Space X Falcon 9 First Stage Landing Prediction

Hands on Lab: Complete the Machine Learning Prediction lab

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

In [1]:
```
import piplite
await piplite.install(['numpy'])
await piplite.install(['pandas'])
await piplite.install(['seaborn'])
```

We will import the following libraries for the lab

In [2]:
```
# Pandas is a software library written for the Python programming language f
import pandas as pd
# NumPy is a library for the Python programming language, adding support for
import numpy as np
# Matplotlib is a plotting library for python and pyplot gives us a MatLab l
import matplotlib.pyplot as plt
#Seaborn is a Python data visualization library based on matplotlib. It prov
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 bes
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 releas
e of pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and bet
ter 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/54
466

  import pandas as pd
```

This function is to plot the confusion matrix.

In [3]:
```
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_ticklabe
    plt.show()
```

Load the dataframe

Load the data

In [4]:
```
from js import fetch
import io

URL1 = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/I
resp1 = await fetch(URL1)
text1 = io.BytesIO((await resp1.arrayBuffer()).to_py())
data = pd.read_csv(text1)
```

In [5]:
```
data.head()
```

Out[5]:

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	F
0	1	2010-06-04	Falcon 9	6104.959412	LEO	CCAFS SLC 40	None None	
1	2	2012-05-22	Falcon 9	525.000000	LEO	CCAFS SLC 40	None None	
2	3	2013-03-01	Falcon 9	677.000000	ISS	CCAFS SLC 40	None None	
3	4	2013-09-29	Falcon 9	500.000000	PO	VAFB SLC 4E	False Ocean	
4	5	2013-12-03	Falcon 9	3170.000000	GTO	CCAFS SLC 40	None None	

In [6]:
```
URL2 = 'https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/I
resp2 = await fetch(URL2)
text2 = io.BytesIO((await resp2.arrayBuffer()).to_py())
X = pd.read_csv(text2)
```

In [7]:
```
X.head(100)
```

Out[7]:

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

90 rows × 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']).

In [10]:
```
Y = data['Class'].to_numpy()
Y = pd.Series(Y)
Y.head(20)
```

Out[10]:
```
0     0
1     0
2     0
3     0
4     0
5     0
6     1
7     1
8     0
9     0
10    0
11    0
12    1
13    0
14    0
15    0
16    1
17    0
18    0
19    1
dtype: int64
```

TASK 2

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

In [14]:
```
# students get this
transform = preprocessing.StandardScaler()

X_scaled = transform.fit_transform(X)
X = pd.DataFrame(X_scaled)
X.head()
```

Out[14]:

	0	1	2	3	4	5	6	
0	-1.712912	-3.321533e-17	-0.653913	-1.575895	-0.97344	-0.106	-0.106	-0.65465
1	-1.674419	-1.195232e+00	-0.653913	-1.575895	-0.97344	-0.106	-0.106	-0.65465
2	-1.635927	-1.162673e+00	-0.653913	-1.575895	-0.97344	-0.106	-0.106	-0.65465
3	-1.597434	-1.200587e+00	-0.653913	-1.575895	-0.97344	-0.106	-0.106	-0.65465
4	-1.558942	-6.286706e-01	-0.653913	-1.575895	-0.97344	-0.106	-0.106	1.52752

