Task -2 Predictive Modeling on Titanic Dataset

Task description: 1.simple binary classification model using Titanic dataset 2.Logistic Regression and evaluate its performance. 3.Visualize key metrics such as accuracy,precision,recall,and the ROC curve.

1.Simple binary clasification model using Titanic dataset.

In [5]:
```
import pandas as pd
```

In [6]:
```
#Load the Titanic dataset
titanic_df = pd.read_csv(r'C:\Users\sathi\Downloads\Titanic.csv')
titanic_df
```

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
413	1305	0	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	1	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	0	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
416	1308	0	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
417	1309	0	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

418 rows × 12 columns

In [8]:
```
titanic_df.head()
```

Out[8]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

In [9]:
```
titanic_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Survived     418 non-null    int64  
 2   Pclass       418 non-null    int64  
 3   Name         418 non-null    object 
 4   Sex          418 non-null    object 
 5   Age          332 non-null    float64
 6   SibSp        418 non-null    int64  
 7   Parch        418 non-null    int64  
 8   Ticket       418 non-null    object 
 9   Fare         417 non-null    float64
 10  Cabin        91 non-null     object 
 11  Embarked     418 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 39.3+ KB
```

In [10]:
```
titanic_df.describe()
```

Out[10]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	0.363636	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.481622	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	0.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	0.000000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	0.000000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	1.000000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	1.000000	3.000000	76.000000	8.000000	9.000000	512.329200

In [11]:
```
titanic_df.columns
```

Out[11]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [27]:
```
titanic_df.isnull().sum()
```

Out[27]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

In [28]:
```
titanic_df.drop(['PassengerId', 'Name', 'Ticket', 'Cabin', 'Embarked'], axis=1, inplace=True)
titanic_df['Age'].fillna(titanic_df['Age'].mean(), inplace=True)
```

In [29]:
```
titanic_df = pd.get_dummies(titanic_df, columns=['Sex'], drop_first=True)
```

In [30]:
```
titanic_df.isnull().sum()
```

Out[30]:
```
Survived    0
Pclass      0
Age         0
SibSp       0
Parch       0
Fare        1
Sex_male    0
dtype: int64
```

2.Select and appropriate algorithm Logistic Regression

In [42]:
```
# Importing necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score

# Step 1: Handle missing values
# Assuming you want to impute missing values with the mean of each feature
imputer = SimpleImputer(strategy='mean')
titanic_df_imputed = imputer.fit_transform(titanic_df)

# Convert the imputed data back to a DataFrame (if necessary)
titanic_df_imputed = pd.DataFrame(titanic_df_imputed, columns=titanic_df.columns)

# Step 2: Split the data into features (X) and target variable (y)
X = titanic_df_imputed.drop('Survived', axis=1)  # Features
y = titanic_df_imputed['Survived']  # Target variable

# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 4: Choose a machine learning algorithm and train the model
```

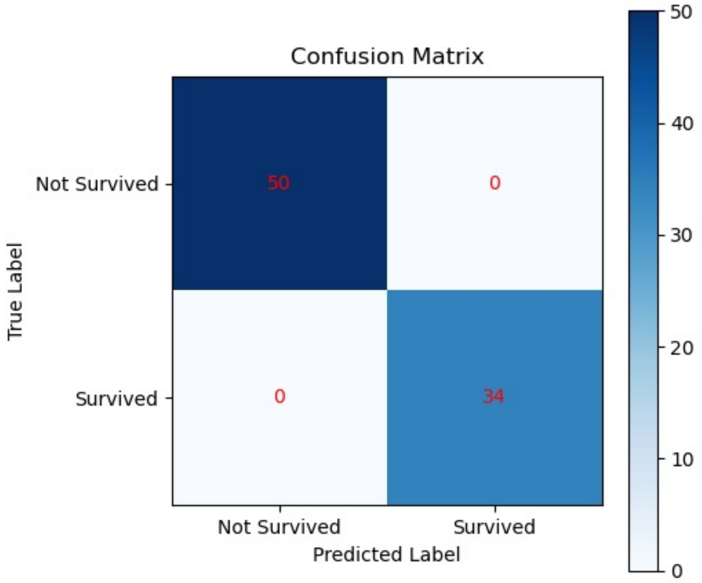
```
model = LogisticRegression()
model.fit(X_train, y_train)

# Step 5: Evaluate the model
y_pred = model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

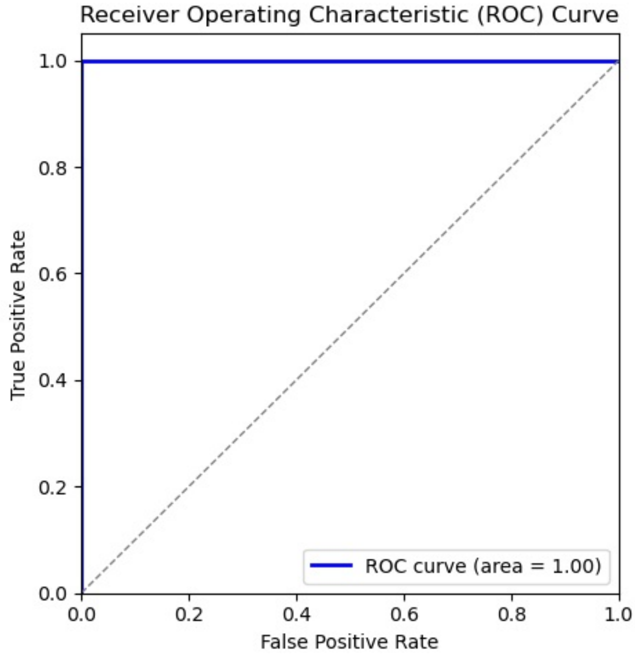
```
Accuracy: 1.0
```

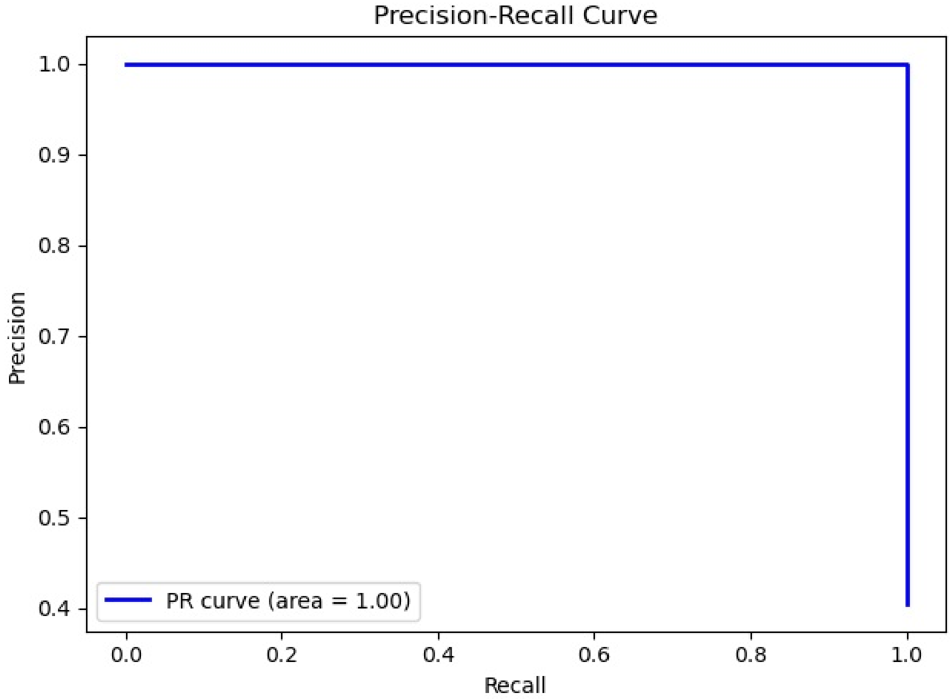
3.Visualize key metrics such as accuracy,precision,recall,and the ROC curve.

In [44]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score, precision_recall_curve, auc

# Calculate confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Calculate ROC curve
fpr, tpr, thresholds_roc = roc_curve(y_test, y_pred)
roc_auc = auc(fpr, tpr)

# Calculate precision-recall curve
precision, recall, thresholds_pr = precision_recall_curve(y_test, y_pred)
pr_auc = auc(recall, precision)

# Plot confusion matrix
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.xticks([0, 1], ['Not Survived', 'Survived'])
plt.yticks([0, 1], ['Not Survived', 'Survived'])
plt.grid(False)
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, cm[i, j], ha='center', va='center', color='red')

# Plot ROC curve
plt.subplot(1, 2, 2)
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', lw=1, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")

plt.tight_layout()
plt.show()

# Plot precision-recall curve
plt.figure()
plt.plot(recall, precision, color='blue', lw=2, label='PR curve (area = %0.2f)' % pr_auc)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc="lower left")

plt.tight_layout()
plt.show()
```







In [ ]:

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