Modeling for IDA 2016

In [1]:
```
######----- Importing dependencies-----#####
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import warnings

from sklearn.metrics import f1_score


np.random.seed(0)
```

In [2]:
```
######----- Setting Working directory-----#####
print(os.getcwd())
os.chdir(r"C:\Users\inabpan4\Desktop\work\Algos\Applied AI\I python notebook\self
print(os.getcwd())
```

```
C:\Users\inabpan4\Desktop\work\Algos\Applied AI\I python notebook\self case stu
dy 1\Code\final\16 aug
C:\Users\inabpan4\Desktop\work\Algos\Applied AI\I python notebook\self case stu
dy 1\to_uci
```

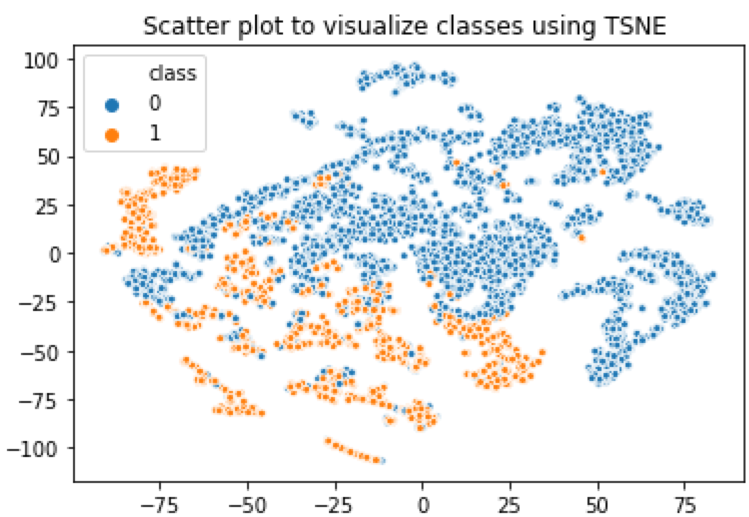
In [3]:
```
#####-----Storing imputed file-----#####
train_df= pd.read_csv("train_data_uncorrelated.csv", index_col=0)
test_df=  pd.read_csv("test_data_uncorrelated.csv", index_col=0)
print("Shape of training dataset is", train_df.shape)
print("Shape of test dataset is", test_df.shape)
```

```
Shape of training dataset is (84004, 103)
Shape of test dataset is (16000, 103)
```

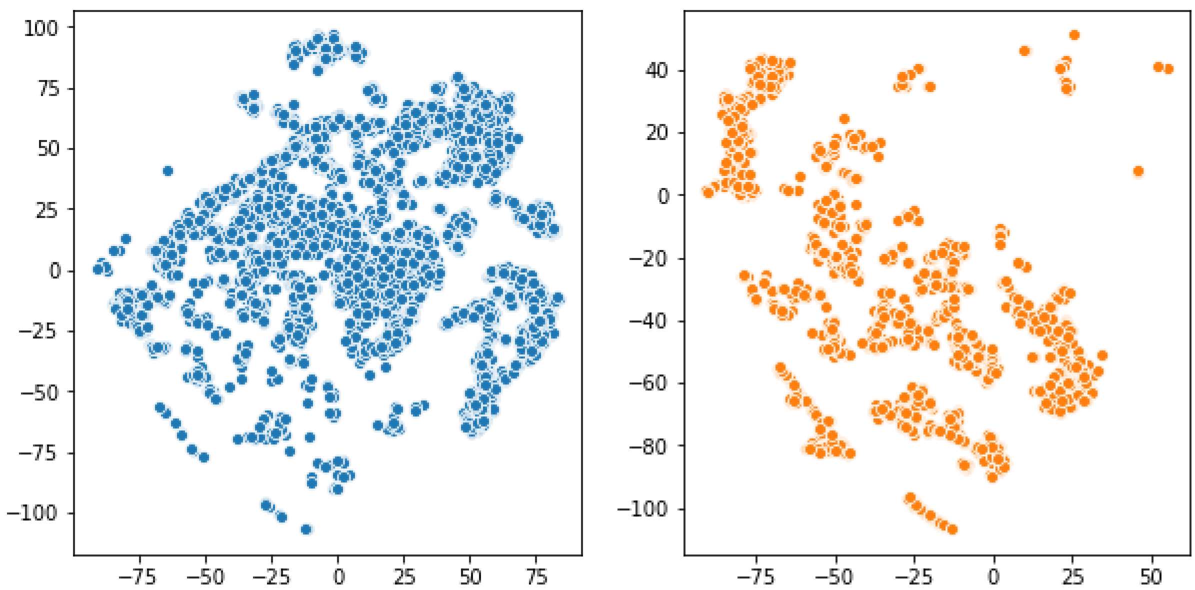
1. Data Visualization

1.1 2D scatter plot for visualizing Data using TSNE

In [57]:
```
#####-----Scatter plot to visualize Data using TSNE ----#####
from sklearn.manifold import TSNE
data_for_plot = train_df.sample(10000)
data_for_plot_x = data_for_plot.drop("class", axis = 1).copy()
data_for_plot_y = data_for_plot["class"].copy()

train_df_embedded = TSNE(n_components=2, perplexity=30).fit_transform(data_for_pl

sns.scatterplot(train_df_embedded[:,0],train_df_embedded[:,1],
                hue = data_for_plot_y, s = 15)
plt.title("Scatter plot to visualize classes using TSNE ")
plt.show()

fig, axes = plt.subplots(1, 2, figsize = (10,5))
sns.scatterplot(train_df_embedded[data_for_plot_y.values==0,0],
                train_df_embedded[data_for_plot_y.values==0,1],
                ax = axes[0],
                color = "C0"
               )
sns.scatterplot(train_df_embedded[data_for_plot_y.values==1,0],
                train_df_embedded[data_for_plot_y.values==1,1],
                ax = axes[1],
                color ="C1"
               )
plt.suptitle("Class-wise Scatter plot ")
plt.show()
```



Class-wise Scatter plot



2 . Feature Selection

2.1 Selecting top 75% features using Mutual Information

In [4]:
```
# import the required functions and object.
from sklearn.feature_selection import mutual_info_classif
from sklearn.feature_selection import SelectKBest

# select the number of features you want to retain.
select_k = 80 # 75% features
import random
random.seed(0)
idx = random.sample(range(train_df.shape[0]),10000)
x_train = train_df.drop("class", axis = 1, inplace = False)
y_train = train_df["class"]
# mi = mutual_info_classif(x_train, y_train)
selection = SelectKBest(mutual_info_classif, k=select_k).fit(x_train.iloc[idx], y
```

In [5]:
```
top_features = x_train.columns[selection.get_support()]

x_train = train_df[top_features].copy()
y_train = train_df["class"].copy()

x_test= test_df[top_features].copy()
y_test = test_df["class"].copy()
```

In [6]:
```
print("Top 5 features based on mutual information are ",list(top_features[0:5]))
```

```
Top 5 features based on mutual information are  ['ac_000', 'ad_000', 'ai_000',
'aj_000', 'al_000']
```

3. Model Evaluation

3.1 Functions

3.1.1 Util functions

In [7]:
```
#####------Funtion to calculate loss give prediction and actual-----#####
def calculate_cost(y_true, y_pred, print_ = False):
    from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(y_true, y_pred).ravel()
    cm = pd.DataFrame(cm.reshape((1,4)), columns=['tn', 'fp', 'fn', 'tp'])
    if print_:
        display(cm)
    total_cost = 10*cm.fp + 500*cm.fn
    return(total_cost)

######----- Function to plot confusion matrix and related metrices-----#####
def plot_confusion_mat(y_true, y_pred):
    from sklearn.metrics import confusion_matrix, accuracy_score
    cnf_mat = confusion_matrix(y_true, y_pred)
    labels= ["True Negative", "False Positive", "False Negative", "True Positive'
    count = ["{0:0.0f}".format(value) for value in cnf_mat.flatten() ]
#     final_labels = [val1+"\n"+"{}".format(val2) for val1, val2 in zip(labels, c

#     sns.heatmap(cnf_mat,annot  = np.array(final_labels).reshape(2,2) ,fmt='', c
#     plt.title("Confusion matrix")
#     plt.xlabel("Predicted condition")
#     plt.ylabel("True condition")
#     plt.show()
    rcall_mat = cnf_mat/ (cnf_mat.sum(axis =1).reshape(-1,1))

    labels= ["True Negative Rate", "False Positive Rate", "False Negative Rate",
    percentage = ["{0:.2%}".format(value) for value in rcall_mat.flatten()]
    final_labels = [val1+"\n"+"{}".format(val3)+"({})".format(val2) for val1, val

    sns.heatmap(rcall_mat,annot  = np.array(final_labels).reshape(2,2),fmt='',  c
    plt.xlabel("Predicted condition")
    plt.ylabel("True condition")
    plt.show()
```

3.1.2 Function for evaluating ML models for building classifier

In [8]:
```
#####----- Crating a custom score object for cross validation-----#####
from sklearn.metrics import make_scorer
score = make_scorer(calculate_cost, greater_is_better=False)## Custom scorer
```

