```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

Data Understanding :

This dataset contains information about general information and detail of each passengers.The dataconsists of demographic and traveling information for 418 of the Titanic passengers, and the goal is to predict the survival of these passengers.

1. Pclass: Passenger class (1 = 1st; 2 = 2nd; 3 = 3rd)
2. Survival: A Boolean indicating whether the passenger survived or not (0 = No; 1 = Yes); this is our target
3. Name: A field rich in information as it contains title and family names.
4. Sex: male/female.
5. Age: Age, asignificant portion of values are missing.
6. Sibsp: Number of siblings/spouses aboard.
7. Parch: Number of parents/children aboard.
8. Ticket: Ticket number.
9. Fare: Passenger fare (British Pound).
10. Cabin: Doesthe location of the cabin influence chances of survival?
11. Embarked: Port of embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

DATA COLLECTION:

```
data=pd.read_csv('/content/tested.csv')
```

```
data
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
413	1305	0	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	1	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	0	3	Saether, Mr.	male	38.5	0	0	SOTON/O.Q.	7.2500	NaN	S

Describing data

```
data.head(6)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

```
#shows dimensionality
data.shape
```

```
(418, 12)
```

```
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

```
data.iloc[0:4]
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S

```
#to see the missing values
data.count()
```

```
PassengerId    418
Survived       418
Pclass         418
Name           418
Sex            418
Age            332
SibSp          418
Parch          418
Ticket         418
Fare           417
Cabin           91
Embarked       418
dtype: int64
```

```
#show unique values
data['Embarked'].unique()
```

```
array(['Q', 'S', 'C'], dtype=object)
```

```
#show counts
data['Embarked'].value_counts()
```

```
S    270
C    102
Q     46
Name: Embarked, dtype: int64
```

```
data['Pclass'].value_counts()
```

```
3    218
1    107
2     93
Name: Pclass, dtype: int64
```

Data - Cleansing

Treating Missing Values

```
#fillling age by mean value
mean_age = data['Age'].mean()
data['Age'].fillna(mean_age, inplace=True)

#filling fare by mean value
mean_fare = data['Fare'].mean()
data['Fare'].fillna(mean_fare,inplace=True)
```

Changing Values and Datatypes for our Comfort Analysis

```
#Changing values

data['Embarked'] = data['Embarked'].map( {'Q': 0,'S':1,'C':2}).astype(int)
data['Sex'] = data['Sex'].map( {'female': 1,'male':0}).astype(int)

#Changing Datatypes
data['Age'] = data['Age'].astype(int)
data['Fare'] = data['Fare'].astype(int)
```

```
data.dtypes
```

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

Dropping Unwanted Features

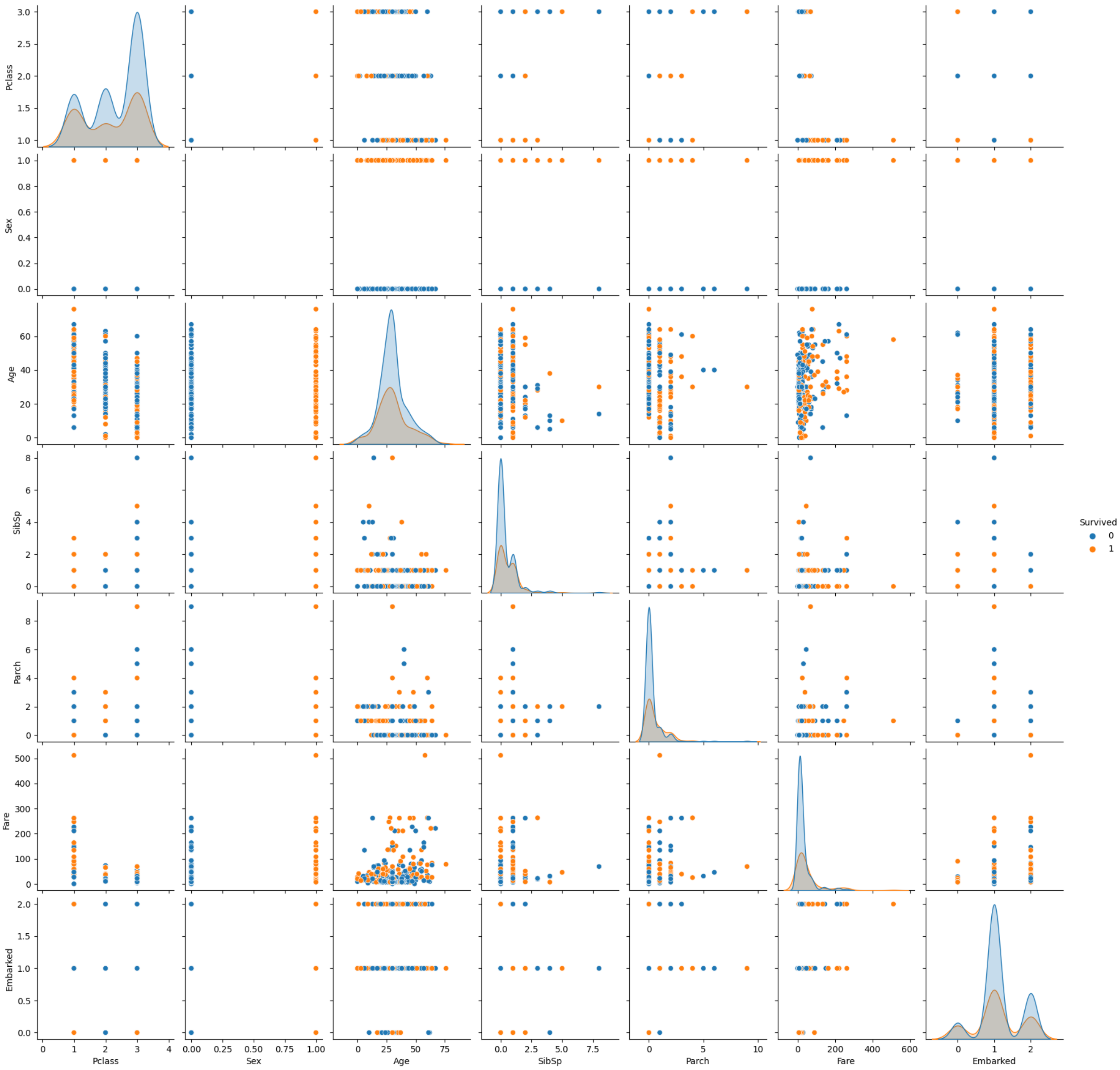
```
data.drop(["PassengerId","Name","Cabin","Ticket"],axis=1,inplace=True)
```

```
data.head(5)
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	0	34	0	0	7	0
1	1	3	1	47	1	0	7	1
2	0	2	0	62	0	0	9	0
3	0	3	0	27	0	0	8	1
4	1	3	1	22	1	1	12	1

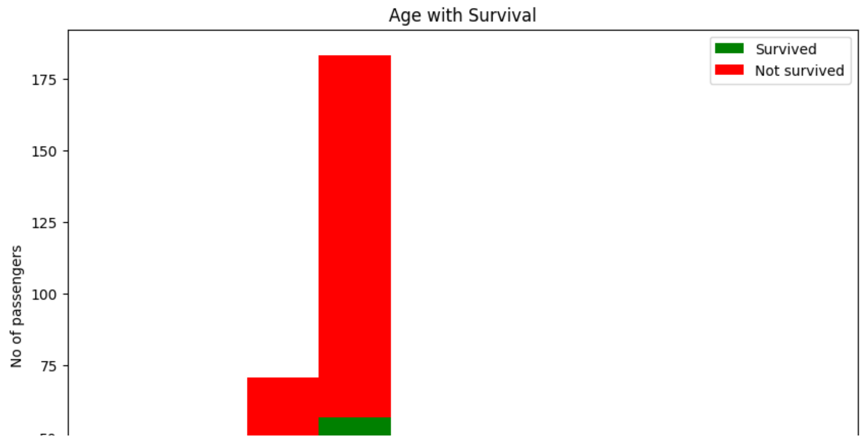
Data Visualization

```
sns.pairplot(data,hue='Survived')
plt.show()
```



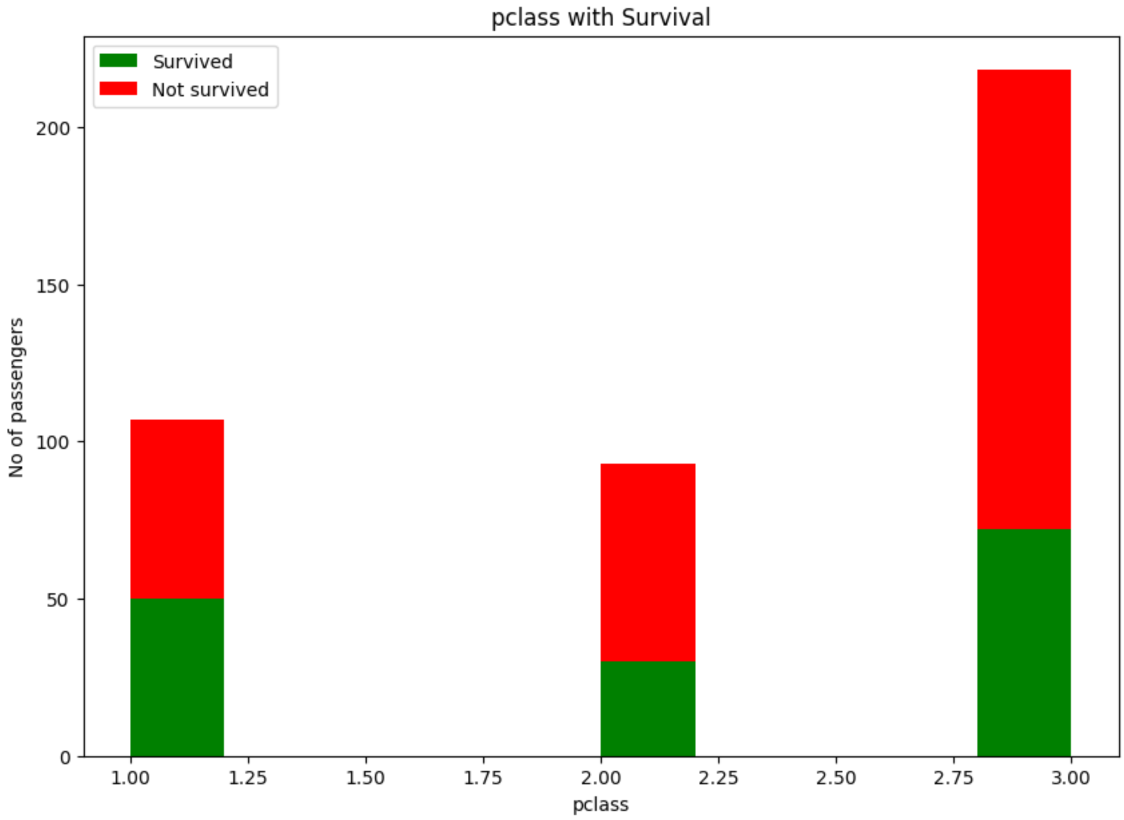

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize =(10, 7))
plt.hist(x = [data[data['Survived']==1]['Age'], data[data['Survived']==0]['Age']],stacked=True, color = ['g','r'
plt.title('Age with Survival')
plt.xlabel('Age')
plt.ylabel('No of passengers')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7c0ddfb15420>
```



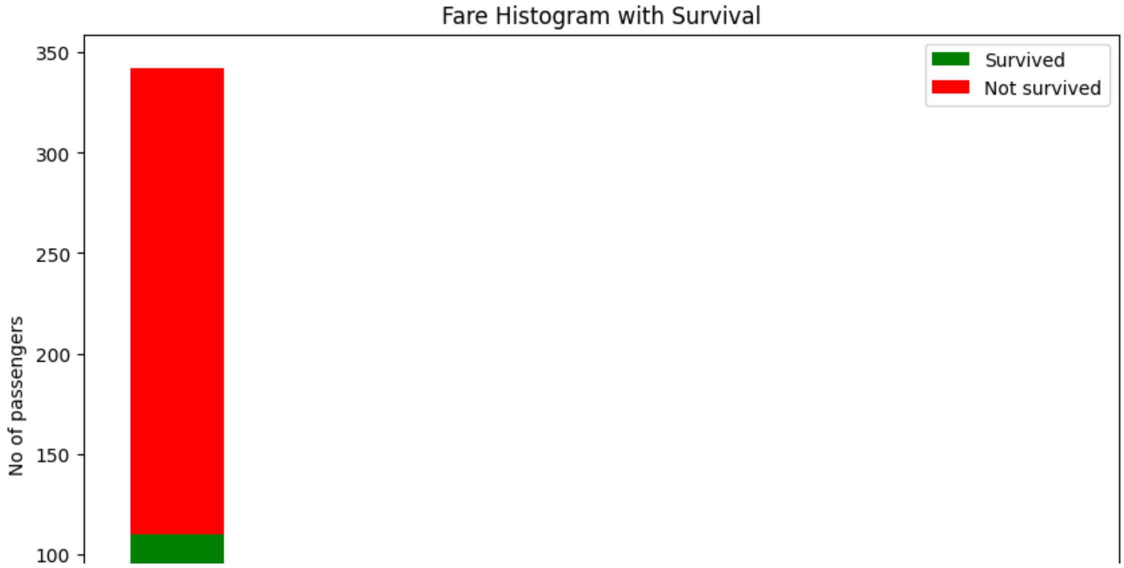

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize =(10, 7))
plt.hist(x = [data[data['Survived']==1]['Pclass'], data[data['Survived']==0]['Pclass']],stacked=True, color = ['g
plt.title('pclass with Survival')
plt.xlabel('pclass')
plt.ylabel('No of passengers')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7c0ddfa6b430>
```

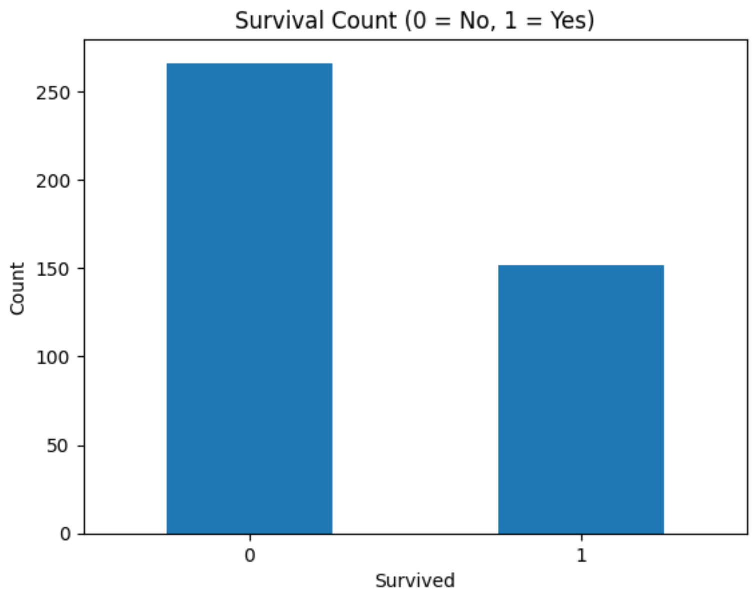



```
fig = plt.figure(figsize =(10, 7))
plt.hist(x = [data[data['Survived']==1]['Fare'], data[data['Survived']==0]['Fare']], stacked=True, color = ['g','
plt.title('Fare Histogram with Survival')
plt.xlabel('Fare')
plt.ylabel('No of passengers')
plt.legend()
```

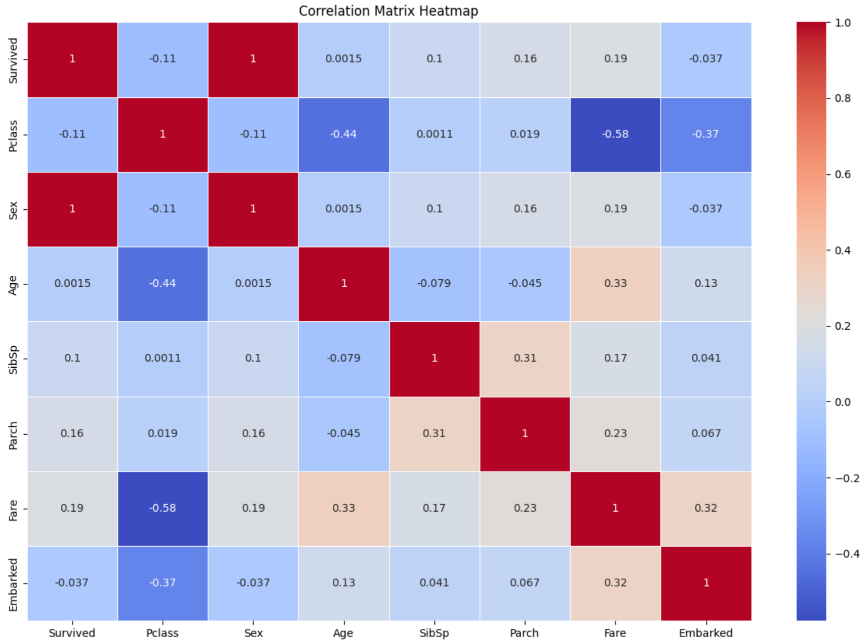
```
<matplotlib.legend.Legend at 0x7c0de3088850>
```



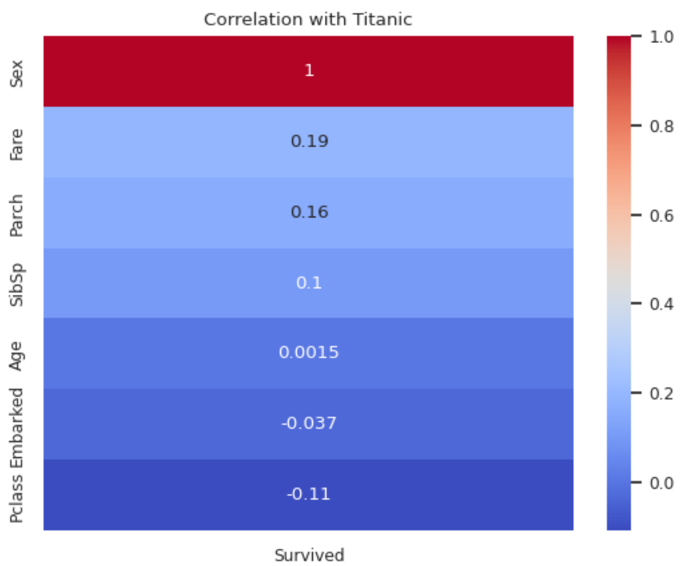

```
column = 'Survived'

# Create a bar chart
survival_counts = data[column].value_counts()
survival_counts.plot(kind='bar', rot=0)

# Adding labels and title
plt.xlabel('Survived')
plt.ylabel('Count')
plt.title('Survival Count (0 = No, 1 = Yes)')

# Show the plot
plt.show()
```




```
#Correlation matrix
correlation_matrix = data.corr()
plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Matrix Heatmap")
plt.show()
```




```
#Target
corr = data.corr()
target_corr = corr['Survived'].drop('Survived')
# Sort correlation values in descending order
target_corr_sorted = target_corr.sort_values(ascending=False)
# Create a heatmap of the correlations with the target column
sns.set(font_scale=0.8)
sns.set_style("white")
sns.set_palette("PuBuGn_d")
sns.heatmap(target_corr_sorted.to_frame(), cmap="coolwarm", annot=True)
plt.title('Correlation with Titanic')
plt.show()
```



DATA MODELLING

```
X = data.drop('Survived', axis=1)
y = data['Survived']
```

```
#splitting train and testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=42)
```

```
print('Shape of training feature:', X_train.shape)
print('Shape of training feature:', X_test.shape)
print('Shape of training label:', y_train.shape)
print('Shape of training label:', y_test.shape)
```

```
Shape of training feature: (209, 7)
Shape of training feature: (209, 7)
Shape of training label: (209,)
Shape of training label: (209,)
```

```
#standardizing the feature
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
 # Initialize the model (e.g., Logistic Regression)
model = LogisticRegression()
```

```
# Train the model on the training data
model.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

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

```
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Classification Report
class_report = classification_report(y_test, y_pred)
print(class_report)
```

```
Accuracy: 1.0
```

Another model validation

```
# Create the Linear Regression model
clf = RandomForestClassifier(random_state = 42)
clf.fit(X, y)
```

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
# feature importances coefficients
feature_importance = clf.feature_importances_
df_feature_importance = pd.DataFrame({'Feature': X.columns, 'Importance': feature_importance})
df_feature_importance = df_feature_importance.sort_values(by='Importance', ascending=False)
```

```
y_pred = clf.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

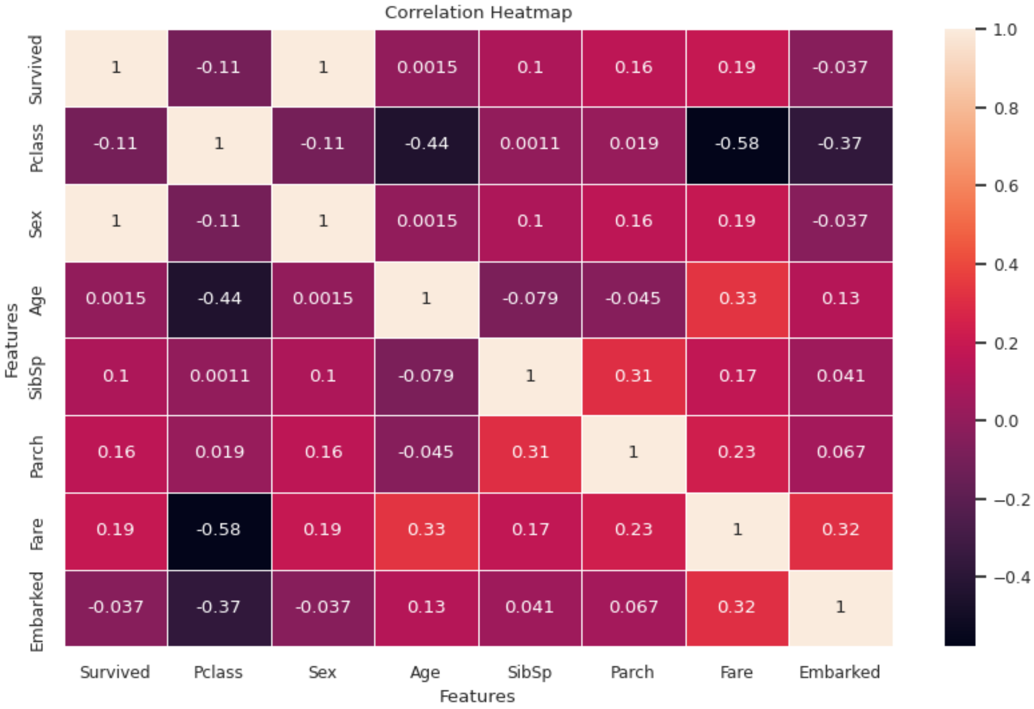
```
Accuracy: 1.0
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       135
           1       1.00      1.00      1.00        74

    accuracy                           1.00       209
   macro avg       1.00      1.00      1.00       209
weighted avg       1.00      1.00      1.00       209

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but RandomForestClas
  warnings.warn(
```

```
 #Correlation Matrix
data.corr()
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
Survived	1.000000	-0.108615	1.000000	0.001538	0.099943	0.159120	0.191156	-0.037432
Pclass	-0.108615	1.000000	-0.108615	-0.443531	0.001087	0.018721	-0.577438	-0.372344
Sex	1.000000	-0.108615	1.000000	0.001538	0.099943	0.159120	0.191156	-0.037432
Age	0.001538	-0.443531	0.001538	1.000000	-0.079203	-0.045259	0.328407	0.127749
SibSp	0.099943	0.001087	0.099943	-0.079203	1.000000	0.306895	0.171884	0.041221
Parch	0.159120	0.018721	0.159120	-0.045259	0.306895	1.000000	0.230308	0.067474
Fare	0.191156	-0.577438	0.191156	0.328407	0.171884	0.230308	1.000000	0.315937
Embarked	-0.037432	-0.372344	-0.037432	0.127749	0.041221	0.067474	0.315937	1.000000

```
# Correlation Heatmap
plt.figure(figsize=(10,6))
```

```
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot = True, cmap = 'rocket', linewidths = 0.5)
plt.title('Correlation Heatmap')
plt.xlabel('Features')
plt.ylabel('Features')
plt.show()
```



Looking at the correlation results, we can see that different Features have varying degrees of correlation with the outcome (Survived).

1. Sex: With a correlation of 1.0, this is the most strongly correlated feature with the outcome. This suggests that Sex is the important factor that describe the survival rate between male and female.
2. Fare: This feature has a correlation of 0.19 with the outcome. While not as strong as sex, this is still a moderate correlation, suggesting that fare is directly-proportional to Passengerclass (1st,2nd,3rd) could also be an important factor in Survival.
3. Age : Age has a correlation of 0.015 with the outcome. This suggests that older individuals may have low chance of Survival.