#CLASSIFICATION : TRUE/FALSE :

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```python
#les imports utilisés dans ce notebook
import sys
from numpy import vstack
import pandas as pd
from pandas import read_csv
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
from torch.utils.data import Dataset
from torch.utils.data import DataLoader
from torch.utils.data import random_split
from torch import Tensor
from torch.nn import Linear
from torch.nn import ReLU
from torch.nn import Sigmoid
from torch.nn import Module
from torch.optim import SGD
from torch.nn import BCELoss
from torch.nn.init import kaiming_uniform_
from torch.nn.init import xavier_uniform_
import re
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from pandas import read_csv
from sklearn.feature_extraction.text import TfidfVectorizer
from  sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
import pickle
import string

import nltk
from nltk.stem import WordNetLemmatizer
from nltk.stem import PorterStemmer
from nltk.corpus import stopwords
from nltk import word_tokenize
from sklearn.pipeline import Pipeline

import sklearn
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
import seaborn as sns
```

```
import matplotlib.pyplot as plt
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics._plot.confusion_matrix import
ConfusionMatrixDisplay
# fonction qui affiche le classification report et la matrice de
confusion
from sklearn import metrics
from sklearn.metrics import confusion_matrix , ConfusionMatrixDisplay
from sklearn.metrics import classification_report

import warnings
warnings.filterwarnings('ignore')

from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

chemin spécifique Google Drive

```
my_local_drive='/content/gdrive/My Drive/'
# Ajout du path pour les librairies, fonctions et données
sys.path.append(my_local_drive)
# Se positionner sur le répertoire associé
%cd $my_local_drive
%ls

%pwd
```

```
[Errno 2] No such file or directory: '/content/gdrive/My Drive/'
/content
drive/  sample_data/
```

{"type":"string"}

La fonction qui sera utilisée pour les prétraitements: MyCleanText

- Mettre le texte en minuscule
- Se débarasser des stopwords
- Se débarasser des nombres
- Stemmatisation
- Lemmatisation ..

La fonction MyshowAllScores prend le y_test et le y_predict, affiche l'accuracy et le classification report avec la matrice de confusion.

```
#..................................................Fonction
MyCleanText ...........................................................
...................
# mettre en minuscule
#enlever les stopwords
#se debarasser des nombres
#stemmatisation
#lemmatisation
#......................................................................
.......................................................................
...........


nltk.download('wordnet')
nltk.download('stopwords')
nltk.download('punkt')
#liste des stopwords en anglais
stop_words = set(stopwords.words('english'))

def MyCleanText(X,
                lowercase=False, #mettre en minuscule
                removestopwords=False, #supprimer les stopwords
                removedigit=False, #supprimer les nombres
                getstemmer=False, #conserver la racine des termes
                getlemmatisation=False #lemmatisation des termes
                ):
  #conversion du texte d'entrée en chaîne de caractères
    sentence=str(X)
    #suppression des caractères spéciaux
    sentence = re.sub(r'[^\w\s]',' ', sentence)
    # suppression de tous les caractères uniques
    sentence = re.sub(r'\s+[a-zA-Z]\s+', ' ', sentence)
    # substitution des espaces multiples par un seul espace
    sentence = re.sub(r'\s+', ' ', sentence, flags=re.I)

    # decoupage en mots
    tokens = word_tokenize(sentence)
    if lowercase:
          tokens = [token.lower() for token in tokens]

    # suppression ponctuation
    table = str.maketrans('', '', string.punctuation)
    words = [token.translate(table) for token in tokens]

    # suppression des tokens non alphabetique ou numerique
    words = [word for word in words if word.isalnum()]
```

```python
    # suppression des tokens numerique
    if removedigit:
        words = [word for word in words if not word.isdigit()]

    # suppression des stopwords
    if removestopwords:
        words = [word for word in words if not word in stop_words]

    # lemmatisation
    if getlemmatisation:
        lemmatizer=WordNetLemmatizer()
        words = [lemmatizer.lemmatize(word)for word in words]


    # racinisation
    if getstemmer:
        ps = PorterStemmer()
        words=[ps.stem(word) for word in words]

    sentence= ' '.join(words)

    return sentence



def MyshowAllScores(y_test,y_pred):
  classes= np.unique(y_test)
  print("Accuracy : %0.3f"%(accuracy_score(y_test,y_pred)))
  print("Classification Report")
  print(classification_report(y_test,y_pred,digits=5))
  cnf_matrix = confusion_matrix(y_test,y_pred)
  disp=ConfusionMatrixDisplay(cnf_matrix,display_labels=classes)
  disp.plot()
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

- La classe TextNormalizer qui contiendra la fonction MyCleanText.
- Fit_transform de mon corpus propre.

```python
#..................................................Etape 1 : prétraitement du texte ...................................................................................................
#..................................................Class
```

```
TextNormalizer  .....................................................
.......................
#fit_transform de mon corpus propre
#....................................................................
.....................................................................
...........

from sklearn.base import BaseEstimator, TransformerMixin

class TextNormalizer(BaseEstimator, TransformerMixin):
    def __init__(self,
                 removestopwords=False, # suppression des stopwords
                 lowercase=False,# passage en minuscule
                 removedigit=False, # supprimer les nombres
                 getstemmer=False,# racinisation des termes
                 getlemmatisation=False # lemmatisation des termes
                ):

        self.lowercase=lowercase
        self.getstemmer=getstemmer
        self.removestopwords=removestopwords
        self.getlemmatisation=getlemmatisation
        self.removedigit=removedigit

    def transform(self, X, **transform_params):
        # Nettoyage du texte
        X=X.copy() # pour conserver le fichier d'origine
        return [MyCleanText(text,lowercase=self.lowercase,
                            getstemmer=self.getstemmer,
                            removestopwords=self.removestopwords,
                            getlemmatisation=self.getlemmatisation,
                            removedigit=self.removedigit) for text in
X]

    def fit(self, X, y=None, **fit_params):
        return self

    def fit_transform(self, X, y=None, **fit_params):
        return self.fit(X).transform(X)

    def get_params(self, deep=True):
        return {
            'lowercase':self.lowercase,
            'getstemmer':self.getstemmer,
            'removestopwords':self.removestopwords,
            'getlemmatisation':self.getlemmatisation,
            'removedigit':self.removedigit
        }

    def set_params (self, **parameters):
```

```
        for parameter, value in parameters.items():
            setattr(self,parameter,value)
        return self
```

##**Etape 1 : Préparer les données**

- Load et preparer les données à partir des 2 fichiers csv
- Sélectionner que les lignes où on a True, False

```
#Ici je cherche à séléctionner que les labels TRUE et FALSE, donc les
LIGNES qui contiennent au rating TRUE et FALSE uniquement, le reste on
enlève

dftrain = pd.read_csv("/content/drive/MyDrive/newsTrain2.csv",
names=['id','text','title','rating'], header=0,sep=',',
encoding='utf8')
dftrain.reset_index(drop = True, inplace = True)

dftrain2 = pd.read_csv("/content/drive/MyDrive/newsTrain_-
_newsTrain.csv", names=['id','text','title','rating'],
header=0,sep=',', encoding='utf8')
dftrain2.reset_index(drop = True, inplace = True)


# concaténer les deux dataframes en ajoutant les lignes du deuxième à
la fin du premier
dftrain = pd.concat([dftrain, dftrain2], ignore_index=True)


dftrain = dftrain.loc[dftrain['rating'].isin(['TRUE','FALSE'])]
#dftest=pd.read_csv("/content/gdrive/MyDrive/newsTest.csv",names=['id'
,'text','title','rating','veracity'], header=0,sep=',',
encoding='utf8')
print("Echantillon de mon dataset \n")
print(dftrain.sample(n=10))
print("\n")
print("Quelques informations importantes \n")
dftrain.info()
#print(dftest.head())
X_text=dftrain.iloc[0:,1:2]

print("le type de X_test est" ,X_text.columns)
X_title=dftrain.iloc[0:,2:3]
print("le texte est")
display(X_text)
print("le titre est")
display(X_title)
#X_test=dftest.iloc[1:, :4]
y=dftrain.iloc[0:,-1]
print("voici la dernière case")
```

```python
display(y)
#y_test=dftest.iloc[1:, -1]
#y = y_train.ravel()
print("la taille de X_text est",X_text.shape)
print("la taille de y_train est " ,y.shape)
print("les valeurs de TRUE et FALSE sont " ,y.value_counts())
```

```
Echantillon de mon dataset

            id                                               text  \
212   4ce1af1d  Martin Gugino is a 75-year-old professional ag...
2250  d1741354  News| [email protected] “If you won’t lead, th...
330   a94e340d  Joseph R. Biden declared last year on the camp...
1289  7c9af097  In Brief The Facts: It is alleged by many in t...
345   0a12bd0d  The NFL has decided to roll back its rule agai...
1043  cef0a3d1  Occupation: President and CEO, Bettencourt Tax...
43    aacdc4d3  Today, Congresswoman Maxine Waters D-CA, Chair...
2315  c9a08752  Tom Clark: Osborne swung his axe without mercy...
71    d0b11b17  163 paid protesters have filed a lawsuit again...
986   d1741354  News| [email protected] “If you won’t lead, th...

                                                  title rating
212   Buffalo Officials Duped By Professional Antifa...  FALSE
2250  IT'S OFFICIAL: Brexit Britain WILL thrive out ...  FALSE
330   Biden's claim about attending historically Bla...  FALSE
1289  Scientist Explains Why He Believes Aluminum Is...  FALSE
345   Pittsburgh Steelers Will Fine ANY Player Kneel...  FALSE
1043  The CDC has admitted face masks do little to p...   TRUE
43    Democratic Lawmaker introduces bill to rename ...  FALSE
2315       Budget 2015: the verdict from our columnists   TRUE
71    163 Paid Protesters Just Filed A Lawsuit Again...  FALSE
986   IT'S OFFICIAL: Brexit Britain WILL thrive out ...  FALSE


Quelques informations importantes

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1578 entries, 0 to 2527
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   id      1578 non-null   object
 1   text    1578 non-null   object
 2   title   1554 non-null   object
 3   rating  1578 non-null   object
dtypes: object(4)
memory usage: 61.6+ KB
le type de X_test est Index(['text'], dtype='object')
le texte est
```

```
                                                   text
0     Distracted driving causes more deaths in Canad...
3     But things took a turn for the worse when riot...
4     It’s no secret that Epstein and Schiff share a...
6     November 23, 2019  The U.S. Food and Drug Admi...
7     Trump confirms this was a bombing, not an acci...
...                                                 ...
2523  More than four million calls to the taxman are...
2524  More under-18s are being taken to court for se...
2525  The Government’s much vaunted Help to Buy Isa ...
2526  The late Robin Williams once called cocaine “G...
2527  The late Robin Williams once called cocaine “G...

[1578 rows x 1 columns]

le titre est

                                                  title
0     You Can Be Fined $1,500 If Your Passenger Is U...
3     Obama’s Daughters Caught on Camera Burning US ...
4     Leaked Visitor Logs Reveal Schiff’s 78 Visits ...
6     FDA Shocking Study: Cells Used In Vaccines Con...
7     Israel Hits Beirut with Nuclear Missile, Trump...
...                                                 ...
2523  Taxman fails to answer four million calls a ye...
2524  Police catch 11-year-olds being used to sell d...
2525  Help to Buy Isa scandal: 500,000 first-time bu...
2526           A coke-snorting generation of hypocrites
2527           A coke-snorting generation of hypocrites

[1578 rows x 1 columns]

voici la dernière case

0       FALSE
3       FALSE
4       FALSE
6       FALSE
7       FALSE
        ...
2523     TRUE
2524     TRUE
2525    FALSE
2526     TRUE
2527     TRUE
Name: rating, Length: 1578, dtype: object

la taille de X_text est (1578, 1)
la taille de y_train est  (1578,)
les valeurs de TRUE et FALSE sont  FALSE    1156
```

```
TRUE      422
Name: rating, dtype: int64
```

Le jeu de données étant déséquilibré, on a pensé à appliquer le downsampling pour équilibrer nos données. On fait en sorte que le nombre de lignes avec en sortie FAUX soit égal au nombre de lignes avec en sortie true.

```
#On applique du sous-échantillonnage (downsampling) : car on a plus de
FALSE (578) que des TRUE (211)


# Séparer les classes en deux dataframes
df_false = dftrain[dftrain['rating'] == 'FALSE']
df_true = dftrain [dftrain['rating'] == 'TRUE']


# Sous-échantillonner la classe majoritaire (FALSE) pour obtenir un
nombre égal d'échantillons pour chaque classe
df_false_subsampled = df_false.sample(n=len(df_true), random_state=42)

# Concaténer les deux dataframes
dftrain = pd.concat([df_false_subsampled, df_true])

# Mélanger aléatoirement les données
dftrain = dftrain.sample(frac=1, random_state=42)


X_text=dftrain["text"]
X_title=dftrain["title"]
y=dftrain.iloc[0:,-1]
print("la taille de X_text est",X_text.shape)
print("\n")
print("la taille de X_title est",X_title.shape)
print("\n")
print("la taille de y_train est " ,y.shape)
print("\n")
print("les valeurs de TRUE et FALSE maintenant sont
" ,y.value_counts())
```

```
la taille de X_text est (844,)


la taille de X_title est (844,)


la taille de y_train est  (844,)


les valeurs de TRUE et FALSE maintenant sont  TRUE     422
```

```
FALSE    422
Name: rating, dtype: int64
```

Découpage du jeu de données en jeu de test et d'entrainement

```
X=dftrain.iloc[0:, 1:3]
print(X)

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size =
0.2,random_state=8)
print("X_train is",X_train.shape)
print("y_train is",y_train.shape)
print("X_test is",X_test.shape)
print("y_test is",y_test.shape)
```

```
                                                   text  \
615   It’s been a long time coming, but finally we h...
1303  Constitutional Attorney Matthew DePerno is an ...
1232  The United States is witnessing a massive, dan...
2022  After three decades on the bench, Sarah Parker...
287   Based on actual results and accounting for sta...
...                                                 ...
1006  5 Million Muslim Children In Yemen Died due to...
1543  The bombshell claim comes from over 20 hours o...
853   BILL GATES EXPLAINS THAT THE COVID VACCINE WIL...
296   Let our journalists help you make sense of the...
1325  Though the whole world relies on RT-PCR to “di...

                                                  title
615   JK Rowling Confirms Stance Against Transgender...
1303  MI Sec of State Official Caught On Video Telli...
1232  What science can tell us about the links betwe...
2022        Sarah Parker leaves legacy on Supreme Court
287   Current Actual Election Result Update: Preside...
...                                                 ...
1006  Re: Meeting the need for isolation space for h...
1543  Breaking: Breonna Taylor’s boyfriend says SHE ...
853   A quote from Politifact: Gates never said that...
296   Before This Election, Newt Gingrich Believed t...
1325   COVID19 PCR Tests are Scientifically Meaningless

[844 rows x 2 columns]
X_train is (675, 2)
y_train is (675,)
X_test is (169, 2)
y_test is (169,)
```

##**Etape 2 : Classification selon la colonne TEXT :**

Tester avec plusieurs classifieurs classiques.

Ici, c'est une étape importante, on va tester différents classifieurs, pour chacun des classifieurs, on va appliquer le prétraitement + Vectorisation TfIdf, et on applique une cross_val_score avec un Kfold de 10 fois, par la suite on stocke dans une liste all_results la moyenne des accuracy + l'écart type et on la trie par ordre décroissant de moyenne d'accuracy et d'écart type. on remarque que les 3 meilleurs sont SVM,LR et RF qu'on va séléctionner pour leur appliquer le GridSearch sur les paramètres des prétraitements + leurs hyperparamètres pour pouvoir choisir le meilleur.

```
score = 'accuracy'
seed = 7
allresults = []
results = []
names = []


X_train_text=X_train['text']
X_train_text.reset_index(drop = True, inplace = True)


# Liste des modèles à tester
models = [
    ('MultinomialNB', MultinomialNB()),
    ('LogisticRegression', LogisticRegression(random_state=42))
]


models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('RF', RandomForestClassifier()))
models.append(('SVM', SVC()))


# Création d'un pipeline pour chaque modèle
pipelines = []
for name,model in models:
    pipeline = Pipeline([
        ('normalize', TextNormalizer()),
        ('tfidf', TfidfVectorizer()),
        (name,model)
    ])
    pipelines.append((name,pipeline))
    #pipeline.fit(X_train_text,y_train)
all_results=[]
scores=[]
for p in pipelines:
    print(p[1])
    # cross validation en 10 fois
    kfold = KFold(n_splits=10,random_state=seed,shuffle=True)
```

```
#    print ("Evaluation de ",p)
    start_time = time.time()
    # application de la classification
    cv_results = cross_val_score(p[1],X_train_text,y_train, cv=kfold, scoring=score)
    #print("Pour le classifieur",p[0],"on a un score de",cv_results.mean(),"et un écart type de",cv_results.std())
    scores.append(cv_results)
    names.append(p[0])

    all_results.append((p[0],cv_results.mean(),cv_results.std()))
    end_time = time.time()

all_results = sorted(all_results, key=lambda x: (-x[1], -x[2]))
print("all resultats", all_results)
    # affichage des résultats
#print ('\nLe meilleur resultat : ',max(results))
```

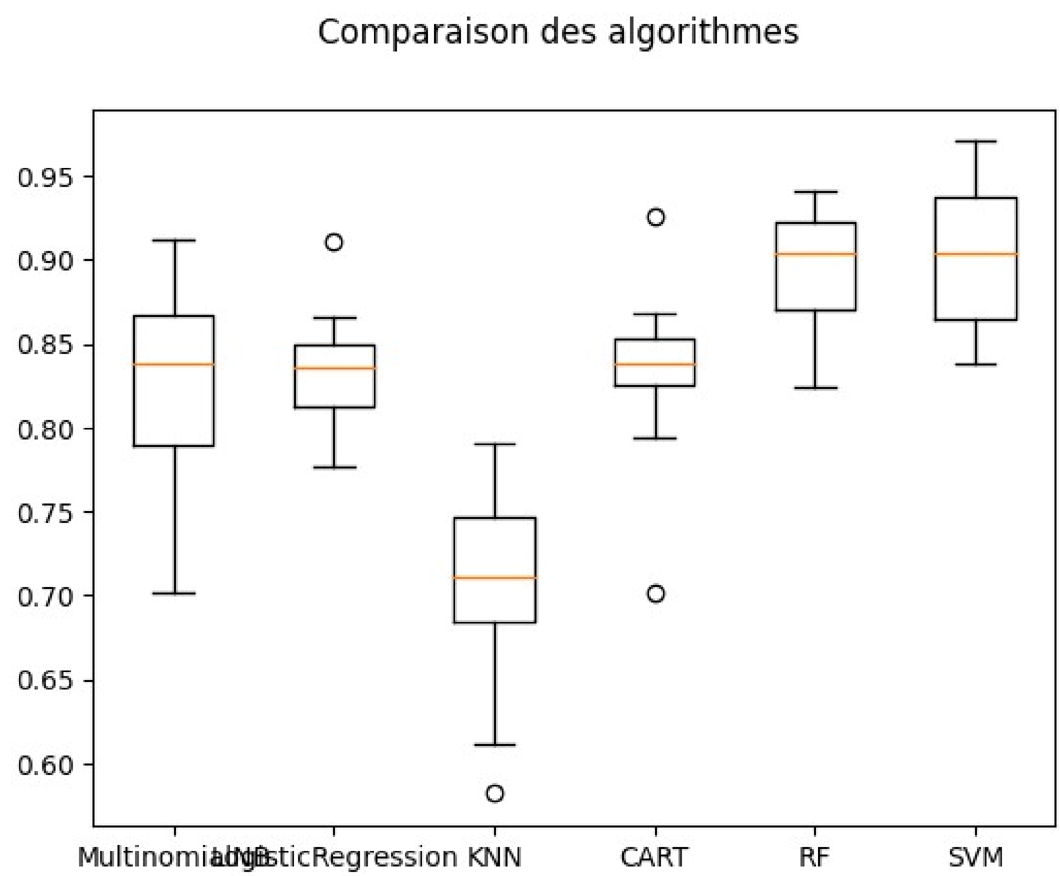
```
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf', TfidfVectorizer()),
                ('MultinomialNB', MultinomialNB())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf', TfidfVectorizer()),
                ('LogisticRegression', LogisticRegression(random_state=42))])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf', TfidfVectorizer()),
                ('KNN', KNeighborsClassifier())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf', TfidfVectorizer()),
                ('CART', DecisionTreeClassifier())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf', TfidfVectorizer()),
                ('RF', RandomForestClassifier())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf', TfidfVectorizer()),
                ('SVM', SVC())])
all resultats [('SVM', 0.9038410886742756, 0.043294516291260216), ('RF', 0.8948200175592624, 0.0370882010820444), ('LogisticRegression', 0.8356233538191397, 0.0345425007546011), ('CART', 0.832550482879719, 0.05427625364367281), ('MultinomialNB', 0.8265144863915715, 0.06346830897936112), ('KNN', 0.7051141352063214, 0.06333815247759318)]
```

On affiche les accuracy de chaque classifieur, on remarque la médiane (en rouge) de chaque et l'écart type aussi.

```
import matplotlib.pyplot as plt
fig = plt.figure()
```

```
fig.suptitle('Comparaison des algorithmes')
ax = fig.add_subplot(111)
plt.boxplot(scores)
ax.set_xticklabels(names)
```

```
[Text(1, 0, 'MultinomialNB'),
 Text(2, 0, 'LogisticRegression'),
 Text(3, 0, 'KNN'),
 Text(4, 0, 'CART'),
 Text(5, 0, 'RF'),
 Text(6, 0, 'SVM')]
```



Choisir les meilleurs paramètres et hyperparamètres pour SVM et RF :

On a un pipeline pour chaque prétraitement différent, on essaye pas mal (miniscule, lemmatisation, miniscule + lemmatisation..) et on stocke le fit_transorm de nos X_train, X_test sur les pipelines dans des listes qui vont contenir tous les fit_transform des pipelines pour chaque classifieur, par la suite on parcourt ces listes là, on itère dessus, et chaque élement de la liste (train) va passer par le GridSearch et puis on predict sur son corresapondant dans liste (test).

```
from sklearn.model_selection import GridSearchCV
```

```python
from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from tabulate import tabulate
import numpy as np
np.random.seed(42)  # Set the random seed for NumPy
print("y_train", y_train.shape)
print("y_test", y_test.shape)
print("X_test", X_test.shape)

X_train_text=X_train['text']
X_train_title=X_train['title']

# le plus simple est de faire un test sur differents pipelines.
# pipeline de l'utilisation de CountVectorizer sur le texte avec
differents pre-traitements
CV_brut = Pipeline([('cleaner', TextNormalizer()),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])
CV_lowcase = Pipeline([('cleaner',
TextNormalizer(removestopwords=False,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])
CV_lowStop = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])

CV_lowStopstem = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=True,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])

# pipeline de l'utilisation de TfidfVectorizer avec differents pre-
traitements
```

```python
TFIDF_brut = Pipeline ([('cleaner', TextNormalizer()),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])

TFIDF_lowcase = Pipeline([('cleaner',
TextNormalizer(removestopwords=False,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])
TFIDF_lowStop = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])

TFIDF_lowStopstem = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=True,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])


# Liste de tous les modeles à tester
all_models = [
    ("CV_brut", CV_brut),
    ("CV_lowcase", CV_lowcase),
    ("CV_lowStop", CV_lowStop),
    ("CV_lowStopstem",CV_lowStopstem),
    ("TFIDF_lowcase", TFIDF_lowcase),
    ("TFIDF_lowStop", TFIDF_lowStop),
    ("TFIDF_lowStopstem",TFIDF_lowStopstem),
    ("TFIDF_brut", TFIDF_brut)
]

X_train_text_SVC = []
X_test_text_SVC = []

X_train_text_RandomForestClassifier = []
X_test_text_RandomForestClassifier = []


for name, pipeline in all_models :

X_train_text_SVC.append(pipeline.fit_transform(X_train['text']).toarra
y())
```

```
X_test_text_SVC.append(pipeline.transform(X_test['text']).toarray())

X_train_text_RandomForestClassifier.append(pipeline.fit_transform(X_tr
ain['text']).toarray())

X_test_text_RandomForestClassifier.append(pipeline.transform(X_test['t
ext']).toarray())




models = {
    'SVC': SVC(random_state=42),
    'RandomForestClassifier': RandomForestClassifier(random_state=42)
}


params = {'SVC': [{'C': [0.001, 0.01, 0.1, 1,2,5,7,10]},
             {'gamma': [0.001, 0.01, 0.1,0.2,0.3,0.5,0.7,1]},
             {'kernel': ['linear', 'rbf']}],
    'RandomForestClassifier': [{'n_estimators': [10, 50, 100, 200,
300]},
                              {'max_features': ['auto', 'sqrt',
'log2']}]
}

for model_name, model in models.items():
    score='accuracy'
    X_train_text = eval('X_train_text_' + model_name)
    X_test_text = eval('X_test_text_' + model_name)
    for i in range (len(X_train_text)):
      grid_search = GridSearchCV(model, params[model_name], n_jobs=-1,
verbose=1,scoring=score)
      print("grid search fait")
      print("X_train",X_train_text[i].shape)
      print("y_train",y_train.shape)
      grid_search.fit(X_train_text[i],y_train)
      print ('meilleur score %0.3f'%(grid_search.best_score_),'\n')
      print ('meilleur estimateur',grid_search.best_estimator_,'\n')
      y_pred = grid_search.predict(X_test_text[i])
      MyshowAllScores(y_test,y_pred)

      print("Ensemble des meilleurs paramètres :")
      best_parameters = grid_search.best_estimator_.get_params()
      for param_dict in params[model_name]:
        for param_name, param_value in param_dict.items():
            print("\t%s: %r" % (param_name,
best_parameters[param_name]))
```

```
y_train (675,)
y_test (169,)
X_test (169, 2)
grid search fait
X_train (675, 24296)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.849

meilleur estimateur SVC(kernel='linear', random_state=42)

Accuracy : 0.870
Classification Report
              precision    recall  f1-score   support

       FALSE    0.89610   0.83133   0.86250        83
        TRUE    0.84783   0.90698   0.87640        86

    accuracy                        0.86982       169
   macro avg    0.87196   0.86915   0.86945       169
weighted avg    0.87154   0.86982   0.86958       169

Ensemble des meilleurs paramètres :
     C: 1.0
     gamma: 'scale'
     kernel: 'linear'
grid search fait
X_train (675, 20741)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.846

meilleur estimateur SVC(gamma=0.01, random_state=42)

Accuracy : 0.905
Classification Report
              precision    recall  f1-score   support

       FALSE    0.83838   1.00000   0.91209        83
        TRUE    1.00000   0.81395   0.89744        86

    accuracy                        0.90533       169
   macro avg    0.91919   0.90698   0.90476       169
weighted avg    0.92063   0.90533   0.90463       169

Ensemble des meilleurs paramètres :
     C: 1.0
     gamma: 0.01
     kernel: 'rbf'
```

```
grid search fait
X_train (675, 20601)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.852

meilleur estimateur SVC(C=10, random_state=42)

Accuracy : 0.882
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90909   0.84337   0.87500        83
        TRUE    0.85870   0.91860   0.88764        86

    accuracy                        0.88166       169
   macro avg    0.88389   0.88099   0.88132       169
weighted avg    0.88345   0.88166   0.88143       169

Ensemble des meilleurs paramètres :
     C: 10
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 14012)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.856

meilleur estimateur SVC(C=10, random_state=42)

Accuracy : 0.882
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88889   0.86747   0.87805        83
        TRUE    0.87500   0.89535   0.88506        86

    accuracy                        0.88166       169
   macro avg    0.88194   0.88141   0.88155       169
weighted avg    0.88182   0.88166   0.88162       169

Ensemble des meilleurs paramètres :
     C: 10
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 20741)
y_train (675,)
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.886

meilleur estimateur SVC(C=2, random_state=42)

Accuracy : 0.911
Classification Report
              precision    recall  f1-score   support

       FALSE    0.92500   0.89157   0.90798        83
        TRUE    0.89888   0.93023   0.91429        86

    accuracy                        0.91124       169
   macro avg    0.91194   0.91090   0.91113       169
weighted avg    0.91171   0.91124   0.91119       169

Ensemble des meilleurs paramètres :
     C: 2
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 20601)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.887

meilleur estimateur SVC(C=1, random_state=42)

Accuracy : 0.917
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88764   0.95181   0.91860        83
        TRUE    0.95000   0.88372   0.91566        86

    accuracy                        0.91716       169
   macro avg    0.91882   0.91776   0.91713       169
weighted avg    0.91937   0.91716   0.91711       169

Ensemble des meilleurs paramètres :
     C: 1
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 14012)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.887
```

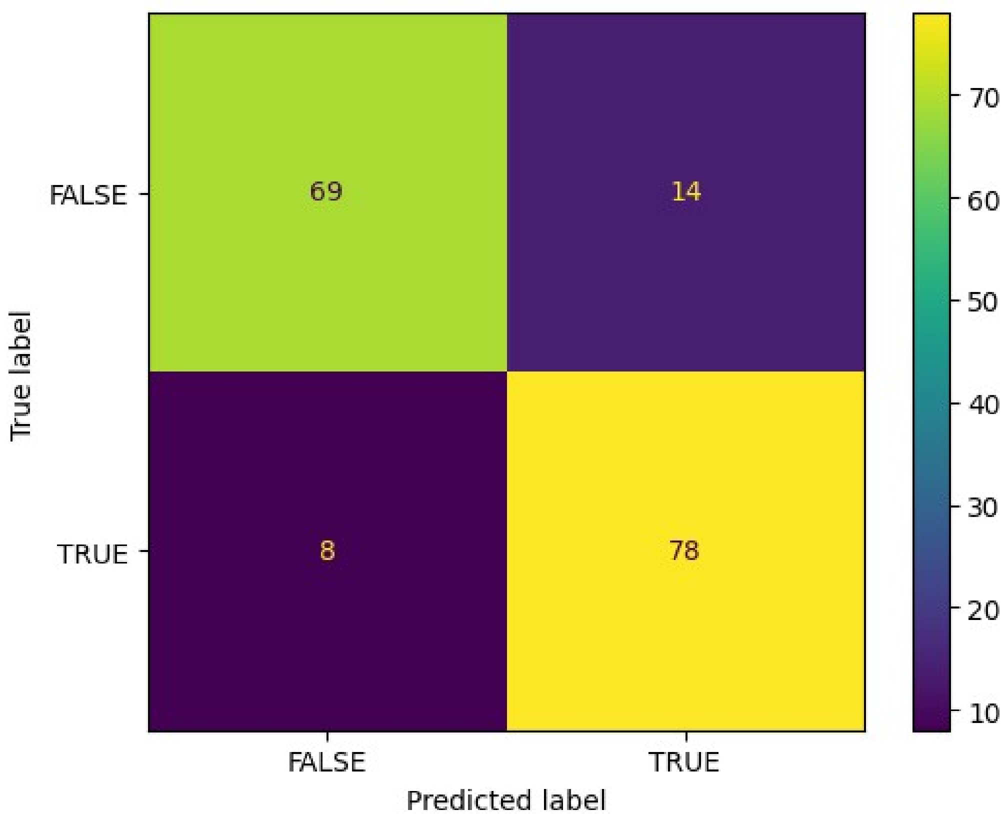
```
meilleur estimateur SVC(C=1, random_state=42)

Accuracy : 0.929
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90805   0.95181   0.92941        83
        TRUE    0.95122   0.90698   0.92857        86

    accuracy                        0.92899       169
   macro avg    0.92963   0.92939   0.92899       169
weighted avg    0.93002   0.92899   0.92898       169

Ensemble des meilleurs paramètres :
     C: 1
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 24296)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.886

meilleur estimateur SVC(C=2, random_state=42)

Accuracy : 0.899
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90244   0.89157   0.89697        83
        TRUE    0.89655   0.90698   0.90173        86

    accuracy                        0.89941       169
   macro avg    0.89950   0.89927   0.89935       169
weighted avg    0.89944   0.89941   0.89939       169

Ensemble des meilleurs paramètres :
     C: 2
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 24296)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.873

meilleur estimateur RandomForestClassifier(random_state=42)

Accuracy : 0.882
```

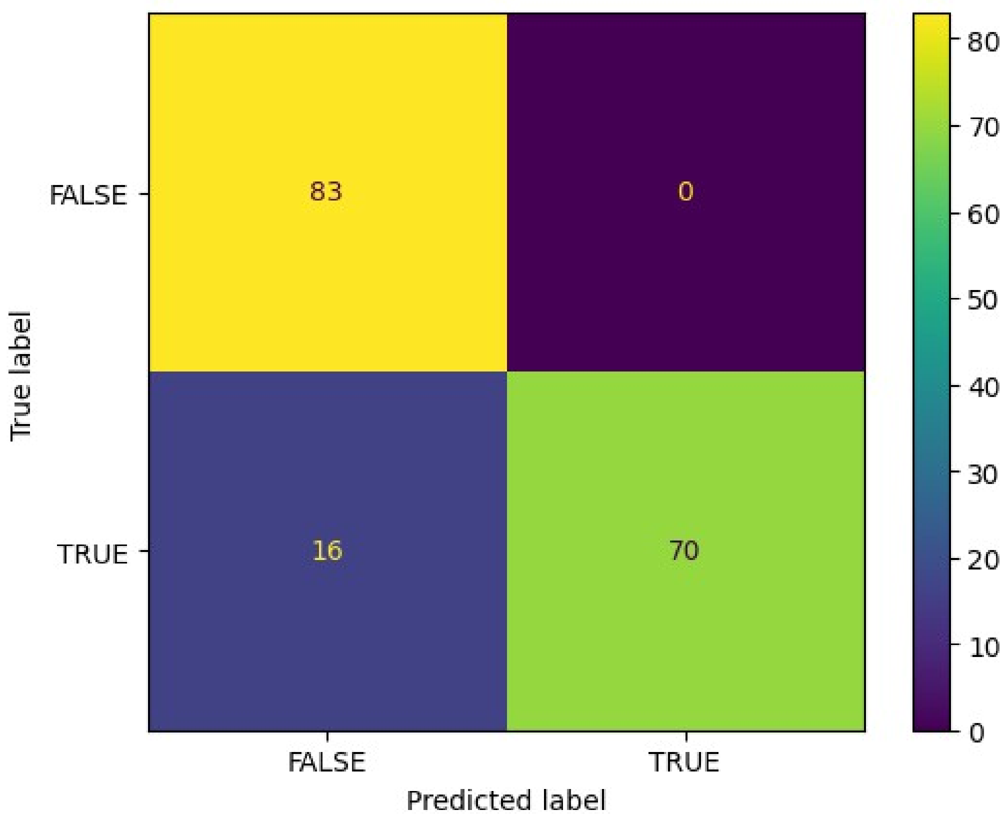
```
Classification Report
              precision    recall  f1-score   support

       FALSE    0.87952   0.87952   0.87952        83
        TRUE    0.88372   0.88372   0.88372        86

    accuracy                        0.88166       169
   macro avg    0.88162   0.88162   0.88162       169
weighted avg    0.88166   0.88166   0.88166       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'sqrt'
grid search fait
X_train (675, 20741)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.867

meilleur estimateur RandomForestClassifier(n_estimators=200,
random_state=42)

Accuracy : 0.864
Classification Report
              precision    recall  f1-score   support

       FALSE    0.87500   0.84337   0.85890        83
        TRUE    0.85393   0.88372   0.86857        86

    accuracy                        0.86391       169
   macro avg    0.86447   0.86355   0.86373       169
weighted avg    0.86428   0.86391   0.86382       169

Ensemble des meilleurs paramètres :
     n_estimators: 200
     max_features: 'sqrt'
grid search fait
X_train (675, 20601)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.868

meilleur estimateur RandomForestClassifier(random_state=42)

Accuracy : 0.893
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90123   0.87952   0.89024        83
```

```
        TRUE    0.88636   0.90698   0.89655        86

    accuracy                        0.89349       169
   macro avg    0.89380   0.89325   0.89340       169
weighted avg    0.89367   0.89349   0.89345       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'sqrt'
grid search fait
X_train (675, 14012)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.867

meilleur estimateur RandomForestClassifier(max_features='log2',
random_state=42)

Accuracy : 0.917
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90588   0.92771   0.91667        83
        TRUE    0.92857   0.90698   0.91765        86

    accuracy                        0.91716       169
   macro avg    0.91723   0.91734   0.91716       169
weighted avg    0.91743   0.91716   0.91717       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'log2'
grid search fait
X_train (675, 20741)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.879

meilleur estimateur RandomForestClassifier(n_estimators=300,
random_state=42)

Accuracy : 0.911
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90476   0.91566   0.91018        83
        TRUE    0.91765   0.90698   0.91228        86

    accuracy                        0.91124       169
```

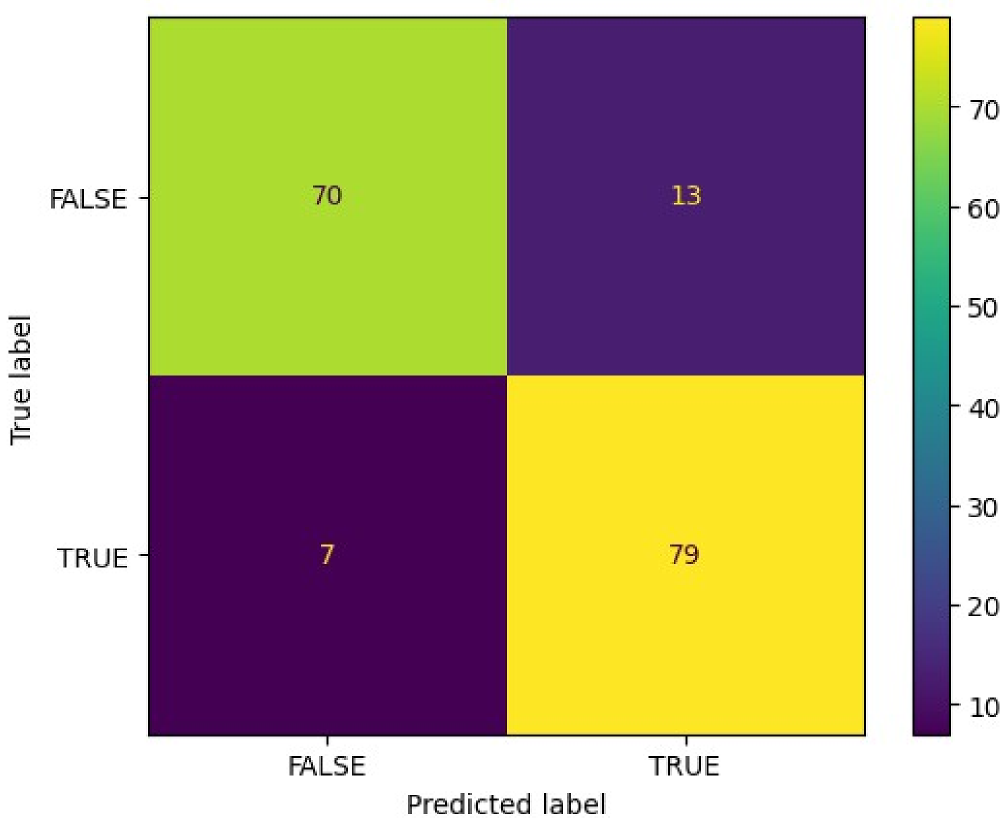
```
   macro avg    0.91120   0.91132   0.91123       169
weighted avg    0.91132   0.91124   0.91125       169

Ensemble des meilleurs paramètres :
     n_estimators: 300
     max_features: 'sqrt'
grid search fait
X_train (675, 20601)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.879

meilleur estimateur RandomForestClassifier(random_state=42)

Accuracy : 0.917
Classification Report
              precision    recall  f1-score   support

       FALSE    0.92593   0.90361   0.91463        83
        TRUE    0.90909   0.93023   0.91954        86

    accuracy                        0.91716       169
   macro avg    0.91751   0.91692   0.91709       169
weighted avg    0.91736   0.91716   0.91713       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'sqrt'
grid search fait
X_train (675, 14012)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.877

meilleur estimateur RandomForestClassifier(n_estimators=300,
random_state=42)

Accuracy : 0.911
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90476   0.91566   0.91018        83
        TRUE    0.91765   0.90698   0.91228        86

    accuracy                        0.91124       169
   macro avg    0.91120   0.91132   0.91123       169
weighted avg    0.91132   0.91124   0.91125       169

Ensemble des meilleurs paramètres :
```

```
     n_estimators: 300
     max_features: 'sqrt'
grid search fait
X_train (675, 24296)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.880

meilleur estimateur RandomForestClassifier(random_state=42)

Accuracy : 0.905
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90361   0.90361   0.90361        83
        TRUE    0.90698   0.90698   0.90698        86

    accuracy                        0.90533       169
   macro avg    0.90530   0.90530   0.90530       169
weighted avg    0.90533   0.90533   0.90533       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'sqrt'
```

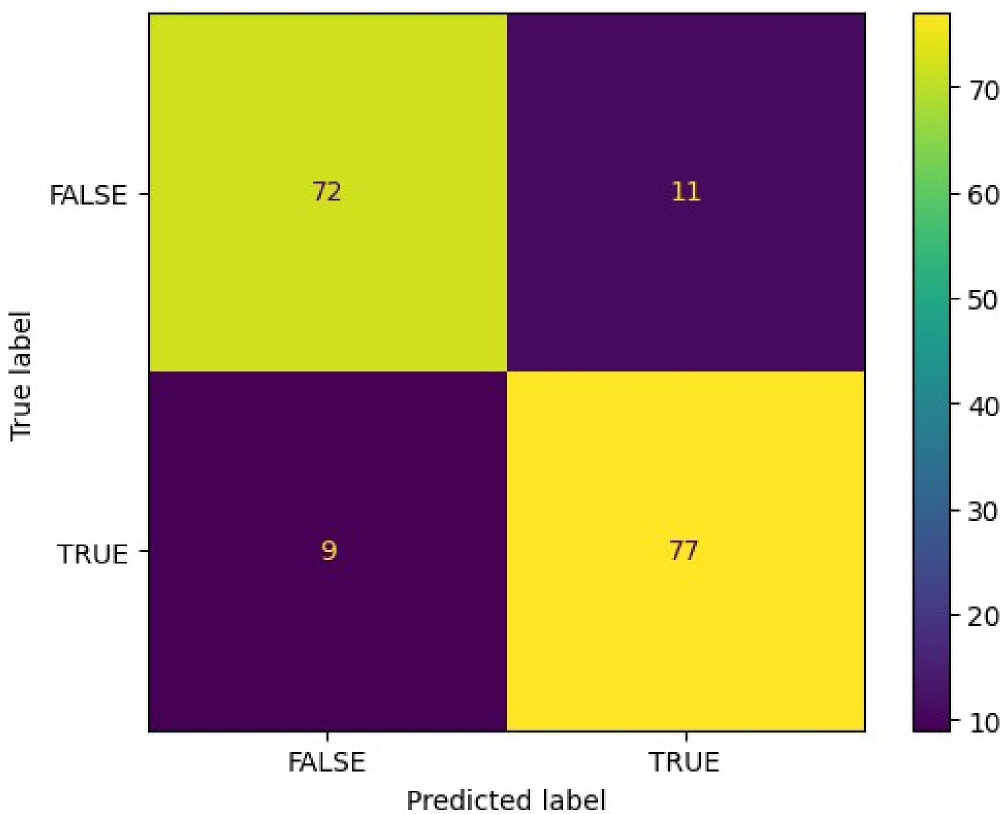




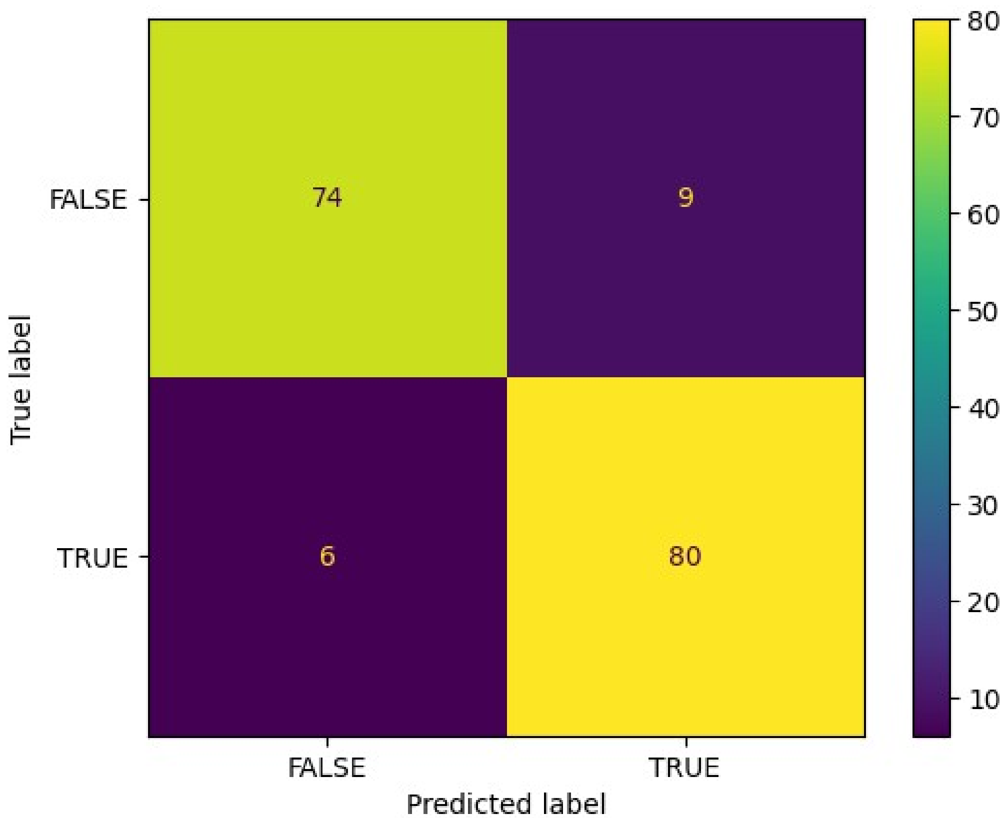
FALSE
TRUE
True label
83
0
16
70
FALSE
TRUE
Predicted label
80
70
60
50
40
30
20
10
0



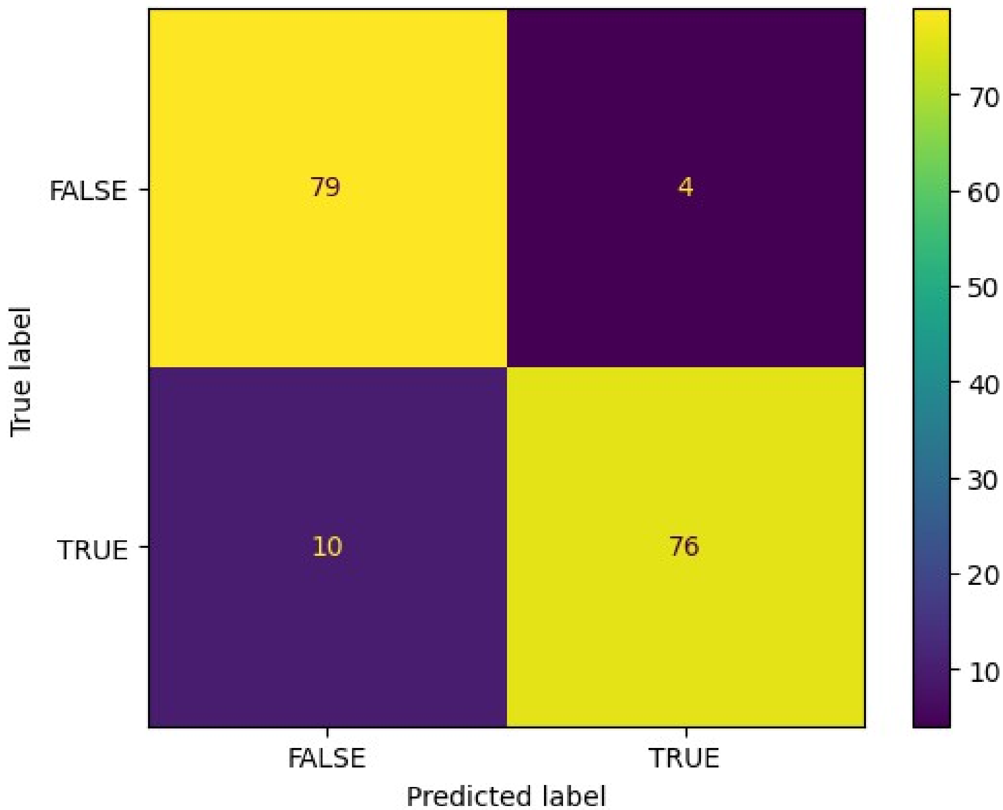
FALSE
TRUE
True label
70
13
7
79
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10

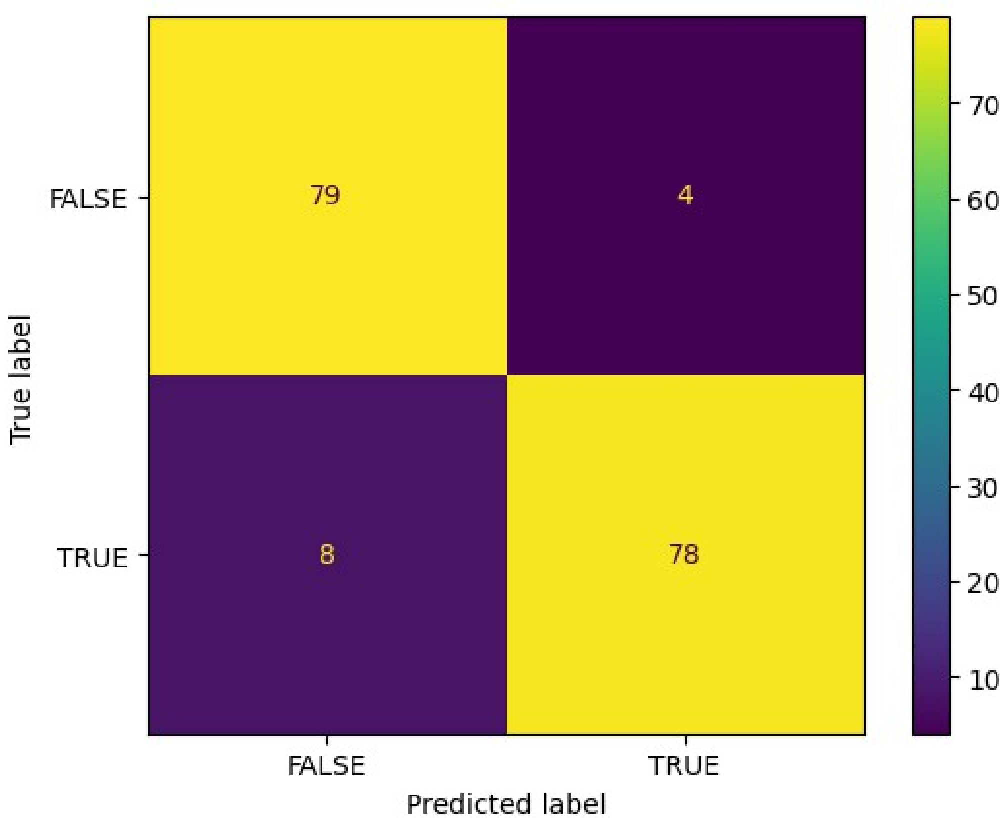


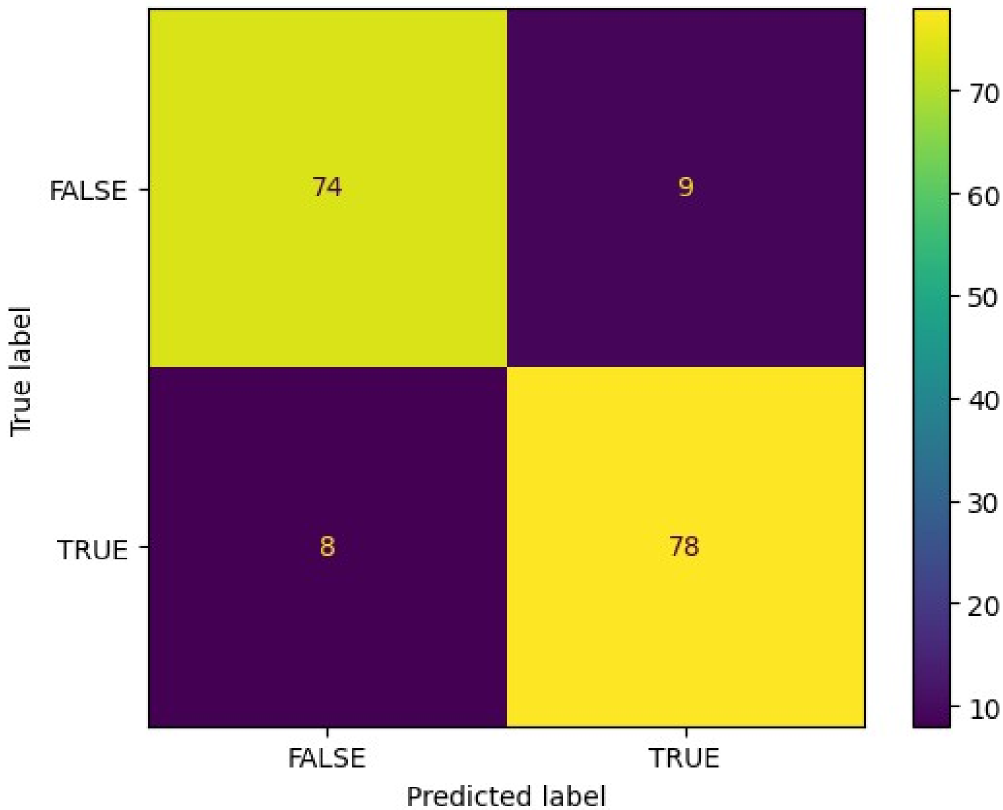
72
11
9
77
FALSE
TRUE
FALSE
TRUE
True label
Predicted label
70
60
50
40
30
20
10



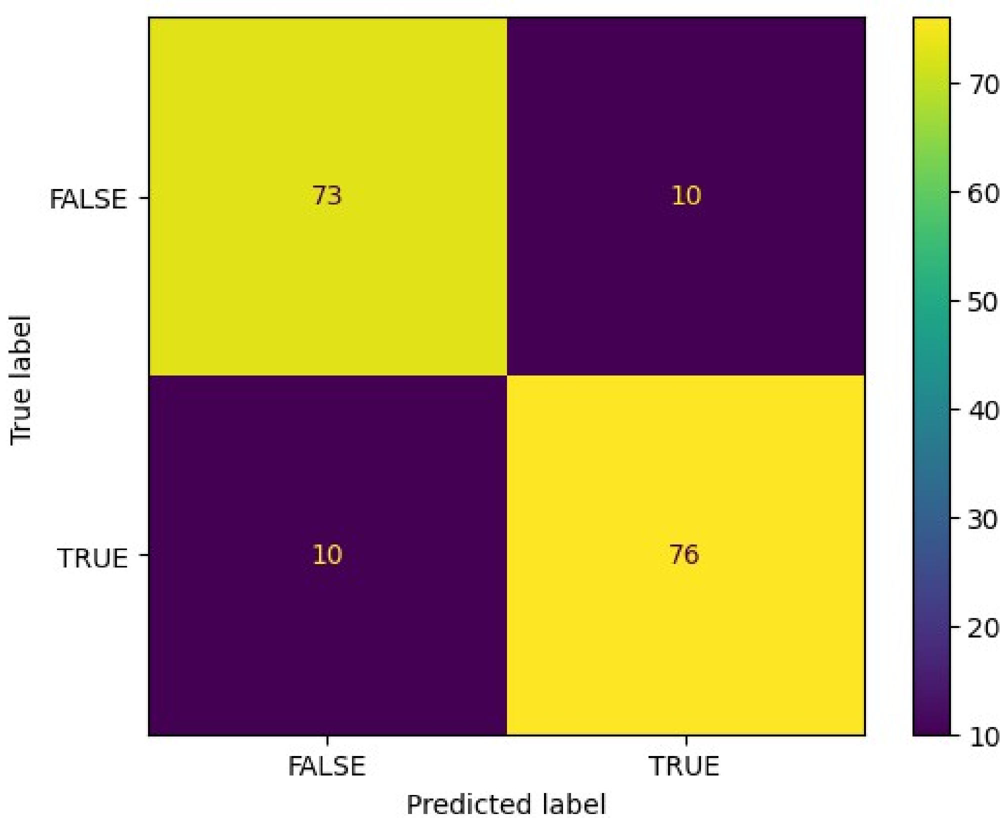
74
9
6
80
FALSE
TRUE
FALSE
TRUE
True label
Predicted label
80
70
60
50
40
30
20
10


79
4
10
76
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10

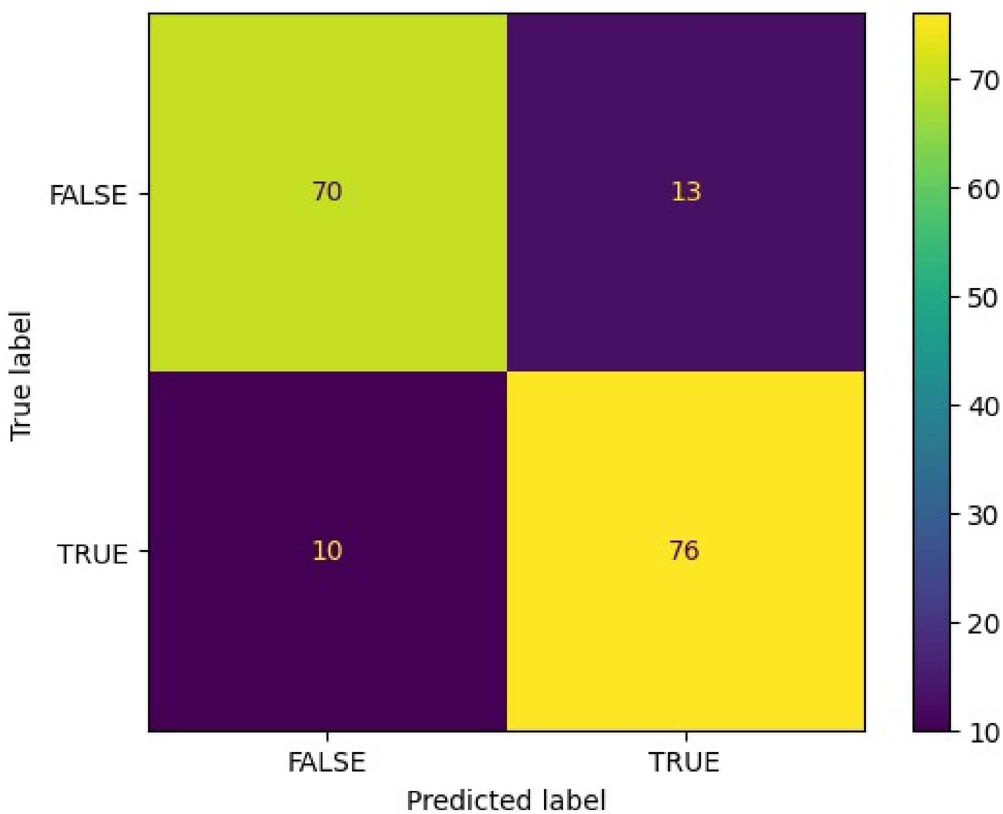

79
4
8
78
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



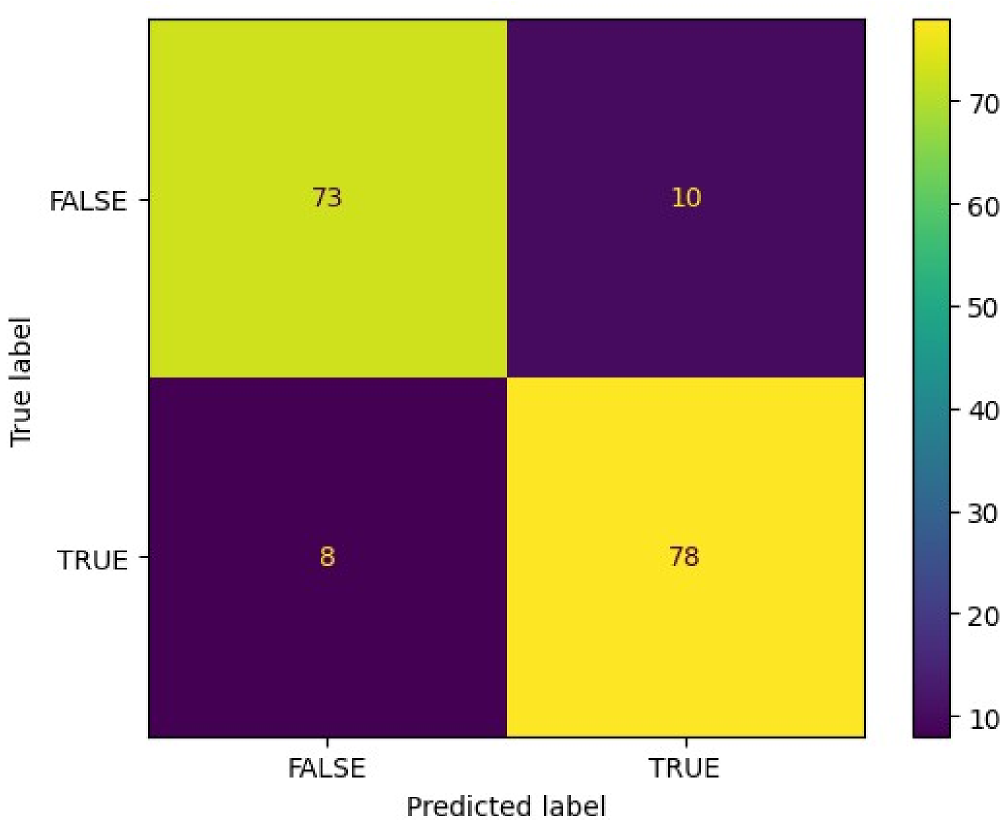
74
9
8
78
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



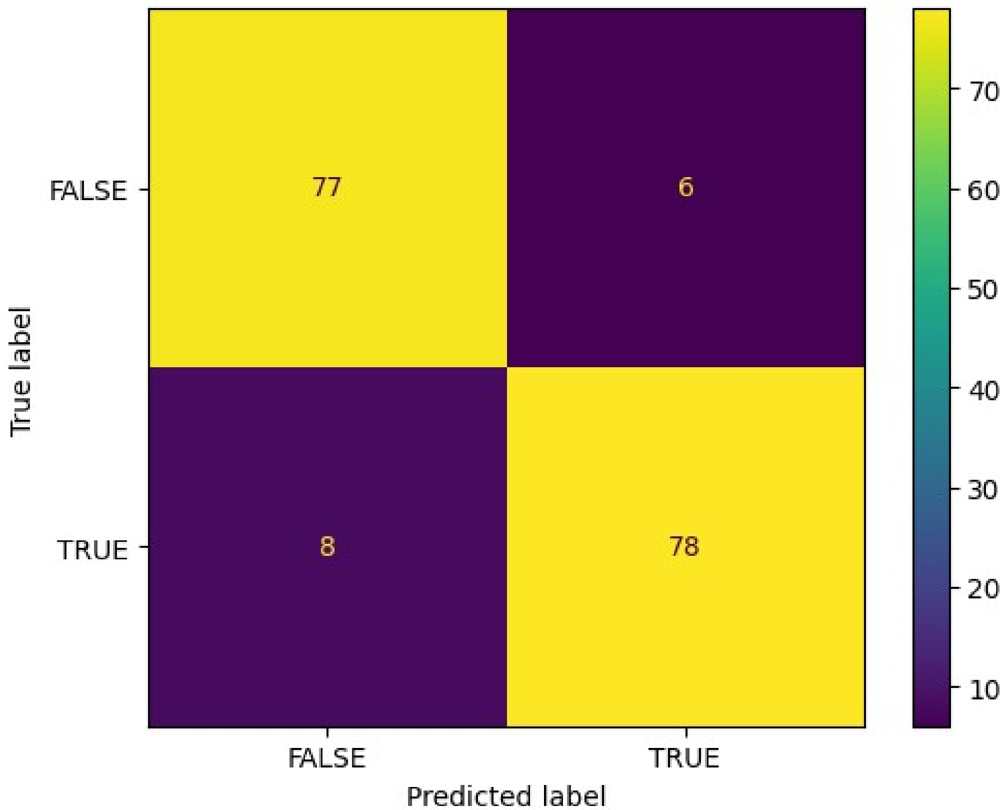
73
10
10
76
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10

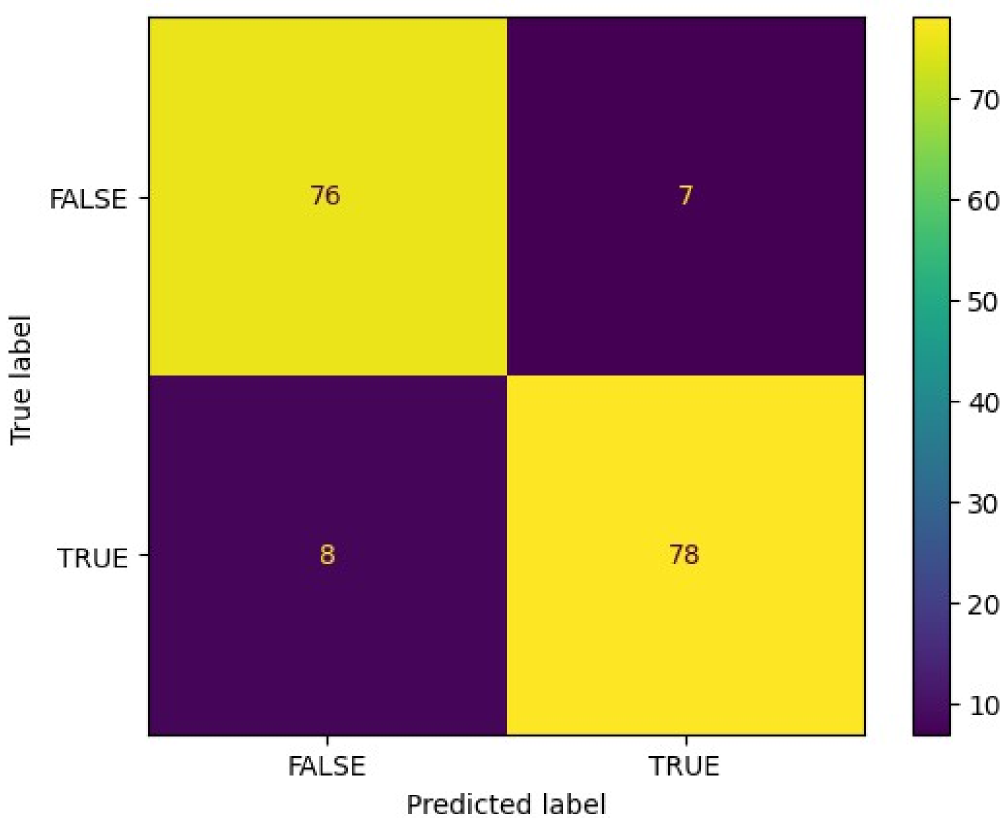


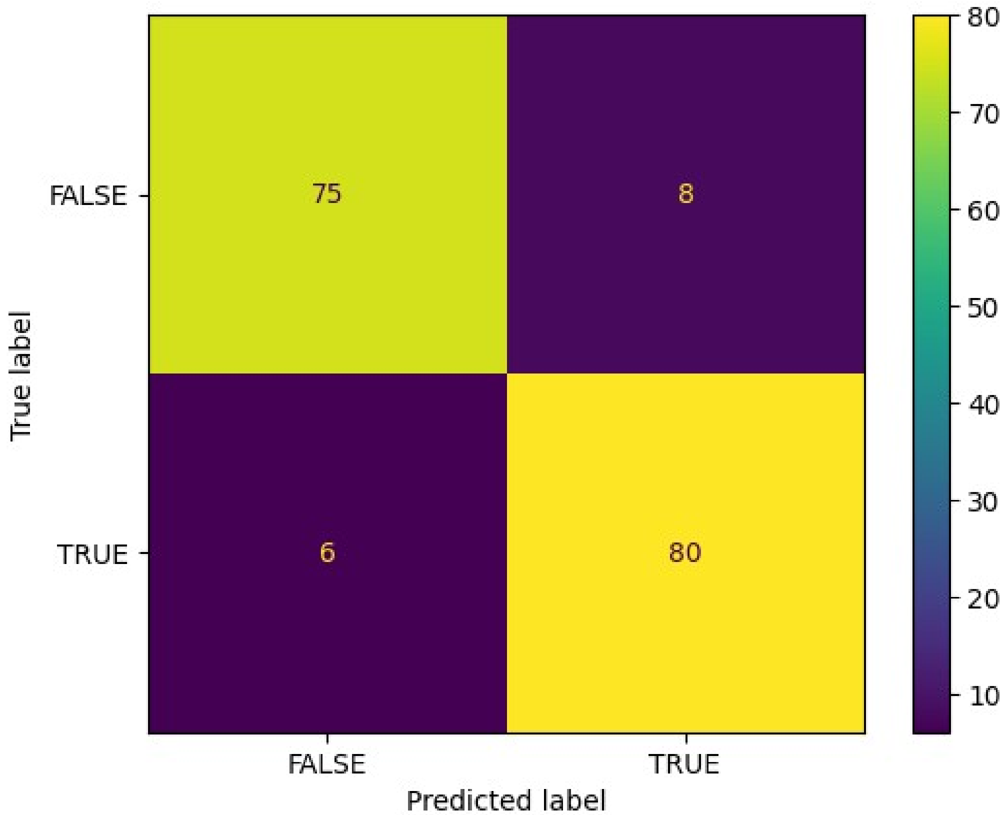
FALSE
TRUE
70
13
10
76
True label
FALSE
TRUE
Predicted label
10
20
30
40
50
60
70



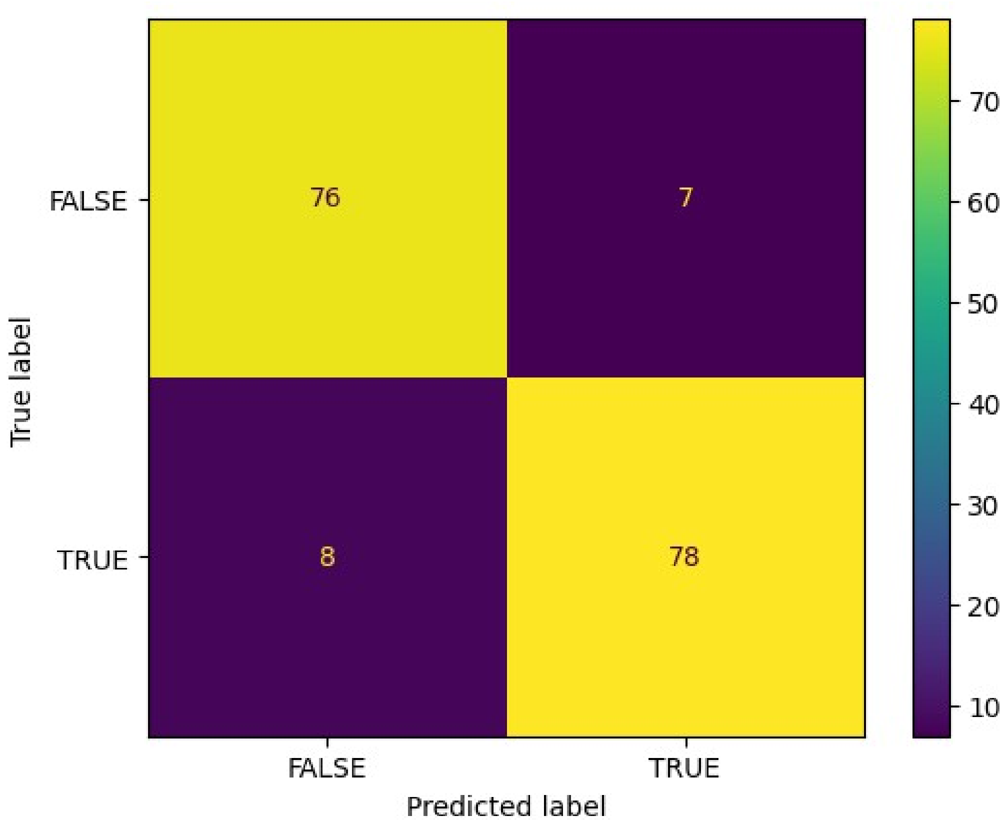
FALSE
TRUE
73
10
8
78
True label
FALSE
TRUE
Predicted label
10
20
30
40
50
60
70


77
6
8
78
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10

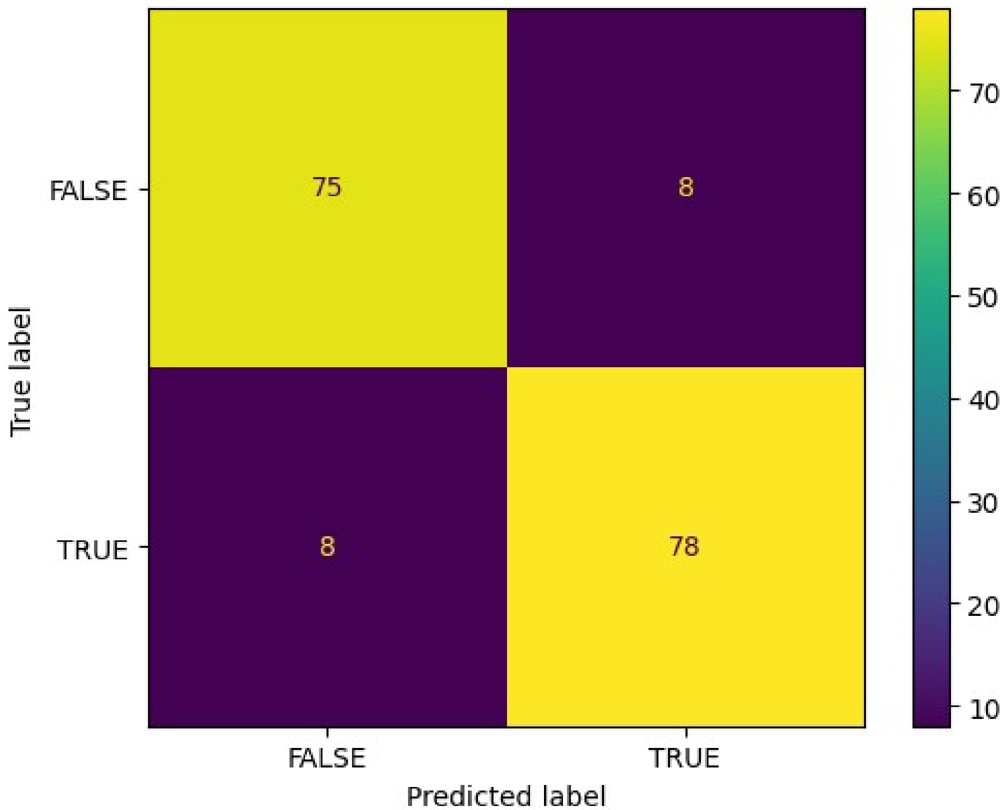

76
7
8
78
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



FALSE
TRUE
True label
75
8
6
80
FALSE
TRUE
Predicted label
80
70
60
50
40
30
20
10



FALSE
TRUE
True label
76
7
8
78
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



##**Etape 3 : Classification selon la colonne TITRE :**

```
from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
import time
import numpy as np

# Utilisez la méthode ravel() pour transformer y_train en un tableau
unidimensionnel
#X_train = np.ravel(X_train)
print("X_train", X_train.shape)
print("y_train", y_train.shape)
np.random.seed(42)  # Set the random seed for NumPy

score = 'accuracy'
seed = 7
allresults = []
```

```python
results = []
names = []


# Liste des modèles à tester
models = [
    ('MultinomialNB', MultinomialNB()),
    ('LogisticRegression', LogisticRegression(random_state=42))
]


models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier(random_state=42)))
models.append(('RF', RandomForestClassifier(random_state=42)))
models.append(('SVM', SVC(random_state=42)))

# Création d'un pipeline pour chaque modèle
pipelines = []
for name,model in models:
    pipeline = Pipeline([
        ('normalize', TextNormalizer()),
        ('tfidf', TfidfVectorizer()),
        (name,model)
    ])
    pipelines.append((name,pipeline))
    #pipeline.fit(X_train,y_train)
all_results=[]
scores=[]
names = []
for p in pipelines:
    print(p[1])
    # cross validation en 10 fois
    kfold = KFold(n_splits=10,random_state=seed,shuffle=True)

#    print ("Evaluation de ",p)
    start_time = time.time()
    # application de la classification
    cv_results = cross_val_score(p[1],X_train['title'],y_train,
cv=kfold, scoring=score)
    #print("Pour le classifieur",p[0],"on a un score
de",cv_results.mean(),"et un écart type de",cv_results.std())
    scores.append(cv_results)
    names.append(p[0])
    all_results.append((p[0],cv_results.mean(),cv_results.std()))
    end_time = time.time()


print("all resultats", all_results)
```

```python
all_results = sorted(all_results, key=lambda x: (-x[1], -x[2]))
print("all resultats", all_results)
    # affichage des résultats
#print ('\nLe meilleur resultat : ',max(results))
```

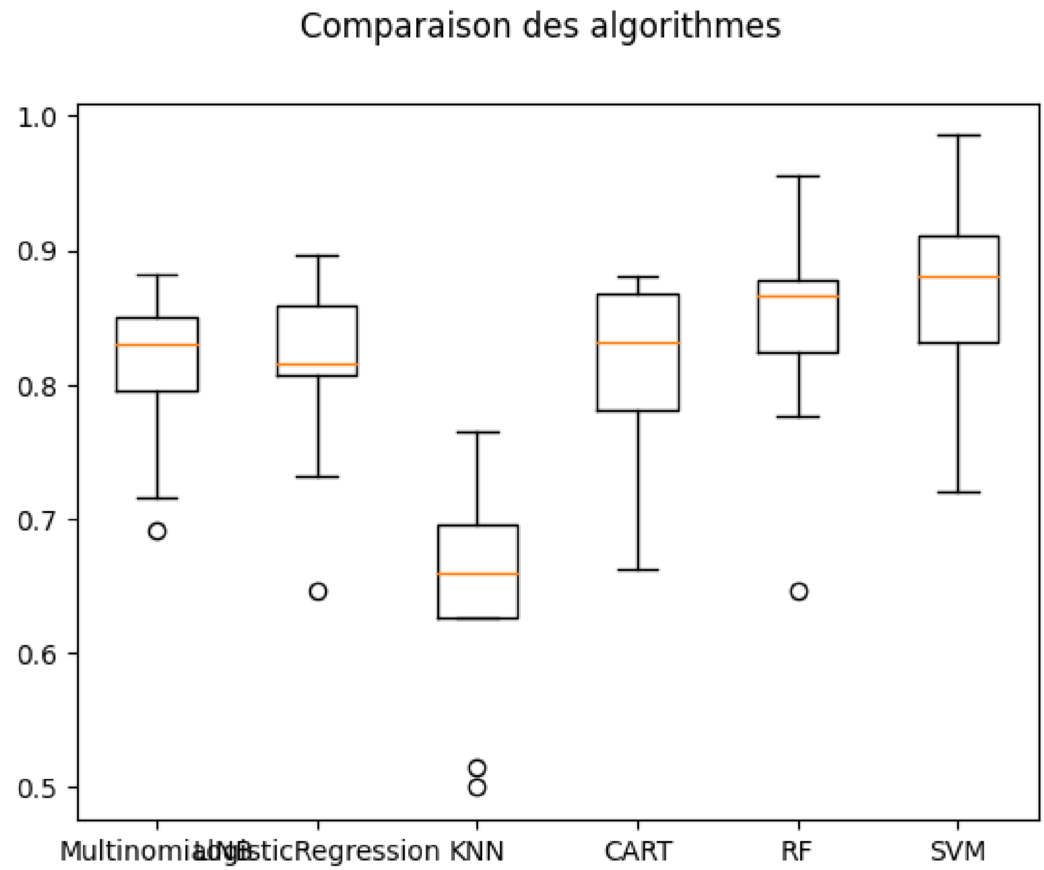
```
X_train (675, 2)
y_train (675,)
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('MultinomialNB', MultinomialNB())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('LogisticRegression',
LogisticRegression(random_state=42))])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('KNN', KNeighborsClassifier())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('CART', DecisionTreeClassifier(random_state=42))])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('RF', RandomForestClassifier(random_state=42))])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('SVM', SVC(random_state=42))])
all resultats [('MultinomialNB', 0.810359964881475,
0.05872410123263959), ('LogisticRegression', 0.8104697102721685,
0.07018958627295246), ('KNN', 0.6446224758560141,
0.07936226071732319), ('CART', 0.8104697102721685,
0.07035617709825927), ('RF', 0.8416154521510096, 0.0799660194065715),
('SVM', 0.8667251975417033, 0.08008579483575896)]
all resultats [('SVM', 0.8667251975417033, 0.08008579483575896),
('RF', 0.8416154521510096, 0.0799660194065715), ('CART',
0.8104697102721685, 0.07035617709825927), ('LogisticRegression',
0.8104697102721685, 0.07018958627295246), ('MultinomialNB',
0.810359964881475, 0.05872410123263959), ('KNN', 0.6446224758560141,
0.07936226071732319)]
```

On affiche les accuracy de chaque classifieur, on remarque la médiane (en rouge) de chaque et l'écart type aussi.

```python
import matplotlib.pyplot as plt
fig = plt.figure()
fig.suptitle('Comparaison des algorithmes')
ax = fig.add_subplot(111)
plt.boxplot(scores)
ax.set_xticklabels(names)
```

```
[Text(1, 0, 'MultinomialNB'),
 Text(2, 0, 'LogisticRegression'),
```

```
 Text(3, 0, 'KNN'),
 Text(4, 0, 'CART'),
 Text(5, 0, 'RF'),
 Text(6, 0, 'SVM')]
```



Choisir les meilleurs paramètres pour SVM et RF :

On a un pipeline pour chaque prétraitement différent, on essaye pas mal (miniscule, lemmatisation, miniscule + lemmatisation..) et on stocke le fit_transorm de nos X_train, X_test sur les pipelines dans des listes qui vont contenir tous les fit_transform des pipelines pour chaque classifieur, par la suite on parcourt ces listes là, on itère dessus, et chaque élement de la liste (train) va passer par le GridSearch et puis on predict sur son corresapondant dans liste (test).

```python
from sklearn.model_selection import GridSearchCV


from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score
```

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from tabulate import tabulate
import numpy as np
np.random.seed(42)  # Set the random seed for NumPy
print("y_train", y_train.shape)
print("y_test", y_test.shape)
#X_test = np.ravel(X_test)
print("X_test", X_test.shape)
# le plus simple est de faire un test sur differents pipelines.
# pipeline de l'utilisation de CountVectorizer sur le texte avec
differents pre-traitements
CV_brut = Pipeline([('cleaner', TextNormalizer()),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])
CV_lowcase = Pipeline([('cleaner',
TextNormalizer(removestopwords=False,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])
CV_lowStop = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])

CV_lowStopstem = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=True,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])

# pipeline de l'utilisation de TfidfVectorizer avec differents pre-
traitements
TFIDF_brut = Pipeline ([('cleaner', TextNormalizer()),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])

TFIDF_lowcase = Pipeline([('cleaner',
TextNormalizer(removestopwords=False,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])
```

```
TFIDF_lowStop = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])

TFIDF_lowStopstem = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=True,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])


# Liste de tous les modeles à tester
all_models = [
    ("CV_brut", CV_brut),
    ("CV_lowcase", CV_lowcase),
    ("CV_lowStop", CV_lowStop),
    ("CV_lowStopstem",CV_lowStopstem),
    ("TFIDF_lowcase", TFIDF_lowcase),
    ("TFIDF_lowStop", TFIDF_lowStop),
    ("TFIDF_lowStopstem",TFIDF_lowStopstem),
    ("TFIDF_brut", TFIDF_brut)
]

X_train_title_SVC = []
X_test_title_SVC = []

X_train_title_RandomForestClassifier = []
X_test_title_RandomForestClassifier = []


for name, pipeline in all_models :

X_train_title_SVC.append(pipeline.fit_transform(X_train['title']).toar
ray())

X_test_title_SVC.append(pipeline.transform(X_test['title']).toarray())

X_train_title_RandomForestClassifier.append(pipeline.fit_transform(X_t
rain['title']).toarray())

X_test_title_RandomForestClassifier.append(pipeline.transform(X_test['
title']).toarray())
```

```
models = {
    'SVC': SVC(random_state=42),
    'RandomForestClassifier': RandomForestClassifier(random_state=42)
}


params = {'SVC': [{'C': [0.001, 0.01, 0.1, 1,2,5,7,10]},
             {'gamma': [0.001, 0.01, 0.1,0.2,0.3,0.5,0.7,1]},
             {'kernel': ['linear', 'rbf']}],
    'RandomForestClassifier': [{'n_estimators': [10, 50, 100, 200,
300]},
                              {'max_features': ['auto', 'sqrt',
'log2']}]
}

for model_name, model in models.items():
    score='accuracy'
    X_train_title = eval('X_train_title_' + model_name)
    X_test_title = eval('X_test_title_' + model_name)
    for i in range (len(X_train_title)):
      grid_search = GridSearchCV(model, params[model_name], n_jobs=-1,
verbose=1,scoring=score)
      print("grid search fait")
      print("X_train",X_train_title[i].shape)
      print("y_train",y_train.shape)
      grid_search.fit(X_train_title[i],y_train)
      print ('meilleur score %0.3f'%(grid_search.best_score_),'\n')
      print ('meilleur estimateur',grid_search.best_estimator_,'\n')
      y_pred = grid_search.predict(X_test_title[i])
      MyshowAllScores(y_test,y_pred)

      print("Ensemble des meilleurs paramètres :")
      best_parameters = grid_search.best_estimator_.get_params()
      for param_dict in params[model_name]:
        for param_name, param_value in param_dict.items():
            print("\t%s: %r" % (param_name,
best_parameters[param_name]))
```

```
y_train (675,)
y_test (169,)
X_test (169, 2)
grid search fait
X_train (675, 5734)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.831

meilleur estimateur SVC(gamma=0.3, random_state=42)
```

```
Accuracy : 0.882
Classification Report
              precision    recall  f1-score   support

       FALSE    0.89873   0.85542   0.87654        83
        TRUE    0.86667   0.90698   0.88636        86

    accuracy                        0.88166       169
   macro avg    0.88270   0.88120   0.88145       169
weighted avg    0.88242   0.88166   0.88154       169

Ensemble des meilleurs paramètres :
	C: 1.0
	gamma: 0.3
	kernel: 'rbf'
grid search fait
X_train (675, 4861)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.840

meilleur estimateur SVC(gamma=0.3, random_state=42)

Accuracy : 0.917
Classification Report
              precision    recall  f1-score   support

       FALSE    0.92593   0.90361   0.91463        83
        TRUE    0.90909   0.93023   0.91954        86

    accuracy                        0.91716       169
   macro avg    0.91751   0.91692   0.91709       169
weighted avg    0.91736   0.91716   0.91713       169

Ensemble des meilleurs paramètres :
	C: 1.0
	gamma: 0.3
	kernel: 'rbf'
grid search fait
X_train (675, 4733)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.831

meilleur estimateur SVC(gamma=0.5, random_state=42)

Accuracy : 0.911
Classification Report
              precision    recall  f1-score   support
```

```
       FALSE    0.94737   0.86747   0.90566        83
        TRUE    0.88172   0.95349   0.91620        86

    accuracy                        0.91124       169
   macro avg    0.91454   0.91048   0.91093       169
weighted avg    0.91396   0.91124   0.91102       169

Ensemble des meilleurs paramètres :
     C: 1.0
     gamma: 0.5
     kernel: 'rbf'
grid search fait
X_train (675, 3613)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.833

meilleur estimateur SVC(gamma=0.7, random_state=42)

Accuracy : 0.905
Classification Report
              precision    recall  f1-score   support

       FALSE    0.86813   0.95181   0.90805        83
        TRUE    0.94872   0.86047   0.90244        86

    accuracy                        0.90533       169
   macro avg    0.90842   0.90614   0.90524       169
weighted avg    0.90914   0.90533   0.90519       169

Ensemble des meilleurs paramètres :
     C: 1.0
     gamma: 0.7
     kernel: 'rbf'
grid search fait
X_train (675, 4861)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.834

meilleur estimateur SVC(C=1, random_state=42)

Accuracy : 0.888
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88095   0.89157   0.88623        83
        TRUE    0.89412   0.88372   0.88889        86
```

```
    accuracy                        0.88757       169
   macro avg    0.88754   0.88764   0.88756       169
weighted avg    0.88765   0.88757   0.88758       169

Ensemble des meilleurs paramètres :
     C: 1
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 4733)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.836

meilleur estimateur SVC(C=1, random_state=42)

Accuracy : 0.888
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88095   0.89157   0.88623        83
        TRUE    0.89412   0.88372   0.88889        86

    accuracy                        0.88757       169
   macro avg    0.88754   0.88764   0.88756       169
weighted avg    0.88765   0.88757   0.88758       169

Ensemble des meilleurs paramètres :
     C: 1
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
X_train (675, 3613)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.830

meilleur estimateur SVC(gamma=1, random_state=42)

Accuracy : 0.893
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88235   0.90361   0.89286        83
        TRUE    0.90476   0.88372   0.89412        86

    accuracy                        0.89349       169
   macro avg    0.89356   0.89367   0.89349       169
```

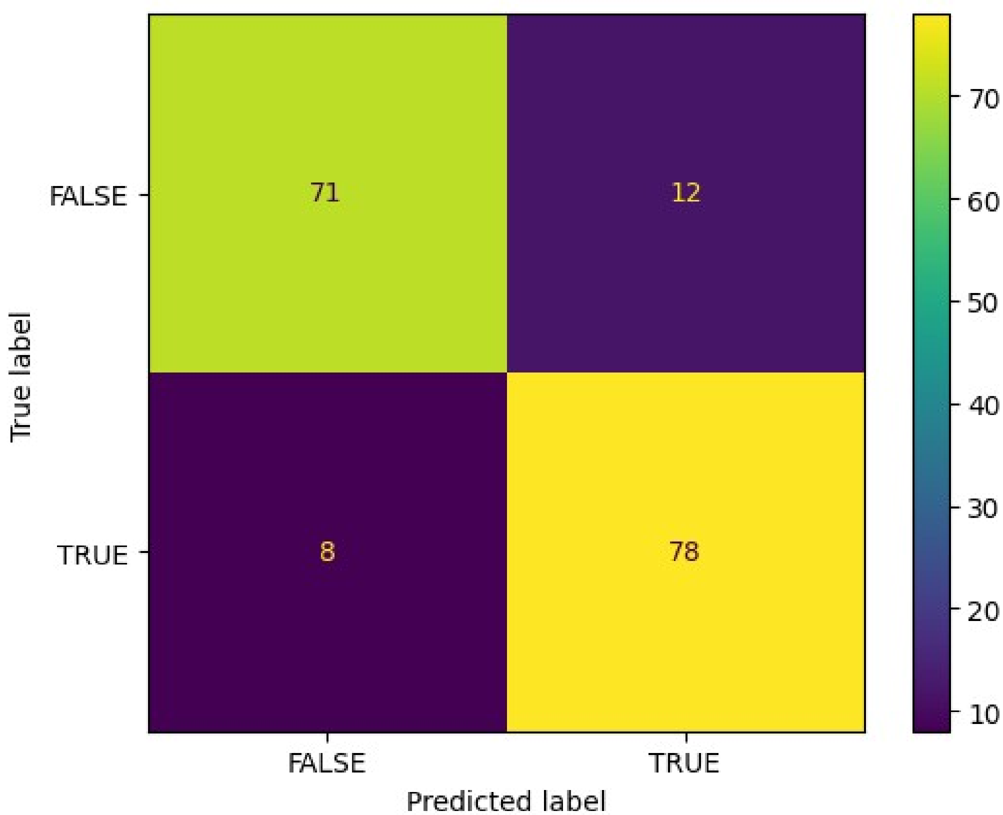
```
weighted avg    0.89376   0.89349   0.89350       169

Ensemble des meilleurs paramètres :
      C: 1.0
      gamma: 1
      kernel: 'rbf'
grid search fait
X_train (675, 5734)
y_train (675,)
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.837

meilleur estimateur SVC(C=1, random_state=42)

Accuracy : 0.893
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88235   0.90361   0.89286        83
        TRUE    0.90476   0.88372   0.89412        86

    accuracy                        0.89349       169
   macro avg    0.89356   0.89367   0.89349       169
weighted avg    0.89376   0.89349   0.89350       169

Ensemble des meilleurs paramètres :
      C: 1
      gamma: 'scale'
      kernel: 'rbf'
grid search fait
X_train (675, 5734)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.824

meilleur estimateur RandomForestClassifier(n_estimators=50,
random_state=42)

Accuracy : 0.911
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90476   0.91566   0.91018        83
        TRUE    0.91765   0.90698   0.91228        86

    accuracy                        0.91124       169
   macro avg    0.91120   0.91132   0.91123       169
weighted avg    0.91132   0.91124   0.91125       169
```

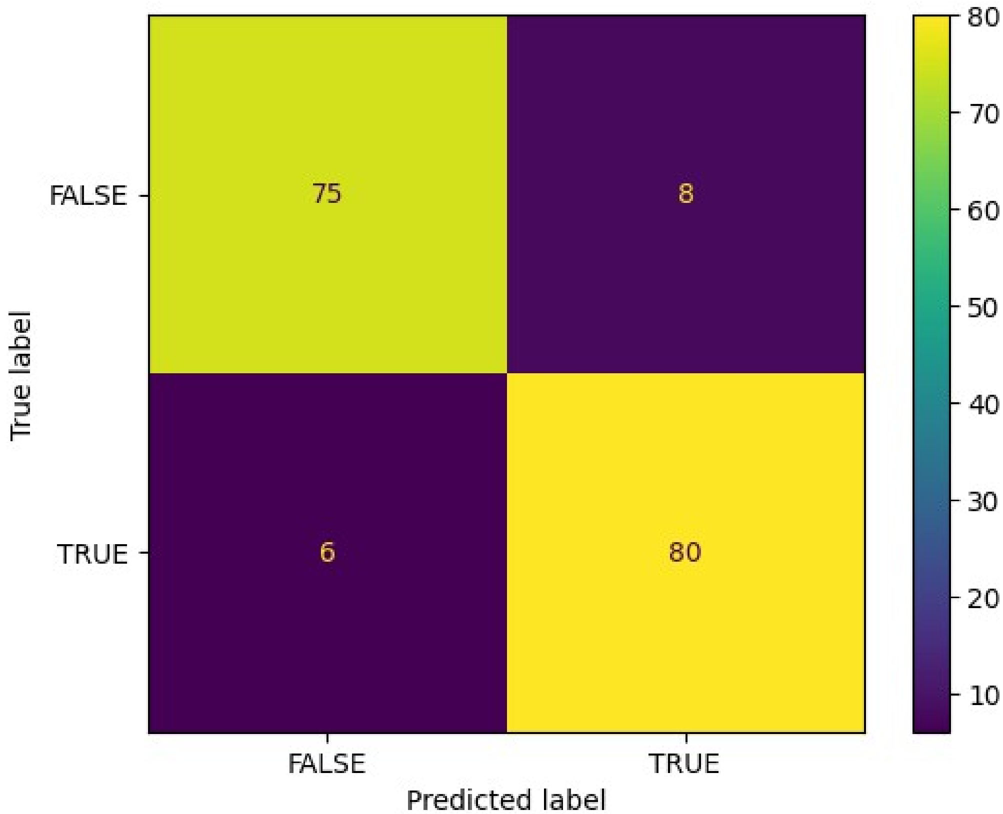
```
Ensemble des meilleurs paramètres :
      n_estimators: 50
      max_features: 'sqrt'
grid search fait
X_train (675, 4861)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.824

meilleur estimateur RandomForestClassifier(random_state=42)

Accuracy : 0.888
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90000   0.86747   0.88344        83
        TRUE    0.87640   0.90698   0.89143        86

    accuracy                        0.88757       169
   macro avg    0.88820   0.88722   0.88743       169
weighted avg    0.88799   0.88757   0.88750       169

Ensemble des meilleurs paramètres :
      n_estimators: 100
      max_features: 'sqrt'
grid search fait
X_train (675, 4733)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.827

meilleur estimateur RandomForestClassifier(n_estimators=50,
random_state=42)

Accuracy : 0.899
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88372   0.91566   0.89941        83
        TRUE    0.91566   0.88372   0.89941        86

    accuracy                        0.89941       169
   macro avg    0.89969   0.89969   0.89941       169
weighted avg    0.89998   0.89941   0.89941       169

Ensemble des meilleurs paramètres :
      n_estimators: 50
      max_features: 'sqrt'
grid search fait
```

```
X_train (675, 3613)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.822

meilleur estimateur RandomForestClassifier(n_estimators=300,
random_state=42)

Accuracy : 0.876
Classification Report
              precision    recall  f1-score   support

       FALSE    0.86047   0.89157   0.87574        83
        TRUE    0.89157   0.86047   0.87574        86

    accuracy                        0.87574       169
   macro avg    0.87602   0.87602   0.87574       169
weighted avg    0.87629   0.87574   0.87574       169

Ensemble des meilleurs paramètres :
     n_estimators: 300
     max_features: 'sqrt'
grid search fait
X_train (675, 4861)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.831

meilleur estimateur RandomForestClassifier(n_estimators=200,
random_state=42)

Accuracy : 0.858
Classification Report
              precision    recall  f1-score   support

       FALSE    0.85542   0.85542   0.85542        83
        TRUE    0.86047   0.86047   0.86047        86

    accuracy                        0.85799       169
   macro avg    0.85794   0.85794   0.85794       169
weighted avg    0.85799   0.85799   0.85799       169

Ensemble des meilleurs paramètres :
     n_estimators: 200
     max_features: 'sqrt'
grid search fait
X_train (675, 4733)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
```

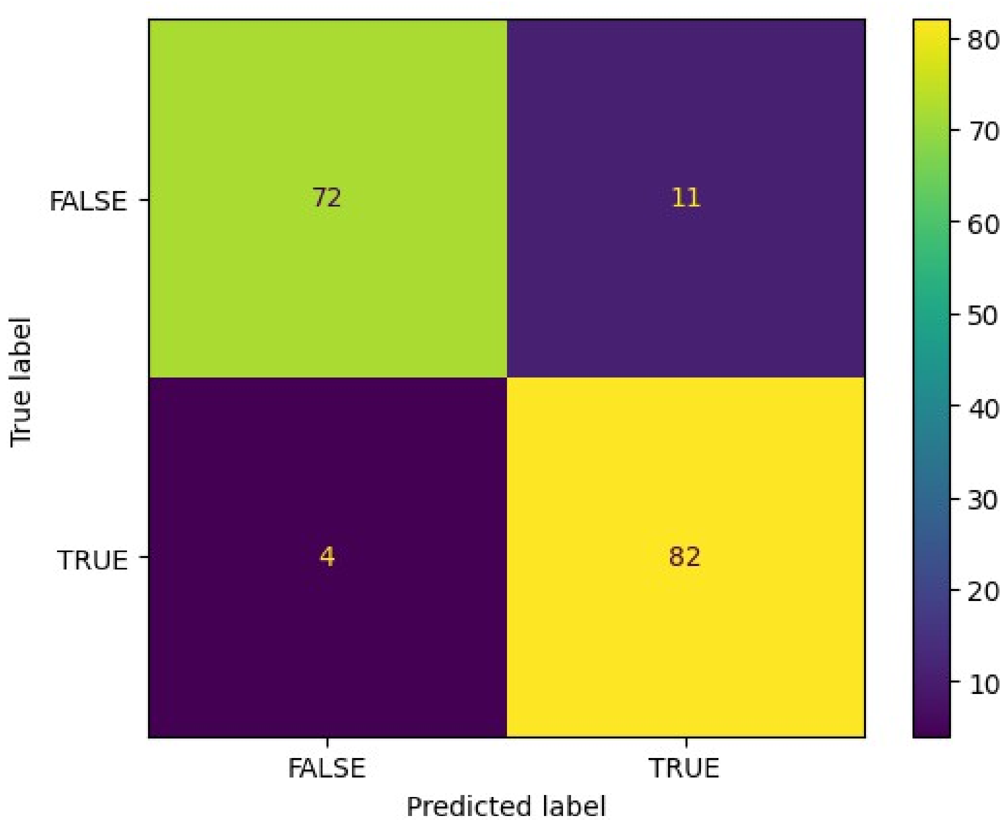
```
meilleur score 0.825

meilleur estimateur RandomForestClassifier(n_estimators=50,
random_state=42)

Accuracy : 0.876
Classification Report
              precision    recall  f1-score   support

       FALSE    0.86047   0.89157   0.87574        83
        TRUE    0.89157   0.86047   0.87574        86

    accuracy                        0.87574       169
   macro avg    0.87602   0.87602   0.87574       169
weighted avg    0.87629   0.87574   0.87574       169

Ensemble des meilleurs paramètres :
     n_estimators: 50
     max_features: 'sqrt'
grid search fait
X_train (675, 3613)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.824

meilleur estimateur RandomForestClassifier(random_state=42)

Accuracy : 0.870
Classification Report
              precision    recall  f1-score   support

       FALSE    0.85882   0.87952   0.86905        83
        TRUE    0.88095   0.86047   0.87059        86

    accuracy                        0.86982       169
   macro avg    0.86989   0.86999   0.86982       169
weighted avg    0.87008   0.86982   0.86983       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'sqrt'
grid search fait
X_train (675, 5734)
y_train (675,)
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.830

meilleur estimateur RandomForestClassifier(n_estimators=50,
random_state=42)
```

```
Accuracy : 0.870
Classification Report
              precision    recall  f1-score   support

       FALSE    0.85882   0.87952   0.86905        83
        TRUE    0.88095   0.86047   0.87059        86

    accuracy                        0.86982       169
   macro avg    0.86989   0.86999   0.86982       169
weighted avg    0.87008   0.86982   0.86983       169

Ensemble des meilleurs paramètres :
      n_estimators: 50
      max_features: 'sqrt'
```

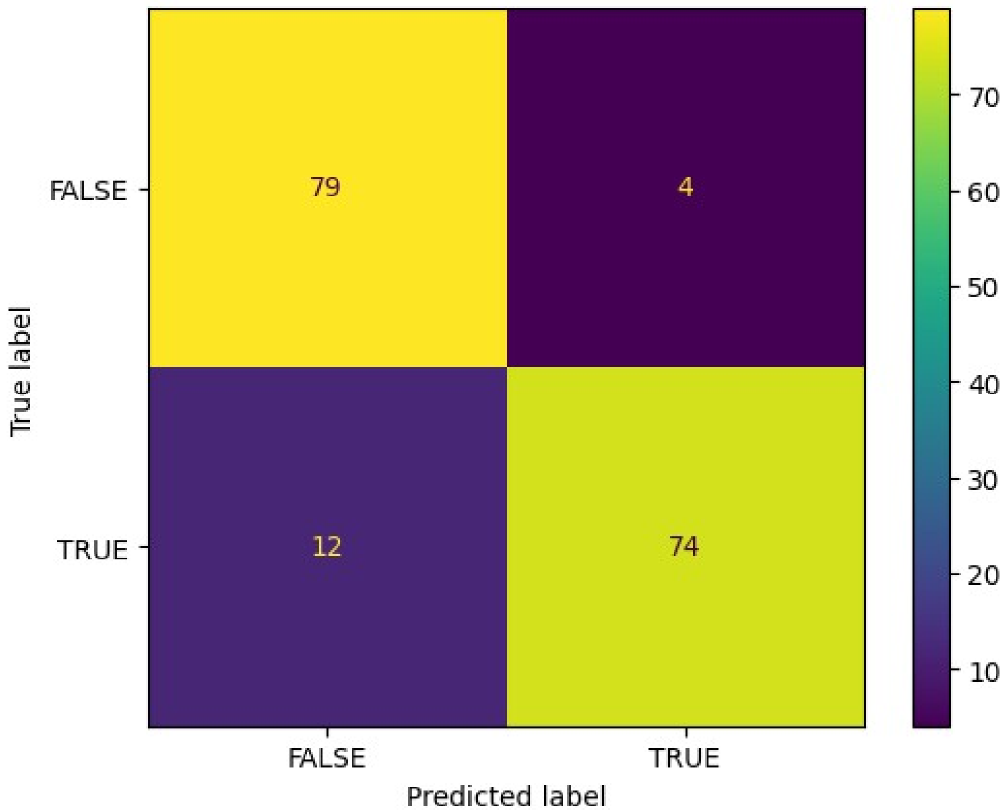


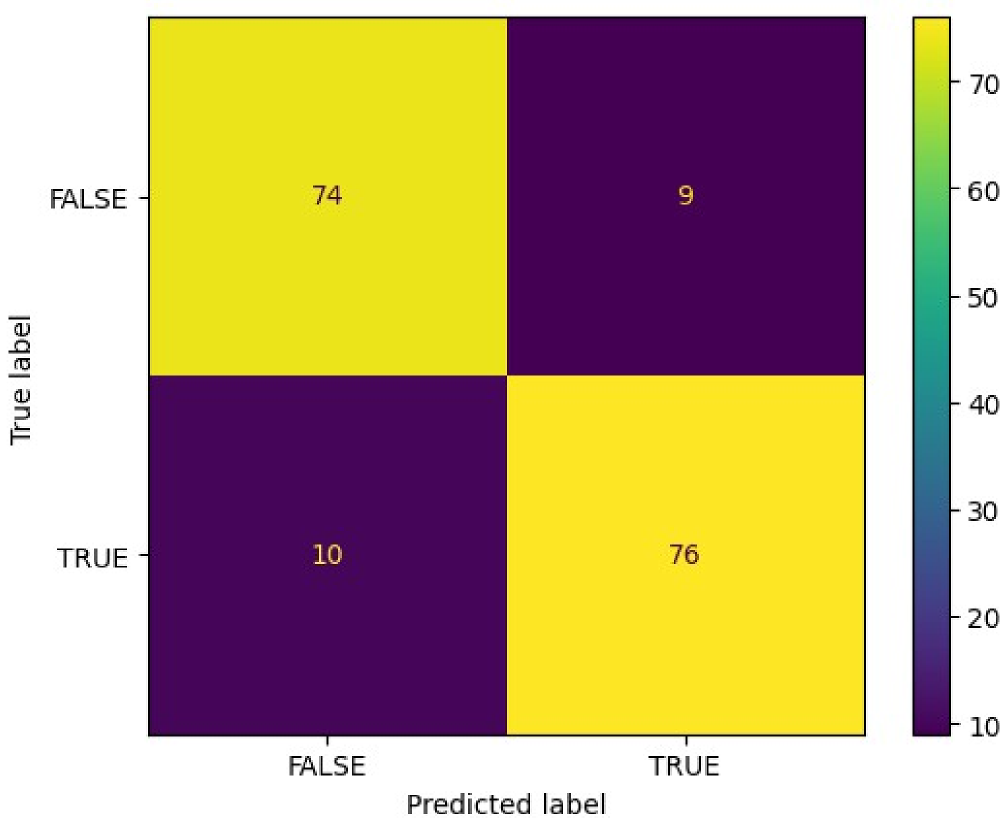


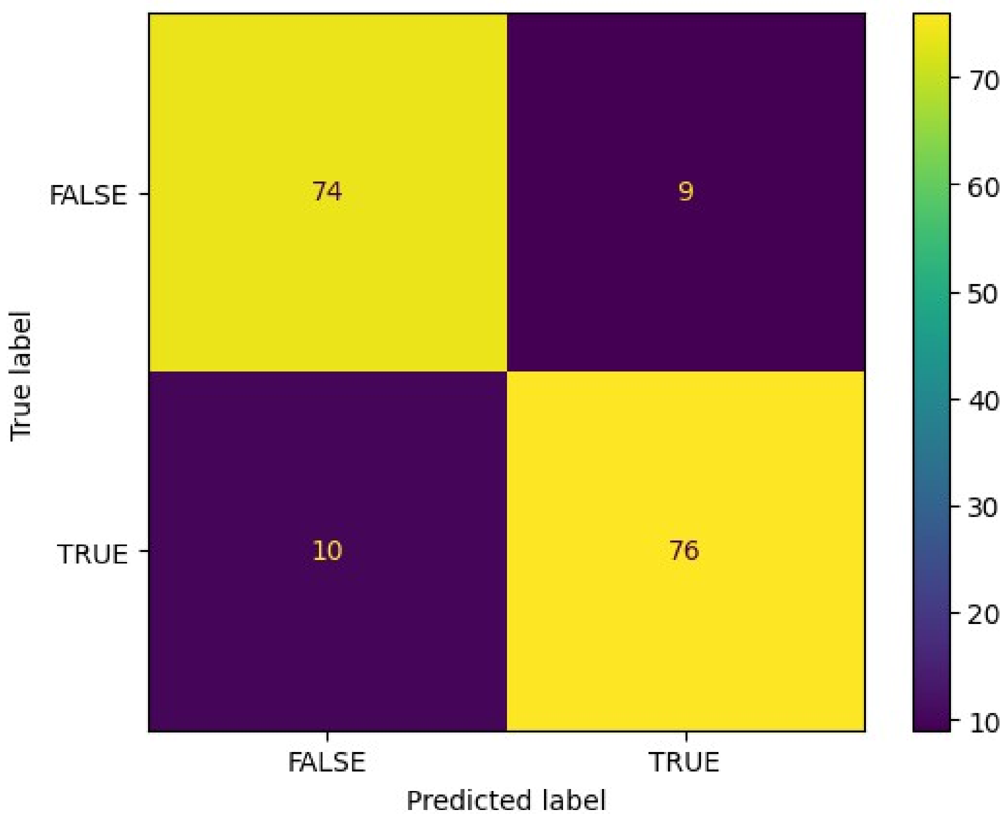
True label
FALSE
TRUE
75
8
6
80
FALSE
TRUE
Predicted label
80
70
60
50
40
30
20
10



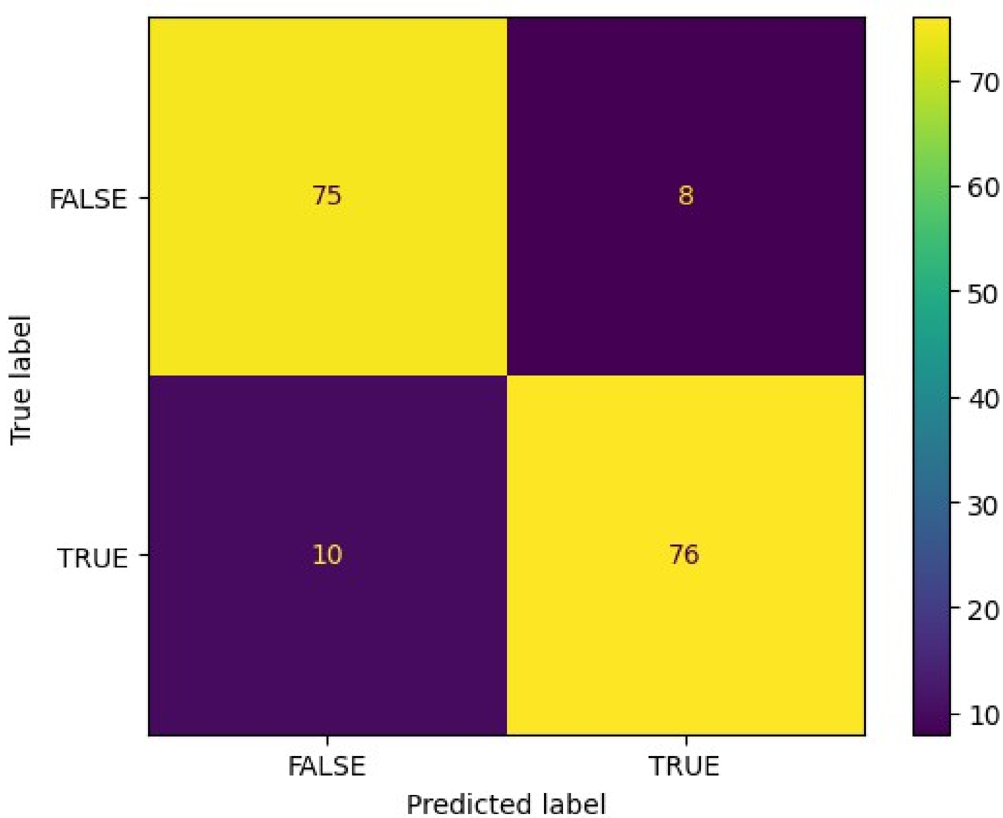
True label
FALSE
TRUE
72
11
4
82
FALSE
TRUE
Predicted label
80
70
60
50
40
30
20
10


79
4
12
74
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10

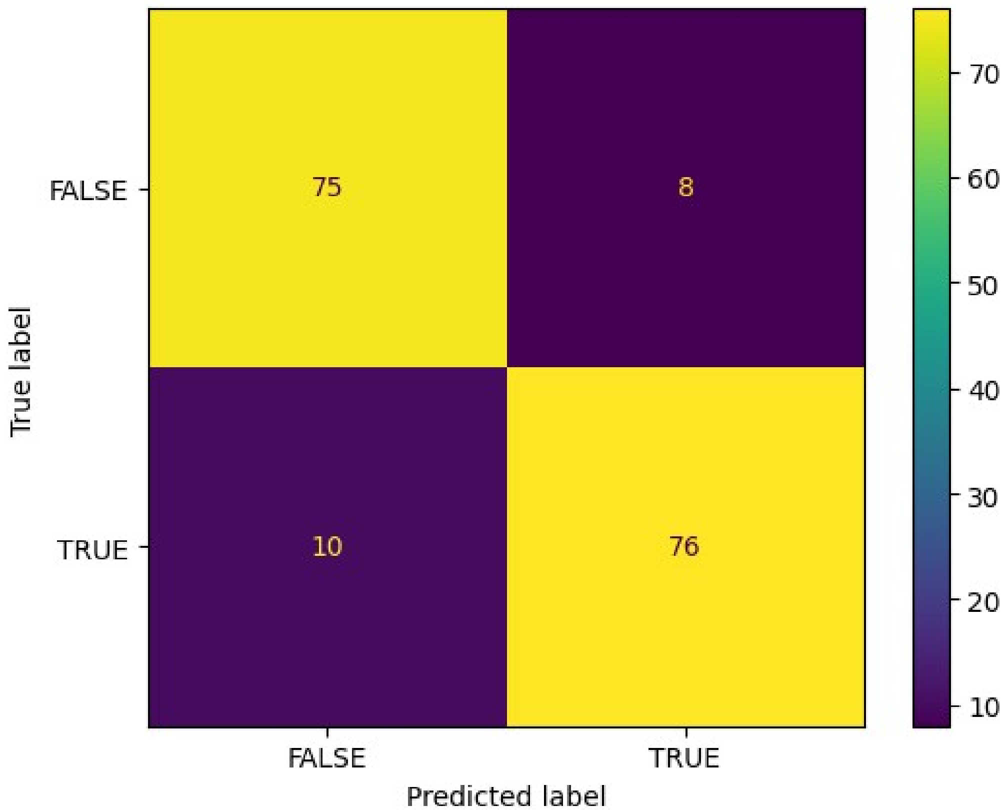

74
9
10
76
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



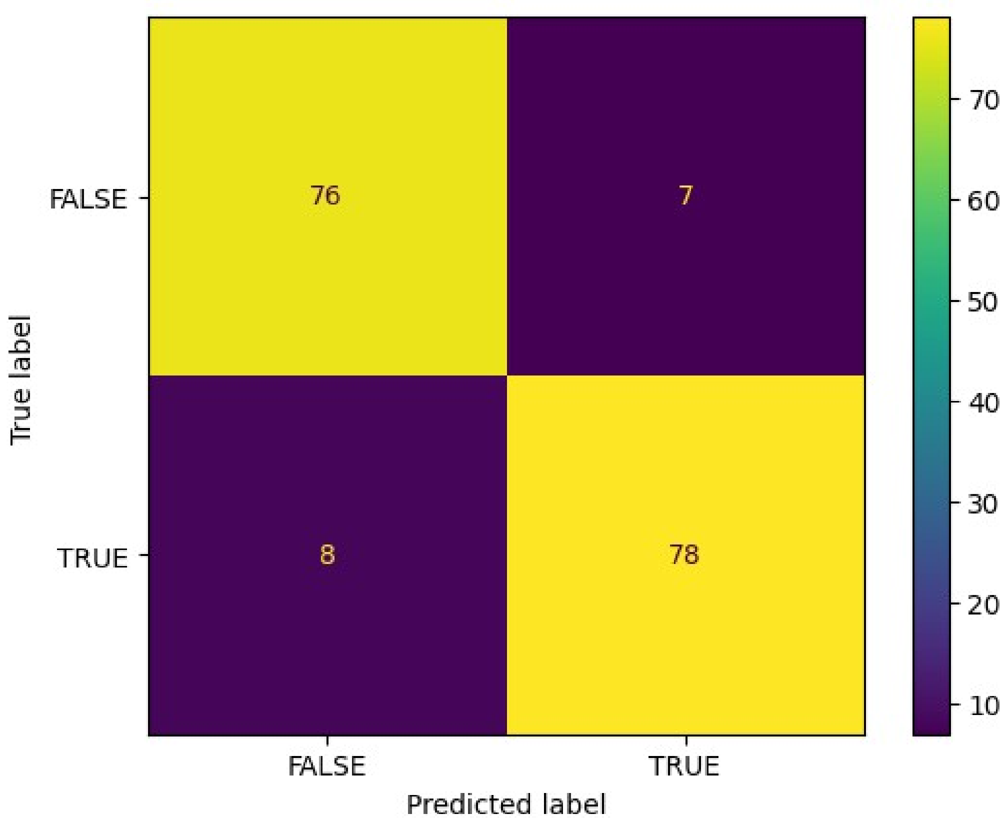
74
9
10
76
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



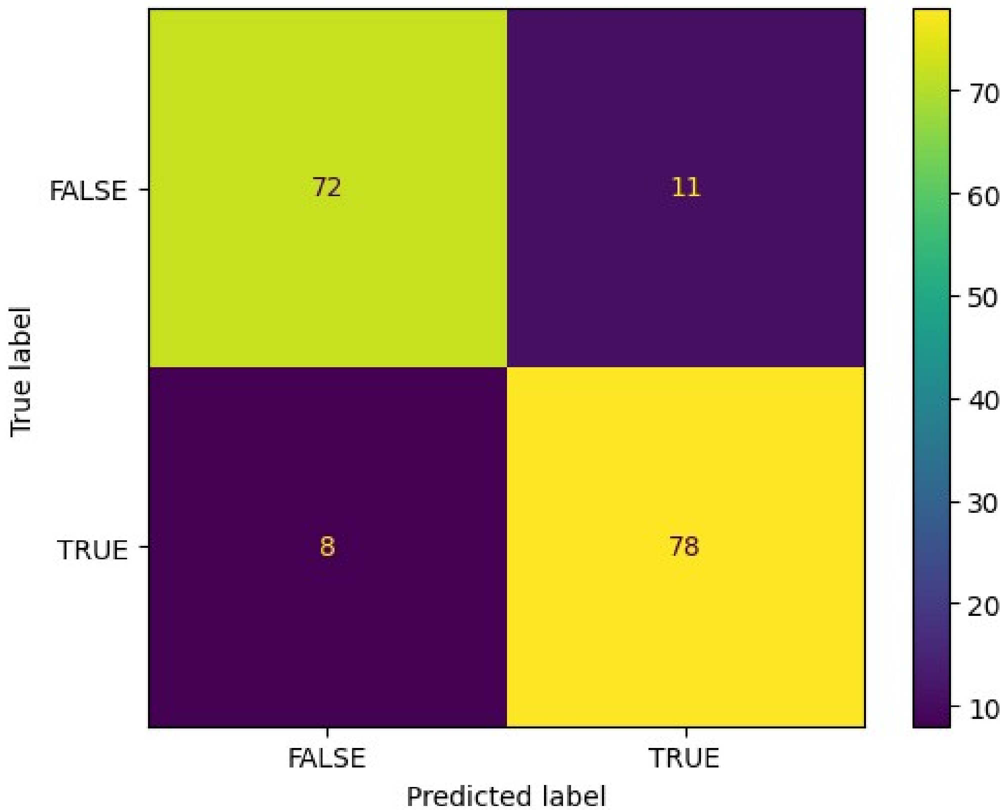
75
8
10
76
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



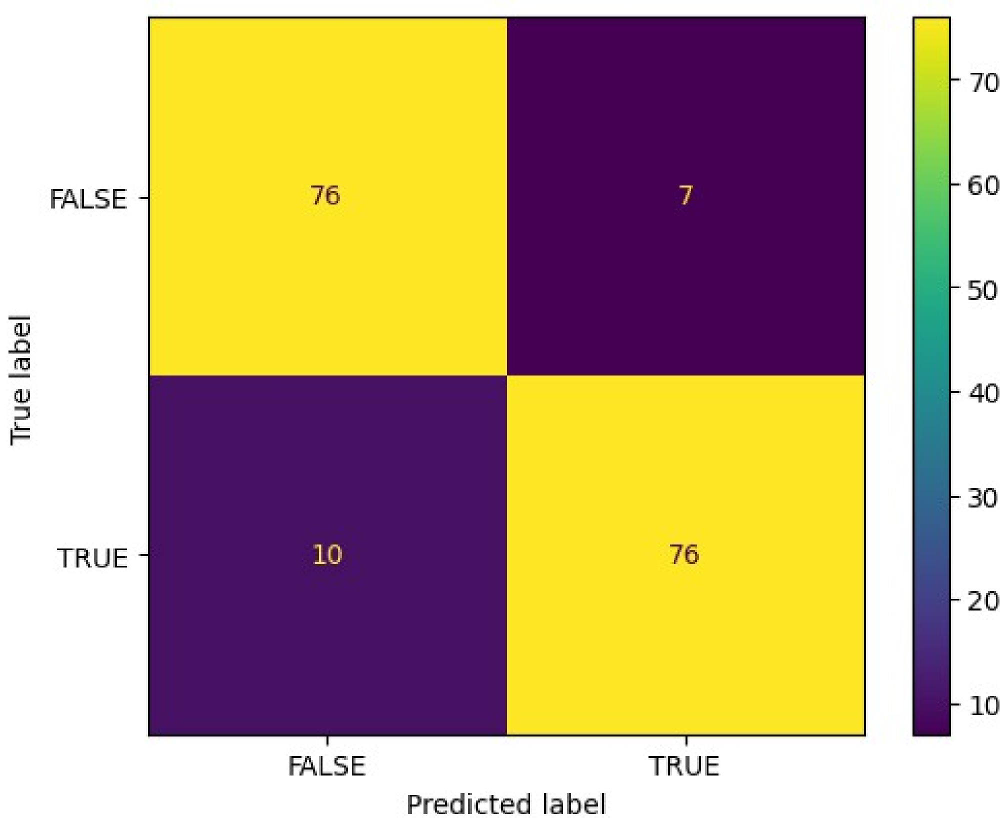
75
8
10
76
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



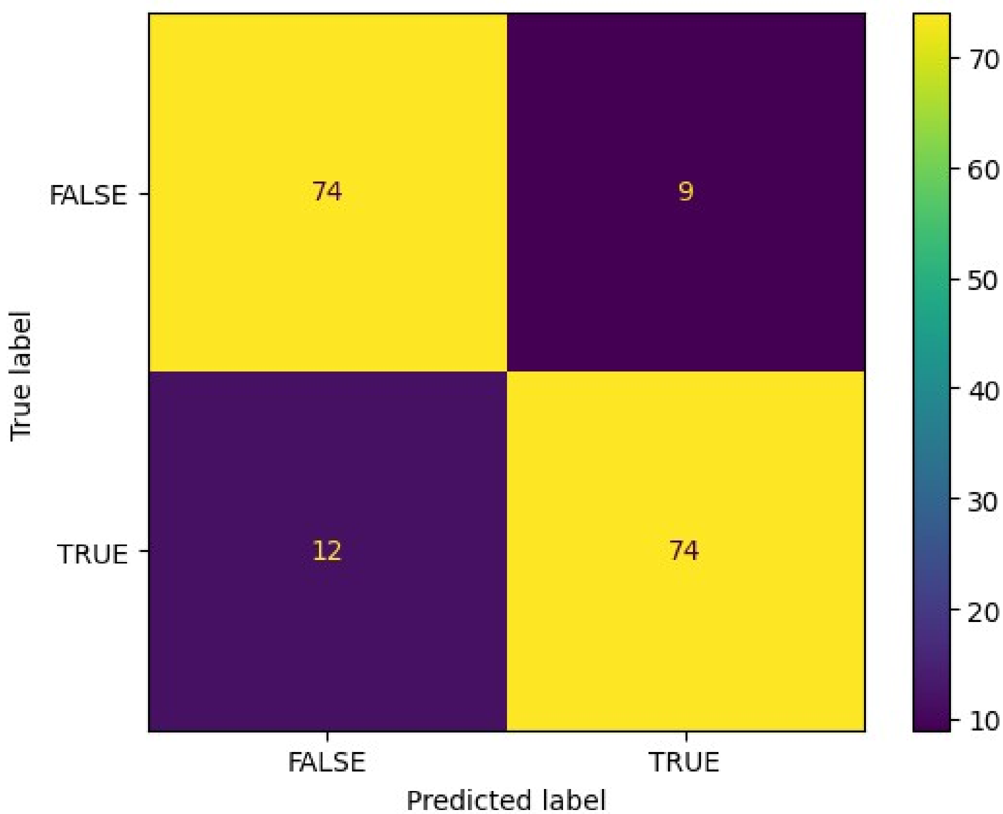
76
7
8
78
FALSE
TRUE
True label
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10

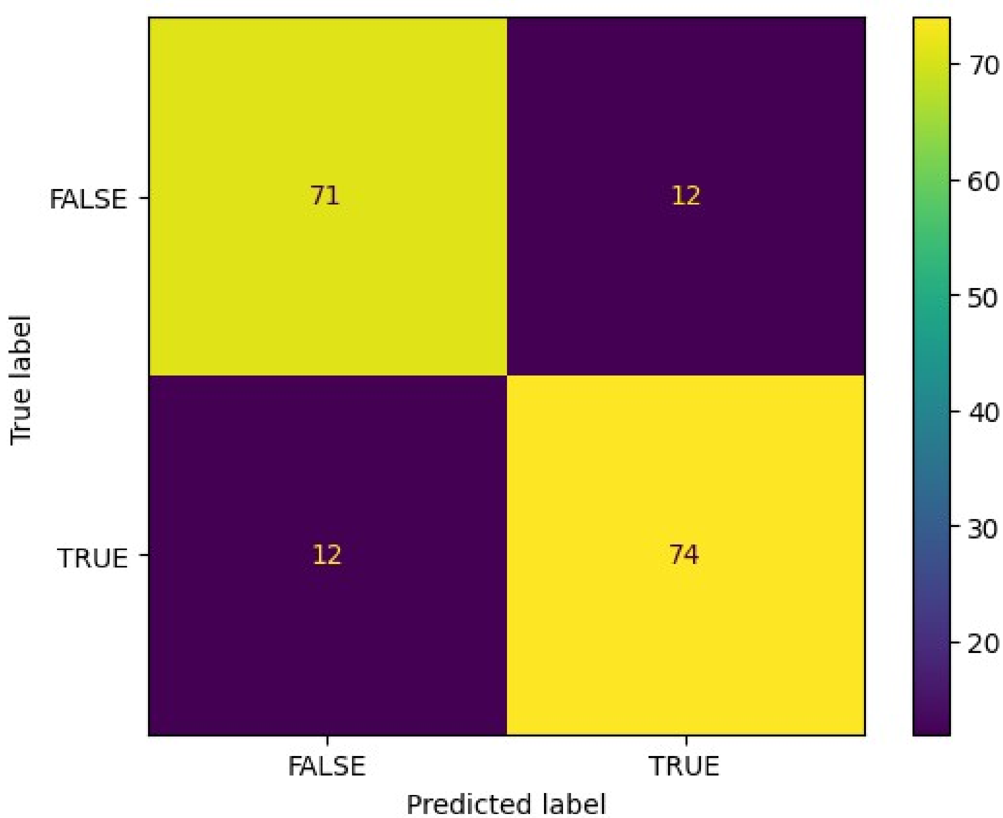


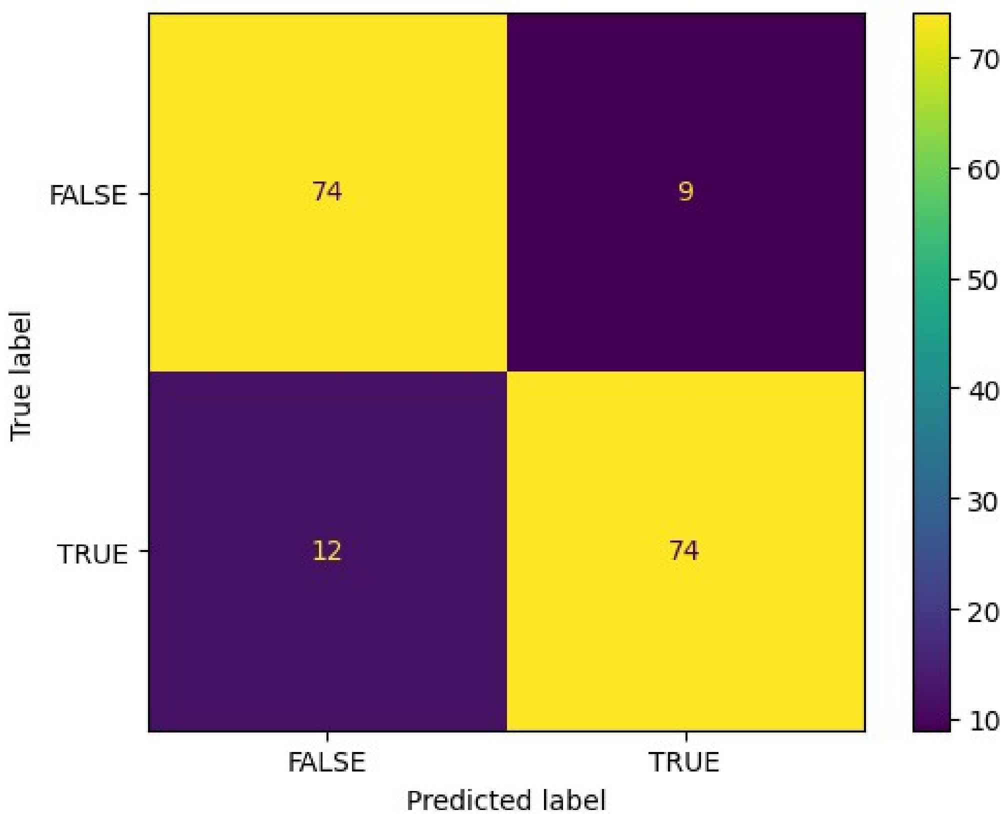
True label
FALSE
TRUE
72
11
8
78
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



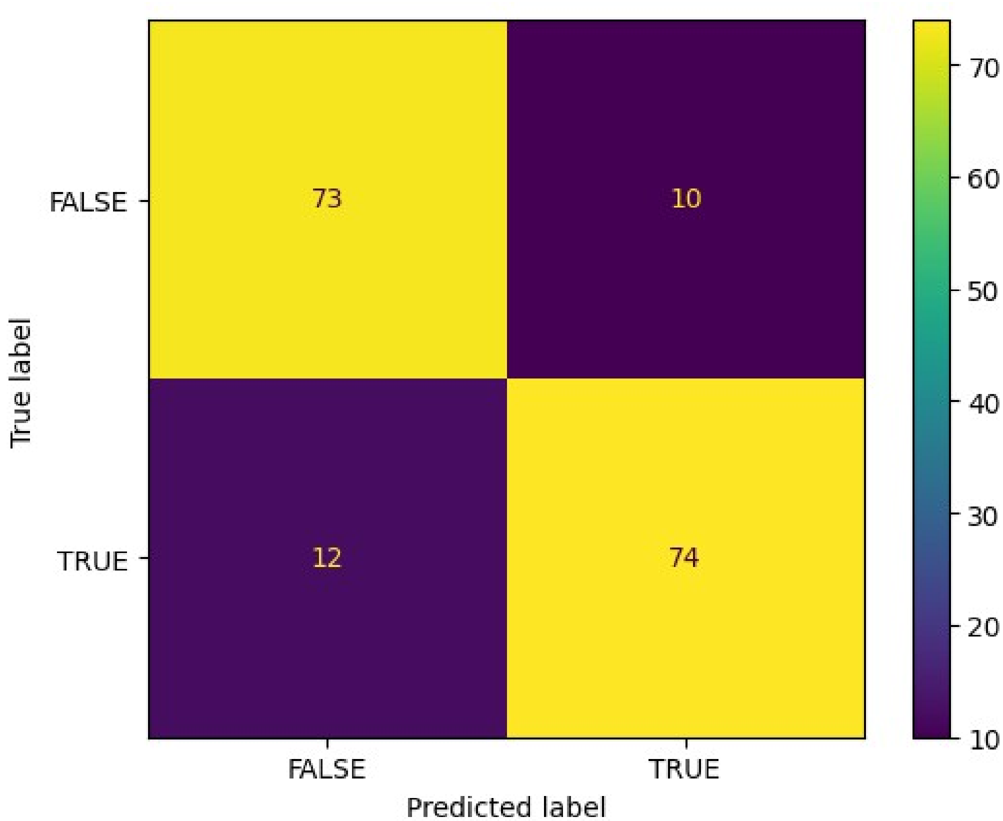
True label
FALSE
TRUE
76
7
10
76
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10


74
9
12
74
FALSE
TRUE
True label
Predicted label
70
60
50
40
30
20
10

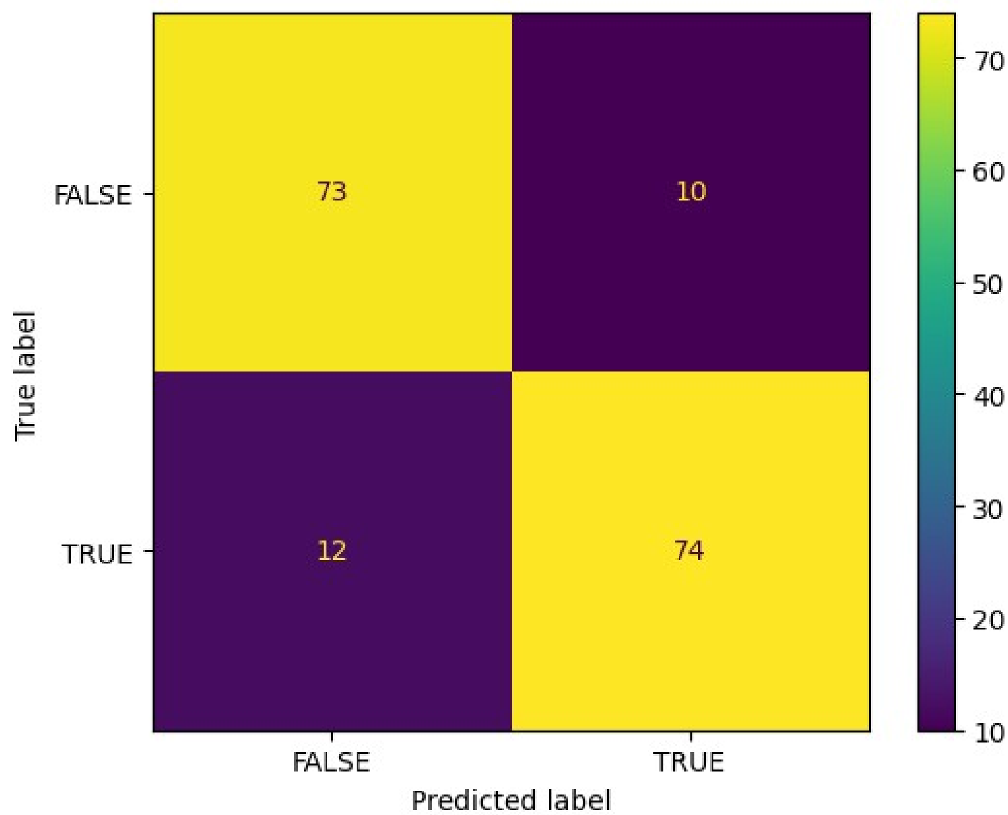

71
12
12
74
FALSE
TRUE
True label
Predicted label
70
60
50
40
30
20



True label
FALSE
TRUE
74
9
12
74
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



True label
FALSE
TRUE
73
10
12
74
FALSE
TRUE
Predicted label
70
60
50
40
30
20
10



##**Etape 4 : Classification selon le TITRE ET TEXT ENSEMBLE (Concaténés):**

- On va à partir de X_train concaténer les 2 colonnes TEXT et TITLE en mettant un espace entre les deux
- Vu qu'on va travailler sur la colonne text_titre qu'on vient de créer, on va séléctionner cette dernière depuis le X_train et X_test pour apprendre et tester après.

```
#concaténation
X_train=X_train.apply(lambda row: ' '.join([str(val) for val in row]), 
axis=1)
X_test=X_test.apply(lambda row: ' '.join([str(val) for val in row]), 
axis=1)
```

Ici, c'est une étape importante, on va tester différents classifieurs, pour chacun des classifieurs, on va appliquer le prétraitement + Vectorisation TfIdf, et on applique une cross_val_score avec un Kfold de 10 fois, par la suite on stocke dans une liste all_results la moyenne des accuracy + l'écart type et on la trie par ordre décroissant de moyenne d'accuracy et d'écart type. on remarque que les 2 meilleurs sont SVM et RF qu'on va séléctionner pour leur appliquer le GridSearch sur les paramètres des prétraitements + leurs hyperparamètres pour pouvoir choisir le meilleur.

```
from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import CountVectorizer
```

```python
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
import time
import numpy as np

# Utilisez la méthode ravel() pour transformer y_train en un tableau
unidimensionnel
y_train = np.ravel(y_train)

np.random.seed(42)  # Set the random seed for NumPy

score = 'accuracy'
seed = 7
allresults = []
results = []
names = []


# Liste des modèles à tester
models = [
    ('MultinomialNB', MultinomialNB()),
    ('LogisticRegression', LogisticRegression(random_state=42))
]


#models.append(('LR', LogisticRegression(solver='lbfgs')))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier(random_state=42)))
models.append(('RF', RandomForestClassifier(random_state=42)))
models.append(('SVM', SVC(random_state=42)))

# Création d'un pipeline pour chaque modèle
pipelines = []
for name,model in models:
    pipeline = Pipeline([
        ('normalize', TextNormalizer()),
        ('tfidf', TfidfVectorizer()),
        (name,model)
    ])
    pipelines.append((name,pipeline))

all_results=[]
scores=[]
```

```
for p in pipelines:
    print(p[1])
    # cross validation en 10 fois
    kfold = KFold(n_splits=10,random_state=seed,shuffle=True)

#    print ("Evaluation de ",p)
    start_time = time.time()
    # application de la classification
    cv_results = cross_val_score(p[1],X_train,y_train, cv=kfold,
scoring=score)
    #print("Pour le classifieur",p[0],"on a un score
de",cv_results.mean(),"et un écart type de",cv_results.std())
    scores.append(cv_results)

    all_results.append((p[0],cv_results.mean(),cv_results.std()))
    end_time = time.time()


print("all resultats", all_results)

all_results = sorted(all_results, key=lambda x: (-x[1], -x[2]))
print("all resultats", all_results)
    # affichage des résultats
#print ('\nLe meilleur resultat : ',max(results))

Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('MultinomialNB', MultinomialNB())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('LogisticRegression',
LogisticRegression(random_state=42))])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('KNN', KNeighborsClassifier())])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('CART', DecisionTreeClassifier(random_state=42))])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('RF', RandomForestClassifier(random_state=42))])
Pipeline(steps=[('normalize', TextNormalizer()), ('tfidf',
TfidfVectorizer()),
                ('SVM', SVC(random_state=42))])
all resultats [('MultinomialNB', 0.8041703248463564,
0.07914308005639414), ('LogisticRegression', 0.8267778753292362,
0.028218150067996238), ('KNN', 0.6814310798946445,
0.07114977093131233), ('CART', 0.8118305531167691,
0.039914873843984094), ('RF', 0.891812993854258,
0.038760785601535896), ('SVM', 0.8949517120280948,
```

```
0.04435236918809594)]
all resultats [('SVM', 0.8949517120280948, 0.04435236918809594),
('RF', 0.891812993854258, 0.038760785601535896),
('LogisticRegression', 0.8267778753292362, 0.028218150067996238),
('CART', 0.8118305531167691, 0.039914873843984094), ('MultinomialNB',
0.8041703248463564, 0.07914308005639414), ('KNN', 0.6814310798946445,
0.07114977093131233)]
```

Choisir les meilleurs paramètres pour SVM et RF :

On a un pipeline pour chaque prétraitement différent, on essaye pas mal (miniscule, lemmatisation, miniscule + lemmatisation..) et on stocke le fit_transorm de nos X_train, X_test sur les pipelines dans des listes qui vont contenir tous les fit_transform des pipelines pour chaque classifieur, par la suite on parcourt ces listes là, on itère dessus, et chaque élement de la liste (train) va passer par le GridSearch et puis on predict sur son corresapondant dans liste (test).

```
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from tabulate import tabulate


# le plus simple est de faire un test sur differents pipelines.
# pipeline de l'utilisation de CountVectorizer sur le texte avec
differents pre-traitements
CV_brut = Pipeline([('cleaner', TextNormalizer()),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])
CV_lowcase = Pipeline([('cleaner',
TextNormalizer(removestopwords=False,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])
CV_lowStop = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])
```

```
CV_lowStopstem = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=True,removedigit=False)),
                    ('count_vectorizer',
CountVectorizer(lowercase=False))])

# pipeline de l'utilisation de TfidfVectorizer avec differents pre-
traitements
TFIDF_brut = Pipeline ([('cleaner', TextNormalizer()),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])

TFIDF_lowcase = Pipeline([('cleaner',
TextNormalizer(removestopwords=False,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])
TFIDF_lowStop = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=False,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])

TFIDF_lowStopstem = Pipeline([('cleaner',
TextNormalizer(removestopwords=True,lowercase=True,

getstemmer=True,removedigit=False)),
                    ('tfidf_vectorizer',
TfidfVectorizer(lowercase=False))])


# Liste de tous les modeles à tester
all_models = [
    ("CV_brut", CV_brut),
    ("CV_lowcase", CV_lowcase),
    ("CV_lowStop", CV_lowStop),
    ("CV_lowStopstem",CV_lowStopstem),
    ("TFIDF_lowcase", TFIDF_lowcase),
    ("TFIDF_lowStop", TFIDF_lowStop),
    ("TFIDF_lowStopstem",TFIDF_lowStopstem),
    ("TFIDF_brut", TFIDF_brut)
]

X_train_text_title_SVC = []
X_test_text_title_SVC = []
```

```
X_train_text_title_RandomForestClassifier = []
X_test_text_title_RandomForestClassifier = []


for name, pipeline in all_models :

X_train_text_title_SVC.append(pipeline.fit_transform(X_train).toarray(
))
    X_test_text_title_SVC.append(pipeline.transform(X_test).toarray())

X_train_text_title_RandomForestClassifier.append(pipeline.fit_transfor
m(X_train).toarray())

X_test_text_title_RandomForestClassifier.append(pipeline.transform(X_t
est).toarray())





models = {
    'SVC': SVC(random_state=42),
    'RandomForestClassifier': RandomForestClassifier(random_state=42)
}


params = {'SVC': [{'C': [0.001, 0.01, 0.1, 1,2,5,7,10]},
             {'gamma': [0.001, 0.01, 0.1,0.2,0.3,0.5,0.7,1]},
             {'kernel': ['linear', 'rbf']}],
    'RandomForestClassifier': [{'n_estimators': [10, 50, 100, 200,
300]},
                              {'max_features': ['auto', 'sqrt',
'log2']}],
}

for model_name, model in models.items():
    score='accuracy'
    X_train_text_title = eval('X_train_text_' + model_name)
    X_test_text_title = eval('X_test_text_' + model_name)
    for i in range (len(X_train_text_title)):
      grid_search = GridSearchCV(model, params[model_name], n_jobs=-1,
verbose=1,scoring=score)
      print("grid search fait")
      grid_search.fit(X_train_text_title[i],y_train)
      print ('meilleur score %0.3f'%(grid_search.best_score_),'\n')
      print ('meilleur estimateur',grid_search.best_estimator_,'\n')
      y_pred = grid_search.predict(X_test_text_tile[i])
      MyshowAllScores(y_test,y_pred)

      print("Ensemble des meilleurs paramètres :")
```

```
      best_parameters = grid_search.best_estimator_.get_params()
      for param_dict in params[model_name]:
        for param_name, param_value in param_dict.items():
            print("\t%s: %r" % (param_name, 
best_parameters[param_name]))
```

```
grid search fait
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.847

meilleur estimateur SVC(kernel='linear', random_state=42)

Accuracy : 0.870
Classification Report
              precision    recall  f1-score   support

       FALSE    0.94203   0.78313   0.85526        83
        TRUE    0.82000   0.95349   0.88172        86

    accuracy                        0.86982       169
   macro avg    0.88101   0.86831   0.86849       169
weighted avg    0.87993   0.86982   0.86873       169

Ensemble des meilleurs paramètres :
	C: 1.0
	gamma: 'scale'
	kernel: 'linear'
grid search fait
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.846

meilleur estimateur SVC(kernel='linear', random_state=42)

Accuracy : 0.846
Classification Report
              precision    recall  f1-score   support

       FALSE    0.91304   0.75904   0.82895        83
        TRUE    0.80000   0.93023   0.86022        86

    accuracy                        0.84615       169
   macro avg    0.85652   0.84463   0.84458       169
weighted avg    0.85552   0.84615   0.84486       169

Ensemble des meilleurs paramètres :
	C: 1.0
	gamma: 'scale'
	kernel: 'linear'
grid search fait
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.849

meilleur estimateur SVC(C=10, random_state=42)

Accuracy : 0.888
Classification Report
              precision    recall  f1-score   support

       FALSE    0.91026   0.85542   0.88199        83
        TRUE    0.86813   0.91860   0.89266        86

    accuracy                        0.88757       169
   macro avg    0.88919   0.88701   0.88732       169
weighted avg    0.88882   0.88757   0.88742       169

Ensemble des meilleurs paramètres :
     C: 10
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.849

meilleur estimateur SVC(C=10, random_state=42)

Accuracy : 0.893
Classification Report
              precision    recall  f1-score   support

       FALSE    0.91139   0.86747   0.88889        83
        TRUE    0.87778   0.91860   0.89773        86

    accuracy                        0.89349       169
   macro avg    0.89459   0.89304   0.89331       169
weighted avg    0.89429   0.89349   0.89339       169

Ensemble des meilleurs paramètres :
     C: 10
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.881

meilleur estimateur SVC(C=5, random_state=42)

Accuracy : 0.882
Classification Report
```

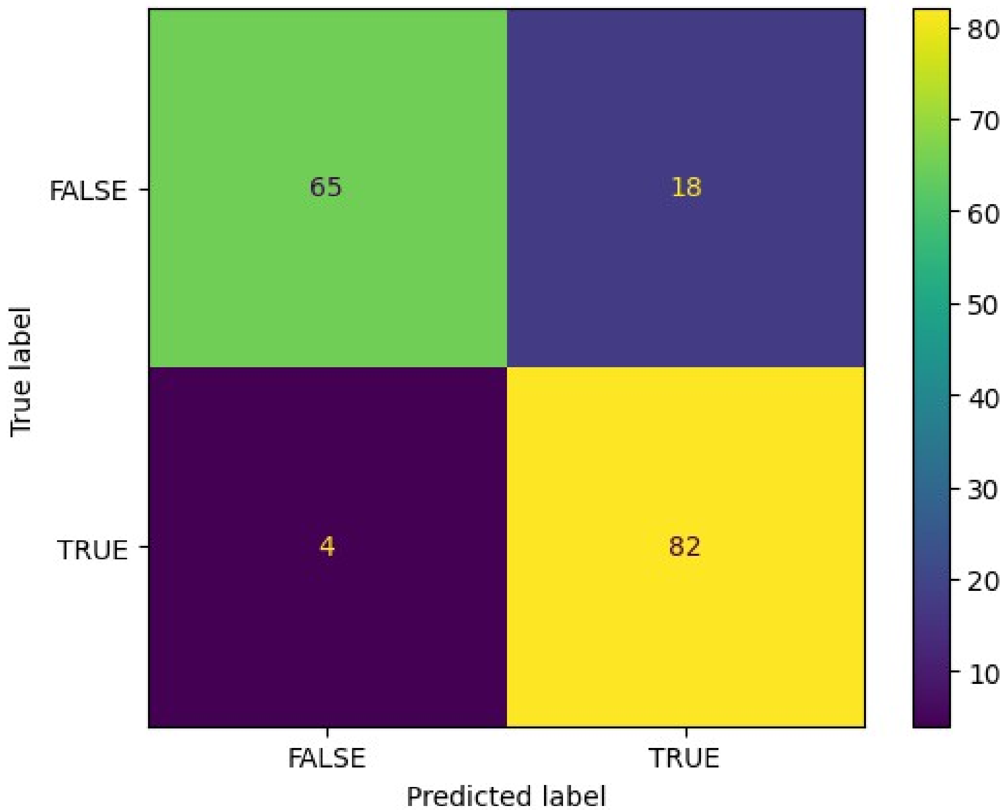
```
              precision    recall  f1-score   support

       FALSE    0.87952   0.87952   0.87952        83
        TRUE    0.88372   0.88372   0.88372        86

    accuracy                        0.88166       169
   macro avg    0.88162   0.88162   0.88162       169
weighted avg    0.88166   0.88166   0.88166       169

Ensemble des meilleurs paramètres :
     C: 5
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.884

meilleur estimateur SVC(C=2, random_state=42)

Accuracy : 0.899
Classification Report
              precision    recall  f1-score   support

       FALSE    0.86667   0.93976   0.90173        83
        TRUE    0.93671   0.86047   0.89697        86

    accuracy                        0.89941       169
   macro avg    0.90169   0.90011   0.89935       169
weighted avg    0.90231   0.89941   0.89931       169

Ensemble des meilleurs paramètres :
     C: 2
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.884

meilleur estimateur SVC(C=2, random_state=42)

Accuracy : 0.899
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88372   0.91566   0.89941        83
        TRUE    0.91566   0.88372   0.89941        86

    accuracy                        0.89941       169
   macro avg    0.89969   0.89969   0.89941       169
```

```
weighted avg    0.89998   0.89941   0.89941       169

Ensemble des meilleurs paramètres :
     C: 2
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
Fitting 5 folds for each of 18 candidates, totalling 90 fits
meilleur score 0.881

meilleur estimateur SVC(C=2, random_state=42)

Accuracy : 0.888
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88095   0.89157   0.88623        83
        TRUE    0.89412   0.88372   0.88889        86

    accuracy                        0.88757       169
   macro avg    0.88754   0.88764   0.88756       169
weighted avg    0.88765   0.88757   0.88758       169

Ensemble des meilleurs paramètres :
     C: 2
     gamma: 'scale'
     kernel: 'rbf'
grid search fait
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.862

meilleur estimateur RandomForestClassifier(max_features='log2',
random_state=42)

Accuracy : 0.870
Classification Report
              precision    recall  f1-score   support

       FALSE    0.85882   0.87952   0.86905        83
        TRUE    0.88095   0.86047   0.87059        86

    accuracy                        0.86982       169
   macro avg    0.86989   0.86999   0.86982       169
weighted avg    0.87008   0.86982   0.86983       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'log2'
grid search fait
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.856

meilleur estimateur RandomForestClassifier(n_estimators=300,
random_state=42)

Accuracy : 0.858
Classification Report
              precision    recall  f1-score   support

       FALSE    0.89333   0.80723   0.84810        83
        TRUE    0.82979   0.90698   0.86667        86

    accuracy                        0.85799       169
   macro avg    0.86156   0.85710   0.85738       169
weighted avg    0.86100   0.85799   0.85755       169

Ensemble des meilleurs paramètres :
     n_estimators: 300
     max_features: 'sqrt'
grid search fait
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.865

meilleur estimateur RandomForestClassifier(max_features='log2',
random_state=42)

Accuracy : 0.876
Classification Report
              precision    recall  f1-score   support

       FALSE    0.86047   0.89157   0.87574        83
        TRUE    0.89157   0.86047   0.87574        86

    accuracy                        0.87574       169
   macro avg    0.87602   0.87602   0.87574       169
weighted avg    0.87629   0.87574   0.87574       169

Ensemble des meilleurs paramètres :
     n_estimators: 100
     max_features: 'log2'
grid search fait
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.867

meilleur estimateur RandomForestClassifier(max_features='log2',
random_state=42)

Accuracy : 0.876
```

```
Classification Report
              precision    recall  f1-score   support

       FALSE    0.82979   0.93976   0.88136        83
        TRUE    0.93333   0.81395   0.86957        86

    accuracy                        0.87574       169
   macro avg    0.88156   0.87686   0.87546       169
weighted avg    0.88248   0.87574   0.87536       169

Ensemble des meilleurs paramètres :
      n_estimators: 100
      max_features: 'log2'
grid search fait
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.862

meilleur estimateur RandomForestClassifier(n_estimators=300,
random_state=42)

Accuracy : 0.882
Classification Report
              precision    recall  f1-score   support

       FALSE    0.87952   0.87952   0.87952        83
        TRUE    0.88372   0.88372   0.88372        86

    accuracy                        0.88166       169
   macro avg    0.88162   0.88162   0.88162       169
weighted avg    0.88166   0.88166   0.88166       169

Ensemble des meilleurs paramètres :
      n_estimators: 300
      max_features: 'sqrt'
grid search fait
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.874

meilleur estimateur RandomForestClassifier(n_estimators=200,
random_state=42)

Accuracy : 0.899
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90244   0.89157   0.89697        83
        TRUE    0.89655   0.90698   0.90173        86

    accuracy                        0.89941       169
```

```
   macro avg    0.89950   0.89927   0.89935       169
weighted avg    0.89944   0.89941   0.89939       169

Ensemble des meilleurs paramètres :
     n_estimators: 200
     max_features: 'sqrt'
grid search fait
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.873

meilleur estimateur RandomForestClassifier(n_estimators=200,
random_state=42)

Accuracy : 0.911
Classification Report
              precision    recall  f1-score   support

       FALSE    0.88636   0.93976   0.91228        83
        TRUE    0.93827   0.88372   0.91018        86

    accuracy                        0.91124       169
   macro avg    0.91232   0.91174   0.91123       169
weighted avg    0.91278   0.91124   0.91121       169

Ensemble des meilleurs paramètres :
     n_estimators: 200
     max_features: 'sqrt'
grid search fait
Fitting 5 folds for each of 8 candidates, totalling 40 fits
meilleur score 0.867

meilleur estimateur RandomForestClassifier(n_estimators=50,
random_state=42)

Accuracy : 0.905
Classification Report
              precision    recall  f1-score   support

       FALSE    0.90361   0.90361   0.90361        83
        TRUE    0.90698   0.90698   0.90698        86

    accuracy                        0.90533       169
   macro avg    0.90530   0.90530   0.90530       169
weighted avg    0.90533   0.90533   0.90533       169

Ensemble des meilleurs paramètres :
     n_estimators: 50
     max_features: 'sqrt'
```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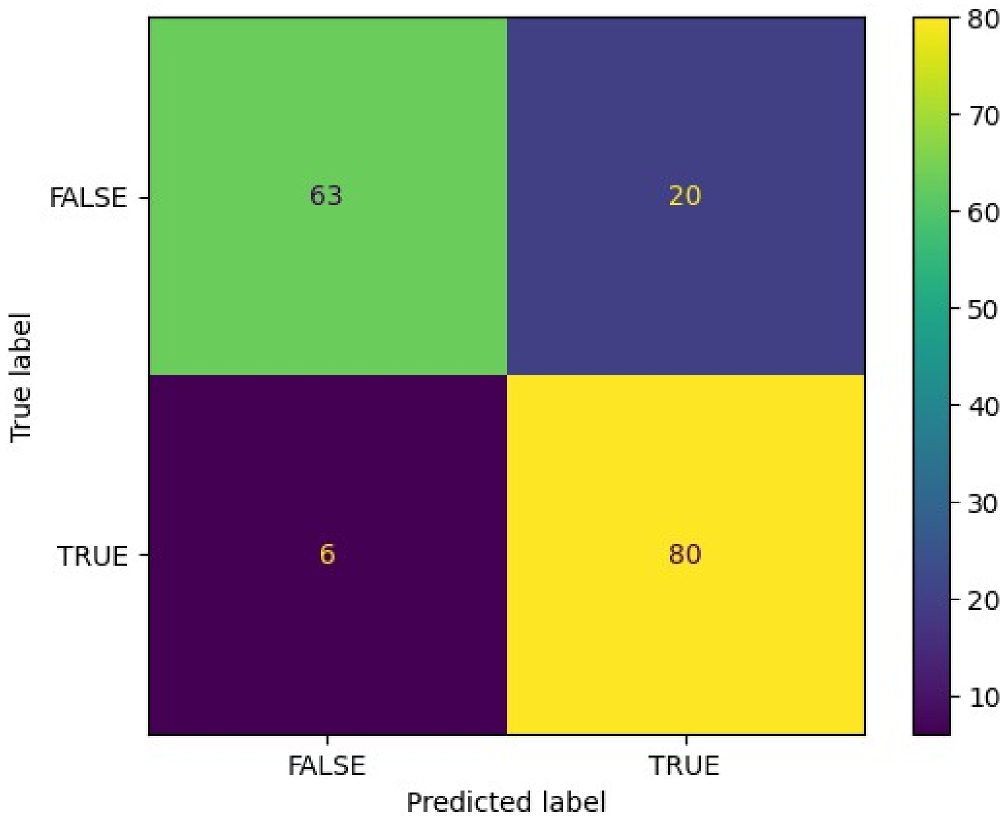
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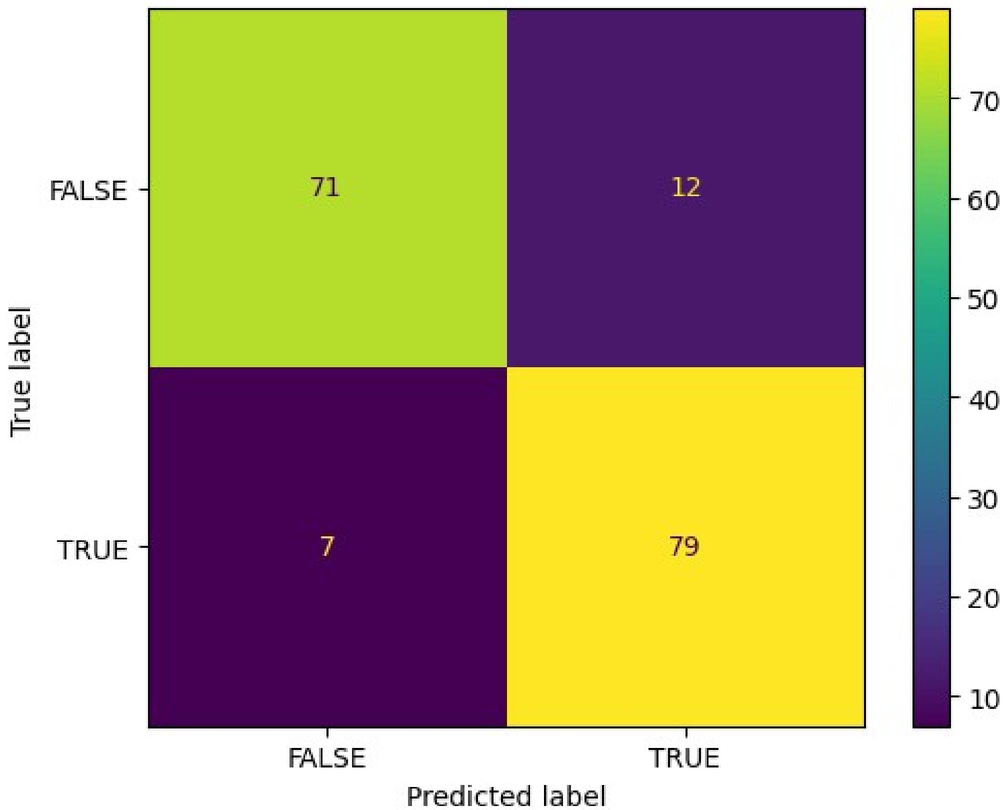
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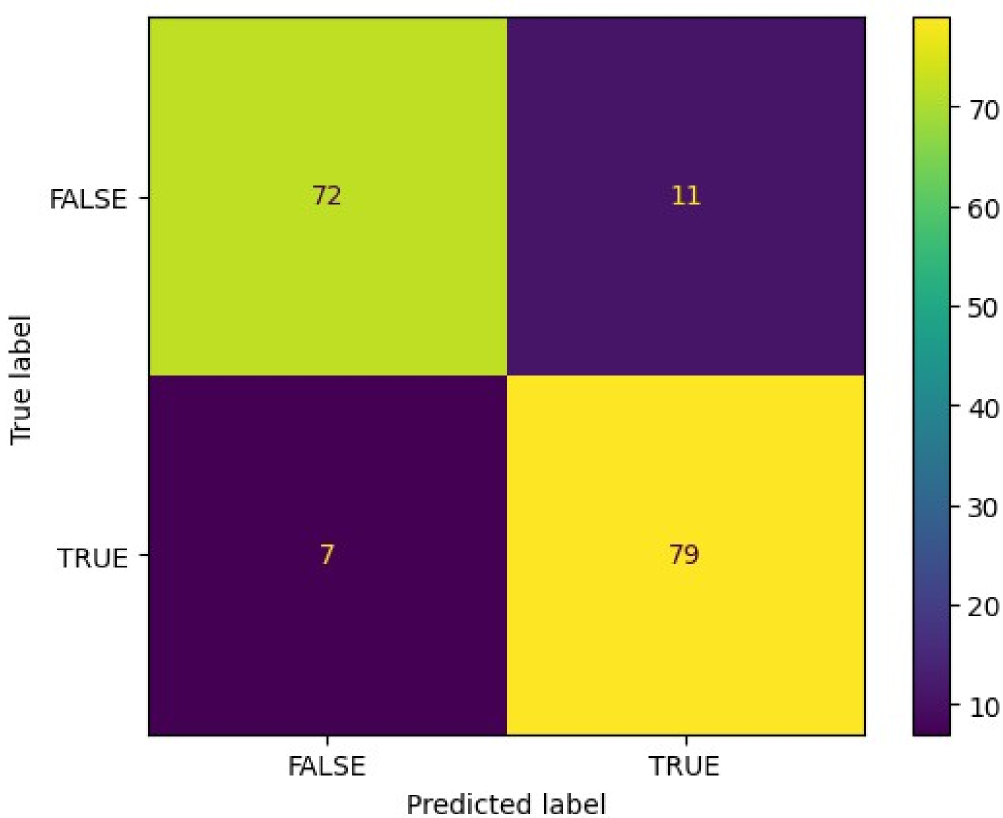
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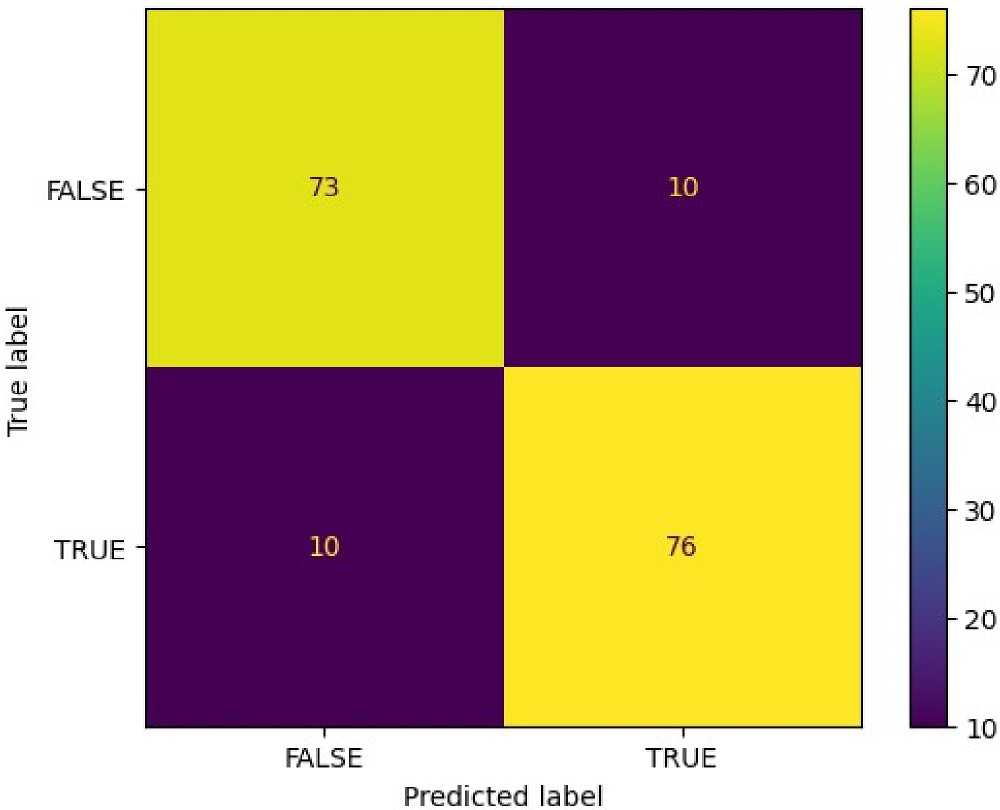

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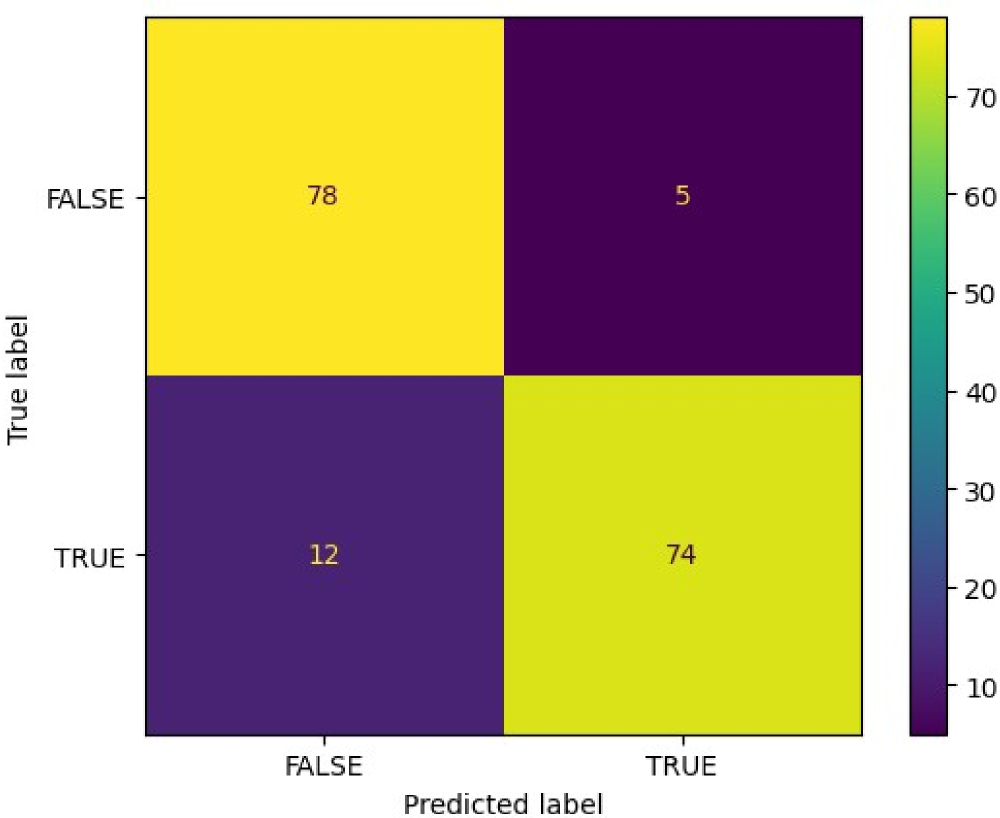

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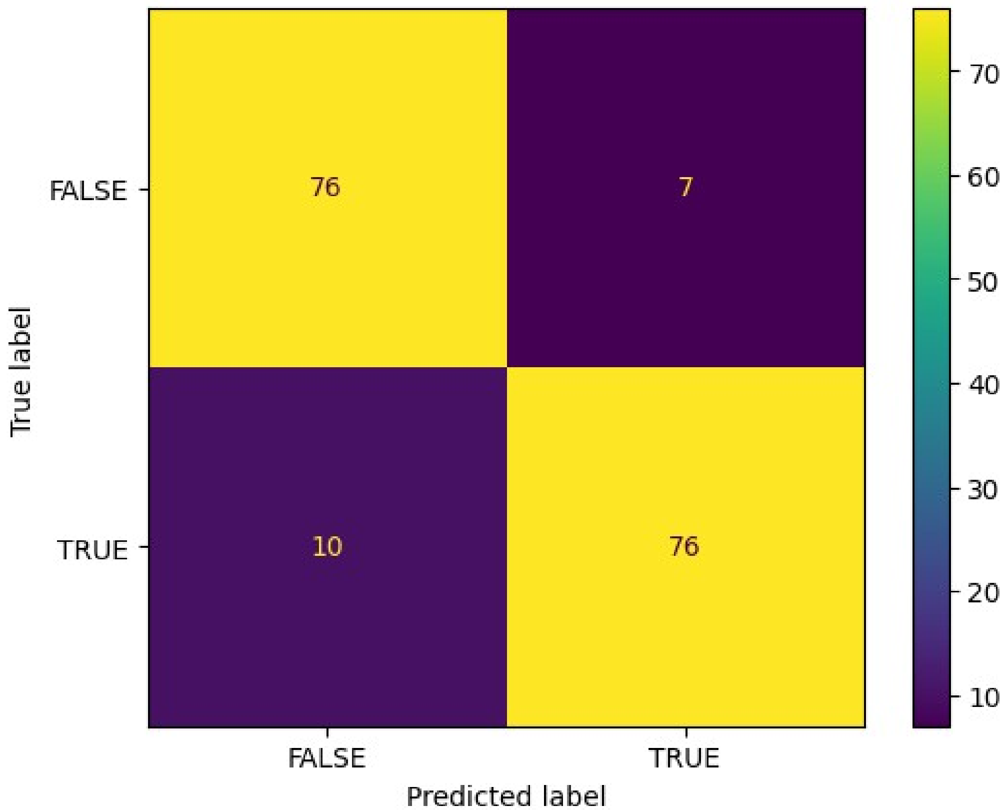
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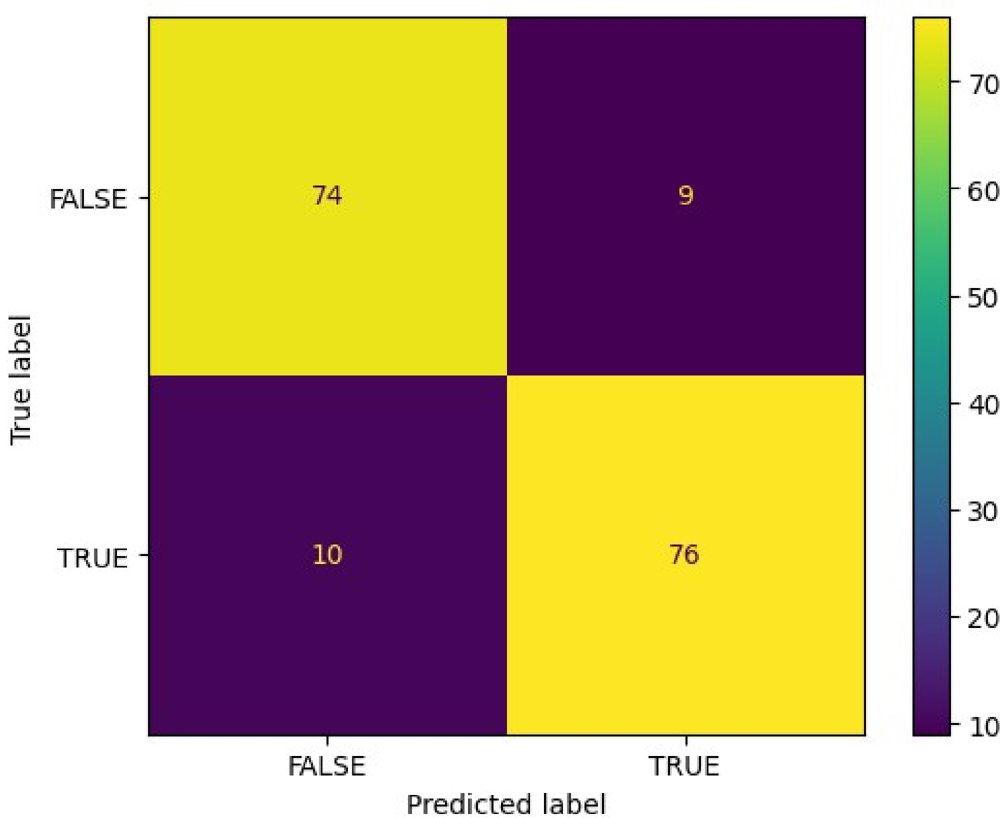
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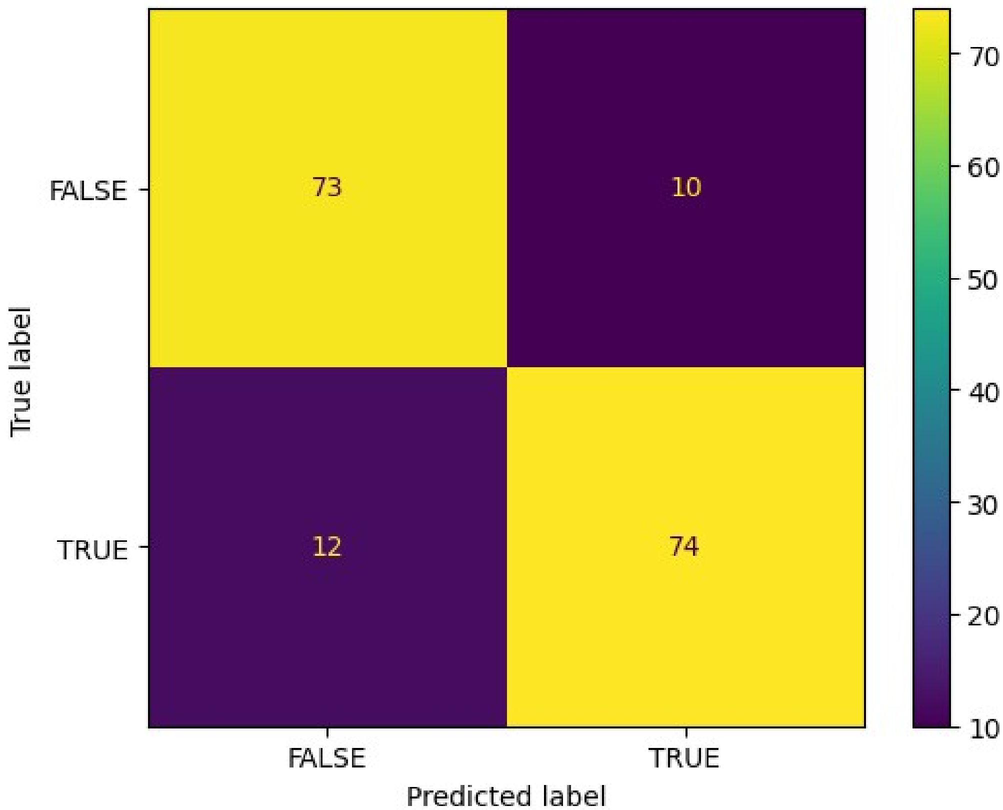
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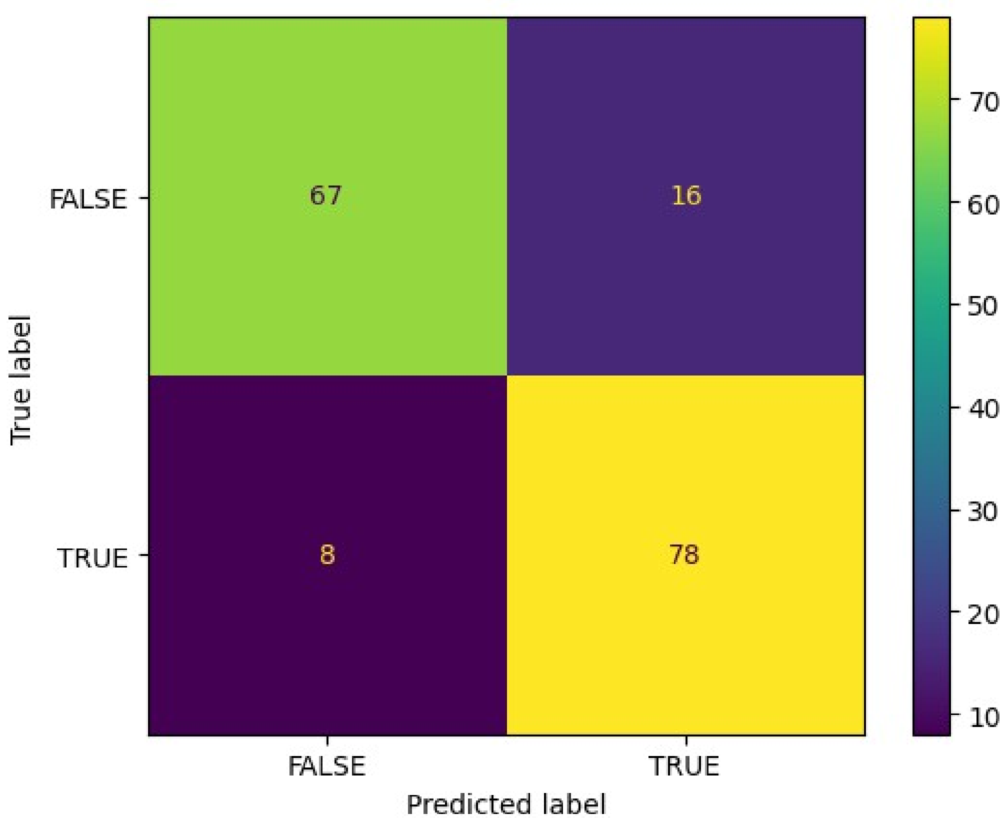
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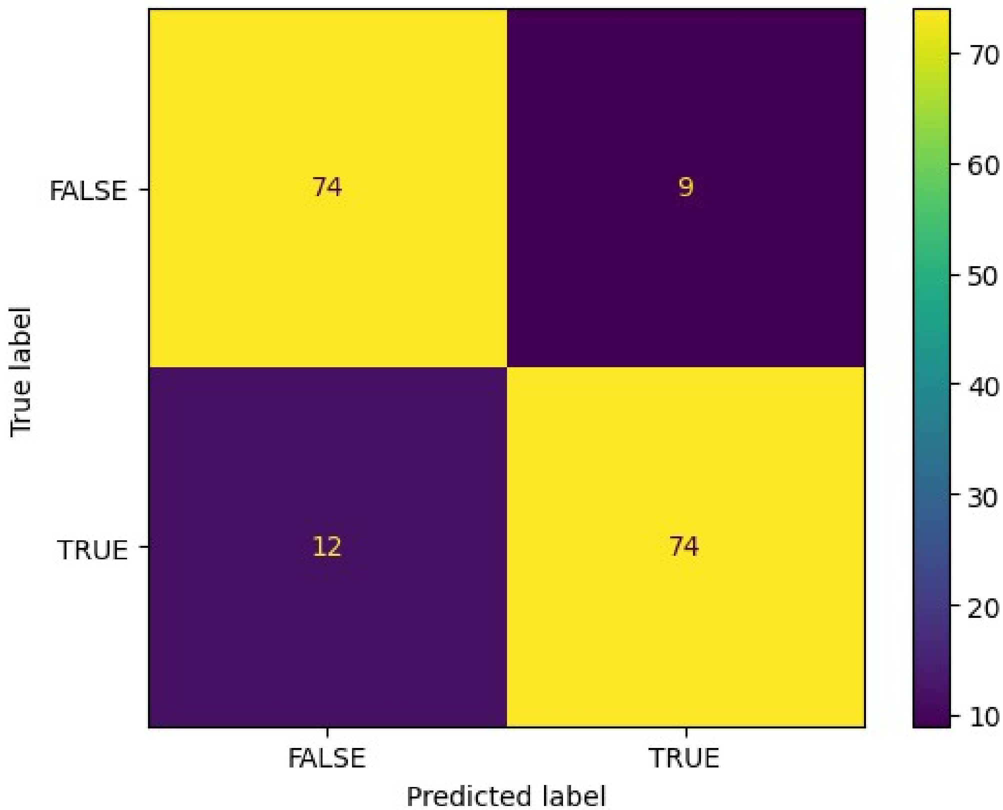

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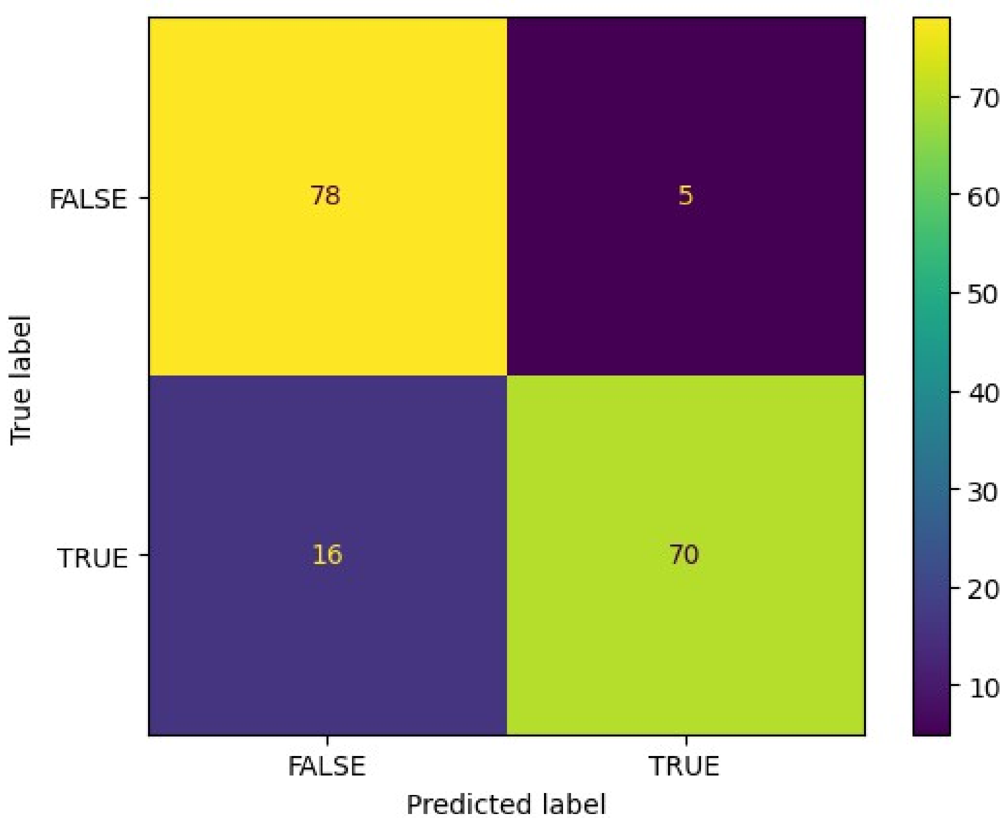

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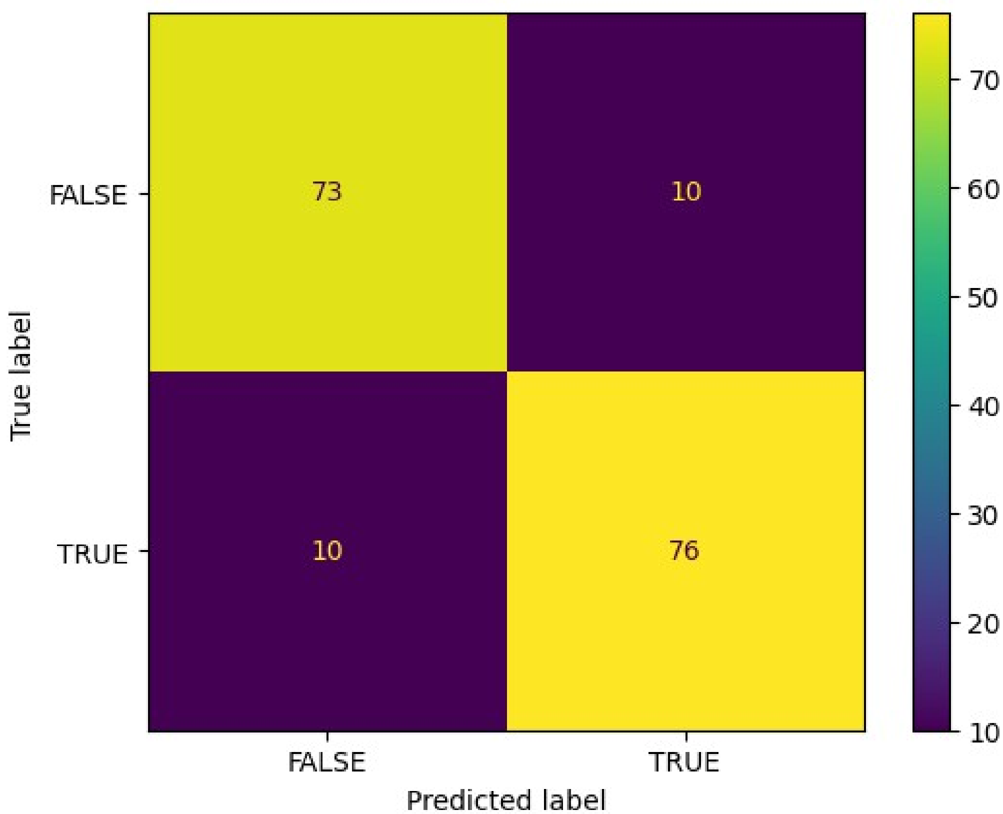

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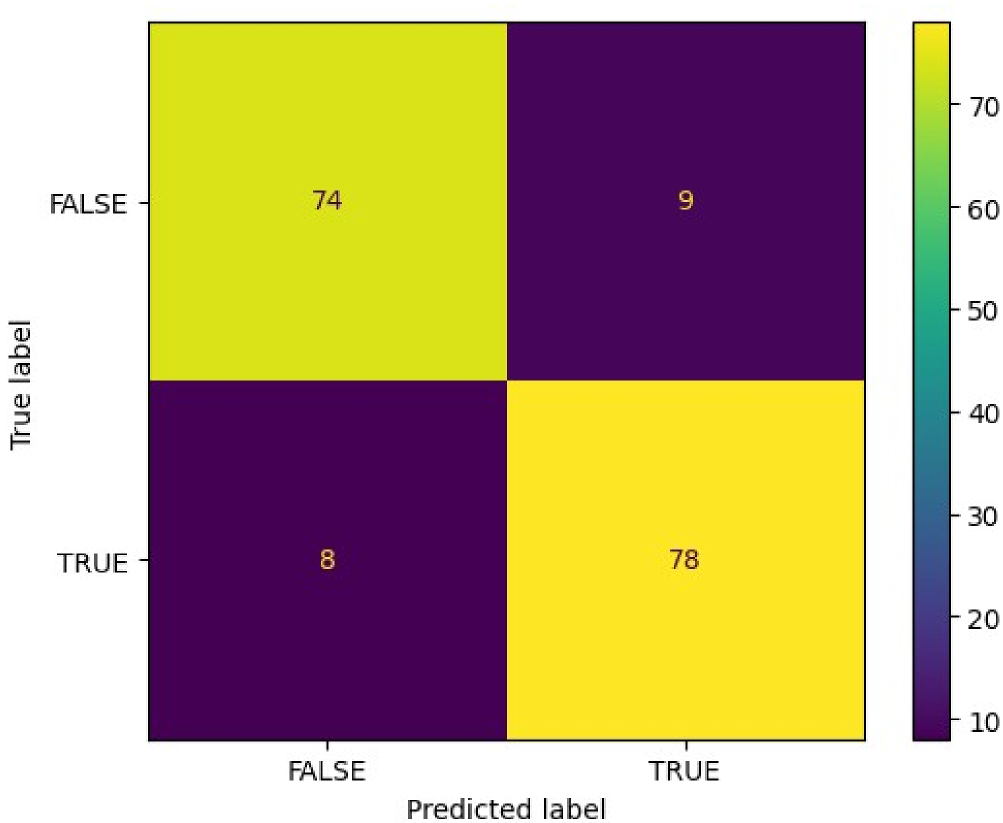

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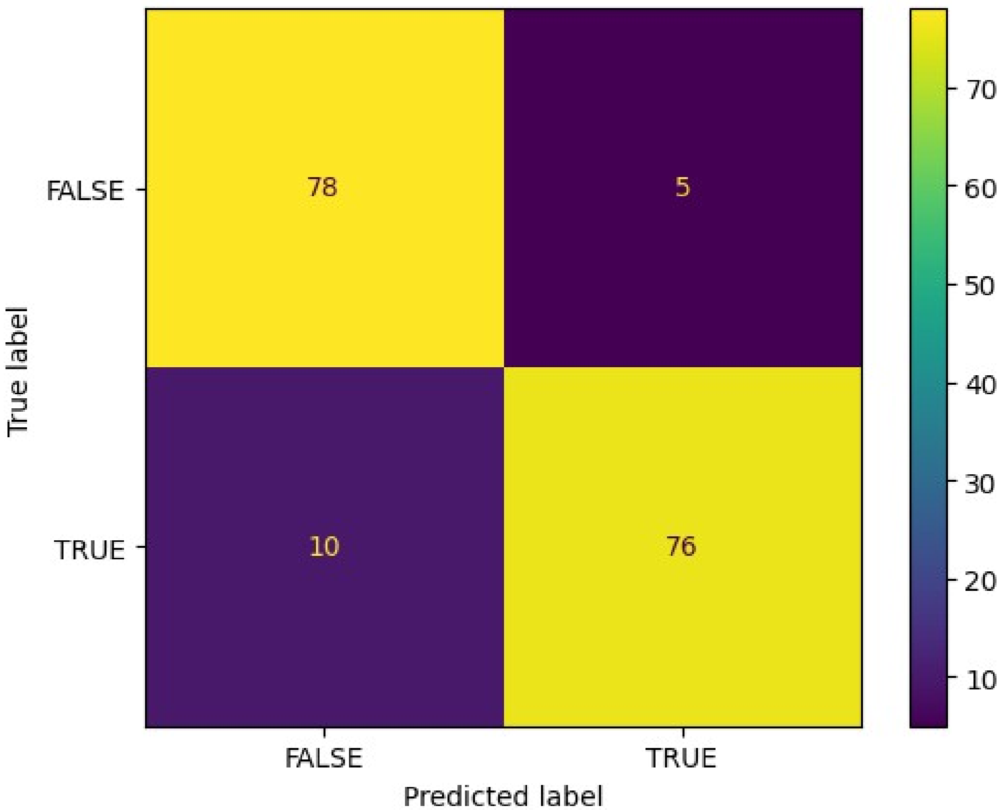
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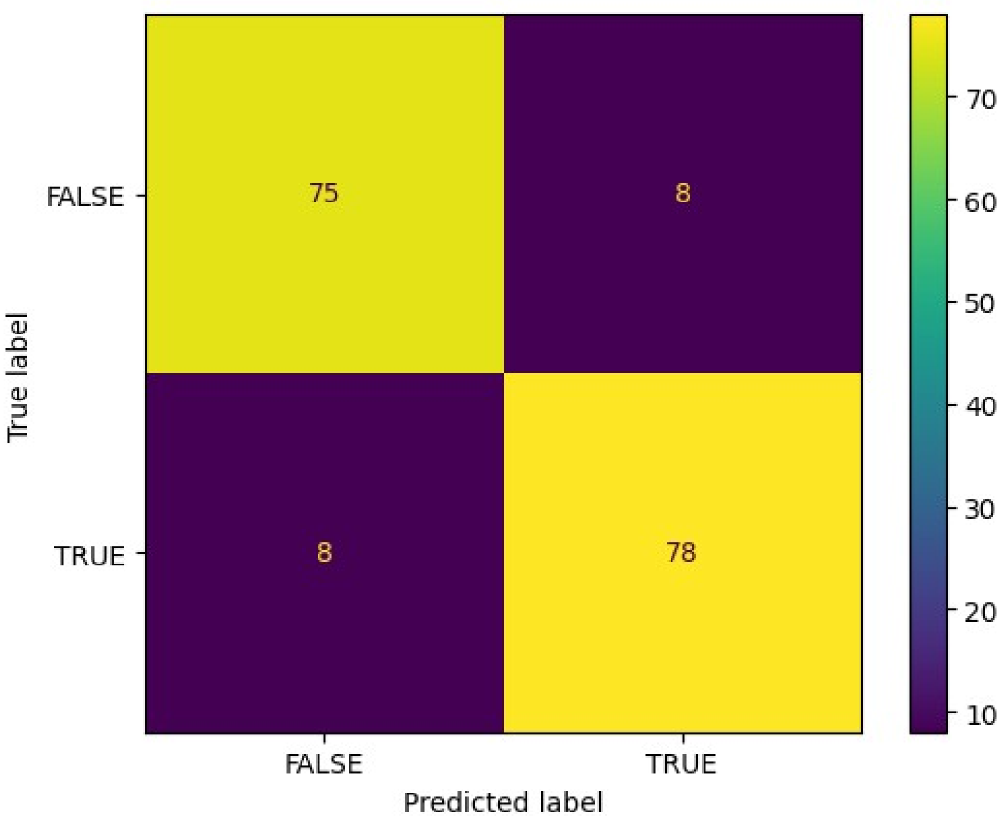
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On réapprends sur le X