Task 01 : TITANIC SURVIVAL PREDICTION

Description: I have used the Titanic dataset to build a model that predicts whether a passenger on the Titanic survived or not. The dataset used for this project contains information about individual passengers, such as their age, gender, ticket class, fare, cabin, and whether or not they survived.

FLOW ANALYSIS:

- Importing Libraries
- Data loading
- Data Pre-Processing
  - Replacing missing values
  - Dropping unnecessary columns
  - Creating new column (Feature Engineering)
  - Encoding categorical columns
  - Scaling numeric columns
- Exploratory Data analysis (EDA)
- Spliting training and test data
- Model training -Logistic Regression
- Model Evaluation - Prediction

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# Importing all the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder


from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

from sklearn.metrics import confusion_matrix, classification_report
```

```
# Data Loading
data = pd.read_csv('/content/drive/MyDrive/CodSoft/tested.csv')
```

```
# Displaying first 5 rows of the dataset
data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000

```
# Displaying information regarding datatype, null values of every column
data.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
```

```
# It will calculate and display count, mean, std, min, max, 25%, 50% and 75% of numeric columns
data.describe()
```

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

```
# Checking for null values
data.isnull().sum()
```

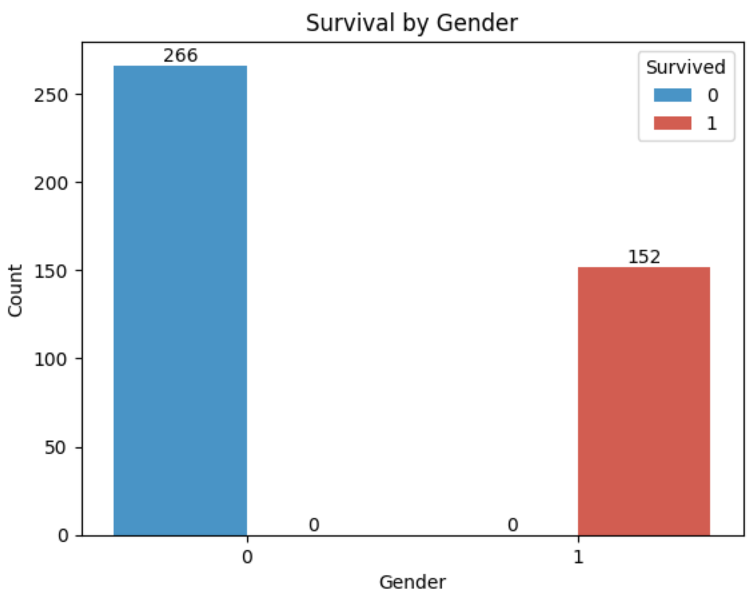
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

```
# Filling null values in Age using mean
mean_age = data['Age'].mean()

data['Age'].fillna(mean_age, inplace=True)


# Filling null values in Fare using mean

mean_fare = data['Fare'].mean()

data['Fare'].fillna(mean_fare, inplace=True)


# Encoding categorical variables
data['Sex'] = data['Sex'].map({'male': 0, 'female': 1})


# Feature engineering - creating a family size column
data['family_size'] = data['SibSp'] + data['Parch']


# Dropping unnecessary columns
data = data.drop(['PassengerId','Name','Cabin','Ticket',], axis =1)


# Creating a LabelEncoder instance
label_encoder = LabelEncoder()
```

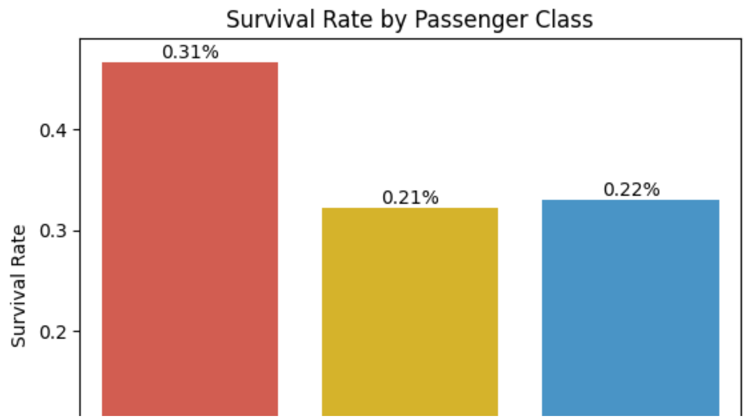
```
# Encoding the 'embarked' column
data['Embarked'] = label_encoder.fit_transform(data['Embarked'])
```

Data Visualization

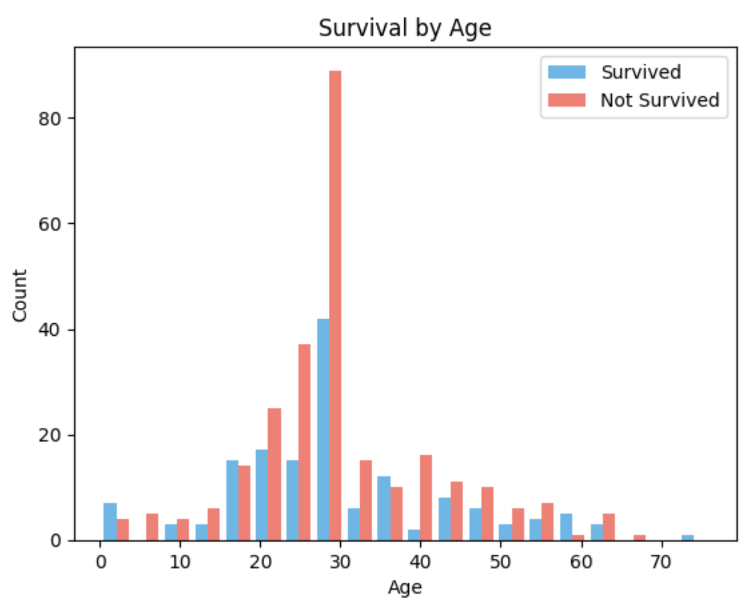
```
sns.set_palette("pastel")

# Survival by gender
ax = sns.countplot(data=data, x='Sex', hue='Survived', palette=["#3498db", "#e74c3c"])
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Survival by Gender')

# Add counts on top of the bars
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2., height, f'{int(height)}', ha='center', va='bottom')

plt.show()
```



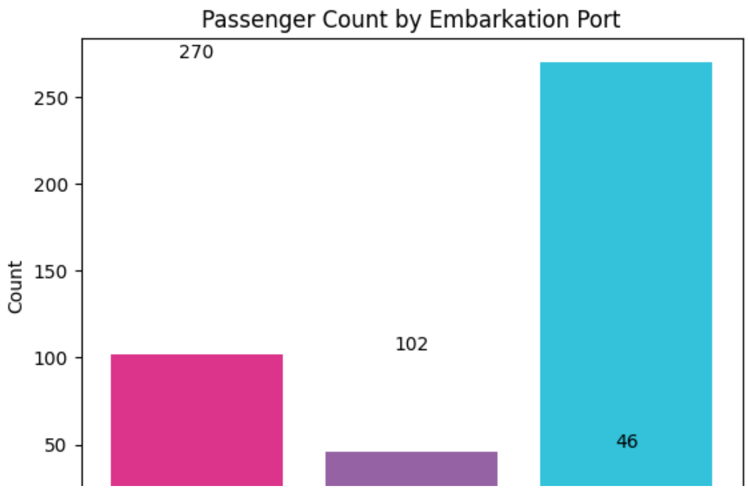

```
custom_palette = ['#e74c3c', '#f1c40f', '#3498db']

# Survival Rate by Passenger Class
sns.set_palette(custom_palette)
ax = sns.barplot(data=data, x='Pclass', y='Survived', errorbar=None)

plt.xlabel('Passenger Class')
plt.ylabel('Survival Rate')
plt.title('Survival Rate by Passenger Class')

total_height = sum(data['Survived'])
for p in ax.patches:
    percentage = f"{100 * p.get_height() / total_height:.2f}%"
    x = p.get_x() + p.get_width() / 2
    y = p.get_height()
    ax.text(x, y, percentage, ha='center', va='bottom')

plt.show()
```



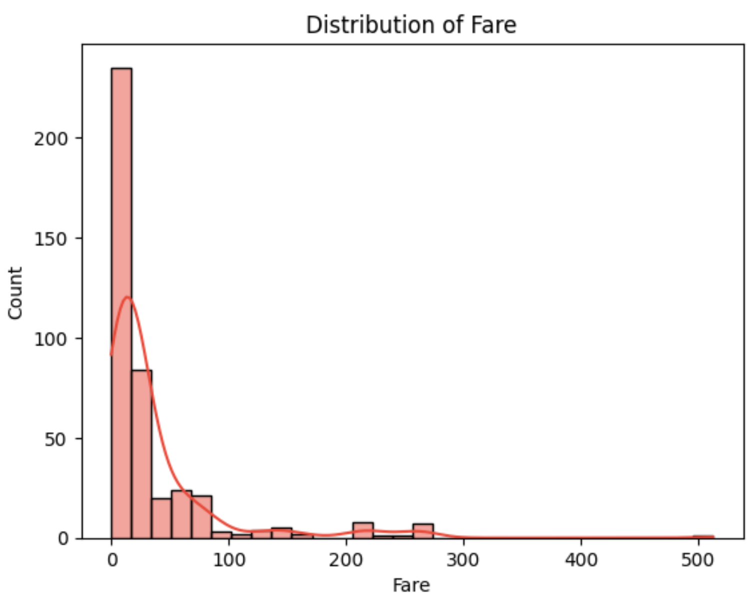

```
colors = ['#3498db', '#e74c3c']

# Creating the histogram for Survival by Age
plt.hist([data[data['Survived'] == 1]['Age'], data[data['Survived'] == 0]['Age']],
         bins=20, label=['Survived', 'Not Survived'], alpha=0.7, color=colors)

plt.xlabel('Age')
plt.ylabel('Count')
plt.legend()
plt.title('Survival by Age')
plt.show()
```




```
embarked_counts = data['Embarked'].value_counts()

colors = ['#34c2db', '#db348a', '#9563a4']

# Creating the barplot
plt.bar(embarked_counts.index, embarked_counts.values, color=colors)

plt.xlabel('Embarkation Port')
plt.ylabel('Count')
plt.title('Passenger Count by Embarkation Port')

for i, count in enumerate(embarked_counts.values):
    plt.text(i, count, str(count), ha='center', va='bottom')

plt.show()
```

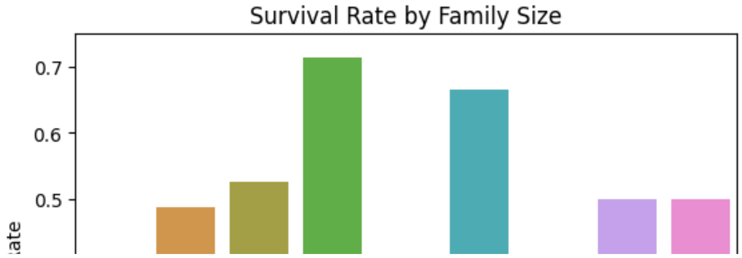



```
# Histplot for the Distribution of Fare
sns.histplot(data=data, x='Fare', bins=30, kde=True)
plt.xlabel('Fare')
plt.ylabel('Count')
plt.title('Distribution of Fare')
plt.show()
```




```
# Barplot for Survival Rate by Family Size
sns.barplot(data=data, x='family_size', y='Survived', ci=None)
plt.xlabel('Family Size')
plt.ylabel('Survival Rate')
plt.title('Survival Rate by Family Size')
plt.xticks(rotation=90)
plt.show()
```

```
<ipython-input-19-303103d80195>:2: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(data=data, x='family_size', y='Survived', ci=None)
```




```
# As we have created a new column "Family Size". So, will drop the previous one's.
data.drop(columns=['SibSp', 'Parch', 'Embarked'], inplace=True)
```

```
data.head()
```

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

```
# Now, Data is cleaned
data.isnull().sum()
```

```
Survived       0
Pclass         0
Sex            0
Age            0
Fare           0
family_size    0
dtype: int64
```

```
# Data Splitting
X = data.drop(["Survived"] , axis = 1)
y = data['Survived']  # Target variable

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Applying MinMax Scaling
scaling = MinMaxScaler()
X_train = scaling.fit_transform(X_train)
X_test = scaling.fit_transform(X_test)
```

```
# Create and train a logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
y_pred = model.predict(X_test)

# Calculating accuracy and its percentage
accuracy = accuracy_score(y_test, y_pred) * 100

# Generating the classification report
report = classification_report(y_test, y_pred)

# Displaying accuracy in percentage
```

```
print(f"Accuracy: {accuracy:.2f}%")
print(report)
```

```
Accuracy: 100.00%
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       1.00      1.00      1.00        34

    accuracy                           1.00        84
   macro avg       1.00      1.00      1.00        84
weighted avg       1.00      1.00      1.00        84
```

```
# Plotting the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

colors = ['#d0bad7', '#c5019c']

cmap = sns.color_palette(colors)

plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap=cmap, cbar=False,
            xticklabels=['Not Survived', 'Survived'], yticklabels=['Not Survived', 'Survived'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```