

IMPORT LIB

```
In [ ]: # Process Data
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt

# Detection model
from sklearn.svm import SVC

# Attack model
from art.attacks.evasion import SaliencyMapMethod
from art.estimators.classification import SklearnClassifier

# Metrics and data visualization
from sklearn.metrics import accuracy_score, classification_report
from sklearn.metrics import confusion_matrix
import seaborn as sns # for statistical data visualization
```

FUNCTION ZONE

```
In [ ]: def get_confusion_matrix(y_true, y_pred):
    # Print the Confusion Matrix and slice it into four pieces
    # y_true: is the correct label of instance
    # y_pred: is the predicted label

    cm = confusion_matrix(y_true, y_pred)

    # Binary classification confusion matrix
    print('Confusion matrix\n\n', cm)

    print('\nTrue Negatives(TN) = ', cm[0,0])

    print('\nTrue Positives(TP) = ', cm[1,1])

    print('\nFalse Positives(FP) = ', cm[0,1])

    print('\nFalse Negatives(FN) = ', cm[1,0])
    return cm
```

```
In [ ]: def draw_binary_confusion_matrix_heatmap(confusion_matrix, title=""):
    # confusion_matrix: from sklearn.metrics import confusion_matrix
    # title: title for your heat map
    # visualize confusion matrix with seaborn heatmap
    cm_matrix = pd.DataFrame(data=confusion_matrix, columns=['Predict Benign: 0', '
                                index=['Actual Benign: 0', 'Actual Malicious: 1

    sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

```
# Add title
plt.title(title)
# Show the plot
plt.show()
```

LOAD DATA

```
In [ ]: # Dataset directory
data_dir = "Dataset\\"
```

```
In [ ]: # Load Data
data = pd.read_csv(data_dir + "drebin215dataset5560malware9476benign.csv")
print("Total missing values : ",sum(list(data.isna().sum())))
```

Total missing values : 0

C:\Users\hai\AppData\Local\Temp\ipykernel_16624\140858179.py:2: DtypeWarning: Columns (92) have mixed types. Specify dtype option on import or set low_memory=False.
data = pd.read_csv(data_dir + "drebin215dataset5560malware9476benign.csv")

PREPROCESS DATA

```
In [ ]: classes,count = np.unique(data['class'],return_counts=True)
#Perform Label Encoding
lbl_enc = LabelEncoder()
print(lbl_enc.fit_transform(classes),classes)
data = data.replace(classes,lbl_enc.fit_transform(classes))

#Dataset contains special characters like '?' and 'S'. Set them to NaN and use dropna
data=data.replace('[?S]',np.NaN,regex=True)
print("Total missing values : ",sum(list(data.isna().sum())))
data.dropna(inplace=True)
for c in data.columns:
    data[c] = pd.to_numeric(data[c])
data
```

C:\Users\hai\AppData\Local\Temp\ipykernel_16624\410007786.py:5: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`

data = data.replace(classes,lbl_enc.fit_transform(classes))

[0 1] ['B' 'S']

Total missing values : 5

Out[]:

	transact	onServiceConnected	bindService	attachInterface	ServiceConnection	and
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	
...
15031	1	1	1	1	1	
15032	0	0	0	0	0	
15033	0	0	0	0	0	
15034	1	1	1	1	1	
15035	1	1	1	1	1	

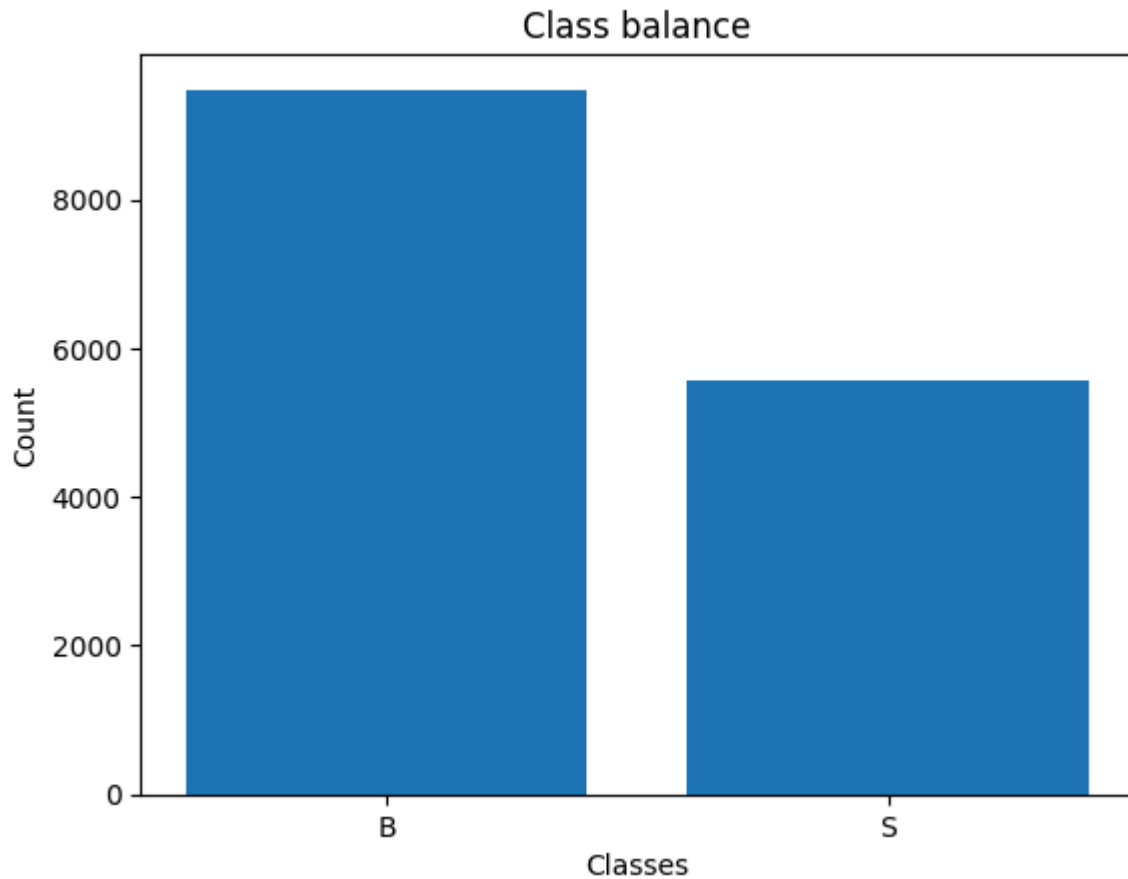
15031 rows × 216 columns



In []: `print("Total Features : ",len(data.columns)-1)`

Total Features : 215

In []: `plt.bar(classes,count)
plt.title("Class balance")
plt.xlabel("Classes")
plt.ylabel("Count")
plt.show()`



SPLIT DATA

```
In [ ]: x = data.iloc[:, 1:].values  
        y = data.iloc[:, 0].values
```

```
In [ ]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_sta
```

```
In [ ]: print("Train features size : ",len(x_train))  
        print("Train labels size : ",len(y_train))  
        print("Test features size : ",len(x_test))  
        print("Test labels size : ",len(y_test))
```

```
Train features size : 12024  
Train labels size : 12024  
Test features size : 3007  
Test labels size : 3007
```

```
In [ ]: print("Train features : ",x_train.shape)  
        print("Train labels : ",y_train.shape)  
        print("Test Features : ",x_test.shape)  
        print("Test labels : ",y_test.shape)
```

```
Train features : (12024, 215)  
Train labels : (12024,)  
Test Features : (3007, 215)  
Test labels : (3007,)
```

TRAIN DETECTION MODEL

```
In [ ]: svm = SVC(kernel='linear', C=1)
```

```
In [ ]: svm.fit(x_train,y_train)
```

```
Out[ ]: SVC(C=1, kernel='linear')
```

```
In [ ]: y_pred = svm.predict(x_test)
```

```
In [ ]: print("Accuracy: ", accuracy_score(y_test,y_pred))
print(classification_report(y_test,y_pred))
```

```
Accuracy: 0.9883604921849019
```

	precision	recall	f1-score	support
0	0.99	0.99	0.99	1752
1	0.99	0.98	0.99	1255
accuracy			0.99	3007
macro avg	0.99	0.99	0.99	3007
weighted avg	0.99	0.99	0.99	3007

```
In [ ]: cm = get_confusion_matrix(y_test, y_pred)
```

Confusion matrix

```
[[1740  12]
 [ 23 1232]]
```

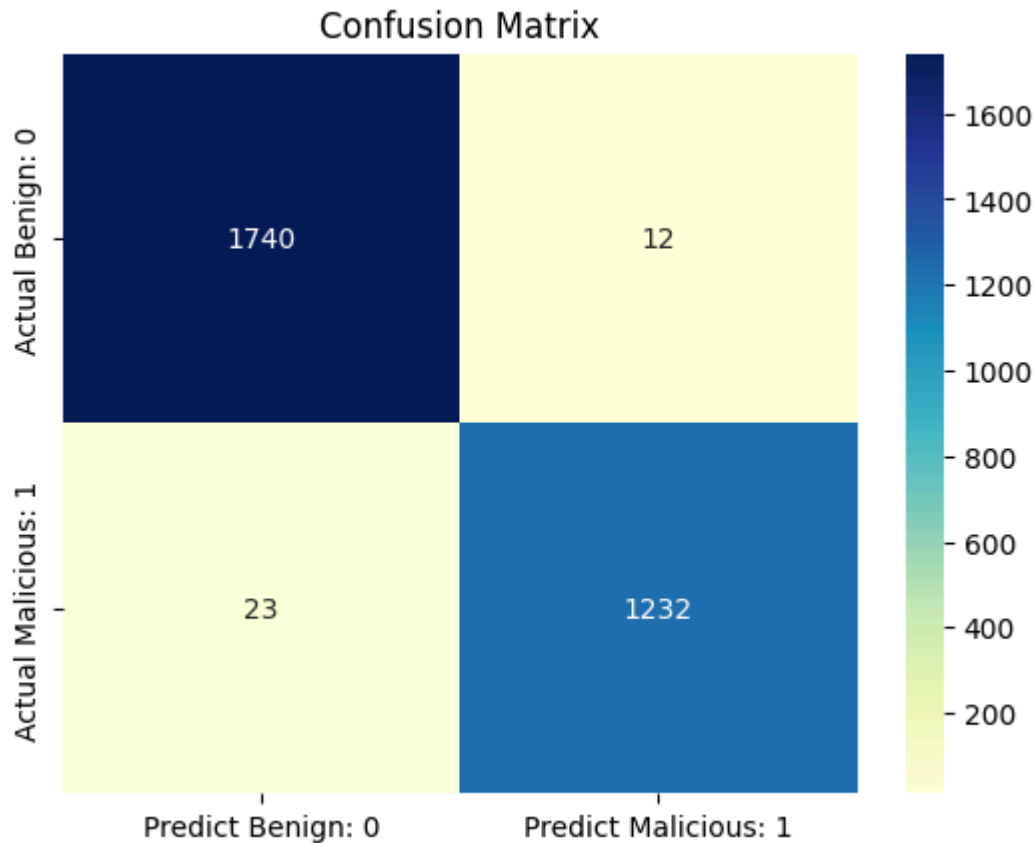
True Negatives(TN) = 1740

True Positives(TP) = 1232

False Positives(FP) = 12

False Negatives(FN) = 23

```
In [ ]: draw_binary_confusion_matrix_heatmap(cm, "Confusion Matrix")
```



SELECT ATTACK INSTANCES

```
In [ ]: # Select an instance to attack (assuming we want to flip a '1' to '0')
        positive_indices = np.where(y_test == 1)
        x_to_attack = x_test[positive_indices]
        y_to_attack = y_test[positive_indices]
```

CREATE ATTACK MODEL

```
In [ ]: # Create an ART classifier wrapper for the SVM
        classifier = SklearnClassifier(model=svm, clip_values=(0, 1))
        # Create attack model
        attack = SaliencyMapMethod(classifier)
```

CREATE ADVERSARIAL EXAMPLES

```
In [ ]: # Generate perturbed instance
        perturbed_instance = attack.generate(x_to_attack, y=np.zeros_like(y_to_attack))
```

```
C:\Users\hai\AppData\Local\Temp\ipykernel_16624\1723329802.py:2: DeprecationWarning:
`product` is deprecated as of NumPy 1.25.0, and will be removed in NumPy 2.0. Please
use `prod` instead.
    perturbed_instance = attack.generate(x_to_attack,y=np.zeros_like(y_to_attack))
JSMA: 100%|██████████| 1255/1255 [00:35<00:00, 35.37it/s]
```

