In [ ]:
```
NAME : lAKSHMI SRUJANA VANKAYALA
REG NO : 21BCE9181
```

1. IMPORT THE LIBRARIES

In [2]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

2. IMPORT THE DATASET

In [4]:
```python
df=pd.read_csv("Titanic-Dataset.csv")
```

In [5]:
```python
df
```

Out[5]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

In [6]:
```python
df.head()
```

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [7]:
```python
df.shape
```

Out[7]:
```
(891, 12)
```

In [8]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
<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 [9]:

```
df.describe()
```

Out[9]:

	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

In [10]:

```
corr=df.corr()
corr
```

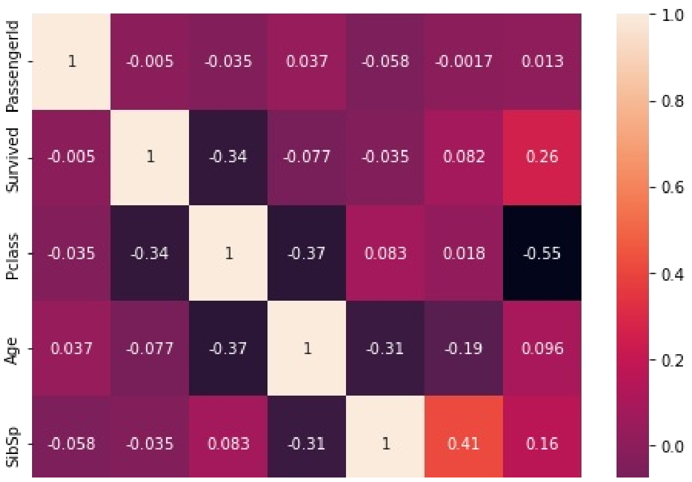
Out[10]:

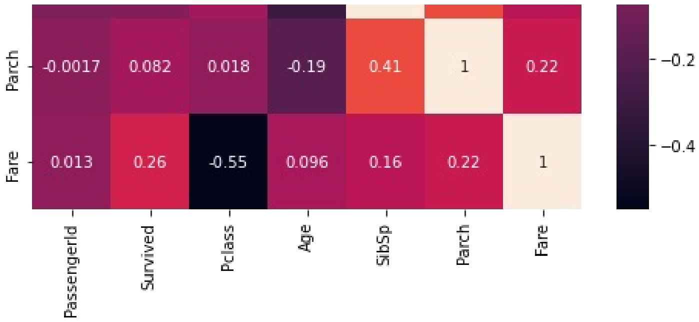
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000

In [11]:

```
plt.subplots(figsize=(8,8))
sns.heatmap(corr,annot=True)
```

Out[11]: <AxesSubplot:>





In [12]:

```
df.Survived.value_counts()
```

Out[12]:

```
0    549
1    342
Name: Survived, dtype: int64
```

In [13]:

```
df.Sex.value_counts()
```

Out[13]:

```
male      577
female    314
Name: Sex, dtype: int64
```

In [14]:

```
df.Embarked.value_counts()
```

Out[14]:

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

3. CHECK FOR NULL VALUES

In [15]:

```
df.isnull().any()
```

Out[15]:

```
PassengerId    False
Survived       False
Pclass         False
Name           False
Sex            False
Age             True
SibSp          False
Parch          False
Ticket         False
Fare           False
Cabin           True
Embarked        True
dtype: bool
```

In [16]:

```
df.isnull().sum()
```

Out[16]:

```
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
```

Fill null values in the 'Age' column with the mean age

In [16]:

```
mean_age = df['Age'].mean()
df['Age'].fillna(mean_age, inplace=True)
```

Fill null values in the 'Embarked' column with the most common value

In [17]:

```
most_common_embarked = df['Embarked'].mode()[0]
df['Embarked'].fillna(most_common_embarked, inplace=True)
```

In [18]:

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

In [19]:

```
df.drop(['Ticket'],axis=1, inplace=True)
```

In [20]:

```
df.drop(['Name'],axis=1,inplace=True)
```

In [21]:

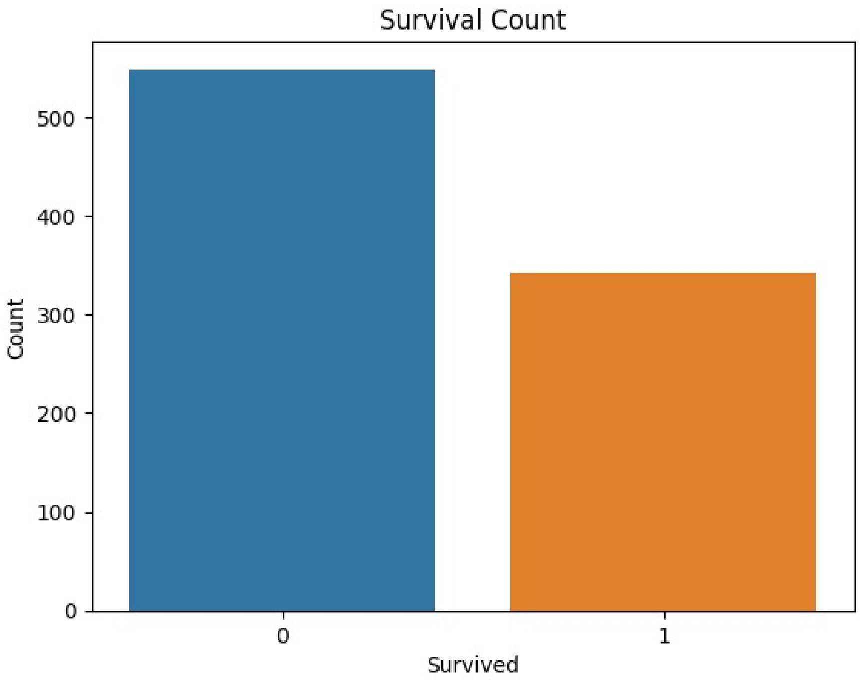
```
print(df.isnull().sum())
```

```
PassengerId    0
Survived       0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Fare           0
Embarked       0
dtype: int64
```

4. Data Visualization

In [22]:

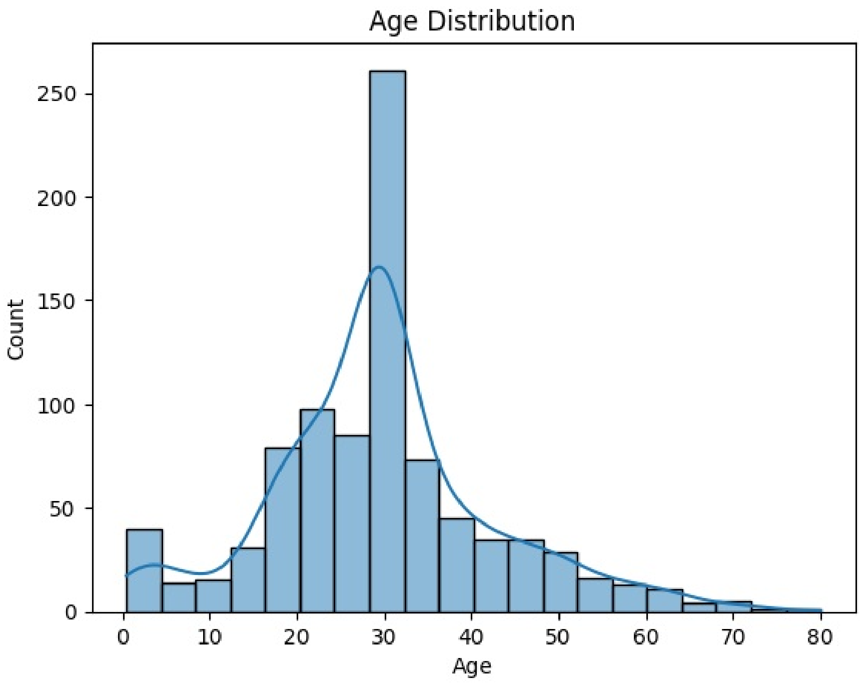
```
# Visualize the distribution of the 'Survived' column (0 = Not Survived, 1 = Survived)
sns.countplot(data=df, x='Survived')
plt.title('Survival Count')
plt.xlabel('Survived')
plt.ylabel('Count')
plt.show()
```



In [23]:

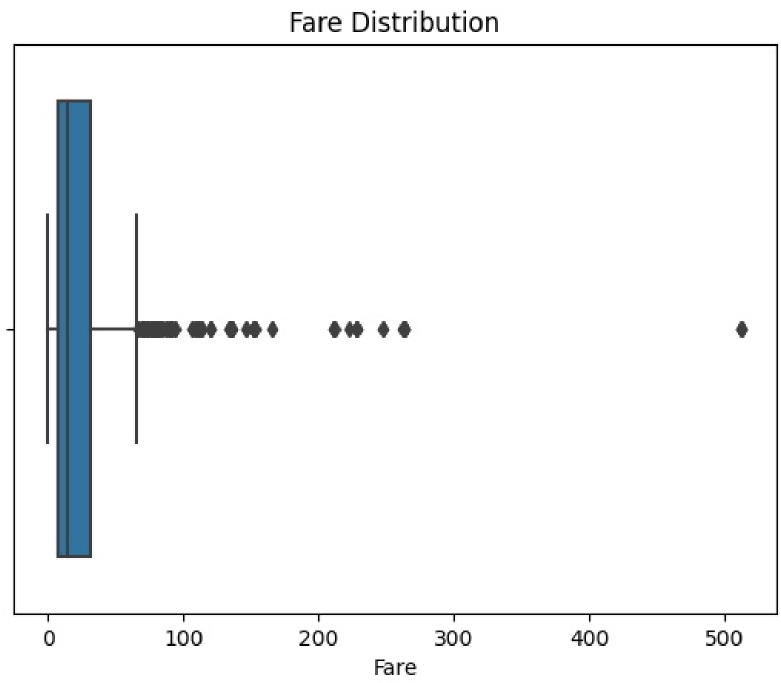
```
#Visualize the distribution of the 'Age' column
sns.histplot(data=df, x='Age', bins=20, kde=True)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
```

```
plt.show()
```



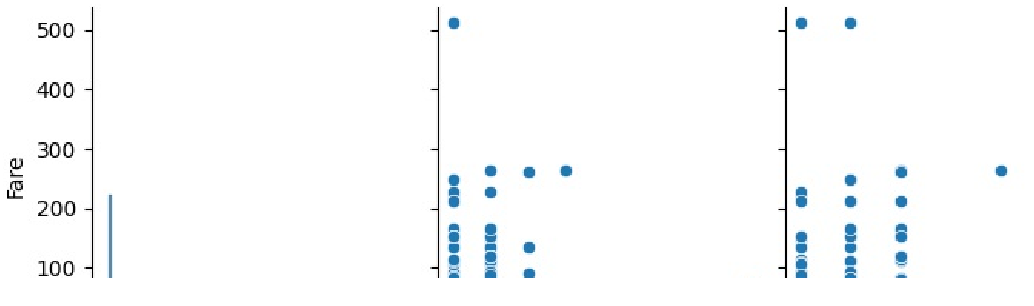
In [24]:

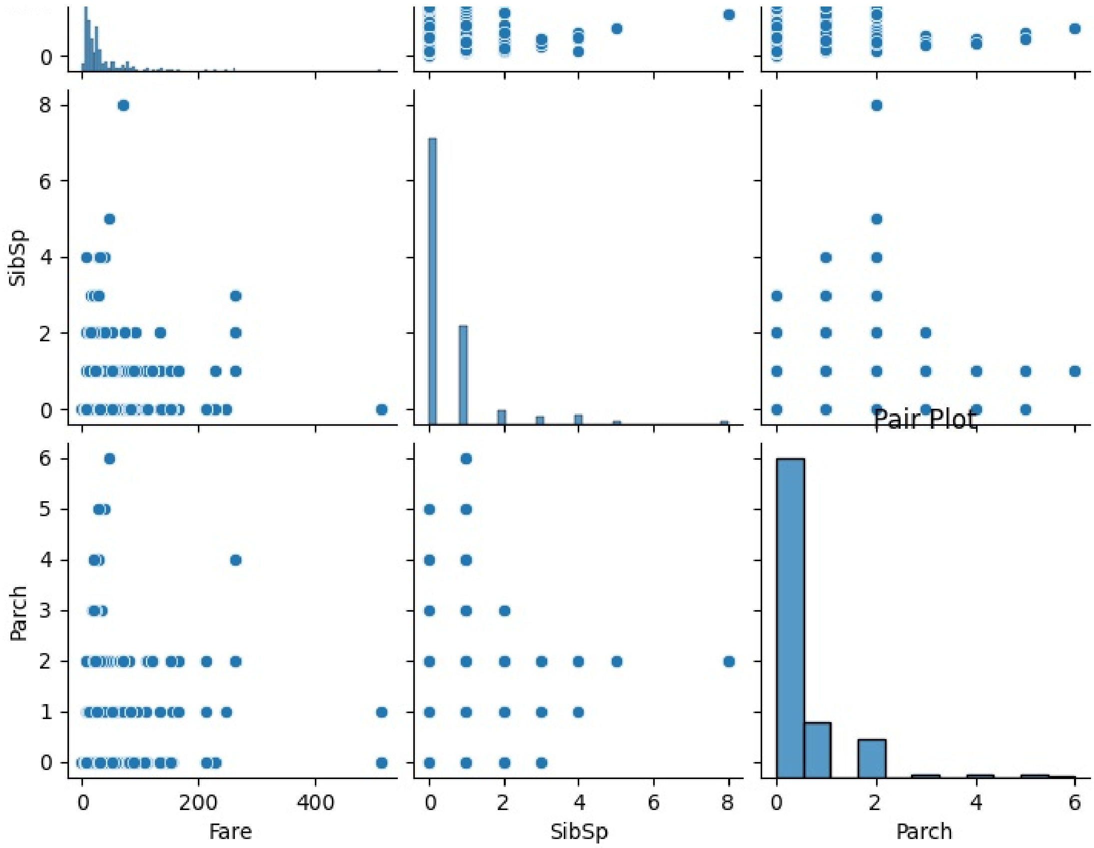
```
#Visualize the distribution of the 'Fare' column and detect outliers we will handle outliers in the next step
sns.boxplot(data=df, x='Fare')
plt.title('Fare Distribution')
plt.xlabel('Fare')
plt.show()
```



In [25]:

```
#Pair plot for selected numerical columns
sns.pairplot(data=df[['Fare', 'SibSp', 'Parch']])
plt.title('Pair Plot')
plt.show()
```

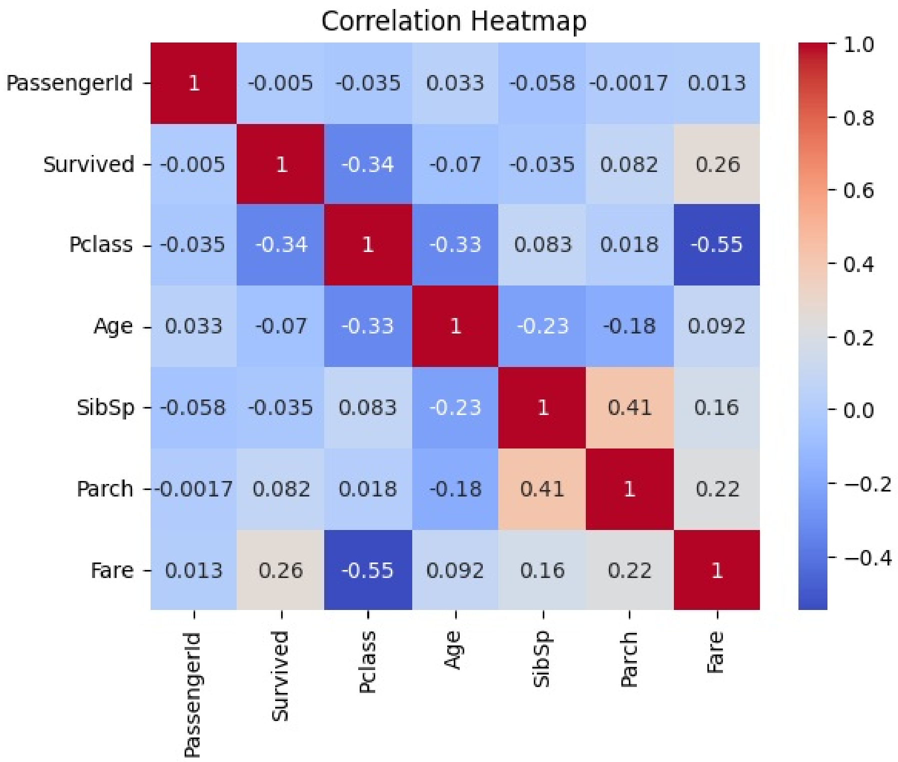




In [26]:

```
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True,cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

```
<ipython-input-26-8dcbd071fff3>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecat
ed. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  corr_matrix = df.corr()
```



5. Detect and Handle Outliers

In [27]:

```python
z_scores = np.abs(stats.zscore(df['Age']))
max_threshold=3
outliers = df['Age'][z_scores > max_threshold]

# Print and visualize the outliers
print("Outliers detected using Z-Score:")
print(outliers)
```

```
Outliers detected using Z-Score:
96     71.0
116    70.5
493    71.0
630    80.0
672    70.0
745    70.0
851    74.0
Name: Age, dtype: float64
```

In [28]:

```python
z_scores = np.abs(stats.zscore(df['Fare']))
max_threshold=3
outliers = df['Fare'][z_scores > max_threshold]

# Print and visualize the outliers
print("Outliers detected using Z-Score:")
print(outliers)
```

```
Outliers detected using Z-Score:
27     263.0000
88     263.0000
118    247.5208
258    512.3292
299    247.5208
311    262.3750
341    263.0000
377    211.5000
380    227.5250
438    263.0000
527    221.7792
557    227.5250
679    512.3292
689    211.3375
700    227.5250
716    227.5250
730    211.3375
737    512.3292
742    262.3750
779    211.3375
Name: Fare, dtype: float64
```

In [29]:

```python
column_name = 'Fare'

# Calculate the first quartile (Q1) and third quartile (Q3)
Q1 = df[column_name].quantile(0.25)
Q3 = df[column_name].quantile(0.75)

# Calculate the IQR
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter rows with values outside the IQR bounds
df_cleaned = df[(df[column_name] > lower_bound) & (df[column_name] <upper_bound)]

# Display the original and cleaned DataFrame sizes
print(f"Original DataFrame size: {df.shape}")
print(f"Cleaned DataFrame size: {df_cleaned.shape}")
df_cleaned
```

```
Original DataFrame size: (891, 9)
Cleaned DataFrame size: (775, 9)
```

Out[29]:

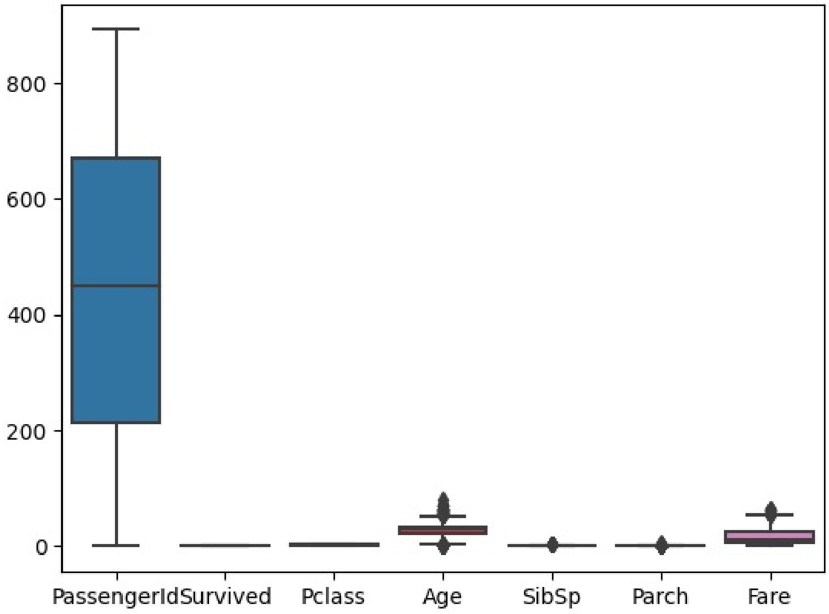
	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	male	22.000000	1	0	7.2500	S
2	3	1	3	female	26.000000	0	0	7.9250	S
3	4	1	1	female	35.000000	1	0	53.1000	S
4	5	0	3	male	35.000000	0	0	8.0500	S

5	6	0	3	male	29.699118	0	0	8.4583	Q
...	...	...	...	...	...	...	...	...	...
886	887	0	2	male	27.000000	0	0	13.0000	S
887	888	1	1	female	19.000000	0	0	30.0000	S
888	889	0	3	female	29.699118	1	2	23.4500	S
889	890	1	1	male	26.000000	0	0	30.0000	C
890	891	0	3	male	32.000000	0	0	7.7500	Q

775 rows × 9 columns

In [30]:
```
sns.boxplot(df_cleaned)
```

Out[30]:
```
<Axes: >
```



In [31]:
```
df=df_cleaned
```

In [32]:
```
x=df.drop('Survived', axis=1)
y=df['Survived']
```

In [33]:
```
x.head()
```

Out[33]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	3	male	22.000000	1	0	7.2500	S
2	3	3	female	26.000000	0	0	7.9250	S
3	4	1	female	35.000000	1	0	53.1000	S
4	5	3	male	35.000000	0	0	8.0500	S
5	6	3	male	29.699118	0	0	8.4583	Q

In [34]:
```
y.head()
```

Out[34]:
```
0    0
2    1
3    1
4    0
5    0
Name: Survived, dtype: int64
```

7. Perform Encoding

7. Perform Encoding

In [35]:
```
en = LabelEncoder()
x['Sex'] = en.fit_transform(x['Sex'])
```

In [36]:
```
x.head()
```

Out[36]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	3	1	22.000000	1	0	7.2500	S
2	3	3	0	26.000000	0	0	7.9250	S
3	4	1	0	35.000000	1	0	53.1000	S
4	5	3	1	35.000000	0	0	8.0500	S
5	6	3	1	29.699118	0	0	8.4583	Q

In [37]:
```
x = pd.get_dummies(x,columns=['Embarked'])
```

In [38]:
```
x.head()
```

Out[38]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S
0	1	3	1	22.000000	1	0	7.2500	0	0	1
2	3	3	0	26.000000	0	0	7.9250	0	0	1
3	4	1	0	35.000000	1	0	53.1000	0	0	1
4	5	3	1	35.000000	0	0	8.0500	0	0	1
5	6	3	1	29.699118	0	0	8.4583	0	1	0

8. Feature Scaling

In [39]:
```
scale = StandardScaler()
x[['Age', 'Fare']] = scale.fit_transform(x[['Age', 'Fare']])
```

In [40]:
```
x.head()
```

Out[40]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_C	Embarked_Q	Embarked_S
0	1	3	1	-0.556219	1	0	-0.779117	0	0	1
2	3	3	0	-0.243027	0	0	-0.729373	0	0	1
3	4	1	0	0.461654	1	0	2.599828	0	0	1
4	5	3	1	0.461654	0	0	-0.720161	0	0	1
5	6	3	1	0.046606	0	0	-0.690071	0	1	0

9. Splitting the data into Train and Test

In [44]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [43]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(620, 10)
(155, 10)
(620,)
(155,)
```