Space X Falcon 9 First Stage Landing Prediction

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 planned. 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

We will import the following libraries for the lab

In [1]:
```
import itertools
import pandas as pd
import numpy as np
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, f1_score, precision
```

This function is to plot the confusion matrix.

In [2]:

```python
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

Load the dataframe

Load the data

In [3]:

```python
data = pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/I
data.head()
```

Out[3]:

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused
0	1	2010-06-04	Falcon 9	6104.959412	LEO	CCAFS SLC 40	None None	1	False	False
1	2	2012-05-22	Falcon 9	525.000000	LEO	CCAFS SLC 40	None None	1	False	False
2	3	2013-03-01	Falcon 9	677.000000	ISS	CCAFS SLC 40	None None	1	False	False

3	4	2013-09-29	Falcon 9	500.000000	PO	VAFB SLC 4E	False Ocean	1	False	False
4	5	2013-12-03	Falcon 9	3170.000000	GTO	CCAFS SLC 40	None None	1	False	False

In [4]:
```
X = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-
X.head()
```

Out[4]:

	FlightNumber	PayloadMass	Flights	Block	ReusedCount	Orbit_ES-L1	Orbit_GEO	Orbit_GTO	Orbit_HEO	Or
0	1.0	6104.959412	1.0	1.0	0.0	0.0	0.0	0.0	0.0	
1	2.0	525.000000	1.0	1.0	0.0	0.0	0.0	0.0	0.0	
2	3.0	677.000000	1.0	1.0	0.0	0.0	0.0	0.0	0.0	
3	4.0	500.000000	1.0	1.0	0.0	0.0	0.0	0.0	0.0	
4	5.0	3170.000000	1.0	1.0	0.0	0.0	0.0	1.0	0.0	

5 rows × 83 columns

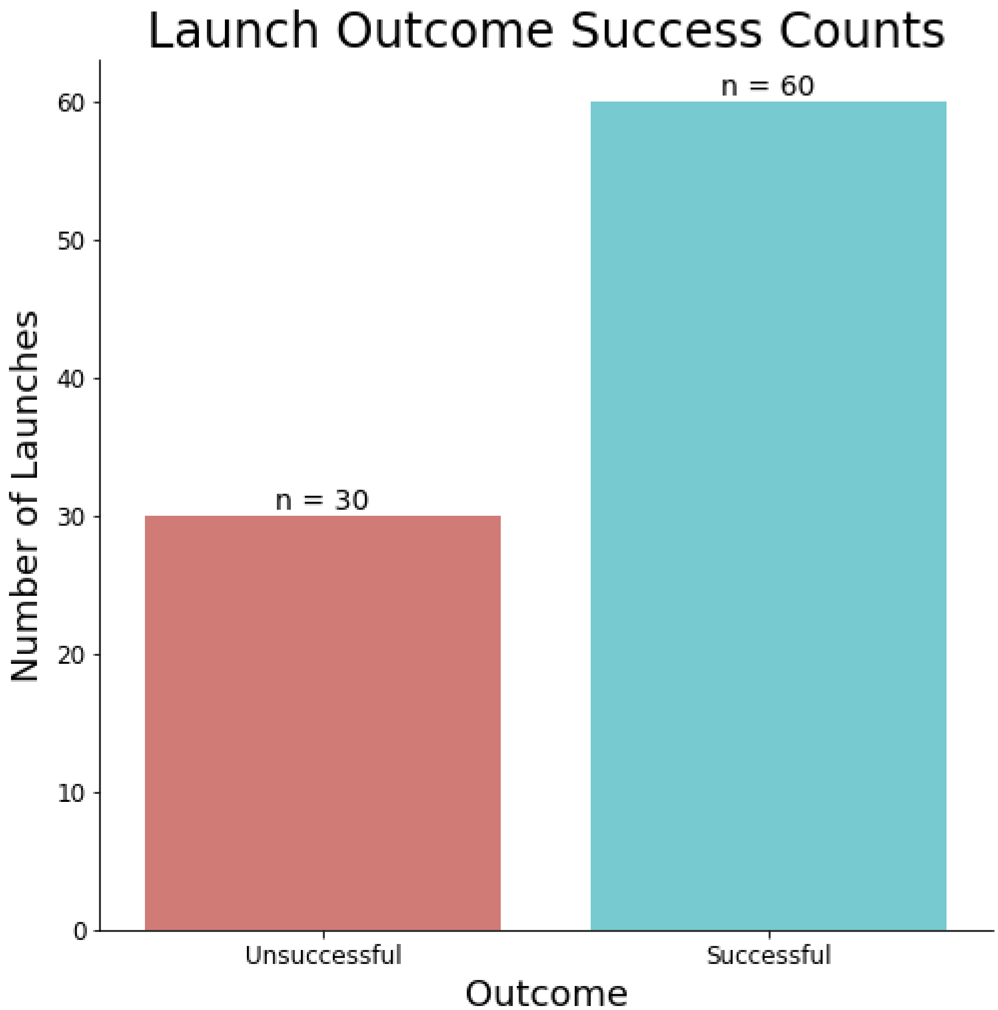
TASK 1

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

In [5]:
```
Y = data['Class']
type(Y)
```

Out[5]:
```
pandas.core.series.Series
```

In [6]:
```
df=Y.value_counts()
plt.figure(figsize=(8,8))
ax=sns.barplot(x=df.index, y=df.values, palette='hls', alpha=0.9)
sns.despine(top=True, right=True, left=False, bottom=False)
for p in ax.patches:
    ax.annotate('n = {:.0f}'.format(p.get_height()), (p.get_x()+0.4, p.get_height()),
                ha='center', va='bottom', color='black', fontsize=14)
ax.set_xticklabels(['Unsuccessful', 'Successful'], minor=False, fontsize=12)
plt.yticks(fontsize=12)
plt.xticks(fontsize=12)
plt.title('Launch Outcome Success Counts', fontsize=24)
plt.ylabel('Number of Launches',fontsize=18)
plt.xlabel('Outcome',fontsize=18)
plt.show()
```



TASK 2

Use the function `train_test_split` to split the data sets `X` and `Y` into training and test data. Set the parameter `test_size` to 0.2 and random_state to 2.

In [7]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
```

In [8]:
```
X_train.shape
```

Out[8]:
```
(72, 83)
```

In [9]:
```
X_test.shape
```

Out[9]:
```
(18, 83)
```

After splitting the data, there are 72 records in our training set and 18 in our test set.

TASK 3

Use the function using `fit_transform()` to standardize the training data so that we can learn the scaling parameters of our training set. Then, use these learned parameters to scale our test data.

In [10]:
```
scaler = preprocessing.StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

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 [11]:
```
parameters ={'C':[0.01,0.1,1],
             'penalty':['l2'],
             'solver':['lbfgs']}
lr=LogisticRegression(random_state=1)
logreg_cv = GridSearchCV(lr, parameters, cv=10, refit=True)
logreg_cv.fit(X_train, Y_train)
```

Out[11]:
```
GridSearchCV(cv=10, estimator=LogisticRegression(random_state=1),
             param_grid={'C': [0.01, 0.1, 1], 'penalty': ['l2'],
                         'solver': ['lbfgs']})
```

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 [12]:
```
print("Tuned hyperparameters:",logreg_cv.best_params_)
print("Cross-validation accuracy:",logreg_cv.best_score_)
```

```
Tuned hyperparameters: {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
Cross-validation accuracy: 0.8464285714285713
```

TASK 5

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

In [13]:
```
glm_acc=logreg_cv.score(X_test, Y_test)
print("Test set accuracy: {:.1%}".format(glm_acc))
glm_probs = logreg_cv.predict_proba(X_test)[:,1]
glm_auc=roc_auc_score(Y_test, glm_probs)
print("Test set AUC: {:.3}".format(glm_auc))
```

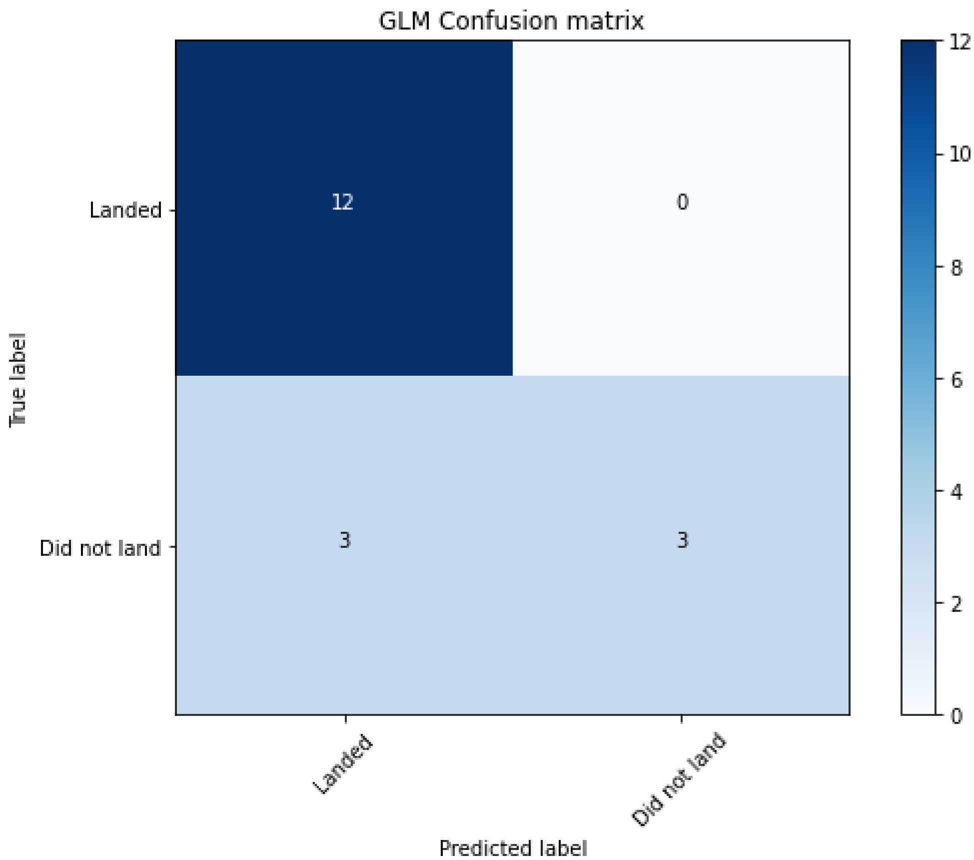
```
Test set accuracy: 83.3%
Test set AUC: 0.889
```

Lets look at the confusion matrix:

In [14]:
```
# Compute confusion matrix
glm_yhat = logreg_cv.predict(X_test)
glm_f1 = f1_score(Y_test, glm_yhat)
glm_prec = precision_score(Y_test, glm_yhat)
glm_rec = recall_score(Y_test, glm_yhat)
cnf_matrix = confusion_matrix(Y_test, glm_yhat, labels=[1,0])
np.set_printoptions(precision=2)
print(classification_report(Y_test, glm_yhat))

# Plot non-normalized confusion matrix
plt.figure(figsize=(8,6))
plot_confusion_matrix(cnf_matrix, classes=['Landed', 'Did not land'], normalize= False,
```

```
              precision    recall  f1-score   support

           0       1.00      0.50      0.67         6
           1       0.80      1.00      0.89        12

    accuracy                           0.83        18
```

```
   macro avg       0.90      0.75      0.78        18
weighted avg       0.87      0.83      0.81        18

Confusion matrix, without normalization
[[12  0]
 [ 3  3]]
```



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`.

In [15]:
```
parameters = {'kernel':('linear', 'rbf','poly','rbf', 'sigmoid'),
              'C': np.logspace(-3, 3, 5),
              'gamma':np.logspace(-3, 3, 5)}
svm = SVC(probability=True, random_state=1)
```

In [16]:
```
svm_cv = GridSearchCV(svm, parameters, cv=10)
svm_cv.fit(X_train, Y_train)
```

Out[16]:
```
GridSearchCV(cv=10, estimator=SVC(probability=True, random_state=1),
             param_grid={'C': array([1.00e-03, 3.16e-02, 1.00e+00, 3.16e+01, 1.00e+03]),
                         'gamma': array([1.00e-03, 3.16e-02, 1.00e+00, 3.16e+01, 1.00e+0
3]),
                         'kernel': ('linear', 'rbf', 'poly', 'rbf', 'sigmoid')})
```

In [17]:
```
print("Tuned hyperparameters:",svm_cv.best_params_)
print("Cross-validation accuracy:",svm_cv.best_score_)
```

```
Tuned hyperparameters: {'C': 1.0, 'gamma': 0.03162277660168379, 'kernel': 'sigmoid'}
Cross-validation accuracy: 0.8482142857142856
```

TASK 7

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

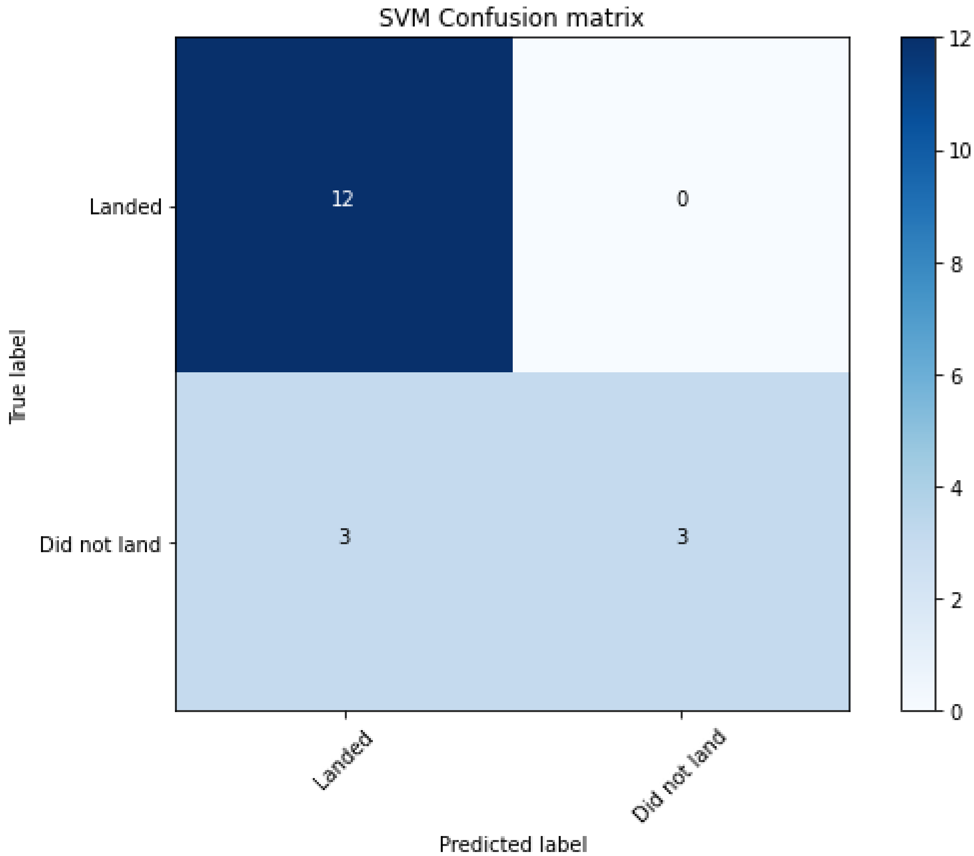
In [18]:
```
svm_acc=svm_cv.score(X_test, Y_test)
print("Test set accuracy: {:.1%}".format(svm_acc))
svm_probs = svm_cv.predict_proba(X_test)[:,1]
svm_auc=roc_auc_score(Y_test, svm_probs)
print("Test set AUC: {:.3}".format(svm_auc))
```

```
Test set accuracy: 83.3%
Test set AUC: 0.958
```

We can plot the confusion matrix

In [19]:
```
# Compute confusion matrix
svm_yhat = svm_cv.predict(X_test)
svm_f1 = f1_score(Y_test, svm_yhat)
svm_prec = precision_score(Y_test, svm_yhat)
svm_rec = recall_score(Y_test, svm_yhat)
cnf_matrix = confusion_matrix(Y_test, svm_yhat, labels=[1,0])
np.set_printoptions(precision=2)
print(classification_report(Y_test, svm_yhat))

# Plot non-normalized confusion matrix
plt.figure(figsize=(8,6))
plot_confusion_matrix(cnf_matrix, classes=['Landed', 'Did not land'], normalize=False, t
```

```
              precision    recall  f1-score   support

           0       1.00      0.50      0.67         6
           1       0.80      1.00      0.89        12

    accuracy                           0.83        18
   macro avg       0.90      0.75      0.78        18
weighted avg       0.87      0.83      0.81        18

Confusion matrix, without normalization
[[12  0]
 [ 3  3]]
```



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 [20]:
```
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(random_state=1)
```

In [21]:
```
tree_cv = GridSearchCV(tree, parameters, cv=10)
tree_cv.fit(X_train, Y_train)
```

Out[21]:
```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(random_state=1),
             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']})
```

In [22]:
```
print("Tuned hyperparameters:",tree_cv.best_params_)
print("Cross-validation Accuracy:",tree_cv.best_score_)
```

```
Tuned hyperparameters: {'criterion': 'gini', 'max_depth': 4, 'max_features': 'auto', 'mi
n_samples_leaf': 1, 'min_samples_split': 10, 'splitter': 'random'}
Cross-validation Accuracy: 0.8357142857142857
```

TASK 9

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

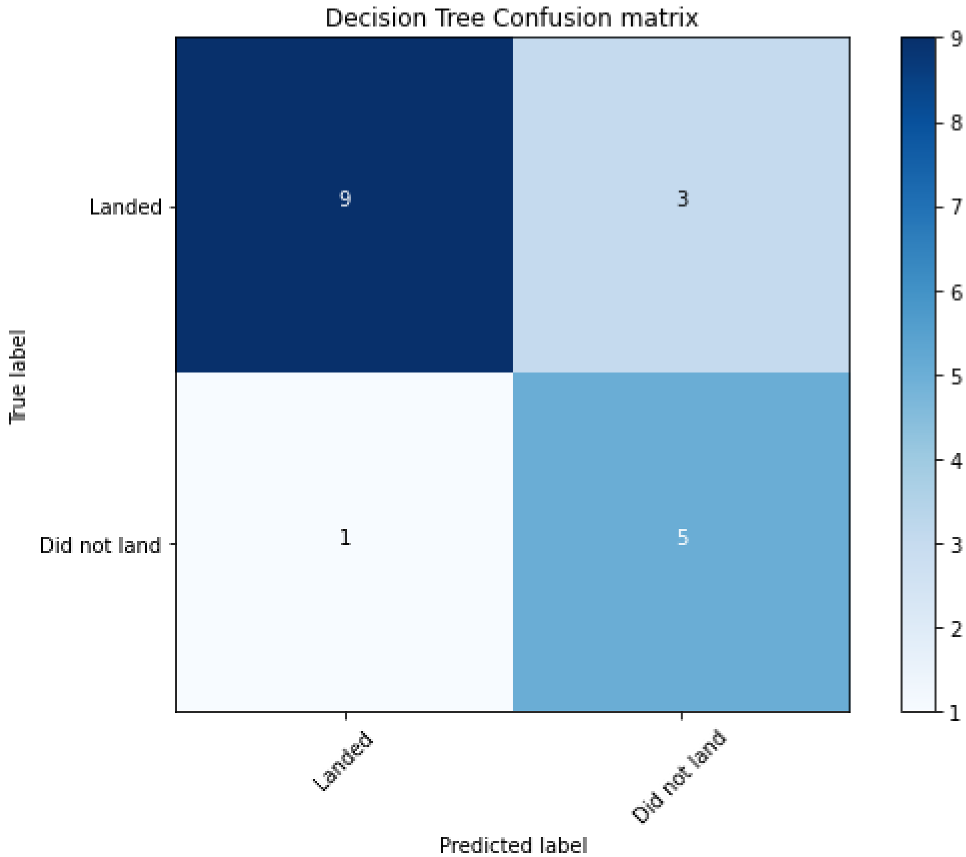
In [23]:
```
tree_acc=tree_cv.score(X_test, Y_test)
print("Test set accuracy: {:.1%}".format(tree_acc))
tree_probs = tree_cv.predict_proba(X_test)[:,1]
tree_auc=roc_auc_score(Y_test, tree_probs)
print("Test set AUC: {:.3}".format(tree_auc))
```

```
Test set accuracy: 77.8%
Test set AUC: 0.792
```

We can plot the confusion matrix

In [24]:
```
# Compute confusion matrix
tree_yhat = tree_cv.predict(X_test)
tree_f1 = f1_score(Y_test, tree_yhat)
tree_prec = precision_score(Y_test, tree_yhat)
tree_rec = recall_score(Y_test, tree_yhat)
cnf_matrix = confusion_matrix(Y_test, tree_yhat, labels=[1,0])
np.set_printoptions(precision=2)
print(classification_report(Y_test, tree_yhat))

# Plot non-normalized confusion matrix
plt.figure(figsize=(8,6))
plot_confusion_matrix(cnf_matrix, classes=['Landed', 'Did not land'], normalize=False, t
```

```
              precision    recall  f1-score   support

           0       0.62      0.83      0.71         6
           1       0.90      0.75      0.82        12

    accuracy                           0.78        18
   macro avg       0.76      0.79      0.77        18
weighted avg       0.81      0.78      0.78        18

Confusion matrix, without normalization
[[9 3]
 [1 5]]
```



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 [25]:
```
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 [26]:
```
knn_cv = GridSearchCV(KNN, parameters, cv=10)
knn_cv.fit(X_train, Y_train)
```

Out[26]:
```
GridSearchCV(cv=10, estimator=KNeighborsClassifier(),
             param_grid={'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
                         'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
                         'p': [1, 2]})
```

In [27]:
```
print("Tuned hyperparameters:",knn_cv.best_params_)
print("Cross-validation accuracy:",knn_cv.best_score_)
```

```
Tuned hyperparameters: {'algorithm': 'auto', 'n_neighbors': 10, 'p': 1}
Cross-validation accuracy: 0.8482142857142858
```

TASK 11

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

In [28]:
```
knn_acc = knn_cv.score(X_test, Y_test)
print("Test set accuracy: {:.1%}".format(knn_acc))
knn_probs = knn_cv.predict_proba(X_test)[:,1]
```

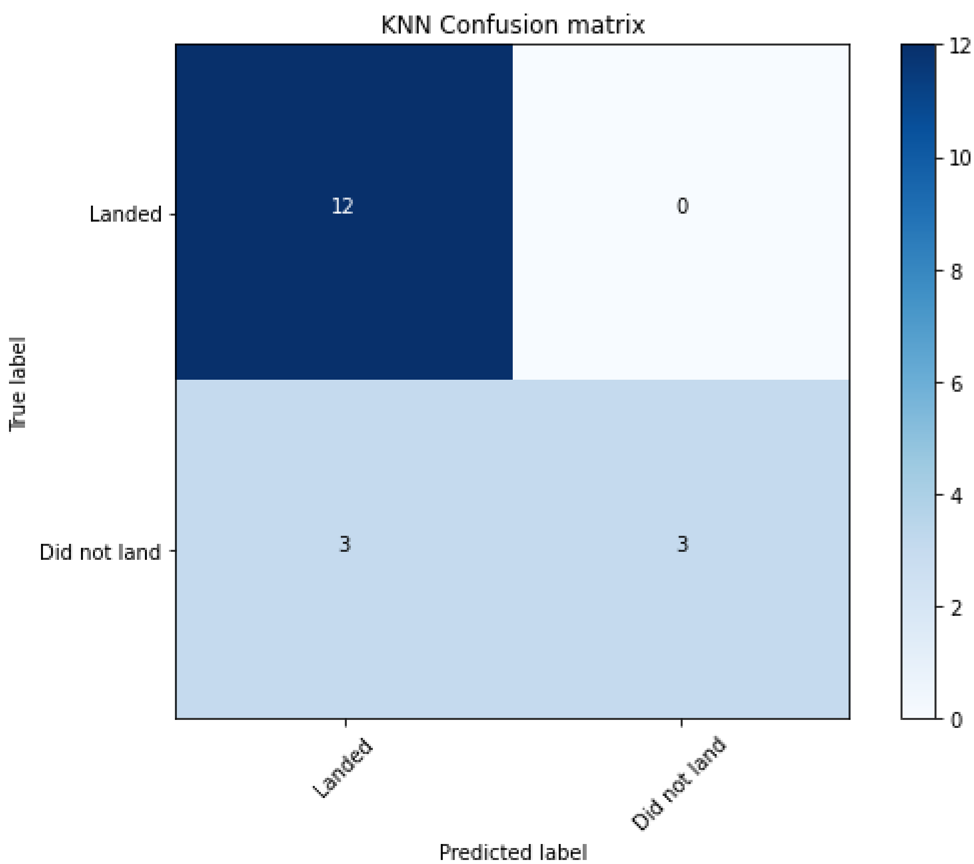
```
knn_auc=roc_auc_score(Y_test, knn_probs)
print("Test set AUC: {:.3}".format(knn_auc))
```

```
Test set accuracy: 83.3%
Test set AUC: 0.847
```

We can plot the confusion matrix

In [29]:
```
# Compute confusion matrix
knn_yhat = knn_cv.predict(X_test)
knn_f1 = f1_score(Y_test, knn_yhat)
knn_prec = precision_score(Y_test, knn_yhat)
knn_rec = recall_score(Y_test, knn_yhat)
cnf_matrix = confusion_matrix(Y_test, knn_yhat, labels=[1,0])
np.set_printoptions(precision=2)
print(classification_report(Y_test, knn_yhat))

# Plot non-normalized confusion matrix
plt.figure(figsize=(8,6))
plot_confusion_matrix(cnf_matrix, classes=['Landed', 'Did not land'], normalize=False, t
```

```
              precision    recall  f1-score   support

           0       1.00      0.50      0.67         6
           1       0.80      1.00      0.89        12

    accuracy                           0.83        18
   macro avg       0.90      0.75      0.78        18
weighted avg       0.87      0.83      0.81        18

Confusion matrix, without normalization
[[12  0]
 [ 3  3]]
```



TASK 12

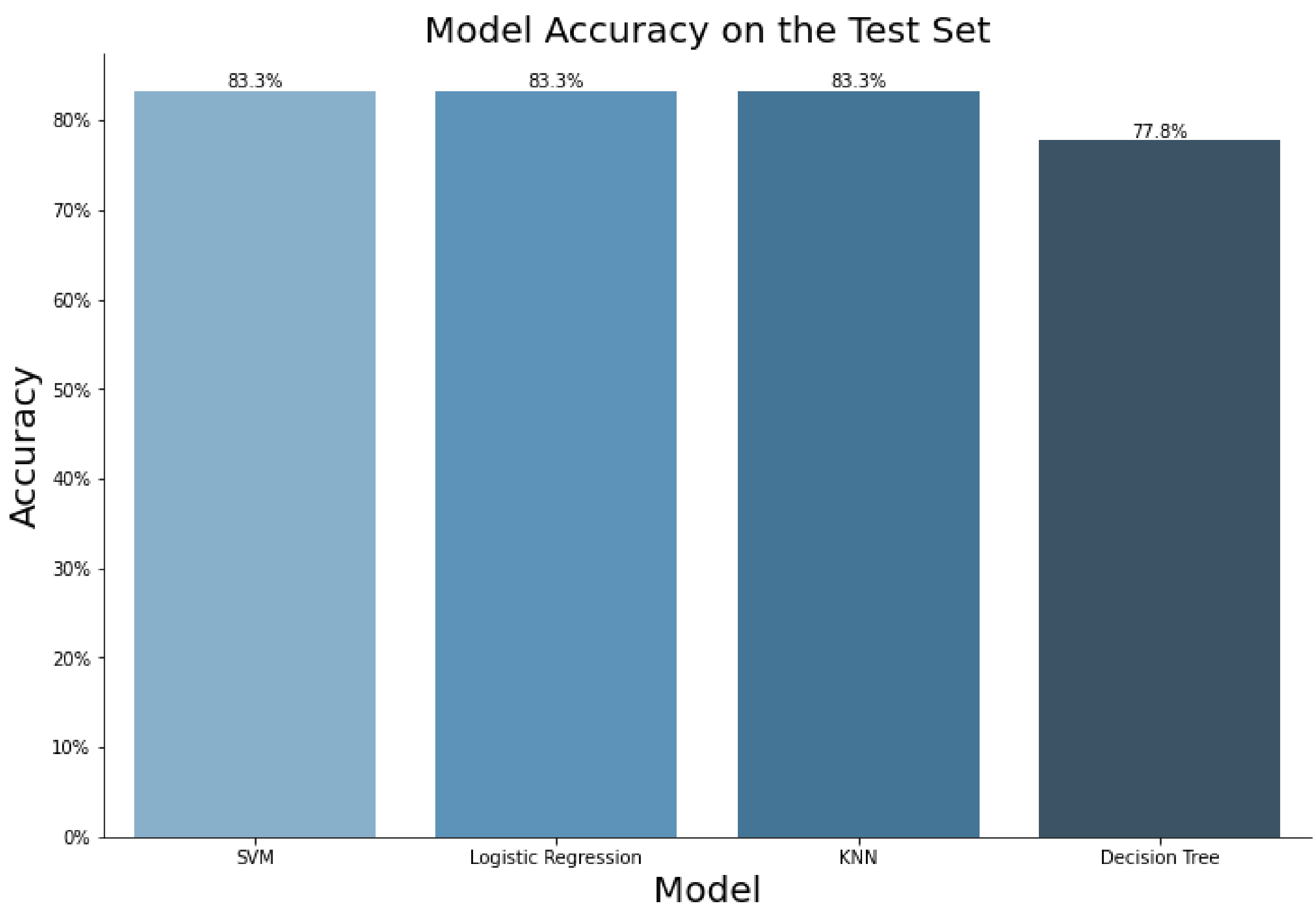
Find the method performs best:

In [30]:
```
data = {'AUC': [glm_auc, svm_auc, tree_auc, knn_auc], 'F1-Score': [glm_f1, svm_f1, tree_
        'Precision': [glm_prec, svm_prec, tree_prec, knn_prec], 'Recall': [glm_rec, svm_
        'Accuracy': [glm_acc, svm_acc, tree_acc, knn_acc]}
res = pd.DataFrame(data, index=['Logistic Regression', 'SVM', 'Decision Tree', 'KNN']).s
res.round(3)
```

Out[30]:

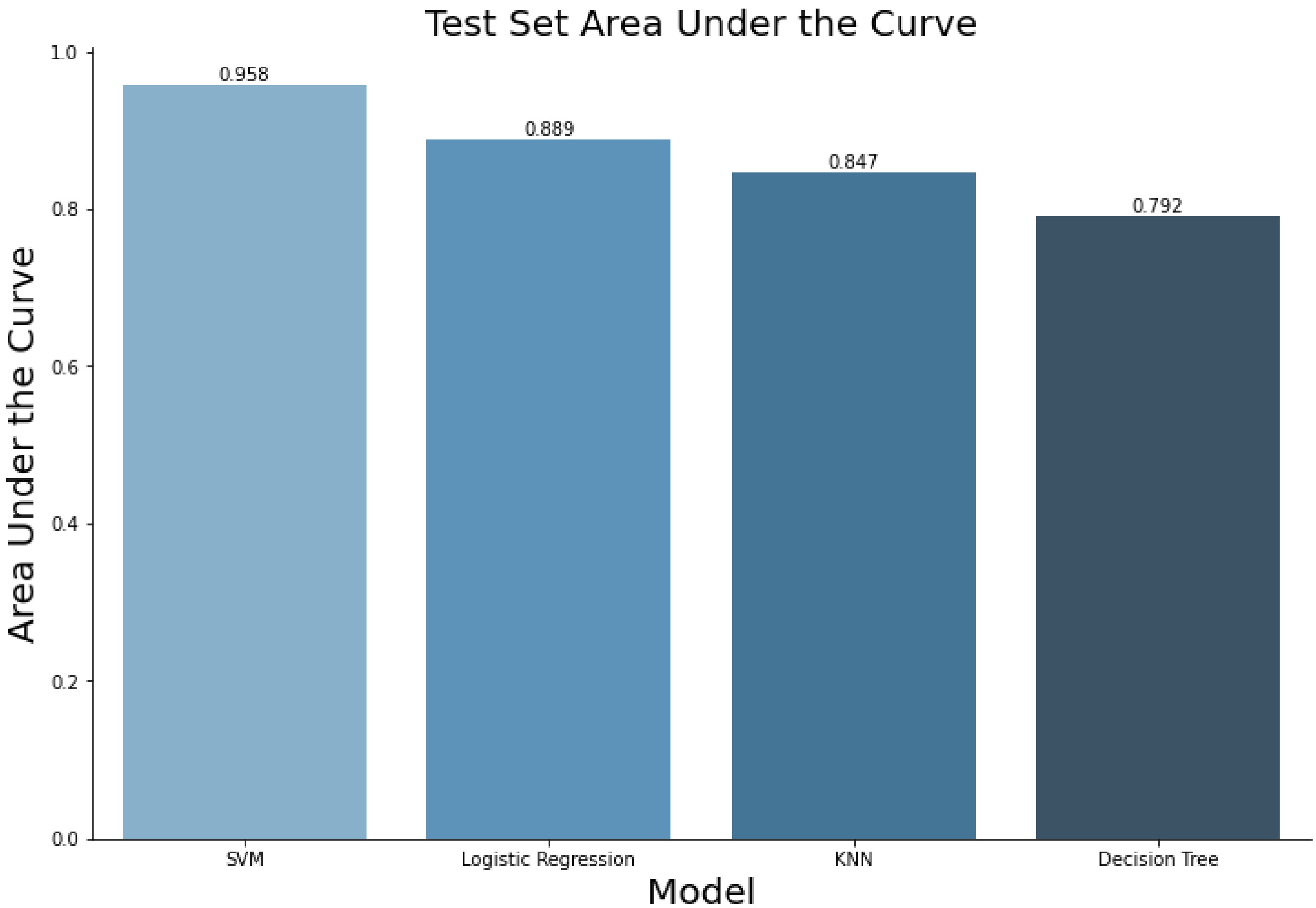
	AUC	F1-Score	Precision	Recall	Accuracy
SVM	0.958	0.889	0.8	1.00	0.833
Logistic Regression	0.889	0.889	0.8	1.00	0.833
KNN	0.847	0.889	0.8	1.00	0.833
Decision Tree	0.792	0.818	0.9	0.75	0.778

In [31]:
```
plt.figure(figsize=(12,8))
ax=sns.barplot(x=res.index, y='Accuracy', data=res, palette='Blues_d')
sns.despine(top=True, right=True, left=False, bottom=False)
plt.xlabel('Model', fontsize=20)
plt.ylabel('Accuracy', fontsize=20)
ax.yaxis.set_major_formatter(plt.FuncFormatter(lambda x, _: '{:.0f}%'.format(x*100)))
for p in ax.patches:
    ax.annotate('{:.1f}%'.format(p.get_height()*100), (p.get_x()+0.4, p.get_height()),
                ha='center', va='bottom',color= 'black')
plt.title('Model Accuracy on the Test Set', fontsize=20)
plt.show()
```



In [32]:
```
plt.figure(figsize=(12,8))
ax=sns.barplot(x=res.index, y='AUC', data=res, palette='Blues_d')
sns.despine(top=True, right=True, left=False, bottom=False)
plt.xlabel('Model', fontsize=20)
```

```python
plt.ylabel('Area Under the Curve', fontsize=20)
for p in ax.patches:
    ax.annotate('{:.3f}'.format(p.get_height()), (p.get_x()+0.4, p.get_height()),
                ha='center', va='bottom',color='black')
plt.title('Test Set Area Under the Curve', fontsize=20)
plt.show()
```



The SVM, KNN, and Logistic Regression model achieved the highest accuracy at 83.3%, while the SVM performs the best in terms of Area Under the Curve at 0.958.