Predicting Material Backorders in Inventory Management

In [201…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import RobustScaler
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from imblearn.over_sampling import SMOTE

from sklearn.metrics import accuracy_score, confusion_matrix, precision_score,
import pickle

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
train = pd.read_csv('preprocessed_train.csv')
test = pd.read_csv('preprocessed_test.csv')
```

In [3]:

```
train.head(2)
```

Out[3]:

	Unnamed: 0	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_
0	0	0.0	7.872267	0.0	0.0	0.0	
1	1	2.0	9.000000	0.0	0.0	0.0	

2 rows × 25 columns

In [4]:

```
test.head(2)
```

Out[4]:

	Unnamed: 0	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_
0	0	62.0	7.872267	0.0	0.0	0.0	
1	1	9.0	7.872267	0.0	0.0	0.0	

2 rows × 25 columns

In [5]:
```
train.drop('Unnamed: 0', axis=1, inplace=True)
test.drop('Unnamed: 0', axis=1, inplace=True)
```

In [6]:
```
train.head()
```

Out[6]:

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sale
0	0.0	7.872267	0.0	0.0	0.0	0.0	
1	2.0	9.000000	0.0	0.0	0.0	0.0	
2	2.0	7.872267	0.0	0.0	0.0	0.0	
3	7.0	8.000000	0.0	0.0	0.0	0.0	
4	8.0	7.872267	0.0	0.0	0.0	0.0	

5 rows × 24 columns

In [7]:
```
test.head()
```

Out[7]:

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sale
0	62.0	7.872267	0.0	0.0	0.0	0.0	
1	9.0	7.872267	0.0	0.0	0.0	0.0	
2	17.0	8.000000	0.0	0.0	0.0	0.0	
3	9.0	2.000000	0.0	0.0	0.0	0.0	
4	2.0	8.000000	0.0	0.0	0.0	0.0	

5 rows × 24 columns

In [8]:
```
y_train = train['went_on_backorder']
```

In [9]:
```
x_train = train.drop('went_on_backorder', axis=1)
```

In [10]:
```
y_test = test['went_on_backorder']
```

In [11]:
```
x_test = test.drop('went_on_backorder', axis=1)
```

In [12]:
```
print(f'x_train: {x_train.shape}')
print(f'y_train: {y_train.shape}')
print(f'x_test: {x_test.shape}')
print(f'y_test: {y_test.shape}')
```

```
x_train: (1687860, 23)
```

```
y_train: (1687860,)
x_test: (242075, 23)
```

Logistic Regression

In [45]:
```
robust_scaler = RobustScaler()
```

In [46]:
```
x_train_scaled = robust_scaler.fit_transform(x_train)
```

In [47]:
```
x_test_scaled = robust_scaler.transform(x_test)
```

In [48]:
```
logistic_regression = SGDClassifier(loss='log', class_weight='balanced', n_jok
```

In [49]:
```
params = {'eta0': [0.1, 0.01, 0.001, 0.0001, 1e-5, 1e-6, 1e-7], 'penalty': ['
```

In [50]:
```
logist_grid_search = GridSearchCV(logistic_regression, params, cv=5, n_jobs=-
```

In [51]:
```
logist_grid_search.fit(x_train_scaled, y_train)
```

Out[51]:
```
GridSearchCV(cv=5,
             estimator=SGDClassifier(class_weight='balanced', loss='log',
                                     n_jobs=-1),
             n_jobs=-1,
             param_grid={'eta0': [0.1, 0.01, 0.001, 0.0001, 1e-05, 1e-06,
                                  1e-07],
                         'penalty': ['l1', 'l2']},
             return_train_score=True, scoring='accuracy')
```

In [52]:
```
best_eta0 = logist_grid_search.best_estimator_.eta0
```

In [53]:
```
best_penalty = logist_grid_search.best_estimator_.penalty
```

In [54]:
```
best_logist = SGDClassifier(loss='log', learning_rate='constant', eta0=best_et
```

In [55]:
```
best_logist.fit(x_train_scaled, y_train)
```

Out[55]:
```
SGDClassifier(class_weight='balanced', eta0=0.001, learning_rate='constant',
              loss='log', n_jobs=-1, penalty='l1')
```

In [56]:
```
logist_y_pred_train = best_logist.predict(x_train_scaled)
logist_y_pred = best_logist.predict(x_test_scaled)
```

In [57]:

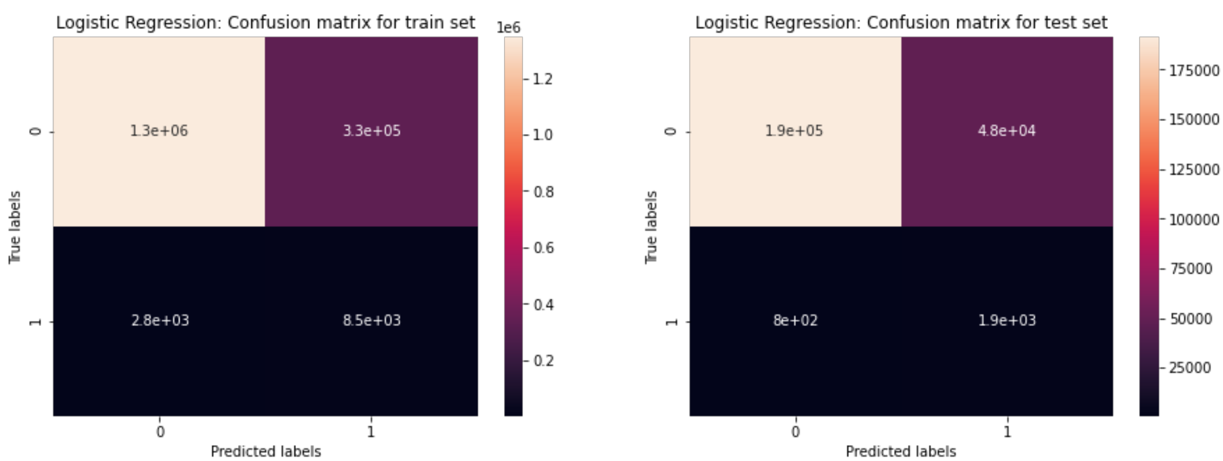
```
print('The accuracy score of the logistic regression model on train set is:',
print('The accuracy score of the logistic regression model on test set is:', a
```

```
The accuracy score of the logistic regression model on train set is: 0.8023408
339554229
The accuracy score of the logistic regression model on test set is: 0.79843023
8562429
```

In [58]:

```
plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.heatmap(confusion_matrix(y_train, logist_y_pred_train), annot=True)
plt.title('Logistic Regression: Confusion matrix for train set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')

plt.subplot(1, 2, 2)
sns.heatmap(confusion_matrix(y_test, logist_y_pred), annot=True)
plt.title('Logistic Regression: Confusion matrix for test set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.show()
```



In [59]:

```
print('The precision score the best logistic regression model on train set is
print('The precision score the best logistic regression model on test set is:
```

```
The precision score the best logistic regression model on train set is: 0.5114
060281441166
The precision score the best logistic regression model on test set is: 0.51689
04036883744
```

In [60]:

```
print('The recall score the best logistic regression model on train set is:',
print('The recall score the best logistic regression model on test set is:', :
```

```
The recall score the best logistic regression model on train set is: 0.7756100
808401734
The recall score the best logistic regression model on test set is: 0.75168054
17637151
```

In [65]:

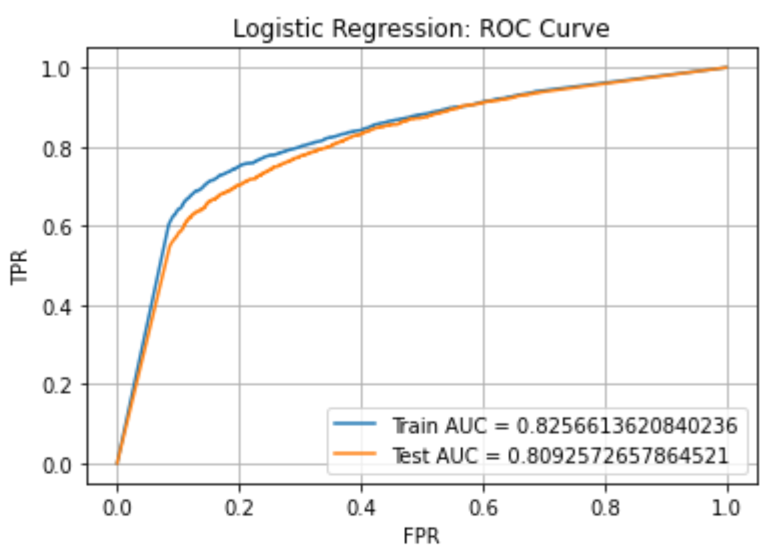
```
print('The AUC score the best logistic regression model on train set is:', roc
print('The AUC score the best logistic regression model on test set is:', roc_
```

```
The AUC score the best logistic regression model on train set is: 0.7756100808
401734
The AUC score the best logistic regression model on test set is: 0.75168054176
37152
```

In [62]:
```
logist_y_train_pred = best_logist.predict_proba(x_train_scaled)[:,1]
logist_y_test_pred = best_logist.predict_proba(x_test_scaled)[:,1]
```

In [63]:
```
train_fpr_logist, train_tpr_logist, train_thresholds_logist = roc_curve(y_tra
test_fpr_logist, test_tpr_logist, test_thresholds_logist = roc_curve(y_test, l
```

In [64]:
```
plt.plot(train_fpr_logist, train_tpr_logist, label="Train AUC ="+' '+str(auc(t
plt.plot(test_fpr_logist, test_tpr_logist, label="Test AUC ="+' '+str(auc(test
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("Logistic Regression: ROC Curve")
plt.grid()
plt.show()
```



Decision Tree

In [82]:
```
cart = DecisionTreeClassifier(criterion='gini', class_weight='balanced')
```

In [83]:
```
params = {'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]}
```

In [85]:
```
cart_grid_search = GridSearchCV(cart, params, cv=5, n_jobs=-1, scoring='roc_au
```

In [86]:
```
cart_grid_search.fit(x_train, y_train)
```

Out[86]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(class_weight='balanced'),
```

```
             n_jobs=-1,
             param_grid={'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,
                                       13, 14, 15]},
```

In [87]:

```
best_max_depth_cart = cart_grid_search.best_estimator_.max_depth
```

In [110…

```
best_cart = DecisionTreeClassifier(criterion='gini', max_depth=best_max_depth_
```

In [111…

```
best_cart.fit(x_train, y_train)
```

Out[111…

```
DecisionTreeClassifier(class_weight='balanced', max_depth=8)
```

In [112…

```
cart_y_pred_train = best_cart.predict(x_train)
cart_y_pred = best_cart.predict(x_test)
```

In [113…

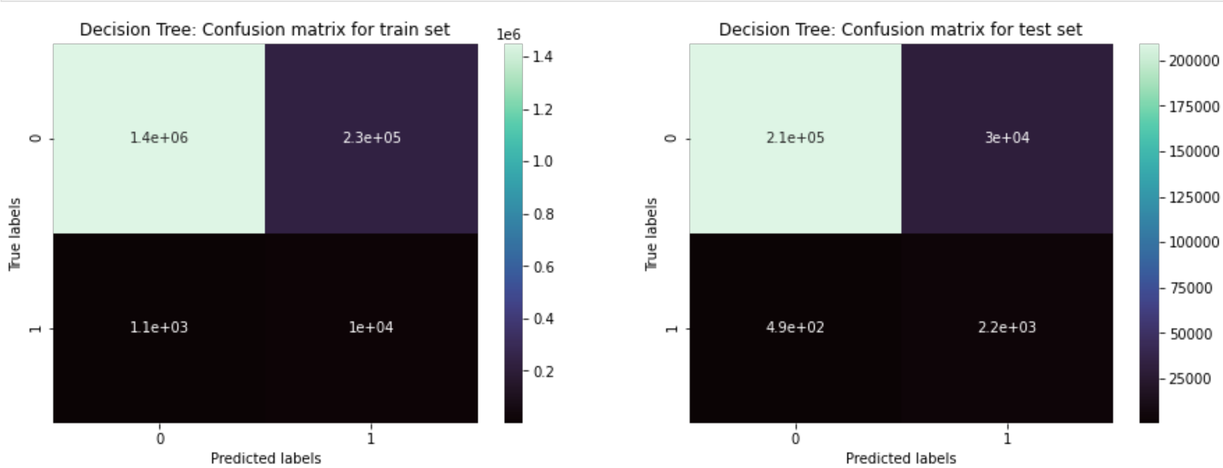
```
print('The accuracy score of the decision tree model on train set is:', accura
print('The accuracy score of the decision tree model on test set is:', accurac
```

```
The accuracy score of the decision tree model on train set is: 0.8645657815221
641
The accuracy score of the decision tree model on test set is: 0.87299803779820
31
```

In [114…

```
plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.heatmap(confusion_matrix(y_train, cart_y_pred_train), annot=True, cmap='ma
plt.title('Decision Tree: Confusion matrix for train set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')

plt.subplot(1, 2, 2)
sns.heatmap(confusion_matrix(y_test, cart_y_pred), annot=True, cmap='mako')
plt.title('Decision Tree: Confusion matrix for test set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.show()
```



In [115…

```
print('The precision score the best decision tree model on train set is:', pre
print('The precision score the best decision tree model on test set is:', prec
```

```
The precision score the best decision tree model on train set is: 0.5211217424
892802
The precision score the best decision tree model on test set is: 0.53271232987
88503
```

In [116…

```
print('The recall score the best decision tree model on train set is:', recall
print('The recall score the best decision tree model on test set is:', recall_
```

```
The recall score the best decision tree model on train set is: 0.8845954794088
201
The recall score the best decision tree model on test set is: 0.84584752399954
29
```

In [117…

```
print('The AUC score the best decision tree model on train set is:', roc_auc_s
print('The AUC score the best decision tree model on test set is:', roc_auc_sc
```

```
The AUC score the best decision tree model on train set is: 0.8845954794088201
The AUC score the best decision tree model on test set is: 0.8458475239995429
```

In [118…

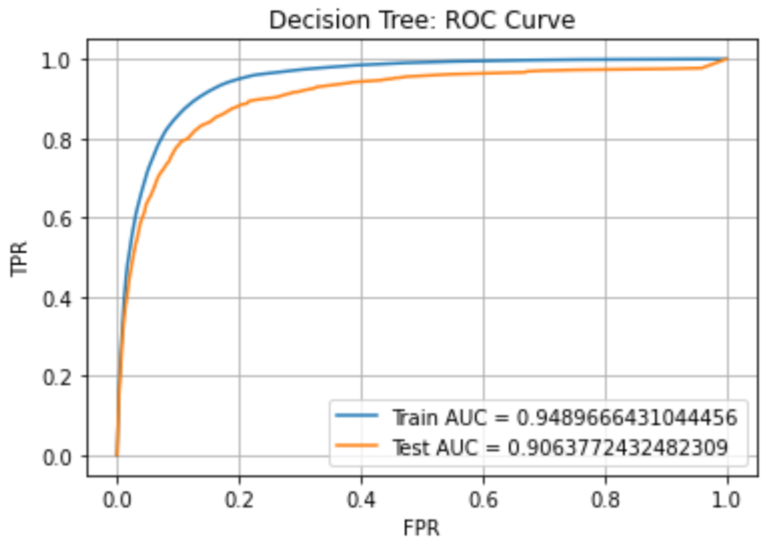
```
cart_y_train_pred = best_cart.predict_proba(x_train)[:,1]
cart_y_test_pred = best_cart.predict_proba(x_test)[:,1]
```

In [119…

```
train_fpr_cart, train_tpr_cart, train_thresholds_cart = roc_curve(y_train, ca
test_fpr_cart, test_tpr_cart, test_thresholds_cart = roc_curve(y_test, cart_y_
```

In [120…

```
plt.plot(train_fpr_cart, train_tpr_cart, label="Train AUC ="+' '+str(auc(trai
plt.plot(test_fpr_cart, test_tpr_cart, label="Test AUC ="+' '+str(auc(test_fp
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("Decision Tree: ROC Curve")
plt.grid()
plt.show()
```



Random Forest

In [86]:

```
#smote = SMOTE()
```

In [87]:

```
#x_train, y_train = smote.fit_resample(x_train, y_train)
```

In [123…

```
random_forest = RandomForestClassifier(criterion='gini', n_jobs=-1, class_wei
```

In [124…

```
params = {'n_estimators': [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 75, 100],
          'max_depth':[None, 2, 5, 7, 9, 10, 12, 15, 17, 20, 30, 50]}
```

In [125…

```
forest_random_search = RandomizedSearchCV(random_forest, params, cv=5, n_jobs=
```

In [126…

```
forest_random_search.fit(x_train, y_train)
```

Out[126…

```
RandomizedSearchCV(cv=5,
                   estimator=RandomForestClassifier(class_weight='balanced_sub
sample',
                                                    n_jobs=-1),
                   n_jobs=-1,
                   param_distributions={'max_depth': [None, 2, 5, 7, 9, 10, 1
2,
```

```
                                                          15, 17, 20, 30, 50],
                                               'n_estimators': [5, 10, 15, 20, 25, 3
0,
                                                                35, 40, 45, 50, 75,
                                                                100]},
                               return_train_score=True, scoring='roc_auc')
```

In [127…

```
best_n_estimators_rf = forest_random_search.best_estimator_.n_estimators
```

In [128…

```
best_max_depth_rf = forest_random_search.best_estimator_.max_depth
```

In [165…

```
best_forest = RandomForestClassifier(criterion='gini', n_estimators=best_n_est
                                     class_weight='balanced_subsample', min_sa
```

In [166…

```
best_forest.fit(x_train, y_train)
```

Out[166…

```
RandomForestClassifier(class_weight='balanced_subsample', max_depth=15,
                       min_samples_leaf=10, min_samples_split=10,
                       n_estimators=50, n_jobs=-1)
```

In [167…

```
forest_y_pred_train = best_forest.predict(x_train)
forest_y_pred = best_forest.predict(x_test)
```

In [168…

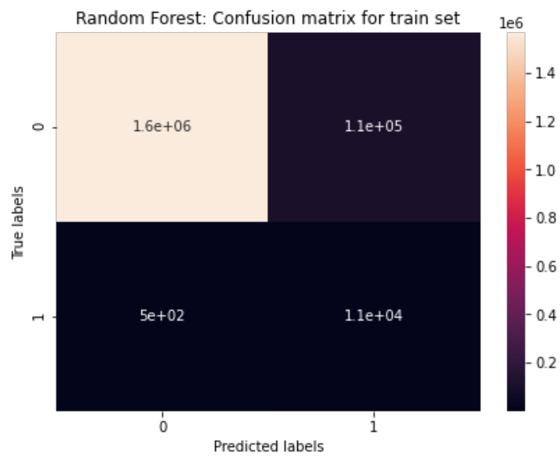
```
print('The accuracy score of the random forest model on train set is:', accura
print('The accuracy score of the random forest model on test set is:', accurac
```

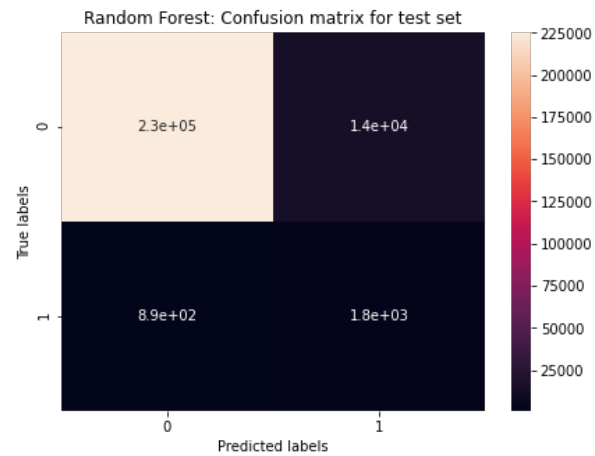
```
The accuracy score of the random forest model on train set is: 0.9349519509911
96
The accuracy score of the random forest model on test set is: 0.93819270887121
76
```

In [169…

```
plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.heatmap(confusion_matrix(y_train, forest_y_pred_train), annot=True)
plt.title('Random Forest: Confusion matrix for train set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')

plt.subplot(1, 2, 2)
sns.heatmap(confusion_matrix(y_test, forest_y_pred), annot=True)
plt.title('Random Forest: Confusion matrix for test set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.show()
```





In [170…

```
print('The precision score the best random forest model on train set is:', pre
print('The precision score the best random forest model on test set is:', pre
```

```
The precision score the best random forest model on train set is: 0.5447832738
107107
The precision score the best random forest model on test set is: 0.55478671218
34514
```

In [171…

```
print('The recall score the best random forest model on train set is:', recal
print('The recall score the best random forest model on test set is:', recall_
```

```
The recall score the best random forest model on train set is: 0.9453123844098
146
The recall score the best random forest model on test set is: 0.80579335964408
69
```

In [172…

```
print('The AUC score the best random forest model on train set is:', roc_auc_s
print('The AUC score the best random forest model on test set is:', roc_auc_s
```

```
The AUC score the best random forest model on train set is: 0.9453123844098146
The AUC score the best random forest model on test set is: 0.8057933596440869
```