5 rows × 83 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`

In [15]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, rar
```

we can see we only have 18 test samples.

In [16]:
```
Y_test.shape
```

Out[16]: (18,)

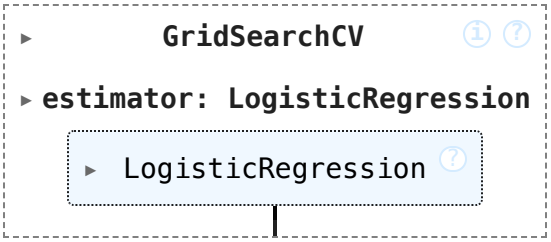
TASK 4

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`.

In [17]:
```
parameters ={'C':[0.01,0.1,1],
             'penalty':['l2'],
             'solver':['lbfgs']}
```

In [21]:
```
parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}# l1 lass
lr=LogisticRegression()
logreg_cv = GridSearchCV(lr, parameters, cv=10)
logreg_cv.fit(X_train, Y_train)
```

Out[21]:



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_`.

In [22]:
```
print("tuned hpyerparameters :(best parameters) ",logreg_cv.best_params_)
print("accuracy :",logreg_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 0.01, 'penalty': 'l2', 'solv
er': 'lbfgs'}
accuracy : 0.8464285714285713
```

TASK 5

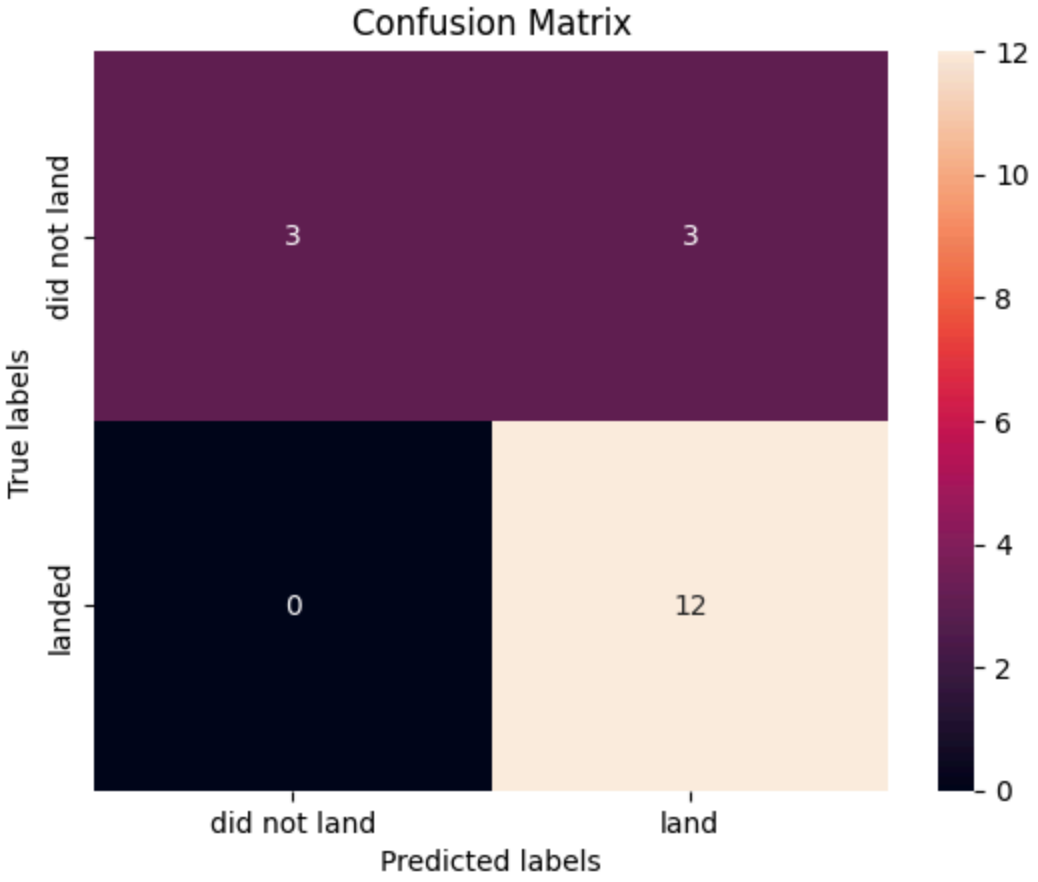
Calculate the accuracy on the test data using the method `score`:

In [24]:
```
acc = logreg_cv.best_estimator_.score(X_test, Y_test)
acc
```

Out[24]: 0.8333333333333334

Lets look at the confusion matrix:

In [25]:
```
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 problem is false positives.

Overview:

True Postive - 12 (True label is landed, Predicted label is also landed)

False Postive - 3 (True label is not landed, Predicted label is landed)

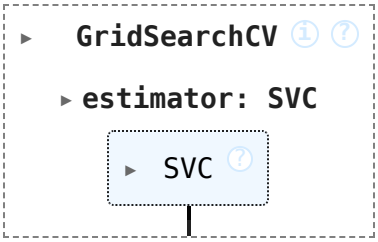
TASK 6

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`.

In [26]:
```
parameters = {'kernel':('linear', 'rbf','poly','rbf', 'sigmoid'),
              'C': np.logspace(-3, 3, 5),
              'gamma':np.logspace(-3, 3, 5)}
svm = SVC()
```

In [27]:
```
svm_cv = GridSearchCV(svm, parameters, cv=10)
svm_cv.fit(X_train, Y_train)
```

Out[27]:



In [28]:
```
print("tuned hpyerparameters :(best parameters) ",svm_cv.best_params_)
print("accuracy :",svm_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 1.0, 'gamma': 0.031622776601
68379, 'kernel': 'sigmoid'}
accuracy : 0.8482142857142856
```

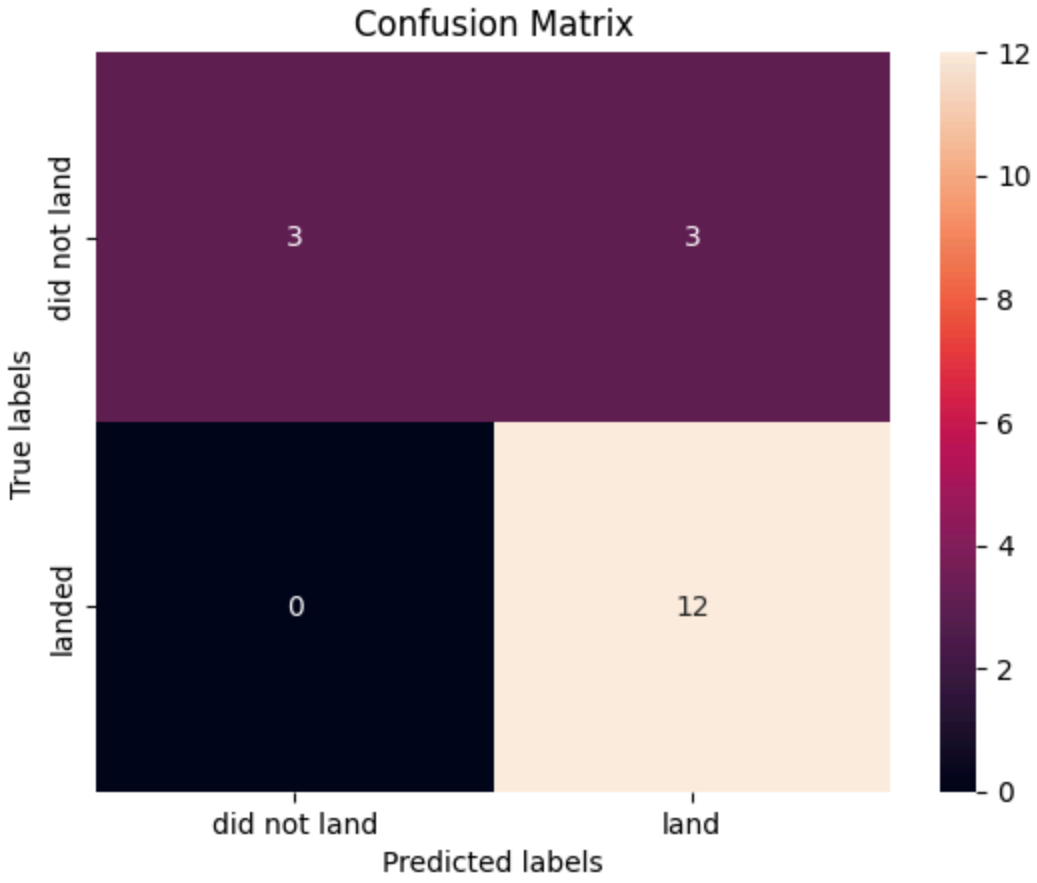
TASK 7

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

In [29]:
```
acc_svm = svm_cv.best_estimator_.score(X_test, Y_test)
```

We can plot the confusion matrix

In [30]:
```
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`.

In [31]:
```
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()
```

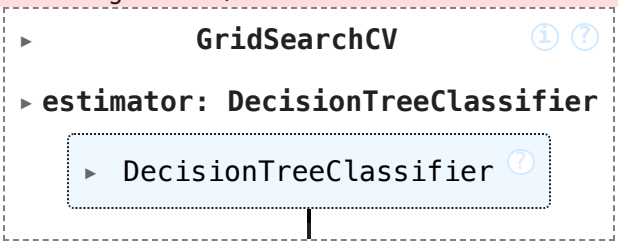
In [36]:
```
tree_cv = GridSearchCV(tree, parameters, cv=10)
tree_cv.fit(X_train, Y_train)
```

```
/lib/python3.12/site-packages/sklearn/model_selection/_validation.py:547: Fi
tFailedWarning:
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 err
or_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.p
y", 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 wrappe
r
    estimator._validate_params()
  File "/lib/python3.12/site-packages/sklearn/base.py", line 666, in _valida
te_params
    validate_parameter_constraints(
  File "/lib/python3.12/site-packages/sklearn/utils/_param_validation.py", l
ine 95, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' pa
rameter of DecisionTreeClassifier must be an int in the range [1, inf), a fl
oat in the range (0.0, 1.0], a str among {'log2', 'sqrt'} or None. Got 'aut
o' instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/lib/python3.12/site-packages/sklearn/model_selection/_search.py:1051: UserW
arning: One or more of the test scores are non-finite: [       nan        na
n        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.75178571 0.71785714 0.70892857 0.84642857 0.75178571 0.75535714
 0.83214286 0.79107143 0.81964286 0.8625     0.86071429 0.77678571
 0.76785714 0.81964286 0.76607143 0.77678571 0.725      0.77321429
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.84821429 0.81964286 0.79107143 0.85       0.73214286 0.81785714
 0.77321429 0.77678571 0.77857143 0.75178571 0.74821429 0.83571429
 0.84285714 0.80357143 0.82857143 0.75       0.76071429 0.79107143
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.81785714 0.77678571 0.77857143 0.76071429 0.77857143 0.83392857
 0.81964286 0.77678571 0.7625     0.76428571 0.76785714 0.84821429
 0.82142857 0.83392857 0.78928571 0.83392857 0.80535714 0.76071429
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
 0.81785714 0.83214286 0.74642857 0.82321429 0.80535714 0.86071429
 0.74642857 0.78214286 0.75892857 0.81785714 0.73392857 0.80892857
```

```
0.80535714 0.78928571 0.80535714 0.78392857 0.77678571 0.80535714
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.78035714 0.775      0.80535714 0.80714286 0.80357143 0.81964286
0.80714286 0.77678571 0.7625     0.80357143 0.75178571 0.81964286
0.86071429 0.84821429 0.81964286 0.81785714 0.74285714 0.79107143
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.75       0.72142857 0.80535714 0.75       0.76071429 0.83214286
0.80535714 0.84642857 0.69285714 0.775      0.80714286 0.80535714
0.68035714 0.78928571 0.775      0.81964286 0.77678571 0.74821429
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.73392857 0.70892857 0.75892857 0.77678571 0.79285714 0.79464286
0.7625     0.77678571 0.71071429 0.77678571 0.78928571 0.69464286
0.74821429 0.79285714 0.72321429 0.73392857 0.81785714 0.81964286
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.75178571 0.78928571 0.69464286 0.79107143 0.86071429 0.80357143
0.77857143 0.7625     0.75892857 0.73571429 0.72142857 0.80357143
0.7625     0.83214286 0.81964286 0.81785714 0.76607143 0.78571429
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.84642857 0.80535714 0.78928571 0.77678571 0.75357143 0.79107143
0.70357143 0.76785714 0.73392857 0.82142857 0.68214286 0.83392857
0.79285714 0.80714286 0.86428571 0.79107143 0.725      0.76428571
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.79107143 0.76785714 0.725      0.79107143 0.79107143 0.84642857
0.7625     0.80535714 0.87678571 0.80357143 0.775      0.875
0.74821429 0.725      0.66785714 0.77857143 0.71964286 0.73928571
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.77857143 0.83392857 0.84821429 0.79107143 0.87321429 0.79642857
0.83392857 0.80535714 0.7625     0.80535714 0.79107143 0.7625
0.7625     0.83392857 0.73571429 0.74107143 0.84642857 0.775
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.80357143 0.76428571 0.83214286 0.77678571 0.81964286 0.75178571
0.80535714 0.79107143 0.76071429 0.775      0.73214286 0.775
0.76071429 0.81964286 0.7625     0.83392857 0.78928571 0.72321429
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.74821429 0.81964286 0.74642857 0.81785714 0.71964286 0.77678571
0.79285714 0.83392857 0.71607143 0.77857143 0.79464286 0.82142857
0.775      0.79107143 0.80714286 0.73214286 0.75178571 0.79107143
       nan        nan        nan        nan        nan        nan
```

```
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.83214286 0.72321429 0.76607143 0.7625     0.80535714 0.77678571
0.74821429 0.73571429 0.73392857 0.76071429 0.75178571 0.81964286
0.79464286 0.81964286 0.83392857 0.83214286 0.79107143 0.875
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.77857143 0.80535714 0.79107143 0.73392857 0.79107143 0.775
0.7625     0.72142857 0.70892857 0.77678571 0.80357143 0.78928571
0.74821429 0.70892857 0.77857143 0.76785714 0.74821429 0.80535714
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.80535714 0.80357143 0.73571429 0.79285714 0.84642857 0.78035714
0.68928571 0.7125     0.775      0.77857143 0.7875     0.83214286
0.75357143 0.76071429 0.7625     0.76071429 0.83214286 0.80714286
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.80535714 0.77857143 0.74821429 0.74821429 0.78928571 0.76428571
0.73035714 0.82142857 0.84821429 0.775      0.82142857 0.83214286
0.76071429 0.80357143 0.81785714 0.79285714 0.80357143 0.81964286
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
       nan        nan        nan        nan        nan        nan
0.87142857 0.76071429 0.78928571 0.75535714 0.77857143 0.80535714
0.73392857 0.75       0.84642857 0.80535714 0.76071429 0.81785714
0.80535714 0.83214286 0.82321429 0.79107143 0.81964286 0.79107143]
 warnings.warn(
```

Out[36]:



In [37]:
```
print("tuned hpyerparameters :(best parameters) ",tree_cv.best_params_)
print("accuracy :",tree_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'criterion': 'entropy', 'max_dept
h': 2, 'max_features': 'sqrt', 'min_samples_leaf': 2, 'min_samples_split':
5, 'splitter': 'best'}
accuracy : 0.8767857142857143
```

TASK 9

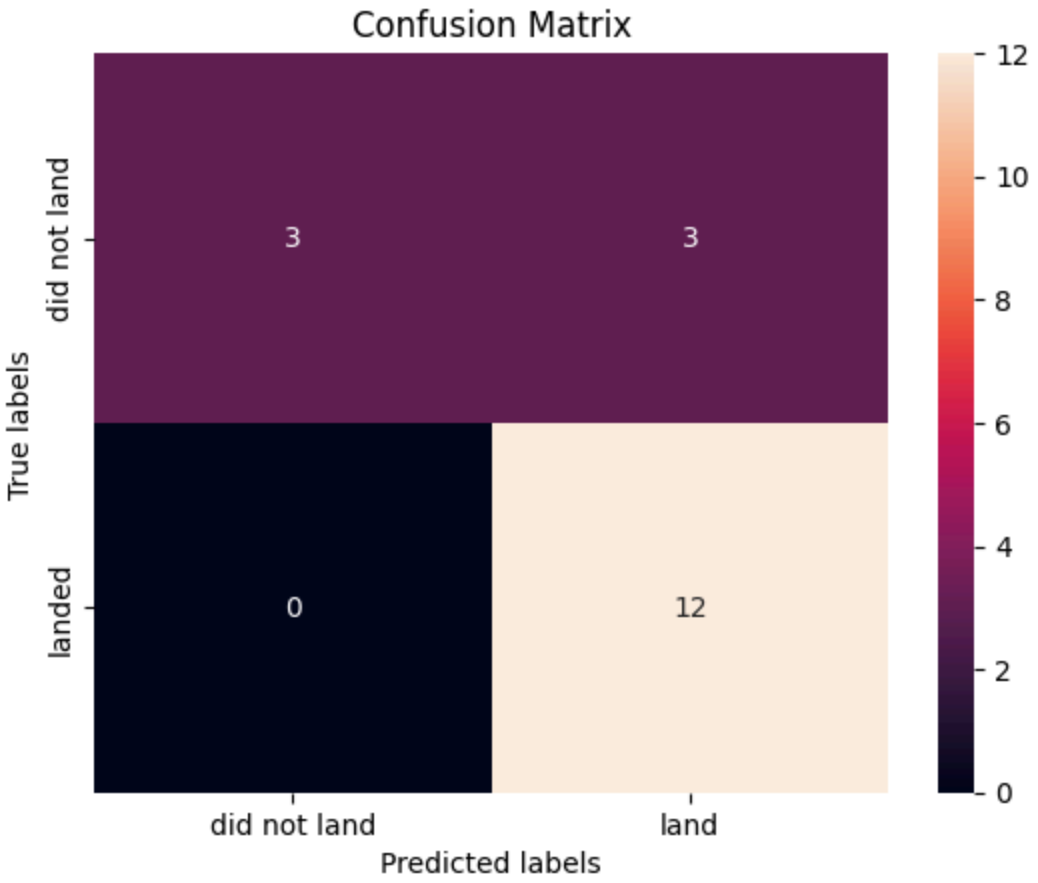
Calculate the accuracy of tree_cv on the test data using the method `score`:

In [40]:
```
acc_tree = tree_cv.best_estimator_.score(X_test, Y_test)
acc_tree
```

Out[40]: 0.8333333333333334

We can plot the confusion matrix

In [39]:
```
yhat = tree_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```



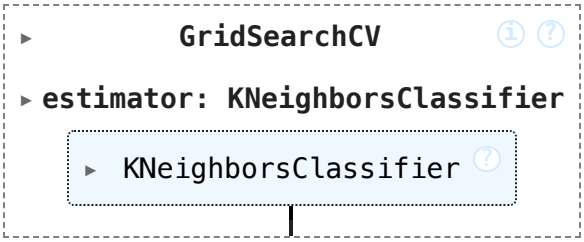
TASK 10

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`.

In [41]:
```
parameters = {'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
              'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
              'p': [1,2]}

KNN = KNeighborsClassifier()
```

In [44]:
```
knn_cv = GridSearchCV(KNN, parameters, cv=10)
knn_cv.fit(X_train, Y_train)
```

Out[44]:



In [45]:
```
print("tuned hpyerparameters :(best parameters) ",knn_cv.best_params_)
print("accuracy :",knn_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'algorithm': 'auto', 'n_neighbor
s': 10, 'p': 1}
accuracy : 0.8482142857142858
```

TASK 11

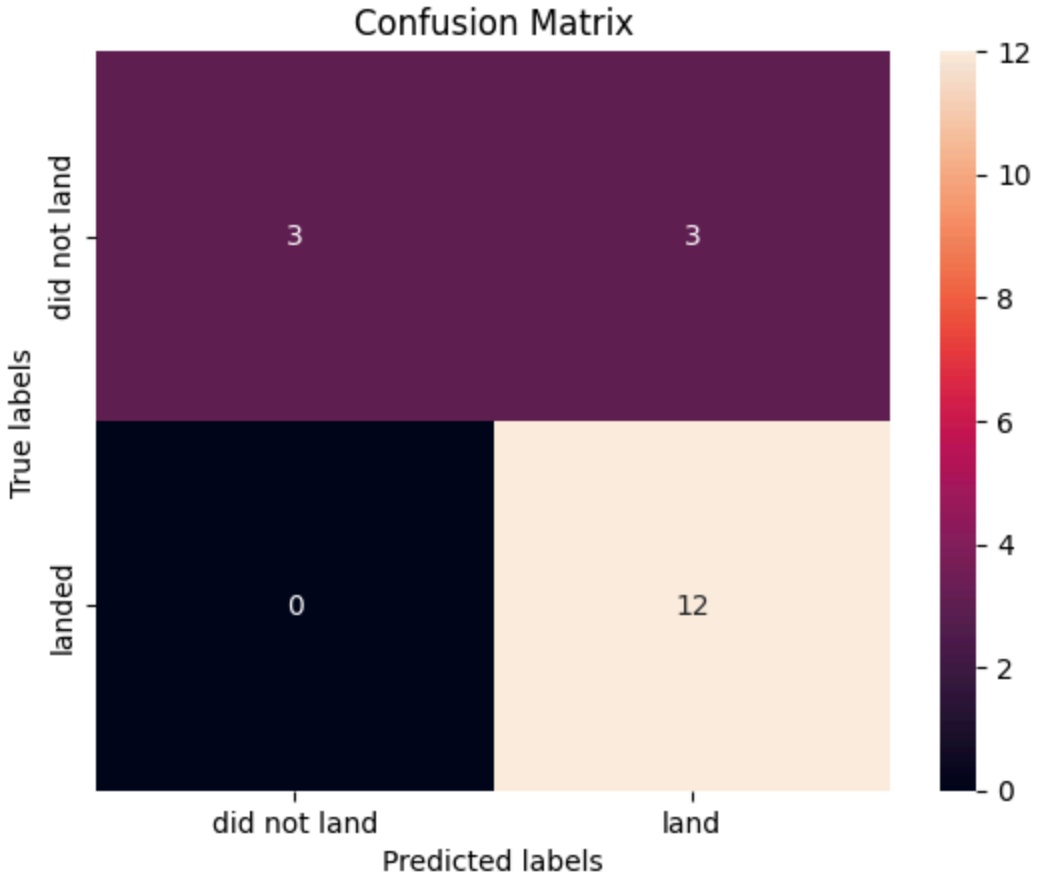
Calculate the accuracy of knn_cv on the test data using the method `score`:

In [47]:
```
acc_knn = knn_cv.best_estimator_.score(X_test, Y_test)
acc_knn
```

Out[47]: 0.8333333333333334

We can plot the confusion matrix

In [48]:
```
yhat = knn_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```



TASK 12

Find the method performs best:

In [ ]:

Authors

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

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