fkpx3as2f

December 11, 2024

1 Classification of direct marketing Compaign Subscriptions

1.0.1 1. importing data, libraries and EDA

[115]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as  sns
from tqdm.auto import tqdm
import warnings
warnings.filterwarnings('ignore')
from scipy.stats import  norm
from pprint import  pprint as p

#Data Preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import  train_test_split

#classifiers

from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import  SVC
from sklearn.linear_model import LogisticRegression
from imblearn.ensemble import BalancedRandomForestClassifier

#metrics
from sklearn.metrics import ␣
↪accuracy_score,confusion_matrix,classification_report,ConfusionMatrixDisplay,roc_curve,roc_
```

2 Dataset Description: Bank marketing

2.1 Client Information

1. **Age**: Client's age *(Numeric)*.

2. **Job**: Client's type of job *(Categorical)*:
   - Options: 'admin.', 'blue-collar', 'entrepreneur', 'housemaid', 'management', 'retired', 'self-employed', 'services', 'student', 'technician', 'unemployed',

'unknown'.

3. **Marital Status**: Client's marital status *(Categorical)*:
   - Options: 'divorced' *(includes divorced or widowed)*, 'married', 'single', 'unknown'.

4. **Education**: Client's level of education *(Categorical)*:
   - Options: 'basic.4y', 'basic.6y', 'basic.9y', 'high.school', 'illiterate', 'professional.course', 'university.degree', 'unknown'.

5. **Default**: Whether the client has credit in default *(Categorical)*:
   - Options: 'no', 'yes', 'unknown'.

6. **Housing Loan**: Whether the client has a housing loan *(Categorical)*:
   - Options: 'no', 'yes', 'unknown'.

7. **Personal Loan**: Whether the client has a personal loan *(Categorical)*:
   - Options: 'no', 'yes', 'unknown'.

2.2 Last Campaign Contact Information

8. **Contact**: Contact communication type *(Categorical)*:
   - Options: 'cellular', 'telephone'.

9. **Month**: Last contact month of the year *(Categorical)*:
   - Options: 'jan', 'feb', 'mar', …, 'nov', 'dec'.

10. **Day of Week**: Last contact day of the week *(Categorical)*:
    - Options: 'mon', 'tue', 'wed', 'thu', 'fri'.

2.3 Campaign Details

11. **Campaign**: Number of contacts performed during this campaign for this client *(Numeric, includes the last contact)*.

12. **Pdays**: Number of days since the client was last contacted in a previous campaign *(Numeric; 999 means the client was not previously contacted)*.

13. **Previous**: Number of contacts performed before this campaign for this client *(Numeric)*.

14. **Poutcome**: Outcome of the previous marketing campaign *(Categorical)*:
    - Options: 'failure', 'nonexistent', 'success'.

2.4 Social and Economic Context Attributes

15. **Employment Variation Rate (emp.var.rate)**: Quarterly indicator for the employment variation rate *(Numeric)*.

16. **Consumer Price Index (cons.price.idx)**: Monthly indicator for the consumer price index *(Numeric)*.

17. **Consumer Confidence Index (cons.conf.idx)**: Monthly indicator measuring consumer optimism or pessimism about the economy *(Numeric)*.

18. **Euribor 3-Month Rate (euribor3m)**: Daily indicator of the 3-month Euribor (Euro Interbank Offered Rate), which reflects the interest rate at which European banks lend to one another *(Numeric)*.

19. **Number of Employees (nr.employed)**: Quarterly indicator of the total number of employees in the economy *(Numeric)*.

2.5 Output Variable (Target)

20. **Subscribed Term Deposit (y)**: Whether the client subscribed to a term deposit *(Binary)*:
    - Options: `'yes'`, `'no'`.

[85]:
```python
df = pd.read_csv('bank.csv')
df.head()
```

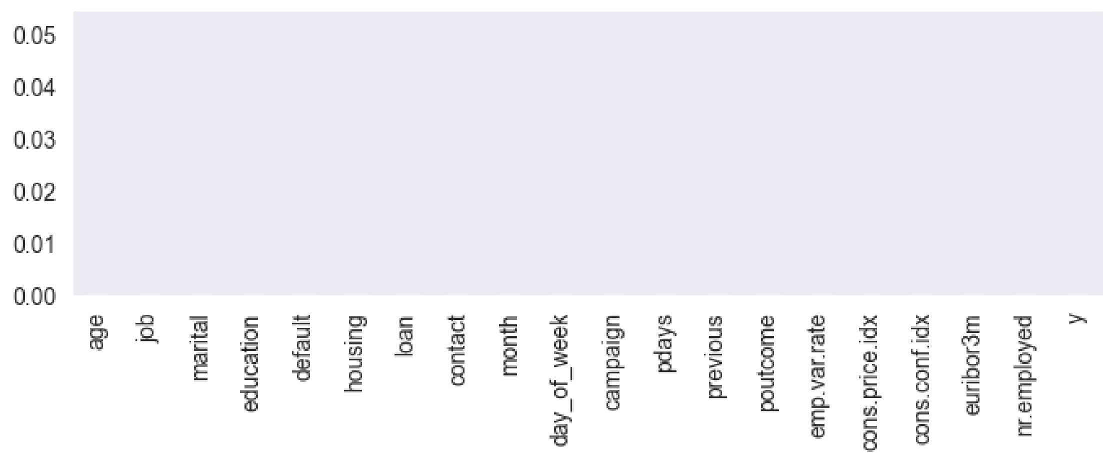
[85]:
```
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week  campaign  pdays  previous     poutcome  emp.var.rate  \
0   may         mon         1    999         0  nonexistent           1.1
1   may         mon         1    999         0  nonexistent           1.1
2   may         mon         1    999         0  nonexistent           1.1
3   may         mon         1    999         0  nonexistent           1.1
4   may         mon         1    999         0  nonexistent           1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0          93.994          -36.4      4.857       5191.0  no
1          93.994          -36.4      4.857       5191.0  no
2          93.994          -36.4      4.857       5191.0  no
3          93.994          -36.4      4.857       5191.0  no
4          93.994          -36.4      4.857       5191.0  no
```

[86]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 20 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  campaign        41188 non-null  int64
 11  pdays           41188 non-null  int64
 12  previous        41188 non-null  int64
 13  poutcome        41188 non-null  object
 14  emp.var.rate    41188 non-null  float64
 15  cons.price.idx  41188 non-null  float64
 16  cons.conf.idx   41188 non-null  float64
 17  euribor3m       41188 non-null  float64
 18  nr.employed     41188 non-null  float64
 19  y               41188 non-null  object
dtypes: float64(5), int64(4), object(11)
memory usage: 6.3+ MB
```

[87]:
```
plt.figure(figsize=(7,3))
df.isna().sum().plot(kind='bar')
plt.ylim(0)
plt.tight_layout()
```

[88]:
```
plt.figure(figsize=(7,3))
df.isnull().sum().plot(kind='bar')
plt.ylim(0)
plt.tight_layout()
```



[89]:
```
df.drop_duplicates(inplace=True)
df.duplicated().sum()
```

[89]:
```
np.int64(0)
```

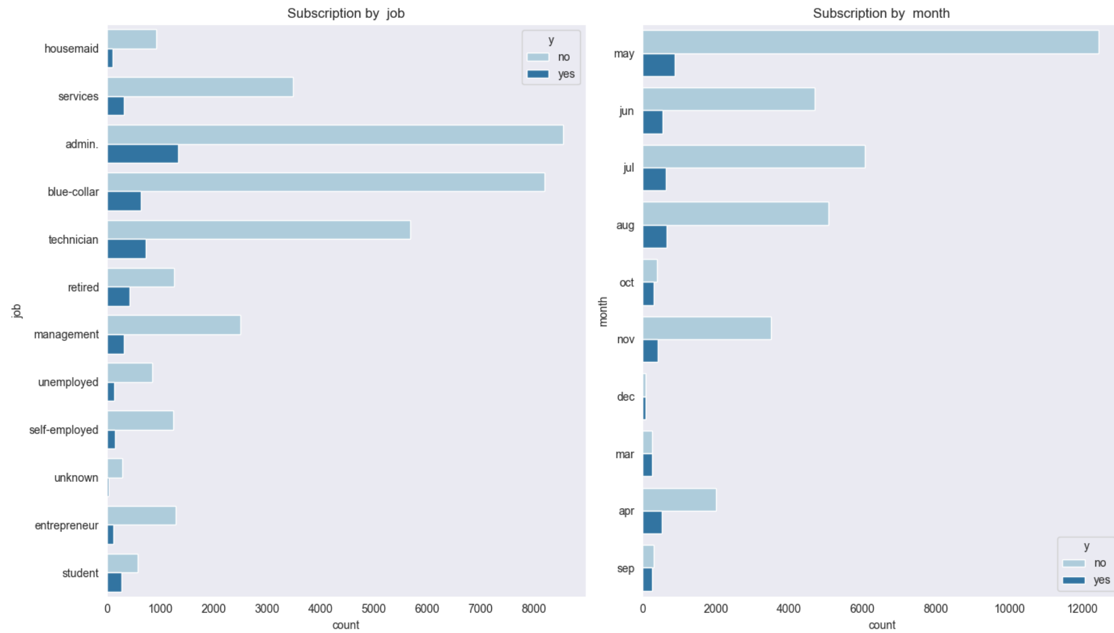
[90]:
```
[col for col in df.columns if df[col].dtype == 'object']
```

[90]:
```
['job',
 'marital',
 'education',
```

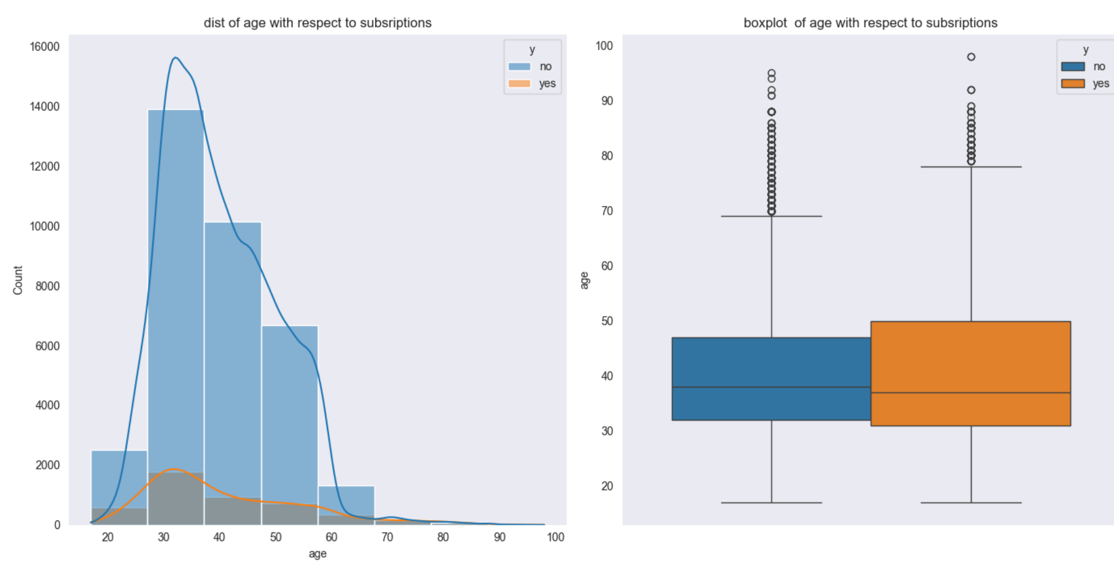
```
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'poutcome',
 'y']
```

[ ]:
```
sns.set_style('dark')
fig,ax = plt.subplots(5,2,figsize=(18,18))
ax = ax.flatten()
axe = 0
for col in df.columns:
    if df[col].dtype == 'object' and len(df[col].unique()) <=8:
        sns.countplot(df,x=col,hue='y',palette='Paired',ax=ax[axe])
        ax[axe].set_title(f'Subscription by  {col}')
        axe +=1
plt.tight_layout()
```

[92]:
```
fig,ax = plt.subplots(1,2,figsize=(14,8))
ax = ax.flatten()
axe = 0
for col in df.columns:
    if df[col].dtype == 'object' and len(df[col].unique()) > 8  :
        sns.countplot(df,y=col,hue='y',palette='Paired',ax=ax[axe])
        ax[axe].set_title(f'Subscription by  {col}')
        axe +=1
plt.tight_layout()
```



[93]:
```
plt.figure(figsize=(14,7))
plt.subplot(1,2,1)
sns.histplot(df,x='age',hue='y',kde=True,bins=8)
plt.title('dist of age with respect to subsriptions')
plt.tight_layout()
plt.subplot(1,2,2)
sns.boxplot(df,y='age',hue='y')
plt.title('boxplot  of age with respect to subsriptions')
plt.tight_layout()
```



[94]:
```python
num = [col for col in df.columns if df[col].dtype in ['float64','int']]
```

[95]:
```python
df[[col for col in df.columns if df[col].dtypes == "object"]]
```

[95]:
```
                job  marital            education  default housing loan  \
0         housemaid  married             basic.4y       no      no   no
1          services  married          high.school  unknown      no   no
2          services  married          high.school       no     yes   no
3            admin.  married             basic.6y       no      no   no
4          services  married          high.school       no      no  yes
…               …        …                    …      …      …    …
41183       retired  married  professional.course       no     yes   no
41184   blue-collar  married  professional.course       no      no   no
41185       retired  married    university.degree       no     yes   no
41186    technician  married  professional.course       no      no   no
41187       retired  married  professional.course       no     yes   no

          contact month day_of_week     poutcome    y
0       telephone   may         mon  nonexistent   no
1       telephone   may         mon  nonexistent   no
2       telephone   may         mon  nonexistent   no
3       telephone   may         mon  nonexistent   no
4       telephone   may         mon  nonexistent   no
…             …   …         …          …  …
41183    cellular   nov         fri  nonexistent  yes
41184    cellular   nov         fri  nonexistent   no
41185    cellular   nov         fri  nonexistent   no
41186    cellular   nov         fri  nonexistent  yes
41187    cellular   nov         fri      failure   no

[39404 rows x 11 columns]
```

2.5.1 2. Data processing : encoding ,standardisation, cleaning

[96]:
```python
for col in df[[col for col in df.columns if df[col].dtypes == "object"]].
 ↪columns :
    print('col name is :', col)
    print(df[col].unique())
    print('_'*100)
```

```
col name is : job
['housemaid' 'services' 'admin.' 'blue-collar' 'technician' 'retired'
 'management' 'unemployed' 'self-employed' 'unknown' 'entrepreneur'
 'student']
________________________________________________________________________________
____________________
```

```
col name is : marital
['married' 'single' 'divorced' 'unknown']
--------------------------------------------------------------------------------
--------------------
col name is : education
['basic.4y' 'high.school' 'basic.6y' 'basic.9y' 'professional.course'
 'unknown' 'university.degree' 'illiterate']
--------------------------------------------------------------------------------
--------------------
col name is : default
['no' 'unknown' 'yes']
--------------------------------------------------------------------------------
--------------------
col name is : housing
['no' 'yes' 'unknown']
--------------------------------------------------------------------------------
--------------------
col name is : loan
['no' 'yes' 'unknown']
--------------------------------------------------------------------------------
--------------------
col name is : contact
['telephone' 'cellular']
--------------------------------------------------------------------------------
--------------------
col name is : month
['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'mar' 'apr' 'sep']
--------------------------------------------------------------------------------
--------------------
col name is : day_of_week
['mon' 'tue' 'wed' 'thu' 'fri']
--------------------------------------------------------------------------------
--------------------
col name is : poutcome
['nonexistent' 'failure' 'success']
--------------------------------------------------------------------------------
--------------------
col name is : y
['no' 'yes']
--------------------------------------------------------------------------------
--------------------
```

[97]:

```
df['y'] = df['y'].apply(lambda x :  0 if x == 'no' else 1)

education_mapping = {
    'illiterate': 0,
    'basic.4y': 1,
```

```
    'basic.6y': 2,
    'basic.9y': 3,
    'high.school': 4,
    'professional.course': 5,
    'university.degree': 6,
    'unknown': 7
}
df['education'] = df['education'].map(education_mapping)

df['day_of_week'] = df['day_of_week'].map({'mon':1,'tue':2,'wed':3,'thu':
 ↪4,'fri':5})

month_mapping = {
    'jan': 1, 'feb': 2, 'mar': 3, 'apr': 4,
    'may': 5, 'jun': 6, 'jul': 7, 'aug': 8,
    'sep': 9, 'oct': 10, 'nov': 11, 'dec': 12
}

df['month'] = df['month'].map(month_mapping)

df = pd.concat([df,pd.get_dummies(df[['job','marital']],drop_first=True)],␣
 ↪axis=1)
df = df.applymap(lambda x: 1 if x == True else 0 if x == False else x)

df['contact'] = df['contact'].apply(lambda x : 0 if x == 'telephone' else 1)


value_mapping = {'yes': 1, 'no': -1, 'unknown': 0}


for col in ['default', 'housing', 'loan']:
    df[col] = df[col].map(value_mapping)

df['poutcome'] = df['poutcome'].map({'nonexistent':0,'failure':-1,'success':1})

df.drop(['job','marital'],axis=1,inplace=True)
df.head()
```

[97]:

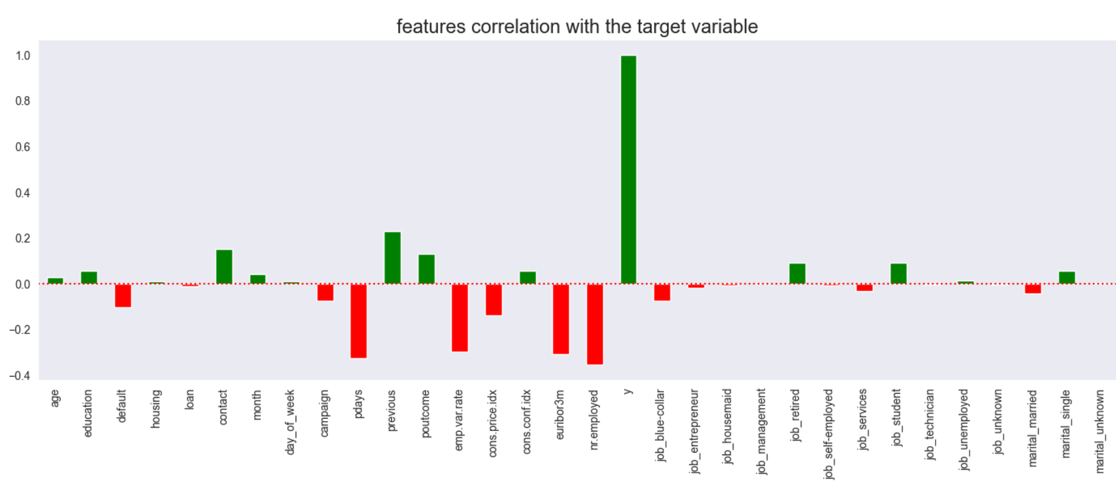
	age	education	default	housing	loan	contact	month	day_of_week	\
0	56	1	-1	-1	-1	0	5	1	
1	57	4	0	-1	-1	0	5	1	
2	37	4	-1	1	-1	0	5	1	
3	40	2	-1	-1	-1	0	5	1	
4	56	4	-1	-1	1	0	5	1	

	campaign	pdays	…	job_retired	job_self-employed	job_services	\
0	1	999	…	0	0	0	

```
1         1    999   ...          0                0               1
2         1    999   ...          0                0               1
3         1    999   ...          0                0               0
4         1    999   ...          0                0               1

   job_student  job_technician  job_unemployed  job_unknown  marital_married  \
0            0               0               0            0                1
1            0               0               0            0                1
2            0               0               0            0                1
3            0               0               0            0                1
4            0               0               0            0                1

   marital_single  marital_unknown
0               0                0
1               0                0
2               0                0
3               0                0
4               0                0

[5 rows x 32 columns]
```

[98]:

```python
plt.figure(figsize=(14,6))
df.corrwith(df['y']).plot(kind='bar',color=['red' if x <=0 else 'green' for x␣
 ↪in df.corrwith(df['y']) ])
plt.axhline(0,color='red',linestyle=':')
plt.title('features correlation with the target variable',size=17)
plt.tight_layout()
```

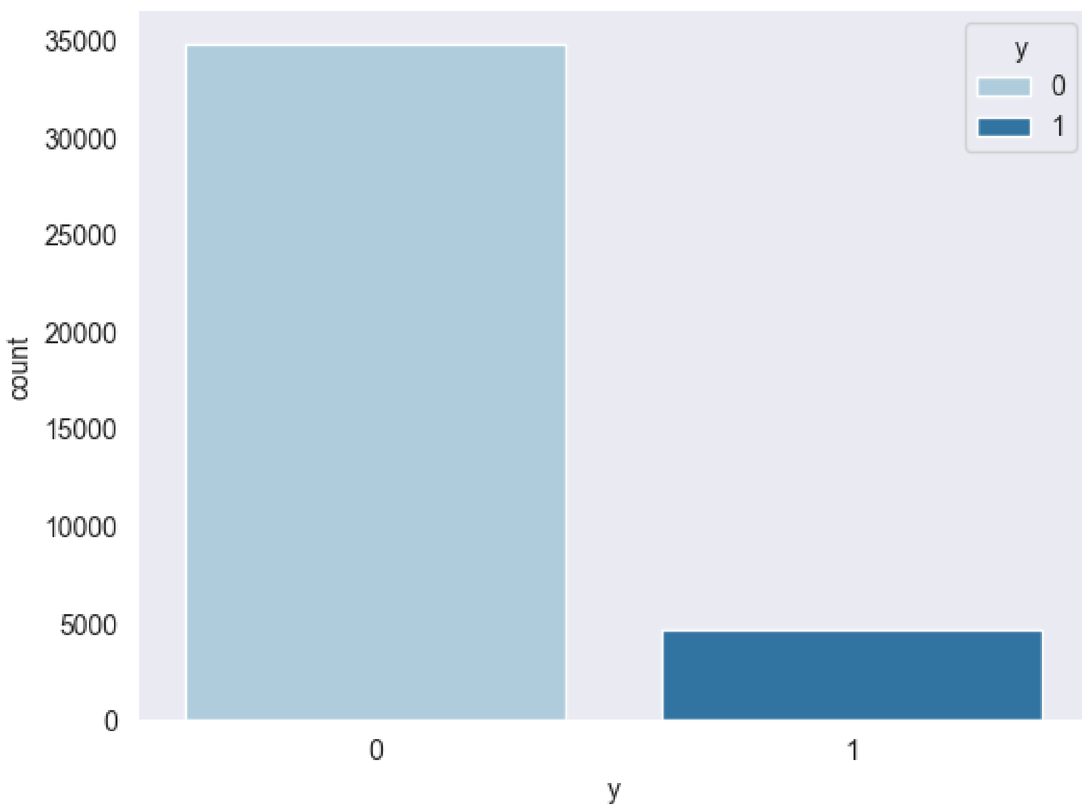


2.5.2 Handling Imbalanced Data with Resampling Techniques

- **SMOTE (Synthetic Minority Over-sampling)**: Generates synthetic samples for the minority class by interpolating between existing minority instances, improving detection of class 1 (subscribed users).
- **Random Over-Sampling**: Duplicates existing minority class samples until it matches the majority class size, but may cause overfitting.
- **Models to Use**:
  - **Random Forest Classifier**: Combines multiple trees, robust and reduces overfitting.
  - **Balanced Random Forest**: Ensures each tree is trained on a balanced dataset.
  - **Support Vector Classifier (SVC)**: Optimizes class separation with class weighting to better detect the minority class.

[99]:
```
sns.countplot(x=df['y'],hue=df['y'],palette='Paired')
```

[99]:
```
<Axes: xlabel='y', ylabel='count'>
```



[100]:
```
#spliting the data

x,y = df.drop('y',axis=1),df['y']

#train test split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.
↪3,random_state=42)
```

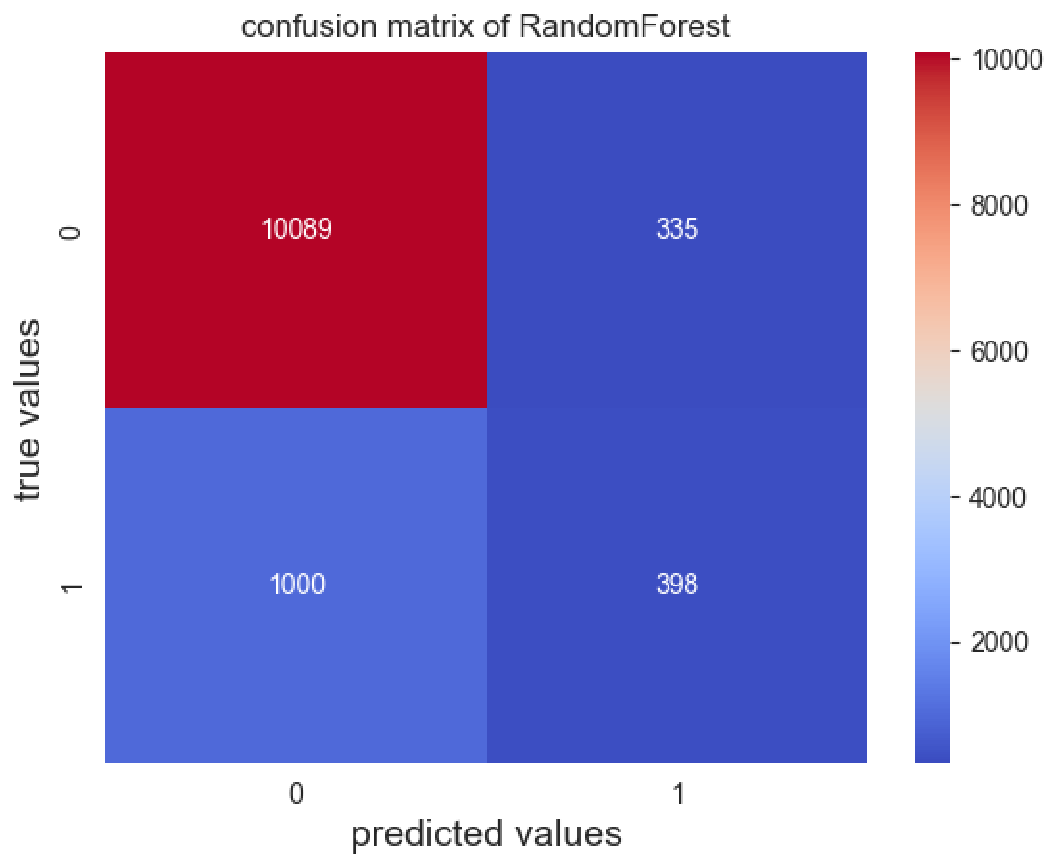
[101]:
```
from pprint import  pprint as p
```

2.5.3 model performance before using SMOTE and Oversampling

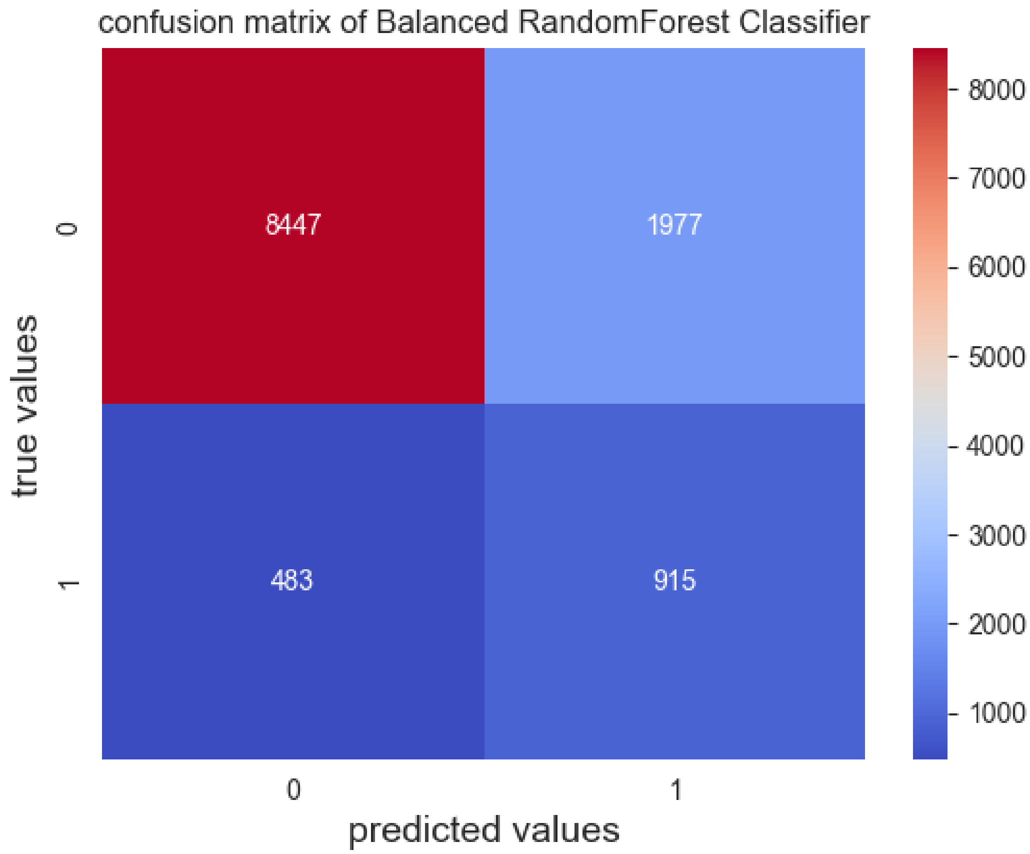
[102]:
```
def models (model, model_name):
    mdl = model(random_state=42)
    mdl.fit(x_train,y_train)
    y_hat = mdl.predict(x_test)

    print(accuracy_score(y_test,y_hat))
    confusion_mat = confusion_matrix(y_test,y_hat)
    sns.heatmap(confusion_mat,fmt='d',annot=True,cmap='coolwarm')
    plt.xlabel('predicted values',size=14)
    plt.ylabel('true values',size=14)
    plt.title(f'confusion matrix of {model_name}',size=12)
    plt.show()
    print(classification_report(y_test,y_hat))
```

[103]:
```
models(RandomForestClassifier,'RandomForest')
models(BalancedRandomForestClassifier,'Balanced RandomForest Classifier')
models(SVC,'support vector classifier')
```

```
0.8870749450177635
```

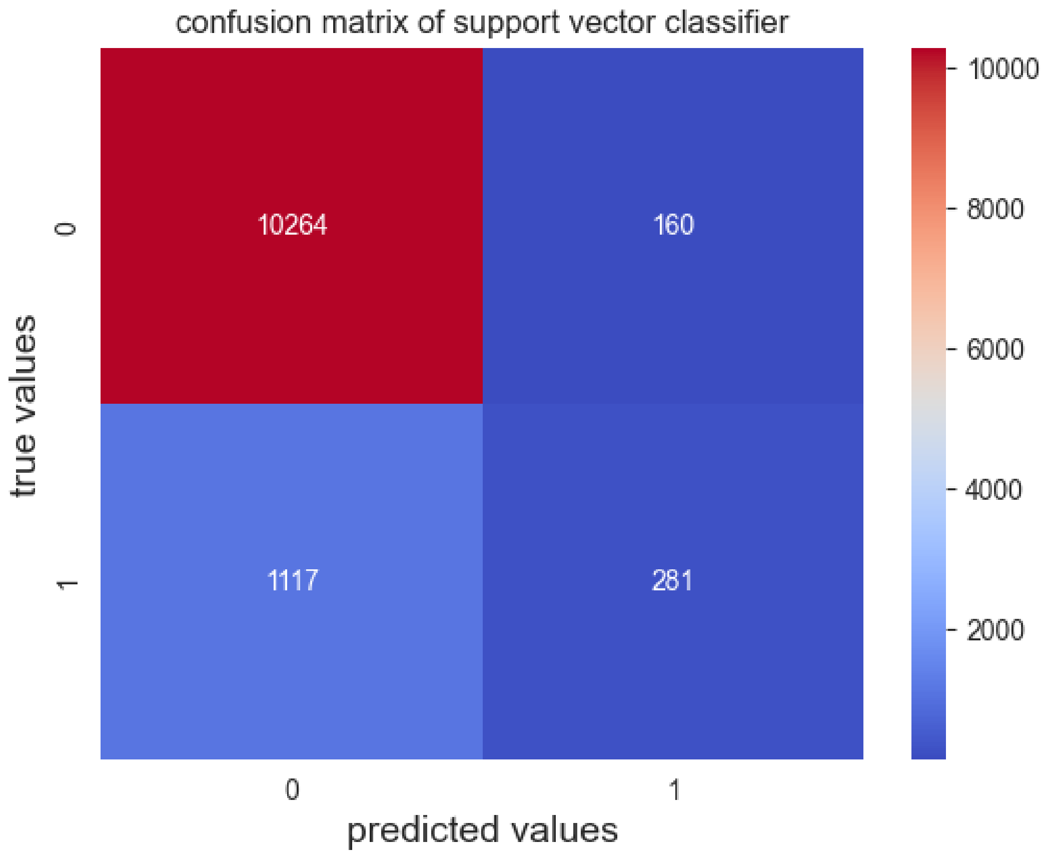



```
              precision    recall  f1-score   support

           0       0.91      0.97      0.94     10424
           1       0.54      0.28      0.37      1398

    accuracy                           0.89     11822
   macro avg       0.73      0.63      0.66     11822
weighted avg       0.87      0.89      0.87     11822

0.7919133818304855
```



	precision	recall	f1-score	support
0	0.95	0.81	0.87	10424
1	0.32	0.65	0.43	1398
accuracy			0.79	11822
macro avg	0.63	0.73	0.65	11822
weighted avg	0.87	0.79	0.82	11822

0.8919810522754187




```
              precision    recall  f1-score   support

           0       0.90      0.98      0.94     10424
           1       0.64      0.20      0.31      1398

    accuracy                           0.89     11822
   macro avg       0.77      0.59      0.62     11822
weighted avg       0.87      0.89      0.87     11822
```

[ ]:

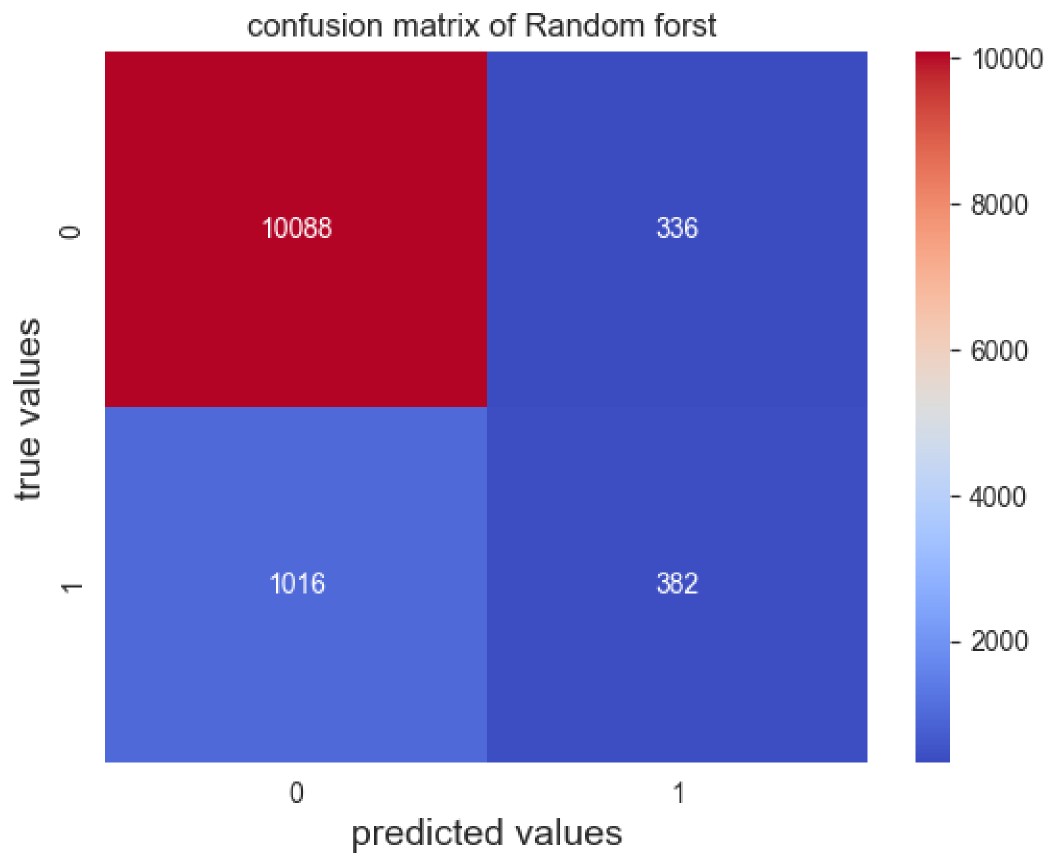
```

```

[104]:

```python
model = RandomForestClassifier(class_weight='balanced', random_state=42)
model.fit(x_train, y_train)

# Predict and evaluate
y_pred = model.predict(x_test)
print(classification_report(y_test, y_pred))
print(accuracy_score(y_test,y_pred))
```

```python
confusion_mat = confusion_matrix(y_test,y_pred)
sns.heatmap(confusion_mat,fmt='d',annot=True,cmap='coolwarm')
plt.xlabel('predicted values',size=14)
plt.ylabel('true values',size=14)
plt.title(f'confusion matrix of Random forst ',size=12)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.91      0.97      0.94     10424
           1       0.53      0.27      0.36      1398

    accuracy                           0.89     11822
   macro avg       0.72      0.62      0.65     11822
weighted avg       0.86      0.89      0.87     11822

0.8856369480629335
```



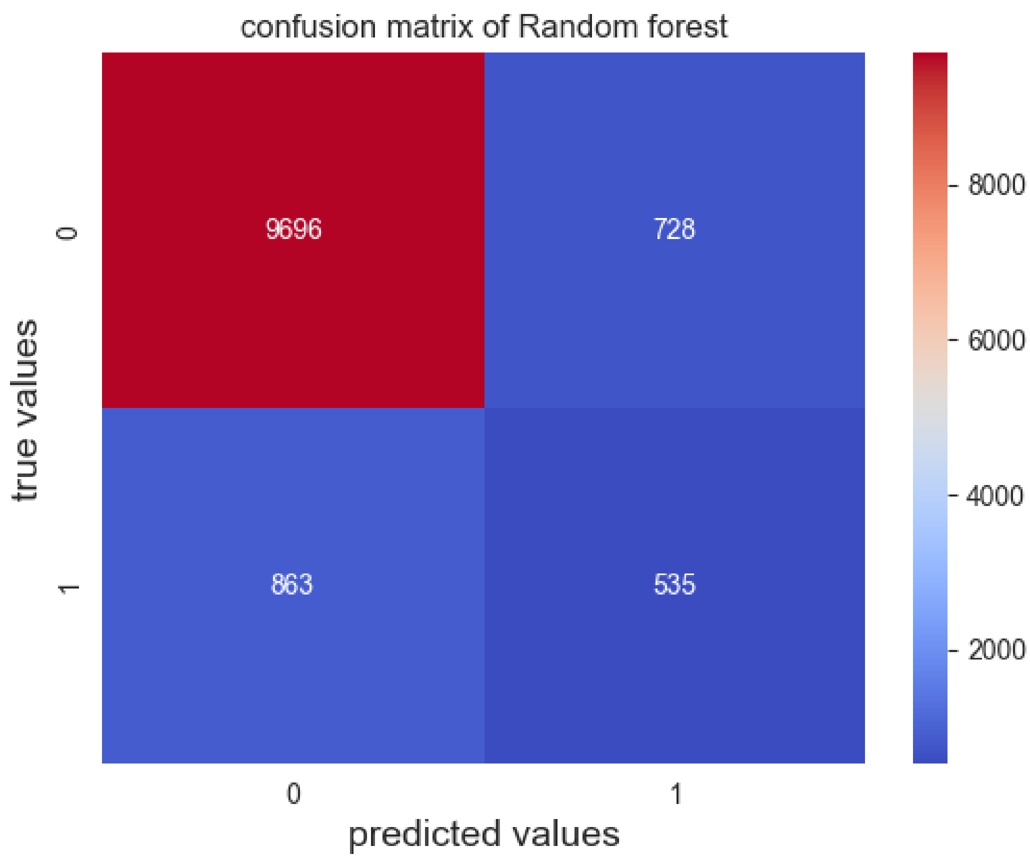
model performance after using the SMOTE technique

[105]:
```
from imblearn.over_sampling import  SMOTE

smote = SMOTE(random_state=42)
x_train_semp,y_train_semp = smote.fit_resample(x_train,y_train)
```

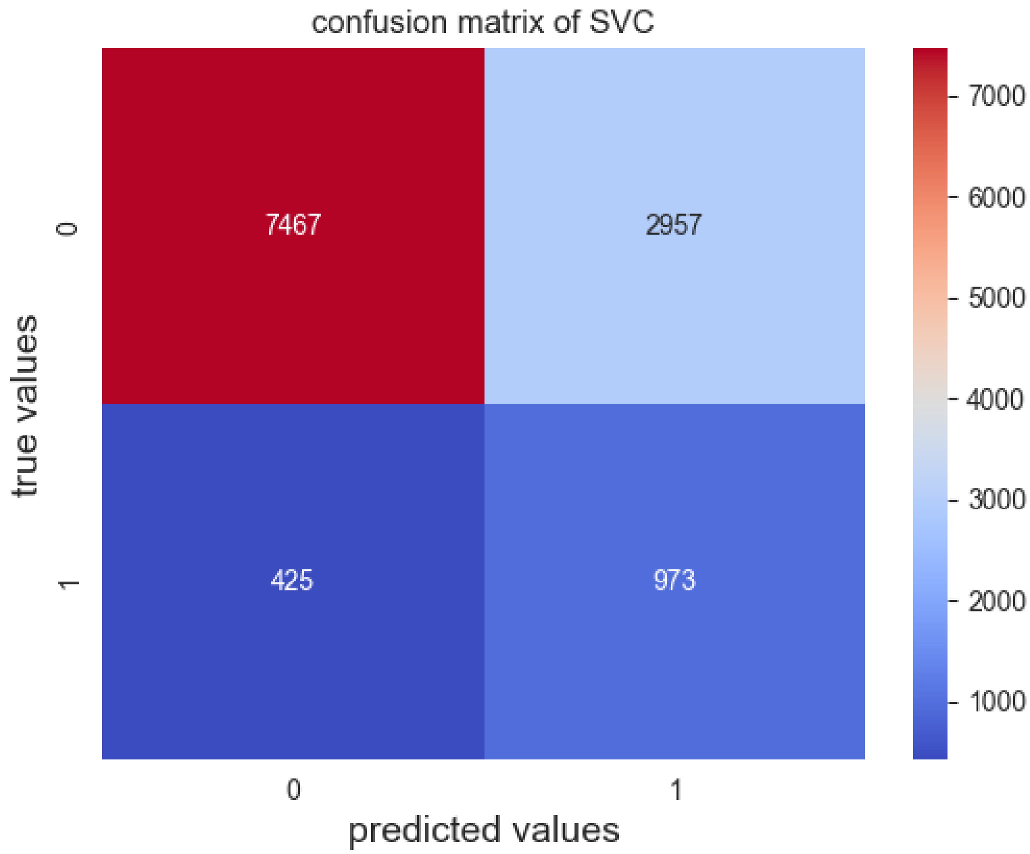
[106]:
```
def models (model, model_name):
    mdl = model(random_state=42)
    mdl.fit(x_train_semp,y_train_semp)
    y_hat = mdl.predict(x_test)

    print(accuracy_score(y_test,y_hat))
    confusion_mat = confusion_matrix(y_test,y_hat)
    sns.heatmap(confusion_mat,fmt='d',annot=True,cmap='coolwarm')
    plt.xlabel('predicted values',size=14)
    plt.ylabel('true values',size=14)
    plt.title(f'confusion matrix of {model_name}',size=12)
    plt.show()
    print(classification_report(y_test,y_hat))
```

[107]:
```
models(RandomForestClassifier,'Random forest')
models(SVC,'SVC')
models(BalancedRandomForestClassifier,'Balanced RandomForest Classifier')
```

```
0.8654204026391473
```

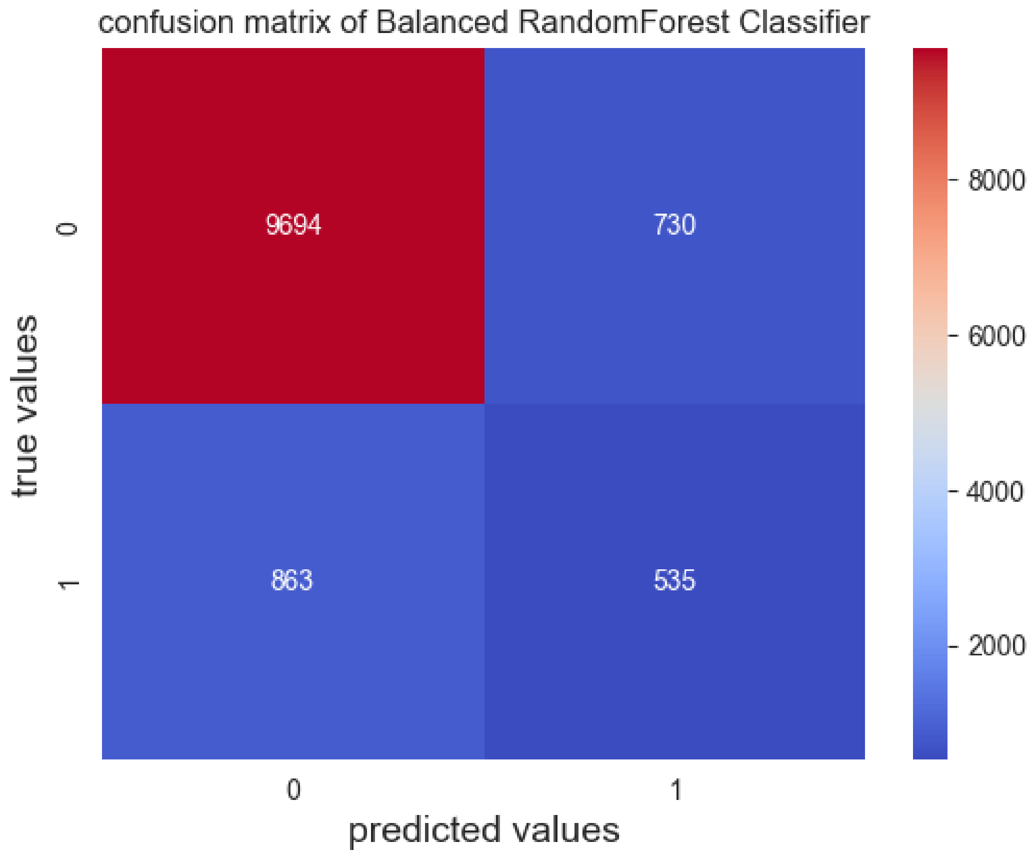



```
              precision    recall  f1-score   support

           0       0.92      0.93      0.92     10424
           1       0.42      0.38      0.40      1398

    accuracy                           0.87     11822
   macro avg       0.67      0.66      0.66     11822
weighted avg       0.86      0.87      0.86     11822

0.7139231940450008
```



	precision	recall	f1-score	support
0	0.95	0.72	0.82	10424
1	0.25	0.70	0.37	1398
accuracy			0.71	11822
macro avg	0.60	0.71	0.59	11822
weighted avg	0.86	0.71	0.76	11822

0.8652512265268144




```
              precision    recall  f1-score   support

           0       0.92      0.93      0.92     10424
           1       0.42      0.38      0.40      1398

    accuracy                           0.87     11822
   macro avg       0.67      0.66      0.66     11822
weighted avg       0.86      0.87      0.86     11822
```

model performance after using the underSampling method technique

[108]:
```
from joblib import dump, load
```

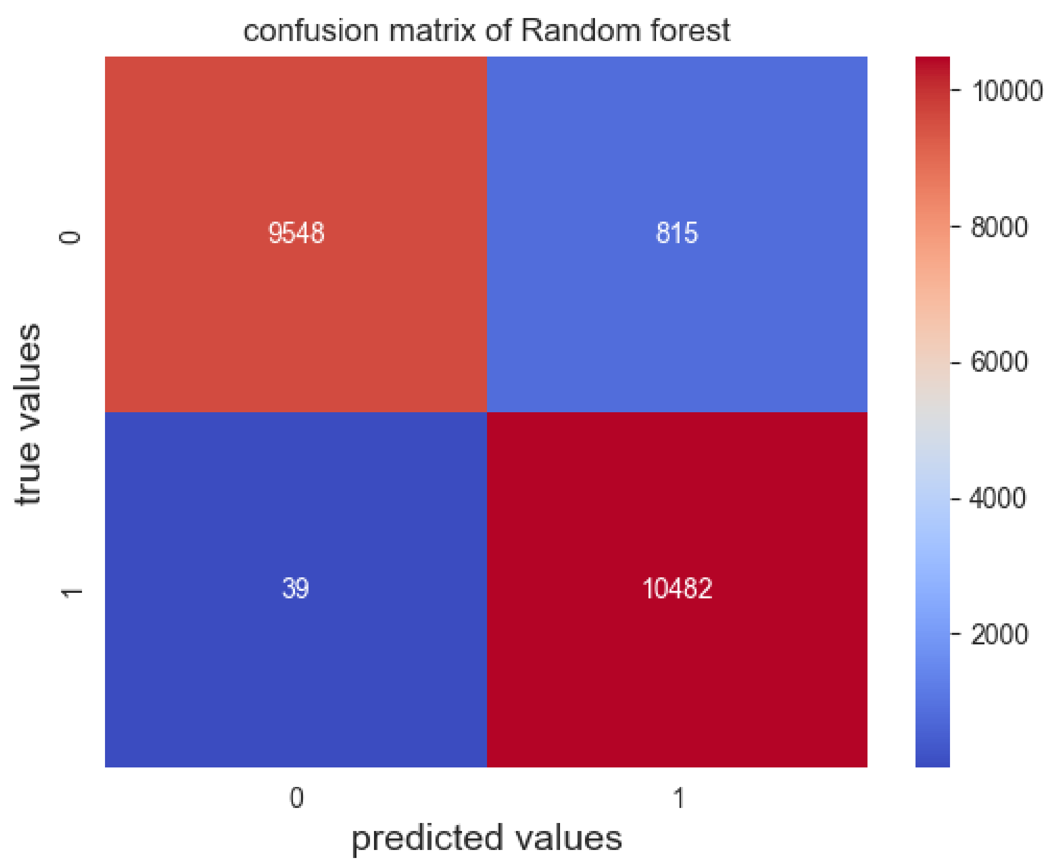
[109]:
```
from imblearn.over_sampling import RandomOverSampler

Oversampler = RandomOverSampler(random_state=42)
x_res, y_res = Oversampler.fit_resample(x, y)
```

```
x_train,x_test,y_train,y_test = train_test_split(x_res,y_res,test_size=0.
↪3,random_state=42)
```

[110]:
```
def models (model, model_name):
    mdl = model(random_state=42)
    mdl.fit(x_train,y_train)
    y_hat = mdl.predict(x_test)

    print(accuracy_score(y_test,y_hat))
    confusion_mat = confusion_matrix(y_test,y_hat)
    sns.heatmap(confusion_mat,fmt='d',annot=True,cmap='coolwarm')
    plt.xlabel('predicted values',size=14)
    plt.ylabel('true values',size=14)
    plt.title(f'confusion matrix of {model_name}',size=12)
    plt.show()
    print(classification_report(y_test,y_hat))
```

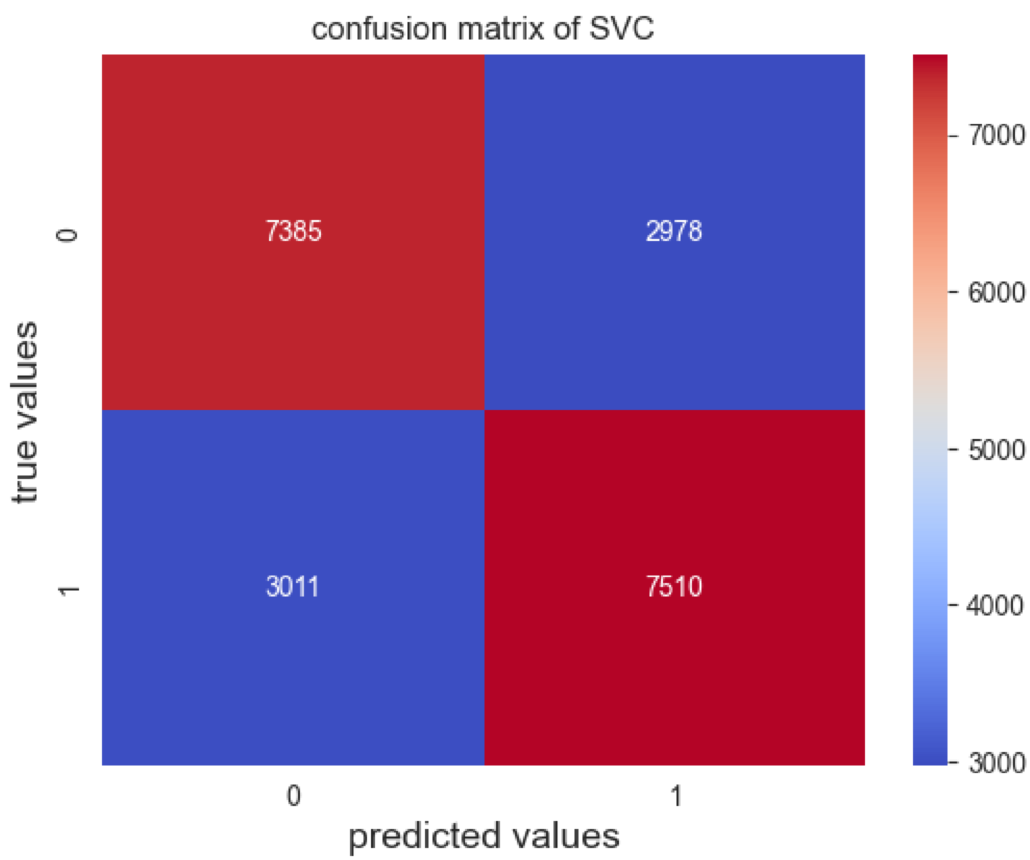
[111]:
```
models(RandomForestClassifier,'Random forest')
models(SVC,'SVC')
models(BalancedRandomForestClassifier,'Balanced RandomForest Classifier')
```

```
0.9591074506799464
```



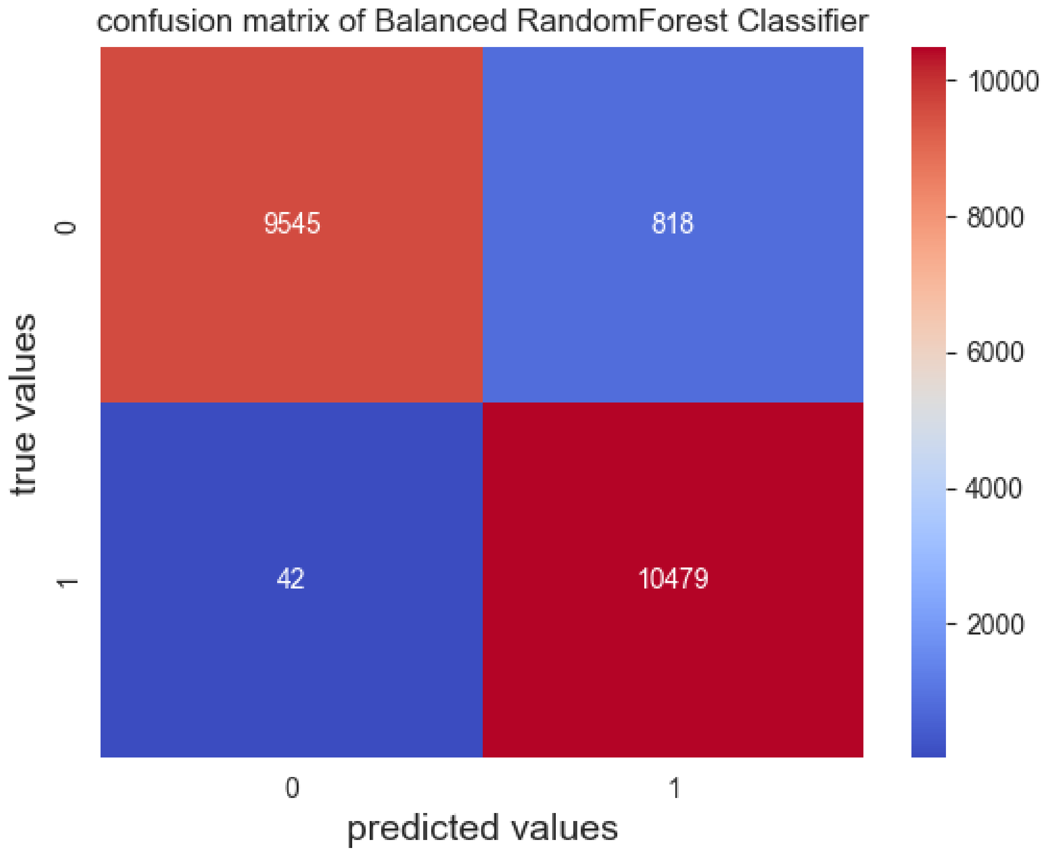
	precision	recall	f1-score	support
0	1.00	0.92	0.96	10363
1	0.93	1.00	0.96	10521
accuracy			0.96	20884
macro avg	0.96	0.96	0.96	20884
weighted avg	0.96	0.96	0.96	20884

0.7132254357402796



	precision	recall	f1-score	support
0	0.71	0.71	0.71	10363
1	0.72	0.71	0.71	10521
accuracy			0.71	20884
macro avg	0.71	0.71	0.71	20884

```
weighted avg       0.71      0.71      0.71     20884

0.9588201493966673
```




```
              precision    recall  f1-score   support

           0       1.00      0.92      0.96     10363
           1       0.93      1.00      0.96     10521

    accuracy                           0.96     20884
   macro avg       0.96      0.96      0.96     20884
weighted avg       0.96      0.96      0.96     20884
```

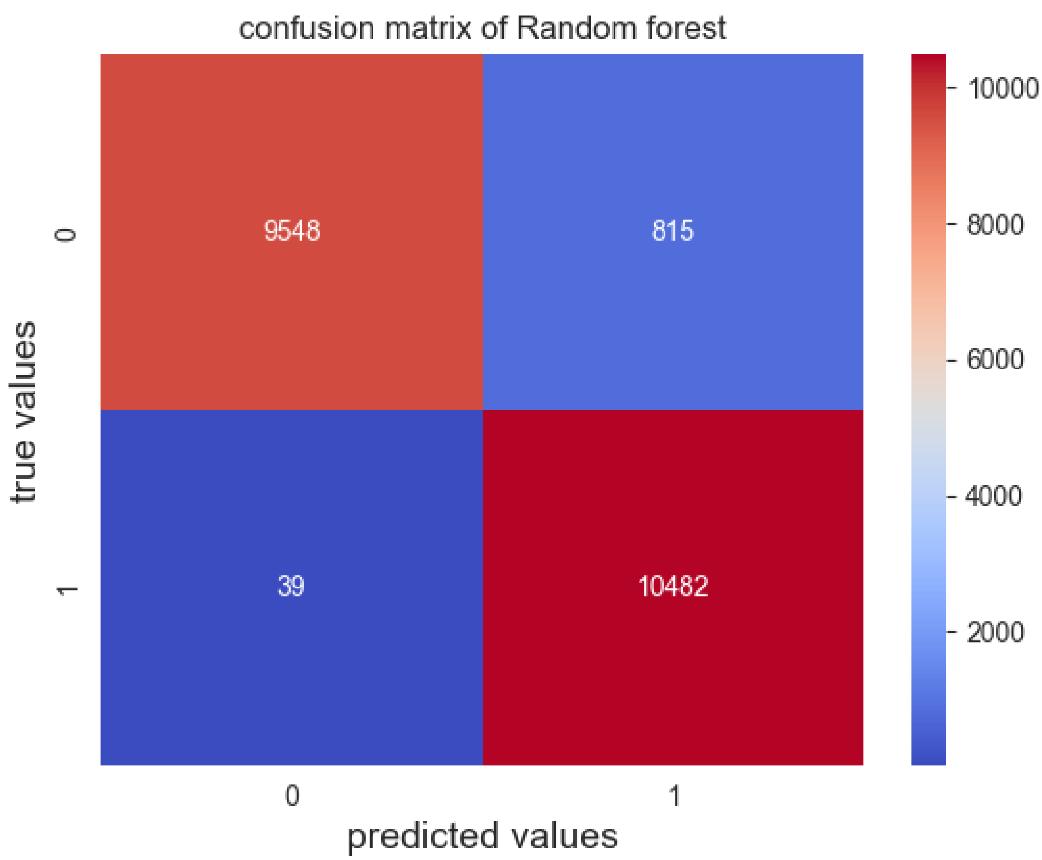
2.5.4 model testing

[112]:

```python
from imblearn.over_sampling import RandomOverSampler

Oversampler = RandomOverSampler(random_state=42)
x_res, y_res = Oversampler.fit_resample(x, y)
```

```
x_train,x_test,y_train,y_test = train_test_split(x_res,y_res,test_size=0.
 ↪3,random_state=42)

model = RandomForestClassifier(random_state=42)
model.fit(x_train,y_train)
y_hat = model.predict(x_test)
print(accuracy_score(y_test,y_hat))
confusion_mat = confusion_matrix(y_test,y_hat)
sns.heatmap(confusion_mat,fmt='d',annot=True,cmap='coolwarm')
plt.xlabel('predicted values',size=14)
plt.ylabel('true values',size=14)
plt.title('confusion matrix of Random forest',size=12)
plt.show()
print(classification_report(y_test,y_hat))
dump(model,'ranf.joblib')
```

```
0.9591074506799464
```




```
              precision    recall  f1-score   support
```

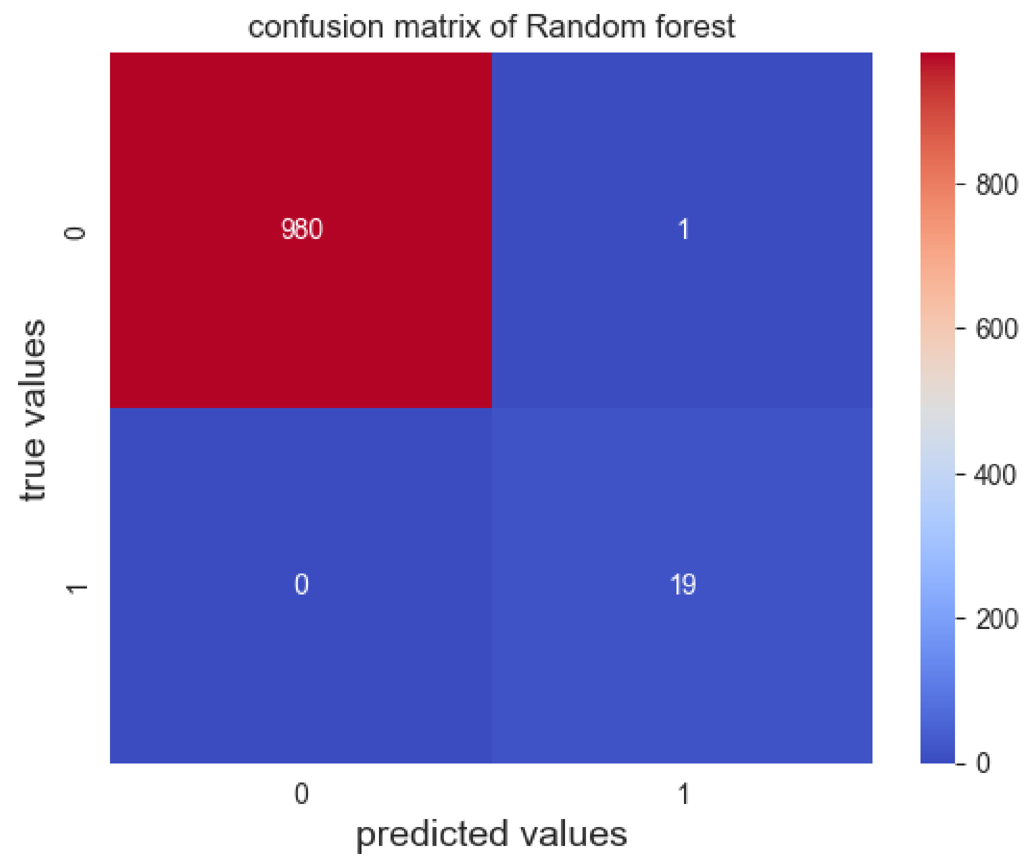
```
              0       1.00      0.92      0.96     10363
              1       0.93      1.00      0.96     10521

       accuracy                           0.96     20884
      macro avg       0.96      0.96      0.96     20884
   weighted avg       0.96      0.96      0.96     20884
```

[112]: ['ranf.joblib']

[113]:
```
y_hat2  = model.predict(x[:1000])
```

[114]:
```
print(accuracy_score(y[:1000],y_hat2))
confusion_mat = confusion_matrix(y[:1000],y_hat2)
sns.heatmap(confusion_mat,fmt='d',annot=True,cmap='coolwarm')
plt.xlabel('predicted values',size=14)
plt.ylabel('true values',size=14)
plt.title('confusion matrix of Random forest',size=12)
plt.show()
print(classification_report(y[:1000],y_hat2))
dump(model,'ranf.joblib')
```

```
0.999
```



	precision	recall	f1-score	support
0	1.00	1.00	1.00	981
1	0.95	1.00	0.97	19
accuracy			1.00	1000
macro avg	0.97	1.00	0.99	1000
weighted avg	1.00	1.00	1.00	1000

```
[114]: ['ranf.joblib']
```