In [2]:

```
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, recall_sco
re, roc_auc_score, roc_curve, auc
import pickle

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

We are loading the preprocessed data from EDA & Feature Engineering from phase 2 for both train and test sets respectively

In [3]:

```
data_path='C:/Users/ganesh.chandra/Proj 87- Determinig items for shortage prior occurence
- Inventory Mgmt/preprocessed_train.csv'

train = pd.read_csv('preprocessed_train.csv')
train.head(10)
```

Out[3]:

	Unnamed: 0	sku	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1
0	0	1026827	0.0	7.872267	0.0	0.0	0.0	0.0	
1	1	1043384	2.0	9.000000	0.0	0.0	0.0	0.0	
2	2	1043696	2.0	7.872267	0.0	0.0	0.0	0.0	
3	3	1043852	7.0	8.000000	0.0	0.0	0.0	0.0	
4	4	1044048	8.0	7.872267	0.0	0.0	0.0	0.0	
5	5	1044198	13.0	8.000000	0.0	0.0	0.0	0.0	
6	6	1044643	1095.0	7.872267	0.0	0.0	0.0	0.0	
7	7	1045098	6.0	2.000000	0.0	0.0	0.0	0.0	
8	8	1045815	140.0	7.872267	0.0	15.0	114.0	152.0	
9	9	1045867	4.0	8.000000	0.0	0.0	0.0	0.0	

10 rows × 26 columns

In [4]:

```
data_path = 'C:/Users/ganesh.chandra/Proj 87- Determinig items for shortage prior occuren
ce- Inventory Mgmt/preprocessed_test.csv'
test = pd.read_csv('preprocessed_test.csv')
```

In [100]:

```
test.head(10)
```

Out[100]:

	Unnamed: 0	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	s
0	0	62.0	7.872267	0.0	0.0	0.0	0.0	0.0	
1	1	9.0	7.872267	0.0	0.0	0.0	0.0	0.0	
2	2	17.0	8.000000	0.0	0.0	0.0	0.0	0.0	
3	3	9.0	2.000000	0.0	0.0	0.0	0.0	0.0	
4	4	2.0	8.000000	0.0	0.0	0.0	0.0	0.0	
5	5	15.0	2.000000	0.0	0.0	0.0	0.0	0.0	
6	6	0.0	7.872267	0.0	0.0	0.0	0.0	0.0	
7	7	28.0	7.872267	0.0	0.0	0.0	0.0	0.0	
8	8	2.0	7.872267	0.0	0.0	0.0	0.0	0.0	
9	9	2.0	7.872267	0.0	0.0	0.0	0.0	0.0	

10 rows × 25 columns

Dropping categorical objects from train and test set created via pre-processed data

In [5]:

```
train.drop('Unnamed: 0', axis=1, inplace=True)
train.drop('sku', axis=1, inplace=True)
test.drop('Unnamed: 0', axis=1, inplace=True)
train.head()
```

Out[5]:

	national_inv	lead_time	in_transit_qty	forecast_3_month	forecast_6_month	forecast_9_month	sales_1_month	sales_3_mont
0	0.0	7.872267	0.0	0.0	0.0	0.0	0.0	0
1	2.0	9.000000	0.0	0.0	0.0	0.0	0.0	0
2	2.0	7.872267	0.0	0.0	0.0	0.0	0.0	0
3	7.0	8.000000	0.0	0.0	0.0	0.0	0.0	0
4	8.0	7.872267	0.0	0.0	0.0	0.0	0.0	0

5 rows × 24 columns

In [6]:

```
y_train = train['went_on_backorder']
x_train = train.drop('went_on_backorder', axis=1)
y_test = test['went_on_backorder']
x_test = test.drop('went_on_backorder', axis=1)

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: (152599, 23)
y_train: (152599,)
x_test: (242075, 23)
y_test: (242075,)
```

Modeling & Performance Analysis

Logistic Regression

In [24]:

```
robust_scaler = RobustScaler()
x_train_scaled = robust_scaler.fit_transform(x_train)
x_test_scaled = robust_scaler.transform(x_test)
logistic_regression = SGDClassifier(loss='log', class_weight='balanced', n_jobs=-1)
params = {'eta0': [0.1, 0.01, 0.001, 0.0001, 1e-5, 1e-6, 1e-7], 'penalty': ['l1', 'l2']}
```

In [25]:

```
logist_grid_search = GridSearchCV(logistic_regression, params, cv=5, n_jobs=-1, scoring=
'accuracy', return_train_score=True)
```

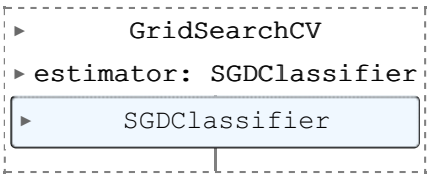
In [26]:

```
y_train=y_train.astype('int')
x_train=x_train.astype('int')
y_train=y_train.astype('int')
x_test=x_test.astype('int')
y_test=y_test.astype('int')
```

In [27]:

```
logist_grid_search.fit(x_train_scaled, y_train)
```

Out[27]:



In [28]:

```
best_eta0 = logist_grid_search.best_estimator_.eta0
best_penalty = logist_grid_search.best_estimator_.penalty
best_logist = SGDClassifier(loss='log', learning_rate='constant', eta0=best_eta0, penalty
=best_penalty, class_weight='balanced', n_jobs=-1)
best_logist.fit(x_train_scaled, y_train)
```

Out[28]:

```
SGDClassifier(class_weight='balanced', eta0=0.001, learning_rate='constant',
              loss='log', n_jobs=-1)
```

In [29]:

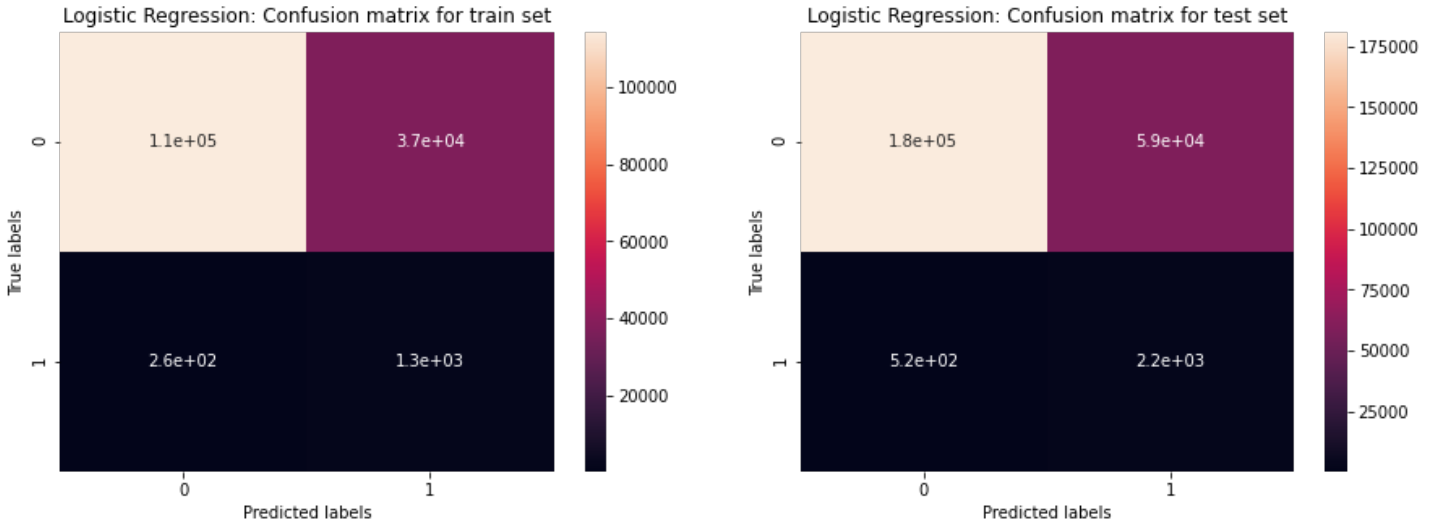
```
logist_y_pred_train = best_logist.predict(x_train_scaled)
logist_y_pred = best_logist.predict(x_test_scaled)
print('The accuracy score of the logistic regression model on train set is:', accuracy_sc
ore(y_train, logist_y_pred_train))
print('The accuracy score of the logistic regression model on test set is:', accuracy_sco
re(y_test, logist_y_pred))
```

```
The accuracy score of the logistic regression model on train set is: 0.7567153126822588
The accuracy score of the logistic regression model on test set is: 0.7554724775379531
```

In [30]:

```
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 [31]:

```
print('The precision score the best logistic regression model on train set is:', precisio
n_score(y_train, logist_y_pred_train, average='macro'))
print('The precision score the best logistic regression model on test set is:', precision
_score(y_test, logist_y_pred, average='macro'))
print('The recall score the best logistic regression model on train set is:', recall_scor
e(y_train, logist_y_pred_train, average='macro'))
print('The recall score the best logistic regression model on test set is:', recall_score
(y_test, logist_y_pred, average='macro'))
print('The AUC score the best logistic regression model on train set is:', roc_auc_score(
y_train, logist_y_pred_train, average='macro'))
print('The AUC score the best logistic regression model on test set is:', roc_auc_score(y
_test, logist_y_pred, average='macro'))
```

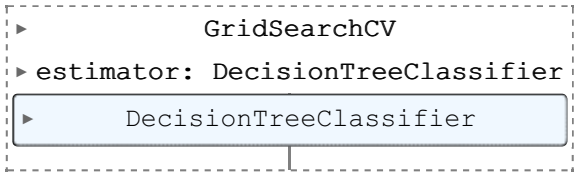
```
The precision score the best logistic regression model on train set is: 0.515418226520385
9
The precision score the best logistic regression model on test set is: 0.51642352051959
The recall score the best logistic regression model on train set is: 0.7928488228873053
The recall score the best logistic regression model on test set is: 0.7814589880313347
The AUC score the best logistic regression model on train set is: 0.7928488228873054
The AUC score the best logistic regression model on test set is: 0.7814589880313348
```

Descision Tree

In [32]:

```
cart = DecisionTreeClassifier(criterion='gini', class_weight='balanced')
params = {'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]}
cart_grid_search = GridSearchCV(cart, params, cv=5, n_jobs=-1, scoring='roc_auc', return
_train_score=True)
cart_grid_search.fit(x_train, y_train)
```

Out[32]:



In [33]:

```
best_max_depth_cart = cart_grid_search.best_estimator_.max_depth
best_cart = DecisionTreeClassifier(criterion='gini', max_depth=best_max_depth_cart, class
_weight='balanced')
best_cart.fit(x_train, y_train)
```

Out[33]:

```
▾                    DecisionTreeClassifier
DecisionTreeClassifier(class_weight='balanced', max_depth=5)
```

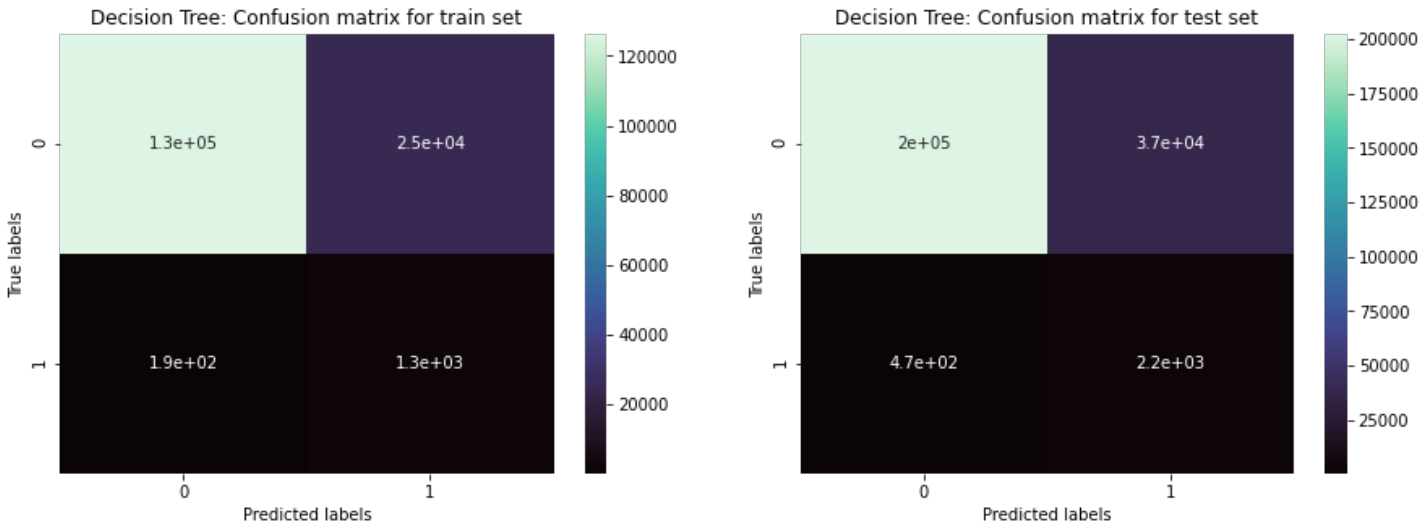
In [34]:

```
cart_y_pred_train = best_cart.predict(x_train)
cart_y_pred = best_cart.predict(x_test)
print('The accuracy score of the decision tree model on train set is:', accuracy_score(y_
train, cart_y_pred_train))
print('The accuracy score of the decision tree model on test set is:', accuracy_score(y_t
est, cart_y_pred))
```

```
The accuracy score of the decision tree model on train set is: 0.8360277590285651
The accuracy score of the decision tree model on test set is: 0.8445399153155014
```

In [35]:

```
plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.heatmap(confusion_matrix(y_train, cart_y_pred_train), annot=True, cmap='mako')
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 [36]:

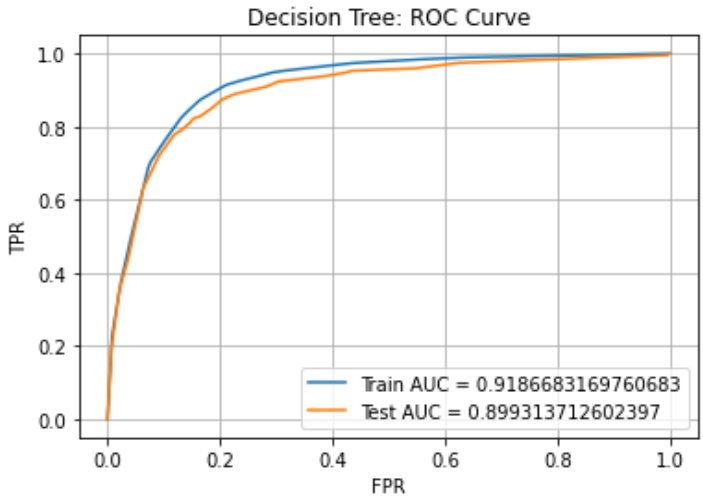
```
print('The precision score the best decision tree model on train set is:', precision_scor
e(y_train, cart_y_pred_train, average='macro'))
print('The precision score the best decision tree model on test set is:', precision_score
(y_test, cart_y_pred, average='macro'))
print('The recall score the best decision tree model on train set is:', recall_score(y_tr
ain, cart_y_pred_train, average='macro'))
print('The recall score the best decision tree model on test set is:', recall_score(y_tes
t, cart_y_pred, average='macro'))
print('The AUC score the best decision tree model on train set is:', roc_auc_score(y_trai
n, cart_y_pred_train, average='macro'))
print('The AUC score the best decision tree model on test set is:', roc_auc_score(y_test,
```

```
cart_y_pred, average='macro'))
```

```
The precision score the best decision tree model on train set is: 0.5246219783672091
The precision score the best decision tree model on test set is: 0.526960235236999
The recall score the best decision tree model on train set is: 0.8543821131743112
The recall score the best decision tree model on test set is: 0.834401460969904
The AUC score the best decision tree model on train set is: 0.8543821131743111
The AUC score the best decision tree model on test set is: 0.834401460969904
```

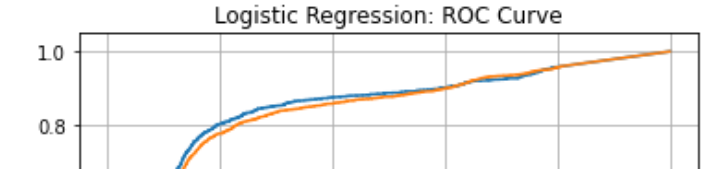
In [37]:

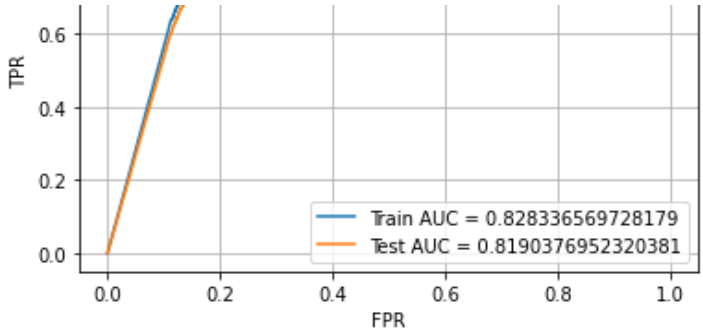
```
cart_y_train_pred = best_cart.predict_proba(x_train)[:,1]
cart_y_test_pred = best_cart.predict_proba(x_test)[:,1]

train_fpr_cart, train_tpr_cart, train_thresholds_cart = roc_curve(y_train, cart_y_train_p
red)
test_fpr_cart, test_tpr_cart, test_thresholds_cart = roc_curve(y_test, cart_y_test_pred)

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



In [38]:

```
logist_y_train_pred = best_logist.predict_proba(x_train_scaled)[:,1]
logist_y_test_pred = best_logist.predict_proba(x_test_scaled)[:,1]
train_fpr_logist, train_tpr_logist, train_thresholds_logist = roc_curve(y_train, logist_y
_train_pred)
test_fpr_logist, test_tpr_logist, test_thresholds_logist = roc_curve(y_test, logist_y_te
st_pred)

plt.plot(train_fpr_logist, train_tpr_logist, label="Train AUC ="+' '+str(auc(train_fpr_lo
gist, train_tpr_logist)))
plt.plot(test_fpr_logist, test_tpr_logist, label="Test AUC ="+' '+str(auc(test_fpr_logist
, test_tpr_logist)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("Logistic Regression: ROC Curve")
plt.grid()
plt.show()
```





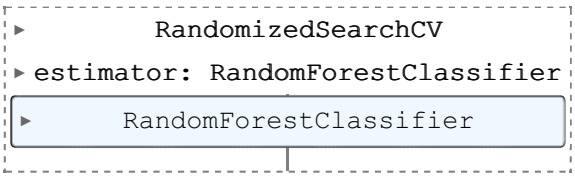
Ensemble Model Implementation

Random Forest

In [39]:

```
random_forest = RandomForestClassifier(criterion='gini', n_jobs=-1, class_weight='balanced_subsample')
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]}
forest_random_search = RandomizedSearchCV(random_forest, params, cv=5, n_jobs=-1, scoring='roc_auc', return_train_score=True)
forest_random_search.fit(x_train, y_train)
```

Out[39]:



In [40]:

```
best_n_estimators_rf = forest_random_search.best_estimator_.n_estimators
best_max_depth_rf = forest_random_search.best_estimator_.max_depth
best_forest = RandomForestClassifier(criterion='gini', n_estimators=best_n_estimators_rf, max_depth=best_max_depth_rf,
                                     class_weight='balanced_subsample', min_samples_leaf=10, min_samples_split=10, n_jobs=-1)
best_forest.fit(x_train, y_train)
```

Out[40]:

```
RandomForestClassifier(class_weight='balanced_subsample', max_depth=9,
                       min_samples_leaf=10, min_samples_split=10,
                       n_estimators=75, n_jobs=-1)
```

In [41]:

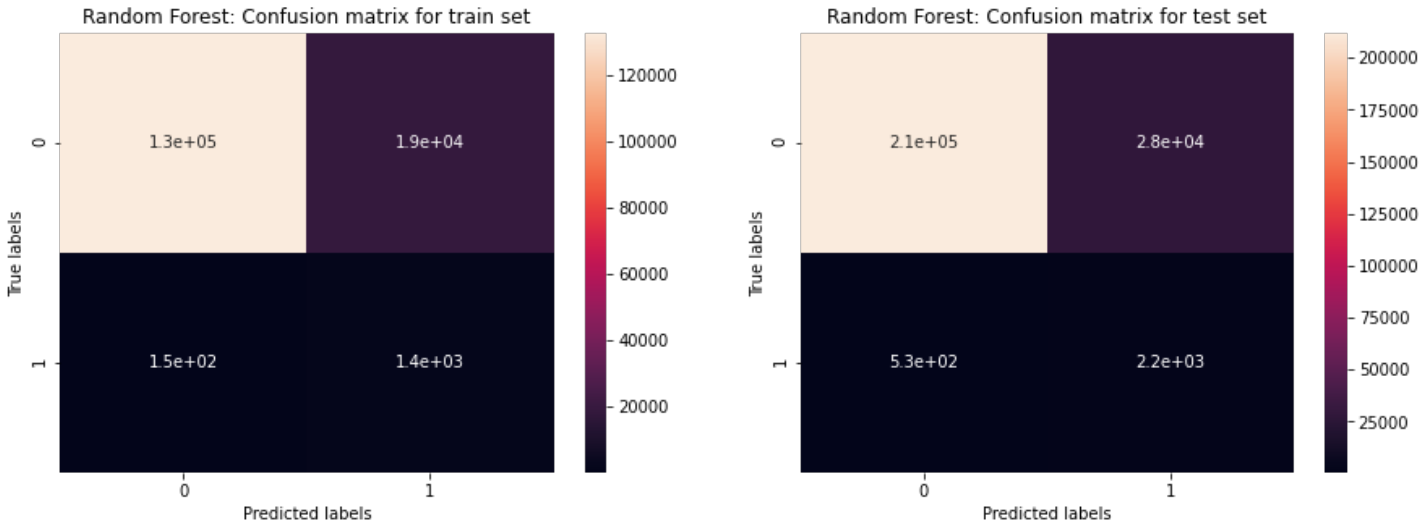
```
forest_y_pred_train = best_forest.predict(x_train)
forest_y_pred = best_forest.predict(x_test)
print('The accuracy score of the random forest model on train set is:', accuracy_score(y_train, forest_y_pred_train))
print('The accuracy score of the random forest model on test set is:', accuracy_score(y_test, forest_y_pred))
```

```
The accuracy score of the random forest model on train set is: 0.877187923905137
The accuracy score of the random forest model on test set is: 0.8838996178870185
```

In [42]:

```
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()
```



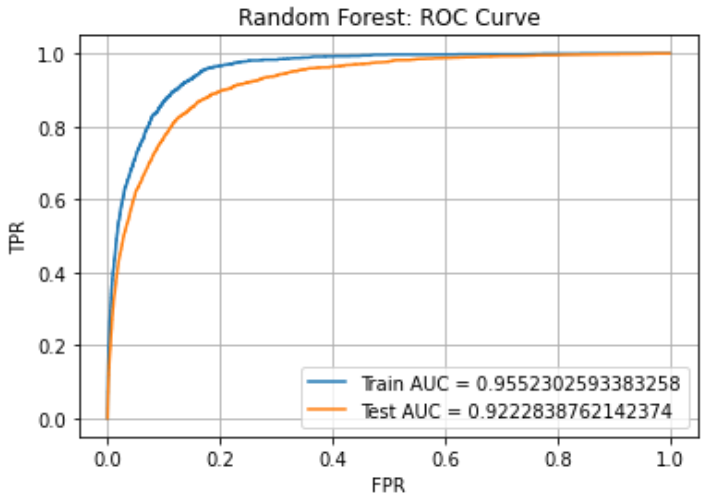
In [43]:

```
print('The precision score the best random forest model on train set is:', precision_score(y_train, forest_y_pred_train, average='macro'))
print('The precision score the best random forest model on test set is:', precision_score(y_test, forest_y_pred, average='macro'))
print('The recall score the best random forest model on train set is:', recall_score(y_train, forest_y_pred_train, average='macro'))
print('The recall score the best random forest model on test set is:', recall_score(y_test, forest_y_pred, average='macro'))
print('The AUC score the best random forest model on train set is:', roc_auc_score(y_train, forest_y_pred_train, average='macro'))
print('The AUC score the best random forest model on test set is:', roc_auc_score(y_test, forest_y_pred, average='macro'))
```

```
The precision score the best random forest model on train set is: 0.5337747933895862
The precision score the best random forest model on test set is: 0.5350750904546019
The recall score the best random forest model on train set is: 0.8891625152392642
The recall score the best random forest model on test set is: 0.844186512992411
The AUC score the best random forest model on train set is: 0.8891625152392642
The AUC score the best random forest model on test set is: 0.844186512992411
```

In [44]:

```
forest_y_train_pred = best_forest.predict_proba(x_train)[:,1]
forest_y_test_pred = best_forest.predict_proba(x_test)[:,1]
train_fpr_forest, train_tpr_forest, train_thresholds_forest = roc_curve(y_train, forest_y_train_pred)
test_fpr_forest, test_tpr_forest, test_thresholds_forest = roc_curve(y_test, forest_y_test_pred)
plt.plot(train_fpr_forest, train_tpr_forest, label="Train AUC ="+' '+str(auc(train_fpr_forest, train_tpr_forest)))
plt.plot(test_fpr_forest, test_tpr_forest, label="Test AUC ="+' '+str(auc(test_fpr_forest, test_tpr_forest)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("Random Forest: ROC Curve")
plt.grid()
plt.show()
```

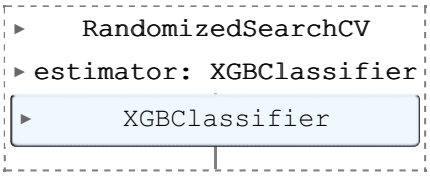


Gradient Boosted Decision Tree

In [45]:

```
gbdt = XGBClassifier(learning_rate=1e-5, scale_pos_weight=148.0, n_jobs=-1)
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]}
gbdt_random_search = RandomizedSearchCV(gbdt, params, cv=5, n_jobs=-1, scoring='roc_auc'
, return_train_score=True)
gbdt_random_search.fit(x_train, y_train)
```

Out[45]:



In [46]:

```
best_n_estimators_gbdt = gbdt_random_search.best_estimator_.n_estimators
best_max_depth_gbdt = gbdt_random_search.best_estimator_.max_depth
best_gbdt = XGBClassifier(n_estimators=best_n_estimators_gbdt, max_depth=best_max_depth_g
bdt, learning_rate=1e-6,
                          reg_lambda=0.3, min_child_weight=0.10, subsample=0.6, colsampl
e_bytree=0.7, n_jobs=-1)
best_gbdt.fit(x_train, y_train)
```

Out[46]:

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=0.7,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=1e-06, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=5, max_leaves=0, min_child_weight=0.
1,
              missing=nan, monotone_constraints='()', n_estimators=25,
              n_jobs=-1, num_parallel_tree=1, predictor='auto', random_state=0
```

In [47]:

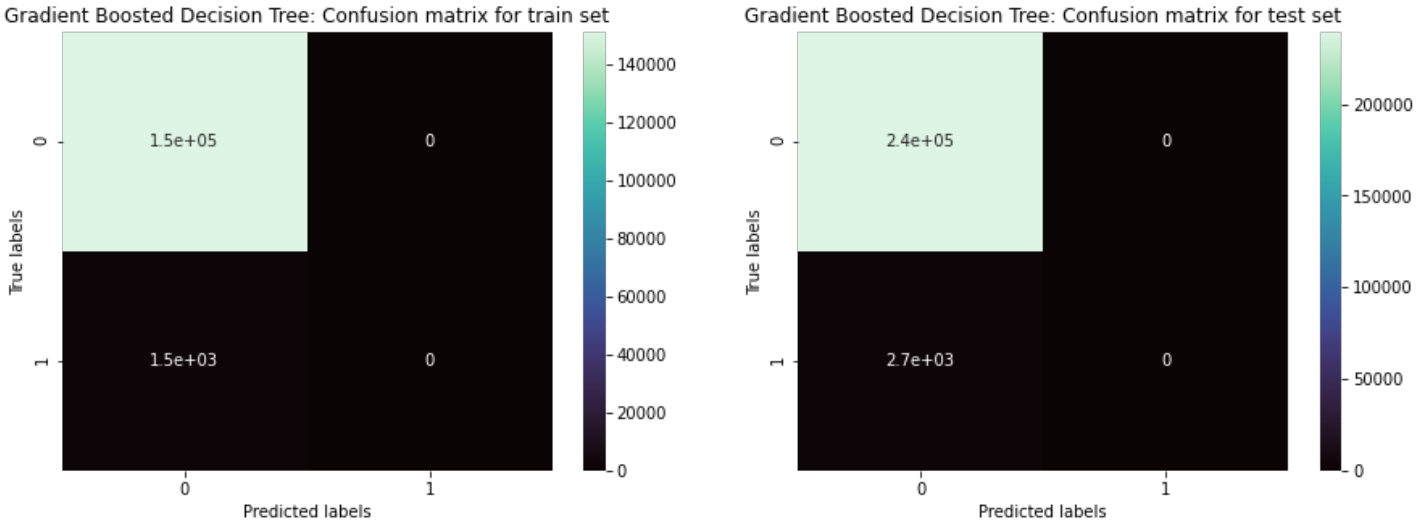
```
gbdt_y_pred_train = best_gbdt.predict(x_train)
gbdt_y_pred = best_gbdt.predict(x_test)
print('The accuracy score of the gradient boosted decision tree model on train set is:',
```

```
accuracy_score(y_train, gbdt_y_pred_train))
print('The accuracy score of the gradient boosted decision tree model on test set is:', a
ccuracy_score(y_test, gbdt_y_pred))
```

```
The accuracy score of the gradient boosted decision tree model on train set is: 0.9900327
000832246
The accuracy score of the gradient boosted decision tree model on test set is: 0.98889600
33047609
```

In [48]:

```
plt.figure(figsize=(15,5))
plt.subplot(1, 2, 1)
sns.heatmap(confusion_matrix(y_train, gbdt_y_pred_train), annot=True, cmap='mako')
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 [49]:

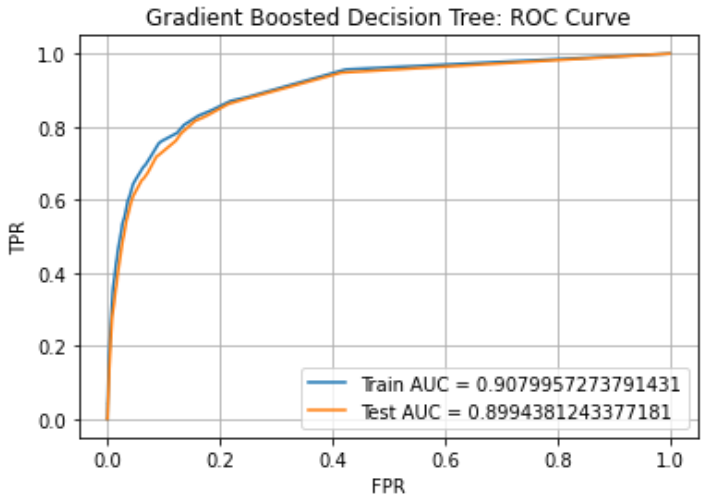
```
print('The precision score the best gradient boosted decision tree model on train set is:
', precision_score(y_train, gbdt_y_pred_train, average='macro'))
print('The precision score the best gradient boosted decision tree model on test set is:'
, precision_score(y_test, gbdt_y_pred, average='macro'))
print('The recall score the best gradient boosted decision tree model on train set is:',
recall_score(y_train, gbdt_y_pred_train, average='macro'))
print('The recall score the best gradient boosted decision tree model on test set is:', r
ecall_score(y_test, gbdt_y_pred, average='macro'))
print('The AUC score the best gradient boosted decision tree model on train set is:', roc
_auc_score(y_train, gbdt_y_pred_train, average='macro'))
print('The AUC score the best gradient boosted decision tree model on test set is:', roc_
auc_score(y_test, gbdt_y_pred, average='macro'))
```

```
The precision score the best gradient boosted decision tree model on train set is: 0.4950
163500416123
The precision score the best gradient boosted decision tree model on test set is: 0.49444
800165238045
The recall score the best gradient boosted decision tree model on train set is: 0.5
The recall score the best gradient boosted decision tree model on test set is: 0.5
The AUC score the best gradient boosted decision tree model on train set is: 0.5
The AUC score the best gradient boosted decision tree model on test set is: 0.5
```

In [50]:

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

```
train_fpr_gbdt, train_tpr_gbdt, train_thresholds_gbdt = roc_curve(y_train, gbdt_y_train_p
red)
test_fpr_gbdt, test_tpr_gbdt, test_thresholds_gbdt = roc_curve(y_test, gbdt_y_test_pred)
plt.plot(train_fpr_gbdt, train_tpr_gbdt, label="Train AUC ="+' '+str(auc(train_fpr_gbdt,
train_tpr_gbdt)))
plt.plot(test_fpr_gbdt, test_tpr_gbdt, label="Test AUC ="+' '+str(auc(test_fpr_gbdt, test
_tpr_gbdt)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("Gradient Boosted Decision Tree: ROC Curve")
plt.grid()
plt.show()
```



Choosing 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 [51]:

```
filename = 'best_model_forest.h5'
pickle.dump(best_forest, open(filename, 'wb'))
best_model = pickle.load(open(filename, 'rb'))
best_model.predict(x_test)
```

Out[51]:

```
array([0, 0, 0, ..., 0, 0, 0])
```

In [52]:

```
accuracy_score(y_test, best_model.predict(x_test))
```

Out[52]:

```
0.8838996178870185
```

In [53]:

```
y_pred = best_model.predict_proba(x_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
auc(fpr, tpr)
```

Out[53]:

```
0.9222838762142374
```

Conclusion

In [54]:

```
from prettytable import PrettyTable

summary = PrettyTable()

summary.field_names = ["Model", "Hyperparameters", "Best Value", "Accuracy", "Precision"
, "Recall", "AUC"]
summary.add_row(['Logistic Regression', 'eta0/penalty', [best_eta0, best_penalty],
                 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_estimators_rf, best_
max_depth_rf],
                 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', [best_n_esti
mators_gbdt, best_max_depth_gbdt],
                 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  | Accuracy | P
recision | Recall |  AUC  |
+---------------------------------+------------------------+---------------+----------+-
----------+--------+-------+
|       Logistic Regression       |      eta0/penalty      | [0.001, '12'] |  0.755   |
0.036    | 0.808  | 0.819 |
|         Decision Tree           |       max_depth        |       5       |  0.845   |
0.056    | 0.824  | 0.899 |
|         Random Forest           | n_estimators/max_depth |    [75, 9]    |  0.884   |
0.073    | 0.804  | 0.922 |
| Gradient Boosted Decision Tree | n_estimators/max_depth |    [25, 5]    |  0.989   |
0.0      |  0.0   | 0.899 |
+---------------------------------+------------------------+---------------+----------+-
----------+--------+-------+
```

We observe that tree based models perform way better than linear models. Ensemble models Random Forest & Gradient Boosted Decision Trees performed the best. The best model is Random Forest model with an AUC of 0.923.