3_classification_allApp

December 20, 2024

[1]:
```
import os  # For interacting with the file system
import pandas as pd  # For handling dataframes and CSVs
import numpy as np
from elasticsearch import helpers, Elasticsearch
from datetime import datetime
from tqdm import tqdm  # Import tqdm for progress tracking
```

[2]:
```
# Retrieve authentication information for Elasticsearch
elastic_host = "https://localhost"
elastic_port = "9200"
elastic_user = "admin"
elastic_password = "motdepasse"
elastic_ca_path = "C:\\elasticsearch-8.15.2\\config\\certs\\http_ca.crt"

# Connect to Elasticsearch
es = Elasticsearch(
     hosts=[f"{elastic_host}:{elastic_port}"],
     basic_auth=(elastic_user, elastic_password),
     ca_certs=elastic_ca_path,
     verify_certs=True
)
print(es.info())

# Check connection
if es.ping():
     print("Connected to Elasticsearch")
else:
     print("Failed to connect to Elasticsearch")
```


```
{'name': 'MSI', 'cluster_name': 'elasticsearch', 'cluster_uuid': 'ylmZI0lnRpa-
pP1lwEKJ7A', 'version': {'number': '8.15.2', 'build_flavor': 'default',
'build_type': 'zip', 'build_hash': '98adf7bf6bb69b66ab95b761c9e5aadb0bb059a3',
'build_date': '2024-09-19T10:06:03.564235954Z', 'build_snapshot': False,
'lucene_version': '9.11.1', 'minimum_wire_compatibility_version': '7.17.0',
'minimum_index_compatibility_version': '7.0.0'}, 'tagline': 'You Know, for
Search'}
```


```
Connected to Elasticsearch
```

[3]:
```python
def fetch_flows_from_elasticsearch(index_name):
     data = []

     # Define the body with a filter on application_name
     body = {
          "query": {
                "match_all": {}
          }
     }

     res = helpers.scan(
                         client=es,
                         scroll='2m',
                         query=body,
                         index=index_name)

     for i in res:
          data.append(i['_source'])

     # Converting into a Pandas dataframe
     df = pd.DataFrame(data)

     # Print the dataframe
     print(f"Network data : \n{df}")
     return df
```

[4]:
```python
df = fetch_flows_from_elasticsearch("network_flows_fan_encoded_final")
```

```
Network data :
        application_name  bidirectional_packets  bidirectional_bytes  \
0                    NFS              -0.433819            -0.272394
1                Unknown              -0.237225            -0.250029
2                    DNS              -0.454513            -0.276022
3                Unknown              -0.371737            -0.224462
4                Unknown              -0.237225            -0.250029
…                    …                    …                    …
1029442             HTTP              -0.371737            -0.220867
1029443              NFS              -0.433819            -0.272394
1029444              DNS              -0.454513            -0.275865
1029445              DNS              -0.454513            -0.275865
1029446          eDonkey              -0.133755            -0.178255

         bidirectional_mean_ps  bidirectional_stddev_ps  src2dst_mean_ps  \
0                    -0.737396                -1.074570         0.082442
1                    -0.823956                -0.812812        -0.246282
2                    -0.917929                -1.172192        -0.388936
3                     1.029816                 1.308895        -0.469566
4                    -0.823956                -0.812812        -0.246282
```

```
…                        …                       …               …
1029442           1.190791                1.308721       -0.181778
1029443          -0.737396               -1.074570        0.082442
1029444          -0.882825               -1.172192       -0.345519
1029445          -0.882825               -1.172192       -0.345519
1029446          -0.015266                0.529262       -0.385652

         src2dst_stddev_ps  dst2src_mean_ps  dst2src_stddev_ps  \
0                -0.498647        -0.792754          -1.018579
1                -0.061147        -0.739314          -0.596313
2                -0.498647        -0.780987          -1.026838
3                -0.488259         1.140897           1.539029
4                -0.061147        -0.739314          -0.596313
…                      …                …                  …
1029442           0.050219         1.594697           1.554270
1029443          -0.498647        -0.792754          -1.018579
1029444          -0.498647        -0.760396          -1.026838
1029445          -0.498647        -0.760396          -1.026838
1029446          -0.370743         0.310920           1.043662

         bidirectional_mean_piat_ms  …  protocol_6  protocol_17  \
0                         -0.049343  …       False         True
1                         -0.051211  …        True        False
2                         -0.050617  …       False         True
3                         -0.046452  …        True        False
4                         -0.051285  …        True        False
…                               …   …        …            …
1029442                   -0.013548  …        True        False
1029443                   -0.049343  …       False         True
1029444                   -0.049502  …       False         True
1029445                   -0.050617  …       False         True
1029446                   -0.050137  …        True        False

         protocol_89  protocol_132  src_port_class_Dynamic  \
0              False         False                    True
1              False         False                   False
2              False         False                   False
3              False         False                   False
4              False         False                   False
…              …            …                      …
1029442        False         False                   False
1029443        False         False                   False
1029444        False         False                   False
1029445        False         False                   False
1029446        False         False                   False

         src_port_class_Registered  src_port_class_WellKnown  \
0                            False                     False
```

```
1                               True                      False
2                               True                      False
3                               True                      False
4                               True                      False
…                               …                        …
1029442                         True                      False
1029443                         True                      False
1029444                         True                      False
1029445                         True                      False
1029446                         True                      False

         dst_port_class_Dynamic  dst_port_class_Registered  \
0                         False                      False
1                         False                       True
2                         False                      False
3                         False                       True
4                         False                       True
…                         …                        …
1029442                   False                      False
1029443                   False                      False
1029444                   False                      False
1029445                   False                      False
1029446                   False                       True

         dst_port_class_WellKnown
0                            True
1                           False
2                            True
3                           False
4                           False
…                           …
1029442                      True
1029443                      True
1029444                      True
1029445                      True
1029446                     False

[1029447 rows x 40 columns]
```

[5]:
```python
from sklearn.model_selection import train_test_split, StratifiedKFold

# Assuming 'application_name' is the target column in df_http for stratification
# Separate features and target
X = df.drop(columns=["label"])  # Features
y = df["label"]  # Target variable

# Step 1: Split data into 80% train and 20% test, with stratification
```

```
X_train, X_test, y_train, y_test = train_test_split(
     X, y, test_size=0.2, stratify=y, random_state=42
)
```

[14]:
```
df["label"].value_counts()
```

[14]:
```
label
0    1021443
1       8004
Name: count, dtype: int64
```

[15]:
```
y_test.value_counts()
```

[15]:
```
label
0    204289
1      1601
Name: count, dtype: int64
```

[35]:
```
from sklearn.preprocessing import LabelEncoder
X_train['application_name'] = LabelEncoder().
 ↪fit_transform(X_train['application_name'])
X_test['application_name'] = LabelEncoder().
 ↪fit_transform(X_test['application_name'])
```

1 Naive Bayes

[36]:
```
train_subsets_NB = []

X_train_NB = X_train.astype(float)  # Convert boolean to float (or int) type
X_test_NB = X_test.astype(float)     # Same for X_test

X_train_NB = X_train_NB - X_train_NB.min()  # Shift all values to be positive
X_test_NB = X_test_NB - X_test_NB.min()  # Shift all values to be positive
```

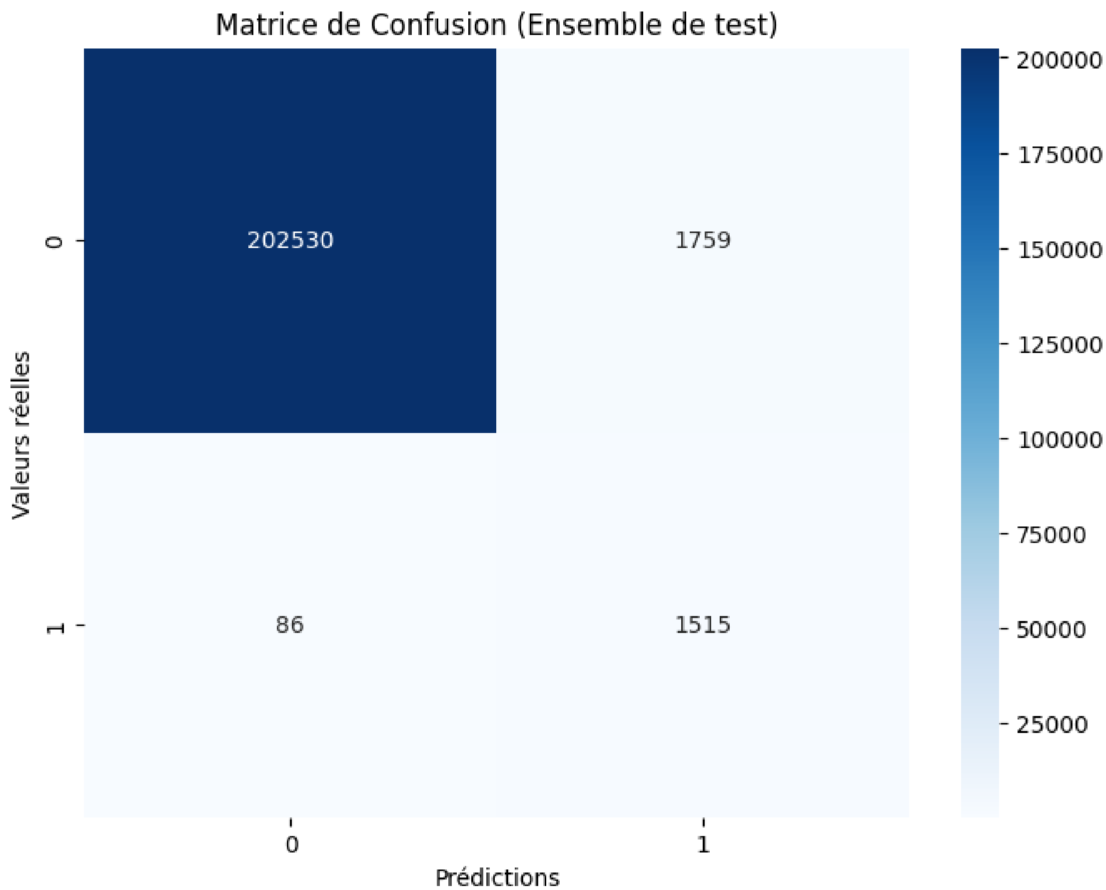
[37]:
```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import roc_curve, auc, accuracy_score, precision_score,␣
 ↪recall_score, f1_score
import numpy as np
import matplotlib.pyplot as plt
```

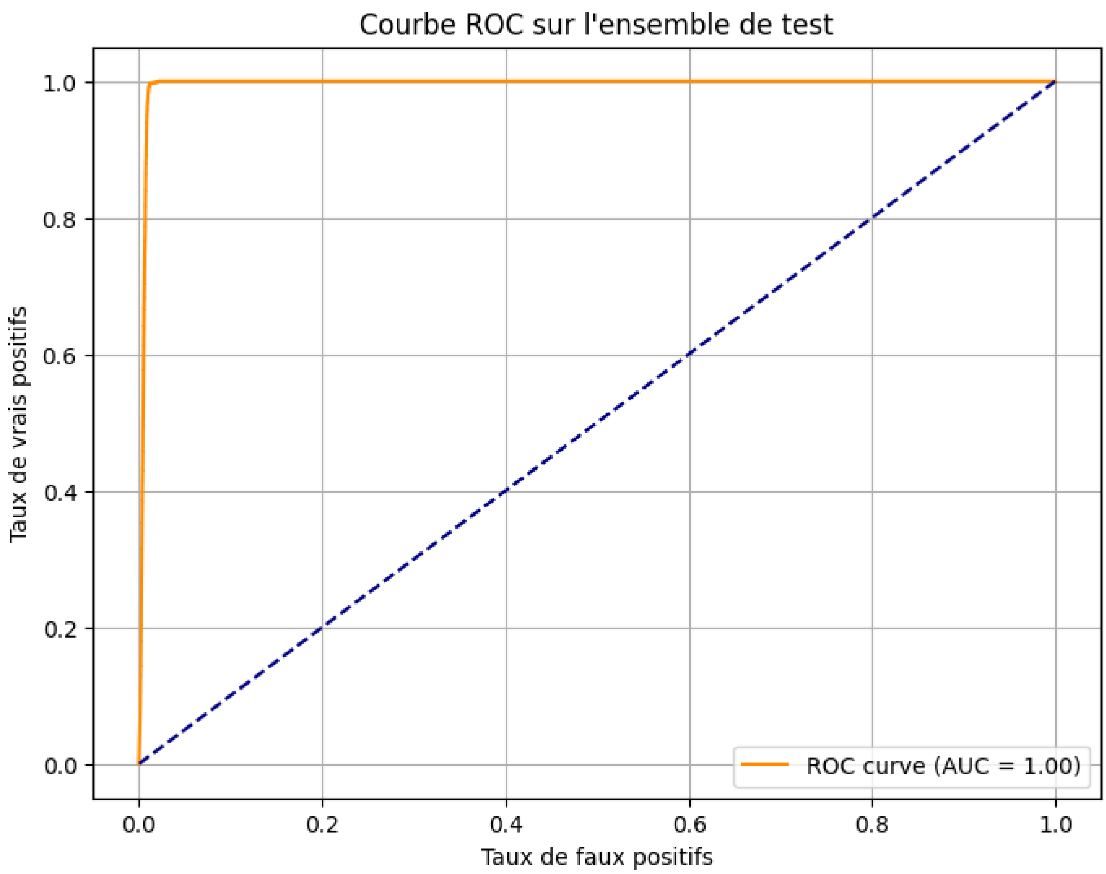
[39]:
```
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns

# =============== VALIDATION FINALE ===============
print("\n=== VALIDATION FINALE SUR L'ENSEMBLE DE TEST ===")
```

```python
# Initialiser le modèle Naive Bayes Multinomial avec le meilleur alpha
best_nb = MultinomialNB(alpha=1e-40)

# Entraîner le modèle
best_nb.fit(X_train_NB, y_train)

# Prédire sur l'ensemble de test
y_pred = best_nb.predict(X_test_NB)
y_pred_proba = best_nb.predict_proba(X_test_NB)

# Calculer les métriques d'évaluation
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, pos_label=1)
recall = recall_score(y_test, y_pred, pos_label=1)
f1 = f1_score(y_test, y_pred, pos_label=1)

# Calculer la courbe ROC et l'AUC pour l'ensemble de test
fpr_test, tpr_test, _ = roc_curve(y_test, y_pred_proba[:, 1])
roc_auc_test = auc(fpr_test, tpr_test)

# Afficher les résultats de validation
print(f"\nRésultats sur l'ensemble de test:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")
print(f"AUC-ROC: {roc_auc_test:.4f}")

# Afficher le rapport de classification détaillé
print("\nRapport de classification détaillé:")
print(classification_report(y_test, y_pred))

# Créer et afficher la matrice de confusion
plt.figure(figsize=(8, 6))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Matrice de Confusion (Ensemble de test)')
plt.xlabel('Prédictions')
plt.ylabel('Valeurs réelles')
plt.show()

# Tracer la courbe ROC finale sur l'ensemble de test
plt.figure(figsize=(8, 6))
plt.plot(fpr_test, tpr_test, color='darkorange',
            label=f'ROC curve (AUC = {roc_auc_test:.2f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('Taux de faux positifs')
```

```python
plt.ylabel('Taux de vrais positifs')
plt.title('Courbe ROC sur l\'ensemble de test')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```

```
=== VALIDATION FINALE SUR L'ENSEMBLE DE TEST ===

Résultats sur l'ensemble de test:
Accuracy: 0.9910
Precision: 0.4627
Recall: 0.9463
F1-score: 0.6215
AUC-ROC: 0.9954

Rapport de classification détaillé:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00    204289
           1       0.46      0.95      0.62      1601

    accuracy                           0.99    205890
   macro avg       0.73      0.97      0.81    205890
weighted avg       1.00      0.99      0.99    205890
```


Matrice de Confusion (Ensemble de test)
202530
1759
86
1515
Valeurs réelles
Prédictions
0
1
0
1
200000
175000
150000
125000
100000
75000
50000
25000



Observation : la précision baisse par rapport à une seule application cosidérée (+ de faux positifs). Le rappel reste élevé avec 94% de détection des intrusions.

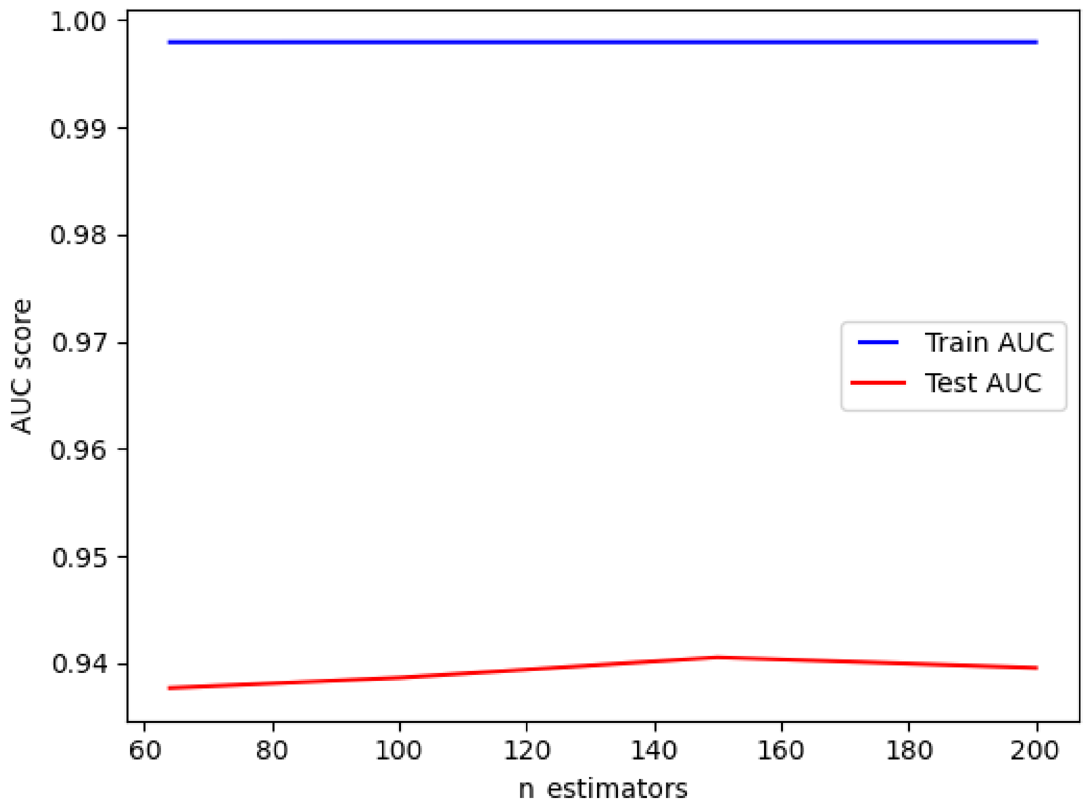
2 RandomForest

[17]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import roc_curve, auc, accuracy_score, precision_score,␣
↪recall_score, f1_score
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2.1 Hyper parameters evaluation, code based on this site : https://medium.com/all-things-ai/in-depth-parameter-tuning-for-random-forest-d67bb7e920d

[77]:
```
n_estimators = [64, 100, 150, 200]
train_results = []
test_results = []
for estimator in n_estimators:
    print(f'Evaluating with {estimator} n_estimators')
    rf = RandomForestClassifier(n_estimators=estimator, n_jobs=-1)
    rf.fit(X_train, y_train)
    train_pred = rf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,␣
 ↪train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = rf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,␣
 ↪y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)

from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(n_estimators, train_results, 'b', label="Train AUC")
line2, = plt.plot(n_estimators, test_results, 'r', label="Test AUC")
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel('AUC score')
plt.xlabel('n_estimators')
plt.show()
```

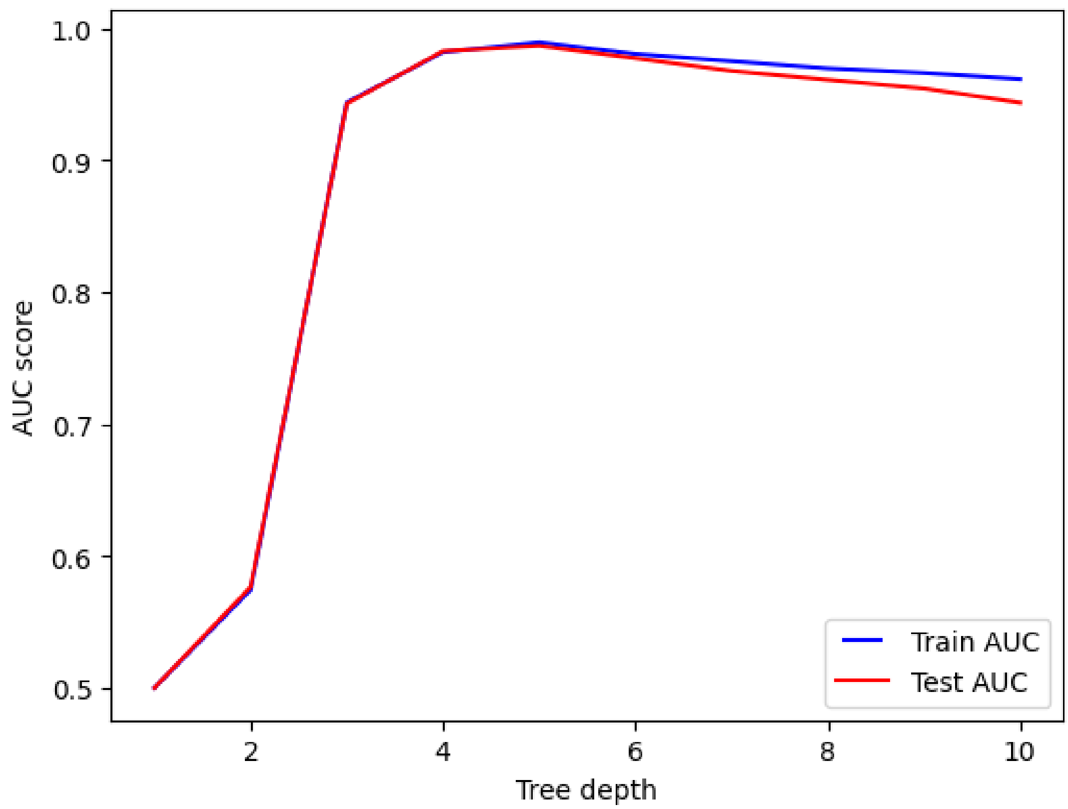
```
Evaluating with 64 n_estimators
Evaluating with 100 n_estimators
Evaluating with 150 n_estimators
Evaluating with 200 n_estimators
```



[85]:
```
max_depths = np.linspace(1, 10, 10, endpoint=True)
train_results = []
test_results = []
for max_depth in max_depths:
    print(f'Evaluating with {int(max_depth)} max_depths')
    rf = RandomForestClassifier(max_depth=int(max_depth), n_jobs=-1)
    rf.fit(X_train, y_train)
    train_pred = rf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,␣
 ↪train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = rf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,␣
 ↪y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)

from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(max_depths, train_results, 'b', label="Train AUC")
line2, = plt.plot(max_depths, test_results, 'r', label="Test AUC")
```

```python
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel('AUC score')
plt.xlabel('Tree depth')
plt.show()
```

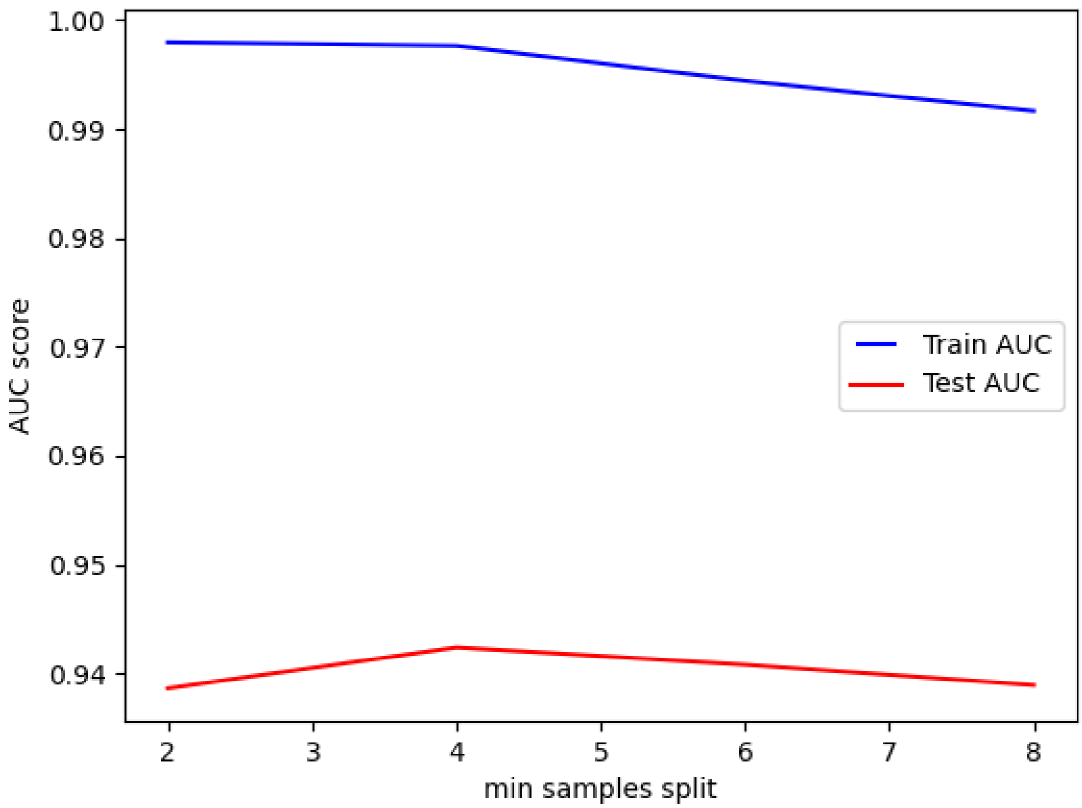
```
Evaluating with 1 max_depths
Evaluating with 2 max_depths
Evaluating with 3 max_depths
Evaluating with 4 max_depths
Evaluating with 5 max_depths
Evaluating with 6 max_depths
Evaluating with 7 max_depths
Evaluating with 8 max_depths
Evaluating with 9 max_depths
Evaluating with 10 max_depths
```



[98]:
```python
min_samples_splits = np.linspace(2, 8, 4, endpoint=True)
train_results = []
test_results = []
for min_samples_split in min_samples_splits:
   print(f'Evaluating with {int(min_samples_split)} min_samples_splits')
```

```
    rf = RandomForestClassifier(min_samples_split=int(min_samples_split))
    rf.fit(X_train, y_train)
    train_pred = rf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,␣
 ↪train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = rf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,␣
 ↪y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)

from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(min_samples_splits, train_results, 'b', label="Train AUC")
line2, = plt.plot(min_samples_splits, test_results, 'r', label="Test AUC")
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel('AUC score')
plt.xlabel('min samples split')
plt.show()
```

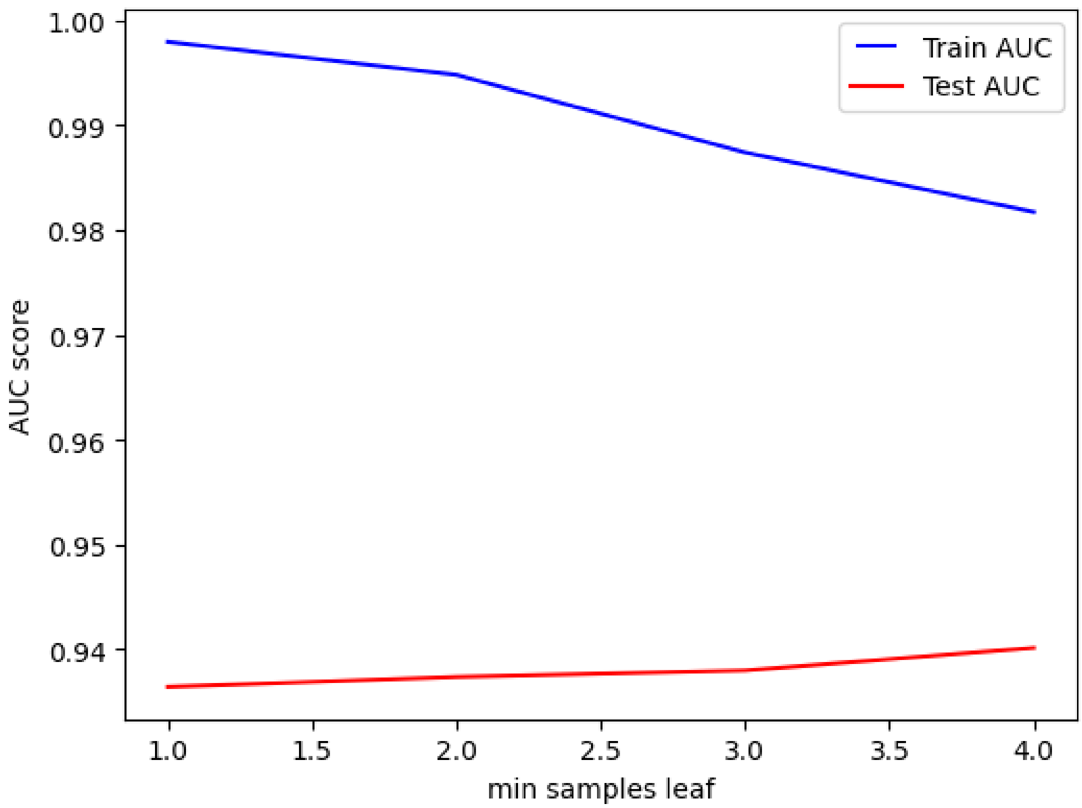
```
Evaluating with 2 min_samples_splits
Evaluating with 4 min_samples_splits
Evaluating with 6 min_samples_splits
Evaluating with 8 min_samples_splits
```



[104]:
```
min_samples_leafs = list(range(1,5))
train_results = []
test_results = []
for min_samples_leaf in min_samples_leafs:
    print(f'Evaluating with {min_samples_leaf} min_samples_leafs')
    rf = RandomForestClassifier(min_samples_leaf=min_samples_leaf)
    rf.fit(X_train, y_train)
    train_pred = rf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,␣
 ↪train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = rf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,␣
 ↪y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)

from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(min_samples_leafs, train_results, 'b', label="Train AUC")
line2, = plt.plot(min_samples_leafs, test_results, 'r', label="Test AUC")
```

```
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel('AUC score')
plt.xlabel('min samples leaf')
plt.show()
```

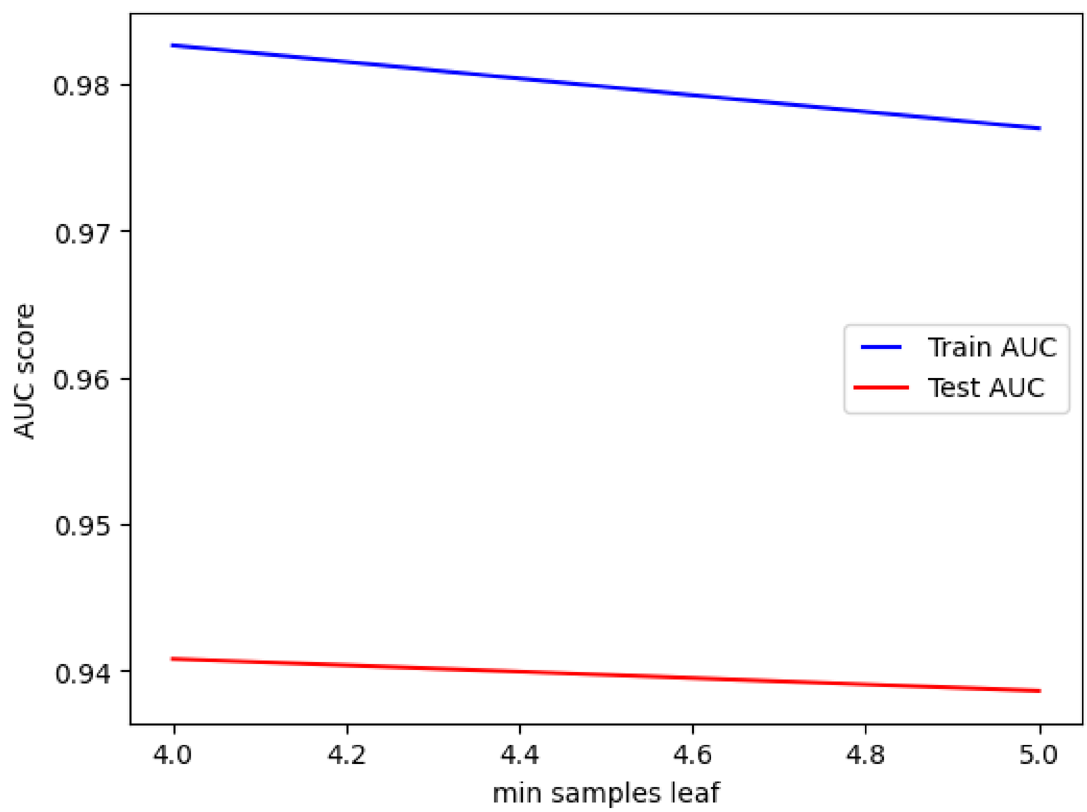
```
Evaluating with 1 min_samples_leafs
Evaluating with 2 min_samples_leafs
Evaluating with 3 min_samples_leafs
Evaluating with 4 min_samples_leafs
```



[105]:
```
min_samples_leafs = list(range(4,6))
train_results = []
test_results = []
for min_samples_leaf in min_samples_leafs:
    print(f'Evaluating with {min_samples_leaf} min_samples_leafs')
    rf = RandomForestClassifier(min_samples_leaf=min_samples_leaf)
    rf.fit(X_train, y_train)
    train_pred = rf.predict(X_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,␣
 ↪train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
```

```
    train_results.append(roc_auc)
    y_pred = rf.predict(X_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,␣
 ↪y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)

from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(min_samples_leafs, train_results, 'b', label="Train AUC")
line2, = plt.plot(min_samples_leafs, test_results, 'r', label="Test AUC")
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel('AUC score')
plt.xlabel('min samples leaf')
plt.show()
```

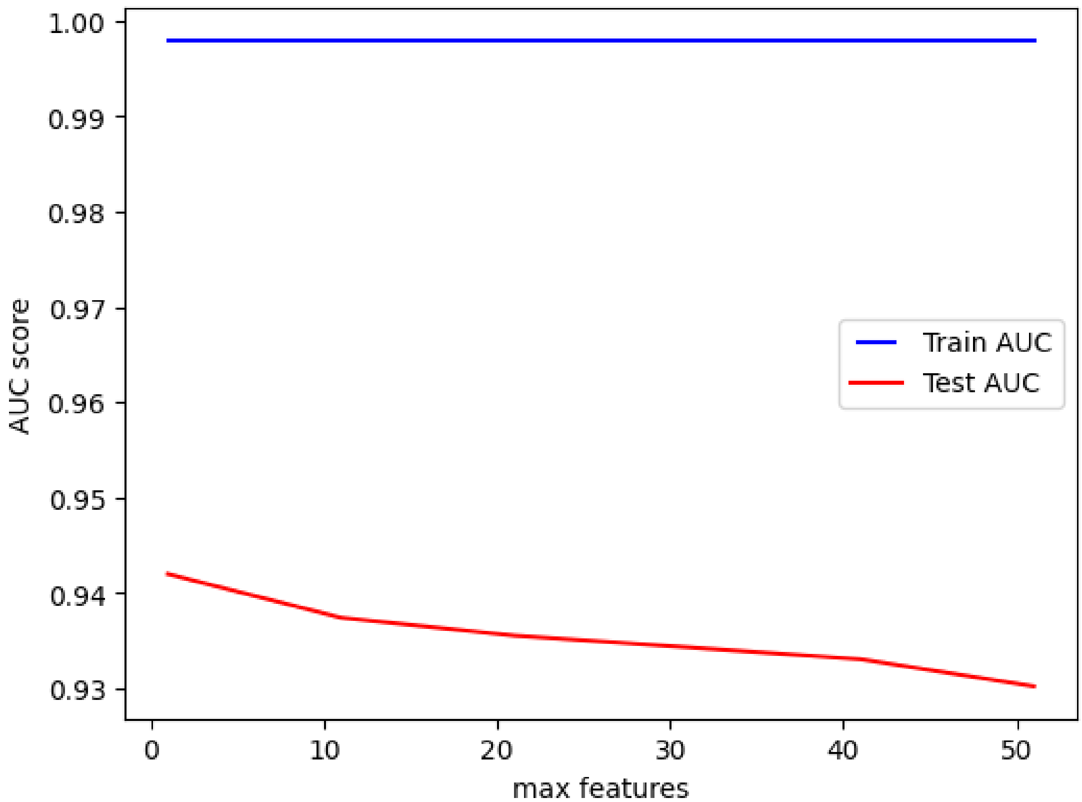
```
Evaluating with 4 min_samples_leafs
Evaluating with 5 min_samples_leafs
```



[102]:
```
max_features = list(range(1,X_train.shape[1], 10))
train_results = []
test_results = []
```

```python
for max_feature in max_features:
   print(f'Evaluating with {max_feature} max_features')
   rf = RandomForestClassifier(max_features=max_feature)
   rf.fit(X_train, y_train)
   train_pred = rf.predict(X_train)
   false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,␣
 ↪train_pred)
   roc_auc = auc(false_positive_rate, true_positive_rate)
   train_results.append(roc_auc)
   y_pred = rf.predict(X_test)
   false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,␣
 ↪y_pred)
   roc_auc = auc(false_positive_rate, true_positive_rate)
   test_results.append(roc_auc)

from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(max_features, train_results, 'b', label="Train AUC")
line2, = plt.plot(max_features, test_results, 'r', label="Test AUC")
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel('AUC score')
plt.xlabel('max features')
plt.show()
```

```
Evaluating with 1 max_features
Evaluating with 11 max_features
Evaluating with 21 max_features
Evaluating with 31 max_features
Evaluating with 41 max_features
Evaluating with 51 max_features
```

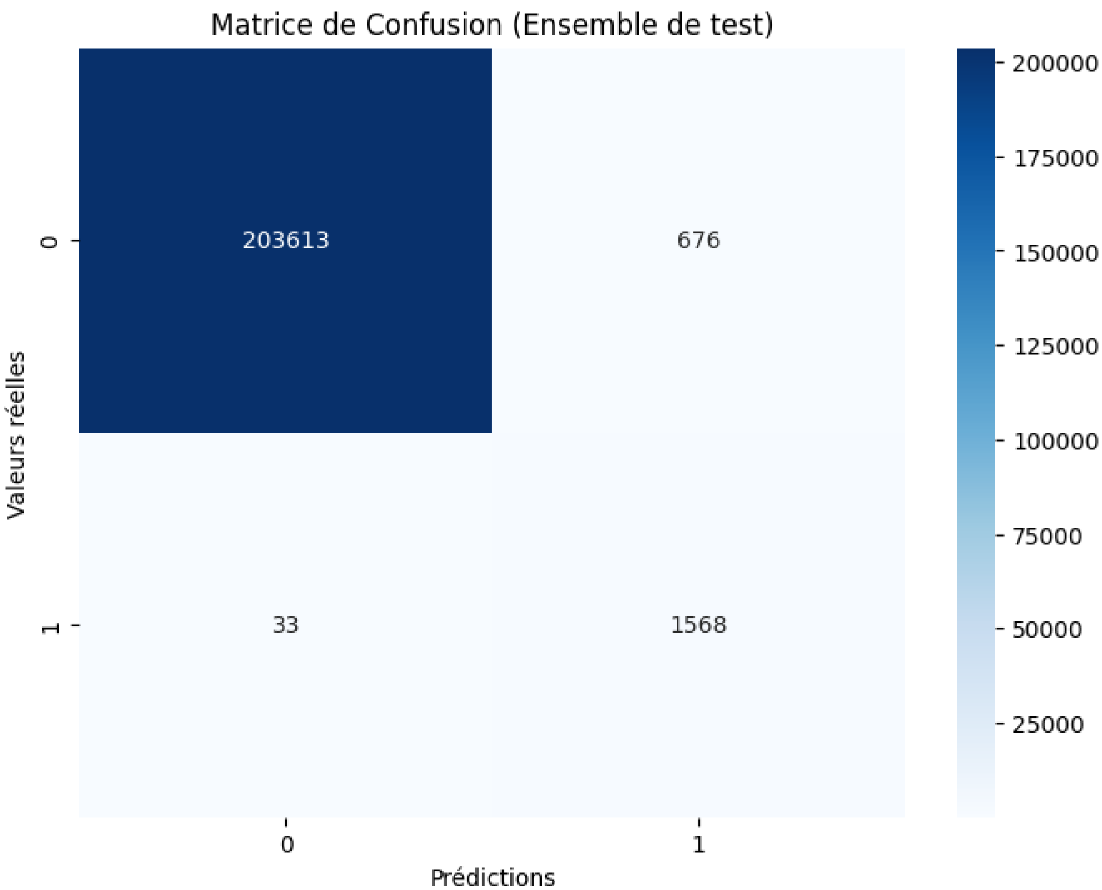


[18]:
```
# =============== VALIDATION FINALE ===============
print("\n=== VALIDATION FINALE SUR L'ENSEMBLE DE TEST AVEC LES MEILLEURS HYPER␣
 ↪PARAMETRES ===")

# Initialiser le modèle Random Forest avec le meilleur n_estimators
best_rf = RandomForestClassifier(
    n_estimators=150,
    random_state=42,
    max_depth=5,
    min_samples_split=4,
    min_samples_leaf=4,
    n_jobs=-1)

# Entraîner le modèle
best_rf.fit(X_train, y_train)

# Prédire sur l'ensemble de test
y_pred = best_rf.predict(X_test)
y_pred_proba = best_rf.predict_proba(X_test)

# Calculer les métriques d'évaluation
```

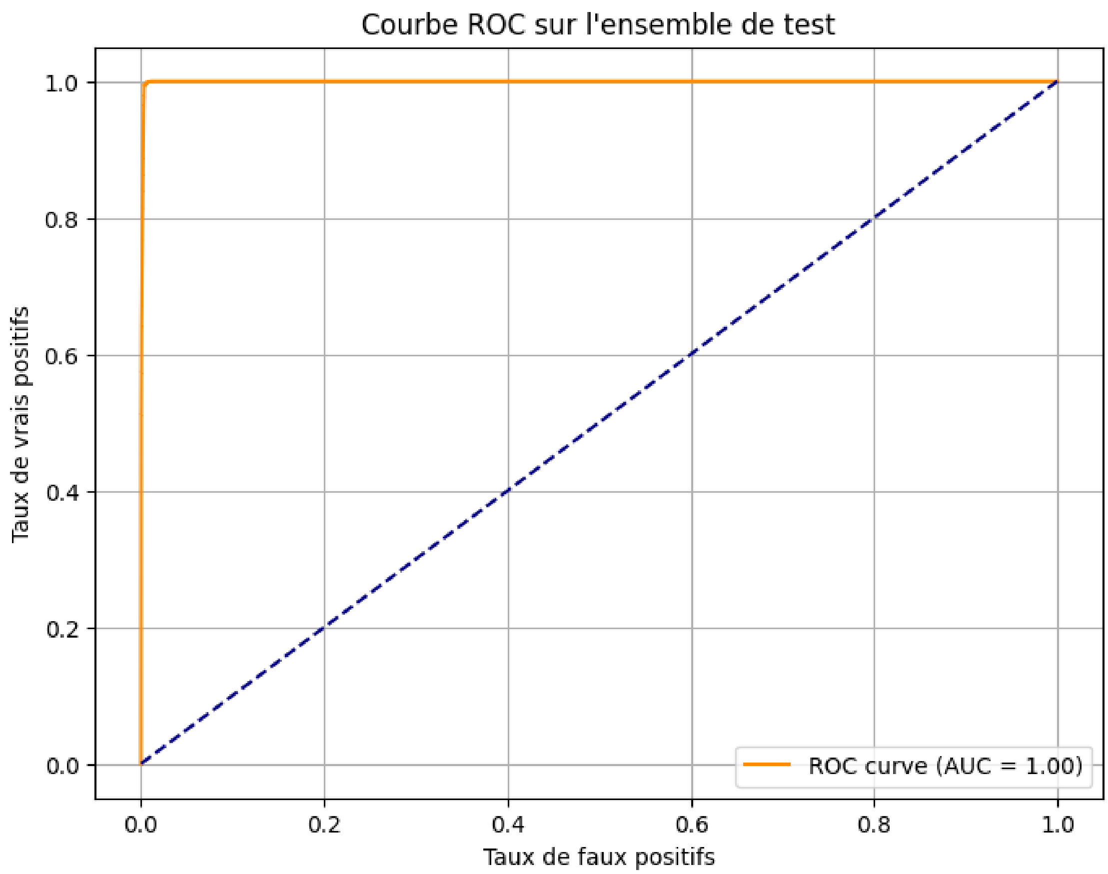
```python
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, pos_label=1)
recall = recall_score(y_test, y_pred, pos_label=1)
f1 = f1_score(y_test, y_pred, pos_label=1)

# Calculer la courbe ROC et l'AUC pour l'ensemble de test
fpr_test, tpr_test, _ = roc_curve(y_test, y_pred_proba[:, 1])
roc_auc_test = auc(fpr_test, tpr_test)

# Afficher les résultats de validation
print(f"\nRésultats sur l'ensemble de test:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")
print(f"AUC-ROC: {roc_auc_test:.4f}")

# Afficher le rapport de classification détaillé
print("\nRapport de classification détaillé:")
print(classification_report(y_test, y_pred))

# Créer et afficher la matrice de confusion
plt.figure(figsize=(8, 6))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Matrice de Confusion (Ensemble de test)')
plt.xlabel('Prédictions')
plt.ylabel('Valeurs réelles')
plt.show()

# Tracer la courbe ROC finale sur l'ensemble de test
plt.figure(figsize=(8, 6))
plt.plot(fpr_test, tpr_test, color='darkorange',
            label=f'ROC curve (AUC = {roc_auc_test:.2f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('Taux de faux positifs')
plt.ylabel('Taux de vrais positifs')
plt.title('Courbe ROC sur l\'ensemble de test')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()

# Afficher l'importance des caractéristiques
feature_importance = pd.DataFrame({
     'feature': X_train.columns,
     'importance': best_rf.feature_importances_
})
```

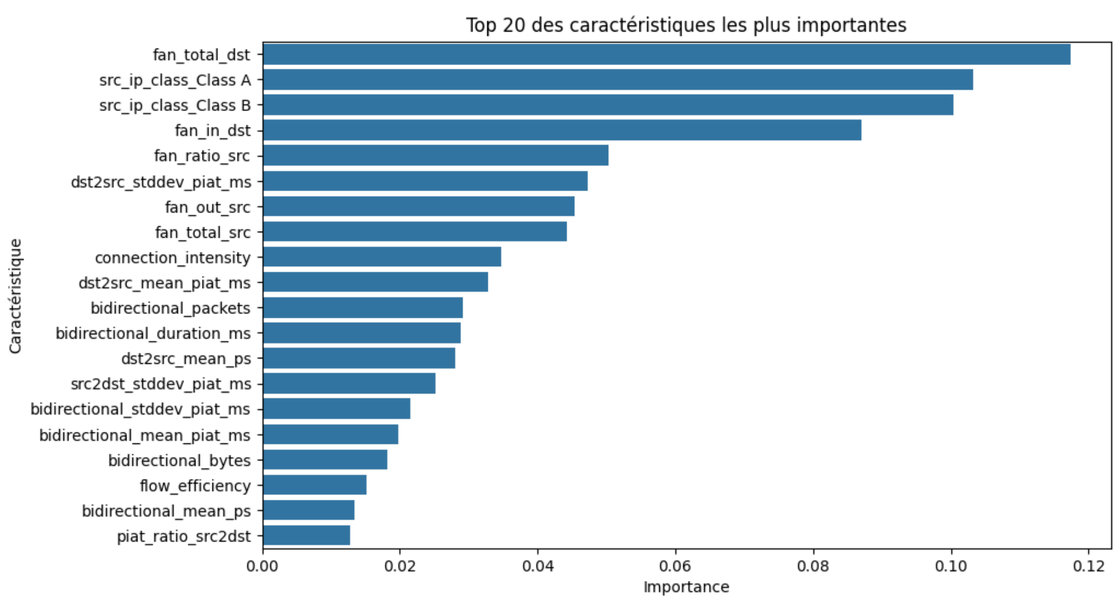
```
feature_importance = feature_importance.sort_values('importance',␣
↪ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(x='importance', y='feature', data=feature_importance.head(20))
plt.title('Top 20 des caractéristiques les plus importantes')
plt.xlabel('Importance')
plt.ylabel('Caractéristique')
plt.show()
```

```
=== VALIDATION FINALE SUR L'ENSEMBLE DE TEST AVEC LES MEILLEURS HYPER PARAMETRES
===

Résultats sur l'ensemble de test:
Accuracy: 0.9966
Precision: 0.6988
Recall: 0.9794
F1-score: 0.8156
AUC-ROC: 0.9992

Rapport de classification détaillé:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    204289
           1       0.70      0.98      0.82      1601

    accuracy                           1.00    205890
   macro avg       0.85      0.99      0.91    205890
weighted avg       1.00      1.00      1.00    205890
```



Matrice de Confusion (Ensemble de test)
203613
676
33
1568
Valeurs réelles
Prédictions
0
1
0
1
200000
175000
150000
125000
100000
75000
50000
25000


Courbe ROC sur l'ensemble de test
Taux de vrais positifs
Taux de faux positifs
ROC curve (AUC = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0


Top 20 des caractéristiques les plus importantes
Caractéristique
Importance
fan_total_dst
src_ip_class_Class A
src_ip_class_Class B
fan_in_dst
fan_ratio_src
dst2src_stddev_piat_ms
fan_out_src
fan_total_src
connection_intensity
dst2src_mean_piat_ms
bidirectional_packets
bidirectional_duration_ms
dst2src_mean_ps
src2dst_stddev_piat_ms
bidirectional_stddev_piat_ms
bidirectional_mean_piat_ms
bidirectional_bytes
flow_efficiency
bidirectional_mean_ps
piat_ratio_src2dst
0.00
0.02
0.04
0.06
0.08
0.10
0.12

[118]:
```python
import joblib

# save model with joblib
filename = 'rfc_70_98_model.sav'
joblib.dump(best_rf, filename)
```

[118]: ['rfc_70_98_model.sav']

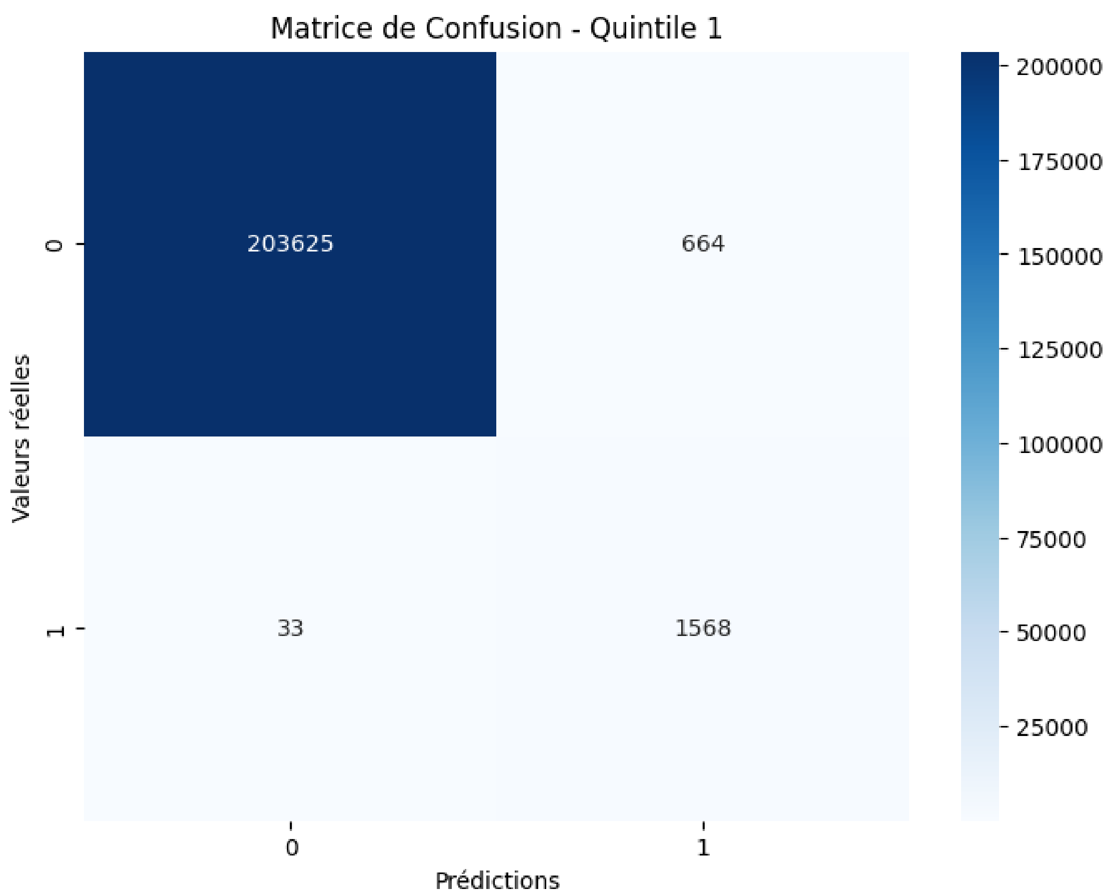
2.2 Validation croisée

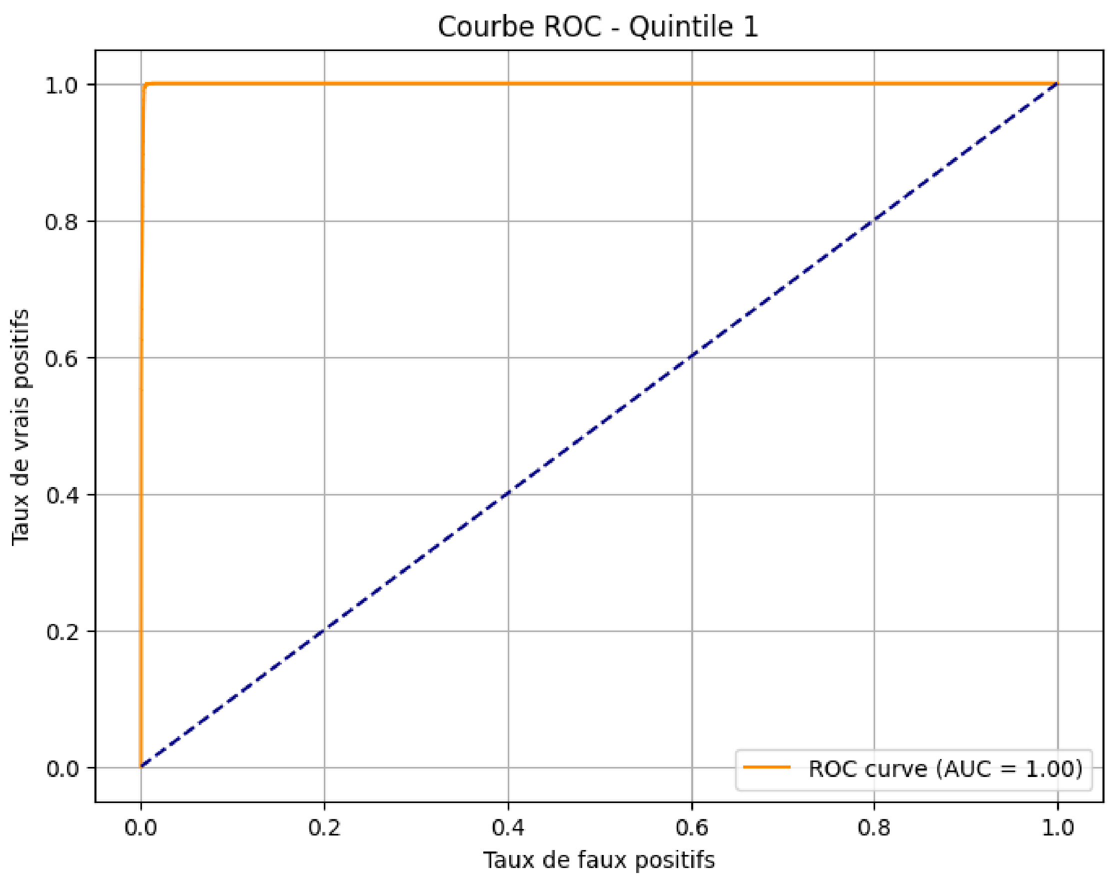
[119]:
```python
from sklearn.model_selection import StratifiedKFold
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score,
    f1_score, roc_curve, auc, classification_report, confusion_matrix
)
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

# Préparation des données
X = enriched_features.drop('label', axis=1, errors='ignore')
y = df['label'] if 'label' in df.columns else None

# Encode la colonne application_name si présente
if 'application_name' in X.columns:
    label_encoder = LabelEncoder()
    X['application_name'] = label_encoder.fit_transform(X['application_name'])

# Configuration du modèle
best_rf = RandomForestClassifier(
    n_estimators=150,
    random_state=42,
    max_depth=5,
    min_samples_split=4,
    min_samples_leaf=4,
    n_jobs=-1
)

# Validation croisée manuelle (5 partitions)
kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
metrics = []

for i, (train_index, test_index) in enumerate(kf.split(X, y), start=1):
    print(f"\n=== Évaluation pour le {i}e cinquième de données utilisé comme␣
 ↪ensemble de test ===")
```

```
    # Diviser les données
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Entraîner le modèle
    best_rf.fit(X_train, y_train)

    # Prédire
    y_pred = best_rf.predict(X_test)
    y_pred_proba = best_rf.predict_proba(X_test)

    # Calculer les métriques
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, pos_label=1)
    recall = recall_score(y_test, y_pred, pos_label=1)
    f1 = f1_score(y_test, y_pred, pos_label=1)
    fpr_test, tpr_test, _ = roc_curve(y_test, y_pred_proba[:, 1])
    roc_auc_test = auc(fpr_test, tpr_test)

    # Stocker les résultats
    metrics.append({
        'Quintile': f'Part {i}',
        'Accuracy': accuracy,
        'Precision': precision,
        'Recall': recall,
        'F1-Score': f1,
        'AUC-ROC': roc_auc_test
    })

    # Afficher la matrice de confusion
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(f'Matrice de Confusion - Quintile {i}')
    plt.xlabel('Prédictions')
    plt.ylabel('Valeurs réelles')
    plt.show()

    # Tracer la courbe ROC
    plt.figure(figsize=(8, 6))
    plt.plot(fpr_test, tpr_test, color='darkorange', label=f'ROC curve (AUC = {roc_auc_test:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
    plt.xlabel('Taux de faux positifs')
    plt.ylabel('Taux de vrais positifs')
    plt.title(f'Courbe ROC - Quintile {i}')
```

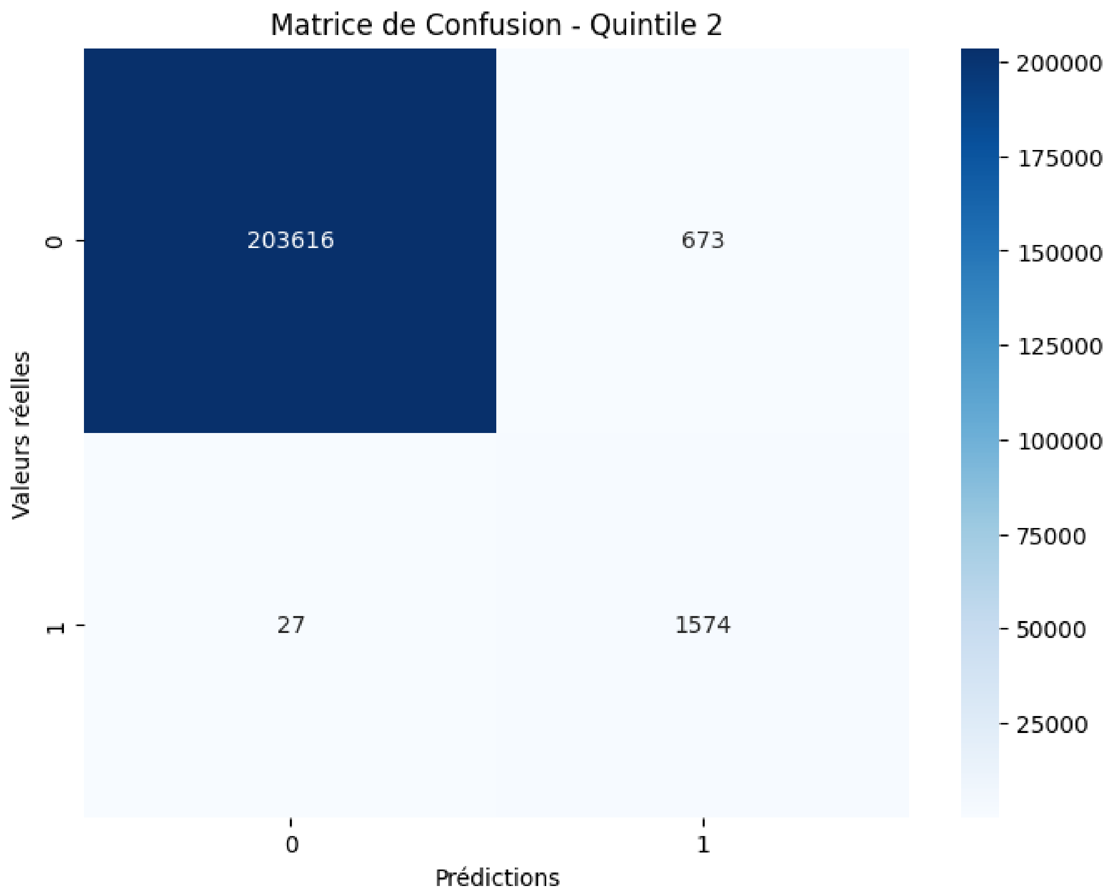
```
    plt.legend(loc="lower right")
    plt.grid(True)
    plt.show()

# Afficher les résultats globaux
metrics_df = pd.DataFrame(metrics)
print("\n=== Résultats globaux ===")
print(metrics_df)

# Visualiser les métriques pour chaque quintile
metrics_df.set_index('Quintile').plot(kind='bar', figsize=(12, 8))
plt.title('Comparaison des métriques pour chaque quintile utilisé comme␣
 ↪ensemble de test')
plt.ylabel('Score')
plt.grid(axis='y')
plt.show()
```

```
=== Évaluation pour le 1e cinquième de données utilisé comme ensemble de test
===
```

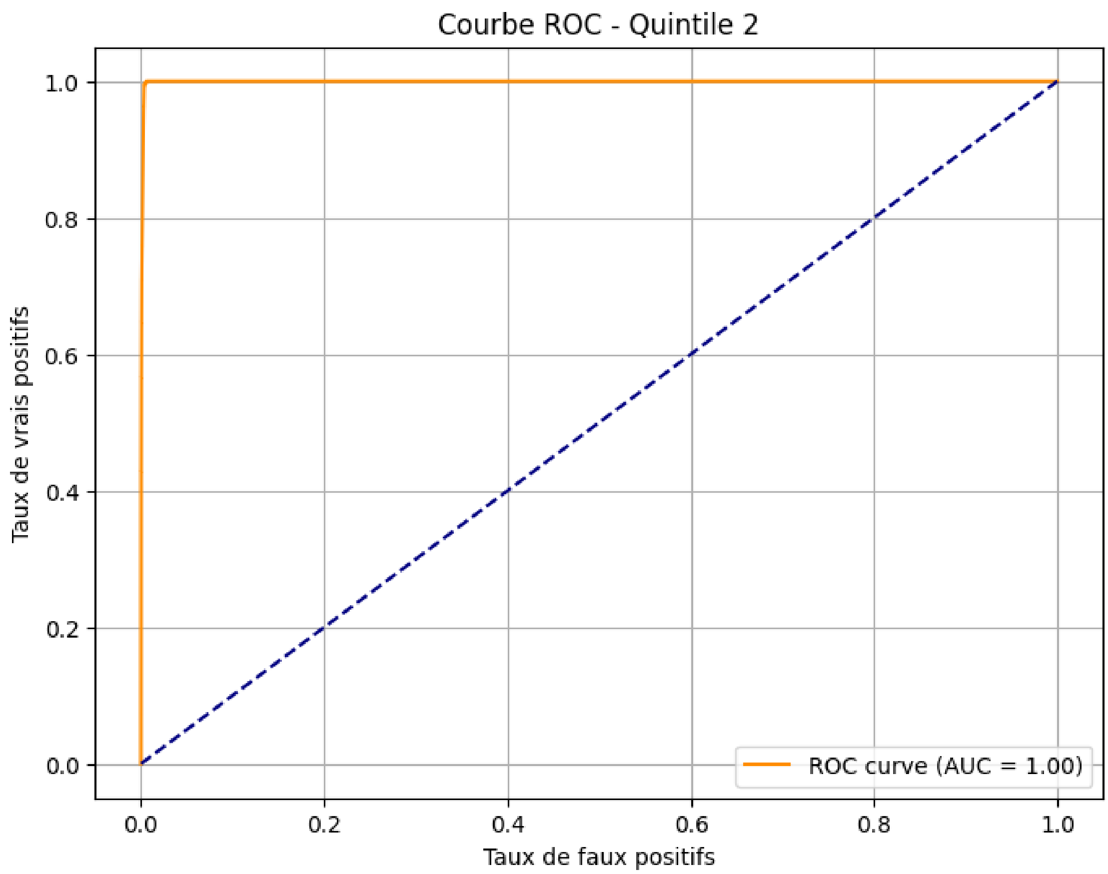




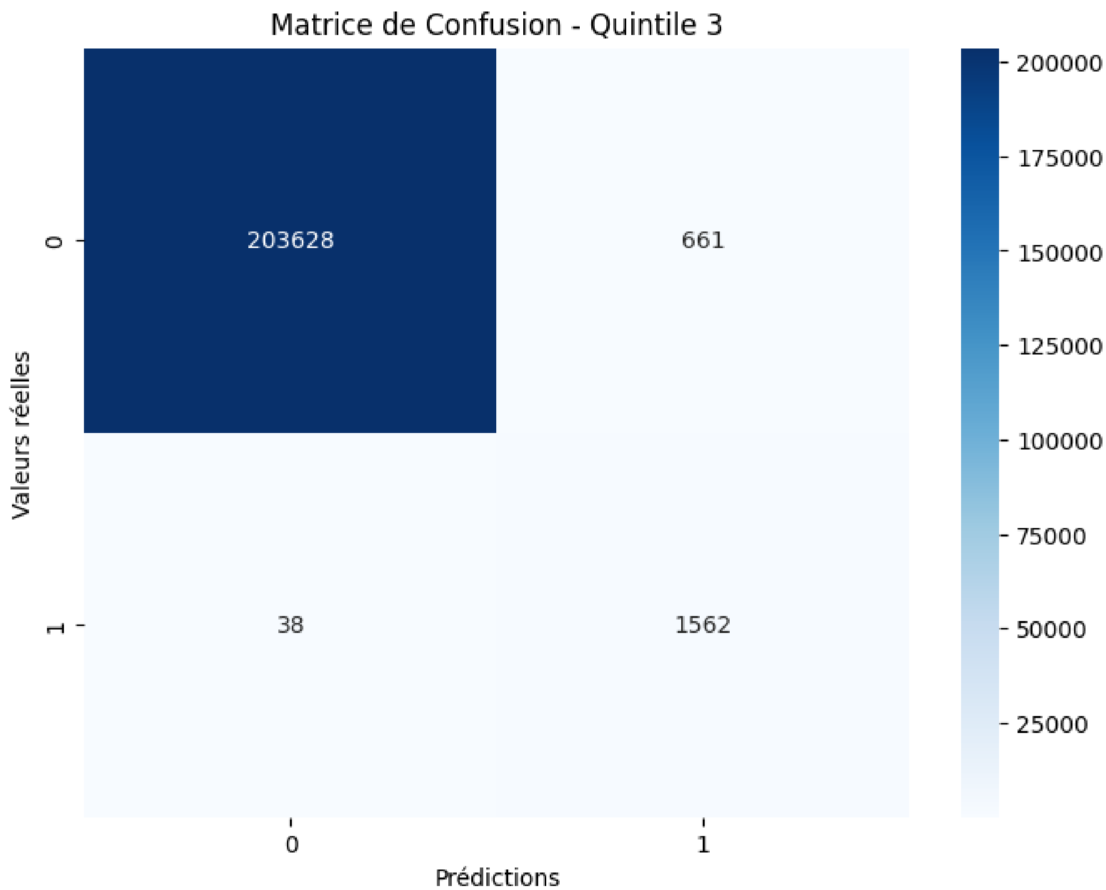

```
=== Évaluation pour le 2e cinquième de données utilisé comme ensemble de test
===
```

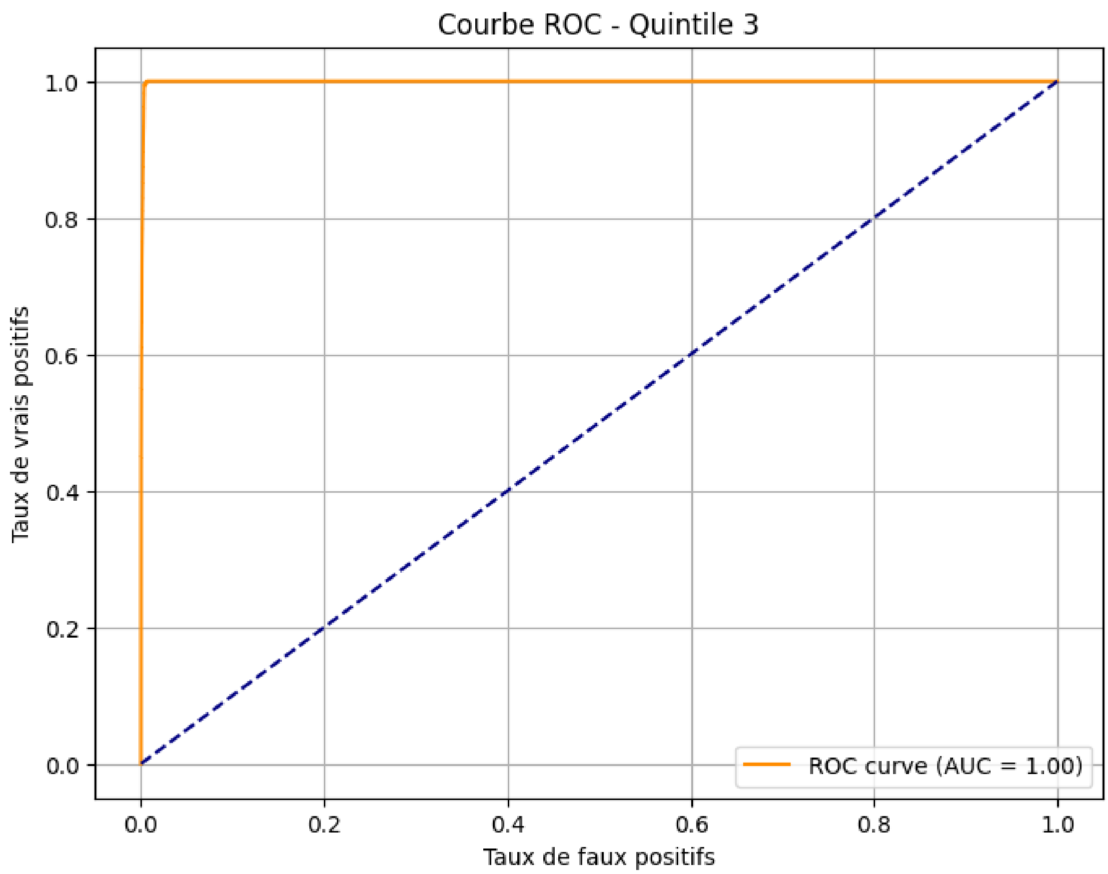


Matrice de Confusion - Quintile 2
203616
673
27
1574
Valeurs réelles
Prédictions
0
1
0
1
200000
175000
150000
125000
100000
75000
50000
25000

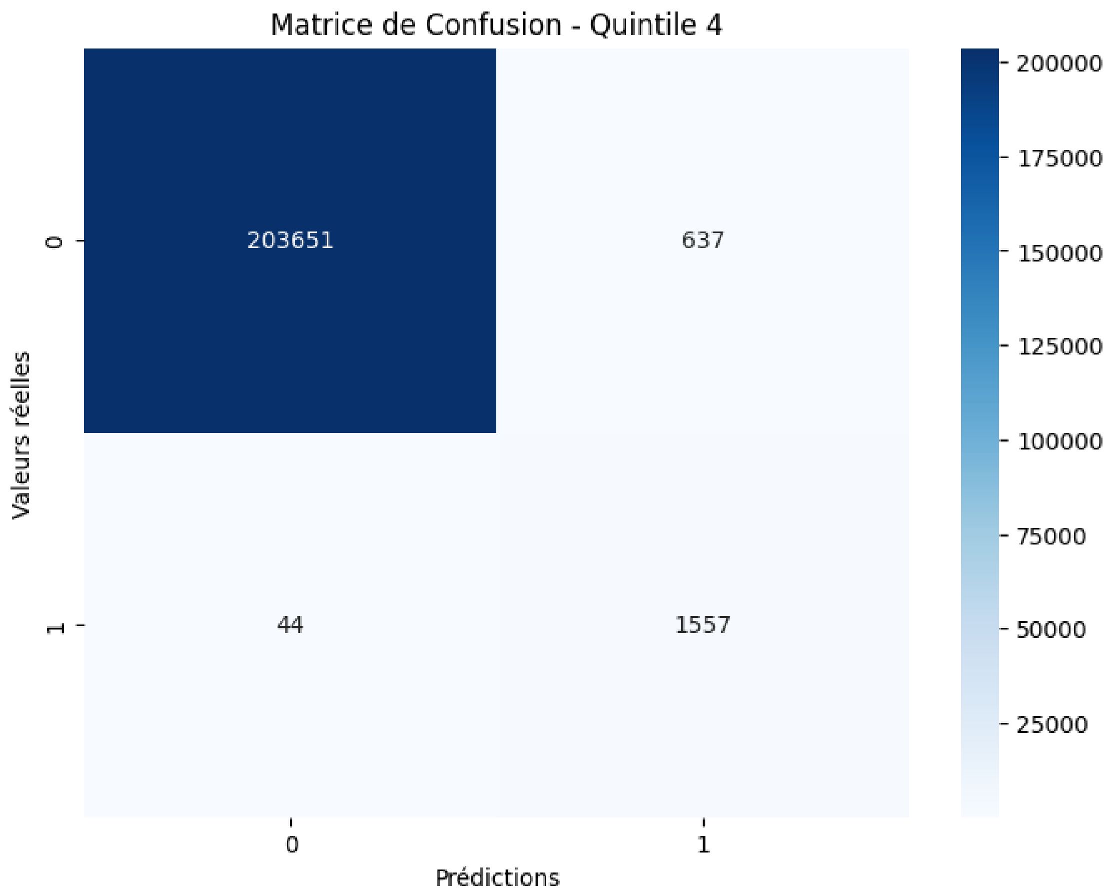



```
=== Évaluation pour le 3e cinquième de données utilisé comme ensemble de test
===
```

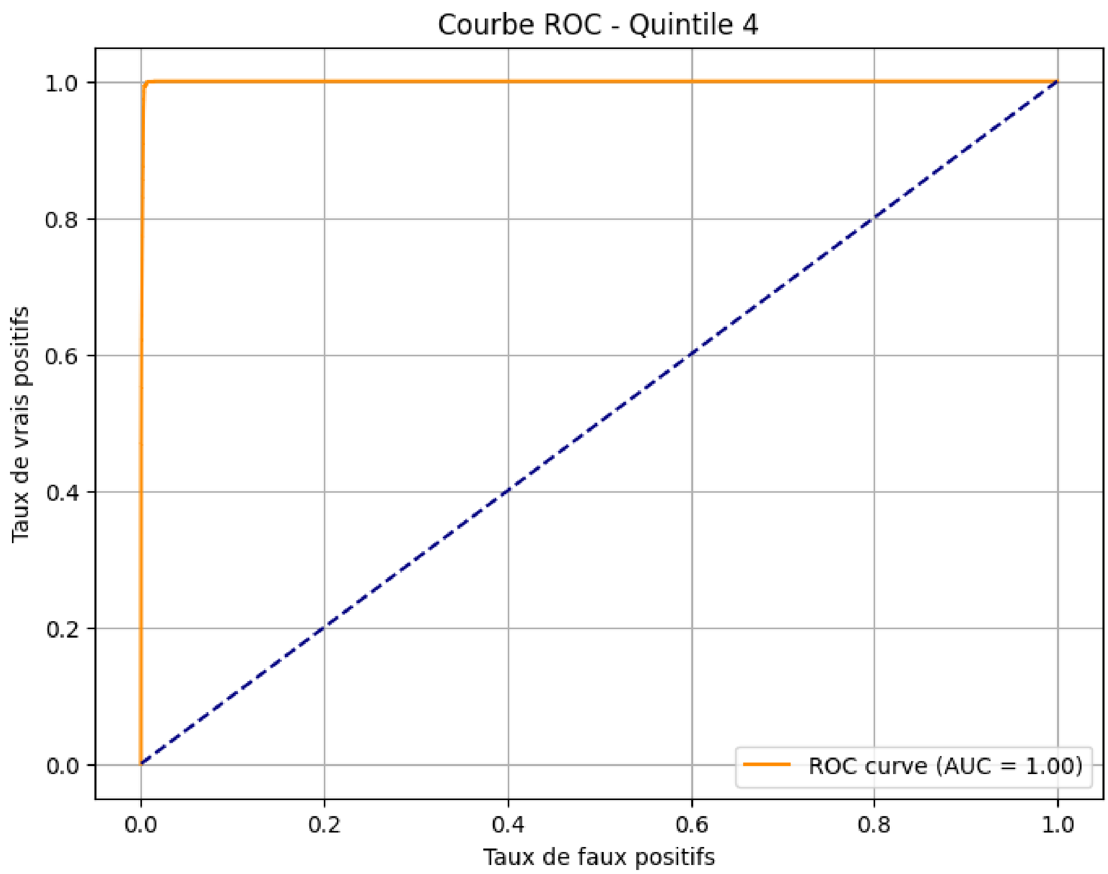

Matrice de Confusion - Quintile 3
203628
661
38
1562
Valeurs réelles
Prédictions
0
1
200000
175000
150000
125000
100000
75000
50000
25000



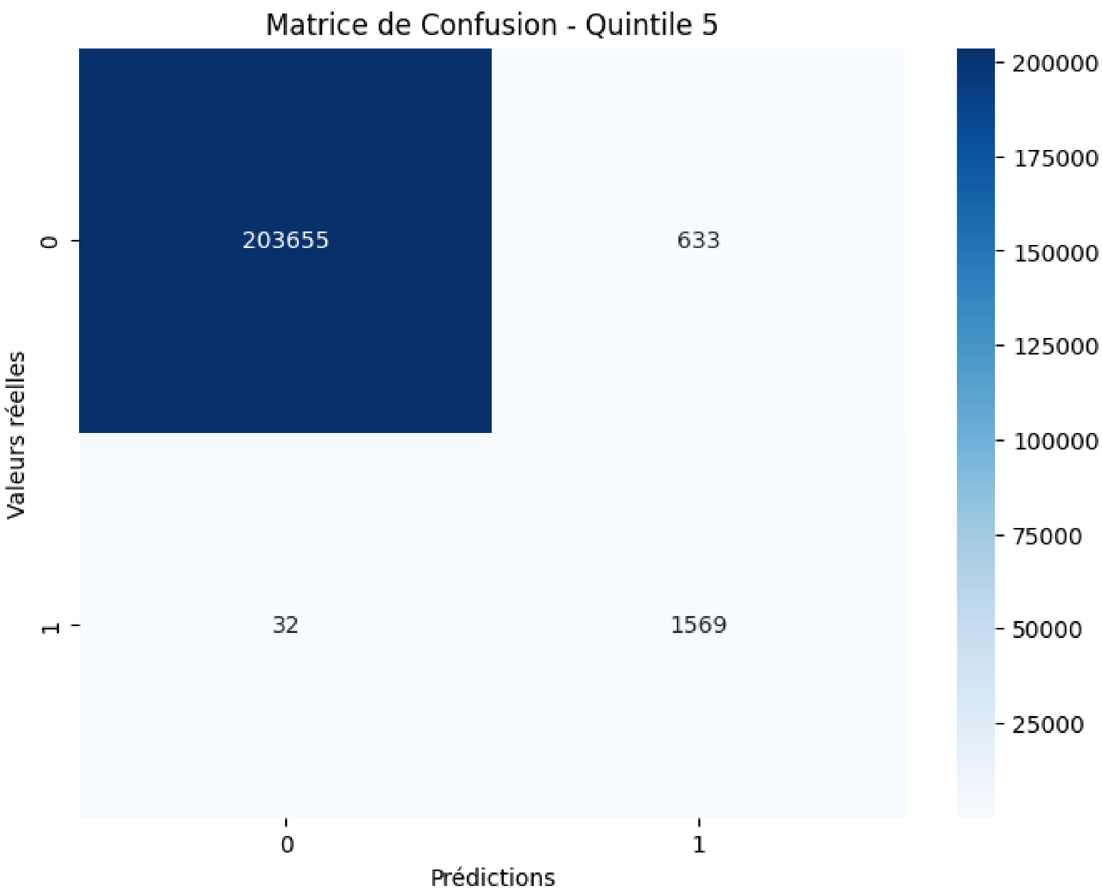

```
=== Évaluation pour le 4e cinquième de données utilisé comme ensemble de test
===
```

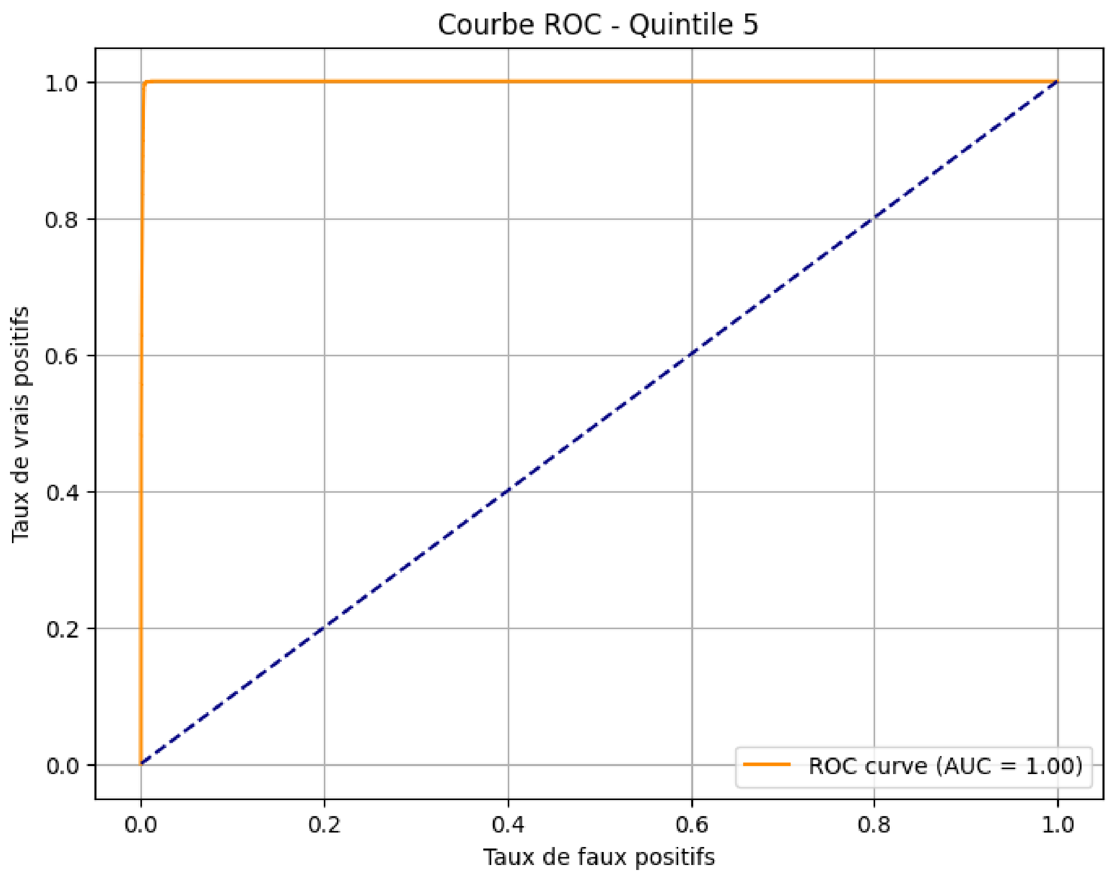


Matrice de Confusion - Quintile 4
Valeurs réelles
Prédictions
0
1
203651
637
44
1557
200000
175000
150000
125000
100000
75000
50000
25000

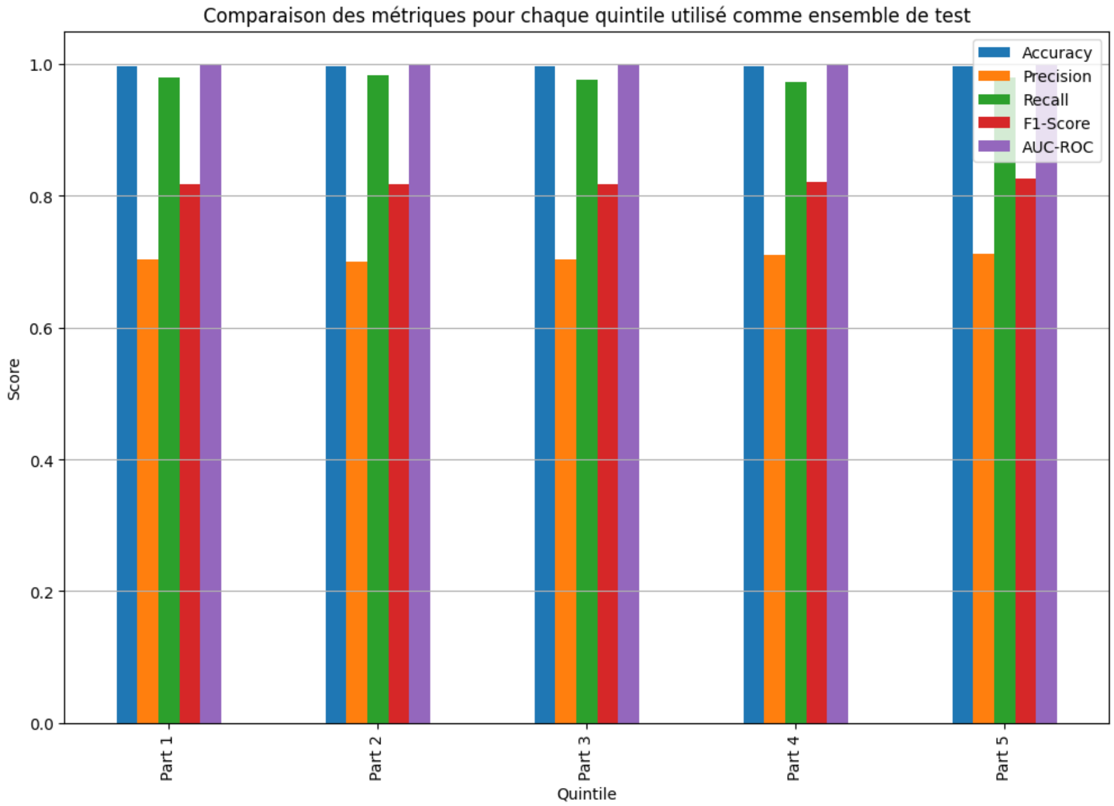



```
=== Évaluation pour le 5e cinquième de données utilisé comme ensemble de test
===
```


Matrice de Confusion - Quintile 5
203655
633
32
1569
Valeurs réelles
Prédictions
0
1
0
1
200000
175000
150000
125000
100000
75000
50000
25000




```
=== Résultats globaux ===
  Quintile  Accuracy  Precision    Recall  F1-Score   AUC-ROC
0   Part 1  0.996615   0.702509  0.979388  0.818158  0.999316
1   Part 2  0.996600   0.700490  0.983136  0.818087  0.999278
2   Part 3  0.996605   0.702654  0.976250  0.817159  0.999230
3   Part 4  0.996692   0.709663  0.972517  0.820553  0.999231
4   Part 5  0.996770   0.712534  0.980012  0.825138  0.999281
```



[121]:
```python
import joblib

# save model with joblib
filename = 'rfc_71_98_model.sav'
joblib.dump(best_rf, filename)
```

[121]: ['rfc_71_98_model.sav']

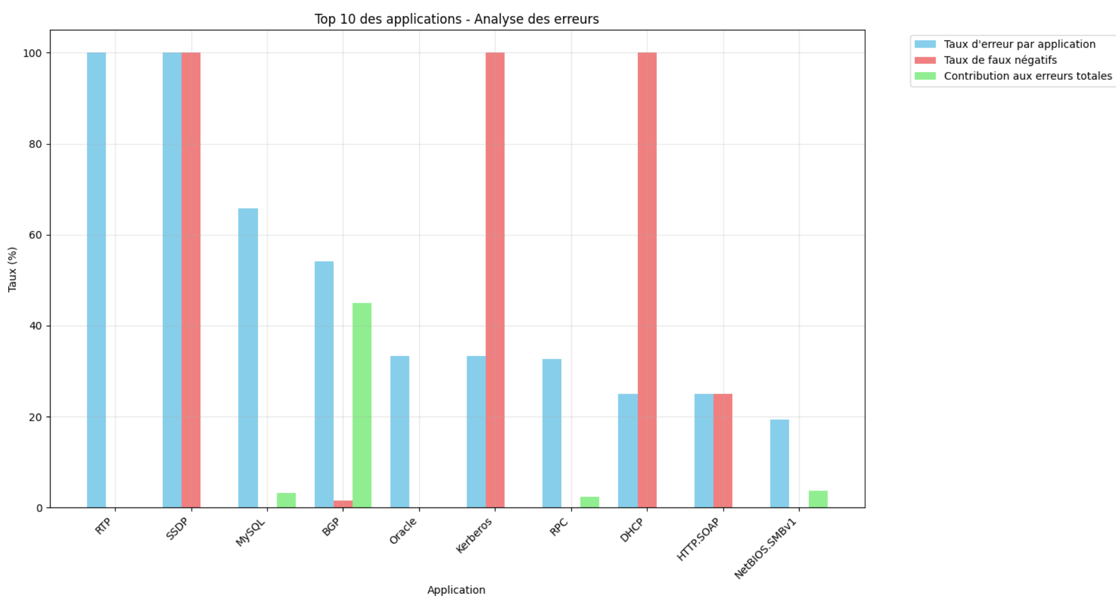
[26]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

def analyser_erreurs_par_application(y_test, y_pred, df_test, label_encoder):
    """
    Analyse détaillée des erreurs et faux négatifs par application avec noms␣
  ↪originaux

    Parameters:
    -----------
    y_test : array-like
```

```
        Valeurs réelles
    y_pred : array-like
        Prédictions du modèle
    df_test : DataFrame
        DataFrame de test contenant la colonne 'application_name' encodée
    label_encoder : LabelEncoder
        L'encodeur utilisé pour transformer les noms d'applications
    """
    # Créer un DataFrame avec les prédictions et les vraies valeurs
    df_erreurs = pd.DataFrame({
        'vraie_valeur': y_test,
        'prediction': y_pred,
        'application_name': label_encoder.
↪inverse_transform(df_test['application_name'])
    })

    # Ajouter une colonne pour identifier les erreurs
    df_erreurs['erreur'] = df_erreurs['prediction'] !=␣
↪df_erreurs['vraie_valeur']
    df_erreurs['faux_negatif'] = (df_erreurs['vraie_valeur'] == 1) &␣
↪(df_erreurs['prediction'] == 0)

    # 1. Analyse globale des erreurs par application
    erreurs_par_app = df_erreurs[df_erreurs['erreur']].
↪groupby('application_name').size()
    total_par_app = df_erreurs.groupby('application_name').size()
    taux_erreur_par_app = (erreurs_par_app / total_par_app * 100).
↪sort_values(ascending=False)

    # 2. Analyse des faux négatifs par application
    faux_neg_par_app = df_erreurs[df_erreurs['faux_negatif']].
↪groupby('application_name').size()
    positifs_par_app = df_erreurs[df_erreurs['vraie_valeur'] == 1].
↪groupby('application_name').size()
    taux_faux_neg_par_app = (faux_neg_par_app / positifs_par_app * 100).
↪sort_values(ascending=False)

    # 3. Calcul de la contribution aux erreurs totales
    total_erreurs = df_erreurs['erreur'].sum()
    contribution_erreurs = (erreurs_par_app / total_erreurs * 100).
↪sort_values(ascending=False)

    # Affichage des résultats
    print("\n=== ANALYSE DES ERREURS PAR APPLICATION ===")
    print(f"\nNombre total d'erreurs : {total_erreurs}")
    print(f"Nombre total de faux négatifs : {df_erreurs['faux_negatif'].sum()}")
```

```python
# Création du DataFrame pour le graphique combiné
df_plot = pd.DataFrame({
    'Taux d\'erreur': taux_erreur_par_app,
    'Taux de faux négatifs': taux_faux_neg_par_app,
    'Contribution aux erreurs totales': contribution_erreurs
}).fillna(0)

# Sélection des top N applications basé sur le taux d'erreur total
N = 10
top_apps = df_plot['Taux d\'erreur'].sort_values(ascending=False).head(N).
↪index
df_plot_top = df_plot.loc[top_apps]

# Création du graphique combiné
plt.figure(figsize=(15, 8))
X = np.arange(len(df_plot_top.index))
width = 0.25  # Réduit pour accommoder 3 barres

plt.bar(X - width, df_plot_top['Taux d\'erreur'], width,
        label='Taux d\'erreur par application', color='skyblue')
plt.bar(X, df_plot_top['Taux de faux négatifs'], width,
        label='Taux de faux négatifs', color='lightcoral')
plt.bar(X + width, df_plot_top['Contribution aux erreurs totales'], width,
        label='Contribution aux erreurs totales', color='lightgreen')

plt.title('Top 10 des applications - Analyse des erreurs')
plt.xlabel('Application')
plt.ylabel('Taux (%)')
plt.xticks(X, df_plot_top.index, rotation=45, ha='right')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# Créer un DataFrame de résumé
resume = pd.DataFrame({
    'Total_Instances': total_par_app,
    'Nombre_Erreurs': erreurs_par_app,
    'Taux_Erreur': taux_erreur_par_app,
    'Nombre_Faux_Negatifs': faux_neg_par_app,
    'Taux_Faux_Negatifs': taux_faux_neg_par_app,
    'Contribution_Erreurs_Totales': contribution_erreurs
}).round(2)

print("\nTop 10 des applications par taux d'erreur :")
print(resume.sort_values('Taux_Erreur', ascending=False).head(10))
```

```python
    print("\nTop 10 des applications par taux de faux négatifs :")
    print(resume.sort_values('Taux_Faux_Negatifs', ascending=False).head(10))

    print("\nTop 10 des applications par contribution aux erreurs totales :")
    print(resume.sort_values('Contribution_Erreurs_Totales', ascending=False).
 ↪head(10))

    return resume

# Exemple d'utilisation:
resume_erreurs = analyser_erreurs_par_application(y_test, y_pred, X_test,␣
 ↪label_encoder)
```

```
=== ANALYSE DES ERREURS PAR APPLICATION ===

Nombre total d'erreurs : 709
Nombre total de faux négatifs : 33
```




```
Top 10 des applications par taux d'erreur :
                  Total_Instances  Nombre_Erreurs  Taux_Erreur  \
application_name
SSDP                            1             1.0       100.00
RTP                             1             1.0       100.00
MySQL                          35            23.0        65.71
BGP                           589           319.0        54.16
```

```
Oracle                         3             1.0         33.33
Kerberos                       3             1.0         33.33
RPC                           52            17.0         32.69
DHCP                           4             1.0         25.00
HTTP.SOAP                      4             1.0         25.00
NetBIOS.SMBv1                139            27.0         19.42

                  Nombre_Faux_Negatifs  Taux_Faux_Negatifs  \
application_name
SSDP                               1.0              100.00
RTP                                NaN                 NaN
MySQL                              NaN                 NaN
BGP                                4.0                1.59
Oracle                             NaN                 NaN
Kerberos                           1.0              100.00
RPC                                NaN                 NaN
DHCP                               1.0              100.00
HTTP.SOAP                          1.0               25.00
NetBIOS.SMBv1                      NaN                 NaN

                  Contribution_Erreurs_Totales
application_name
SSDP                                      0.14
RTP                                       0.14
MySQL                                     3.24
BGP                                      44.99
Oracle                                    0.14
Kerberos                                  0.14
RPC                                       2.40
DHCP                                      0.14
HTTP.SOAP                                 0.14
NetBIOS.SMBv1                             3.81

Top 10 des applications par taux de faux négatifs :
                  Total_Instances  Nombre_Erreurs  Taux_Erreur  \
application_name
DHCP                            4             1.0        25.00
Kerberos                        3             1.0        33.33
SSDP                            1             1.0       100.00
Syslog                         90             1.0         1.11
OSPF                          154             8.0         5.19
HTTP.SOAP                       4             1.0        25.00
Unknown                     25388            73.0         0.29
NetBIOS                        12             1.0         8.33
DNS                         38814             4.0         0.01
BGP                           589           319.0        54.16

                  Nombre_Faux_Negatifs  Taux_Faux_Negatifs  \
```

```
application_name
DHCP                              1.0              100.00
Kerberos                          1.0              100.00
SSDP                              1.0              100.00
Syslog                            1.0              100.00
OSPF                              8.0               72.73
HTTP.SOAP                         1.0               25.00
Unknown                           8.0                8.70
NetBIOS                           1.0                8.33
DNS                               1.0                4.00
BGP                               4.0                1.59

                  Contribution_Erreurs_Totales
application_name
DHCP                                      0.14
Kerberos                                  0.14
SSDP                                      0.14
Syslog                                    0.14
OSPF                                      1.13
HTTP.SOAP                                 0.14
Unknown                                  10.30
NetBIOS                                   0.14
DNS                                       0.56
BGP                                      44.99

Top 10 des applications par contribution aux erreurs totales :
                  Total_Instances  Nombre_Erreurs  Taux_Erreur  \
application_name
BGP                           589           319.0        54.16
HTTP                        19135           209.0         1.09
Unknown                     25388            73.0         0.29
NetBIOS.SMBv1                 139            27.0        19.42
MySQL                          35            23.0        65.71
RPC                            52            17.0        32.69
OSPF                          154             8.0         5.19
SMBv23                         33             6.0        18.18
PPTP                           29             5.0        17.24
FTP_CONTROL                  4781             5.0         0.10

                  Nombre_Faux_Negatifs  Taux_Faux_Negatifs  \
application_name
BGP                                4.0                1.59
HTTP                               4.0                0.82
Unknown                            8.0                8.70
NetBIOS.SMBv1                      NaN                 NaN
MySQL                              NaN                 NaN
RPC                                NaN                 NaN
OSPF                               8.0               72.73
```

```
SMBv23                            NaN                 NaN
PPTP                              NaN                 NaN
FTP_CONTROL                       NaN                 NaN

                  Contribution_Erreurs_Totales
application_name
BGP                                      44.99
HTTP                                     29.48
Unknown                                  10.30
NetBIOS.SMBv1                             3.81
MySQL                                     3.24
RPC                                       2.40
OSPF                                      1.13
SMBv23                                    0.85
PPTP                                      0.71
FTP_CONTROL                               0.71
```

[ ]: