In [32]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

In [2]:
```
train= pd.read_csv('train.csv')
```

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

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
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

STEP1:Remove duplicates from the dataset.

In [4]:
```
Duplicate_Rows=train[train.duplicated()]
```

In [5]:
```
Duplicate_Rows
```

Out[5]:

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked

No duplicate data

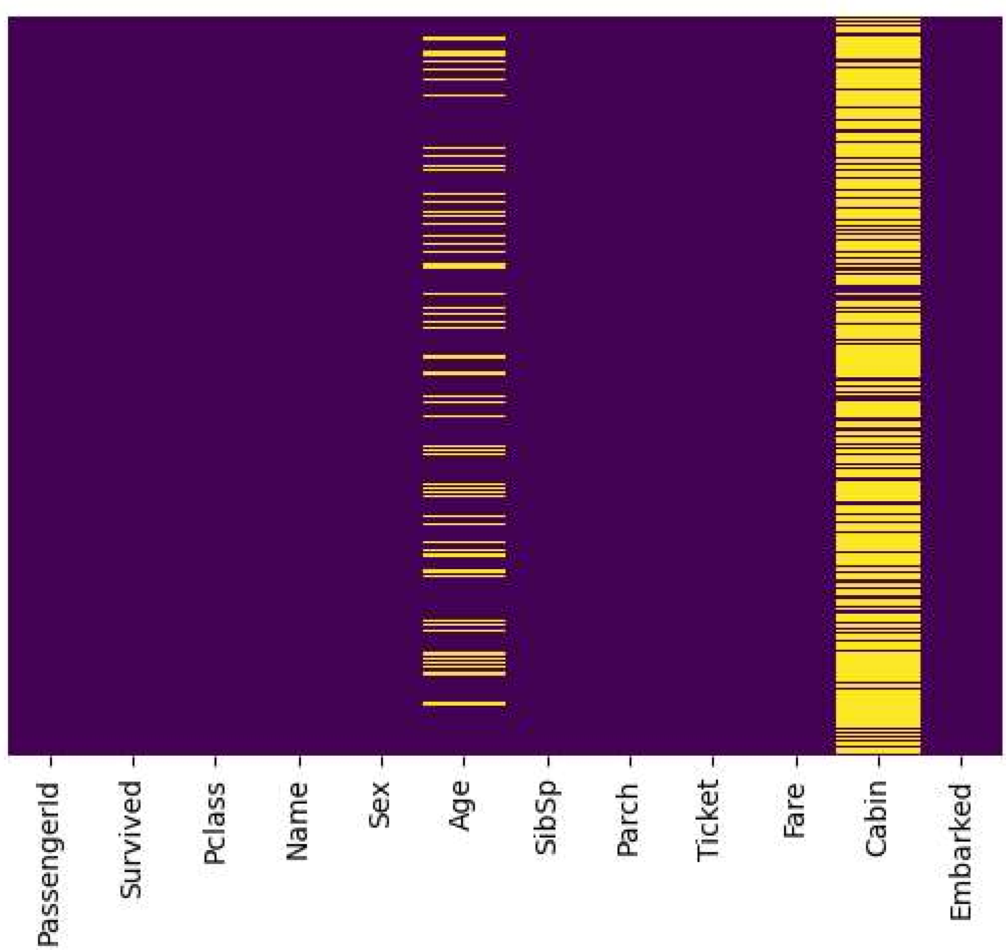
Step 2: Handle missing values by imputing or removing them.

In [6]:
```
train.isnull().sum()
```

Out[6]:
```
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
```

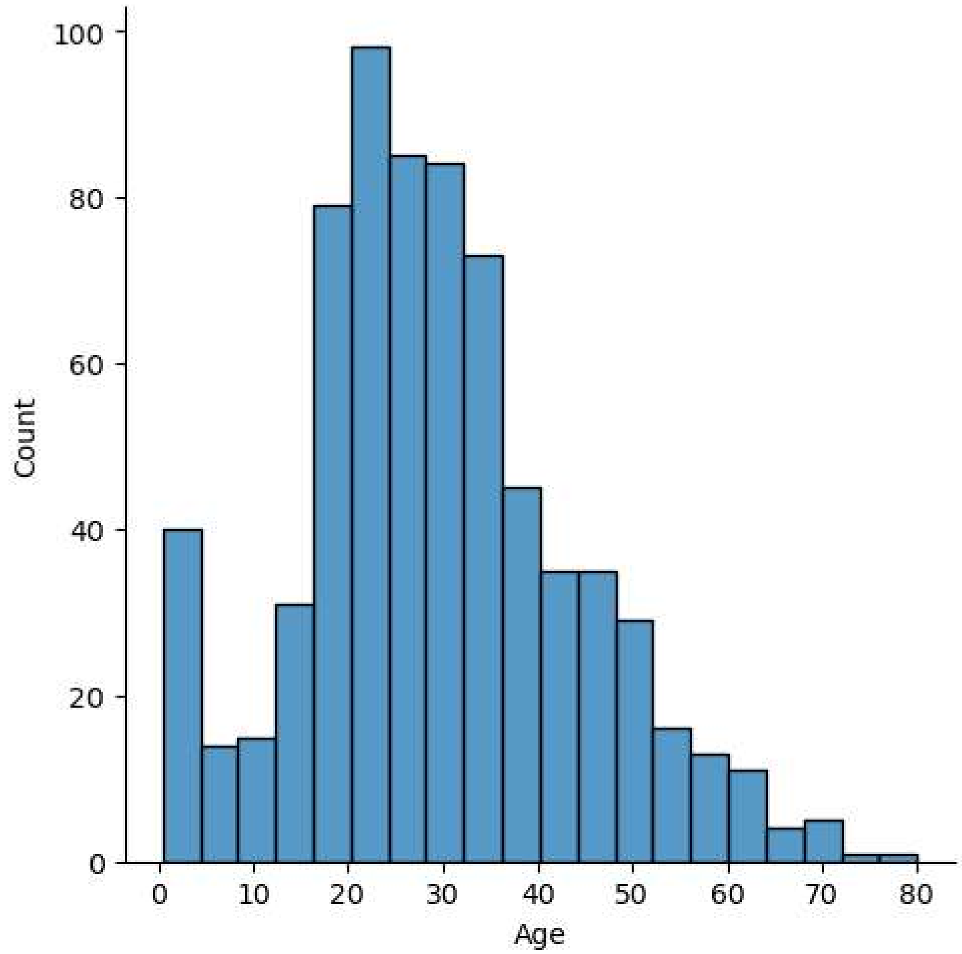
In [7]:
```
sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[7]: <Axes: >



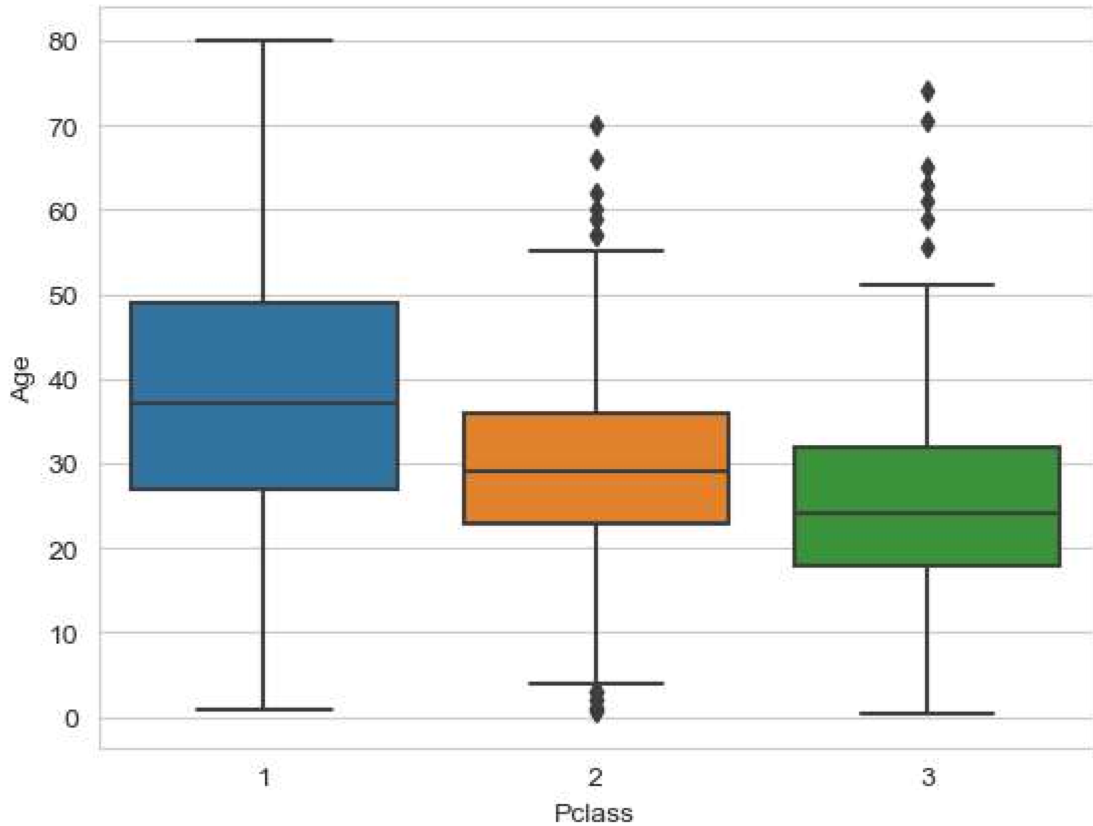
In [8]:
```
#Applying Imputation on Ages factor
sns.displot(train['Age'].dropna())
```

Out[8]: <seaborn.axisgrid.FacetGrid at 0x1db715b9e10>



In [9]:
```
sns.set_style('whitegrid')
sns.boxplot(x='Pclass',y='Age' ,data=train)
```

Out[9]: <Axes: xlabel='Pclass', ylabel='Age'>



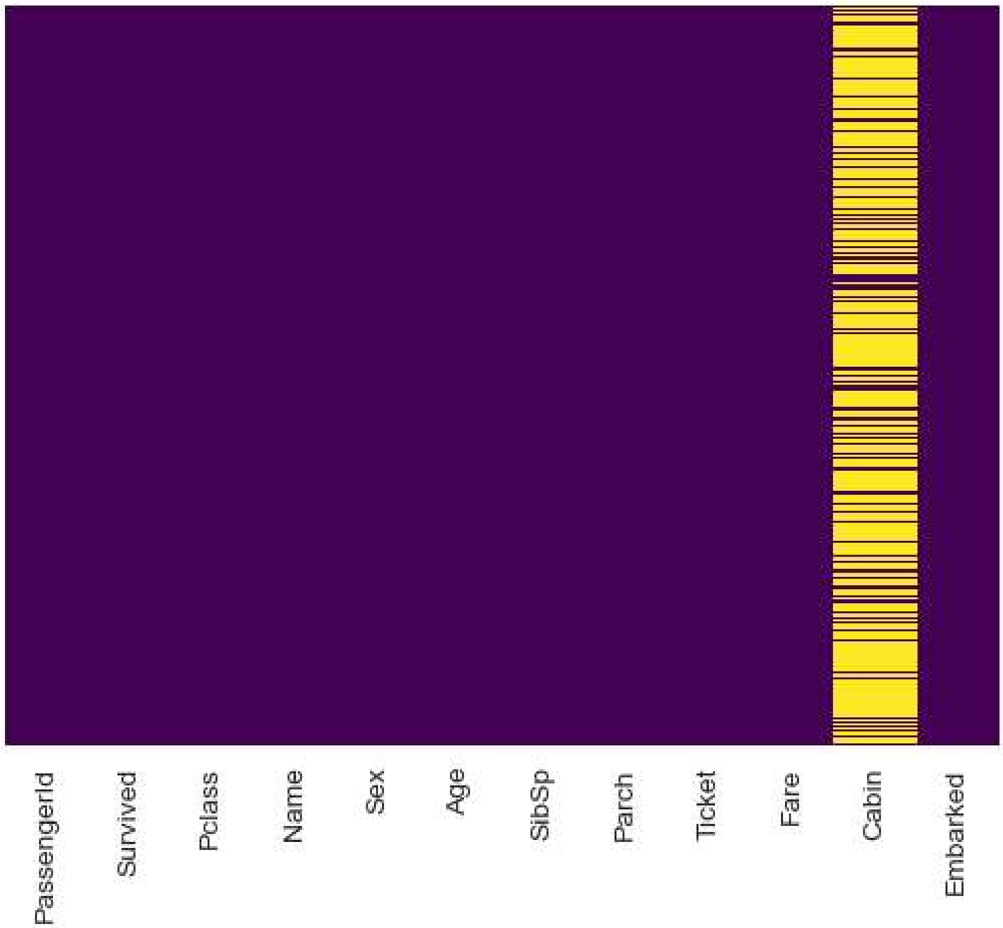
In [10]:
```
def impute_age(cols):
    Age = cols[0]
    Pclass = cols[1]

    if pd.isnull(Age):
        if Pclass == 1:
            return 38
        elif Pclass == 2:
            return 29
        else:
            return 23
    else:
        return Age
```

In [11]:
```
train['Age'] = train[['Age', 'Pclass']].apply(impute_age, axis=1)
```

In [12]:
```
sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

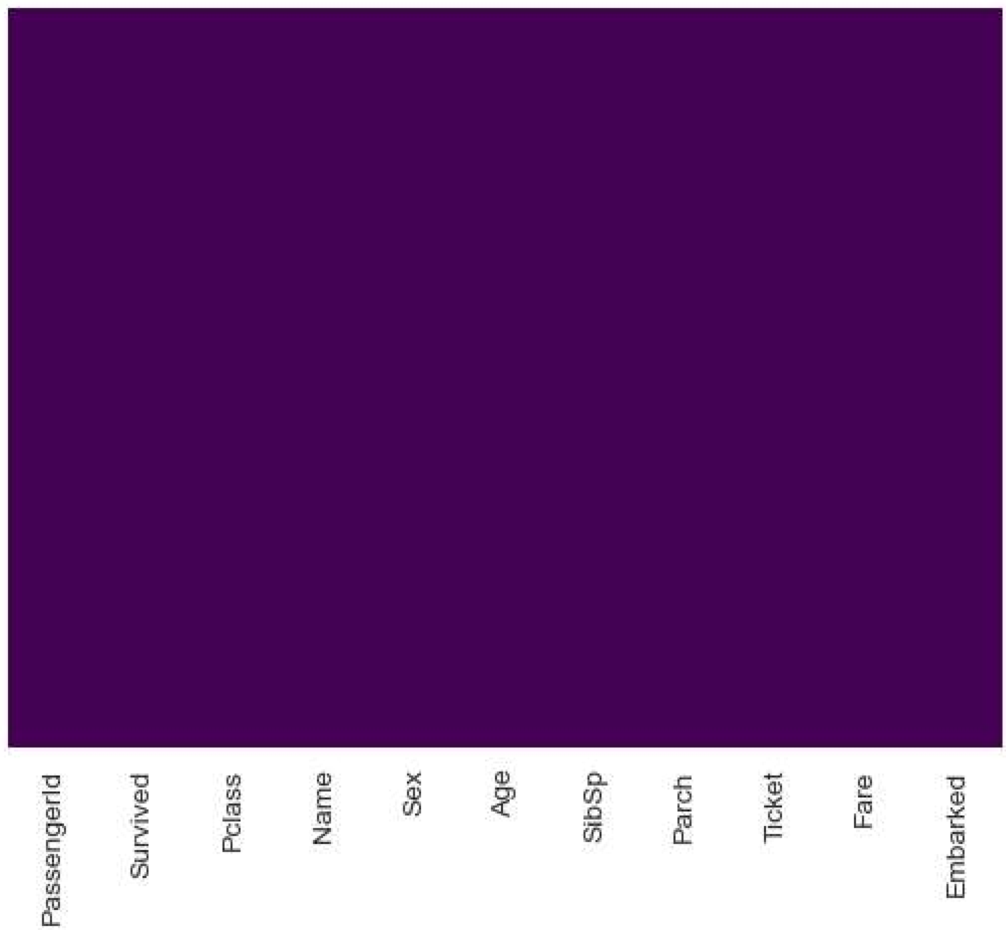
Out[12]: <Axes: >



In [13]:
```
train.drop('Cabin',axis=1,inplace=True)
```

In [14]:
```
sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis' )
```

Out[14]: <Axes: >



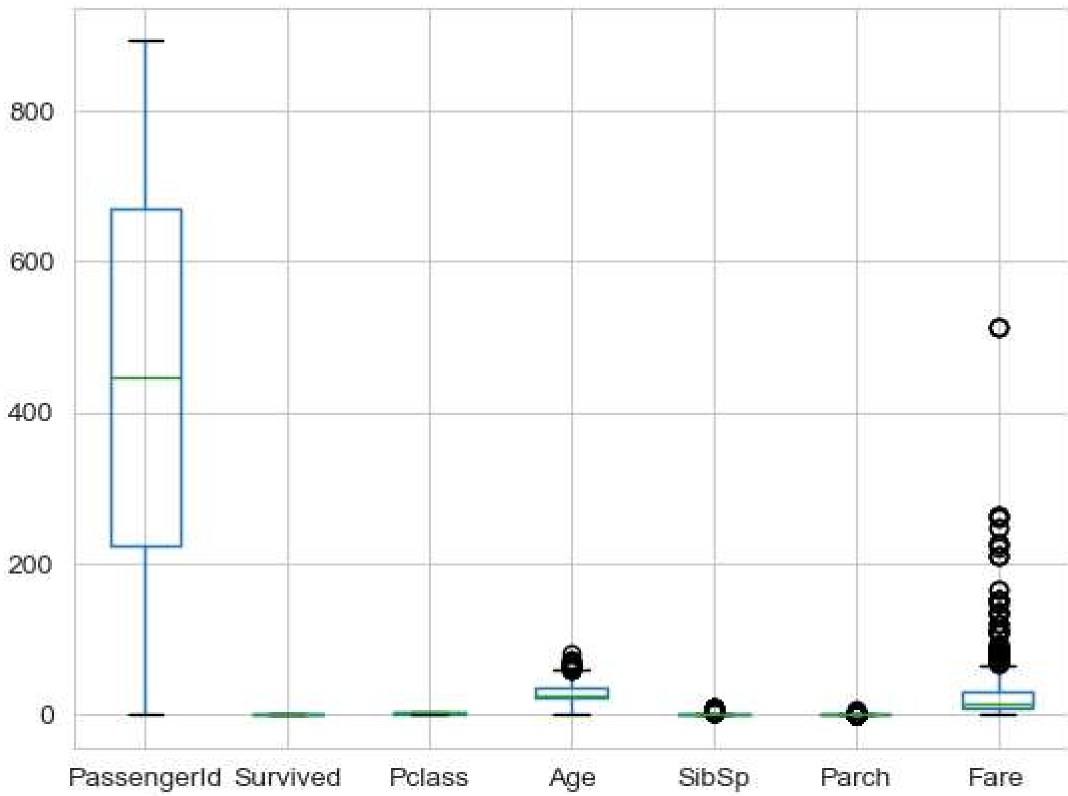
In [15]:
```
#Our missing data has been handeld
```

Step 3: Check and handle outliers in the data.

In [16]:
```
#In order to check outliers we will use Inter Quantile Range(IQR)
```

In [17]:
```
train.boxplot()
```

Out[17]: <Axes: >



In [18]:
```
Q1=train['Age'].quantile(0.25)
Q3=train['Age'].quantile(0.75)
IQR=Q3-Q1
Lower_Bond=Q1-(1.5*IQR)
Upper_Bond=Q3+(1.5*IQR)
outlier=train[(train['Age']<Lower_Bond)|(train['Age']>Upper_Bond)]
train.dropna(inplace=True)
```

In [19]:
```
outlier
```

Out[19]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
33	34	0	2	Wheadon, Mr. Edward H	male	66.0	0	0	C.A. 24579	10.5000
54	55	0	1	Ostby, Mr. Engelhart Cornelius	male	65.0	0	1	113509	61.9792
96	97	0	1	Goldschmidt, Mr. George B	male	71.0	0	0	PC 17754	34.6542
116	117	0	3	Connors, Mr. Patrick	male	70.5	0	0	370369	7.7500
170	171	0	1	Van der hoef, Mr. Wyckoff	male	61.0	0	0	111240	33.5000
252	253	0	1	Stead, Mr. William Thomas	male	62.0	0	0	113514	26.5500
275	276	1	1	Andrews, Miss. Kornelia Theodosia	female	63.0	1	0	13502	77.9583
280	281	0	3	Duane, Mr. Frank	male	65.0	0	0	336439	7.7500
326	327	0	3	Nysveen, Mr. Johan Hansen	male	61.0	0	0	345364	6.2375
366	367	1	1	Warren, Mrs. Frank Manley (Anna Sophia Atkinson)	female	60.0	1	0	110813	75.2500
438	439	0	1	Fortune, Mr. Mark	male	64.0	1	4	19950	263.0000
456	457	0	1	Millet, Mr. Francis Davis	male	65.0	0	0	13509	26.5500
483	484	1	3	Turkula, Mrs. (Hedwig)	female	63.0	0	0	4134	9.5875
493	494	0	1	Artagaveytia, Mr. Ramon	male	71.0	0	0	PC 17609	49.5042
545	546	0	1	Nicholson, Mr. Arthur Ernest	male	64.0	0	0	693	26.0000
555	556	0	1	Wright, Mr. George	male	62.0	0	0	113807	26.5500
570	571	1	2	Harris, Mr. George	male	62.0	0	0	S.W./PP 752	10.5000
587	588	1	1	Frolicher-Stehli, Mr. Maxmillian	male	60.0	1	1	13567	79.2000

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
625	626	0	1	Sutton, Mr. Frederick	male	61.0	0	0	36963	32.3208
630	631	1	1	Barkworth, Mr. Algernon Henry Wilson	male	80.0	0	0	27042	30.0000
672	673	0	2	Mitchell, Mr. Henry Michael	male	70.0	0	0	C.A. 24580	10.5000
684	685	0	2	Brown, Mr. Thomas William Solomon	male	60.0	1	1	29750	39.0000
694	695	0	1	Weir, Col. John	male	60.0	0	0	113800	26.5500
745	746	0	1	Crosby, Capt. Edward Gifford	male	70.0	1	1	WE/P 5735	71.0000
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.0	0	0	113572	80.0000
851	852	0	3	Svensson, Mr. Johan	male	74.0	0	0	347060	7.7750

In [20]:

```
Q1=train['Fare'].quantile(0.25)
Q3=train['Fare'].quantile(0.75)
IQR=Q3-Q1
Lower_Bond=Q1-(1.5*IQR)
Upper_Bond=Q3+(1.5*IQR)
outlier=train[(train['Fare']<Lower_Bond)|(train['Fare']>Upper_Bond)]
train.dropna(inplace=True)
```

In [21]:
```
outlier
```

Out[21]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	E
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
27	28	0	1	Fortune, Mr. Charles Alexander	male	19.0	3	2	19950	263.0000	
31	32	1	1	Spencer, Mrs. William Augustus (Marie Eugenie)	female	38.0	1	0	PC 17569	146.5208	
34	35	0	1	Meyer, Mr. Edgar Joseph	male	28.0	1	0	PC 17604	82.1708	
52	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.0	1	0	PC 17572	76.7292	
...	...	...	...	...	...	...	...	...	...	...	
846	847	0	3	Sage, Mr. Douglas Bullen	male	23.0	8	2	CA. 2343	69.5500	
849	850	1	1	Goldenberg, Mrs. Samuel L (Edwiga Grabowska)	female	38.0	1	0	17453	89.1042	
856	857	1	1	Wick, Mrs. George Dennick (Mary Hitchcock)	female	45.0	1	1	36928	164.8667	
863	864	0	3	Sage, Miss. Dorothy Edith "Dolly"	female	23.0	8	2	CA. 2343	69.5500	
879	880	1	1	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	female	56.0	0	1	11767	83.1583	

114 rows × 11 columns

Step 4: Normalize or standardize numerical features.

In [ ]:

In [22]:
```
print(train.dtypes)
```

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Embarked        object
dtype: object
```

In [23]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
numerical_features = ['Age', 'Fare', 'SibSp', 'Parch']

min_max_scaler = MinMaxScaler()
train[numerical_features] = min_max_scaler.fit_transform(train[numerical_featur


standard_scaler = StandardScaler()
train[numerical_features] = standard_scaler.fit_transform(train[numerical_featu
```

In [24]:
```
train
```

Out[24]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket
0	1	0	3	Braund, Mr. Owen Harris	male	-0.519303	0.431350	-0.474326	A/5 21171
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	0.684864	0.431350	-0.474326	PC 17599
2	3	1	3	Heikkinen, Miss. Laina	female	-0.218261	-0.475199	-0.474326	STON/O2. 3101282
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	0.459082	0.431350	-0.474326	113803
4	5	0	3	Allen, Mr. William Henry	male	0.459082	-0.475199	-0.474326	373450
...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	-0.143001	-0.475199	-0.474326	211536
887	888	1	1	Graham, Miss. Margaret Edith	female	-0.745084	-0.475199	-0.474326	112053
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	-0.444042	0.431350	2.006119	W./C. 6607
889	890	1	1	Behr, Mr. Karl Howell	male	-0.218261	-0.475199	-0.474326	111369
890	891	0	3	Dooley, Mr. Patrick	male	0.233301	-0.475199	-0.474326	370376

889 rows × 11 columns

Step 5: Encode categorical variables.

In [25]:
```
train.drop('Name',axis=1,inplace=True)
```

In [26]:
```
train.drop('Ticket',axis=1,inplace=True)
```

In [27]:
```
train.head()
```

Out[27]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	male	-0.519303	0.431350	-0.474326	-0.500240	S
1	2	1	1	female	0.684864	0.431350	-0.474326	0.788947	C
2	3	1	3	female	-0.218261	-0.475199	-0.474326	-0.486650	S
3	4	1	1	female	0.459082	0.431350	-0.474326	0.422861	S
4	5	0	3	male	0.459082	-0.475199	-0.474326	-0.484133	S

In [28]:
```
from sklearn.preprocessing import LabelEncoder
cols=['Sex','Embarked']
Le=LabelEncoder()
for col in cols:
    train[col]=Le.fit_transform(train[col])
```

In [29]:
```
train.head()
```

Out[29]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	1	-0.519303	0.431350	-0.474326	-0.500240	2
1	2	1	1	0	0.684864	0.431350	-0.474326	0.788947	0
2	3	1	3	0	-0.218261	-0.475199	-0.474326	-0.486650	2
3	4	1	1	0	0.459082	0.431350	-0.474326	0.422861	2
4	5	0	3	1	0.459082	-0.475199	-0.474326	-0.484133	2

In [30]:

```
# Encode categorical variables (if any)
le = LabelEncoder()
train['Sex'] = le.fit_transform(train['Sex'])

# Split the data into features (X) and target variable (y)
X = train.drop('Survived', axis=1)
y = train['Survived']

# 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, randor

# Create a linear regression model
model = LinearRegression()

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

# Make predictions on the test data
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'R^2 Score: {r2}')
```

```
Mean Squared Error: 0.14646788999915136
R^2 Score: 0.3829692026681144
```

In [33]:
```
# Split the data into features (X) and target variable (y)
X = train.drop('Survived', axis=1)
y = train['Survived']

# 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, randor

# Linear Regression
linear_model = LinearRegression()
linear_model.fit(X_train, y_train)
linear_pred = linear_model.predict(X_test)
linear_acc = accuracy_score(y_test, [round(pred) for pred in linear_pred])

# Decision Tree
tree_model = DecisionTreeClassifier()
tree_model.fit(X_train, y_train)
tree_pred = tree_model.predict(X_test)
tree_acc = accuracy_score(y_test, tree_pred)

# Random Forest
forest_model = RandomForestClassifier()
forest_model.fit(X_train, y_train)
forest_pred = forest_model.predict(X_test)
forest_acc = accuracy_score(y_test, forest_pred)

# Evaluate models
print(f'Linear Regression Accuracy: {linear_acc}')
print(f'Decision Tree Accuracy: {tree_acc}')
print(f'Random Forest Accuracy: {forest_acc}')
```

```
Linear Regression Accuracy: 0.797752808988764
Decision Tree Accuracy: 0.7303370786516854
Random Forest Accuracy: 0.797752808988764
```

both Linear Regression and Random Forest models have similar accuracy on the test set, and they outperform the Decision Tree model.

suggestion

Feature Engineering: Hyperparameter Tuning: Model-Specific Strategies:

In [ ]: