In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings

from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix,f1_score,recall_score,precisior
from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import cross_val_score

from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split

from sklearn.feature_selection import SelectPercentile
from sklearn.feature_selection import chi2,f_classif
from mlxtend .plotting import plot_confusion_matrix
from sklearn.metrics import mean_absolute_error,r2_score,mean_squared_error
from sklearn.feature_selection import RFE
warnings.filterwarnings('ignore')
```

In [2]:

```
data=pd.read_csv(r"C:\Users\DELL\Downloads\archive\diabetes_binary_health_ir
```

In [3]:
```
data
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDis
0	0.0	0	1.0	1	15.0	1.0	0.0	0.0
1	1.0	1	0.0	1	28.0	0.0	0.0	1.0
2	1.0	1	1.0	1	33.0	0.0	0.0	0.0
3	1.0	0	1.0	1	29.0	0.0	1.0	1.0
4	0.0	0	0.0	1	24.0	1.0	0.0	0.0
...	...	...	...	...	...	...	...	...
236373	1.0	1	1.0	1	21.0	0.0	0.0	0.0
236374	0.0	1	0.0	1	25.0	1.0	0.0	0.0
236375	0.0	0	1.0	1	31.0	0.0	0.0	0.0
236376	0.0	1	0.0	1	24.0	0.0	0.0	0.0
236377	0.0	0	1.0	1	32.0	0.0	0.0	0.0

236378 rows × 22 columns

In [4]:
```
data.head()
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDisease
0	0.0	0	1.0	1	15.0	1.0	0.0	0.0
1	1.0	1	0.0	1	28.0	0.0	0.0	1.0
2	1.0	1	1.0	1	33.0	0.0	0.0	0.0
3	1.0	0	1.0	1	29.0	0.0	1.0	1.0
4	0.0	0	0.0	1	24.0	1.0	0.0	0.0

5 rows × 22 columns

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 236378 entries, 0 to 236377
Data columns (total 22 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   Diabetes_binary       236378 non-null  float64
 1   HighBP                236378 non-null  int64  
 2   HighChol              236378 non-null  float64
 3   CholCheck             236378 non-null  int64  
 4   BMI                   236378 non-null  float64
 5   Smoker                236378 non-null  float64
 6   Stroke                236378 non-null  float64
 7   HeartDiseaseorAttack  236378 non-null  float64
 8   PhysActivity          236378 non-null  int64  
 9   Fruits                236378 non-null  int64  
 10  Veggies               236378 non-null  int64  
 11  HvyAlcoholConsump     236378 non-null  int64  
 12  AnyHealthcare         236378 non-null  int64  
 13  NoDocbcCost           236378 non-null  float64
 14  GenHlth               236378 non-null  float64
 15  MentHlth              236378 non-null  float64
 16  PhysHlth              236378 non-null  float64
 17  DiffWalk              236378 non-null  float64
 18  Sex                   236378 non-null  int64  
 19  Age                   236378 non-null  int64  
 20  Education             236378 non-null  float64
 21  Income                236378 non-null  float64
dtypes: float64(13), int64(9)
memory usage: 39.7 MB
```

In [6]:
```
data.describe()
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Sn
count	236378.000000	236378.000000	236378.000000	236378.000000	236378.000000	236378.0
mean	0.142010	0.418558	0.402059	0.963347	28.953579	0.411997
std	0.349061	0.493324	0.490315	0.187909	6.552055	0.492196
min	0.000000	0.000000	0.000000	0.000000	12.000000	0.000000
25%	0.000000	0.000000	0.000000	1.000000	24.000000	0.000000
50%	0.000000	0.000000	0.000000	1.000000	28.000000	0.000000
75%	0.000000	1.000000	1.000000	1.000000	32.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000	99.000000	1.000000

8 rows × 22 columns

In [7]:
```
data["Diabetes_binary"] = data["Diabetes_binary"].astype(int)
data["HighBP"] = data["HighBP"].astype(int)
data["HighChol"] = data["HighChol"].astype(int)
data["CholCheck"] = data["CholCheck"].astype(int)
data["BMI"] = data["BMI"].astype(int)
data["Smoker"] = data["Smoker"].astype(int)
data["Stroke"] = data["Stroke"].astype(int)
data["HeartDiseaseorAttack"] = data["HeartDiseaseorAttack"].astype(int)
data["PhysActivity"] = data["PhysActivity"].astype(int)
data["Fruits"] = data["Fruits"].astype(int)
data["Veggies"] = data["Veggies"].astype(int)
data["HvyAlcoholConsump"] = data["HvyAlcoholConsump"].astype(int)
data["AnyHealthcare"] = data["AnyHealthcare"].astype(int)
data["NoDocbcCost"] = data["NoDocbcCost"].astype(int)
data["GenHlth"] = data["GenHlth"].astype(int)
data["MentHlth"] = data["MentHlth"].astype(int)
data["PhysHlth"] = data["PhysHlth"].astype(int)
data["DiffWalk"] = data["DiffWalk"].astype(int)
data["Sex"] = data["Sex"].astype(int)
data["Age"] = data["Age"].astype(int)
data["Education"] = data["Education"].astype(int)
data["Income"] =data["Income"].astype(int)
```

In [8]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 236378 entries, 0 to 236377
Data columns (total 22 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Diabetes_binary       236378 non-null  int32
 1   HighBP                236378 non-null  int32
 2   HighChol              236378 non-null  int32
 3   CholCheck             236378 non-null  int32
 4   BMI                   236378 non-null  int32
 5   Smoker                236378 non-null  int32
 6   Stroke                236378 non-null  int32
 7   HeartDiseaseorAttack  236378 non-null  int32
 8   PhysActivity          236378 non-null  int32
 9   Fruits                236378 non-null  int32
 10  Veggies               236378 non-null  int32
 11  HvyAlcoholConsump     236378 non-null  int32
 12  AnyHealthcare         236378 non-null  int32
 13  NoDocbcCost           236378 non-null  int32
 14  GenHlth               236378 non-null  int32
 15  MentHlth              236378 non-null  int32
 16  PhysHlth              236378 non-null  int32
 17  DiffWalk              236378 non-null  int32
 18  Sex                   236378 non-null  int32
 19  Age                   236378 non-null  int32
 20  Education             236378 non-null  int32
 21  Income                236378 non-null  int32
dtypes: int32(22)
memory usage: 19.8 MB
```

In [9]:

```
data.shape
```

```
(236378, 22)
```

In [10]:
```
data.isnull().sum()
```

```
Diabetes_binary         0
HighBP                  0
HighChol                0
CholCheck               0
BMI                     0
Smoker                  0
Stroke                  0
HeartDiseaseorAttack    0
PhysActivity            0
Fruits                  0
Veggies                 0
HvyAlcoholConsump       0
AnyHealthcare           0
NoDocbcCost             0
GenHlth                 0
MentHlth                0
PhysHlth                0
DiffWalk                0
Sex                     0
Age                     0
Education               0
Income                  0
dtype: int64
```

In [11]:
```
#checking for any duplicated data from all the dataset
data.drop_duplicates(inplace=True)
```

In [12]:
```
data.shape
```

```
(223243, 22)
```

In [13]:
```
#outlier detection
from sklearn.ensemble import IsolationForest
model=IsolationForest()
model.fit(data)
data['anomaly']=model.predict(data)
```

In [14]:
```
data
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDis
0	0	0	1	1	15	1	0	0
1	1	1	0	1	28	0	0	1
2	1	1	1	1	33	0	0	0
3	1	0	1	1	29	0	1	1
4	0	0	0	1	24	1	0	0
...	...	...	...	...	...	...	...	...
236373	1	1	1	1	21	0	0	0
236374	0	1	0	1	25	1	0	0
236375	0	0	1	1	31	0	0	0
236376	0	1	0	1	24	0	0	0
236377	0	0	1	1	32	0	0	0

223243 rows × 23 columns

In [15]:
```
#checking the outliers that have been detected
data[data['anomaly']==-1]
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDis
0	0	0	1	1	15	1	0	0
1	1	1	0	1	28	0	0	1
3	1	0	1	1	29	0	1	1
4	0	0	0	1	24	1	0	0
5	0	1	0	1	40	1	0	0
...	...	...	...	...	...	...	...	...
236364	0	0	0	1	37	0	0	0
236369	1	1	1	1	33	0	0	0
236371	0	1	1	0	21	0	0	0
236373	1	1	1	1	21	0	0	0
236374	0	1	0	1	25	1	0	0

68533 rows × 23 columns

In [16]:
```
data[data['anomaly']==-1].shape
```

```
(68533, 23)
```

In [17]:
```
# we have to remove the outliers(anomalies)detected
data.drop(data[data['anomaly']==-1].index,inplace=True)
```

In [18]:
```
data.shape
```
(154710, 23)

In [19]:
```
data
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDis
2	1	1	1	1	33	0	0	0
8	0	1	1	1	30	0	0	0
9	0	1	1	1	36	1	0	0
11	1	1	1	1	30	0	0	0
14	0	1	1	1	27	1	0	0
...	...	...	...	...	...	...	...	...
236370	0	0	0	1	19	0	0	0
236372	0	0	0	1	29	0	0	0
236375	0	0	1	1	31	0	0	0
236376	0	1	0	1	24	0	0	0
236377	0	0	1	1	32	0	0	0

154710 rows × 23 columns

In [20]:
```
# now we have to remove the column 'anomaly ' that has been created for the
data.drop(columns=['anomaly'],inplace=True)
```

In [21]:
```
data.shape
```
(154710, 22)

Scaling the data

In [22]:
```
x=data.drop(['Diabetes_binary'],axis=1)
y=data['Diabetes_binary']
```

In [23]:
```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
scaler.fit(x)
```

▾ StandardScaler

StandardScaler()

In [24]:
```
scaled_features=scaler.transform(x)
x=pd.DataFrame(scaled_features,columns=data.columns[1:])
x.head(10)
```

	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	I
0	1.321513	1.318273	0.122084	0.810077	-0.760388	-0.089448	-0.171712	(
1	1.321513	1.318273	0.122084	0.287202	-0.760388	-0.089448	-0.171712	-
2	1.321513	1.318273	0.122084	1.332953	1.315118	-0.089448	-0.171712	-
3	1.321513	1.318273	0.122084	0.287202	-0.760388	-0.089448	-0.171712	-
4	1.321513	1.318273	0.122084	-0.235673	1.315118	-0.089448	-0.171712	-
5	1.321513	1.318273	0.122084	1.158661	1.315118	-0.089448	-0.171712	(
6	1.321513	1.318273	0.122084	0.287202	-0.760388	-0.089448	-0.171712	(
7	-0.756708	-0.758568	0.122084	0.461494	-0.760388	-0.089448	-0.171712	(
8	1.321513	1.318273	0.122084	0.810077	-0.760388	-0.089448	-0.171712	-
9	-0.756708	-0.758568	0.122084	0.461494	1.315118	-0.089448	-0.171712	(

10 rows × 21 columns

In [25]:
```
#Spliting the data
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.35,random_sta
```

In [26]:
```
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(x_train,y_train)
```

▾ KNeighborsClassifier

KNeighborsClassifier()

In [27]:
```
y_pred = knn.predict(x_test)
```

In [28]:
```
print(x_test.dtypes)
```

```
HighBP                  float64
HighChol                float64
CholCheck               float64
BMI                     float64
Smoker                  float64
Stroke                  float64
HeartDiseaseorAttack    float64
PhysActivity            float64
Fruits                  float64
Veggies                 float64
HvyAlcoholConsump       float64
AnyHealthcare           float64
NoDocbcCost             float64
GenHlth                 float64
MentHlth                float64
PhysHlth                float64
DiffWalk                float64
Sex                     float64
Age                     float64
Education               float64
Income                  float64
dtype: object
```

In [29]:
```
!pip install --upgrade scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\dell\anaconda3\lib\site-packages (1.3.2)
Requirement already satisfied: numpy<2.0,>=1.17.3 in c:\users\dell\anaconda3\lib\site-packages (f
Requirement already satisfied: scipy>=1.5.0 in c:\users\dell\anaconda3\lib\site-packages (from sc
Requirement already satisfied: joblib>=1.1.1 in c:\users\dell\anaconda3\lib\site-packages (from s
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\dell\anaconda3\lib\site-packages
```

In [30]:
```
y_pred
```

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

In [31]:
```
data['Diabetes_binary'].value_counts()
```

```
0    143556
1     11154
Name: Diabetes_binary, dtype: int64
```

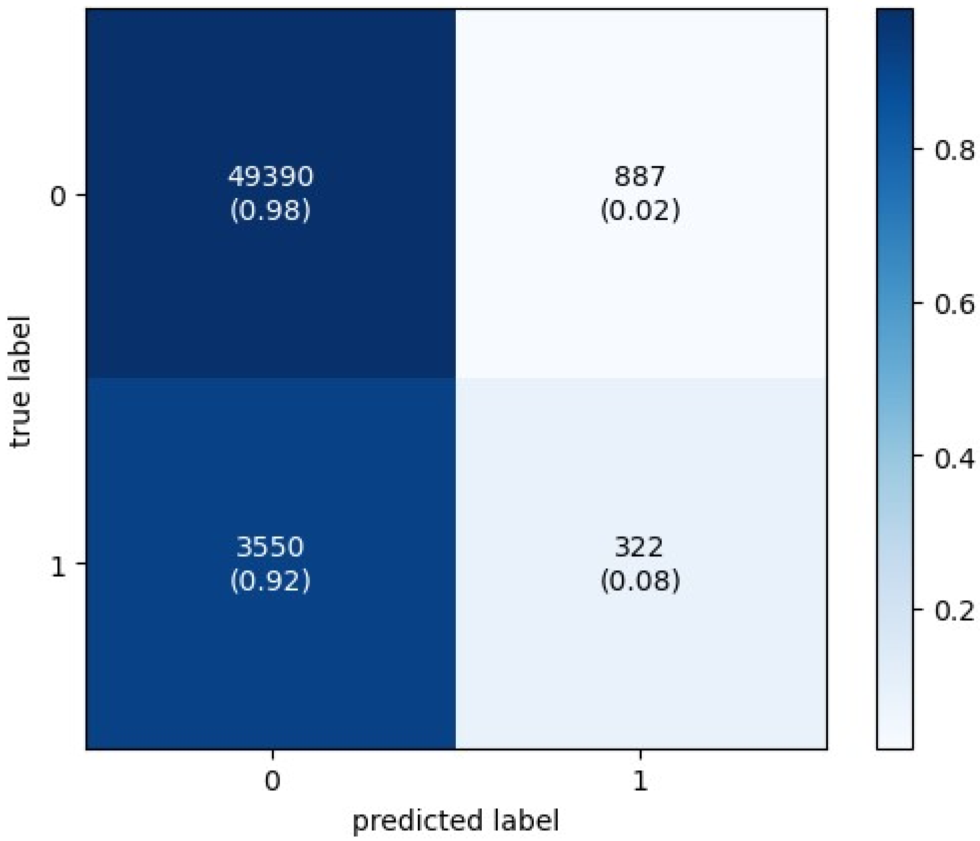
In [32]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.93      0.98      0.96     50277
           1       0.27      0.08      0.13      3872

    accuracy                           0.92     54149
   macro avg       0.60      0.53      0.54     54149
weighted avg       0.89      0.92      0.90     54149
```

In [33]:

```
cm1=confusion_matrix(y_test,y_pred)
plot_confusion_matrix(conf_mat=cm1,show_absolute=True,show_normed=True,color
plt.show()
```



Addressing Imbalanced Data for Improved Diabetes Prediction

One of the challenges in predicting diabetes using machine learning models a
means that the number of individuals with diabetes is significantly lower comp
diabetes. This imbalance can lead to skewed model predictions, favoring the r
underestimating the true risk of diabetes for individuals in the minority class.

To address this issue, we will employ a combined technique known as SMOTE

- SMOTE (Synthetic Minority Oversampling Technique): This technique arti
data points in the minority class by generating synthetic samples based o
balance the class distribution and provides the model with more informati

to improved predictions.
- ENN (Edited Nearest Neighbors): This technique removes noisy data poir minority classes. It identifies data points whose nearest neighbors belong them from the training set. This helps eliminate misclassified data that cou cleaner and more accurate representation of the underlying class structur

Combined effect of SMOTE + ENN: By combining SMOTE and ENN, we achie

- Increased representation of the minority class: SMOTE generates synthet the number of data points in the minority class and providing the model wi
- Enhanced data quality: ENN removes noisy data points from both classes consistent training set. This improves the model's ability to learn the true r the target variable, leading to more accurate and reliable predictions.

Overall, the combination of SMOTE and ENN is a powerful technique for addre improving the accuracy of diabetes prediction models. By balancing the class quality, these techniques ensure that the model learns from a representative a to more reliable and accurate predictions for individuals with and without diabe

In [34]:
```
from imblearn.combine import SMOTEENN
sm=SMOTEENN()
x_resampled,y_resampled = sm.fit_resample(x,y)
```

In [35]:
```
xre_train,xre_test,yre_train,yre_test = train_test_split(x_resampled, y_resa
```

In [36]:
```
knn_smote = KNeighborsClassifier(n_neighbors = 5)
knn_smote.fit(xre_train,yre_train)
```

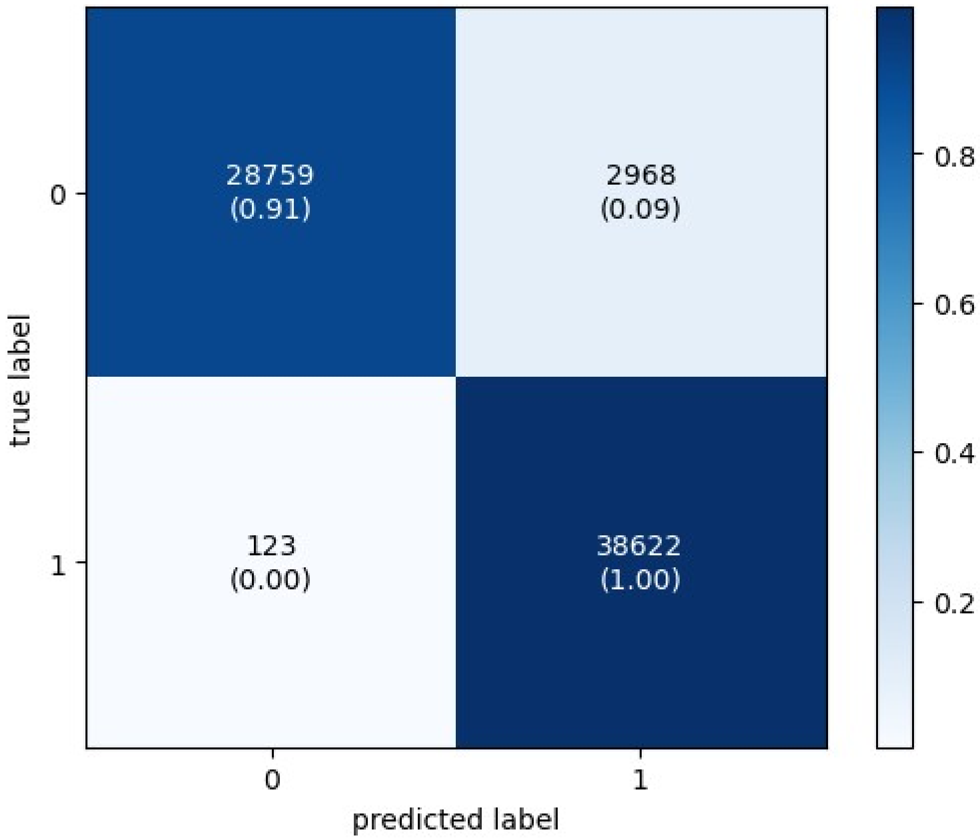
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [37]:
```
yre_pred = knn_smote.predict(xre_test)
```

In [38]:
```
print(classification_report(yre_test,yre_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.91      0.95     31727
           1       0.93      1.00      0.96     38745

    accuracy                           0.96     70472
   macro avg       0.96      0.95      0.96     70472
weighted avg       0.96      0.96      0.96     70472
```

In [39]:
```
cm1=confusion_matrix(yre_test,yre_pred)
plot_confusion_matrix(conf_mat=cm1,show_absolute=True,show_normed=True,color
plt.show()
```



Modeling(RF,SVM,&XGB)
RANDOM FOREST(RF)

In [40]:
```
rf = RandomForestClassifier(n_estimators=100, max_features=16 , max_depth=16
rf.fit(xre_train,yre_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=16, max_f
eatures=16)
```

In [41]:
```
print(rf.score(xre_train, yre_train))
print(rf.score(xre_test, yre_test))
```

```
0.949985404300866
0.9390396185719151
```

In [42]:

```
y_pred_train_rf = rf.predict(xre_train)
acc_train_rf = accuracy_score(yre_train, y_pred_train_rf)

y_pred_test_rf = rf.predict(xre_test)
acc_test_rf = accuracy_score(yre_test, y_pred_test_rf)
print(acc_train_rf)
print(acc_test_rf)
```

```
0.949985404300866
0.9390396185719151
```

In [43]:

```
print(classification_report(yre_test, y_pred_test_rf))
```

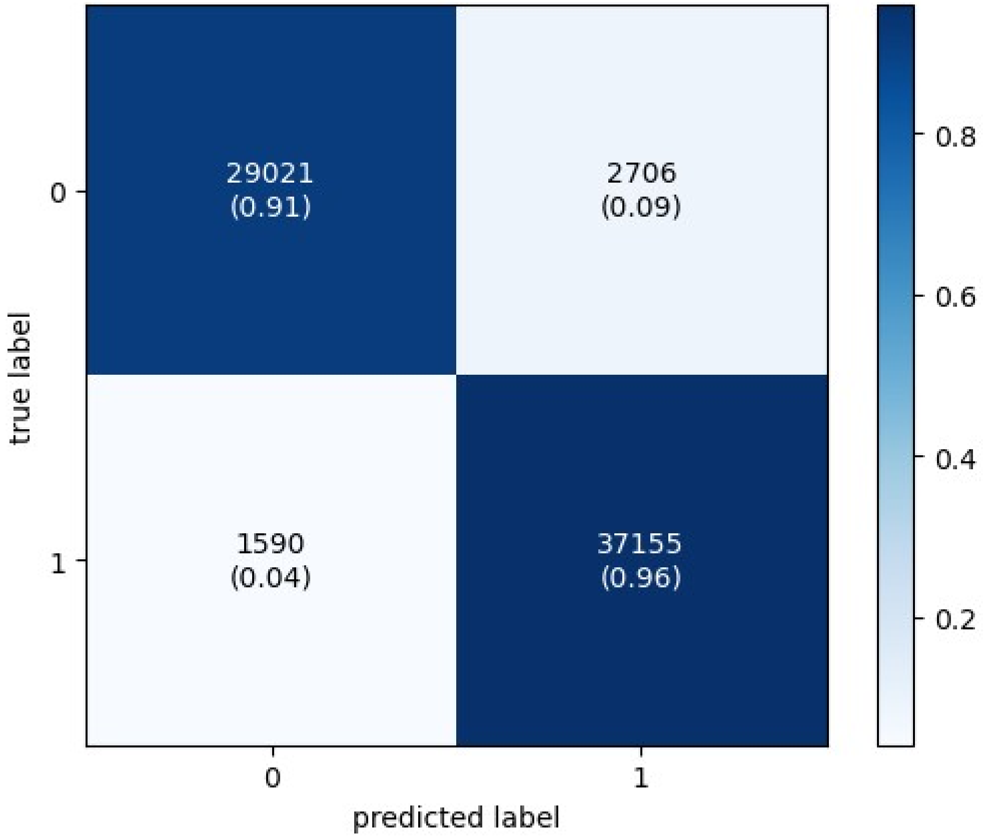
```
              precision    recall  f1-score   support

           0       0.95      0.91      0.93     31727
           1       0.93      0.96      0.95     38745

    accuracy                           0.94     70472
   macro avg       0.94      0.94      0.94     70472
weighted avg       0.94      0.94      0.94     70472
```

In [44]:

```
print('Precision: %.3f' % precision_score(yre_test, y_pred_test_rf,average="
print('Recall: %.3f' % recall_score(yre_test, y_pred_test_rf,average="micro"
print('F-measure: %.3f' % f1_score(yre_test, y_pred_test_rf,average="micro")
```

```
Precision: 0.939
Recall: 0.939
F-measure: 0.939
```

In [45]:
```
cm1 = confusion_matrix(yre_test,y_pred_test_rf)
plot_confusion_matrix(conf_mat=cm1,show_absolute=True,
                                show_normed=True,
                                colorbar=True)
plt.show()
```



Support Vector Machine (SVM)

In [46]:
```
svm = SVC(C=1.0, kernel='rbf', gamma='scale')
svm.fit(xre_train, yre_train)
```

```
▾ SVC
SVC()
```

In [47]:
```
print(svm.score(xre_train, yre_train))
print(svm.score(xre_test, yre_test))
```

```
0.8822917680256884
0.8807185832671132
```

In [48]:
```
y_pred_train_svm = svm.predict(xre_train)
acc_train_svm = accuracy_score(yre_train, y_pred_train_svm)

y_pred_test_svm = svm.predict(xre_test)
acc_test_svm = accuracy_score(yre_test, y_pred_test_svm)
print(acc_train_svm)
print(acc_test_svm)
```

```
0.8822917680256884
0.8807185832671132
```

In [49]:
```
print(classification_report(yre_test, y_pred_test_svm))
```

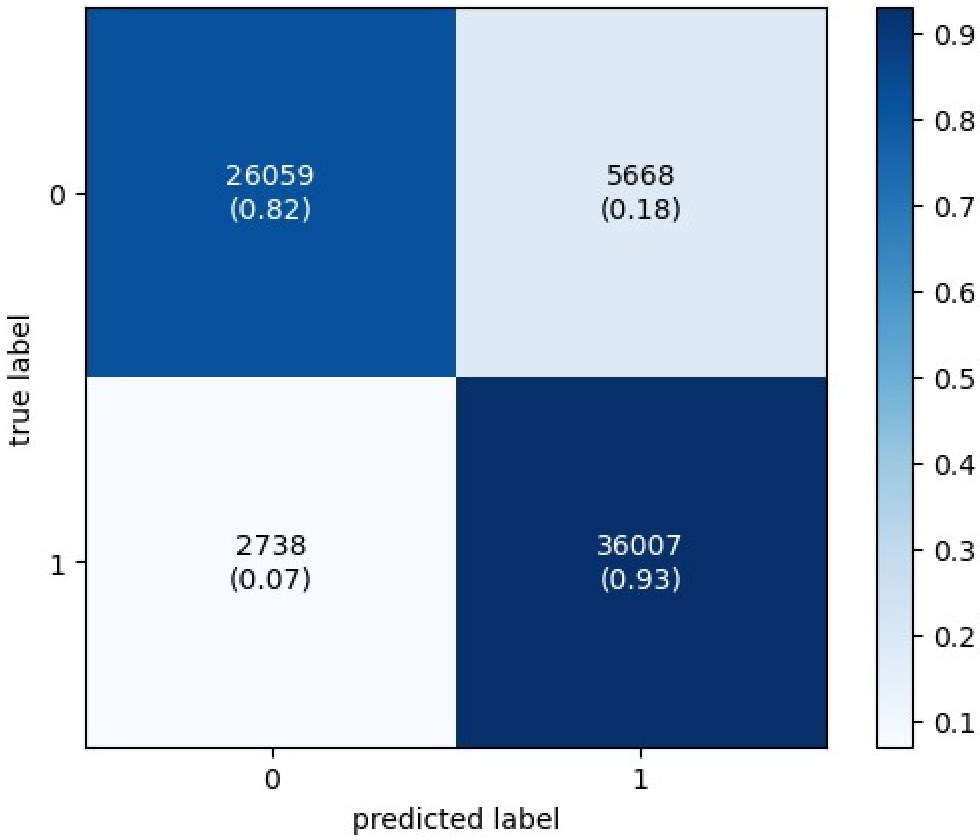
```
              precision    recall  f1-score   support

           0       0.90      0.82      0.86     31727
           1       0.86      0.93      0.90     38745

    accuracy                           0.88     70472
   macro avg       0.88      0.88      0.88     70472
weighted avg       0.88      0.88      0.88     70472
```

In [50]:
```
print('Precision: %.3f' % precision_score(yre_test, y_pred_test_svm,average=
print('Recall: %.3f' % recall_score(yre_test, y_pred_test_svm,average="micrc
print('F-measure: %.3f' % f1_score(yre_test, y_pred_test_svm,average="micro"
```

```
Precision: 0.881
Recall: 0.881
F-measure: 0.881
```

In [51]:

```
# calculating and plotting the confusion matrix
cm1 = confusion_matrix(yre_test,y_pred_test_svm)
plot_confusion_matrix(conf_mat=cm1,show_absolute=True,
                                show_normed=True,
                                colorbar=True)
plt.show()
```



Extreme Gradient Boosting (XGB)

In [52]:
```python
xgb=XGBClassifier(max_depth=20)
xgb.fit(xre_train,yre_train)
```

▾ XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stoppi
ng_rounds=None,
              enable_categorical=False, eval_metric=None, feat
ure_types=None,
              gamma=None, grow_policy=None, importance_type=No
ne,
```

In [53]:
```python
print(xgb.score(xre_train,yre_train))
print(xgb.score(xre_test,yre_test))
```

```
0.999787146054296
0.9682285162901578
```

In [55]:
```python
y_pred_train_xgb = xgb.predict(xre_train)
acc_train_xgb = accuracy_score(yre_train,y_pred_train_xgb)
y_pred_test_xgb=xgb.predict(xre_test)
acc_test_xgb = accuracy_score(yre_test,y_pred_test_xgb)
print(acc_train_xgb)
print(acc_test_xgb)
```

```
0.999787146054296
0.9682285162901578
```

In [56]:

```
print(classification_report(yre_test,y_pred_test_xgb))
```

```
              precision    recall  f1-score   support

           0       0.95      0.98      0.97     31727
           1       0.98      0.96      0.97     38745

    accuracy                           0.97     70472
   macro avg       0.97      0.97      0.97     70472
weighted avg       0.97      0.97      0.97     70472
```

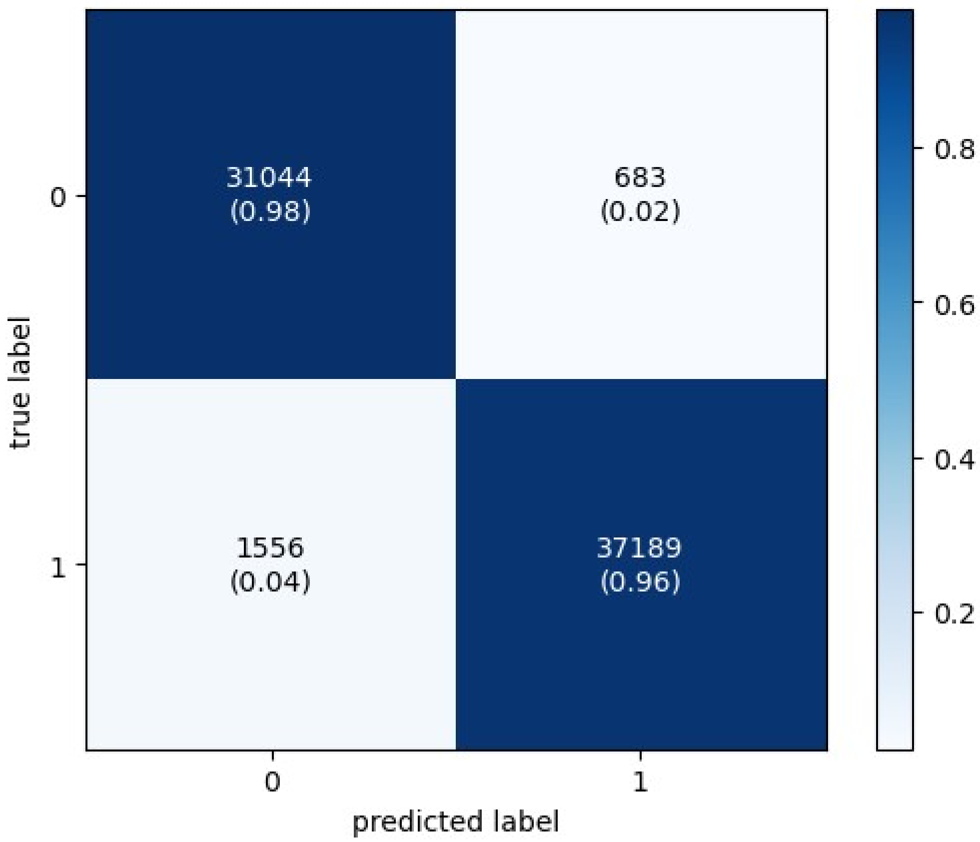
In [57]:

```
print('Precision: %.3f' % precision_score(yre_test, y_pred_test_xgb,average=
print('Recall: %.3f' % recall_score(yre_test, y_pred_test_xgb,average="micrc
print('F-measure: %.3f' % f1_score(yre_test, y_pred_test_xgb,average="micro"
```

```
Precision: 0.968
Recall: 0.968
F-measure: 0.968
```

In [58]:

```
# calculating and plotting the confusion matrix
cm1 = confusion_matrix(yre_test,y_pred_test_xgb)
plot_confusion_matrix(conf_mat=cm1,show_absolute=True,
                                show_normed=True,
                                colorbar=True)
plt.show()
```



In [ ]: