Lijing Yang Project

Part1:

Pre-processing

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
np.random.seed(2048)
```

In [2]:
```
df = pd.read_csv('Data/bank-additional-full.csv',delimiter=';')
df=df.drop_duplicates(keep='first')
```

Step1: Replace missing value with the most frequent value

In [3]:
```
df = df[df != 'unknown']

imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imputer = imputer.fit(df[['job']])
df['job'] = imputer.transform(df[['job']])

imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imputer = imputer.fit(df[['marital']])
df['marital'] = imputer.transform(df[['marital']])

imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imputer = imputer.fit(df[['education']])
df['education'] = imputer.transform(df[['education']])

imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imputer = imputer.fit(df[['default']])
df['default'] = imputer.transform(df[['default']])

imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imputer = imputer.fit(df[['housing']])
df['housing'] = imputer.transform(df[['housing']])

imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imputer = imputer.fit(df[['loan']])
df['loan'] = imputer.transform(df[['loan']])

df=df.drop(columns=['duration'])
df
```

Out[3]:

	age	job	marital	education	default	housing	loan	contact	month
0	56	housemaid	married	basic.4y	no	no	no	telephone	may
1	57	services	married	high.school	no	no	no	telephone	may
2	37	services	married	high.school	no	yes	no	telephone	may
3	40	admin.	married	basic.6y	no	no	no	telephone	may
4	56	services	married	high.school	no	no	yes	telephone	may
...	...	...	...	...	...	...	...	...	...
41183	73	retired	married	professional.course	no	yes	no	cellular	nov
41184	46	blue-collar	married	professional.course	no	no	no	cellular	nov
41185	56	retired	married	university.degree	no	yes	no	cellular	nov
41186	44	technician	married	professional.course	no	no	no	cellular	nov
41187	74	retired	married	professional.course	no	yes	no	cellular	nov

41176 rows × 20 columns

In [4]:
```
pd.set_option('display.max_columns', 500)
df.describe(include='all')# Calss is not balance
```

Out[4]:

	age	job	marital	education	default	housing	loan	contact	mo
count	41176.00000	41176	41176	41176	41176	41176	41176	41176	41
unique	NaN	11	3	7	2	2	2	2	
top	NaN	admin.	married	university.degree	no	yes	no	cellular	
freq	NaN	10749	25001	13894	41173	22561	34928	26135	13
mean	40.02380	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
std	10.42068	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
min	17.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
25%	32.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
50%	38.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
75%	47.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
max	98.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I

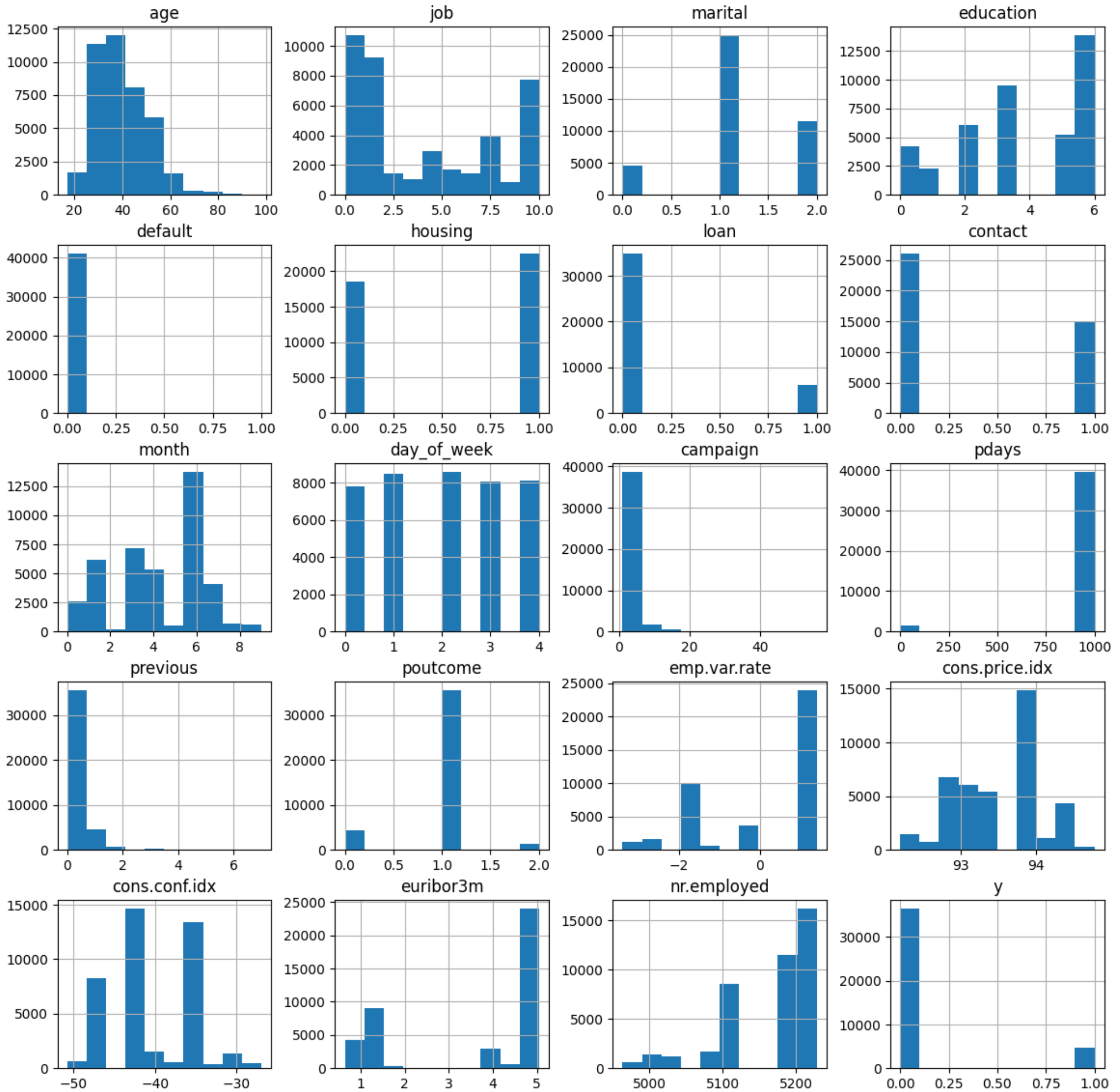
Step2: Use numeric categories to replace the original string categories

In [5]:
```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
df['job']=encoder.fit_transform(df['job'])
df['marital']=encoder.fit_transform(df['marital'])
df['education']=encoder.fit_transform(df['education'])
df['default']=encoder.fit_transform(df['default'])
df['housing']=encoder.fit_transform(df['housing'])
df['loan']=encoder.fit_transform(df['loan'])
df['contact']=encoder.fit_transform(df['contact'])
df['month']=encoder.fit_transform(df['month'])
df['day_of_week']=encoder.fit_transform(df['day_of_week'])
df['poutcome']=encoder.fit_transform(df['poutcome'])
df['y']=encoder.fit_transform(df['y'])
pd.DataFrame.hist(df,figsize=[14,14])
df
```

Out[5]:

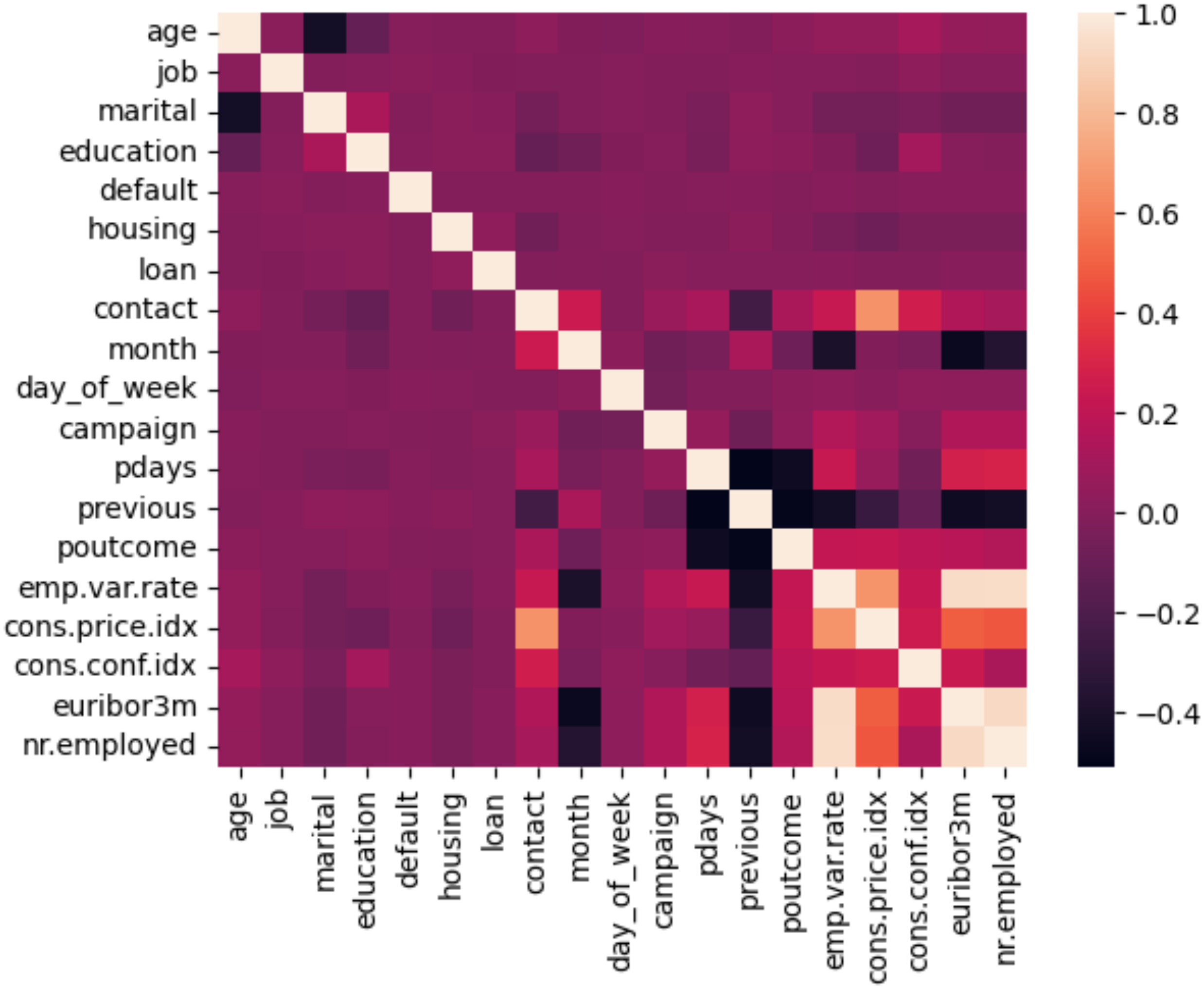
	age	job	marital	education	default	housing	loan	contact	month	day_of_week
0	56	3	1	0	0	0	0	1	6	1
1	57	7	1	3	0	0	0	1	6	1
2	37	7	1	3	0	1	0	1	6	1
3	40	0	1	1	0	0	0	1	6	1
4	56	7	1	3	0	0	1	1	6	1
...	...	...	...	...	...	...	...	...	...	...
41183	73	5	1	5	0	1	0	0	7	0
41184	46	1	1	5	0	0	0	0	7	0
41185	56	5	1	6	0	1	0	0	7	0
41186	44	9	1	5	0	0	0	0	7	0
41187	74	5	1	5	0	1	0	0	7	0

41176 rows × 20 columns



Step3: Automatic Feature Selection

In [6]:
```
Y=df['y'].values
X=df.drop('y',axis=1)
corr = X.corr(method = 'spearman')
sns.heatmap(corr, annot =False)
plt.show()
```



In [7]:
```
from featurewiz import featurewiz
features, df = featurewiz(df, 'y',corr_limit=0.8)
```

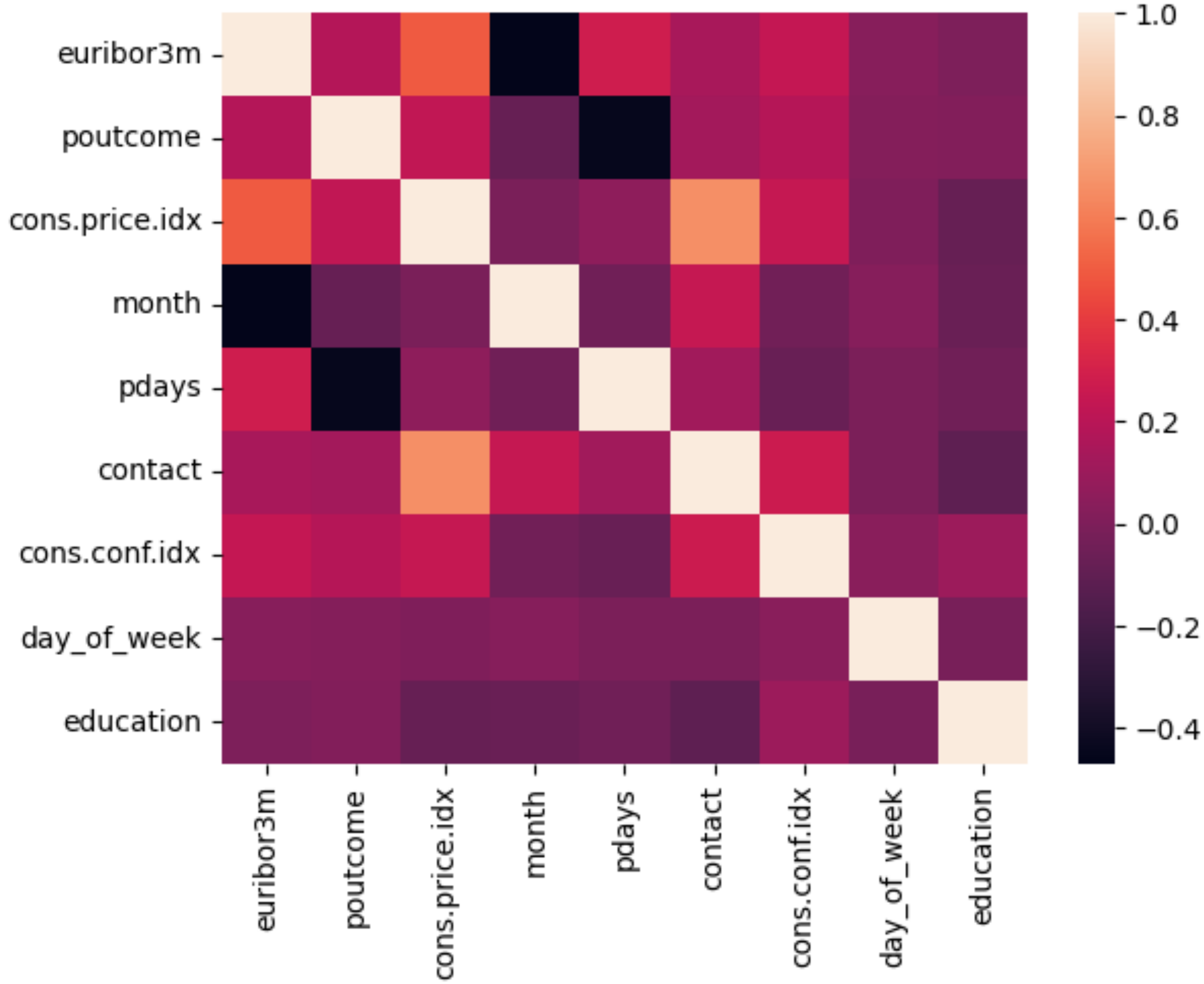
```
Imported 0.2.03 version. Select nrows to a small number when running on huge
datasets.
output = featurewiz(dataname, target, corr_limit=0.90, verbose=2, sep=',',
                header=0, test_data='',feature_engg='', category_encoders=''
,
                dask_xgboost_flag=False, nrows=None, skip_sulov=False)
Create new features via 'feature_engg' flag : ['interactions','groupby','tar
get']

############################################################################
################
############       F A S T   F E A T U R E  E N G G    A N D    S E L E C T
I O N ! ########
# Be judicious with featurewiz. Don't use it to create too many un-interpret
able features! #
############################################################################
################
Correlation Limit = 0.8
```

```
Skipping feature engineering since no feature_engg input...
Skipping category encoding since no category encoders specified in input...
#### Single_Label Binary_Classification problem ####
    Loaded train data. Shape = (41176, 20)
    Some column names had special characters which were removed...
#### Single_Label Binary_Classification problem ####
No test data filename given...
Classifying features using a random sample of 10000 rows from dataset...
#### Single_Label Binary_Classification problem ####
    loading a random sample of 10000 rows into pandas for EDA
############################################################################
###########
######################## C L A S S I F Y I N G  V A R I A B L E S  #########
###########
############################################################################
###########
        No variables were removed since no ID or low-information variables f
ound in data set
############################################################################
###########
#####  Searching for Uncorrelated List Of Variables (SULOV) in 19 features #
###########
############################################################################
###########
    there are no null values in dataset...
    Removing (2) highly correlated variables:
    ['empvarrate', 'nremployed']
    Following (17) vars selected: ['age', 'campaign', 'consconfidx', 'conspr
iceidx', 'contact', 'day_of_week', 'default', 'education', 'housing', 'job',
'loan', 'marital', 'month', 'pdays', 'poutcome', 'previous', 'euribor3m']
Completed SULOV. 17 features selected
Time taken for SULOV method = 1 seconds
Finally 17 vars selected after SULOV
Converting all features to numeric before sending to XGBoost...
############################################################################
###########
#####    R E C U R S I V E   X G B O O S T : F E A T U R E   S E L E C T I O
N  #######
############################################################################
###########
Current number of predictors before recursive XGBoost = 17
Number of booster rounds = 100
            selecting 8 features in this iteration
            selecting 6 features in this iteration
            selecting 5 features in this iteration
            selecting 3 features in this iteration
            selecting 2 features in this iteration
    Completed XGBoost feature selection in 0 seconds
############################################################################
###########
#####          F E A T U R E   S E L E C T I O N   C O M P L E T E D
#######
############################################################################
```

```
###########
Selected 9 important features:
['euribor3m', 'poutcome', 'conspriceidx', 'month', 'pdays', 'contact', 'cons
confidx', 'day_of_week', 'education']
Total Time taken for featurewiz selection = 3 seconds
Output contains a list of 9 important features and a train dataframe
```

In [8]:
```
print('Selected features: ',features)
Y=df['y'].values
X=df.drop('y',axis=1)
corr = X.corr(method = 'spearman')
sns.heatmap(corr, annot = False)
plt.show()
```

```
Selected features:  ['euribor3m', 'poutcome', 'cons.price.idx', 'month', 'pd
ays', 'contact', 'cons.conf.idx', 'day_of_week', 'education']
```



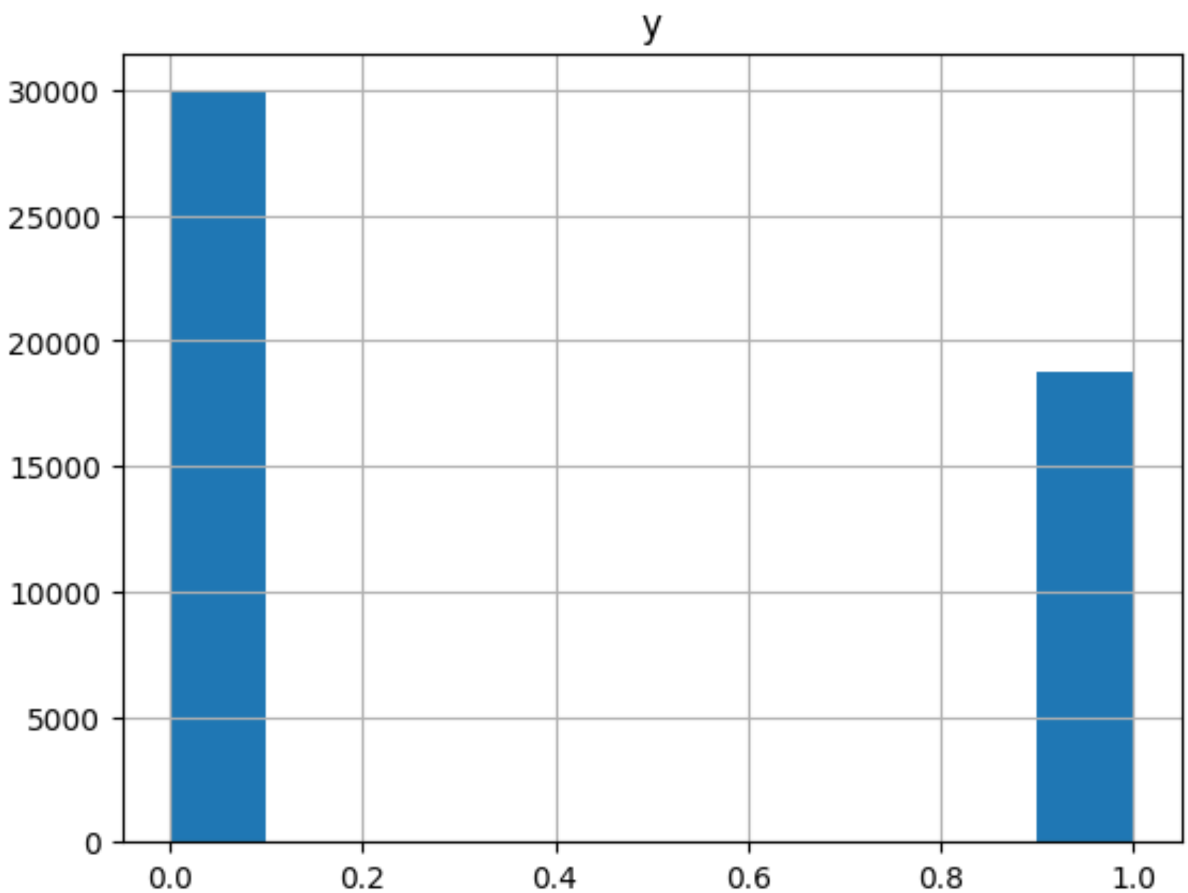
Step4: Balancing data

In [9]:
```
from imblearn.combine import SMOTEENN
smoteenn=SMOTEENN(random_state=42)
X_B,Y_B=smoteenn.fit_resample(X, Y)
Dataset=X_B
Dataset['y'] = Y_B
pd.DataFrame.hist(Dataset[['y']])
Dataset
```

Out[9]:

	euribor3m	poutcome	cons.price.idx	month	pdays	contact	cons.conf.idx	day_of_
0	4.857000	1	93.994	6	999	1	-36.4	
1	4.857000	1	93.994	6	999	1	-36.4	
2	4.857000	1	93.994	6	999	1	-36.4	
3	4.857000	1	93.994	6	999	1	-36.4	
4	4.857000	1	93.994	6	999	1	-36.4	
...	...	...	...	...	...	...	...	
48708	4.857243	1	93.994	6	999	1	-36.4	
48709	0.649469	2	93.369	5	10	0	-34.8	
48710	4.856616	1	93.994	6	999	1	-36.4	
48711	0.739748	0	92.431	8	999	0	-26.9	
48712	0.879000	1	94.199	9	999	0	-37.5	

48713 rows × 10 columns



Step5: Standardized numerical value

In [10]:
```
std= StandardScaler()
#['euribor3m', 'duration', 'month', 'cons.conf.idx', 'pdays', 'cons.price.ic
X=std.fit_transform(Dataset[['pdays','cons.price.idx','euribor3m','cons.conf
Dataset['pdays'] = X[:,0]
Dataset['cons.price.idx'] = X[:,1]
Dataset['euribor3m'] = X[:,2]
Dataset['cons.conf.idx'] = X[:,3]
#df['nr.employed'] = X[:,9]
#df['age'] = X[:,0]
#df['campaign'] = X[:,2]
#df['previous'] = X[:,4]
#df['emp.var.rate'] = X[:,5]
```

Step6: Dataset Split (Train Set, Train set without label, Test Set)

In [11]:
```
y=Dataset['y'].values
x=Dataset.drop('y',axis=1)
x_data,x_test,y_data,y_test = train_test_split(x,y, train_size=0.5, random_s
A=x_data
A['y']=y_data
New_data=A.sample(n = 10000)
y_data=New_data['y'].values
x_data=New_data.drop('y',axis=1)
x_train1,x_train2,y_train1,y_train2 = train_test_split(x_data,y_data, train_
x_test=x_test.reset_index(drop=True)
```

Part2: Supervised learning

In [12]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import plot_roc_curve
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.model_selection import GridSearchCV

from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
```

In [13]:
```
def Analyze(Y_pred,Y_test,classifier):
    ACC=accuracy_score(Y_test, Y_pred)
    AUC = roc_auc_score(Y_test, Y_pred)
    print('AUC: {:.4f}'.format(AUC))
    print('Accuracy Score: {:.4f}'.format(ACC))
    print(classification_report(Y_test, Y_pred))
    mat = confusion_matrix(Y_test, Y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=mat)
    disp.plot()
    plt.show()
    '''sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False)
    plt.xlabel('True label')
    plt.ylabel('Predicted label')
    plt.show()
    ROC(Y_pred,Y_test,classifier)'''

'''def ROC(model, Y_pred,Y_test,classifier):
    false_positive_rate, true_positive_rate, threshold = roc_curve(Y_test, Y
```

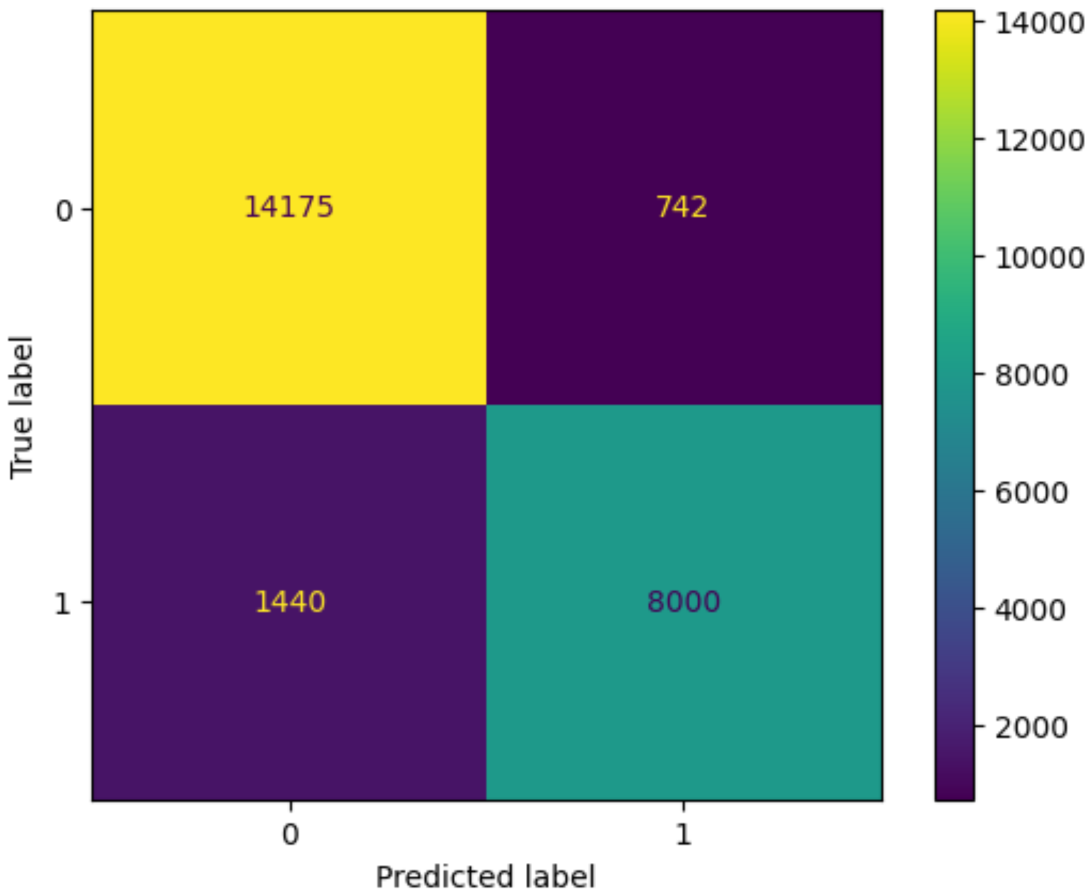
```
    plt.plot(false_positive_rate, true_positive_rate)
    plt.plot(false_positive_rate, true_positive_rate, linewidth=2)
    plt.title('ROC curve for '+classifier)
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()'''
def KNN_ROC(x_train,x_test,y_train,y_test,fig):
    knn=KNeighborsClassifier(n_neighbors = 5)
    knn.fit(x_train, y_train)
    plot_roc_curve(estimator=knn,X=x_test,y=y_test,ax = fig.ax_)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')

def KNN(x_train,x_test,y_train,y_test,n=5):
    knn=KNeighborsClassifier(n_neighbors = n)
    knn.fit(x_train, y_train)
    y_pred = knn.predict(x_test)
    classifier='KNN'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=knn,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test

def LRC(x_train,x_test,y_train,y_test):
    lr = LogisticRegression()
    lr.fit(x_train, y_train)
    y_pred = lr.predict(x_test)
    classifier='Logistic Regression Classification'
    Analyze(y_pred,y_test,classifier)
    fig=plot_roc_curve(estimator=lr,X=x_test,y=y_test)
    KNN_ROC(x_train,x_test,y_train,y_test,fig)
    return y_pred,y_test

def NB(x_train,x_test,y_train,y_test):
    nb = GaussianNB()
    nb.fit(x_train, y_train )
    y_pred = nb.predict(x_test)
    classifier='GaussianNB Classification'
    Analyze(y_pred,y_test,classifier)
    fig=plot_roc_curve(estimator=nb,X=x_test,y=y_test)
    KNN_ROC(x_train,x_test,y_train,y_test,fig)
    return y_pred,y_test

def SVM(x_train,x_test,y_train,y_test):
    svc = SVC(probability=True, gamma="auto")
    svc.fit( x_train, y_train )
    y_pred = svc.predict(x_test)
    classifier='SVM'
    Analyze(y_pred,y_test,classifier)
    fig=plot_roc_curve(estimator=svc,X=x_test,y=y_test)
    KNN_ROC(x_train,x_test,y_train,y_test,fig)
    return y_pred,y_test

def DecisionTree(x_train,x_test,y_train,y_test):
```

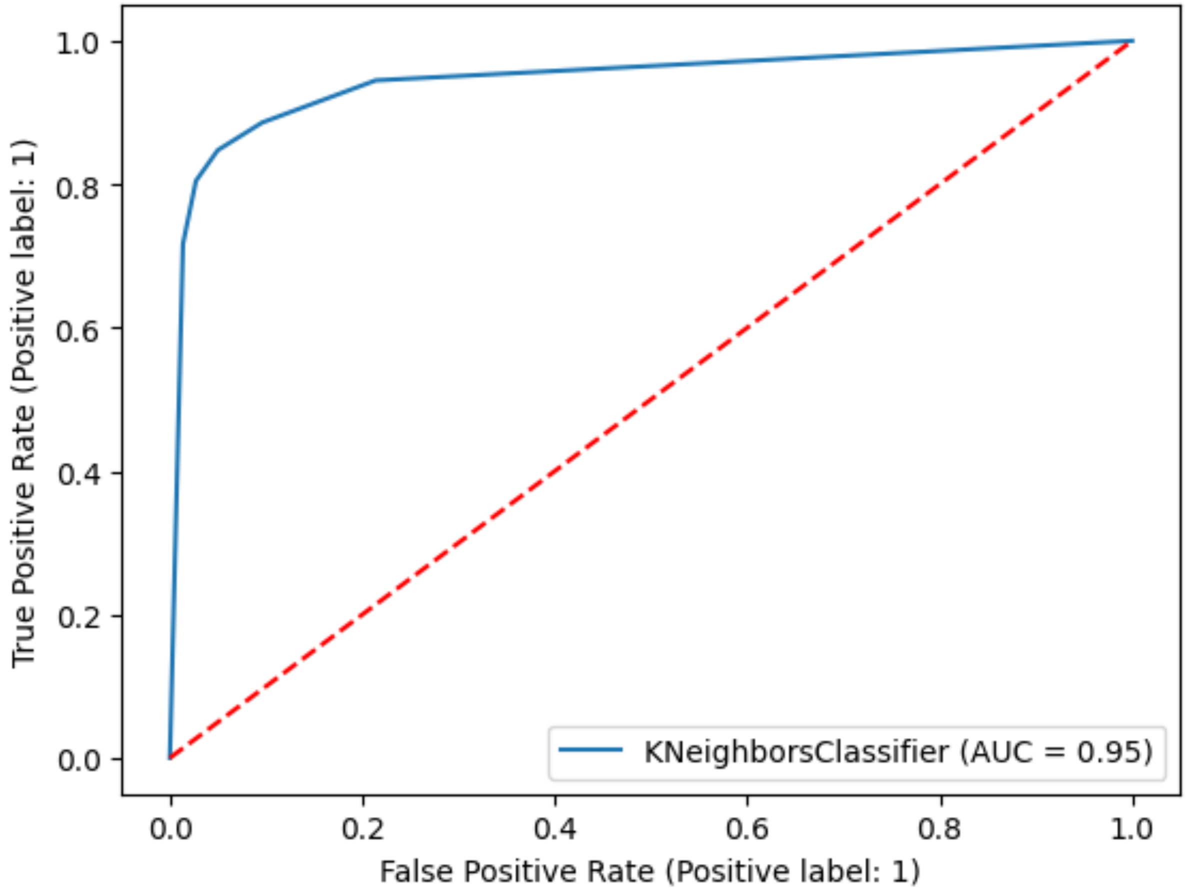
```
    parameters = {'splitter':('best','random'),
                  'criterion':("gini","entropy"),
                  "max_depth":[*range(1, 20)]}
    # Change parameters
    DT = DecisionTreeClassifier()
    model=GridSearchCV(DT,param_grid=parameters,cv=5,scoring='f1')
    model.fit(x_train, y_train )
    y_pred = model.best_estimator_.predict(x_test)
    classifier='Decision Tree Classification'
    Analyze(y_pred,y_test,classifier)
    fig=plot_roc_curve(estimator=model.best_estimator_,X=x_test,y=y_test)
    KNN_ROC(x_train,x_test,y_train,y_test,fig)
    return y_pred,y_test

def RandomForest(x_train,x_test,y_train,y_test):
    RF = RandomForestClassifier()
    parameters = {'criterion':("gini","entropy"),
                  "max_depth":[*range(1, 20)],
                  "n_estimators":[5,10,20,40]}
    model=GridSearchCV(RF,param_grid=parameters,cv=5,scoring='f1')
    model.fit(x_train, y_train)
    y_pred = model.best_estimator_.predict(x_test)
    classifier='Random Forest Classification'
    Analyze(y_pred,y_test,classifier)
    fig=plot_roc_curve(estimator=model.best_estimator_,X=x_test,y=y_test)
    KNN_ROC(x_train,x_test,y_train,y_test,fig)
    return y_pred,y_test

def Gradient_Boosting(x_train,x_test,y_train,y_test):
    gb = GradientBoostingClassifier()
    parameters = {'max_depth':[*range(1, 10)]}
    model=GridSearchCV(gb,param_grid=parameters,cv=5,scoring='f1')
    model.fit(x_train, y_train)
    y_pred = model.best_estimator_.predict(x_test)
    classifier='Gradient Boost Classification'
    Analyze(y_pred,y_test,classifier)
    fig=plot_roc_curve(estimator=model.best_estimator_,X=x_test,y=y_test)
    KNN_ROC(x_train,x_test,y_train,y_test,fig)
    return y_pred,y_test

def LDA(x_train,x_test,y_train,y_test):
    lda = LinearDiscriminantAnalysis()
    lda.fit(x_train,y_train )
    y_pred = lda.predict(x_test )
    classifier='Linear Discriminant Analysis Classification'
    Analyze(y_pred,y_test,classifier)
    fig=plot_roc_curve(estimator=lda,X=x_test,y=y_test)
    KNN_ROC(x_train,x_test,y_train,y_test,fig)
    return y_pred,y_test
```

KNN Classifier

In [14]:
```
y_pred_KNN,y_test_KNN=KNN(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.8989
Accuracy Score: 0.9104
              precision    recall  f1-score   support

           0       0.91      0.95      0.93     14917
           1       0.92      0.85      0.88      9440

    accuracy                           0.91     24357
   macro avg       0.91      0.90      0.90     24357
weighted avg       0.91      0.91      0.91     24357
```

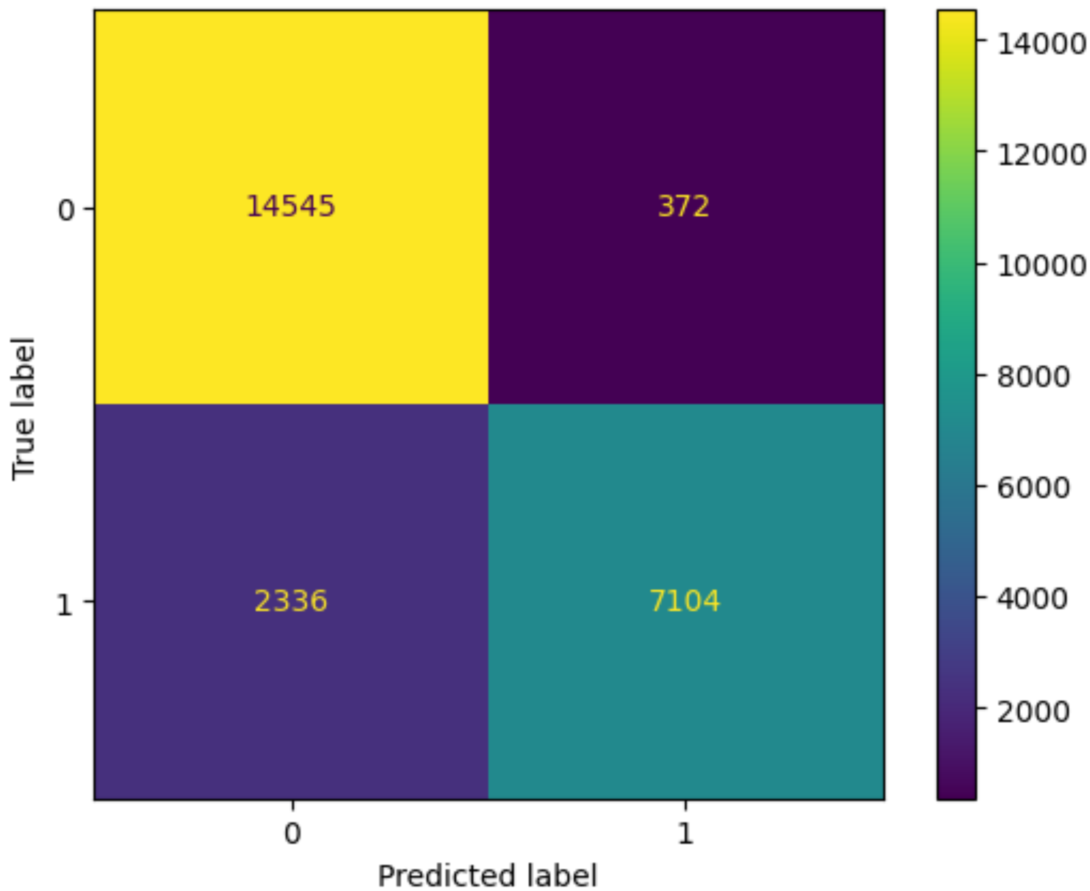


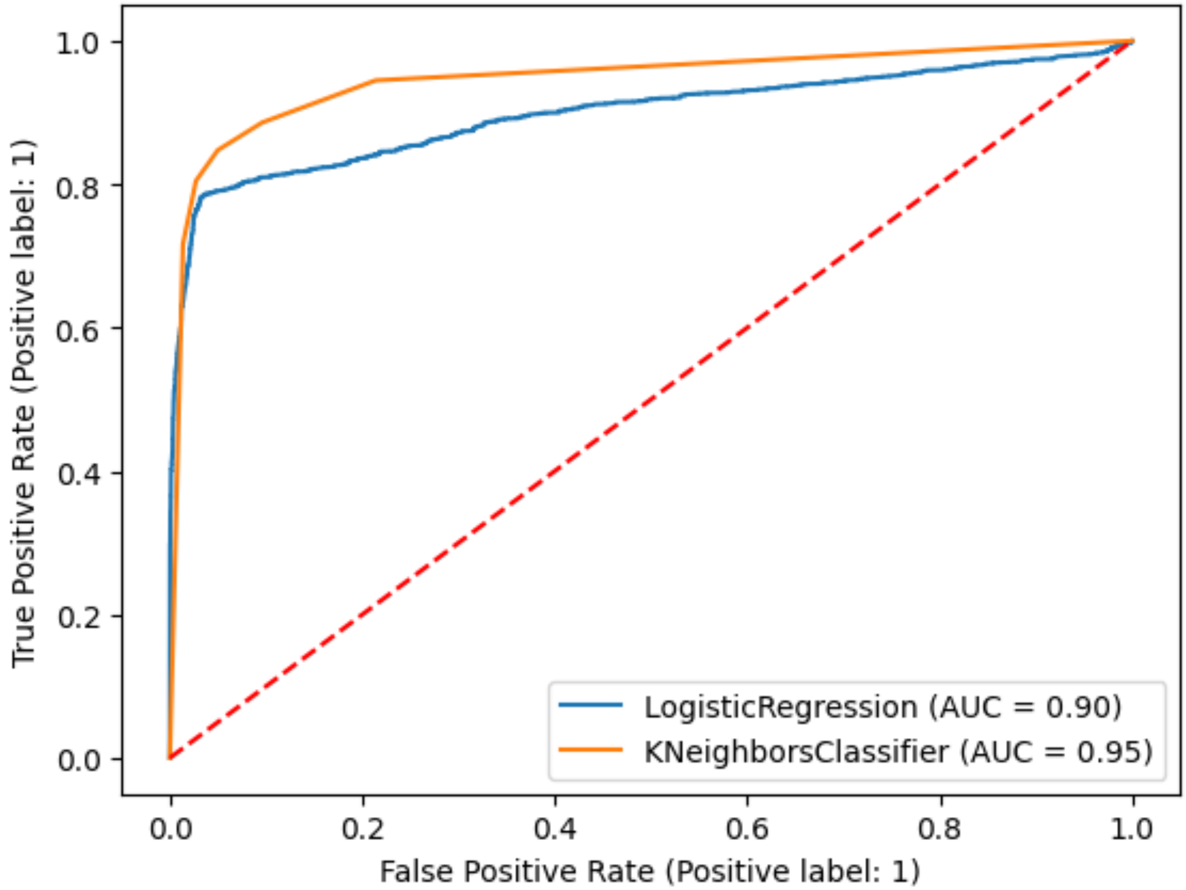


Logistic Regression Classification

In [15]:
```
y_pred_LRC,y_test_LRC=LRC(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.8638
Accuracy Score: 0.8888
              precision    recall  f1-score   support

           0       0.86      0.98      0.91     14917
           1       0.95      0.75      0.84      9440

    accuracy                           0.89     24357
   macro avg       0.91      0.86      0.88     24357
weighted avg       0.90      0.89      0.89     24357
```

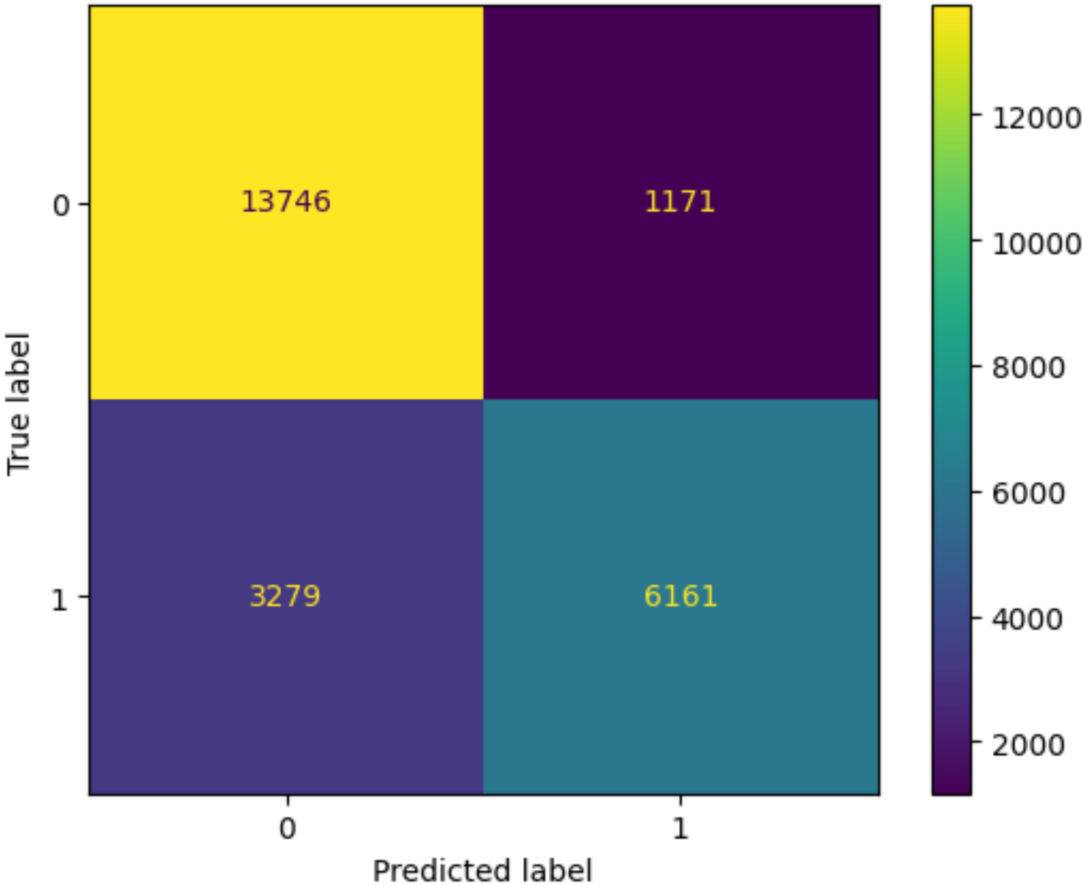

14545
372
2336
7104
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000

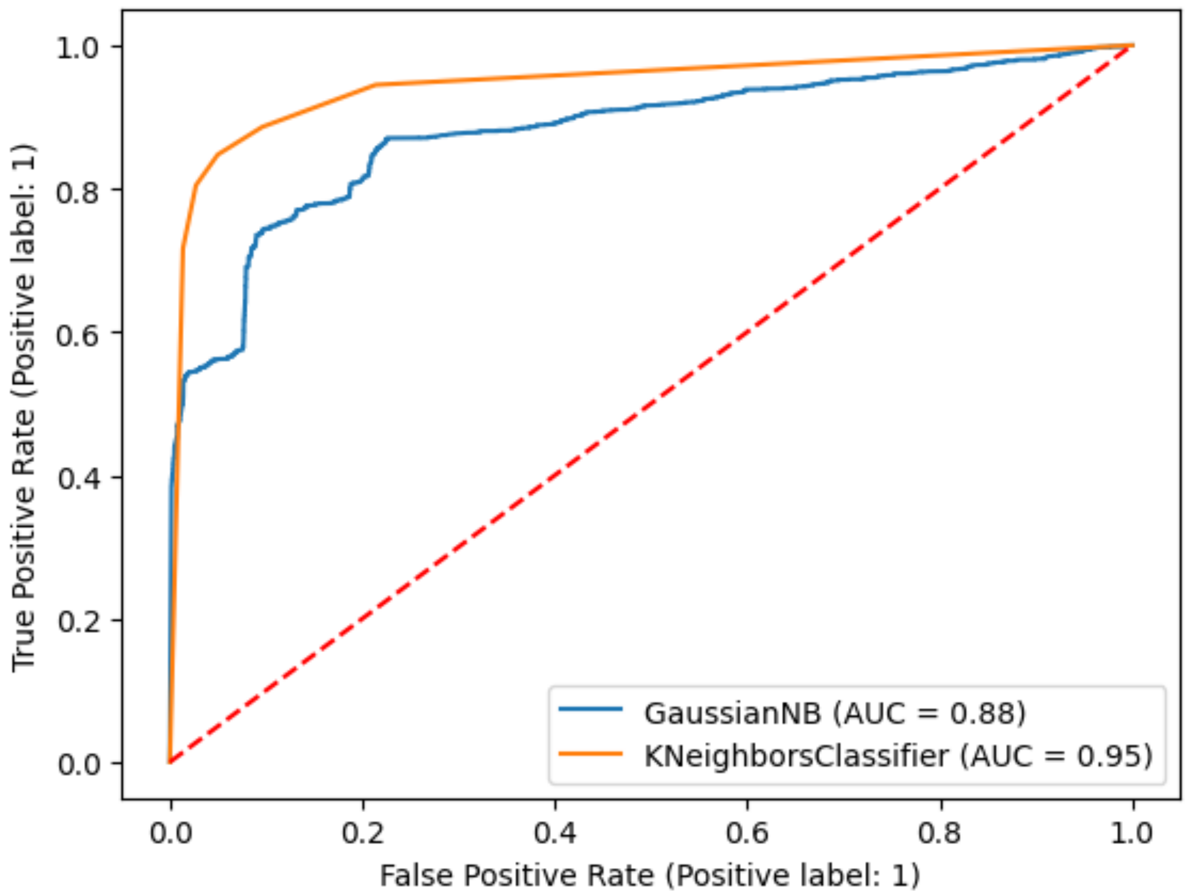


GaussianNB Classification

In [16]:
```
y_pred_NB,y_test_NB=NB(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.7871
Accuracy Score: 0.8173
              precision    recall  f1-score   support

           0       0.81      0.92      0.86     14917
           1       0.84      0.65      0.73      9440

    accuracy                           0.82     24357
   macro avg       0.82      0.79      0.80     24357
weighted avg       0.82      0.82      0.81     24357
```

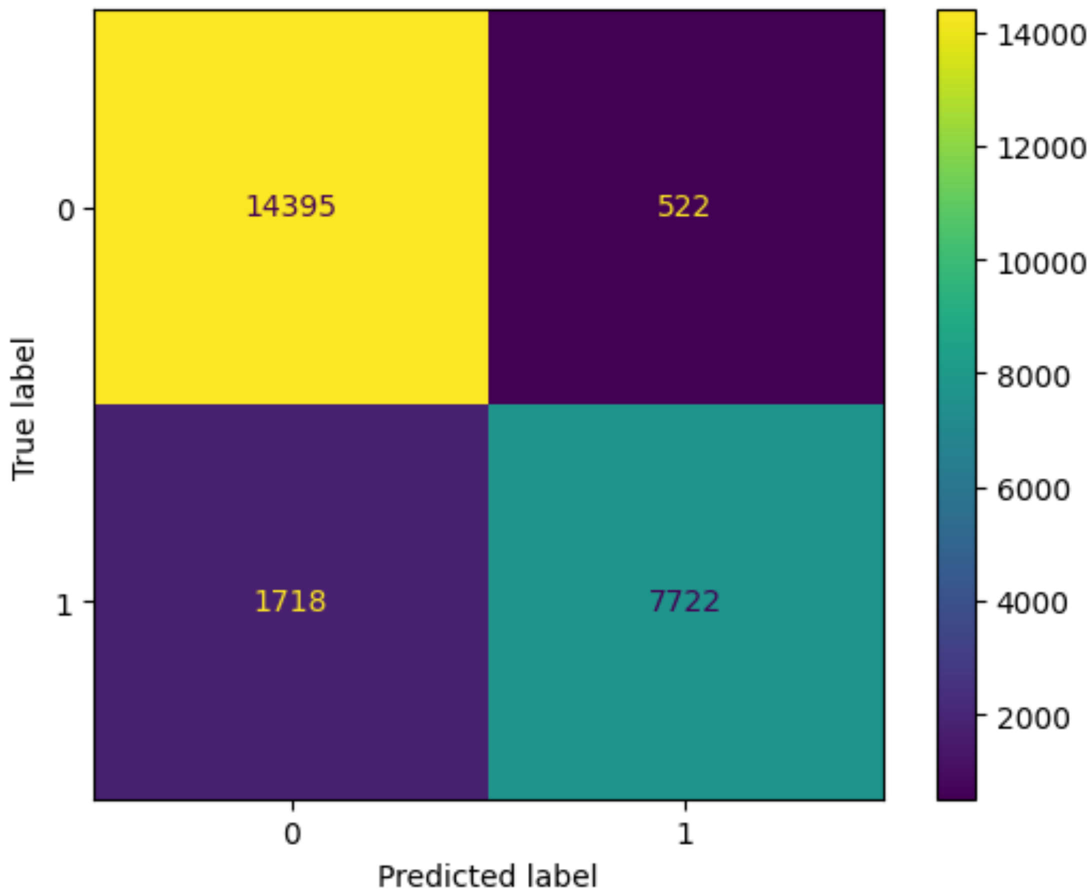

13746
1171
3279
6161
0
1
True label
0
1
Predicted label
12000
10000
8000
6000
4000
2000

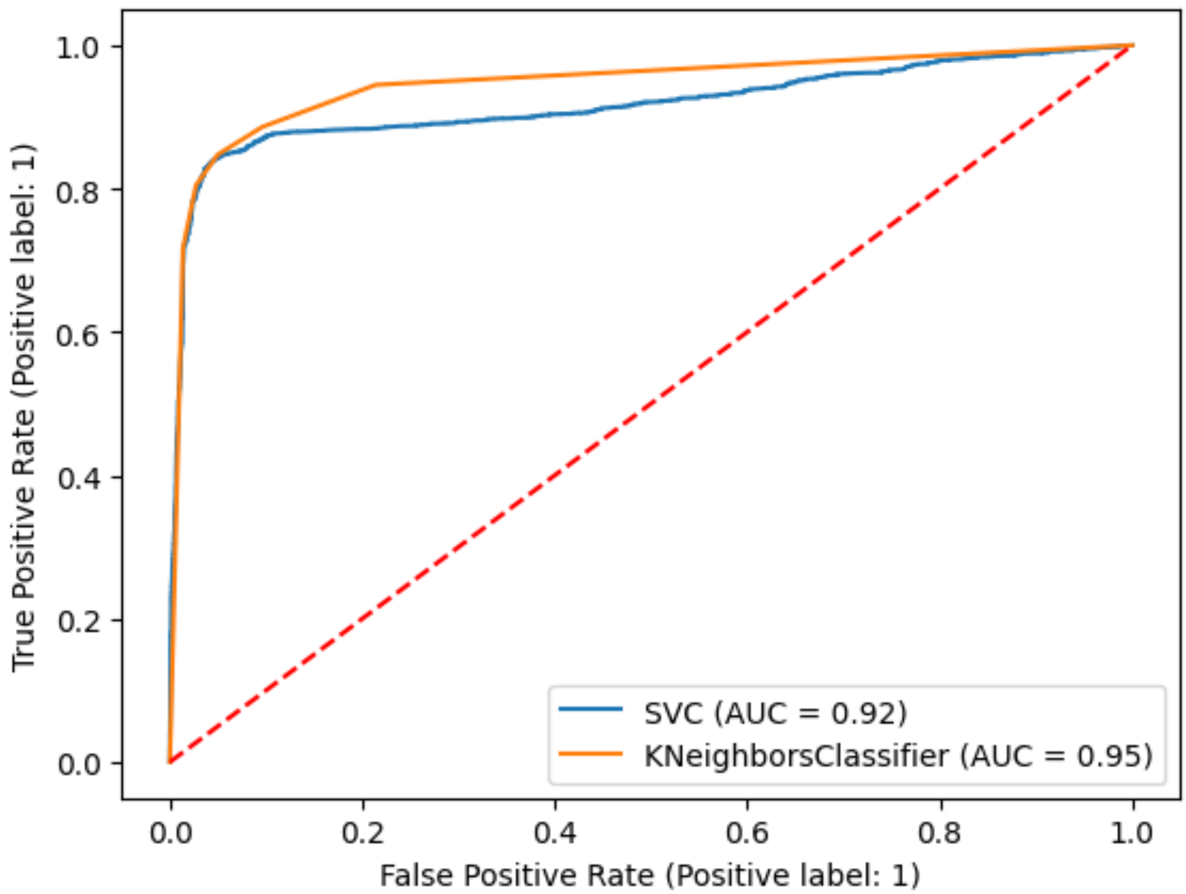


SVM Classification

In [17]:
```
y_pred_SVM,y_test_SVM=SVM(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.8915
Accuracy Score: 0.9080
              precision    recall  f1-score   support

           0       0.89      0.97      0.93     14917
           1       0.94      0.82      0.87      9440

    accuracy                           0.91     24357
   macro avg       0.92      0.89      0.90     24357
weighted avg       0.91      0.91      0.91     24357
```

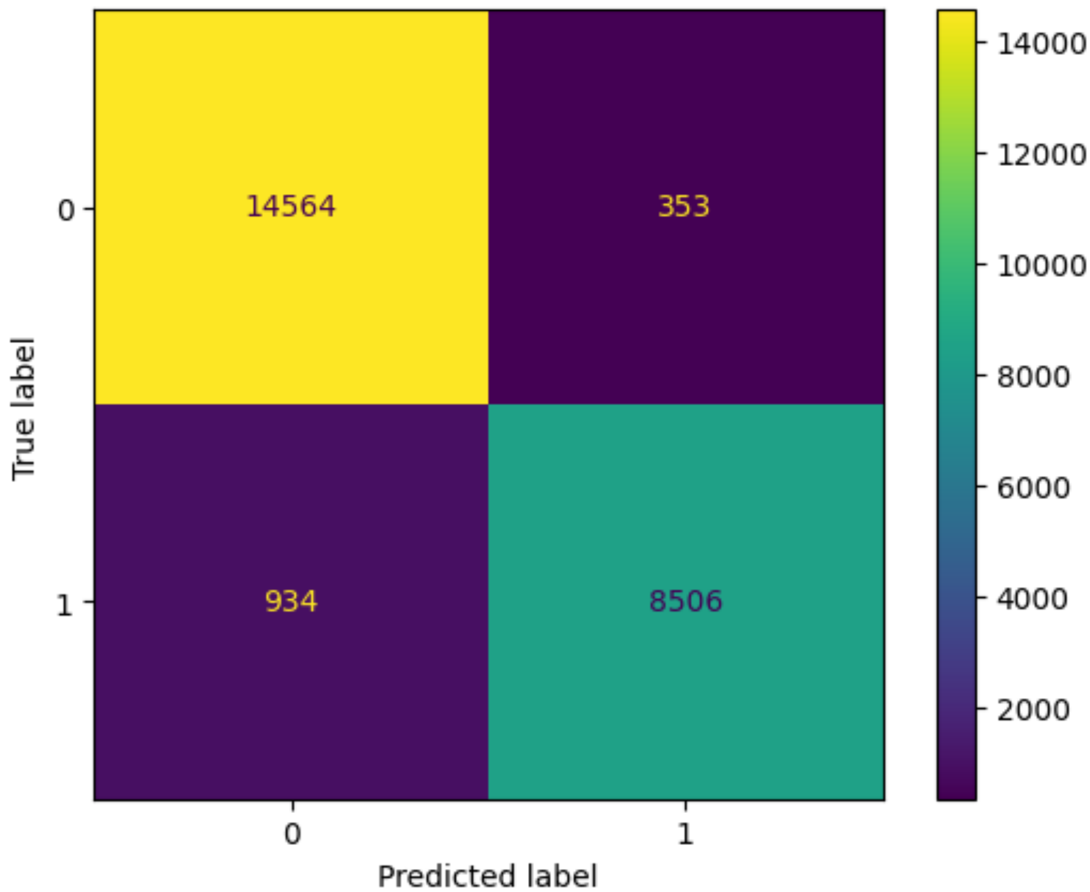

14395
522
1718
7722
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000



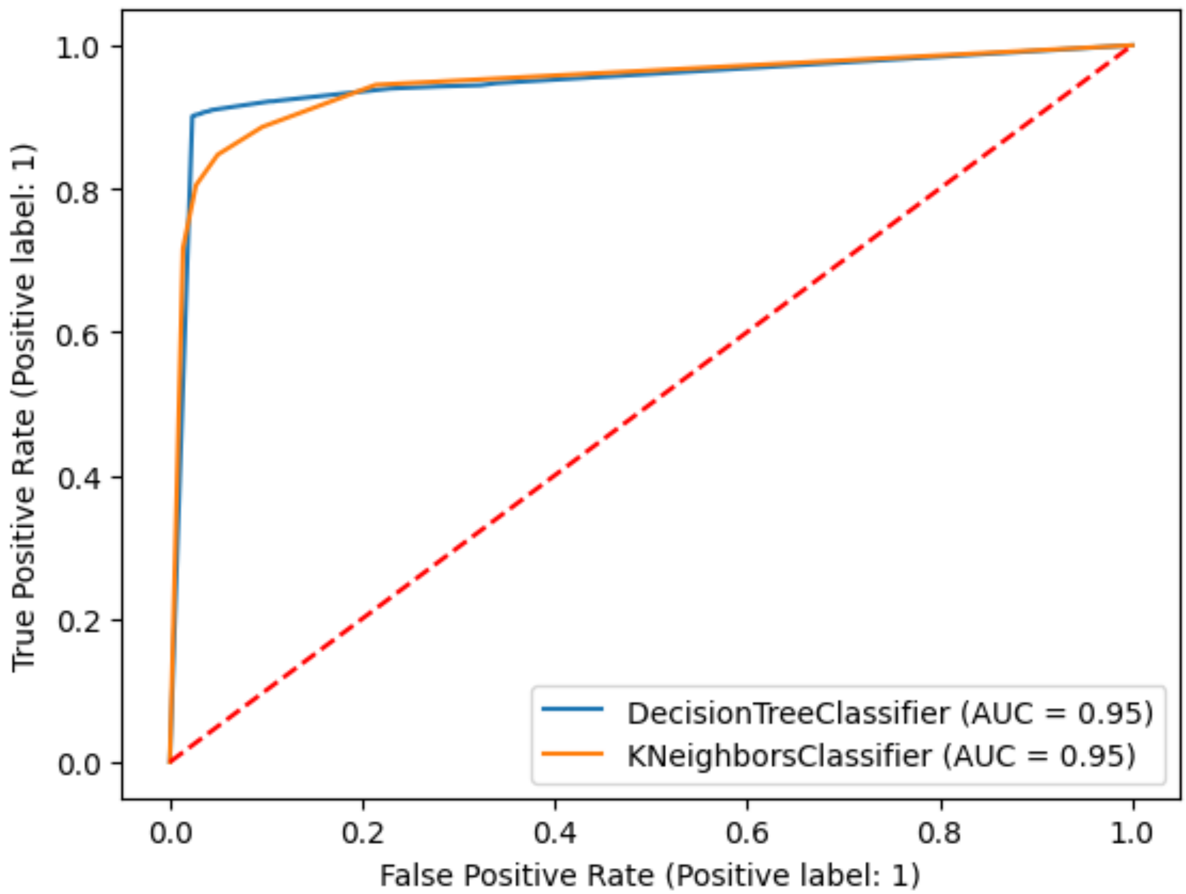
Decision Tree Classification

In [18]:
```
y_pred_DT,y_test_DT=DecisionTree(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.9387
Accuracy Score: 0.9472
              precision    recall  f1-score   support

           0       0.94      0.98      0.96     14917
           1       0.96      0.90      0.93      9440

    accuracy                           0.95     24357
   macro avg       0.95      0.94      0.94     24357
weighted avg       0.95      0.95      0.95     24357
```



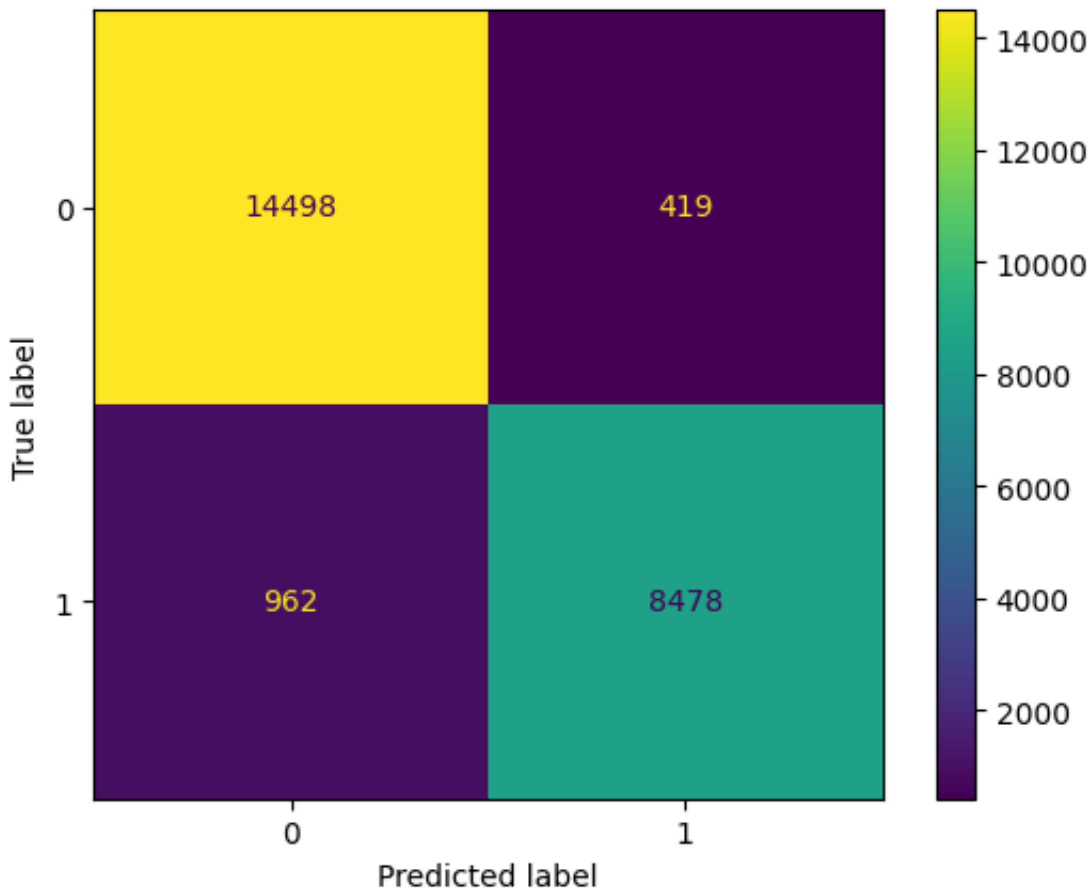
14564
353
934
8506
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000

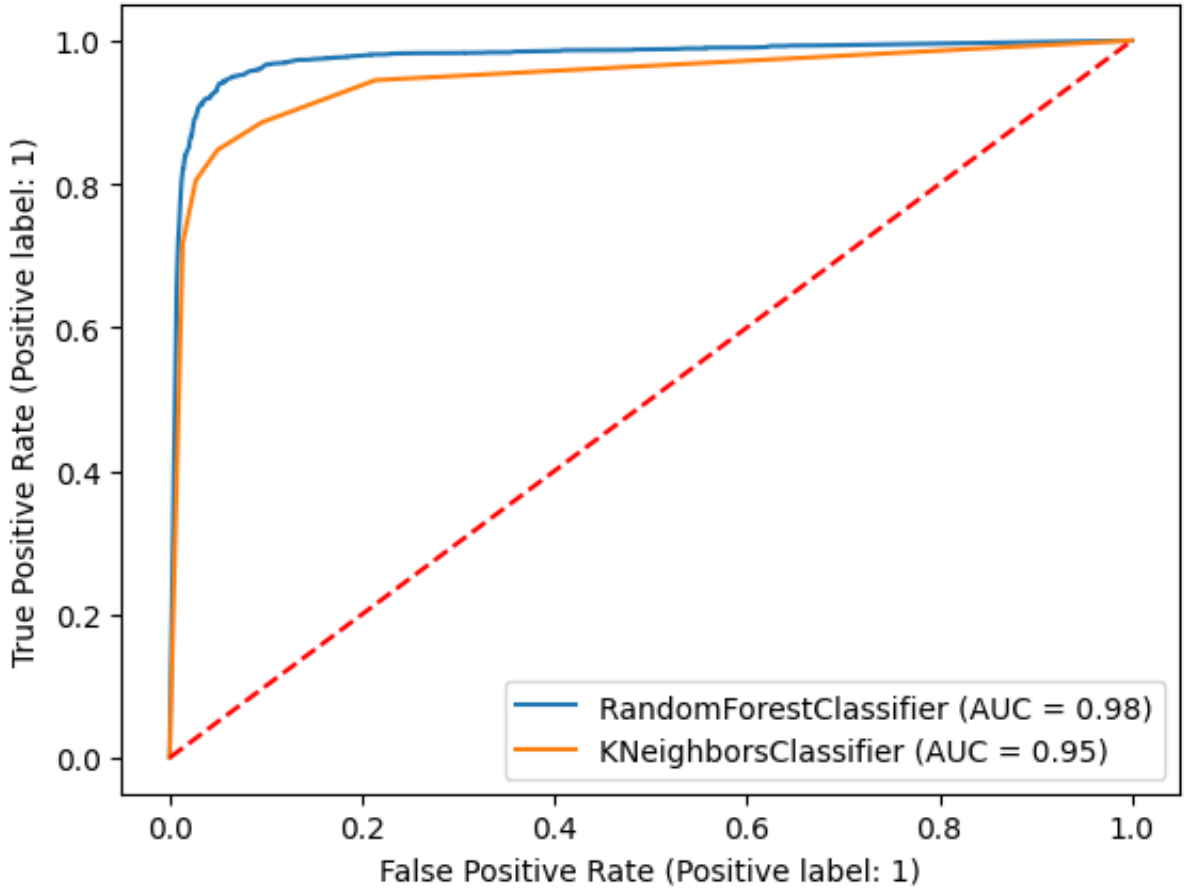


Random Forest Classification

In [19]:
```
y_pred_DF,y_test_RF=RandomForest(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.9350
Accuracy Score: 0.9433
              precision    recall  f1-score   support

           0       0.94      0.97      0.95     14917
           1       0.95      0.90      0.92      9440

    accuracy                           0.94     24357
   macro avg       0.95      0.94      0.94     24357
weighted avg       0.94      0.94      0.94     24357
```

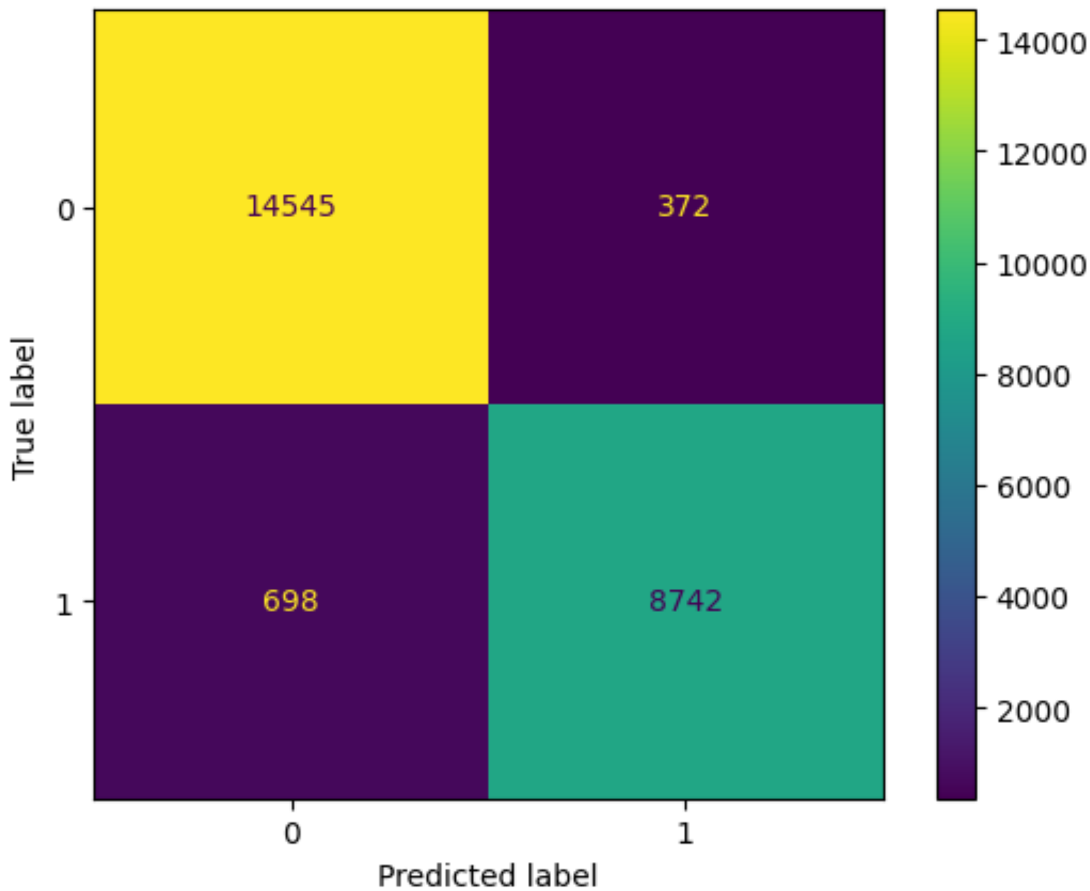

14498
419
962
8478
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000

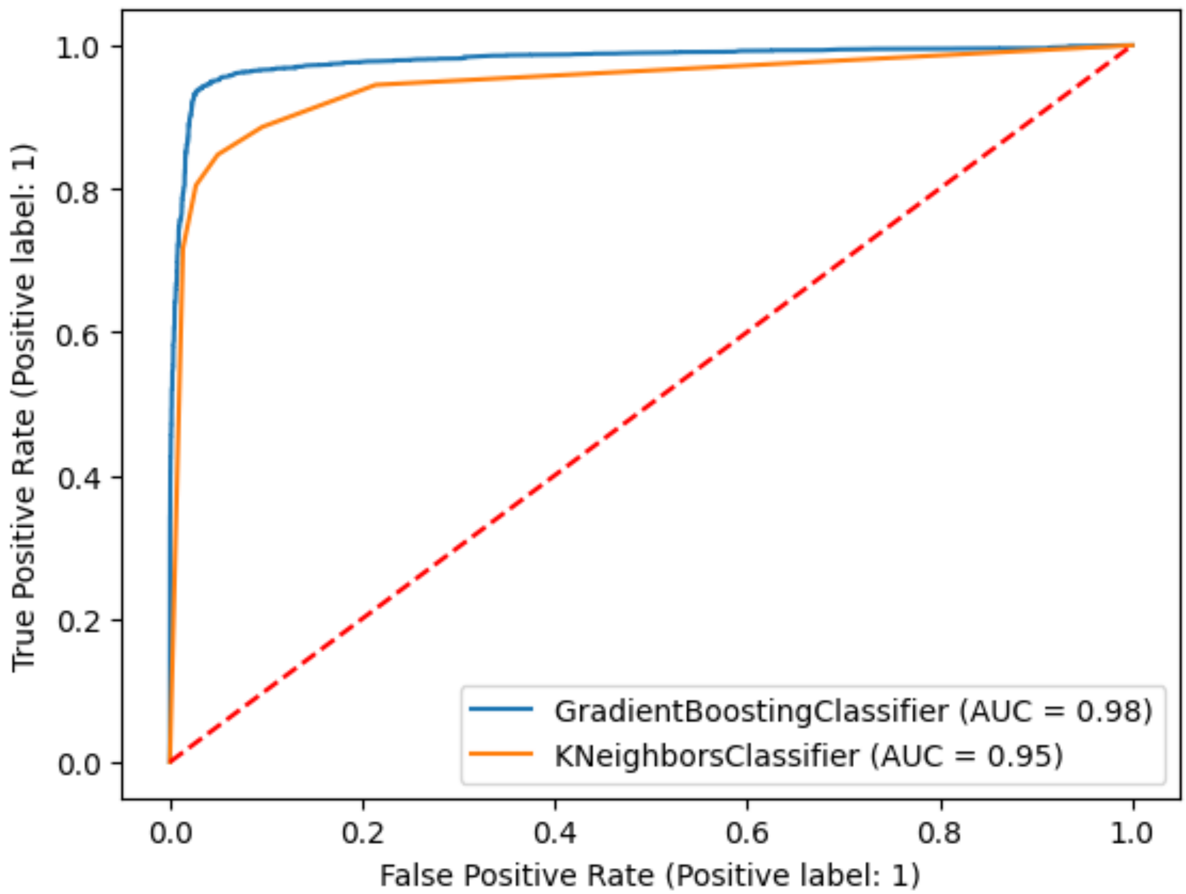


Gradient Boost Classification

In [20]:
```
y_pred_GB,y_test_GB=Gradient_Boosting(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.9506
Accuracy Score: 0.9561
              precision    recall  f1-score   support

           0       0.95      0.98      0.96     14917
           1       0.96      0.93      0.94      9440

    accuracy                           0.96     24357
   macro avg       0.96      0.95      0.95     24357
weighted avg       0.96      0.96      0.96     24357
```

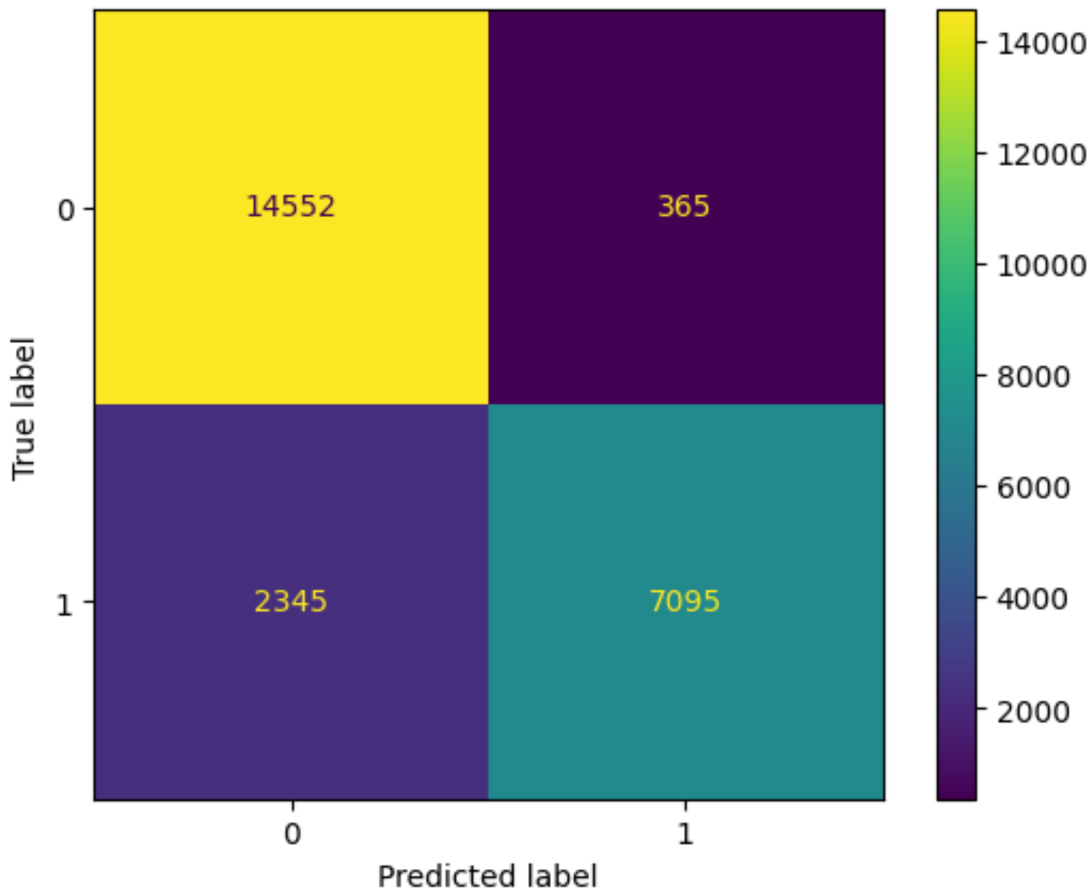

14545
372
698
8742
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000

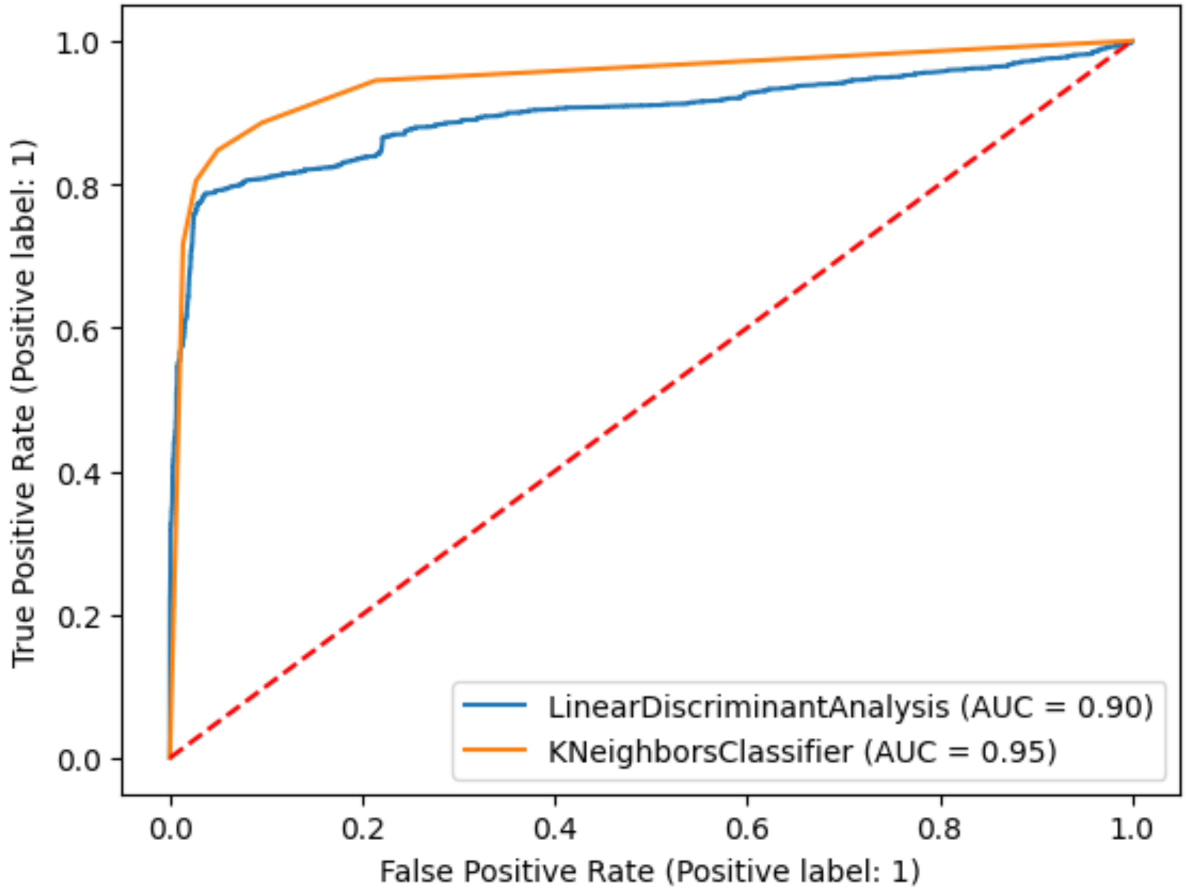


Linear Discriminant Analysis Classification

In [21]:
```
y_pred_LDA,y_test_LDA=LDA(x_train1,x_test,y_train1,y_test)
```

```
AUC: 0.8636
Accuracy Score: 0.8887
              precision    recall  f1-score   support

           0       0.86      0.98      0.91     14917
           1       0.95      0.75      0.84      9440

    accuracy                           0.89     24357
   macro avg       0.91      0.86      0.88     24357
weighted avg       0.90      0.89      0.89     24357
```


14552
365
2345
7095
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000



Part3: Semi-Supervised learning

Self Training Classifier

In [14]:
```
from sklearn.semi_supervised import SelfTrainingClassifier
```

In [15]:
```
def data_process(x_train1,x_train2,y_train1):
    dataset=x_train1
    dataset['y']=y_train1
    dataset2=x_train2
    dataset2['y']=-1
    dataset=dataset.append(dataset2, ignore_index=True)
    dataset = dataset[np.isfinite(dataset).all(1)]
    dataset.reset_index()
    return dataset

def SS_KNN(x_train,x_test,y_train,y_test,n=5):
    knn=KNeighborsClassifier(n_neighbors = n)
    SS_model = SelfTrainingClassifier(knn)
    SS_model.fit(x_train, y_train)
```

```
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS KNN'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test

def SS_LRC(x_train,x_test,y_train,y_test):
    lr = LogisticRegression()
    SS_model = SelfTrainingClassifier(lr)
    SS_model.fit(x_train, y_train)
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS Logistic Regression Classification'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test

def SS_NB(x_train,x_test,y_train,y_test):
    nb = GaussianNB()
    SS_model = SelfTrainingClassifier(nb)
    SS_model.fit(x_train, y_train)
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS GaussianNB Classification'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test

def SS_SVM(x_train,x_test,y_train,y_test,x,y):
    svc = SVC(probability=True, gamma="auto")
    '''svc.fit(x,y)
    svc.predict_proba(x_test)'''
    SS_model = SelfTrainingClassifier(svc)
    SS_model.fit(x_train, y_train)
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS SVM'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test

def SS_DecisionTree(x_train,x_test,y_train,y_test,x,y):
    parameters = {'splitter':('best','random'),
                'criterion':("gini","entropy"),
                "max_depth":[*range(1, 20)]}
    DT = DecisionTreeClassifier()
    model=GridSearchCV(DT,param_grid=parameters,cv=5,scoring='f1')
    model.fit(x, y)
    SS_model = SelfTrainingClassifier(model.best_estimator_)
    SS_model.fit(x_train, y_train)
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS Decision Tree Classification'
```

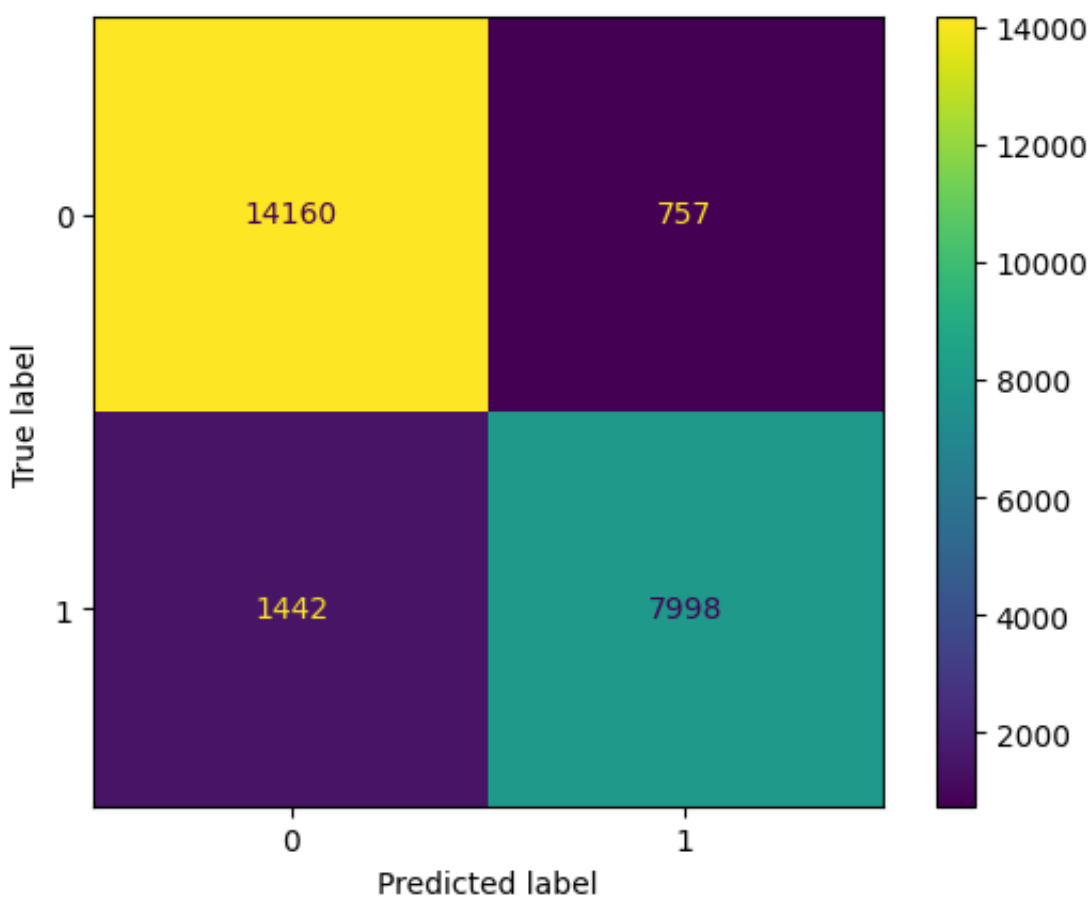
```
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    '''SS_model = SelfTrainingClassifier(DT)
    model=GridSearchCV(SS_model,param_grid=parameters,cv=10,scoring='f1')
    model.fit(x_train, y_train)
    y_pred = model.best_estimator_.predict(x_test)
    classifier='Self Training SS Decision Tree Classification'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=model.best_estimator_,X=x_test,y=y_test)'''
    return y_pred,y_test

def SS_RandomForest(x_train,x_test,y_train,y_test,x,y):
    RF = RandomForestClassifier()
    parameters = {'criterion':("gini","entropy"),
                "max_depth":[*range(1, 20)],
                "n_estimators":[5,10,20,40]}
    model=GridSearchCV(RF,param_grid=parameters,cv=5,scoring='f1')
    model.fit(x, y)
    SS_model = SelfTrainingClassifier(model.best_estimator_)
    SS_model.fit(x_train, y_train)
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS Random Forest Classification'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test

def SS_Gradient_Boosting(x_train,x_test,y_train,y_test,x,y):
    gb = GradientBoostingClassifier()
    parameters = {'max_depth':[*range(1, 10)]}
    model=GridSearchCV(gb,param_grid=parameters,cv=5,scoring='f1')
    model.fit(x, y)
    SS_model = SelfTrainingClassifier(model.best_estimator_)
    SS_model.fit(x_train, y_train)
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS Gradient Boost Classification'
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test

def SS_LDA(x_train,x_test,y_train,y_test):
    lda = LinearDiscriminantAnalysis()
    SS_model = SelfTrainingClassifier(lda)
    SS_model.fit(x_train, y_train)
    y_pred = SS_model.predict(x_test)
    classifier='Self Training SS Linear Discriminant Analysis Classification
    Analyze(y_pred,y_test,classifier)
    plot_roc_curve(estimator=SS_model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test
```

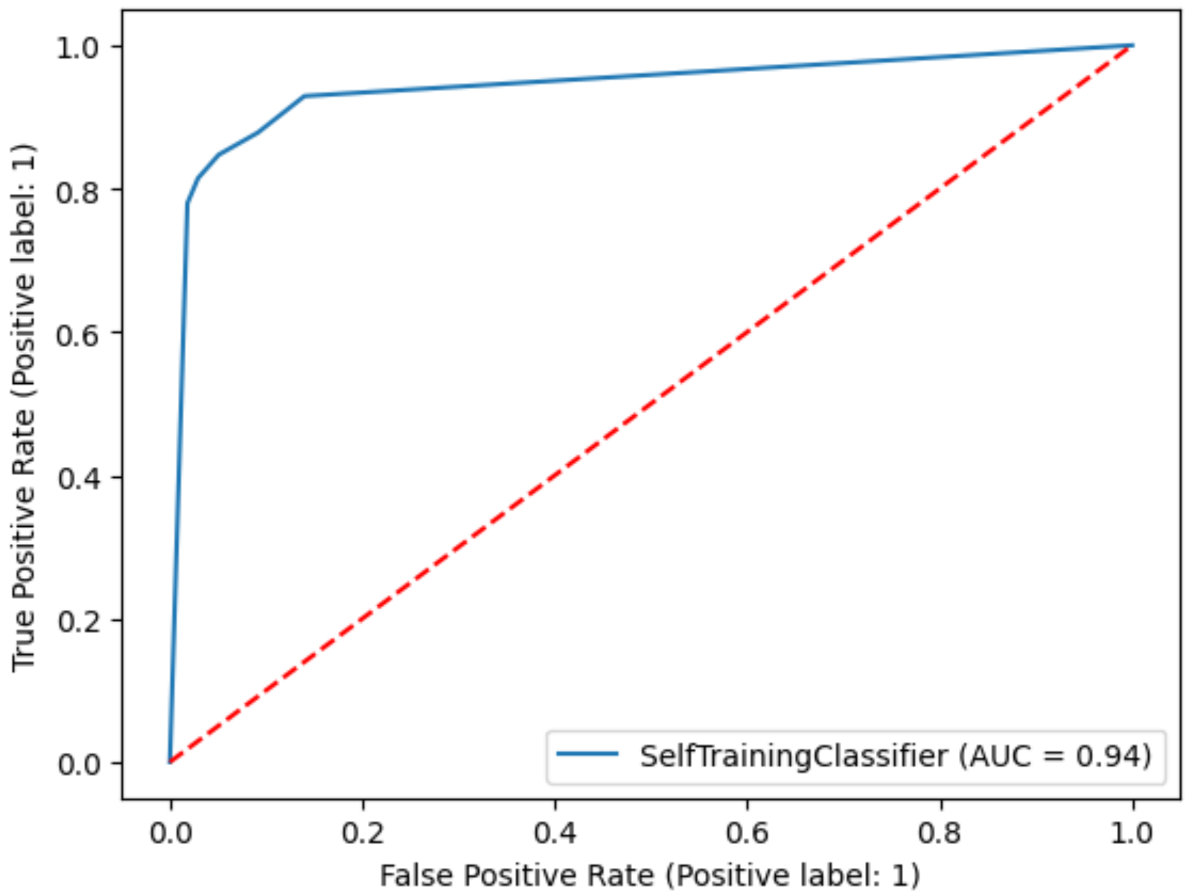
```
D=data_process(x_train1,x_train2,y_train1)
y_train_SSL=D['y'].values
x_train_SSL=D.drop('y',axis=1)
```

Semi-Supervised Self Training KNN Classification

In [24]:
```
y_pred_SS_KNN,y_test_SS_KNN=SS_KNN(x_train_SSL,x_test,y_train_SSL,y_test)
```

```
AUC: 0.8982
Accuracy Score: 0.9097
              precision    recall  f1-score   support

           0       0.91      0.95      0.93     14917
           1       0.91      0.85      0.88      9440

    accuracy                           0.91     24357
   macro avg       0.91      0.90      0.90     24357
weighted avg       0.91      0.91      0.91     24357
```

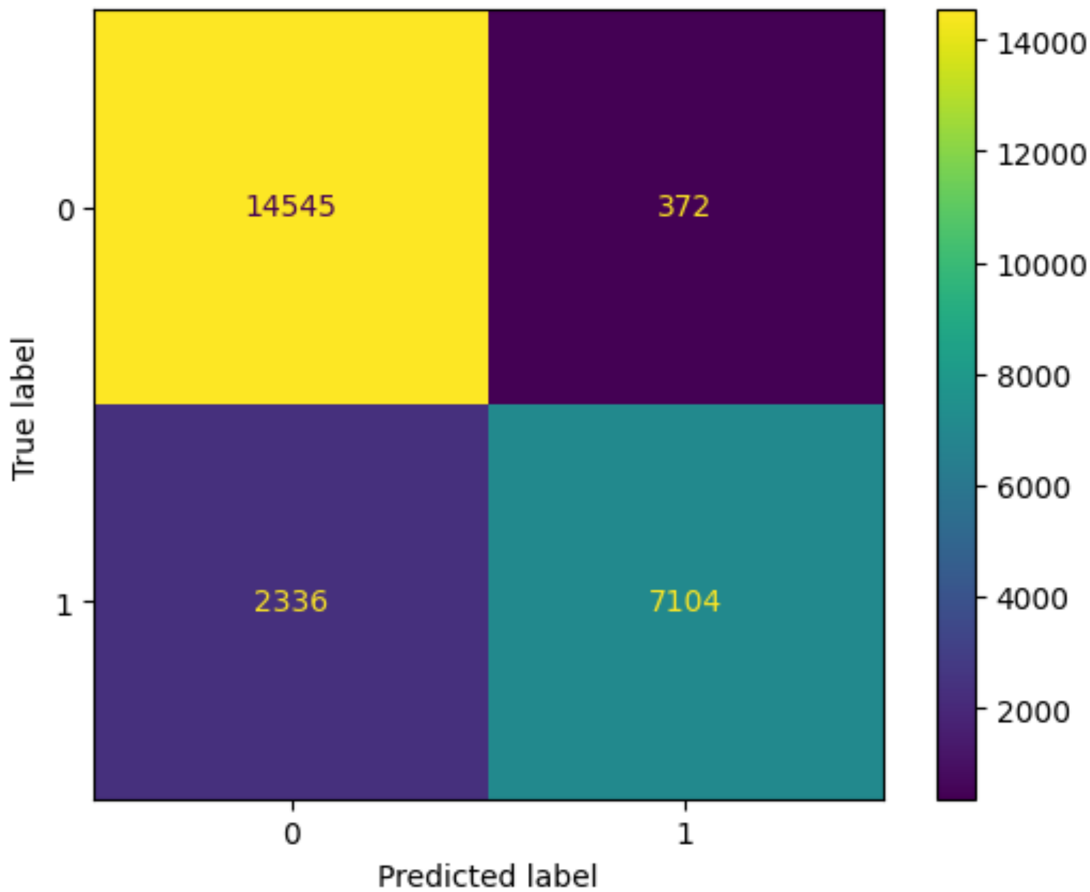


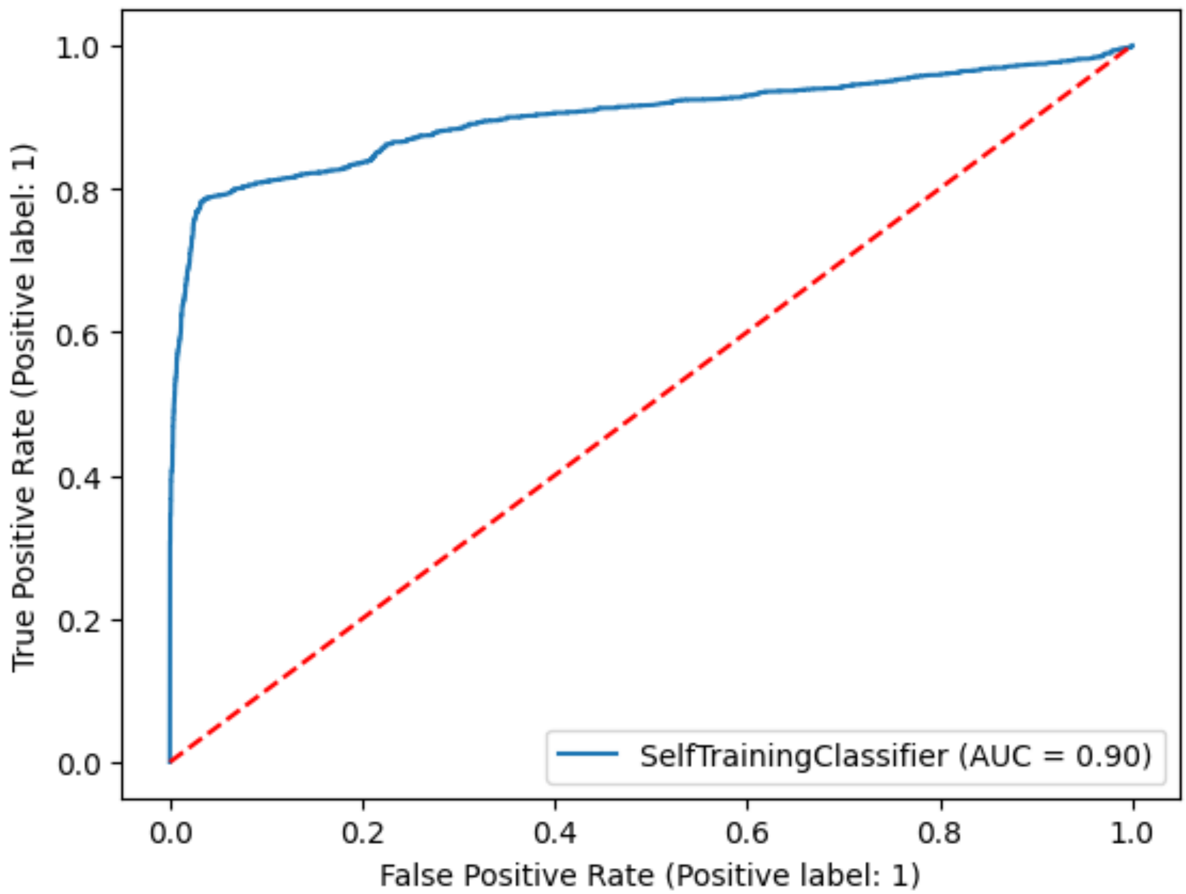


Semi-Supervised Self Training Logistic Regression Classification

In [25]:
```
y_pred_SS_DT,y_test_SS_DT=SS_LRC(x_train_SSL,x_test,y_train_SSL,y_test)
```

```
AUC: 0.8638
Accuracy Score: 0.8888
              precision    recall  f1-score   support

           0       0.86      0.98      0.91     14917
           1       0.95      0.75      0.84      9440

    accuracy                           0.89     24357
   macro avg       0.91      0.86      0.88     24357
weighted avg       0.90      0.89      0.89     24357
```

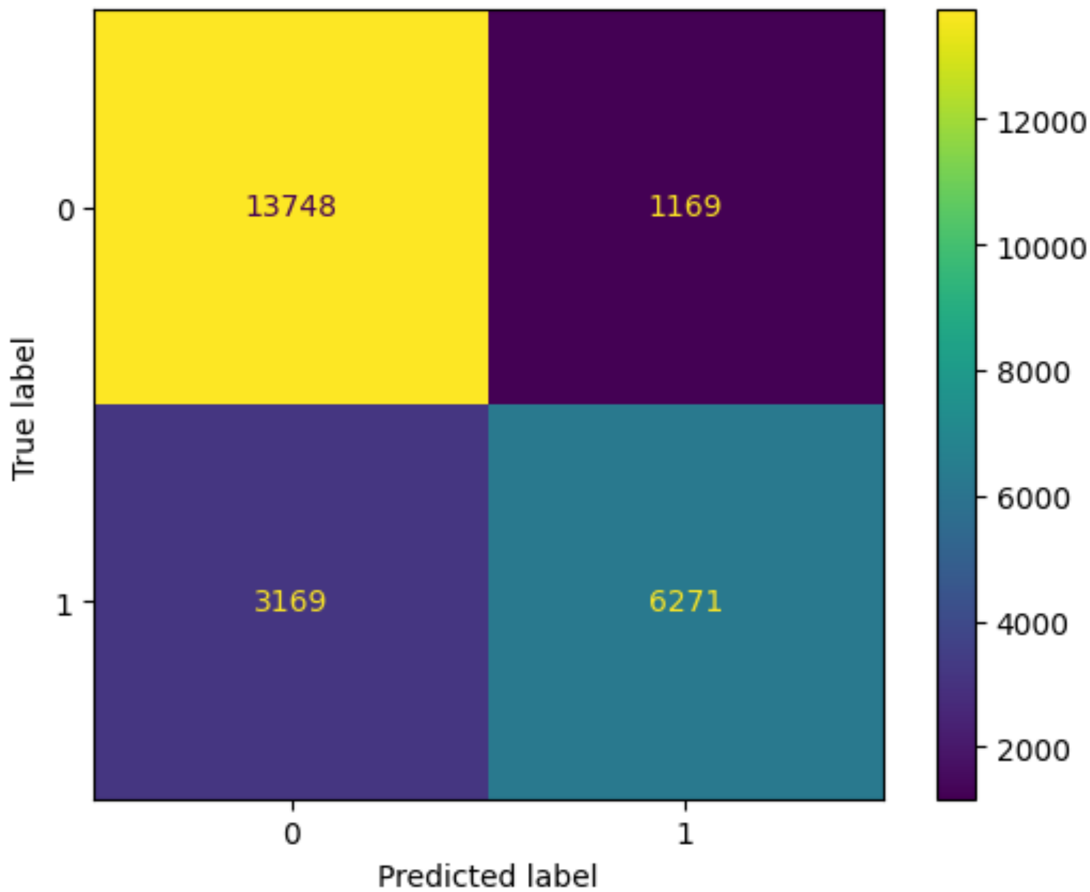

14545
372
2336
7104
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000

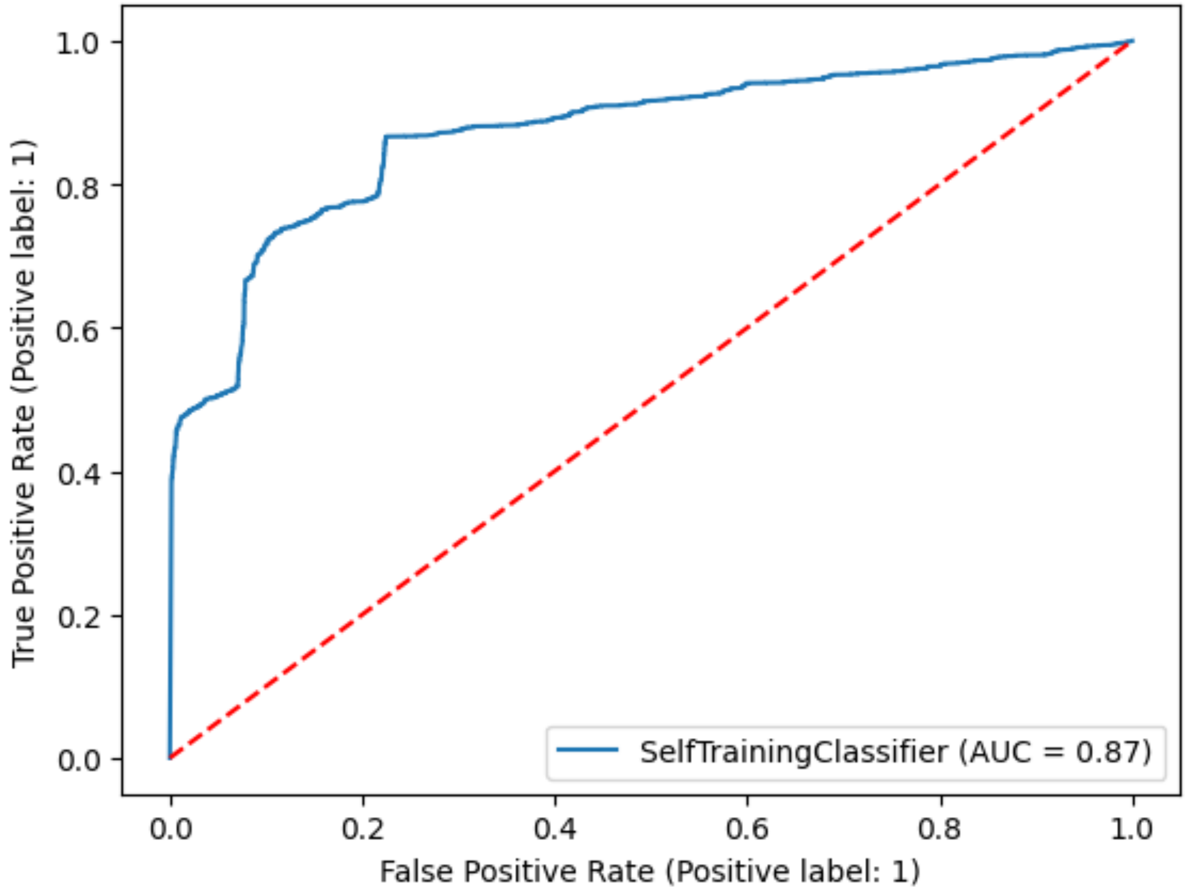


Semi-Supervised Self Training GaussianNB Classification

In [26]:
```
y_pred_SS_NB,y_test_SS_NB=SS_NB(x_train_SSL,x_test,y_train_SSL,y_test)
```

```
AUC: 0.7930
Accuracy Score: 0.8219
              precision    recall  f1-score   support

           0       0.81      0.92      0.86     14917
           1       0.84      0.66      0.74      9440

    accuracy                           0.82     24357
   macro avg       0.83      0.79      0.80     24357
weighted avg       0.82      0.82      0.82     24357
```

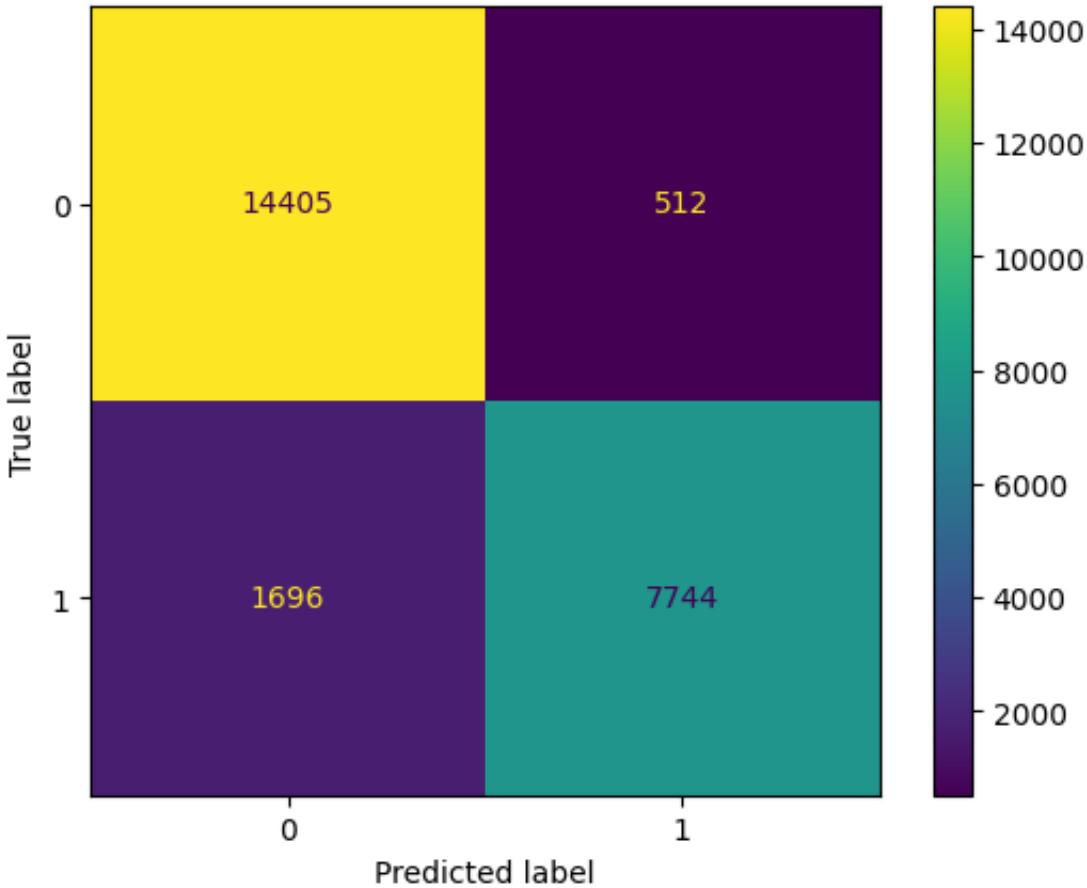

13748
1169
3169
6271
0
1
True label
0
1
Predicted label
12000
10000
8000
6000
4000
2000

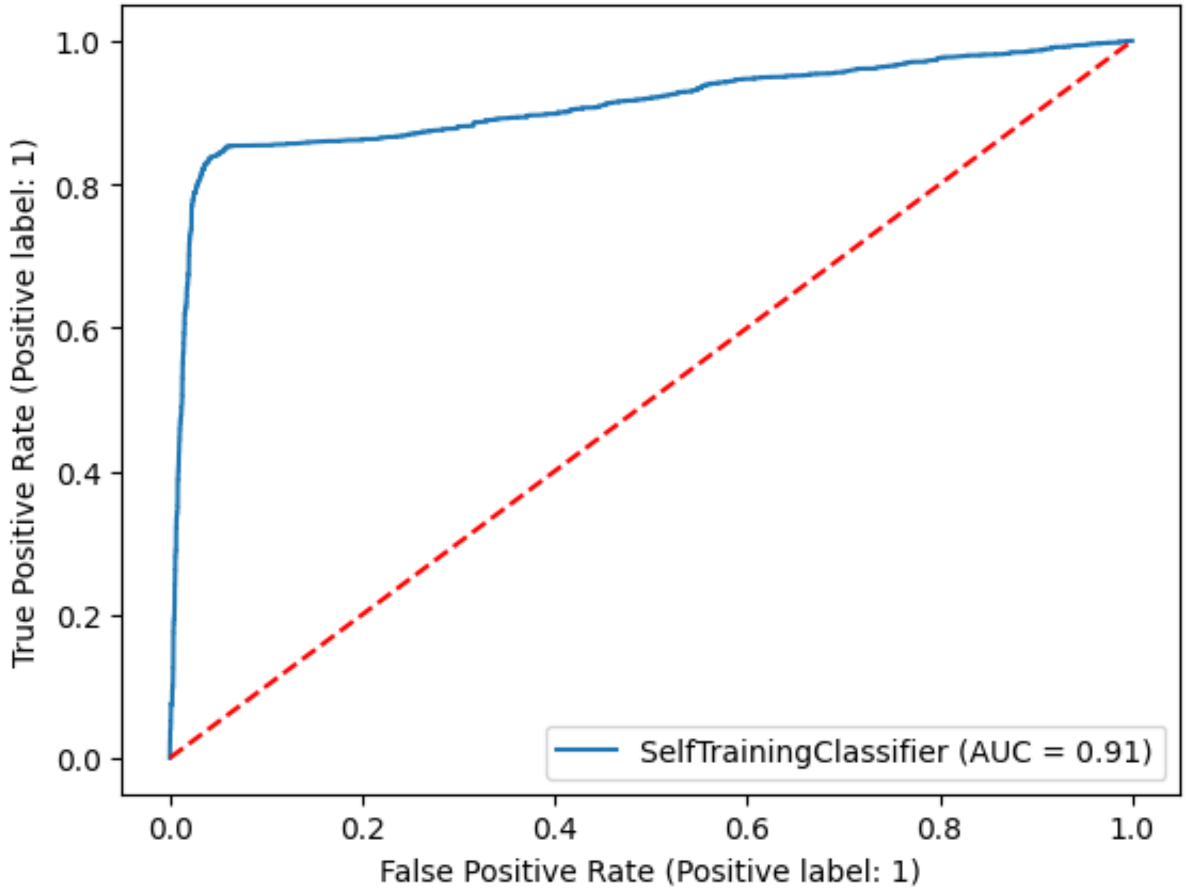


Semi-Supervised Self Training SVM Classification

In [27]:
```
y_pred_SS_SVM,y_test_SS_SVM=SS_SVM(x_train_SSL,x_test,y_train_SSL,y_test,x_t
```

```
AUC: 0.8930
Accuracy Score: 0.9093
              precision    recall  f1-score   support

           0       0.89      0.97      0.93     14917
           1       0.94      0.82      0.88      9440

    accuracy                           0.91     24357
   macro avg       0.92      0.89      0.90     24357
weighted avg       0.91      0.91      0.91     24357
```

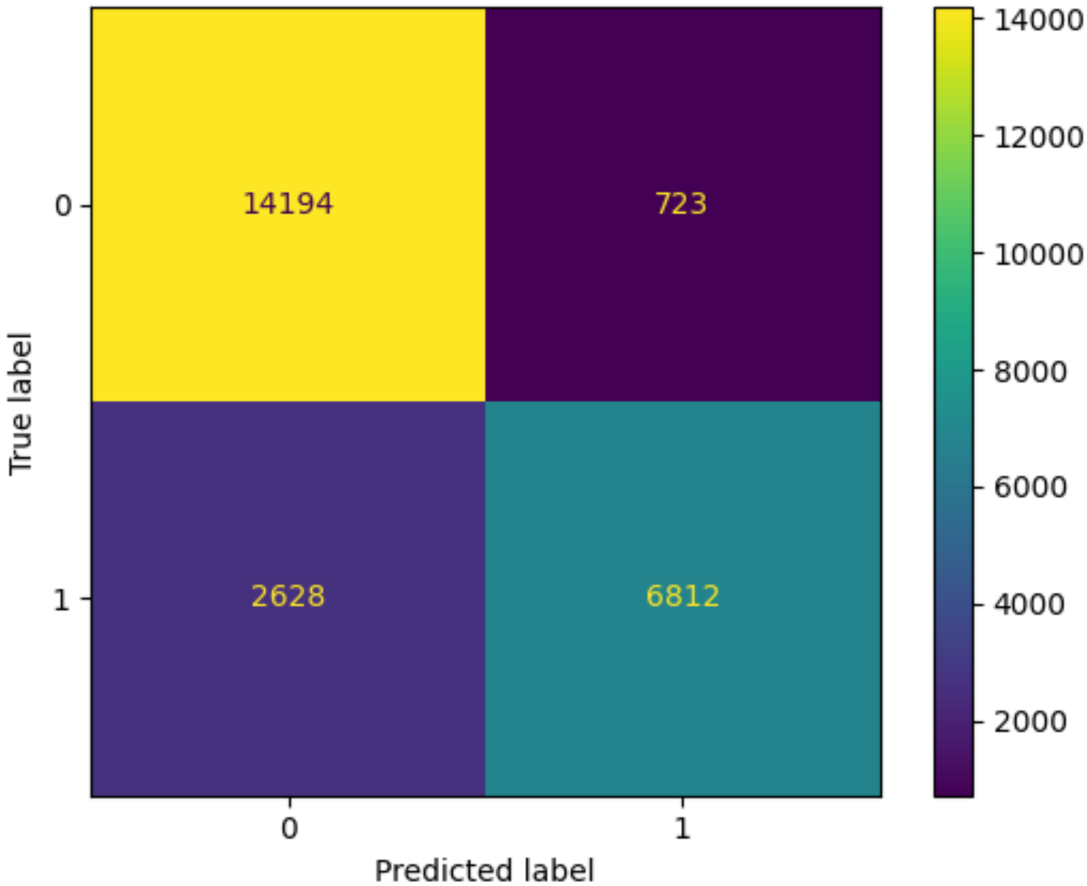

14405
512
1696
7744
0
1
True label
0
1
Predicted label
14000
12000
10000
8000
6000
4000
2000

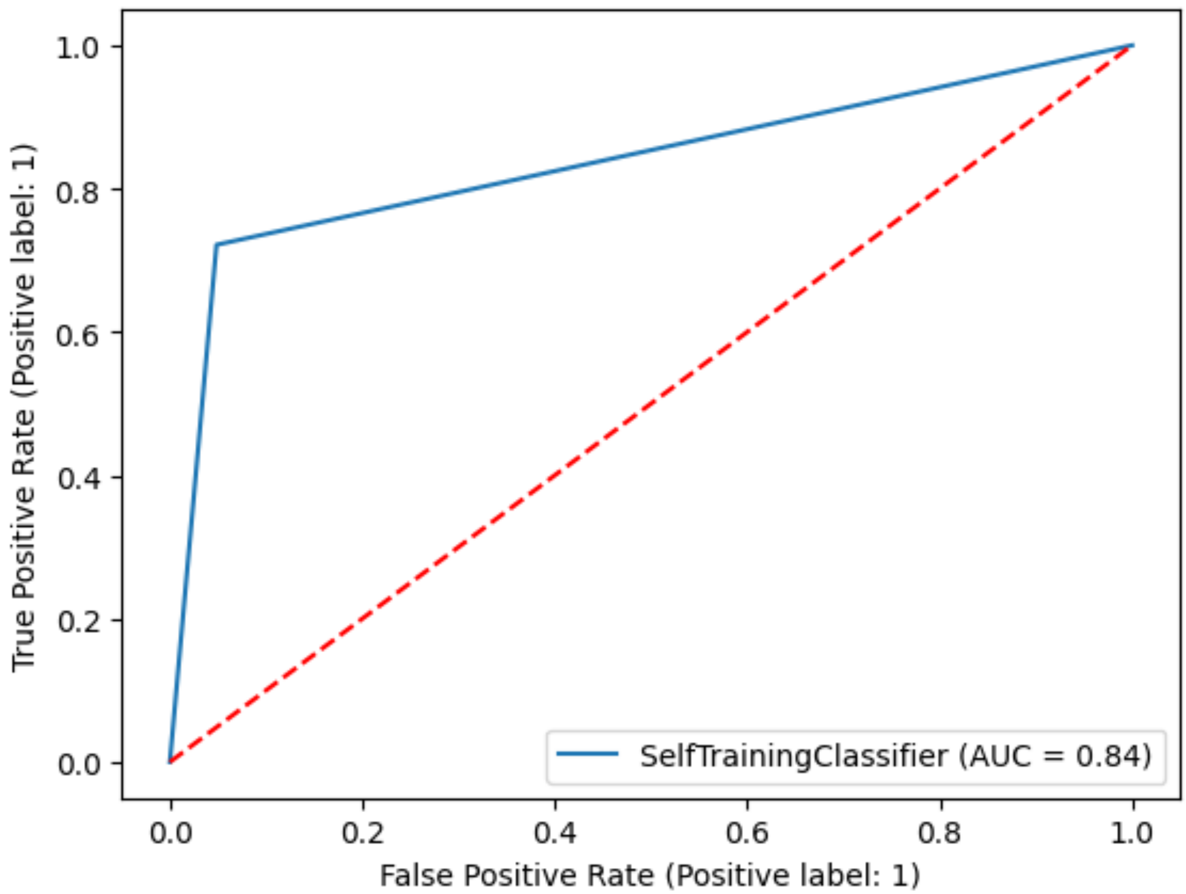


Semi-Supervised Self Training Decision Tree Classification

In [28]:
```
y_pred_SS_DT,y_test_SS_DT=SS_DecisionTree(x_train_SSL,x_test,y_train_SSL,y_t
```

```
AUC: 0.8366
Accuracy Score: 0.8624
              precision    recall  f1-score   support

           0       0.84      0.95      0.89     14917
           1       0.90      0.72      0.80      9440

    accuracy                           0.86     24357
   macro avg       0.87      0.84      0.85     24357
weighted avg       0.87      0.86      0.86     24357
```

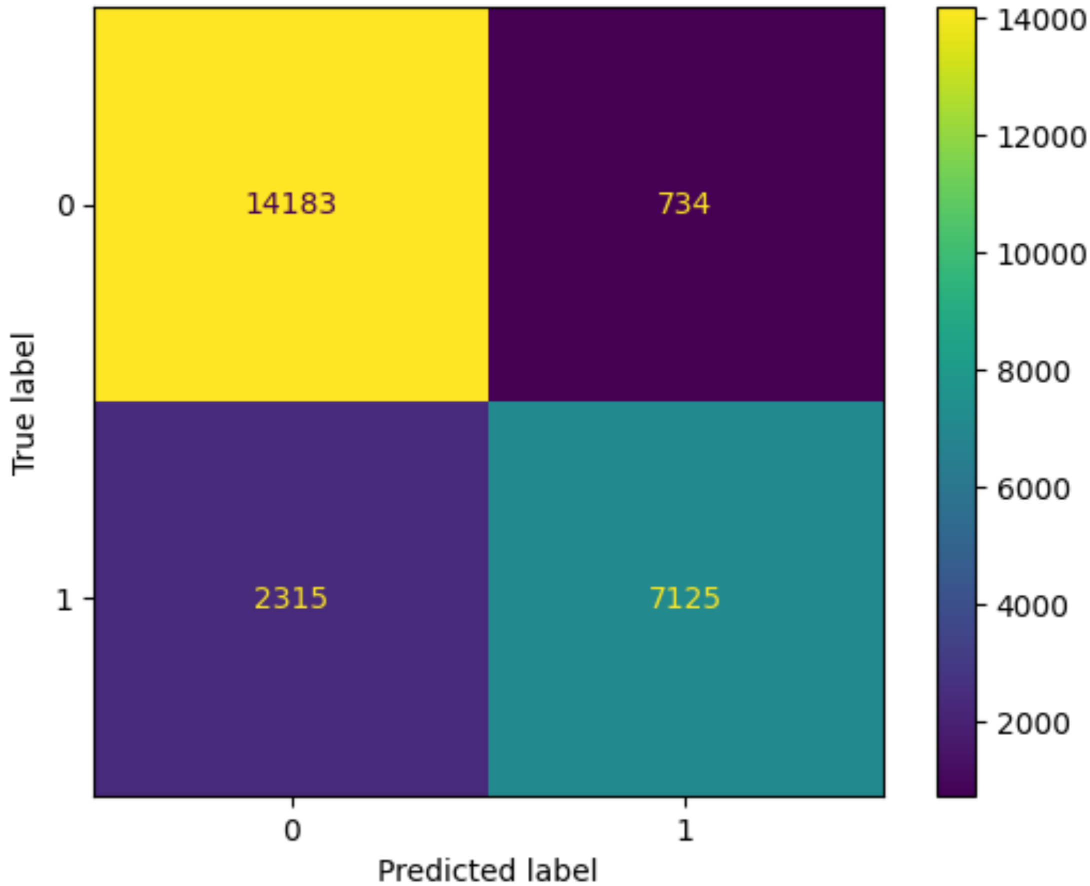

14194
723
2628
6812
0
1
0
1
True label
Predicted label
14000
12000
10000
8000
6000
4000
2000

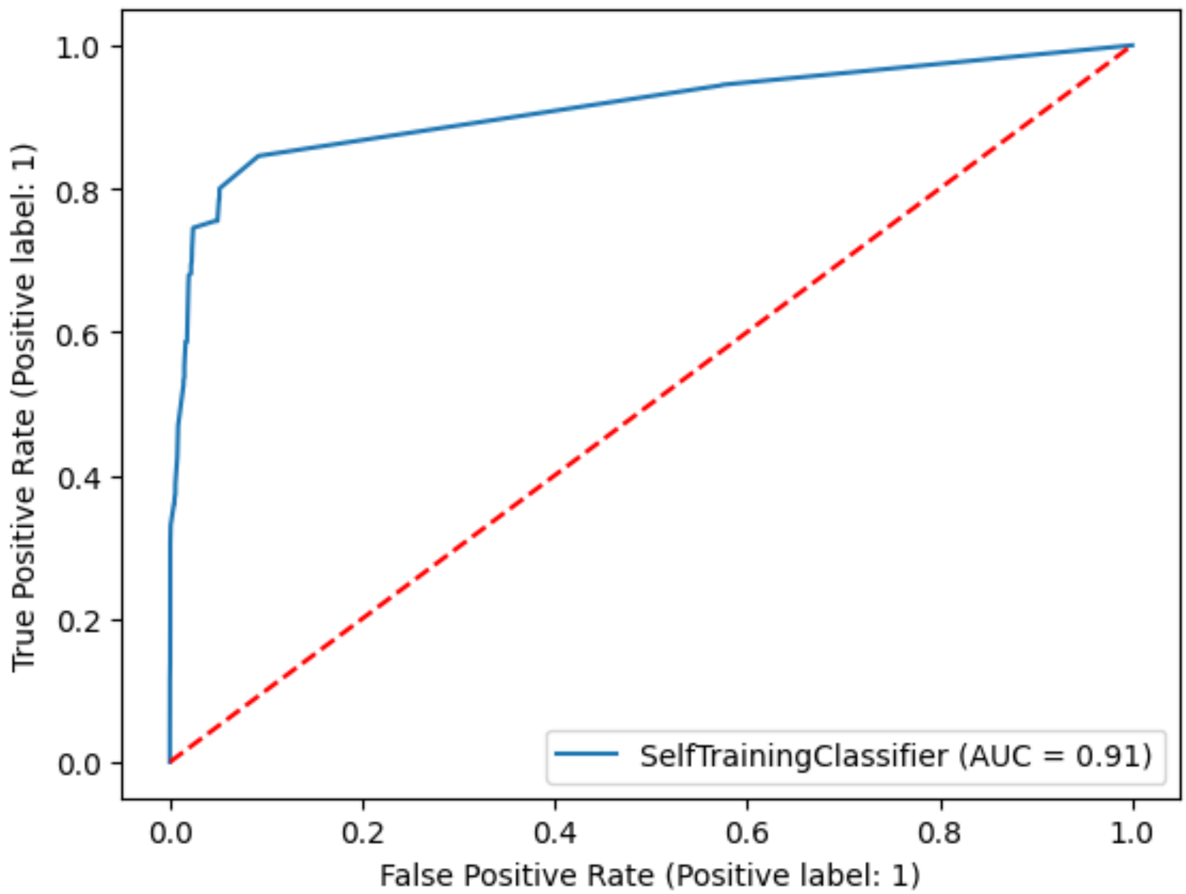


Semi-Supervised Self Training Random Forest Classification

In [29]:
```
y_pred_SS_RF,y_test_SS_RF=SS_RandomForest(x_train_SSL,x_test,y_train_SSL,y_t
```

```
AUC: 0.8528
Accuracy Score: 0.8748
              precision    recall  f1-score   support

           0       0.86      0.95      0.90     14917
           1       0.91      0.75      0.82      9440

    accuracy                           0.87     24357
   macro avg       0.88      0.85      0.86     24357
weighted avg       0.88      0.87      0.87     24357
```

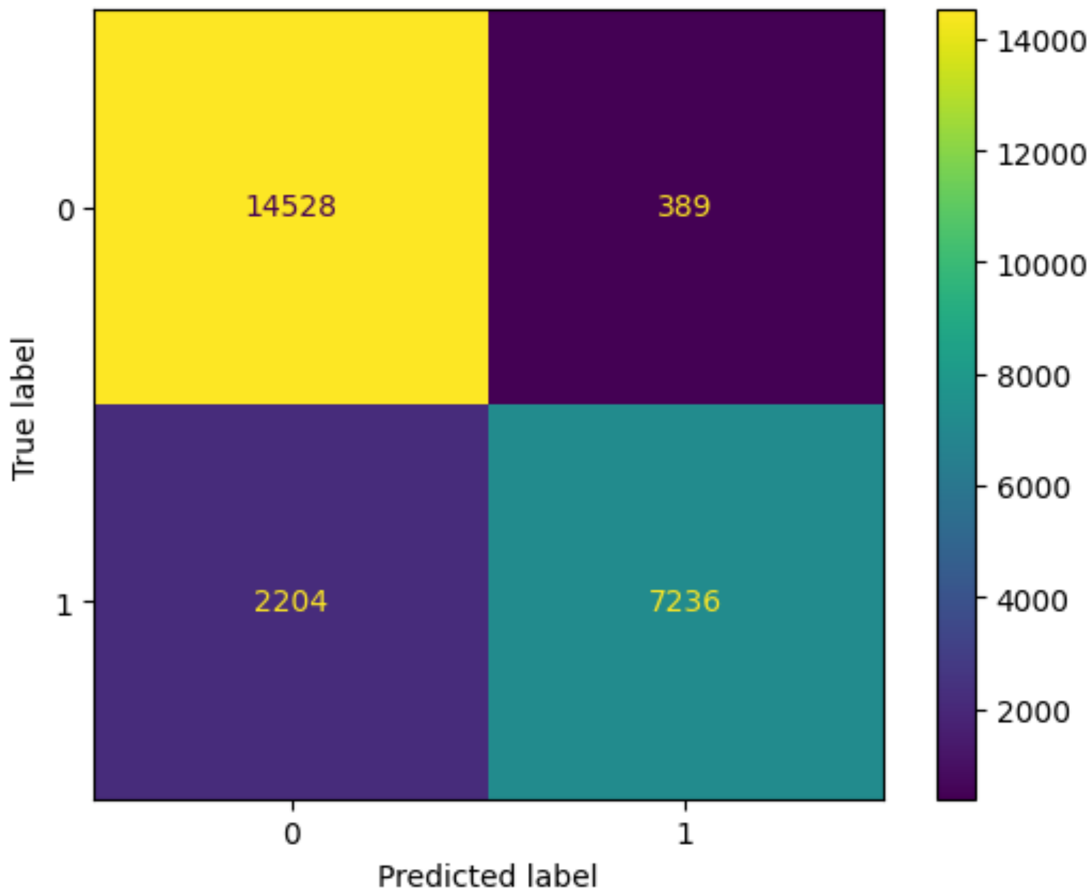

14183
734
2315
7125
True label
Predicted label
0
1
0
1
14000
12000
10000
8000
6000
4000
2000

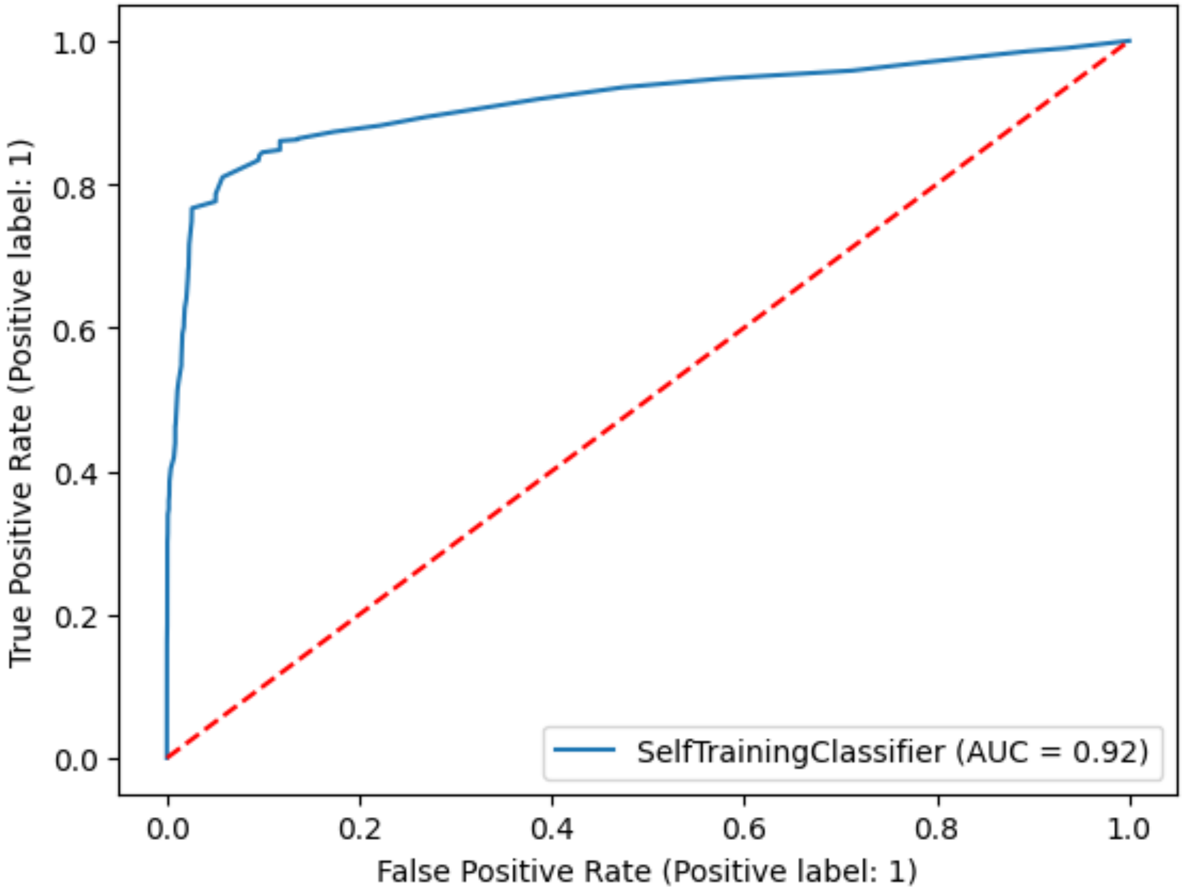


Semi-Supervised Self Training Gradient Boost Classification

In [30]:
```
y_pred_SS_GB,y_test_SS_BG=SS_Gradient_Boosting(x_train_SSL,x_test,y_train_SS
```

```
AUC: 0.8702
Accuracy Score: 0.8935
              precision    recall  f1-score   support

           0       0.87      0.97      0.92     14917
           1       0.95      0.77      0.85      9440

    accuracy                           0.89     24357
   macro avg       0.91      0.87      0.88     24357
weighted avg       0.90      0.89      0.89     24357
```

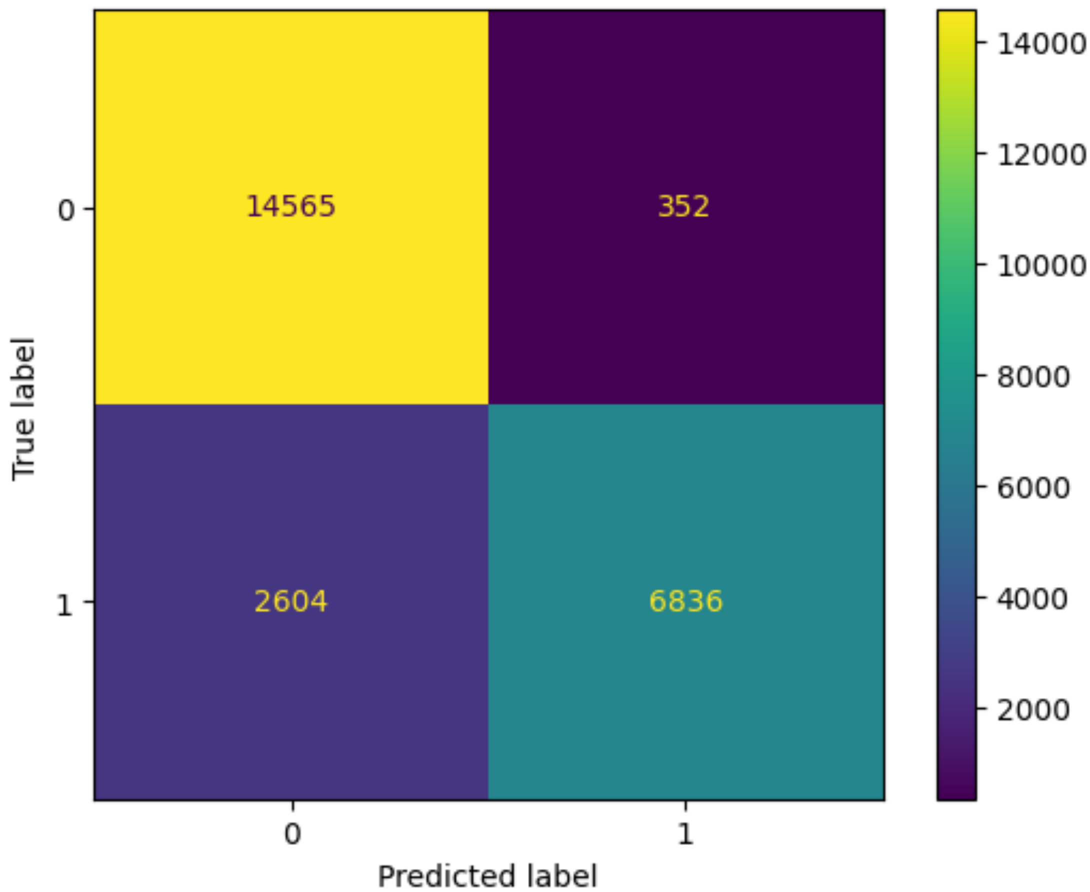

14528
389
2204
7236
True label
Predicted label
0
1
0
1
14000
12000
10000
8000
6000
4000
2000

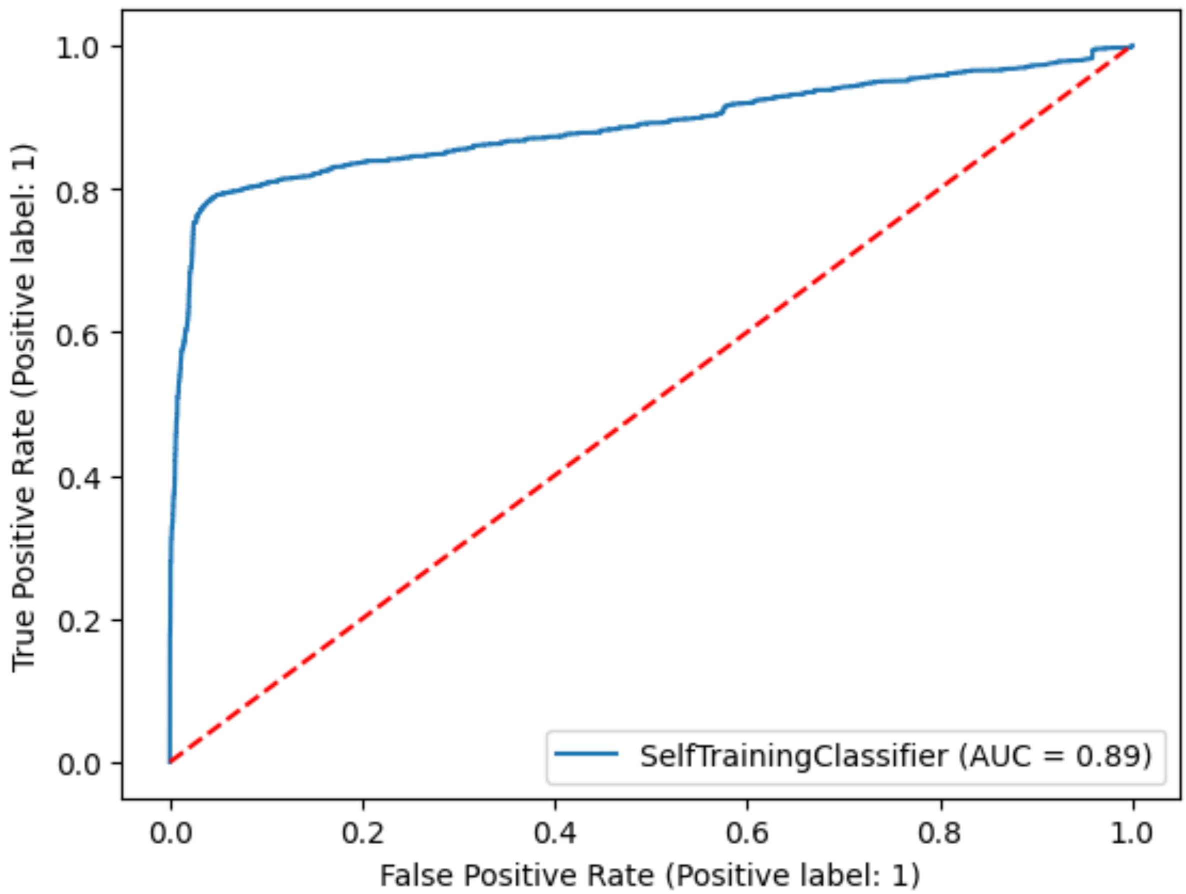


Semi-Supervised Self Training Linear Discriminant Analysis Classification

In [31]:
```
y_pred_SS_LDA,y_test_SS_LDA=SS_LDA(x_train_SSL,x_test,y_train_SSL,y_test)
```

```
AUC: 0.8503
Accuracy Score: 0.8786
              precision    recall  f1-score   support

           0       0.85      0.98      0.91     14917
           1       0.95      0.72      0.82      9440

    accuracy                           0.88     24357
   macro avg       0.90      0.85      0.87     24357
weighted avg       0.89      0.88      0.87     24357
```


14565
352
2604
6836
True label
Predicted label
0
1
0
1
14000
12000
10000
8000
6000
4000
2000



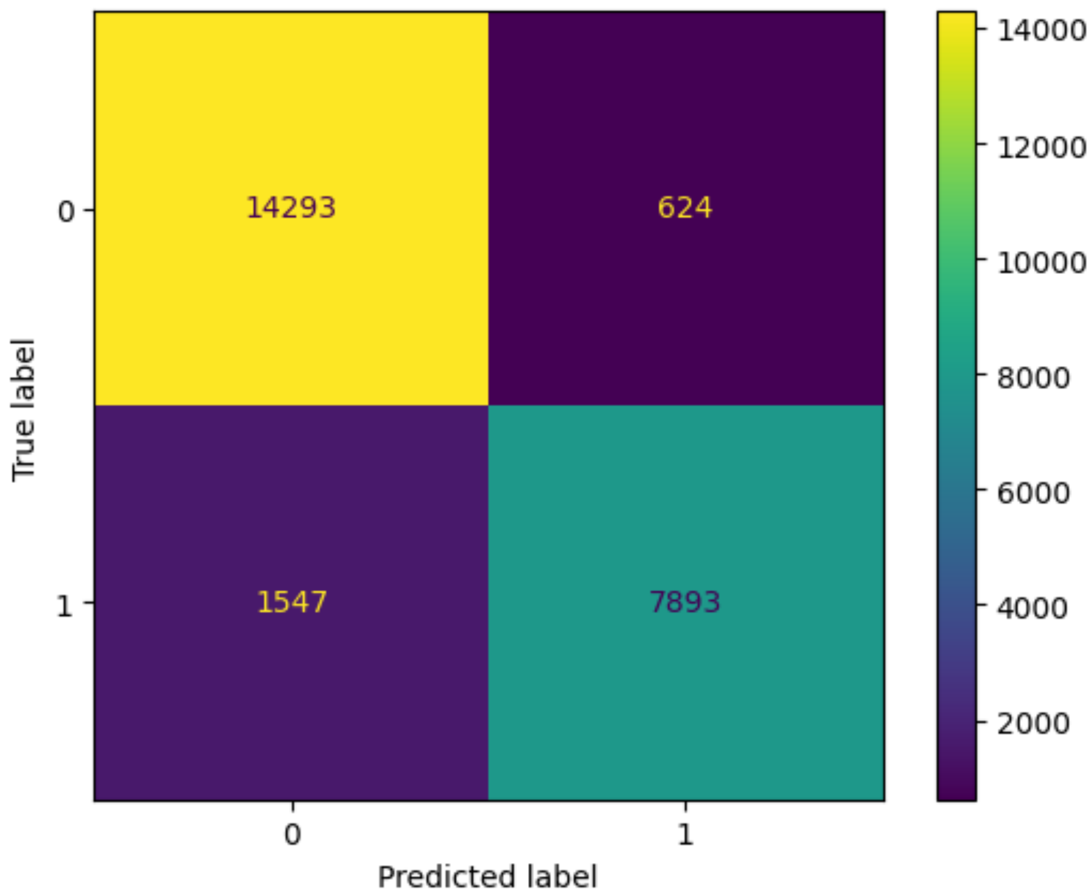
Label Propagation Classifier

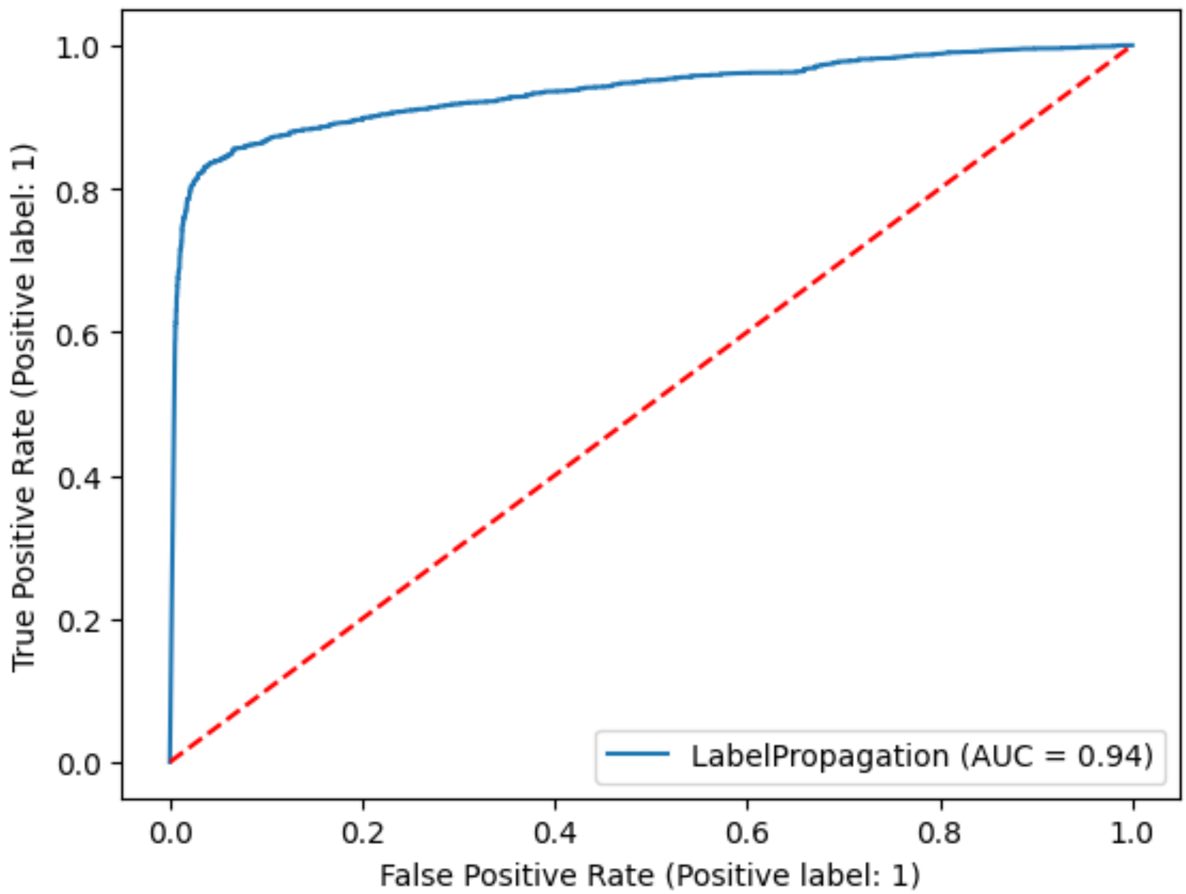
Semi-Supervised Label Propagation

In [16]:
```
from sklearn.semi_supervised import LabelPropagation

def SSLP(x_train,x_test,y_train,y_test):
    model = LabelPropagation()
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    classifier='Semi-Supervised Label Propagation'
    Analyze(y_pred,y_test,classifier)
    x_test=x_test.drop([9169])
    y_test=np.delete(y_test, 9169, 0)
    plot_roc_curve(estimator=model,X=x_test,y=y_test)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    return y_pred,y_test
```

In [17]:
```
y_pred_SSLP,y_test_SSLP=SSLP(x_train_SSL,x_test,y_train_SSL,y_test)
```

```
AUC: 0.8971
Accuracy Score: 0.9109
              precision    recall  f1-score   support

           0       0.90      0.96      0.93     14917
           1       0.93      0.84      0.88      9440

    accuracy                           0.91     24357
   macro avg       0.91      0.90      0.90     24357
weighted avg       0.91      0.91      0.91     24357
```



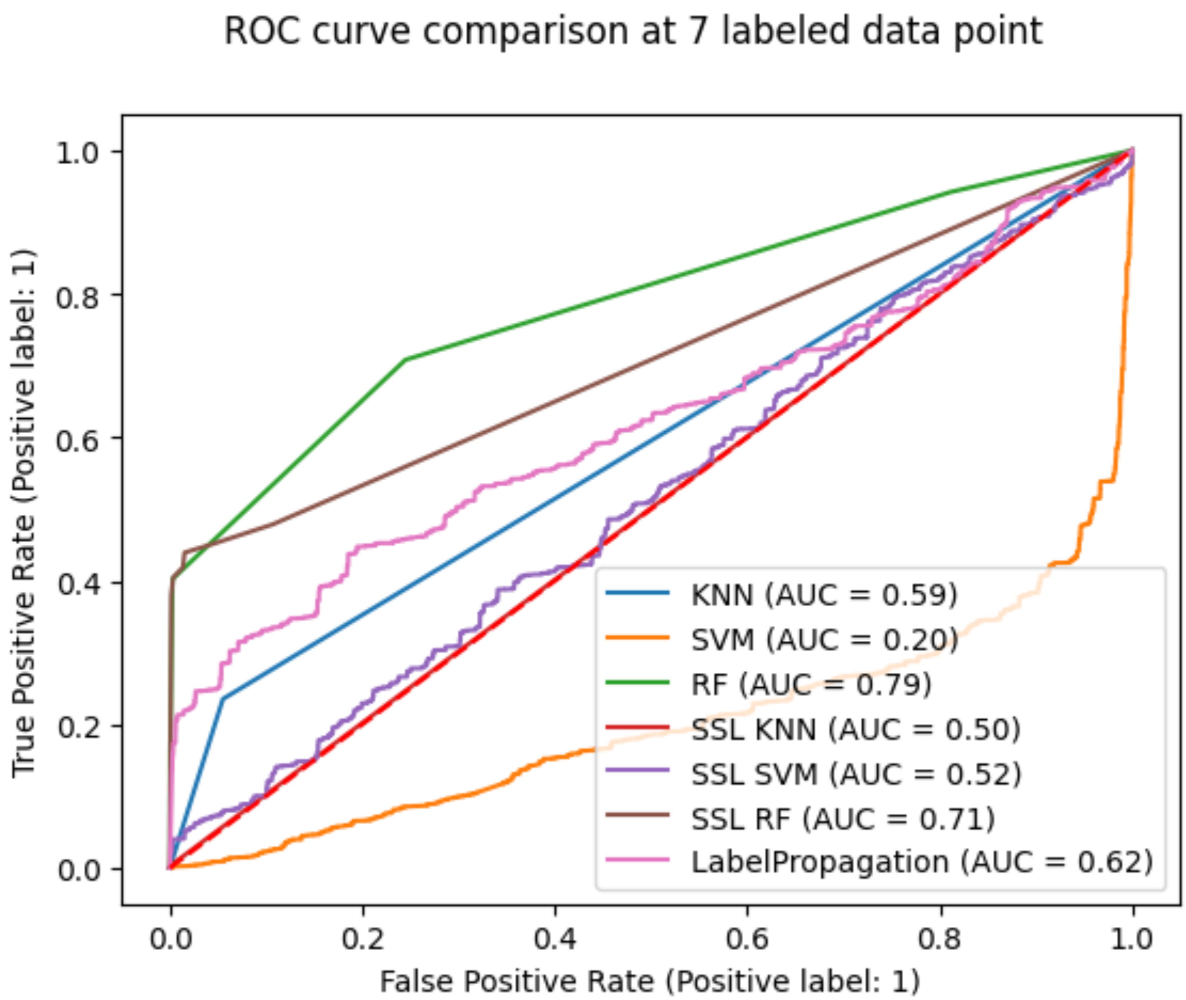


Part4: Test with different number of labeled data

In [18]:
```
def plt_roc(x_train1,x_train2,y_train1,y_train2,x_test,y_test):

    knn=KNeighborsClassifier(n_neighbors = 5)
    knn.fit(x_train1,y_train1)
    fig=plot_roc_curve(estimator=knn,X=x_test,y=y_test,name='KNN')

    svc = SVC(probability=True, gamma="auto")
    svc.fit(x_train1,y_train1)
    fig=plot_roc_curve(estimator=svc,X=x_test,y=y_test,ax = fig.ax_,name='SV

    RF = RandomForestClassifier()
    parameters = {'criterion':("gini","entropy"),
                 "max_depth":[*range(1, 20)],
                 "n_estimators":[5,10,20,40]}
    model=GridSearchCV(RF,param_grid=parameters,cv=5,scoring='f1')
    model.fit(x_train1,y_train1)
    fig=plot_roc_curve(estimator=model,X=x_test,y=y_test,ax = fig.ax_,name='


    D=data_process(x_train1,x_train2,y_train1)
    y_train_SSL=D['y'].values
    x_train_SSL=D.drop('y',axis=1)

    SS_model = SelfTrainingClassifier(knn)
    SS_model.fit(x_train_SSL, y_train_SSL)
    fig=plot_roc_curve(estimator=SS_model,X=x_test,y=y_test,ax = fig.ax_,nam

    SS_model = SelfTrainingClassifier(svc)
    SS_model.fit(x_train_SSL, y_train_SSL)
    fig=plot_roc_curve(estimator=SS_model,X=x_test,y=y_test,ax = fig.ax_,nam

    SS_model = SelfTrainingClassifier(model.best_estimator_)
    SS_model.fit(x_train_SSL, y_train_SSL)
    fig=plot_roc_curve(estimator=SS_model,X=x_test,y=y_test,ax = fig.ax_,nam

    model = LabelPropagation()
    model.fit(x_train_SSL, y_train_SSL)
    A=x_test.drop([9169])
    B=np.delete(y_test, 9169, 0)
    plot_roc_curve(estimator=model,X=A,y=B,ax = fig.ax_)
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    fig.figure_.suptitle("ROC curve comparison at "+str(x_train1.shape[0])+"

    plt.show()
```

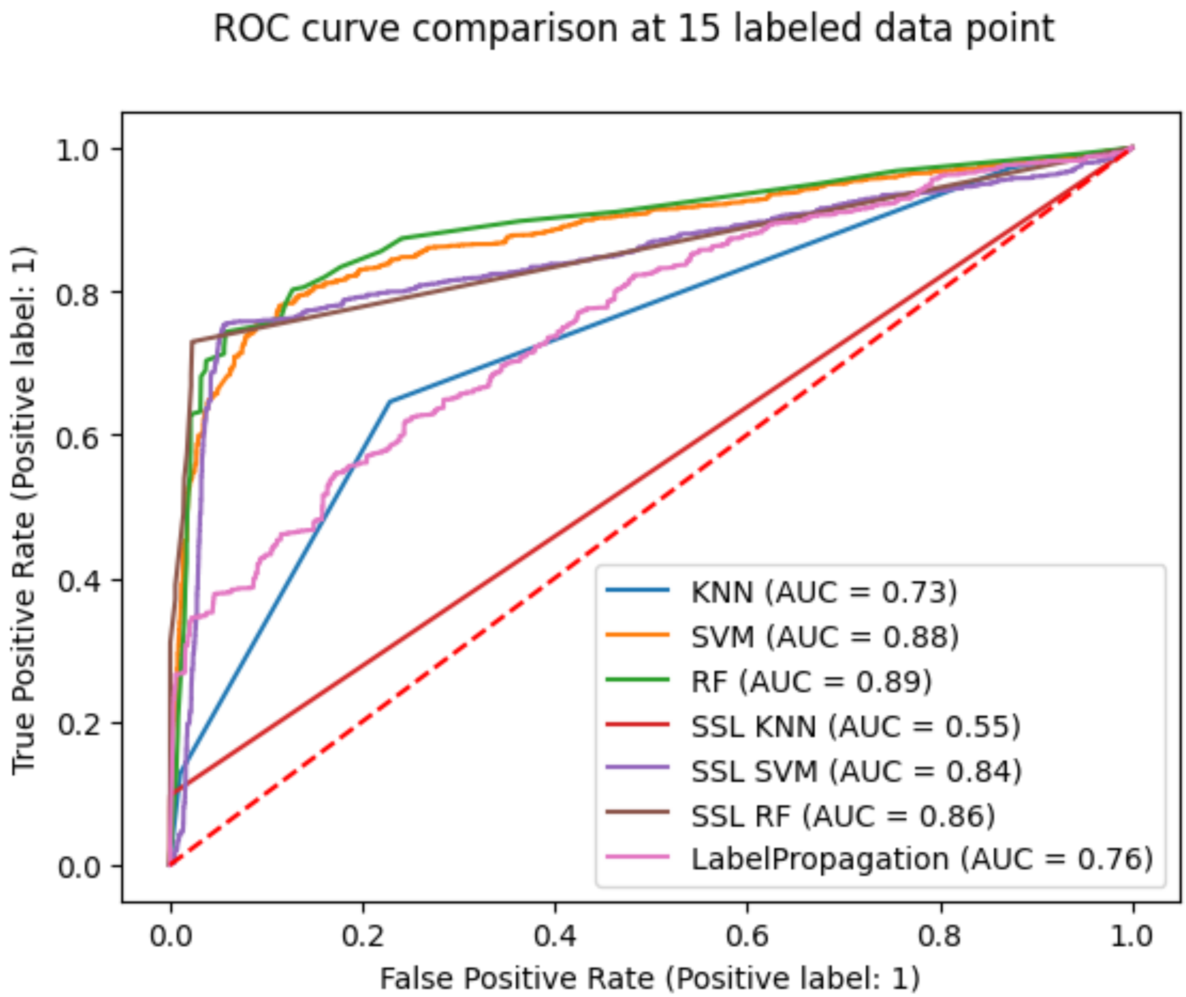
7 labeled data

In [20]:
```
New_data=A.sample(n = 10000)
y_data=New_data['y'].values
x_data=New_data.drop('y',axis=1)
x_train1,x_train2,y_train1,y_train2 = train_test_split(x_data,y_data, train_
x_test=x_test.reset_index(drop=True)
plt_roc(x_train1,x_train2,y_train1,y_train2,x_test,y_test)
```



15 labeled data

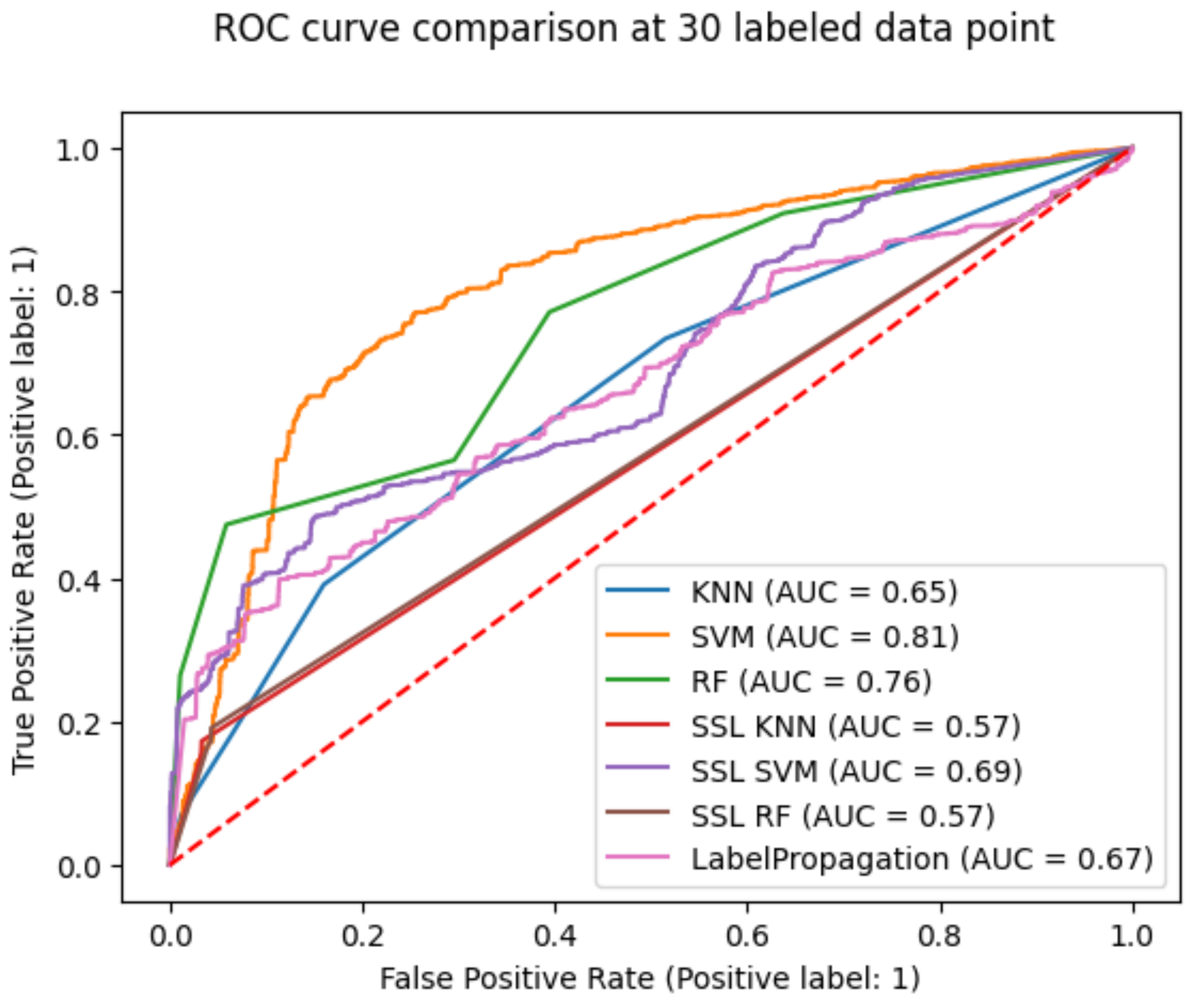
In [21]:
```
New_data=A.sample(n = 10000)
y_data=New_data['y'].values
x_data=New_data.drop('y',axis=1)
x_train1,x_train2,y_train1,y_train2 = train_test_split(x_data,y_data, train_
x_test=x_test.reset_index(drop=True)
plt_roc(x_train1,x_train2,y_train1,y_train2,x_test,y_test)
```



30 labeled data

In [22]:

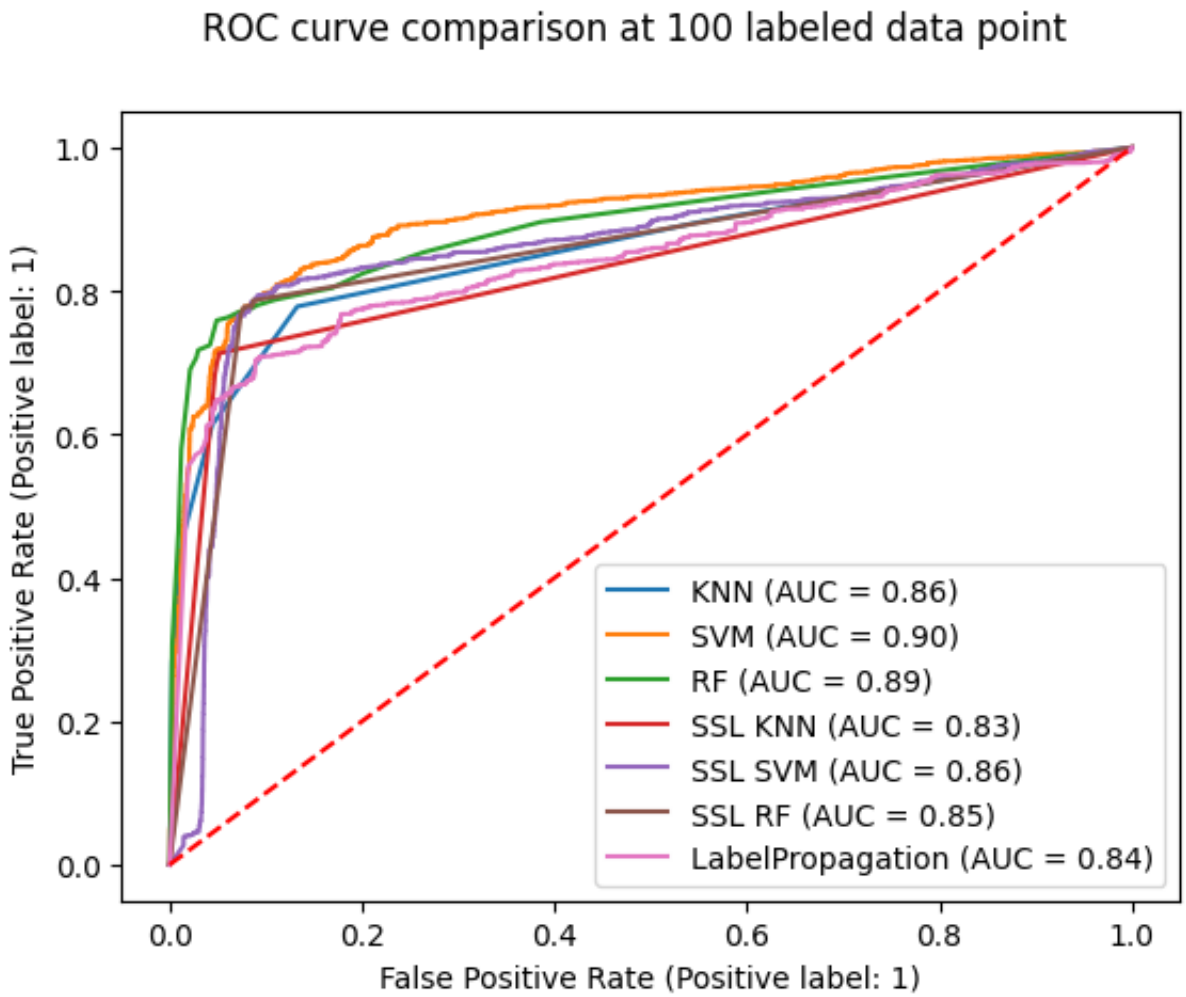
```
New_data=A.sample(n = 10000)
y_data=New_data['y'].values
x_data=New_data.drop('y',axis=1)
x_train1,x_train2,y_train1,y_train2 = train_test_split(x_data,y_data, train_
x_test=x_test.reset_index(drop=True)
plt_roc(x_train1,x_train2,y_train1,y_train2,x_test,y_test)
```



100 labeled data

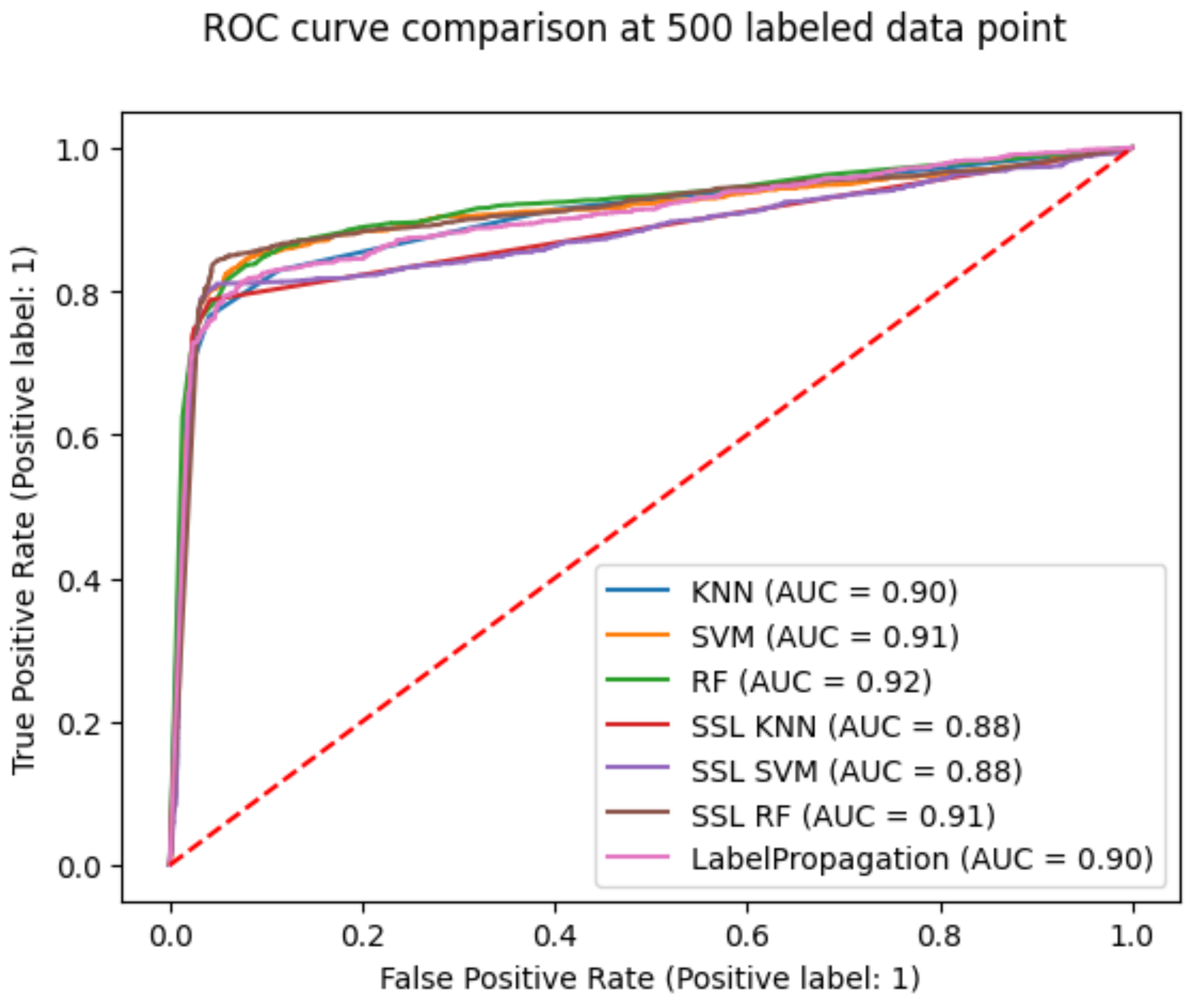
In [23]:

```
New_data=A.sample(n = 10000)
y_data=New_data['y'].values
x_data=New_data.drop('y',axis=1)
x_train1,x_train2,y_train1,y_train2 = train_test_split(x_data,y_data, train_
x_test=x_test.reset_index(drop=True)
plt_roc(x_train1,x_train2,y_train1,y_train2,x_test,y_test)
```



500 labeled data

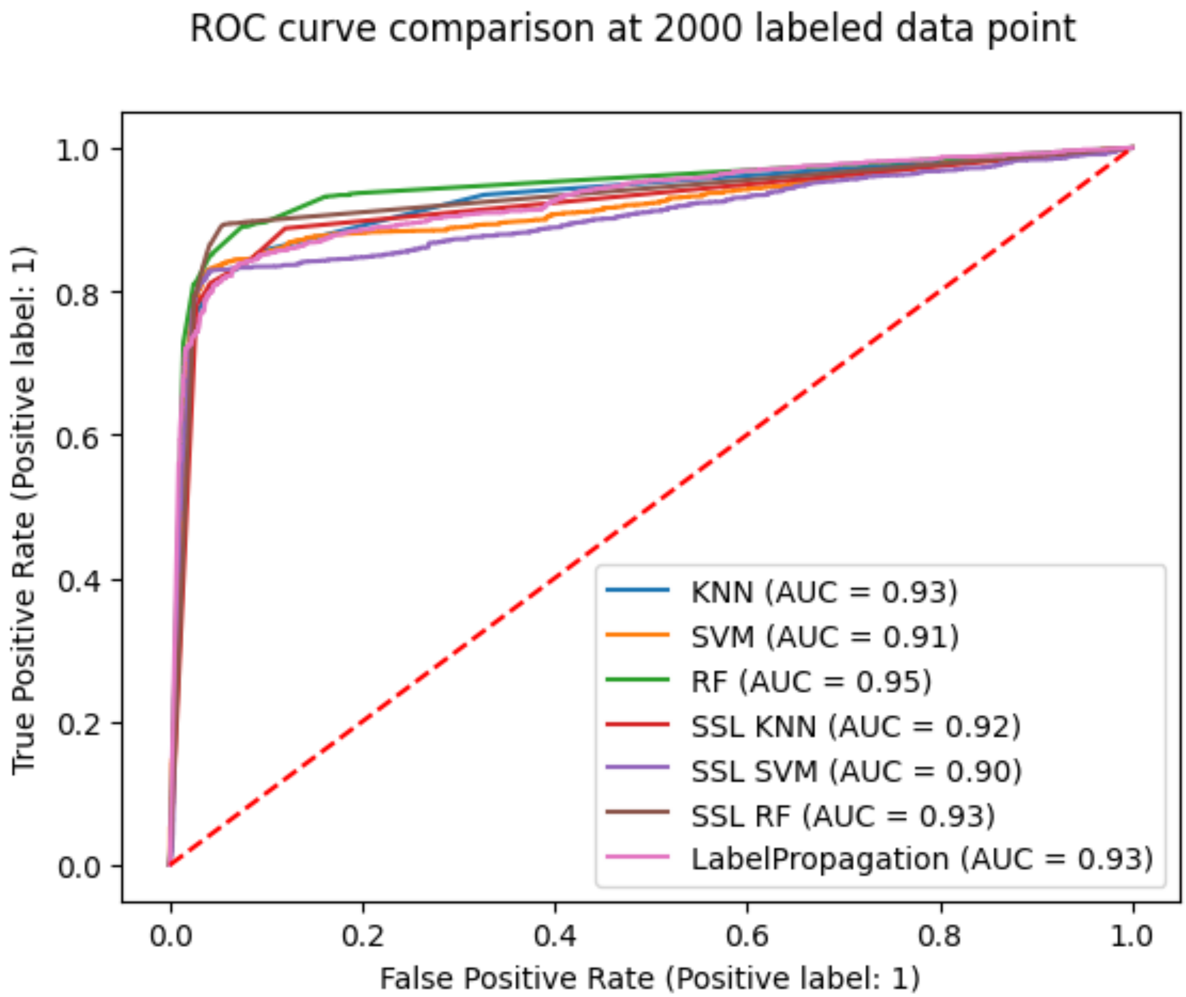
In [24]:
```
New_data=A.sample(n = 10000)
y_data=New_data['y'].values
x_data=New_data.drop('y',axis=1)
x_train1,x_train2,y_train1,y_train2 = train_test_split(x_data,y_data, train_
x_test=x_test.reset_index(drop=True)
plt_roc(x_train1,x_train2,y_train1,y_train2,x_test,y_test)
```



2000 labeled data

In [25]:

```
New_data=A.sample(n = 10000)
y_data=New_data['y'].values
x_data=New_data.drop('y',axis=1)
x_train1,x_train2,y_train1,y_train2 = train_test_split(x_data,y_data, train_
x_test=x_test.reset_index(drop=True)
plt_roc(x_train1,x_train2,y_train1,y_train2,x_test,y_test)
```


ROC curve comparison at 2000 labeled data point
True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
0.0
0.2
0.4
0.6
0.8
1.0
KNN (AUC = 0.93)
SVM (AUC = 0.91)
RF (AUC = 0.95)
SSL KNN (AUC = 0.92)
SSL SVM (AUC = 0.90)
SSL RF (AUC = 0.93)
LabelPropagation (AUC = 0.93)

```
In [ ]:
```