Titanic Survived project

Project Description: The Titanic Problem is a data analysis and predictive modeling challenge centered around the tragic sinking of the supposedly 'Unsinkable' ship Titanic in early 1912. This problem provides a dataset containing various details about passengers, including their age, gender, number of siblings, embarkation points, and their survival outcome. The objective is to create a predictive model capable of determining whether an arbitrary Titanic passenger would have survived the disaster based on these provided features.

Variables in Dataset:

- PassengerId: A unique identifier assigned to each passenger.
- Survived: Indicates whether a passenger survived the sinking of the Titanic. (0 = No, 1 = Yes)
- Pclass: The passenger's ticket class. (1 = 1st class, 2 = 2nd class, 3 = 3rd class)
- Name: The name of the passenger.
- Sex: The gender of the passenger. (Male or Female)
- Age: The age of the passenger in years.
- SibSp: The number of siblings or spouses the passenger had aboard the Titanic.
- Parch: The number of parents or children the passenger had aboard the Titanic.
- Ticket: The ticket number.
- Fare: The fare or price paid for the ticket.
- Cabin: The cabin number.
- Embarked: The port of embarkation for the passenger. (C = Cherbourg, Q = Queenstown, S = Southampton)

In [1]:

```
#Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#Loading Dataset
df=pd.read_csv('https://raw.githubusercontent.com/dsrscientist/dataset1/master/
df.head()
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cal
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	N
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	N
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	N

In [3]:
```
#checking the shape of dataset
print("There are {} rows and {} columns respectively present in the dataset.".f
```

```
There are 891 rows and 12 columns respectively present in the dataset.
```

In [4]:
```
# checking columns in Dataset
print("These are the columns present in the dataset:\n", df.columns)
```

```
These are the columns present in the dataset:
 Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

Observation: We have 12 columns in our dataset. One column is our target variable contain categorical data

In [5]:
```
# statistical info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [6]:
```
# statistical Summary
df.describe()
```

Out[6]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

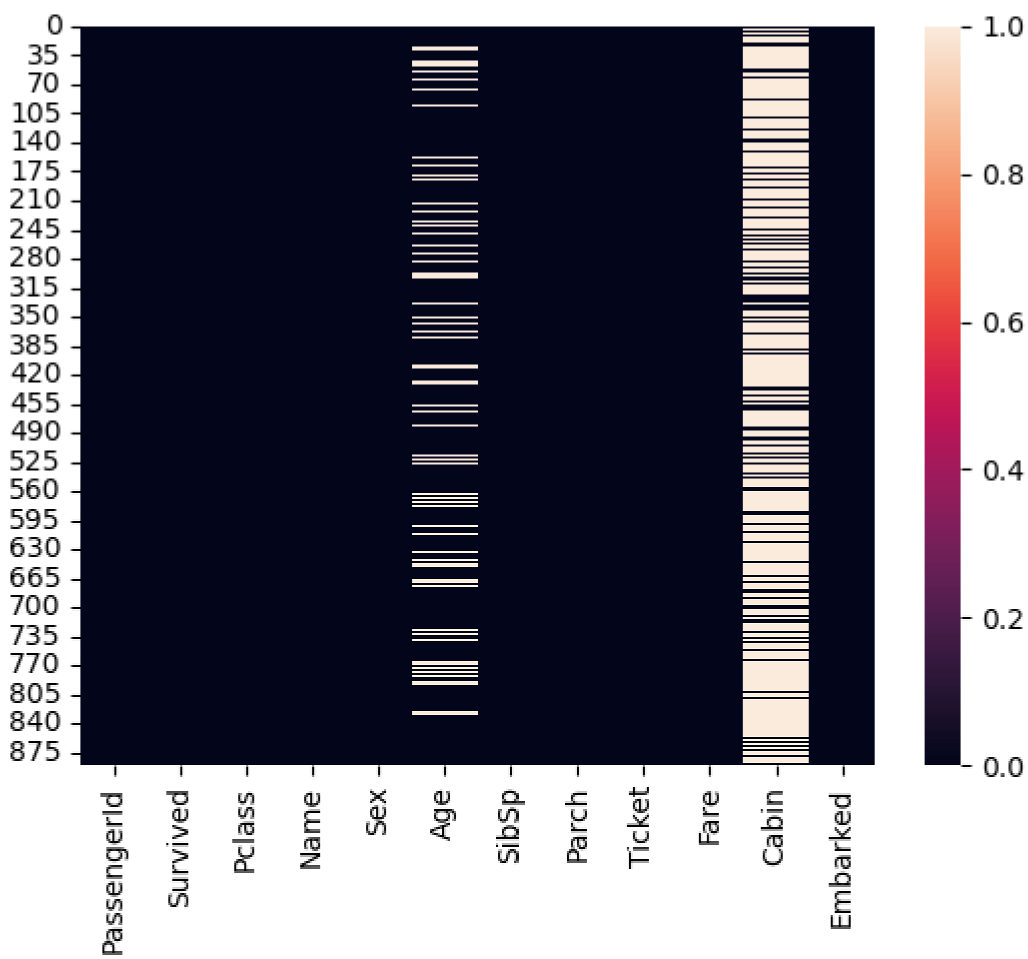
Observations

- Here we can clearly see that there are 2 columns contains float64, 5 columns contains int64 and 5 columns contains object values.
- Memory Usage 83.7+ KB

In [7]:
```
#checking for Missing values
df.isnull().sum()
```

Out[7]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [8]:
```
#Visualizing with heatmap
sns.heatmap(df.isnull())
plt.show()
```



Observations:

- We can clearly see there are missing values in Age, Cabin and Embarked column
- We can see that Cabin has maximum missing values so we will drop the Cabin column

- Few columns have inappropriate data types.

In [9]:
```
# Dropping cabin column as most of the values are missing in the dataset
# PassegerId is the same as the index number and it isnot relevant to survival
df.drop(columns=['Cabin','PassengerId','Name'], inplace=True)
```

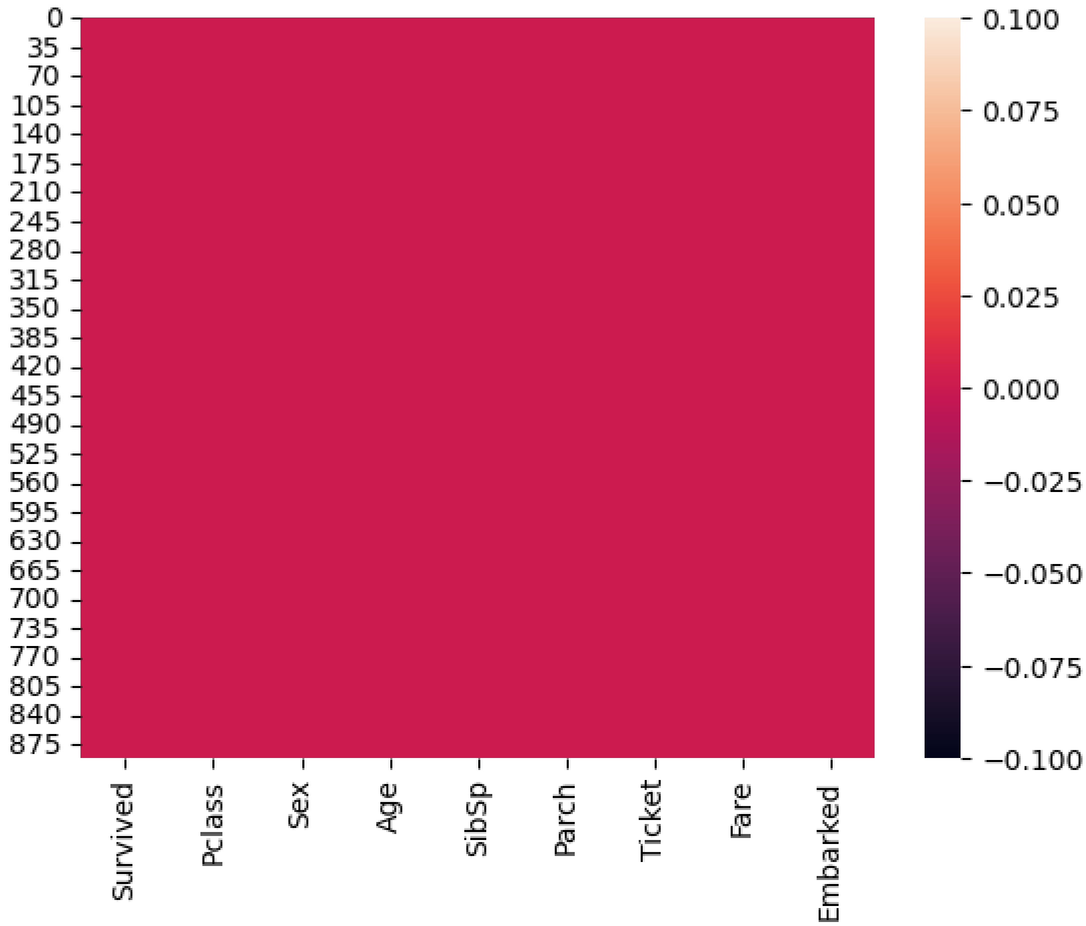
In [10]:
```
#Handling Missing Values for Age Column
df['Age'].fillna(df['Age'].mean(),inplace=True)

# Impute missing values for Embarked Column
df['Embarked'].fillna(df['Embarked'].mode()[0],inplace=True)
```

In [11]:
```
#Checking Null Values
df.isnull().sum()
```

Out[11]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Ticket      0
Fare        0
Embarked    0
dtype: int64
```

In [12]:
```python
# Visualise it
sns.heatmap(df.isnull())
```

Out[12]: <Axes: >



Observations: We have handled all the missing Values in the dataframe

In [13]:
```python
#checking unique values in the dataset
df.nunique()
```

Out[13]:
```
Survived      2
Pclass        3
Sex           2
Age          89
SibSp         7
Parch         7
Ticket      681
Fare        248
Embarked      3
dtype: int64
```

Observations: These are unique values in each column in our dataset.

Columns Types

- **Numerical column:** Age, Fare
- **Categorical column:** Survived, Pclass,Sex, Sibsp, Parch, Embarked
- **Mixed column:** Ticket

Univariate Analysis

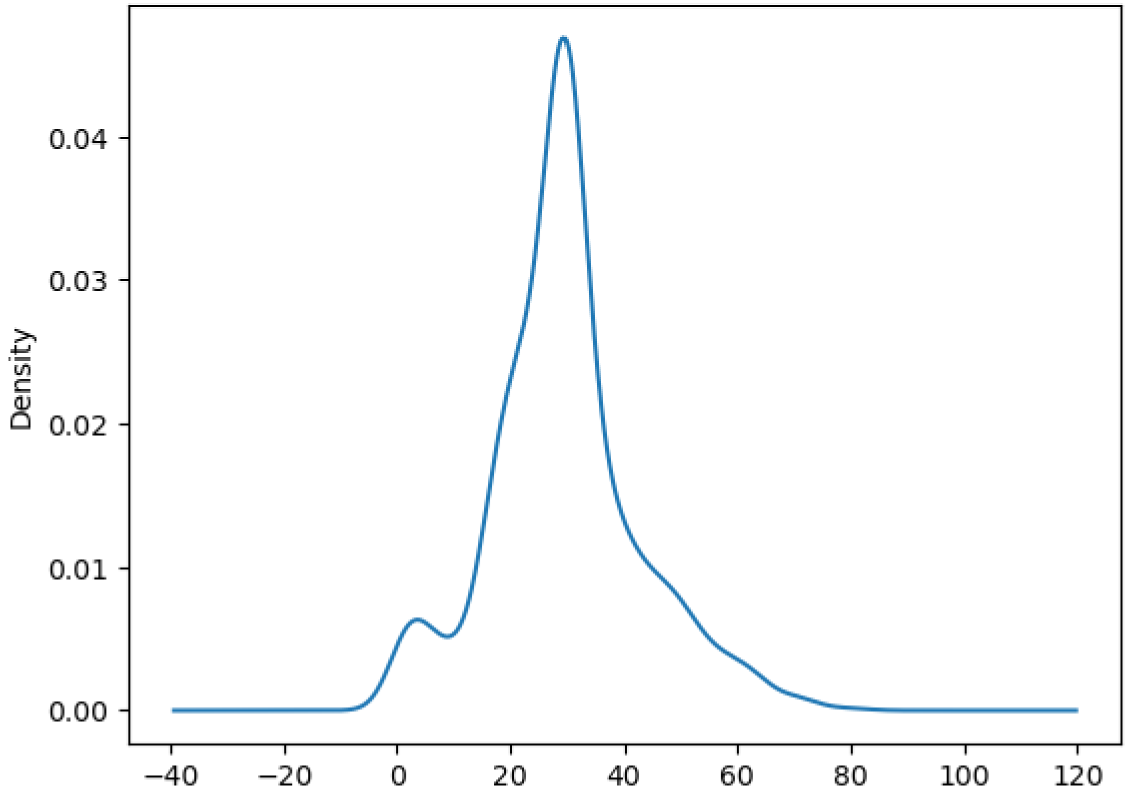
Numerical Columns

In [14]:
```
#Handling  Age
df['Age'].describe()
```

Out[14]:
```
count    891.000000
mean      29.699118
std       13.002015
min        0.420000
25%       22.000000
50%       29.699118
75%       35.000000
max       80.000000
Name: Age, dtype: float64
```

In [15]:
```
df['Age'].plot(kind='kde')
```

Out[15]: <Axes: ylabel='Density'>

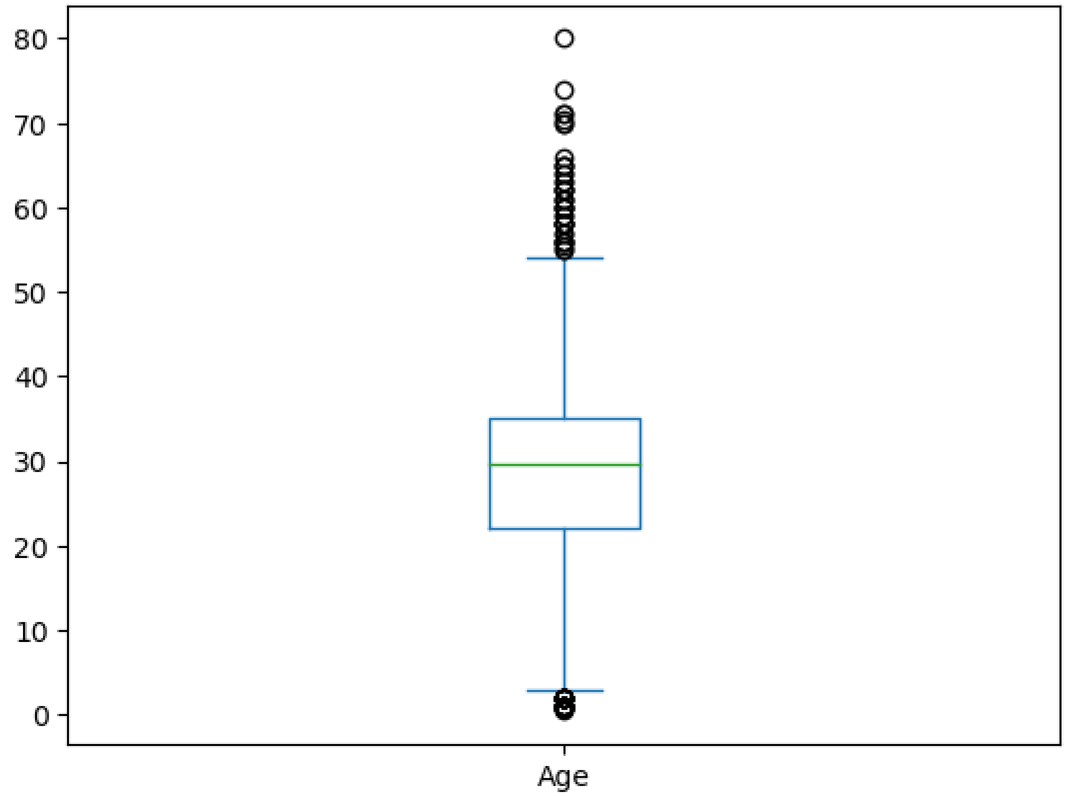


In [16]:
```
print("Skewness :",df['Age'].skew())
print("Kurtosis :",df['Age'].kurt())
```

```
Skewness : 0.4344880940129925
Kurtosis : 0.9662793026645233
```

In [17]:

```python
#checking for outliers
df['Age'].plot(kind='box')
plt.show()
```



In [18]:

```python
#analysis whether the outliers are valid or invalid
df[df['Age']>65]
```

Out[18]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
33	0	2	male	66.0	0	0	C.A. 24579	10.5000	S
96	0	1	male	71.0	0	0	PC 17754	34.6542	C
116	0	3	male	70.5	0	0	370369	7.7500	Q
493	0	1	male	71.0	0	0	PC 17609	49.5042	C
630	1	1	male	80.0	0	0	27042	30.0000	S
672	0	2	male	70.0	0	0	C.A. 24580	10.5000	S
745	0	1	male	70.0	1	1	WE/P 5735	71.0000	S
851	0	3	male	74.0	0	0	347060	7.7750	S

In [19]:
```
df[df['Age']<5]
```

Out[19]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
7	0	3	male	2.00	3	1	349909	21.0750	S
10	1	3	female	4.00	1	1	PP 9549	16.7000	S
16	0	3	male	2.00	4	1	382652	29.1250	Q
43	1	2	female	3.00	1	2	SC/Paris 2123	41.5792	C
63	0	3	male	4.00	3	2	347088	27.9000	S
78	1	2	male	0.83	0	2	248738	29.0000	S
119	0	3	female	2.00	4	2	347082	31.2750	S
164	0	3	male	1.00	4	1	3101295	39.6875	S
171	0	3	male	4.00	4	1	382652	29.1250	Q
172	1	3	female	1.00	1	1	347742	11.1333	S
183	1	2	male	1.00	2	1	230136	39.0000	S
184	1	3	female	4.00	0	2	315153	22.0250	S
193	1	2	male	3.00	1	1	230080	26.0000	S
205	0	3	female	2.00	0	1	347054	10.4625	S
261	1	3	male	3.00	4	2	347077	31.3875	S
297	0	1	female	2.00	1	2	113781	151.5500	S
305	1	1	male	0.92	1	2	113781	151.5500	S
340	1	2	male	2.00	1	1	230080	26.0000	S
348	1	3	male	3.00	1	1	C.A. 37671	15.9000	S
374	0	3	female	3.00	3	1	349909	21.0750	S
381	1	3	female	1.00	0	2	2653	15.7417	C
386	0	3	male	1.00	5	2	CA 2144	46.9000	S
407	1	2	male	3.00	1	1	29106	18.7500	S
445	1	1	male	4.00	0	2	33638	81.8583	S
469	1	3	female	0.75	2	1	2666	19.2583	C
479	1	3	female	2.00	0	1	3101298	12.2875	S
530	1	2	female	2.00	1	1	26360	26.0000	S
618	1	2	female	4.00	2	1	230136	39.0000	S
642	0	3	female	2.00	3	2	347088	27.9000	S
644	1	3	female	0.75	2	1	2666	19.2583	C
691	1	3	female	4.00	0	1	349256	13.4167	C
750	1	2	female	4.00	1	1	29103	23.0000	S
755	1	2	male	0.67	1	1	250649	14.5000	S
788	1	3	male	1.00	1	2	C.A. 2315	20.5750	S
803	1	3	male	0.42	0	1	2625	8.5167	C
824	0	3	male	2.00	4	1	3101295	39.6875	S

	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
827	1	2	male	1.00	0	2	S.C./PARIS 2079	37.0042	C
831	1	2	male	0.83	1	1	29106	18.7500	S
850	0	3	male	4.00	4	2	347082	31.2750	S
869	1	3	male	4.00	1	1	347742	11.1333	S

Observations:

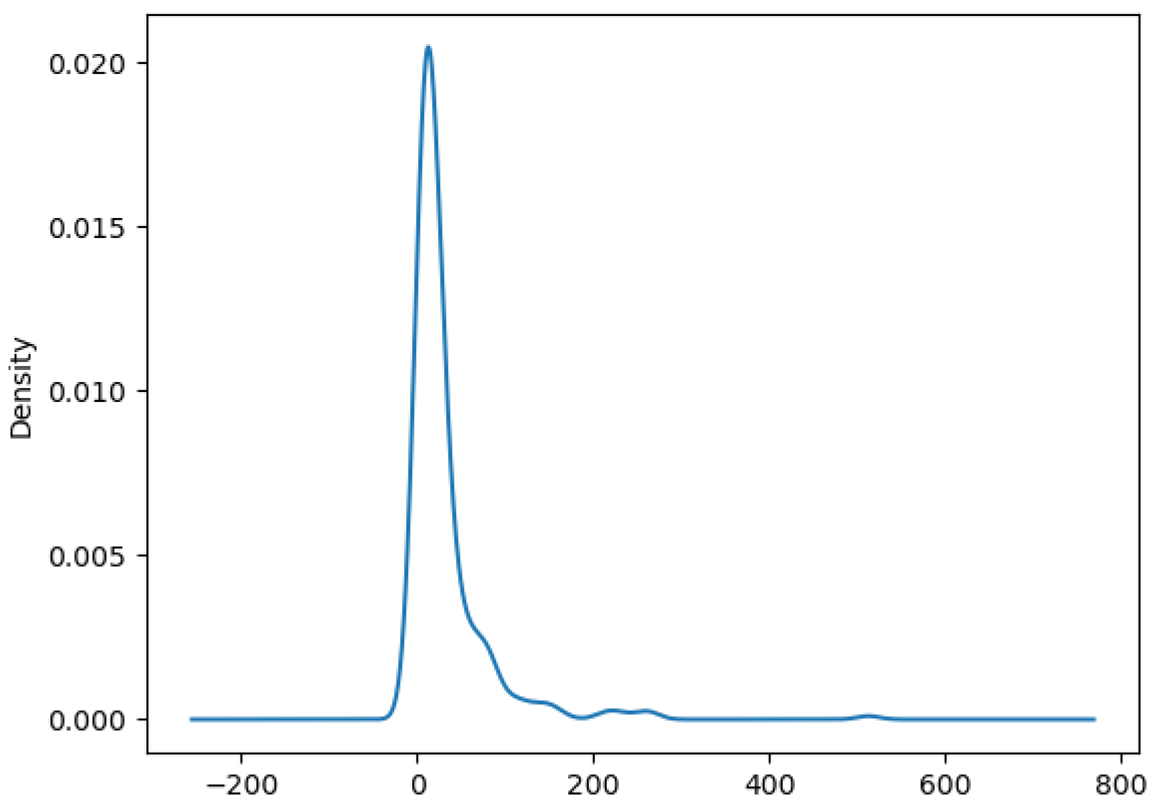
- Age is almost normally distributed and has heavier tails compared to a normal distribution.
- There are some outliers. But we will not consider them as outliers because the data is valid

In [20]:
```
#Fare Column
df['Fare'].describe()
```

Out[20]:
```
count    891.000000
mean      32.204208
std       49.693429
min        0.000000
25%        7.910400
50%       14.454200
75%       31.000000
max      512.329200
Name: Fare, dtype: float64
```

In [21]:
```
df['Fare'].plot(kind='kde')
```

Out[21]:
```
<Axes: ylabel='Density'>
```



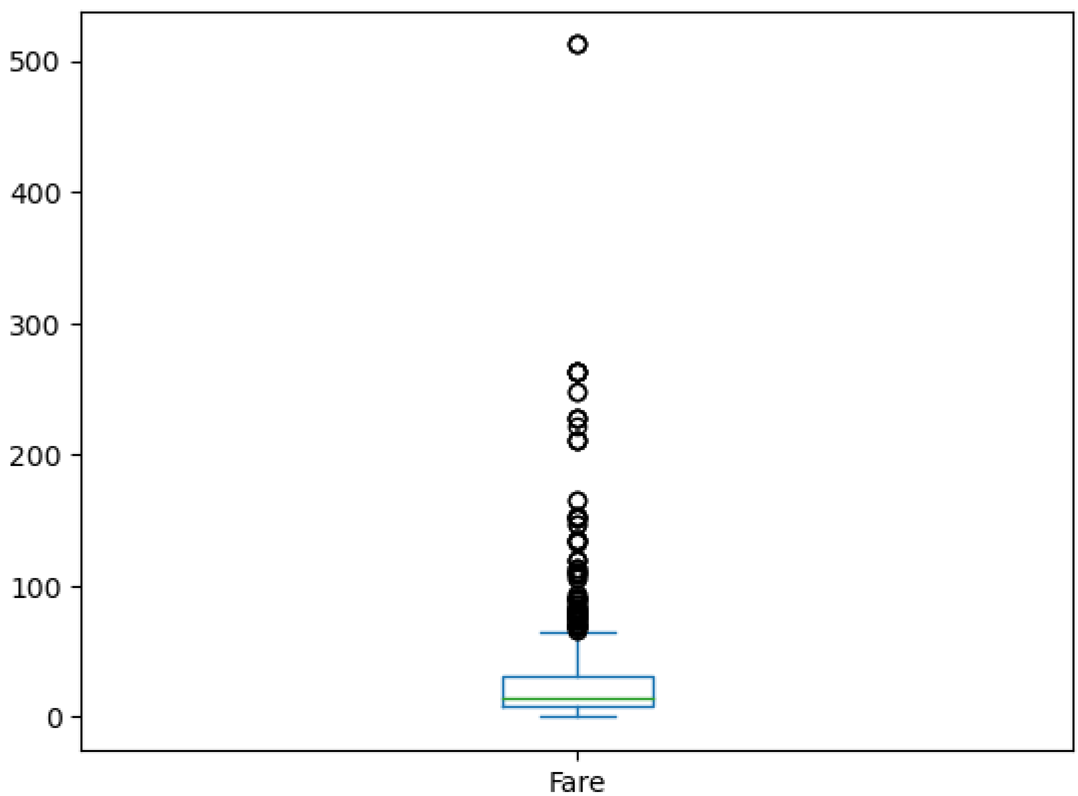
In [22]:
```
print("Skewness :",df['Fare'].skew())
print("Kurtosis :",df['Fare'].kurt())
```

```
Skewness : 4.787316519674893
Kurtosis : 33.39814088089868
```

Observations: Considering the skewness and kurtosis values, it's evident that the 'Fare' distribution is strongly positively skewed, featuring a prolonged right tail and exceptionally heavy tails when compared to a typical normal distribution.

In [23]:
```
df['Fare'].plot(kind='box')
```

Out[23]: <Axes: >



In [24]:
```
df[df['Fare'] > 250]
```

Out[24]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
27	0	1	male	19.0	3	2	19950	263.0000	S
88	1	1	female	23.0	3	2	19950	263.0000	S
258	1	1	female	35.0	0	0	PC 17755	512.3292	C
311	1	1	female	18.0	2	2	PC 17608	262.3750	C
341	1	1	female	24.0	3	2	19950	263.0000	S
438	0	1	male	64.0	1	4	19950	263.0000	S
679	1	1	male	36.0	0	1	PC 17755	512.3292	C
737	1	1	male	35.0	0	0	PC 17755	512.3292	C
742	1	1	female	21.0	2	2	PC 17608	262.3750	C

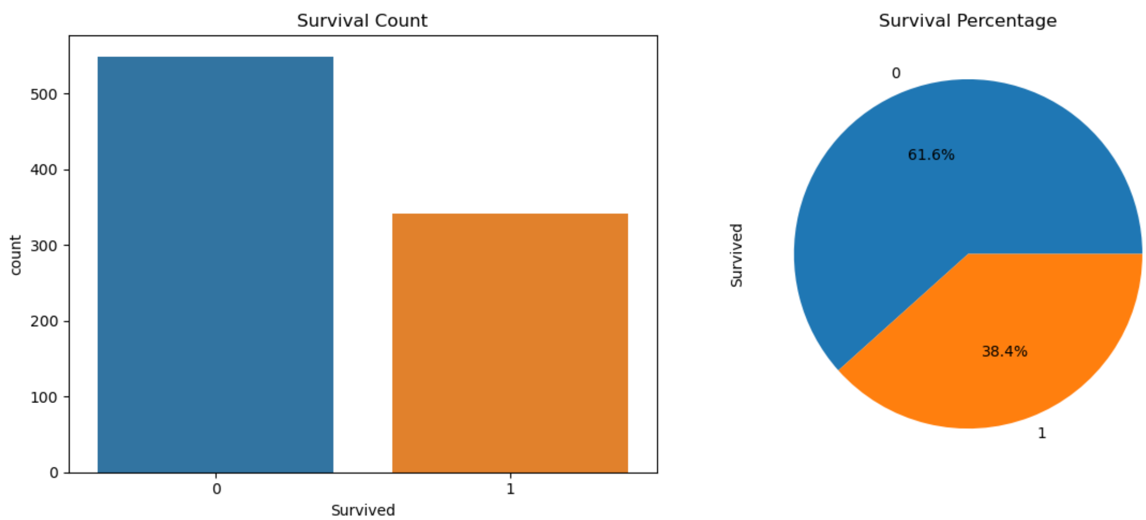
Observations:

- The data is highly(positively) skewed
- Fare column actually contains the group fare and not the individual fare
- We need to create a new column called individual fare

Categorical Column

In [25]:
```
#survived columns

print('Unique values present in Survived :', len(df['Survived'].value_counts()))
print(df['Survived'].value_counts())

# Checking the Survived
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.countplot(x='Survived', data=df, ax=axes[0])
axes[0].set_title("Survival Count")

# Checking the Survived percentage
df['Survived'].value_counts().plot(kind='pie', autopct='%0.1f%%', ax=axes[1])
axes[1].set_title("Survival Percentage")
plt.tight_layout()
plt.show()
```

```
Unique values present in Survived : 2
0    549
1    342
Name: Survived, dtype: int64
```

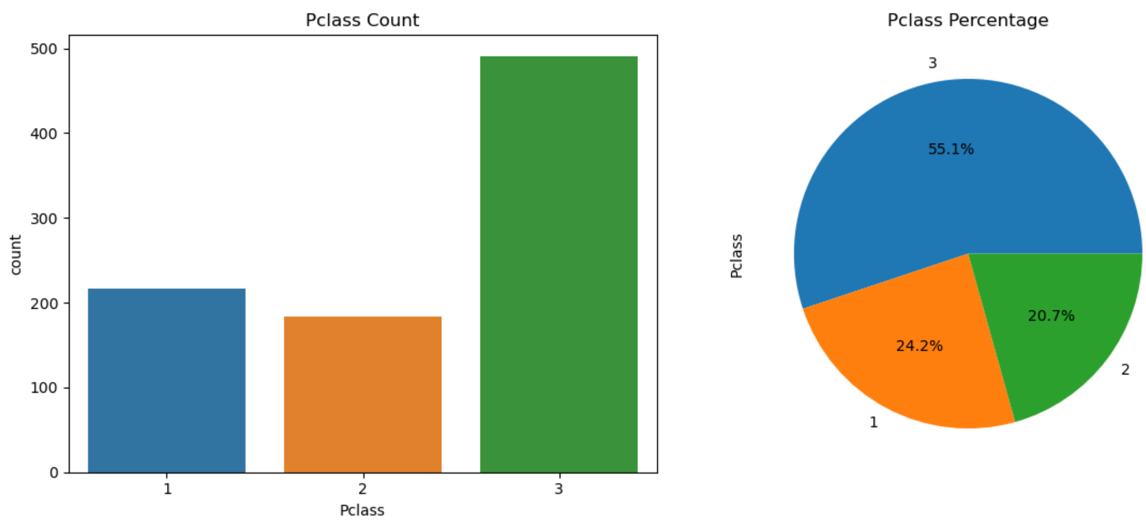


Obseration:

- We can clearly visiualize that Survived colum has 2 unique values which are 0 and 1, 0 represent died and 1 represent survived.
- More than 61% people died in the incident.
- No Null Values present.

In [26]:
```
#Pclass Column
print('Unique values present in Pclass :', len(df['Pclass'].value_counts()))
print(df['Pclass'].value_counts())

#Plot the first countplot on the first subplot
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.countplot(x='Pclass', data=df, ax=axes[0])
axes[0].set_title("Pclass Count")

# Plot the second pie chart on the second subplot
df['Pclass'].value_counts().plot(kind='pie', autopct='%0.1f%%', ax=axes[1])
axes[1].set_title("Pclass Percentage")

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

```
Unique values present in Pclass : 3
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

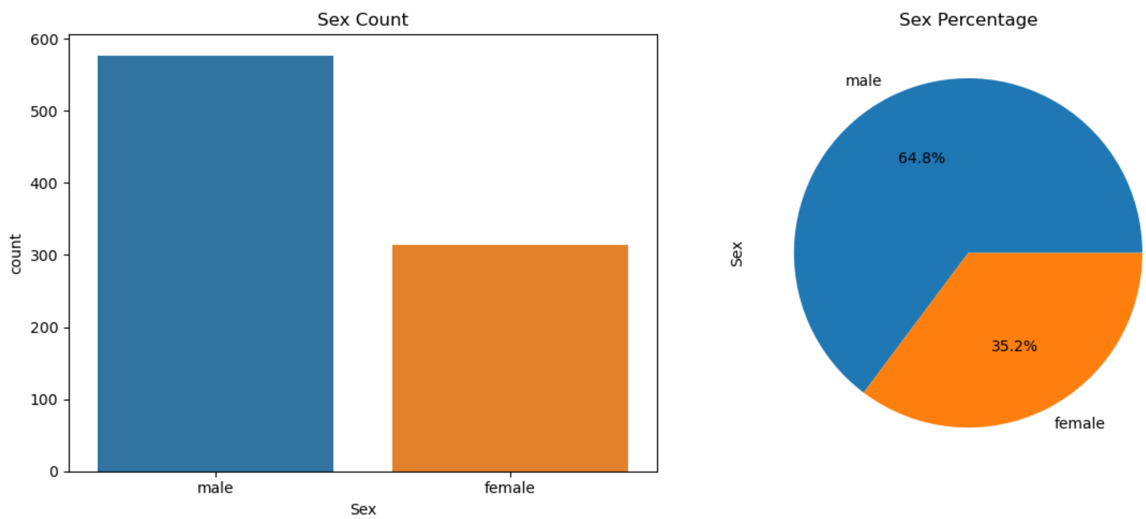


Observations:

- The dataset contains three distinct values for passenger class: PClass 1, PClass 2, and PClass 3.
- PClass 3 had the highest passenger representation, accounting for 55.1% of the total passengers.
- PClass 1 had a higher passenger count at 24.2% compared to PClass 2, which had 20.7% of the total passengers.

In [27]:
```
# Sex Column
print('Unique values present in Sex :', len(df['Sex'].value_counts()))
print(df['Sex'].value_counts())

#Plot the first countplot on the first subplot
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.countplot(x='Sex', data=df, ax=axes[0])
axes[0].set_title("Sex Count")

# Plot the second pie chart on the second subplot
df['Sex'].value_counts().plot(kind='pie', autopct='%0.1f%%', ax=axes[1])
axes[1].set_title("Sex Percentage")

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

```
Unique values present in Sex : 2
male      577
female    314
Name: Sex, dtype: int64
```

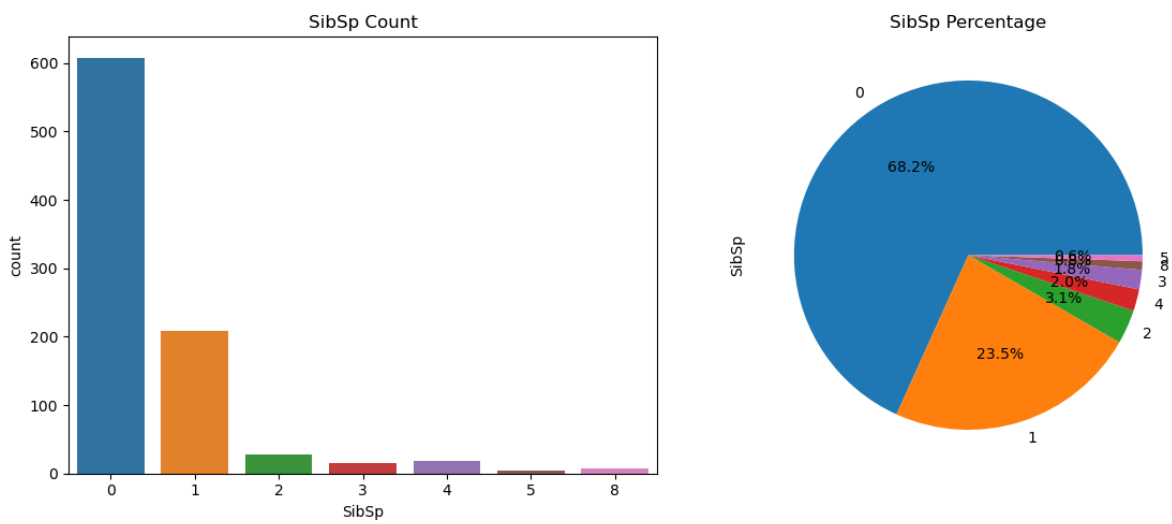


Observations:

- In the dataset, there are two distinct values for gender: 'male' and 'female.'
- Males accounted for the majority, comprising 64% of the passengers, while females made up 35.2% of the total passengers.

In [28]:
```python
# SibSp Column
print('Unique values present in SibSp :', len(df['SibSp'].value_counts()))
print(df['SibSp'].value_counts())

#Plot the first countplot on the first subplot
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.countplot(x='SibSp', data=df, ax=axes[0])
axes[0].set_title("SibSp Count")

# Plot the second pie chart on the second subplot
df['SibSp'].value_counts().plot(kind='pie', autopct='%0.1f%%', ax=axes[1])
axes[1].set_title("SibSp Percentage")

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

```
Unique values present in SibSp : 7
0    608
1    209
2     28
4     18
3     16
8      7
5      5
Name: SibSp, dtype: int64
```

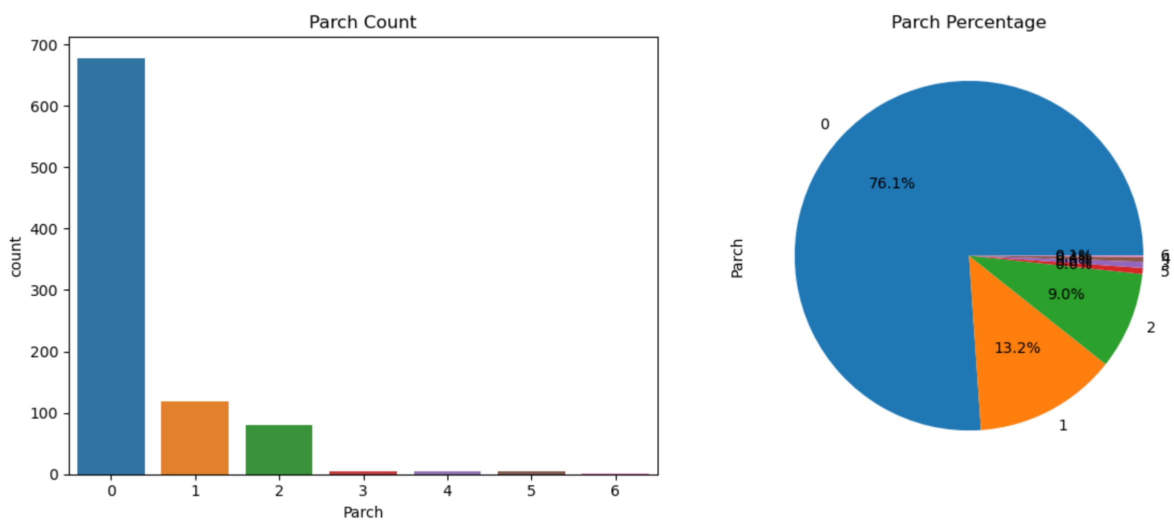


Observations:

- The majority of passengers traveled alone, representing the highest count.
- The second-highest count of passengers was observed among those traveling with one sibling or spouse.
- The count of passengers traveling with two siblings or spouses ranked third in terms of frequency.

In [29]:
```python
# Parch Column
print('Unique values present in Parch :', len(df['Parch'].value_counts()))
print(df['Parch'].value_counts())

#Plot the first countplot on the first subplot
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.countplot(x='Parch', data=df, ax=axes[0])
axes[0].set_title("Parch Count")

# Plot the second pie chart on the second subplot
df['Parch'].value_counts().plot(kind='pie', autopct='%0.1f%%', ax=axes[1])
axes[1].set_title("Parch Percentage")

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

```
Unique values present in Parch : 7
0    678
1    118
2     80
5      5
3      5
4      4
6      1
Name: Parch, dtype: int64
```

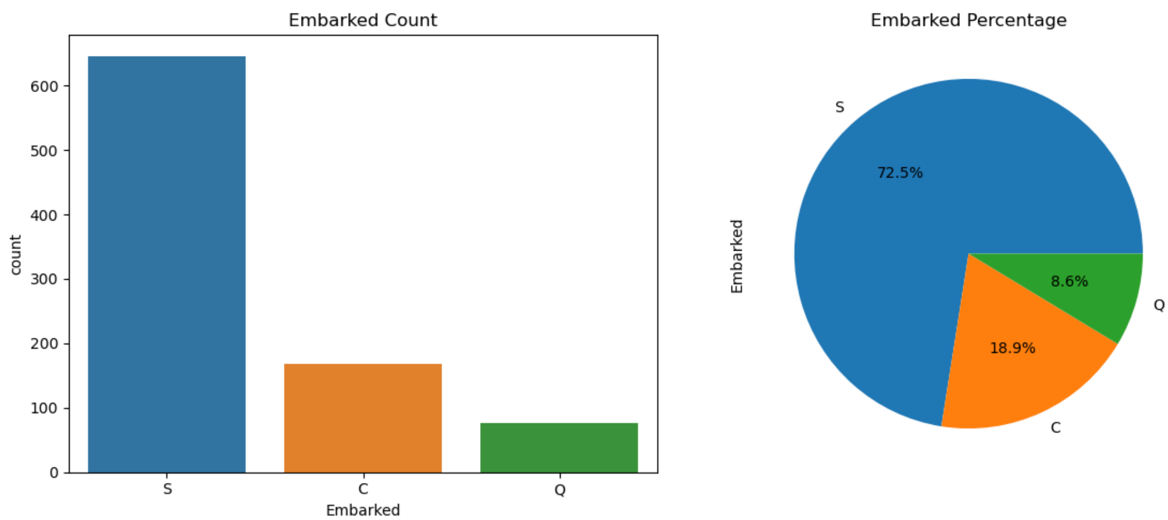


Observation:

- The most common scenario in the column involves passengers traveling alone, followed by those traveling with one parent or child, and then by those traveling with two parents or children.
- The 'Parch' and 'SibSp' columns can be combined to create a new column called 'family_size as this two columns contain family size details.

In [30]:
```python
# Embarked Column
print('Unique values present in Embarked :', len(df['Embarked'].value_counts()))
print(df['Embarked'].value_counts())

#Plot the first countplot on the first subplot
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.countplot(x='Embarked', data=df, ax=axes[0])
axes[0].set_title("Embarked Count")

# Plot the second pie chart on the second subplot
df['Embarked'].value_counts().plot(kind='pie', autopct='%0.1f%%', ax=axes[1])
axes[1].set_title("Embarked Percentage")

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

```
Unique values present in Embarked : 3
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```



Observations: The highest number of passengers embarked from Southampton (S), followed by Cherbourg (C), while Queenstown (Q) had the lowest passenger count. This pattern could be attributed to Southampton being the ship's initial departure point.

Mixed Columns

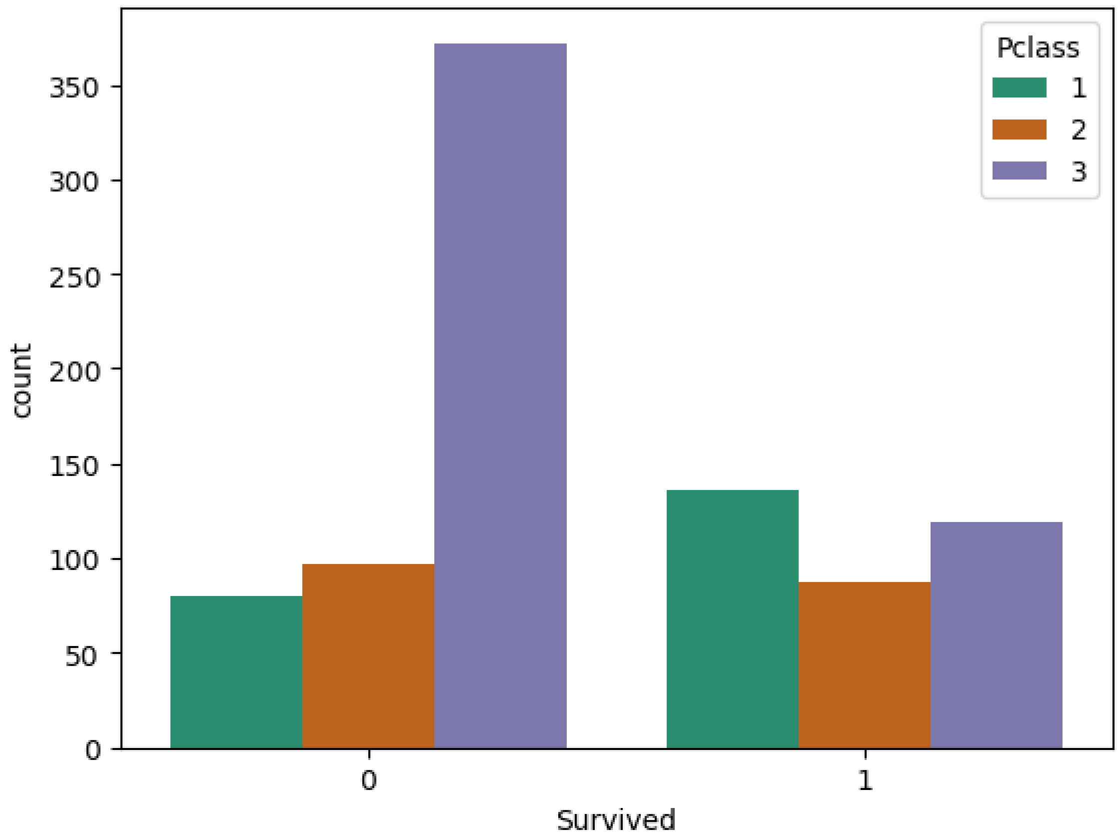
In [31]:
```python
#Ticket columns is our mixed column so we will drop the column
df.drop(['Ticket'],axis=1,inplace=True)
```

Bivariate Analysis

In [32]:
```
#Survived and Pclass
sns.countplot(x='Survived', data=df, hue='Pclass', palette='Dark2')
(pd.crosstab(df['Survived'],df['Pclass'], normalize='columns')*100).round(2)
```

Out[32]:

Pclass	1	2	3
Survived			
0	37.04	52.72	75.76
1	62.96	47.28	24.24



Observation:

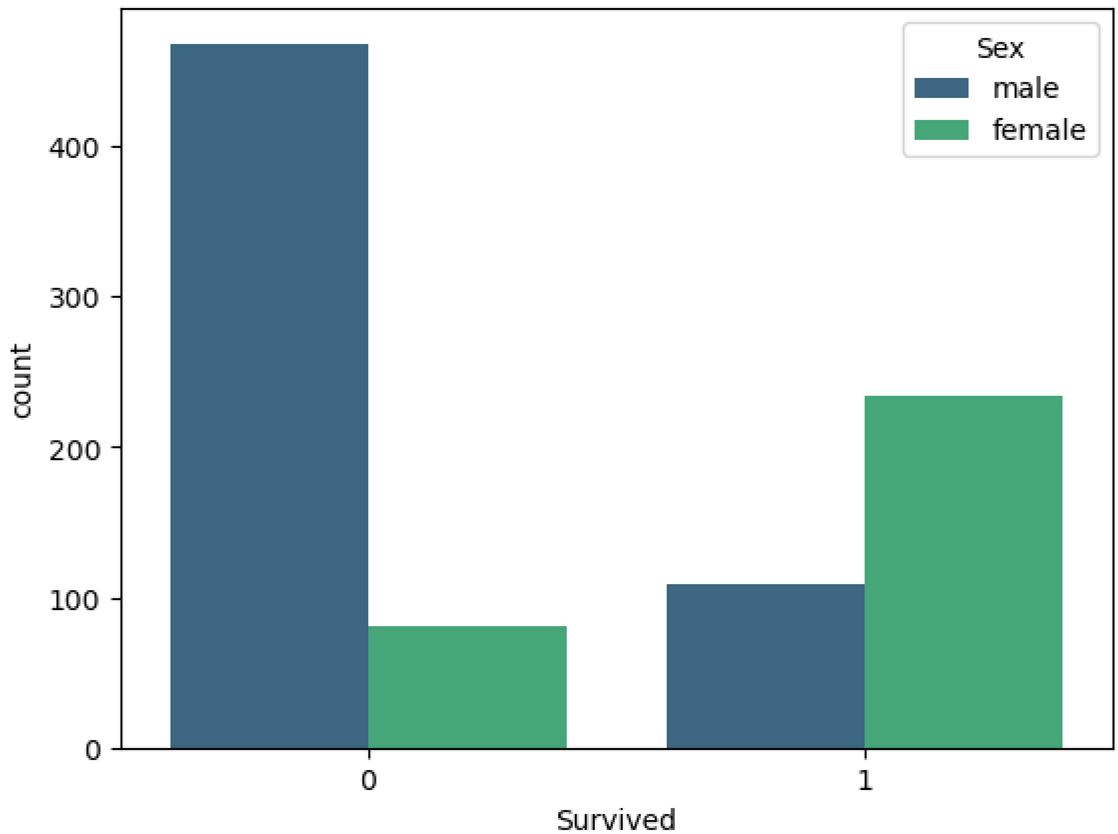
- Pclass 3 had the highest risk, with a 75% mortality rate and only a 24% survival rate.
- Pclass 1 was the safest, with 62% of its passengers surviving and a death rate of 37%.

In [33]:

```python
#Survived and Sex
sns.countplot(x='Survived', data=df, hue='Sex', palette='viridis')
(pd.crosstab(df['Survived'],df['Sex'], normalize='columns')*100).round(2)
```

Out[33]:

Sex Survived	female	male
0	25.8	81.11
1	74.2	18.89



Observation:

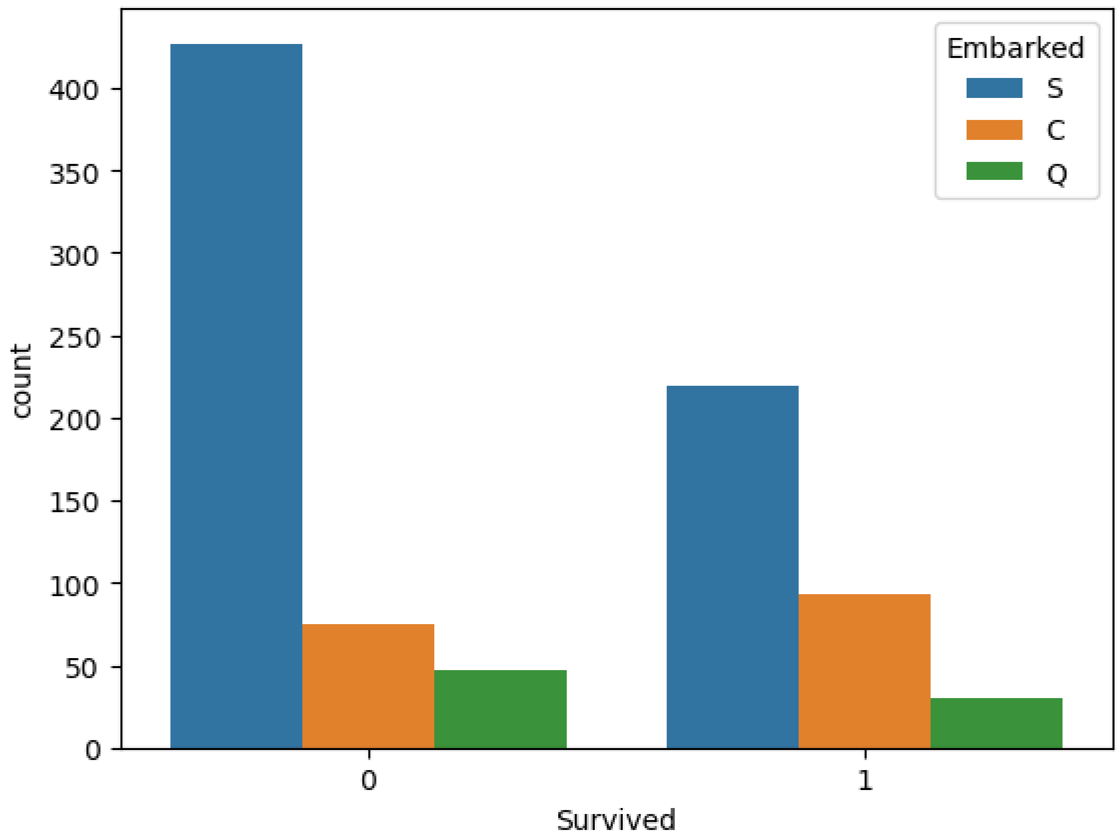
- The visualization makes it evident that the survival rate among females is significantly higher, at 74%, in stark contrast to males, where the rate is only 18%.

In [34]:

```
#Survived and Embarked
sns.countplot(x='Survived', data=df, hue='Embarked')
(pd.crosstab(df['Survived'],df['Embarked'], normalize='columns')*100).round(2)
```

Out[34]:

Embarked	C	Q	S
Survived			
0	44.64	61.04	66.1
1	55.36	38.96	33.9

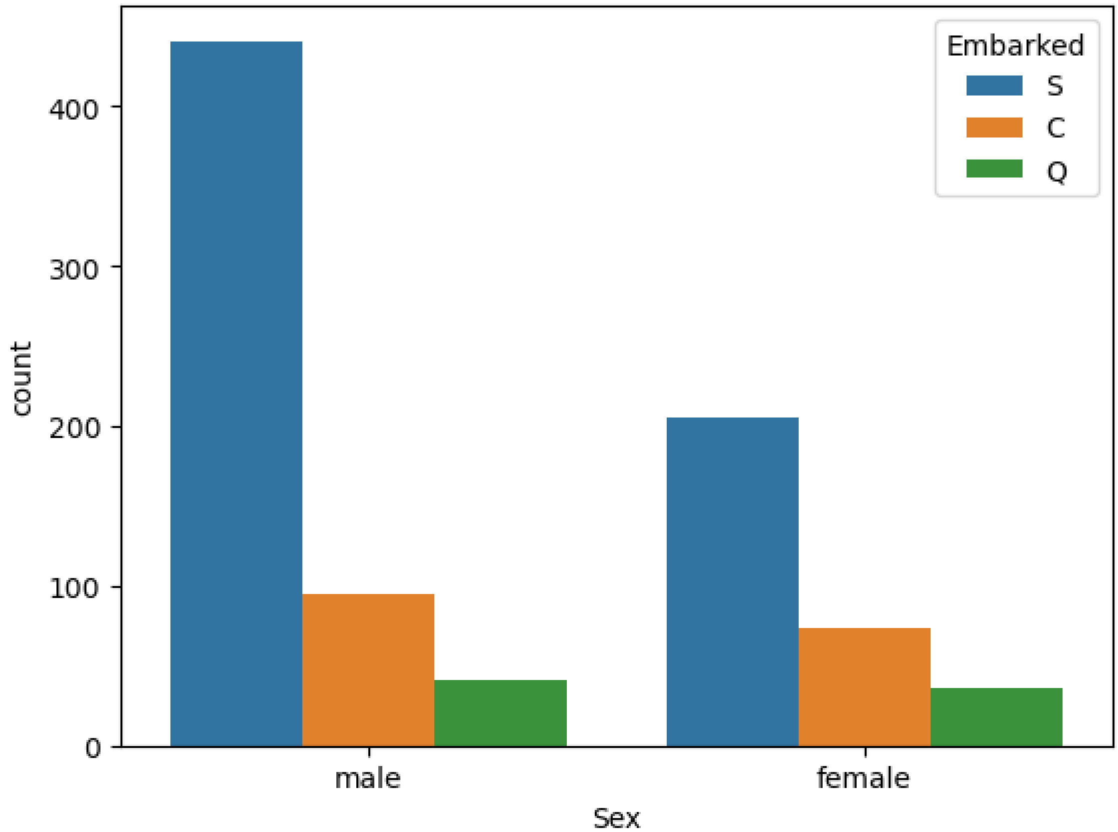


Observation: It's evident from the data that the survival rate of passengers who embarked from Cherbourg is notably higher than those from Queenstown and Southampton. This suggests that passengers boarding from Cherbourg may predominantly belong to Pclass 1 or be of the female gender. Further analysis can provide more insights into this pattern.

In [35]:
```python
# Sex and Embarked
sns.countplot(x='Sex', data=df, hue='Embarked',)
(pd.crosstab(df['Sex'],df['Embarked'], normalize='columns')*100).round(2)
```

Out[35]:

Embarked	C	Q	S
Sex			
female	43.45	46.75	31.73
male	56.55	53.25	68.27

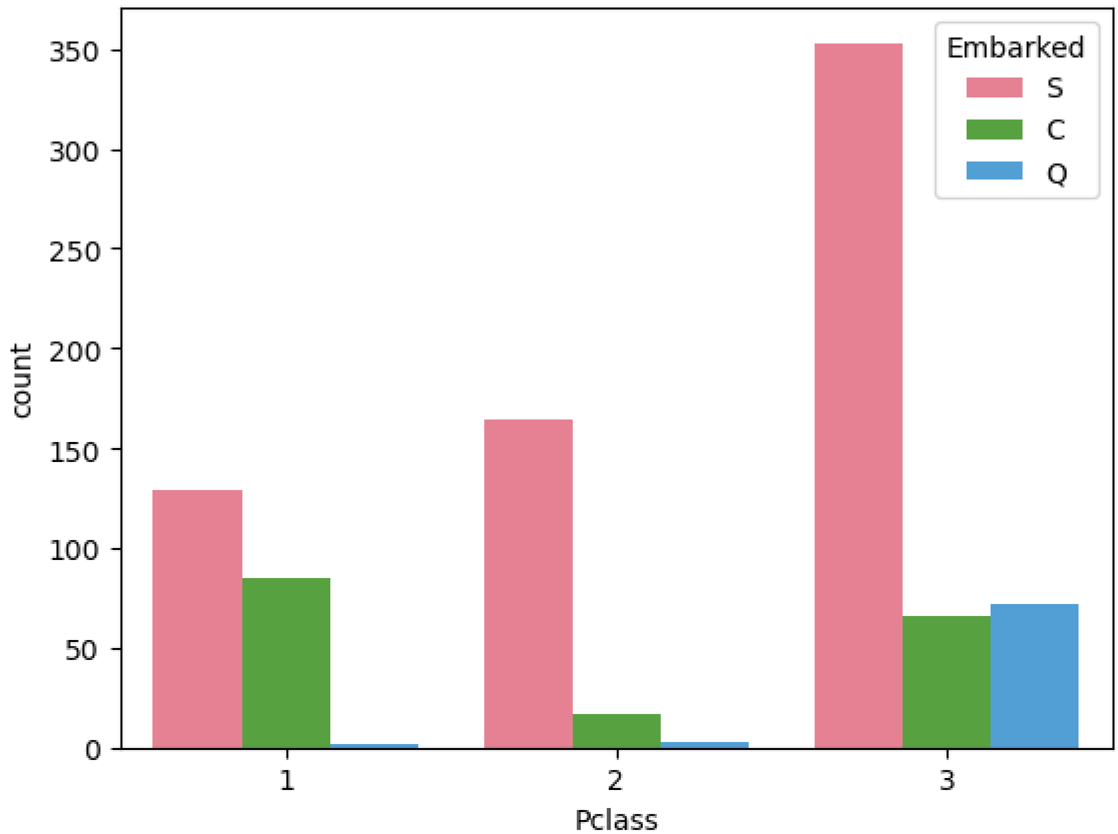


In [36]:

```
#PClass and Embarked
sns.countplot(x='Pclass', data=df, hue='Embarked', palette='husl')
(pd.crosstab(df['Pclass'],df['Embarked'], normalize='columns')*100).round(2)
```

Out[36]:

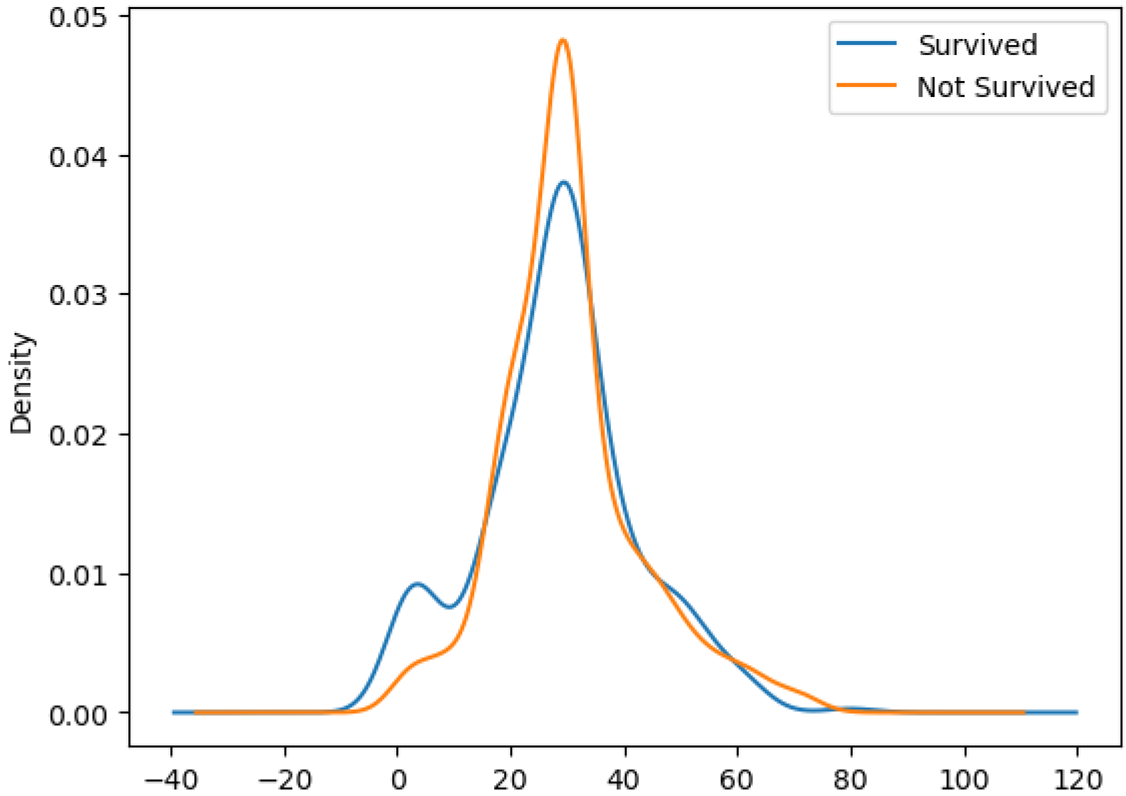
Embarked Pclass	C	Q	S
1	50.60	2.60	19.97
2	10.12	3.90	25.39
3	39.29	93.51	54.64



Observation:

- Based on the provided information, it is evident that the largest group of passengers who embarked from Cherbourg belonged to PClass 1. This explains why the survival rate for this group is significantly higher compared to Queenstown and Southampton.
- Additionally, it's noteworthy that the majority of passengers who boarded from Queenstown were in PClass 3, aligning with our observation that the highest mortality rate is associated with PClass 3.

In [37]:
```
#survived and Age
df[df['Survived'] == 1]['Age'].plot(kind='kde',label='Survived')
df[df['Survived'] == 0]['Age'].plot(kind='kde',label='Not Survived')

plt.legend()
plt.show()
```



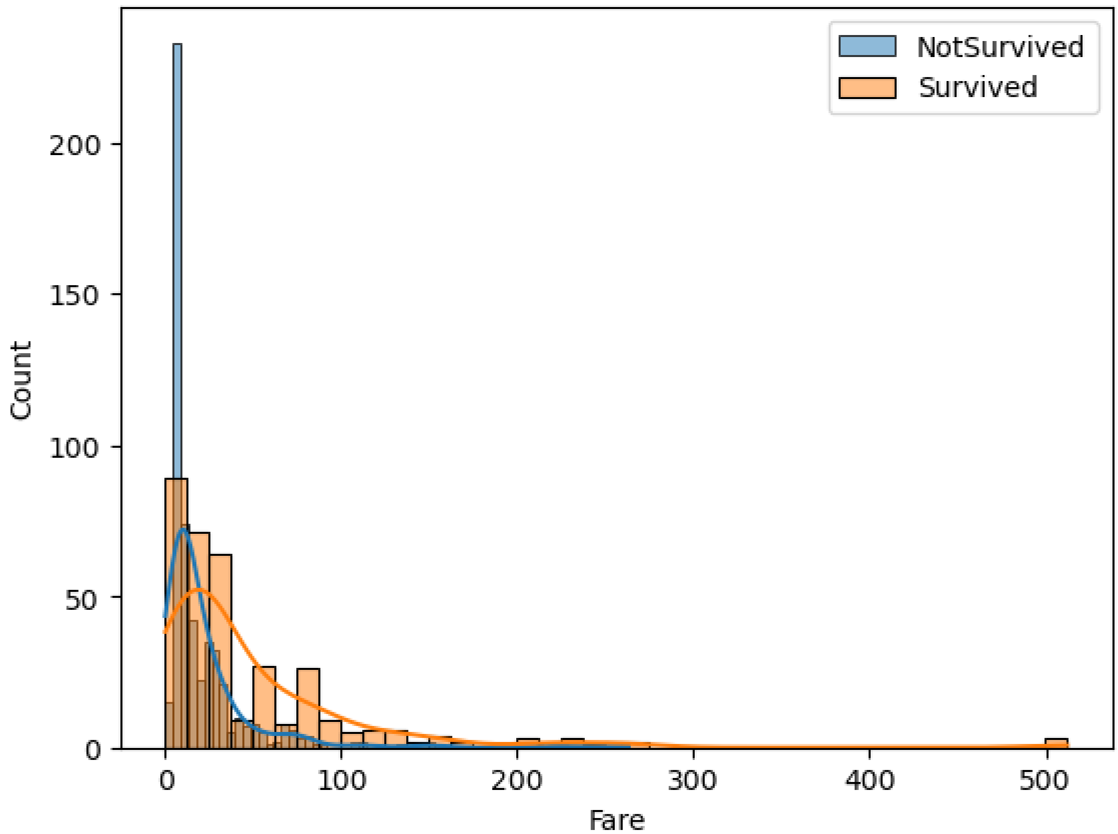
In [38]:
```
df[df['Pclass']==1]['Age'].mean()
```

Out[38]: 37.04811819172113

Observations:

- It's evident that the age group from 0 to 10 exhibits a notably high survival rate.
- In the age range from 10 to 40, the mortality rate surpasses the survival rate.
- Between the ages of 40 and 50, we observe a relatively higher survival rate, possibly due to the presence of Pclass 1 passengers.
- Beyond the age of 60 and above, the mortality rate tends to be higher.

In [39]:
```
#survived by fare
sns.histplot(df['Fare'][df['Survived']==0],kde=True, label='NotSurvived')
sns.histplot(df['Fare'][df['Survived']==1],kde=True, label='Survived')
plt.legend()
plt.show()
```



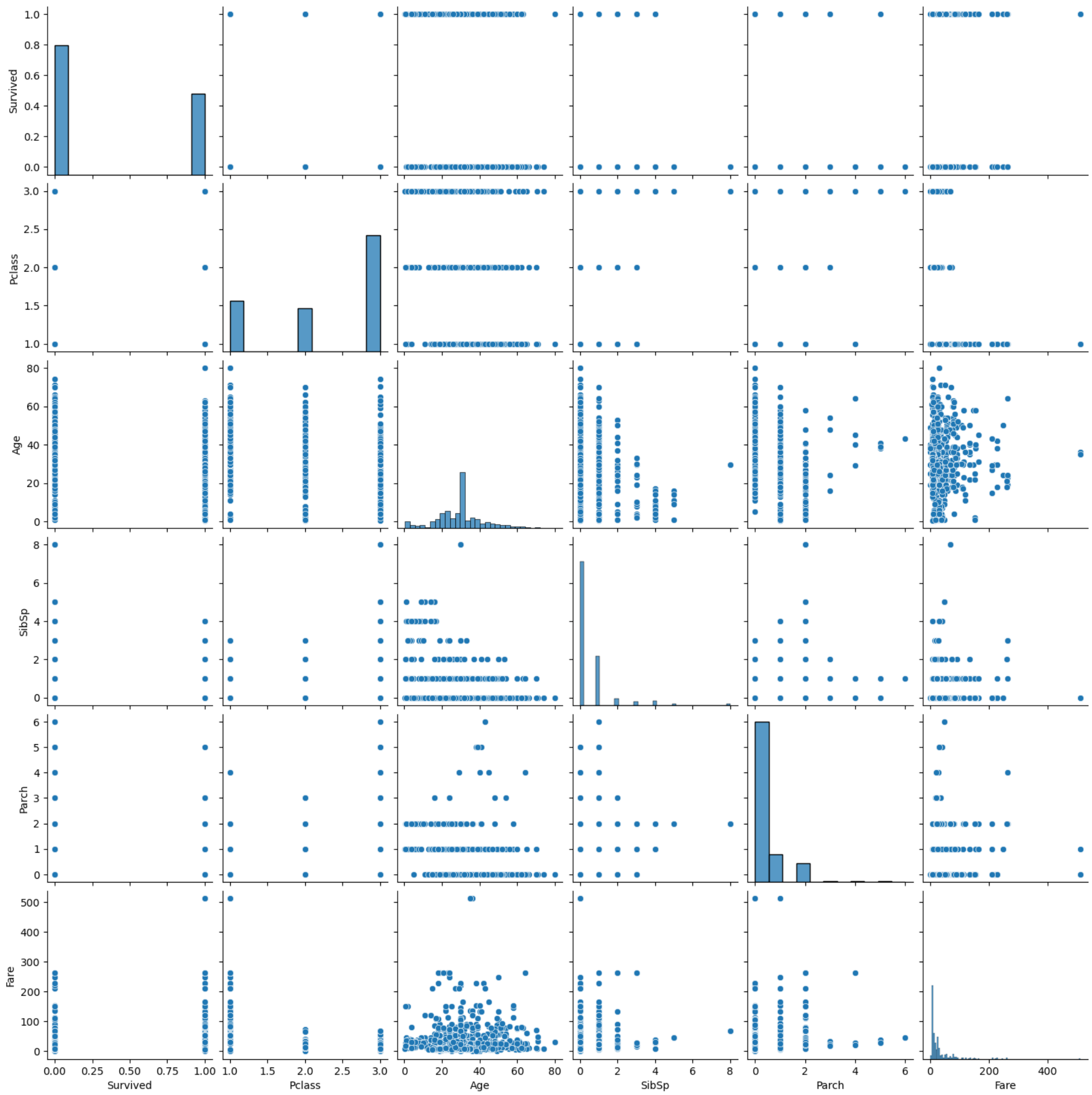
Observation:

- Passengers with higher fares exhibit a significantly greater survival rate compared to those with lower fares.

Multivariate Analysis

In [40]:
```
sns.pairplot(df)
```

Out[40]: <seaborn.axisgrid.PairGrid at 0x192f0f4f0d0>



Feature Engineer

SibSp & Parch Column

In [41]:
```
#Creating a new column by the name of family which will be the sum of SibSp and
df['family_size'] = df['SibSp'] + df['Parch'] + 1
df
```

Out[41]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	family_size
0	0	3	male	22.000000	1	0	7.2500	S	2
1	1	1	female	38.000000	1	0	71.2833	C	2
2	1	3	female	26.000000	0	0	7.9250	S	1
3	1	1	female	35.000000	1	0	53.1000	S	2
4	0	3	male	35.000000	0	0	8.0500	S	1
...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.000000	0	0	13.0000	S	1
887	1	1	female	19.000000	0	0	30.0000	S	1
888	0	3	female	29.699118	1	2	23.4500	S	4
889	1	1	male	26.000000	0	0	30.0000	C	1
890	0	3	male	32.000000	0	0	7.7500	Q	1

891 rows × 9 columns

In [42]:
```
# Now we will enginer a new feature by the name of family type
# 1 -> alone
# 2-4 -> small
# >5 -> large

def transform_family_size(num):
    if num == 1:
        return 'alone'
    elif num>1 and num <5:
        return "small"
    else:
        return "large"
```

In [43]:
```python
df['family_type'] = df['family_size'].apply(transform_family_size)
df
```

Out[43]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	family_size	family_t
0	0	3	male	22.000000	1	0	7.2500	S	2	sı
1	1	1	female	38.000000	1	0	71.2833	C	2	sı
2	1	3	female	26.000000	0	0	7.9250	S	1	al
3	1	1	female	35.000000	1	0	53.1000	S	2	sı
4	0	3	male	35.000000	0	0	8.0500	S	1	al
...	...	...	...	...	...	...	...	...	...	
886	0	2	male	27.000000	0	0	13.0000	S	1	al
887	1	1	female	19.000000	0	0	30.0000	S	1	al
888	0	3	female	29.699118	1	2	23.4500	S	4	sı
889	1	1	male	26.000000	0	0	30.0000	C	1	al
890	0	3	male	32.000000	0	0	7.7500	Q	1	al

891 rows × 10 columns

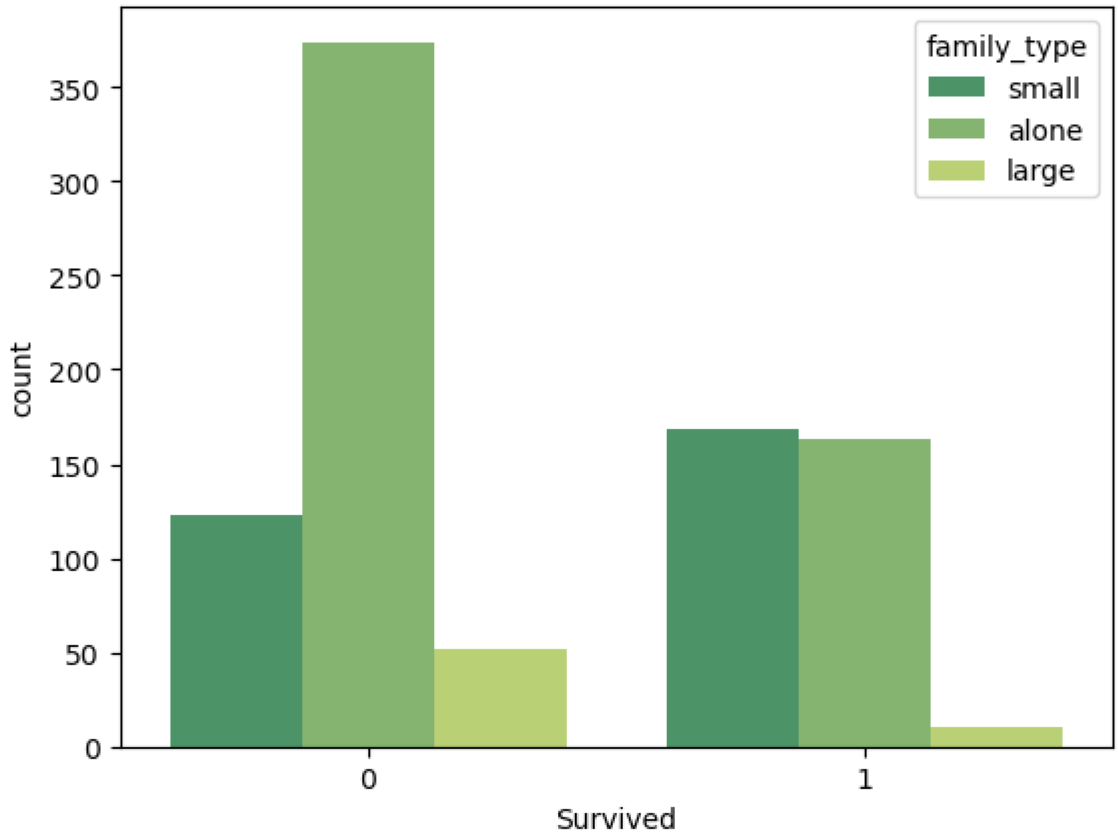
In [44]:
```python
#Dropping columns
df.drop(columns=['SibSp', 'Parch', 'family_size'],inplace=True)
```

In [45]:

```
#survived by family type
sns.countplot(x='Survived', data=df, hue='family_type', palette='summer')
(pd.crosstab(df['Survived'],df['family_type'],normalize='columns')*100).round(2
```

Out[45]:

family_type	alone	large	small
Survived			
0	69.65	83.87	42.12
1	30.35	16.13	57.88



Observations:

- **Alone:** Among passengers who traveled alone, without any family members onboard, approximately 30.4% survived, while 69.6% did not survive.
- **Large:** For passengers who were part of large families, approximately 14.9% survived, while 85.1% did not survive.
- **Small:** Among passengers who were part of medium-sized families, approximately 56.0% survived, while 44.0% did not survive.

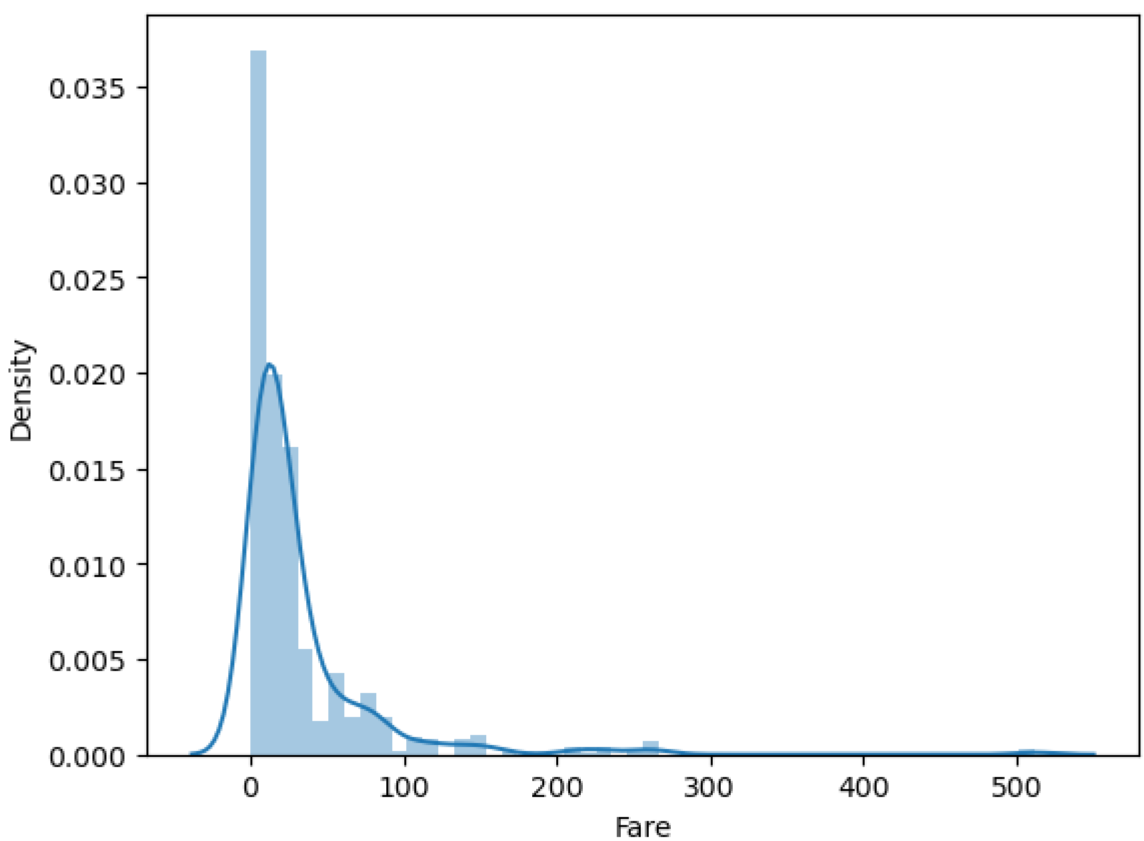
In [46]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Survived     891 non-null    int64  
 1   Pclass       891 non-null    int64  
 2   Sex          891 non-null    object 
 3   Age          891 non-null    float64
 4   Fare         891 non-null    float64
 5   Embarked     891 non-null    object 
 6   family_type  891 non-null    object 
dtypes: float64(2), int64(2), object(3)
memory usage: 48.9+ KB
```

Log transformation for uniform data distribution

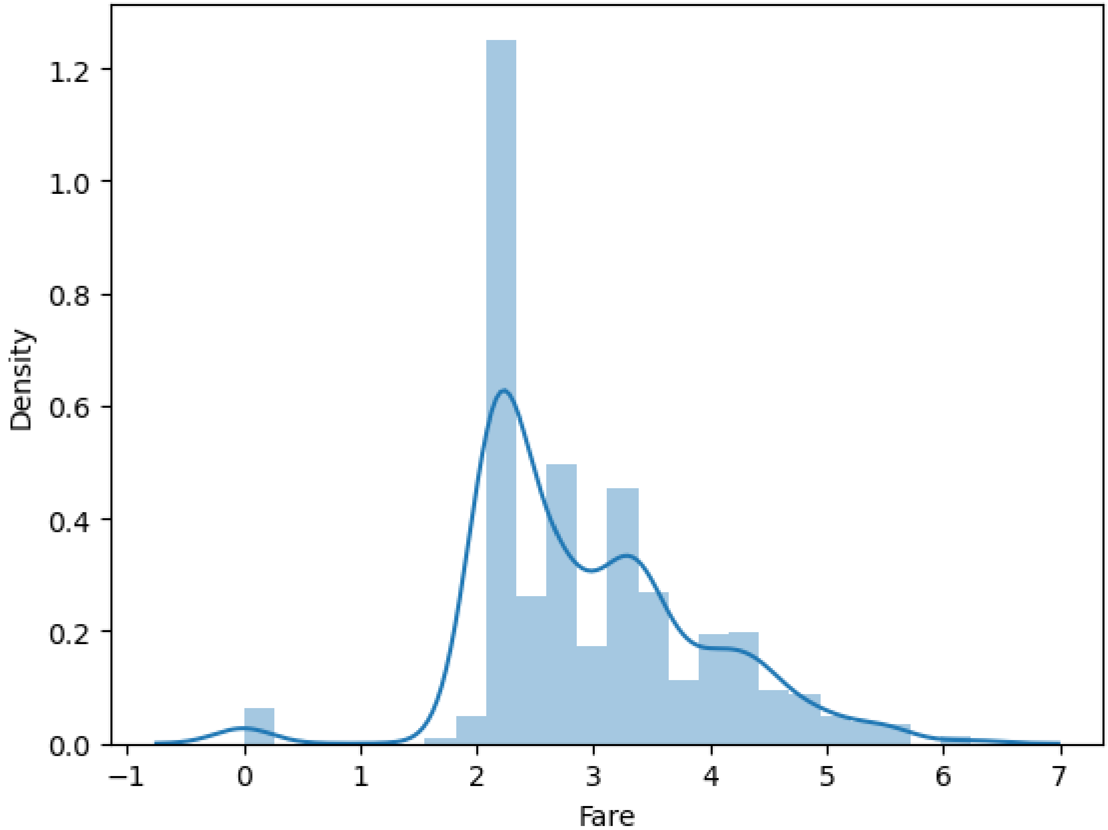
In [47]:
```
sns.distplot(df['Fare'],kde=True)
```

Out[47]:
```
<Axes: xlabel='Fare', ylabel='Density'>
```



In [48]:
```python
df['Fare'] = np.log(df['Fare']+1)
sns.distplot(df['Fare'])
```

Out[48]: <Axes: xlabel='Fare', ylabel='Density'>



Label Encoding

In [49]:
```python
from sklearn.preprocessing import LabelEncoder
cols = ['Sex', 'Embarked', 'family_type']
le = LabelEncoder()

for col in cols:
    df[col] = le.fit_transform(df[col])
df.head()
```

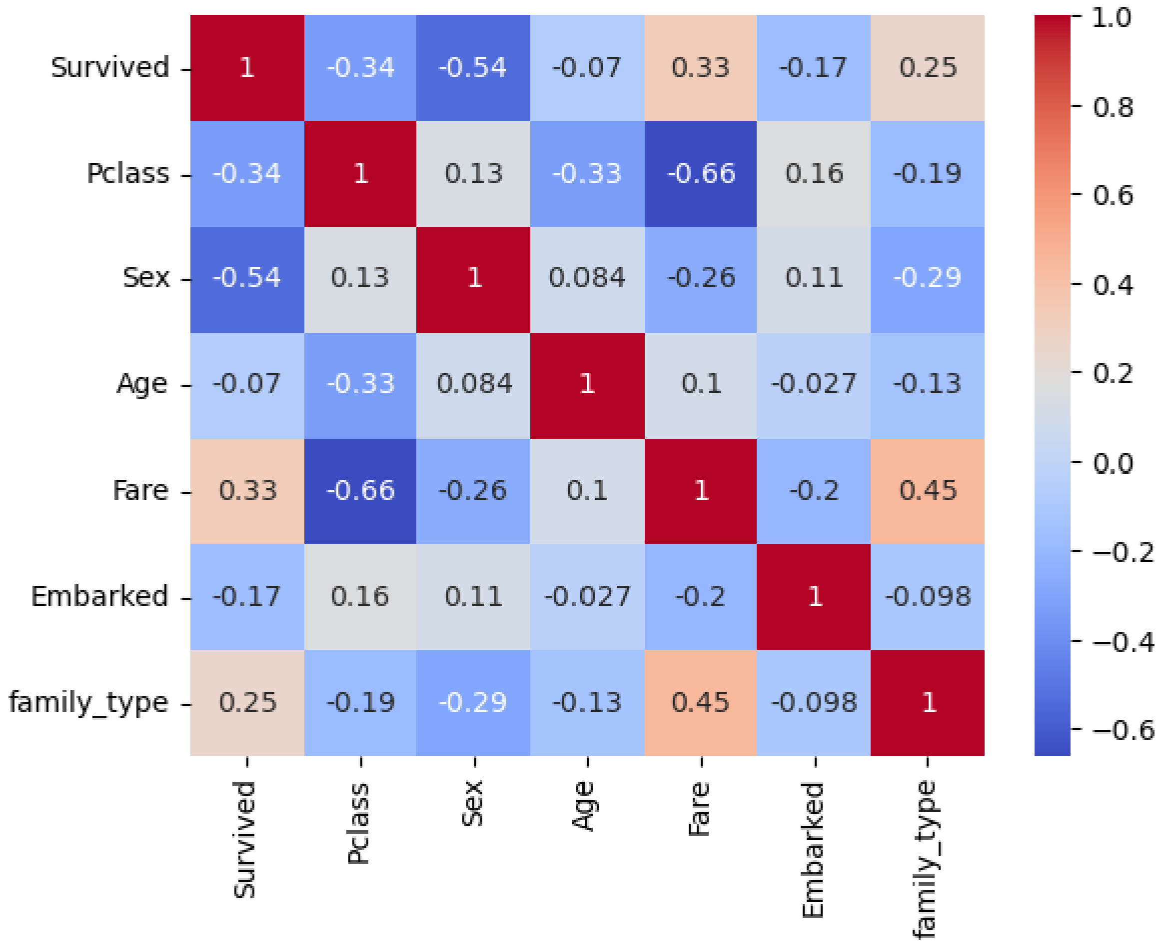
Out[49]:

	Survived	Pclass	Sex	Age	Fare	Embarked	family_type
0	0	3	1	22.0	2.110213	2	2
1	1	1	0	38.0	4.280593	0	2
2	1	3	0	26.0	2.188856	2	0
3	1	1	0	35.0	3.990834	2	2
4	0	3	1	35.0	2.202765	2	0

Correlation Matrix

In [50]:
```
corr = df.corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
```

Out[50]:
```
<Axes: >
```



In [51]:
```
df['Survived'].value_counts()
```

Out[51]:
```
0    549
1    342
Name: Survived, dtype: int64
```

Observation:

- data is looks imbalanced as survived(0) shows 342 and not survived (1) shows 549

Scaling data Using StandardScaler

In [52]:
```
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
features_to_scale =['Pclass','Age','Fare']
scaled_features = scaler.fit_transform(df[features_to_scale])
scaled_df = df.copy()
scaled_df[features_to_scale] = scaled_features
```

In [53]:
```
scaled_df
```

Out[53]:

	Survived	Pclass	Sex	Age	Fare	Embarked	family_type
0	0	0.827377	1	-0.592481	-0.879741	2	2
1	1	-1.566107	0	0.638789	1.361220	0	2
2	1	0.827377	0	-0.284663	-0.798540	2	0
3	1	-1.566107	0	0.407926	1.062038	2	2
4	0	0.827377	1	0.407926	-0.784179	2	0
...	...	...	...	...	...	...	...
886	0	-0.369365	1	-0.207709	-0.333698	2	0
887	1	-1.566107	0	-0.823344	0.487082	2	0
888	0	0.827377	0	0.000000	0.242007	2	2
889	1	-1.566107	1	-0.284663	0.487082	0	0
890	0	0.827377	1	0.177063	-0.818987	1	0

891 rows × 7 columns

Dividing Features and Label

In [54]:
```
X = scaled_df.drop('Survived', axis = 1)
y = scaled_df['Survived']
```

Handling Imbalance Data Using SMOTE

In [55]:
```
smote = SMOTE()
X_resampled, y_resampled = smote.fit_resample(X, y)
```

In [56]:
```
y_resampled.value_counts()
```

Out[56]:
```
0    549
1    549
Name: Survived, dtype: int64
```

Observations: We have balanced data now.

Train Test Split

In [57]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, t
```

In [58]:
```
#Importing Required Libraries
from sklearn.model_selection import GridSearchCV,cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
import xgboost
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier,ExtraTreesClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix, accuracy_s
from sklearn.metrics import roc_auc_score,roc_curve
```

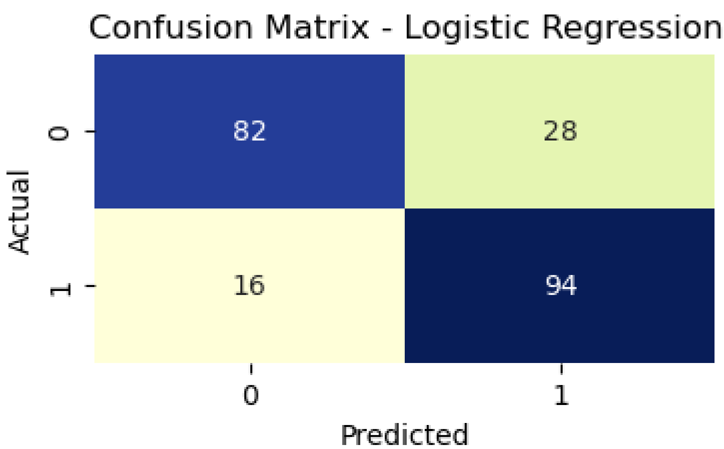
Model Selection

Logistic Regression with Hyperparameter Tuning

In [59]:

```python
# Define the parameter grid
param_grid = {
    'C': [0.1, 1, 10],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear', 'saga']
}

# Create the Logistic Regression Classifier
LG = LogisticRegression()

# Create the grid search object
grid_search = GridSearchCV(LG, param_grid, cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Create the Logistic Regression Classifier with the best parameters
best_LG = LogisticRegression(**best_params)

# Fit the model on the training data
best_LG.fit(X_train, y_train)

# Make predictions on the test set
LG_y_pred = best_LG.predict(X_test)

print("Logistic Regression with Hyperparameter Tuning:")
# Classification Report
print("Classification Report:")
print(classification_report(y_test, LG_y_pred))

# Cross-Validation Score
scores = cross_val_score(best_LG, X, y, cv=5)
print("Cross-Validation Scores:", scores)
mean_score = scores.mean()
print("Mean Cross-Validation Score:", mean_score)

# Plot confusion matrix as a heatmap
cm = confusion_matrix(y_test, LG_y_pred)
plt.figure(figsize=(4, 2))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix - Logistic Regression")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

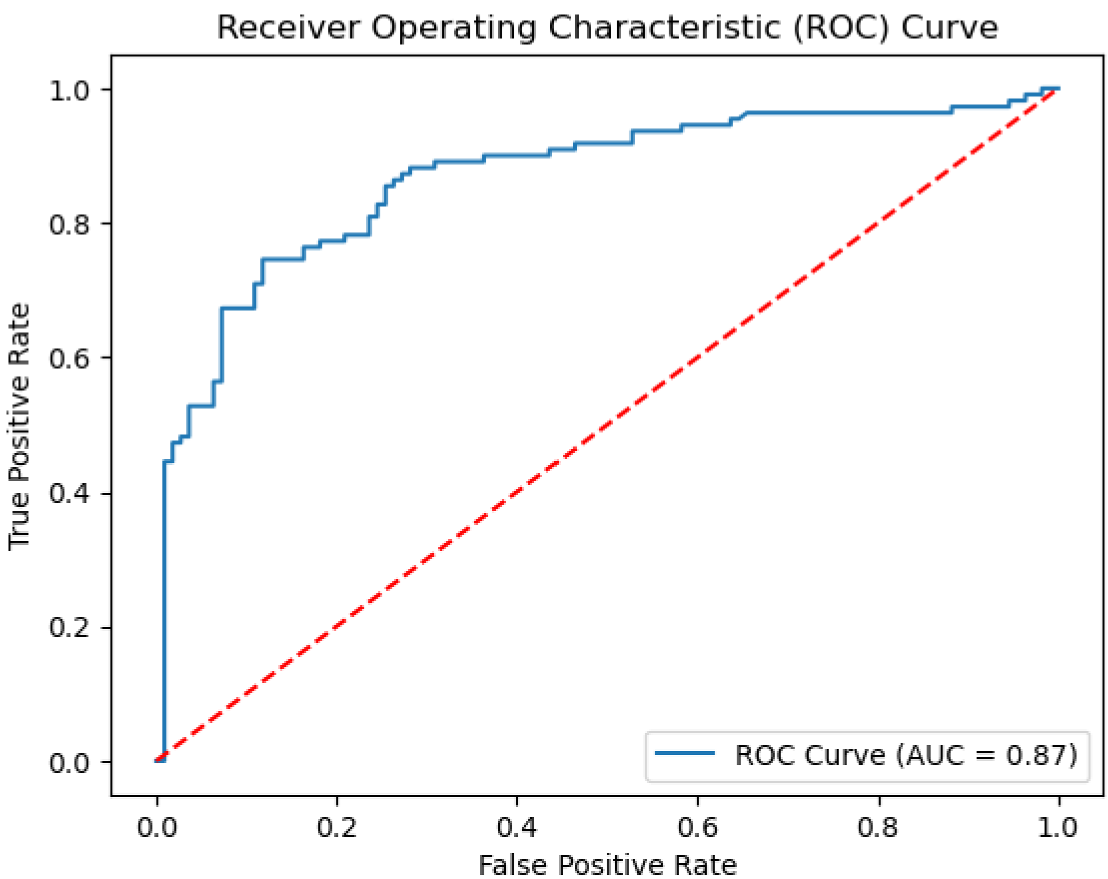
```
Logistic Regression with Hyperparameter Tuning:
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.75      0.79       110
           1       0.77      0.85      0.81       110

    accuracy                           0.80       220
   macro avg       0.80      0.80      0.80       220
weighted avg       0.80      0.80      0.80       220

Cross-Validation Scores: [0.70391061 0.79775281 0.80898876 0.76404494 0.83146
067]
Mean Cross-Validation Score: 0.7812315611072751
```



ROC AUC Curve

In [60]:
```
y_prob = best_LG.predict_proba(X_test)[:, 1]
auc_score = roc_auc_score(y_test, y_prob)
print("ROC AUC Score:", auc_score)
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

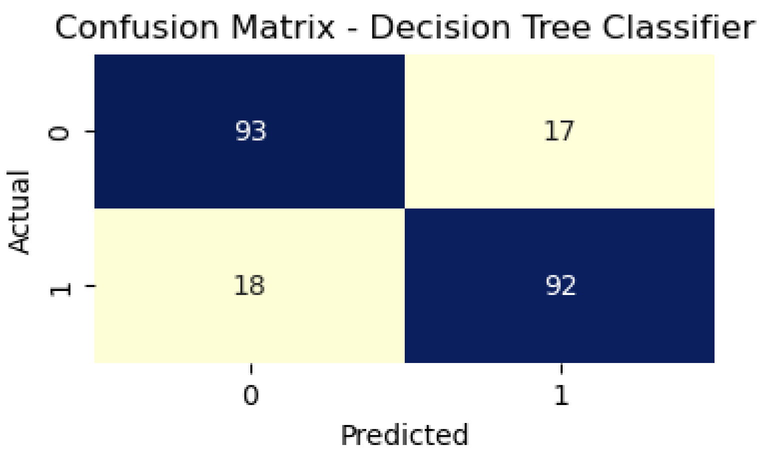
```
ROC AUC Score: 0.8680578512396695
```



Decision Tree Classifier with Hyperparameter Tuning

In [61]:
```
# Define the parameter grid
param_grid = {
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5, 10]
}

# Create the Decision Tree Classifier
dt = DecisionTreeClassifier()

# Create the grid search object
grid_search = GridSearchCV(dt, param_grid, cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Create the Decision Tree Classifier with the best parameters
best_dt = DecisionTreeClassifier(**best_params)

# Fit the model on the training data
best_dt.fit(X_train, y_train)

# Make predictions on the test set
dt_y_pred = best_dt.predict(X_test)

print("Decision Tree Classifier with Hyperparameter Tuning:")
# Classification Report
print("Classification Report:")
print(classification_report(y_test, dt_y_pred))

# Cross-Validation Score
scores = cross_val_score(best_dt, X, y, cv=5)
print("Cross-Validation Scores:", scores)
mean_score = scores.mean()
print("Mean Cross-Validation Score:", mean_score)

# Plot confusion matrix as a heatmap
cm = confusion_matrix(y_test, dt_y_pred)
plt.figure(figsize=(4, 2))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix - Decision Tree Classifier")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

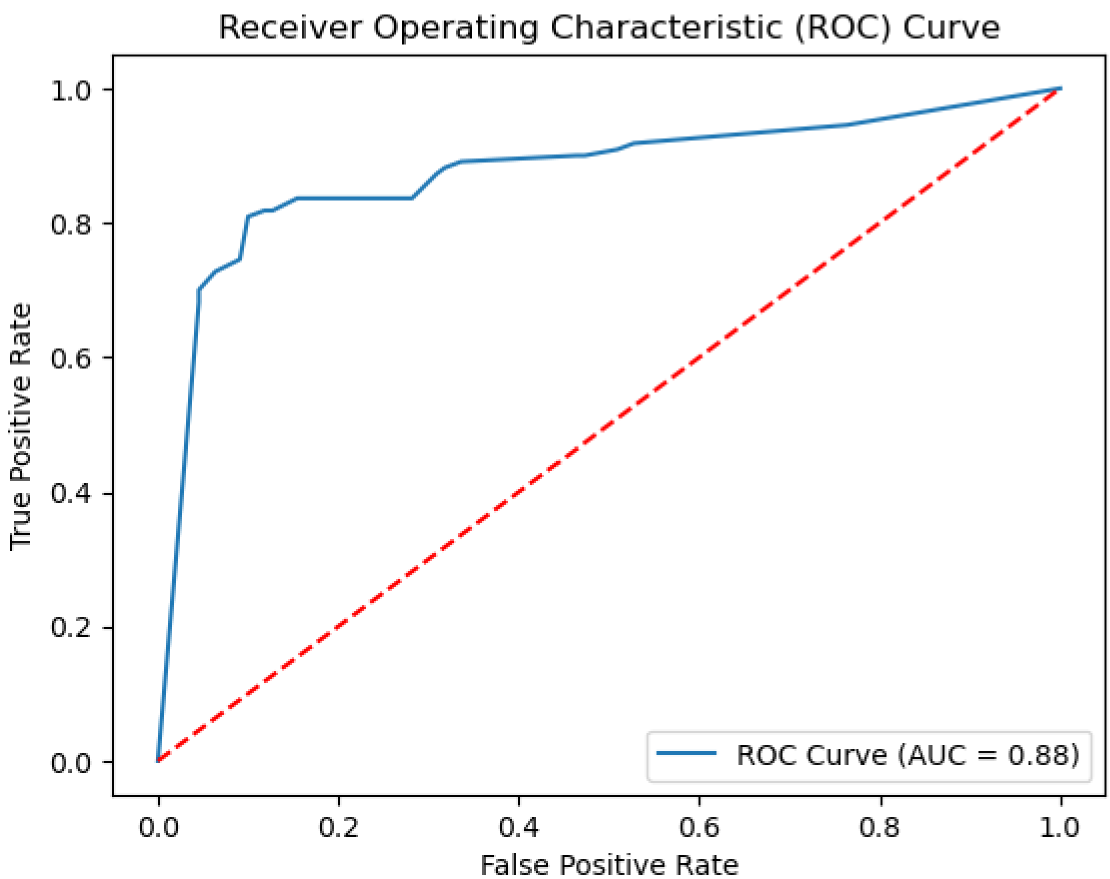
```
Decision Tree Classifier with Hyperparameter Tuning:
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.85      0.84       110
           1       0.84      0.84      0.84       110

    accuracy                           0.84       220
   macro avg       0.84      0.84      0.84       220
weighted avg       0.84      0.84      0.84       220

Cross-Validation Scores: [0.78212291 0.80337079 0.83146067 0.82022472 0.82584
27 ]
Mean Cross-Validation Score: 0.8126043562864854
```



ROC AUC Curve

In [62]:
```
y_prob = best_dt.predict_proba(X_test)[:, 1]
auc_score = roc_auc_score(y_test, y_prob)
print("ROC AUC Score:", auc_score)
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

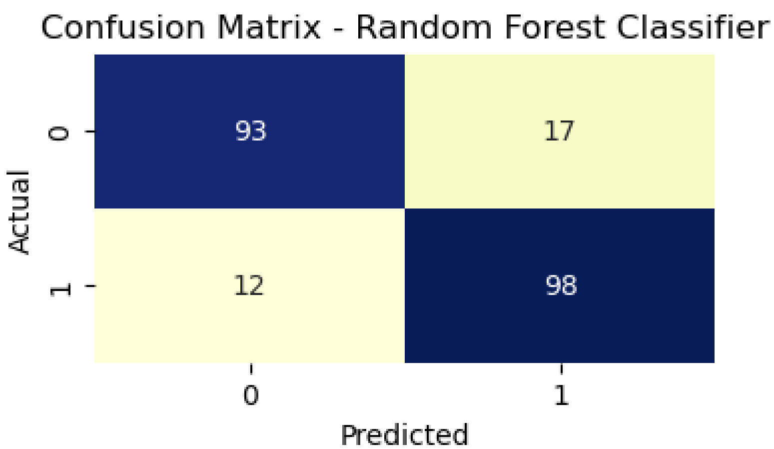
```
ROC AUC Score: 0.8760743801652893
```



Random Forest Classifier with Hyperparameter Tuning

In [63]:
```
# Define the parameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5, 10]
}

# Create the Random Forest Classifier
RF = RandomForestClassifier()

# Create the grid search object
grid_search = GridSearchCV(RF, param_grid, cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Create the Random Forest Classifier with the best parameters
best_RF = RandomForestClassifier(**best_params)

# Fit the model on the training data
best_RF.fit(X_train, y_train)

# Make predictions on the test set
RF_y_pred = best_RF.predict(X_test)

print("Random Forest Classifier with Hyperparameter Tuning:")
# Classification Report
print("Classification Report:")
print(classification_report(y_test, RF_y_pred))

# Cross-Validation Score
scores = cross_val_score(best_RF, X, y, cv=5)
print("Cross-Validation Scores:", scores)
mean_score = scores.mean()
print("Mean Cross-Validation Score:", mean_score)

# Plot confusion matrix as a heatmap
cm = confusion_matrix(y_test, RF_y_pred)
plt.figure(figsize=(4, 2))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix - Random Forest Classifier")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

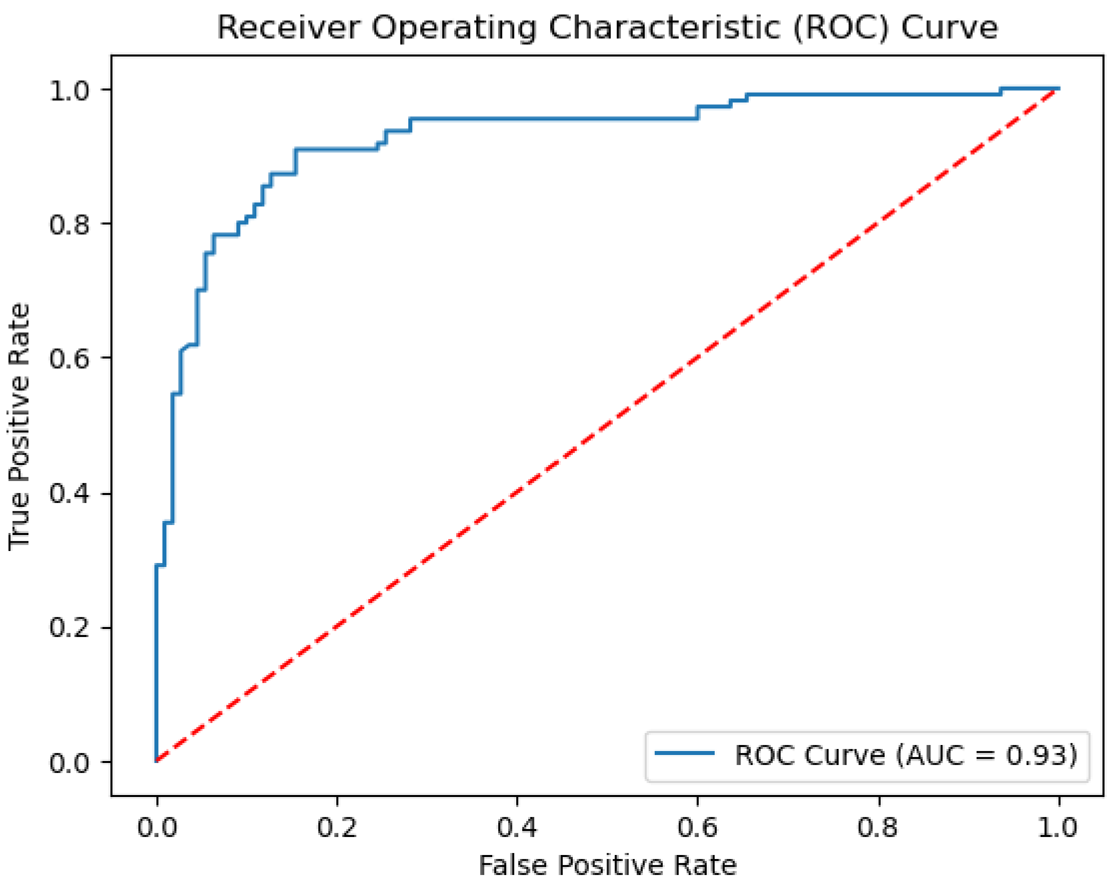
```
Random Forest Classifier with Hyperparameter Tuning:
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.85      0.87       110
           1       0.85      0.89      0.87       110

    accuracy                           0.87       220
   macro avg       0.87      0.87      0.87       220
weighted avg       0.87      0.87      0.87       220

Cross-Validation Scores: [0.80446927 0.80898876 0.83707865 0.80337079 0.84831
461]
Mean Cross-Validation Score: 0.8204444165463561
```



ROC AUC Curve

In [64]:
```
y_prob = best_RF.predict_proba(X_test)[:, 1]
auc_score = roc_auc_score(y_test, y_prob)
print("ROC AUC Score:", auc_score)
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
ROC AUC Score: 0.9266528925619835
```

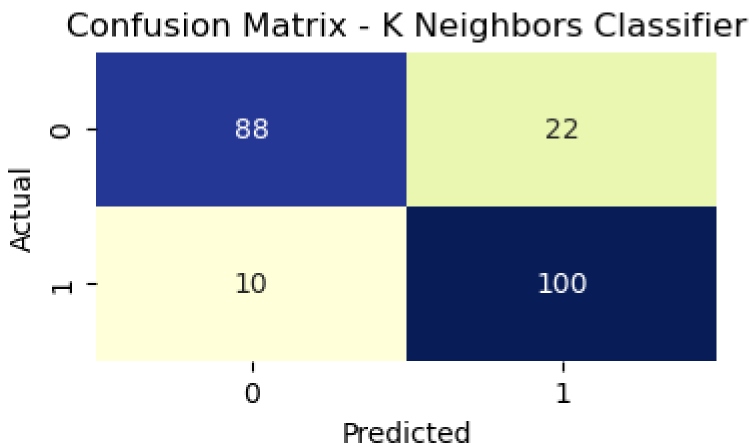


K Neighbour Classifier with Hyperparameter Tuning

In [65]:

```
# Define the parameter grid
param_grid = {
    'n_neighbors': [3, 5, 7],
    'weights': ['uniform', 'distance'],
    'p': [1, 2]
}

# Create the K Neighbors Classifier
KN = KNeighborsClassifier()

# Create the grid search object
grid_search = GridSearchCV(KN, param_grid, cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Create the K Neighbors Classifier with the best parameters
best_KN = KNeighborsClassifier(**best_params)

# Fit the model on the training data
best_KN.fit(X_train, y_train)

# Make predictions on the test set
KN_y_pred = best_KN.predict(X_test)

print("K Neighbors Classifier with Hyperparameter Tuning:")
# Classification Report
print("Classification Report:")
print(classification_report(y_test, KN_y_pred))

# Cross-Validation Score
scores = cross_val_score(best_KN, X, y, cv=5)
print("Cross-Validation Scores:", scores)
mean_score = scores.mean()
print("Mean Cross-Validation Score:", mean_score)

# Plot confusion matrix as a heatmap
cm = confusion_matrix(y_test, KN_y_pred)
plt.figure(figsize=(4, 2))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix - K Neighbors Classifier")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

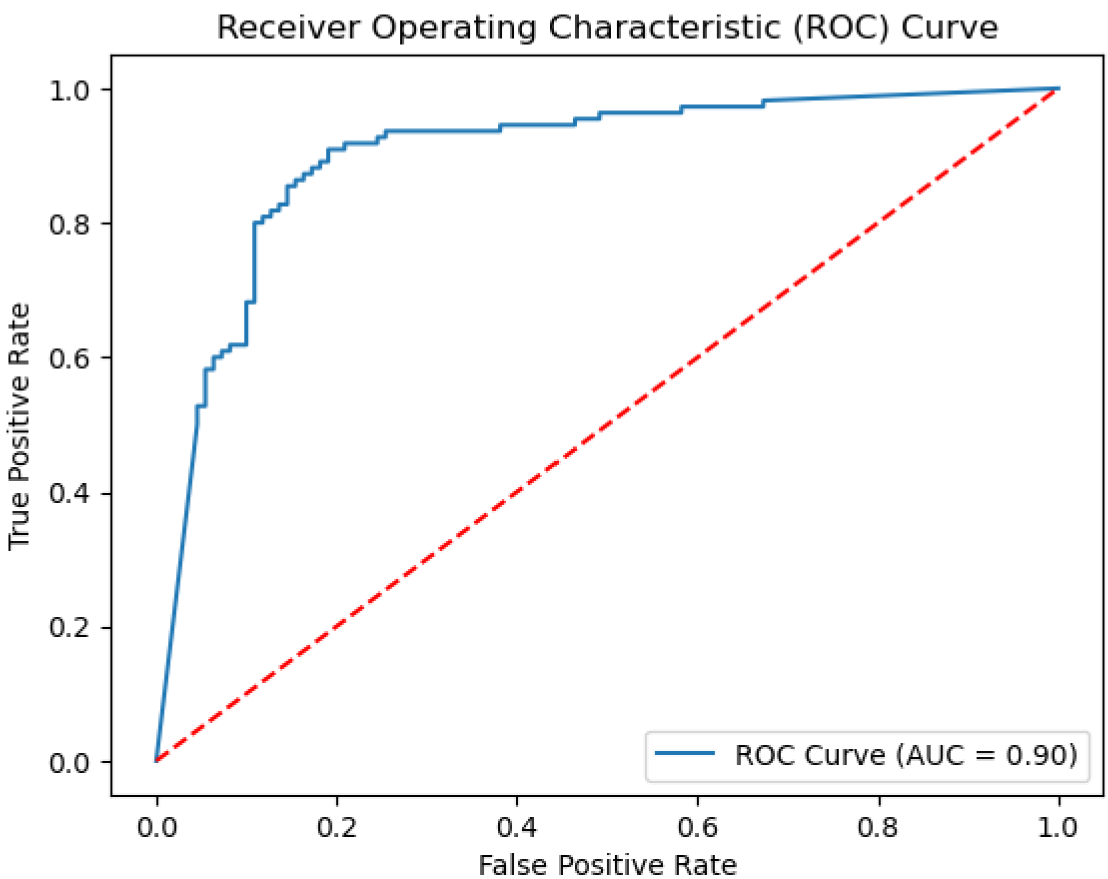
```
K Neighbors Classifier with Hyperparameter Tuning:
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.80      0.85       110
           1       0.82      0.91      0.86       110

    accuracy                           0.85       220
   macro avg       0.86      0.85      0.85       220
weighted avg       0.86      0.85      0.85       220

Cross-Validation Scores: [0.78212291 0.7752809  0.84269663 0.76404494 0.81460
674]
Mean Cross-Validation Score: 0.7957504237022157
```



ROC AUC Curve

In [66]:
```
y_prob = best_KN.predict_proba(X_test)[:, 1]
auc_score = roc_auc_score(y_test, y_prob)
print("ROC AUC Score:", auc_score)
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

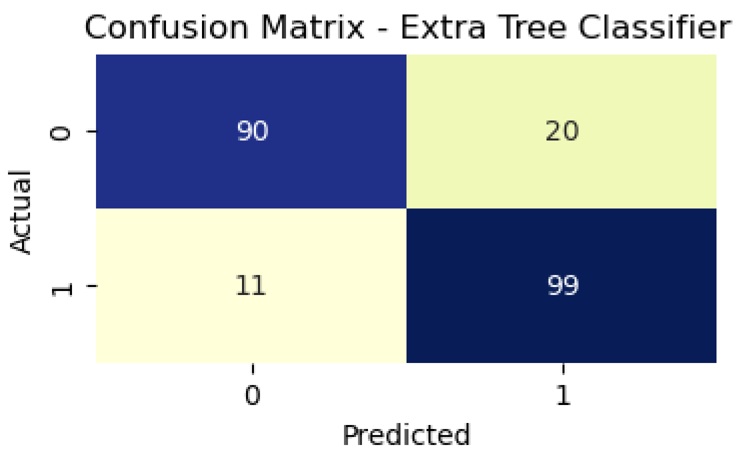
```
ROC AUC Score: 0.9003719008264462
```



Extra Tree Classifier with Hyperparameter Tuning

In [67]:
```
# Define the parameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5, 10]
}

# Create the Extra Trees Classifier
ET = ExtraTreesClassifier()

# Create the grid search object
grid_search = GridSearchCV(ET, param_grid, cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_


# Create the Extra Trees Classifier with the best parameters
best_ET = ExtraTreesClassifier(**best_params)

# Fit the model on the training data
best_ET.fit(X_train, y_train)

# Make predictions on the test set
ET_y_pred = best_ET.predict(X_test)

print("Extra Tree Classifier with Hyperparameter Tuning:")
# Classification Report
print("Classification Report:")
print(classification_report(y_test, ET_y_pred))

# Cross-Validation Score
scores = cross_val_score(best_ET, X, y, cv=5)
print("Cross-Validation Scores:", scores)
mean_score = scores.mean()
print("Mean Cross-Validation Score:", mean_score)

# Plot confusion matrix as a heatmap
cm = confusion_matrix(y_test, ET_y_pred)
plt.figure(figsize=(4, 2))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix - Extra Tree Classifier")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

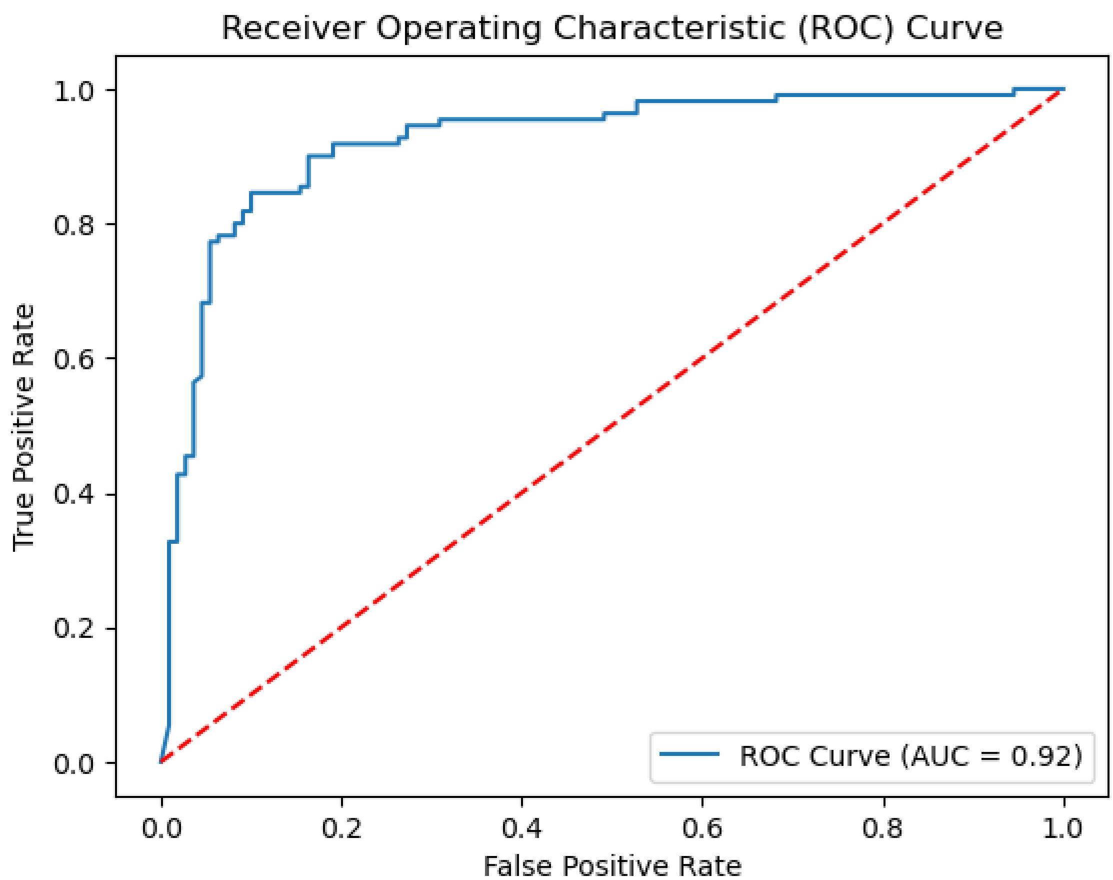
```
Extra Tree Classifier with Hyperparameter Tuning:
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.82      0.85       110
           1       0.83      0.90      0.86       110

    accuracy                           0.86       220
   macro avg       0.86      0.86      0.86       220
weighted avg       0.86      0.86      0.86       220

Cross-Validation Scores: [0.81005587 0.79213483 0.87078652 0.81460674 0.84831
461]
Mean Cross-Validation Score: 0.8271797125102001
```



ROC AUC Curve

In [68]:
```python
y_prob = best_ET.predict_proba(X_test)[:, 1]
auc_score = roc_auc_score(y_test, y_prob)
print("ROC AUC Score:", auc_score)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
ROC AUC Score: 0.9226859504132231
```

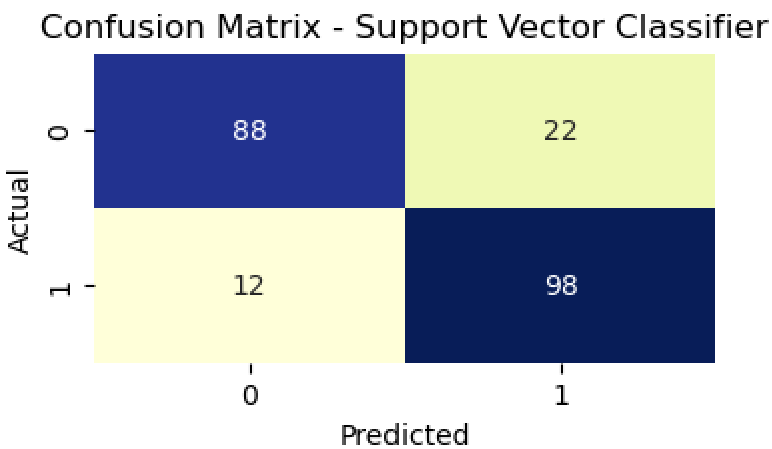


Support Vector Classifier with Hyperparameter Tuning

In [69]:

```
# Define the parameter grid
param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale', 'auto']
}

# Create the SVC
SV = SVC()

# Create the grid search object
grid_search = GridSearchCV(SV, param_grid, cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Create the SVC with the best parameters
best_SV = SVC(**best_params)

# Fit the model on the training data
best_SV.fit(X_train, y_train)

# Make predictions on the test set
SV_y_pred = best_SV.predict(X_test)

print("Support Vector Classifier with Hyperparameter Tuning:")
# Classification Report
print("Classification Report:")
print(classification_report(y_test, SV_y_pred))

# Cross-Validation Score
scores = cross_val_score(best_SV, X, y, cv=5)
print("Cross-Validation Scores:", scores)
mean_score = scores.mean()
print("Mean Cross-Validation Score:", mean_score)

# Plot confusion matrix as a heatmap
cm = confusion_matrix(y_test, SV_y_pred)
plt.figure(figsize=(4, 2))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix - Support Vector Classifier")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
Support Vector Classifier with Hyperparameter Tuning:
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.80      0.84       110
           1       0.82      0.89      0.85       110

    accuracy                           0.85       220
   macro avg       0.85      0.85      0.85       220
weighted avg       0.85      0.85      0.85       220

Cross-Validation Scores: [0.77653631 0.78651685 0.81460674 0.79213483 0.84269
663]
Mean Cross-Validation Score: 0.8024982738057874
```

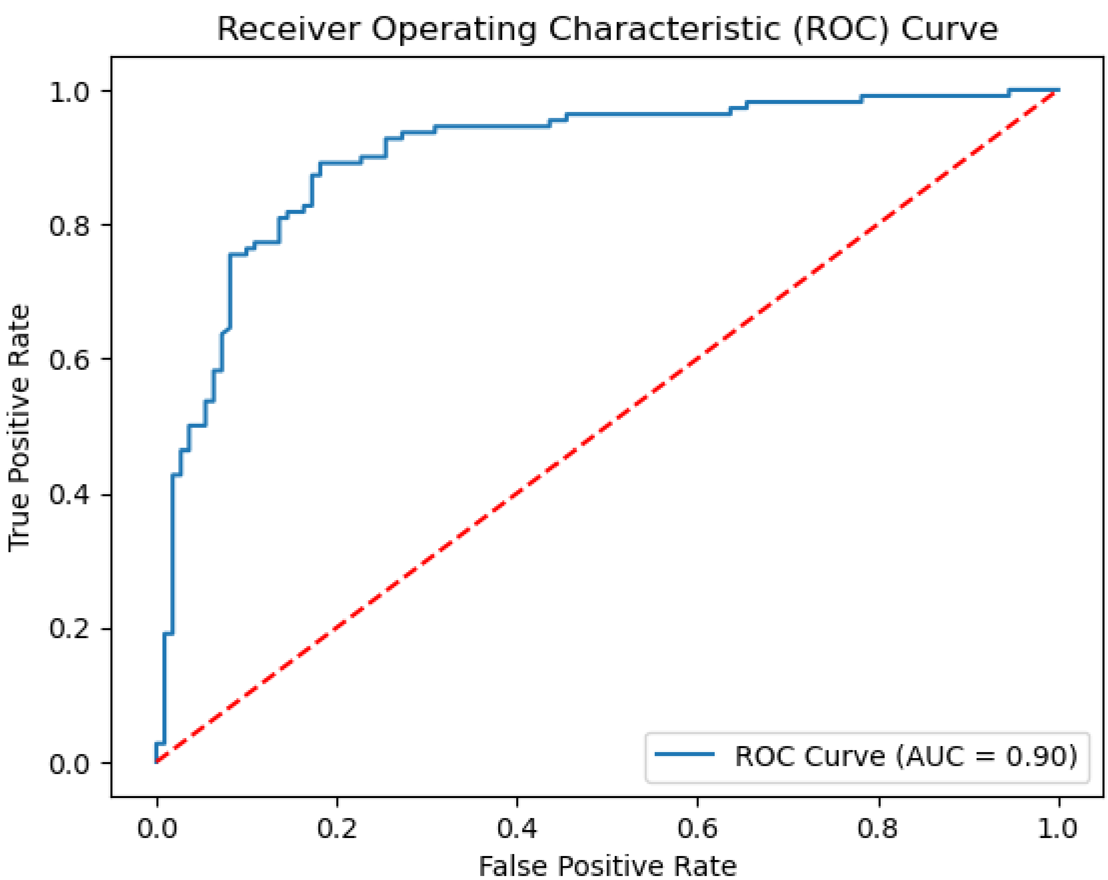


ROC AUC curve

In [70]:

```
y_prob = best_SV.decision_function(X_test)

# Compute ROC AUC score
auc_score = roc_auc_score(y_test, y_prob)

print("ROC AUC Score:", auc_score)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
ROC AUC Score: 0.9027685950413223
```



XGBoost Classifier with Hyperparameter Tuning

In [ ]:
```
# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.1, 0.01, 0.001],
    'max_depth': [3, 5, 7],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

# Create the XGBoost classifier
XGB = XGBClassifier()

# Create the grid search object
grid_search = GridSearchCV(XGB, param_grid, cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# Create the XGBoost classifier with the best parameters
best_XGB = XGBClassifier(**best_params)

# Fit the model on the training data and make prediction on test data
best_XGB.fit(X_train, y_train)
XGB_y_pred = best_XGB.predict(X_test)


print("XGBoost Classifier :")
# Classification Report
print("Classification Report:")
print(classification_report(y_test, XGB_y_pred))


# Cross-Validation Score
scores = cross_val_score(best_XGB, X, y, cv=5, scoring='roc_auc')
print("Cross-Validation Scores:", scores)
mean_score = scores.mean()
print("Mean Cross-Validation Score:", mean_score)

# Plot confusion matrix as a heatmap
cm = confusion_matrix(y_test, XGB_y_pred)
plt.figure(figsize=(4, 2))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix - XGBoost Classifier")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

ROC AUC Curve

In [ ]:
```
y_prob = best_XGB.predict_proba(X_test)[:, 1]

# Compute ROC AUC score
auc_score = roc_auc_score(y_test, y_prob)

print("ROC AUC Score:", auc_score)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

Creating DataFrame of All the Models in Their descending Order

In [ ]:
```
# Create a list of model names
model_names = ['Extra Tree Classifier', 'Support Vector Classifier', 'K Neighbo

# Create a list of models and their corresponding accuracy scores
models = [ET, SV, KN, RF, dt, LG]
accuracy_scores = [accuracy_score(y_test, ET_y_pred), accuracy_score(y_test, SV

# Create a dataframe with model name and accuracy score
df = pd.DataFrame({'Model Name': model_names, 'Accuracy Score': accuracy_scores

# Sort the dataframe by accuracy score in descending order
df = df.sort_values('Accuracy Score', ascending=False)

# Print the dataframe
df.index = range(1, len(df)+1)
print(df)
```

Save Best Model

In [ ]:
```
import pickle
filename = 'RFClassifier.pkl'
pickle.dump(XGB, open(filename, 'wb'))
```

In [ ]: