МИНОБРНАУКИ РОССИИ

Федеральное государственное бюджетное образовательное учреждение
высшего образования
«МИРЭА – Российский технологический университет»
РТУ МИРЭА

ИКБ направление «Кибербразведка и противодействие угрозам с применением технологий искусственного интеллекта» 10.04.01

Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Лабораторная работа №1

по дисциплине: «Анализ защищенности систем искусственного интеллекта»

Группа:

ББМО-01-22

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Проверил:

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Содержание

Цель работы:

Целью данной работы является отразить отличия для fgsm_eps=(0.001, 0.02, 0.5, 0.9, 10) и выявить закономерность/обнаружить отсутсвие влияние параметра eps для сетей FC LeNet на датасете MNIST, NiN LeNEt на датасете CIFAR.

Ход работы:

1. Скопировать проект по ссылке в локальную среду выполнения Jupyter (Google Colab): https://github.com/ewatson2/EEL6812_DeepFool_Project

```
[1]  !git clone https://github.com/ewatson2/EEL6812_DeepFool_Project
```

```
Cloning into 'EEL6812_DeepFool_Project'...
remote: Enumerating objects: 96, done.
remote: Counting objects: 100% (3/3), done.
remote: Compressing objects: 100% (2/2), done.
remote: Total 96 (delta 2), reused 1 (delta 1), pack-reused 93
Receiving objects: 100% (96/96), 33.99 MiB | 25.90 MiB/s, done.
Resolving deltas: 100% (27/27), done.
```

2. Сменим директорию исполнения на вновь созданную папку "EEL6812_DeepFool_Project" проекта:

```
%cd /content/EEL6812_DeepFool_Project
```

```
/content/EEL6812_DeepFool_Project
```

3. Импортируем библиотеки:

```
import numpy as np
import json, torch, os
from torch.utils.data import DataLoader, random_split
from torchvision import datasets, models
from torchvision.transforms import transforms
```

4. Импортируем вспомогательные библиотеки из локальных файлов проекта:

```
from models.project_models import FC_500_150, LeNet_CIFAR, LeNet_MNIST, Net
from utils.project_utils import get_clip_bounds, evaluate_attack, display_attack
```

5. Установим случайное значение в виде переменной rand_seed=(порядковый номер в списке гугл-таблицы 11) и установим его для np.random.seed и torch.manual_seed:

```
rand_seed = 11
np.random.seed(rand_seed)
torch.manual_seed(rand_seed)
```

```
<torch._C.Generator at 0x787bb422e3d0>
```

6. Используем в качестсве устройства видеокарту (Среды выполнения -> Сменить среду выполнения --> T4 GPU)

```
use_cuda = torch.cuda.is_available()
device = torch.device('cuda' if use_cuda else 'cpu')
```

7. Загрузим датасет MNIST с параметрами:

```
mnist_mean = 0.5
mnist_std = 0.5
mnist_dim = 28

mnist_min, mnist_max = get_clip_bounds(mnist_mean, mnist_std, mnist_dim)
mnist_min = mnist_min.to(device)
mnist_max = mnist_max.to(device)

mnist_tf = transforms.Compose([ transforms.ToTensor( ), transforms.Normalize( mean=mnist_mean, std=mnist_std)])
mnist_tf_train = transforms.Compose([transforms.RandomHorizontalFlip(), transforms.ToTensor(), transforms.Normalize(mean=mnist_mean, std=mnist_std)])
mnist_tf_inv = transforms.Compose([transforms.Normalize(mean=0.0, std=np.divide(1.0, mnist_std)), transforms.Normalize(mean=np.multiply(-1.0, mnist_std), std=1.0)])

mnist_temp = datasets.MNIST(root='datasets/mnist', train=True, download=True, transform=mnist_tf_train)
mnist_train, mnist_val = random_split(mnist_temp, [50000, 10000])
mnist_test = datasets.MNIST(root='datasets/mnist', train=False, download=True, transform=mnist_tf)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to datasets/mnist/MNIST/raw/train-images-idx3-ubyte.gz
100%|██████████| 9912422/9912422 [00:00<00:00, 132257617.99it/s]Extracting datasets/mnist/MNIST/raw/train-images-idx3-ubyte.gz to datasets/mnist/MNIST/raw


Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to datasets/mnist/MNIST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 28881/28881 [00:00<00:00, 42563490.45it/s]
Extracting datasets/mnist/MNIST/raw/train-labels-idx1-ubyte.gz to datasets/mnist/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to datasets/mnist/MNIST/raw/t10k-images-idx3-ubyte.gz
100%|██████████| 1648877/1648877 [00:00<00:00, 44599088.12it/s]Extracting datasets/mnist/MNIST/raw/t10k-images-idx3-ubyte.gz to datasets/mnist/MNIST/raw


Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to datasets/mnist/MNIST/raw/t10k-labels-idx1-ubyte.gz
100%|██████████| 4542/4542 [00:00<00:00, 18126097.78it/s]
Extracting datasets/mnist/MNIST/raw/t10k-labels-idx1-ubyte.gz to datasets/mnist/MNIST/raw
```

8. Загрузим датасет CIFAR-10 с параметрами:

```
cifar_mean = [0.491, 0.482, 0.447]
cifar_std = [0.202, 0.199, 0.201]
cifar_dim = 32

cifar_min, cifar_max = get_clip_bounds(cifar_mean, cifar_std, cifar_dim)
cifar_min = cifar_min.to(device)
cifar_max = cifar_max.to(device)

cifar_tf = transforms.Compose([transforms.ToTensor(), transforms.Normalize(mean=cifar_mean, std=cifar_std)])
cifar_tf_train = transforms.Compose([transforms.RandomCrop(size=cifar_dim, padding=4), transforms.RandomHorizontalFlip(), transforms.ToTensor(), transforms.Normalize(mean=
cifar_tf_inv = transforms.Compose([transforms.Normalize( mean=[0.0, 0.0, 0.0], std=np.divide(1.0,cifar_std)), transforms.Normalize(mean=np.multiply(-1.0, cifar_mean), std=

cifar_temp = datasets.CIFAR10(root='datasets/cifar-10', train=True, download=True, transform=cifar_tf_train)
cifar_train, cifar_val = random_split(cifar_temp, [40000, 10000])
cifar_test = datasets.CIFAR10(root='datasets/cifar-10', train=False, download=True, transform=cifar_tf)

cifar_classes = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to datasets/cifar-10/cifar-10-python.tar.gz
100%|██████████| 170498071/170498071 [00:04<00:00, 34575494.82it/s]
Extracting datasets/cifar-10/cifar-10-python.tar.gz to datasets/cifar-10
Files already downloaded and verified
```

9. Выполним настройку гиперпараметров и загрузку DataLoader:

```
batch_size = 64
workers = 4

mnist_loader_train = DataLoader(mnist_train, batch_size=batch_size, shuffle=True, num_workers=workers)
mnist_loader_val = DataLoader(mnist_val, batch_size=batch_size, shuffle=False, num_workers=workers)
mnist_loader_test = DataLoader(mnist_test, batch_size=batch_size, shuffle=False, num_workers=workers)

cifar_loader_train = DataLoader(cifar_train, batch_size=batch_size, shuffle=True, num_workers=workers)
cifar_loader_val = DataLoader(cifar_val, batch_size=batch_size, shuffle=False, num_workers=workers)
cifar_loader_test = DataLoader(cifar_test, batch_size=batch_size, shuffle=False, num_workers=workers)
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number o
  warnings.warn(_create_warning_msg(
```

10. Зададим параметры deep_args:

```
deep_batch_size = 10
deep_num_classes = 10
deep_overshoot = 0.02
deep_max_iters = 50

deep_args = [deep_batch_size, deep_num_classes, deep_overshoot, deep_max_iters]
```

11. Загрузим и оценим стойкость модели Network-In-Network Model к FGSM и DeepFool атакам на основе датасета CIFAR-10:

```
fgsm_eps = 0.2
model = Net().to(device)
model.load_state_dict(torch.load('weights/clean/cifar_nin.pth', map_location=torch.device('cpu')))

evaluate_attack('cifar_nin_fgsm.csv', 'results', device, model, cifar_loader_test, cifar_min, cifar_max, fgsm_eps, is_fgsm=True)
print('')
evaluate_attack('cifar_nin_deepfool.csv', 'results', device, model, cifar_loader_test, cifar_min, cifar_max, deep_args, is_fgsm=False)

if device.type == 'cuda': torch.cuda.empty_cache()
```

```
FGSM Test Error : 81.29%
FGSM Robustness : 1.77e-01
FGSM Time (All Images) : 0.67 s
FGSM Time (Per Image) : 67.07 us

DeepFool Test Error : 93.76%
DeepFool Robustness : 2.12e-02
DeepFool Time (All Images) : 185.12 s
DeepFool Time (Per Image) : 18.51 ms
```

12. Загрузим и оценим стойкость модели LeNet к FGSM и DeepFool атакам на основе датасета CIFAR-10:

```
fgsm_eps = 0.1
model = LeNet_CIFAR().to(device)
model.load_state_dict(torch.load('weights/clean/cifar_lenet.pth', map_location=torch.device('cpu')))

evaluate_attack('cifar_lenet_fgsm.csv', 'results', device, model, cifar_loader_test, cifar_min, cifar_max, fgsm_eps, is_fgsm=True)
print('')
evaluate_attack('cifar_lenet_deepfool.csv', 'results', device, model, cifar_loader_test, cifar_min, cifar_max, deep_args, is_fgsm=False)

if device.type == 'cuda': torch.cuda.empty_cache()
```

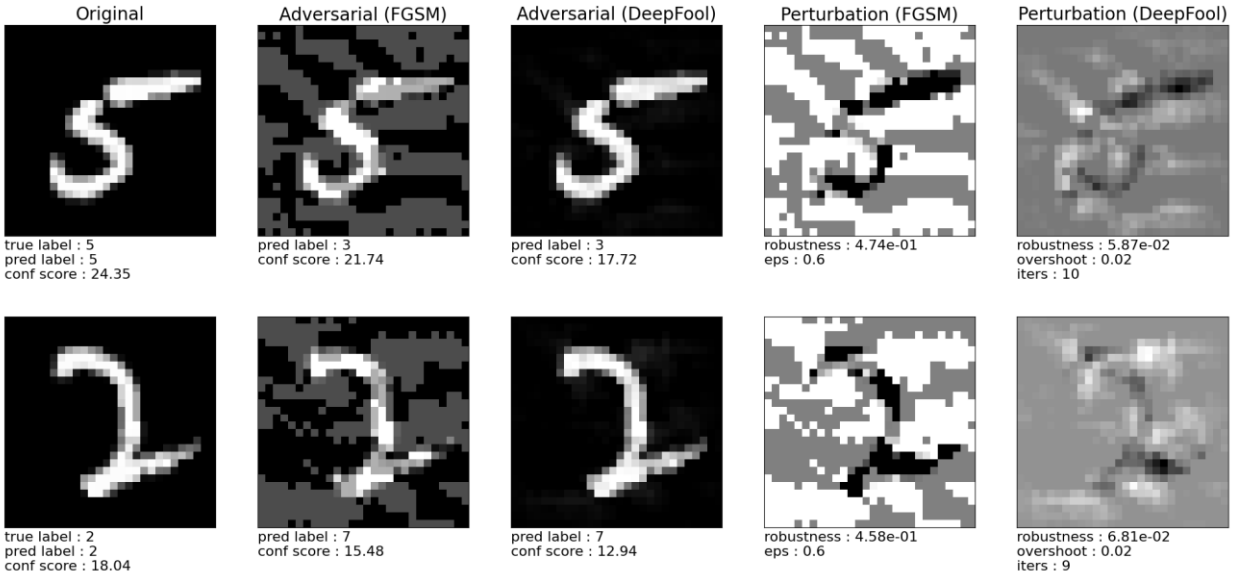
```
FGSM Test Error : 91.71%
FGSM Robustness : 8.90e-02
FGSM Time (All Images) : 0.40 s
FGSM Time (Per Image) : 40.08 us

DeepFool Test Error : 87.81%
DeepFool Robustness : 1.78e-02
DeepFool Time (All Images) : 73.27 s
DeepFool Time (Per Image) : 7.33 ms
```

13. Выполним оценку атакующих примеров для сетей:

13.1. LeNet на датасет MNIST:

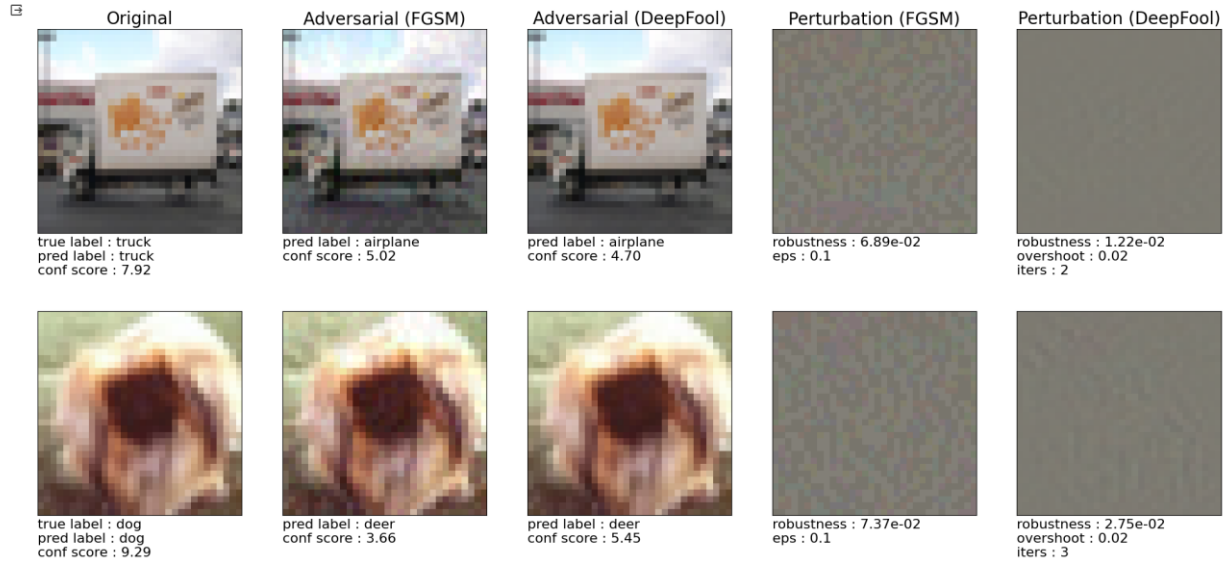
```
fgsm_eps = 0.6
model = LeNet_MNIST().to(device)
model.load_state_dict(torch.load('weights/clean/mnist_lenet.pth', map_location=device))

display_attack(device, model, mnist_test, mnist_tf_inv, mnist_min, mnist_max, fgsm_eps, deep_args, has_labels=False, l2_norm=True, pert_scale=1.0, fig_rows=2, fig_width=2

if device.type == 'cuda': torch.cuda.empty_cache()
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
  warnings.warn(_create_warning_msg(
```



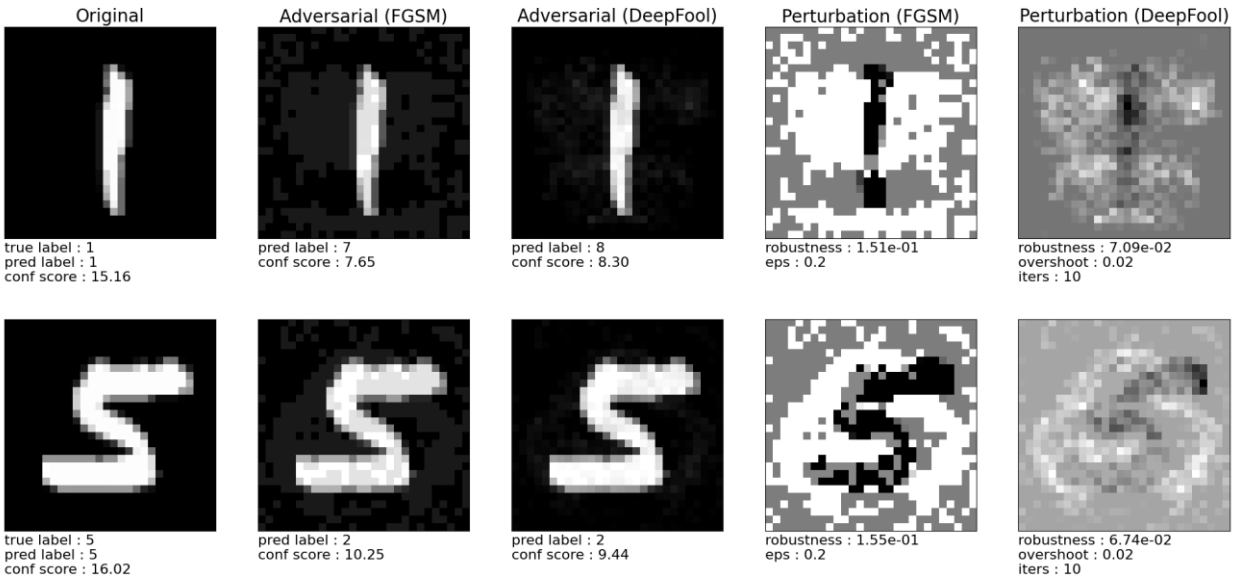
13.2. LeNet на датасете CIFAR-10:

```
fgsm_eps = 0.1
model = LeNet_CIFAR().to(device)
model.load_state_dict(torch.load('weights/clean/cifar_lenet.pth'))

display_attack(device, model, cifar_test, cifar_tf_inv, cifar_min, cifar_max, fgsm_eps, deep_args, has_labels=False, l2_norm=True, pert_scale=1.0, fig_rows=2, fig_width=25, fig_height=11, label_map=cifar_classes)

if device.type == 'cuda': torch.cuda.empty_cache()
```

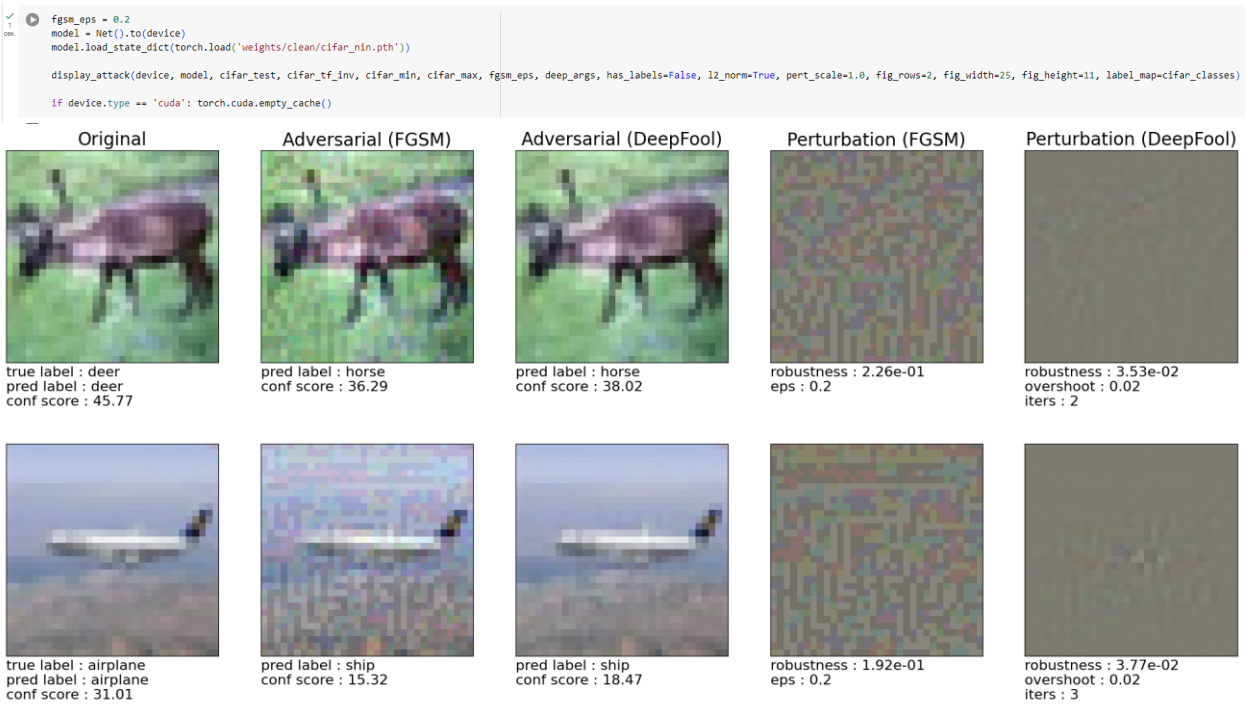


13.3. FCNet на датасете MNIST:

```
fgsm_eps = 0.2
model = FC_500_150().to(device)
model.load_state_dict(torch.load('weights/clean/mnist_fc.pth'))

display_attack(device, model, mnist_test, mnist_tf_inv, mnist_min, mnist_max, fgsm_eps, deep_args, has_labels=False, l2_norm=True, pert_scale=1.0, fig_rows=2, fig_width=25, fig_height=11)

if device.type == 'cuda': torch.cuda.empty_cache()
```



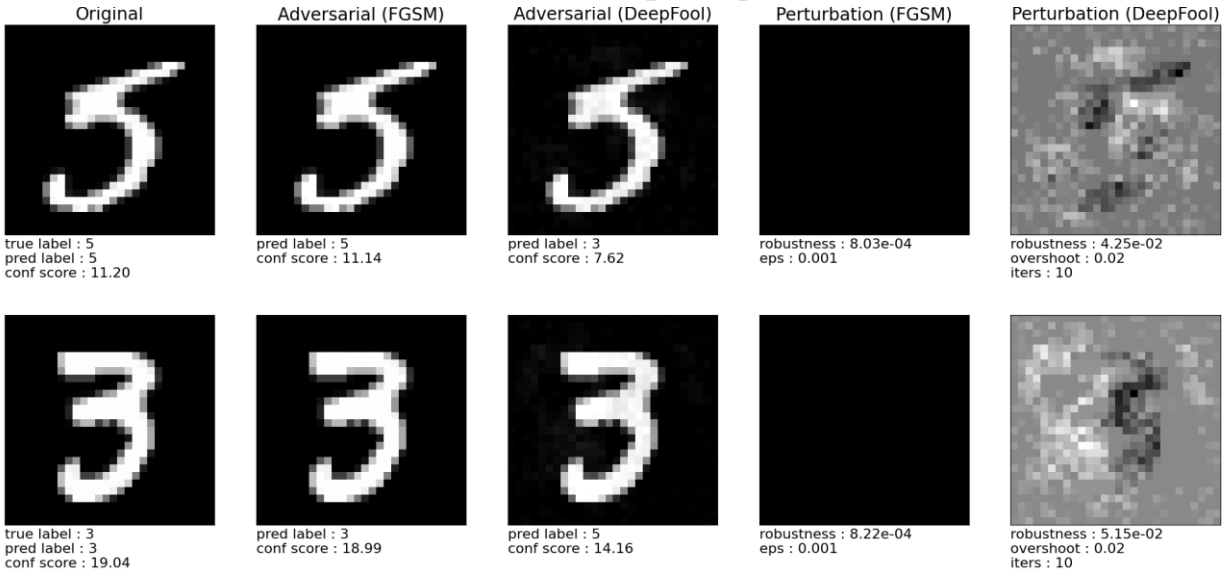
13.4. Network-in-Network на датасете CIFAR:



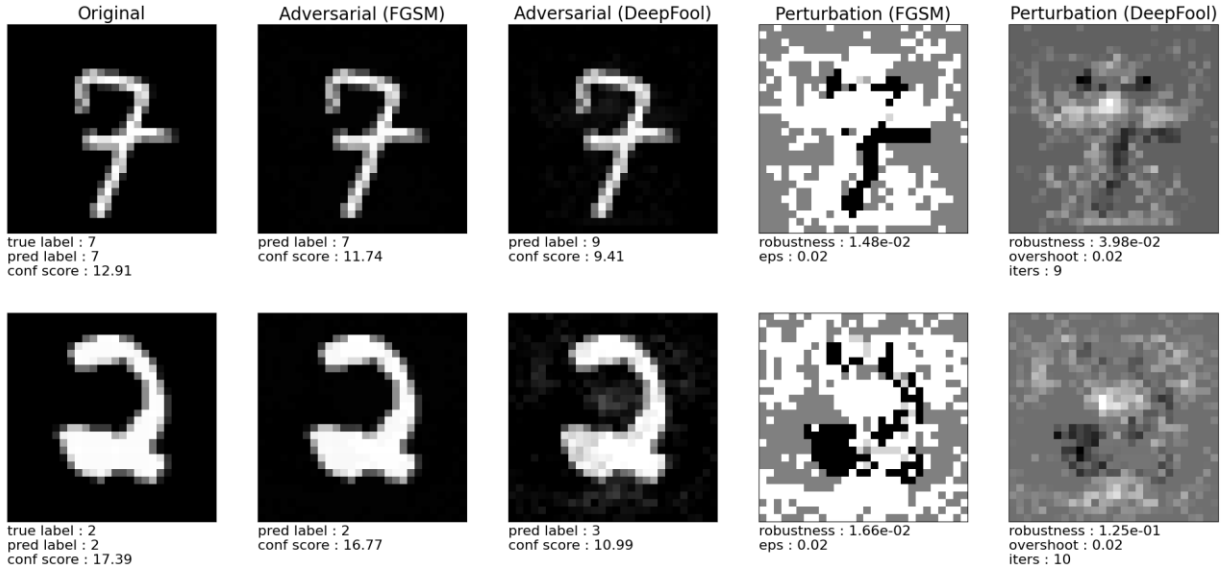
14. Отразим отличия для fgsm_eps=(0.001, 0.02, 0.5, 0.9, 10) и выявим закономерности/обнаружим отсутсвие влияние параметра eps для сетей FC LeNet на датасете MNIST, NiN LeNEt на датасете CIFAR:
Для выполнения данной задачи реализуем просто цикл который будет перебирать уже известный нам массив значений:

```
fgsm_epsf = [0.001, 0.02, 0.5, 0.9, 10]

for fgsm_eps in fgsm_epsf:

    model = FC_500_150().to(device)
    model.load_state_dict(torch.load('weights/clean/mnist_fc.pth'))

    display_attack(device, model, mnist_test, mnist_tf_inv, mnist_min, mnist_max, fgsm_eps, deep_args, has_labels=False, l2_norm=True, pert_scale=1.0, fig_rows=2, fig_width=25, fig_height=11)

    if device.type == 'cuda':
      torch.cuda.empty_cache()

for fgsm_eps in fgsm_epsf:

    model = FC_500_150().to(device)
    model.load_state_dict(torch.load('weights/clean/mnist_fc.pth'))

    evaluate_attack(f'mnist_fc_fgsm_eps{fgsm_eps}.csv', 'results', device, model, mnist_loader_test, mnist_min, mnist_max, fgsm_eps, is_fgsm=True)

    if device.type == 'cuda':
      torch.cuda.empty_cache()

for fgsm_eps in fgsm_epsf:

    model = Net().to(device)
    model.load_state_dict(torch.load('weights/clean/cifar_nin.pth'))

    display_attack(device, model, cifar_test, cifar_tf_inv, cifar_min, cifar_max, fgsm_eps, deep_args, has_labels=False, l2_norm=True, pert_scale=1.0, fig_rows=2, fig_width=25, fig_height=11, label_map=cifar_classes)

    if device.type == 'cuda':
      torch.cuda.empty_cache()

for fgsm_eps in fgsm_epsf:

    model = Net().to(device)
    model.load_state_dict(torch.load('weights/clean/cifar_nin.pth'))

    evaluate_attack(f'cifar_nin_fgsm_eps{fgsm_eps}.csv', 'results', device, model, cifar_loader_test, cifar_min, cifar_max, fgsm_eps, is_fgsm=True)

    if device.type == 'cuda':
      torch.cuda.empty_cache()
```

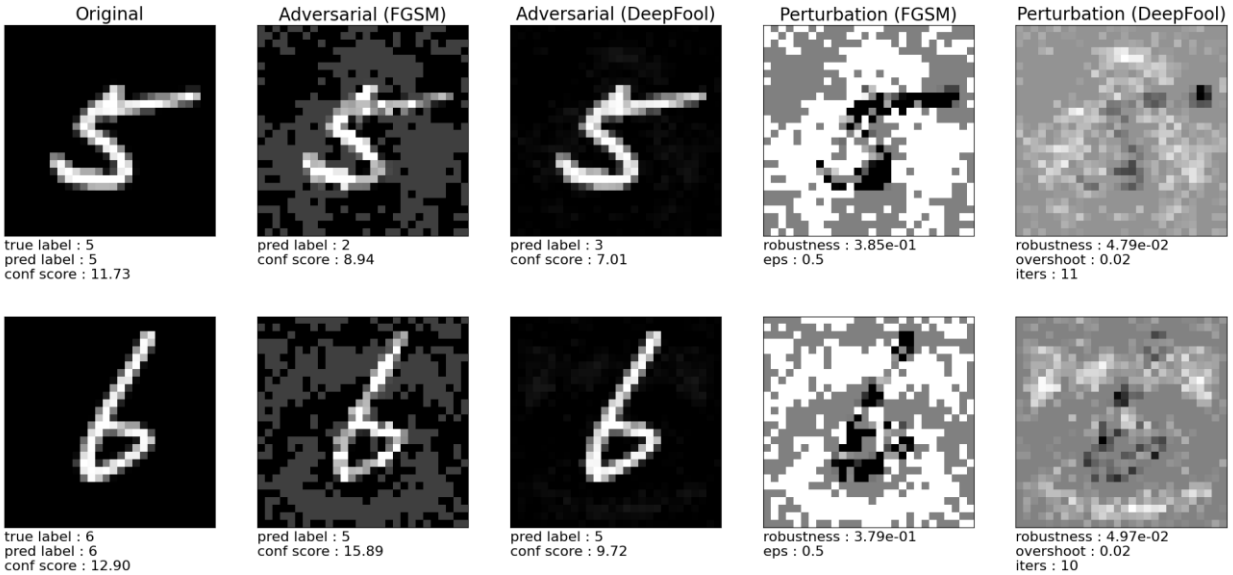
14.1. FC на MNIST при Esp 0.001



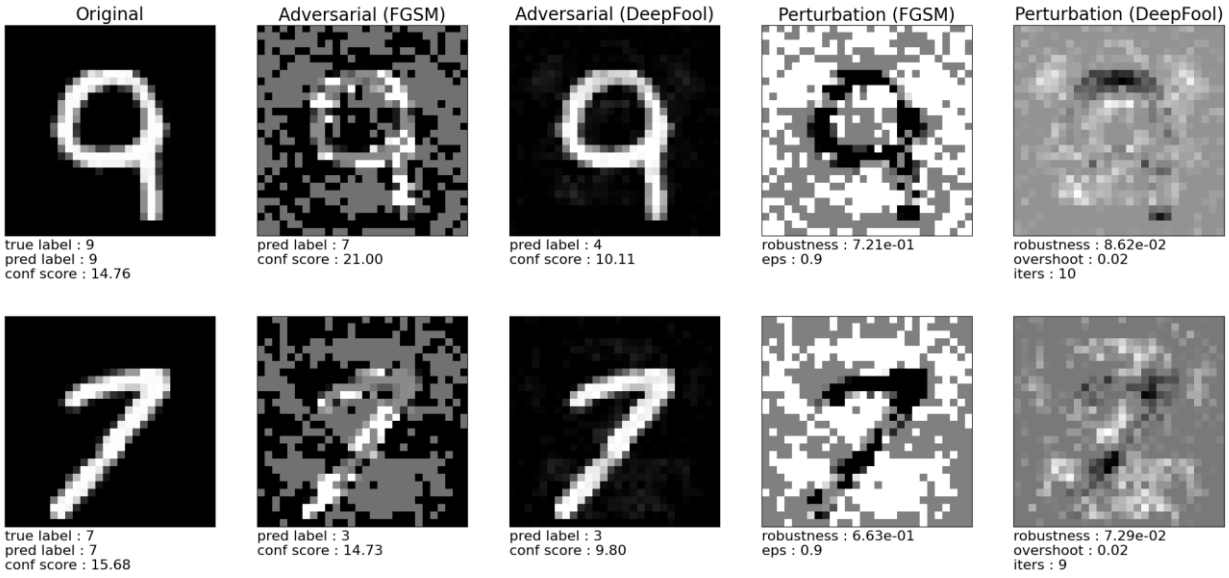
14.1. FC на MNIST при Esp 0.02



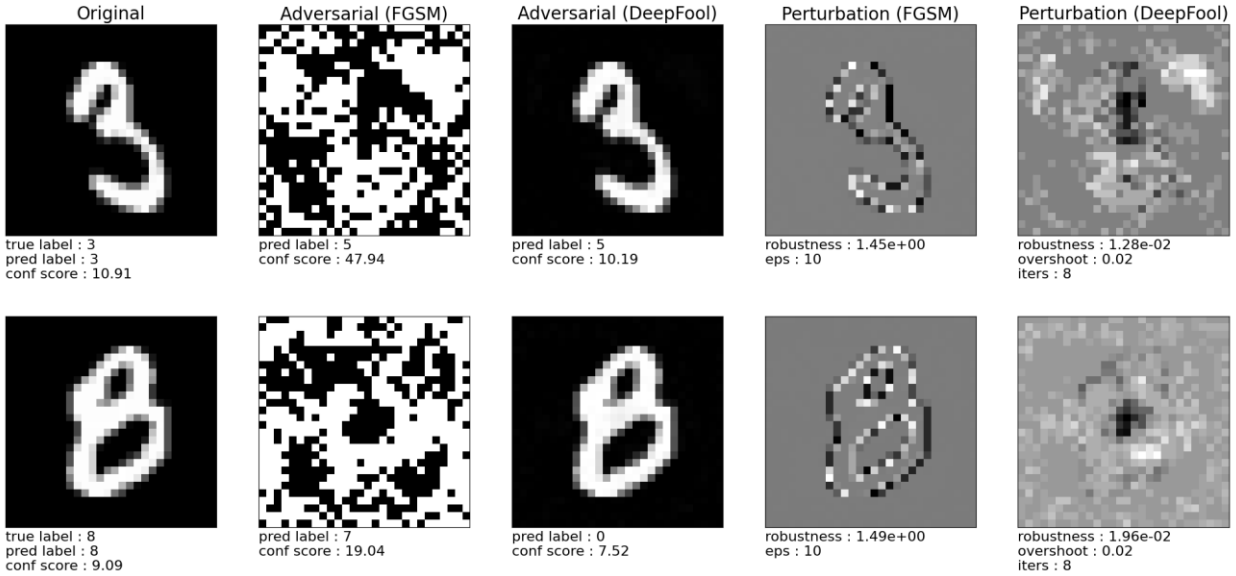
14.2. FC на MNIST при Esp 0.5



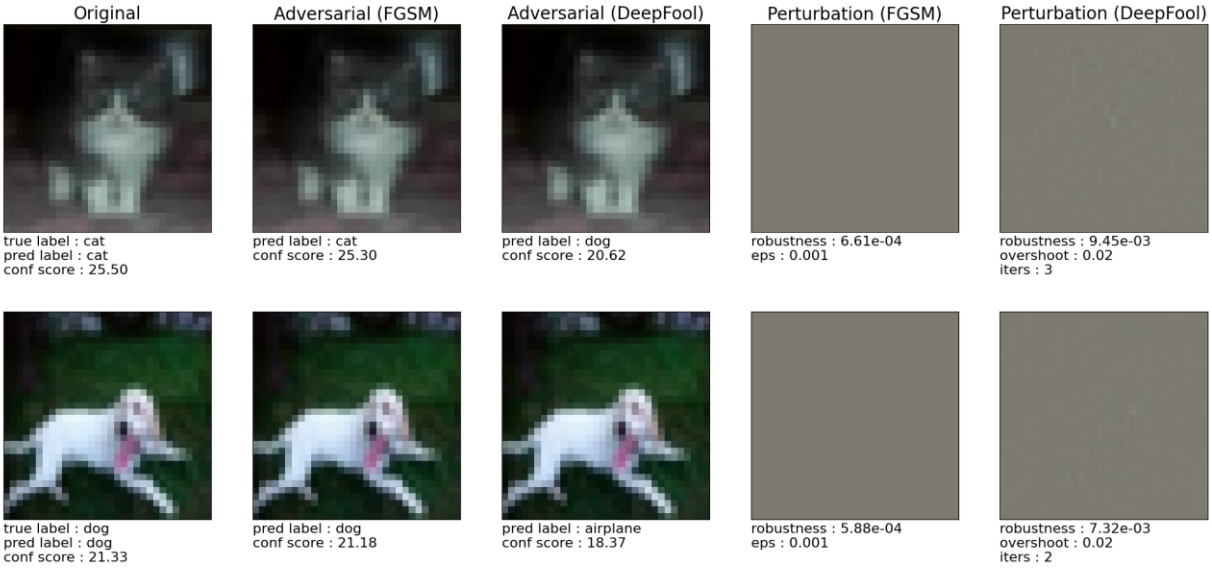
14.3. FC на MNIST при Esp 0.9



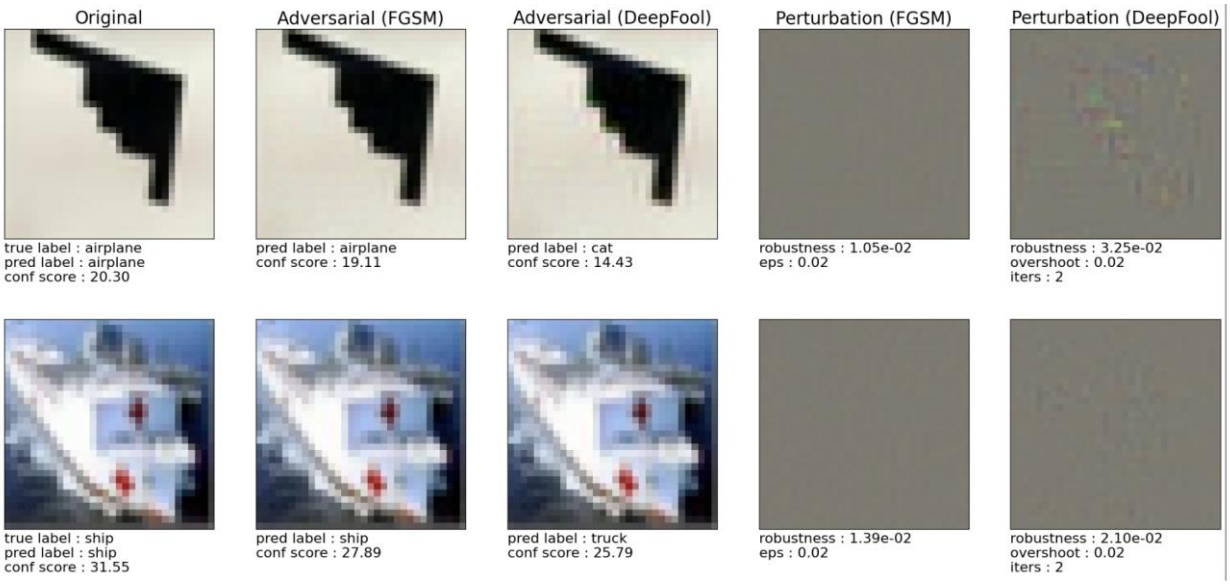
14.4. FC на MNIST при Esp 10



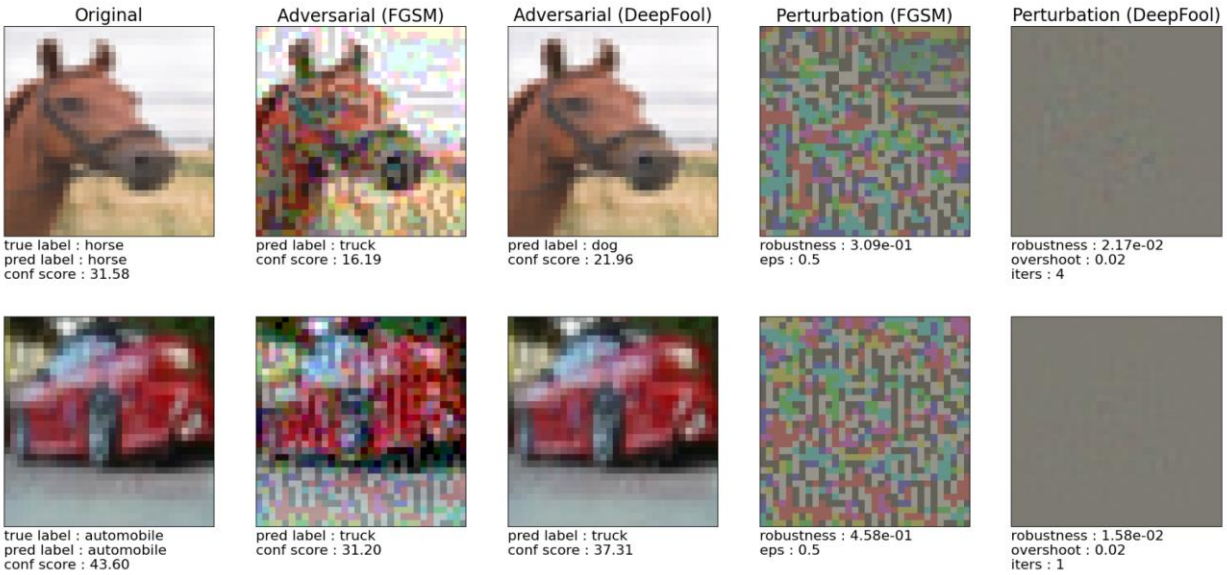
14.2. Esp 0.001



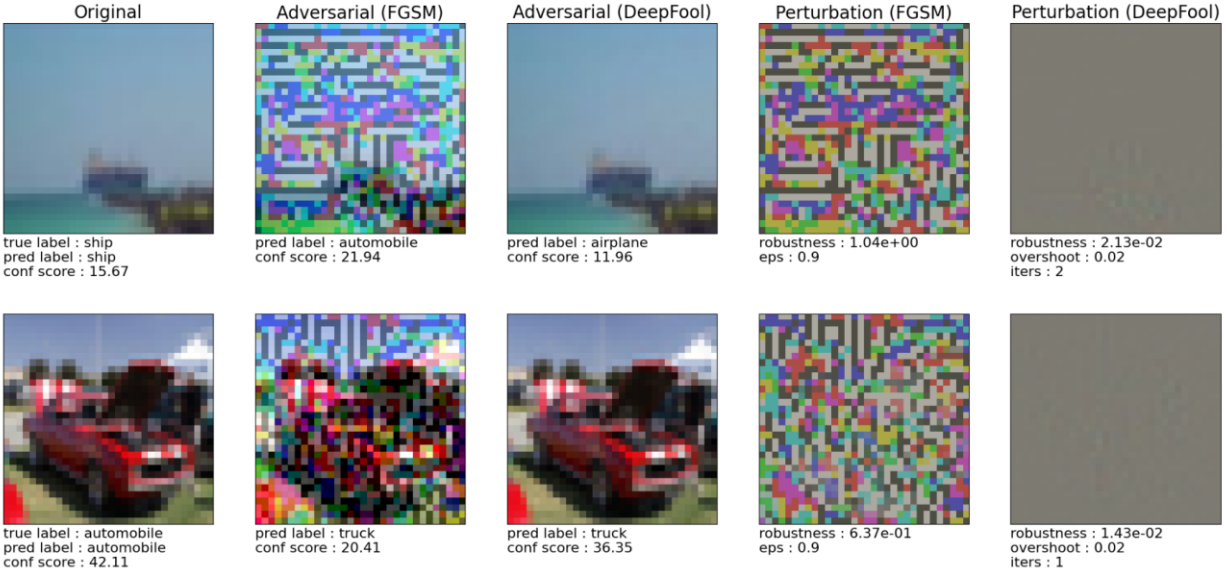
14.5. Esp 0.02



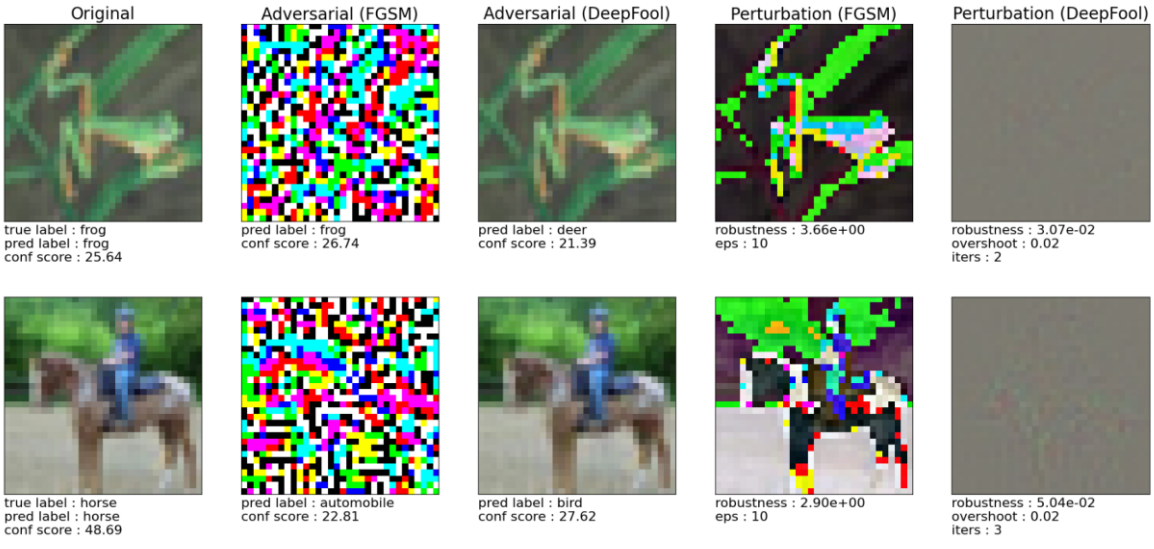
14.6. Esp 0.5



14.7. Esp 0.9



14.8. Esp 10



```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or
  warnings.warn(_create_warning_msg(
FGSM Batches Complete : (157 / 157)
FGSM Test Error : 10.12%
FGSM Robustness : 8.92e-04
FGSM Time (All Images) : 1.33 s
FGSM Time (Per Image) : 132.79 us
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or
  warnings.warn(_create_warning_msg(
FGSM Batches Complete : (157 / 157)
FGSM Test Error : 30.76%
FGSM Robustness : 1.78e-02
FGSM Time (All Images) : 1.25 s
FGSM Time (Per Image) : 125.36 us
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or
  warnings.warn(_create_warning_msg(
FGSM Batches Complete : (157 / 157)
FGSM Test Error : 82.65%
FGSM Robustness : 4.40e-01
FGSM Time (All Images) : 1.36 s
FGSM Time (Per Image) : 135.72 us
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or
  warnings.warn(_create_warning_msg(
FGSM Batches Complete : (157 / 157)
FGSM Test Error : 84.60%
FGSM Robustness : 7.79e-01
FGSM Time (All Images) : 1.39 s
FGSM Time (Per Image) : 139.40 us
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or
  warnings.warn(_create_warning_msg(
FGSM Batches Complete : (157 / 157)
FGSM Test Error : 87.53%
FGSM Robustness : 2.46e+00
FGSM Time (All Images) : 1.11 s
FGSM Time (Per Image) : 110.99 us
```

Заключение

При рассмотрении результатов эксперимента, проведенного в рамках данной лабораторий работы, была выявлена закономерность, обозначающая, что при увеличении значения eps, сети становятся более уязвимыми и допускают больше ошибок классификации, нежели при низком значении eps.