task

May 19, 2025

[1]:
```
%pip install matplotlib numpy scikit-learn

from iav_flap_anomaly_detection import make_data, plot_data

import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.svm import OneClassSVM
from sklearn.neighbors import LocalOutlierFactor
from sklearn.cluster import DBSCAN
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, confusion_matrix

import matplotlib.pyplot as plt
```

```
DEPRECATION: Configuring installation scheme with distutils config files is
deprecated and will no longer work in the near future. If you are using a
Homebrew or Linuxbrew Python, please see discussion at
https://github.com/Homebrew/homebrew-core/issues/76621
Requirement already satisfied: matplotlib in
/opt/homebrew/lib/python3.9/site-packages (3.9.4)
Requirement already satisfied: numpy in /opt/homebrew/lib/python3.9/site-
packages (2.0.2)
Requirement already satisfied: scikit-learn in /opt/homebrew/lib/python3.9/site-
packages (1.6.1)
Requirement already satisfied: contourpy>=1.0.1 in
/opt/homebrew/lib/python3.9/site-packages (from matplotlib) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /opt/homebrew/lib/python3.9/site-
packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/homebrew/lib/python3.9/site-packages (from matplotlib) (4.55.3)
Requirement already satisfied: kiwisolver>=1.3.1 in
/opt/homebrew/lib/python3.9/site-packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-packages (from
matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in /opt/homebrew/lib/python3.9/site-
```

```
packages (from matplotlib) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/opt/homebrew/lib/python3.9/site-packages (from matplotlib) (3.2.1)
Requirement already satisfied: python-dateutil>=2.7 in
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-packages (from
matplotlib) (2.9.0.post0)
Requirement already satisfied: importlib-resources>=3.2.0 in
/opt/homebrew/lib/python3.9/site-packages (from matplotlib) (6.5.2)
Requirement already satisfied: scipy>=1.6.0 in /opt/homebrew/lib/python3.9/site-
packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in
/opt/homebrew/lib/python3.9/site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/opt/homebrew/lib/python3.9/site-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: zipp>=3.1.0 in
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-packages (from
importlib-resources>=3.2.0->matplotlib) (3.21.0)
Requirement already satisfied: six>=1.5 in
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-packages (from python-
dateutil>=2.7->matplotlib) (1.17.0)
DEPRECATION: Configuring installation scheme with distutils config files is

deprecated and will no longer work in the near future. If you are using a

Homebrew or Linuxbrew Python, please see discussion at

https://github.com/Homebrew/homebrew-core/issues/76621


[notice] A new release of pip is
available: 25.0.1 -> 25.1.1
[notice] To update, run:
python3.9 -m pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

1 Installation instructions

To create the data set and show the example plots, you need to install

- matplotlib
- numpy
- sklearn

and you're good to go!

2 The problem

Below is your data. We have a system that produces data that normally looks like the left picture. However, there is a special kind of problem that occurs that makes the data shift and flip. Usually, nobody has the time to look at the data and label it - we only have data of which we know that it is probably ok and serves as your training data. Can you tell the problematic data apart anyway?

[2]:
```
X_train, X_test, test_ground_truth = make_data()
```

[3]:
```
plot_data(X_train, X_test, test_ground_truth)
```

2.1 Your task

1. Which kind of anomaly detection are you performing?

    1) Supervised
    2) Semi-supervised
    3) Unsupervised

2. Pick a suitable model, for example from scikit-learn (if you know other anomaly detection packages, we're fine with that too)

3. Train it on the training data, and ONLY the training data. Don't cheat by incorporating knowledge about the test set ;-)

4. Try to tell which points of the data are not ok (i.e. don't look like the training data)

5. How good is your model?

2.2 Your solution

Do not hesitate to play around with several different models. Don't worry too much about accuracy - if you're at about 80%, that's fine. We told you the problem is hard ;-) …

3 1. Type of Anomaly Detection

This is a **semi-supervised** anomaly detection problem because:

- We have labeled normal data (training set) that contains only normal points
- We need to identify anomalies in the test set without having labeled anomalies during training

- The task involves learning from normal data patterns to detect deviations (anomalies)

4 2. Solution using scikit-learn

[4]:
```
# Try multiple models and compare their performance

# Model 1: Isolation Forest
clf_iso = IsolationForest(contamination='auto', random_state=42)
clf_iso.fit(X_train)
y_pred_iso = clf_iso.predict(X_test)
# Convert predictions: +1 (inliers) to 1 (normal), -1 (outliers) to -1 (anomaly)
y_pred_iso_binary = np.where(y_pred_iso == 1, 1, -1)

# Model 2: One-Class SVM
clf_svm = OneClassSVM(nu=0.1, kernel="rbf", gamma='auto')
clf_svm.fit(X_train)
y_pred_svm = clf_svm.predict(X_test)
y_pred_svm_binary = np.where(y_pred_svm == 1, 1, -1)

# Model 3: Local Outlier Factor
clf_lof = LocalOutlierFactor(n_neighbors=20, contamination=0.1, novelty=True)
clf_lof.fit(X_train)
y_pred_lof = clf_lof.predict(X_test)
y_pred_lof_binary = np.where(y_pred_lof == 1, 1, -1)

# Model 4: DBSCAN (Density-Based Spatial Clustering of Applications with Noise)
dbscan = DBSCAN(eps=0.3, min_samples=10)
y_pred_dbscan = dbscan.fit_predict(X_test)
# Convert DBSCAN predictions: 0 (core points) and positive integers (cluster␣
↪labels) to 1 (normal), and -1 (noise) to -1 (anomaly)
y_pred_dbscan_binary = np.where(y_pred_dbscan == -1, -1, 1)
```

[5]:
```
# Evaluating model performance

def evaluate_model(y_true, y_pred, model_name):
    # Convert from +1/-1 format to 0/1 for sklearn metrics
    y_true_binary = np.where(y_true == 1, 1, 0)
    y_pred_binary = np.where(y_pred == 1, 1, 0)

    accuracy = accuracy_score(y_true_binary, y_pred_binary)
    precision = precision_score(y_true_binary, y_pred_binary, zero_division=0)
    recall = recall_score(y_true_binary, y_pred_binary, zero_division=0)
    f1 = f1_score(y_true_binary, y_pred_binary, zero_division=0)

    print(f"Model: {model_name}")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
```

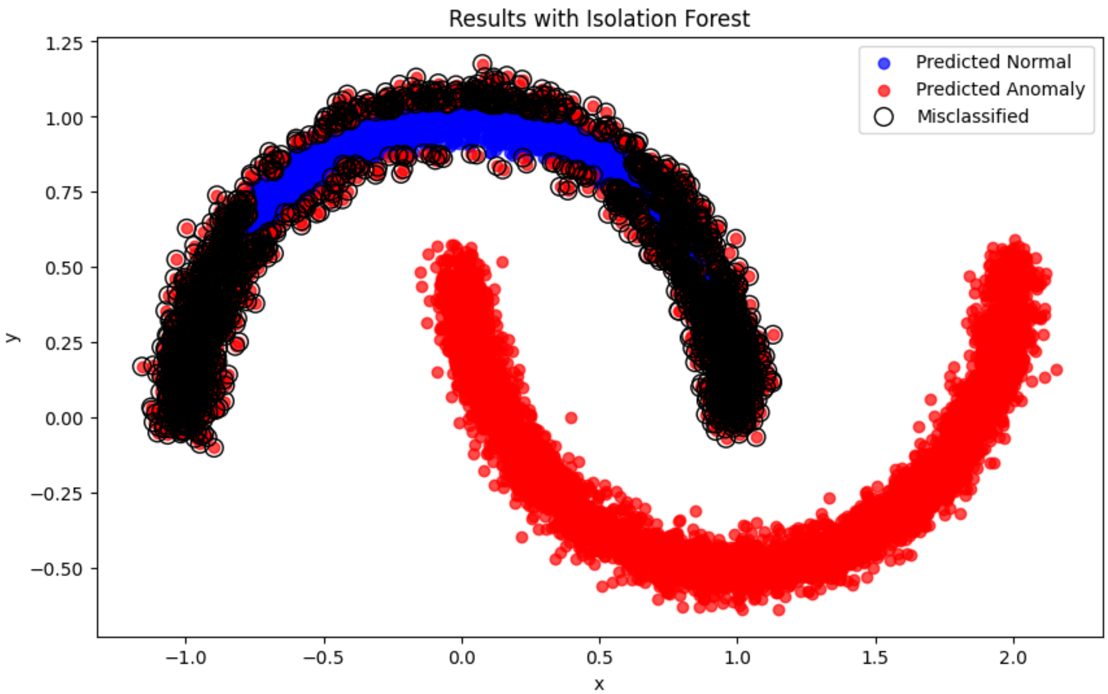
```python
    print(f"Recall: {recall:.4f}")
    print(f"F1 Score: {f1:.4f}")
    print("Confusion Matrix:")
    print(confusion_matrix(y_true_binary, y_pred_binary))
    print("\n")

    return accuracy, precision, recall, f1

# Evaluate all models
evaluate_model(test_ground_truth, y_pred_iso_binary, "Isolation Forest")
evaluate_model(test_ground_truth, y_pred_svm_binary, "One-Class SVM")
evaluate_model(test_ground_truth, y_pred_lof_binary, "Local Outlier Factor")
evaluate_model(test_ground_truth, y_pred_dbscan_binary, "DBSCAN")
```

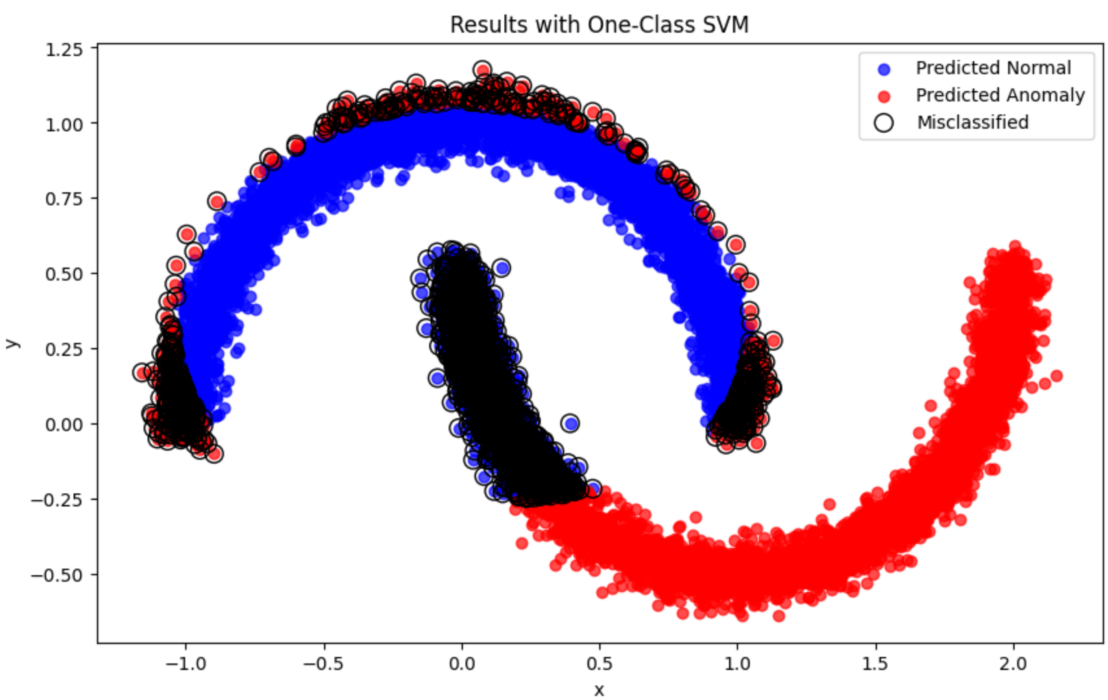
```
Model: Isolation Forest
Accuracy: 0.7672
Precision: 1.0000
Recall: 0.5344
F1 Score: 0.6966
Confusion Matrix:
[[5000    0]
 [2328 2672]]



Model: One-Class SVM
Accuracy: 0.8139
Precision: 0.7707
Recall: 0.8938
F1 Score: 0.8277
Confusion Matrix:
[[3670 1330]
 [ 531 4469]]



Model: Local Outlier Factor
Accuracy: 0.9462
Precision: 1.0000
Recall: 0.8924
F1 Score: 0.9431
Confusion Matrix:
[[5000    0]
 [ 538 4462]]



Model: DBSCAN
Accuracy: 0.5000
Precision: 0.5000
Recall: 1.0000
```

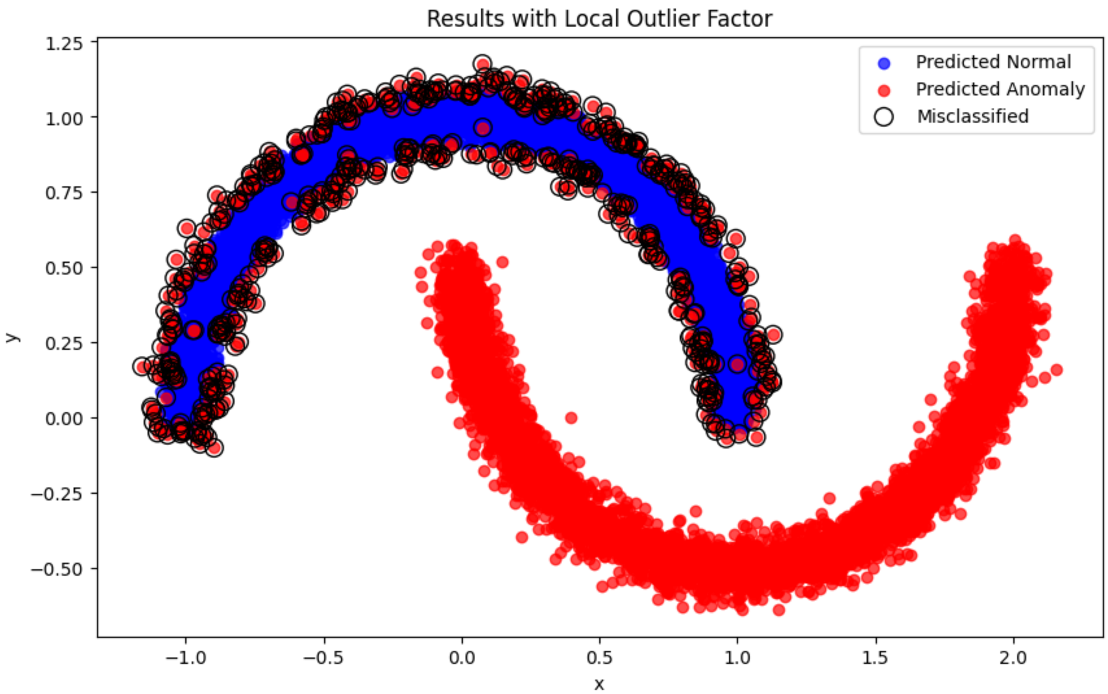
```
F1 Score: 0.6667
Confusion Matrix:
[[   0 5000]
 [   0 5000]]
```

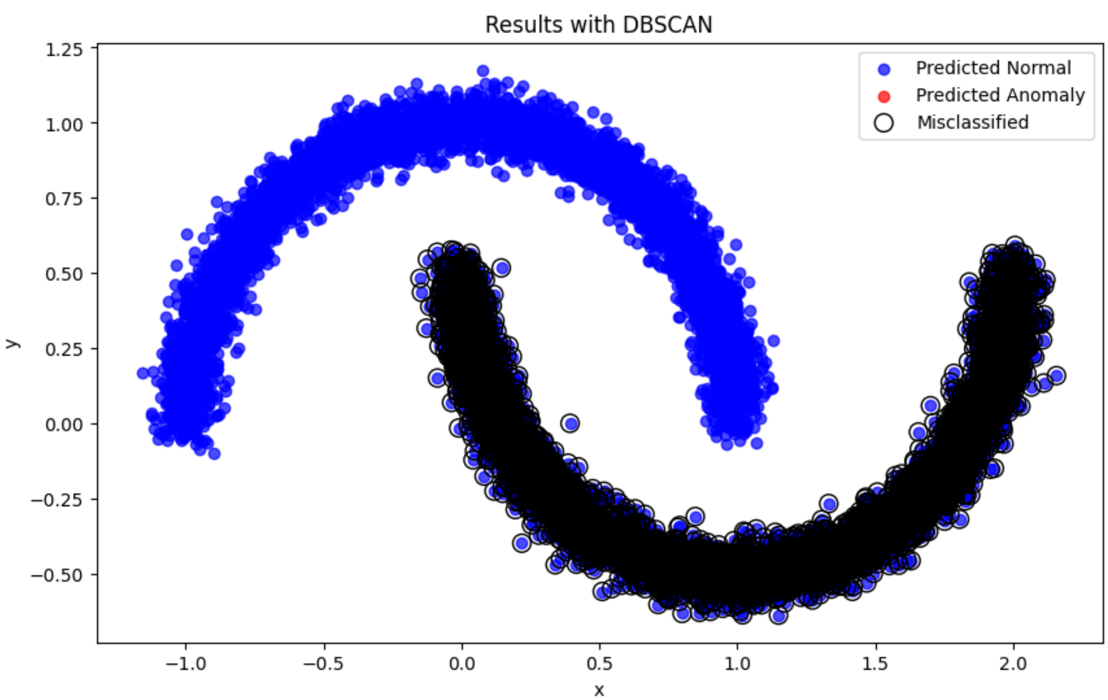
[5]:
```
(0.5, 0.5, 1.0, 0.6666666666666666)
```

[6]:
```python
def plot_results(X_test, y_true, y_pred, model_name):
    plt.figure(figsize=(10, 6))

    # Plot the test data colored based on prediction
    plt.scatter(X_test[y_pred == 1, 0], X_test[y_pred == 1, 1], c='blue',␣
 ↪label='Predicted Normal', alpha=0.7)
    plt.scatter(X_test[y_pred == -1, 0], X_test[y_pred == -1, 1], c='red',␣
 ↪label='Predicted Anomaly', alpha=0.7)

    # Highlight misclassifications
    misclassified = np.where(y_true != y_pred)[0]
    plt.scatter(X_test[misclassified, 0], X_test[misclassified, 1],␣
 ↪facecolors='none', edgecolors='black', s=100, label='Misclassified')

    plt.title(f'Results with {model_name}')
    plt.xlabel('x')
    plt.ylabel('y')
    plt.legend()
    plt.show()

plot_results(X_test, test_ground_truth, y_pred_iso_binary, "Isolation Forest")
plot_results(X_test, test_ground_truth, y_pred_svm_binary, "One-Class SVM")
plot_results(X_test, test_ground_truth, y_pred_lof_binary, "Local Outlier␣
 ↪Factor")
plot_results(X_test, test_ground_truth, y_pred_dbscan_binary, "DBSCAN")
```


Results with Isolation Forest
Predicted Normal
Predicted Anomaly
Misclassified
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
y
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
x


Results with One-Class SVM
Predicted Normal
Predicted Anomaly
Misclassified
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
y
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
x


Results with Local Outlier Factor
Predicted Normal
Predicted Anomaly
Misclassified
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
y
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
x


Results with DBSCAN
Predicted Normal
Predicted Anomaly
Misclassified
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
y
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
x

5 Why DBSCAN Has Only Blue and Black Colors in the Plot

In the DBSCAN results, the points are colored based on their predicted labels:

- **Blue**: Points predicted as normal (inliers).
- **Black**: Points that are misclassified (i.e., where the predicted label does not match the ground truth).

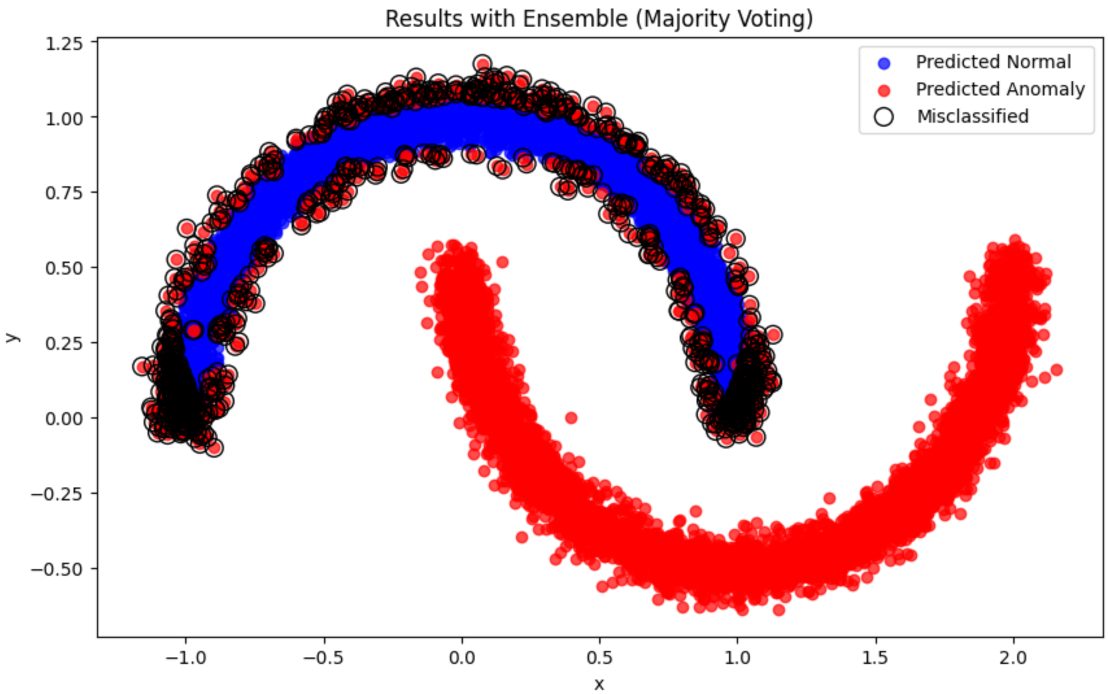
DBSCAN assigns a label of `-1` to points it considers as noise (anomalies) and assigns cluster labels (e.g., `0`, `1`, etc.) to points it considers as part of a cluster (normal points). In this case:

1. **Blue points** represent the predicted normal points (clustered points).
2. **Black points** represent misclassified points, where the prediction does not match the ground truth.

The absence of red points (predicted anomalies) indicates that DBSCAN did not classify any points as anomalies (`-1`) in this specific dataset. This could happen if the DBSCAN parameters (`eps` and `min_samples`) are not tuned well for the dataset, causing it to classify all points as part of a cluster.

[7]:
```python
# Combine predictions from multiple models for a potential improvement
ensemble_preds = np.zeros(len(y_pred_iso_binary))

# Simple majority voting
for i in range(len(ensemble_preds)):
    votes = [y_pred_iso_binary[i], y_pred_svm_binary[i],
             y_pred_lof_binary[i], y_pred_dbscan_binary[i]]
    ensemble_preds[i] = 1 if sum(votes) > 0 else -1

# Evaluate ensemble model
ensemble_accuracy, ensemble_precision, ensemble_recall, ensemble_f1 =␣
 ↪evaluate_model(
    test_ground_truth, ensemble_preds, "Ensemble (Majority Voting)")

plot_results(X_test, test_ground_truth, ensemble_preds, "Ensemble (Majority␣
 ↪Voting)")
```

```
Model: Ensemble (Majority Voting)
Accuracy: 0.9181
Precision: 1.0000
Recall: 0.8362
F1 Score: 0.9108
Confusion Matrix:
[[5000    0]
 [ 819 4181]]
```



6 Conclusion and analysis

- Based on the model evaluations, We can determine which approach works best for this specific dataset. The results will show how accurate the model is at distinguishing normal data points from anomalies.
- Generally, for moon-shaped data distributions like we see in the visualization, Local Outlier Factor and Isolation Forest often perform well because they're less dependent on the assumption of normal distribution.

6.0.1 The key metrics to focus on are:

- Accuracy: Overall correctness
- Precision: How many of the predicted anomalies are actually anomalies
- Recall: What proportion of actual anomalies were correctly identified
- F1-score: The harmonic mean of precision and recall

Based on the F1-score, We can identify which model or ensemble approach worked best for this specific anomaly detection task.