# **Credit Card Fraud Detection (Classification)**

X = credit.drop(['Class'], 1).to\_numpy()

```
In [1]:
         import pandas as pd
         import numpy as np
         from sklearn.model_selection import train_test_split
         import matplotlib.pyplot as plt
         from imblearn.over_sampling import RandomOverSampler, SMOTE, ADASYN, BorderlineSMOTE
         from imblearn.under_sampling import RandomUnderSampler, NearMiss
In [2]:
         from sklearn.model_selection import cross_val_predict
         from sklearn.preprocessing import StandardScaler
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score
         from sklearn.metrics import precision_recall_curve, roc_curve, confusion_matrix, ConfusionMatrixDisplay
In [3]:
          credit = pd.read_csv('creditcard.csv')
          credit.head()
                       V1
                                 V2
                                          V3
                                                    V4
                                                             V5
                                                                                V7
                                                                                          V8
                                                                                                                V21
                                                                                                                         V22
                                                                                                                                   V23
                                                                                                                                             V24
Out[3]:
            Time
                                                                       V6
                                                                                                    V9 ...
             0.0 -1.359807 -0.072781 2.536347
                                               1.378155 -0.338321
                                                                  0.462388
                                                                            0.239599
                                                                                     0.098698
                                                                                               0.363787 ... -0.018307
                                                                                                                     0.277838
                                                                                                                              -0.110474
                                                                                                                                         0.066928
             0.0 1.191857
                            0.266151 0.166480
                                               0.448154
                                                        0.060018
                                                                 -0.082361
                                                                           -0.078803
                                                                                     0.085102
                                                                                              -0.255425 ... -0.225775
                                                                                                                     -0.638672
                                                                                                                               0.101288
                                                                                                                                        -0.339846
                                                                                                                                        -0.689281 -0.
             1.0 -1.358354 -1.340163 1.773209
                                               0.379780
                                                       -0.503198
                                                                  1.800499
                                                                            0.791461
                                                                                     0.247676
                                                                                             -1.514654 ...
                                                                                                            0.247998
                                                                                                                               0.909412
                                                                                                                     0.771679
             1.0 -0.966272 -0.185226 1.792993
                                              -0.863291
                                                        -0.010309
                                                                  1.247203
                                                                            0.237609
                                                                                     0.377436
                                                                                             -1.387024 ... -0.108300
                                                                                                                     0.005274
                                                                                                                              -0.190321 -1.175575
                                              0.403034 -0.407193
                                                                  0.095921
                                                                            0.592941 -0.270533
                                                                                                                     0.798278 -0.137458
                            0.877737 1.548718
                                                                                               0.817739 ... -0.009431
                                                                                                                                         0.141267 -0.
        5 rows × 31 columns
In [4]:
          credit.isna().sum()
         Time
                   0
Out[4]:
                   0
         V2
                   0
         V3
                   0
         V4
         V5
         V6
         V7
         V8
         V9
         V10
         V11
         V12
         V13
         V15
         V16
         V17
         V18
         V19
         V20
         V21
         V22
         V23
         V24
         V25
         V26
         V27
         V28
         Amount
         Class
         dtype: int64
In [5]:
         credit['Class'].value_counts()
              284315
Out[5]:
                 492
         Name: Class, dtype: int64
In [6]:
         X = credit.drop(['Class'], 1).to_numpy()
         y = credit['Class'].to_numpy()
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
         C:\Users\Seneca\AppData\Local\Temp/ipykernel_18096/4172792951.py:1: FutureWarning: In a future version of pandas all arguments of
         DataFrame.drop except for the argument 'labels' will be keyword-only
```

```
X_train_s = scaler.fit_transform(X_train)
         X_test_s = scaler.fit_transform(X_test)
In [8]:
         def run_sampler_batch(run_model, samplers = [], incROC = False):
             metrics = []
             conf_disps = []
             rocs = []
             # make sure there are samplers to run
             if(len(samplers) > 0):
                 for sampler, name in samplers:
                     # get samples
                     X_train_re, y_train_re = sampler.fit_resample(X_train_s, y_train)
                     # run model
                     if(incROC):
                         mets, conf_disp, roc = run_model(X_train_re, y_train_re, name)
                         rocs.append(roc)
                     else:
                         mets, conf_disp = run_model(X_train_re, y_train_re, name)
                     # store performance stats in lists
                     metrics.append(mets)
                     conf_disps.append(conf_disp)
             else: # run model with original scaled training data
                 if(incROC):
                     mets, conf_disp, roc = run_model(X_train_s, y_train, "No Sampling Method")
                     rocs.append(roc)
                 else:
                     mets, conf_disp = run_model(X_train_s, y_train, "No Sampling Method")
                 # store performance stats in lists
                 metrics.append(mets)
                 conf_disps.append(conf_disp)
             # return performance stats
             if(incROC):
                 return metrics, conf_disps, rocs
             return metrics, conf_disps
In [9]:
         def print_metrics(metrics):
             for item in metrics:
                 print("********************************")
                 print(item["name"])
                 print("Accuracy Score: ", item["accuracy"])
                 print("Precision: ", item["precision"])
                 print("Recall: ", item["recall"])
                 print("F1: ", item["f1"])
                 print()
         def plot_conf_disps(conf_disps):
             for item in conf_disps:
                 print(item["name"])
                 item["disp"].plot()
                 plt.show()
         def plot_rocs(rocs):
             for item in rocs:
                 plt.plot(item["fpr"], item["tpr"])
                 plt.title(item["name"])
                 plt.xlabel("False Positive Rate")
                 plt.ylabel("True Positive Rate (Recall)")
                 plt.show()
```

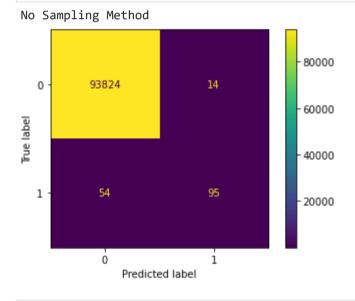
# **Logistic Regression**

scaler = StandardScaler()

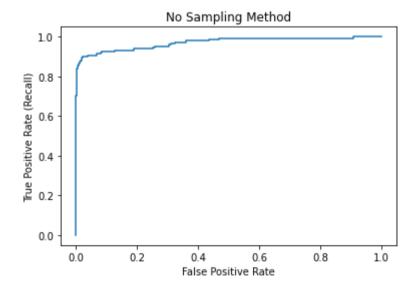
In [7]:

## Logistic regression without accounting for class imbalances

In [13]: plot\_conf\_disps(conf\_disps)



In [14]: plot\_rocs(rocs)



## **Logistic Regression with Oversampling**

RUNNING LOGISTIC REGRESSION CLASSIFIER ON DATA: RandomOverSampler RUNNING LOGISTIC REGRESSION CLASSIFIER ON DATA: SMOTE

In [17]:

print\_metrics(metrics)

\*\*\*\*\*\*\*\*\*\*\*

RandomOverSampler

Accuracy Score: 0.9728792279783375 Precision: 0.05089820359281437 Recall: 0.912751677852349

F1: 0.09641970932293513

\*\*\*\*\*\*\*\*\*\*\*

Accuracy Score: 0.9721344441252514 Precision: 0.049927113702623906 Recall: 0.9194630872483222 F1: 0.0947113722779122

\*\*\*\*\*\*\*\*\*\*\*\*

ADASYN

Accuracy Score: 0.9053805313500803 Precision: 0.015621537779747396 Recall: 0.9463087248322147

F1: 0.030735694822888286

\*\*\*\*\*\*\*\*\*\*\*\*

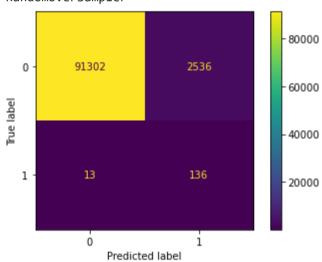
BorderLineSMOTE

Accuracy Score: 0.9909774756083288 Precision: 0.13403141361256546 Recall: 0.8590604026845637 F1: 0.23188405797101452

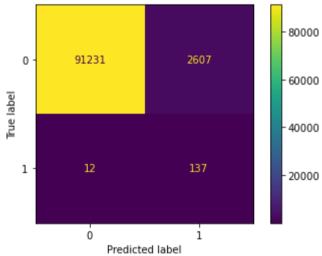
In [18]:

plot\_conf\_disps(conf\_disps)

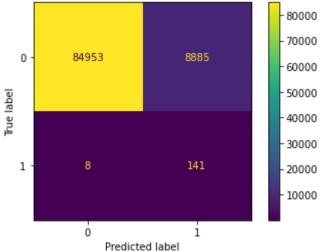




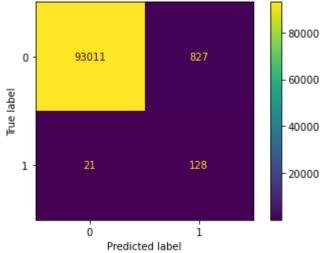
SMOTE



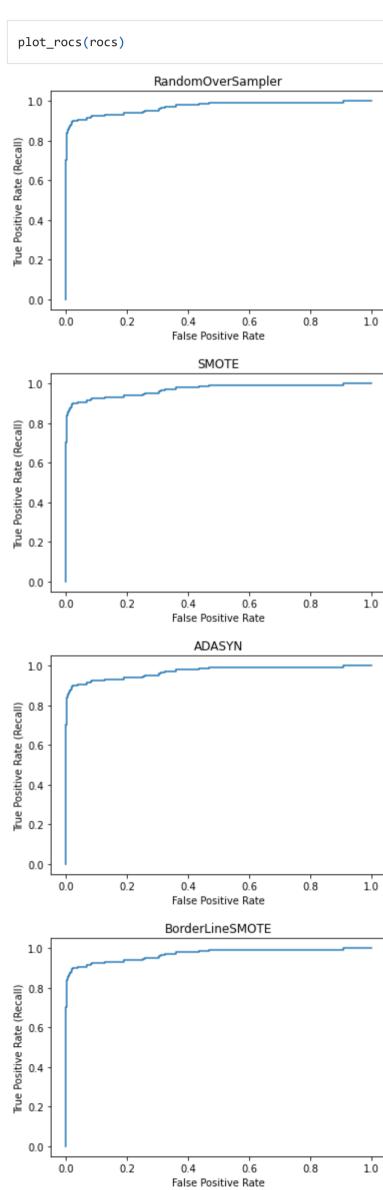
**ADASYN** 



 ${\tt BorderLineSMOTE}$ 







**Logistic Regression with Undersampling** 

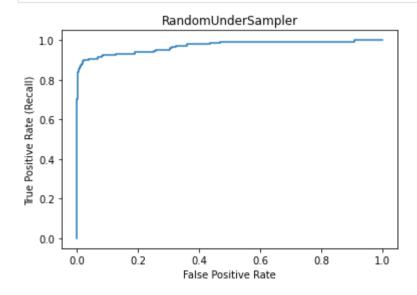
```
under_samplers = [[RandomUnderSampler(random_state=42), "RandomUnderSampler"],
In [20]:
                          [NearMiss(), "NearMiss"]
In [21]:
         metrics, conf_disps, rocs = run_sampler_batch(run_model=run_log_reg, samplers=under_samplers, incROC=True)
         RUNNING LOGISTIC REGRESSION CLASSIFIER ON DATA: RandomUnderSampler
         RUNNING LOGISTIC REGRESSION CLASSIFIER ON DATA: NearMiss
In [22]:
         print_metrics(metrics)
         ************
         RandomUnderSampler
         Accuracy Score: 0.9584517007671274
         Precision: 0.03422619047619048
         Recall: 0.9261744966442953
         F1: 0.06601291557043769
         ***********
         NearMiss
         Accuracy Score: 0.585197952908381
         Precision: 0.0034774604311028153
         Recall: 0.912751677852349
         F1: 0.006928524122471852
In [23]:
         plot_conf_disps(conf_disps)
         RandomUnderSampler
                                               80000
                                               70000
                  9e+04
                                 3894
           0
                                              60000
         True label
                                              50000
                                              40000
                                              30000
                                 138
           1 -
                                              20000
                                              10000
```

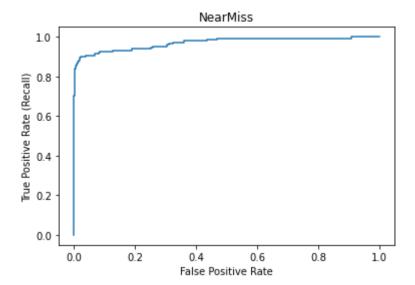
## NearMiss

- 50000 - 40000 - 30000 - 20000 - 1 - 13 136 - 10000 - Predicted label

Predicted label

In [24]: plot\_rocs(rocs)





#### **Neural Network**

```
In [25]:
          import keras
          from keras.models import Sequential
          from keras.layers import Dense
In [26]:
          np.shape(X_train_s[0])
          (30,)
Out[26]:
In [27]:
          def run_nn(X_tr_nn, y_tr_nn, name):
              print("RUNNING NEURAL NETWORK ON DATA: ", name)
              classifier = Sequential()
              classifier.add(keras.layers.Dense(units=60, kernel_initializer='uniform', activation='tanh', input_dim=30))
              classifier.add(keras.layers.Dense(units=30, kernel_initializer='uniform', activation='tanh'))
              classifier.add(keras.layers.Dense(units=10, kernel_initializer='uniform', activation='tanh'))
              classifier.add(keras.layers.Dense(units=1, kernel_initializer='uniform', activation='sigmoid'))
              classifier.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
              history = classifier.fit(X_tr_nn, y_tr_nn, epochs=20, batch_size=10)
              y_pred = classifier.predict(X_test_s)
              y_pred = np.where(y_pred > 0.5, 1, 0)
              # get metrics to be printed later
              metrics_nn = {"name": name,
                          "accuracy": accuracy_score(y_test, y_pred),
                          "precision": precision_score(y_test, y_pred, zero_division=False),
                          "recall": recall_score(y_test, y_pred),
                          "f1": f1_score(y_test, y_pred),
              # generate confusion matrix visualizations
              conf_matrix = confusion_matrix(y_test, y_pred)
              conf_disp_nn = {"name": name,
                            "disp": ConfusionMatrixDisplay(conf_matrix)
              return metrics_nn, conf_disp_nn
```

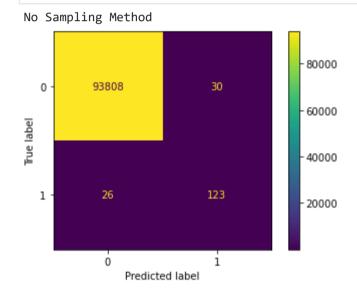
## Neural Network without accounting for class imbalance

```
In [28]:
 metrics, conf_disps = run_sampler_batch(run_nn)
 RUNNING NEURAL NETWORK ON DATA: No Sampling Method
 Epoch 2/20
 Epoch 3/20
 Epoch 4/20
 Epoch 5/20
 Epoch 6/20
 Epoch 7/20
 Epoch 8/20
 Epoch 9/20
 Epoch 10/20
 Epoch 11/20
```

```
Epoch 12/20
   Epoch 13/20
    Epoch 14/20
   19082/19082 [:
              =========== ] - 21s 1ms/step - loss: 0.0023 - accuracy: 0.9995
    Epoch 15/20
   19082/19082 [=====
             Epoch 16/20
             19082/19082 [=====
   Epoch 17/20
   19082/19082 [=
               Epoch 18/20
   19082/19082 [===
               Epoch 19/20
   19082/19082 [=
               Epoch 20/20
             19082/19082 [======
In [29]:
    print_metrics(metrics)
    ***********
    No Sampling Method
   Accuracy Score: 0.9994041729175311
   Precision: 0.803921568627451
    Recall: 0.825503355704698
    F1: 0.8145695364238411
```

In [30]:

```
plot_conf_disps(conf_disps)
```



#### Neural Network with Oversampling

In [32]: | metrics, conf\_disps = run\_sampler\_batch(run\_nn, over\_samplers)

```
RUNNING NEURAL NETWORK ON DATA: RandomOverSampler
Epoch 1/20
Epoch 2/20
38096/38096 [=
   Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
```

```
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
RUNNING NEURAL NETWORK ON DATA: SMOTE
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
RUNNING NEURAL NETWORK ON DATA: ADASYN
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
38096/38096 [================== - - 40s 1ms/step - loss: 0.0030 - accuracy: 0.9994
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
```

```
Epoch 20/20
RUNNING NEURAL NETWORK ON DATA: BorderLineSMOTE
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
print_metrics(metrics)
```

In [33]:

\*\*\*\*\*\*\*\*\*\*\*\*\*

RandomOverSampler

Accuracy Score: 0.9992020173002649 Precision: 0.7151162790697675 Recall: 0.825503355704698 F1: 0.7663551401869161

\*\*\*\*\*\*\*\*\*\*\*\*

SMOTE

Accuracy Score: 0.9984572334471788 Precision: 0.5078740157480315 Recall: 0.8657718120805369 F1: 0.6401985111662531

\*\*\*\*\*\*\*\*\*\*\*\*

ADASYN

Accuracy Score: 0.9989466628363497 Precision: 0.631578947368421 Recall: 0.8053691275167785 F1: 0.7079646017699115

\*\*\*\*\*\*\*\*\*\*\*\*

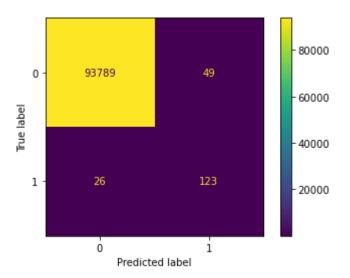
BorderLineSMOTE

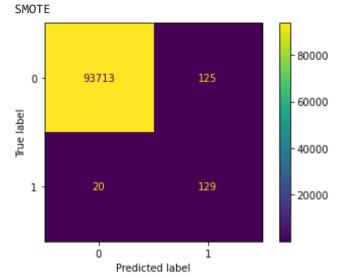
Accuracy Score: 0.9992764956855735 Precision: 0.7755102040816326 Recall: 0.7651006711409396 F1: 0.7702702702702703

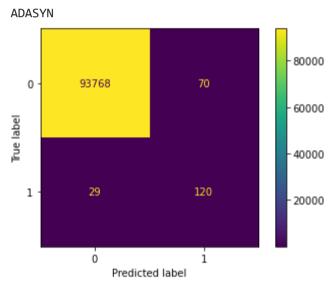
In [34]:

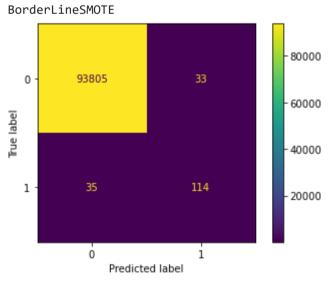
plot\_conf\_disps(conf\_disps)

RandomOverSampler









# **Neural Network with Undersampling**

Epoch 4/20

```
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
RUNNING NEURAL NETWORK ON DATA: NearMiss
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
print metrics(metrics)
```

## In [37]:

\*\*\*\*\*\*\*\*\*\*\*\*

RandomUnderSampler

Accuracy Score: 0.9410663176822327 Precision: 0.02435580656547829 Recall: 0.9261744966442953 F1: 0.047463456577815984

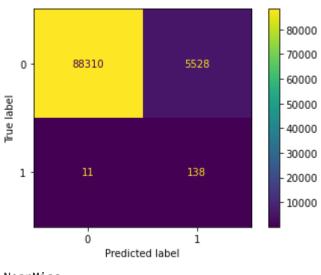
\*\*\*\*\*\*\*\*\*\*\*\*

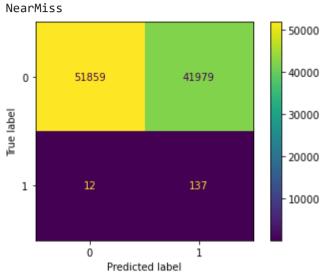
NearMiss

Accuracy Score: 0.5532254460723292 Precision: 0.003252920505271156 Recall: 0.9194630872483222 F1: 0.006482905477345322

In [38]:

plot conf disps(conf disps)





## **Random Forest Classifier**

```
In [39]:
          from sklearn.ensemble import RandomForestClassifier
In [40]:
          def run_rfc(X_tr_nn, y_tr_nn, name):
              print("RUNNING RANDOM FOREST CLASSIFIER ON DATA: ", name)
              rfc = RandomForestClassifier(random_state=42)
              rfc.fit(X_tr_nn, y_tr_nn)
              y_pred = rfc.predict(X_test_s)
              \# y_{pred} = np.where(y_{pred} > 0.5, 1, 0)
              # get metrics to be printed later
              metrics_rf = {"name": name,
                         "accuracy": accuracy_score(y_test, y_pred),
                         "precision": precision_score(y_test, y_pred, zero_division=False),
                         "recall": recall_score(y_test, y_pred),
                         "f1": f1_score(y_test, y_pred),
              # generate confusion matrix visualizations
              conf_matrix = confusion_matrix(y_test, y_pred)
              conf disp rf = {"name": name,
                           "disp": ConfusionMatrixDisplay(conf_matrix)
              # get false and true positive rates to graph later
              y_scores = cross_val_predict(rfc, X_test_s, y_test, cv=3)
              fpr, tpr, thresholds_roc = roc_curve(y_test, y_scores)
              roc_rf = {"name": name,
                     "fpr": fpr,
                      "tpr": tpr
                    }
              return metrics_rf, conf_disp_rf, roc_rf
```

In [41]: metrics, conf\_disps, rocs = run\_sampler\_batch(run\_model=run\_rfc, incROC=True)

RUNNING RANDOM FOREST CLASSIFIER ON DATA: No Sampling Method

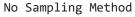
In [42]: print\_metrics(metrics)

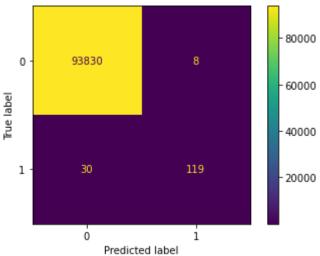
No Sampling Method

Accuracy Score: 0.9995956887654676 Precision: 0.937007874015748 Recall: 0.7986577181208053 F1: 0.8623188405797101

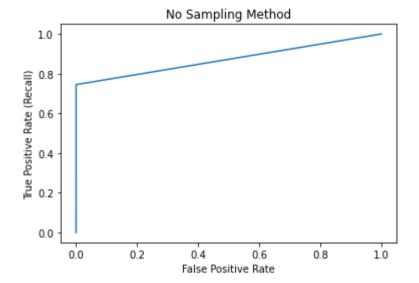
\*\*\*\*\*\*\*\*\*\*\*\*

```
plot_conf_disps(conf_disps)
```





```
In [44]: plot_rocs(rocs)
```



## **Random Forest Classifier with Oversampling**

In [47]: print\_metrics(metrics)

\*\*\*\*\*\*\*\*\*\*\*\*

RandomOverSampler
Accuracy Score: 0.9996488876121166

Precision: 0.9603174603174603

Recall: 0.8120805369127517

F1: 0.8800000000000001

\*\*\*\*\*\*\*\*\*\*\*\*

SMOTE

Accuracy Score: 0.999574409226808 Precision: 0.8707482993197279 Recall: 0.8590604026845637 F1: 0.8648648648648649

\*\*\*\*\*\*\*\*\*\*\*\*

ADASYN

Accuracy Score: 0.9995105706108292 Precision: 0.8551724137931035 Recall: 0.8322147651006712 F1: 0.8435374149659864

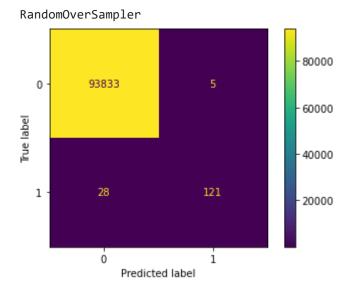
\*\*\*\*\*\*\*\*\*\*\*\*

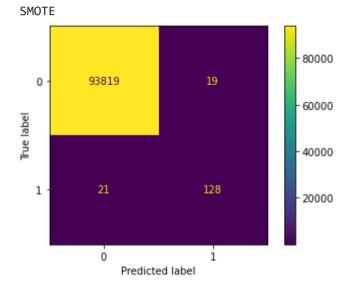
BorderLineSMOTE

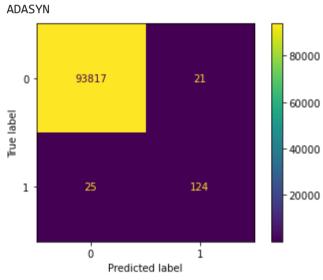
Accuracy Score: 0.9995956887654676 Precision: 0.9302325581395349 Recall: 0.8053691275167785 F1: 0.8633093525179855

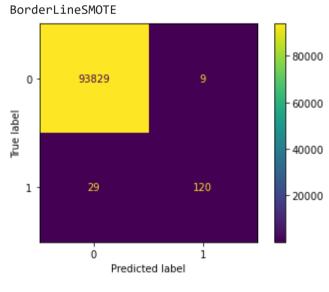
In [48]:

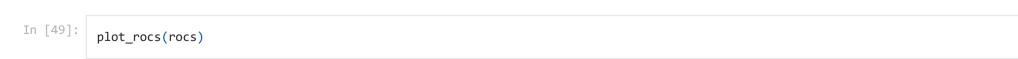
plot\_conf\_disps(conf\_disps)

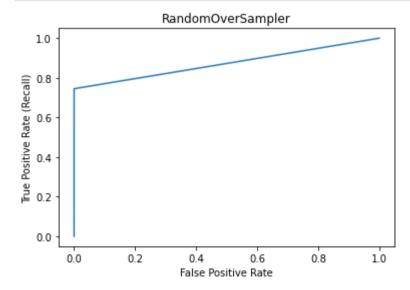


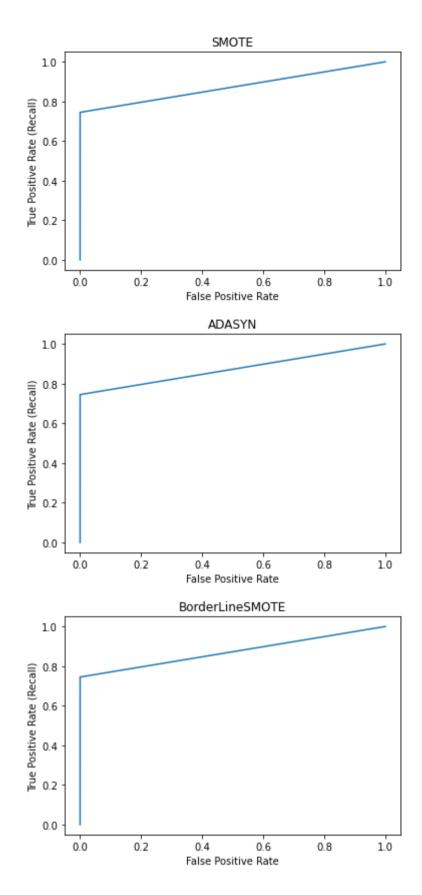








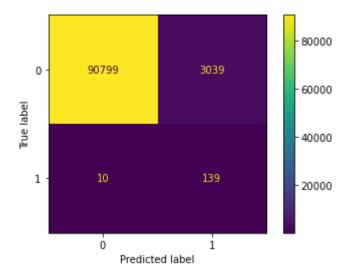




# **Random Forest Classifier with Undersampling**

RandomUnderSampler

```
In [50]:
         under_samplers = [[RandomUnderSampler(random_state=42), "RandomUnderSampler"],
                         [NearMiss(), "NearMiss"]
In [51]:
         metrics, conf_disps, rocs = run_sampler_batch(run_model=run_rfc, samplers=under_samplers, incROC=True)
        RUNNING RANDOM FOREST CLASSIFIER ON DATA: RandomUnderSampler
        RUNNING RANDOM FOREST CLASSIFIER ON DATA: NearMiss
In [52]:
         print_metrics(metrics)
        ***********
        RandomUnderSampler
        Accuracy Score: 0.967559343313437
        Precision: 0.04373820012586532
        Recall: 0.9328859060402684
        F1: 0.08355876164712954
        ***********
        NearMiss
        Accuracy Score: 0.0606573249491951
        Precision: 0.0016623129897886488
        Recall: 0.9865771812080537
        F1: 0.0033190336419056223
In [53]:
         plot_conf_disps(conf_disps)
```



# NearMiss 0 - 5554 88284 - 60000 - 70000 - 60000 - 50000 - 40000 - 30000 - 20000 - 10000

Predicted label

i

In [54]: plot\_rocs(rocs)

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