In [173…

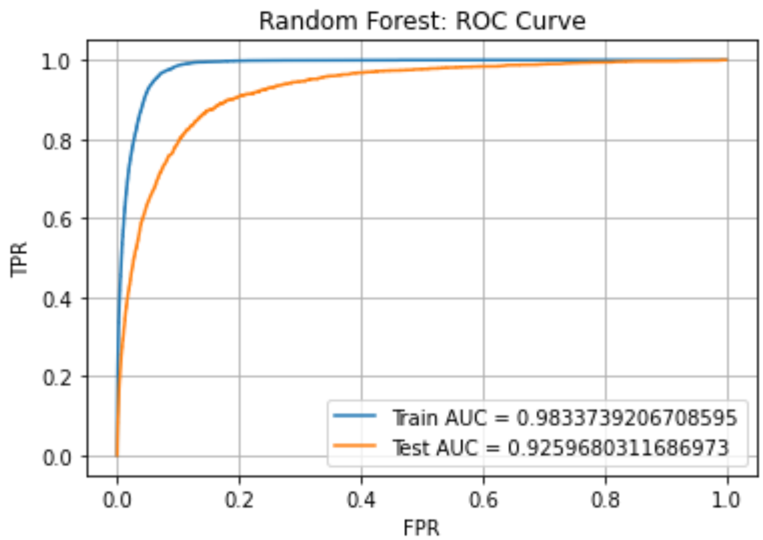
```
forest_y_train_pred = best_forest.predict_proba(x_train)[:,1]
forest_y_test_pred = best_forest.predict_proba(x_test)[:,1]
```

In [174…

```
train_fpr_forest, train_tpr_forest, train_thresholds_forest = roc_curve(y_tra
test_fpr_forest, test_tpr_forest, test_thresholds_forest = roc_curve(y_test,
```

In [175…

```
plt.plot(train_fpr_forest, train_tpr_forest, label="Train AUC ="+' '+str(auc(
plt.plot(test_fpr_forest, test_tpr_forest, label="Test AUC ="+' '+str(auc(test
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("Random Forest: ROC Curve")
plt.grid()
plt.show()
```



Gradient Boosted Decision Tree

In [177…

```
gbdt = XGBClassifier(learning_rate=1e-5, scale_pos_weight=148.0, n_jobs=-1)
```

In [178…

```
params = {'n_estimators': [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 75, 100],
          'max_depth':[2, 3, 5, 7, 9, 10, 12, 15, 17, 20, 30, 50]}
```

In [179…

```
gbdt_random_search = RandomizedSearchCV(gbdt, params, cv=5, n_jobs=-1, scorinc
```

In [180…

```
gbdt_random_search.fit(x_train, y_train)
```

```
[13:39:33] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.
4.0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation met
ric used with the objective 'binary:logistic' was changed from 'error' to 'log
loss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[180…

```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain
',
                                           interaction_constraints=None,
                                           learning_rate=1e-05,
                                           max_delta_step=None, max_depth=Non
e,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,
                                           n_estimators=100, n_jobs=-1,
                                           num_parallel_tree=None,
                                           random_state=None, reg_alpha=None,
                                           reg_lambda=None,
                                           scale_pos_weight=148.0,
                                           subsample=None, tree_method=None,
                                           validate_parameters=None,
                                           verbosity=None),
```

```
                    n_jobs=-1,
                    param_distributions={'max_depth': [2, 3, 5, 7, 9, 10, 12, 1
5,
                                                       17, 20, 30, 50],
                                         'n_estimators': [5, 10, 15, 20, 25, 3
0,
                                                          35, 40, 45, 50, 75,
                                                          100]},
```

In [181…

```
best_n_estimators_gbdt = gbdt_random_search.best_estimator_.n_estimators
```

In [182…

```
best_max_depth_gbdt = gbdt_random_search.best_estimator_.max_depth
```

In [185…

```
best_gbdt = XGBClassifier(n_estimators=best_n_estimators_gbdt, max_depth=best_
                          reg_lambda=0.3, min_child_weight=0.10, subsample=0.
```

In [186…

```
best_gbdt.fit(x_train, y_train)
```

```
[14:00:36] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.
4.0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation met
ric used with the objective 'binary:logistic' was changed from 'error' to 'log
loss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[186…

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.7, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=1e-06, max_delta_step=0, max_depth=50,
              min_child_weight=0.1, missing=nan, monotone_constraints='()',
              n_estimators=30, n_jobs=-1, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=0.3, scale_pos_weight=1, subsample=0.6,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

In [187…

```
gbdt_y_pred_train = best_gbdt.predict(x_train)
gbdt_y_pred = best_gbdt.predict(x_test)
```

In [188…

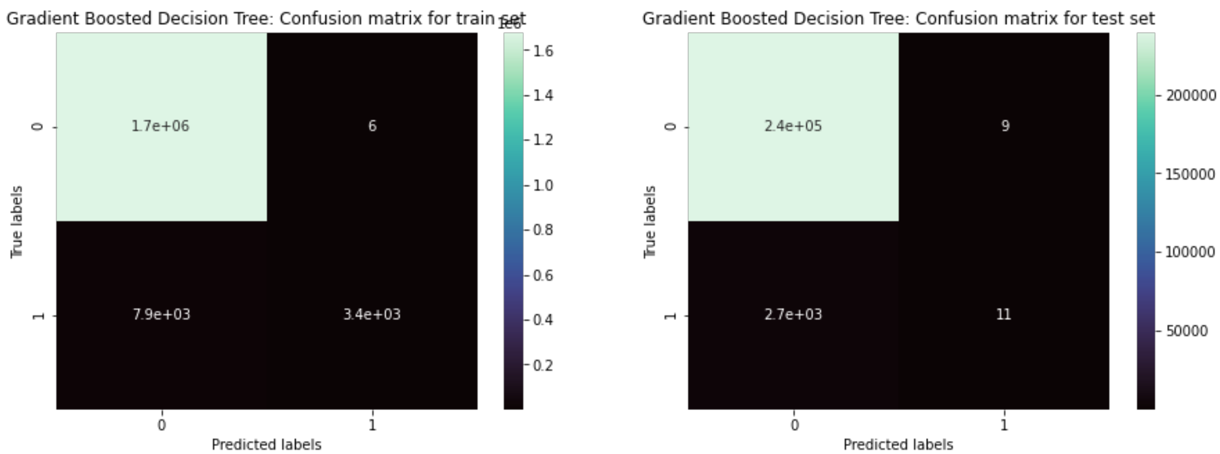
```
print('The accuracy score of the gradient boosted decision tree model on trai
print('The accuracy score of the gradient boosted decision tree model on test
```

```
The accuracy score of the gradient boosted decision tree model on train set i
s: 0.9953218868863531
The accuracy score of the gradient boosted decision tree model on test set is:
0.988904265207064
```

In [189…

```
plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.heatmap(confusion_matrix(y_train, gbdt_y_pred_train), annot=True, cmap='ma
plt.title('Gradient Boosted Decision Tree: Confusion matrix for train set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')

plt.subplot(1, 2, 2)
sns.heatmap(confusion_matrix(y_test, gbdt_y_pred), annot=True, cmap='mako')
plt.title('Gradient Boosted Decision Tree: Confusion matrix for test set')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.show()
```



In [196…

```
print('The precision score the best gradient boosted decision tree model on t
print('The precision score the best gradient boosted decision tree model on te
```

```
The precision score the best gradient boosted decision tree model on train set
is: 0.9967779671777308
The precision score the best gradient boosted decision tree model on test set
is: 0.7694702650224123
```

In [197…

```
print('The recall score the best gradient boosted decision tree model on train
print('The recall score the best gradient boosted decision tree model on test 
```

```
The recall score the best gradient boosted decision tree model on train set i
s: 0.6506667663717156
The recall score the best gradient boosted decision tree model on test set is:
0.502027332939122
```

In [198…

```
print('The AUC score the best gradient boosted decision tree model on train se
print('The AUC score the best gradient boosted decision tree model on test set
```

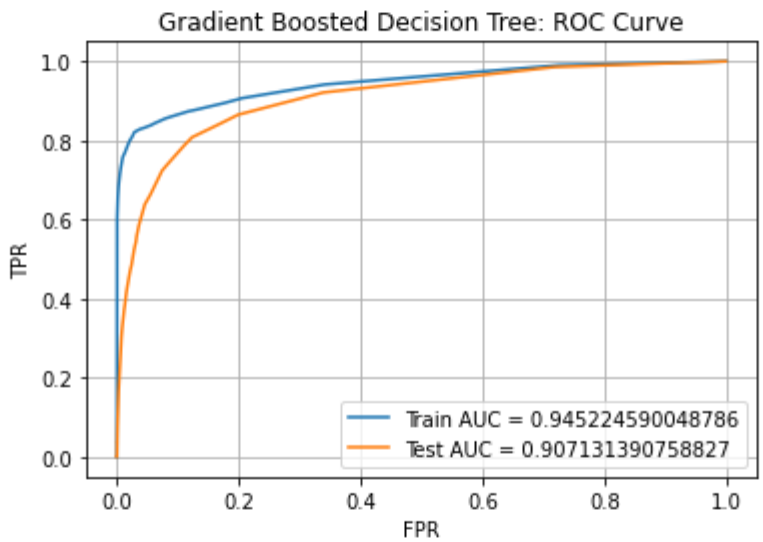
```
The AUC score the best gradient boosted decision tree model on train set is:
0.6506667663717157
The AUC score the best gradient boosted decision tree model on test set is: 0.
502027332939122
```

In [193…

```
gbdt_y_train_pred = best_gbdt.predict_proba(x_train)[:,1]
gbdt_y_test_pred = best_gbdt.predict_proba(x_test)[:,1]
```

In [194…
```
train_fpr_gbdt, train_tpr_gbdt, train_thresholds_gbdt = roc_curve(y_train, gbd
test_fpr_gbdt, test_tpr_gbdt, test_thresholds_gbdt = roc_curve(y_test, gbdt_y_
```

In [195…
```
plt.plot(train_fpr_gbdt, train_tpr_gbdt, label="Train AUC ="+' '+str(auc(trai
plt.plot(test_fpr_gbdt, test_tpr_gbdt, label="Test AUC ="+' '+str(auc(test_fp
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("Gradient Boosted Decision Tree: ROC Curve")
plt.grid()
plt.show()
```



Saving best model

We have built 4 models for this case study i.e, Logistic Regression, Decision Tree, Random Forest and Gradient Boosted Decision Tree. Among them we see that Random Forest and Gradient Boosted Decision Tree are the best performing models. Both of them are giving us a perfect score on all the metrics. Therefore, we can finalize either of the models as our best model. For this case study, we are choosing Gradient Boosted Decision Trees as our best model.

In [202…
```
filename = 'best_model_forest.h5'
pickle.dump(best_forest, open(filename, 'wb'))
```

In [205…
```
best_model = pickle.load(open(filename, 'rb'))
```

In [206…
```
best_model.predict(x_test)
```

Out[206…
```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [207…
```
accuracy_score(y_test, best_model.predict(x_test))
```

Out[207… 0.9381927088712176

In [208…
```
y_pred = best_model.predict_proba(x_test)[:,1]
```

In [209…
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
```

In [212…
```
auc(fpr, tpr)
```

Out[212… 0.9259680311686973

Summary

In [199…
```
from prettytable import PrettyTable

summary = PrettyTable()

summary.field_names = ["Model", "Hyperparameters", "Best Value", "Accuracy", '
summary.add_row(['Logistic Regression', 'eta0/penalty', [best_eta0, best_pena
                 round(accuracy_score(y_test, logist_y_pred), 3),
                 round(precision_score(y_test, logist_y_pred), 3),
                 round(recall_score(y_test, logist_y_pred), 3),
                 round(auc(test_fpr_logist, test_tpr_logist), 3)])
summary.add_row(['Decision Tree', 'max_depth', best_max_depth_cart,
                 round(accuracy_score(y_test, cart_y_pred), 3),
                 round(precision_score(y_test, cart_y_pred), 3),
                 round(recall_score(y_test, cart_y_pred), 3),
                 round(auc(test_fpr_cart, test_tpr_cart), 3)])
summary.add_row(['Random Forest', 'n_estimators/max_depth', [best_n_estimator
                 round(accuracy_score(y_test, forest_y_pred), 3),
                 round(precision_score(y_test, forest_y_pred), 3),
                 round(recall_score(y_test, forest_y_pred), 3),
                 round(auc(test_fpr_forest, test_tpr_forest), 3)])
summary.add_row(['Gradient Boosted Decision Tree', 'n_estimators/max_depth',
                 round(accuracy_score(y_test, gbdt_y_pred), 3),
                 round(precision_score(y_test, gbdt_y_pred), 3),
                 round(recall_score(y_test, gbdt_y_pred), 3),
                 round(auc(test_fpr_gbdt, test_tpr_gbdt), 3)])
print(summary)
```

```
+---------------------------------+-------------------------+----------------+---
-------+-----------+--------+-------+
|              Model              |     Hyperparameters     |   Best Value   | Ac
curacy | Precision | Recall |  AUC  |
+---------------------------------+-------------------------+----------------+---
-------+-----------+--------+-------+
|       Logistic Regression       |       eta0/penalty      | [0.001, 'l1'] |
0.798    |   0.038   | 0.704  | 0.809 |
|          Decision Tree          |        max_depth        |       8        |
0.873    |   0.068   | 0.818  | 0.906 |
|          Random Forest          | n_estimators/max_depth |    [50, 15]    |
0.938    |   0.113   |  0.67  | 0.926 |
| Gradient Boosted Decision Tree | n_estimators/max_depth |    [30, 50]    |
0.989    |    0.55   | 0.004  | 0.907 |
```

```
+--------------------------------+------------------------+----------------+---
```

We see that tree based models perform way better than linear models. Ensemble models like Random Forest and Gradient Boosted Decision Trees performed the best. We see that the best model is Random Forest model with an AUC of 0.926