```
In [ ]: original_prediction = svm.predict(x_to_attack)
        perturbed_prediction = svm.predict(perturbed_instance)
        print("Accuracy before attack: ", accuracy_score(y_to_attack, original_prediction))
        print(classification_report(y_to_attack, original_prediction))
        print("Accuracy after attack: ", accuracy_score(y_to_attack, perturbed_prediction))
        print(classification_report(y_to_attack, perturbed_prediction))
```

```
Accuracy before attack: 0.9816733067729083
      precision    recall  f1-score   support

         0         0.00      0.00      0.00          0
         1         1.00      0.98      0.99     1255

    accuracy                   0.98     1255
   macro avg              0.50      0.49      0.50     1255
weighted avg              1.00      0.98      0.99     1255
```

```
Accuracy after attack: 0.0
      precision    recall  f1-score   support

         0         0.00      0.00      0.00          0
         1         0.00      0.00      0.00    1255.0

    accuracy                   0.00    1255.0
   macro avg              0.00      0.00      0.00    1255.0
weighted avg              0.00      0.00      0.00    1255.0
```

```

c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Precision is 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, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Precision is 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, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Precision is 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, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Precision is 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, f"{metric.capitalize()} is", len(result))
c:\Users\hai\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_classification.py:1517: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

```

VISUALIZE RESULT

AVERAGE DISTORTION

```

In [ ]: # Distortion is the number of value that has been changed to evade detection
        temp = 0

```



```

count = 0
while temp < len(x_to_attack):
    array1 = x_to_attack[temp]
    array2 = perturbed_instance[temp]

    # Calculate the differences between consecutive elements
    result = np.diff(array1 - array2)
    for i in result:
        if i != 0:
            count+=1
    temp+=1
avg_distortion = count/len(x_to_attack)
print("Average Distortion: ", avg_distortion)

```

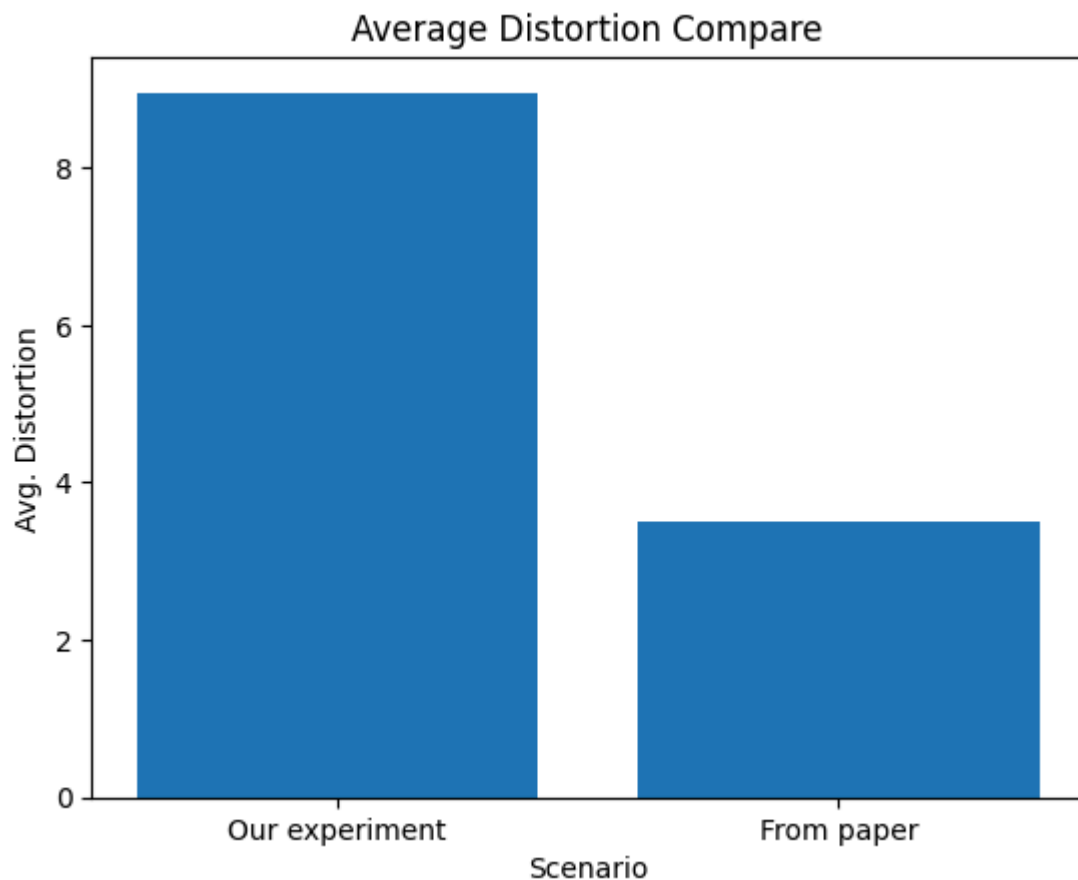
Average Distortion: 8.952988047808764

```

In [ ]: x_bar = ["Our experiment", "From paper"]
        y_bar = [avg_distortion, 3.5]

        plt.bar(x_bar,y_bar)
        plt.title("Average Distortion Compare")
        plt.xlabel("Scenario")
        plt.ylabel("Avg. Distortion")
        plt.show()

```



CONFUSION MATRIX

```
In [ ]: cm_before_attack = get_confusion_matrix(y_to_attack, original_prediction)
```

Confusion matrix

```
[[ 0  0]
 [23 1232]]
```

True Negatives(TN) = 0

True Positives(TP) = 1232

False Positives(FP) = 0

False Negatives(FN) = 23

```
In [ ]: cm_after_attack = get_confusion_matrix(y_to_attack, perturbed_prediction)
```

Confusion matrix

```
[[ 0  0]
 [1255  0]]
```

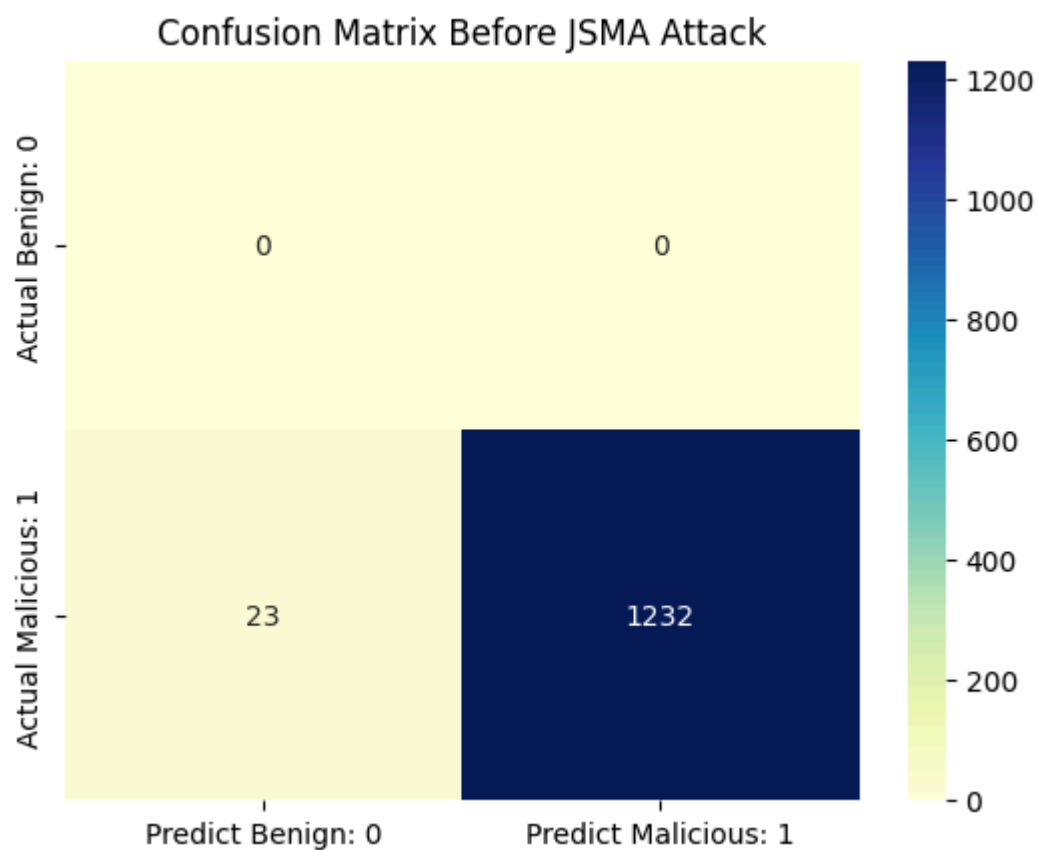
True Negatives(TN) = 0

True Positives(TP) = 0

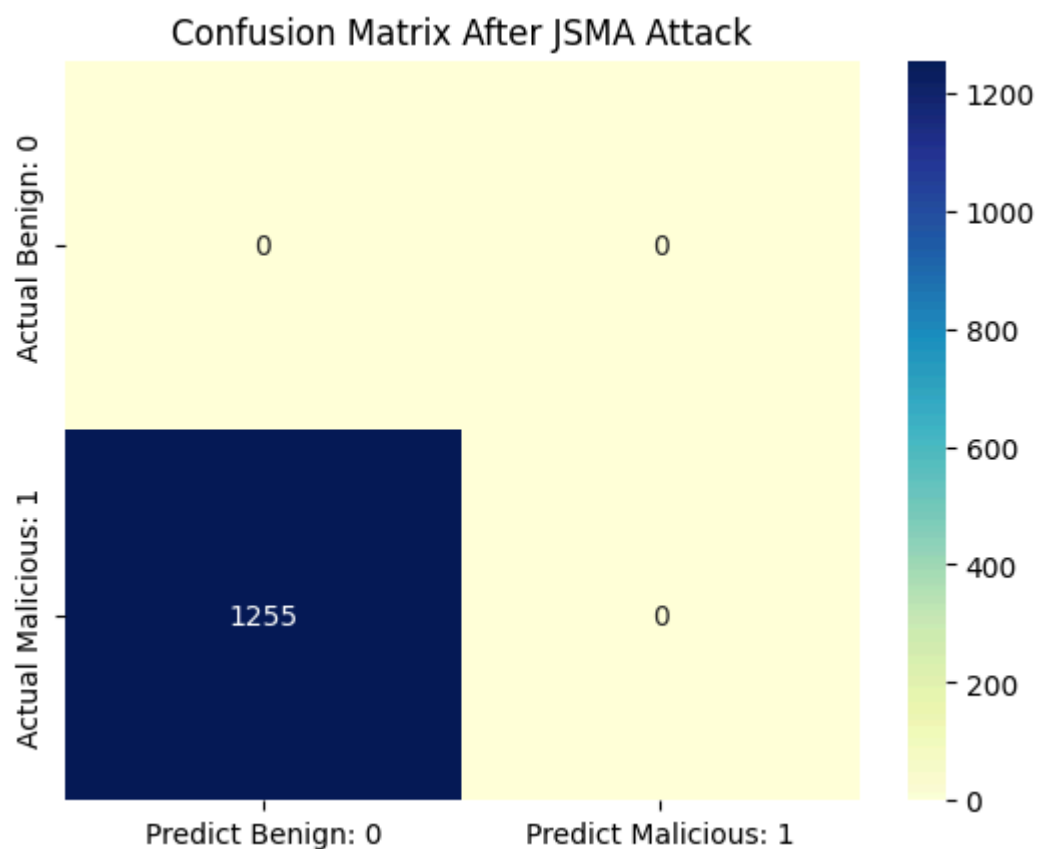
False Positives(FP) = 0

False Negatives(FN) = 1255

```
In [ ]: draw_binary_confusion_matrix_heatmap(cm_before_attack, "Confusion Matrix Before JSM")
```



```
In [ ]: draw_binary_confusion_matrix_heatmap(cm_after_attack, "Confusion Matrix After JSMA
```



EVASION RATE

```
In [ ]: # evasion rate = (FN)/len(attack_instances)
evasion_rate = cm_after_attack[1,0] / len(x_to_attack)

x_bar = ["Our experiment", "From paper"]
y_bar = [evasion_rate, 1]

plt.bar(x_bar, y_bar)
plt.title("Evasion Rate Compare")
plt.xlabel("Scenario")
plt.ylabel("Evasion Rate")
plt.show()
```

