Space X Falcon 9 First Stage Landing Prediction

Assignment: Machine Learning Prediction

Estimated time needed: **60** minutes

Space X advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is because Space X can reuse the first stage. Therefore if we can determine if the first stage will land, we can determine the cost of a launch. This information can be used if an alternate company wants to bid against space X for a rocket launch. In this lab, you will create a machine learning pipeline to predict if the first stage will land given the data from the preceding labs.

Several examples of an unsuccessful landing are shown here:

Most unsuccessful landings are planed. Space X; performs a controlled landing in the oceans.

Objectives

Perform exploratory Data Analysis and determine Training Labels

- create a column for the class
- Standardize the data
- Split into training data and test data

-Find best Hyperparameter for SVM, Classification Trees and Logistic Regression

- Find the method performs best using test data

Import Libraries and Define Auxiliary Functions

```
import piplite
await piplite.install(['numpy'])
await piplite.install(['pandas'])
await piplite.install(['seaborn'])
```

We will import the following libraries for the lab

```
# Pandas is a software library written for the Python programming language for data manipulation and analysis.
import pandas as pd
# NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays
import numpy as np
```

```python
# Matplotlib is a plotting library for python and pyplot gives us a MatLab like plotting framework. We will use this in our plotter function to plot data.
import matplotlib.pyplot as plt
#Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics
import seaborn as sns
# Preprocessing allows us to standarsize our data
from sklearn import preprocessing
# Allows us to split our data into training and testing data
from sklearn.model_selection import train_test_split
# Allows us to test parameters of classification algorithms and find the best one
from sklearn.model_selection import GridSearchCV
# Logistic Regression classification algorithm
from sklearn.linear_model import LogisticRegression
# Support Vector Machine classification algorithm
from sklearn.svm import SVC
# Decision Tree classification algorithm
from sklearn.tree import DecisionTreeClassifier
# K Nearest Neighbors classification algorithm
from sklearn.neighbors import KNeighborsClassifier
```

```
<ipython-input-2-b7d446354769>:2: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interoperability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

This function is to plot the confusion matrix.

```python
def plot_confusion_matrix(y,y_predict):
    "this function plots the confusion matrix"
    from sklearn.metrics import confusion_matrix

    cm = confusion_matrix(y, y_predict)
    ax= plt.subplot()
    sns.heatmap(cm, annot=True, ax = ax); #annot=True to annotate cells
    ax.set_xlabel('Predicted labels')
    ax.set_ylabel('True labels')
    ax.set_title('Confusion Matrix');
```

```
    ax.xaxis.set_ticklabels(['did not land', 'land']);
ax.yaxis.set_ticklabels(['did not land', 'landed'])
    plt.show()
```

Load the dataframe

Load the data

```
from js import fetch
import io

URL1 = "https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/
dataset_part_2.csv"
resp1 = await fetch(URL1)
text1 = io.BytesIO((await resp1.arrayBuffer()).to_py())
data = pd.read_csv(text1)

data.head()

   FlightNumber        Date BoosterVersion  PayloadMass Orbit
LaunchSite  \
0             1  2010-06-04       Falcon 9  6104.959412   LEO   CCAFS
SLC 40
1             2  2012-05-22       Falcon 9   525.000000   LEO   CCAFS
SLC 40
2             3  2013-03-01       Falcon 9   677.000000   ISS   CCAFS
SLC 40
3             4  2013-09-29       Falcon 9   500.000000    PO    VAFB
SLC 4E
4             5  2013-12-03       Falcon 9  3170.000000   GTO   CCAFS
SLC 40

       Outcome  Flights  GridFins  Reused   Legs LandingPad  Block  \
0    None None        1     False   False  False        NaN    1.0
1    None None        1     False   False  False        NaN    1.0
2    None None        1     False   False  False        NaN    1.0
3  False Ocean        1     False   False  False        NaN    1.0
4    None None        1     False   False  False        NaN    1.0

   ReusedCount Serial   Longitude   Latitude  Class
0            0  B0003  -80.577366  28.561857      0
1            0  B0005  -80.577366  28.561857      0
2            0  B0007  -80.577366  28.561857      0
3            0  B1003 -120.610829  34.632093      0
4            0  B1004  -80.577366  28.561857      0

URL2 = 'https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/
dataset_part_3.csv'
```

