correlation_target _label_87 7030 split .04 threshold

January 3, 2023

[ ]:
```
# Importing the packages
import sys
import numpy as np
np.set_printoptions(threshold=sys.maxsize)
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import sklearn
import random
from sklearn.metrics import␣
↪confusion_matrix,accuracy_score,classification_report,RocCurveDisplay,ConfusionMatrixDispla
```

[ ]:
```
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', None)
```

[ ]:
```
# Importing the dataset
df = pd.read_csv('dataset_phishing.csv')
df.drop(['url'], axis=1, inplace=True)
#df.head(50)
```

[ ]:
```
# if your dataset contains missing value, check which column has missing values
#df.isnull().sum()
```

[ ]:
```
#df.dropna(inplace=True)
```

[ ]:
```
from sklearn import preprocessing


col = [df.columns[-1]]

lab_en= preprocessing.LabelEncoder()

for c in col:
    df[c]= lab_en.fit_transform(df[c])

#df.head(50)
```

[ ]:
```
##print(df.corr()['Result'].sort_values())
## correlation values of features with target label
corr_col = abs(df.corr()['status']).sort_values(ascending=False)
corr_col = corr_col.rename_axis('Col').reset_index(name='Correlation')
corr_col
```

[ ]:

	Col	Correlation
0	status	1.000000e+00
1	google_index	7.311708e-01
2	page_rank	5.111371e-01
3	nb_www	4.434677e-01
4	ratio_digits_url	3.563946e-01
5	domain_in_title	3.428070e-01
6	nb_hyperlinks	3.426283e-01
7	phish_hints	3.353927e-01
8	domain_age	3.318891e-01
9	ip	3.216978e-01
10	nb_qm	2.943191e-01
11	length_url	2.485805e-01
12	ratio_intHyperlinks	2.439821e-01
13	nb_slash	2.422700e-01
14	length_hostname	2.383224e-01
15	nb_eq	2.333863e-01
16	ratio_digits_host	2.243349e-01
17	shortest_word_host	2.230840e-01
18	prefix_suffix	2.146807e-01
19	longest_word_path	2.127091e-01
20	tld_in_subdomain	2.088842e-01
21	empty_title	2.070428e-01
22	nb_dots	2.070288e-01
23	longest_words_raw	2.001466e-01
24	avg_word_path	1.972561e-01
25	avg_word_host	1.935017e-01
26	ratio_intMedia	1.933331e-01
27	length_words_raw	1.920105e-01
28	links_in_tags	1.844011e-01
29	safe_anchor	1.733973e-01
30	domain_with_copyright	1.730985e-01
31	nb_and	1.705464e-01
32	avg_words_raw	1.675637e-01
33	domain_registration_length	1.617188e-01
34	nb_com	1.562835e-01
35	ratio_extRedirection	1.508267e-01
36	external_favicon	1.465654e-01
37	statistical_report	1.439435e-01
38	nb_at	1.429146e-01
39	ratio_extMedia	1.404059e-01

40	abnormal_subdomain	1.281598e-01
41	longest_word_host	1.245156e-01
42	dns_record	1.221190e-01
43	https_token	1.146691e-01
44	nb_subdomains	1.128907e-01
45	suspecious_tld	1.100896e-01
46	shortening_service	1.061200e-01
47	nb_semicolumn	1.035541e-01
48	nb_hyphens	1.001075e-01
49	domain_in_brand	9.822216e-02
50	nb_colon	9.283531e-02
51	nb_extCSS	8.356663e-02
52	ratio_extHyperlinks	8.335725e-02
53	tld_in_path	7.914651e-02
54	shortest_word_path	7.436495e-02
55	nb_dslash	7.260234e-02
56	http_in_path	7.077624e-02
57	whois_registered_domain	6.697907e-02
58	brand_in_path	6.515575e-02
59	brand_in_subdomain	6.425702e-02
60	web_traffic	6.038772e-02
61	popup_window	5.760197e-02
62	nb_external_redirection	5.620994e-02
63	shortest_words_raw	3.936361e-02
64	nb_underscore	3.809134e-02
65	ratio_extErrors	3.470251e-02
66	nb_tilde	3.014233e-02
67	nb_percent	2.810129e-02
68	nb_star	2.646512e-02
69	nb_dollar	2.496206e-02
70	nb_redirection	2.440520e-02
71	random_domain	1.963062e-02
72	login_form	1.900010e-02
73	punycode	1.871039e-02
74	char_repeat	1.473217e-02
75	iframe	1.208332e-02
76	nb_comma	1.186465e-02
77	port	9.011116e-03
78	onmouseover	7.787061e-03
79	right_clic	4.680056e-03
80	nb_space	4.193222e-03
81	path_extension	5.592660e-17
82	nb_or	NaN
83	ratio_nullHyperlinks	NaN
84	ratio_intRedirection	NaN
85	ratio_intErrors	NaN
86	submit_email	NaN

```
87                           sfh            NaN
```

[ ]:
```
def correlation (corr_col, threshold):
        corr_feature = set()
        for index, row in corr_col.iterrows():
                if row['Correlation'] < threshold or np.
 ↪isnan(row['Correlation']):
                        corr_feature.add(row['Col'])
        return corr_feature
```

[ ]:
```
corr_feature = correlation(corr_col,.04)
len(set(corr_feature))
```

[ ]:
```
25
```

[ ]:
```
corr_feature
```

[ ]:
```
{'char_repeat',
 'iframe',
 'login_form',
 'nb_comma',
 'nb_dollar',
 'nb_or',
 'nb_percent',
 'nb_redirection',
 'nb_space',
 'nb_star',
 'nb_tilde',
 'nb_underscore',
 'onmouseover',
 'path_extension',
 'port',
 'punycode',
 'random_domain',
 'ratio_extErrors',
 'ratio_intErrors',
 'ratio_intRedirection',
 'ratio_nullHyperlinks',
 'right_clic',
 'sfh',
 'shortest_words_raw',
 'submit_email'}
```

[ ]:
```
df.drop(corr_feature, axis=1, inplace=True)
```

[ ]:
```
len(df.columns)
```

[ ]: 63

[ ]:
```
#df.head()
```

[ ]:
```
a=len(df[df.status==0])
b=len(df[df.status==1])
```

[ ]:
```
print("Count of Legitimate Websites = ", a)
print("Count of Phishy Websites = ", b)
```

```
Count of Legitimate Websites =  5715
Count of Phishy Websites =  5715
```

[ ]:
```
X = df.drop(['status'], axis=1, inplace=False)
#X.head()
#same work
##inplace true modifies the og data & does not return anything
##inplace false does not modify og data but returns something whoch we store in␣
 ↪a var
# X= df.drop(columns='Result')
# X.head()
```

[ ]:
```
#df.head()
```

[ ]:
```
y = df['status']
y = pd.DataFrame(y)
y.head()
```

[ ]:

	status
0	0
1	1
2	1
3	0
4	0

[ ]:
```
# separate dataset into train and test
from cProfile import label
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X,
    y,
    test_size=0.3,
    random_state=10)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[ ]: ((8001, 62), (3429, 62), (8001, 1), (3429, 1))

[ ]:
```
#X_test.head()
```

[ ]:
```
print("Training set has {} samples.".format(X_train.shape[0]))
print("Testing set has {} samples.".format(X_test.shape[0]))
```

```
Training set has 8001 samples.
Testing set has 3429 samples.
```

[ ]:
```
from sklearn.preprocessing import MinMaxScaler

scaler= MinMaxScaler()

col_X_train = [X_train.columns[:]]

for c in col_X_train:
    X_train[c]= scaler.fit_transform(X_train[c])

#X_train.head(5)
```

[ ]:
```
col_X_test = [X_test.columns[:]]

for c in col_X_test:
    X_test[c]= scaler.transform(X_test[c])

#X_test.head(5)
```

[ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

# defining parameter range
param_grid = {'penalty' : ['l2'],
             'C' : [10, 20, 30], #0.1, 1, 10, 20,
             'solver' : ['lbfgs','newton-cg','liblinear','sag','saga'],
             'max_iter' : [2500]} #5000

grid_logr = GridSearchCV(LogisticRegression(), param_grid, refit = True, cv =
 ↪10, verbose = 3, n_jobs = -1)

# fitting the model for grid search
grid_logr.fit(X_train, y_train.values.ravel())

# print best parameter after tuning
print(grid_logr.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid_logr.best_estimator_)
print(grid_logr.best_score_)
```

```
Fitting 10 folds for each of 15 candidates, totalling 150 fits
{'C': 30, 'max_iter': 2500, 'penalty': 'l2', 'solver': 'lbfgs'}
LogisticRegression(C=30, max_iter=2500)
0.9416324906367042
```

```
[ ]: logr_model = grid_logr.best_estimator_

     # Performing training
     #logr_model = logr.fit(X_train, y_train.values.ravel())
```

```
[ ]: logr_predict  =  logr_model.predict(X_test)
```

```
[ ]: # from sklearn.metrics import confusion_matrix,accuracy_score
     # cm = confusion_matrix(y_test, dct_pred)
     # ac = accuracy_score(y_test, dct_pred)
```

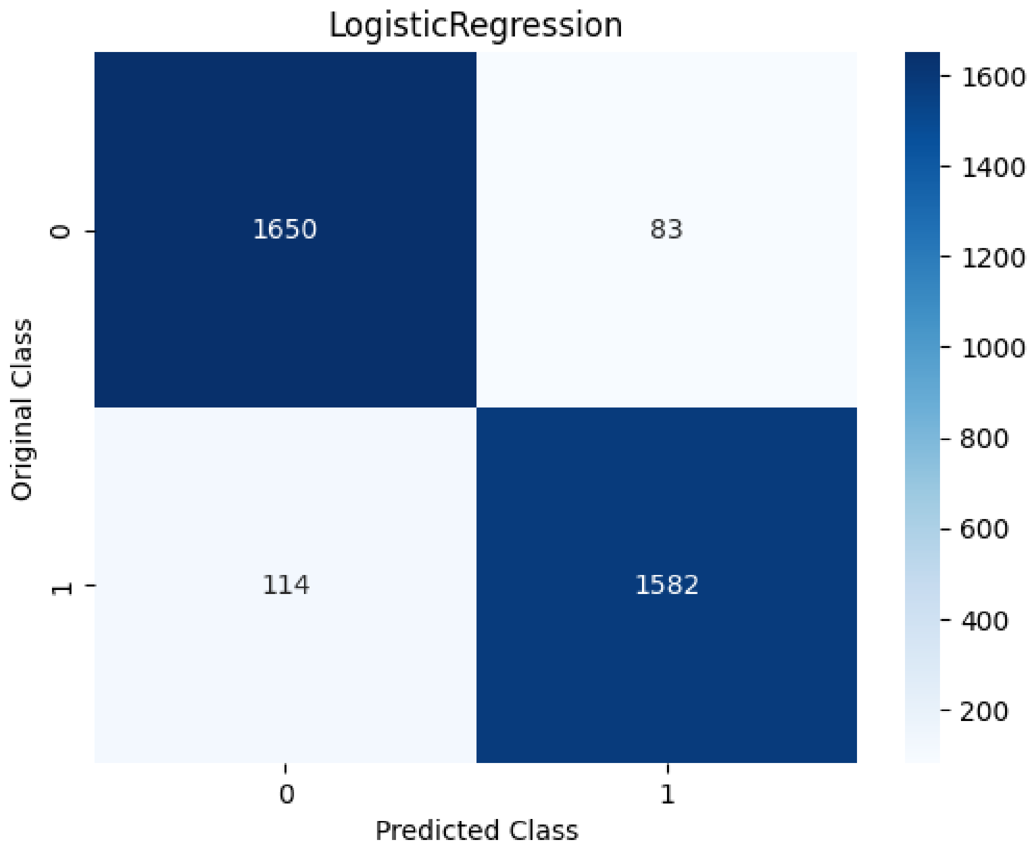
```
[ ]: print ("Accuracy of logr classifier : ", accuracy_score(y_test,␣
      ↪logr_predict)*100)
```

```
Accuracy of logr classifier :  94.2548848060659
```

```
[ ]: print(classification_report(y_test, logr_predict))
```

```
              precision    recall  f1-score   support

           0       0.94      0.95      0.94      1733
           1       0.95      0.93      0.94      1696

    accuracy                           0.94      3429
   macro avg       0.94      0.94      0.94      3429
weighted avg       0.94      0.94      0.94      3429
```

```
[ ]: sns.heatmap(confusion_matrix(y_test, logr_predict), annot=True, fmt='g',␣
      ↪cmap='Blues')
     plt.title("LogisticRegression")
     plt.xlabel('Predicted Class')
     plt.ylabel('Original Class')
     plt.show()
```




```
[ ]: # from sklearn.neighbors import KNeighborsClassifier

# #training_accuracy=[]
# test_accuracy=[]

# neighbors=range(1,10)
# ##values.ravel() converts vector y to flattened array
# for i in neighbors:
#     knn=KNeighborsClassifier(n_neighbors=i)
#     knn_model = knn.fit(X_train,y_train.values.ravel())
#     #training_accuracy.append(knn.score(X_train,y_train.values.ravel()))
#     test_accuracy.append(knn_model.score(X_test,y_test.values.ravel()))
```

```
[ ]: # plt.plot(neighbors,test_accuracy,label="test accuracy")
# plt.ylabel("Accuracy")
# plt.xlabel("number of neighbors")
# plt.legend()
# plt.show()
```

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier

# defining parameter range
param_grid = {'n_neighbors': [1,2,3,4,5,6,7,8,9,10]}

grid_knn = GridSearchCV(KNeighborsClassifier(), param_grid, refit = True, cv =␣
    ↪10, verbose = 3, n_jobs = -1)

# fitting the model for grid search
grid_knn.fit(X_train, y_train.values.ravel())

# print best parameter after tuning
print(grid_knn.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid_knn.best_estimator_)
print(grid_knn.best_score_)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
{'n_neighbors': 3}
KNeighborsClassifier(n_neighbors=3)
0.9235095193508114
```

[ ]:
```
knn_model = grid_knn.best_estimator_
#knn_model = knn.fit(X_train,y_train.values.ravel())
```

[ ]:
```
#print ("Accuracy of knn classifier: ", max(test_accuracy)*100)
knn_predict = knn_model.predict(X_test)
```

[ ]:
```
print('The accuracy of knn Classifier is: ', 100.0 * accuracy_score(y_test,␣
    ↪knn_predict))
```

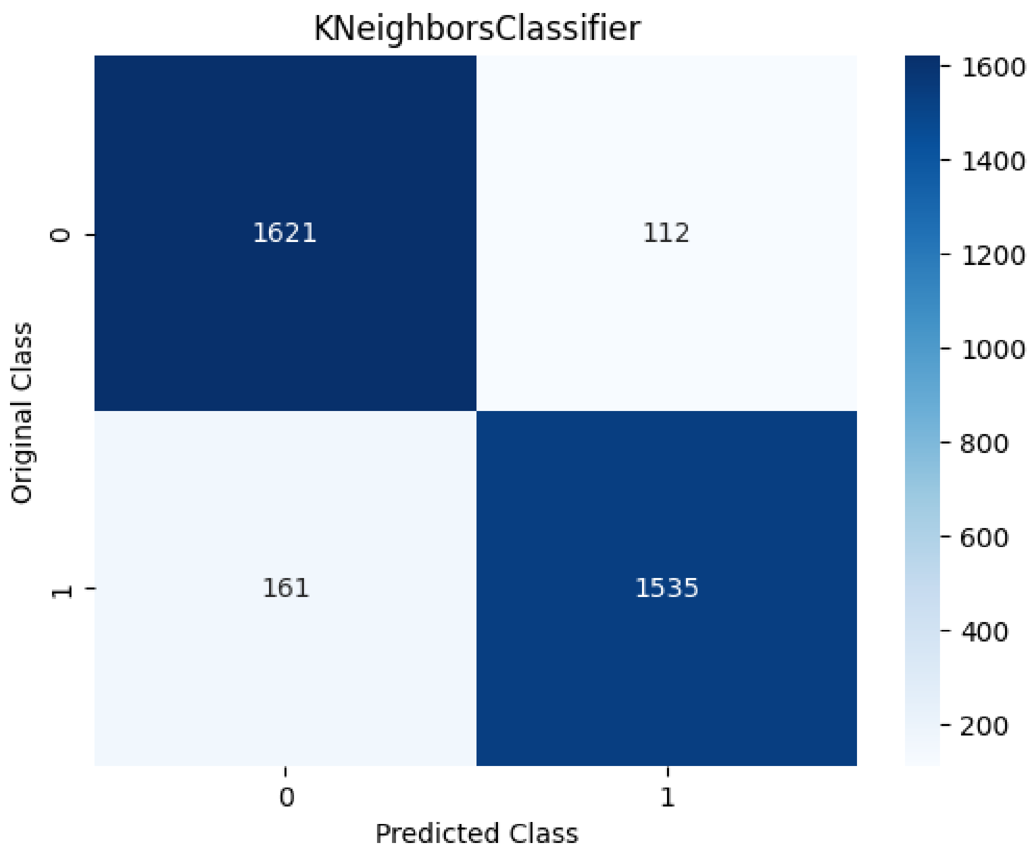
```
The accuracy of knn Classifier is:  92.03849518810149
```

[ ]:
```
print(classification_report(y_test, knn_predict))
```

```
              precision    recall  f1-score   support

           0       0.91      0.94      0.92      1733
           1       0.93      0.91      0.92      1696

    accuracy                           0.92      3429
   macro avg       0.92      0.92      0.92      3429
weighted avg       0.92      0.92      0.92      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, knn_predict), annot=True, fmt='g',␣
    ↪cmap='Blues')
plt.title("KNeighborsClassifier")
```

```
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```



[ ]:
```
# # here is the change
# knn_y_pred_proba = knn.predict_proba(X_test)
# knn_y_pred_proba_positive = knn_y_pred_proba[:, 1]

# RocCurveDisplay.from_predictions(y_test,knn_y_pred_proba_positive)

# fig, ax = plt.subplots()
# RocCurveDisplay.from_estimator(
#     logreg, X_test, y_test, ax = ax)

# logreg_y_decision = logreg.decision_function(X_test)
# metrics.RocCurveDisplay.
 ↪from_predictions(y_test,logreg_y_decision,ax=ax,name="logreg predictions")
```

```
[ ]: from sklearn.svm import SVC

     # defining parameter range
     param_grid = {'C': [1, 10],  #0.1, 1, 10
                   'gamma': [1, 0.1], #
                   'kernel': ['rbf']}   #'linear','poly', 'rbf', 'sigmoid'

     grid_svc = GridSearchCV(SVC(), param_grid, refit = True, cv = 10, verbose = 3,␣
      ↪n_jobs = -1)

     # fitting the model for grid search
     grid_svc.fit(X_train, y_train.values.ravel())

     # print best parameter after tuning
     print(grid_svc.best_params_)

     # print how our model looks after hyper-parameter tuning
     print(grid_svc.best_estimator_)
     print(grid_svc.best_score_)
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits
{'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
SVC(C=10, gamma=0.1)
0.9542551498127342
```

```
[ ]: svc_model = grid_svc.best_estimator_
     #svc_model = svc.fit(X_train,y_train.values.ravel())
```

```
[ ]: svc_predict = svc_model.predict(X_test)
```

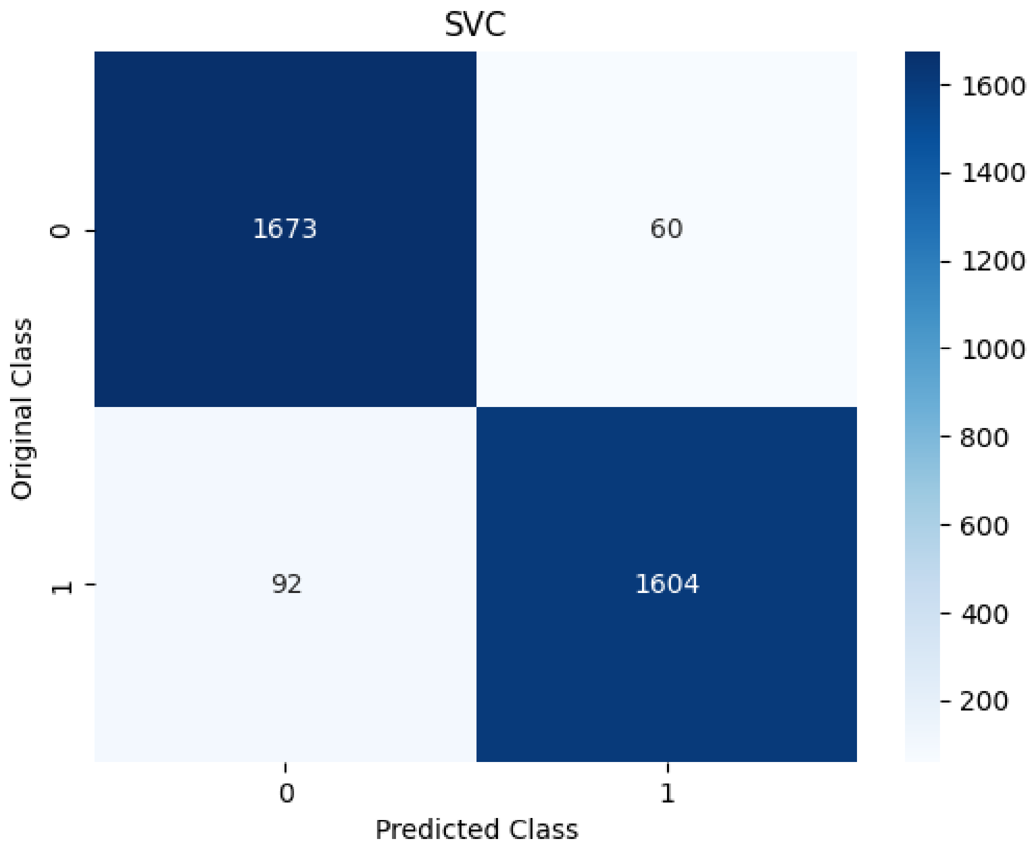
```
[ ]: print('The accuracy of svc Classifier is: ', 100.0 * accuracy_score(y_test,␣
      ↪svc_predict))
```

```
The accuracy of svc Classifier is:  95.56722076407115
```

```
[ ]: print(classification_report(y_test, svc_predict))
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96      1733
           1       0.96      0.95      0.95      1696

    accuracy                           0.96      3429
   macro avg       0.96      0.96      0.96      3429
weighted avg       0.96      0.96      0.96      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, svc_predict), annot=True, fmt='g',␣
↪cmap='Blues')
plt.title("SVC")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```



[ ]:
```
from sklearn.svm import NuSVC

# defining parameter range
param_grid = {'nu': [0.1], #.5
                        'gamma': [.1,1],  #1,.01
                        'kernel': ['rbf']} #'linear','poly', 'rbf', 'sigmoid'

grid_nusvc = GridSearchCV(NuSVC(), param_grid, refit = True, verbose = 3, cv =␣
↪10, n_jobs = -1)

# fitting the model for grid search
grid_nusvc.fit(X_train, y_train.values.ravel())
```

```
# print best parameter after tuning
print(grid_nusvc.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid_nusvc.best_estimator_)
print(grid_nusvc.best_score_)
```

```
Fitting 10 folds for each of 2 candidates, totalling 20 fits
{'gamma': 0.1, 'kernel': 'rbf', 'nu': 0.1}
NuSVC(gamma=0.1, nu=0.1)
0.9530054619225968
```

[ ]:
```
nusvc_model = grid_nusvc.best_estimator_
#nusvc_model = nusvc.fit(X_train, y_train.values.ravel())
```

[ ]:
```
nusvc_predict = nusvc_model.predict(X_test)
```

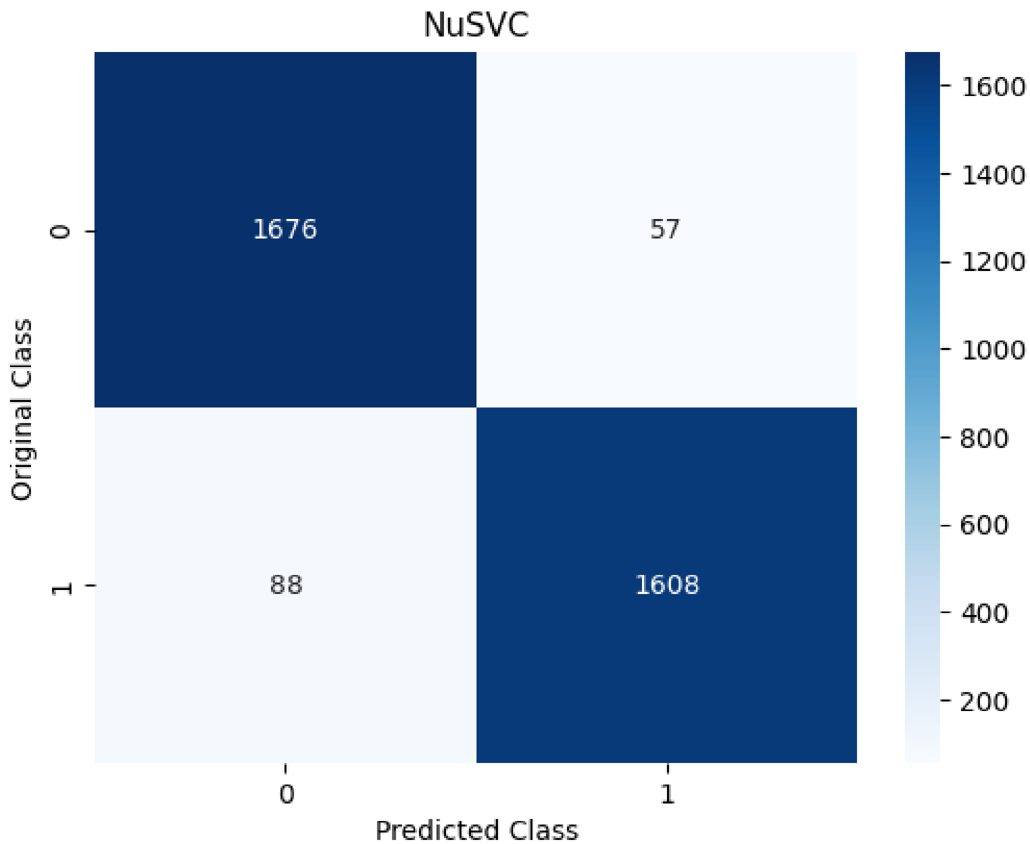
[ ]:
```
print('The accuracy of nusvc Classifier is: ', 100.0 * accuracy_score(y_test,␣
↪nusvc_predict))
```

```
The accuracy of nusvc Classifier is:  95.7713619130942
```

[ ]:
```
print(classification_report(y_test, nusvc_predict))
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96      1733
           1       0.97      0.95      0.96      1696

    accuracy                           0.96      3429
   macro avg       0.96      0.96      0.96      3429
weighted avg       0.96      0.96      0.96      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, nusvc_predict), annot=True, fmt='g',␣
↪cmap='Blues')
plt.title("NuSVC")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```




```
[ ]: from sklearn.svm import LinearSVC

# defining parameter range
param_grid = {'C': [0.1, 1, 10, 20, 30],
              'penalty': ['l1','l2'],
              'loss': ['squared_hinge'],
              'dual': [False],
              'tol': [.1,.01,.001]}

grid_lsvc = GridSearchCV(LinearSVC(), param_grid, refit = True, verbose = 3, cv␣
 ↪= 10, n_jobs = -1)

# fitting the model for grid search
grid_lsvc.fit(X_train, y_train.values.ravel())

# print best parameter after tuning
print(grid_lsvc.best_params_)

# print how our model looks after hyper-parameter tuning
```

```
print(grid_lsvc.best_estimator_)
print(grid_lsvc.best_score_)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
{'C': 20, 'dual': False, 'loss': 'squared_hinge', 'penalty': 'l1', 'tol': 0.001}
LinearSVC(C=20, dual=False, penalty='l1', tol=0.001)
0.9417571785268415
```

[ ]:
```
lsvc_model = grid_lsvc.best_estimator_
#lsvc_model = lsvc.fit(X_train, y_train.values.ravel())
```

[ ]:
```
lsvc_predict = lsvc_model.predict(X_test)
```

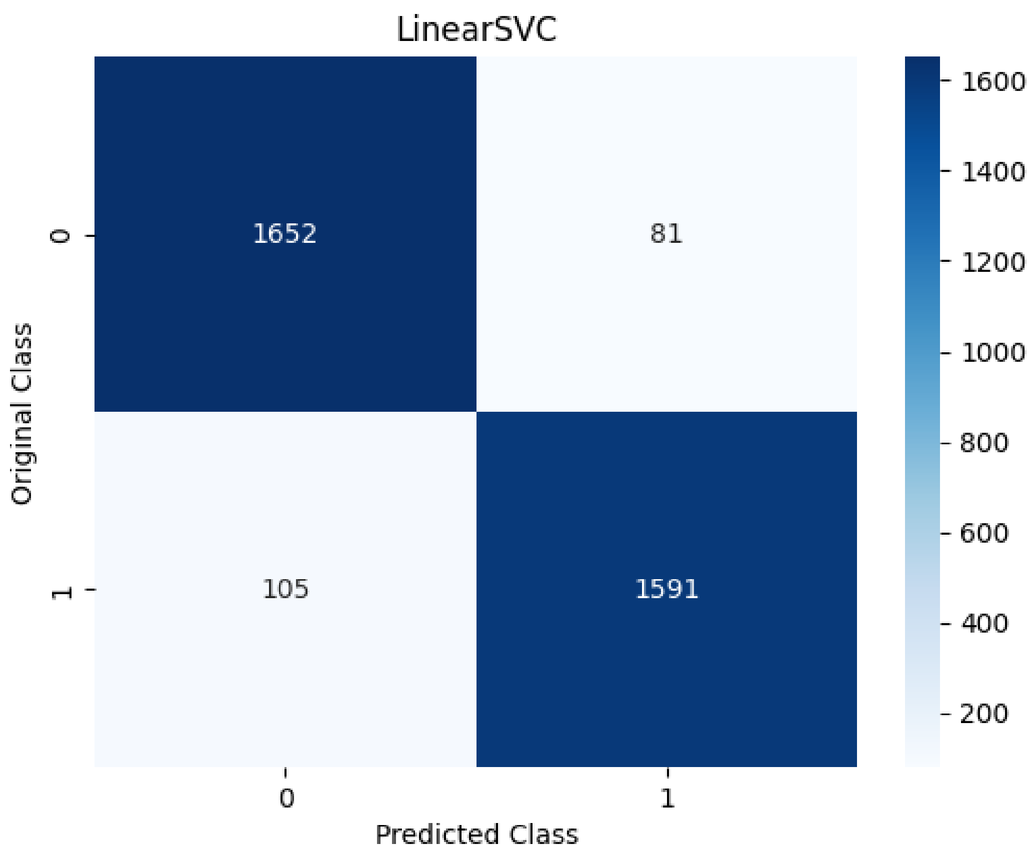
[ ]:
```
print('The accuracy of lsvc Classifier is: ', 100.0 * accuracy_score(y_test,␣
↪lsvc_predict))
```

```
The accuracy of lsvc Classifier is:  94.57567804024497
```

[ ]:
```
print(classification_report(y_test, lsvc_predict))
```

```
              precision    recall  f1-score   support

           0       0.94      0.95      0.95      1733
           1       0.95      0.94      0.94      1696

    accuracy                           0.95      3429
   macro avg       0.95      0.95      0.95      3429
weighted avg       0.95      0.95      0.95      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, lsvc_predict), annot=True, fmt='g',␣
↪cmap='Blues')
plt.title("LinearSVC")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```



[ ]:
```
from sklearn.ensemble import AdaBoostClassifier

# defining parameter range
param_grid = {'n_estimators': [100,200,300]}

grid_ada = GridSearchCV(AdaBoostClassifier(), param_grid, refit = True, verbose␣
↪= 3, cv = 10, n_jobs = -1)

# fitting the model for grid search
grid_ada.fit(X_train, y_train.values.ravel())

# print best parameter after tuning
print(grid_ada.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid_ada.best_estimator_)
print(grid_ada.best_score_)
```

```
Fitting 10 folds for each of 3 candidates, totalling 30 fits
{'n_estimators': 300}
```

```
AdaBoostClassifier(n_estimators=300)
0.9557554619225966
```

[ ]:
```python
ada_model = grid_ada.best_estimator_
#ada_model = ada.fit(X_train,y_train.values.ravel())
```

[ ]:
```python
ada_predict = ada_model.predict(X_test)
```

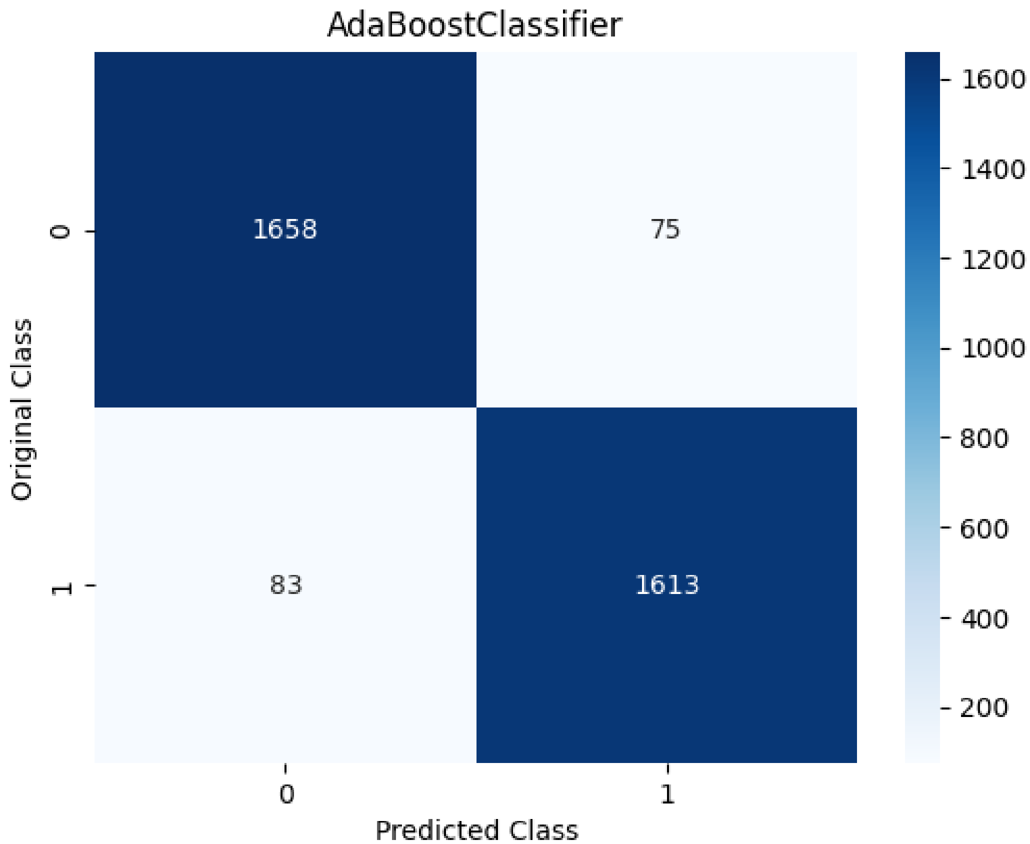
[ ]:
```python
print('The accuracy of Ada Boost Classifier is: ', 100.0 *␣
↪accuracy_score(ada_predict,y_test))
```

```
The accuracy of Ada Boost Classifier is:  95.39224263633712
```

[ ]:
```python
print(classification_report(y_test, ada_predict))
```

```
              precision    recall  f1-score   support

           0       0.95      0.96      0.95      1733
           1       0.96      0.95      0.95      1696

    accuracy                           0.95      3429
   macro avg       0.95      0.95      0.95      3429
weighted avg       0.95      0.95      0.95      3429
```

[ ]:
```python
sns.heatmap(confusion_matrix(y_test, ada_predict), annot=True, fmt='g',␣
↪cmap='Blues')
plt.title("AdaBoostClassifier")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```




```
[ ]: from xgboost import XGBClassifier


     # defining parameter range
     param_grid = {
         "gamma": [.01, .1, .5], #
         "n_estimators": [150,200,250]
     }

     grid_xgb = GridSearchCV(XGBClassifier(), param_grid, refit = True, verbose = 3,␣
      ↪cv = 10, n_jobs = -1)

     # fitting the model for grid search
     grid_xgb.fit(X_train, y_train.values.ravel())

     # print best parameter after tuning
     print(grid_xgb.best_params_)

     # print how our model looks after hyper-parameter tuning
```

```
print(grid_xgb.best_estimator_)
print(grid_xgb.best_score_)
```

```
Fitting 10 folds for each of 9 candidates, totalling 90 fits
{'gamma': 0.1, 'n_estimators': 150}
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0.1, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=150,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, …)
0.9692534332084894
```

```
[ ]: xgb_model = grid_xgb.best_estimator_
     #xgb_model = xgb.fit(X_train,y_train)
```

```
[ ]: xgb_predict=xgb_model.predict(X_test)
```

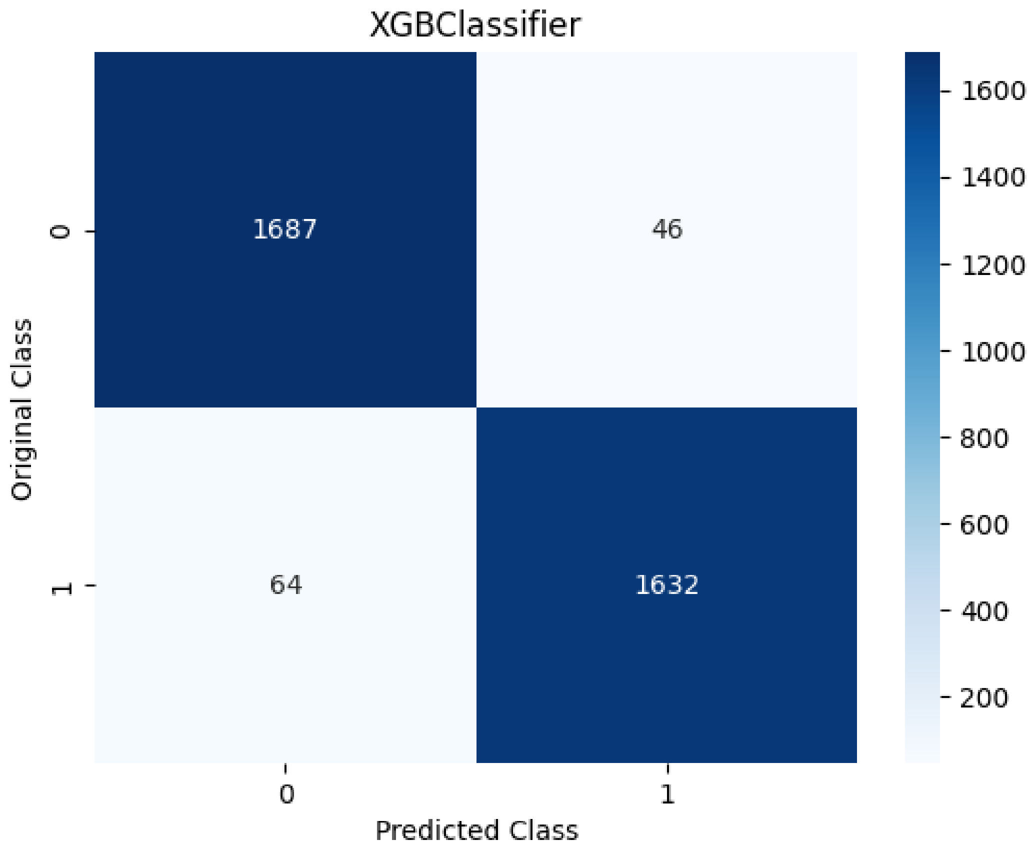
```
[ ]: print('The accuracy of XGBoost Classifier is: ' , 100.0 *␣
      ↪accuracy_score(xgb_predict,y_test))
```

```
The accuracy of XGBoost Classifier is:  96.79206765820939
```

```
[ ]: print(classification_report(y_test, xgb_predict))
```

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.97      1733
           1       0.97      0.96      0.97      1696

    accuracy                           0.97      3429
   macro avg       0.97      0.97      0.97      3429
weighted avg       0.97      0.97      0.97      3429
```

```
[ ]: sns.heatmap(confusion_matrix(y_test, xgb_predict), annot=True, fmt='g',␣
      ↪cmap='Blues')
     plt.title("XGBClassifier")
     plt.xlabel('Predicted Class')
     plt.ylabel('Original Class')
     plt.show()
```



[ ]:
```
from sklearn.ensemble import GradientBoostingClassifier

# defining parameter range
param_grid = {
    "learning_rate": [.5], #.1,.5,1
    "n_estimators": [150,200,250]
}

grid_gbc = GridSearchCV(GradientBoostingClassifier(), param_grid, refit = True,
 ↪verbose = 3, cv = 10, n_jobs = -1)

# fitting the model for grid search
grid_gbc.fit(X_train, y_train.values.ravel())

# print best parameter after tuning
print(grid_gbc.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid_gbc.best_estimator_)
```

```
print(grid_gbc.best_score_)
```

```
Fitting 10 folds for each of 3 candidates, totalling 30 fits
{'learning_rate': 0.5, 'n_estimators': 250}
GradientBoostingClassifier(learning_rate=0.5, n_estimators=250)
0.9670035892634207
```

[ ]:
```
gbc_model = grid_gbc.best_estimator_
#gbc_model = gbc.fit(X_train,y_train.values.ravel())

#clf = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0,
#    max_depth=1, random_state=0).fit(X_train, y_train)
#clf.score(X_test, y_test)
```

[ ]:
```
gbc_predict = gbc_model.predict(X_test)
```

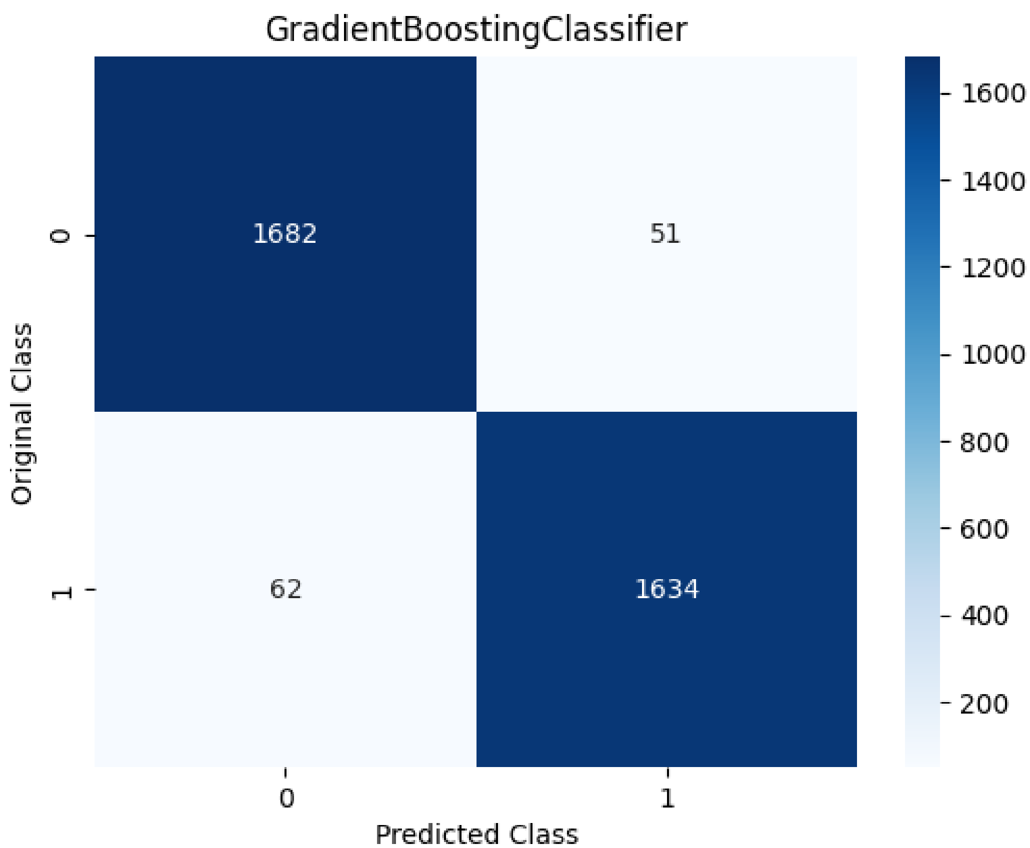
[ ]:
```
print('The accuracy of GradientBoost Classifier is: ' , 100.0 *␣
↪accuracy_score(gbc_predict,y_test))
```

```
The accuracy of GradientBoost Classifier is:  96.70457859434237
```

[ ]:
```
print(classification_report(y_test, gbc_predict))
```

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.97      1733
           1       0.97      0.96      0.97      1696

    accuracy                           0.97      3429
   macro avg       0.97      0.97      0.97      3429
weighted avg       0.97      0.97      0.97      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, gbc_predict), annot=True, fmt='g',␣
↪cmap='Blues')
plt.title("GradientBoostingClassifier")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```



[ ]:
```
# gbc_model.get_params().keys()
```

[ ]:
```
# import inspect
# import sklearn
# import xgboost

# models = [xgboost.XGBClassifier]
# for m in models:
#     hyperparams = inspect.signature(m.__init__)
#     print(hyperparams)
# #or
# xgb_model.get_params().keys()
```

[ ]:
```
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

# defining parameter range
param_grid = {
    "base_estimator": [DecisionTreeClassifier()],
    "n_estimators": [150,200,250]
```

```
}

grid_bag = GridSearchCV(BaggingClassifier(), param_grid, refit = True, verbose
 ↪= 3, cv = 10, n_jobs = -1)

# fitting the model for grid search
grid_bag.fit(X_train, y_train.values.ravel())

# print best parameter after tuning
print(grid_bag.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid_bag.best_estimator_)
print(grid_bag.best_score_)
```

```
Fitting 10 folds for each of 3 candidates, totalling 30 fits
{'base_estimator': DecisionTreeClassifier(), 'n_estimators': 150}
BaggingClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=150)
0.9571293695380774
```

[ ]:
```
bag_model = grid_bag.best_estimator_
#bag_model = bag.fit(X_train, y_train.values.ravel())
```

[ ]:
```
bag_predict = bag_model.predict(X_test)
```

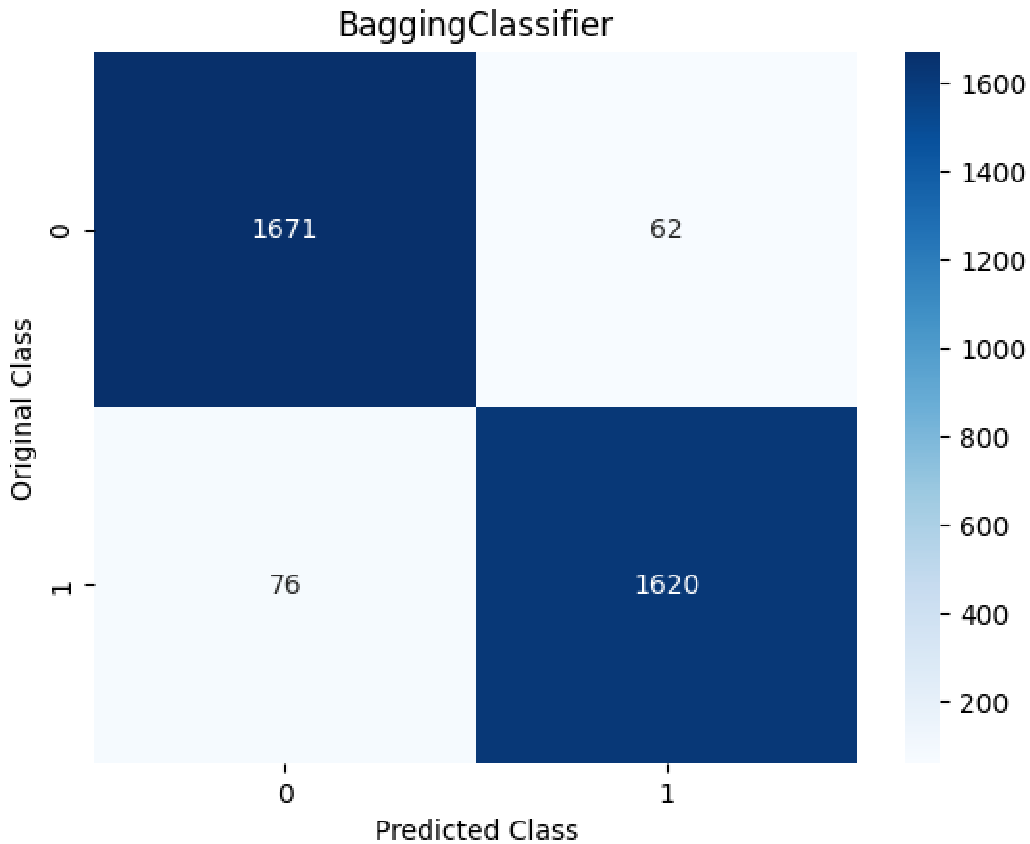
[ ]:
```
print('The accuracy of Bagging Classifier is: ' , 100.0 *
 ↪accuracy_score(y_test, bag_predict))
```

```
The accuracy of Bagging Classifier is:  95.97550306211724
```

[ ]:
```
print(classification_report(y_test, bag_predict))
```

```
              precision    recall  f1-score   support

           0       0.96      0.96      0.96      1733
           1       0.96      0.96      0.96      1696

    accuracy                           0.96      3429
   macro avg       0.96      0.96      0.96      3429
weighted avg       0.96      0.96      0.96      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, bag_predict), annot=True, fmt='g',
 ↪cmap='Blues')
plt.title("BaggingClassifier")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```




```
[ ]: from sklearn.ensemble import RandomForestClassifier

     # defining parameter range
     param_grid = {
         "n_estimators": [50,100,150,200]
     }

     grid_rfc = GridSearchCV(RandomForestClassifier(), param_grid, refit = True,␣
      ↪verbose = 3, cv = 10, n_jobs = -1)

     # fitting the model for grid search
     grid_rfc.fit(X_train, y_train.values.ravel())

     # print best parameter after tuning
     print(grid_rfc.best_params_)

     # print how our model looks after hyper-parameter tuning
     print(grid_rfc.best_estimator_)
     print(grid_rfc.best_score_)
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits
{'n_estimators': 150}
RandomForestClassifier(n_estimators=150)
0.9648785892634206
```

[ ]:
```
rfc_model = grid_rfc.best_estimator_
#rfc_model = rfc.fit(X_train,y_train.values.ravel())
```

[ ]:
```
rfc_predict = rfc_model.predict(X_test)
```

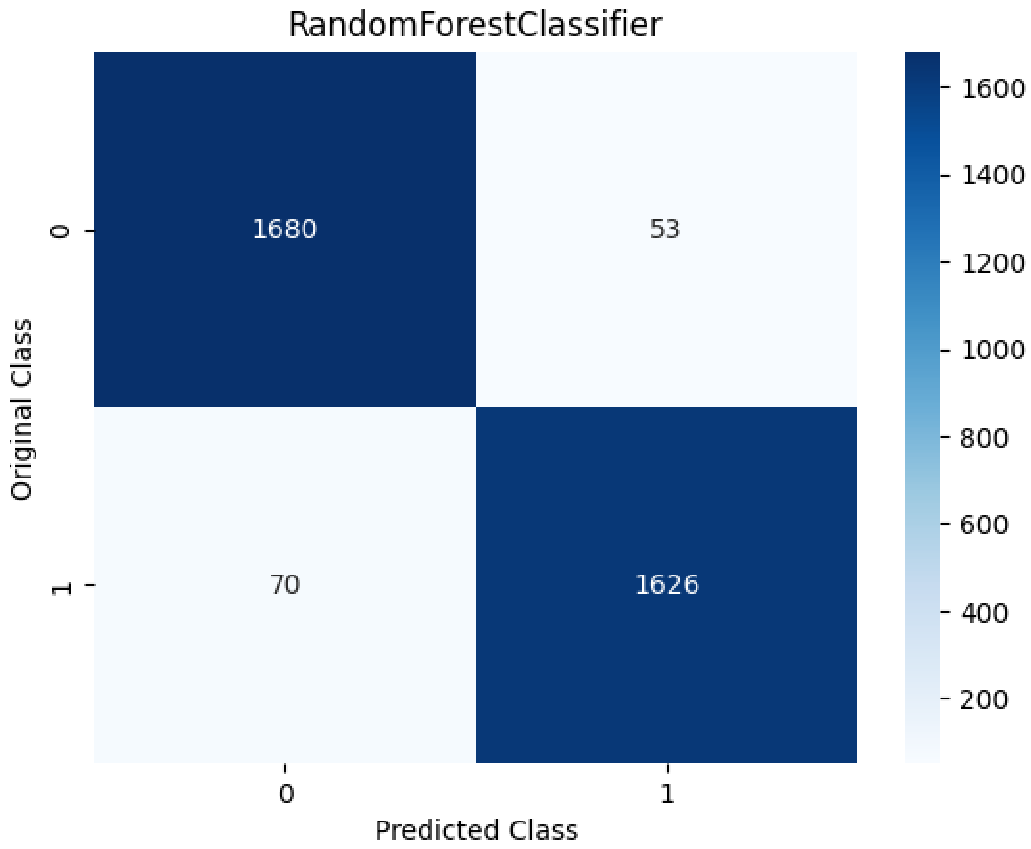
[ ]:
```
print('The accuracy of RandomForest Classifier is: ' , 100.0 *␣
 ↪accuracy_score(rfc_predict,y_test))
```

```
The accuracy of RandomForest Classifier is:  96.41294838145232
```

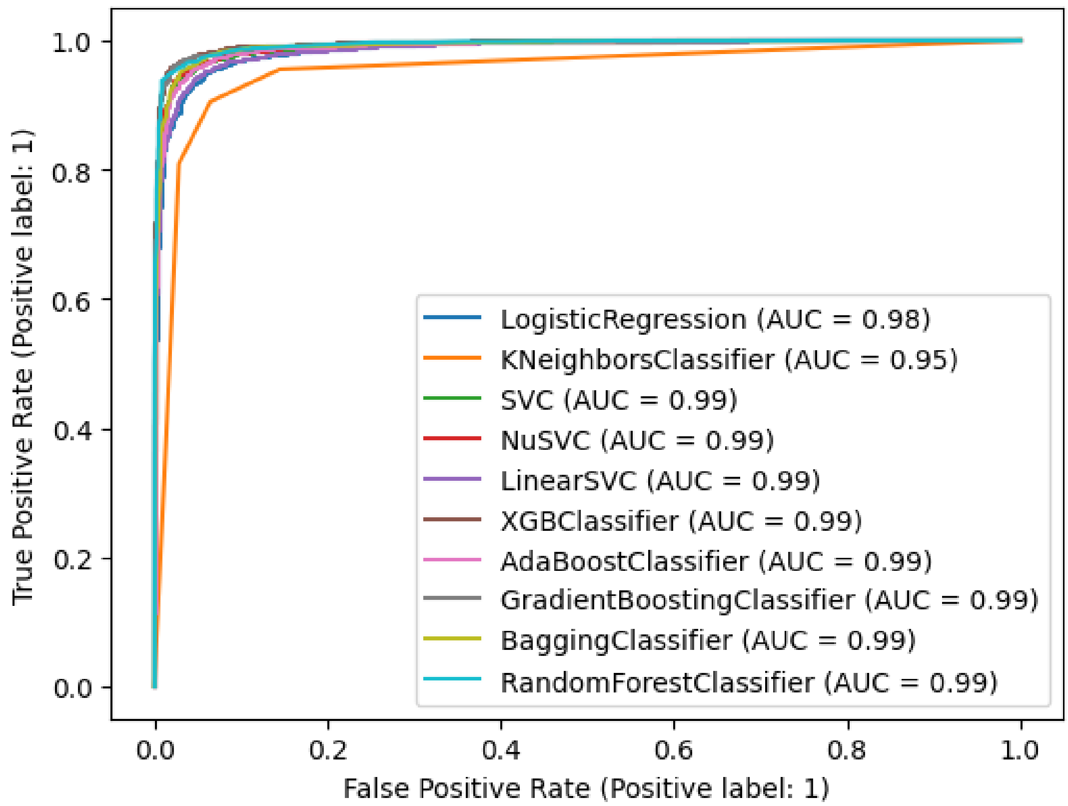
[ ]:
```
print(classification_report(y_test, rfc_predict))
```

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.96      1733
           1       0.97      0.96      0.96      1696

    accuracy                           0.96      3429
   macro avg       0.96      0.96      0.96      3429
weighted avg       0.96      0.96      0.96      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, rfc_predict), annot=True, fmt='g',␣
 ↪cmap='Blues')
plt.title("RandomForestClassifier")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```



[ ]:
```
estimators =␣
↪[logr_model,knn_model,svc_model,nusvc_model,lsvc_model,xgb_model,ada_model,gbc_model,bag_mo

for estimator in estimators:
    RocCurveDisplay.from_estimator(estimator,X_test,y_test,ax=plt.gca())
```



[ ]:
```
import tensorflow as tf
#from tensorflow.keras.datasets import imdb
from keras.layers import Embedding, Dense, LSTM, BatchNormalization
from keras.losses import BinaryCrossentropy
from keras.models import Sequential
from keras.optimizers import Adam
#from tensorflow.keras.preprocessing.sequence import pad_sequences

# Model configuration
additional_metrics = ['accuracy']
batch_size = 32
#embedding_output_dims = (X_train.shape[1])
loss_function = BinaryCrossentropy()
#max_sequence_length = (X_train.shape[1])
#num_distinct_words = (X_train.shape[1])
number_of_epochs = 100
optimizer = Adam()
validation_split = 0.20
verbosity_mode = 1

# reshape from [samples, features] into [samples, timesteps, features]
```

```
timesteps = 1
X_train_reshape = X_train.values.ravel().reshape(X_train.shape[0],timesteps,␣
↪X_train.shape[1])
X_test_reshape = X_test.values.ravel().reshape(X_test.shape[0],timesteps,␣
↪X_test.shape[1])

# Disable eager execution
#tf.compat.v1.disable_eager_execution()

# Load dataset
# (x_train, y_train), (x_test, y_test) = imdb.
↪load_data(num_words=num_distinct_words)
# print(x_train.shape)
# print(x_test.shape)

# Pad all sequences
# padded_inputs = pad_sequences(X_train, maxlen=max_sequence_length, value = 0.
↪0) # 0.0 because it corresponds with <PAD>
# padded_inputs_test = pad_sequences(X_test, maxlen=max_sequence_length, value␣
↪= 0.0) # 0.0 because it corresponds with <PAD>

# Define the Keras model
def build_model_lstm():
    model = Sequential()
    #model.add(Embedding(num_distinct_words, embedding_output_dims,␣
↪input_length=max_sequence_length))
    model.add(LSTM(100, input_shape = (timesteps,X_train_reshape.shape[2])))
    model.add(BatchNormalization())
    model.add(Dense(50, activation='relu'))
    model.add(Dense(25, activation='relu'))
    model.add(Dense(10, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))

    # Compile the model
    model.compile(optimizer=optimizer, loss=loss_function,␣
↪metrics=additional_metrics)
    return model

#from keras.wrappers.scikit_learn import KerasClassifier
lstm_model = build_model_lstm()
# Give a summary
lstm_model.summary()

# Train the model
```

```
history = lstm_model.fit(X_train_reshape, y_train.values.ravel(),␣
↪batch_size=batch_size, epochs=number_of_epochs, verbose=verbosity_mode,␣
↪validation_split=validation_split)

# Test the model after training
#lstm_predict = lstm_model.predict(X_test_reshape)
test_results = lstm_model.evaluate(X_test_reshape, y_test.values.ravel(),␣
↪verbose=False)
print(f'Test results - Loss: {test_results[0]} - Accuracy:␣
↪{100*test_results[1]}%')
```

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_9 (LSTM)               (None, 100)               65200

 batch_normalization_9 (Batc  (None, 100)              400
 hNormalization)


_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_9 (LSTM)               (None, 100)               65200

 batch_normalization_9 (Batc  (None, 100)              400
 hNormalization)

 dense_36 (Dense)            (None, 50)                5050

 dense_37 (Dense)            (None, 25)                1275

 dense_38 (Dense)            (None, 10)                260

 dense_39 (Dense)            (None, 1)                 11

=================================================================
Total params: 72,196
Trainable params: 71,996
Non-trainable params: 200
_________________________________________________________________
Epoch 1/100
200/200 [==============================] - 3s 7ms/step - loss: 0.2330 -
accuracy: 0.9158 - val_loss: 0.4371 - val_accuracy: 0.9119
Epoch 2/100
200/200 [==============================] - 1s 4ms/step - loss: 0.1566 -
accuracy: 0.9434 - val_loss: 0.2634 - val_accuracy: 0.9388
```

```
Epoch 3/100
200/200 [==============================] - 1s 4ms/step - loss: 0.1405 -
accuracy: 0.9475 - val_loss: 0.1696 - val_accuracy: 0.9363
Epoch 4/100
200/200 [==============================] - 1s 4ms/step - loss: 0.1247 -
accuracy: 0.9528 - val_loss: 0.1644 - val_accuracy: 0.9400
Epoch 5/100
200/200 [==============================] - 1s 4ms/step - loss: 0.1194 -
accuracy: 0.9561 - val_loss: 0.1603 - val_accuracy: 0.9425
Epoch 6/100
200/200 [==============================] - 1s 4ms/step - loss: 0.1111 -
accuracy: 0.9566 - val_loss: 0.1646 - val_accuracy: 0.9388
Epoch 7/100
200/200 [==============================] - 1s 4ms/step - loss: 0.1027 -
accuracy: 0.9631 - val_loss: 0.1501 - val_accuracy: 0.9513
Epoch 8/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0964 -
accuracy: 0.9645 - val_loss: 0.1644 - val_accuracy: 0.9457
Epoch 9/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0924 -
accuracy: 0.9670 - val_loss: 0.1739 - val_accuracy: 0.9500
Epoch 10/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0897 -
accuracy: 0.9641 - val_loss: 0.1736 - val_accuracy: 0.9469
Epoch 11/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0854 -
accuracy: 0.9694 - val_loss: 0.1794 - val_accuracy: 0.9450
Epoch 12/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0750 -
accuracy: 0.9720 - val_loss: 0.2166 - val_accuracy: 0.9350
Epoch 13/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0765 -
accuracy: 0.9714 - val_loss: 0.1652 - val_accuracy: 0.9513
Epoch 14/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0683 -
accuracy: 0.9750 - val_loss: 0.1978 - val_accuracy: 0.9438
Epoch 15/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0588 -
accuracy: 0.9783 - val_loss: 0.1800 - val_accuracy: 0.9482
Epoch 16/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0706 -
accuracy: 0.9747 - val_loss: 0.1837 - val_accuracy: 0.9469
Epoch 17/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0591 -
accuracy: 0.9798 - val_loss: 0.2522 - val_accuracy: 0.9300
Epoch 18/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0571 -
accuracy: 0.9792 - val_loss: 0.1829 - val_accuracy: 0.9500
```

```
Epoch 19/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0564 -
accuracy: 0.9789 - val_loss: 0.1920 - val_accuracy: 0.9482
Epoch 20/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0517 -
accuracy: 0.9798 - val_loss: 0.2127 - val_accuracy: 0.9463
Epoch 21/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0492 -
accuracy: 0.9802 - val_loss: 0.2038 - val_accuracy: 0.9525
Epoch 22/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0461 -
accuracy: 0.9839 - val_loss: 0.2258 - val_accuracy: 0.9413
Epoch 23/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0408 -
accuracy: 0.9855 - val_loss: 0.2283 - val_accuracy: 0.9444
Epoch 24/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0500 -
accuracy: 0.9806 - val_loss: 0.2470 - val_accuracy: 0.9444
Epoch 25/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0465 -
accuracy: 0.9817 - val_loss: 0.2274 - val_accuracy: 0.9457
Epoch 26/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0390 -
accuracy: 0.9848 - val_loss: 0.2306 - val_accuracy: 0.9432
Epoch 27/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0364 -
accuracy: 0.9881 - val_loss: 0.2406 - val_accuracy: 0.9500
Epoch 28/100
200/200 [==============================] - 1s 6ms/step - loss: 0.0374 -
accuracy: 0.9853 - val_loss: 0.2853 - val_accuracy: 0.9425
Epoch 29/100
200/200 [==============================] - 2s 8ms/step - loss: 0.0344 -
accuracy: 0.9864 - val_loss: 0.2339 - val_accuracy: 0.9444
Epoch 30/100
200/200 [==============================] - 1s 6ms/step - loss: 0.0379 -
accuracy: 0.9850 - val_loss: 0.2564 - val_accuracy: 0.9394
Epoch 31/100
200/200 [==============================] - 1s 6ms/step - loss: 0.0317 -
accuracy: 0.9883 - val_loss: 0.2408 - val_accuracy: 0.9463
Epoch 32/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0388 -
accuracy: 0.9845 - val_loss: 0.2681 - val_accuracy: 0.9463
Epoch 33/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0310 -
accuracy: 0.9877 - val_loss: 0.2613 - val_accuracy: 0.9375
Epoch 34/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0345 -
accuracy: 0.9875 - val_loss: 0.2805 - val_accuracy: 0.9419
```

```
Epoch 35/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0272 -
accuracy: 0.9895 - val_loss: 0.2627 - val_accuracy: 0.9407
Epoch 36/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0272 -
accuracy: 0.9895 - val_loss: 0.2505 - val_accuracy: 0.9457
Epoch 37/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0259 -
accuracy: 0.9900 - val_loss: 0.2521 - val_accuracy: 0.9513
Epoch 38/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0213 -
accuracy: 0.9931 - val_loss: 0.2845 - val_accuracy: 0.9444
Epoch 39/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0323 -
accuracy: 0.9880 - val_loss: 0.2777 - val_accuracy: 0.9457
Epoch 40/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0302 -
accuracy: 0.9875 - val_loss: 0.2994 - val_accuracy: 0.9413
Epoch 41/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0270 -
accuracy: 0.9905 - val_loss: 0.3291 - val_accuracy: 0.9425
Epoch 42/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0304 -
accuracy: 0.9895 - val_loss: 0.2893 - val_accuracy: 0.9457
Epoch 43/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0198 -
accuracy: 0.9931 - val_loss: 0.2796 - val_accuracy: 0.9469
Epoch 44/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0217 -
accuracy: 0.9919 - val_loss: 0.3026 - val_accuracy: 0.9469
Epoch 45/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0230 -
accuracy: 0.9919 - val_loss: 0.2907 - val_accuracy: 0.9469
Epoch 46/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0149 -
accuracy: 0.9941 - val_loss: 0.3325 - val_accuracy: 0.9438
Epoch 47/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0179 -
accuracy: 0.9945 - val_loss: 0.3308 - val_accuracy: 0.9388
Epoch 48/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0175 -
accuracy: 0.9945 - val_loss: 0.3021 - val_accuracy: 0.9450
Epoch 49/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0297 -
accuracy: 0.9889 - val_loss: 0.3148 - val_accuracy: 0.9444
Epoch 50/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0176 -
accuracy: 0.9936 - val_loss: 0.2981 - val_accuracy: 0.9482
```

```
Epoch 51/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0166 -
accuracy: 0.9937 - val_loss: 0.3362 - val_accuracy: 0.9463
Epoch 52/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0199 -
accuracy: 0.9934 - val_loss: 0.3247 - val_accuracy: 0.9469
Epoch 53/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0157 -
accuracy: 0.9941 - val_loss: 0.3207 - val_accuracy: 0.9507
Epoch 54/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0178 -
accuracy: 0.9934 - val_loss: 0.3509 - val_accuracy: 0.9457
Epoch 55/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0208 -
accuracy: 0.9917 - val_loss: 0.3753 - val_accuracy: 0.9438
Epoch 56/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0189 -
accuracy: 0.9930 - val_loss: 0.3249 - val_accuracy: 0.9407
Epoch 57/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0198 -
accuracy: 0.9925 - val_loss: 0.3053 - val_accuracy: 0.9507
Epoch 58/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0184 -
accuracy: 0.9936 - val_loss: 0.3405 - val_accuracy: 0.9475
Epoch 59/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0157 -
accuracy: 0.9937 - val_loss: 0.3643 - val_accuracy: 0.9400
Epoch 60/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0133 -
accuracy: 0.9953 - val_loss: 0.3445 - val_accuracy: 0.9513
Epoch 61/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0138 -
accuracy: 0.9948 - val_loss: 0.2865 - val_accuracy: 0.9488
Epoch 62/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0135 -
accuracy: 0.9952 - val_loss: 0.3298 - val_accuracy: 0.9469
Epoch 63/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0111 -
accuracy: 0.9956 - val_loss: 0.3532 - val_accuracy: 0.9469
Epoch 64/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0181 -
accuracy: 0.9955 - val_loss: 0.3942 - val_accuracy: 0.9400
Epoch 65/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0145 -
accuracy: 0.9941 - val_loss: 0.3597 - val_accuracy: 0.9475
Epoch 66/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0125 -
accuracy: 0.9958 - val_loss: 0.3427 - val_accuracy: 0.9494
```

```
Epoch 67/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0151 -
accuracy: 0.9948 - val_loss: 0.3839 - val_accuracy: 0.9450
Epoch 68/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0160 -
accuracy: 0.9936 - val_loss: 0.4108 - val_accuracy: 0.9494
Epoch 69/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0152 -
accuracy: 0.9942 - val_loss: 0.3846 - val_accuracy: 0.9450
Epoch 70/100
200/200 [==============================] - 1s 5ms/step - loss: 0.0104 -
accuracy: 0.9964 - val_loss: 0.4035 - val_accuracy: 0.9438
Epoch 71/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0154 -
accuracy: 0.9942 - val_loss: 0.3670 - val_accuracy: 0.9519
Epoch 72/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0173 -
accuracy: 0.9930 - val_loss: 0.3647 - val_accuracy: 0.9457
Epoch 73/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0105 -
accuracy: 0.9959 - val_loss: 0.3710 - val_accuracy: 0.9488
Epoch 74/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0073 -
accuracy: 0.9973 - val_loss: 0.3762 - val_accuracy: 0.9519
Epoch 75/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0090 -
accuracy: 0.9964 - val_loss: 0.4047 - val_accuracy: 0.9444
Epoch 76/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0193 -
accuracy: 0.9925 - val_loss: 0.3808 - val_accuracy: 0.9469
Epoch 77/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0118 -
accuracy: 0.9972 - val_loss: 0.4038 - val_accuracy: 0.9444
Epoch 78/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0120 -
accuracy: 0.9964 - val_loss: 0.3798 - val_accuracy: 0.9488
Epoch 79/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0152 -
accuracy: 0.9934 - val_loss: 0.3833 - val_accuracy: 0.9388
Epoch 80/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0108 -
accuracy: 0.9959 - val_loss: 0.3722 - val_accuracy: 0.9457
Epoch 81/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0109 -
accuracy: 0.9964 - val_loss: 0.3628 - val_accuracy: 0.9475
Epoch 82/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0072 -
accuracy: 0.9983 - val_loss: 0.3941 - val_accuracy: 0.9500
```

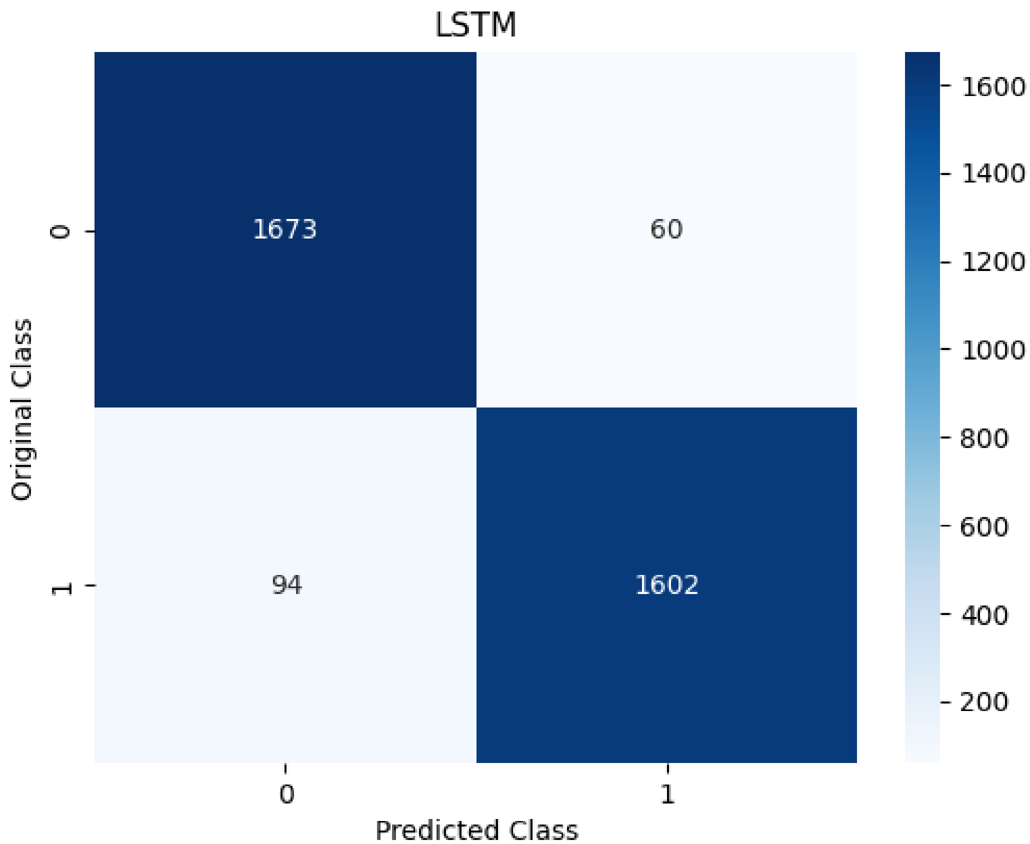
```
Epoch 83/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0060 -
accuracy: 0.9980 - val_loss: 0.4322 - val_accuracy: 0.9482
Epoch 84/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0100 -
accuracy: 0.9967 - val_loss: 0.4167 - val_accuracy: 0.9444
Epoch 85/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0108 -
accuracy: 0.9961 - val_loss: 0.4218 - val_accuracy: 0.9444
Epoch 86/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0096 -
accuracy: 0.9964 - val_loss: 0.4268 - val_accuracy: 0.9457
Epoch 87/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0101 -
accuracy: 0.9966 - val_loss: 0.4036 - val_accuracy: 0.9444
Epoch 88/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0137 -
accuracy: 0.9948 - val_loss: 0.3706 - val_accuracy: 0.9513
Epoch 89/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0132 -
accuracy: 0.9967 - val_loss: 0.4287 - val_accuracy: 0.9363
Epoch 90/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0070 -
accuracy: 0.9980 - val_loss: 0.3784 - val_accuracy: 0.9513
Epoch 91/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0064 -
accuracy: 0.9972 - val_loss: 0.3814 - val_accuracy: 0.9500
Epoch 92/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0099 -
accuracy: 0.9966 - val_loss: 0.4355 - val_accuracy: 0.9457
Epoch 93/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0151 -
accuracy: 0.9944 - val_loss: 0.3903 - val_accuracy: 0.9413
Epoch 94/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0122 -
accuracy: 0.9967 - val_loss: 0.4076 - val_accuracy: 0.9419
Epoch 95/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0110 -
accuracy: 0.9956 - val_loss: 0.3919 - val_accuracy: 0.9457
Epoch 96/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0085 -
accuracy: 0.9981 - val_loss: 0.3931 - val_accuracy: 0.9457
Epoch 97/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0076 -
accuracy: 0.9977 - val_loss: 0.3930 - val_accuracy: 0.9494
Epoch 98/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0163 -
accuracy: 0.9950 - val_loss: 0.3911 - val_accuracy: 0.9500
```

```
Epoch 99/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0091 -
accuracy: 0.9969 - val_loss: 0.3969 - val_accuracy: 0.9532
Epoch 100/100
200/200 [==============================] - 1s 4ms/step - loss: 0.0085 -
accuracy: 0.9969 - val_loss: 0.4187 - val_accuracy: 0.9519
Test results - Loss: 0.3108710050582886 - Accuracy: 95.50889730453491%
```

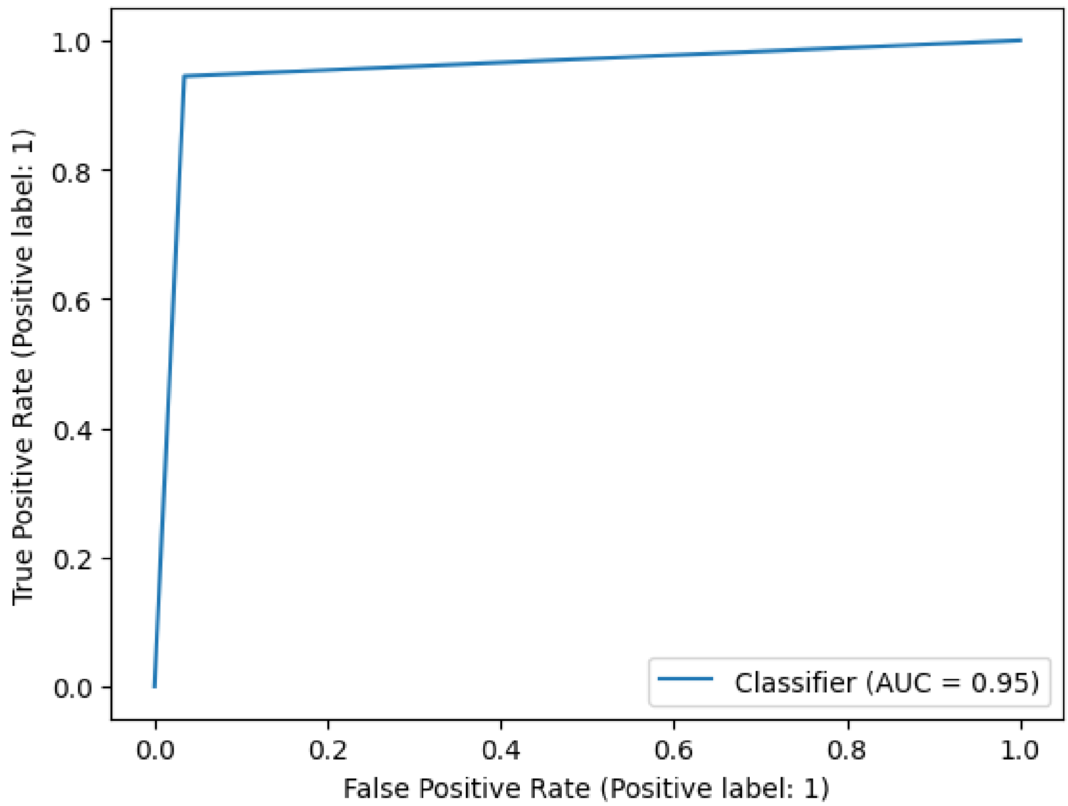
[ ]:
```
lstm_predict_proba = lstm_model.predict(X_test_reshape, batch_size=32)
lstm_predict_class = (lstm_predict_proba > 0.5).astype("int32")
print(classification_report(y_test, lstm_predict_class))
```

```
108/108 [==============================] - 1s 2ms/step
              precision    recall  f1-score   support

           0       0.95      0.97      0.96      1733
           1       0.96      0.94      0.95      1696

    accuracy                           0.96      3429
   macro avg       0.96      0.95      0.96      3429
weighted avg       0.96      0.96      0.96      3429
```

[ ]:
```
sns.heatmap(confusion_matrix(y_test, lstm_predict_class), annot=True, fmt='g',␣
 ↪cmap='Blues')
plt.title("LSTM")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
```



[ ]:
```
RocCurveDisplay.from_predictions(y_test,lstm_predict_class)
plt.show()
```


1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)
Classifier (AUC = 0.95)