



МИНОБРНАУКИ РОССИИ

Федеральное государственное бюджетное образовательное учреждение
высшего образования

«МИРЭА— Российский технологический университет»

РТУМИРЭА

Институт кибербезопасности и цифровых технологий направление 10.04.01

«Информационная безопасность»

Кафедра КБ-4«Интеллектуальные системы информационной безопасности»

Лабораторная работа №2

По дисциплине

«Анализ защищенности систем искусственного интеллекта»

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Группа: ББМО-02-22

Москва 2023

Задание 1

Установка adversarial-robustness-toolbox

```
!pip install adversarial-robustness-toolbox

Collecting adversarial-robustness-toolbox
  Downloading adversarial_robustness_toolbox-1.17.0-py3-none-any.whl (1.7 MB)
    1.7/1.7 MB 8.6 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.18.0 in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox)
Requirement already satisfied: scipy>=1.4.1 in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox)
Collecting scikit-learn<1.2.0,>=0.22.2 (from adversarial-robustness-toolbox)
  Downloading scikit_learn-1.1.3-cp310-cp310-manylinux_2_17_x86_64_manylinux2014_x86_64.whl (30.5 MB)
    30.5/30.5 MB 34.3 MB/s eta 0:00:00
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (1.16.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (6)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (4.66.1)
Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn<1.2.0,>=0.22.2->ad)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn<1.2.0,>=0.22.2->ad)
Installing collected packages: scikit-learn, adversarial-robustness-toolbox
  Attempting uninstall: scikit-learn
    Found existing installation: scikit-learn 1.2.2
```

Импорт библиотек

```
import cv2
import os
import torch
import random
import pickle
import zipfile
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from sklearn.model_selection import train_test_split
from keras.utils import to_categorical
from keras.applications import ResNet50
from keras.applications import VGG16
from keras.applications.resnet50 import preprocess_input
from keras.preprocessing import image
from keras.models import load_model, save_model
from keras.layers import Dense, Flatten, GlobalAveragePooling2D
from keras.models import Model
from keras.optimizers import Adam
from keras.losses import categorical_crossentropy
from keras.metrics import categorical_accuracy
from keras.callbacks import ModelCheckpoint, EarlyStopping, TensorBoard
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D, AvgPool2D, BatchNormalization, Reshape, Lambda
from art.estimators.classification import KerasClassifier
from art.attacks.evasion import FastGradientMethod, ProjectedGradientDescent
%matplotlib inline
```

Распаковка архива

```
zip_file = '/content/drive/MyDrive/data/archive (1).zip'
z = zipfile.ZipFile(zip_file, 'r')
z.extractall()
```

Чтение и предварительная обработка изображений

```

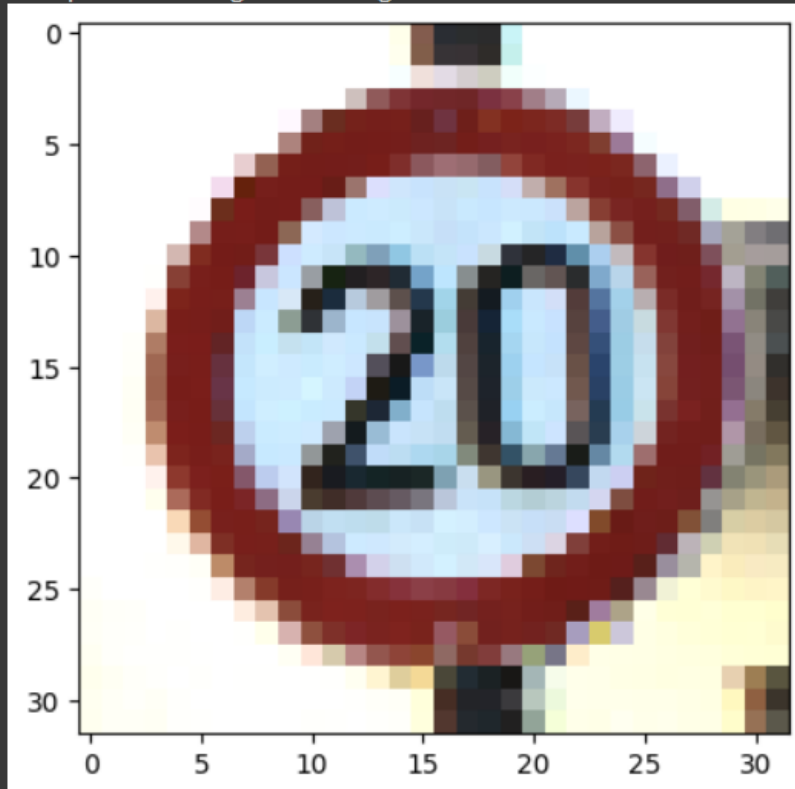
data = []
labels = []
class_count = 43
for i in range(class_count):
    img_path = os.path.join(train_data_path, str(i))
    for img in os.listdir(img_path):
        img = image.load_img(img_path + '/' + img, target_size=(32, 32))
        img_array = image.img_to_array(img)
        img_array = img_array / 255
        data.append(img_array)
        labels.append(i)
data = np.array(data)
labels = np.array(labels)
labels = to_categorical(labels, 43)
print("data[0]:\n",data[0])

```

Первое изображение

```
plt.imshow(data[0])
```

<matplotlib.image.AxesImage at 0x7ef4fdcdfa30>



Создание модели для классификации изображений

```

model = Sequential()
model.add(ResNet50(include_top = False, pooling = 'avg'))
model.add(Dropout(0.1))
model.add(Dense(256, activation="relu"))
model.add(Dropout(0.1))
model.add(Dense(43, activation = 'softmax'))
model.layers[2].trainable = False
print(model.summary())

```

Downloading data from <https://storage.googleapis.com/tensorflow/keras-applications/94765736/94765736> [=====] - 1s 0us/step
 Model: "sequential"

Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 2048)	23587712
dropout (Dropout)	(None, 2048)	0
dense (Dense)	(None, 256)	524544
dropout_1 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 43)	11051

=====
 Total params: 24123307 (92.02 MB)
 Trainable params: 23545643 (89.82 MB)
 Non-trainable params: 577664 (2.20 MB)

Обучаем модель ResNet50 с заданными параметрами

```

# обучение модели в течение 5 эпох, используя оптимизатор Adam и
# функция потерь categorical_crossentropy
model.compile(loss='categorical_crossentropy', optimizer="adam", metrics=['accuracy'])
# сохранение истории обучения для последующего анализа
history = model.fit(x_train, y_train, validation_data=(x_val, y_val), epochs = 5, batch_size = 64)

```

Epoch 1/5
 429/429 [=====] - 90s 106ms/step - loss: 0.9471 - accuracy: 0.7478 - val_loss: 3.5791 - val_accuracy: 0.1792
 Epoch 2/5
 429/429 [=====] - 25s 58ms/step - loss: 0.1905 - accuracy: 0.9496 - val_loss: 0.7315 - val_accuracy: 0.8216
 Epoch 3/5
 429/429 [=====] - 25s 57ms/step - loss: 0.1286 - accuracy: 0.9671 - val_loss: 0.1399 - val_accuracy: 0.9598
 Epoch 4/5
 429/429 [=====] - 25s 58ms/step - loss: 0.1117 - accuracy: 0.9716 - val_loss: 2.2064 - val_accuracy: 0.9073
 Epoch 5/5
 429/429 [=====] - 26s 60ms/step - loss: 0.0753 - accuracy: 0.9802 - val_loss: 0.1128 - val_accuracy: 0.9708

Создание второй модели для классификации изображений

```
# создание модели для классификации изображений (VGG16)
model2 = Sequential()
model2.add(VGG16(include_top=False, pooling = 'avg'))
model2.add(Dropout(0.1))
model2.add(Dense(256, activation="relu"))
model2.add(Dropout(0.1))
model2.add(Dense(43, activation = 'softmax'))
model2.layers[2].trainable = False
# отобразим итоговую сводку по модели
print(model2.summary())
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16\_weights\_tf\_dim\_ordering\_tf\_data\_format.h5
58889256/58889256 [=====] - 0s 0us/step
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 512)	14714688
dropout_2 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 256)	131328
dropout_3 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 43)	11051
Total params: 14857067 (56.68 MB)		
Trainable params: 14725739 (56.17 MB)		
Non-trainable params: 131328 (513.00 KB)		

Обучение модели VGG16 с заданные параметрами

```
model2.compile(loss='categorical_crossentropy', optimizer="adam", metrics=['accuracy'])
history2 = model2.fit(x_train, y_train, validation_data=(x_val, y_val), epochs = 5, batch_size = 64)
```

```
Epoch 1/5
429/429 [=====] - 36s 57ms/step - loss: 2.6600 - accuracy: 0.2216 - val_loss: 1.3523 - val_accuracy: 0.5113
Epoch 2/5
429/429 [=====] - 19s 43ms/step - loss: 0.9010 - accuracy: 0.6751 - val_loss: 0.4558 - val_accuracy: 0.8386
Epoch 3/5
429/429 [=====] - 18s 42ms/step - loss: 0.4077 - accuracy: 0.8669 - val_loss: 0.2478 - val_accuracy: 0.9273
Epoch 4/5
429/429 [=====] - 18s 41ms/step - loss: 0.1692 - accuracy: 0.9534 - val_loss: 0.1062 - val_accuracy: 0.9729
Epoch 5/5
429/429 [=====] - 18s 43ms/step - loss: 0.1257 - accuracy: 0.9684 - val_loss: 0.2111 - val_accuracy: 0.9543
```

Оценка двух моделей

```

from tabulate import tabulate
train_accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']
test_accuracy = history_test.history['accuracy']

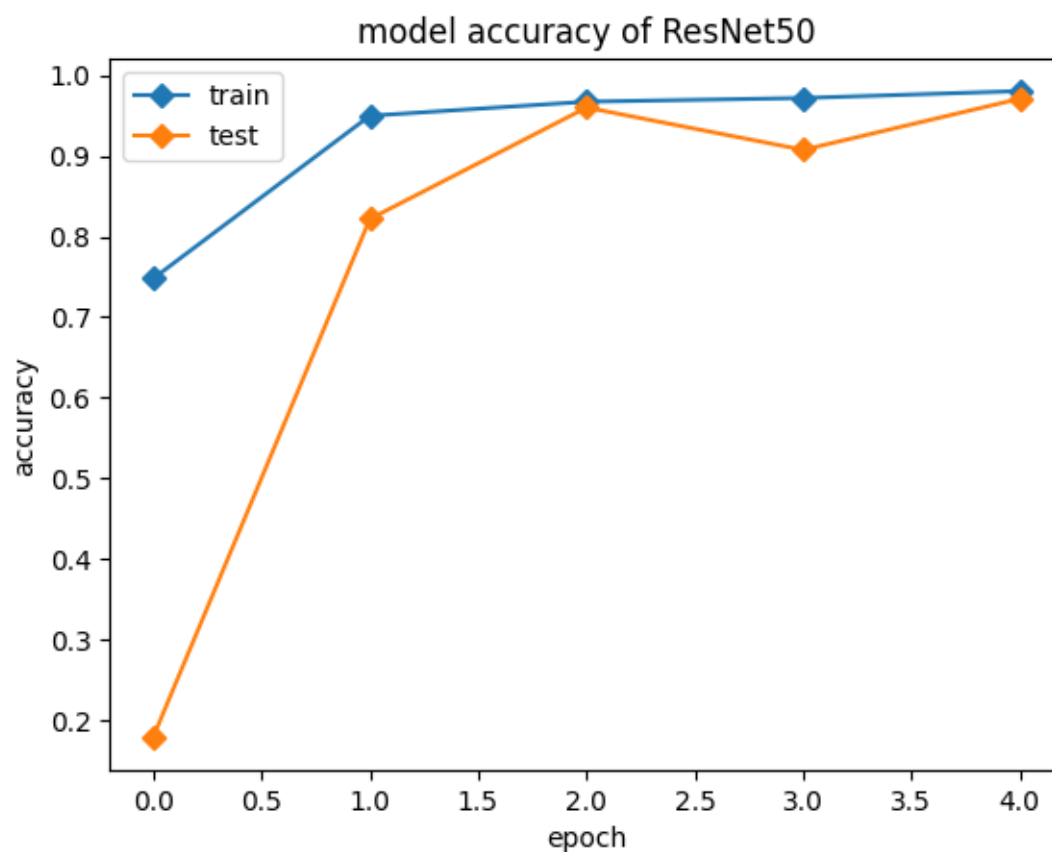
train_accuracy2 = history2_test.history['accuracy']
val_accuracy2 = history2_test.history['val_accuracy']
test_accuracy2 = history2_test.history['accuracy']

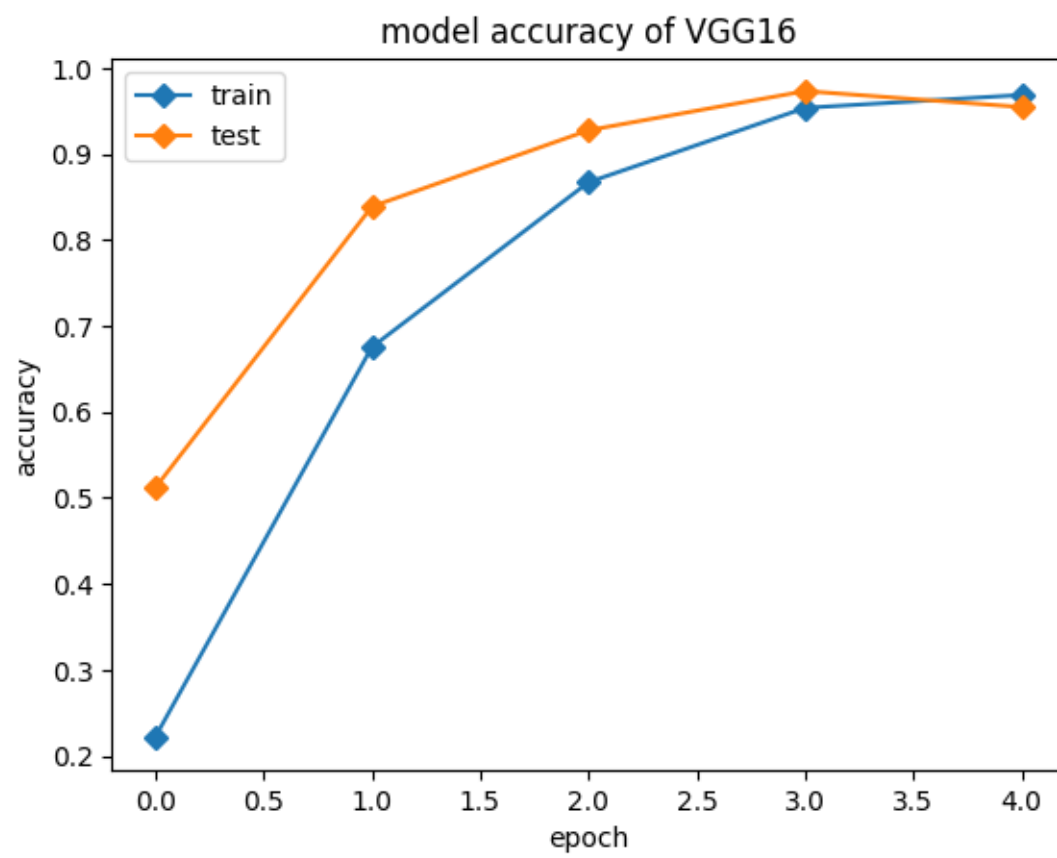
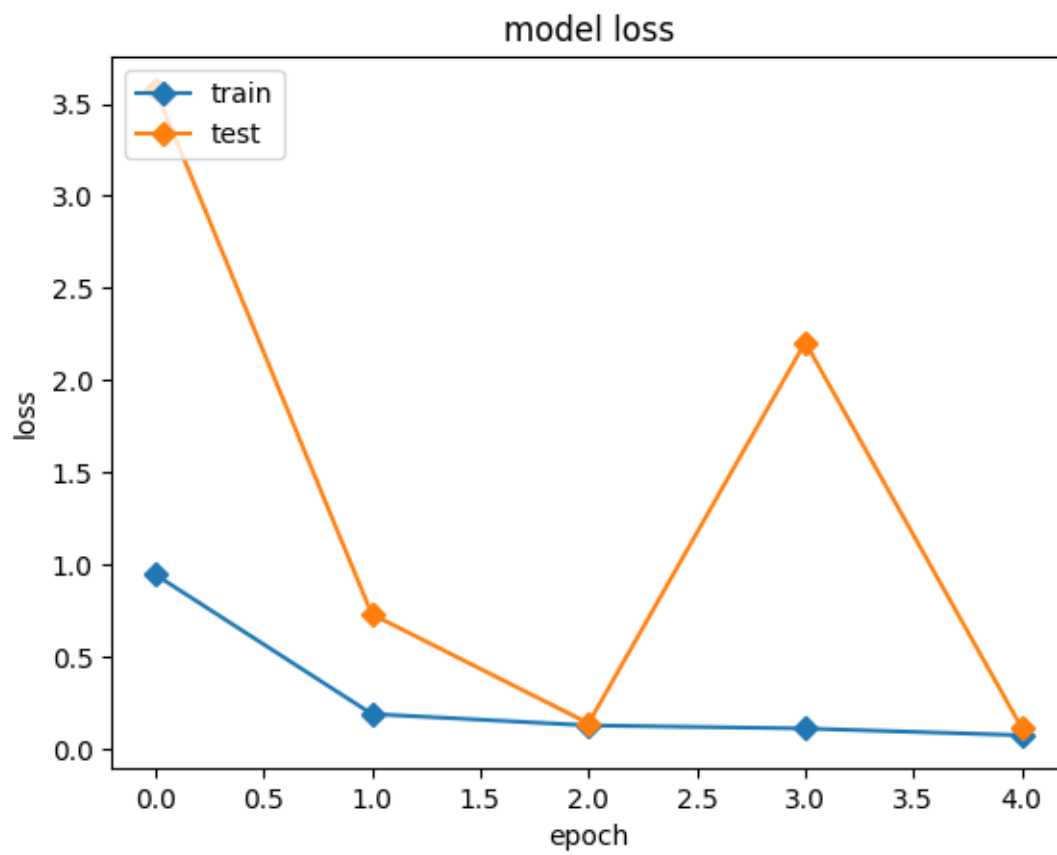
table = [
    ["Model", "Training Accuracy", "Validation Accuracy", "Test Accuracy"],
    ["Resnet50", train_accuracy[4]*100, val_accuracy[4]*100, test_accuracy[4]*100],
    ["VGG16", train_accuracy2[4]*100, val_accuracy2[4]*100, test_accuracy2[4]*100]

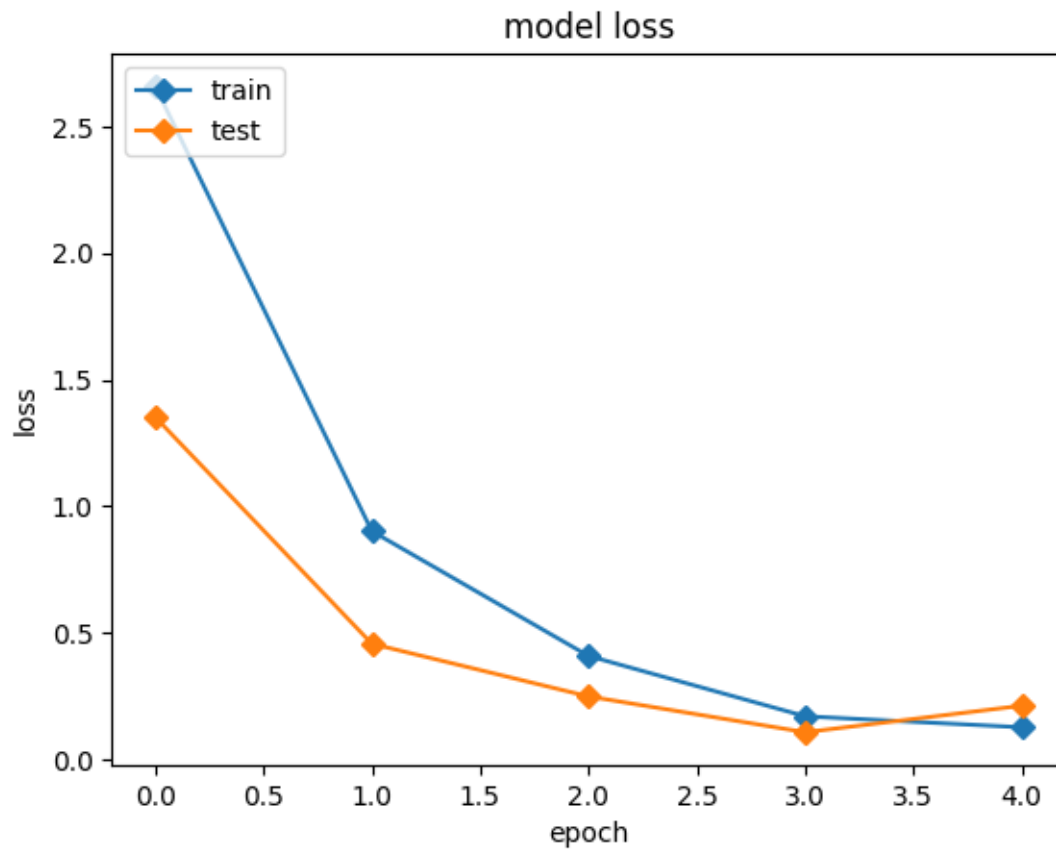
table1 = tabulate(table, headers="firstrow", tablefmt="grid")
print(table1)

```

Model	Training Accuracy	Validation Accuracy	Test Accuracy
Resnet50	98.0216	97.0756	98.6143
VGG16	98.6653	97.1181	98.6653







Вывод: как видно из таблицы выше, модели показывают схожие результаты.

Задание 2

Загружаем модель из предыдущего задания

```
tf.compat.v1.disable_eager_execution()
model=load_model('ResNet50.h5')
x_test = data[:1000]
y_test = y_test[:1000]
classifier = KerasClassifier(model=model, clip_values=(np.min(x_test), np.max(x_test)))
```

WARNING:tensorflow:From /usr/local/lib/python3.10/dist-packages/keras/src/layers/normalization.py:114: The name tf.nn.batch_normalization is deprecated. Please use tf.nn.dynamic_batch_normalization instead. Instructions for updating:
Colocations handled automatically by placer.

Создание атаки FGSM

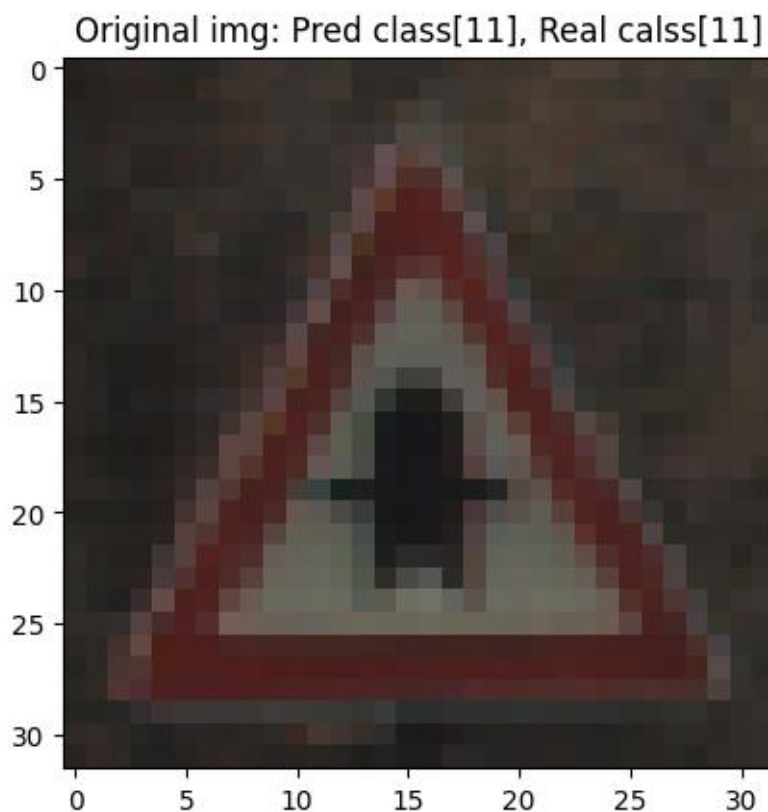

```

# создание атаки FGSM
attack_fgsm = FastGradientMethod(estimator=classifier, eps=0.3)
eps_range = [1/255, 2/255, 3/255, 4/255, 5/255, 8/255, 10/255, 20/255, 50/255, 80/255]
true_accuracies = []
adv_accuracies_fgsm = []
true_losses = []
adv_losses_fgsm = []

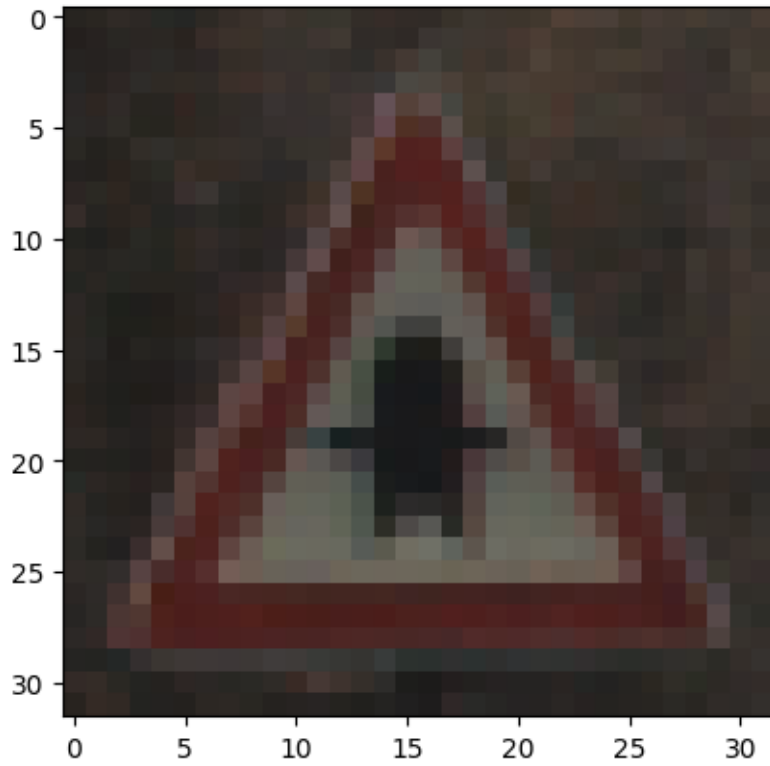
for eps in eps_range:
    attack_fgsm.set_params(**{'eps': eps})
    print(f"Eps: {eps}")
    x_test_adv = attack_fgsm.generate(x_test, y_test)
    loss, accuracy = model.evaluate(x_test_adv, y_test)
    adv_accuracies_fgsm.append(accuracy)
    adv_losses_fgsm.append(loss)
    print(f"Adv Loss: {loss}")
    print(f"Adv Accuracy: {accuracy}")
    loss, accuracy = model.evaluate(x_test, y_test)
    true_accuracies.append(accuracy)
    true_losses.append(loss)
    print(f"True Loss: {loss}")
    print(f"True Accuracy: {accuracy}")

```

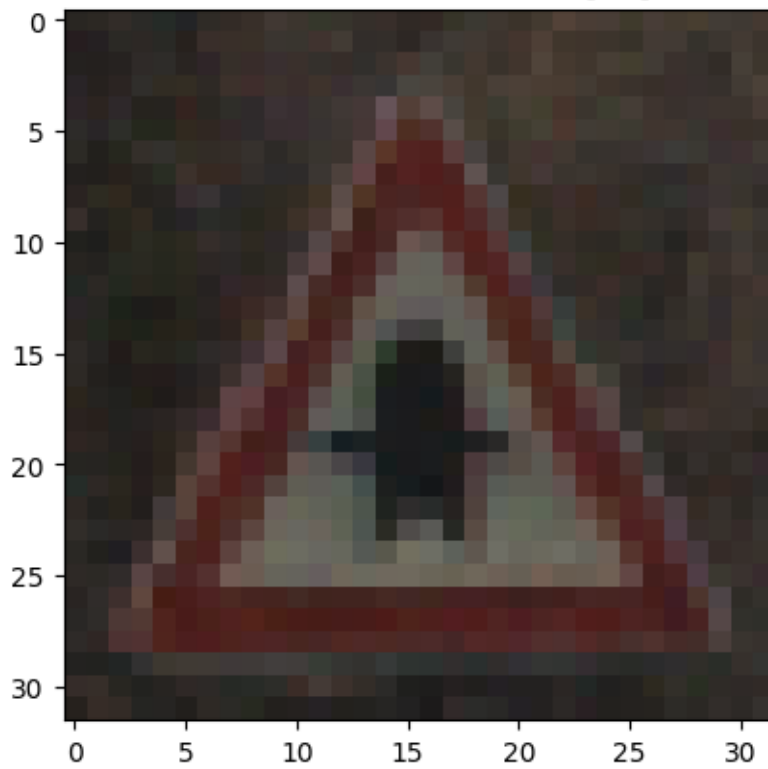
Отображение исходных и адверсариальных изображений



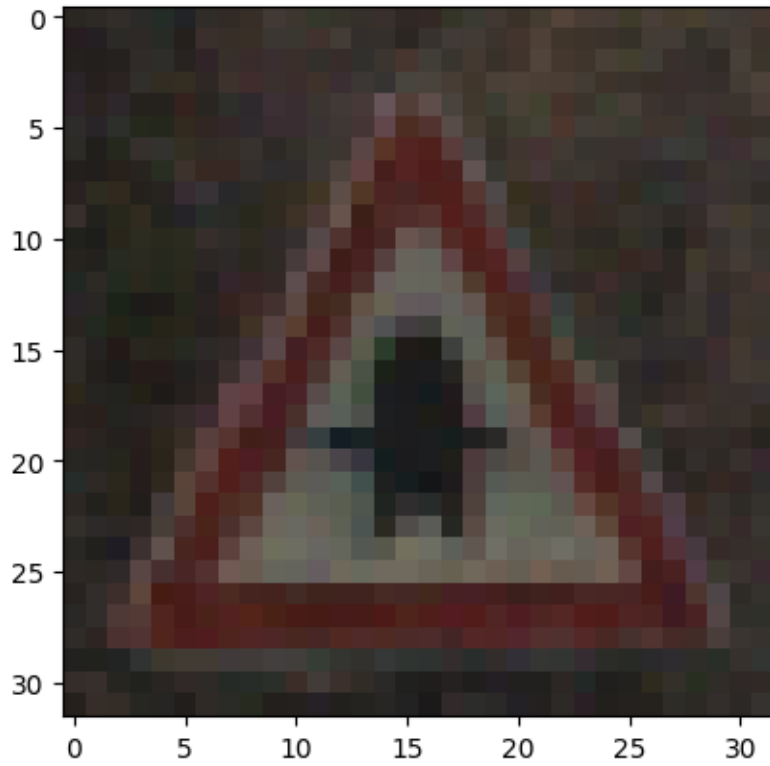
eps 0.00392156862745098: Pred class[11], Real class[11]



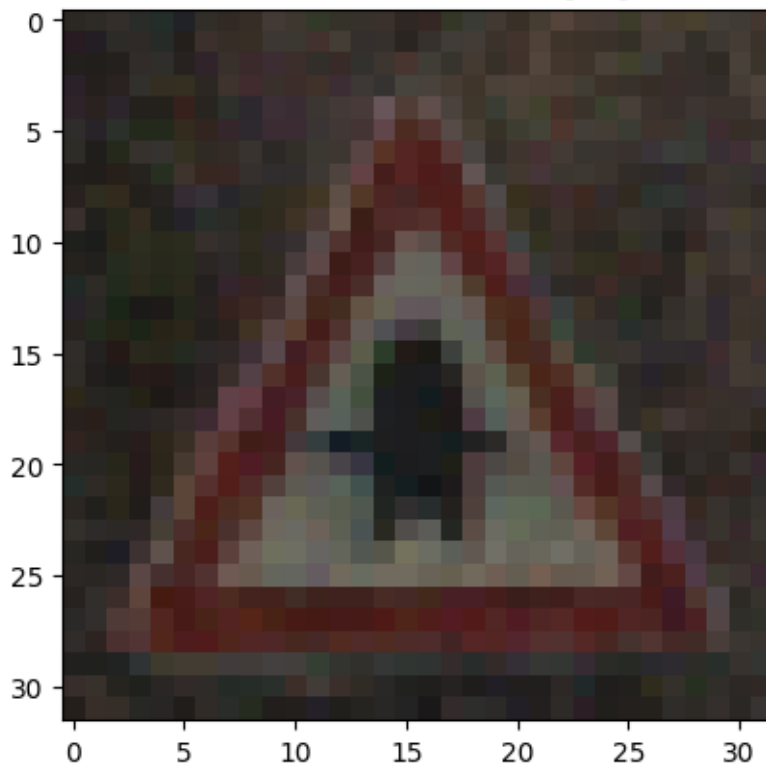
eps 0.011764705882352941: Pred class[11], Real class[11]



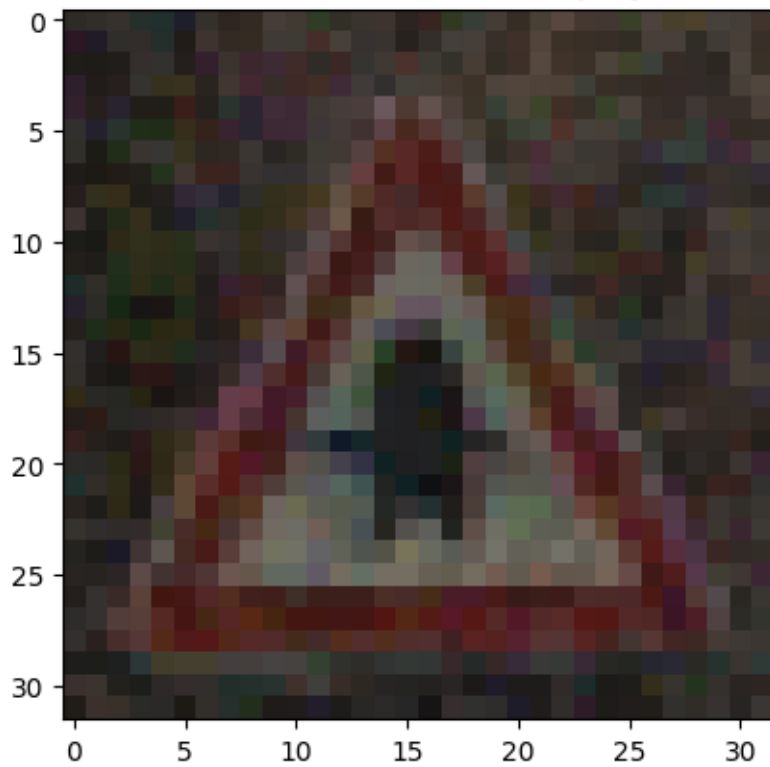
eps 0.01568627450980392: Pred class[11], Real class[11]



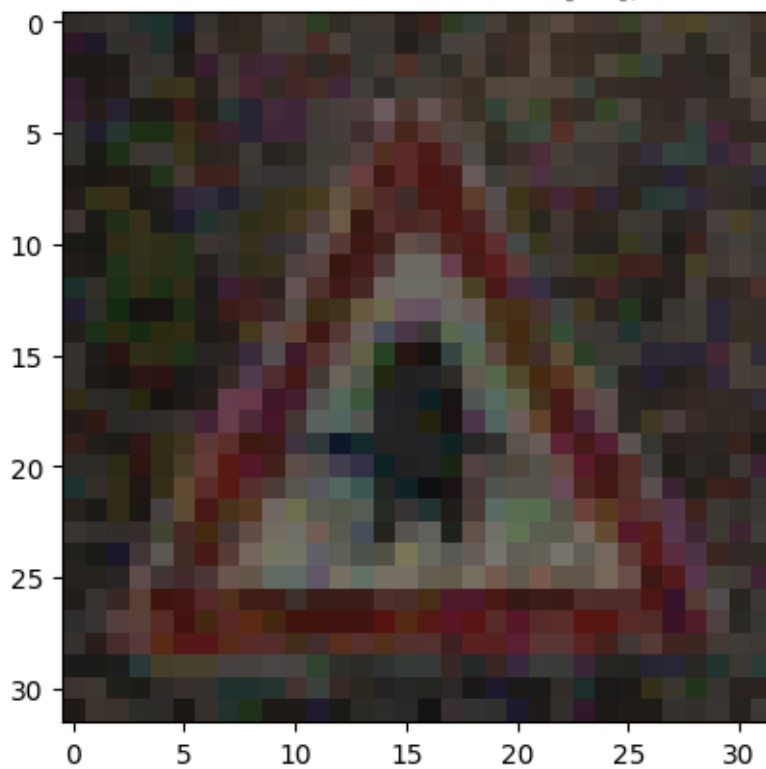
eps 0.0196078431372549: Pred class[25], Real class[11]



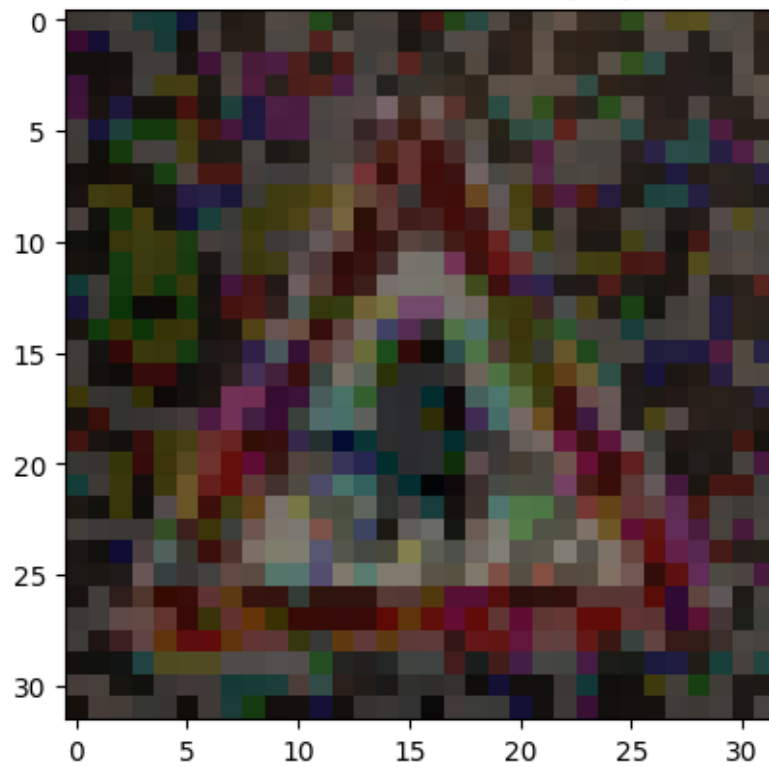
eps 0.03137254901960784: Pred class[25], Real class[11]



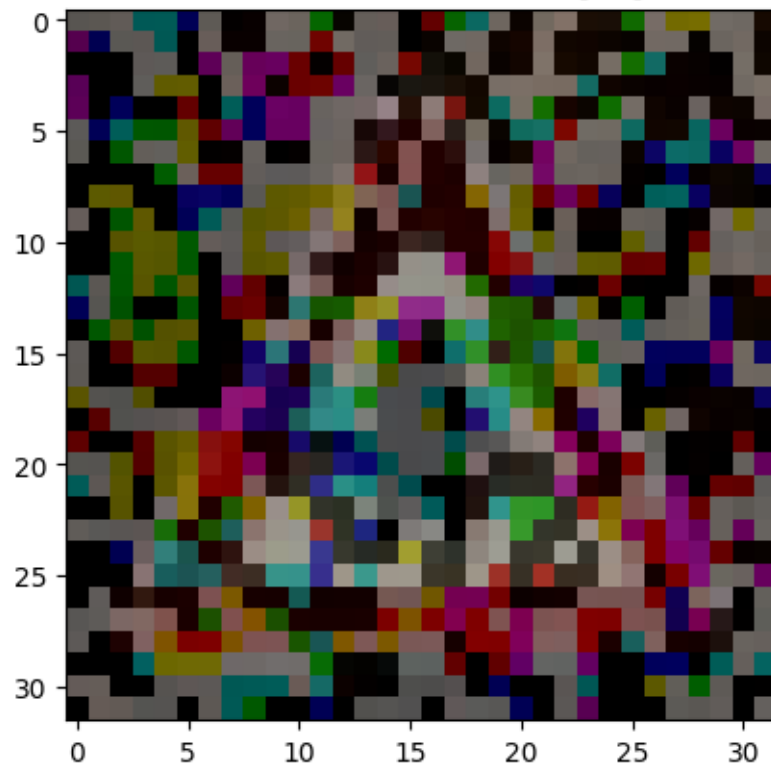
eps 0.0392156862745098: Pred class[25], Real class[11]



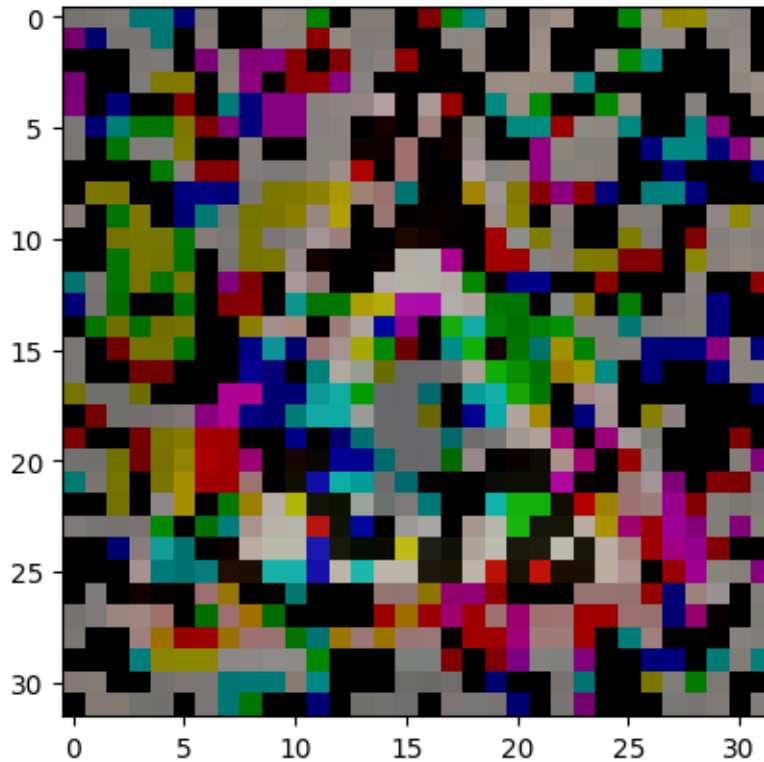
eps 0.0784313725490196: Pred class[24], Real class[11]



eps 0.19607843137254902: Pred class[24], Real class[11]



eps 0.3137254901960784: Pred class[24], Real class[11]



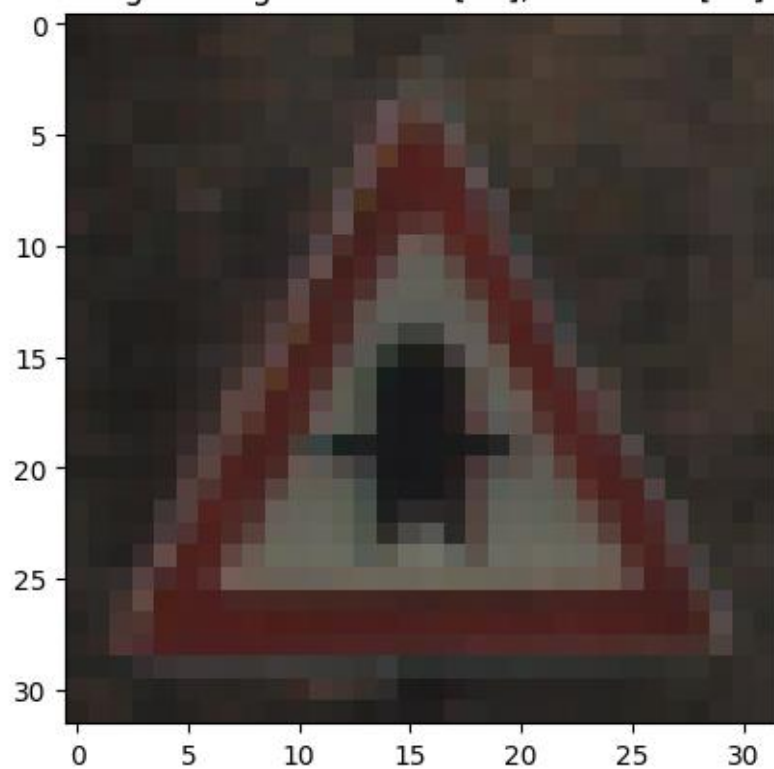
Создание атаки PGD

```
tf.compat.v1.disable_eager_execution()
model=load_model('ResNet50.h5')
x_test = data[:1000]
y_test = y_test[:1000]
classifier = KerasClassifier(model=model, clip_values=(np.min(x_test), np.max(x_test)))
attack_pgd = ProjectedGradientDescent(estimator=classifier, eps=0.3, max_iter=4, verbose=False)
eps_range = [1/255, 2/255, 3/255, 4/255, 5/255, 8/255, 10/255, 20/255, 50/255, 80/255]
true_accuracies = []
adv_accuracies_pgd = []
true_losses = []
adv_losses_pgd = []

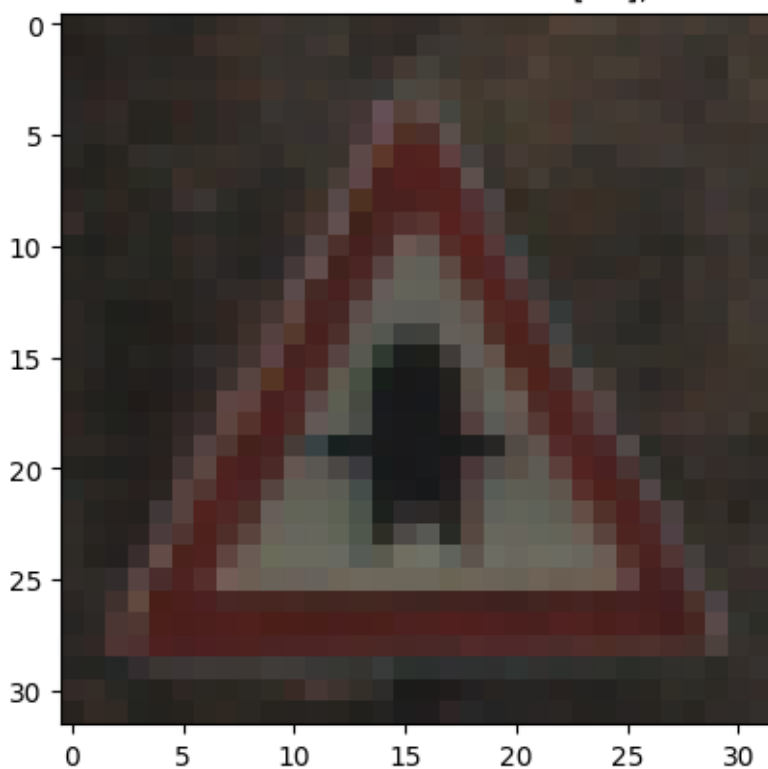
for eps in eps_range:
    attack_pgd.set_params(**{'eps': eps})
    print(f"Eps: {eps}")
    x_test_adv = attack_pgd.generate(x_test, y_test)
    loss, accuracy = model.evaluate(x_test_adv, y_test)
    adv_accuracies_pgd.append(accuracy)
    adv_losses_pgd.append(loss)
    print(f"Adv Loss: {loss}")
    print(f"Adv Accuracy: {accuracy}")
    loss, accuracy = model.evaluate(x_test, y_test)
    true_accuracies.append(accuracy)
    true_losses.append(loss)
    print(f"True Loss: {loss}")
    print(f"True Accuracy: {accuracy}")
```

Отображение исходных и адверсариальных изображений

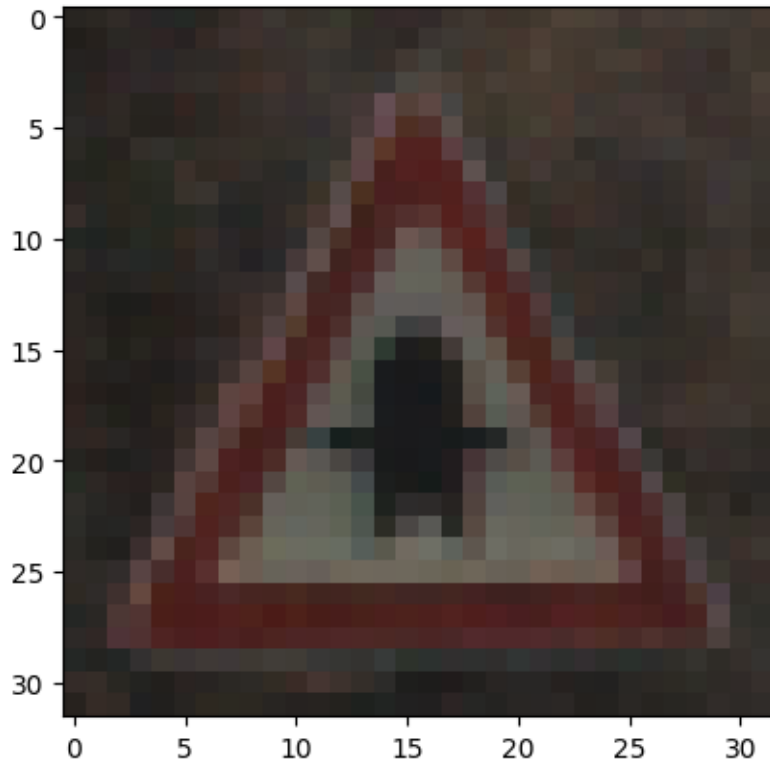
Original img: Pred class[11], Real calss[11]



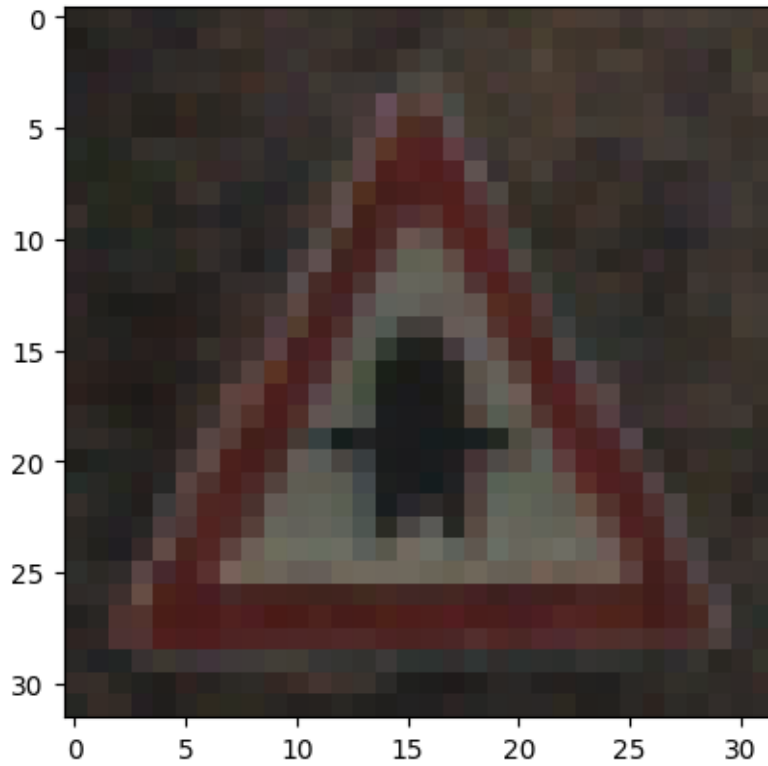
eps 0.00392156862745098: Pred class[11], Real class[11]



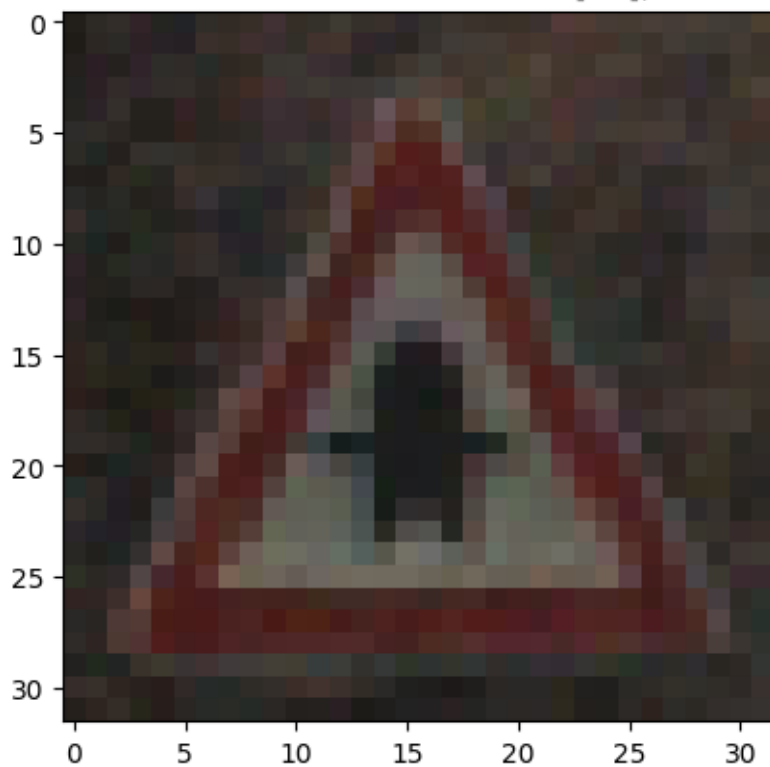
eps 0.00784313725490196: Pred class[11], Real class[11]



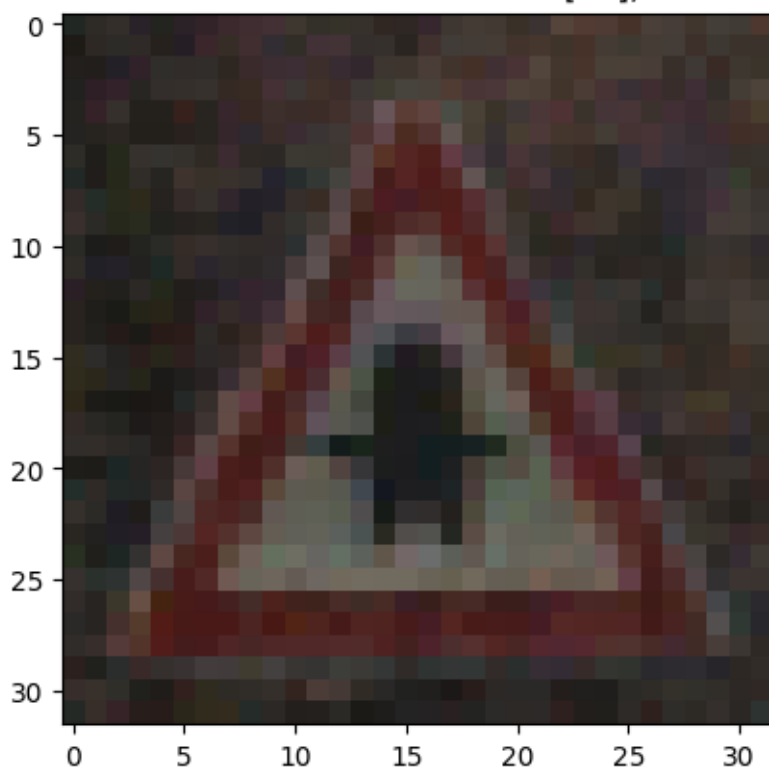
eps 0.011764705882352941: Pred class[11], Real class[11]



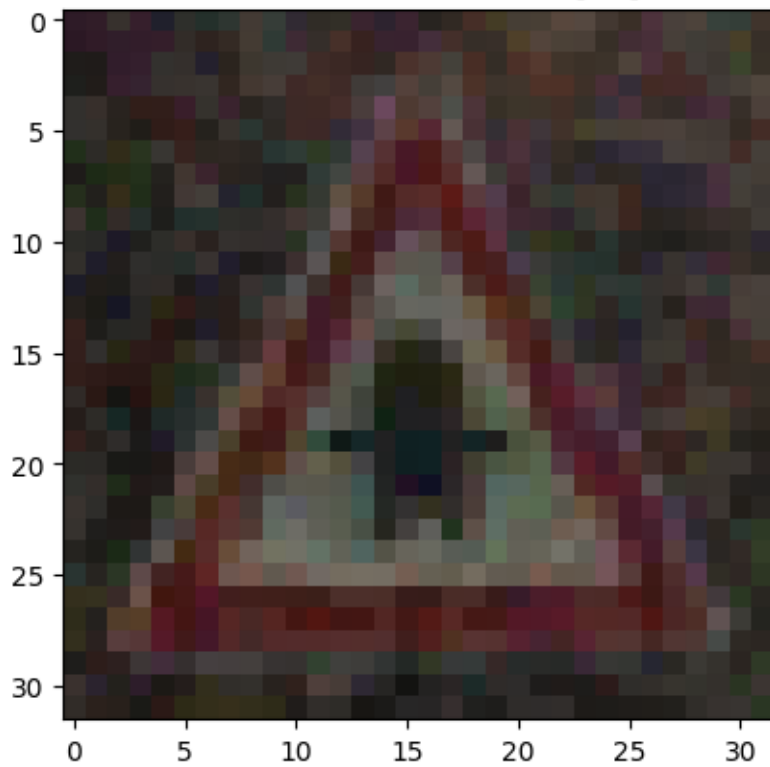
eps 0.01568627450980392: Pred class[11], Real class[11]



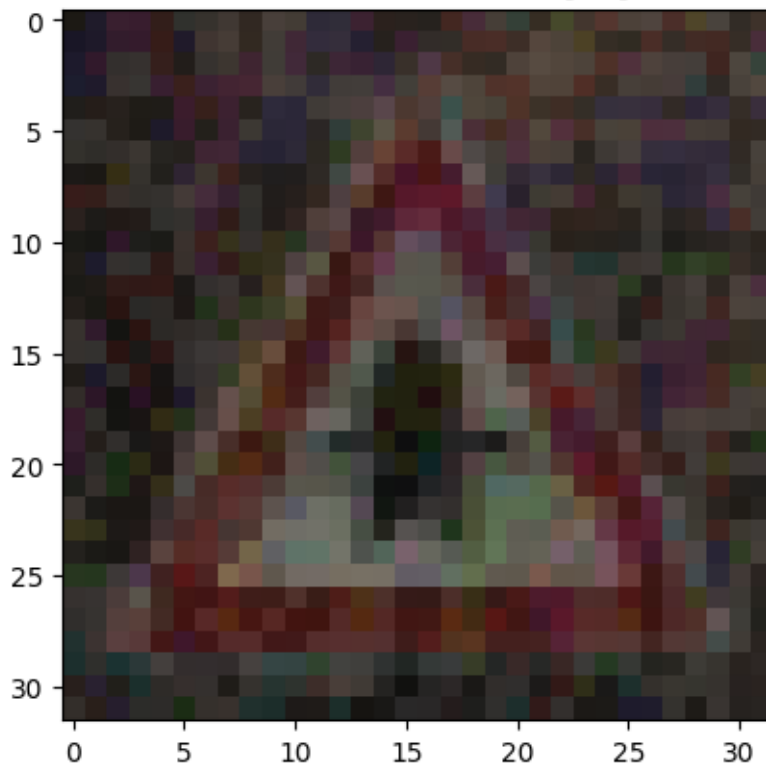
eps 0.0196078431372549: Pred class[25], Real class[11]



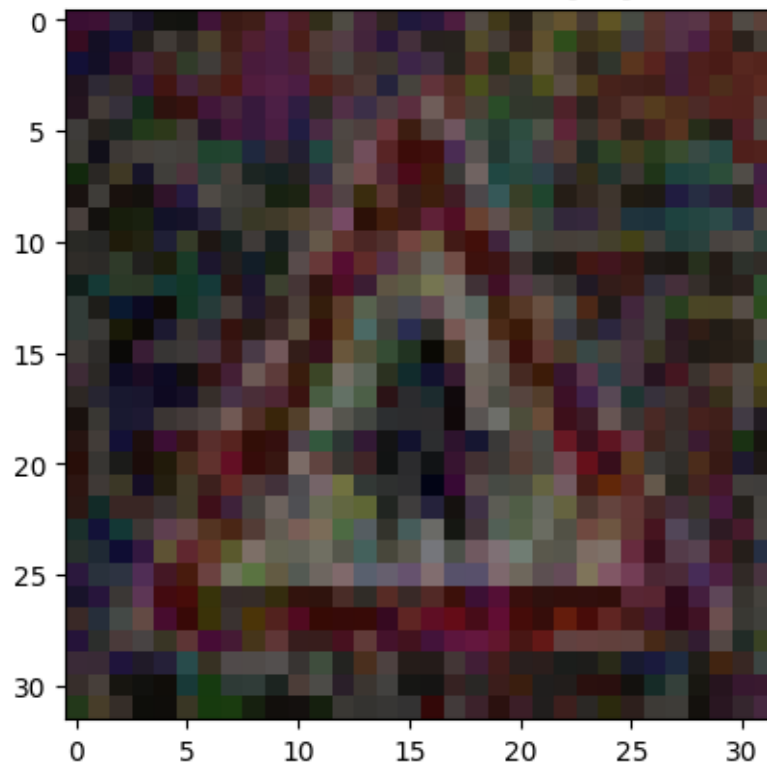
eps 0.03137254901960784: Pred class[25], Real class[11]



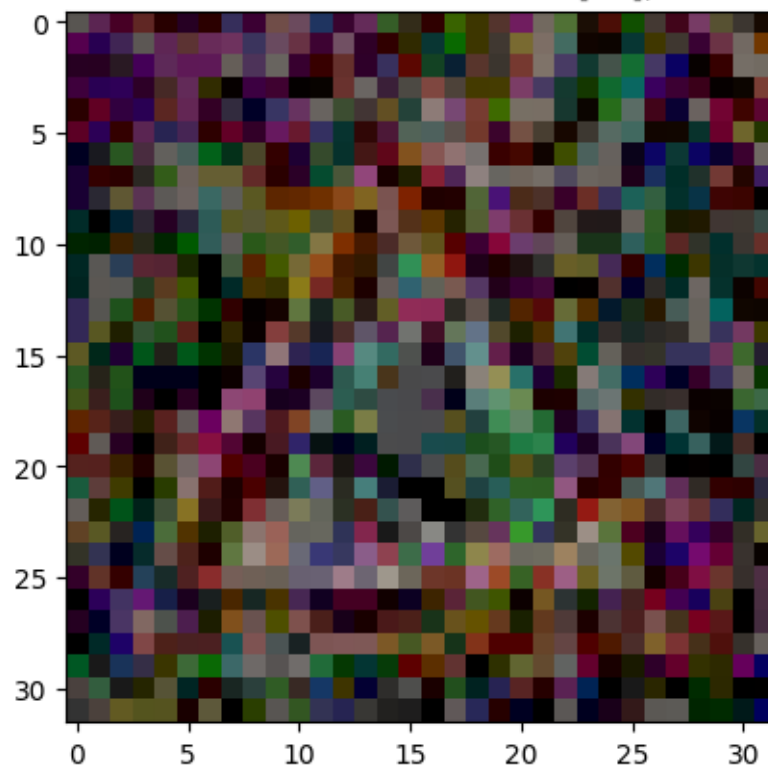
eps 0.0392156862745098: Pred class[11], Real class[11]



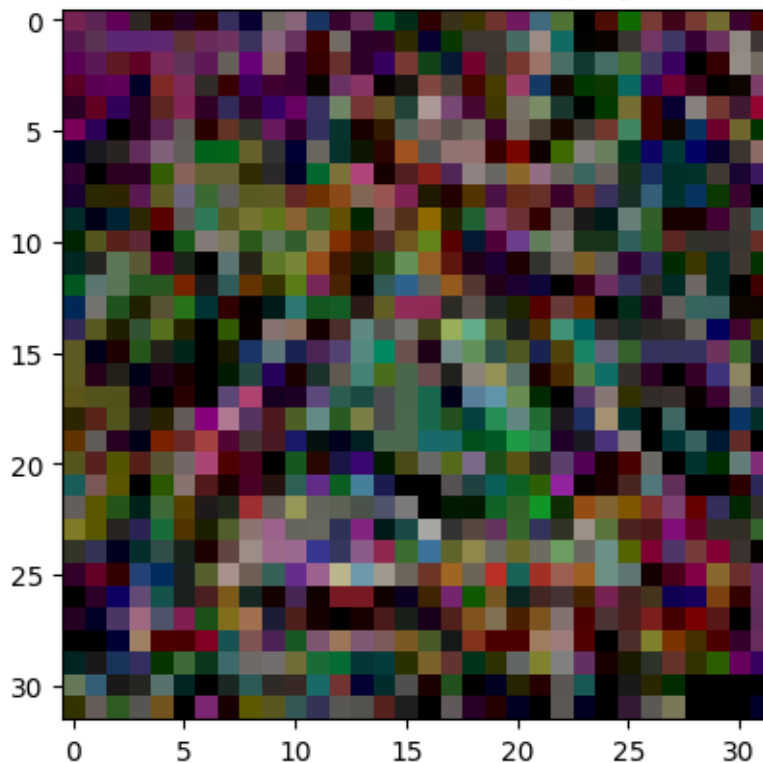
eps 0.0784313725490196: Pred class[24], Real class[11]



eps 0.19607843137254902: Pred class[29], Real class[11]



eps 0.3137254901960784: Pred class[29], Real class[11]



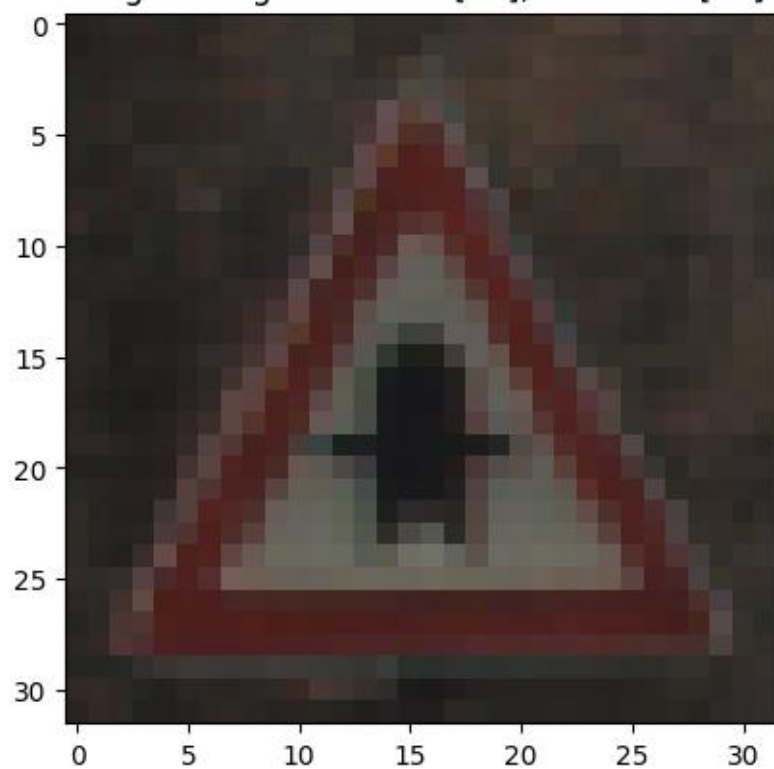
Создание атаки PGD

```
attack_pgd = ProjectedGradientDescent(estimator=classifier, eps=0.3, max_iter=4, verbose=False)
eps_range = [1/255, 2/255, 3/255, 4/255, 5/255, 8/255, 10/255, 20/255, 50/255, 80/255]
true_accuracies = []
adv_accuracises_pgd = []
true_losses = []
adv_losses_pgd = []

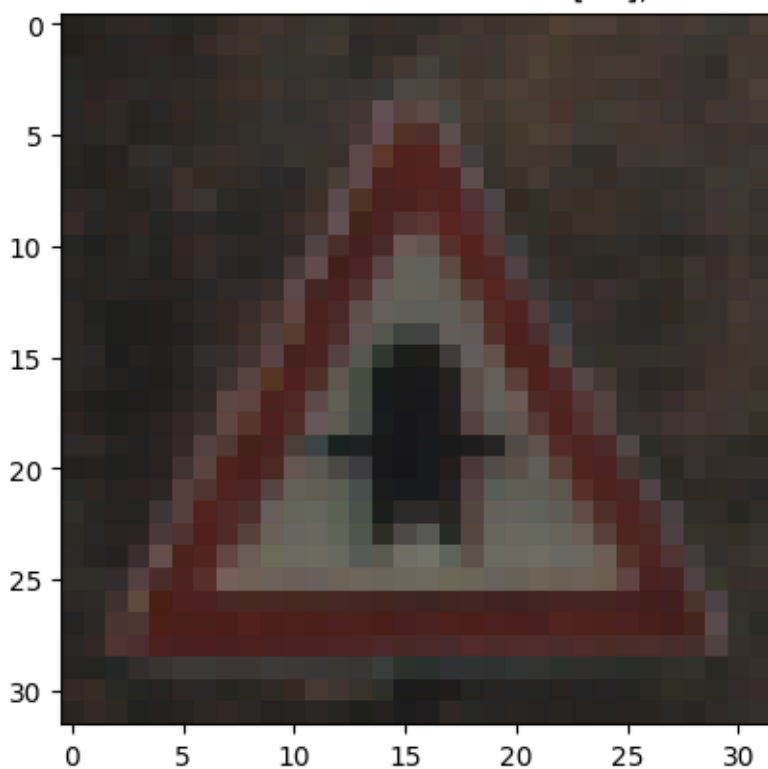
for eps in eps_range:
    attack_pgd.set_params(**{'eps': eps})
    print(f"Eps: {eps}")
    x_test_adv = attack_pgd.generate(x_test, y_test)
    loss, accuracy = model.evaluate(x_test_adv, y_test)
    adv_accuracises_pgd.append(accuracy)
    adv_losses_pgd.append(loss)
    print(f"Adv Loss: {loss}")
    print(f"Adv Accuracy: {accuracy}")
    loss, accuracy = model.evaluate(x_test, y_test)
    true_accuracies.append(accuracy)
    true_losses.append(loss)
    print(f"True Loss: {loss}")
    print(f"True Accuracy: {accuracy}")
```

Отображение исходных и адверсариальных изображений

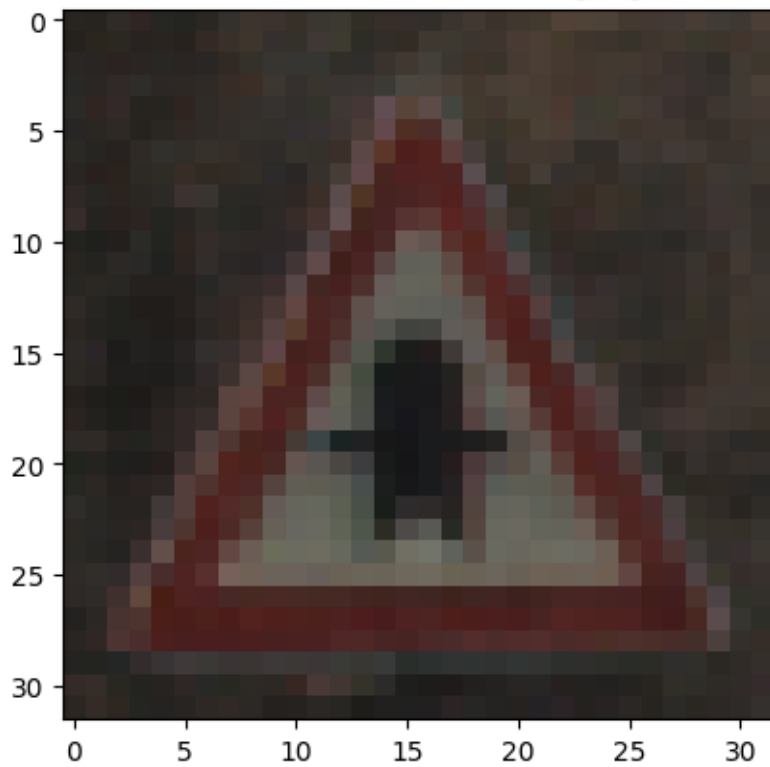
Original img: Pred class[11], Real class[11]



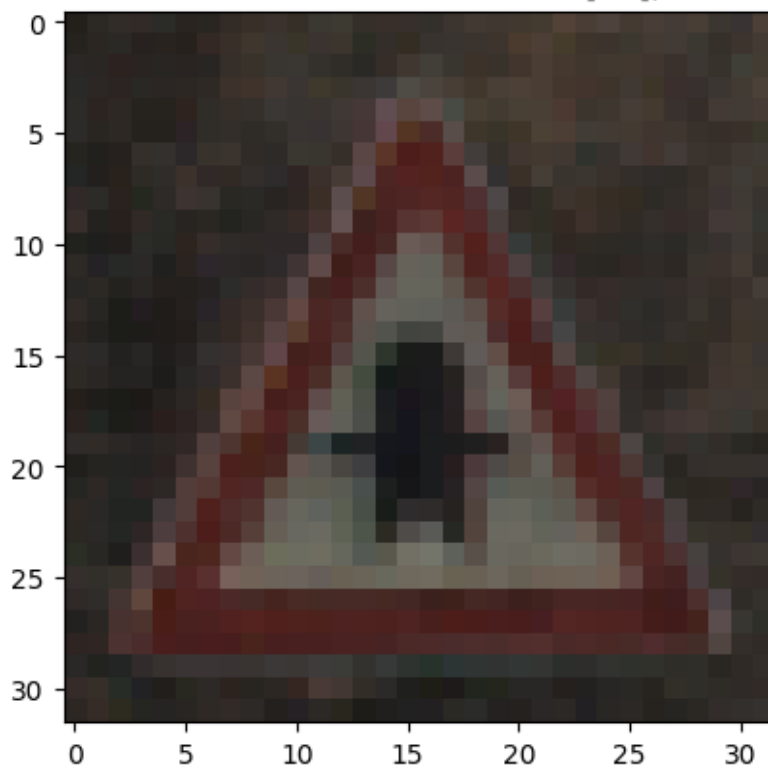
eps 0.00392156862745098: Pred class[11], Real class[11]



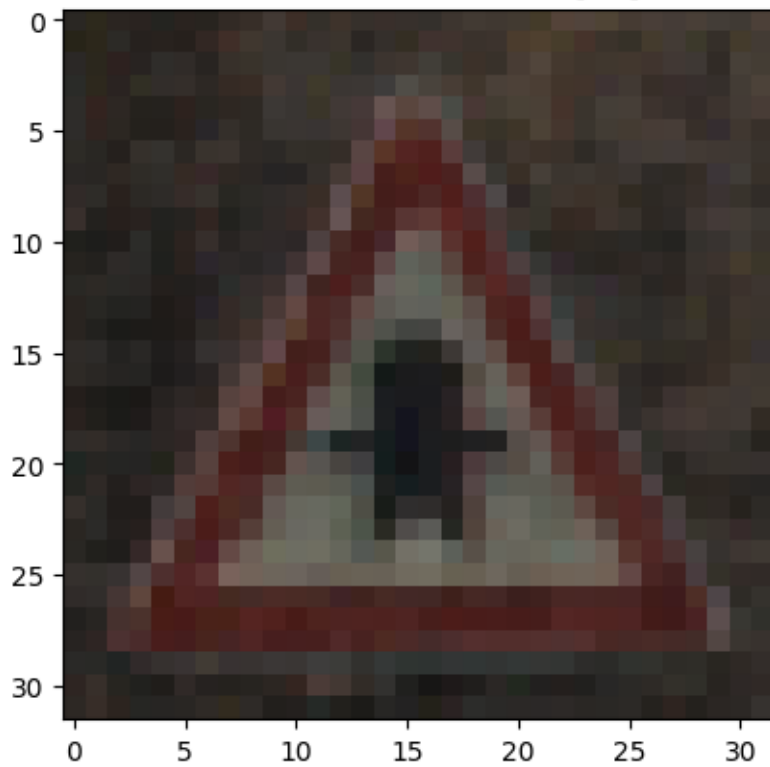
eps 0.00784313725490196: Pred class[11], Real class[11]



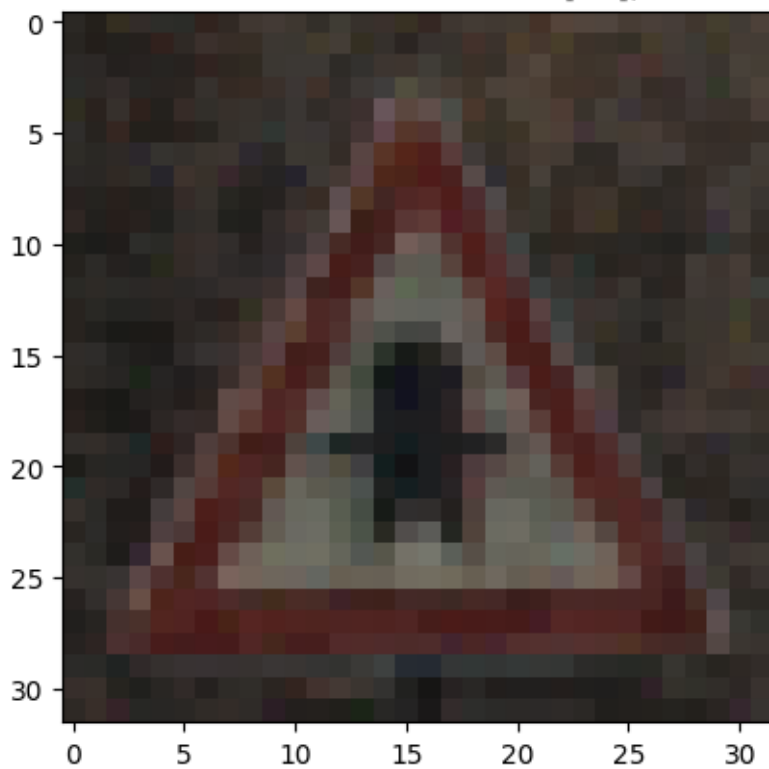
eps 0.011764705882352941: Pred class[11], Real class[11]



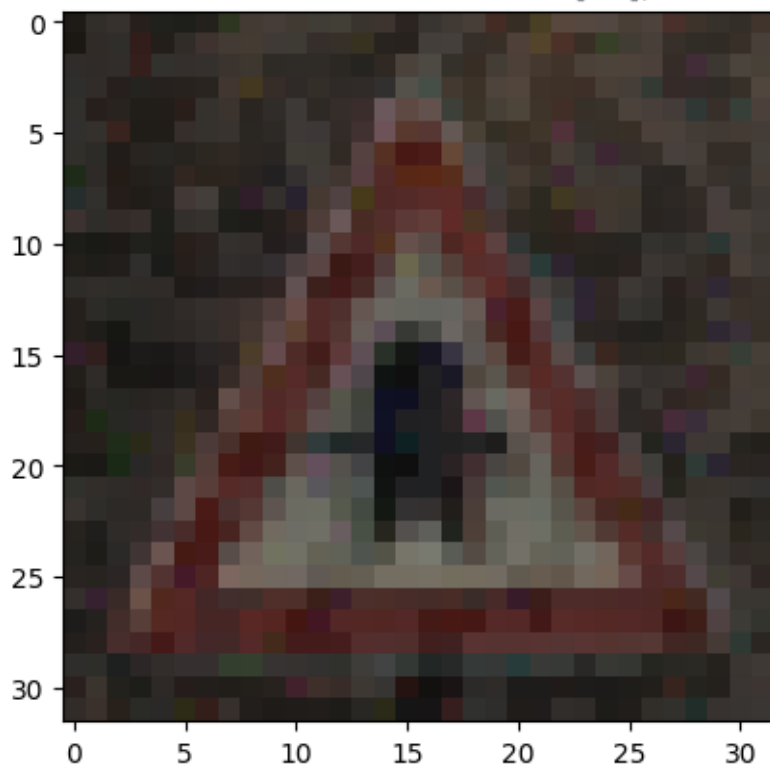
eps 0.01568627450980392: Pred class[11], Real class[11]



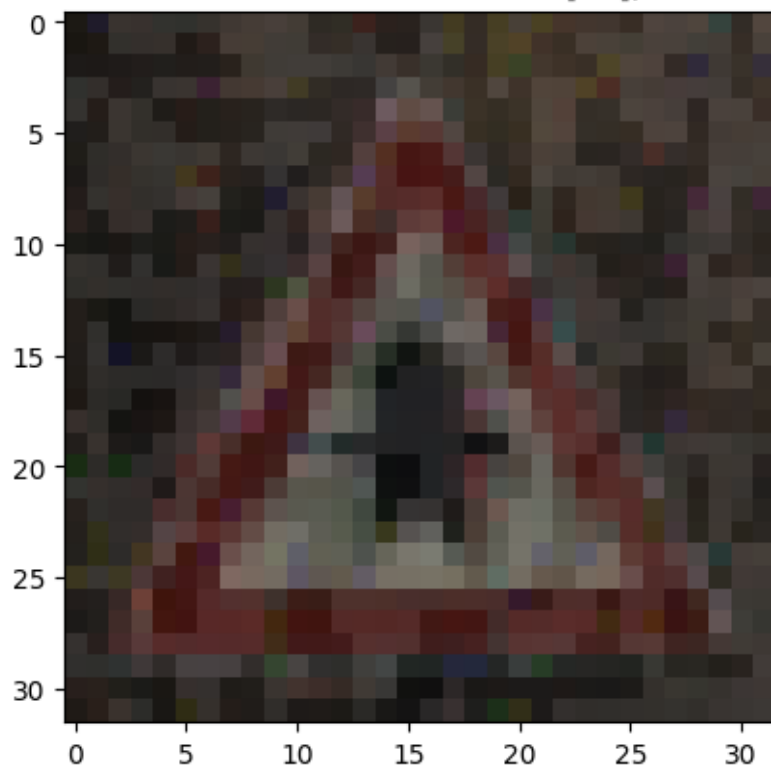
eps 0.0196078431372549: Pred class[11], Real class[11]



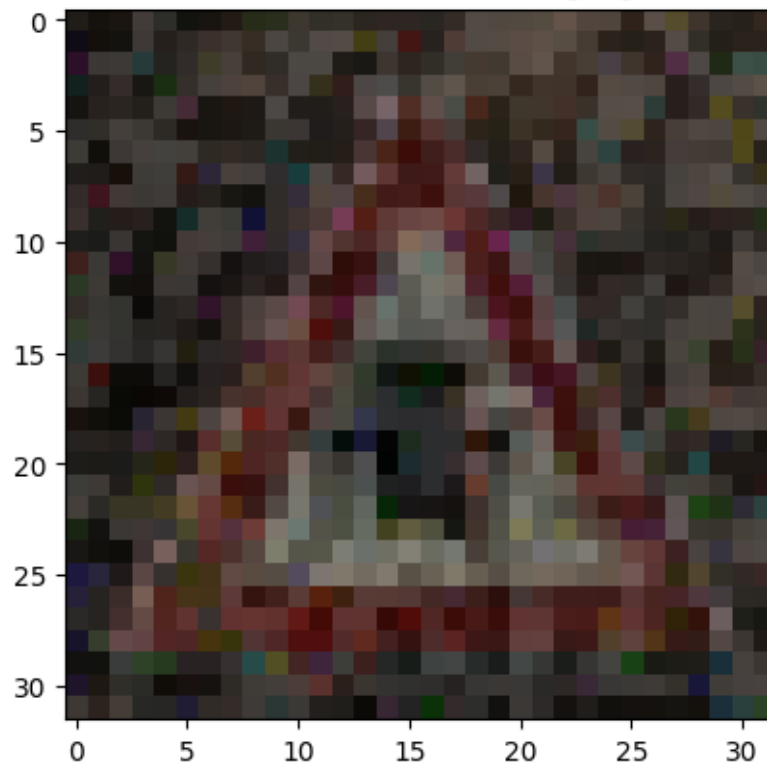
eps 0.03137254901960784: Pred class[27], Real class[11]



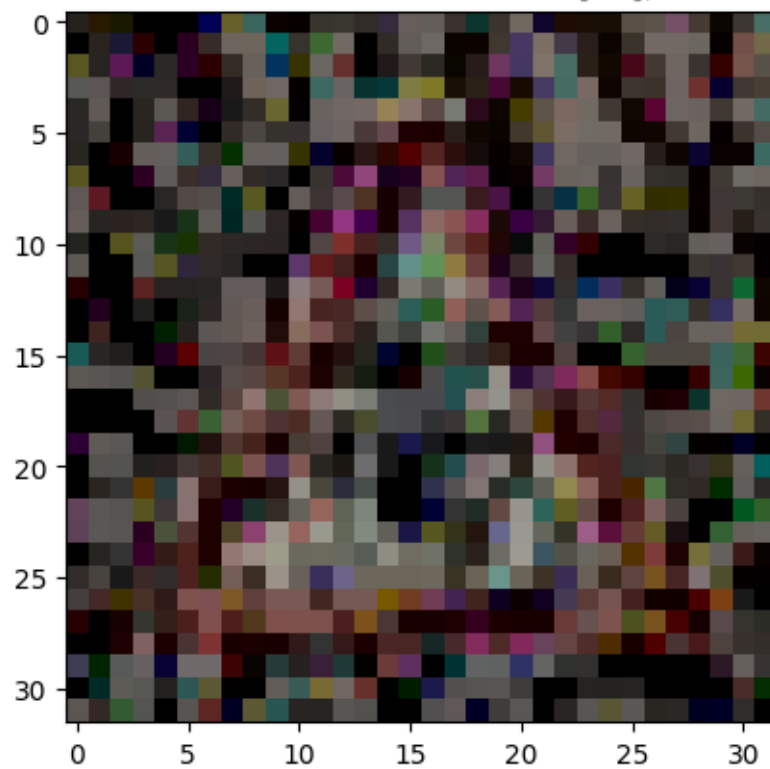
eps 0.0392156862745098: Pred class[27], Real class[11]



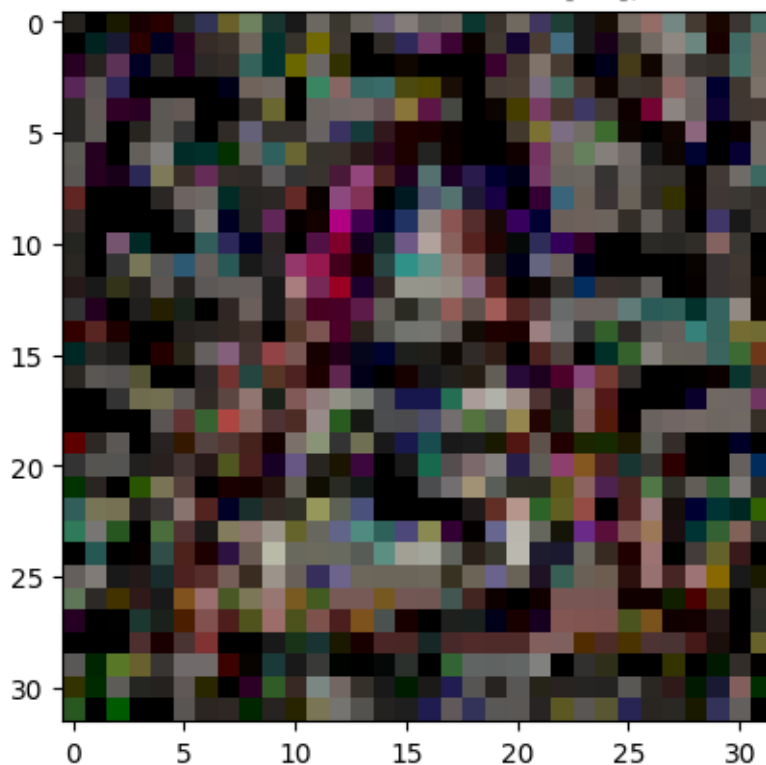
eps 0.0784313725490196: Pred class[28], Real class[11]



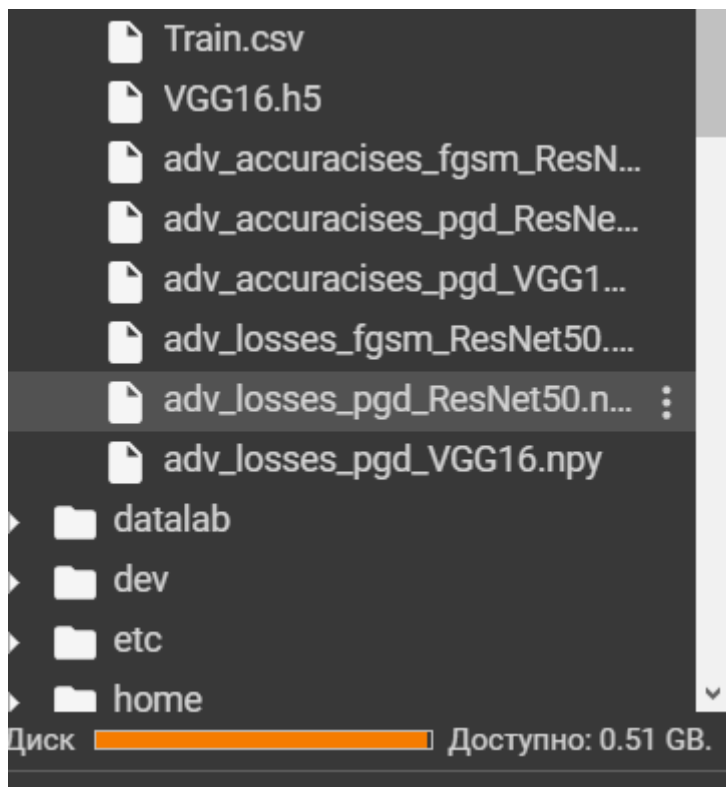
eps 0.19607843137254902: Pred class[19], Real class[11]

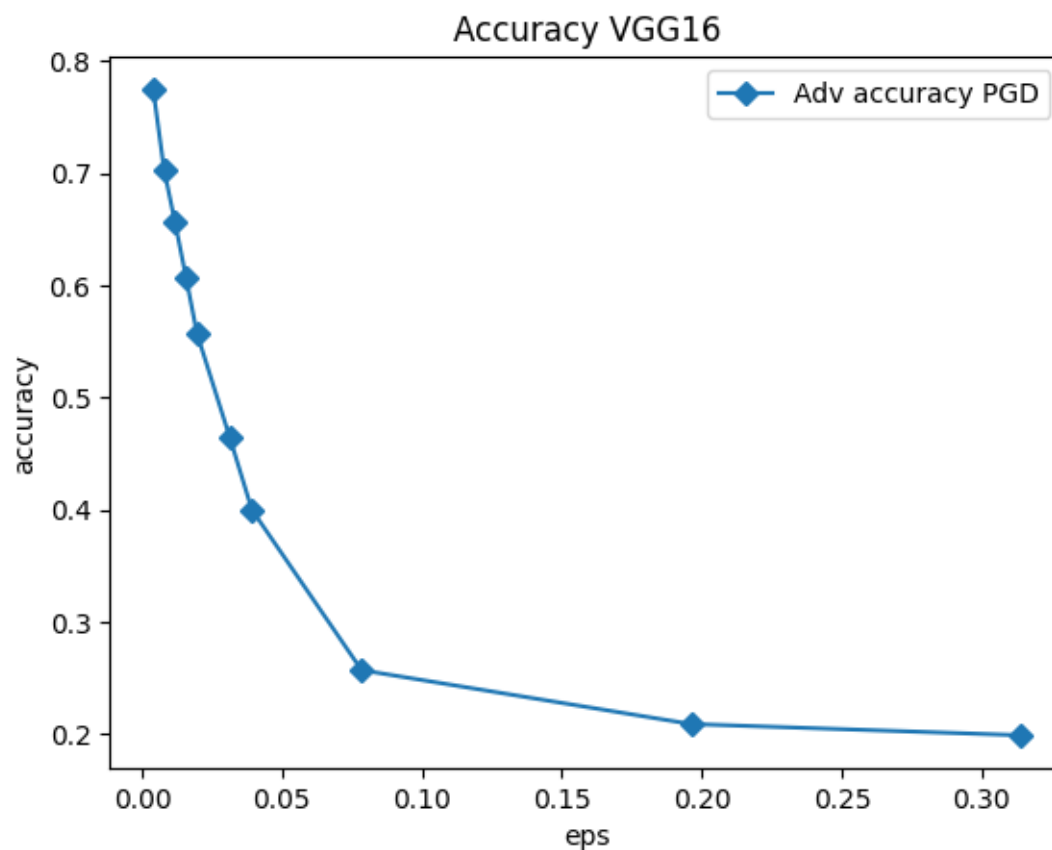


eps 0.3137254901960784: Pred class[23], Real class[11]



Когда пришло время строить графики и смотреть зависимости, обратил внимание на то, что из-за нехватки места в гугл колабе, нужные файлы, видимо, стерлись. Поэтому продемонстрирую то, что есть.





```
[43] adv_acc_pgd_v16 = np.load("adv_accuracises_pgd_VGG16.npy")

table = [
    ["Model", "Original accuracy", "eps = 1/255", "eps = 2/255", "eps = 3/255", "eps = 4/255", "eps = 5/255", "eps = 8/255", "eps = 10/255"],
    ["Resnet50 FGSM", train_accuracy[4]*100, adv_acc_fgsm_rn50[0]*100, adv_acc_fgsm_rn50[1]*100, adv_acc_fgsm_rn50[2]*100, adv_acc_fgsm_rn50[3]*100, adv_acc_fgsm_rn50[4]*100, adv_acc_fgsm_rn50[5]*100, adv_acc_fgsm_rn50[6]*100, adv_acc_fgsm_rn50[7]*100, adv_acc_fgsm_rn50[8]*100, adv_acc_fgsm_rn50[9]*100],
    ["Resnet50 PGD", train_accuracy[4]*100, adv_acc_pgd_rn50[0]*100, adv_acc_pgd_rn50[1]*100, adv_acc_pgd_rn50[2]*100, adv_acc_pgd_rn50[3]*100, adv_acc_pgd_rn50[4]*100, adv_acc_pgd_rn50[5]*100, adv_acc_pgd_rn50[6]*100, adv_acc_pgd_rn50[7]*100, adv_acc_pgd_rn50[8]*100, adv_acc_pgd_rn50[9]*100],
    ["VGG16 PGD", train_accuracy2[4]*100, adv_acc_pgd_v16[0]*100, adv_acc_pgd_v16[1]*100, adv_acc_pgd_v16[2]*100, adv_acc_pgd_v16[3]*100, adv_acc_pgd_v16[4]*100, adv_acc_pgd_v16[5]*100, adv_acc_pgd_v16[6]*100, adv_acc_pgd_v16[7]*100, adv_acc_pgd_v16[8]*100, adv_acc_pgd_v16[9]*100],
]

table2 = tabulate(table, headers="firstrow", tablefmt="grid")
print(table2)
```

Model	Original accuracy	eps = 1/255	eps = 2/255	eps = 3/255	eps = 4/255	eps = 5/255	eps = 8/255	eps = 10/255
Resnet50 FGSM	98.0216	76.7	64	53	44.9	37.9	24.5	20.5
Resnet50 PGD	98.0216	74.4	59.7	48.3	42	36.5	27.7	20.5
VGG16 PGD	98.6653	77.5	70.3	65.6	60.7	55.7	46.4	40.5

Задание 3

Загрузка тестового набора данных и извлечения изображения с меткой 14

```

test = pd.read_csv("Test.csv")
test_imgs = test['Path'].values
data = []
y_test = []
labels = test['ClassId'].values.tolist()
i = -1

for img in test_imgs:
    i += 1
    if labels[i] != 14:
        continue
    img = image.load_img(img, target_size=(32, 32))
    img_array = image.img_to_array(img)
    img_array = img_array / 255
    data.append(img_array)
    y_test.append(labels[i])
data = np.array(data)
y_test = np.array(y_test)
y_test = to_categorical(y_test, 43)

```

Реализация атаки FGSM

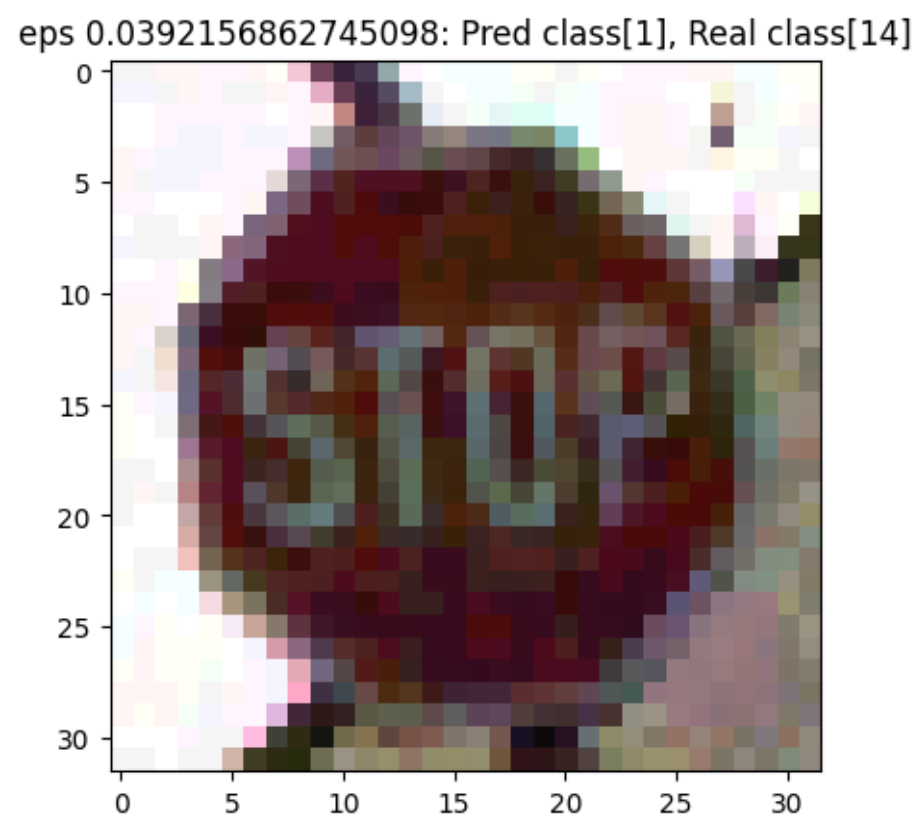
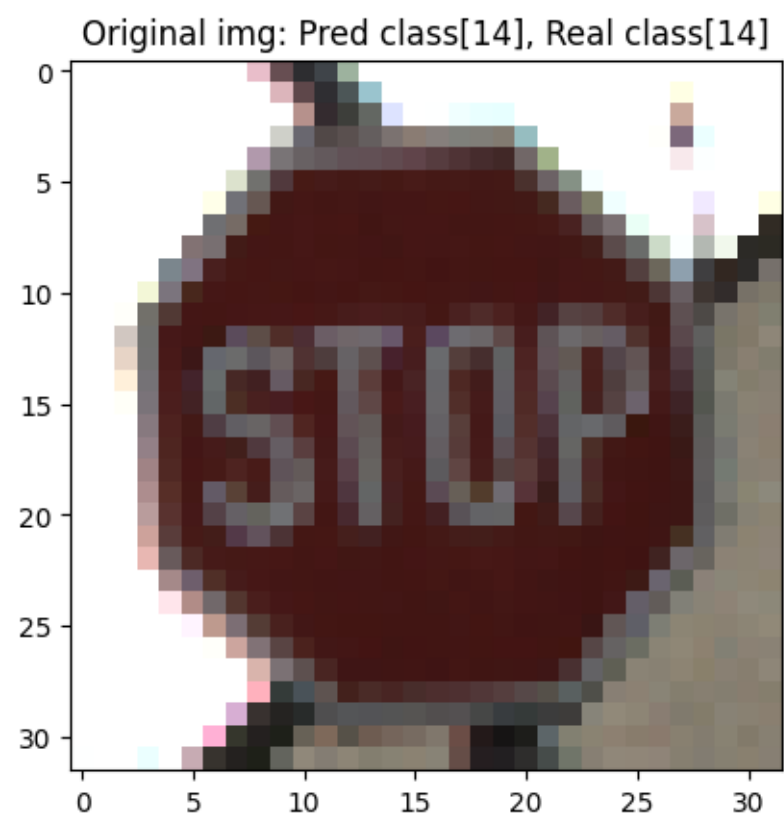
```

model=load_model('ResNet50.h5')
tf.compat.v1.disable_eager_execution()
t_class = 1
t_class = to_categorical(t_class, 43)
t_classes = np.tile(t_class, (270, 1))
x_test = data
classifier = KerasClassifier(model=model, clip_values=(np.min(x_test), np.max(x_test)))
attack_fgsm = FastGradientMethod(estimator=classifier, eps=0.2, targeted=True, batch_size=64)
eps_range = [1/255, 2/255, 3/255, 4/255, 5/255, 8/255, 10/255, 20/255, 50/255, 80/255]

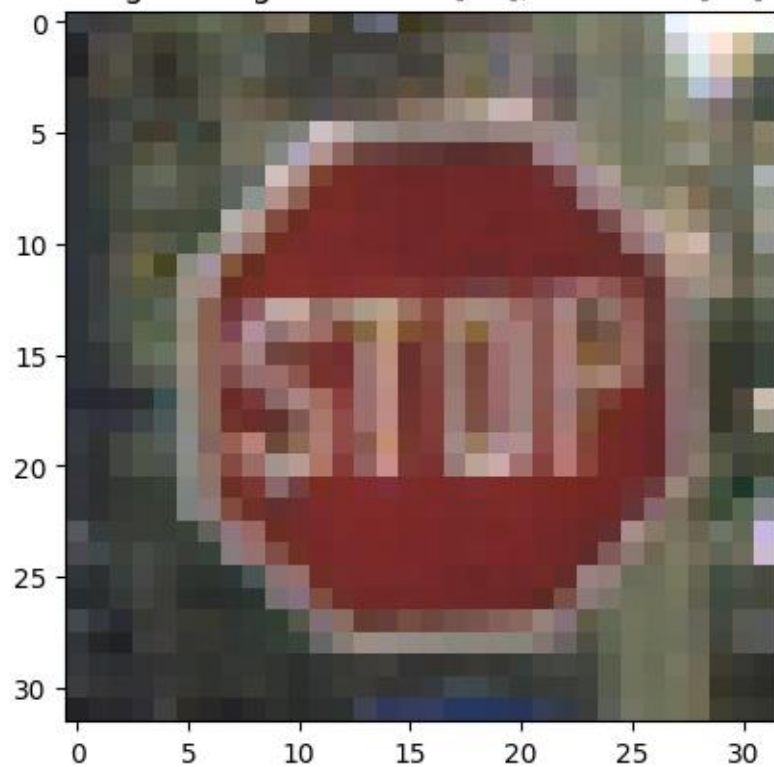
for eps in eps_range:
    attack_fgsm.set_params(**{'eps': eps})
    print(f"Eps: {eps}")
    x_test_adv = attack_fgsm.generate(x_test, t_classes)
    loss, accuracy = model.evaluate(x_test_adv, y_test)
    print(f"Adv Loss: {loss}")
    print(f"Adv Accuracy: {accuracy}")
    loss, accuracy = model.evaluate(x_test, y_test)
    print(f"True Loss: {loss}")
    print(f"True Accuracy: {accuracy}")

```

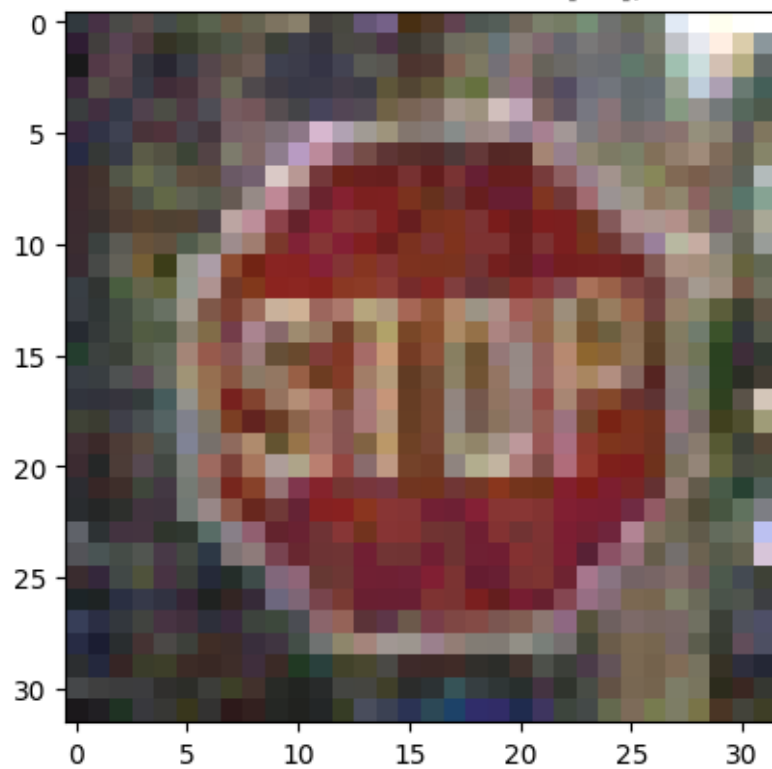
Визуализация последствий атаки

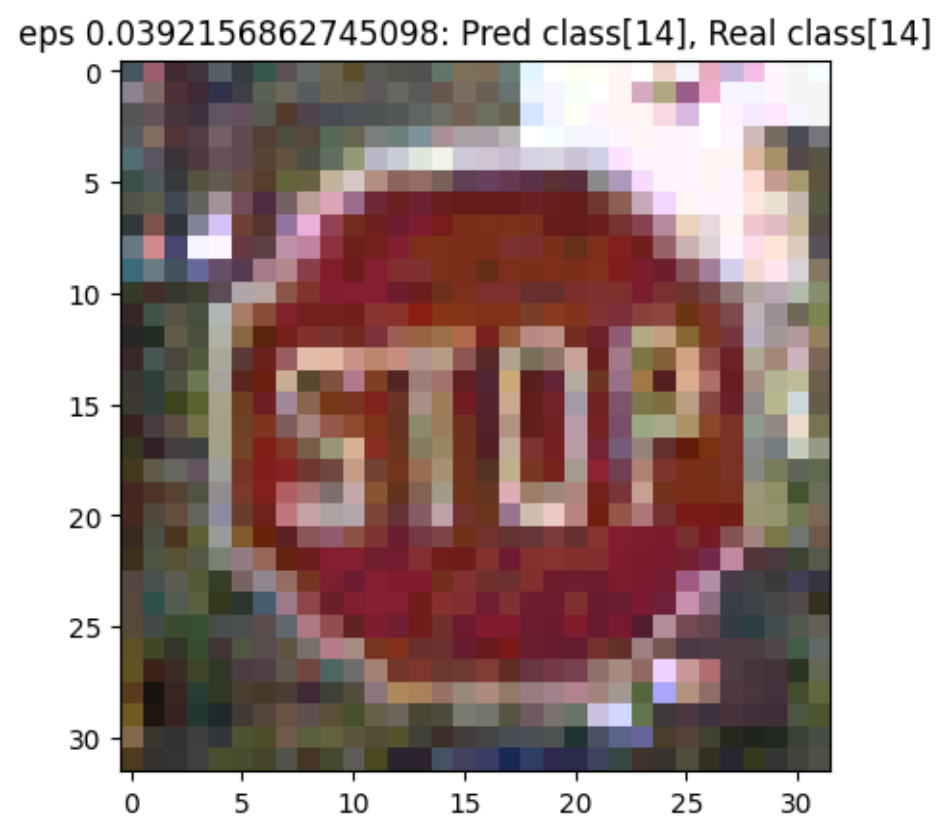
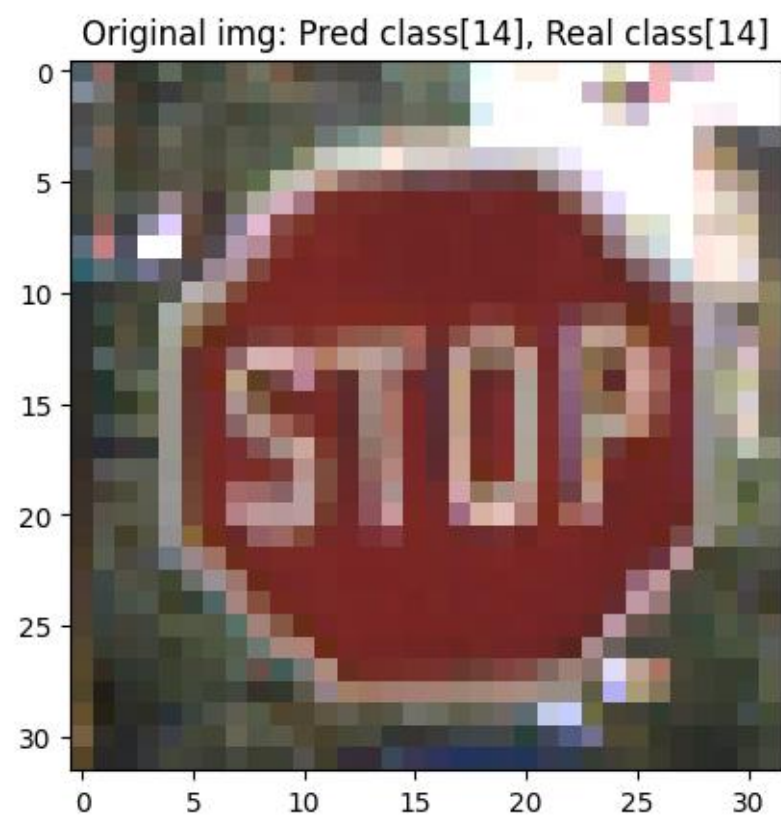


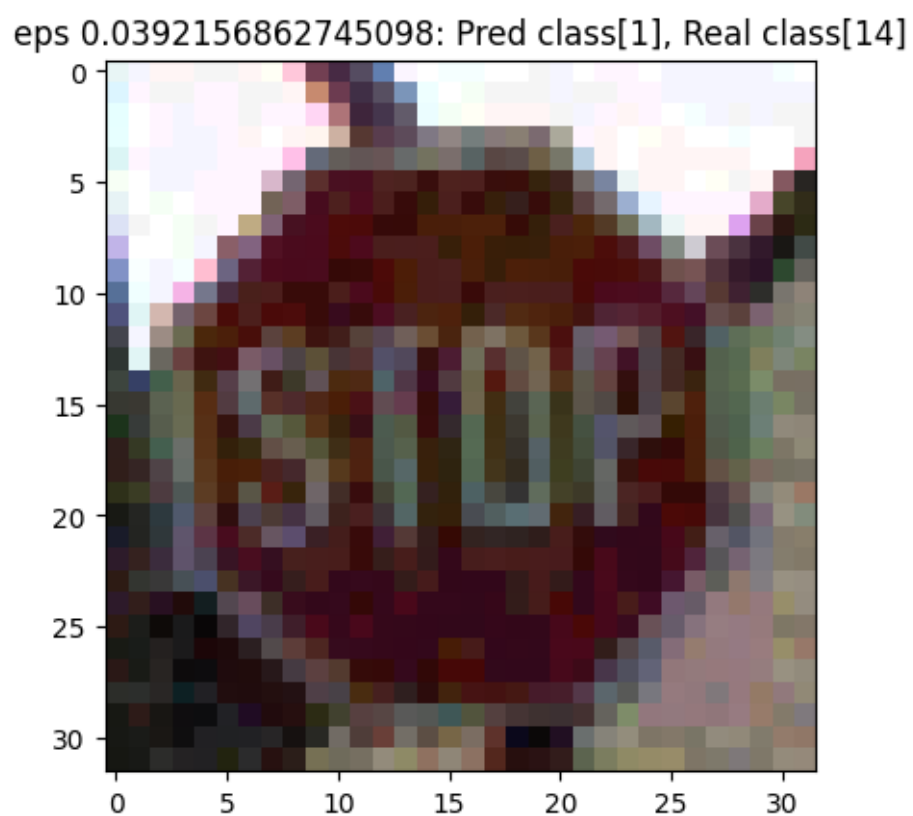
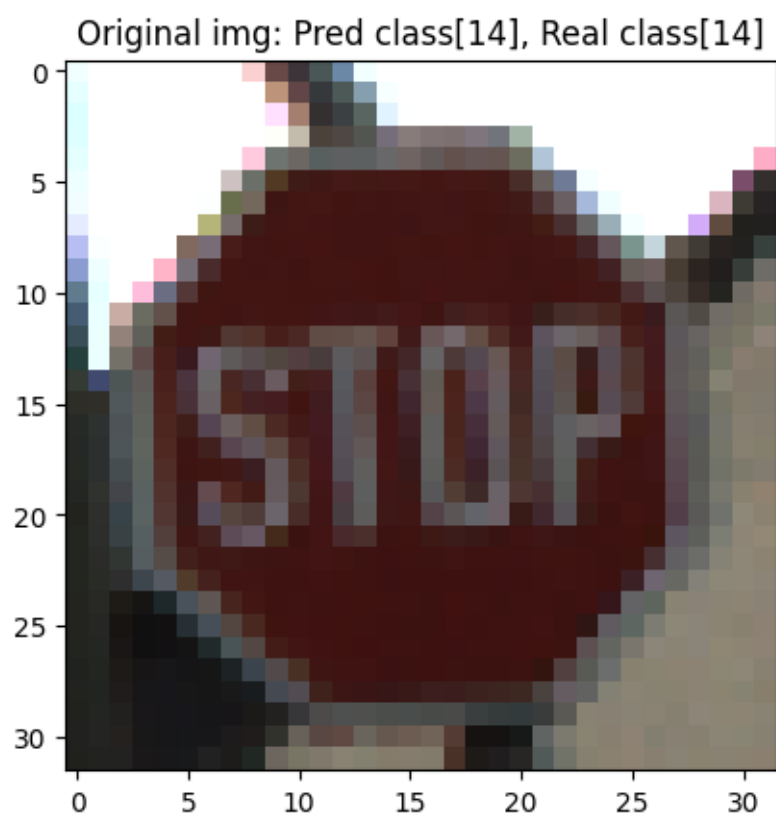
Original img: Pred class[14], Real class[14]

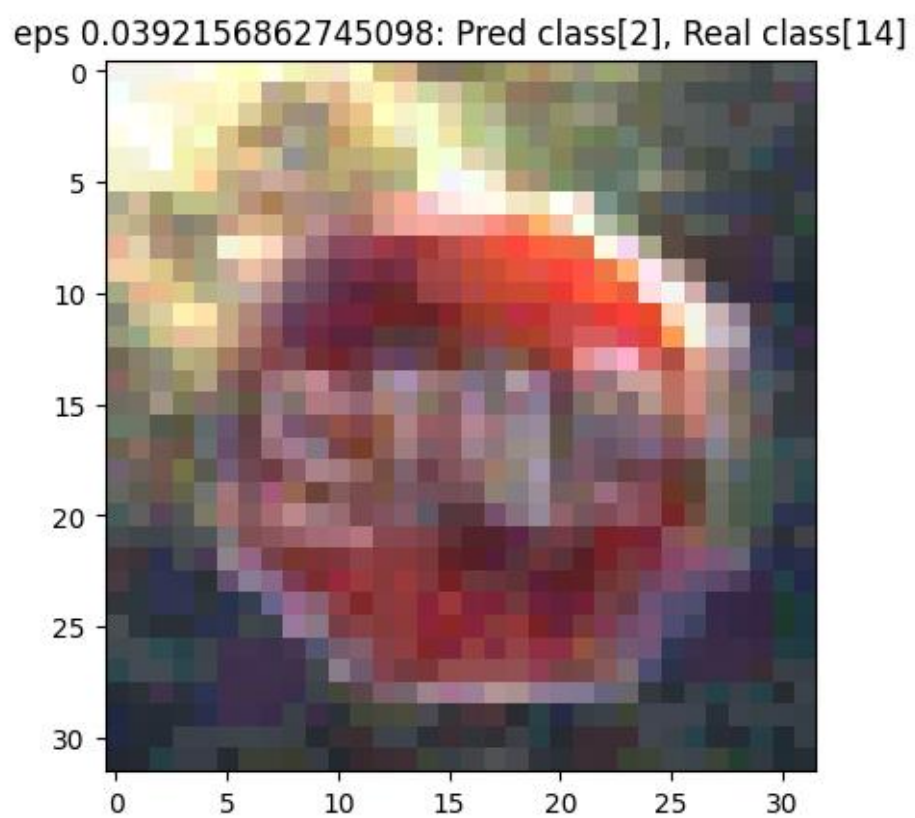
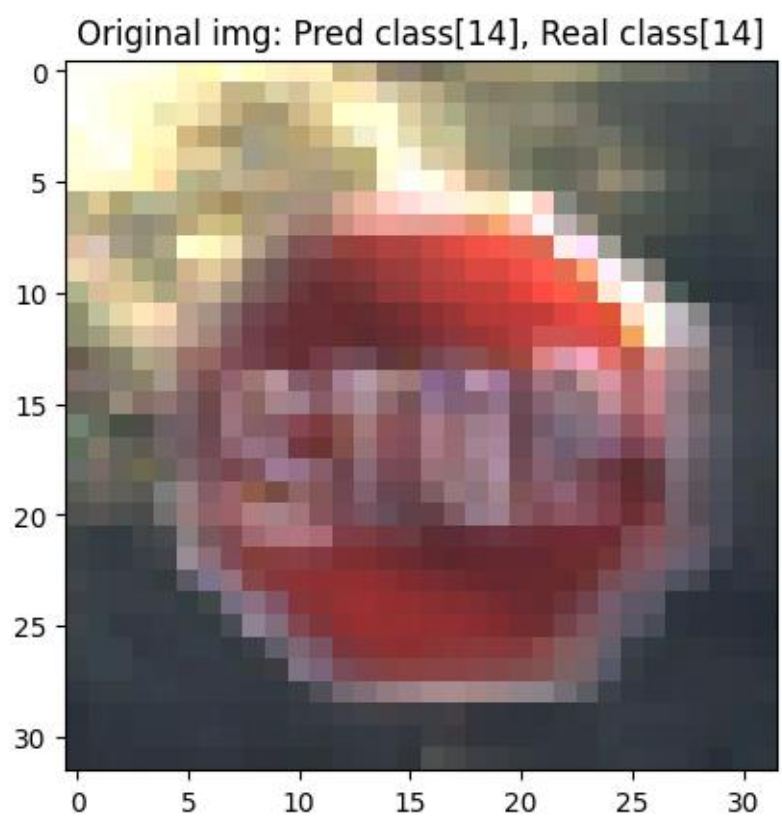


eps 0.0392156862745098: Pred class[14], Real class[14]









Реализация атаки PGD

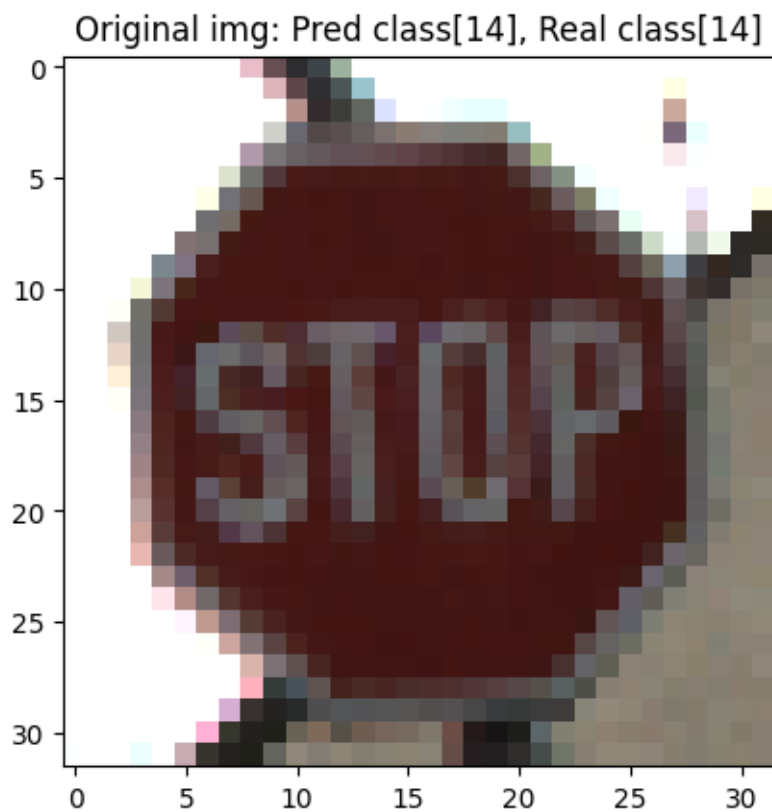
```

model=load_model('ResNet50.h5')
classifier = KerasClassifier(model=model, clip_values=(np.min(x_test), np.max(x_test)))
attack_pgd = ProjectedGradientDescent(estimator=classifier, eps=0.3, max_iter=4, verbose=False, targeted=True)
eps_range = [1/255, 2/255, 3/255, 4/255, 5/255, 8/255, 10/255, 20/255, 50/255, 80/255]

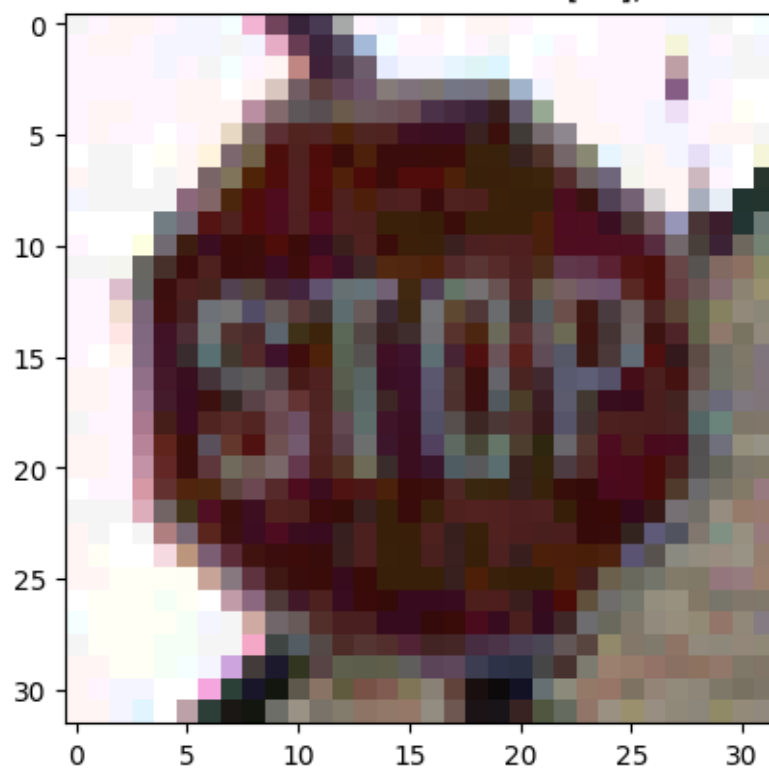
for eps in eps_range:
    attack_pgd.set_params(**{'eps': eps})
    print(f"Eps: {eps}")
    x_test_adv = attack_pgd.generate(x_test, t_classes)
    loss, accuracy = model.evaluate(x_test_adv, y_test)
    print(f"Adv Loss: {loss}")
    print(f"Adv Accuracy: {accuracy}")
    loss, accuracy = model.evaluate(x_test, y_test)
    print(f"True Loss: {loss}")
    print(f"True Accuracy: {accuracy}")

```

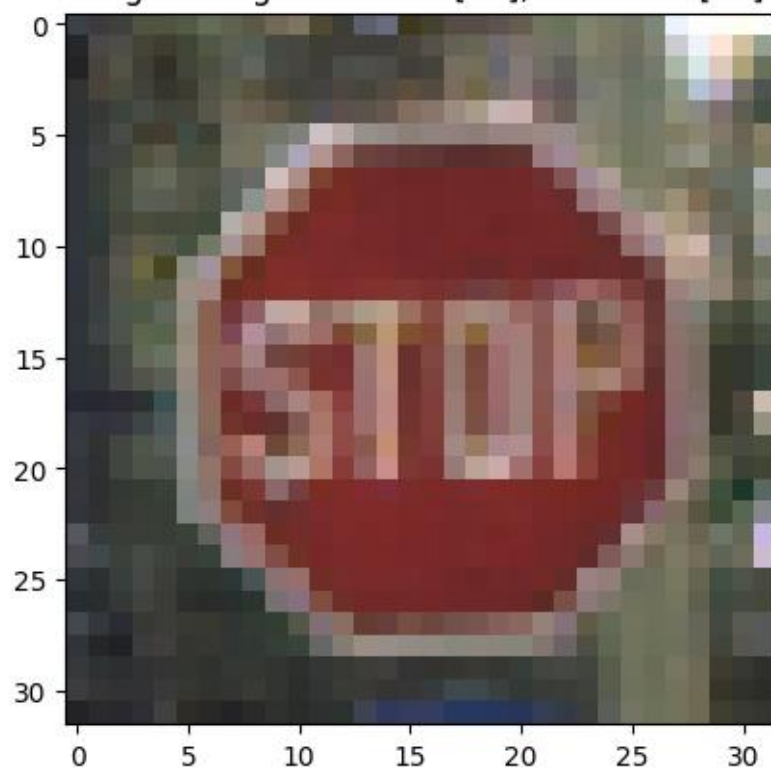
Визуализация последствий атаки



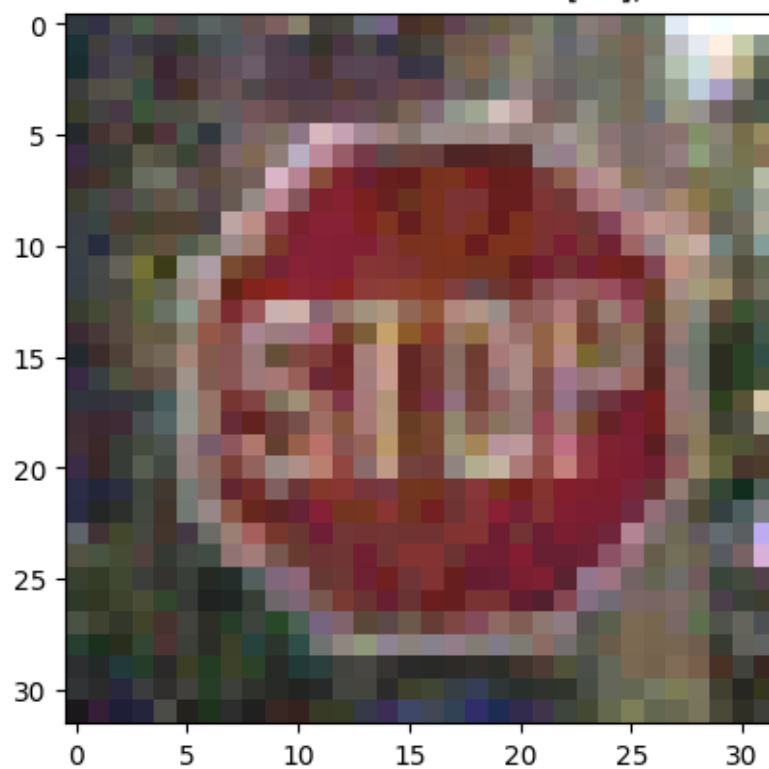
eps 0.0392156862745098: Pred class[14], Real class[14]



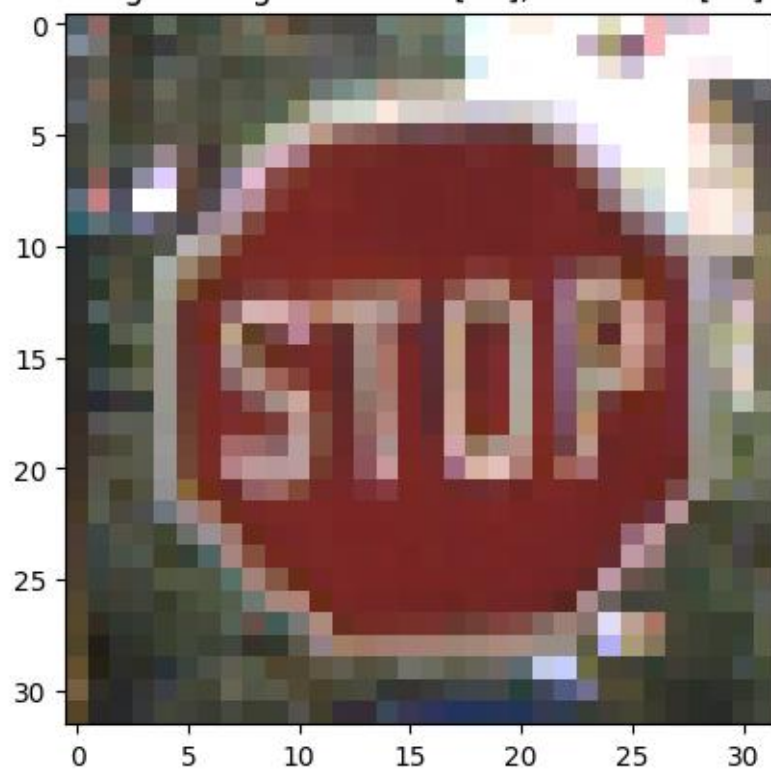
Original img: Pred class[14], Real class[14]



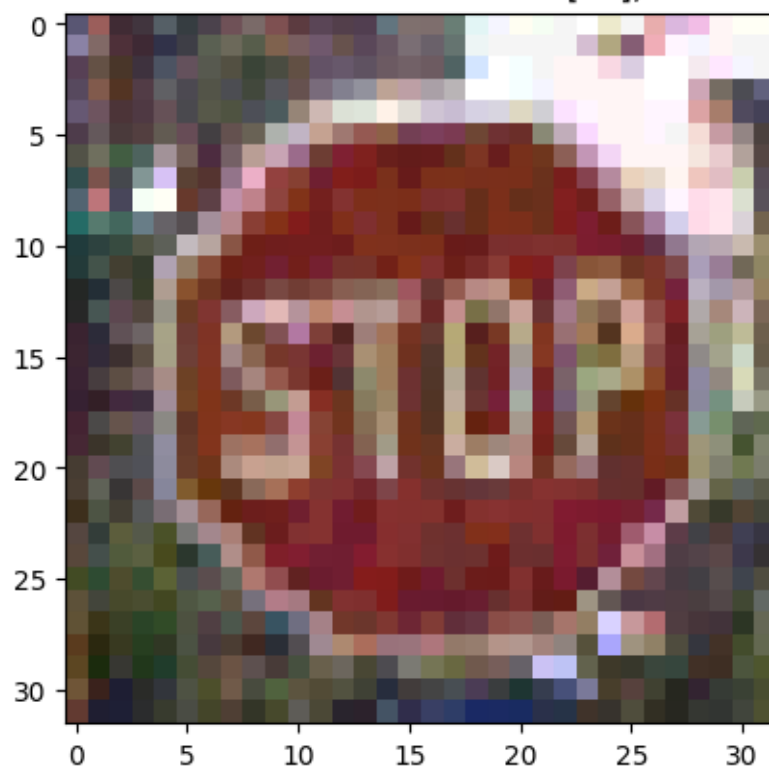
eps 0.0392156862745098: Pred class[14], Real class[14]



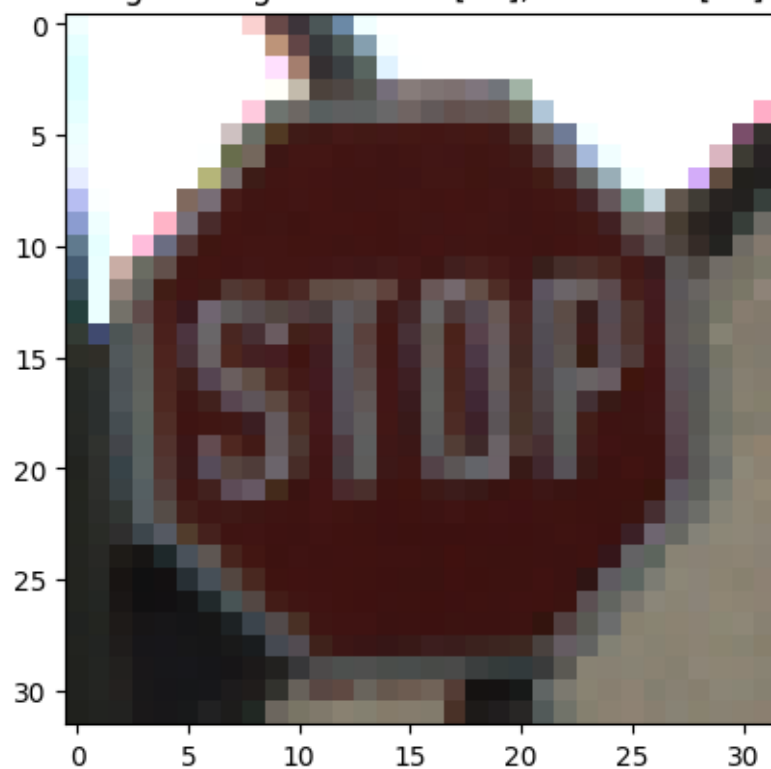
Original img: Pred class[14], Real class[14]



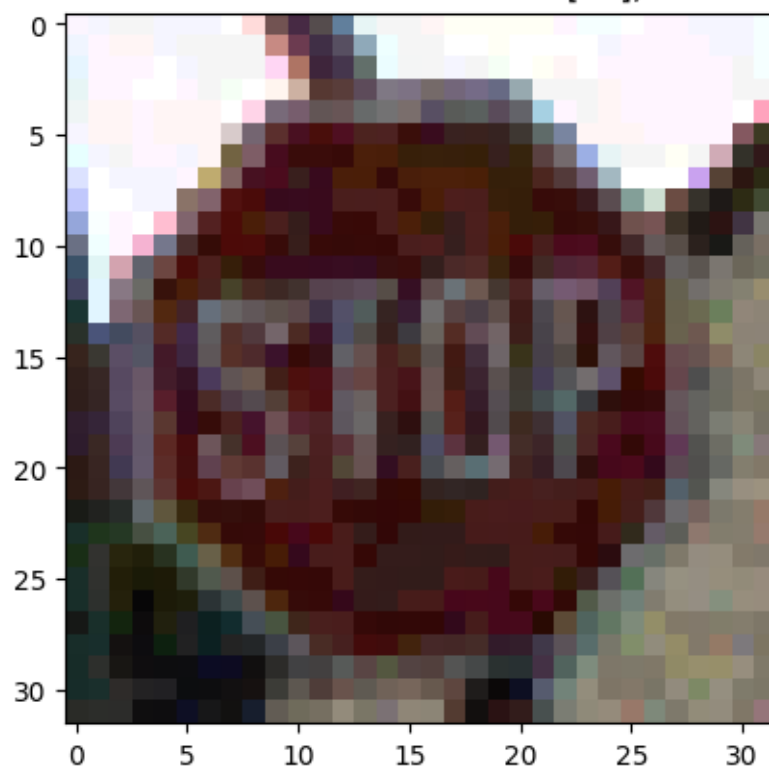
eps 0.0392156862745098: Pred class[14], Real class[14]



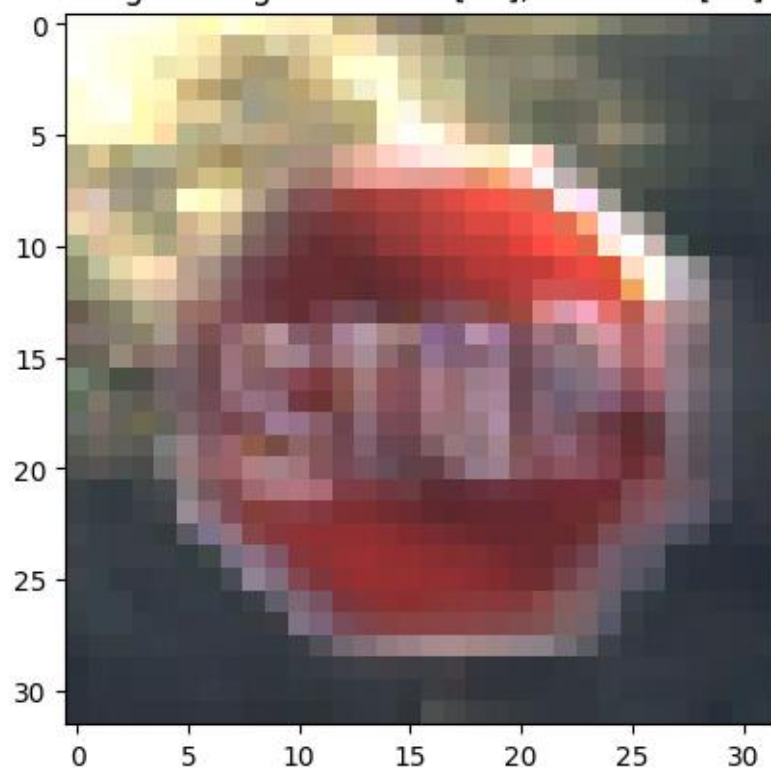
Original img: Pred class[14], Real class[14]



eps 0.0392156862745098: Pred class[14], Real class[14]



Original img: Pred class[14], Real class[14]



eps 0.0392156862745098: Pred class[1], Real class[14]

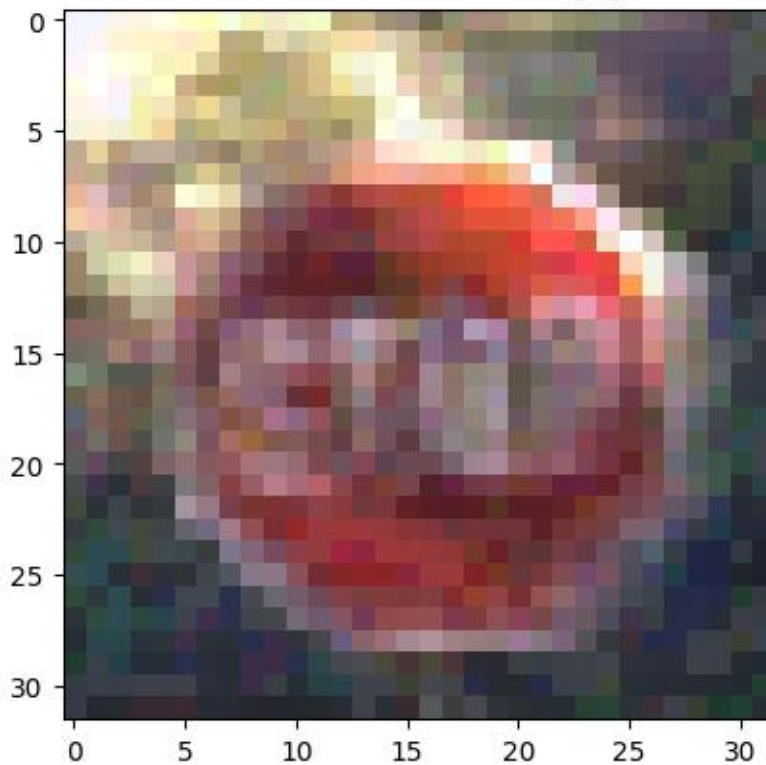


Таблица со значениями точности при двух атаках

Искажение	FGSM	PGD
$\epsilon=1/255$	85%	97%
$\epsilon=2/255$	76%	93%
$\epsilon=3/255$	62%	87%
$\epsilon=4/255$	52%	86%
$\epsilon=5/255$	45%	79%
$\epsilon=8/255$	19%	76%
$\epsilon=10/255$	13%	75%
$\epsilon=20/255$	4%	38%
$\epsilon=50/255$	1%	5%
$\epsilon=80/255$	1%	3%