```
resp2 = await fetch(URL2)
text2 = io.BytesIO((await resp2.arrayBuffer()).to_py())
X = pd.read_csv(text2)

X.head(100)
```

```
    FlightNumber   PayloadMass  Flights  Block  ReusedCount  Orbit_ES-
L1  \
0            1.0   6104.959412      1.0    1.0          0.0
0.0
1            2.0    525.000000      1.0    1.0          0.0
0.0
2            3.0    677.000000      1.0    1.0          0.0
0.0
3            4.0    500.000000      1.0    1.0          0.0
0.0
4            5.0   3170.000000      1.0    1.0          0.0
0.0
..           ...           ...      ...    ...          ...          .
..
85          86.0  15400.000000      2.0    5.0          2.0
0.0
86          87.0  15400.000000      3.0    5.0          2.0
0.0
87          88.0  15400.000000      6.0    5.0          5.0
0.0
88          89.0  15400.000000      3.0    5.0          2.0
0.0
89          90.0   3681.000000      1.0    5.0          0.0
0.0

    Orbit_GEO  Orbit_GTO  Orbit_HEO  Orbit_ISS  ...  Serial_B1058  \
0         0.0        0.0        0.0        0.0  ...           0.0
1         0.0        0.0        0.0        0.0  ...           0.0
2         0.0        0.0        0.0        1.0  ...           0.0
3         0.0        0.0        0.0        0.0  ...           0.0
4         0.0        1.0        0.0        0.0  ...           0.0
..        ...        ...        ...        ...  ...           ...
85        0.0        0.0        0.0        0.0  ...           0.0
86        0.0        0.0        0.0        0.0  ...           1.0
87        0.0        0.0        0.0        0.0  ...           0.0
88        0.0        0.0        0.0        0.0  ...           0.0
89        0.0        0.0        0.0        0.0  ...           0.0

    Serial_B1059  Serial_B1060  Serial_B1062  GridFins_False
GridFins_True  \
0            0.0           0.0           0.0             1.0
0.0
1            0.0           0.0           0.0             1.0
0.0
```

```
2           0.0         0.0         0.0              1.0
0.0
3           0.0         0.0         0.0              1.0
0.0
4           0.0         0.0         0.0              1.0
0.0
..          ...         ...         ...              ...
...
85          0.0         1.0         0.0              0.0
1.0
86          0.0         0.0         0.0              0.0
1.0
87          0.0         0.0         0.0              0.0
1.0
88          0.0         1.0         0.0              0.0
1.0
89          0.0         0.0         1.0              0.0
1.0

    Reused_False  Reused_True  Legs_False  Legs_True
0            1.0          0.0         1.0        0.0
1            1.0          0.0         1.0        0.0
2            1.0          0.0         1.0        0.0
3            1.0          0.0         1.0        0.0
4            1.0          0.0         1.0        0.0
..           ...          ...         ...        ...
85           0.0          1.0         0.0        1.0
86           0.0          1.0         0.0        1.0
87           0.0          1.0         0.0        1.0
88           0.0          1.0         0.0        1.0
89           1.0          0.0         0.0        1.0

[90 rows x 83 columns]
```

TASK 1

Create a NumPy array from the column Class in data, by applying the method to_numpy() then assign it to the variable Y,make sure the output is a Pandas series (only one bracket df['name of column']).

```
import pandas as pd
import numpy as np

# Assuming 'data' is already loaded as per your initial code
Y = data['Class'].to_numpy()
```

TASK 2

Standardize the data in X then reassign it to the variable X using the transform provided below.

```python
from sklearn.preprocessing import StandardScaler

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the data in X
X_standardized = scaler.fit_transform(X)

# Convert the standardized data back to a DataFrame (if needed)
X = pd.DataFrame(X_standardized, columns=X.columns)
```

We split the data into training and testing data using the function train_test_split. The training data is divided into validation data, a second set used for training data; then the models are trained and hyperparameters are selected using the function GridSearchCV.

TASK 3

Use the function train_test_split to split the data X and Y into training and test data. Set the parameter test_size to 0.2 and random_state to 2. The training data and test data should be assigned to the following labels.

X_train, X_test, Y_train, Y_test

```python
from sklearn.model_selection import train_test_split

# Split the data into training and test sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.2, random_state=2)
```

we can see we only have 18 test samples.

```python
Y_test.shape
```

```
(18,)
```

TASK 4

Create a logistic regression object then create a GridSearchCV object logreg_cv with cv = 10. Fit the object to find the best parameters from the dictionary parameters.

```python
parameters = {
    'C': [0.01, 0.1, 1],
    'penalty': ['l2'],
    'solver': ['lbfgs']
}

parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}#
l1 lasso l2 ridge
lr=LogisticRegression()
```

We output the GridSearchCV object for logistic regression. We display the best parameters using the data attribute best_params_ and the accuracy on the validation data using the data attribute best_score_.

```
lr = LogisticRegression()
logreg_cv = GridSearchCV(estimator=lr, param_grid=parameters, cv=10)
logreg_cv.fit(X_train, Y_train)
print("Tuned hyperparameters (best parameters):",
logreg_cv.best_params_)
print("Accuracy on validation data:", logreg_cv.best_score_)
```

```
Tuned hyperparameters (best parameters): {'C': 0.01, 'penalty': 'l2',
'solver': 'lbfgs'}
Accuracy on validation data: 0.8464285714285713
```

TASK 5

Calculate the accuracy on the test data using the method score:

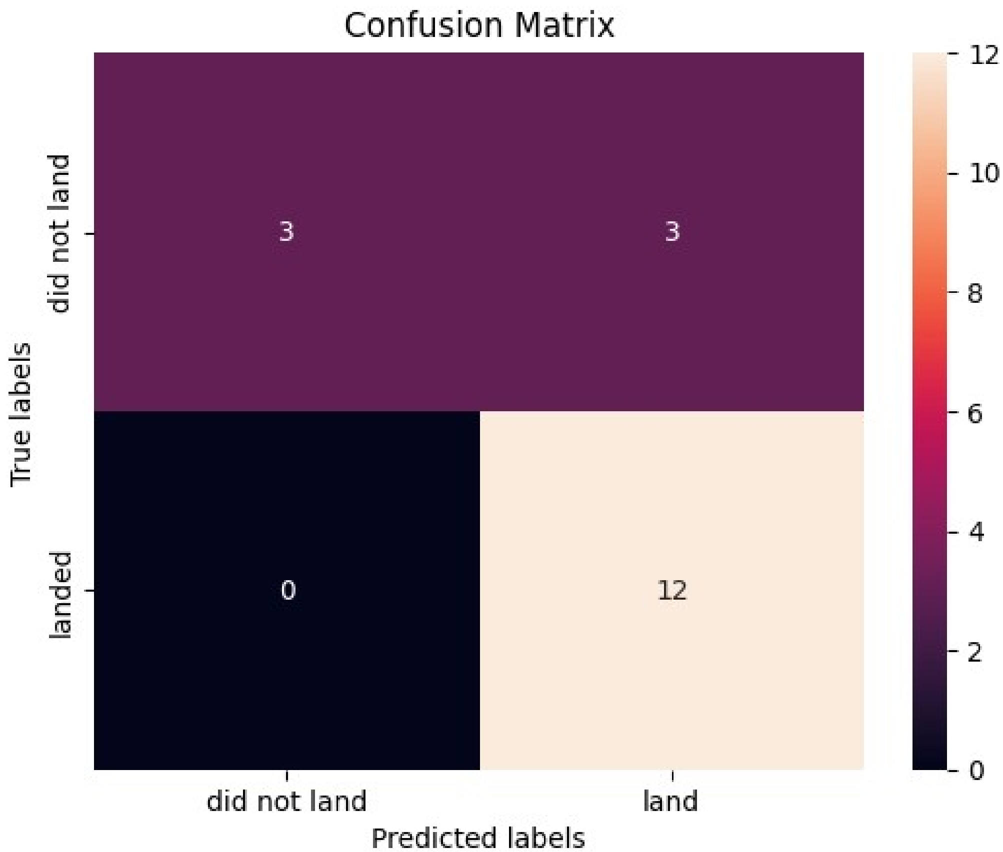
```
# Calculate the accuracy on the test data
test_accuracy = logreg_cv.best_estimator_.score(X_test, Y_test)

# Print the accuracy
print("Accuracy on test data:", test_accuracy)
```

```
Accuracy on test data: 0.8333333333333334
```

Lets look at the confusion matrix:

```
yhat=logreg_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```



Examining the confusion matrix, we see that logistic regression can distinguish between the different classes. We see that the major problem is false positives.

TASK 6

Create a support vector machine object then create a GridSearchCV object svm_cv with cv = 10. Fit the object to find the best parameters from the dictionary parameters.

```
parameters = {'kernel':('linear', 'rbf','poly','rbf', 'sigmoid'),
              'C': np.logspace(-3, 3, 5),
              'gamma':np.logspace(-3, 3, 5)}
svm = SVC()

parameters = {
    'C': [0.1, 1, 10],               # Regularization parameter
    'kernel': ['linear', 'rbf'],      # Kernel types
    'gamma': ['scale', 'auto']        # Kernel coefficient
}

svm_cv = GridSearchCV(estimator=svm, param_grid=parameters, cv=10)
svm_cv.fit(X_train, Y_train)
```

```
GridSearchCV(cv=10, estimator=SVC(),
             param_grid={'C': [0.1, 1, 10], 'gamma': ['scale',
'auto'],
                         'kernel': ['linear', 'rbf']})
```

```
print("tuned hpyerparameters :(best parameters) ",svm_cv.best_params_)
print("accuracy :",svm_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 1, 'gamma': 'scale',
'kernel': 'rbf'}
accuracy : 0.8196428571428571
```

TASK 7

Calculate the accuracy on the test data using the method score:

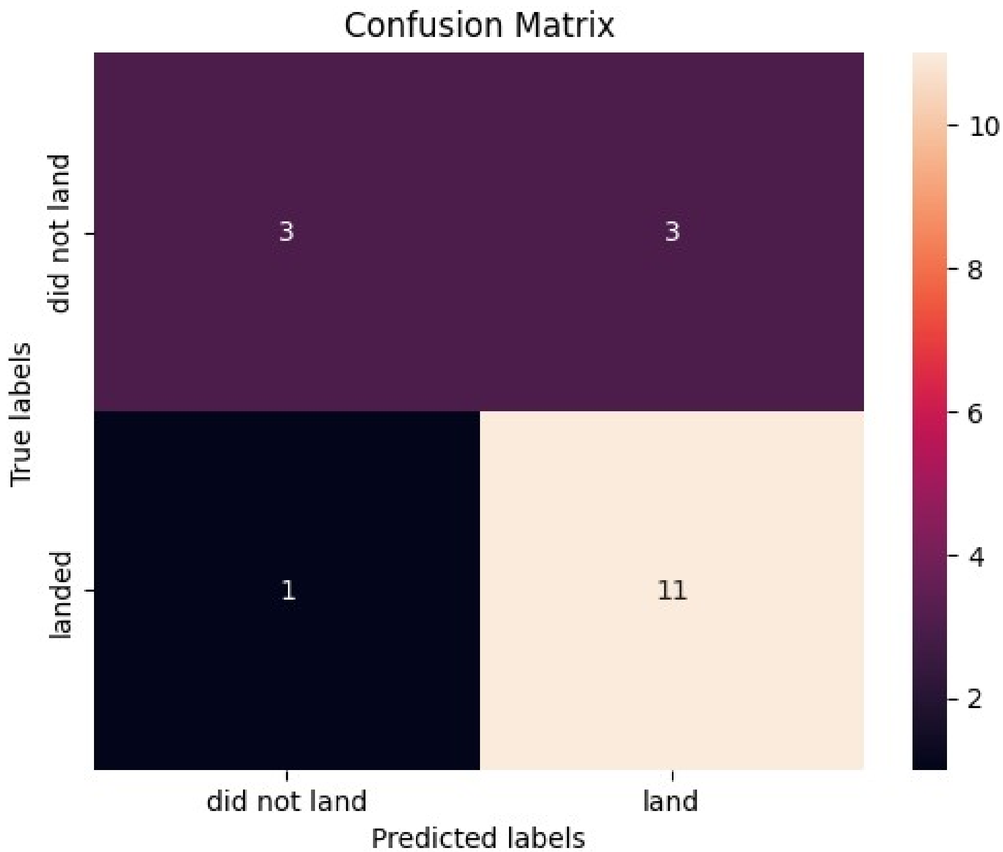
```
# Calculate the accuracy on the test data
test_accuracy_svm = svm_cv.best_estimator_.score(X_test, Y_test)

# Print the accuracy
print("Accuracy on test data with SVM:", test_accuracy_svm)
```

```
Accuracy on test data with SVM: 0.7777777777777778
```

We can plot the confusion matrix

```
yhat=svm_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```



TASK 8

Create a decision tree classifier object then create a GridSearchCV object tree_cv with cv = 10. Fit the object to find the best parameters from the dictionary parameters.

```
parameters = {'criterion': ['gini', 'entropy'],
     'splitter': ['best', 'random'],
     'max_depth': [2*n for n in range(1,10)],
     'max_features': ['auto', 'sqrt'],
     'min_samples_leaf': [1, 2, 4],
     'min_samples_split': [2, 5, 10]}

tree = DecisionTreeClassifier()

tree_cv = GridSearchCV(estimator=tree, param_grid=parameters, cv=10)
tree_cv.fit(X_train, Y_train)
```

```
/lib/python3.12/site-packages/sklearn/model_selection/
_validation.py:547: FitFailedWarning:
3240 fits failed out of a total of 6480.
The score on these train-test partitions for these parameters will be
set to nan.
If these failures are not expected, you can try to debug them by
```

```
setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
----------
3240 fits failed with the following error:
Traceback (most recent call last):
  File
"/lib/python3.12/site-packages/sklearn/model_selection/_validation.py"
, line 895, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/lib/python3.12/site-packages/sklearn/base.py", line 1467, in
wrapper
    estimator._validate_params()
  File "/lib/python3.12/site-packages/sklearn/base.py", line 666, in
_validate_params
    validate_parameter_constraints(
  File
"/lib/python3.12/site-packages/sklearn/utils/_param_validation.py",
line 95, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The
'max_features' parameter of DecisionTreeClassifier must be an int in
the range [1, inf), a float in the range (0.0, 1.0], a str among
{'log2', 'sqrt'} or None. Got 'auto' instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/lib/python3.12/site-packages/sklearn/model_selection/_search.py:1051:
UserWarning: One or more of the test scores are non-finite:
[       nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.78035714 0.79107143 0.73035714 0.76071429 0.83214286 0.76785714
 0.80892857 0.77678571 0.78928571 0.80535714 0.79107143 0.775
 0.73035714 0.75       0.81964286 0.78214286 0.775      0.76071429
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.83392857 0.8        0.79285714 0.84642857 0.71785714 0.83571429
 0.77678571 0.80178571 0.74821429 0.79107143 0.775      0.79642857
 0.81607143 0.79107143 0.7625     0.80535714 0.75       0.79107143
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.79107143 0.75178571 0.79107143 0.875      0.78928571 0.83392857
 0.76071429 0.79285714 0.77857143 0.79107143 0.76428571 0.775
 0.72321429 0.76428571 0.76607143 0.83392857 0.72678571 0.7375
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
```

```
        nan        nan        nan        nan        nan        nan
 0.82321429 0.79285714 0.80714286 0.83392857 0.84821429 0.80357143
 0.75       0.79285714 0.69285714 0.77857143 0.80535714 0.775
 0.7625     0.79642857 0.81785714 0.76071429 0.77678571 0.77857143
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.79285714 0.76428571 0.70714286 0.79285714 0.76071429 0.73571429
 0.725      0.78035714 0.77857143 0.71964286 0.76071429 0.79107143
 0.70714286 0.79107143 0.74821429 0.79285714 0.79285714 0.80535714
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.80178571 0.82142857 0.76428571 0.78928571 0.77321429 0.87321429
 0.7375     0.775      0.73392857 0.76428571 0.78928571 0.84642857
 0.77678571 0.71785714 0.78928571 0.83392857 0.83392857 0.76428571
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.83392857 0.77678571 0.79107143 0.77857143 0.77857143 0.80535714
 0.80357143 0.72142857 0.80357143 0.81785714 0.79107143 0.80714286
 0.78928571 0.77678571 0.76071429 0.83571429 0.76428571 0.78035714
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.72321429 0.80178571 0.73571429 0.69464286 0.74821429 0.80178571
 0.72142857 0.7375     0.70535714 0.73571429 0.80535714 0.80714286
 0.775      0.83214286 0.81785714 0.80714286 0.80535714 0.81964286
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.80535714 0.77857143 0.81964286 0.76071429 0.81785714 0.80714286
 0.75       0.775      0.75       0.78928571 0.80357143 0.73928571
 0.81964286 0.83392857 0.81785714 0.76785714 0.79464286 0.81785714
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.80535714 0.76428571 0.84464286 0.80357143 0.81964286 0.80535714
 0.83214286 0.80357143 0.81785714 0.77678571 0.76071429 0.72321429
 0.75178571 0.78035714 0.83214286 0.75357143 0.79107143 0.78214286
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.81428571 0.81785714 0.70714286 0.78214286 0.775      0.83214286
 0.79285714 0.7875     0.79285714 0.81607143 0.84642857 0.875
 0.66785714 0.70714286 0.81964286 0.76071429 0.71964286 0.74642857
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
```

```
 0.81785714 0.81964286 0.83214286 0.81785714 0.76428571 0.86071429
 0.74821429 0.69107143 0.81607143 0.8625     0.79285714 0.775
 0.79642857 0.7625     0.81785714 0.775      0.83214286 0.7625
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.83392857 0.775      0.75       0.775      0.73571429 0.80535714
 0.80357143 0.75178571 0.76428571 0.79107143 0.775      0.81785714
 0.73214286 0.81785714 0.78928571 0.775      0.74642857 0.80357143
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.77678571 0.69285714 0.8375     0.79107143 0.76607143 0.79285714
 0.775      0.81785714 0.77678571 0.80178571 0.82142857 0.82142857
 0.83214286 0.72678571 0.80535714 0.78928571 0.79107143 0.75357143
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.77857143 0.77678571 0.73392857 0.75       0.76428571 0.84642857
 0.82321429 0.79107143 0.74821429 0.79642857 0.81964286 0.81785714
 0.79107143 0.71071429 0.77678571 0.76428571 0.76428571 0.77678571
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.84642857 0.77857143 0.81964286 0.79107143 0.73392857 0.81964286
 0.76071429 0.73392857 0.775      0.80357143 0.83214286 0.79285714
 0.7625     0.7625     0.74642857 0.71785714 0.71964286 0.80535714
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.79107143 0.7375     0.80357143 0.76428571 0.79107143 0.81785714
 0.80714286 0.81785714 0.77678571 0.77678571 0.78928571 0.79285714
 0.775      0.79285714 0.81964286 0.79107143 0.80714286 0.7625
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.75       0.81964286 0.73571429 0.77857143 0.80357143 0.74821429
 0.78928571 0.73392857 0.70714286 0.76607143 0.80357143 0.84642857
 0.78928571 0.81785714 0.77678571 0.79107143 0.74821429 0.80535714]
  warnings.warn(

GridSearchCV(cv=10, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [2, 4, 6, 8, 10, 12, 14, 16,
18],
                         'max_features': ['auto', 'sqrt'],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'splitter': ['best', 'random']})
```

```
print("tuned hpyerparameters :(best parameters)
",tree_cv.best_params_)
print("accuracy :",tree_cv.best_score_)

