Autoencoder_xgboost

February 22, 2025

[1]:
```python
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import xgboost as xgb
from sklearn.metrics import accuracy_score, classification_report
```

[2]:
```python
# Load dataset (Replace 'your_data.csv' with your actual dataset path)
df = pd.read_csv("cleaned_data2_iotid23.csv")
```

[3]:
```python
print(df.shape)
```

```
(1230402, 35)
```

[4]:
```python
df.columns
```

[4]:
```
Index(['Protocol', 'Flow Duration', 'Total Fwd Packet',
       'Total Length of Fwd Packet', 'Fwd Packet Length Max',
       'Fwd Packet Length Min', 'Bwd Packet Length Max',
       'Bwd Packet Length Min', 'Flow Bytes/s', 'Flow Packets/s',
       'Flow IAT Mean', 'Flow IAT Std', 'Flow IAT Max', 'Fwd IAT Std',
       'Bwd IAT Mean', 'Bwd IAT Std', 'Packet Length Max',
       'Packet Length Mean', 'FIN Flag Count', 'SYN Flag Count',
       'RST Flag Count', 'PSH Flag Count', 'Down/Up Ratio',
       'Bwd Bulk Rate Avg', 'FWD Init Win Bytes', 'Bwd Init Win Bytes',
       'Fwd Act Data Pkts', 'Fwd Seg Size Min', 'Active Mean', 'Active Std',
       'Idle Mean', 'Idle Std', 'Idle Max', 'Connection Type', 'Label'],
      dtype='object')
```

[3]:
```python
# Assuming 'label' is the target column
X = df.drop(columns=["Label"])  # Features (34 columns)
y = df["Label"]  # Target
```

[4]:
```
# Encode categorical labels if necessary
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)
```

[5]:
```
df.replace([np.inf, -np.inf], np.nan, inplace=True)
```

[7]:
```
import numpy as np
import pandas as pd

# Check for infinite values
print("Number of infinite values in X:", np.isinf(X).sum().sum())

# Replace infinite values with NaN (if any)
X.replace([np.inf, -np.inf], np.nan, inplace=True)

# Check for NaN values
print("Number of NaN values in X:", X.isna().sum().sum())

# Fill or drop NaN values
X.fillna(X.median(), inplace=True)  # Replace NaN with median values
```

```
Number of infinite values in X: 1830
Number of NaN values in X: 1830
```

[8]:
```
# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

[9]:
```
# Split data
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)
```

[10]:
```
# Autoencoder Model
dim_input = X_train.shape[1]
encoding_dim = 16  # Choose a lower dimension for the encoded representation

input_layer = Input(shape=(dim_input,))
encoded = Dense(encoding_dim, activation="relu")(input_layer)
decoded = Dense(dim_input, activation="sigmoid")(encoded)

autoencoder = Model(input_layer, decoded)
autoencoder.compile(optimizer="adam", loss="mse")
```

[11]:
```
# Train Autoencoder
autoencoder.fit(
    X_train,
    X_train,
```

```
    epochs=50,
    batch_size=32,
    shuffle=True,
    validation_data=(X_test, X_test),
    verbose=1,
)
```

```
Epoch 1/50
30761/30761 [==============================] - 38s 1ms/step - loss: 0.7041 -
val_loss: 0.7844
Epoch 2/50
30761/30761 [==============================] - 57s 2ms/step - loss: 0.6948 -
val_loss: 0.7833
Epoch 3/50
30761/30761 [==============================] - 40s 1ms/step - loss: 0.6943 -
val_loss: 0.7830
Epoch 4/50
30761/30761 [==============================] - 46s 1ms/step - loss: 0.6941 -
val_loss: 0.7829
Epoch 5/50
30761/30761 [==============================] - 60s 2ms/step - loss: 0.6940 -
val_loss: 0.7828
Epoch 6/50
30761/30761 [==============================] - 42s 1ms/step - loss: 0.6939 -
val_loss: 0.7827
Epoch 7/50
30761/30761 [==============================] - 33s 1ms/step - loss: 0.6939 -
val_loss: 0.7827
Epoch 8/50
30761/30761 [==============================] - 46s 2ms/step - loss: 0.6938 -
val_loss: 0.7826
Epoch 9/50
30761/30761 [==============================] - 49s 2ms/step - loss: 0.6938 -
val_loss: 0.7827
Epoch 10/50
30761/30761 [==============================] - 67s 2ms/step - loss: 0.6938 -
val_loss: 0.7826
Epoch 11/50
30761/30761 [==============================] - 78s 3ms/step - loss: 0.6938 -
val_loss: 0.7826
Epoch 12/50
30761/30761 [==============================] - 66s 2ms/step - loss: 0.6937 -
val_loss: 0.7826
Epoch 13/50
30761/30761 [==============================] - 37s 1ms/step - loss: 0.6937 -
val_loss: 0.7825
Epoch 14/50
30761/30761 [==============================] - 38s 1ms/step - loss: 0.6937 -
```

```
val_loss: 0.7825
Epoch 15/50
30761/30761 [==============================] - 38s 1ms/step - loss: 0.6937 -
val_loss: 0.7825
Epoch 16/50
30761/30761 [==============================] - 38s 1ms/step - loss: 0.6937 -
val_loss: 0.7825
Epoch 17/50
30761/30761 [==============================] - 38s 1ms/step - loss: 0.6937 -
val_loss: 0.7825
Epoch 18/50
30761/30761 [==============================] - 39s 1ms/step - loss: 0.6937 -
val_loss: 0.7825
Epoch 19/50
30761/30761 [==============================] - 42s 1ms/step - loss: 0.6936 -
val_loss: 0.7825
Epoch 20/50
30761/30761 [==============================] - 36s 1ms/step - loss: 0.6936 -
val_loss: 0.7825
Epoch 21/50
30761/30761 [==============================] - 38s 1ms/step - loss: 0.6936 -
val_loss: 0.7825
Epoch 22/50
30761/30761 [==============================] - 43s 1ms/step - loss: 0.6936 -
val_loss: 0.7824
Epoch 23/50
30761/30761 [==============================] - 47s 2ms/step - loss: 0.6936 -
val_loss: 0.7824
Epoch 24/50
30761/30761 [==============================] - 39s 1ms/step - loss: 0.6936 -
val_loss: 0.7824
Epoch 25/50
30761/30761 [==============================] - 41s 1ms/step - loss: 0.6936 -
val_loss: 0.7825
Epoch 26/50
30761/30761 [==============================] - 49s 2ms/step - loss: 0.6936 -
val_loss: 0.7824
Epoch 27/50
30761/30761 [==============================] - 40s 1ms/step - loss: 0.6936 -
val_loss: 0.7824
Epoch 28/50
30761/30761 [==============================] - 39s 1ms/step - loss: 0.6936 -
val_loss: 0.7823
Epoch 29/50
30761/30761 [==============================] - 39s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 30/50
30761/30761 [==============================] - 39s 1ms/step - loss: 0.6935 -
```

```
val_loss: 0.7823
Epoch 31/50
30761/30761 [==============================] - 52s 2ms/step - loss: 0.6935 -
val_loss: 0.7824
Epoch 32/50
30761/30761 [==============================] - 40s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 33/50
30761/30761 [==============================] - 39s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 34/50
30761/30761 [==============================] - 44s 1ms/step - loss: 0.6935 -
val_loss: 0.7824
Epoch 35/50
30761/30761 [==============================] - 52s 2ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 36/50
30761/30761 [==============================] - 41s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 37/50
30761/30761 [==============================] - 44s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 38/50
30761/30761 [==============================] - 40s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 39/50
30761/30761 [==============================] - 44s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 40/50
30761/30761 [==============================] - 43s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 41/50
30761/30761 [==============================] - 38s 1ms/step - loss: 0.6935 -
val_loss: 0.7822
Epoch 42/50
30761/30761 [==============================] - 34s 1ms/step - loss: 0.6935 -
val_loss: 0.7823
Epoch 43/50
30761/30761 [==============================] - 35s 1ms/step - loss: 0.6934 -
val_loss: 0.7823
Epoch 44/50
30761/30761 [==============================] - 35s 1ms/step - loss: 0.6935 -
val_loss: 0.7822
Epoch 45/50
30761/30761 [==============================] - 36s 1ms/step - loss: 0.6934 -
val_loss: 0.7823
Epoch 46/50
30761/30761 [==============================] - 36s 1ms/step - loss: 0.6935 -
```

```
val_loss: 0.7823
Epoch 47/50
30761/30761 [==============================] - 36s 1ms/step - loss: 0.6934 -
val_loss: 0.7823
Epoch 48/50
30761/30761 [==============================] - 37s 1ms/step - loss: 0.6934 -
val_loss: 0.7823
Epoch 49/50
30761/30761 [==============================] - 37s 1ms/step - loss: 0.6934 -
val_loss: 0.7824
Epoch 50/50
30761/30761 [==============================] - 69s 2ms/step - loss: 0.6934 -
val_loss: 0.7823
```

[11]:
```
<keras.src.callbacks.History at 0x1fa4bd065d0>
```

[12]:
```
# Extract Encoder part
encoder = Model(input_layer, encoded)
X_train_encoded = encoder.predict(X_train)
X_test_encoded = encoder.predict(X_test)
```

```
30761/30761 [==============================] - 26s 828us/step
7691/7691 [==============================] - 7s 855us/step
```

[13]:
```
# Train XGBoost on Encoded Features
xgb_classifier = xgb.XGBClassifier(
    n_estimators=100, max_depth=5, learning_rate=0.1, random_state=42
)
xgb_classifier.fit(X_train_encoded, y_train)
```

[13]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=5, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=100, n_jobs=None,
              num_parallel_tree=None, objective='multi:softprob', …)
```

[14]:
```
# Predictions
y_pred = xgb_classifier.predict(X_test_encoded)
accuracy = accuracy_score(y_test, y_pred)

print(f"Accuracy: {accuracy:.4f}")
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.9954

c:\Users\emada\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\Users\emada\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      0.99      0.99     65616
           2       1.00      0.99      1.00      9422
           3       1.00      1.00      1.00      1302
           4       1.00      1.00      1.00     44983
           5       1.00      1.00      1.00      7611
           6       0.96      0.99      0.98     14479
           7       1.00      1.00      1.00     88041
           8       1.00      1.00      1.00      2839
           9       1.00      1.00      1.00      3713
          10       0.84      0.42      0.56       144
          11       1.00      1.00      1.00      7929

    accuracy                           1.00    246081
   macro avg       0.90      0.87      0.88    246081
weighted avg       1.00      1.00      1.00    246081


c:\Users\emada\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[18]:
```python
print(type(xgb))
```

```
<class 'module'>
```

[19]:
```python
from xgboost import XGBClassifier
import joblib

# Train the model (example)
xgb_model = XGBClassifier()
```

```python
xgb_model.fit(X_train, y_train)

# Save the trained model
joblib.dump(xgb_model, "xgboost_model.pkl")
print("XGBClassifier model saved successfully!")

# Save the StandardScaler
joblib.dump(scaler, "scaler.pkl")
print("Scaler saved successfully!")
```

```
XGBClassifier model saved successfully!
Scaler saved successfully!
```

[20]:

```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import (
    classification_report,
    confusion_matrix,
    roc_curve,
    auc,
    precision_recall_curve,
)
from sklearn.preprocessing import label_binarize

# Predict on test data
y_pred = xgb_model.predict(X_test)
y_prob = xgb_model.predict_proba(X_test)  # For ROC & PR curves

# 1  Classification Report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# 2  Confusion Matrix
plt.figure(figsize=(10, 6))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()

# 3  ROC Curve (One-vs-Rest for Multi-Class)
n_classes = len(np.unique(y_test))  # Number of classes
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))

plt.figure(figsize=(8, 6))
```

```python
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f"Class {i} (AUC = {roc_auc:.2f})")

plt.plot([0, 1], [0, 1], linestyle="--", color="gray")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()

# 4 Precision-Recall Curve
plt.figure(figsize=(8, 6))
for i in range(n_classes):
    precision, recall, _ = precision_recall_curve(y_test_bin[:, i], y_prob[:,␣
 ↪i])
    plt.plot(recall, precision, label=f"Class {i}")

plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.legend()
plt.show()
```

```
Classification Report:

c:\Users\emada\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
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  _warn_prf(average, modifier, msg_start, len(result))
c:\Users\emada\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
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packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      0.99      0.99     65616
           2       1.00      1.00      1.00      9422
           3       1.00      1.00      1.00      1302
```
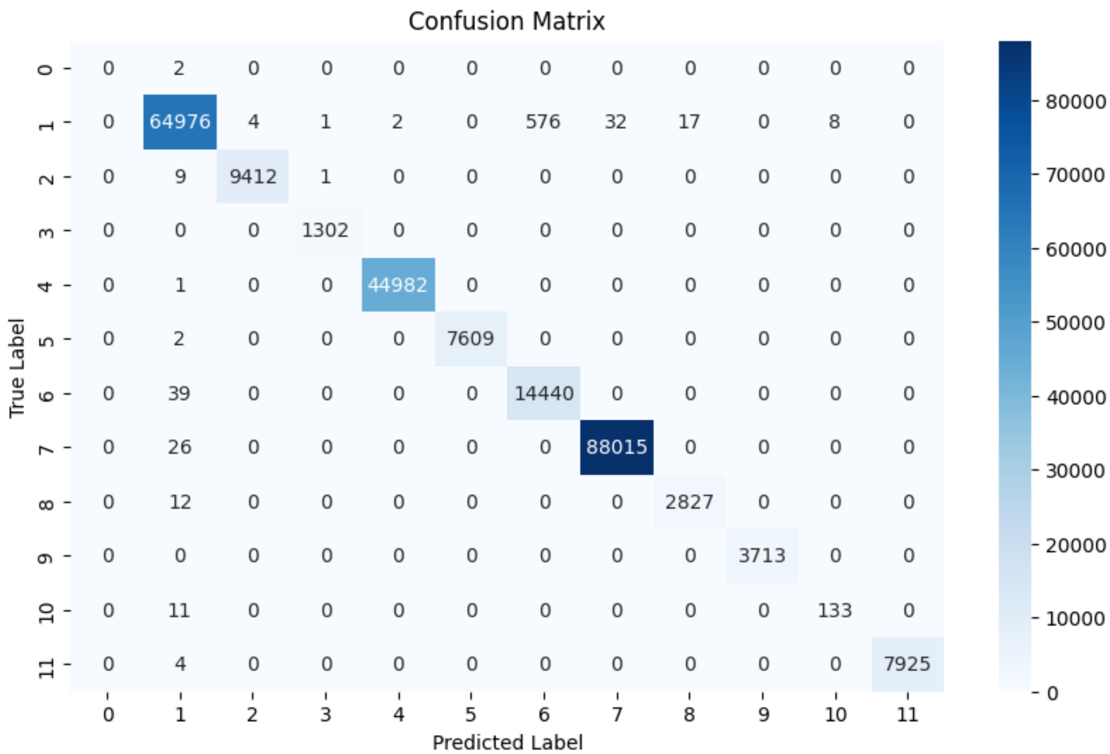
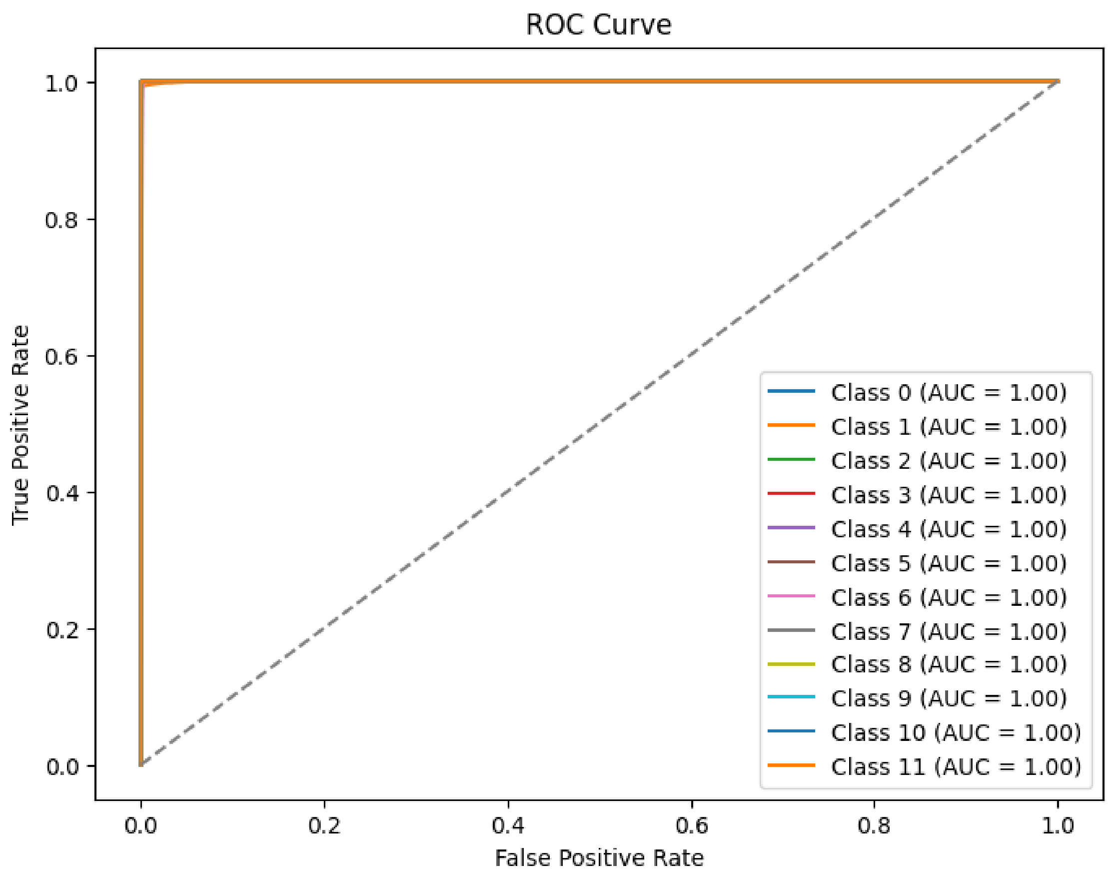
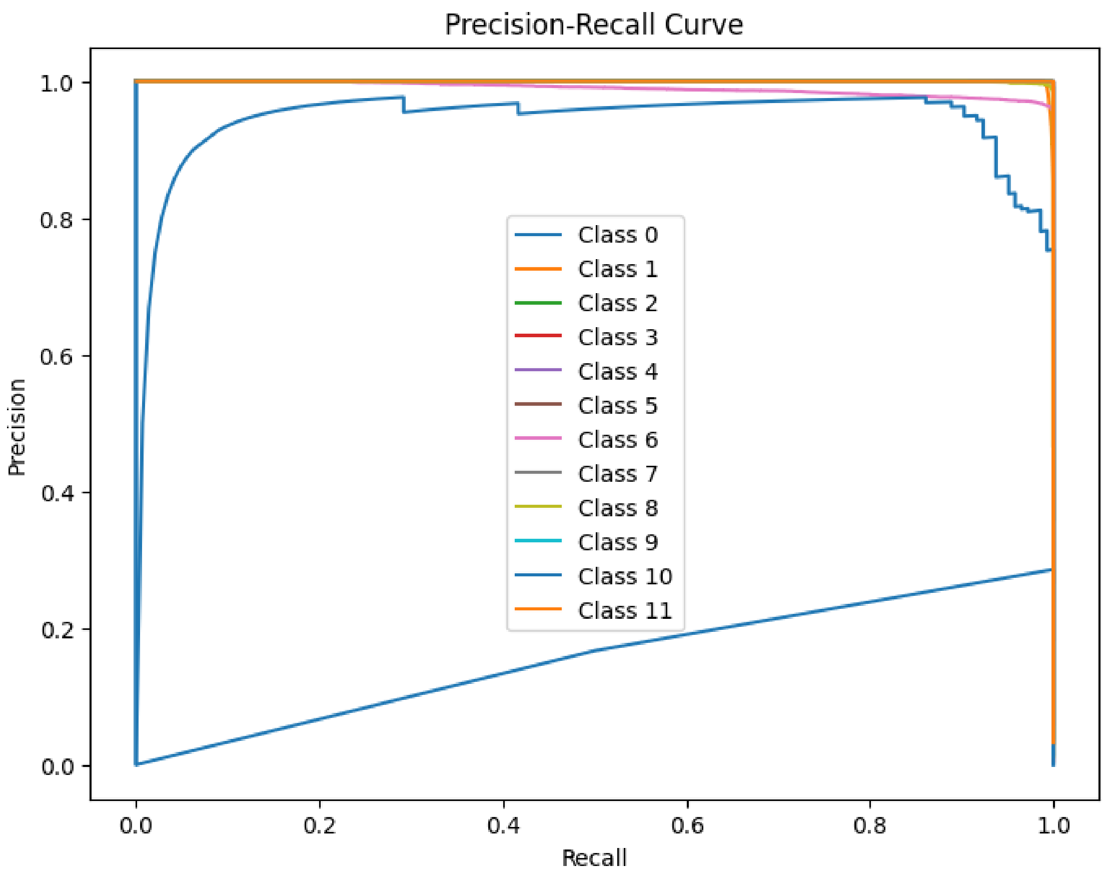

4	1.00	1.00	1.00	44983
5	1.00	1.00	1.00	7611
6	0.96	1.00	0.98	14479
7	1.00	1.00	1.00	88041
8	0.99	1.00	0.99	2839
9	1.00	1.00	1.00	3713
10	0.94	0.92	0.93	144
11	1.00	1.00	1.00	7929
accuracy			1.00	246081
macro avg	0.91	0.91	0.91	246081
weighted avg	1.00	1.00	1.00	246081





ROC Curve
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
True Positive Rate
False Positive Rate
Class 0 (AUC = 1.00)
Class 1 (AUC = 1.00)
Class 2 (AUC = 1.00)
Class 3 (AUC = 1.00)
Class 4 (AUC = 1.00)
Class 5 (AUC = 1.00)
Class 6 (AUC = 1.00)
Class 7 (AUC = 1.00)
Class 8 (AUC = 1.00)
Class 9 (AUC = 1.00)
Class 10 (AUC = 1.00)
Class 11 (AUC = 1.00)



Precision-Recall Curve
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Class 0
Class 1
Class 2
Class 3
Class 4
Class 5
Class 6
Class 7
Class 8
Class 9
Class 10
Class 11