Import necessary libraries

In [1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confus
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree
```

Load the Titanic dataset

In [2]:
```
df = pd.read_csv('/kaggle/input/test-file/tested.csv')
```

Explore the dataset

Display the first few rows of the DataFrame

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

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.829
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.000
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.687
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.662
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.287

Display descriptive statistics of numerical columns

In [4]:
```
df.describe()
```

Out[4]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	
count	418.000000	418.000000	418.000000	332.000000	418.000000	418.000000	417.0
mean	1100.500000	0.363636	2.265550	30.272590	0.447368	0.392344	35.6
std	120.810458	0.481622	0.841838	14.181209	0.896760	0.981429	55.9
min	892.000000	0.000000	1.000000	0.170000	0.000000	0.000000	0.0
25%	996.250000	0.000000	1.000000	21.000000	0.000000	0.000000	7.8
50%	1100.500000	0.000000	3.000000	27.000000	0.000000	0.000000	14.4
75%	1204.750000	1.000000	3.000000	39.000000	1.000000	0.000000	31.5
max	1309.000000	1.000000	3.000000	76.000000	8.000000	9.000000	512.3

Display descriptive statistics of all columns, including categorical ones

In [5]:
```
print(df.describe(include='all'))
```

```
        PassengerId    Survived      Pclass                Name   Sex  \
count    418.000000  418.000000  418.000000                 418   418
unique          NaN         NaN         NaN                 418     2
top             NaN         NaN         NaN  Kelly, Mr. James  male
freq            NaN         NaN         NaN                   1   266
mean    1100.500000    0.363636    2.265550                 NaN   NaN
std      120.810458    0.481622    0.841838                 NaN   NaN
min      892.000000    0.000000    1.000000                 NaN   NaN
25%      996.250000    0.000000    1.000000                 NaN   NaN
50%     1100.500000    0.000000    3.000000                 NaN   NaN
75%     1204.750000    1.000000    3.000000                 NaN   NaN
max     1309.000000    1.000000    3.000000                 NaN   NaN

               Age       SibSp       Parch    Ticket        Fare  \
count   332.000000  418.000000  418.000000       418  417.000000
unique         NaN         NaN         NaN       363         NaN
top            NaN         NaN         NaN  PC 17608         NaN
freq           NaN         NaN         NaN         5         NaN
mean     30.272590    0.447368    0.392344       NaN   35.627188
std      14.181209    0.896760    0.981429       NaN   55.907576
min       0.170000    0.000000    0.000000       NaN    0.000000
25%      21.000000    0.000000    0.000000       NaN    7.895800
50%      27.000000    0.000000    0.000000       NaN   14.454200
75%      39.000000    1.000000    0.000000       NaN   31.500000
max      76.000000    8.000000    9.000000       NaN  512.329200

                  Cabin Embarked
count                91      418
unique               76        3
top     B57 B59 B63 B66        S
freq                  3      270
mean                NaN      NaN
std                 NaN      NaN
min                 NaN      NaN
25%                 NaN      NaN
50%                 NaN      NaN
75%                 NaN      NaN
max                 NaN      NaN
```

Display information about the DataFrame

In [6]:
```
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
```

missing values

Display the count of missing values for each column

In [7]:
```
df.isna().sum()
```

Out[7]:
```
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
```

Calculate the percentage of missing values for each column

In [8]:
```
df.isna().sum() / len(df) * 100
```

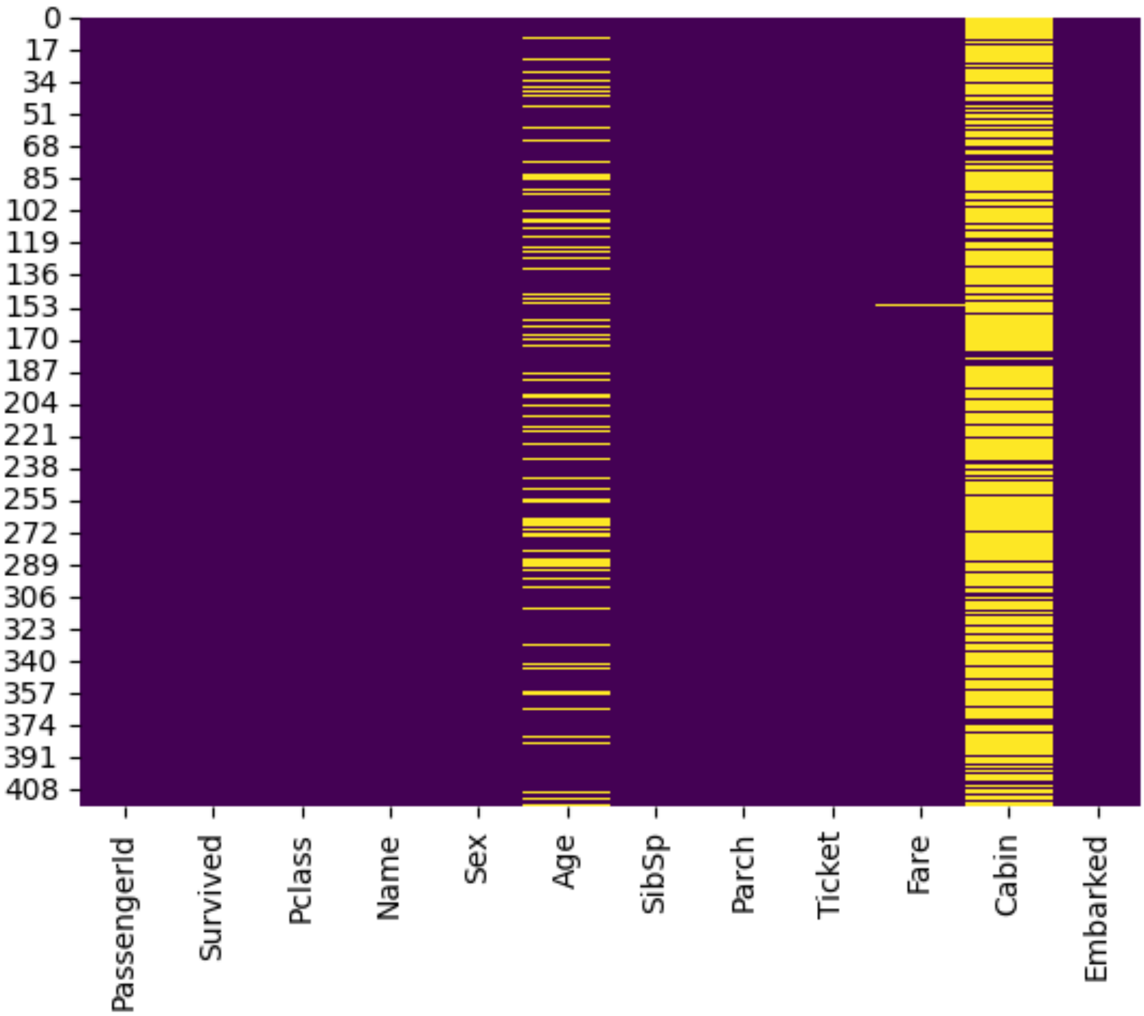
Out[8]:
```
PassengerId     0.000000
Survived        0.000000
Pclass          0.000000
Name            0.000000
Sex             0.000000
Age            20.574163
SibSp           0.000000
Parch           0.000000
Ticket          0.000000
Fare            0.239234
Cabin          78.229665
Embarked        0.000000
dtype: float64
```

In [9]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

Display a heatmap of missing values

In [10]:
```
sns.heatmap(df.isnull(), cmap='viridis', cbar=False)
```

Out[10]: <Axes: >



In [11]:
```
import numpy as np
```

Replace missing values in the 'Age' column with the mean

In [12]:
```
df['Age'].replace(np.nan, df['Age'].mean(), inplace=True)
```

Replace missing values in the 'Fare' column with the mean

In [13]:
```
df['Fare'].replace(np.nan, df['Fare'].mean(), inplace=True)
```

Drop the 'Cabin' column

In [14]:
```
df.head()
```

Out[14]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.829
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.000
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.687
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.662
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.287

In [15]:
```
df.drop('Cabin', axis=1,inplace=True)
```

In [16]:
```
df.head()
```

Out[16]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.829
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.000
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.687
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.662
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.287

Display the count of missing values after handling missing data

In [17]:
```
df.isna().sum()
```

Out[17]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

Display the number of unique values for each column

In [18]:
```
df.nunique()
```

Out[18]:
```
PassengerId    418
Survived         2
Pclass           3
Name           418
Sex              2
Age             80
SibSp            7
Parch            8
Ticket         363
Fare           170
Embarked         3
dtype: int64
```

seperate list of categorical and numerical variables

In [19]:
```
cat_var = ['Pclass', 'Sex', 'SibSp', 'Parch', 'Embarked']
num_var = ['Age', 'Fare']
```

Calculate the percentage distribution of 'Survived' variable and round to 2 decimal places

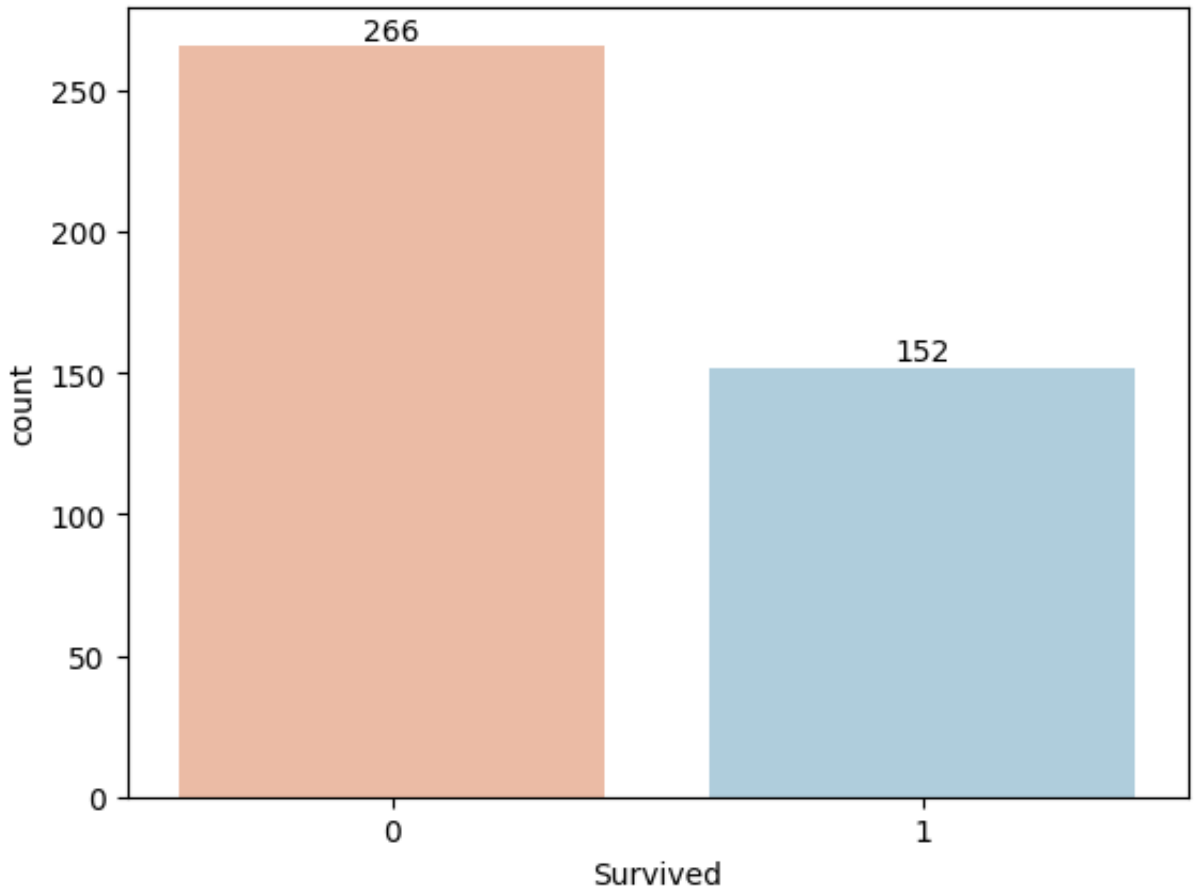
In [20]:
```
round(df['Survived'].value_counts(normalize=True)*100, 2)
```

Out[20]:
```
Survived
0    63.64
1    36.36
Name: proportion, dtype: float64
```

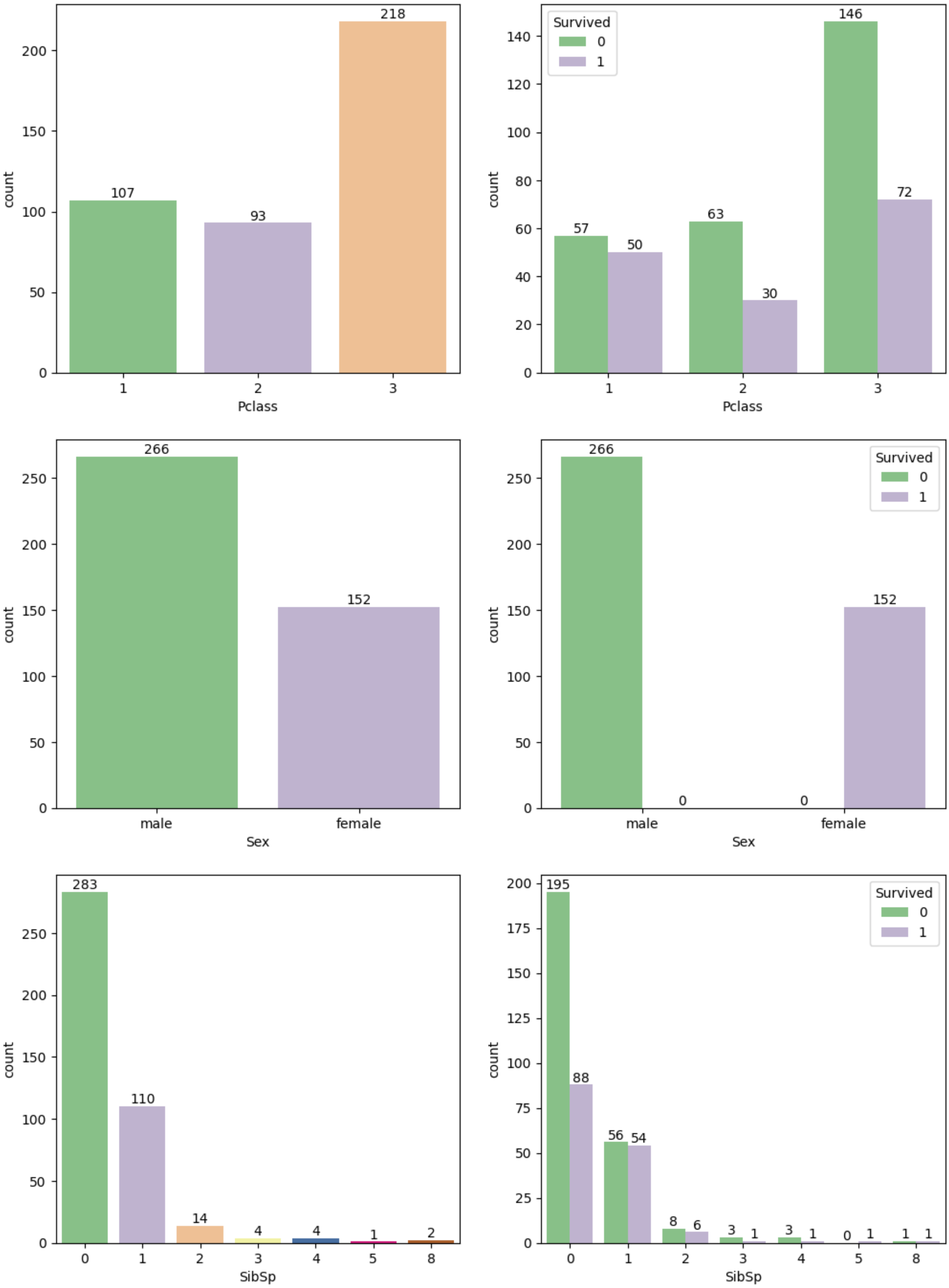
The dataset exhibits a slight imbalance, with 36.36% of passengers having survived the Titanic disaster and 63.64% of passengers not surviving.

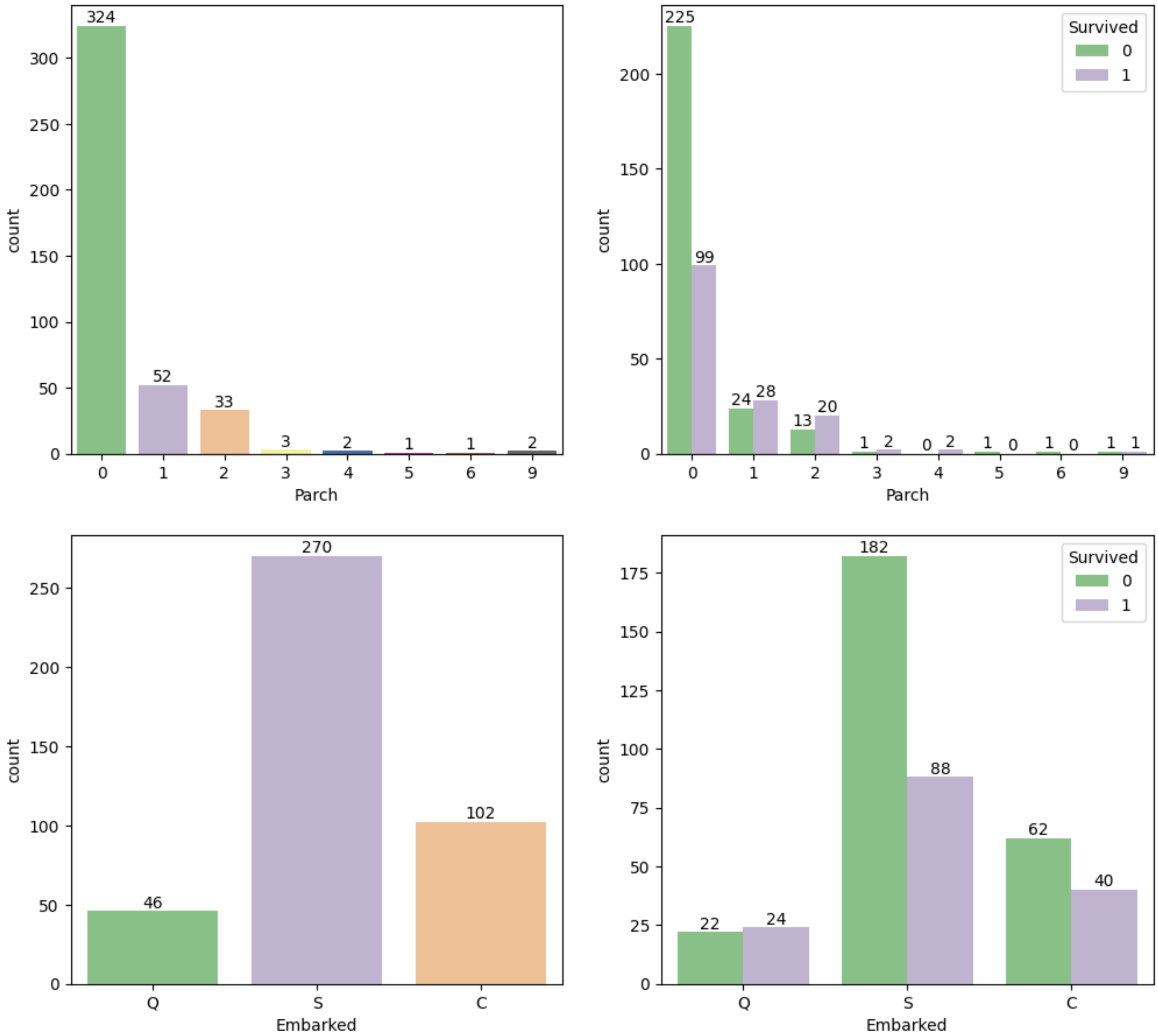
Create a countplot for 'Survived'

In [21]:
```
ax = sns.countplot(x=df['Survived'], palette='RdBu')
ax.bar_label(ax.containers[0])
plt.show()
```



In [22]:
```
# Loop through categorical variables
for column in cat_var:
    plt.figure(figsize=(12,5))

 # Plot count for each category
    plt.subplot(1,2,1)
    ax = sns.countplot(x=column, data=df, palette='Accent')
    ax.bar_label(ax.containers[0])

# Plot count for each category with 'Survived' as hue
    plt.subplot(1,2,2)
    ax = sns.countplot(x=column, data=df, hue='Survived', palette='Accent
    ax.bar_label(ax.containers[0])
    ax.bar_label(ax.containers[1])
    plt.show()
```


count
Pclass
107
93
218
Survived
0
1
57
50
63
30
146
72
Sex
male
female
266
152
0
SibSp
283
110
14
4
1
2
195
88
56
54
8
6
3



Display summary statistics for numerical variables

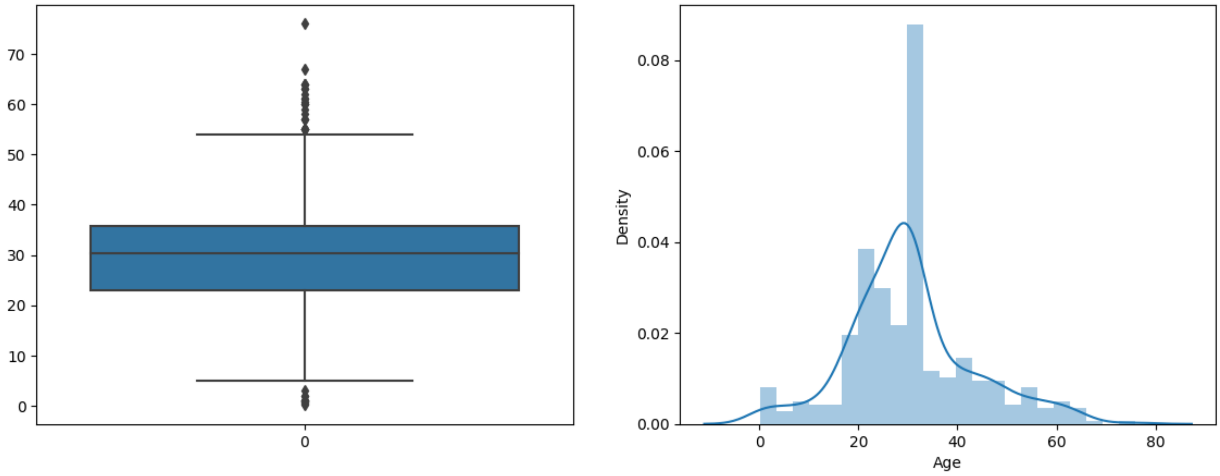
In [23]:
```
df[num_var].describe()
```

Out[23]:

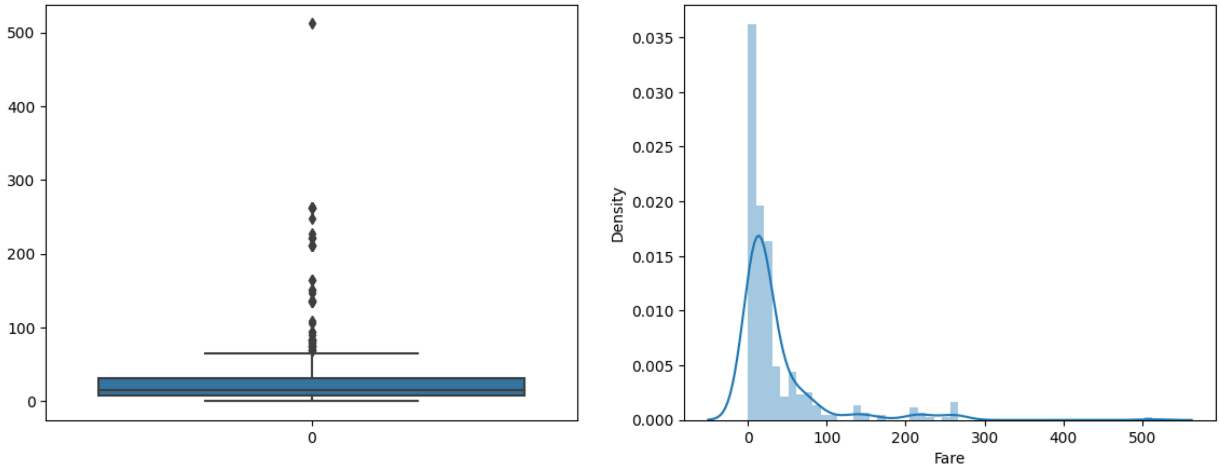
	Age	Fare
count	418.000000	418.000000
mean	30.272590	35.627188
std	12.634534	55.840500
min	0.170000	0.000000
25%	23.000000	7.895800
50%	30.272590	14.454200
75%	35.750000	31.500000
max	76.000000	512.329200

In [24]:
```
for column in num_var:
    plt.figure(figsize=(14,5))

# Boxplot
    plt.subplot(1,2,1)
    ax = sns.boxplot(df[column])

# Distribution plot
    plt.subplot(1,2,2)
    ax = sns.distplot(df[column])
    plt.show()
```

```
/tmp/ipykernel_88/860440053.py:10: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.
0.

Please adapt your code to use either `displot` (a figure-level function w
ith
similar flexibility) or `histplot` (an axes-level function for histogram
s).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  ax = sns.distplot(df[column])
```



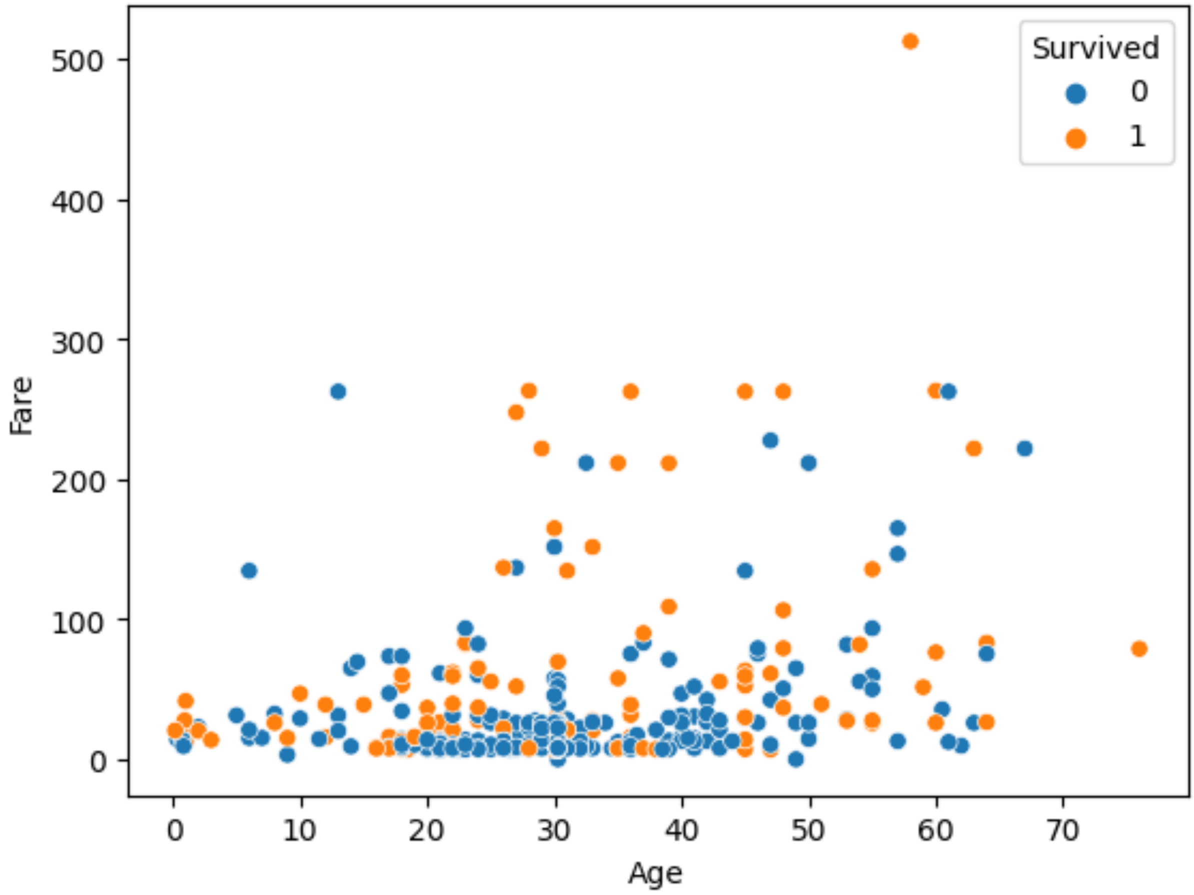

```
/tmp/ipykernel_88/860440053.py:10: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.
0.

Please adapt your code to use either `displot` (a figure-level function w
ith
similar flexibility) or `histplot` (an axes-level function for histogram
s).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  ax = sns.distplot(df[column])
```



Scatter plot with 'Age' on the x-axis, 'Fare' on the y-axis, and colored by 'Survived'

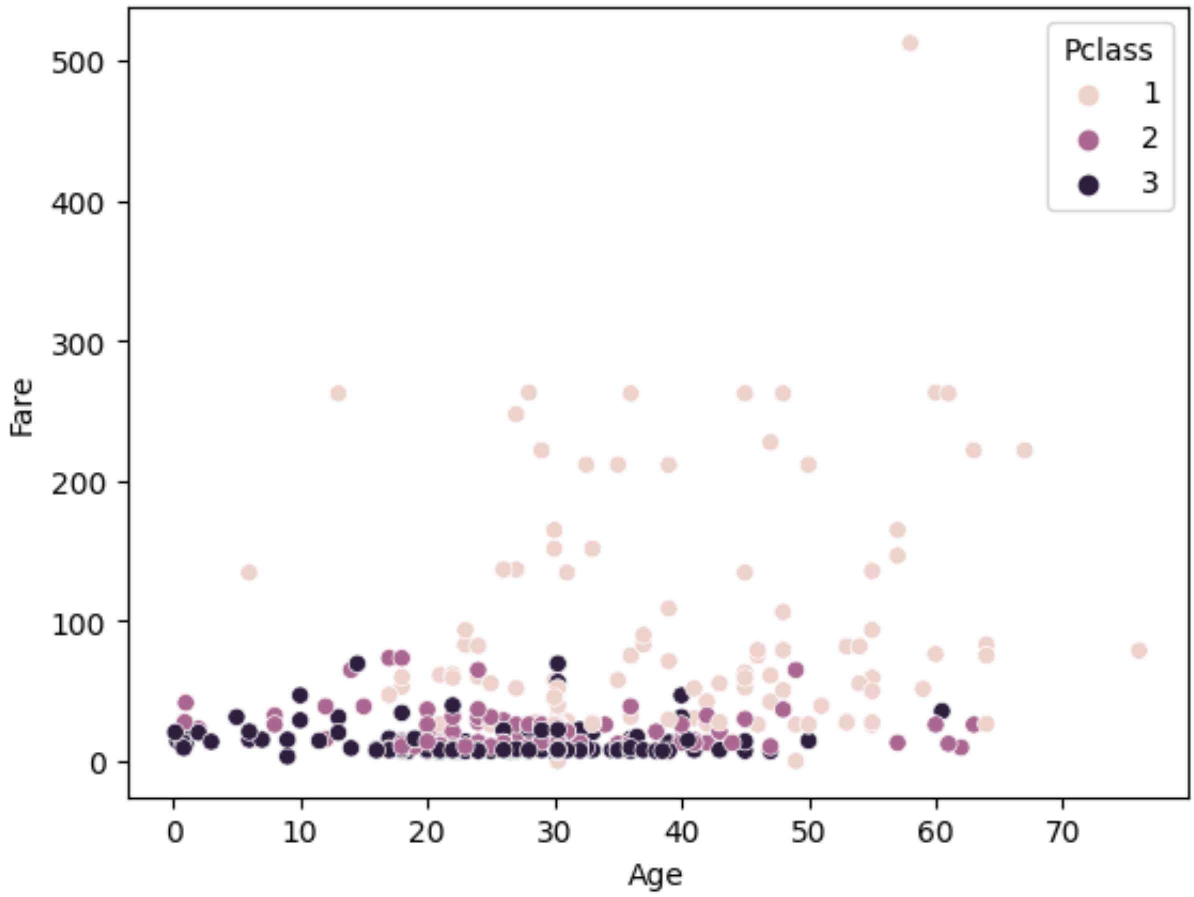
In [25]:
```
import seaborn as sns
```

In [26]:
```
sns.scatterplot(data=df, x='Age', y='Fare', hue='Survived')
plt.show()
```



Scatter plot with 'Age' on the x-axis, 'Fare' on the y-axis, and colored by 'Pclass'

In [27]:
```
sns.scatterplot(data=df, x='Age', y='Fare', hue='Pclass')
plt.show()
```



Drop specified features from the DataFrame

In [28]:
```
df_update = df.drop(['PassengerId','Name', 'Ticket'], axis=1)
df_update.head()
```

Out[28]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	34.5	0	0	7.8292	Q
1	1	3	female	47.0	1	0	7.0000	S
2	0	2	male	62.0	0	0	9.6875	Q
3	0	3	male	27.0	0	0	8.6625	S
4	1	3	female	22.0	1	1	12.2875	S

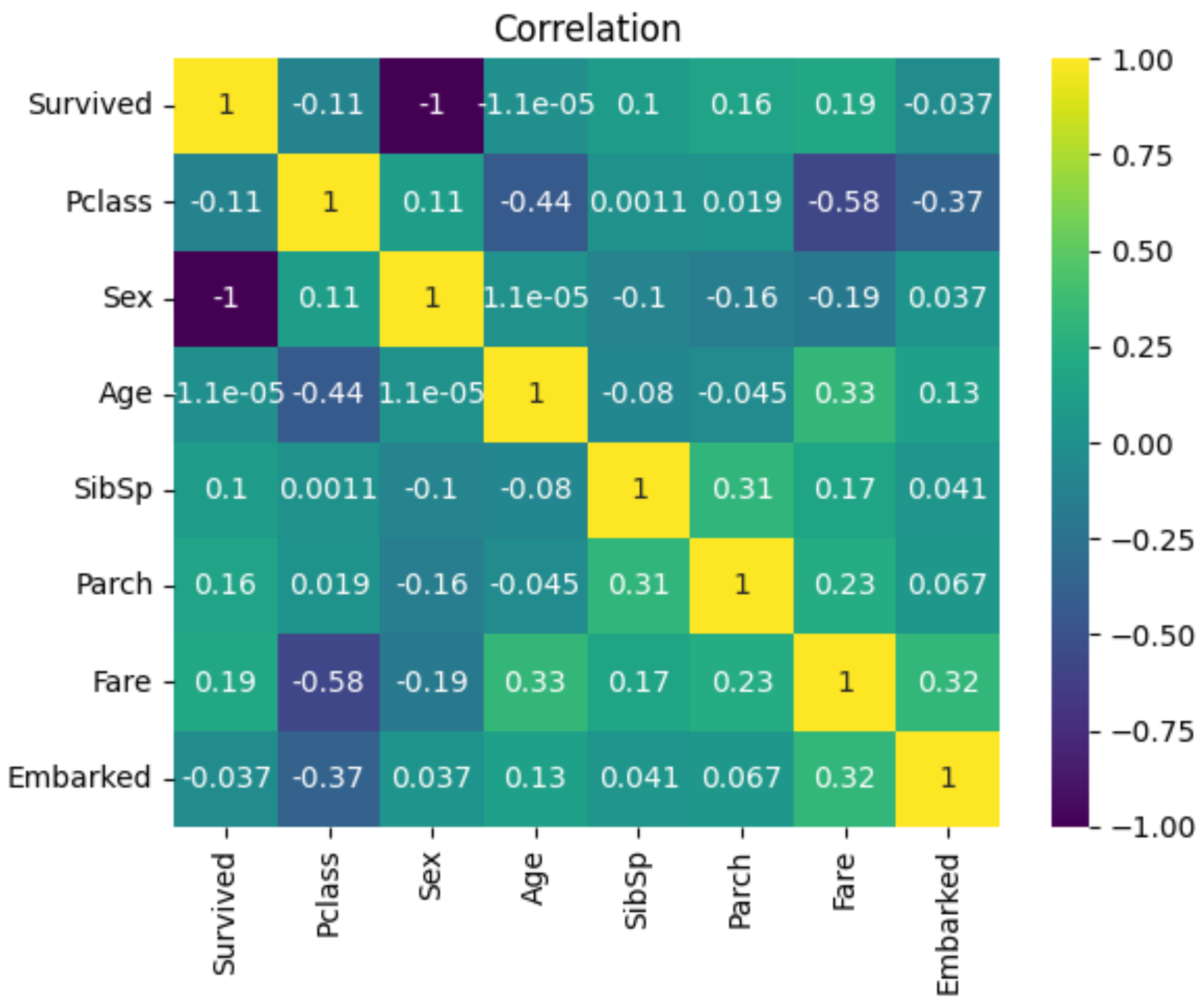
In [29]:
```
# Replace 'male' with 1 and 'female' with 0 in the 'Sex' column

df_update['Sex'].replace({'male':1, 'female':0}, inplace=True)
# Replace 'Q' with 0, 'S' with 1, and 'C' with 2 in the 'Embarked' column

df_update['Embarked'].replace({'Q':0, 'S':1, 'C':2}, inplace=True)
df_update.head()
```

Out[29]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	34.5	0	0	7.8292	0
1	1	3	0	47.0	1	0	7.0000	1
2	0	2	1	62.0	0	0	9.6875	0
3	0	3	1	27.0	0	0	8.6625	1
4	1	3	0	22.0	1	1	12.2875	1

Create a heatmap of the correlation matrix

In [30]:
```
sns.heatmap(df_update.corr(), annot=True, cmap='viridis')
plt.title('Correlation')
plt.show()
```



Construct and Evaluate Models

Logistic regression model

In [31]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score
confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay
```

In [32]:
```
X = df_update.drop('Survived', axis=1)
y = df_update['Survived']
X.head()
```

Out[32]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	3	1	34.5	0	0	7.8292	0
1	3	0	47.0	1	0	7.0000	1
2	2	1	62.0	0	0	9.6875	0
3	3	1	27.0	0	0	8.6625	1
4	3	0	22.0	1	1	12.2875	1

Split data into training and testing sets

In [33]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
```

In [34]:
```
LR = LogisticRegression(random_state=42)
LR.fit(X_train, y_train)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.p
y:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression
  n_iter_i = _check_optimize_result(
```

Out[34]:

```
▾ LogisticRegression
LogisticRegression(random_state=42)
```

Print the coefficients

In [35]:
```
LR.coef_
```

Out[35]:
```
array([[-1.74124850e-02, -6.13296513e+00,  1.66648140e-04,
         6.07157074e-02, -1.04665099e-02,  4.61842972e-03,
        -2.33451352e-01]])
```

Print the intercept

In [37]:
```
LR.intercept_
```

Out[37]:
```
array([2.8408376])
```

save predictions

In [40]:
```
y_pred_train = LR.predict(X_train)
```

In [41]:
```
print('Accuracy: ', accuracy_score(y_train, y_pred_train))
print('Precision: ', precision_score(y_train, y_pred_train))
print('Recall: ', recall_score(y_train, y_pred_train))
print('F1 Score: ', f1_score(y_train, y_pred_train))
```

```
Accuracy:  1.0
Precision:  1.0
Recall:  1.0
F1 Score:  1.0
```

Save predictions

In [42]:
```
y_pred_LR = LR.predict(X_test)
```

LR.predict(X_test)

Print out the predicted labels

In [43]:
```
LR.predict(X_test)
```

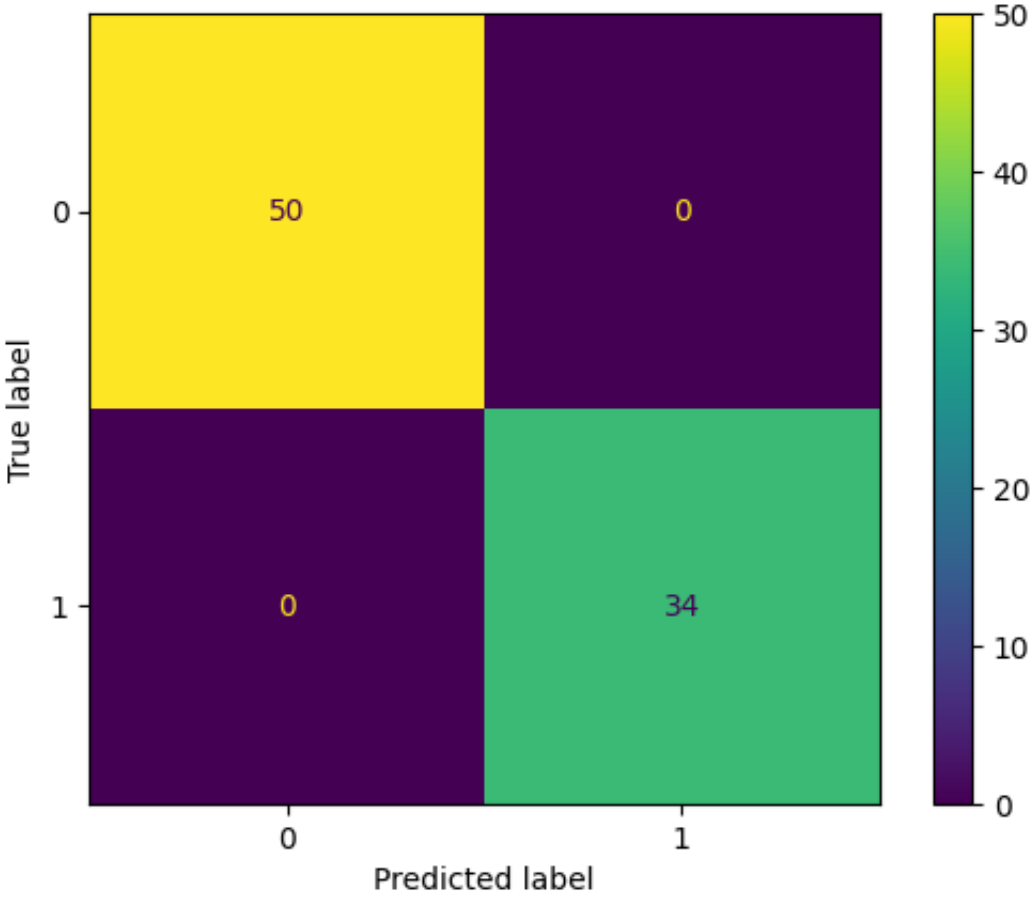
Out[43]:
```
array([0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0,
       0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1])
```

In [44]:
```
print('Accuracy: ', accuracy_score(y_test, y_pred_LR))
print('Precision: ', precision_score(y_test, y_pred_LR))
print('Recall: ', recall_score(y_test, y_pred_LR))
print('F1 Score: ', f1_score(y_test, y_pred_LR))
```

```
Accuracy:  1.0
Precision:  1.0
Recall:  1.0
F1 Score:  1.0
```

Create confusion matrix

In [45]:
```
cm = confusion_matrix(y_test, y_pred_LR, labels=LR.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=LR.clas
disp.plot();
```



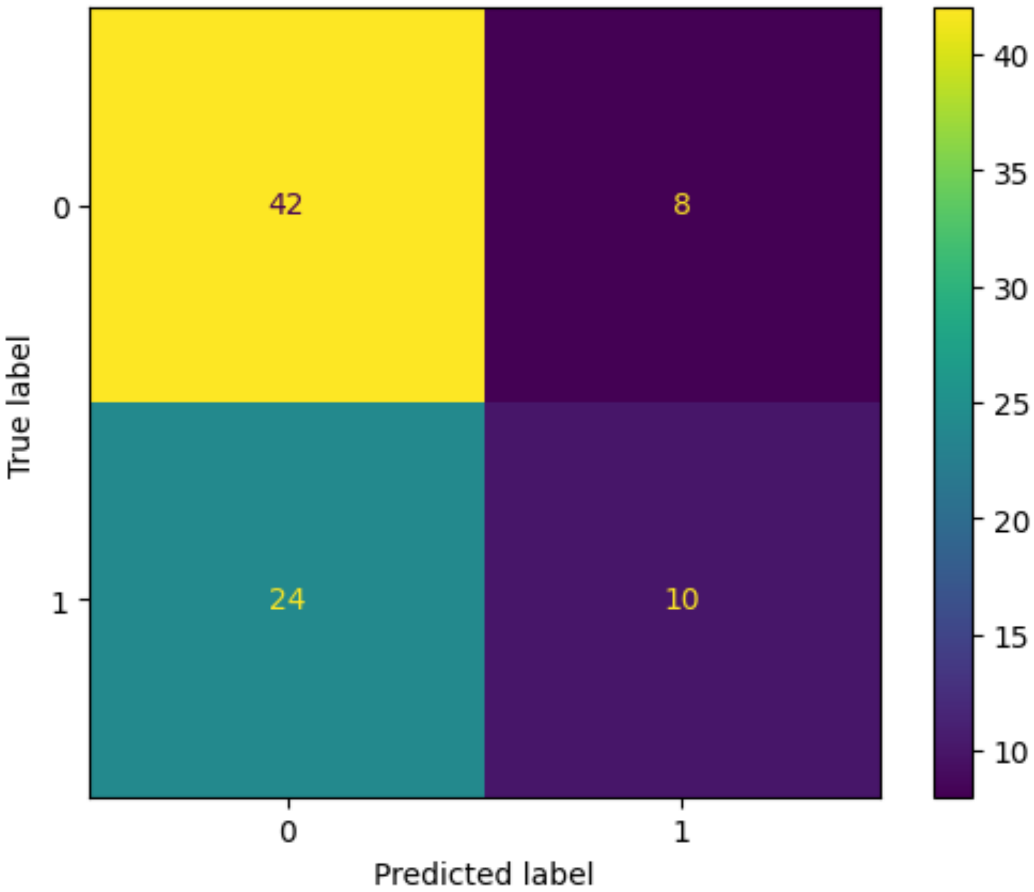
K-Nearest Neighbour

In [46]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()
knn.fit(X_train,y_train)
y_pred_knn = knn.predict(X_test)
```

In [47]:
```
print('Accuracy: ', accuracy_score(y_test, y_pred_knn))
print('Precision: ', precision_score(y_test, y_pred_knn))
print('Recall: ', recall_score(y_test, y_pred_knn))
print('F1 Score: ', f1_score(y_test, y_pred_knn))
```

```
Accuracy:  0.6190476190476191
Precision:  0.5555555555555556
Recall:  0.29411764705882354
F1 Score:  0.3846153846153846
```

In [48]:
```
cm = confusion_matrix(y_test, y_pred_knn, labels=knn.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=knn.cla
disp.plot();
```



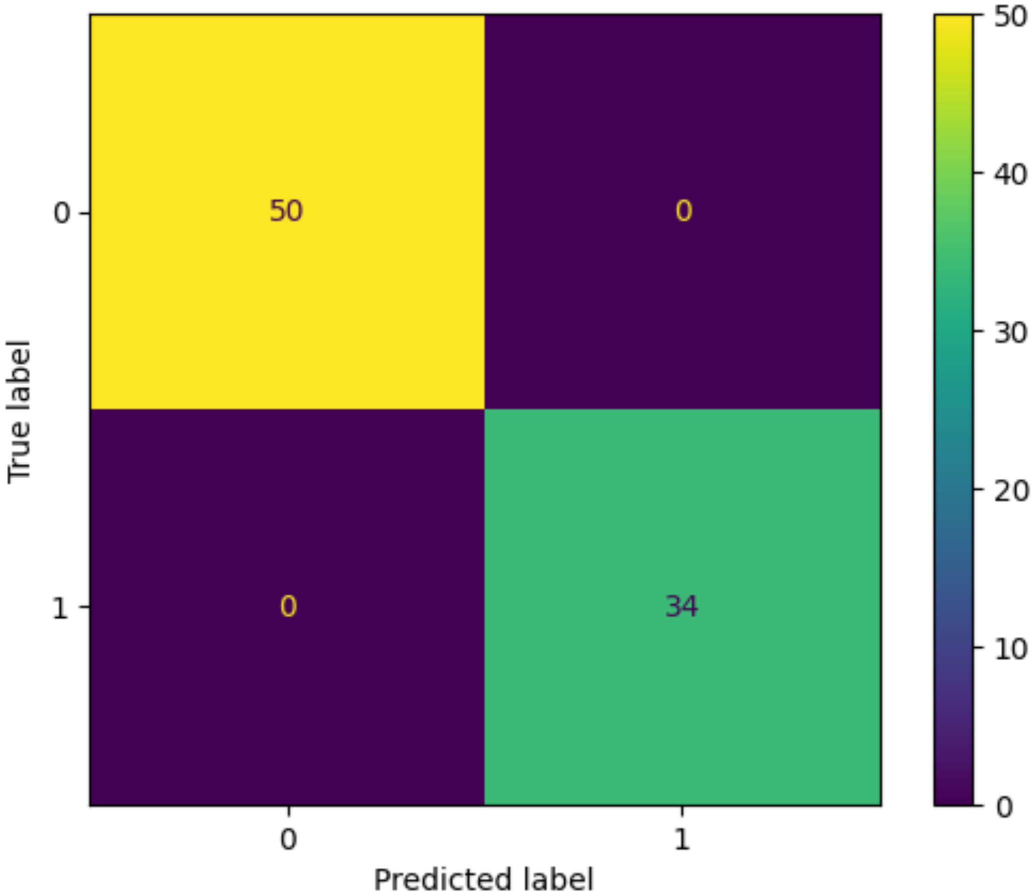
Decision Tree

In [49]:
```
from sklearn.tree import DecisionTreeClassifier

tree = DecisionTreeClassifier()
tree.fit(X_train,y_train)
y_pred_tree = tree.predict(X_test)
```

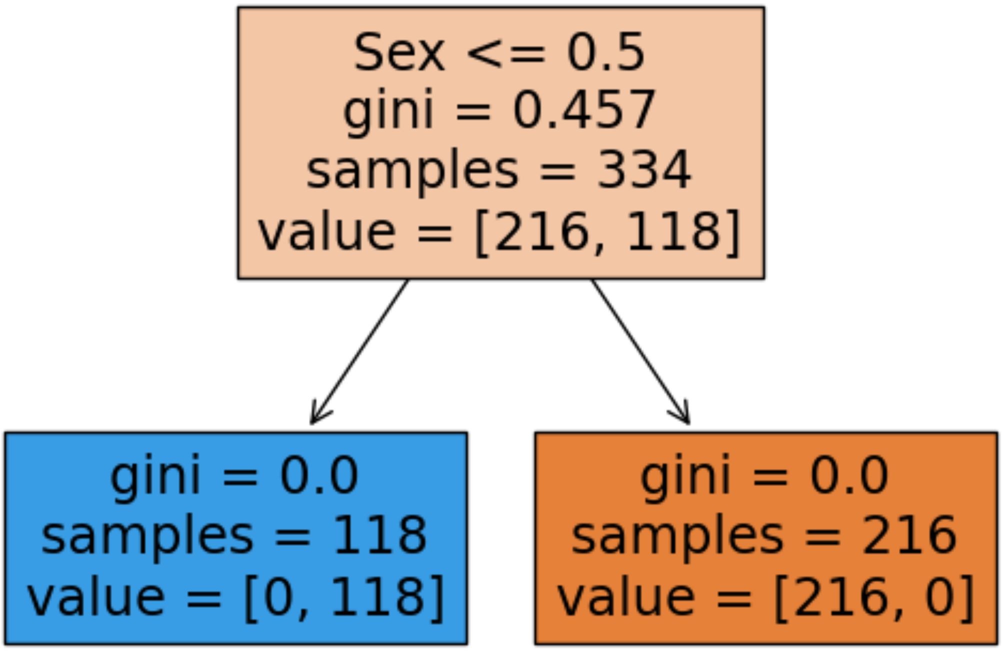
In [50]:
```
print('Accuracy: ', accuracy_score(y_test, y_pred_tree))
print('Precision: ', precision_score(y_test, y_pred_tree))
print('Recall: ', recall_score(y_test, y_pred_tree))
print('F1 Score: ', f1_score(y_test, y_pred_tree))
```

```
Accuracy:  1.0
Precision:  1.0
Recall:  1.0
F1 Score:  1.0
```

In [51]:
```
cm = confusion_matrix(y_test, y_pred_tree, labels=tree.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=tree.cl
disp.plot();
```



In [52]:
```
from sklearn.tree import plot_tree
plot_tree(tree, filled=True, feature_names=list(X.columns))
plt.show()
```



summary

In the Titanic dataset, 36.36% of passengers survived, while 63.64% did not survive. All females survived, whereas none of the males survived. A significant number of passengers in classes 3 and 2 did not survive. Passengers without siblings/spouses or parents/children aboard had lower chances of survival. Those embarking from Queenstown had a higher likelihood of survival, while those embarking from Southampton had lower chances.

Both the Logistic Regression and Decision Tree models achieved 100% accuracy.