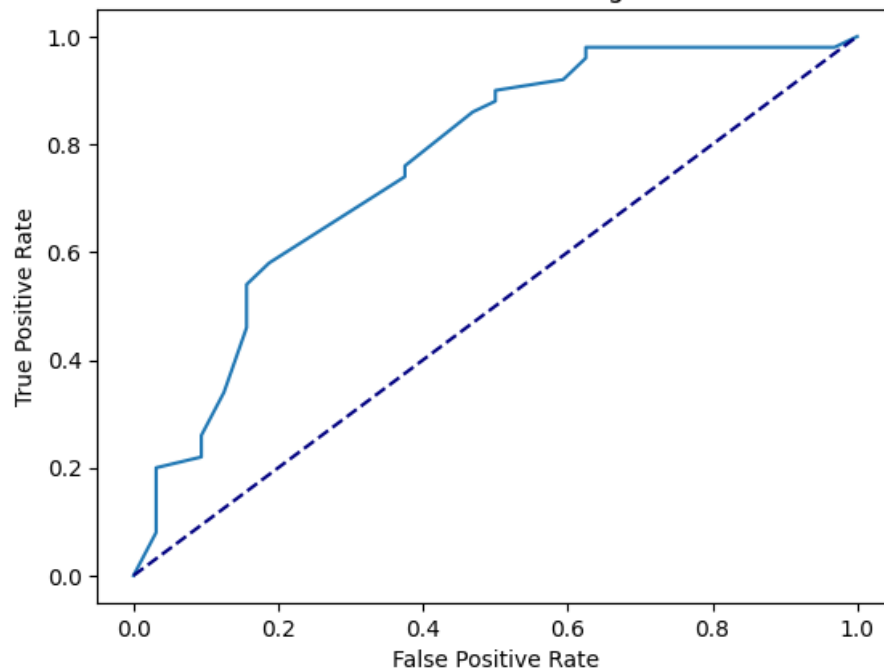
```

The best parameters are: {'learning\_rate': 1, 'max\_depth': 3, 'n\_estimators': 30}  
The AUC-ROC score for Gradient Boosting After Tuning is: 0.6956249999999999  
The F1 score for Gradient Boosting After Tuning is : 0.7962962962962963

**Confusion Matrix For Tuned Gradient Boosting on Validation**



**ROC Curve for Gradient Boosting on Validation**



▼ ON THE TEST

```
gb.fit(x_train_final, y_train_final)
y_gb_final_preds = gb.predict(x_test)

### TEST EVALUATION

f1_gb_grid_test = f1_score(y_test, y_gb_final_preds)
roc_gb_grid_test = roc_auc_score(y_test, y_gb_final_preds)
print('The AUC-ROC score for Gradient Boosting After Tuning is:', roc_gb_grid_test)
print('The F1 score for Gradient Boosting After Tuning is :', f1_gb_grid_test)

### CONFUSION MATRIX

cm = confusion_matrix(y_test, y_gb_final_preds)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned Gradient Boosting on Test")

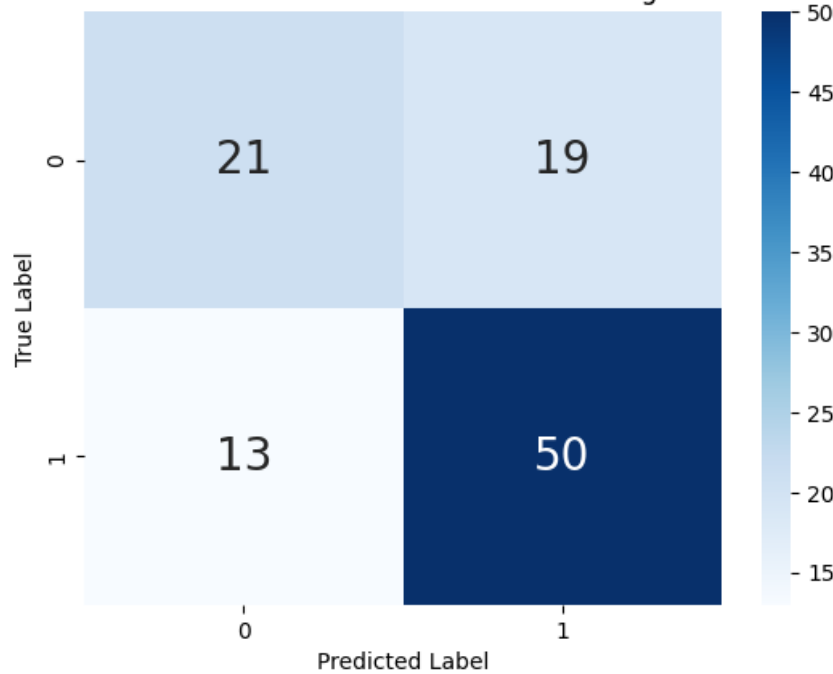
# Show the plot
plt.show()

### ROC CURVE
y_pred_gb_grid_proba = gb.predict_proba(x_test)[:,:1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_gb_grid_proba)

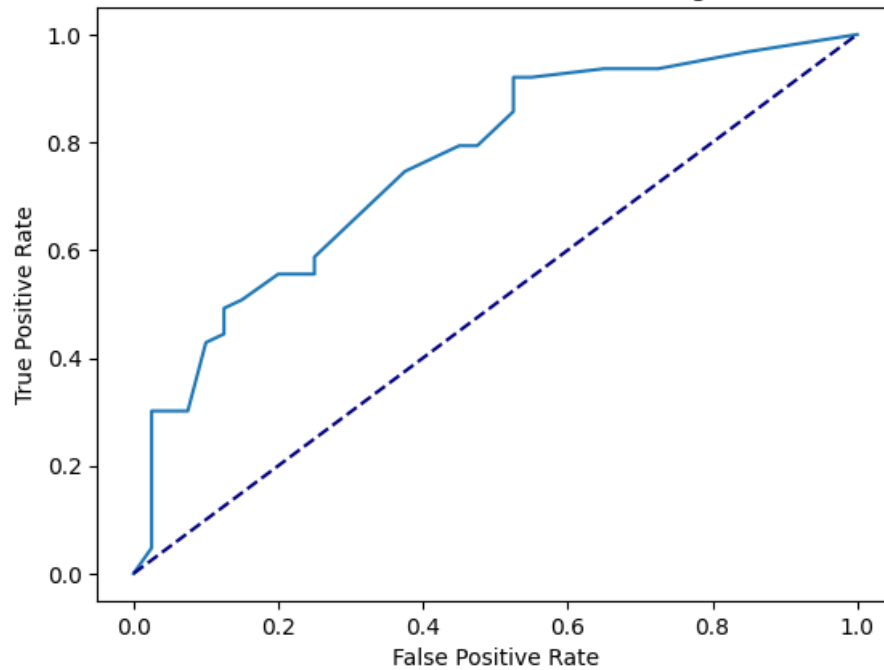
#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned Gradient Boosting on Test')
plt.show()
```

The AUC-ROC score for Gradient Boosting After Tuning is: 0.6593253968253968  
The F1 score for Gradient Boosting After Tuning is : 0.7575757575757576

Confusion Matrix For Tuned Gradient Boosting on Test



ROC Curve for Tuned Gradient Boosting on Test



✓ SVC

✓ SVC Instance

```
from sklearn.svm import SVC  
  
svc = SVC(random_state=42, probability = True)
```



## ✓ BASE MODEL

```
# Train, Fit, and Predict
svc.fit(x_over, y_over)

# predict the outcomes of the penalty kicks using the trained model
y_svm_base = svc.predict(x_val)

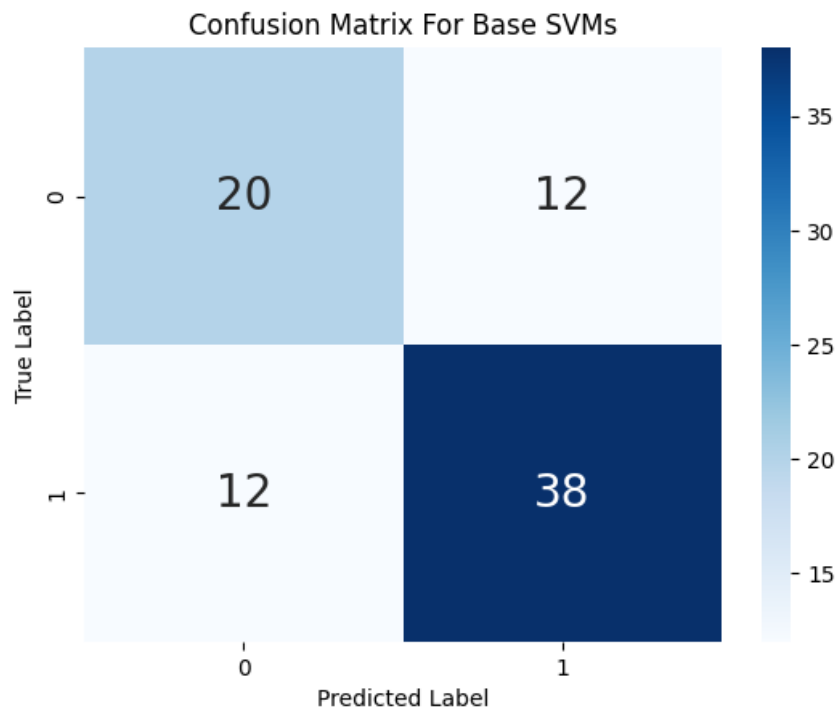
# Evaluation Metrics
roc_svm_base = roc_auc_score(y_val, y_svm_base)
f1_svm_base = f1_score(y_val, y_svm_base)
print('The AUC-ROC score for SVM is:', roc_svm_base)
print('The F1 score for SVM is:', f1_svm_base)
cm = confusion_matrix(y_val, y_svm_base)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Base SVMs")

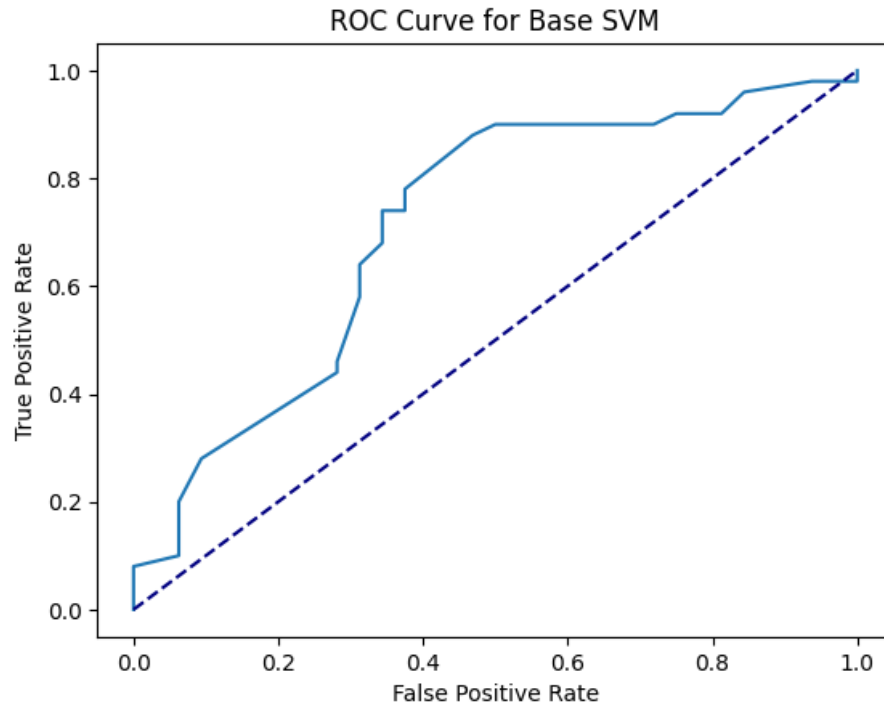
# Show the plot
plt.show()
```

The AUC-ROC score for SVM is: 0.6925000000000001  
The F1 score for SVM is: 0.76



```
#define metrics
y_pred_svm_base_proba = svc.predict_proba(x_val)[:,-1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_svm_base_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.title('ROC Curve for Base SVM')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



## ▼ TUNE THE HYPERPARAMETERS

```
# Define the parameter grid to search over
param_grid = {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf'], 'gamma': [0.1, 1, 10]}
grid_search = GridSearchCV(estimator=svc, param_grid=param_grid, cv=5, scoring='f1', n_jobs=-1)
grid_search.fit(x_over, y_over)

### GET THE BEST PARAMS
best_params = grid_search.best_params_
print('The best parameters are:', best_params)

### FIT & PREDICT BASED ON THE NEW PARAMS
svc.set_params(random_state = 42, **best_params)
print('rfc parameters:', svc.get_params())
svc.fit(x_over, y_over)
y_svm_grid = svc.predict(x_val)

### EVALUATION

f1_svm_grid = f1_score(y_val, y_svm_grid)
roc_svm_grid = roc_auc_score(y_val, y_svm_grid)
print('The AUC-ROC score for Random Forest After Tuning is:', roc_svm_grid)
print('The F1 score for Random Forest Tree After Tuning is :', f1_svm_grid)

### CONFUSION MATRIX

cm = confusion_matrix(y_val, y_svm_grid)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

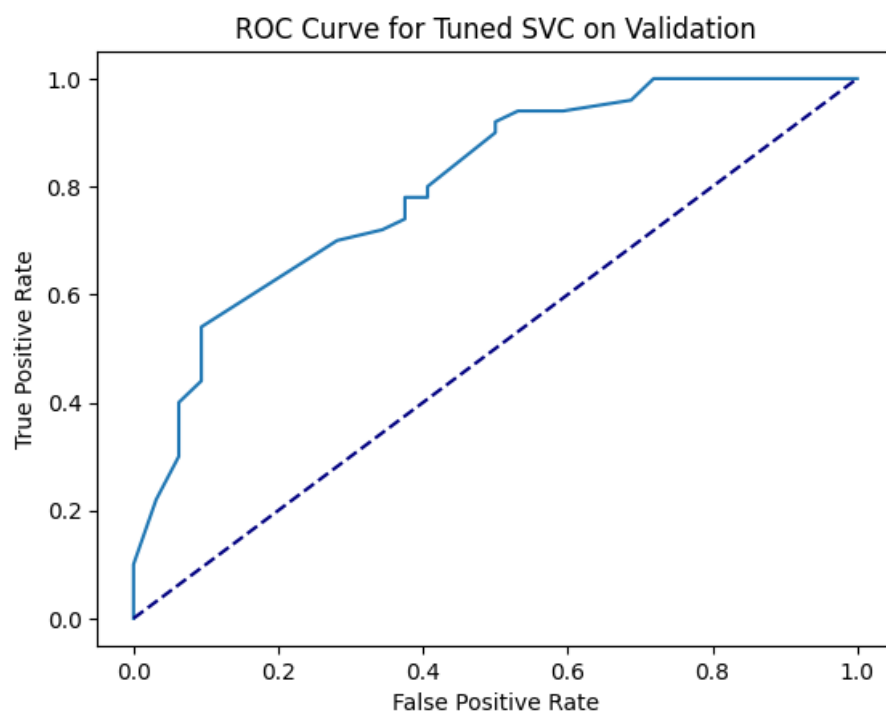
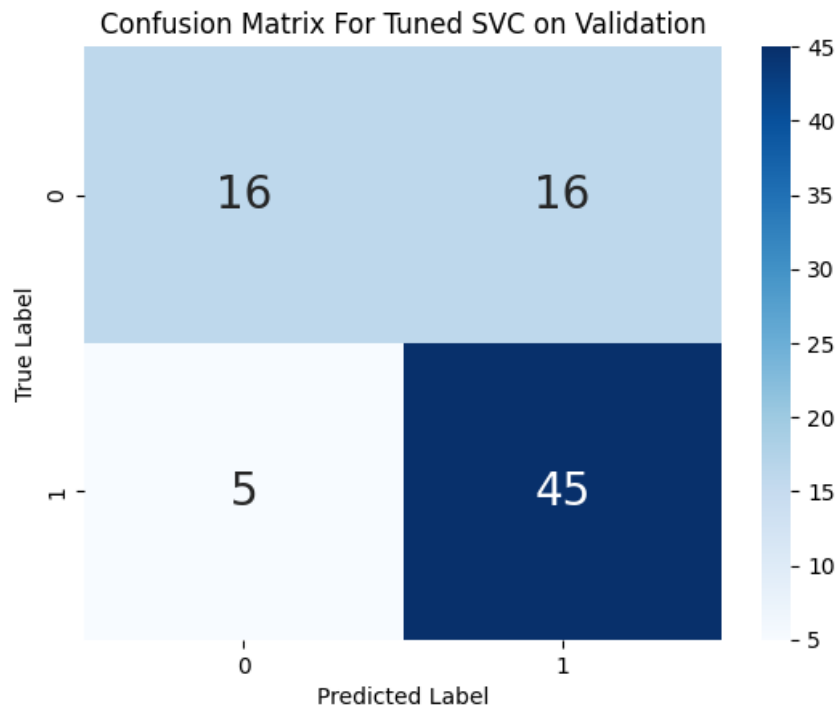
# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned SVC on Validation")

# Show the plot
plt.show()

### ROC CURVE
y_pred_svm_grid_proba = svc.predict_proba(x_val)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_svm_grid_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned SVC on Validation')
plt.show()
```

The best parameters are: {'C': 0.1, 'gamma': 10, 'kernel': 'rbf'}  
rfc parameters: {'C': 0.1, 'break\_ties': False, 'cache\_size': 200, 'class\_weight': 'balanced', 'criterion': 'entropy', 'max\_depth': 10, 'max\_features': 'sqrt', 'max\_leaf\_nodes': 100, 'min\_impurity\_decrease': 0.0001, 'min\_impurity\_split': 0.05, 'min\_samples\_leaf': 10, 'min\_samples\_split': 10, 'n\_estimators': 100, 'oob\_score': False, 'random\_state': 42, 'verbose': 0}  
The AUC-ROC score for Random Forest After Tuning is: 0.7  
The F1 score for Random Forest Tree After Tuning is : 0.8108108108108109



▼ NOW WITH THE TEST

```

svc.fit(x_over, y_over)
y_svm_test = svc.predict(x_test)

### EVALUATION

f1_svm_test = f1_score(y_test, y_svm_test)
roc_svm_test = roc_auc_score(y_test, y_svm_test)
print('The AUC-ROC score for Random Forest After Tuning is:', roc_svm_test)
print('The F1 score for Random Forest Tree After Tuning is :', f1_svm_test)

### CONFUSION MATRIX

cm = confusion_matrix(y_test, y_svm_test)

# Create heatmap of confusion matrix using seaborn
sns.heatmap(cm, annot=True, cmap = 'Blues', fmt="d", annot_kws={"size": 20})

# Set plot labels and title
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix For Tuned SVC on Test")

# Show the plot
plt.show()

### ROC CURVE
y_pred_svm_test_proba = svc.predict_proba(x_val)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_svm_test_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve for Tuned SVC on Test')
plt.show()

```

The AUC-ROC score for Random Forest After Tuning is: 0.6593253968253968  
The F1 score for Random Forest Tree After Tuning is : 0.7575757575757576