In [9]:
```
#####-----Function for classifier selection -----#####

def train_classifier(x, y, classifier):
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.svm import SVC
    from sklearn.linear_model import SGDClassifier
    from sklearn.tree import DecisionTreeClassifier

    from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
    global score
    weights= [(1,5000), (1,1000), (1,500), (1,100), (1,10),
              (5000,1), (1000,1), (500,1), (100,1), (10,1), (1,1)]

##########---------- 1. LOGISTIC REGRESSION----------##########

    if classifier == "logistic":
        grid = {"l1_ratio": [0.1, 0.5, 0.7],
                "alpha": [10**val for val in np.arange(-4,4, dtype=float) ],
                "class_weight": [{0: x[0], 1: x[1]} for x in weights]
               }
        clf = SGDClassifier(loss ="log" , n_jobs = 4, random_state=0, penalty = '

##########---------- 2. LINEAR SVM----------##########

    if classifier == "linsvm":
        grid = {"l1_ratio": [0.1, 0.5, 0.7],
                "alpha": [10**val for val in np.arange(-4,4, dtype=float) ],
                "class_weight": [{0: x[0], 1: x[1]} for x in weights]
               }
        clf = SGDClassifier(loss ="hinge" , n_jobs = 4, random_state=0, penalty =


##########---------- 3. SVM----------##########

    if classifier == "SVM":
        grid = {"C":[10**val for val in np.arange(-3,3, dtype=float)],
                "class_weight": [{0: x[0], 1: x[1]} for x in weights]
               }
        clf = SVC(random_state =0)


##########----------4. DECISION TREE ----------##########

    if classifier == "Decision_tree":
        grid = {"criterion":["gini", "entropy"],
                "max_depth": [20,50,100,200,None],
                "min_samples_split": [2,10,20,50],
                "min_samples_leaf": [1,5,10,25],
                "class_weight": [{0: x[0], 1: x[1]} for x in weights]
               }
        clf = DecisionTreeClassifier( random_state = 0)

##########----------5. RANDOM FOREST ----------##########

    if classifier == "Random_forest":
        grid = {"n_estimators":[100,500, 1000],
```

```
                "class_weight": [{0: x[0], 1: x[1]} for x in weights]
               }
        clf = RandomForestClassifier(n_jobs = 4, random_state=0)


    Grid_cv = GridSearchCV(estimator=clf,
                           param_grid= grid,
                           scoring= score,
                           cv=3,
                           n_jobs=4,
                           verbose= 0
                          )
    Grid_cv.fit(x, y)
    return(Grid_cv)
```

3.2. Train and compare models

Standardizing data before training models

In [10]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)
```

In [11]:

```
## Selecting random 20k sample for faster crossvalidation
idx = random.sample(range(x_train.shape[0]),20000)
x_train_scaled_sampled = x_train_scaled[idx].copy()
y_train_sampled = y_train[idx].copy()
```

3.2.1. Logistic Rgression

In [66]:

```
CV_log = train_classifier(x = x_train_scaled_sampled, y= y_train_sampled, classi
```

In [67]:

```
print("Loss on train data\n: ", calculate_cost(y_pred=CV_log.best_estimator_.pred
print("F1 score on train data\n: ", f1_score(y_pred=CV_log.best_estimator_.predi

print("="*100)
print("Loss on test data\n: ", calculate_cost(y_pred=CV_log.best_estimator_.predi
print("F1 score on test data\n: ", f1_score(y_pred=CV_log.best_estimator_.predict
```

	tn	fp	fn	tp
0	45180	13820	0	25048

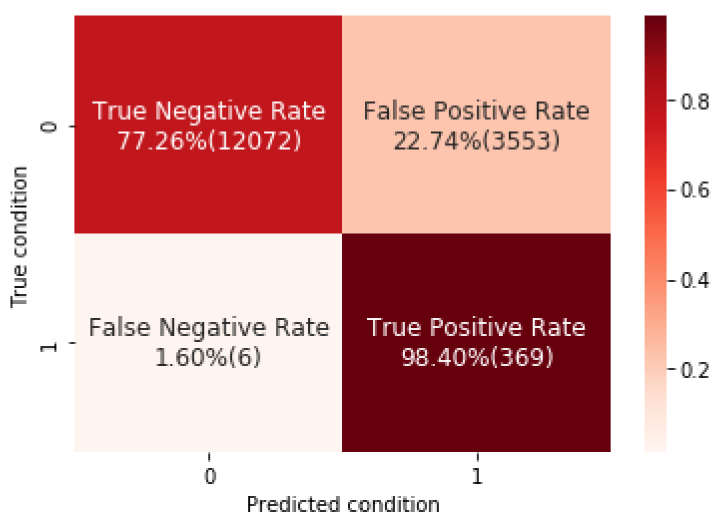
```
Loss on train data
:  [138200]
F1 score on train data
:  0.7837787095562927
================================================================================
====================
```

	tn	fp	fn	tp
0	12072	3553	6	369

```
Loss on test data
:  [38530]
F1 score on test data
:  0.17174773097509888
```

In [68]:

```
plot_confusion_mat(y_pred=CV_log.best_estimator_.predict(x_test_scaled), y_true=
```



3.2.2. Linear SVM

In [69]:

```
CV_linSVM = train_classifier(x = x_train_scaled_sampled, y= y_train_sampled, clas
```

In [70]:
```
print("Loss on train data\n: ", calculate_cost(y_pred=CV_linSVM.best_estimator_.p
print("F1 score on train data\n: ", f1_score(y_pred=CV_linSVM.best_estimator_.pre

print("="*100)
print("Loss on test data\n: ", calculate_cost(y_pred=CV_linSVM.best_estimator_.pr
print("F1 score on test data\n: ", f1_score(y_pred=CV_linSVM.best_estimator_.prec
```

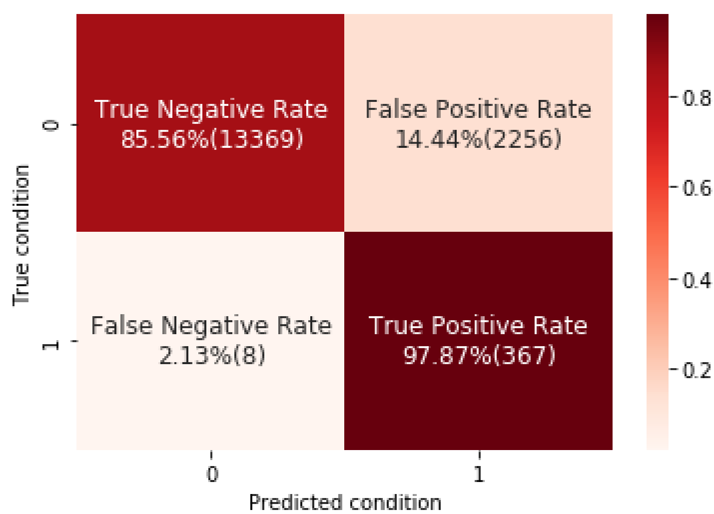
	tn	fp	fn	tp
0	50168	8832	34	25014

```
Loss on train data
:  [105320]
F1 score on train data
:  0.8494583488980201
================================================================================
====================
```

	tn	fp	fn	tp
0	13369	2256	8	367

```
Loss on test data
:  [26560]
F1 score on test data
:  0.24482988659106075
```

In [71]:
```
plot_confusion_mat(y_pred=CV_linSVM.best_estimator_.predict(x_test_scaled), y_tru
```



3.2.3. SVM with RBF Kernel

In [72]:
```
CV_SVC = train_classifier(x = x_train_scaled_sampled, y= y_train_sampled, classi1
```

In [73]:
```
print("Loss on train data\n: ", calculate_cost(y_pred=CV_SVC.best_estimator_.pre(
print("F1 score on train data\n: ", f1_score(y_pred=CV_SVC.best_estimator_.predi(

print("="*100)
print("Loss on test data\n: ", calculate_cost(y_pred=CV_SVC.best_estimator_.predi
print("F1 score on test data\n: ", f1_score(y_pred=CV_SVC.best_estimator_.predict
```

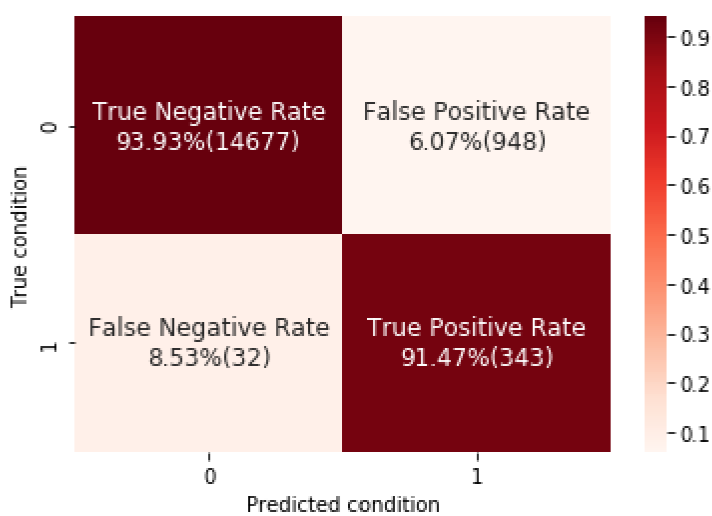
	tn	fp	fn	tp
0	55407	3593	16	25032

```
Loss on train data
:  [43930]
F1 score on train data
:  0.9327594880107317
==============================================================================
=====================
```

	tn	fp	fn	tp
0	14677	948	32	343

```
Loss on test data
:  [25480]
F1 score on test data
:  0.4117647058823529
```

In [74]:
```
plot_confusion_mat(y_pred=CV_SVC.best_estimator_.predict(x_test_scaled), y_true=
```



3.2.4. Decision Tree

In [75]:
```
CV_DT = train_classifier(x = x_train_scaled_sampled, y= y_train_sampled, classifi
```

In [76]:
```
print("Loss on train data\n: ", calculate_cost(y_pred=CV_DT.best_estimator_.predi
print("F1 score on train data\n: ", f1_score(y_pred=CV_DT.best_estimator_.predict

print("="*100)
print("Loss on test data\n: ", calculate_cost(y_pred=CV_DT.best_estimator_.predic
print("F1 score on test data\n: ", f1_score(y_pred=CV_DT.best_estimator_.predict(
```

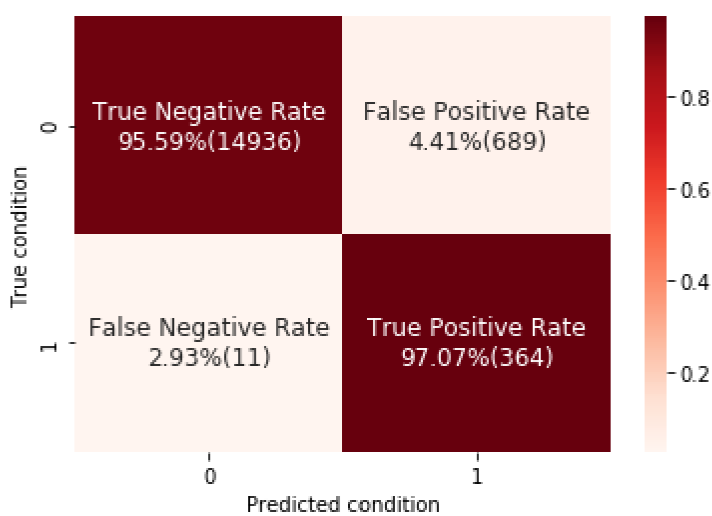
	tn	fp	fn	tp
0	56441	2559	83	24965

```
Loss on train data
:  [67090]
F1 score on train data
:  0.9497451114661797
================================================================================
====================
```

	tn	fp	fn	tp
0	14936	689	11	364

```
Loss on test data
:  [12390]
F1 score on test data
:  0.5098039215686275
```

In [80]:
```
plot_confusion_mat(y_pred=CV_DT.best_estimator_.predict(x_test_scaled), y_true= y
```



3.2.5. Random Forest

In [15]:
```
CV_RF = train_classifier(x = x_train_scaled_sampled, y= y_train_sampled, classifi
```

...

In [16]:
```
print("Loss on train data\n: ", calculate_cost(y_pred=CV_RF.best_estimator_.predi
print("F1 score on train data\n: ", f1_score(y_pred=CV_RF.best_estimator_.predict

print("="*100)
print("Loss on test data\n: ", calculate_cost(y_pred=CV_RF.best_estimator_.predic
print("F1 score on test data\n: ", f1_score(y_pred=CV_RF.best_estimator_.predict(
```

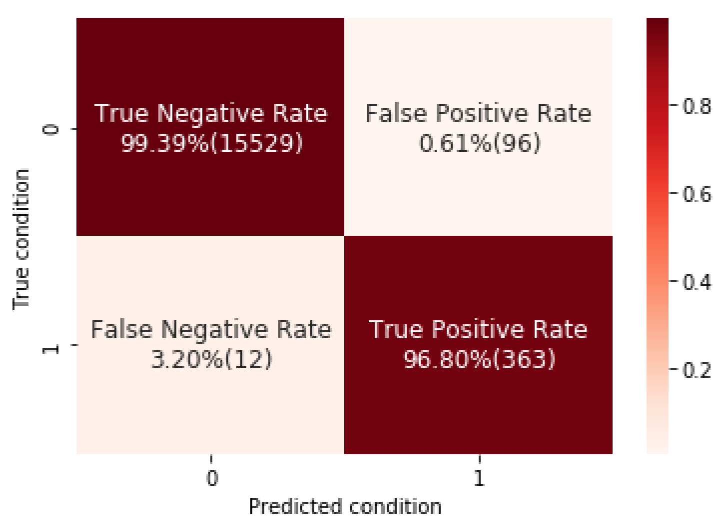
	tn	fp	fn	tp
0	58713	287	55	24993

```
Loss on train data
:  [30370]
F1 score on train data
:  0.9932045779685265
================================================================================
====================
```

	tn	fp	fn	tp
0	15529	96	12	363

```
Loss on test data
:  [6960]
F1 score on test data
:  0.8705035971223022
```

In [18]:
```
plot_confusion_mat(y_pred=CV_RF.best_estimator_.predict(x_test_scaled), y_true= y
```



3.2.6 Comparison

Algorithm	Train Loss	Train F1 Score	Test Loss	Test F1 Score
Logistic regression	138200	0.784	38530	0.171
Linear SVM	105320	0.849	26560	0.245
SVM with RBF kernel	43930	0.933	25480	0.411
Decision Tree	67090	0.950	12390	0.51
Random Forest	30370	0.993	6960	0.870

```
From above table we can conclude that
    1. Over all linear classifiers that is logistic regression and linea
r SVM have poor performance.
    2. SVM with RBF kernel has better performance compared to linear met
hods, however if we compare test and train scores, we can observe overfi
tting. Though the obtained result for SVM with RBF kernel is after hyper
parameter tuning, overfitting issue can still be addressed. However furt
her hyperparameter tuning may not improve test loss (most likely).
    3.Compared to SVM decision tree performance is better with relativel
y leaser overfitting.
    4. Random forest algorithm outperforms all above algorithms with bes
t performance and almost no overfitting
    5. It was also observed that SVM was the slowest to train due to lar
ge sample size(O(n^3))
    Based on above analysis Random Forest algorithm has been selected fo
r building classifier on entire training data
```

**Above analysis on performance has been obtained on 20K points randomly sampled from training data

4. Training a classifier using Random Forest

In [27]:
```
from sklearn.ensemble import RandomForestClassifier
RF_clf = RandomForestClassifier(n_estimators= 700,class_weight={0:1500,1:1},rando
RF_clf.fit(x_train_scaled, y_train)
```

Out[27]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                       class_weight={0: 1500, 1: 1}, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=Non
e,
                       max_samples=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=1,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       n_estimators=700, n_jobs=4, oob_score=False,
                       random_state=0, verbose=0, warm_start=False)
```

In [28]:
```
y_pred_tr = RF_clf.predict(x_train_scaled)
y_pred_te = RF_clf.predict(x_test_scaled)
```

In [29]:
```
print("Loss on train data\n: ", calculate_cost(y_pred = y_pred_tr, y_true= y_trai
print("F1 score on train data\n: ", f1_score(y_pred = y_pred_tr, y_true= y_train)

print("="*100)
print("Loss on test data\n: ", calculate_cost(y_pred = y_pred_te, y_true= y_test,
print("F1 score on test data\n: ", f1_score(y_pred = y_pred_te, y_true= y_test) )
```

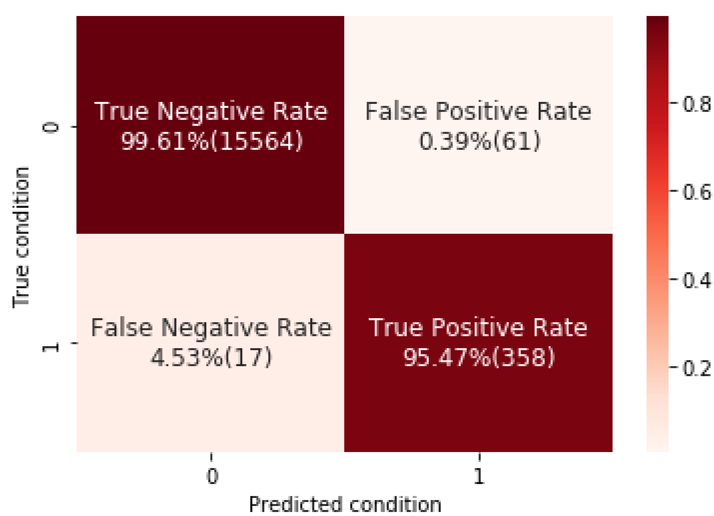
	tn	fp	fn	tp
0	59000	0	0	25004

```
Loss on train data
:  [0]
F1 score on train data
:  1.0
================================================================================
====================
```

	tn	fp	fn	tp
0	15564	61	17	358

```
Loss on test data
:  [9110]
F1 score on test data
:  0.9017632241813602
```

In [30]:
```
plot_confusion_mat(y_pred= y_pred_te, y_true= y_test)
```

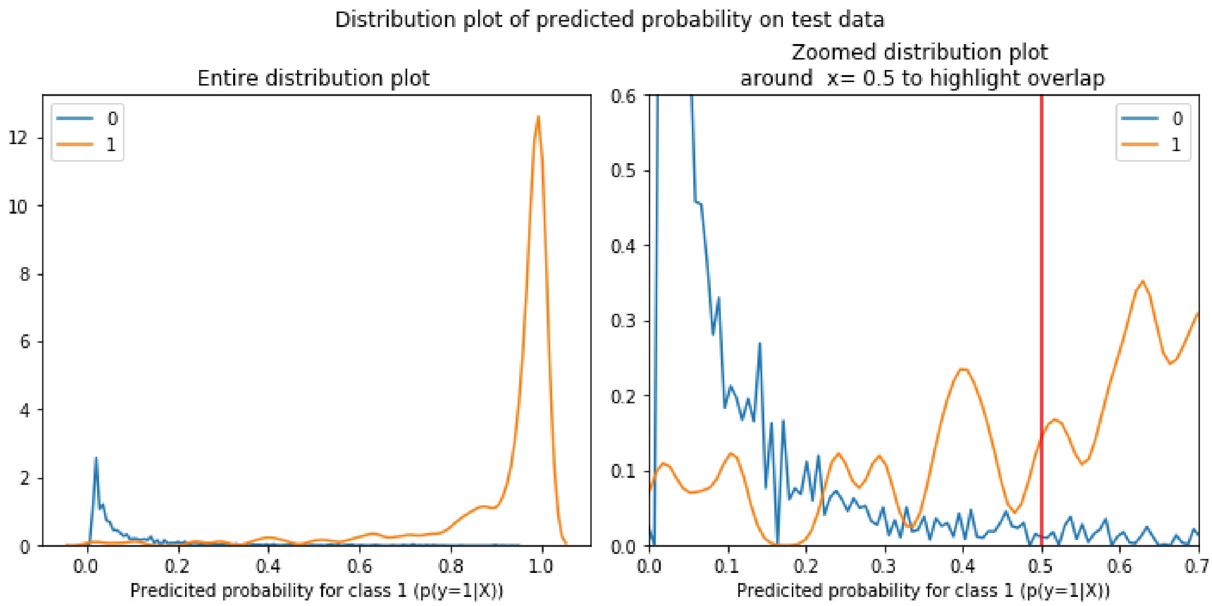


4.1. Distribution plot of predicted probability

This plot is to identify if there is an overlap between class-wise distributions of predicted probability for test data

In [31]:
```
prob_df =pd.DataFrame({"actual":y_test,
                       "prediction": y_pred_te,
                       "prob": RF_clf.predict_proba(x_test_scaled)[:,1],
                      })
```

In [32]:
```
## elipse around x= 0.4
x= np.arange(0.28,0.521, 0.001)
y1 = 5*np.sqrt(np.round(0.0144-(x-0.4)**2, 4))
y2 = y1*(-1)
fig, axes = plt.subplots(1, 2, figsize = (10,5))
sns.kdeplot(prob_df.loc[prob_df["actual"] ==0, "prob"], label = "0", ax= axes[0])
sns.kdeplot(prob_df.loc[prob_df["actual"] ==1, "prob"], label ="1", ax= axes[0])
axes[0].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[0].set_title("Entire distribution plot ")

sns.kdeplot(prob_df.loc[prob_df["actual"] ==0, "prob"], label = "0", ax= axes[1])
sns.kdeplot(prob_df.loc[prob_df["actual"] ==1, "prob"], label ="1", ax= axes[1])
plt.plot([0.5,0.5], [0,0.6],  color='red') ## A vertical line to show default thr
axes[1].set_xlim(0,0.7)
axes[1].set_ylim(0,0.6)
axes[1].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[1].set_title("\nZoomed distribution plot \naround  x= 0.5 to highlight overl

fig.suptitle("Distribution plot of predicted probability on test data")
plt.tight_layout()

plt.show()
```



From the above distribution plots following are the observations

1. Predicted probability p(y=1|X) for most of the samples belonging

```
 to negative class(y=0) is less than 0.5.  Similarly for samples belongi
ng to positive class predicted probability is greater than 0.5. With the
default threshold of 0.5(vertical line) for class assignment these sampl
es will be correctly classified
    2. However there are samples from negative class with predicted prob
ability p(y=1|X) greater than =0.5. Similarly there are few samples belo
nging to positive class(y=1) with predicted probability <0.5.
Samples from point 2 will be misclassified as either false negative (FN)
or false Positive(FP). Since in this problem loss weightage for FN is 50
times more than that of FP, changing probability threshold to reduce num
ber of FNs at the cost of higher number of FPs may further reduce test l
oss. This idea will be examined in below section.


To evaluate impact of changing probability threshold K fold cross valida
tion approach has been adapted. A threshold range of 0.1 to 0.7 has been
selected. For each threshold value 5 fold CV is performed.
    i.    In each CV iteration actual training data is divided into trai
n and CV dataset.
    ii.    A classifier is trained using  the new training data obtained
after step ii and loss is calculated using CV data.
    iii.    After end of 5 CV iterations mean of 5 CV losses are taken a
s average loss occurred with corresponding probability threshold.
```

5. Improving trained classifier by changing probability threshold

5.1. Kfold Cv to obtain best threshold value

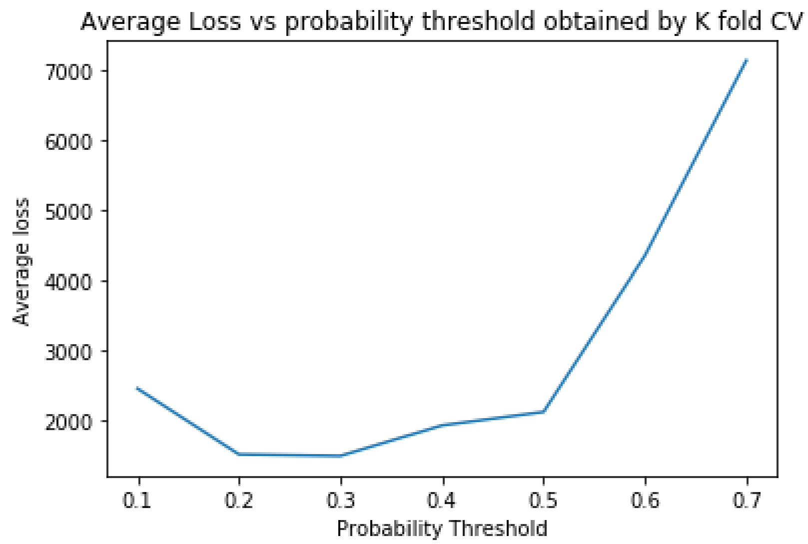
In [33]:
```
## Selecting random 20k sample for faster crossvalidation
idx = random.sample(range(x_train.shape[0]),30000)
x_train_scaled_sampled = x_train_scaled[idx].copy()
y_train_sampled = y_train[idx].copy().values
```

In [34]:
```
from tqdm import tqdm
k_folds = 5

cv_size = x_train_scaled_sampled.shape[0]//k_folds
thresholds = np.arange(0.1,0.8,0.1)
K_fold_loss =[]
for threshold in tqdm(thresholds):
    loss =0
    start_idx  =0
    for k in range(k_folds):
        end_idx = start_idx+cv_size
        cv_idx = random.sample(range(x_train_scaled_sampled.shape[0]), cv_size)
        train_idx = [x for x in  np.arange(x_train_scaled_sampled.shape[0]) if x
        ###---Spliting Data ---###
        X_cv = x_train_scaled_sampled[cv_idx].copy()
        y_cv = y_train_sampled[cv_idx].copy()

        x_tr = x_train_scaled_sampled[train_idx].copy()
        y_tr = y_train_sampled[train_idx].copy()

        ###--- Model---###
        RF_clf = RandomForestClassifier(n_estimators= 500,class_weight={0:500,1:1
        RF_clf.fit(x_tr, y_tr)

        ###---Prediction based on threshiold---###
        pred = np.zeros(cv_size)
        prob = RF_clf.predict_proba(X_cv)[:,1]
        pred[prob>threshold] =1
        print(loss, calculate_cost(y_pred = pred, y_true= y_cv) .values)
        loss += calculate_cost(y_pred = pred, y_true= y_cv) .values
        start_idx = end_idx
    print(loss)
    K_fold_loss.extend(loss/k_folds)
    print(K_fold_loss)
```

...

5.1.1. Plot of average CV loss vs corrresponding probability threshold

In [43]:
```
plt.plot(thresholds, K_fold_loss)
plt.xlabel("Probability Threshold")
plt.ylabel("Average loss")
plt.title("Average Loss vs probability threshold obtained by K fold CV")
plt.show()

display(pd.DataFrame (dict({"Thresholds": thresholds,
                            "Average CV Loss": K_fold_loss    }
                          )))
```



	Thresholds	Average CV Loss
0	0.1	2462.0
1	0.2	1522.0
2	0.3	1500.0
3	0.4	1936.0
4	0.5	2128.0
5	0.6	4356.0
6	0.7	7142.0

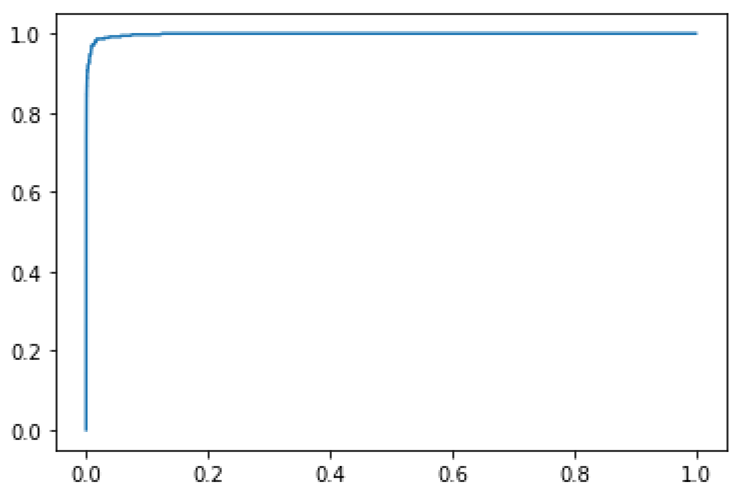
```
 1. As explained earlier by changing probability threshold lower CV loss
has changed.
 2. For probability threshold of 0.3 average CV loss is lowest followed
 by 0.2. The difference is marginal
 3. As we move towards leftor right from 0.3 or we can observe a rapid i
ncrease in average CV loss values.

From these observation we can conclude that instead of using the default
threshold of 0.5 it is better to reduce it. Note this is working as FN h
as 50 times more weightage  compared to FP in loss calculation.

The selected probability threshold is 0.3
    prediction = 0 if P(y=1|X) < 0.3
                 1 otherwise
```

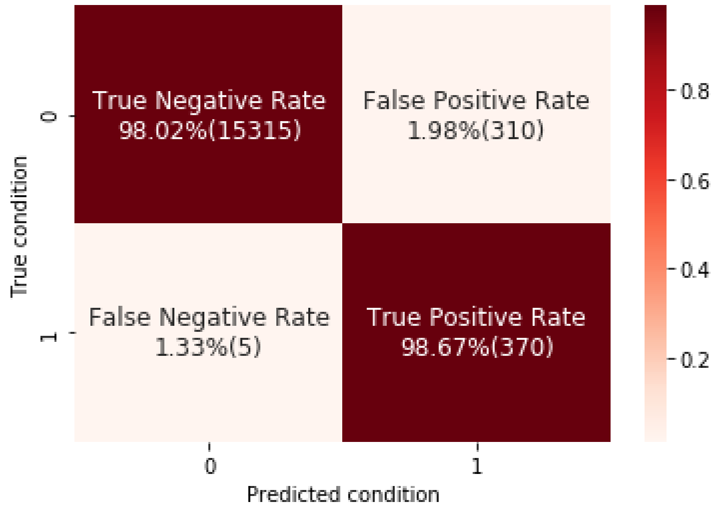
5.2 Model evaluation with probability threshold = 0.3

In [36]:
```
new_y_pred = np.zeros(x_test_scaled.shape[0])
new_y_pred[RF_clf.predict_proba(x_test_scaled)[:,1] >=0.3] =1

print("Loss on test data\n: ", calculate_cost(y_pred = new_y_pred, y_true= y_test
print("F1 score on test data\n: ", f1_score(y_pred = new_y_pred, y_true= y_test)
print("ROC-AUC score on test data\n: ", roc_auc_score(y_score = RF_clf.predict_pr
                                                       y_true= y_test) )



fpr, tpr , thresholds= roc_curve( y_score = RF_clf.predict_proba(x_test_scaled)[:
                                 y_true= y_test)
plt.plot(fpr, tpr)
plt.show()

plot_confusion_mat(y_pred=new_y_pred, y_true= y_test)
```

	tn	fp	fn	tp
0	15315	310	5	370

```
Loss on test data
:  [5600]
F1 score on test data
:  0.7014218009478673
ROC-AUC score on test data
:  0.9983463253333333
```





5.3 Observations

Probability Threshold	Loss	F1 Score	False Negative	FNR	False Positive	FPR
0.5 (Default)	9100	0.902	17	4.53%	60	0.38%
0.3	4890	0.834	7	1.87%	139	0.89%

```
1. From the above test scoe obtained, impact of threshold change is appr
ent. By changing probability threshold from 0.5 to 0.3, test loss reduce
d from 9100 to 4890. This happened as number of FN reduced from 17(4.5
3%) to 7 (1.8%). However the F1 Score decreased from 0.902 to 0.834. Thi
s happened as FP incresed from 60(0.38%) to 139(0.89%).
2. We could achieve((9100-4890)/9100) 46%  improvement in test loss by c
hanging probability threshold from 0.5 to 0.3 with a 7% reduction in ove
rall F1 Score.
```

6.Some more Ensemble model please

```
As shown earlier the classifier using Random forest(RF) algorithm outper
formed all other classical algorithms. RF is an ensemble model and there
fore few more ensemble models should be evaluated. In the following sect
ion we will evaluate
1. Boosting based ensemble model (GBDT)
2. Stacking
```

6.1. GBDT

In [21]:
```
import  xgboost as xgb
from sklearn.model_selection import GridSearchCV
data_dmatrix = xgb.DMatrix(data=x_train_scaled,label=y_train)

###---Hyperparameter tunning---###
params = {'n_estimators': [50, 100, 150, 200],
          'learning_rate': [0.01, 0.1, 0.2, 0.3],
          'max_depth': range(3, 10),
          'colsample_bytree': [i/10.0 for i in range(1, 3)],
          'gamma': [i/10.0 for i in range(3)],
          'reg_lambda ': [i/10.0 for i in range(3)]
         }

clf_GBDT = xgb.XGBRFClassifier(objective ='binary:logistic', random_state  = 0)
# Define grid search
Grid_cv_GBDT = GridSearchCV(clf_GBDT,
                            param_grid=params,
                            cv=3,
                            scoring=score,
                            verbose=1,
                            n_jobs=-4
                           )
Grid_cv_GBDT.fit(x_train_scaled_sampled, y_train_sampled)
```

```
Fitting 3 folds for each of 2016 candidates, totalling 6048 fits

[Parallel(n_jobs=-4)]: Using backend LokyBackend with 5 concurrent workers.
[Parallel(n_jobs=-4)]: Done  40 tasks      | elapsed:   12.8s
[Parallel(n_jobs=-4)]: Done 190 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-4)]: Done 440 tasks      | elapsed:  3.5min
[Parallel(n_jobs=-4)]: Done 790 tasks      | elapsed:  6.5min
[Parallel(n_jobs=-4)]: Done 1240 tasks      | elapsed: 10.4min
[Parallel(n_jobs=-4)]: Done 1790 tasks      | elapsed: 15.1min
[Parallel(n_jobs=-4)]: Done 2440 tasks      | elapsed: 20.8min
[Parallel(n_jobs=-4)]: Done 3190 tasks      | elapsed: 28.0min
[Parallel(n_jobs=-4)]: Done 4040 tasks      | elapsed: 42.6min
[Parallel(n_jobs=-4)]: Done 4990 tasks      | elapsed: 59.2min
[Parallel(n_jobs=-4)]: Done 6048 out of 6048 | elapsed: 79.5min finished
```

Out[21]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=XGBRFClassifier(base_score=0.5, colsample_bylevel=1,
                                       colsample_bynode=0.8, colsample_bytree
=1,
                                       gamma=0, learning_rate=1,
                                       max_delta_step=0, max_depth=3,
                                       min_child_weight=1, missing=None,
                                       n_estimators=100, n_jobs=1, nthread=No
ne,
                                       objective='binary:logistic',
                                       random_state=0, reg_alpha=0,
                                       reg_lambda=1, scale_pos_weight=1,
                                       seed...
                                       verbosity=1),
             iid='deprecated', n_jobs=-4,
             param_grid={'colsample_bytree': [0.1, 0.2],
                         'gamma': [0.0, 0.1, 0.2],
```

```
                         'learning_rate': [0.01, 0.1, 0.2, 0.3],
                         'max_depth': range(3, 10),
                         'n_estimators': [50, 100, 150, 200],
                         'reg_lambda ': [0.0, 0.1, 0.2]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=make_scorer(calculate_cost, greater_is_better=False),
             verbose=1)
```

In [22]:
```
Grid_cv_GBDT.best_estimator_
```

Out[22]:
```
XGBRFClassifier(base_score=0.5, colsample_bylevel=1, colsample_bynode=0.8,
                colsample_bytree=0.2, gamma=0.0, learning_rate=0.01,
                max_delta_step=0, max_depth=9, min_child_weight=1, missing=Non
e,
                n_estimators=50, n_jobs=1, nthread=None,
                objective='binary:logistic', random_state=0, reg_alpha=0,
                reg_lambda=1, reg_lambda =0.0, scale_pos_weight=1, seed=None,
                silent=None, subsample=0.8, verbosity=1)
```

In [23]:
```
# import pickle
# (scaler2, RF_clf2, clf_GBDT,  clf_meta2 ) = pickle.load(open("ALL_model_data.pk
# (base_clf_1_2, base_clf_2_2,base_clf_3_2, base_clf_4_2, Meta_clf_2) = clf_meta2
```

In [24]:
```
clf_GBDT = Grid_cv_GBDT.best_estimator_
clf_GBDT.fit(x_train_scaled_sampled, y_train_sampled)

y_pred_GBDT_tr = clf_GBDT.predict(x_train_scaled)
y_pred_GBDT_te = clf_GBDT.predict(x_test_scaled)
```

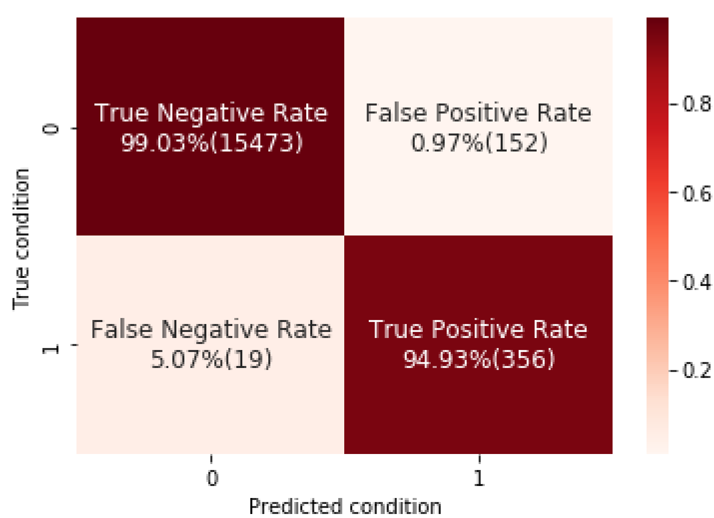
In [25]:
```
print("Loss on train data\n: ", calculate_cost(y_pred = y_pred_GBDT_tr, y_true= y
print("F1 score on train data\n: ", f1_score(y_pred = y_pred_GBDT_tr, y_true= y_t

print("="*100)
print("Loss on test data\n: ", calculate_cost(y_pred = y_pred_GBDT_te, y_true= y_
print("F1 score on test data\n: ", f1_score(y_pred = y_pred_GBDT_te, y_true= y_te


plot_confusion_mat(y_pred= y_pred_GBDT_te, y_true= y_test)
```

	tn	fp	fn	tp
0	58472	528	436	24568

```
Loss on train data
:  [223280]
F1 score on train data
:  0.9807584830339322
================================================================================
====================
```

	tn	fp	fn	tp
0	15473	152	19	356

```
Loss on test data
:  [11020]
F1 score on test data
:  0.8063420158550396
```

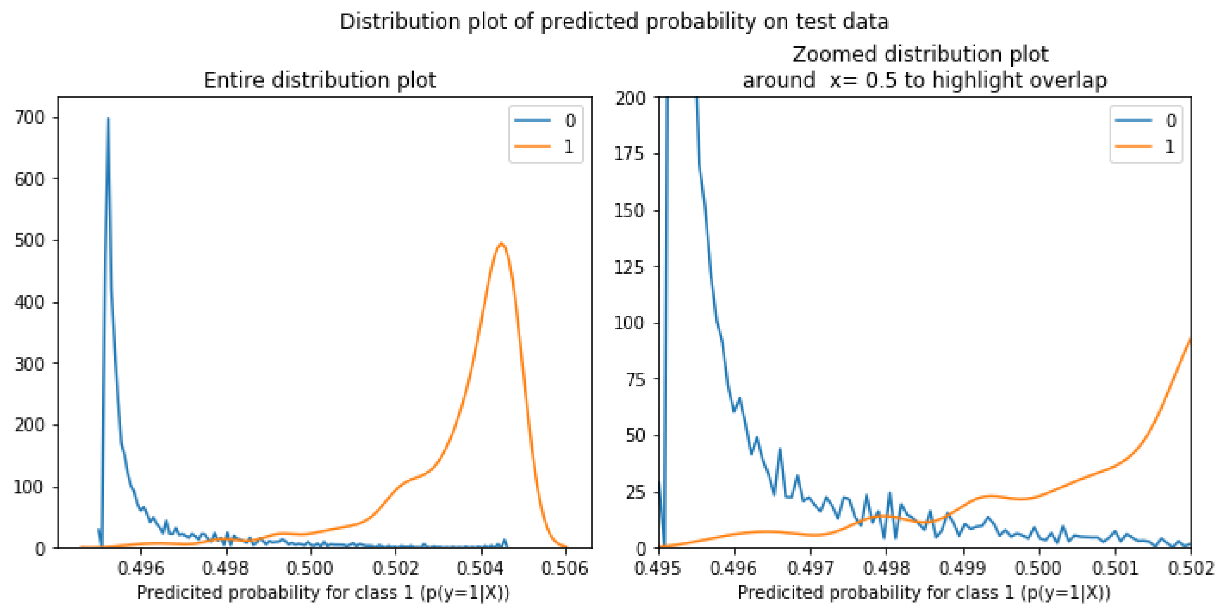


6.1.1 Improving GBDT classifier performance by changing probability threshold

In [26]:
```
prob_df_GBDT =pd.DataFrame({"actual":y_test,
                       "prediction": y_pred_GBDT_te,
                       "prob": clf_GBDT.predict_proba(x_test_scaled)[:,1],
                      })
```

In [27]:

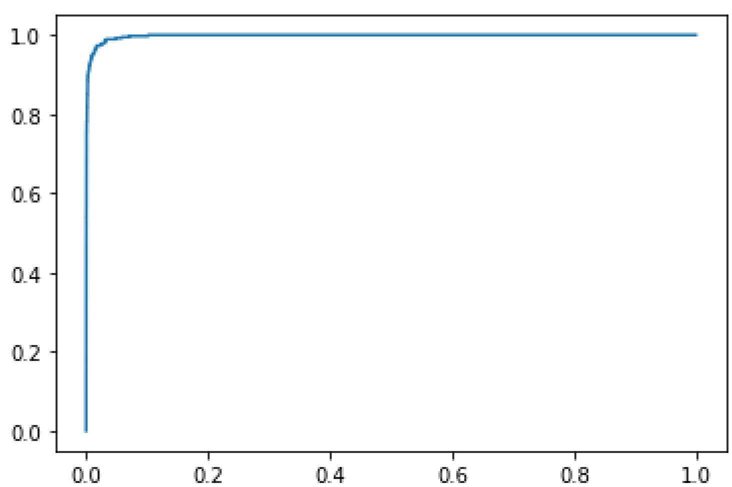
```
fig, axes = plt.subplots(1, 2, figsize = (10,5))
sns.kdeplot(prob_df_GBDT.loc[prob_df_GBDT["actual"] ==0, "prob"], label = "0", ax
sns.kdeplot(prob_df_GBDT.loc[prob_df_GBDT["actual"] ==1, "prob"], label ="1", ax=
axes[0].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[0].set_title("Entire distribution plot ")

sns.kdeplot(prob_df_GBDT.loc[prob_df_GBDT["actual"] ==0, "prob"], label = "0", ax
sns.kdeplot(prob_df_GBDT.loc[prob_df_GBDT["actual"] ==1, "prob"], label ="1", ax=
# plt.plot([0.5,0.5], [0,0.6],  color='red') ## A vertical line to show default t
axes[1].set_xlim(0.495,0.502)
axes[1].set_ylim(0,200)
axes[1].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[1].set_title("\nZoomed distribution plot \naround  x= 0.5 to highlight overl

fig.suptitle("Distribution plot of predicted probability on test data")
plt.tight_layout()

plt.show()
```

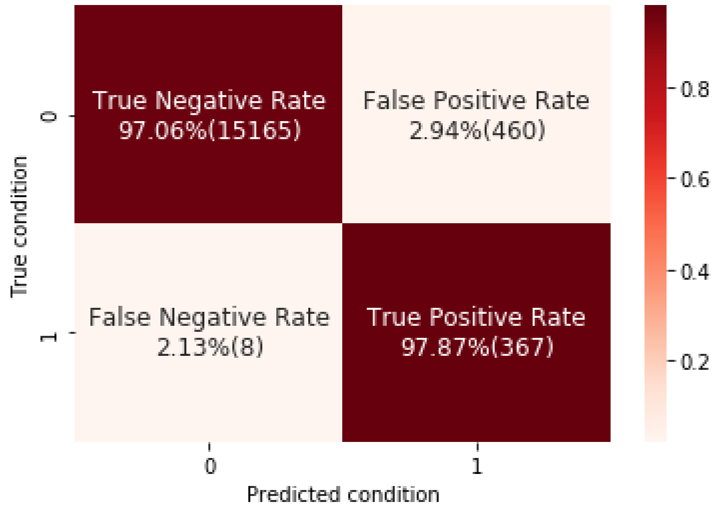


In [30]:
```
from sklearn.metrics import roc_curve, roc_auc_score

new_y_pred_GBDT = np.zeros(x_test_scaled.shape[0])
new_y_pred_GBDT[clf_GBDT.predict_proba(x_test_scaled)[:,1] >= 0.497] =1

print("Loss on test data\n: ", calculate_cost(y_pred = new_y_pred_GBDT, y_true= y
print("F1 score on test data\n: ", f1_score(y_pred = new_y_pred_GBDT, y_true= y_t

print("ROC-AUC score on test data\n: ", roc_auc_score(y_score = clf_GBDT.predict_
                                                       y_true= y_test) )



fpr, tpr , thresholds= roc_curve( y_score = clf_GBDT.predict_proba(x_test_scaled)
                                  y_true= y_test)
plt.plot(fpr, tpr)
plt.show()

plot_confusion_mat(y_pred= new_y_pred_GBDT, y_true= y_test)
```

	tn	fp	fn	tp
0	15165	460	8	367

```
Loss on test data
:  [8600]
F1 score on test data
:  0.610648918469218
ROC-AUC score on test data
:  0.9977202346666667
```





6.1.2 Observations

Probability Threshold	Loss	F1 Score
0.5 (Default)	11020	0.80
0.497	8600	0.610

```
1. From the above test score obtained, impact of threshold change is app
arent. However the reduction in loss is 28% unlike 46% in case of random
forest.
2. The PDFs of predicted probability for class 0 and class 1 are not ver
y well separated and this model though produces low loss value not suita
ble if probability is of interest. In such cases an additional calibrati
on model can be used.
```

6.2. Stacking based ensemble model

In [36]:
```
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split



#####----- Creating data fro base classifiers and meta learner-----#####
x_tr_stack_D1, x_tr_stack_D2, y_tr_stack_D1, y_tr_stack_D2 = train_test_split(x_t
                                                                                te
                                                                                st
                                                                               )


#####----- Building 3 base classifiers -----#####

###---Spliting D1 dataset into three groups ---###

random.seed(0)
idx1 = random.sample(range(x_tr_stack_D1.shape[0]),40000)
idx2 = random.sample(range(x_tr_stack_D1.shape[0]),40000)
idx3 = random.sample(range(x_tr_stack_D1.shape[0]),40000)
idx4 = random.sample(range(x_tr_stack_D1.shape[0]),40000)

## data for first base classifier (KNN clasifier)
x_tr_stack_D11 = x_tr_stack_D1[idx1].copy()
y_tr_stack_D11 = y_tr_stack_D1[idx1].copy()

## data for second base classifier (SVM clasifier)
x_tr_stack_D12 = x_tr_stack_D1[idx2].copy()
y_tr_stack_D12 = y_tr_stack_D1[idx2].copy()

## data for third base classifier (DT clasifier)
x_tr_stack_D13 = x_tr_stack_D1[idx3].copy()
y_tr_stack_D13 = y_tr_stack_D1[idx3].copy()

## data for third base classifier (RF clasifier)
x_tr_stack_D14 = x_tr_stack_D1[idx4].copy()
y_tr_stack_D14 = y_tr_stack_D1[idx4].copy()

###--- Creating Base classifiers---###
base_clf_1 =   KNeighborsClassifier(weights= "distance",
                                    n_neighbors =7 )

base_clf_2 =  SVC(C =10, class_weight={0: 1, 1: 10}, probability=True)

base_clf_3 = DecisionTreeClassifier(class_weight=  {0: 1, 1: 100},
                                    max_depth = 20,
                                    min_samples_leaf = 25,
                                    min_samples_split = 2)
base_clf_4 = RandomForestClassifier(n_estimators= 700,
                                    class_weight={0:1500,1:1},
                                    random_state=0,
                                    n_jobs=4)
```

```
#####----- Training Base Classifier -----#####


base_clf_1.fit(x_tr_stack_D11, y_tr_stack_D11)
base_clf_2.fit(x_tr_stack_D12, y_tr_stack_D12)
base_clf_3.fit(x_tr_stack_D13, y_tr_stack_D13)
base_clf_4.fit(x_tr_stack_D14, y_tr_stack_D14)
```

Out[36]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                       class_weight={0: 1500, 1: 1}, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=Non
e,
                       max_samples=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=1,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       n_estimators=700, n_jobs=4, oob_score=False,
                       random_state=0, verbose=0, warm_start=False)
```

In [37]:

```
## we will take predicted probability of base learners as X

X_tr_base_clf_1 = base_clf_1.predict_proba(x_tr_stack_D2)
X_tr_base_clf_2 = base_clf_2.predict_proba(x_tr_stack_D2)
X_tr_base_clf_3 = base_clf_3.predict_proba(x_tr_stack_D2)
X_tr_base_clf_4 = base_clf_4.predict_proba(x_tr_stack_D2)

x_tr_meta= np.vstack([X_tr_base_clf_1[:,1],
                      X_tr_base_clf_2[:,1],
                      X_tr_base_clf_3[:,1],
                      X_tr_base_clf_4[:,1]]
                    ).T
```

In [38]:

```
# Meta_clf = SVC(C = 100,
#                class_weight={0: 1, 1: 60},
#                gamma = 0.05,
#                probability= True,
#                random_state=0
#               )
Meta_clf = LogisticRegression(class_weight={0: 1, 1: 100})


Meta_clf.fit(x_tr_meta, y_tr_stack_D2)
```

Out[38]:

```
LogisticRegression(C=1.0, class_weight={0: 1, 1: 100}, dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [39]:
```
print("Loss on train data\n: ", calculate_cost(y_pred = Meta_clf.predict(x_tr_met
print("F1 score on train data\n: ", f1_score(y_pred = Meta_clf.predict(x_tr_meta)
```

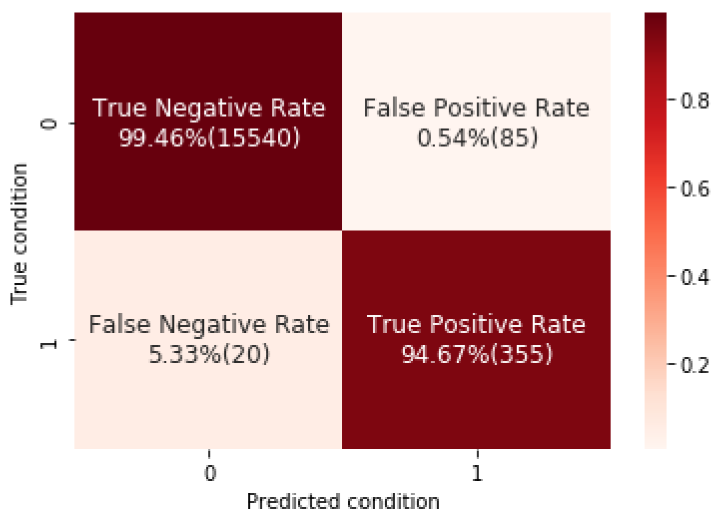
	tn	fp	fn	tp
0	17601	99	0	7515

```
Loss on train data
:  [990]
F1 score on train data
:  0.9934562760261749
```

In [40]:
```
X_te_base_clf_1 = base_clf_1.predict_proba(x_test_scaled)
X_te_base_clf_2 = base_clf_2.predict_proba(x_test_scaled)
X_te_base_clf_3 = base_clf_3.predict_proba(x_test_scaled)
X_te_base_clf_4 = base_clf_4.predict_proba(x_test_scaled)

x_te_meta= np.vstack([X_te_base_clf_1[:,1],
                      X_te_base_clf_2[:,1],
                      X_te_base_clf_3[:,1],
                      X_te_base_clf_4[:,1]]
                    ).T


print("Loss on test data\n: ", calculate_cost(y_pred = Meta_clf.predict(x_te_meta
print("F1 score on test data\n: ", f1_score(y_pred = Meta_clf.predict(x_te_meta),


plot_confusion_mat(y_pred= Meta_clf.predict(x_te_meta), y_true= y_test)
```

	tn	fp	fn	tp
0	15540	85	20	355

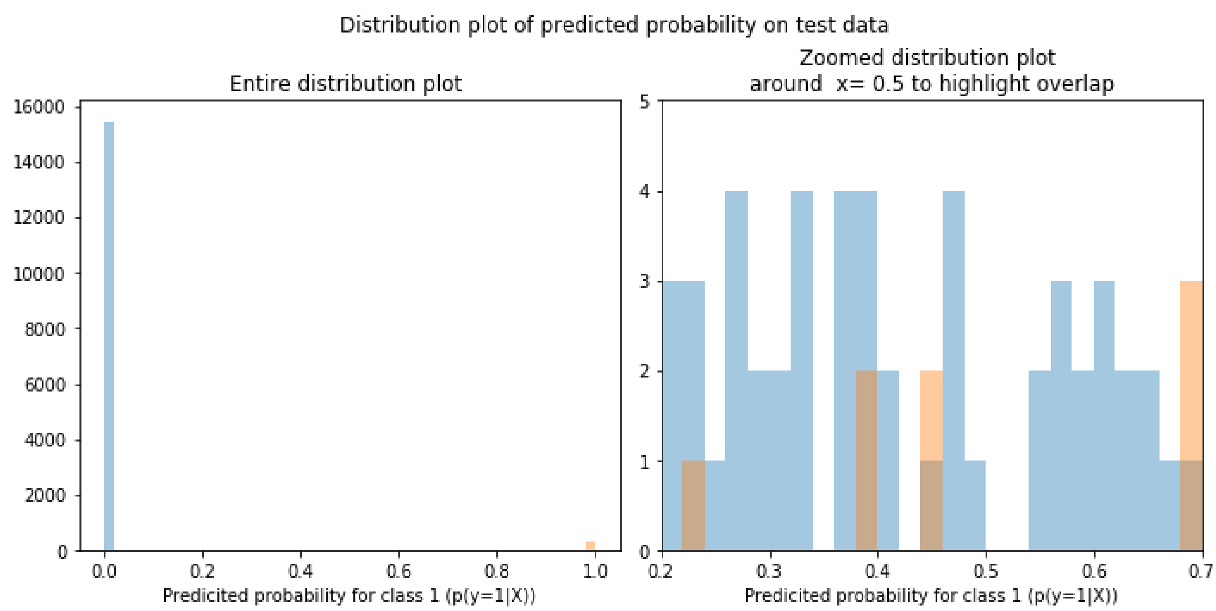
```
Loss on test data
:  [10850]
F1 score on test data
:  0.871165644171779
```



In [41]:
```
prob =Meta_clf.predict_proba(x_te_meta)[:,1]
prob_df_stack =pd.DataFrame({"actual":y_test,
                       "prediction": Meta_clf.predict(x_te_meta),
                       "prob": prob
                      })
```

In [42]:

```
## elipse around x= 0.4

fig, axes = plt.subplots(1, 2, figsize = (10,5))
sns.distplot(prob_df_stack.loc[prob_df_stack["actual"] ==0, "prob"],
            label = "0", ax= axes[0],
            kde =False)
sns.distplot(prob_df_stack.loc[prob_df_stack["actual"] ==1, "prob"],
            label ="1", ax= axes[0],
            kde =False)
axes[0].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[0].set_title("Entire distribution plot ")

sns.distplot(prob_df_stack.loc[prob_df_stack["actual"] ==0, "prob"],
            label = "0", ax= axes[1],
            kde =False)

sns.distplot(prob_df_stack.loc[prob_df_stack["actual"] ==1, "prob"],
            label ="1", ax= axes[1],
           kde =False)
# plt.plot([0.5,0.5], [0,0.6],  color='red') ## A vertical line to show default t
axes[1].set_xlim(0.2,0.7)
axes[1].set_ylim(0,5)
axes[1].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[1].set_title("\nZoomed distribution plot \naround  x= 0.5 to highlight overl

fig.suptitle("Distribution plot of predicted probability on test data")
plt.tight_layout()

plt.show()
```

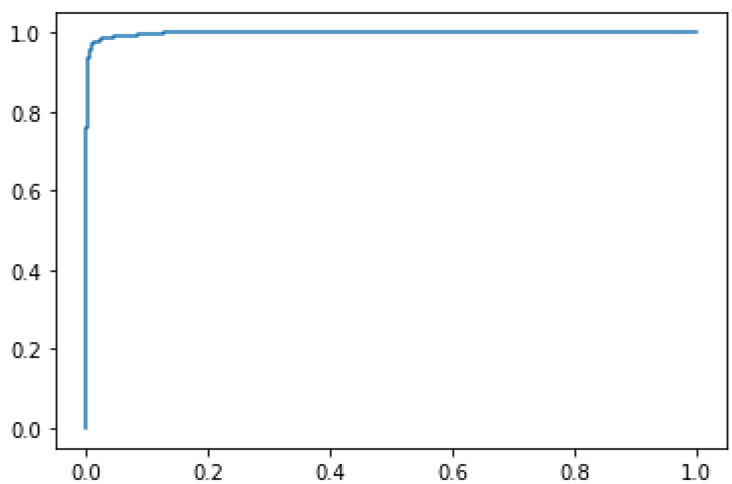


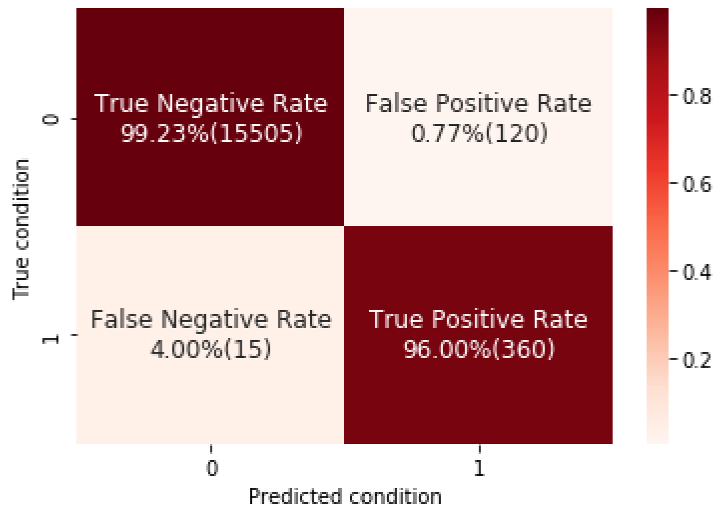
6.2.1 Improving Stacking classifier performance by changing probability threshold

In [70]:
```
new_y_pred_stack = np.zeros(x_test_scaled.shape[0])
new_y_pred_stack[prob >= 0.2] =1

print("Loss on test data\n: ", calculate_cost(y_pred = new_y_pred_stack, y_true=
print("F1 score on test data\n: ", f1_score(y_pred = new_y_pred_stack, y_true= y_
print("ROC-AUC score on test data\n: ", roc_auc_score(y_score = prob, y_true= y_t



fpr, tpr , thresholds= roc_curve( y_score = prob, y_true= y_test)
plt.plot(fpr, tpr)
plt.show()

plot_confusion_mat(y_pred= new_y_pred_stack, y_true= y_test)
```

	tn	fp	fn	tp
0	15505	120	15	360

```
Loss on test data
:  [8700]
F1 score on test data
:  0.8421052631578947
ROC-AUC score on test data
:  0.9980404053333334
```





6.2.2 Observations

```
Just like Random forest and GBDT loss of stacking based ensemble techniq
ue reduced by changing probability threshold from 10850 to 8700 (20%). T
his is not a lot compared to improvement in random forest approach.
However this model has better classification power than GBDT as predicte
d probability for class 0 abd 1 are well separated.
```

7. Deep Neural Network

In [90]:
```
import tensorflow as tf
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from tensorflow.keras.callbacks import EarlyStopping

tf.random.set_seed(0)
```

7.1 Build Model

In [91]:
```
from tensorflow.keras.utils import to_categorical
y_train_encode = to_categorical(y_train)
y_test_encode = to_categorical(y_test)
```

In [103]:

```
clf_nn = Sequential()

clf_nn.add(Dense(16, input_shape = (x_train_scaled.shape[1], ), activation = "rel
clf_nn.add(Dropout(0.5))

clf_nn.add(BatchNormalization())
clf_nn.add(Dense(16, activation = "relu"))
clf_nn.add(Dropout(0.5))

clf_nn.add(Dense(2, activation = "sigmoid"))
```

In [104]:

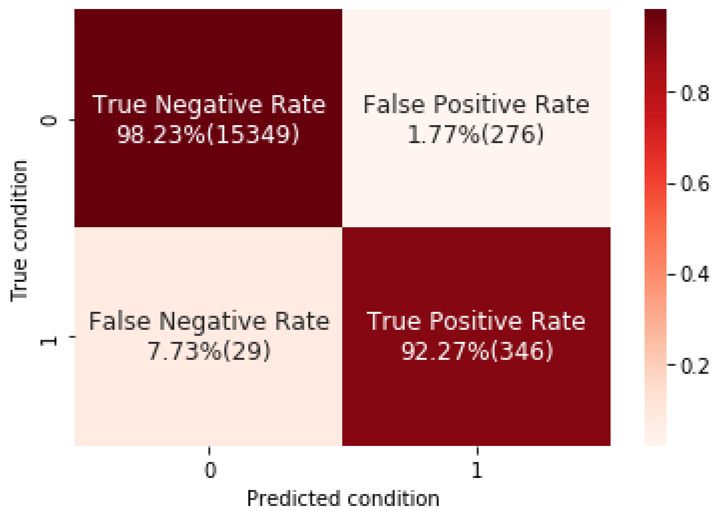
```
ES = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=10)
clf_nn.compile(loss='binary_crossentropy',
              optimizer=Adam(0.0002),
              metrics=['accuracy'])
clf_nn.fit(x_train_scaled, y_train_encode,
           class_weight = {0:0.1,1:1},
           batch_size=512,
           epochs= 250,
           verbose=1,
           validation_data=(x_test_scaled, y_test_encode),
           callbacks= [ES]
          )
```

```
Train on 84048 samples, validate on 16000 samples
Epoch 1/250
84048/84048 [==============================] - 1s 13us/sample - loss: 0.2469
- accuracy: 0.5039 - val_loss: 0.7360 - val_accuracy: 0.4292
Epoch 2/250
84048/84048 [==============================] - 1s 7us/sample - loss: 0.1768 -
accuracy: 0.5288 - val_loss: 0.8243 - val_accuracy: 0.4273
Epoch 3/250
84048/84048 [==============================] - 1s 7us/sample - loss: 0.1433 -
accuracy: 0.5429 - val_loss: 0.8646 - val_accuracy: 0.4621
Epoch 4/250
84048/84048 [==============================] - 1s 7us/sample - loss: 0.1226 -
accuracy: 0.5700 - val_loss: 0.8492 - val_accuracy: 0.5266
Epoch 5/250
84048/84048 [==============================] - 1s 7us/sample - loss: 0.1072 -
accuracy: 0.6078 - val_loss: 0.8240 - val_accuracy: 0.5923
Epoch 6/250
84048/84048 [==============================] - 1s 7us/sample - loss: 0.0944 -
accuracy: 0.6624 - val_loss: 0.7948 - val_accuracy: 0.6655
```

In [105]:
```
y_pred_nn = clf_nn.predict_classes(x_test_scaled)

print("Loss on test data\n: ", calculate_cost(y_pred = y_pred_nn, y_true= y_test,
print("F1 score on test data\n: ", f1_score(y_pred = y_pred_nn, y_true= y_test) )

plot_confusion_mat(y_pred= y_pred_nn, y_true= y_test)
```

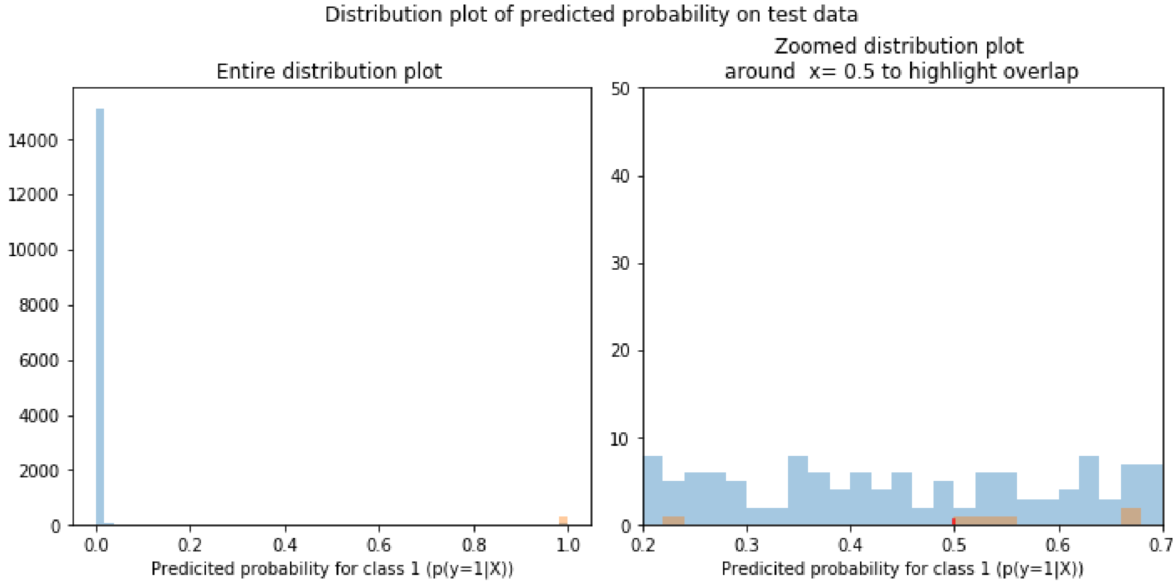
	tn	fp	fn	tp
0	15349	276	29	346

```
Loss on test data
:  [17260]
F1 score on test data
:  0.6940822467402206
```



In [106]:
```
prob_df_nn =pd.DataFrame({"actual":y_test,
                          "prediction": y_pred_nn,
                          "prob": clf_nn.predict(x_test_scaled)[:,1],
                         })
```

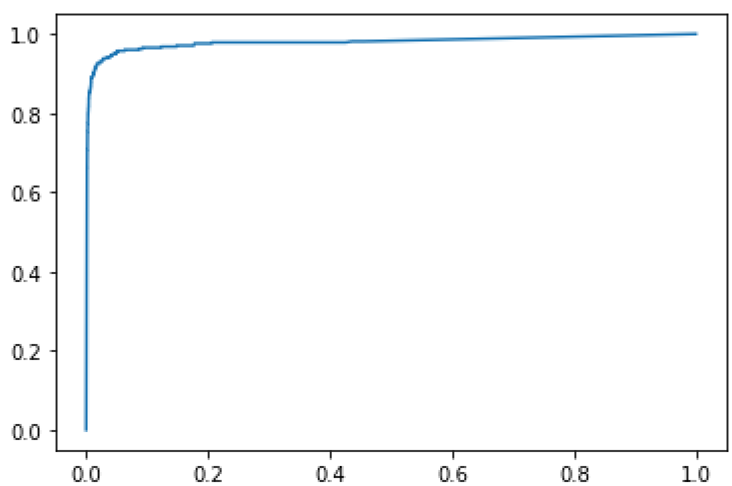
In [107]:
```
fig, axes = plt.subplots(1, 2, figsize = (10,5))
sns.distplot(prob_df_nn.loc[prob_df_nn["actual"] ==0, "prob"],
             label = "0",
             ax= axes[0],
             kde= False
            )

sns.distplot(prob_df_nn.loc[prob_df_nn["actual"] ==1, "prob"],
             label ="1",
             ax= axes[0],
             kde= False
            )
axes[0].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[0].set_title("Entire distribution plot ")

sns.distplot(prob_df_nn.loc[prob_df_nn["actual"] ==0, "prob"],
             label = "0",
             ax= axes[1],
             kde= False
            )

sns.distplot(prob_df_nn.loc[prob_df_nn["actual"] ==1, "prob"],
             label ="1",
             ax= axes[1],
             kde= False
            )

plt.plot([0.5,0.5], [0,0.6],  color='red') ## A vertical line to show default thr
axes[1].set_xlim(0.2 ,0.7)
axes[1].set_ylim(0,50)
axes[1].set_xlabel("Predicited probability for class 1 (p(y=1|X))")
axes[1].set_title("\nZoomed distribution plot \naround  x= 0.5 to highlight overl

fig.suptitle("Distribution plot of predicted probability on test data")
plt.tight_layout()

plt.show()
```

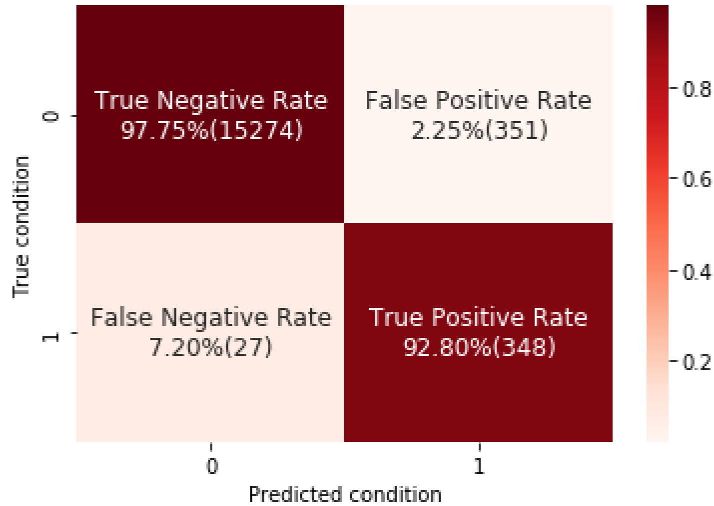

Distribution plot of predicted probability on test data
Entire distribution plot
Zoomed distribution plot
around x= 0.5 to highlight overlap
14000
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Predicited probability for class 1 (p(y=1|X))
50
40
30
20
10
0
0.2
0.3
0.4
0.5
0.6
0.7
Predicited probability for class 1 (p(y=1|X))

In [109]:
```
from sklearn.metrics import roc_curve, roc_auc_score

new_y_pred_nn = np.zeros(x_test_scaled.shape[0])
new_y_pred_nn[clf_nn.predict(x_test_scaled)[:,1] >= 0.2] =1

print("Loss on test data\n: ", calculate_cost(y_pred = new_y_pred_nn, y_true= y_t
print("F1 score on test data\n: ", f1_score(y_pred = new_y_pred_nn, y_true= y_tes
print("ROC-AUC score on test data\n: ", roc_auc_score(y_score = clf_nn.predict(x_



fpr, tpr , thresholds= roc_curve( y_score = clf_nn.predict(x_test_scaled)[:,1], y
plt.plot(fpr, tpr)
plt.show()

plot_confusion_mat(y_pred= new_y_pred_nn, y_true= y_test)
```

	tn	fp	fn	tp
0	15274	351	27	348

```
Loss on test data
:  [17010]
F1 score on test data
:  0.6480446927374303
ROC-AUC score on test data
:  0.9796097706666668
```





7. Conclusion

Ensemble Method	loss	F1 Score	ROC_AUC scoce
Random Forest	4890	0.834	0.999
GBDT	8600	0.61	0.997
Stacking	8700	0.842	0.998
Neural Network	17010	0.648	0.980

```
1. We can observe that both classes have overlapping regions from 2D sca
tter plot .
2. After comparing multiple approached for training classifier Random fo
rest was selected as it outperformed other algorithms.
3.  From above test result we can conclude that RF has the best performa
nce with minimum loss . It also has good separation between predicted pr
obability for class 0 1nd 1. Performance of RF can be further improved b
y reducing probability threshold for class assignment.
4. By changing probability threshold from 0.5 to 0.3, 46% reduction in c
os was achieved.
5. Though GBDT has low loss value compared to stacking due to poor proba
bility separation between class 0 and 1, an additional calibration model
has to be used incase probbility is of intrest.
6. The loss value obtained by neural network is significantly higher tha
n ensmble methods.
```

In [ ]: