

correlation_target_label_87 9010 split .02 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, ConfusionMatrixDisplay

[ ]: 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	suspicious_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

```
[ ]: 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,.02)
len(set(corr_feature))
```

```
[ ]: 17
```

```
[ ]: corr_feature
```

```
[ ]: {'char_repeat',
      'iframe',
      'login_form',
      'nb_comma',
      'nb_or',
      'nb_space',
      'onmouseover',
      'path_extension',
      'port',
      'punycode',
      'random_domain',
      'ratio_intErrors',
      'ratio_intRedirection',
      'ratio_nullHyperlinks',
      'right_clic',
      'sfh',
      'submit_email'}
```

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

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

```
[ ]: 71
```

```
[ ]: #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 which 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=0.1,
          random_state=10)

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

```
[ ]: ((10287, 70), (1143, 70), (10287, 1), (1143, 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 10287 samples.

Testing set has 1143 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' : [0.1, 1, 10, 20, 30],
              '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 50 candidates, totalling 500 fits
{'C': 30, 'max_iter': 2500, 'penalty': 'l2', 'solver': 'lbfgs'}
LogisticRegression(C=30, max_iter=2500)
0.9430352463386689

```

[ ]: 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)
```

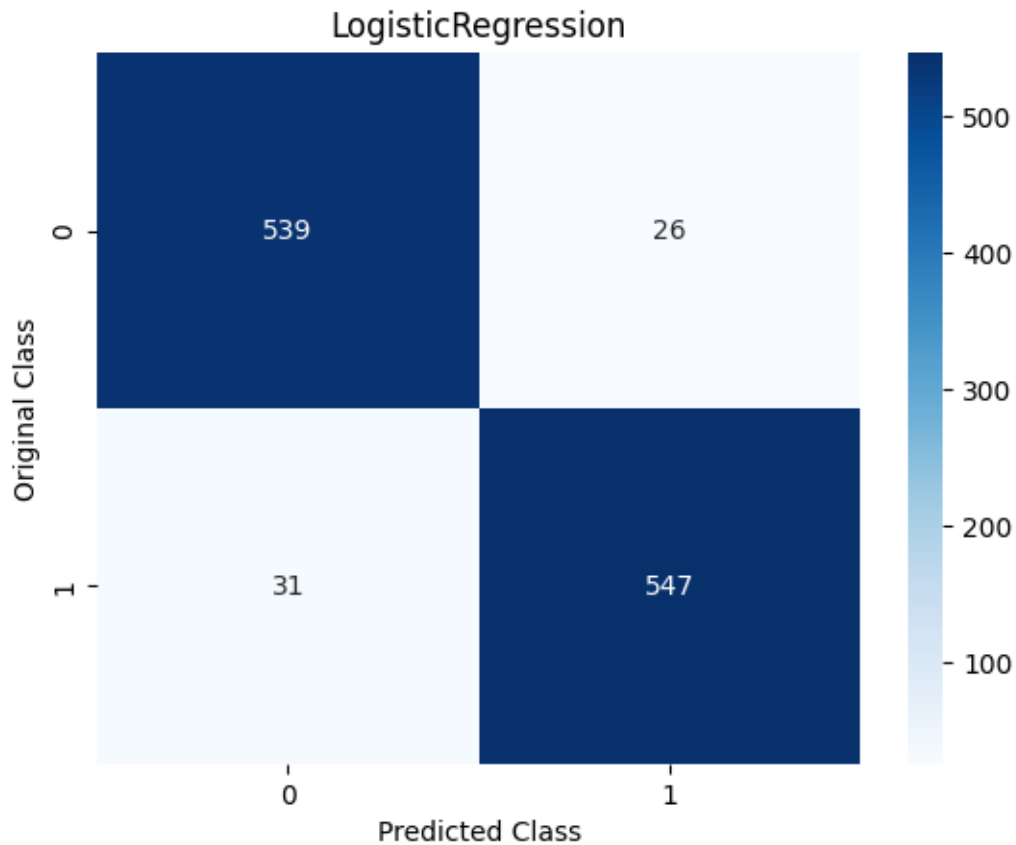
```
[ ]: print ("Accuracy of logr classifier : ", accuracy_score(y_test,   
↳logr_predict)*100)
```

Accuracy of logr classifier : 95.01312335958005

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

	precision	recall	f1-score	support
0	0.95	0.95	0.95	565
1	0.95	0.95	0.95	578
accuracy			0.95	1143
macro avg	0.95	0.95	0.95	1143
weighted avg	0.95	0.95	0.95	1143

```
[ ]: 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': 5}
KNeighborsClassifier()
0.9258289752810518
```

```
[ ]: 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))
```

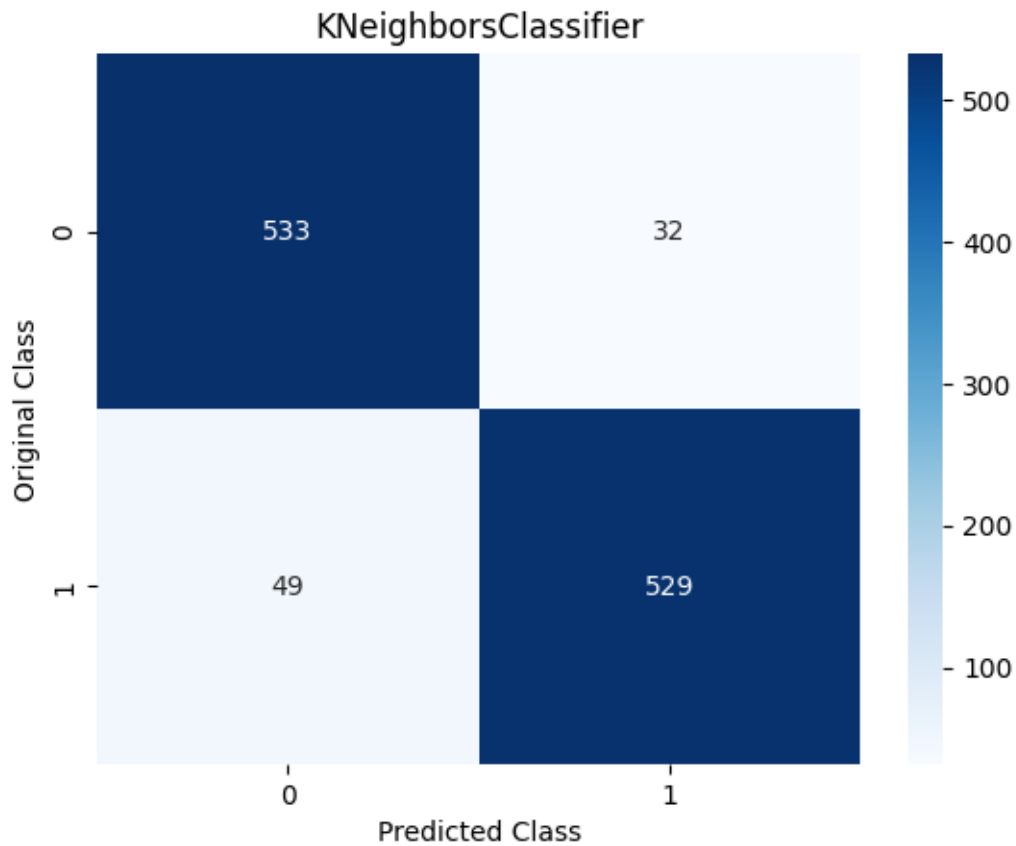
```
The accuracy of knn Classifier is: 92.91338582677166
```

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

	precision	recall	f1-score	support
0	0.92	0.94	0.93	565
1	0.94	0.92	0.93	578
accuracy			0.93	1143
macro avg	0.93	0.93	0.93	1143
weighted avg	0.93	0.93	0.93	1143

```
[ ]: 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': [0.1, 1, 10],
              'gamma': [1, 0.1, 0.01],
              'kernel': ['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 36 candidates, totalling 360 fits
{'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
SVC(C=10, gamma=0.1)
0.9574217346749704

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

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

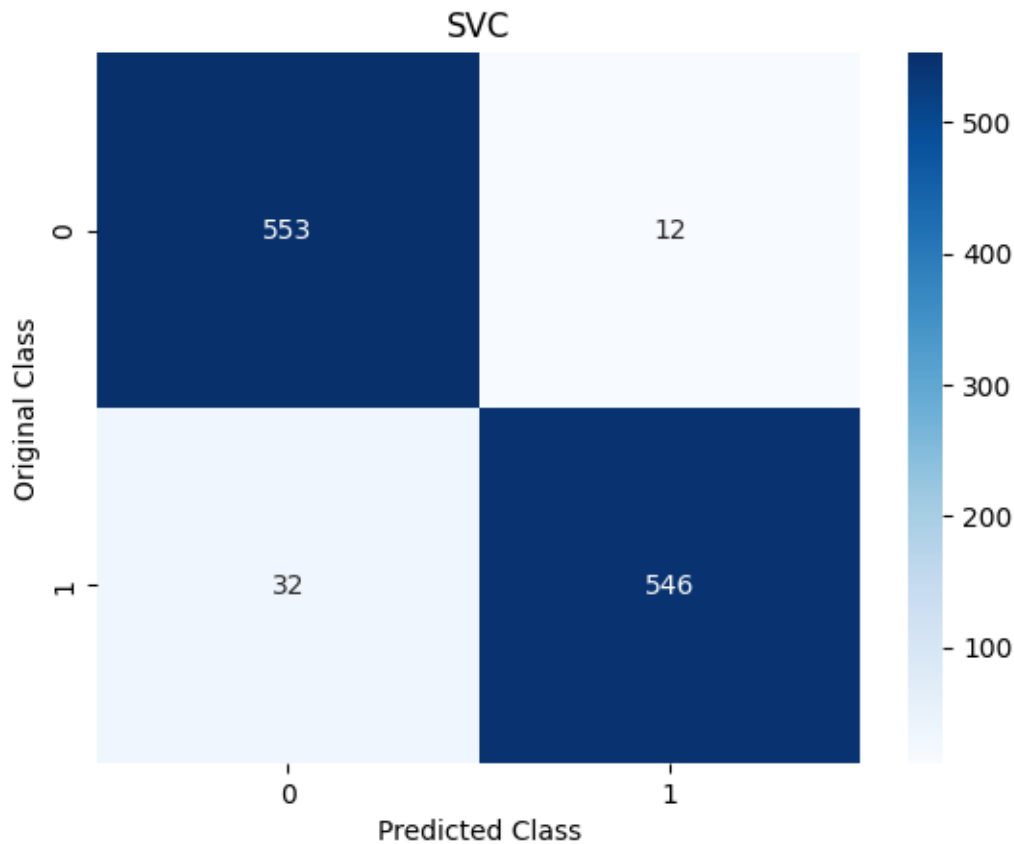
```
[ ]: print('The accuracy of svc Classifier is: ', 100.0 * accuracy_score(y_test,
↪svc_predict))
```

The accuracy of svc Classifier is: 96.15048118985126

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

	precision	recall	f1-score	support
0	0.95	0.98	0.96	565
1	0.98	0.94	0.96	578
accuracy			0.96	1143
macro avg	0.96	0.96	0.96	1143
weighted avg	0.96	0.96	0.96	1143

```
[ ]: 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, 0.5],  
              'gamma': [1, 0.1, 0.01],  
              'kernel': ['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 24 candidates, totalling 240 fits
{'gamma': 0.1, 'kernel': 'rbf', 'nu': 0.1}
NuSVC(gamma=0.1, nu=0.1)
0.9582966538477538
```

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

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

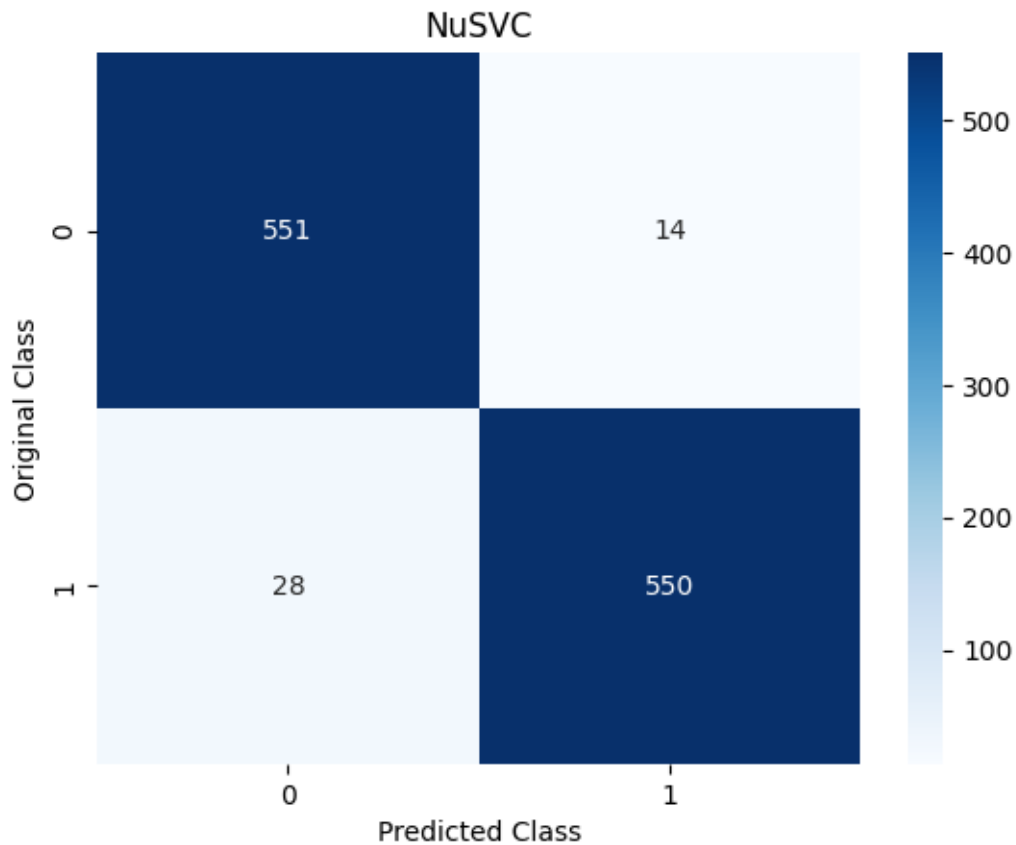
```
[ ]: print('The accuracy of nusvc Classifier is: ', 100.0 * accuracy_score(y_test,
      ↪nusvc_predict))
```

```
The accuracy of nusvc Classifier is: 96.3254593175853
```

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

	precision	recall	f1-score	support
0	0.95	0.98	0.96	565
1	0.98	0.95	0.96	578
accuracy			0.96	1143
macro avg	0.96	0.96	0.96	1143
weighted avg	0.96	0.96	0.96	1143

```
[ ]: 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': 10, 'dual': False, 'loss': 'squared_hinge', 'penalty': 'l1', 'tol': 0.001}
LinearSVC(C=10, dual=False, penalty='l1', tol=0.001)
0.9437154239127559

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

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

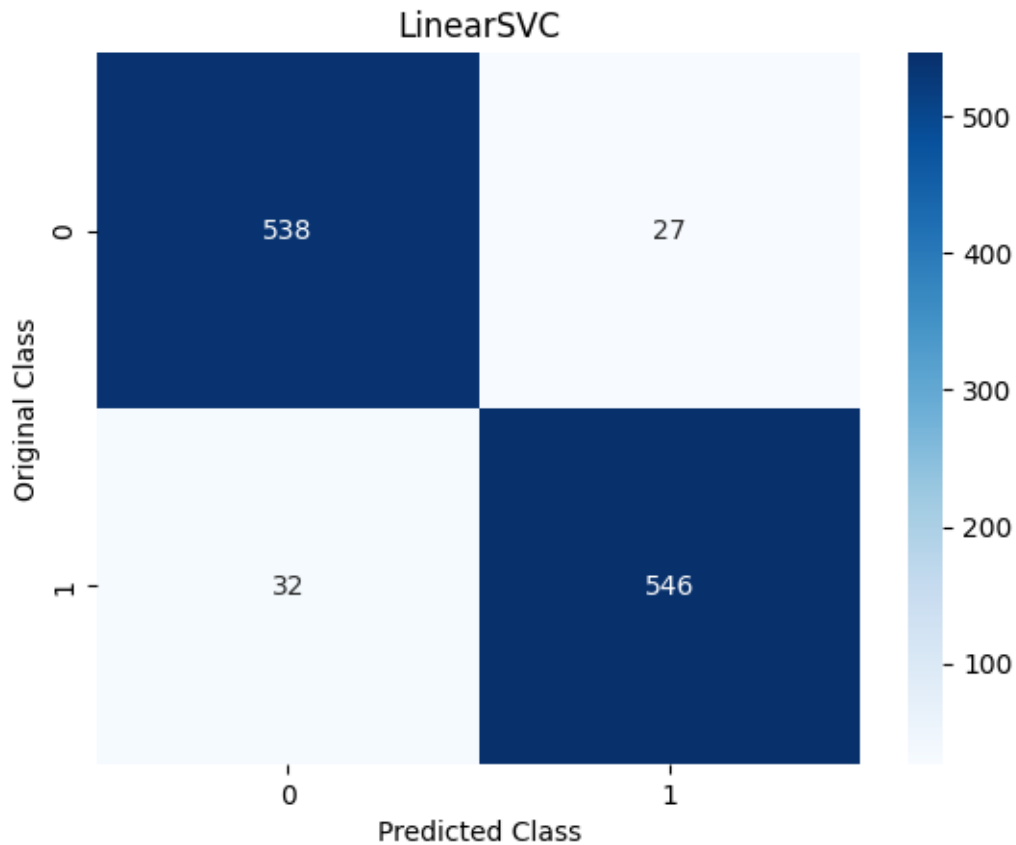
```
[ ]: print('The accuracy of lsvc Classifier is: ', 100.0 * accuracy_score(y_test,
      ↪lsvc_predict))
```

The accuracy of lsvc Classifier is: 94.83814523184601

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

	precision	recall	f1-score	support
0	0.94	0.95	0.95	565
1	0.95	0.94	0.95	578
accuracy			0.95	1143
macro avg	0.95	0.95	0.95	1143
weighted avg	0.95	0.95	0.95	1143

```
[ ]: 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': [40,50,100,200,300]}

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 5 candidates, totalling 50 fits
 {'n_estimators': 200}


```
AdaBoostClassifier(n_estimators=200)
0.9563529247163011
```

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

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

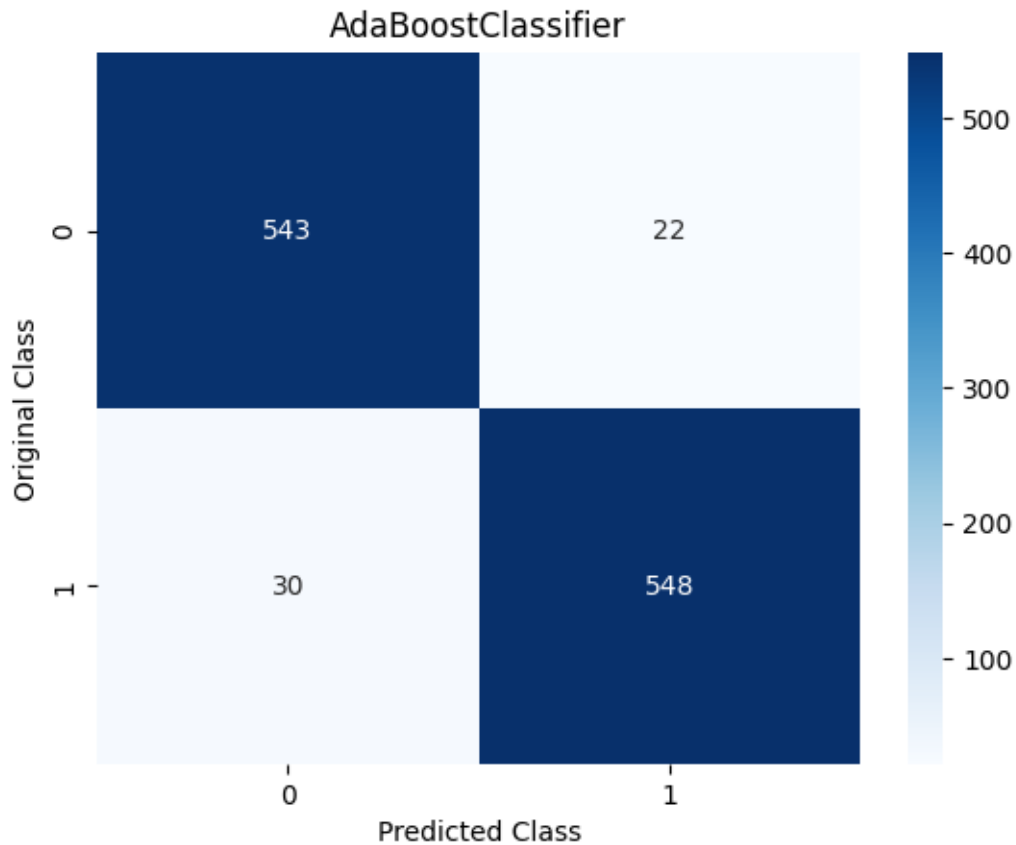
```
[ ]: print('The accuracy of Ada Boost Classifier is: ', 100.0 *  
      ↪accuracy_score(ada_predict,y_test))
```

The accuracy of Ada Boost Classifier is: 95.45056867891513

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

	precision	recall	f1-score	support
0	0.95	0.96	0.95	565
1	0.96	0.95	0.95	578
accuracy			0.95	1143
macro avg	0.95	0.95	0.95	1143
weighted avg	0.95	0.95	0.95	1143

```
[ ]: 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": [50,100,150,200,250]
}

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 15 candidates, totalling 150 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, ...)
```

0.9716139540863592

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

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

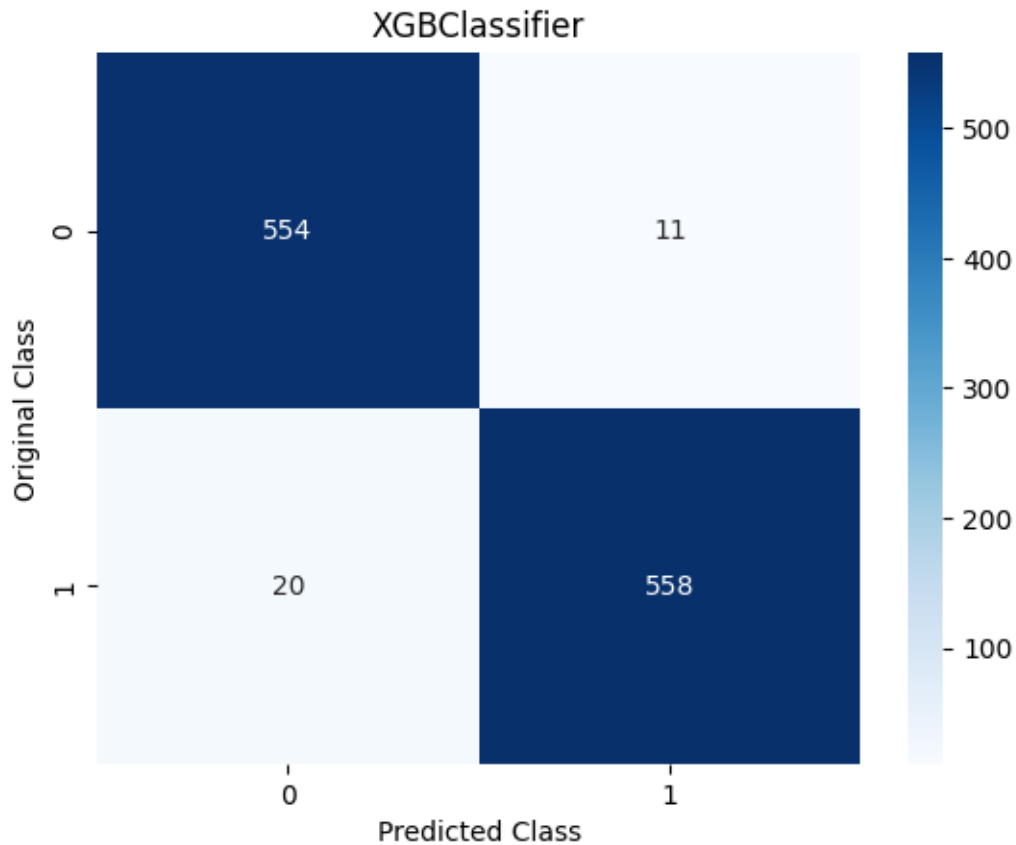
```
[ ]: print('The accuracy of XGBoost Classifier is: ', 100.0 *
      ↪accuracy_score(xgb_predict,y_test))
```

The accuracy of XGBoost Classifier is: 97.28783902012248

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

	precision	recall	f1-score	support
0	0.97	0.98	0.97	565
1	0.98	0.97	0.97	578
accuracy			0.97	1143
macro avg	0.97	0.97	0.97	1143
weighted avg	0.97	0.97	0.97	1143

```
[ ]: 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": [.1,.5,1],
    "n_estimators": [50,100,150,200,250]
}

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 15 candidates, totalling 150 fits
{'learning_rate': 0.5, 'n_estimators': 250}
GradientBoostingClassifier(learning_rate=0.5, n_estimators=250)
0.96675373317754

```
[ ]: 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)
```

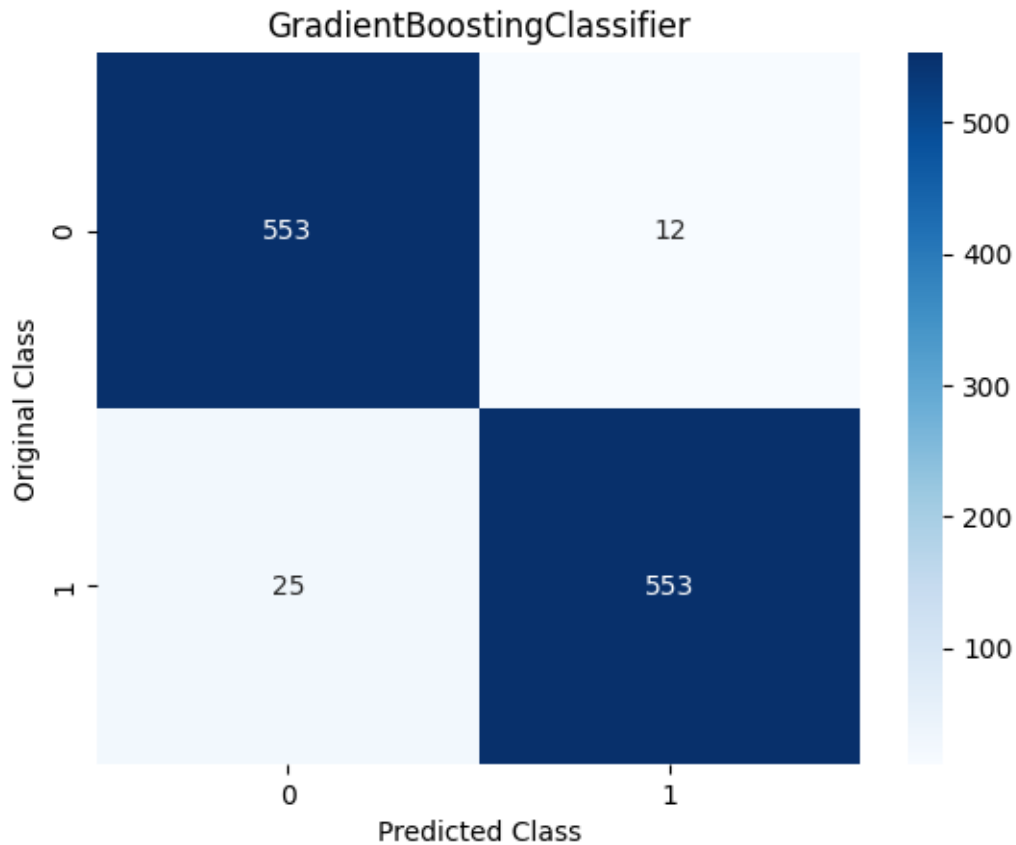
```
[ ]: print('The accuracy of GradientBoost Classifier is: ', 100.0 *  
      ↪accuracy_score(gbc_predict,y_test))
```

The accuracy of GradientBoost Classifier is: 96.76290463692038

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

	precision	recall	f1-score	support
0	0.96	0.98	0.97	565
1	0.98	0.96	0.97	578
accuracy			0.97	1143
macro avg	0.97	0.97	0.97	1143
weighted avg	0.97	0.97	0.97	1143

```
[ ]: 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": [50,100,150,200,250]
```

```

}

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 5 candidates, totalling 50 fits
{'base_estimator': DecisionTreeClassifier(), 'n_estimators': 100}
BaggingClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=100)
0.9603380373828241

```

```

[ ]: 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: 96.50043744531933

```

```

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

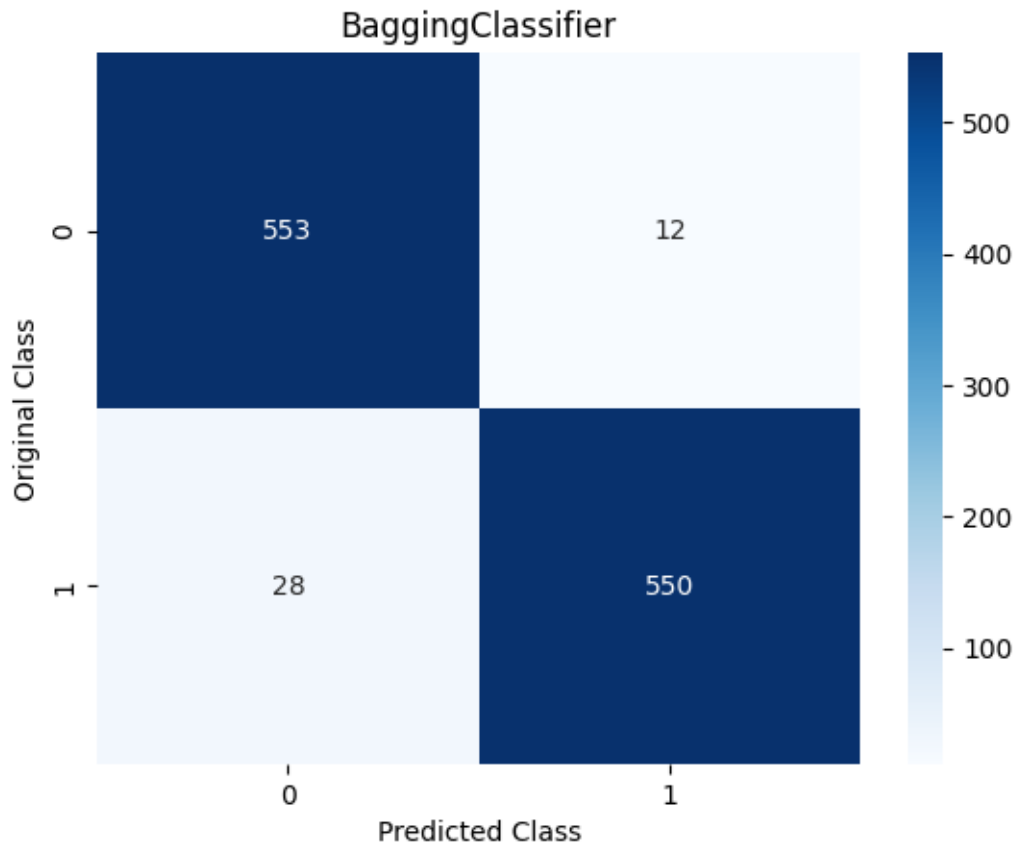
```

	precision	recall	f1-score	support
0	0.95	0.98	0.97	565
1	0.98	0.95	0.96	578
accuracy			0.97	1143
macro avg	0.97	0.97	0.97	1143
weighted avg	0.97	0.97	0.97	1143

```

[ ]: 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": [50,100,150,200,250]
}

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 5 candidates, totalling 50 fits
{'n_estimators': 50}
RandomForestClassifier(n_estimators=50)
0.966558991578844
```

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

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

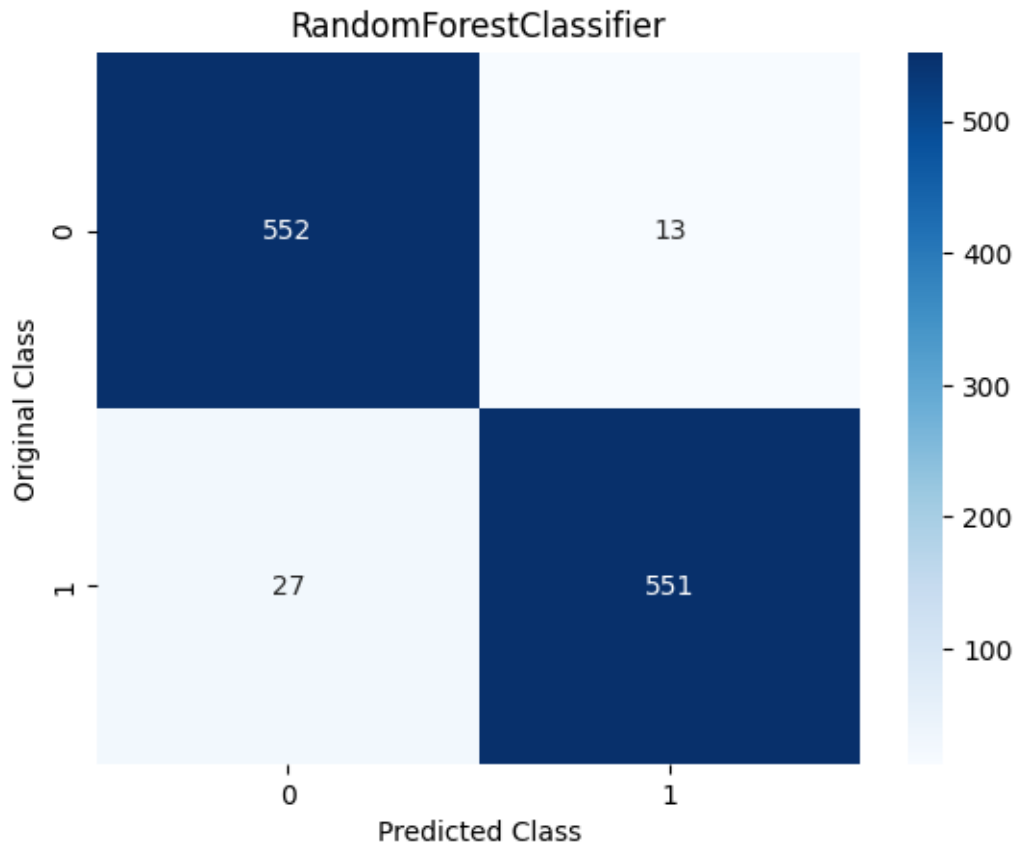
```
[ ]: print('The accuracy of RandomForest Classifier is: ' , 100.0 *
      ↪accuracy_score(rfc_predict,y_test))
```

The accuracy of RandomForest Classifier is: 96.50043744531933

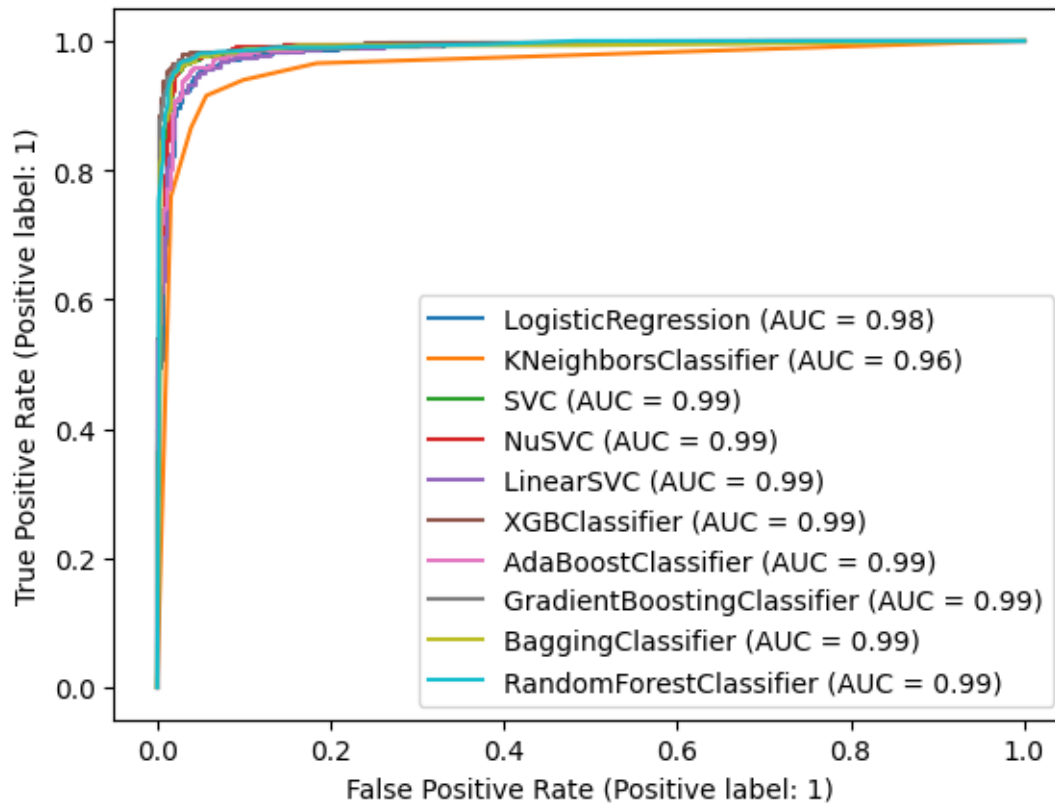
```
[ ]: print(classification_report(y_test, rfc_predict))
```

	precision	recall	f1-score	support
0	0.95	0.98	0.97	565
1	0.98	0.95	0.96	578
accuracy			0.97	1143
macro avg	0.97	0.97	0.97	1143
weighted avg	0.97	0.97	0.97	1143

```
[ ]: 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_2"

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 100)	68400
batch_normalization_2 (Batch Normalization)	(None, 100)	400

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 100)	68400
batch_normalization_2 (Batch Normalization)	(None, 100)	400
dense_8 (Dense)	(None, 50)	5050
dense_9 (Dense)	(None, 25)	1275
dense_10 (Dense)	(None, 10)	260
dense_11 (Dense)	(None, 1)	11

```

=====
Total params: 75,396
Trainable params: 75,196
Non-trainable params: 200

```

```

-----
Epoch 1/100
258/258 [=====] - 4s 7ms/step - loss: 0.2210 -
accuracy: 0.9147 - val_loss: 0.3899 - val_accuracy: 0.9354
Epoch 2/100
258/258 [=====] - 1s 5ms/step - loss: 0.1484 -
accuracy: 0.9451 - val_loss: 0.1934 - val_accuracy: 0.9407

```

Epoch 3/100
258/258 [=====] - 1s 4ms/step - loss: 0.1419 -
accuracy: 0.9474 - val_loss: 0.1482 - val_accuracy: 0.9431

Epoch 4/100
258/258 [=====] - 1s 4ms/step - loss: 0.1247 -
accuracy: 0.9542 - val_loss: 0.1507 - val_accuracy: 0.9436

Epoch 5/100
258/258 [=====] - 1s 5ms/step - loss: 0.1130 -
accuracy: 0.9581 - val_loss: 0.1470 - val_accuracy: 0.9500

Epoch 6/100
258/258 [=====] - 1s 5ms/step - loss: 0.1091 -
accuracy: 0.9593 - val_loss: 0.1406 - val_accuracy: 0.9538

Epoch 7/100
258/258 [=====] - 1s 5ms/step - loss: 0.0995 -
accuracy: 0.9628 - val_loss: 0.1394 - val_accuracy: 0.9529

Epoch 8/100
258/258 [=====] - 2s 6ms/step - loss: 0.0970 -
accuracy: 0.9642 - val_loss: 0.1573 - val_accuracy: 0.9451

Epoch 9/100
258/258 [=====] - 2s 9ms/step - loss: 0.0920 -
accuracy: 0.9649 - val_loss: 0.1477 - val_accuracy: 0.9485

Epoch 10/100
258/258 [=====] - 2s 7ms/step - loss: 0.0897 -
accuracy: 0.9676 - val_loss: 0.1491 - val_accuracy: 0.9553

Epoch 11/100
258/258 [=====] - 1s 6ms/step - loss: 0.0843 -
accuracy: 0.9699 - val_loss: 0.1524 - val_accuracy: 0.9495

Epoch 12/100
258/258 [=====] - 1s 5ms/step - loss: 0.0747 -
accuracy: 0.9727 - val_loss: 0.1497 - val_accuracy: 0.9524

Epoch 13/100
258/258 [=====] - 1s 5ms/step - loss: 0.0737 -
accuracy: 0.9711 - val_loss: 0.1569 - val_accuracy: 0.9490

Epoch 14/100
258/258 [=====] - 1s 5ms/step - loss: 0.0660 -
accuracy: 0.9764 - val_loss: 0.1734 - val_accuracy: 0.9529

Epoch 15/100
258/258 [=====] - 1s 5ms/step - loss: 0.0648 -
accuracy: 0.9780 - val_loss: 0.1723 - val_accuracy: 0.9504

Epoch 16/100
258/258 [=====] - 1s 5ms/step - loss: 0.0630 -
accuracy: 0.9759 - val_loss: 0.2005 - val_accuracy: 0.9397

Epoch 17/100
258/258 [=====] - 1s 5ms/step - loss: 0.0604 -
accuracy: 0.9774 - val_loss: 0.1811 - val_accuracy: 0.9504

Epoch 18/100
258/258 [=====] - 1s 5ms/step - loss: 0.0542 -
accuracy: 0.9784 - val_loss: 0.1820 - val_accuracy: 0.9543

Epoch 19/100
258/258 [=====] - 1s 5ms/step - loss: 0.0540 -
accuracy: 0.9797 - val_loss: 0.1865 - val_accuracy: 0.9470
Epoch 20/100
258/258 [=====] - 2s 6ms/step - loss: 0.0471 -
accuracy: 0.9830 - val_loss: 0.1838 - val_accuracy: 0.9524
Epoch 21/100
258/258 [=====] - 1s 6ms/step - loss: 0.0487 -
accuracy: 0.9818 - val_loss: 0.1788 - val_accuracy: 0.9500
Epoch 22/100
258/258 [=====] - 1s 5ms/step - loss: 0.0525 -
accuracy: 0.9790 - val_loss: 0.2012 - val_accuracy: 0.9470
Epoch 23/100
258/258 [=====] - 2s 6ms/step - loss: 0.0446 -
accuracy: 0.9825 - val_loss: 0.1896 - val_accuracy: 0.9529
Epoch 24/100
258/258 [=====] - 1s 6ms/step - loss: 0.0424 -
accuracy: 0.9834 - val_loss: 0.2089 - val_accuracy: 0.9519
Epoch 25/100
258/258 [=====] - 1s 5ms/step - loss: 0.0424 -
accuracy: 0.9831 - val_loss: 0.2121 - val_accuracy: 0.9538
Epoch 26/100
258/258 [=====] - 1s 5ms/step - loss: 0.0375 -
accuracy: 0.9849 - val_loss: 0.2280 - val_accuracy: 0.9490
Epoch 27/100
258/258 [=====] - 1s 5ms/step - loss: 0.0426 -
accuracy: 0.9829 - val_loss: 0.2188 - val_accuracy: 0.9500
Epoch 28/100
258/258 [=====] - 1s 6ms/step - loss: 0.0368 -
accuracy: 0.9854 - val_loss: 0.2173 - val_accuracy: 0.9475
Epoch 29/100
258/258 [=====] - 1s 5ms/step - loss: 0.0325 -
accuracy: 0.9872 - val_loss: 0.2149 - val_accuracy: 0.9529
Epoch 30/100
258/258 [=====] - 1s 5ms/step - loss: 0.0294 -
accuracy: 0.9888 - val_loss: 0.2250 - val_accuracy: 0.9514
Epoch 31/100
258/258 [=====] - 1s 5ms/step - loss: 0.0309 -
accuracy: 0.9882 - val_loss: 0.2242 - val_accuracy: 0.9543
Epoch 32/100
258/258 [=====] - 1s 5ms/step - loss: 0.0396 -
accuracy: 0.9854 - val_loss: 0.2473 - val_accuracy: 0.9514
Epoch 33/100
258/258 [=====] - 1s 6ms/step - loss: 0.0337 -
accuracy: 0.9876 - val_loss: 0.2101 - val_accuracy: 0.9475
Epoch 34/100
258/258 [=====] - 1s 6ms/step - loss: 0.0299 -
accuracy: 0.9885 - val_loss: 0.2320 - val_accuracy: 0.9524

Epoch 35/100
258/258 [=====] - 1s 5ms/step - loss: 0.0281 -
accuracy: 0.9894 - val_loss: 0.2328 - val_accuracy: 0.9485
Epoch 36/100
258/258 [=====] - 1s 5ms/step - loss: 0.0247 -
accuracy: 0.9903 - val_loss: 0.2422 - val_accuracy: 0.9490
Epoch 37/100
258/258 [=====] - 1s 6ms/step - loss: 0.0289 -
accuracy: 0.9889 - val_loss: 0.2358 - val_accuracy: 0.9543
Epoch 38/100
258/258 [=====] - 1s 5ms/step - loss: 0.0240 -
accuracy: 0.9920 - val_loss: 0.2798 - val_accuracy: 0.9480
Epoch 39/100
258/258 [=====] - 1s 5ms/step - loss: 0.0250 -
accuracy: 0.9897 - val_loss: 0.2342 - val_accuracy: 0.9577
Epoch 40/100
258/258 [=====] - 1s 6ms/step - loss: 0.0313 -
accuracy: 0.9892 - val_loss: 0.2376 - val_accuracy: 0.9563
Epoch 41/100
258/258 [=====] - 1s 5ms/step - loss: 0.0241 -
accuracy: 0.9902 - val_loss: 0.2619 - val_accuracy: 0.9538
Epoch 42/100
258/258 [=====] - 1s 5ms/step - loss: 0.0253 -
accuracy: 0.9914 - val_loss: 0.2630 - val_accuracy: 0.9524
Epoch 43/100
258/258 [=====] - 1s 5ms/step - loss: 0.0220 -
accuracy: 0.9915 - val_loss: 0.2718 - val_accuracy: 0.9529
Epoch 44/100
258/258 [=====] - 1s 5ms/step - loss: 0.0255 -
accuracy: 0.9900 - val_loss: 0.2693 - val_accuracy: 0.9388
Epoch 45/100
258/258 [=====] - 1s 5ms/step - loss: 0.0216 -
accuracy: 0.9925 - val_loss: 0.2737 - val_accuracy: 0.9490
Epoch 46/100
258/258 [=====] - 1s 5ms/step - loss: 0.0228 -
accuracy: 0.9919 - val_loss: 0.2525 - val_accuracy: 0.9485
Epoch 47/100
258/258 [=====] - 1s 5ms/step - loss: 0.0188 -
accuracy: 0.9922 - val_loss: 0.2632 - val_accuracy: 0.9514
Epoch 48/100
258/258 [=====] - 1s 5ms/step - loss: 0.0196 -
accuracy: 0.9933 - val_loss: 0.2750 - val_accuracy: 0.9475
Epoch 49/100
258/258 [=====] - 1s 6ms/step - loss: 0.0172 -
accuracy: 0.9936 - val_loss: 0.2858 - val_accuracy: 0.9466
Epoch 50/100
258/258 [=====] - 1s 5ms/step - loss: 0.0256 -
accuracy: 0.9902 - val_loss: 0.3053 - val_accuracy: 0.9529

Epoch 51/100
258/258 [=====] - 1s 5ms/step - loss: 0.0168 -
accuracy: 0.9933 - val_loss: 0.2780 - val_accuracy: 0.9461
Epoch 52/100
258/258 [=====] - 1s 5ms/step - loss: 0.0224 -
accuracy: 0.9909 - val_loss: 0.2795 - val_accuracy: 0.9519
Epoch 53/100
258/258 [=====] - 1s 5ms/step - loss: 0.0151 -
accuracy: 0.9948 - val_loss: 0.2857 - val_accuracy: 0.9587
Epoch 54/100
258/258 [=====] - 1s 5ms/step - loss: 0.0190 -
accuracy: 0.9927 - val_loss: 0.3132 - val_accuracy: 0.9480
Epoch 55/100
258/258 [=====] - 1s 5ms/step - loss: 0.0190 -
accuracy: 0.9926 - val_loss: 0.3099 - val_accuracy: 0.9519
Epoch 56/100
258/258 [=====] - 1s 6ms/step - loss: 0.0141 -
accuracy: 0.9940 - val_loss: 0.3071 - val_accuracy: 0.9514
Epoch 57/100
258/258 [=====] - 1s 5ms/step - loss: 0.0162 -
accuracy: 0.9942 - val_loss: 0.3234 - val_accuracy: 0.9524
Epoch 58/100
258/258 [=====] - 1s 5ms/step - loss: 0.0167 -
accuracy: 0.9938 - val_loss: 0.2958 - val_accuracy: 0.9519
Epoch 59/100
258/258 [=====] - 1s 6ms/step - loss: 0.0131 -
accuracy: 0.9951 - val_loss: 0.3259 - val_accuracy: 0.9524
Epoch 60/100
258/258 [=====] - 1s 5ms/step - loss: 0.0199 -
accuracy: 0.9930 - val_loss: 0.2970 - val_accuracy: 0.9461
Epoch 61/100
258/258 [=====] - 1s 5ms/step - loss: 0.0192 -
accuracy: 0.9932 - val_loss: 0.2989 - val_accuracy: 0.9495
Epoch 62/100
258/258 [=====] - 1s 5ms/step - loss: 0.0146 -
accuracy: 0.9950 - val_loss: 0.3702 - val_accuracy: 0.9519
Epoch 63/100
258/258 [=====] - 1s 5ms/step - loss: 0.0150 -
accuracy: 0.9956 - val_loss: 0.3195 - val_accuracy: 0.9509
Epoch 64/100
258/258 [=====] - 1s 5ms/step - loss: 0.0191 -
accuracy: 0.9931 - val_loss: 0.3856 - val_accuracy: 0.9354
Epoch 65/100
258/258 [=====] - 1s 5ms/step - loss: 0.0161 -
accuracy: 0.9954 - val_loss: 0.2875 - val_accuracy: 0.9500
Epoch 66/100
258/258 [=====] - 1s 5ms/step - loss: 0.0118 -
accuracy: 0.9960 - val_loss: 0.3297 - val_accuracy: 0.9514

Epoch 67/100
258/258 [=====] - 1s 5ms/step - loss: 0.0137 -
accuracy: 0.9954 - val_loss: 0.2901 - val_accuracy: 0.9553
Epoch 68/100
258/258 [=====] - 1s 5ms/step - loss: 0.0214 -
accuracy: 0.9925 - val_loss: 0.2971 - val_accuracy: 0.9514
Epoch 69/100
258/258 [=====] - 1s 5ms/step - loss: 0.0093 -
accuracy: 0.9967 - val_loss: 0.3122 - val_accuracy: 0.9524
Epoch 70/100
258/258 [=====] - 1s 5ms/step - loss: 0.0143 -
accuracy: 0.9948 - val_loss: 0.3280 - val_accuracy: 0.9490
Epoch 71/100
258/258 [=====] - 1s 5ms/step - loss: 0.0141 -
accuracy: 0.9953 - val_loss: 0.3149 - val_accuracy: 0.9500
Epoch 72/100
258/258 [=====] - 1s 5ms/step - loss: 0.0123 -
accuracy: 0.9955 - val_loss: 0.3355 - val_accuracy: 0.9446
Epoch 73/100
258/258 [=====] - 1s 5ms/step - loss: 0.0147 -
accuracy: 0.9947 - val_loss: 0.3103 - val_accuracy: 0.9509
Epoch 74/100
258/258 [=====] - 1s 5ms/step - loss: 0.0093 -
accuracy: 0.9959 - val_loss: 0.3537 - val_accuracy: 0.9495
Epoch 75/100
258/258 [=====] - 1s 6ms/step - loss: 0.0177 -
accuracy: 0.9936 - val_loss: 0.3043 - val_accuracy: 0.9524
Epoch 76/100
258/258 [=====] - 1s 5ms/step - loss: 0.0089 -
accuracy: 0.9976 - val_loss: 0.3207 - val_accuracy: 0.9534
Epoch 77/100
258/258 [=====] - 1s 5ms/step - loss: 0.0113 -
accuracy: 0.9965 - val_loss: 0.3377 - val_accuracy: 0.9534
Epoch 78/100
258/258 [=====] - 1s 6ms/step - loss: 0.0160 -
accuracy: 0.9957 - val_loss: 0.3656 - val_accuracy: 0.9451
Epoch 79/100
258/258 [=====] - 1s 5ms/step - loss: 0.0085 -
accuracy: 0.9971 - val_loss: 0.3506 - val_accuracy: 0.9461
Epoch 80/100
258/258 [=====] - 1s 5ms/step - loss: 0.0164 -
accuracy: 0.9955 - val_loss: 0.3584 - val_accuracy: 0.9490
Epoch 81/100
258/258 [=====] - 1s 6ms/step - loss: 0.0174 -
accuracy: 0.9948 - val_loss: 0.2978 - val_accuracy: 0.9485
Epoch 82/100
258/258 [=====] - 1s 5ms/step - loss: 0.0094 -
accuracy: 0.9964 - val_loss: 0.3359 - val_accuracy: 0.9475

Epoch 83/100
258/258 [=====] - 1s 5ms/step - loss: 0.0110 -
accuracy: 0.9955 - val_loss: 0.3412 - val_accuracy: 0.9504
Epoch 84/100
258/258 [=====] - 1s 6ms/step - loss: 0.0072 -
accuracy: 0.9974 - val_loss: 0.3441 - val_accuracy: 0.9500
Epoch 85/100
258/258 [=====] - 1s 5ms/step - loss: 0.0113 -
accuracy: 0.9959 - val_loss: 0.3178 - val_accuracy: 0.9466
Epoch 86/100
258/258 [=====] - 1s 5ms/step - loss: 0.0133 -
accuracy: 0.9957 - val_loss: 0.3655 - val_accuracy: 0.9451
Epoch 87/100
258/258 [=====] - 1s 6ms/step - loss: 0.0116 -
accuracy: 0.9962 - val_loss: 0.3445 - val_accuracy: 0.9500
Epoch 88/100
258/258 [=====] - 1s 5ms/step - loss: 0.0116 -
accuracy: 0.9949 - val_loss: 0.3540 - val_accuracy: 0.9466
Epoch 89/100
258/258 [=====] - 1s 5ms/step - loss: 0.0123 -
accuracy: 0.9961 - val_loss: 0.3467 - val_accuracy: 0.9509
Epoch 90/100
258/258 [=====] - 1s 5ms/step - loss: 0.0080 -
accuracy: 0.9968 - val_loss: 0.3480 - val_accuracy: 0.9509
Epoch 91/100
258/258 [=====] - 1s 5ms/step - loss: 0.0091 -
accuracy: 0.9971 - val_loss: 0.3660 - val_accuracy: 0.9495
Epoch 92/100
258/258 [=====] - 1s 5ms/step - loss: 0.0084 -
accuracy: 0.9967 - val_loss: 0.3310 - val_accuracy: 0.9538
Epoch 93/100
258/258 [=====] - 1s 5ms/step - loss: 0.0041 -
accuracy: 0.9984 - val_loss: 0.3616 - val_accuracy: 0.9553
Epoch 94/100
258/258 [=====] - 1s 5ms/step - loss: 0.0057 -
accuracy: 0.9983 - val_loss: 0.3703 - val_accuracy: 0.9509
Epoch 95/100
258/258 [=====] - 1s 5ms/step - loss: 0.0093 -
accuracy: 0.9971 - val_loss: 0.3870 - val_accuracy: 0.9524
Epoch 96/100
258/258 [=====] - 1s 6ms/step - loss: 0.0128 -
accuracy: 0.9961 - val_loss: 0.3676 - val_accuracy: 0.9529
Epoch 97/100
258/258 [=====] - 1s 5ms/step - loss: 0.0126 -
accuracy: 0.9955 - val_loss: 0.3641 - val_accuracy: 0.9490
Epoch 98/100
258/258 [=====] - 1s 5ms/step - loss: 0.0095 -
accuracy: 0.9974 - val_loss: 0.3794 - val_accuracy: 0.9548

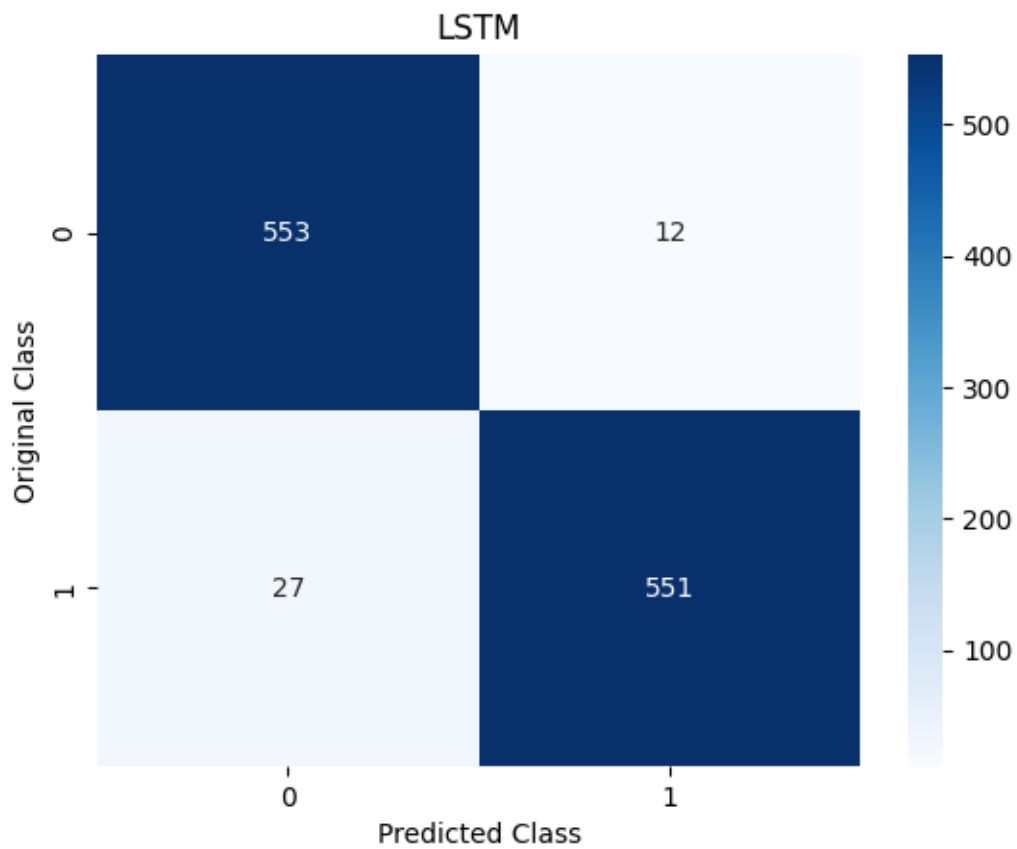
```
Epoch 99/100
258/258 [=====] - 1s 5ms/step - loss: 0.0094 -
accuracy: 0.9968 - val_loss: 0.3477 - val_accuracy: 0.9519
Epoch 100/100
258/258 [=====] - 1s 5ms/step - loss: 0.0135 -
accuracy: 0.9957 - val_loss: 0.3468 - val_accuracy: 0.9529
Test results - Loss: 0.27952027320861816 - Accuracy: 96.58792614936829%
```

```
[ ]: 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))
```

```
36/36 [=====] - 1s 2ms/step
```

	precision	recall	f1-score	support
0	0.95	0.98	0.97	565
1	0.98	0.95	0.97	578
accuracy			0.97	1143
macro avg	0.97	0.97	0.97	1143
weighted avg	0.97	0.97	0.97	1143

```
[ ]: 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()
```

