

## 4\_eval

August 26, 2025

# 1 Evaluate Prediction API

## 1.1 Import lib

```
[17]: import requests
      from pathlib import Path
      import pandas as pd
      import json
      from sklearn.metrics import multilabel_confusion_matrix, confusion_matrix,
      ↪ ConfusionMatrixDisplay, classification_report
      import numpy as np
      import matplotlib.pyplot as plt

[18]: API_ENDPOINT = 'http://localhost:8000/api'
      ROOT_PATH = Path.cwd().parent

[26]: def plot_confuse(y_true, y_pred, labels=[]):
      if len(labels) > 0:
          yt = y_true.values if hasattr(y_true, "values") else np.asarray(y_true)
          yp = y_pred.values if hasattr(y_pred, "values") else np.asarray(y_pred)
          if yt.ndim != 1 or yp.ndim != 1:
              raise ValueError("For single-label, y_true and y_pred must be 1D.")
          if yt.shape[0] != yp.shape[0]:
              raise ValueError(f"Length mismatch: y_true {yt.shape[0]} vs y_pred_
          ↪ {yp.shape[0]}")
          cm = confusion_matrix(yt, yp, labels=[0,1])
          fig, ax = plt.subplots(figsize=(4.5, 4.5))
          disp = ConfusionMatrixDisplay(confusion_matrix=cm,
          ↪ display_labels=labels if labels else
          ↪ [0,1])
          disp.plot(cmap=plt.cm.Blues, ax=ax, values_format="d", colorbar=False)
          plt.tight_layout()
          plt.show()

      else:
          cm_list = multilabel_confusion_matrix(y_true, y_pred)
          n = len(y_true.columns)
          _, axs = plt.subplots(1, n, figsize=(6*n, 5))
```

```

        for i in range(n):
            disp = ConfusionMatrixDisplay(confusion_matrix=cm_list[i],
            ↪display_labels=[f"Not {y_true.columns[i]}", y_true.columns[i]])
            disp.plot(cmap=plt.cm.Blues, ax=axes[i] if n > 1 else axes,
            ↪values_format="d", colorbar=False)
            axes[i].set_title(y_true.columns[i])
plt.show()

```

## 1.2 Current Version

```

[4]: meta = requests.get(API_ENDPOINT + '/system/versions')
meta = meta.json()
print(json.dumps(meta, indent=4))
{
  "status": "Rug Pull Detection API is running.",
  "is_trained": true,
  "current_version": "20250825_151608_1_1",
  "timestamp": "2025-08-26T09:31:50.398328",
  "version_last_modified": "2025-08-26T06:41:53.979620",
  "label_names": [
    "Address Restrict",
    "Amount Restrict",
    "Hidden Balance Modification",
    "Hidden Mint/Burn",
    "Leak",
    "Limit",
    "Mint",
    "Modifiable External Call",
    "Modifiable Tax Address",
    "Modifiable Tax Rate",
    "TimeStamp Restrict",
    "Amount Limit",
    "Exchange Permission",
    "Exchange Suspension",
    "Fee Manipulation",
    "Invalid Callback",
    "Trapdoor"
  ],
  "n_labels": 17,
  "train_size": 1200,
  "test_size": 300,
  "notes": "Optuna 15 trials per model; test split=0.2.",
  "model_files": {
    "general_model": {
      "exists": true,
      "size": 313962,
      "mtime": "2025-08-26T03:24:03.950378",

```

```

        "path": "/app/backend/models/current/general_model.pkl"
    },
    "sol_model": {
        "exists": true,
        "size": 1446125,
        "mtime": "2025-08-26T03:24:06.852992",
        "path": "/app/backend/models/current/sol_model.pkl"
    },
    "opcode_model": {
        "exists": true,
        "size": 54686366,
        "mtime": "2025-08-26T03:26:05.864065",
        "path": "/app/backend/models/current/opcode_model.pkl"
    },
    "gru_model": {
        "exists": true,
        "size": 8415724,
        "mtime": "2025-08-26T06:32:35.902299",
        "path": "/app/backend/models/current/gru_model.keras"
    },
    "if_general_model": {
        "exists": true,
        "size": 3955928,
        "mtime": "2025-08-26T06:33:21.274483",
        "path": "/app/backend/models/current/if_general_model.pkl"
    },
    "if_sol_model": {
        "exists": true,
        "size": 33554840,
        "mtime": "2025-08-26T06:33:26.407297",
        "path": "/app/backend/models/current/if_sol_model.pkl"
    },
    "if_opcode_model": {
        "exists": true,
        "size": 1005911,
        "mtime": "2025-08-26T06:33:34.808594",
        "path": "/app/backend/models/current/if_opcode_model.pkl"
    },
    "gru_ae_model": {
        "exists": true,
        "size": 5083048,
        "mtime": "2025-08-26T06:37:44.855742",
        "path": "/app/backend/models/current/gru_ae_model.keras"
    }
},
"clf_fusion": {
    "weights": {
        "general": 0.7872198690796577,

```

```

        "sol": 0.24218493956991577,
        "opcode": 0.2589465892599484,
        "gru": 0.46554199075819136
    },
    "thresholds": {
        "Address Restrict": 0.3836877787446481,
        "Amount Restrict": 0.3580143690717003,
        "Hidden Balance Modification": 0.5566704448221383,
        "Hidden Mint/Burn": 0.525055494560247,
        "Leak": 0.5654100693921833,
        "Limit": 0.3735308474361557,
        "Mint": 0.342498671716905,
        "Modifiable External Call": 0.4173173319928712,
        "Modifiable Tax Address": 0.47807790074691203,
        "Modifiable Tax Rate": 0.5868287198333723,
        "TimeStamp Restrict": 0.4355932567675713,
        "Amount Limit": 0.5167708130191594,
        "Exchange Permission": 0.3853885406918155,
        "Exchange Suspension": 0.6031984910527495,
        "Fee Manipulation": 0.5987357592236902,
        "Invalid Callback": 0.44855869045511043,
        "Trapdoor": 0.4183144951733215
    },
    "f1_score": 0.847257965795563
},
"anomaly_fusion": {
    "weights": {
        "if_general": 0.7659883326636499,
        "if_sol": 0.19525049383601167,
        "if_opcode": 0.5658932543556239,
        "ae_timeline": 0.12992522927882935
    },
    "threshold": 0.3200121097809793,
    "f1_score": 0.4881253158160687,
    "ae_threshold": 0.0
},
"backup_versions": []
}

```

### 1.3 Evaluate on CRPWarning Ground Truth

```

[5]: ground_df = pd.read_excel(ROOT_PATH / 'data/external/crpwarner/dataset/
    ↳groundtruth/groundTruth.xlsx', index_col='address')
    ground_df.index = ground_df.index.str.lower()

```

```

[6]: ground_df.head()

```

	Mint	Leak	Limit
address			
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0	1
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0	1
0x94b7d24552933f50a5a5705c446528806dcea381	0	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0	1

```
[7]: res = requests.post(API_ENDPOINT + "/predict", json={"addresses": ground_df.
      ↪index.to_list()})
print("Status:", res.status_code)
print("Elapsed:", res.elapsed.total_seconds(), "seconds")
res = res.json()['results']
df = pd.DataFrame.from_dict(res, orient="index")
df.head()
```

Status: 200

Elapsed: 213.620452 seconds

	labels \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	{'Address Restrict': 1, 'Amount Restrict': 1, ...
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	{'Address Restrict': 1, 'Amount Restrict': 0, ...
0x94b7d24552933f50a5a5705c446528806dcea381	{'Address Restrict': 0, 'Amount Restrict': 1, ...
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	{'Address Restrict': 0, 'Amount Restrict': 0, ...
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	{'Address Restrict': 0, 'Amount Restrict': 0, ...

	label_probs \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	{'Address Restrict': 0.6057556970940429, 'Amou...
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	{'Address Restrict': 0.6905174535481907, 'Amou...
0x94b7d24552933f50a5a5705c446528806dcea381	{'Address Restrict': 0.21008467032827421, 'Amo...
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	{'Address Restrict': 0.21073564104015546, 'Amo...
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	{'Address Restrict': 0.17137202234071047, 'Amo...

	anomaly	anomaly_score
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0.462258
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	1	0.580088
0x94b7d24552933f50a5a5705c446528806dcea381	1	0.462258
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	1	0.462258

0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0.462258
--	---	----------

### 1.3.1 Labels

```
[8]: label_df = pd.DataFrame.from_records(df['labels'].tolist(), index=df.index)
label_df.head()
```

```
[8]:
```

	Address Restrict	Amount Restrict	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	1	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	1	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	1	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	0	

	Hidden Balance Modification	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	

	Hidden Mint/Burn	Leak	Limit	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	0	1	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0	1	
0x94b7d24552933f50a5a5705c446528806dcea381	0	0	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	1	0	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0	1	

	Mint	Modifiable	External	Call	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1			0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0			0	
0x94b7d24552933f50a5a5705c446528806dcea381	0			0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0			0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1			0	

	Modifiable Tax Address	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	

	Modifiable Tax Rate	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	

0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	
	TimeStamp Restrict	Amount Limit \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0
0x94b7d24552933f50a5a5705c446528806dcea381	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	1
	Exchange Permission	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	
	Exchange Suspension	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	
	Fee Manipulation	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	
	Invalid Callback	Trapdoor
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0
0x94b7d24552933f50a5a5705c446528806dcea381	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	1

```
[9]: y_true = ground_df
      y_pred = label_df.loc[y_true.index, y_true.columns]
```

```
[10]: y_true.head()
```

```
[10]:
```

	Mint	Leak	Limit
address			
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0	1
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0	1
0x94b7d24552933f50a5a5705c446528806dcea381	0	0	0

0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0	1

```
[11]: y_pred.head()
```

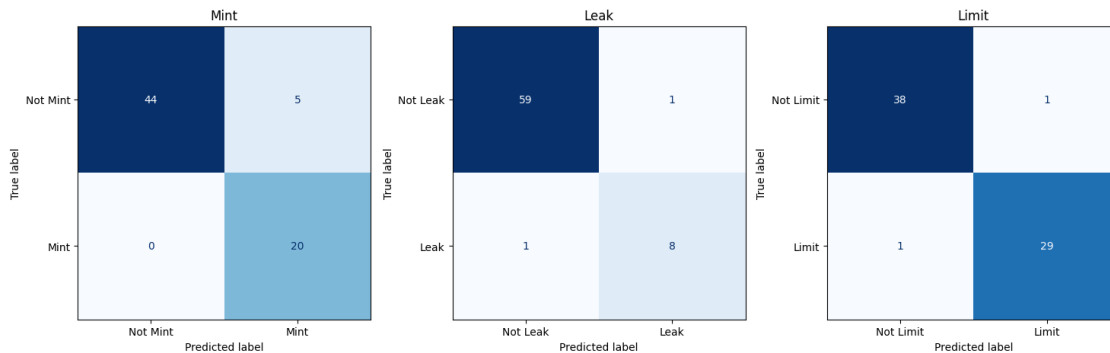
```
[11]:
```

	Mint	Leak	Limit
address			
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0	1
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0	1
0x94b7d24552933f50a5a5705c446528806dcea381	0	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0	1

```
[20]: print(classification_report(
    y_true.values,
    y_pred.values,
    target_names=y_true.columns,
    zero_division=0))
```

	precision	recall	f1-score	support
Mint	0.80	1.00	0.89	20
Leak	0.89	0.89	0.89	9
Limit	0.97	0.97	0.97	30
micro avg	0.89	0.97	0.93	59
macro avg	0.89	0.95	0.91	59
weighted avg	0.90	0.97	0.93	59
samples avg	0.59	0.59	0.59	59

```
[23]: plot_confuse(y_true, y_pred)
```





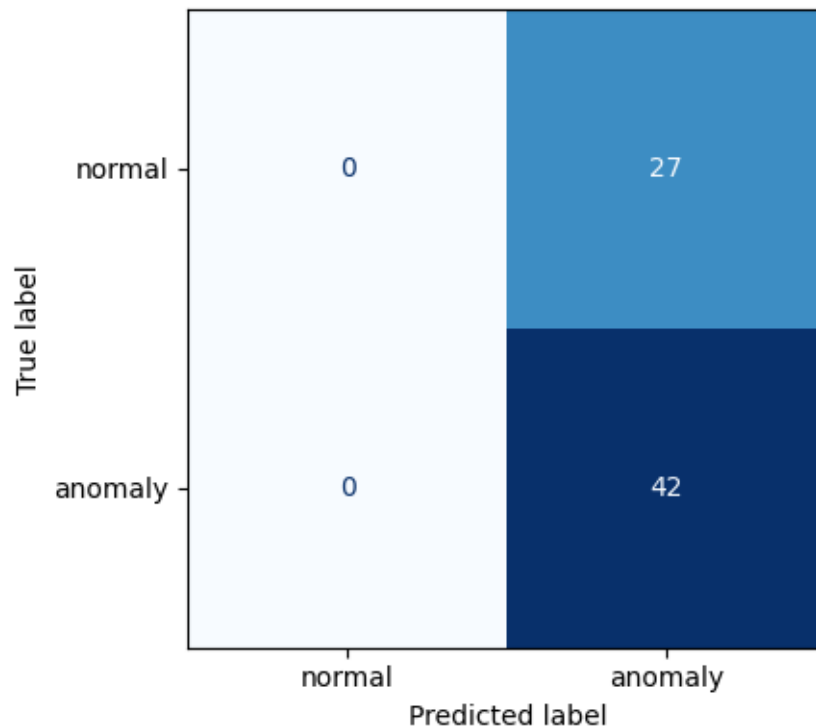
### 1.3.2 Anomaly

```
[14]: anomaly_true = (y_true.astype(int).sum(axis=1) > 0).astype(int)
      anomaly_pred = df.loc[y_true.index, "anomaly"].astype(int)
```

```
[15]: labels = ['normal', 'anomaly']
      print(classification_report(
          anomaly_true,
          anomaly_pred,
          target_names=labels,
          zero_division=0))
```

	precision	recall	f1-score	support
normal	0.00	0.00	0.00	27
anomaly	0.61	1.00	0.76	42
accuracy			0.61	69
macro avg	0.30	0.50	0.38	69
weighted avg	0.37	0.61	0.46	69

```
[27]: plot_confuse(anomaly_true, anomaly_pred, labels)
```



## 1.4 Evaluate on Large Sample (Mint)

```
[52]: label = 'Mint'
temp_df = pd.read_excel(ROOT_PATH / f'data/external/crpwarner/dataset/large/
↳sample/{label.lower()}.xlsx', index_col='Address')
temp_df['TP?'] = temp_df['TP?'].map({'Yes': 1, 'No': 0})
temp_df = temp_df.rename(columns={'TP?': label})
temp_df.index = temp_df.index.str.lower()
```

```
[54]: temp_df.head()
```

```
[54]:
```

	Mint
Address	
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	1
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	1
0xa1b756be589441519b1a08e16bc4f60ab177d916	1
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	1
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	1

```
[31]: res = requests.post(API_ENDPOINT + "/predict", json={"addresses": temp_df.index.
↳to_list()})
print("Status:", res.status_code)
print("Elapsed:", res.elapsed.total_seconds(), "seconds")
res = res.json()['results']
df = pd.DataFrame.from_dict(res, orient="index")
df.head()
```

Status: 200

Elapsed: 288.838395 seconds

```
[31]:
```

labels \	
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	{'Address Restrict': 0, 'Amount Restrict': 0, ...
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	{'Address Restrict': 0, 'Amount Restrict': 1, ...
0xa1b756be589441519b1a08e16bc4f60ab177d916	{'Address Restrict': 0, 'Amount Restrict': 0, ...
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	{'Address Restrict': 0, 'Amount Restrict': 0, ...
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	{'Address Restrict': 0, 'Amount Restrict': 1, ...

label_probs \	
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	{'Address Restrict': 0.07362741922920765, 'Amo...
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	{'Address Restrict': 0.02257792597178286, 'Amo...
0xa1b756be589441519b1a08e16bc4f60ab177d916	{'Address Restrict': ...

```

0.06266966197385725, 'Amo...
0x514bc174df04a4b04ae2be81ee8c788c3796b06b {'Address Restrict':
0.28235612910726376, 'Amo...
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46 {'Address Restrict':
0.026694638981940244, 'Am...

```

	anomaly	anomaly_score
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	1	0.462258
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	1	0.462258
0xa1b756be589441519b1a08e16bc4f60ab177d916	1	0.580088
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	1	0.462258
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	1	0.462258

#### 1.4.1 Labels

```

[32]: label_df = pd.DataFrame.from_records(df['labels'].tolist(), index=df.index)
      label_df.head()

```

```

[32]:
Address Restrict  Amount Restrict  \
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8      0      0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04      0      1
0xa1b756be589441519b1a08e16bc4f60ab177d916      0      0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b      0      0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46      0      1

Hidden Balance Modification  \
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8      0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04      0
0xa1b756be589441519b1a08e16bc4f60ab177d916      0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b      0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46      0

Hidden Mint/Burn  Leak  Limit  \
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8      0      1      1
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04      1      0      1
0xa1b756be589441519b1a08e16bc4f60ab177d916      1      0      1
0x514bc174df04a4b04ae2be81ee8c788c3796b06b      0      1      1
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46      1      0      1

Mint  Modifiable External Call  \
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8      1      0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04      1      0
0xa1b756be589441519b1a08e16bc4f60ab177d916      1      0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b      1      0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46      1      0

Modifiable Tax Address  \

```

0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	0
0xa1b756be589441519b1a08e16bc4f60ab177d916	0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	0

Modifiable Tax Rate \

0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	0
0xa1b756be589441519b1a08e16bc4f60ab177d916	0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	0

TimeStamp Restrict Amount Limit \

0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	0	0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	0	0
0xa1b756be589441519b1a08e16bc4f60ab177d916	0	0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	0	0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	0	0

Exchange Permission \

0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	0
0xa1b756be589441519b1a08e16bc4f60ab177d916	0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	0

Exchange Suspension \

0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	0
0xa1b756be589441519b1a08e16bc4f60ab177d916	0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	0

Fee Manipulation \

0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	0
0xa1b756be589441519b1a08e16bc4f60ab177d916	0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	0
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	0

Invalid Callback Trapdoor

0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	0	0
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	0	0
0xa1b756be589441519b1a08e16bc4f60ab177d916	0	0
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	0	1
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	0	0

```
[33]: y_true = temp_df
      y_pred = label_df.loc[y_true.index, y_true.columns]
```

```
[34]: y_true.head()
```

```
[34]:
```

	Mint
Address	
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	1
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	1
0xa1b756be589441519b1a08e16bc4f60ab177d916	1
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	1
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	1

```
[35]: y_pred.head()
```

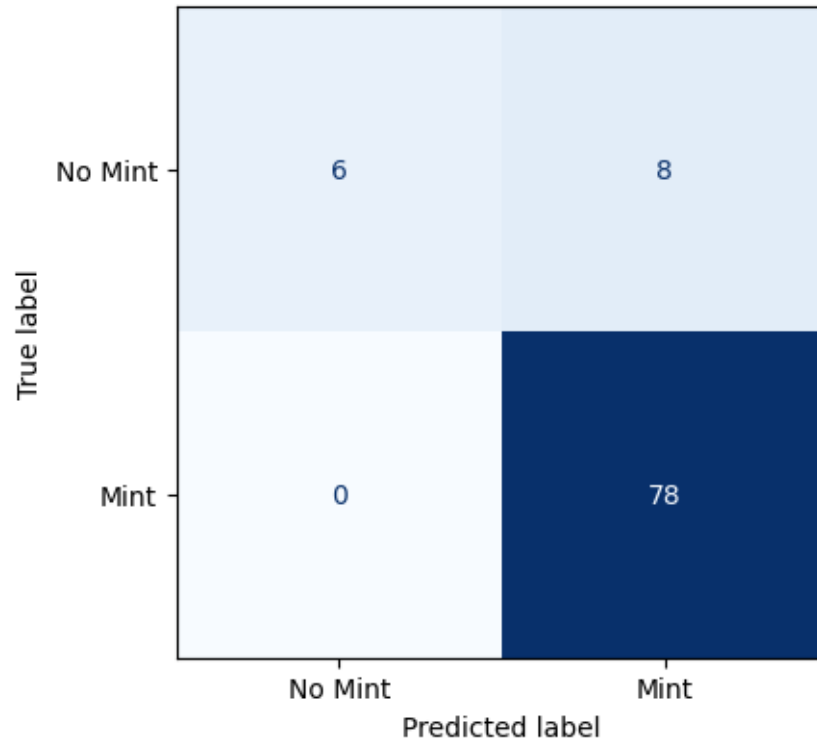
```
[35]:
```

	Mint
Address	
0x0fef20d2c4ee011fa0389e69e9fa92a2291b63c8	1
0xd7cc0deb9dd11be95068bf2d7a3d082b8ba9bf04	1
0xa1b756be589441519b1a08e16bc4f60ab177d916	1
0x514bc174df04a4b04ae2be81ee8c788c3796b06b	1
0x1354c8c1a66c2573ce9cc3e92e98d17869501a46	1

```
[36]: labels = [f'No {label}', label]
      print(classification_report(
          y_true.values,
          y_pred.values,
          target_names=labels,
          zero_division=0))
```

	precision	recall	f1-score	support
No Mint	1.00	0.43	0.60	14
Mint	0.91	1.00	0.95	78
accuracy			0.91	92
macro avg	0.95	0.71	0.78	92
weighted avg	0.92	0.91	0.90	92

```
[49]: plot_confuse(y_true.iloc[:, 0].astype(int).to_numpy(), y_pred.iloc[:, 0].
      ↪astype(int).to_numpy(), labels)
```



### 1.5 Evaluate on Large Sample (Leak)

```
[68]: label = 'Leak'
temp_df = pd.read_excel(ROOT_PATH / f'data/external/crpwarner/dataset/large/
↳sample/{label.lower()}.xlsx', index_col='Address')
temp_df['TP?'] = temp_df['TP?'].map({'Yes': 1, 'No': 0})
temp_df = temp_df.rename(columns={'TP?': label})
temp_df.index = temp_df.index.str.lower()
```

```
[69]: temp_df.head()
```

```
[69]:
```

Address	Leak
0x0290ea3c728981725689187763f6c63a68e192b8	1
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	1
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	1
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	1

```
[70]: res = requests.post(API_ENDPOINT + "/predict", json={"addresses": temp_df.index.
↳to_list()})
print("Status:", res.status_code)
```

```
print("Elapsed:", res.elapsed.total_seconds(), "seconds")
res = res.json()['results']
df = pd.DataFrame.from_dict(res, orient="index")
df.head()
```

Status: 200

Elapsed: 315.922271 seconds

```
[70]:      labels \
0x0290ea3c728981725689187763f6c63a68e192b8 {'Address Restrict': 0, 'Amount
Restrict': 0, ...
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6 {'Address Restrict': 0, 'Amount
Restrict': 1, ...
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60 {'Address Restrict': 0, 'Amount
Restrict': 1, ...
0x10c8324b20b7266c445944f043f53f6a77ea0bd4 {'Address Restrict': 0, 'Amount
Restrict': 1, ...
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73 {'Address Restrict': 1, 'Amount
Restrict': 0, ...
```

```
      label_probs \
0x0290ea3c728981725689187763f6c63a68e192b8 {'Address Restrict':
0.048798204743014884, 'Am...
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6 {'Address Restrict':
0.01176696857294976, 'Amo...
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60 {'Address Restrict':
0.02293397199611057, 'Amo...
0x10c8324b20b7266c445944f043f53f6a77ea0bd4 {'Address Restrict':
0.02781452631039047, 'Amo...
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73 {'Address Restrict':
0.6620448897415417, 'Amou...
```

	anomaly	anomaly_score
0x0290ea3c728981725689187763f6c63a68e192b8	1	0.462258
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	1	0.462258
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	1	0.462258
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	1	0.462258
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	1	0.462258

### 1.5.1 Labels

```
[71]: label_df = pd.DataFrame.from_records(df['labels'].tolist(), index=df.index)
label_df.head()
```

```
[71]:      Address Restrict  Amount Restrict \
0x0290ea3c728981725689187763f6c63a68e192b8      0      0
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6      0      1
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60      0      1
```

0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0	1
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	1	0

	Hidden Balance Modification	\
0x0290ea3c728981725689187763f6c63a68e192b8	0	
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0	
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0	
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0	
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0	

	Hidden Mint/Burn	Leak	Limit	\
0x0290ea3c728981725689187763f6c63a68e192b8	1	1	1	
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	1	1	1	
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	1	0	1	
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	1	1	1	
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0	1	1	

	Mint	Modifiable	External	Call	\
0x0290ea3c728981725689187763f6c63a68e192b8	1			0	
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	1			0	
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	1			0	
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	1			0	
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	1			0	

	Modifiable Tax Address	\
0x0290ea3c728981725689187763f6c63a68e192b8	0	
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0	
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0	
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0	
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0	

	Modifiable Tax Rate	\
0x0290ea3c728981725689187763f6c63a68e192b8	0	
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0	
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0	
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0	
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0	

	TimeStamp Restrict	Amount	Limit	\
0x0290ea3c728981725689187763f6c63a68e192b8	0		0	
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0		0	
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0		0	
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0		0	
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0		0	

	Exchange Permission	\
0x0290ea3c728981725689187763f6c63a68e192b8	0	



0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	1

	Exchange Suspension \
0x0290ea3c728981725689187763f6c63a68e192b8	0
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0

	Fee Manipulation \
0x0290ea3c728981725689187763f6c63a68e192b8	0
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0

	Invalid Callback	Trapdoor
0x0290ea3c728981725689187763f6c63a68e192b8	0	0
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	0	0
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0	0
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	0	0
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	0	1

```
[72]: y_true = temp_df
      y_pred = label_df.loc[y_true.index, y_true.columns]
```

```
[73]: y_true.head()
```

	Leak
Address	
0x0290ea3c728981725689187763f6c63a68e192b8	1
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	1
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	1
0x10cc060f6f9b2e5dcdb23f1361e4b368a7daec73	1

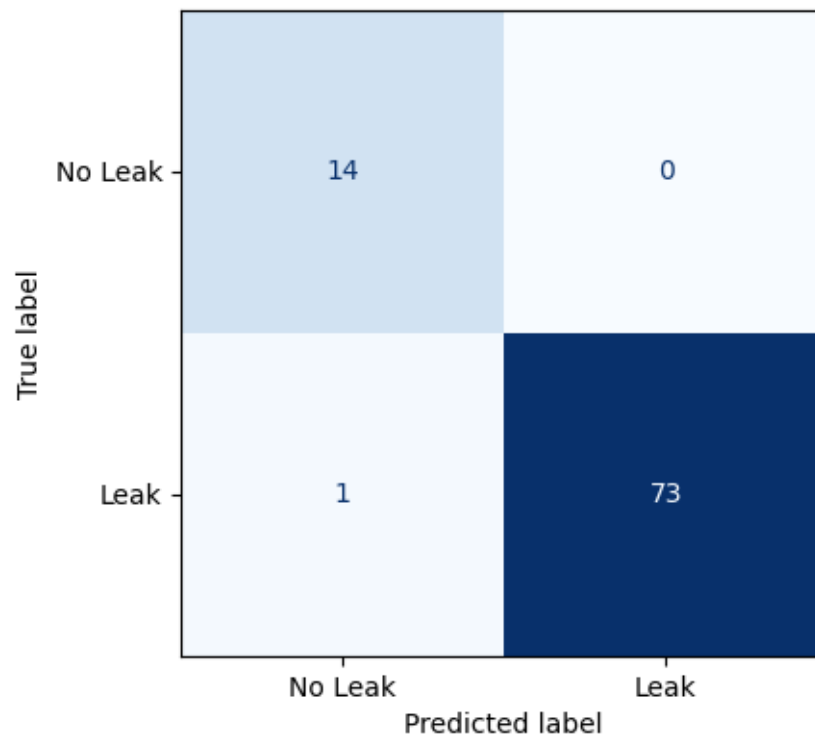
```
[74]: y_pred.head()
```

	Leak
Address	
0x0290ea3c728981725689187763f6c63a68e192b8	1
0x054ad3cd4a66f14bf5c0de2548a53be66995a4f6	1
0x0566c17dc2a9efcaa2f63e04cf06a69e8fc77f60	0
0x10c8324b20b7266c445944f043f53f6a77ea0bd4	1

```
[75]: labels = [f'No {label}', label]
print(classification_report(
    y_true.values,
    y_pred.values,
    target_names=labels,
    zero_division=0))
```

	precision	recall	f1-score	support
No Leak	0.93	1.00	0.97	14
Leak	1.00	0.99	0.99	74
accuracy			0.99	88
macro avg	0.97	0.99	0.98	88
weighted avg	0.99	0.99	0.99	88

```
[76]: plot_confuse(y_true.iloc[:, 0].astype(int).to_numpy(), y_pred.iloc[:, 0].
    ↳astype(int).to_numpy(), labels)
```



## 1.6 Evaluate on Large Sample (Limit)

```
[77]: label = 'Limit'
temp_df = pd.read_excel(ROOT_PATH / f'data/external/crpwarner/dataset/large/
↳sample/{label.lower()}.xlsx', index_col='Address')
temp_df['TP?'] = temp_df['TP?'].map({'Yes': 1, 'No': 0})
temp_df = temp_df.rename(columns={'TP?': label})
temp_df.index = temp_df.index.str.lower()
```

```
[78]: temp_df.head()
```

```
[78]:
```

	Limit
Address	
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	1
0xa623b5a542c0d7daadef321042a04c600b03a8cb	1
0xe412189da2dfa188a1a61633114b8732bbbfba19	1
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	1
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	1

```
[79]: res = requests.post(API_ENDPOINT + "/predict", json={"addresses": temp_df.index.
↳to_list()})
print("Status:", res.status_code)
print("Elapsed:", res.elapsed.total_seconds(), "seconds")
res = res.json()['results']
df = pd.DataFrame.from_dict(res, orient="index")
df.head()
```

Status: 200

Elapsed: 304.757515 seconds

```
[79]:
```

labels \	
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	{'Address Restrict': 0, 'Amount Restrict': 1, ...
0xa623b5a542c0d7daadef321042a04c600b03a8cb	{'Address Restrict': 0, 'Amount Restrict': 0, ...
0xe412189da2dfa188a1a61633114b8732bbbfba19	{'Address Restrict': 0, 'Amount Restrict': 0, ...
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	{'Address Restrict': 0, 'Amount Restrict': 0, ...
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	{'Address Restrict': 0, 'Amount Restrict': 0, ...

```
label_probs \
```

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	{'Address Restrict': 0.0382126769557718, 'Amou...
0xa623b5a542c0d7daadef321042a04c600b03a8cb	{'Address Restrict': 0.018721354330240796, 'Am...
0xe412189da2dfa188a1a61633114b8732bbbfba19	{'Address Restrict': ...

```

0.07091774129934543, 'Amo...
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844 {'Address Restrict':
0.016461383458478366, 'Am...
0x921a5dce3dfed5cccfbb2e593f2978533bc66110 {'Address Restrict':
0.048491252370566174, 'Am...

```

	anomaly	anomaly_score
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	1	0.462258
0xa623b5a542c0d7daadef321042a04c600b03a8cb	1	0.462258
0xe412189da2dfa188a1a61633114b8732bbbfba19	1	0.462258
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	1	0.462258
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	1	0.462258

### 1.6.1 Labels

```

[80]: label_df = pd.DataFrame.from_records(df['labels'].tolist(), index=df.index)
      label_df.head()

```

```

[80]:
Address Restrict  Amount Restrict  \
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8      0      1
0xa623b5a542c0d7daadef321042a04c600b03a8cb      0      0
0xe412189da2dfa188a1a61633114b8732bbbfba19      0      0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844      0      0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110      0      0

Hidden Balance Modification  \
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8      0
0xa623b5a542c0d7daadef321042a04c600b03a8cb      0
0xe412189da2dfa188a1a61633114b8732bbbfba19      0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844      0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110      0

Hidden Mint/Burn  Leak  Limit  \
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8      1      0      1
0xa623b5a542c0d7daadef321042a04c600b03a8cb      0      0      1
0xe412189da2dfa188a1a61633114b8732bbbfba19      1      0      1
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844      1      1      1
0x921a5dce3dfed5cccfbb2e593f2978533bc66110      0      0      1

Mint  Modifiable External Call  \
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8      1      0
0xa623b5a542c0d7daadef321042a04c600b03a8cb      1      0
0xe412189da2dfa188a1a61633114b8732bbbfba19      1      0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844      1      0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110      1      0

Modifiable Tax Address  \

```

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	0
0xa623b5a542c0d7daadef321042a04c600b03a8cb	0
0xe412189da2dfa188a1a61633114b8732bbbfba19	0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	0

Modifiable Tax Rate \

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	0
0xa623b5a542c0d7daadef321042a04c600b03a8cb	0
0xe412189da2dfa188a1a61633114b8732bbbfba19	0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	0

TimeStamp Restrict Amount Limit \

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	0	0
0xa623b5a542c0d7daadef321042a04c600b03a8cb	0	0
0xe412189da2dfa188a1a61633114b8732bbbfba19	0	0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	0	0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	0	0

Exchange Permission \

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	0
0xa623b5a542c0d7daadef321042a04c600b03a8cb	0
0xe412189da2dfa188a1a61633114b8732bbbfba19	0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	0

Exchange Suspension \

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	0
0xa623b5a542c0d7daadef321042a04c600b03a8cb	0
0xe412189da2dfa188a1a61633114b8732bbbfba19	0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	0

Fee Manipulation \

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	0
0xa623b5a542c0d7daadef321042a04c600b03a8cb	0
0xe412189da2dfa188a1a61633114b8732bbbfba19	0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	0

Invalid Callback Trapdoor

0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	0	0
0xa623b5a542c0d7daadef321042a04c600b03a8cb	0	0
0xe412189da2dfa188a1a61633114b8732bbbfba19	0	0
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	0	0
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	0	0

```
[81]: y_true = temp_df
      y_pred = label_df.loc[y_true.index, y_true.columns]
```

```
[82]: y_true.head()
```

```
[82]:
```

	Limit
Address	
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	1
0xa623b5a542c0d7daadef321042a04c600b03a8cb	1
0xe412189da2dfa188a1a61633114b8732bbbfba19	1
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	1
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	1

```
[83]: y_pred.head()
```

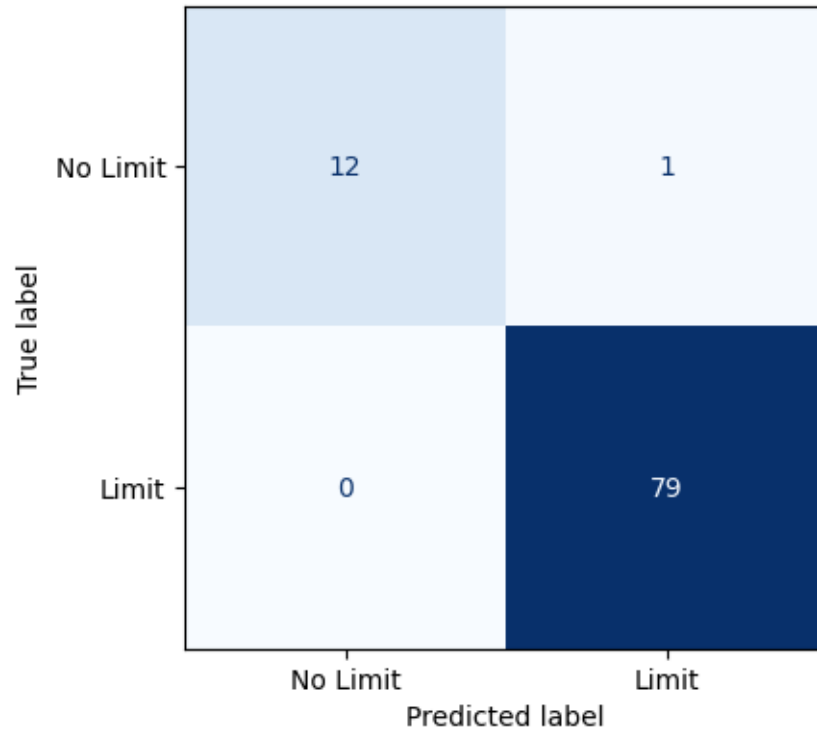
```
[83]:
```

	Limit
Address	
0xe5f3c6d2b47cbe2cf936b9521466bac2422ebef8	1
0xa623b5a542c0d7daadef321042a04c600b03a8cb	1
0xe412189da2dfa188a1a61633114b8732bbbfba19	1
0x9fcf7acdc11fd904c4b73a009909c7f00efc4844	1
0x921a5dce3dfed5cccfbb2e593f2978533bc66110	1

```
[84]: labels = [f'No {label}', label]
      print(classification_report(
          y_true.values,
          y_pred.values,
          target_names=labels,
          zero_division=0))
```

	precision	recall	f1-score	support
No Limit	1.00	0.92	0.96	13
Limit	0.99	1.00	0.99	79
accuracy			0.99	92
macro avg	0.99	0.96	0.98	92
weighted avg	0.99	0.99	0.99	92

```
[85]: plot_confuse(y_true.iloc[:, 0].astype(int).to_numpy(), y_pred.iloc[:, 0].
      ↪astype(int).to_numpy(), labels)
```



## 1.7 Evaluate on RPHunter

```
[92]: rphunter_df = pd.read_csv(ROOT_PATH / 'data/rphunter-cleaned.csv',
    ↪index_col='Address')
rphunter_df.index = rphunter_df.index.str.lower()
```

```
[93]: rphunter_df.head()
```

```
[93]:
```

Address	Hidden Balance Modification \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0
0x11cbc781dadaad13fc3a361772c80b1c027820af	0
0x3e597ea168a85aa2ae5e2c4333665bcd875ed10f	0

Address	Hidden Mint/Burn \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1
0x11cbc781dadaad13fc3a361772c80b1c027820af	0
0x3e597ea168a85aa2ae5e2c4333665bcd875ed10f	0

	Address Restrict	Amount Restrict	\
Address			
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	1	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	0	
0x11cbc781dadaad13fc3a361772c80b1c027820af	1	0	
0x3e597ea168a85aa2ae5e2c4333665bcd875ed10f	1	0	

	Modifiable External Call	\
Address		
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	
0x11cbc781dadaad13fc3a361772c80b1c027820af	0	
0x3e597ea168a85aa2ae5e2c4333665bcd875ed10f	0	

	TimeStamp Restrict	\
Address		
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	
0x11cbc781dadaad13fc3a361772c80b1c027820af	0	
0x3e597ea168a85aa2ae5e2c4333665bcd875ed10f	0	

	Modifiable Tax Address	\
Address		
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	
0x11cbc781dadaad13fc3a361772c80b1c027820af	0	
0x3e597ea168a85aa2ae5e2c4333665bcd875ed10f	0	

	Modifiable Tax Rate
Address	
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1
0x11cbc781dadaad13fc3a361772c80b1c027820af	0
0x3e597ea168a85aa2ae5e2c4333665bcd875ed10f	0

```
[ ]: res = requests.post(API_ENDPOINT + "/predict", json={"addresses": rphunter_df.
    ↪index.to_list()})
print("Status:", res.status_code)
print("Elapsed:", res.elapsed.total_seconds(), "seconds")
res = res.json()['results']
df = pd.DataFrame.from_dict(res, orient="index")
```



```
df.head()
```

### 1.7.1 Labels

```
[ ]: label_df = pd.DataFrame.from_records(df['labels'].tolist(), index=df.index)
label_df.head()
```

	Address Restrict	Amount Restrict	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	1	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	1	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	1	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	0	

	Hidden Balance Modification	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	

	Hidden Mint/Burn	Leak	Limit	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	0	1	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0	1	
0x94b7d24552933f50a5a5705c446528806dcea381	0	0	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	1	0	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0	1	

	Mint	Modifiable	External	Call	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1			0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0			0	
0x94b7d24552933f50a5a5705c446528806dcea381	0			0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0			0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1			0	

	Modifiable Tax Address	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	

	Modifiable Tax Rate	\
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	
0x94b7d24552933f50a5a5705c446528806dcea381	0	
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	

	TimeStamp Restrict	Amount Limit \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0
0x94b7d24552933f50a5a5705c446528806dcea381	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	1

	Exchange Permission \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0
0x94b7d24552933f50a5a5705c446528806dcea381	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1

	Exchange Suspension \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0
0x94b7d24552933f50a5a5705c446528806dcea381	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1

	Fee Manipulation \
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0
0x94b7d24552933f50a5a5705c446528806dcea381	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1

	Invalid Callback	Trapdoor
0x93023f1d3525e273f291b6f76d2f5027a39bf302	0	0
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0
0x94b7d24552933f50a5a5705c446528806dcea381	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	0	1

```
[ ]: y_true = ground_df
      y_pred = label_df.loc[y_true.index, y_true.columns]
```

```
[ ]: y_true.head()
```

	Mint	Leak	Limit
address			
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0	1
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0	1
0x94b7d24552933f50a5a5705c446528806dcea381	0	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0	1

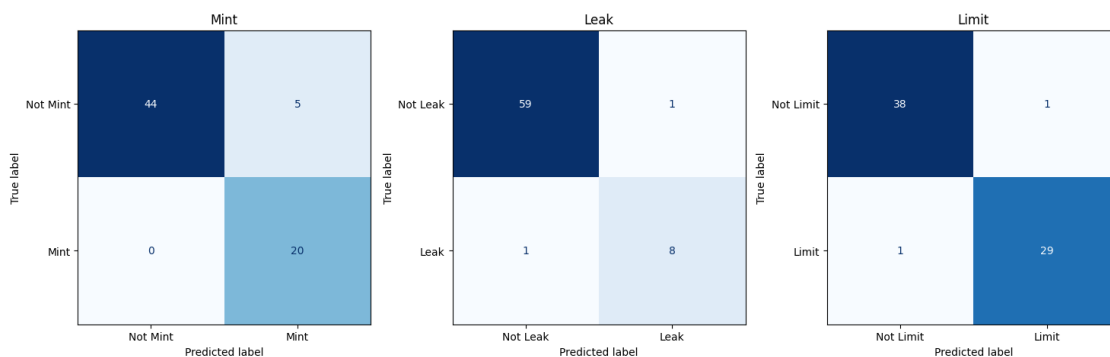
```
[ ]: y_pred.head()
```

	Mint	Leak	Limit
address			
0x93023f1d3525e273f291b6f76d2f5027a39bf302	1	0	1
0x2753dce37a7edb052a77832039bcc9aa49ad8b25	0	0	1
0x94b7d24552933f50a5a5705c446528806dcea381	0	0	0
0xe0b9d4146aad6936cbfcbe4dae47e34aab96b093	0	0	0
0x10f6f2b97f3ab29583d9d38babf2994df7220c21	1	0	1

```
[ ]: print(classification_report(
    y_true.values,
    y_pred.values,
    target_names=y_true.columns,
    zero_division=0))
```

	precision	recall	f1-score	support
Mint	0.80	1.00	0.89	20
Leak	0.89	0.89	0.89	9
Limit	0.97	0.97	0.97	30
micro avg	0.89	0.97	0.93	59
macro avg	0.89	0.95	0.91	59
weighted avg	0.90	0.97	0.93	59
samples avg	0.59	0.59	0.59	59

```
[ ]: plot_confuse(y_true, y_pred)
```



### 1.7.2 Anomaly

```
[ ]: anomaly_true = (y_true.astype(int).sum(axis=1) > 0).astype(int)
      anomaly_pred = df.loc[y_true.index, "anomaly"].astype(int)
```

```
[ ]: labels = ['normal', 'anomaly']
      print(classification_report(
          anomaly_true,
          anomaly_pred,
          target_names=labels,
          zero_division=0))
```

	precision	recall	f1-score	support
normal	0.00	0.00	0.00	27
anomaly	0.61	1.00	0.76	42
accuracy			0.61	69
macro avg	0.30	0.50	0.38	69
weighted avg	0.37	0.61	0.46	69

```
[ ]: plot_confuse(anomaly_true, anomaly_pred, labels)
```

