5_More_Supervised_Models

June 5, 2024

1 Supervised Learning Algorithms

In this notebook, several supervised learning algorithms are used to create binary classifiers that distinguish between benign and malicious traffics in the ids-2017 dataset. Hyperparameters are optimized to obtain a model with the best results and the models are compared

[1]:
```
from notebook_utils import load_processed_dataset_2017, plot_confusion_matrix,␣
↪metrics_report, upsample_dataset, extract_and_plot_metrics
from sklearn.decomposition import PCA

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import glob
import os
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, average_precision_score,␣
↪make_scorer, precision_score, accuracy_score, confusion_matrix
from notebook_utils import upsample_dataset
%matplotlib inline
%load_ext autoreload
%autoreload 2
file_path =␣
↪r"CIC-IDS-2017\CSVs\GeneratedLabelledFlows\TrafficLabelling\processed\ids2017_processed.
↪csv"
```

[2]:
```
X_train, Y_train, X_eval, Y_eval, X_test, Y_test, scaler =␣
↪load_processed_dataset_2017(file_path)
```

[3]:
```
performance_models = {}
```

[4]:
```
import joblib

def save_model(model, model_name):
    file_path = f'models/{model_name}.pkl'
    joblib.dump(model, file_path)
```

```
    print(f'Model saved to {file_path}')

def load_model(model_name):
    file_path = f'models/{model_name}.pkl'
    model = joblib.load(file_path)
    print(f'Model loaded from {file_path}')
    return model

os.makedirs('models', exist_ok=True)
```

1.1 1. Naive Bayes

[5]:

```
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV

# Define a small parameter grid
param_grid_nb = {
    'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5]
}

# Initialize the GaussianNB model
nb_model = GaussianNB()

# Initialize GridSearchCV
grid_search_nb = GridSearchCV(estimator=nb_model, param_grid=param_grid_nb,␣
 ↪scoring='accuracy', n_jobs=2, cv=2, verbose=2)

# Fit the model on the scaled training data
grid_search_nb.fit(scaler.transform(X_train), Y_train.is_attack)

# Get the best model
best_nb_model = grid_search_nb.best_estimator_
save_model(best_nb_model, 'gaussian_nb_model.pkl')
```

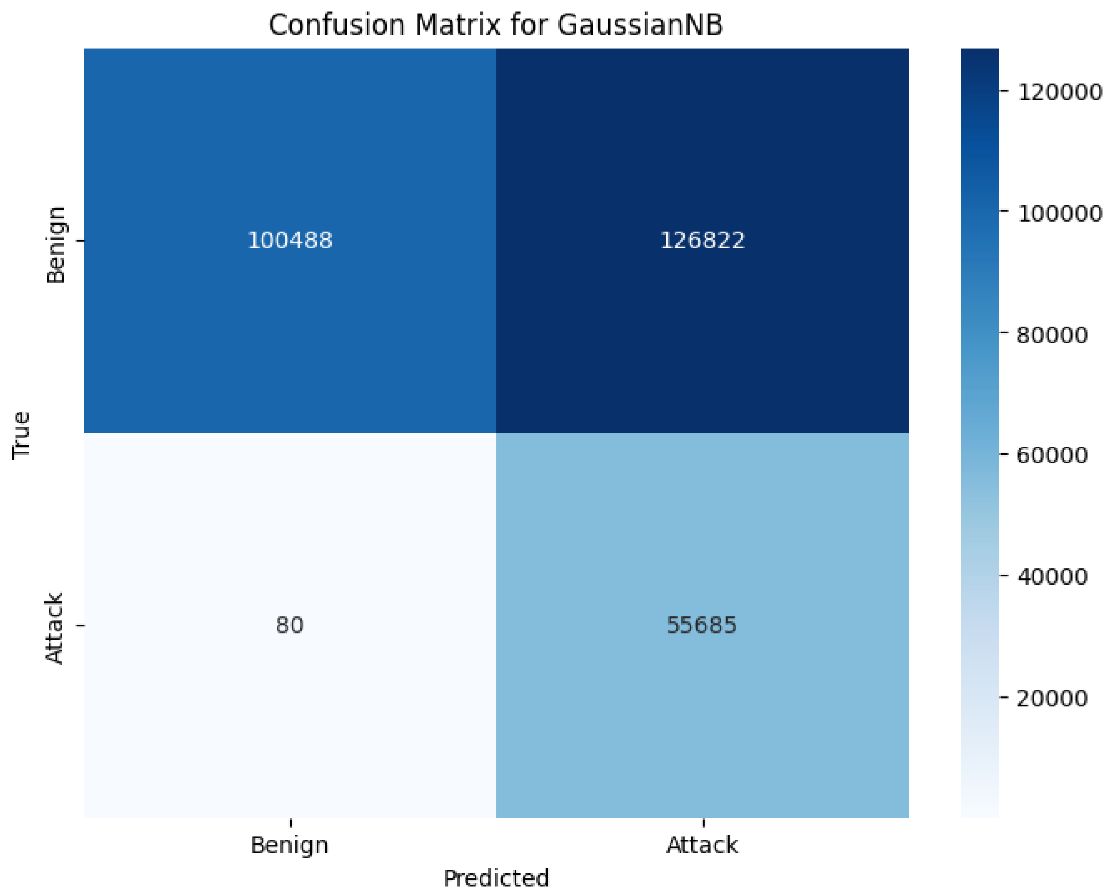
```
Fitting 2 folds for each of 5 candidates, totalling 10 fits
Model saved to models/gaussian_nb_model.pkl.pkl
```

[6]:

```
# Predict and evaluate on the evaluation set
print("Evaluation Set Performance")
metrics_report("Evaluation", Y_eval.is_attack, best_nb_model.predict(scaler.
 ↪transform(X_eval)), print_avg=False)

# Predict and evaluate on the test set
print("Test Set Performance")
Y_pred = best_nb_model.predict(scaler.transform(X_test))
performance_models["GaussianNB"] = metrics_report("Test", Y_test.is_attack,␣
 ↪Y_pred, print_avg=False)
```

```python
plot_confusion_matrix("GaussianNB", Y_test, Y_pred)
```

```
Evaluation Set Performance
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9992    0.4445    0.6153    227310
           1     0.3060    0.9985    0.4685     55764

    accuracy                         0.5537    283074
   macro avg     0.6526    0.7215    0.5419    283074
weighted avg     0.8626    0.5537    0.5864    283074

Accuracy: 0.5536714781293938
Test Set Performance
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9992    0.4421    0.6130    227310
           1     0.3051    0.9986    0.4674     55765

    accuracy                         0.5517    283075
   macro avg     0.6522    0.7203    0.5402    283075
weighted avg     0.8625    0.5517    0.5843    283075

Accuracy: 0.5517018458005829
```



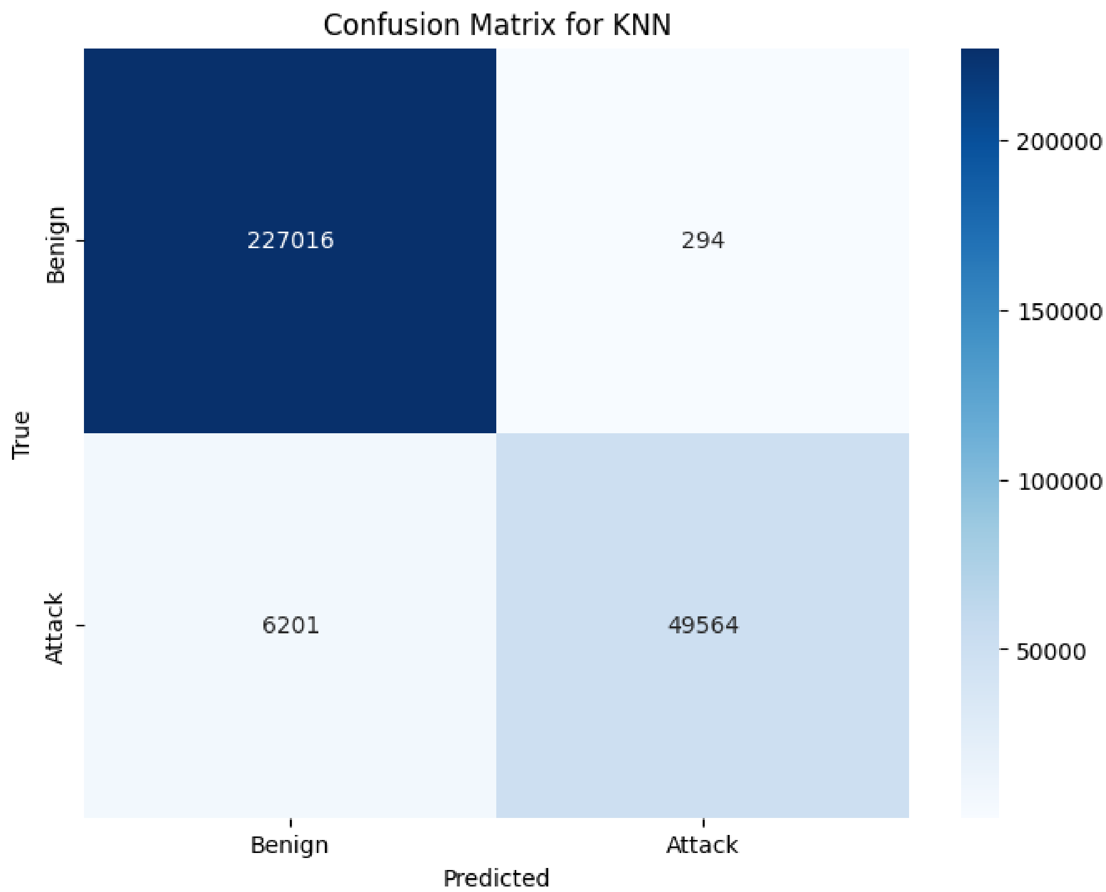
[15]:
```
performance_models["GaussianNB"] = metrics_report("Test", Y_test.is_attack,
    Y_pred, print_avg=False)
```

```
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9446    0.6808    0.7913    227310
           1     0.3916    0.8373    0.5336     55765

    accuracy                         0.7117    283075
   macro avg     0.6681    0.7591    0.6625    283075
weighted avg     0.8357    0.7117    0.7406    283075

Accuracy: 0.7116559215755541
```

1.2 2. K-Nearest Neighbors (KNN)

[8]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(scaler.transform(X_train), Y_train.is_attack)

# Predict and evaluate on the evaluation set
print("Evaluation Set Performance")
metrics_report("Evaluation", Y_eval.is_attack, knn_model.predict(scaler.
 ↪transform(X_eval)), print_avg=False)

# Predict and evaluate on the test set
print("Test Set Performance")
Y_pred = knn_model.predict(scaler.transform(X_test))
performance_models["KNN"] = metrics_report("Test", Y_test.is_attack, Y_pred,␣
 ↪print_avg=False)
plot_confusion_matrix("KNN", Y_test, Y_pred)

save_model(knn_model, 'knn_model')
```

```
Evaluation Set Performance
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9735    0.9986    0.9858    227310
           1     0.9934    0.8890    0.9383     55764

    accuracy                         0.9770    283074
   macro avg     0.9834    0.9438    0.9621    283074
weighted avg     0.9774    0.9770    0.9765    283074

Accuracy: 0.9769742187555197
Test Set Performance
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9734    0.9987    0.9859    227310
           1     0.9941    0.8888    0.9385     55765

    accuracy                         0.9771    283075
   macro avg     0.9838    0.9438    0.9622    283075
weighted avg     0.9775    0.9771    0.9766    283075

Accuracy: 0.9770555506491213
```




```
Model saved to models/knn_model.pkl
```

[14]:
```
performance_models["KNN"] = metrics_report("Test", Y_test.is_attack, Y_pred,␣
↪print_avg=False)
```

```
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9446    0.6808    0.7913    227310
           1     0.3916    0.8373    0.5336     55765

    accuracy                         0.7117    283075
   macro avg     0.6681    0.7591    0.6625    283075
weighted avg     0.8357    0.7117    0.7406    283075

Accuracy: 0.7116559215755541
```

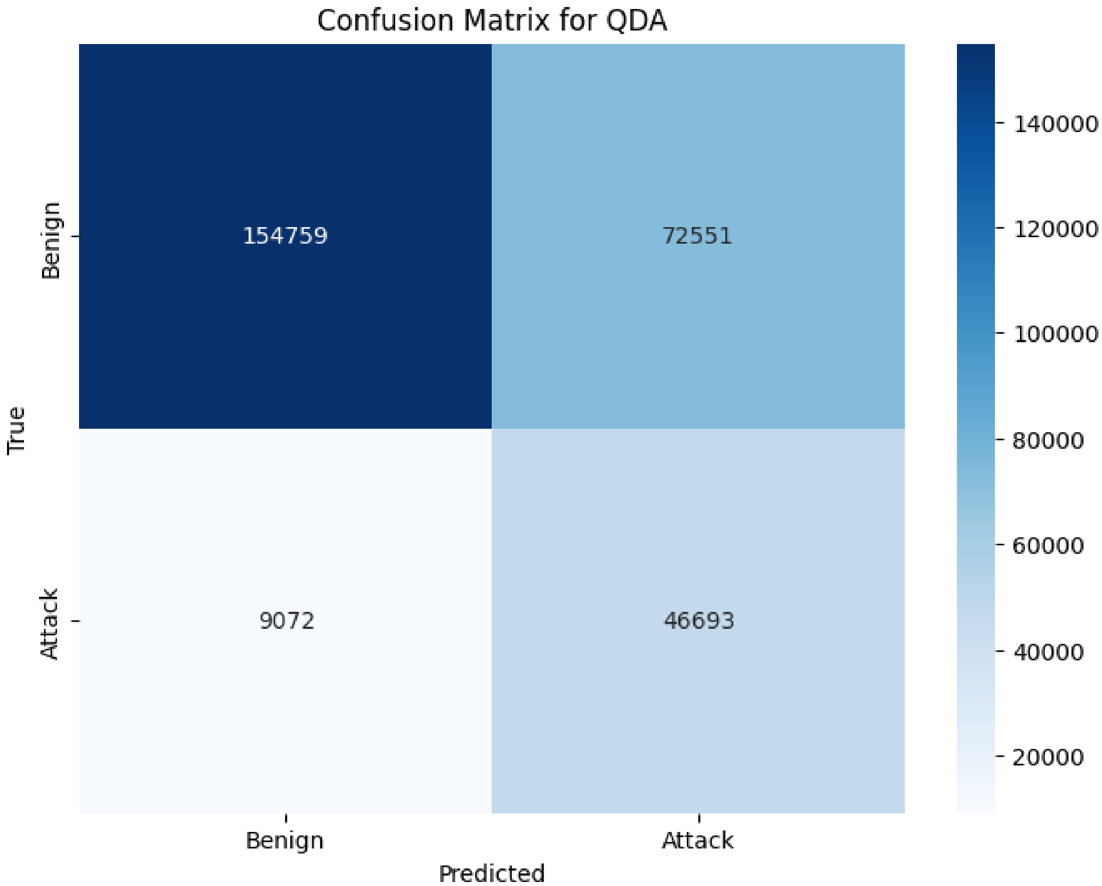
1.3 3. Quadratic Discriminant Analysis (QDA)

[9]:
```
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.model_selection import GridSearchCV
# Apply PCA
pca = PCA(n_components=0.90)
X_train_pca = pca.fit_transform(scaler.transform(X_train))
X_eval_pca = pca.transform(scaler.transform(X_eval))
X_test_pca = pca.transform(scaler.transform(X_test))
# Define a small parameter grid
param_grid_qda = {
    'reg_param': [0.0, 0.1, 0.2, 0.3],
    'tol': [1e-4, 1e-5, 1e-6]
}

# Initialize the QDA model
qda_model = QuadraticDiscriminantAnalysis()

# Initialize GridSearchCV with reduced number of folds
grid_search_qda = GridSearchCV(estimator=qda_model, param_grid=param_grid_qda,␣
↪scoring='accuracy', n_jobs=2, cv=2, verbose=2)

# Fit the model on the PCA-transformed training data
grid_search_qda.fit(X_train_pca, Y_train.is_attack)

# Get the best model
best_qda_model = grid_search_qda.best_estimator_

# Print the best hyperparameters
print("Best Hyperparameters for QDA:", grid_search_qda.best_params_)
save_model(best_qda_model, 'qda_model.pkl')
```

```
Fitting 2 folds for each of 12 candidates, totalling 24 fits
Best Hyperparameters for QDA: {'reg_param': 0.3, 'tol': 0.0001}
Model saved to models/qda_model.pkl.pkl
```

[10]:
```
# Predict and evaluate on the evaluation set
print("Evaluation Set Performance")
metrics_report("Evaluation", Y_eval.is_attack, best_qda_model.
↪predict(X_eval_pca), print_avg=False)

# Predict and evaluate on the test set
print("Test Set Performance")
Y_pred = best_qda_model.predict(X_test_pca)
performance_models["QDA"] = metrics_report("Test", Y_test.is_attack, Y_pred,␣
↪print_avg=False)
plot_confusion_matrix("QDA", Y_test, Y_pred)
```

```
Evaluation Set Performance
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9444    0.6844    0.7936    227310
           1     0.3938    0.8357    0.5353     55764

    accuracy                         0.7142    283074
   macro avg     0.6691    0.7600    0.6645    283074
weighted avg     0.8359    0.7142    0.7427    283074

Accuracy: 0.7141772116125112
Test Set Performance
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9446    0.6808    0.7913    227310
           1     0.3916    0.8373    0.5336     55765

    accuracy                         0.7117    283075
   macro avg     0.6681    0.7591    0.6625    283075
weighted avg     0.8357    0.7117    0.7406    283075

Accuracy: 0.7116559215755541
```



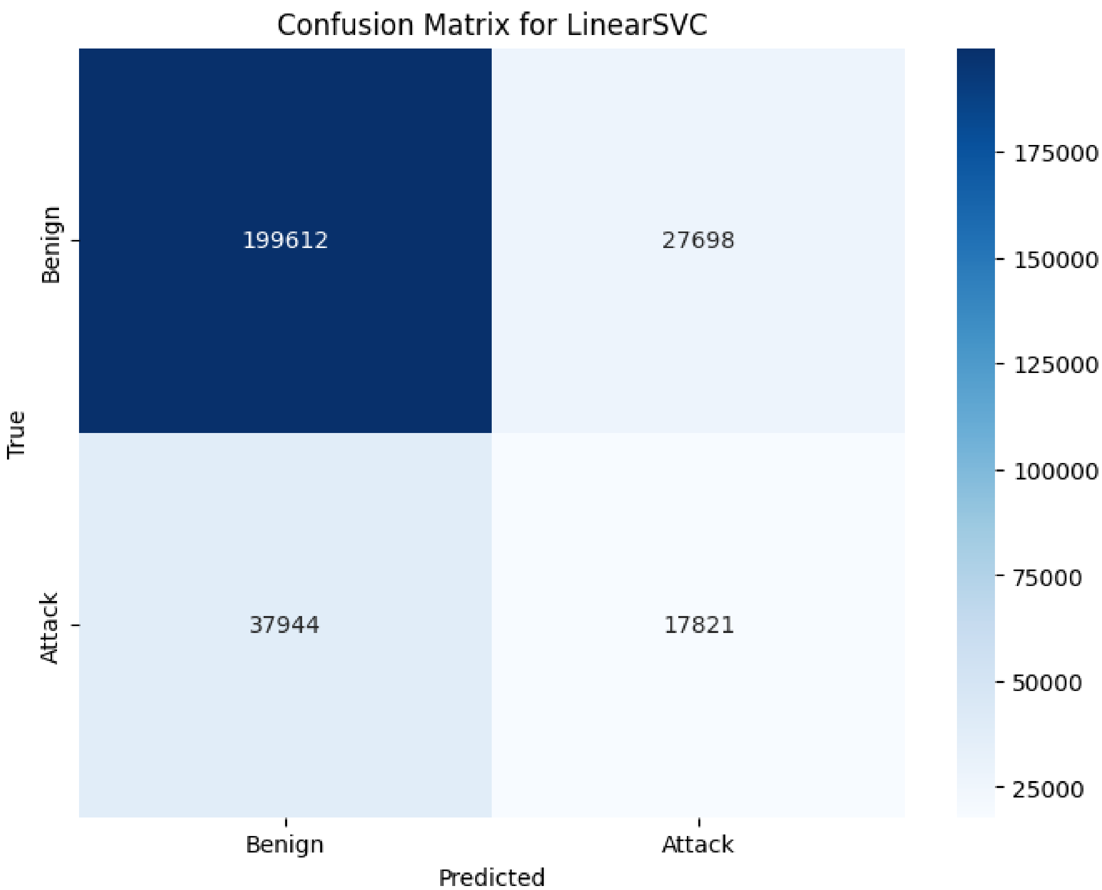
1.4 4. Support Vector Machine

The SVM takes too long with the number of features and number of training examples. PCA components are used to reduce the number of features.

[11]:
```
from sklearn.svm import LinearSVC
from sklearn.decomposition import PCA
import joblib
import os

# Apply PCA to reduce the number of features
pca = PCA(n_components=5)
X_train_pca = pca.fit_transform(X_train)
X_eval_pca = pca.transform(X_eval)
X_test_pca = pca.transform(X_test)

# Define the LinearSVC model with chosen hyperparameters
linear_svc_model = LinearSVC(C=1, max_iter=10000, dual="auto")
```

```
# Fit the model on the training data
linear_svc_model.fit(X_train_pca, Y_train.is_attack)

# Save the model
save_model(linear_svc_model, 'linear_svc_binary_pca')

# Evaluate the model
# Predict on the evaluation set
y_pred_eval = linear_svc_model.predict(X_eval_pca)
performance_eval = metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval,␣
↪print_avg=False)

# Predict and evaluate on the test set
y_pred_test = linear_svc_model.predict(X_test_pca)
performance_models["LinearSVC"] = metrics_report("Test", Y_test.is_attack,␣
↪y_pred_test, print_avg=False)

# Plot the confusion matrix
plot_confusion_matrix("LinearSVC", Y_test, y_pred_test)
```

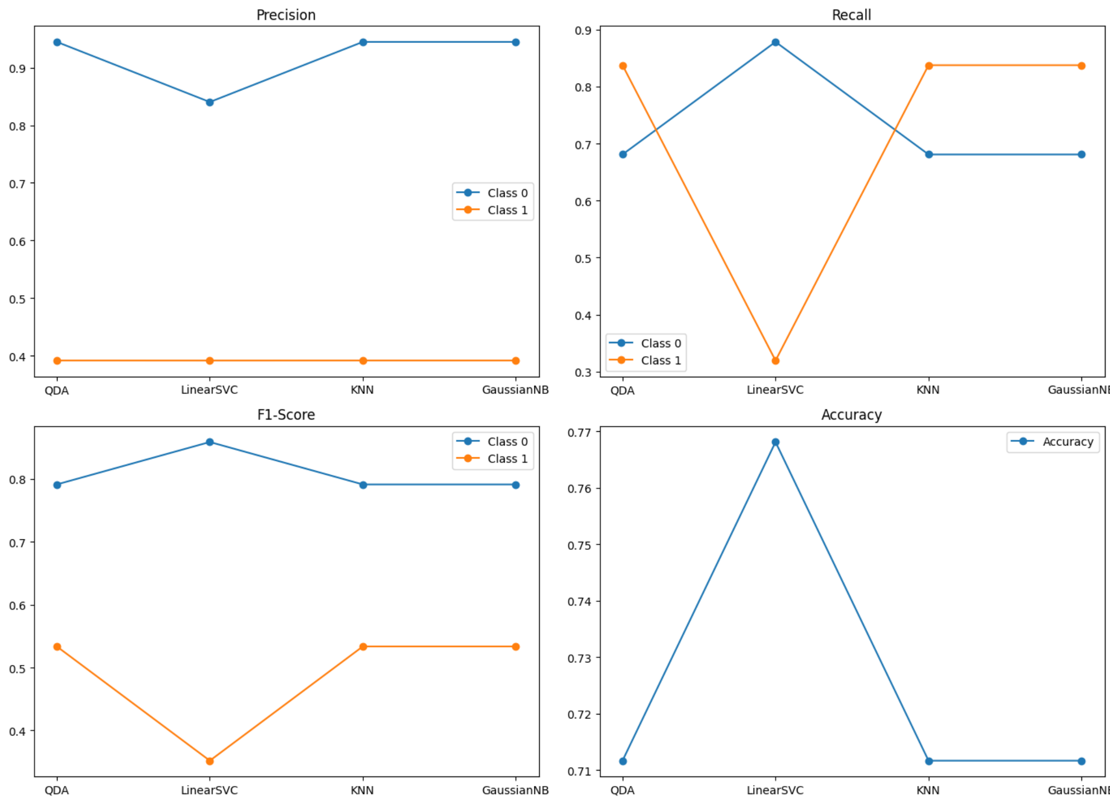
```
Model saved to models/linear_svc_binary_pca.pkl
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.8403    0.8796    0.8595    227310
           1     0.3935    0.3186    0.3521     55764

    accuracy                         0.7690    283074
   macro avg     0.6169    0.5991    0.6058    283074
weighted avg     0.7523    0.7690    0.7595    283074

Accuracy: 0.7690497891010831
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.8403    0.8781    0.8588    227310
           1     0.3915    0.3196    0.3519     55765

    accuracy                         0.7681    283075
   macro avg     0.6159    0.5989    0.6053    283075
weighted avg     0.7519    0.7681    0.7589    283075

Accuracy: 0.7681109246666078
```



1.5 5. Conclusion

[16]:
```
extract_and_plot_metrics(performance_models)
```

```
[0.7116559215755541, 0.7681109246666078, 0.7116559215755541, 0.7116559215755541]
['QDA', 'LinearSVC', 'KNN', 'GaussianNB']
```



In conclusion, the models used perfrom worse than the tree based and deep neural networks. Therefore, they won't be tested with the ids2018 dataset.