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

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

Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Практическая работа №6

по дисциплине «Анализ защищенности систем искусственного интеллекта»

Выполнила:
Котюкова В.О.

Проверил: Спирин А.А.

Москва 2023

В данной работе мы применим алгоритм для защиты модели. После отработки данного алгоритма мы увидим улучшение в работе модели, которая была подвергнута атаке.

Выполняем импорт необходимых библиотек.

```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import transforms,datasets
```

Зададим нормализующие преобразования и загрузим набор данных (MNIST), разбить данные на подвыборки

```
transform = transforms.Compose([transforms.ToTensor(),
transforms.Normalize((0.0,), (1.0,))])
dataset = datasets.MNIST(root = './data', train=True, transform =
transform, download=True)
train_set, val_set = torch.utils.data.random_split(dataset, [50000,
10000])
test_set = datasets.MNIST(root = './data', train=False, transform =
transform, download=True)
train_loader =
torch.utils.data.DataLoader(train_set,batch_size=1,shuffle=True)
val_loader =
torch.utils.data.DataLoader(val_set,batch_size=1,shuffle=True)
test_loader =
torch.utils.data.DataLoader(test_set,batch_size=1,shuffle=True)
print("Training data:",len(train_loader),"Validation
data:",len(val_loader),"Test data: ",len(test_loader))
```

```
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 ./data/MNIST/raw/train-images-idx3-ubyte.gz

100%|██████████| 9912422/9912422 [00:00<00:00, 61439365.22it/s]

Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to
./data/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 ./data/MNIST/raw/train-labels-idx1-ubyte.gz

100%|██████████| 28881/28881 [00:00<00:00, 27872916.20it/s]
```

```
Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to
./data/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 ./data/MNIST/raw/t10k-images-idx3-ubyte.gz

100%|██████████| 1648877/1648877 [00:00<00:00, 41238924.75it/s]

Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to
./data/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 ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz

100%|██████████| 4542/4542 [00:00<00:00, 9225437.66it/s]

Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to
./data/MNIST/raw

Training data: 50000 Validation data: 10000 Test data:  10000
```

Настроим использование графического ускорителя.

```
use_cuda=True
device = torch.device("cuda" if (use_cuda and
torch.cuda.is_available()) else "cpu")
```

Создадим класс НС на основе фреймворка torch.

```
class Net(nn.Module):
 def __init__(self):
  super(Net, self).__init__()
  self.conv1 = nn.Conv2d(1, 32, 3, 1)
  self.conv2 = nn.Conv2d(32, 64, 3, 1)
  self.dropout1 = nn.Dropout2d(0.25)
  self.dropout2 = nn.Dropout2d(0.5)
  self.fc1 = nn.Linear(9216, 128)
  self.fc2 = nn.Linear(128, 10)
 def forward(self, x):
  x = self.conv1(x)
  x = F.relu(x)
  x = self.conv2(x)
  x = F.relu(x)
  x = F.max_pool2d(x, 2)
  x = self.dropout1(x)
  x = torch.flatten(x, 1)
  x = self.fc1(x)
  x = F.relu(x)
```

```
  x = self.dropout2(x)
  x = self.fc2(x)
  output = F.log_softmax(x, dim=1)
  return output
```

Проверим работоспособность созданного класса НС.

```
model = Net().to(device)
```

Создадим оптимизатор, функцию потерь и трейнер сети.

```
optimizer = optim.Adam(model.parameters(),lr=0.0001, betas=(0.9,
0.999))
criterion = nn.NLLLoss()
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer,
mode='min', factor=0.1, patience=3)
```

Определим функцию обучения сети.

```
def fit(model,device,train_loader,val_loader,epochs):
  data_loader = {'train':train_loader,'val':val_loader}
  print("Fitting the model...")
  train_loss,val_loss=[],[]
  for epoch in range(epochs):
    loss_per_epoch,val_loss_per_epoch=0,0
    for phase in ('train','val'):
      for i,data in enumerate(data_loader[phase]):
        input,label = data[0].to(device),data[1].to(device)
        output = model(input)
        #calculating loss on the output
        loss = criterion(output,label)
        if phase == 'train':
          optimizer.zero_grad()
          #grad calc w.r.t Loss func
          loss.backward()
          #update weights
          optimizer.step()
          loss_per_epoch+=loss.item()
        else:
          val_loss_per_epoch+=loss.item()
    scheduler.step(val_loss_per_epoch/len(val_loader))
    print("Epoch: {} Loss: {} Val_Loss:
{}".format(epoch+1,loss_per_epoch/len(train_loader),val_loss_per_epoch
/len(val_loader)))
    train_loss.append(loss_per_epoch/len(train_loader))
    val_loss.append(val_loss_per_epoch/len(val_loader))
  return train_loss,val_loss
```

Обучим модель.

```
loss,val_loss=fit(model,device,train_loader,val_loader,10)
```

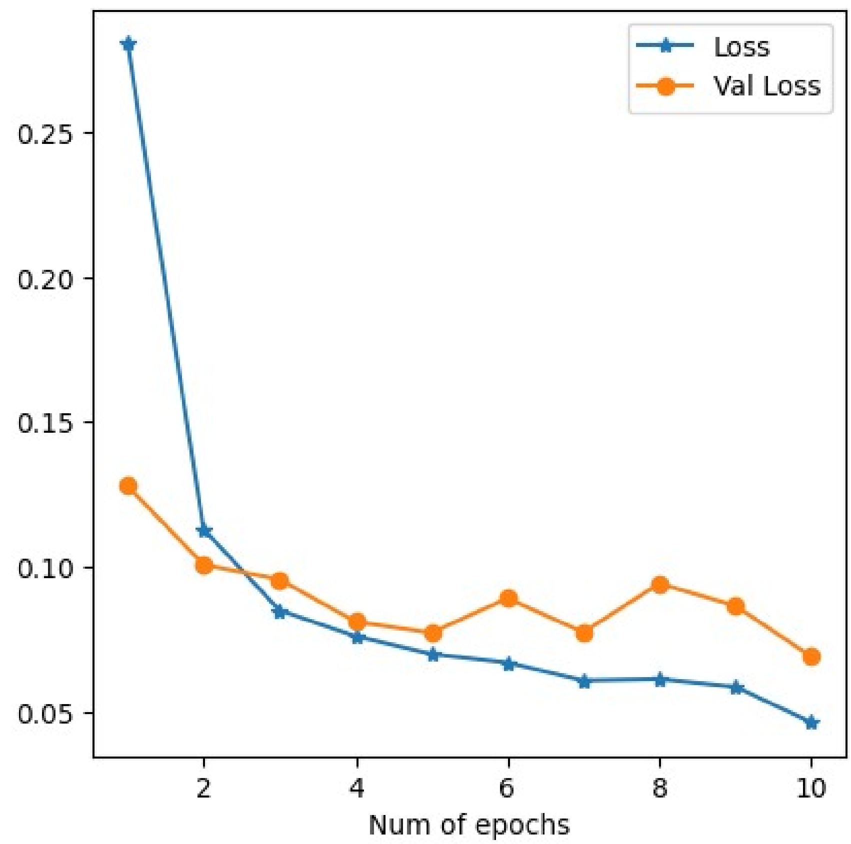
```
Fitting the model...
```

```
/usr/local/lib/python3.10/dist-packages/torch/nn/functional.py:1345:
UserWarning: dropout2d: Received a 2-D input to dropout2d, which is
deprecated and will result in an error in a future release. To retain
the behavior and silence this warning, please use dropout instead.
Note that dropout2d exists to provide channel-wise dropout on inputs
with 2 spatial dimensions, a channel dimension, and an optional batch
dimension (i.e. 3D or 4D inputs).
  warnings.warn(warn_msg)
```

```
Epoch: 1 Loss: 0.2806496279286237 Val_Loss: 0.12787441771870753
Epoch: 2 Loss: 0.11299285361314047 Val_Loss: 0.10075318533363575
Epoch: 3 Loss: 0.0849774527908649 Val_Loss: 0.09567143414565794
Epoch: 4 Loss: 0.07608217686837153 Val_Loss: 0.08107877253171125
Epoch: 5 Loss: 0.0699291657627842 Val_Loss: 0.07728377175676672
Epoch: 6 Loss: 0.06695735126908428 Val_Loss: 0.0891313714174519
Epoch: 7 Loss: 0.06077906305478593 Val_Loss: 0.07742812868754662
Epoch: 8 Loss: 0.06131529724478225 Val_Loss: 0.09425340551983312
Epoch: 9 Loss: 0.05858486058967601 Val_Loss: 0.08656207511608456
Epoch: 10 Loss: 0.04640337399357746 Val_Loss: 0.06904277380505101
```

Построим графики потерь при обучении и валидации в зависимости от эпохи.

```
fig = plt.figure(figsize=(5,5))
plt.plot(np.arange(1,11), loss, "*-", label="Loss")
plt.plot(np.arange(1,11), val_loss,"o-",label="Val Loss")
plt.xlabel("Num of epochs")
plt.legend()
plt.show()
```



Создадим функции атак FGSM, I-FGSM, MI-FGSM.

```
def fgsm_attack(input,epsilon,data_grad):
  pert_out = input + epsilon*data_grad.sign()
  pert_out = torch.clamp(pert_out, 0, 1)
  return pert_out

def ifgsm_attack(input,epsilon,data_grad):
  pert_out = input + epsilon*data_grad.sign()
  pert_out = torch.clamp(pert_out, 0, 1)
  return pert_out

def mifgsm_attack(input,epsilon,data_grad):
  iter=10
  decay_factor=1.0
  pert_out = input
  alpha = epsilon/iter
  g=0
  for i in range(iter-1):
    g = decay_factor*g + data_grad/torch.norm(data_grad,p=1)
    pert_out = pert_out + alpha*torch.sign(g)
    pert_out = torch.clamp(pert_out, 0, 1)
    if torch.norm((pert_out-input),p=float('inf')) > epsilon:
```

```
      break
  return pert_out
```

Создадим функцию проверки.

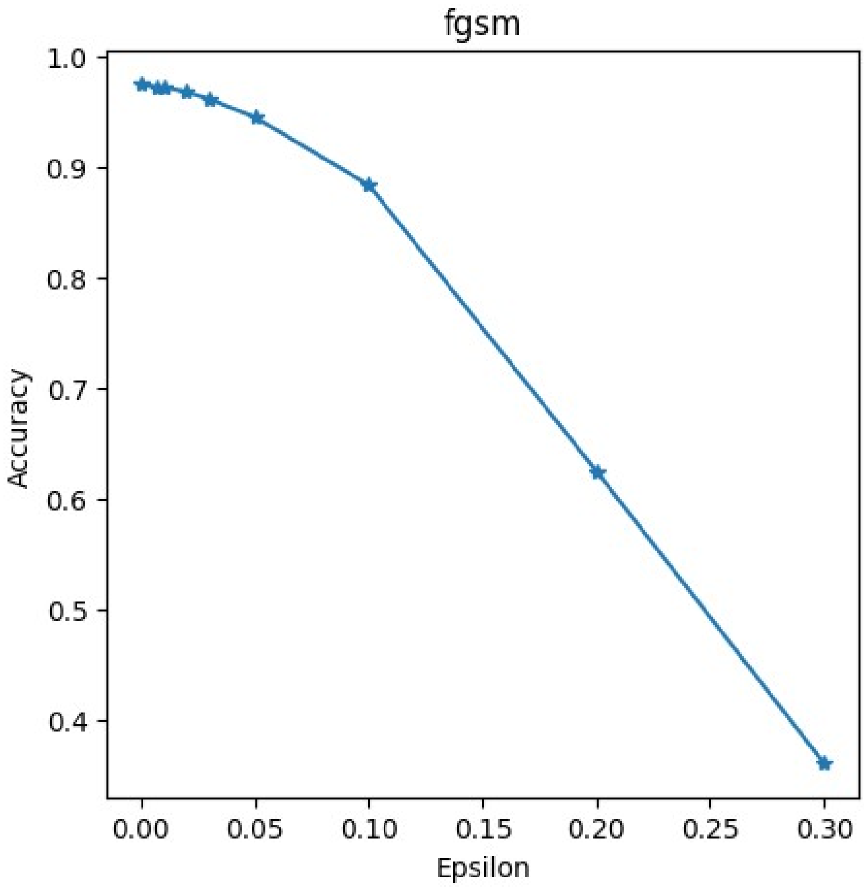
```
def test(model,device,test_loader,epsilon,attack):
  correct = 0
  adv_examples = []
  for data, target in test_loader:
    data, target = data.to(device), target.to(device)
    data.requires_grad = True
    output = model(data)
    init_pred = output.max(1, keepdim=True)[1]
    if init_pred.item() != target.item():
      continue
    loss = F.nll_loss(output, target)
    model.zero_grad()
    loss.backward()
    data_grad = data.grad.data
    if attack == "fgsm":
      perturbed_data = fgsm_attack(data,epsilon,data_grad)
    elif attack == "ifgsm":
      perturbed_data = ifgsm_attack(data,epsilon,data_grad)
    elif attack == "mifgsm":
      perturbed_data = mifgsm_attack(data,epsilon,data_grad)
    output = model(perturbed_data)
    final_pred = output.max(1, keepdim=True)[1]
    if final_pred.item() == target.item():
      correct += 1
    if (epsilon == 0) and (len(adv_examples) < 5):
      adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
      adv_examples.append( (init_pred.item(), final_pred.item(),
adv_ex) )
    else:
      if len(adv_examples) < 5:
        adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
        adv_examples.append( (init_pred.item(), final_pred.item(),
adv_ex) )
  final_acc = correct/float(len(test_loader))
  print("Epsilon: {}\tTest Accuracy = {} / {} = {}".format(epsilon,
correct, len(test_loader), final_acc))
  return final_acc, adv_examples
```

Построим графики успешности атак (Accuracy/эпсилон) и примеры выполненных атак в зависимости от степени возмущения epsilon.

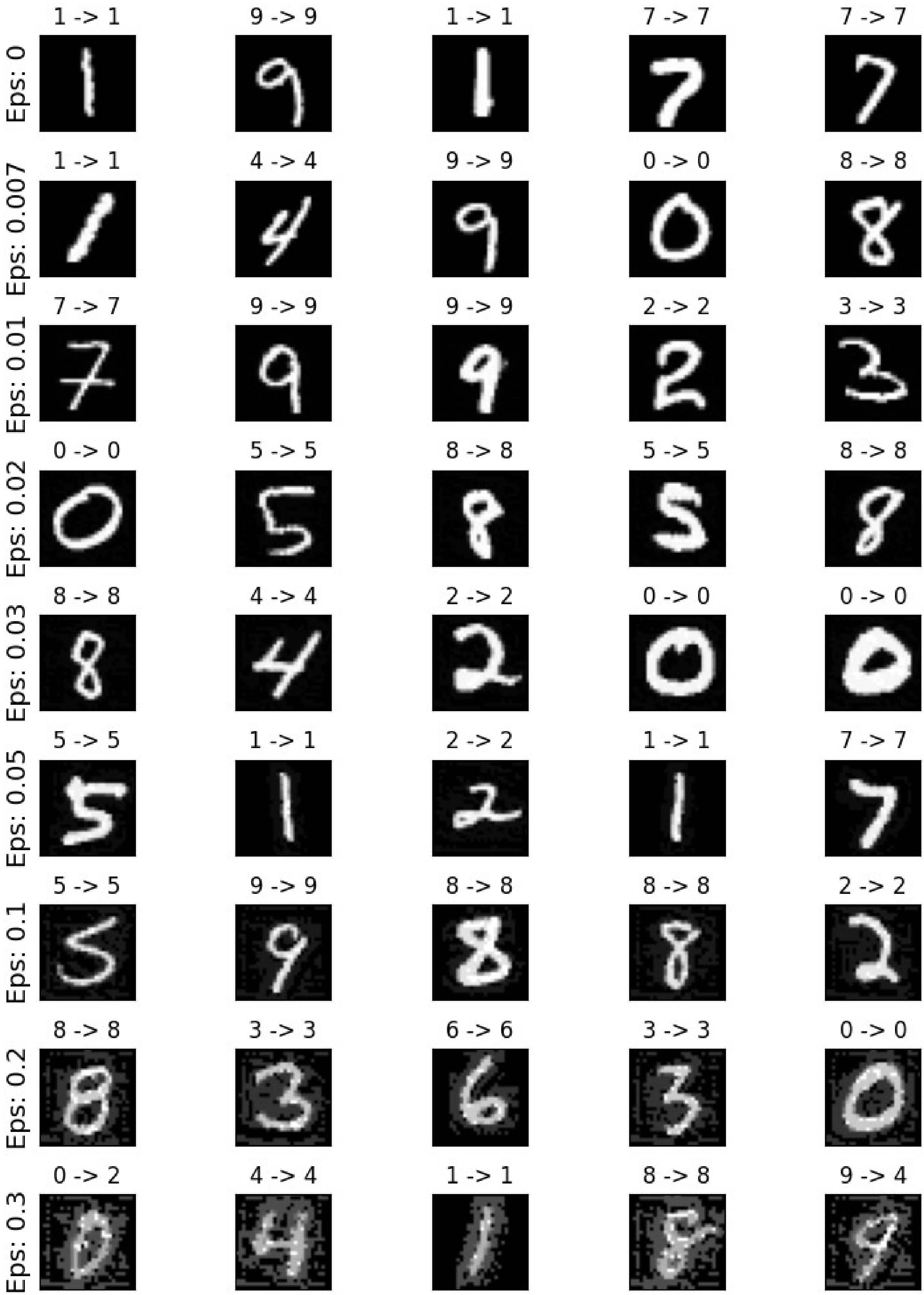
```
epsilons = [0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
for attack in ("fgsm","ifgsm","mifgsm"):
  accuracies = []
```

```
  examples = []
  for eps in epsilons:
    acc, ex = test(model, device,test_loader,eps,attack)
    accuracies.append(acc)
    examples.append(ex)
  plt.figure(figsize=(5,5))
  plt.plot(epsilons, accuracies, "*-")
  plt.title(attack)
  plt.xlabel("Epsilon")
  plt.ylabel("Accuracy")
  plt.show()

  cnt = 0
  plt.figure(figsize=(8,10))
  for i in range(len(epsilons)):
    for j in range(len(examples[i])):
      cnt += 1
      plt.subplot(len(epsilons),len(examples[0]),cnt)
      plt.xticks([], [])
      plt.yticks([], [])
      if j == 0:
        plt.ylabel("Eps: {}".format(epsilons[i]), fontsize=14)
      orig,adv,ex = examples[i][j]
      plt.title("{} -> {}".format(orig, adv))
      plt.imshow(ex, cmap="gray")
  plt.tight_layout()
  plt.show()
```

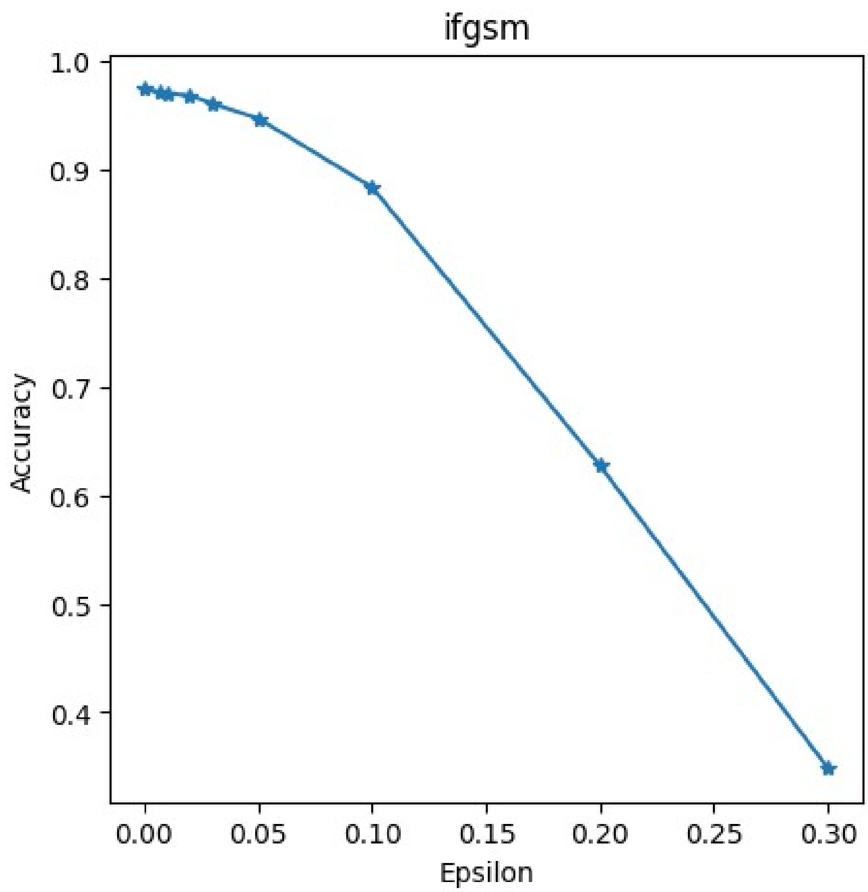
```
Epsilon: 0 Test Accuracy = 9750 / 10000 = 0.975
Epsilon: 0.007   Test Accuracy = 9722 / 10000 = 0.9722
Epsilon: 0.01    Test Accuracy = 9723 / 10000 = 0.9723
Epsilon: 0.02    Test Accuracy = 9679 / 10000 = 0.9679
Epsilon: 0.03    Test Accuracy = 9613 / 10000 = 0.9613
Epsilon: 0.05    Test Accuracy = 9450 / 10000 = 0.945
Epsilon: 0.1     Test Accuracy = 8837 / 10000 = 0.8837
Epsilon: 0.2     Test Accuracy = 6246 / 10000 = 0.6246
Epsilon: 0.3     Test Accuracy = 3601 / 10000 = 0.3601
```