tuned hpyerparameters :(best parameters)  {'criterion': 'gini',
'max_depth': 6, 'max_features': 'sqrt', 'min_samples_leaf': 1,
'min_samples_split': 5, 'splitter': 'random'}
accuracy : 0.875
```

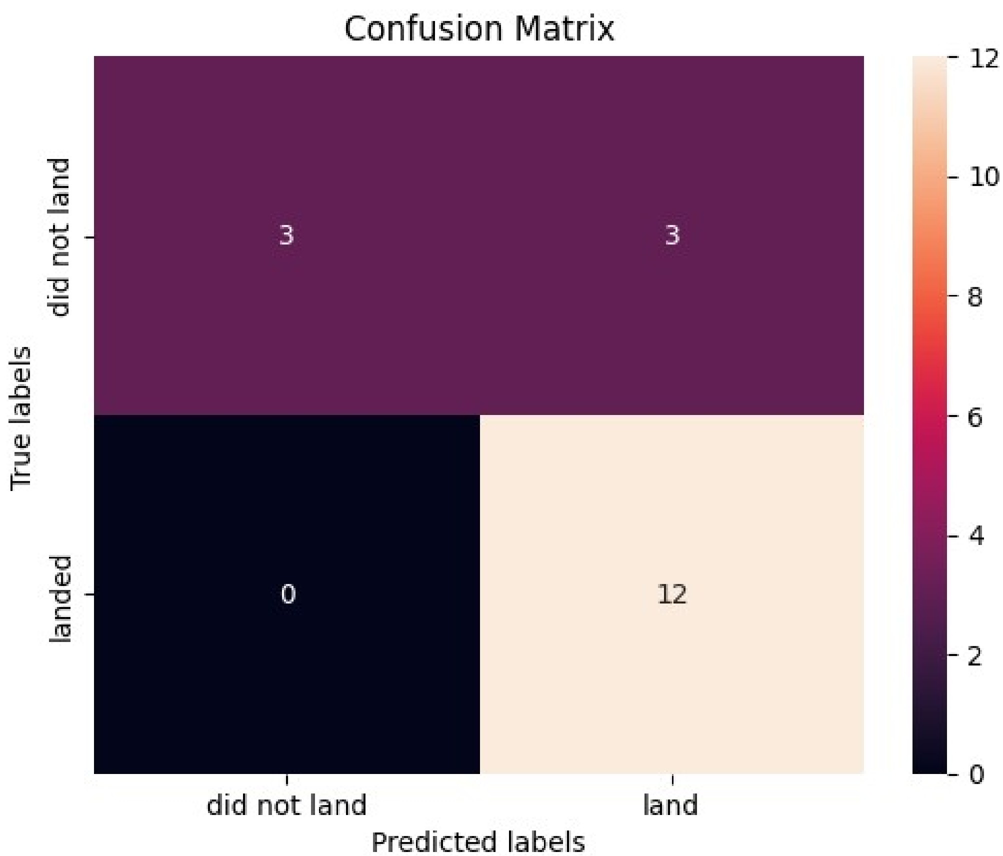
TASK 9

Calculate the accuracy of tree_cv on the test data using the method score:

```
test_accuracy_tree = tree_cv.best_estimator_.score(X_test, Y_test)
```

We can plot the confusion matrix

```
yhat = tree_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```



TASK 10

Create a k nearest neighbors object then create a GridSearchCV object knn_cv with cv = 10. Fit the object to find the best parameters from the dictionary parameters.

```
knn = KNeighborsClassifier()

# Step 2: Define the parameter grid for hyperparameter tuning
parameters = {
    'n_neighbors': [3, 5, 7, 10],         # Number of neighbors to use
    'weights': ['uniform', 'distance'],   # Weight function used in
prediction
    'p': [1, 2]                           # Power parameter for the
Minkowski distance (1 for Manhattan, 2 for Euclidean)
}

knn_cv = GridSearchCV(estimator=knn, param_grid=parameters, cv=10)
knn_cv.fit(X_train, Y_train)

GridSearchCV(cv=10, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': [3, 5, 7, 10], 'p': [1, 2],
                         'weights': ['uniform', 'distance']})

print("tuned hpyerparameters :(best parameters) ",knn_cv.best_params_)
print("accuracy :",knn_cv.best_score_)

tuned hpyerparameters :(best parameters)  {'n_neighbors': 10, 'p': 1,
'weights': 'uniform'}
accuracy : 0.8482142857142858
```

TASK 11

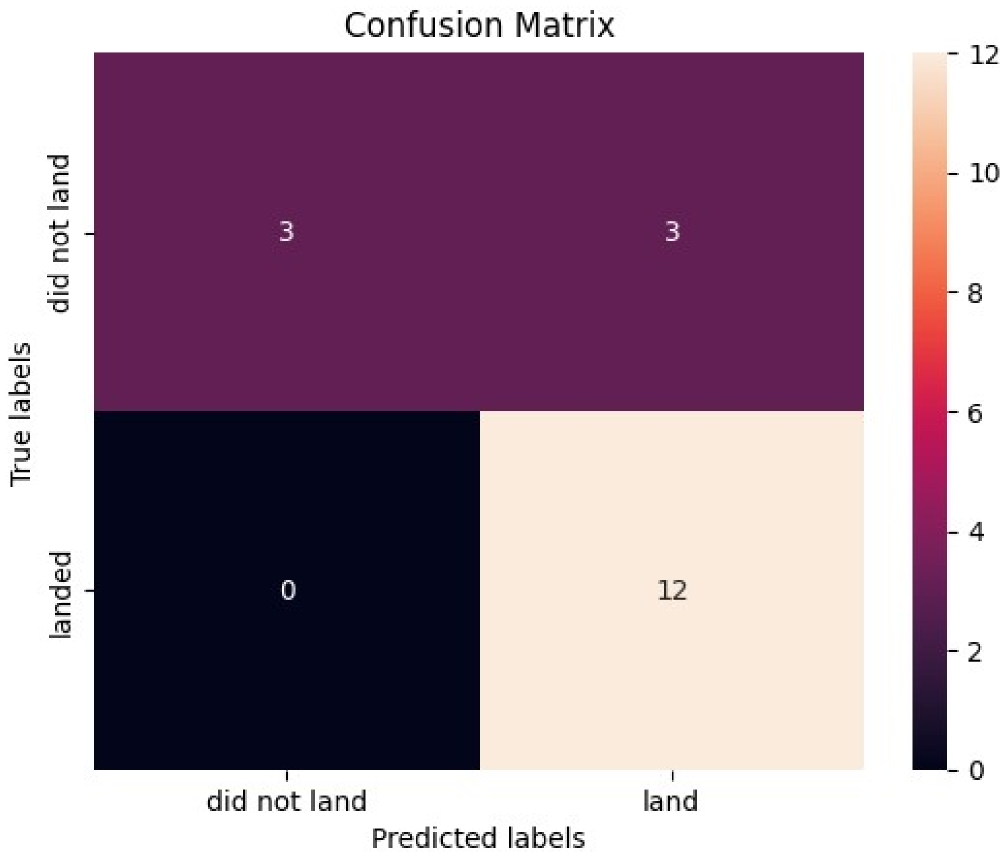
Calculate the accuracy of knn_cv on the test data using the method score:

```
test_accuracy_knn = knn_cv.best_estimator_.score(X_test, Y_test)
print("Accuracy on test data with KNN:", test_accuracy_knn)

Accuracy on test data with KNN: 0.8333333333333334
```

We can plot the confusion matrix

```
yhat = knn_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```



TASK 12

Find the method performs best:

```
# Accuracy for Logistic Regression
test_accuracy_logreg = logreg_cv.best_estimator_.score(X_test, Y_test)

# Accuracy for SVM
test_accuracy_svm = svm_cv.best_estimator_.score(X_test, Y_test)

# Accuracy for Decision Tree
test_accuracy_tree = tree_cv.best_estimator_.score(X_test, Y_test)

# Accuracy for KNN
test_accuracy_knn = knn_cv.best_estimator_.score(X_test, Y_test)

# Print the accuracy of each model on the test data
print("Accuracy on test data with Logistic Regression:",
test_accuracy_logreg)
print("Accuracy on test data with SVM:", test_accuracy_svm)
print("Accuracy on test data with Decision Tree:", test_accuracy_tree)
print("Accuracy on test data with KNN:", test_accuracy_knn)
```

```
# Find the best performing model
best_accuracy = max(test_accuracy_logreg, test_accuracy_svm,
test_accuracy_tree, test_accuracy_knn)
if best_accuracy == test_accuracy_logreg:
    best_model = "Logistic Regression"
elif best_accuracy == test_accuracy_svm:
    best_model = "SVM"
elif best_accuracy == test_accuracy_tree:
    best_model = "Decision Tree"
else:
    best_model = "KNN"

# Print the best performing model
print(f"The best performing model is {best_model} with an accuracy of
{best_accuracy:.2f}.")
```

```
Accuracy on test data with Logistic Regression: 0.8333333333333334
Accuracy on test data with SVM: 0.7777777777777778
Accuracy on test data with Decision Tree: 0.8333333333333334
Accuracy on test data with KNN: 0.8333333333333334
The best performing model is Logistic Regression with an accuracy of
0.83.
```

```
# Number of records in the test sample
num_records_test = X_test.shape[0]
print("Number of records in the test sample:", num_records_test)
```

```
Number of records in the test sample: 18
```

```
# Best kernel for SVM
best_kernel_svm = svm_cv.best_params_['kernel']
print("Best kernel for SVM:", best_kernel_svm)
```

```
Best kernel for SVM: rbf
```

Authors

Pratiksha Verma

<!--## Change Log--!>

<!--	Date (YYYY-MM-DD)	Version	Changed By
2022-11-09	1.0	Pratiksha Verma	Converted initial version to Jupyterlite