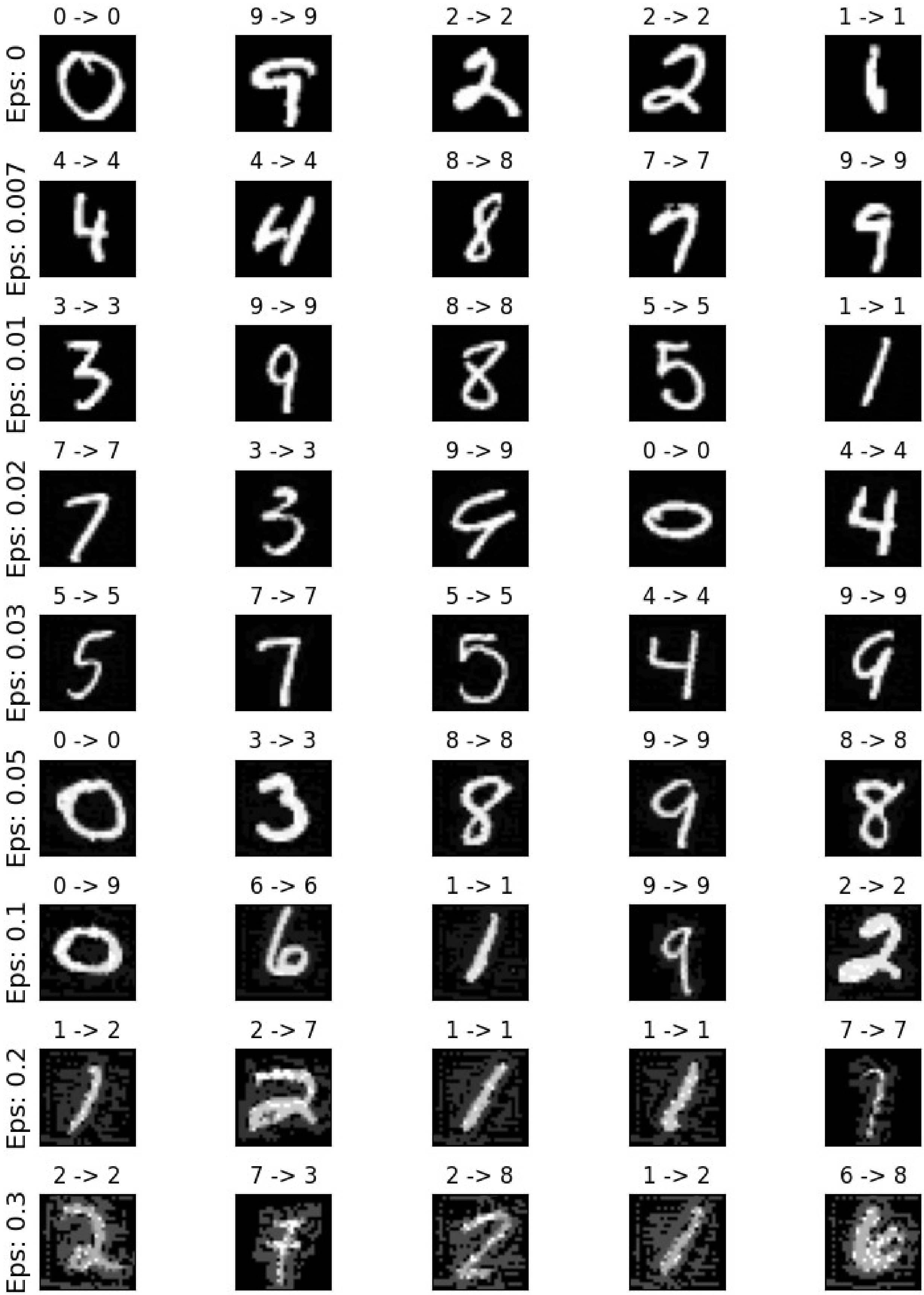


fgsm
Accuracy
Epsilon
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.00
0.05
0.10
0.15
0.20
0.25
0.30

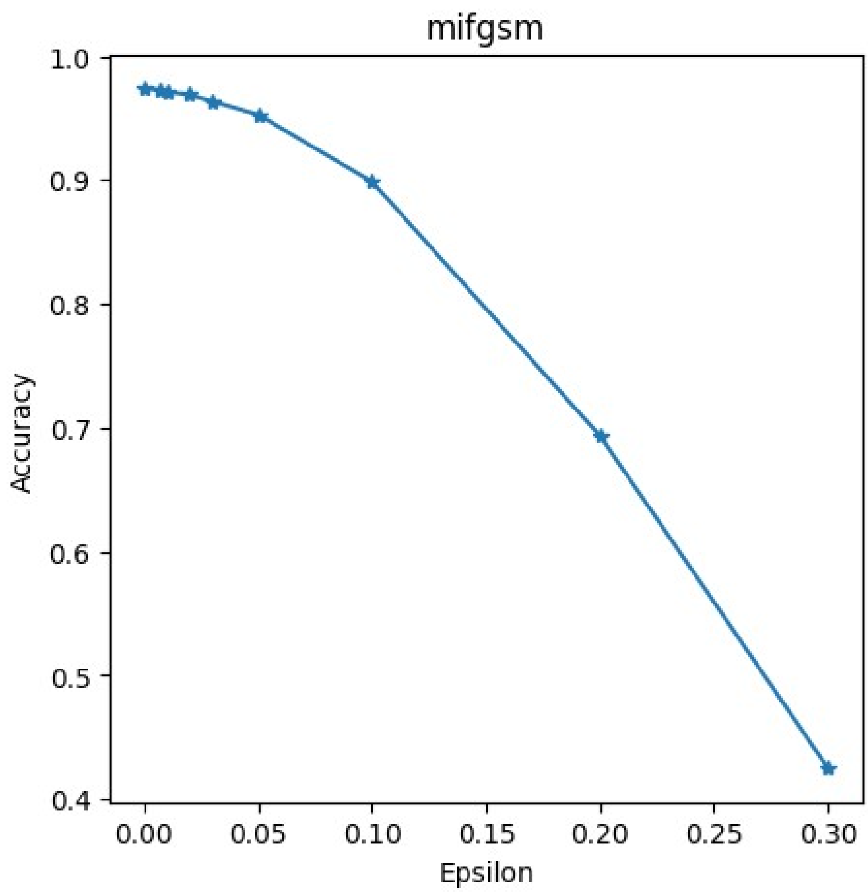

Eps: 0
1 -> 1
9 -> 9
1 -> 1
7 -> 7
7 -> 7
Eps: 0.007
1 -> 1
4 -> 4
9 -> 9
0 -> 0
8 -> 8
Eps: 0.01
7 -> 7
9 -> 9
9 -> 9
2 -> 2
3 -> 3
Eps: 0.02
0 -> 0
5 -> 5
8 -> 8
5 -> 5
8 -> 8
Eps: 0.03
8 -> 8
4 -> 4
2 -> 2
0 -> 0
0 -> 0
Eps: 0.05
5 -> 5
1 -> 1
2 -> 2
1 -> 1
7 -> 7
Eps: 0.1
5 -> 5
9 -> 9
8 -> 8
8 -> 8
2 -> 2
Eps: 0.2
8 -> 8
3 -> 3
6 -> 6
3 -> 3
0 -> 0
Eps: 0.3
0 -> 2
4 -> 4
1 -> 1
8 -> 8
9 -> 4

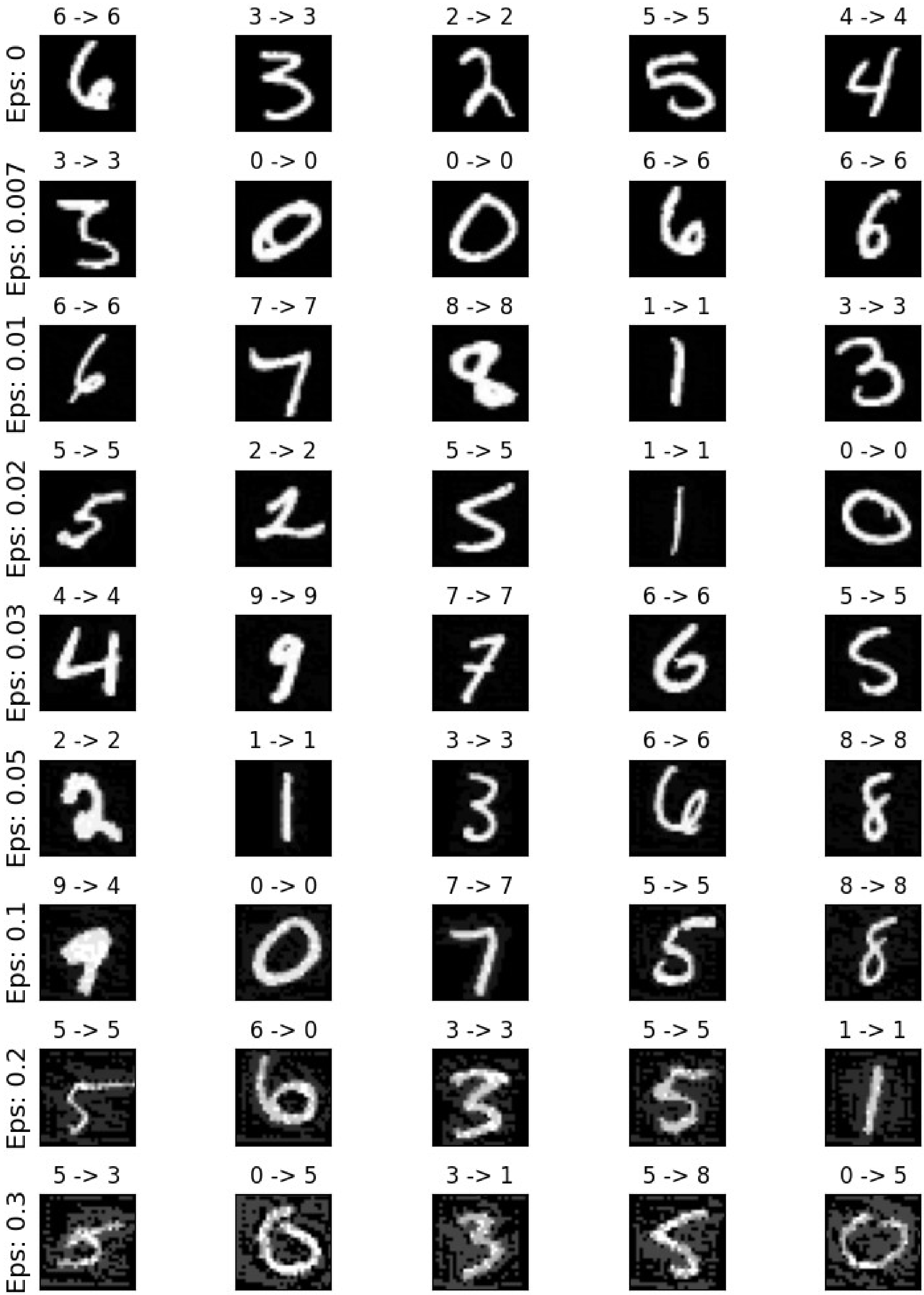
```
Epsilon: 0 Test Accuracy = 9751 / 10000 = 0.9751
Epsilon: 0.007  Test Accuracy = 9715 / 10000 = 0.9715
Epsilon: 0.01   Test Accuracy = 9709 / 10000 = 0.9709
Epsilon: 0.02   Test Accuracy = 9688 / 10000 = 0.9688
Epsilon: 0.03   Test Accuracy = 9612 / 10000 = 0.9612
Epsilon: 0.05   Test Accuracy = 9476 / 10000 = 0.9476
Epsilon: 0.1    Test Accuracy = 8841 / 10000 = 0.8841
Epsilon: 0.2    Test Accuracy = 6273 / 10000 = 0.6273
Epsilon: 0.3    Test Accuracy = 3484 / 10000 = 0.3484
```




Eps: 0
0 -> 0
9 -> 9
2 -> 2
2 -> 2
1 -> 1
Eps: 0.007
4 -> 4
4 -> 4
8 -> 8
7 -> 7
9 -> 9
Eps: 0.01
3 -> 3
9 -> 9
8 -> 8
5 -> 5
1 -> 1
Eps: 0.02
7 -> 7
3 -> 3
9 -> 9
0 -> 0
4 -> 4
Eps: 0.03
5 -> 5
7 -> 7
5 -> 5
4 -> 4
9 -> 9
Eps: 0.05
0 -> 0
3 -> 3
8 -> 8
9 -> 9
8 -> 8
Eps: 0.1
0 -> 9
6 -> 6
1 -> 1
9 -> 9
2 -> 2
Eps: 0.2
1 -> 2
2 -> 7
1 -> 1
1 -> 1
7 -> 7
Eps: 0.3
2 -> 2
7 -> 3
2 -> 8
1 -> 2
6 -> 8

```
Epsilon: 0 Test Accuracy = 9738 / 10000 = 0.9738
Epsilon: 0.007  Test Accuracy = 9728 / 10000 = 0.9728
Epsilon: 0.01   Test Accuracy = 9713 / 10000 = 0.9713
Epsilon: 0.02   Test Accuracy = 9687 / 10000 = 0.9687
Epsilon: 0.03   Test Accuracy = 9634 / 10000 = 0.9634
Epsilon: 0.05   Test Accuracy = 9527 / 10000 = 0.9527
Epsilon: 0.1    Test Accuracy = 8986 / 10000 = 0.8986
Epsilon: 0.2    Test Accuracy = 6933 / 10000 = 0.6933
Epsilon: 0.3    Test Accuracy = 4250 / 10000 = 0.425
```





Eps: 0
6 -> 6
3 -> 3
2 -> 2
5 -> 5
4 -> 4
Eps: 0.007
3 -> 3
0 -> 0
0 -> 0
6 -> 6
6 -> 6
Eps: 0.01
6 -> 6
7 -> 7
8 -> 8
1 -> 1
3 -> 3
Eps: 0.02
5 -> 5
2 -> 2
5 -> 5
1 -> 1
0 -> 0
Eps: 0.03
4 -> 4
9 -> 9
7 -> 7
6 -> 6
5 -> 5
Eps: 0.05
2 -> 2
1 -> 1
3 -> 3
6 -> 6
8 -> 8
Eps: 0.1
9 -> 4
0 -> 0
7 -> 7
5 -> 5
8 -> 8
Eps: 0.2
5 -> 5
6 -> 0
3 -> 3
5 -> 5
1 -> 1
Eps: 0.3
5 -> 3
0 -> 5
3 -> 1
5 -> 8
0 -> 5

Создадим 2 класса НС.

```
class NetF(nn.Module):
  def __init__(self):
    super(NetF, self).__init__()
    self.conv1 = nn.Conv2d(1, 32, 3, 1)
    self.conv2 = nn.Conv2d(32, 64, 3, 1)
    self.dropout1 = nn.Dropout2d(0.25)
    self.dropout2 = nn.Dropout2d(0.5)
    self.fc1 = nn.Linear(9216, 128)
    self.fc2 = nn.Linear(128, 10)

  def forward(self, x):
    x = self.conv1(x)
    x = F.relu(x)
    x = self.conv2(x)
    x = F.relu(x)
    x = F.max_pool2d(x, 2)
    x = self.dropout1(x)
    x = torch.flatten(x, 1)
    x = self.fc1(x)
    x = F.relu(x)
    x = self.dropout2(x)
    x = self.fc2(x)
    return x

class NetF1(nn.Module):
  def __init__(self):
    super(NetF1, self).__init__()
    self.conv1 = nn.Conv2d(1, 16, 3, 1)
    self.conv2 = nn.Conv2d(16, 32, 3, 1)
    self.dropout1 = nn.Dropout2d(0.25)
    self.dropout2 = nn.Dropout2d(0.5)
    self.fc1 = nn.Linear(4608, 64)
    self.fc2 = nn.Linear(64, 10)

  def forward(self, x):
    x = self.conv1(x)
    x = F.relu(x)
    x = self.conv2(x)
    x = F.relu(x)
    x = F.max_pool2d(x, 2)
    x = self.dropout1(x)
    x = torch.flatten(x, 1)
    x = self.fc1(x)
    x = F.relu(x)
    x = self.dropout2(x)
    x = self.fc2(x)
    return x
```

Переопределим функцию обучения и тестирования.

```
def
fit(model,device,optimizer,scheduler,criterion,train_loader,val_loader
,Temp,epochs):
  data_loader = {'train':train_loader,'val':val_loader}
  print("Fitting the model...")
  train_loss,val_loss=[],[]
  for epoch in range(epochs):
    loss_per_epoch,val_loss_per_epoch=0,0
    for phase in ('train','val'):
      for i,data in enumerate(data_loader[phase]):
        input,label = data[0].to(device),data[1].to(device)
        output = model(input)
        output = F.log_softmax(output/Temp,dim=1)
        #calculating loss on the output
        loss = criterion(output,label)
        if phase == 'train':
          optimizer.zero_grad()
          #grad calc w.r.t Loss func
          loss.backward()
          #update weights
          optimizer.step()
          loss_per_epoch+=loss.item()
      else:
        val_loss_per_epoch+=loss.item()
    scheduler.step(val_loss_per_epoch/len(val_loader))
    print("Epoch: {} Loss: {} Val_Loss:
{}".format(epoch+1,loss_per_epoch/len(train_loader),val_loss_per_epoch
/len(val_loader)))
    train_loss.append(loss_per_epoch/len(train_loader))
    val_loss.append(val_loss_per_epoch/len(val_loader))
  return train_loss,val_loss
  def test(model,device,test_loader,epsilon,Temp,attack):
    correct=0
    adv_examples = []
    for data, target in test_loader:
      data, target = data.to(device), target.to(device)
      data.requires_grad = True
      output = model(data)
      output = F.log_softmax(output/Temp,dim=1)
      init_pred = output.max(1, keepdim=True)[1]
      if init_pred.item() != target.item():
        continue
      loss = F.nll_loss(output, target)
      model.zero_grad()
      loss.backward()
      data_grad = data.grad.data
      if attack == "fgsm":
        perturbed_data = fgsm_attack(data,epsilon,data_grad)
```

```
      elif attack == "ifgsm":
        perturbed_data = ifgsm_attack(data,epsilon,data_grad)
      elif attack == "mifgsm":
        perturbed_data = mifgsm_attack(data,epsilon,data_grad)
      output = model(perturbed_data)
      final_pred = output.max(1, keepdim=True)[1]
      if final_pred.item() == target.item():
        correct += 1
        if (epsilon == 0) and (len(adv_examples) < 5):
          adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
          adv_examples.append( (init_pred.item(), final_pred.item(),
adv_ex) )
        else:
          if len(adv_examples) < 5:
            adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
            adv_examples.append( (init_pred.item(), final_pred.item(),
adv_ex) )
  final_acc = correct/float(len(test_loader))
  print("Epsilon: {}\tTest Accuracy = {} / {} = {}".format(epsilon,
correct, len(test_loader), final_acc))
  return final_acc,adv_examples
```

Создатдим функцию защиты методом дистилляции.

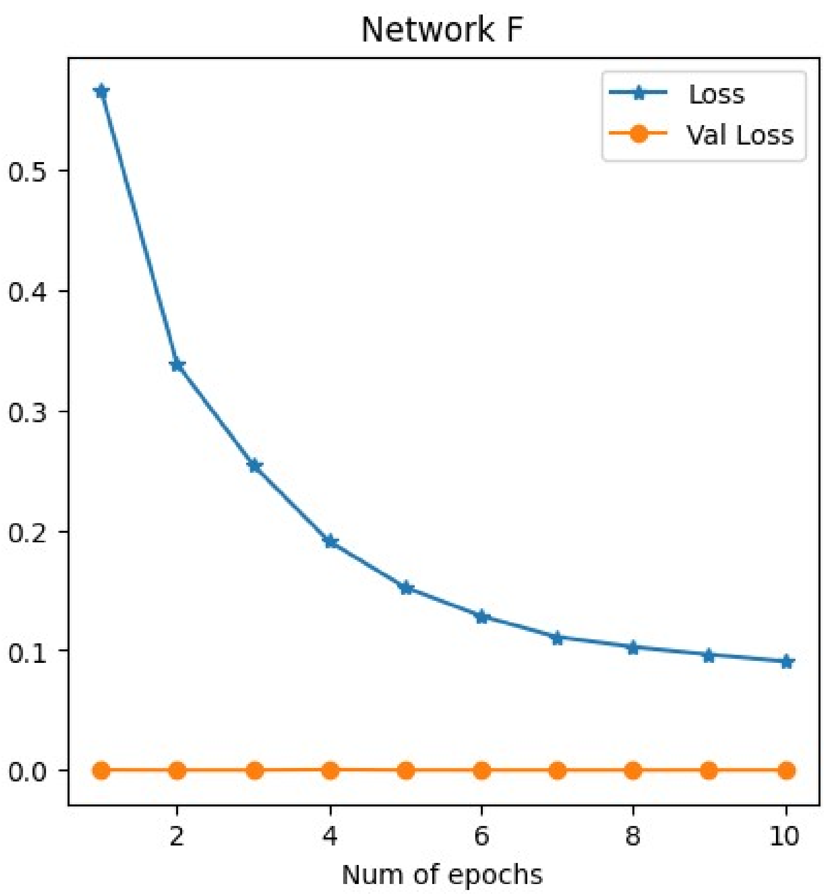
```
def
defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilon
s):
  modelF = NetF().to(device)
  optimizerF = optim.Adam(modelF.parameters(),lr=0.0001, betas=(0.9,
0.999))
  schedulerF = optim.lr_scheduler.ReduceLROnPlateau(optimizerF,
mode='min', factor=0.1, patience=3)
  modelF1 = NetF1().to(device)
  optimizerF1 = optim.Adam(modelF1.parameters(),lr=0.0001, betas=(0.9,
0.999))
  schedulerF1 = optim.lr_scheduler.ReduceLROnPlateau(optimizerF1,
mode='min', factor=0.1, patience=3)
  criterion = nn.NLLLoss()

lossF,val_lossF=fit(modelF,device,optimizerF,schedulerF,criterion,trai
n_loader,val_loader,Temp,epochs)
  fig = plt.figure(figsize=(5,5))
  plt.plot(np.arange(1,epochs+1), lossF, "*-",label="Loss")
  plt.plot(np.arange(1,epochs+1), val_lossF,"o-",label="Val Loss")
  plt.title("Network F")
  plt.xlabel("Num of epochs")
  plt.legend()
  plt.show()
  #converting target labels to soft labels
```

```
  for data in train_loader:
    input, label = data[0].to(device),data[1].to(device)
    softlabel = F.log_softmax(modelF(input),dim=1)
    data[1] = softlabel

lossF1,val_lossF1=fit(modelF1,device,optimizerF1,schedulerF1,criterion
,train_loader,val_loader,Temp,epochs)
  fig = plt.figure(figsize=(5,5))
  plt.plot(np.arange(1,epochs+1), lossF1, "*-",label="Loss")
  plt.plot(np.arange(1,epochs+1), val_lossF1,"o-",label="Val Loss")
  plt.title("Network F'")
  plt.xlabel("Num of epochs")
  plt.legend()
  plt.show()
  model = NetF1().to(device)
  model.load_state_dict(modelF1.state_dict())
  for attack in ("fgsm","ifgsm","mifgsm"):
    accuracies = []
    examples = []
    for eps in epsilons:
      acc, ex = test(model,device,test_loader,eps,"fgsm")
      accuracies.append(acc)
      examples.append(ex)
  plt.figure(figsize=(5,5))
  plt.plot(epsilons, accuracies, "*-")
  plt.title(attack)
  plt.xlabel("Epsilon")
  plt.ylabel("Accuracy")
  plt.show()

  cnt = 0
  plt.figure(figsize=(8,10))
  for i in range(len(epsilons)):
    for j in range(len(examples[i])):
      cnt += 1
      plt.subplot(len(epsilons),len(examples[0]),cnt)
      plt.xticks([], [])
      plt.yticks([], [])
      if j == 0:
        plt.ylabel("Eps: {}".format(epsilons[i]), fontsize=14)
      orig,adv,ex = examples[i][j]
      plt.title("{} -> {}".format(orig, adv))
      plt.imshow(ex, cmap="gray")
  plt.tight_layout()
  plt.show()
```

Получим результаты оценки защищенных сетей.

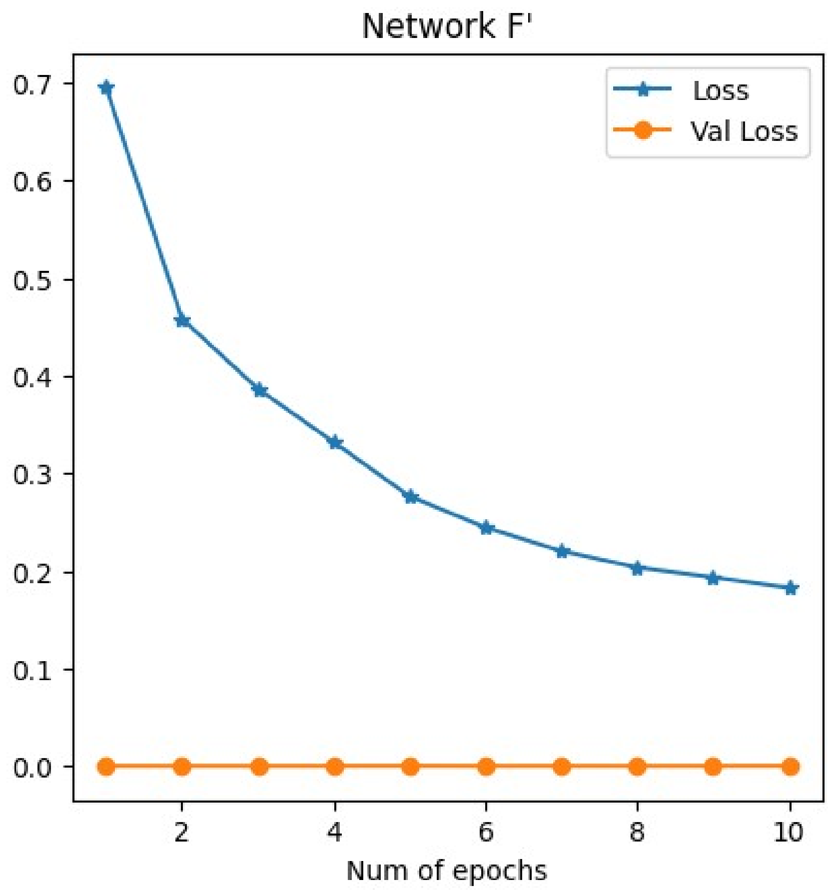
```
Temp=100
epochs=10
epsilons=[0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilon
s)
```

```
Fitting the model...
Epoch: 1 Loss: 0.5662047301409073 Val_Loss: 0.00018231202587485313
Epoch: 2 Loss: 0.3385203243374718 Val_Loss: 1.2374566635116935e-06
Epoch: 3 Loss: 0.25428086451666876 Val_Loss: 3.757412723643938e-07
Epoch: 4 Loss: 0.19064711203381343 Val_Loss: 0.00048478846549874106
Epoch: 5 Loss: 0.15228855001899314 Val_Loss: 1.921464577317238e-05
Epoch: 6 Loss: 0.1285232472288784 Val_Loss: 1.4979687286540866e-06
Epoch: 7 Loss: 0.11097932044940916 Val_Loss: 2.742809010669589e-08
Epoch: 8 Loss: 0.10269630508215549 Val_Loss: 7.760227151720756e-09
Epoch: 9 Loss: 0.09628898256426938 Val_Loss: 1.327698947279714e-05
Epoch: 10 Loss: 0.09052555274544327 Val_Loss: 1.2294865399599076e-05
```



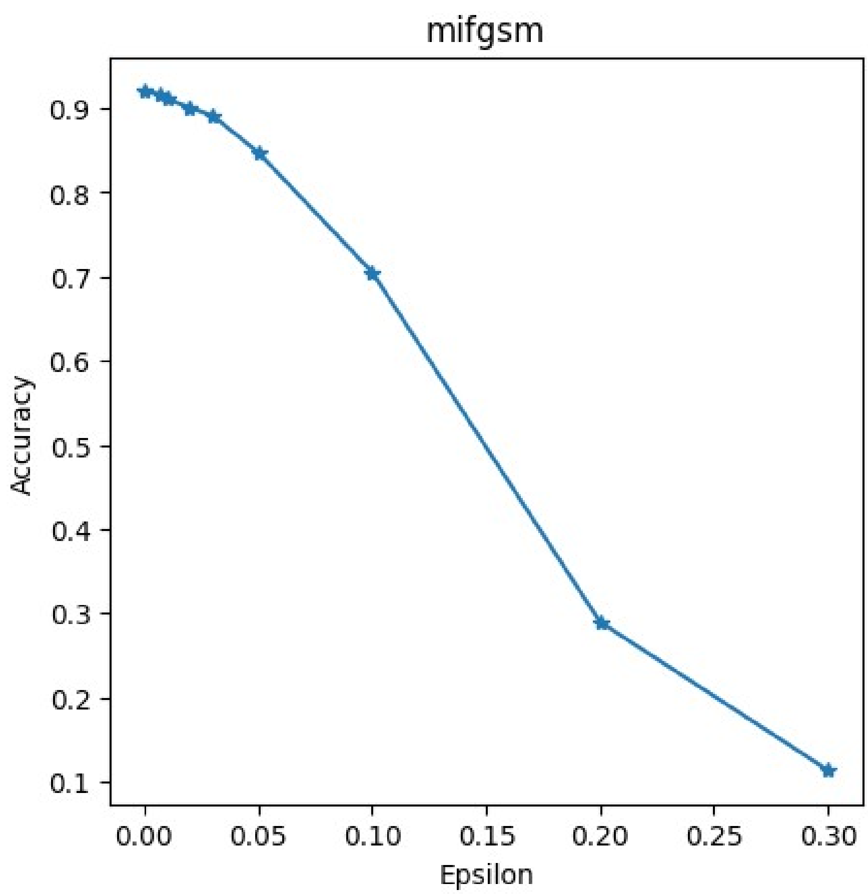

```
Fitting the model...
Epoch: 1 Loss: 0.6954153548508452 Val_Loss: 3.698446452617645e-05
Epoch: 2 Loss: 0.4583256354506680 7 Val_Loss: 1.771830189973116e-05
Epoch: 3 Loss: 0.3865080458324801 Val_Loss: 1.3489030115306378e-05
```

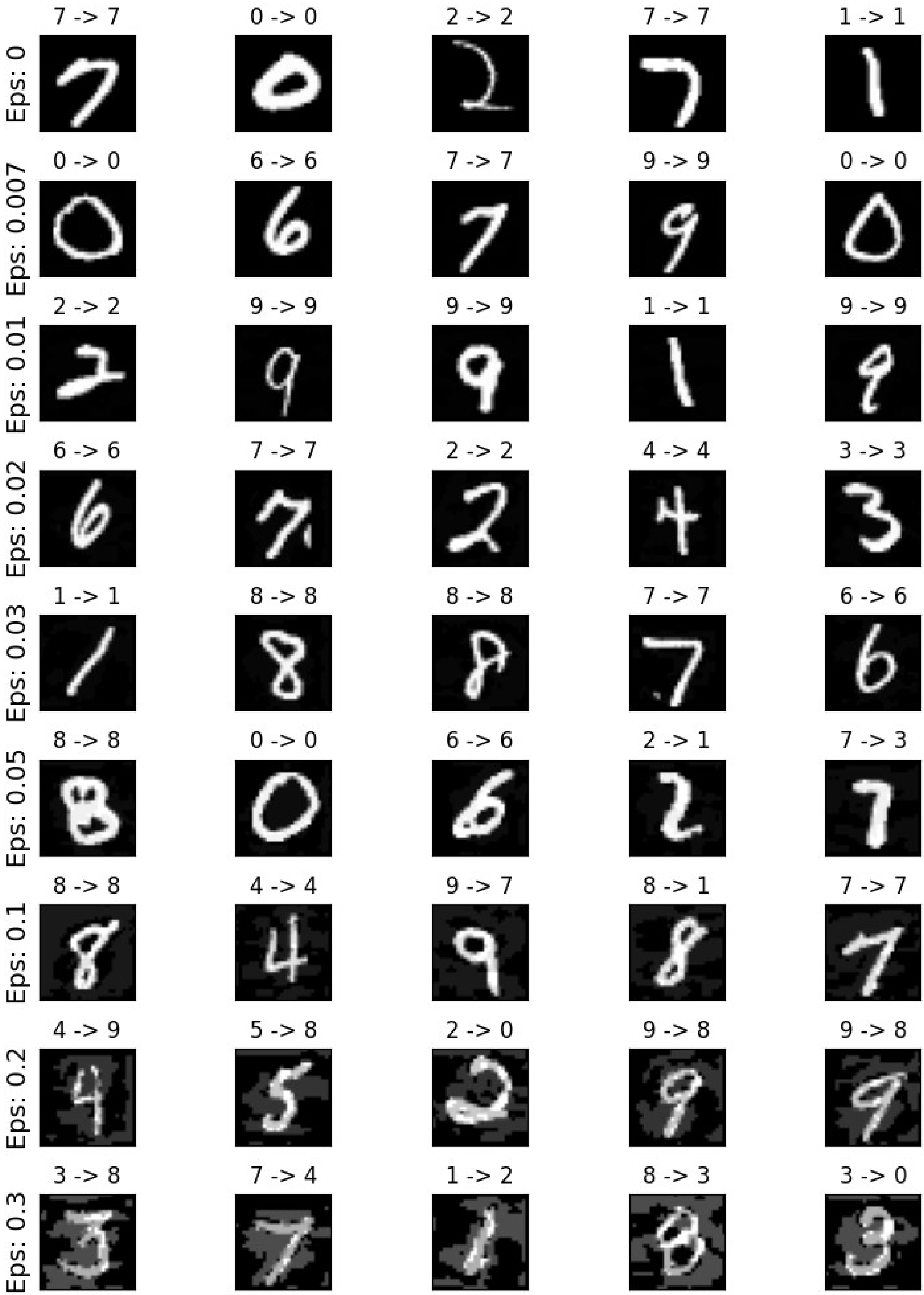
```
Epoch: 4 Loss: 0.3318358400624503 Val_Loss: 5.6694397889077666e-05
Epoch: 5 Loss: 0.2763107574661768 Val_Loss: 0.00014575666207820178
Epoch: 6 Loss: 0.2445015275636196 Val_Loss: 4.863006553932791e-07
Epoch: 7 Loss: 0.22031390263005912 Val_Loss: 1.8023547500524728e-05
Epoch: 8 Loss: 0.20348487243809338 Val_Loss: 3.601938886276912e-07
Epoch: 9 Loss: 0.19343684324045543 Val_Loss: 5.017868280410767e-05
Epoch: 10 Loss: 0.1826015582433685 Val_Loss: 0.00013195873200893402
```




```
Epsilon: 0 Test Accuracy = 9263 / 10000 = 0.9263
Epsilon: 0.007  Test Accuracy = 9170 / 10000 = 0.917
Epsilon: 0.01   Test Accuracy = 9107 / 10000 = 0.9107
Epsilon: 0.02   Test Accuracy = 9016 / 10000 = 0.9016
Epsilon: 0.03   Test Accuracy = 8894 / 10000 = 0.8894
Epsilon: 0.05   Test Accuracy = 8496 / 10000 = 0.8496
Epsilon: 0.1    Test Accuracy = 7037 / 10000 = 0.7037
Epsilon: 0.2    Test Accuracy = 2894 / 10000 = 0.2894
Epsilon: 0.3    Test Accuracy = 1105 / 10000 = 0.1105
Epsilon: 0 Test Accuracy = 9214 / 10000 = 0.9214
Epsilon: 0.007  Test Accuracy = 9185 / 10000 = 0.9185
Epsilon: 0.01   Test Accuracy = 9117 / 10000 = 0.9117
Epsilon: 0.02   Test Accuracy = 9012 / 10000 = 0.9012
```

```
Epsilon: 0.03	Test Accuracy = 8906 / 10000 = 0.8906
Epsilon: 0.05	Test Accuracy = 8507 / 10000 = 0.8507
Epsilon: 0.1	Test Accuracy = 6995 / 10000 = 0.6995
Epsilon: 0.2	Test Accuracy = 2945 / 10000 = 0.2945
Epsilon: 0.3	Test Accuracy = 1156 / 10000 = 0.1156
Epsilon: 0 Test Accuracy = 9203 / 10000 = 0.9203
Epsilon: 0.007	Test Accuracy = 9167 / 10000 = 0.9167
Epsilon: 0.01	Test Accuracy = 9106 / 10000 = 0.9106
Epsilon: 0.02	Test Accuracy = 9008 / 10000 = 0.9008
Epsilon: 0.03	Test Accuracy = 8911 / 10000 = 0.8911
Epsilon: 0.05	Test Accuracy = 8476 / 10000 = 0.8476
Epsilon: 0.1	Test Accuracy = 7052 / 10000 = 0.7052
Epsilon: 0.2	Test Accuracy = 2897 / 10000 = 0.2897
Epsilon: 0.3	Test Accuracy = 1136 / 10000 = 0.1136
```




Eps: 0
7 -> 7
0 -> 0
2 -> 2
7 -> 7
1 -> 1
Eps: 0.007
0 -> 0
6 -> 6
7 -> 7
9 -> 9
0 -> 0
Eps: 0.01
2 -> 2
9 -> 9
9 -> 9
1 -> 1
9 -> 9
Eps: 0.02
6 -> 6
7 -> 7
2 -> 2
4 -> 4
3 -> 3
Eps: 0.03
1 -> 1
8 -> 8
8 -> 8
7 -> 7
6 -> 6
Eps: 0.05
8 -> 8
0 -> 0
6 -> 6
2 -> 1
7 -> 3
Eps: 0.1
8 -> 8
4 -> 4
9 -> 7
8 -> 1
7 -> 7
Eps: 0.2
4 -> 9
5 -> 8
2 -> 0
9 -> 8
9 -> 8
Eps: 0.3
3 -> 8
7 -> 4
1 -> 2
8 -> 3
3 -> 0

Дистилляция (или обучение с учителем) - это метод, при котором более крупная модель (учитель) используется для обучения более компактной модели (ученика) путем передачи знаний из учителя в ученика. В контексте защиты от адверсариальных атак, дистилляция может применяться для создания модели, более устойчивой к таким атакам.

Учительская модель может обучить ученическую модель выделять более стабильные и робастные паттерны в данных, что может помочь предотвратить некоторые виды адверсариальных атак. Дистилляция может сделать модель менее чувствительной к мелким изменениям входных данных, затруднить успешное проведение атаки, но также может снизить точность модели (особенно если не подобрать оптимальные параметры процесса дистилляции),повлечь за собой увеличение вычислительной сложности обучения и инференса.

В нашел случае, мы можем видеть такие показатели точности атак:

```
fgsm   - 0.97 / 0.36
ifgsm  - 0.97 / 0.34
mifgsm - 0.97 / 0.42
```

А точность модели остается в пределах 0.9