МИНОБРНАУКИ РОССИИ
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Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Отчет по лабораторной работе 4 + прз6

по дисциплине
««Анализ защищенности систем искусственного интеллекта»»

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Изучение методов защиты от атак на модели НС

Защитная дистилляция

1. Выполнить импорт необходимых библиотек.

```
[1] 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
```

2. Задать нормализующие преобразования? загрузить 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)
```

```
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, 119437486.34it/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, 123356103.69it/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, 30845322.27it/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, 1712099.29it/s]Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```

3. Настроить использование графического ускорителя (если возможно)

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

Создание атак на модель НС

4. Создать класс НС на основе фреймворка torch

```
[4] 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.Dropout(0.25)
        self.dropout2 = nn.Dropout(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
```

5. Проверить работоспособность созданного класса НС

```
✓ 0 сек.
model = Net().to(device)
```

6. Создать оптимизатор, функцию потерь и трейнер сети.

```
✓ 0 сек.
[6] 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)
```

7. Определить 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
```

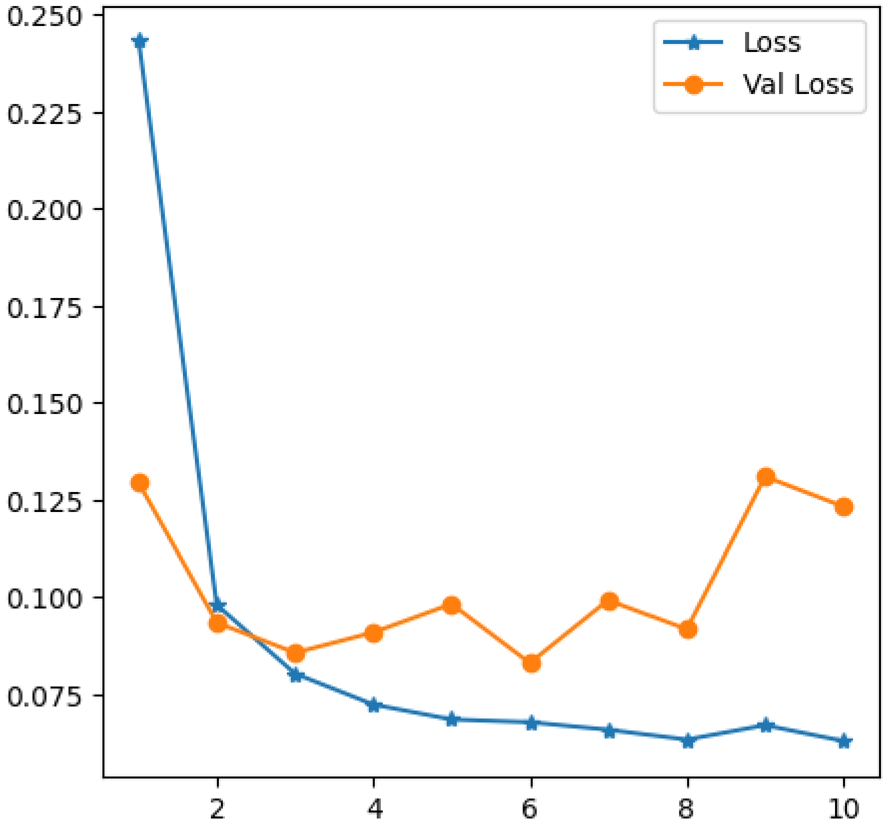
8. Обучить модель

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

```
Fitting the model...
Epoch: 1 Loss: 0.2433923526893967 Val_Loss: 0.12942566162898214
Epoch: 2 Loss: 0.09804235486729618 Val_Loss: 0.09347756677153753
Epoch: 3 Loss: 0.08034730895797922 Val_Loss: 0.08573553512156357
Epoch: 4 Loss: 0.07238819115314364 Val_Loss: 0.09097555525576781
Epoch: 5 Loss: 0.06854760753432296 Val_Loss: 0.09829834021660507
Epoch: 6 Loss: 0.06783519976754503 Val_Loss: 0.08309482305348924
Epoch: 7 Loss: 0.06590201110334912 Val_Loss: 0.09927177124091173
Epoch: 8 Loss: 0.06335777162092911 Val_Loss: 0.09180139065947131
Epoch: 9 Loss: 0.06706383737350674 Val_Loss: 0.1309880346000726
Epoch: 10 Loss: 0.06300391186826652 Val_Loss: 0.1232997803737502
```

9. Построить графики потерь при обучении и валидации в зависимости от эпохи

```
[9] 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()
```



10. Создать функции атак FGSM, I-FGSM, MI-FGSM

```
[10] 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
```

```
[11] def ifgsm_attack(input,epsilon,data_grad):
      iter = 10
      alpha = epsilon/iter
      pert_out = input
      for i in range(iter-1):
       pert_out = pert_out + alpha*data_grad.sign()
       pert_out = torch.clamp(pert_out, 0, 1)
       if torch.norm((pert_out-input),p=float('inf')) > epsilon:
         break
      return pert_out
```

```
[12] 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
```

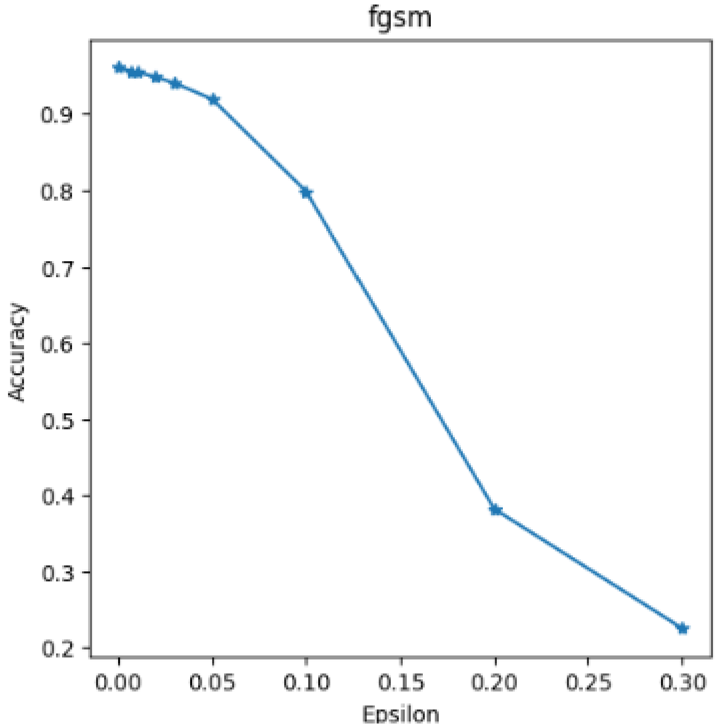
11. Создать функцию проверки

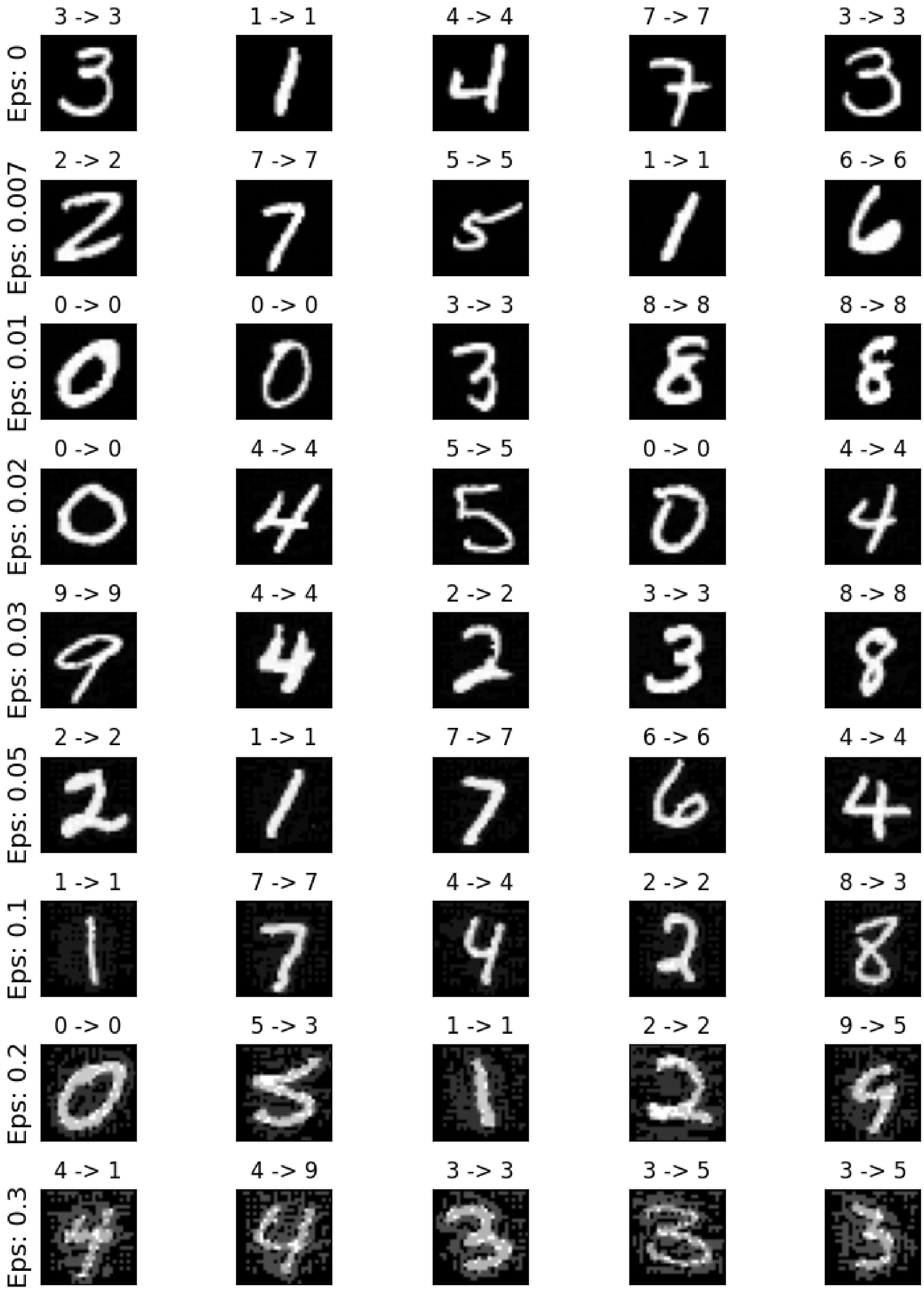
```python
def test(model,device,test_loader,epsilon,attack):
  correct = 0
  adv_examples = []
  for data, target in test_loader:
    data, target = data.to(device), target.to(device)
    data.requires_grad = True
    output = model(data)
    init_pred = output.max(1, keepdim=True)[1]
    if init_pred.item() != 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
```

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

```python
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()
```

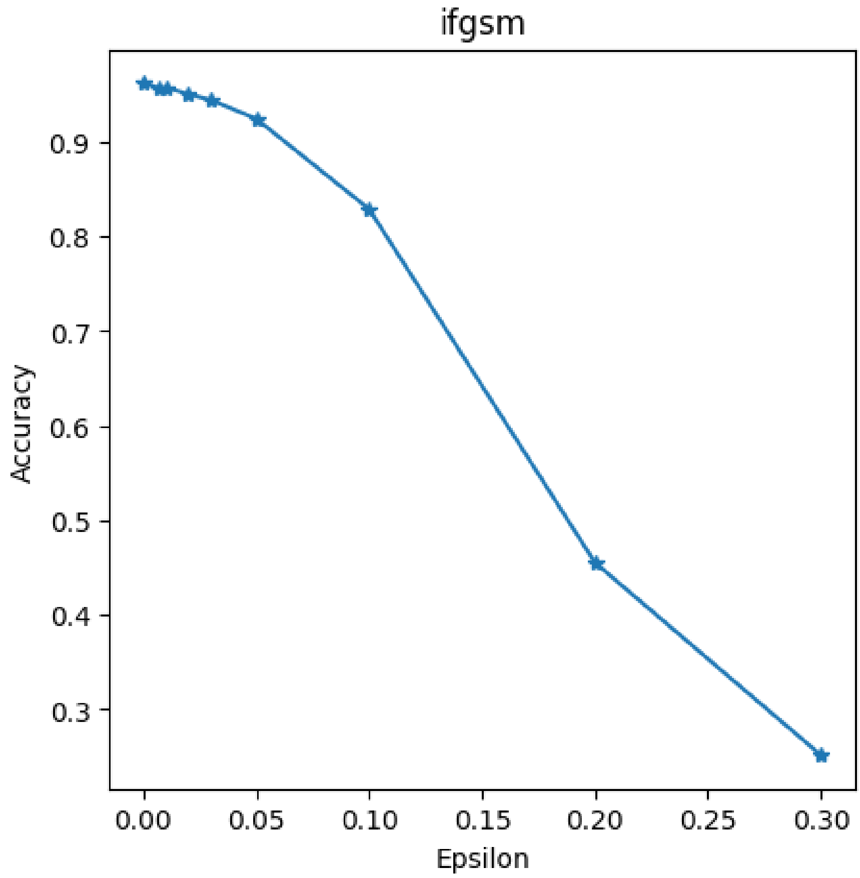
```
Epsilon: 0      Test Accuracy = 9613 / 10000 = 0.9613
Epsilon: 0.007  Test Accuracy = 9564 / 10000 = 0.9564
Epsilon: 0.01   Test Accuracy = 9550 / 10000 = 0.955
Epsilon: 0.02   Test Accuracy = 9485 / 10000 = 0.9485
Epsilon: 0.03   Test Accuracy = 9406 / 10000 = 0.9406
Epsilon: 0.05   Test Accuracy = 9197 / 10000 = 0.9197
Epsilon: 0.1    Test Accuracy = 7986 / 10000 = 0.7986
Epsilon: 0.2    Test Accuracy = 3821 / 10000 = 0.3821
Epsilon: 0.3    Test Accuracy = 2255 / 10000 = 0.2255
```

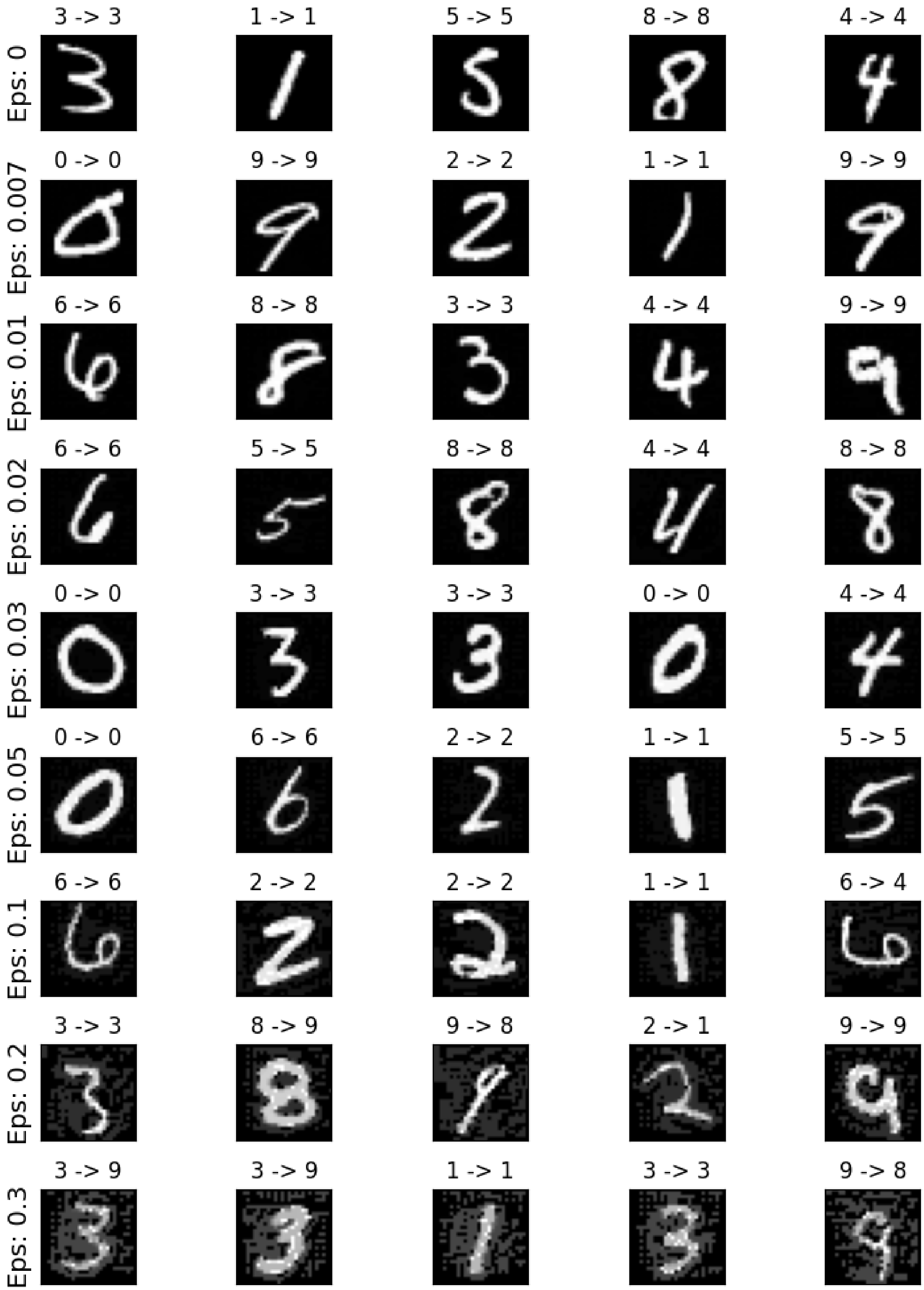



Eps: 0
3 -> 3
1 -> 1
4 -> 4
7 -> 7
3 -> 3
Eps: 0.007
2 -> 2
7 -> 7
5 -> 5
1 -> 1
6 -> 6
Eps: 0.01
0 -> 0
0 -> 0
3 -> 3
8 -> 8
8 -> 8
Eps: 0.02
0 -> 0
4 -> 4
5 -> 5
0 -> 0
4 -> 4
Eps: 0.03
9 -> 9
4 -> 4
2 -> 2
3 -> 3
8 -> 8
Eps: 0.05
2 -> 2
1 -> 1
7 -> 7
6 -> 6
4 -> 4
Eps: 0.1
1 -> 1
7 -> 7
4 -> 4
2 ->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

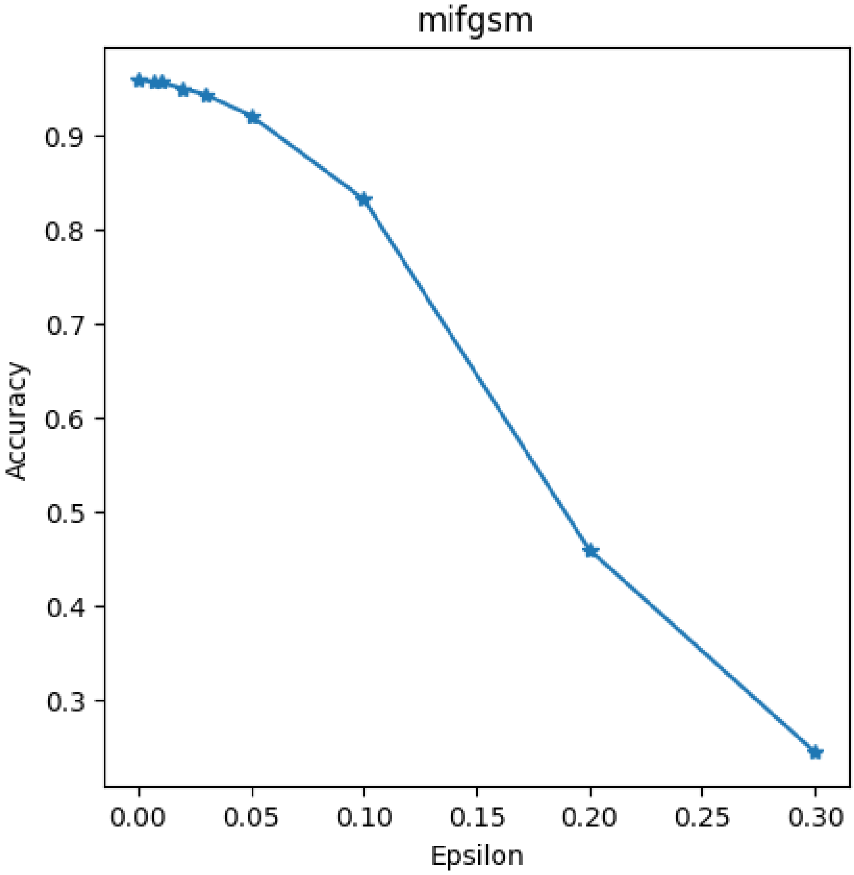
E [redacted] [redacted] [redacted]

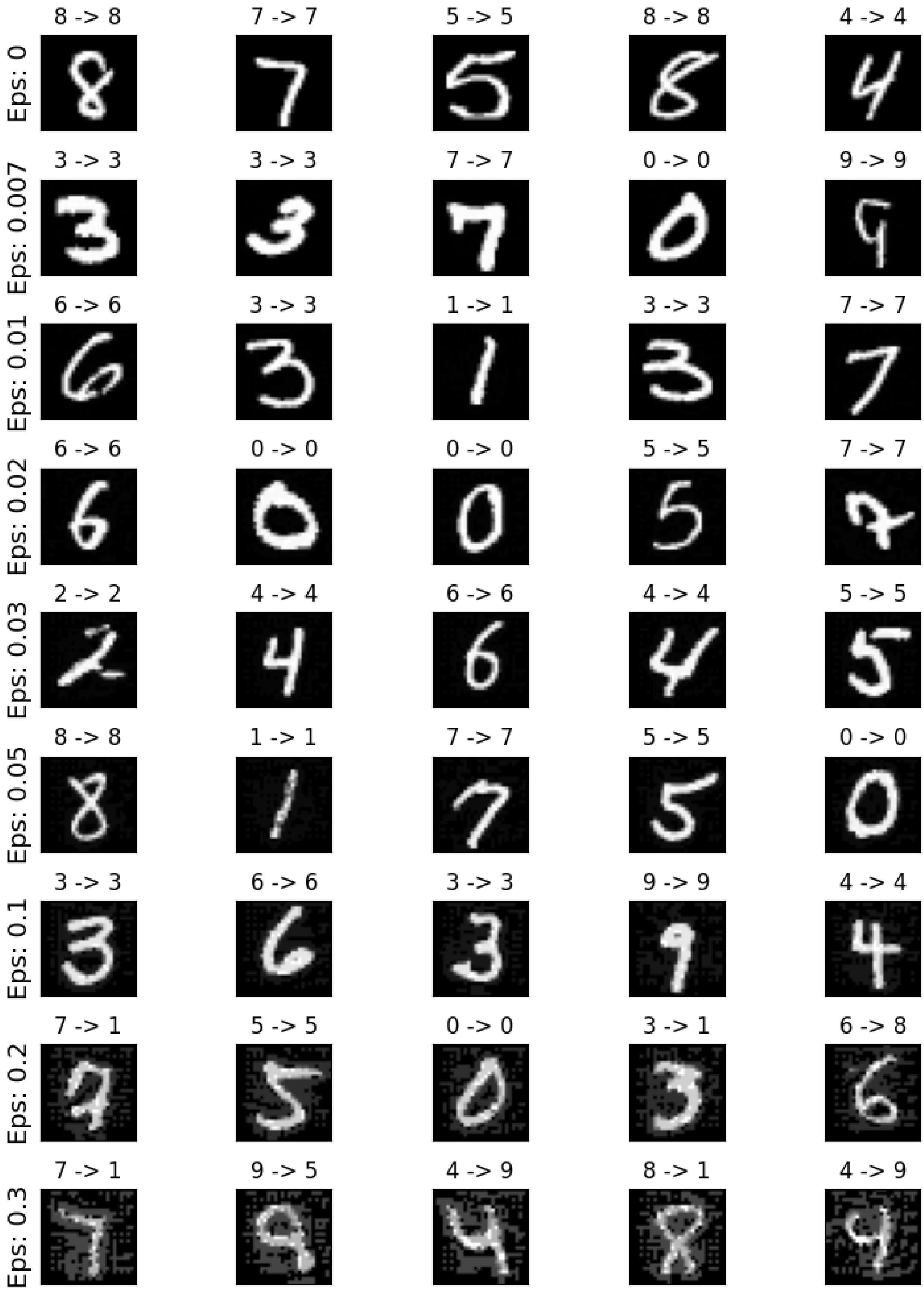
```
Epsilon: 0      Test Accuracy = 9626 / 10000 = 0.9626
Epsilon: 0.007  Test Accuracy = 9574 / 10000 = 0.9574
Epsilon: 0.01   Test Accuracy = 9579 / 10000 = 0.9579
Epsilon: 0.02   Test Accuracy = 9510 / 10000 = 0.951
Epsilon: 0.03   Test Accuracy = 9445 / 10000 = 0.9445
Epsilon: 0.05   Test Accuracy = 9248 / 10000 = 0.9248
Epsilon: 0.1    Test Accuracy = 8292 / 10000 = 0.8292
Epsilon: 0.2    Test Accuracy = 4552 / 10000 = 0.4552
Epsilon: 0.3    Test Accuracy = 2516 / 10000 = 0.2516
```




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

```
Epsilon: 0      Test Accuracy = 9595 / 10000 = 0.9595
Epsilon: 0.007  Test Accuracy = 9576 / 10000 = 0.9576
Epsilon: 0.01   Test Accuracy = 9569 / 10000 = 0.9569
Epsilon: 0.02   Test Accuracy = 9506 / 10000 = 0.9506
Epsilon: 0.03   Test Accuracy = 9438 / 10000 = 0.9438
Epsilon: 0.05   Test Accuracy = 9217 / 10000 = 0.9217
Epsilon: 0.1    Test Accuracy = 8329 / 10000 = 0.8329
Epsilon: 0.2    Test Accuracy = 4603 / 10000 = 0.4603
Epsilon: 0.3    Test Accuracy = 2452 / 10000 = 0.2452
```




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

Защита от атак

13. Создать 2 класса НС

```
[15] class NetF(nn.Module):
       def __init__(self):
         super(NetF, self).__init__()
         self.conv1 = nn.Conv2d(1, 32, 3,
         self.conv2 = nn.Conv2d(32, 64, 3,
         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
```

```python
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
```

14. Переопределить функцию обучения и тестирования

```python
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
```

```python
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
```

15. Создать функцию защиты методом дистилляции

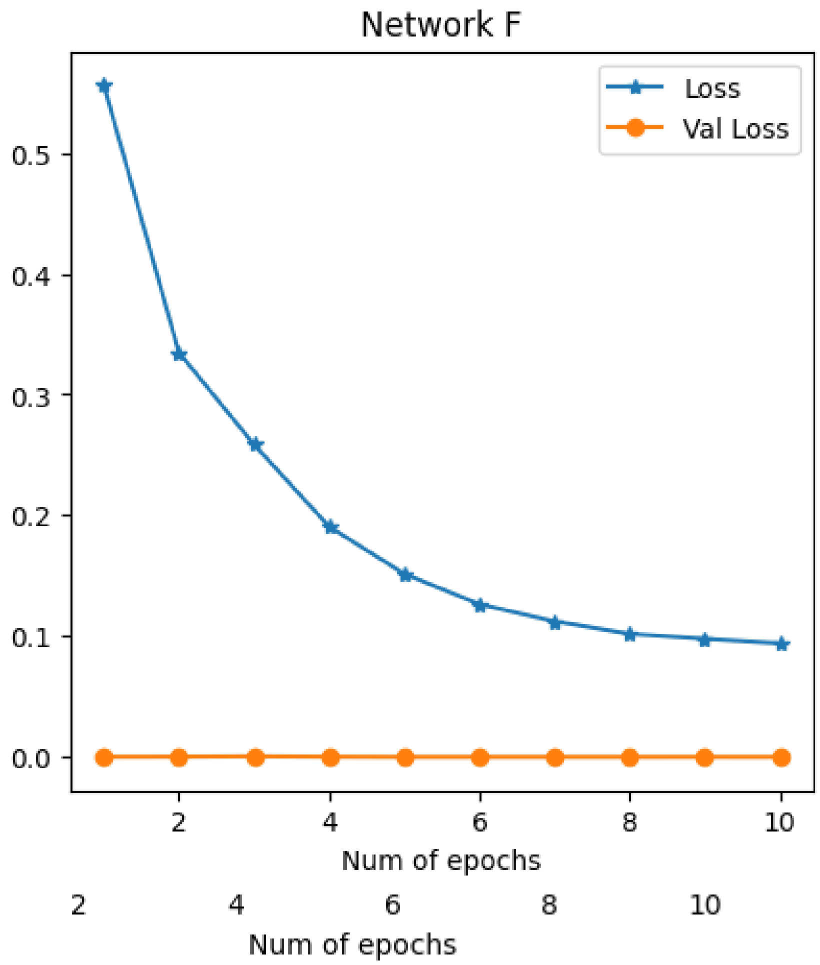
```python
def defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons):
    modelF = NetF().to(device)
    optimizerF = optim.Adam(modelF.parameters(),lr=0.0001, betas=(0.9, 0.999))
    schedulerF = optim.lr_scheduler.ReduceLROnPlateau(optimizerF, mode='min', factor=0.1, patience=3)
    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,train_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,1,"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()
```

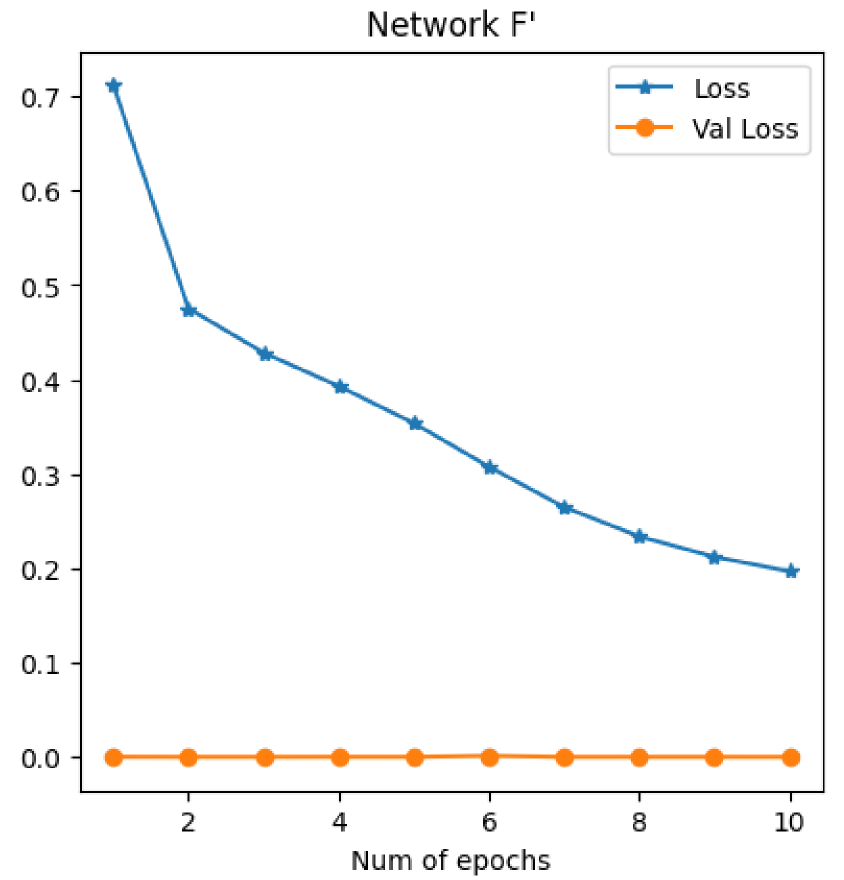
16. Получить результаты оценки защищенных сетей

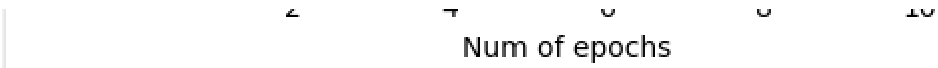
```
[19] Temp=100
     epochs=10
     epsilons=[0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
     defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons)
```

```
Fitting the model...
/usr/local/lib/python3.10/dist-packages/torch/nn/functional.py:1345: UserWa
  warnings.warn(warn_msg)
Epoch: 1 Loss: 0.5562089400215493 Val_Loss: 0.00011149379387497902
Epoch: 2 Loss: 0.33475335555931 Val_Loss: 0.00020087575912475586
Epoch: 3 Loss: 0.25862170539046975 Val_Loss: 0.0005296089589595795
Epoch: 4 Loss: 0.190677157099624 Val_Loss: 0.0001693984378071036
Epoch: 5 Loss: 0.15163088443849942 Val_Loss: 2.4187059607356785e-07
Epoch: 6 Loss: 0.1265160101849321 Val_Loss: 1.1801024810864647e-08
Epoch: 7 Loss: 0.11237314078307879 Val_Loss: 2.801398568408331e-09
Epoch: 8 Loss: 0.10201299918591994 Val_Loss: 6.668312940746546e-07
Epoch: 9 Loss: 0.09792410799153581 Val_Loss: 1.558509894821327e-05
Epoch: 10 Loss: 0.0941891972631892 Val_Loss: 1.9588666036725045e-07
```

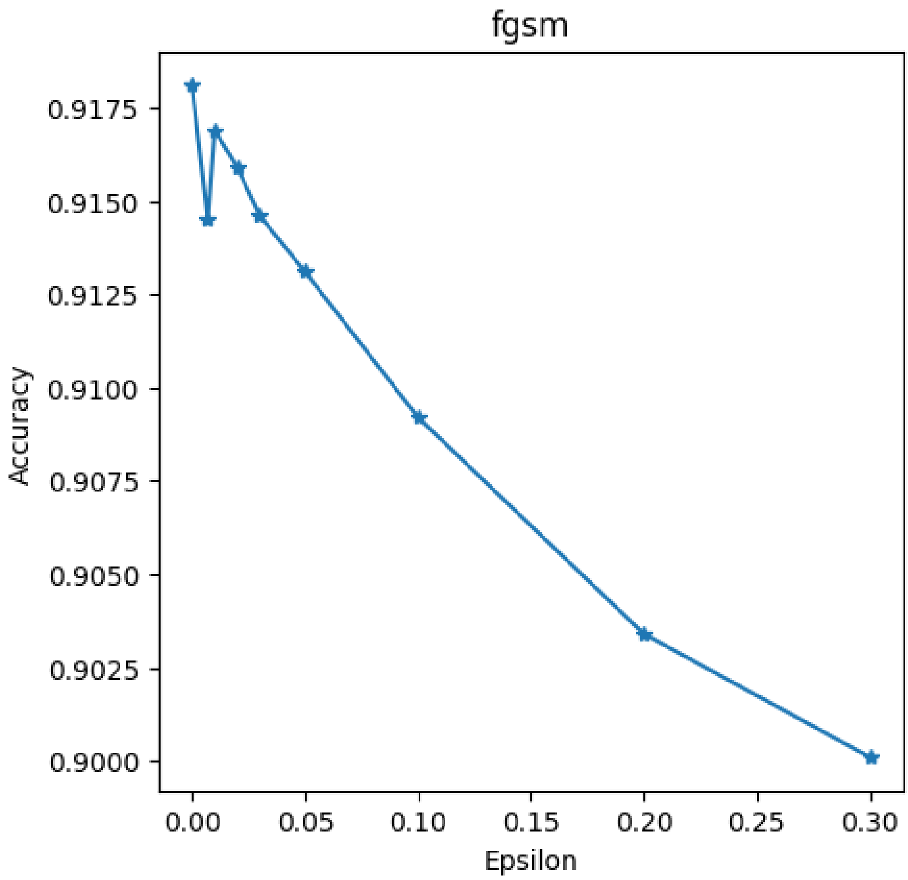



```
Fitting the model...
Epoch: 1 Loss: 0.7119057472861273 Val_Loss: 0.00015477910935878753
Epoch: 2 Loss: 0.47526786822583317 Val_Loss: 1.474692989140749e-05
Epoch: 3 Loss: 0.42827975793901213 Val_Loss: 2.931312449800316e-06
Epoch: 4 Loss: 0.3929323631814547 Val_Loss: 8.954685032367706e-05
Epoch: 5 Loss: 0.3537366056917966 Val_Loss: 3.729340583086014e-05
Epoch: 6 Loss: 0.3075665797859794 Val_Loss: 0.0013252342419698834
Epoch: 7 Loss: 0.2648324794200162 Val_Loss: 2.7755777118727567e-07
Epoch: 8 Loss: 0.2337261026564832 Val_Loss: 1.949940137565136e-05
Epoch: 9 Loss: 0.21211580473073624 Val_Loss: 1.9940164024592376e-05
Epoch: 10 Loss: 0.19684954207914504 Val_Loss: 1.1350713593856199e-07
```



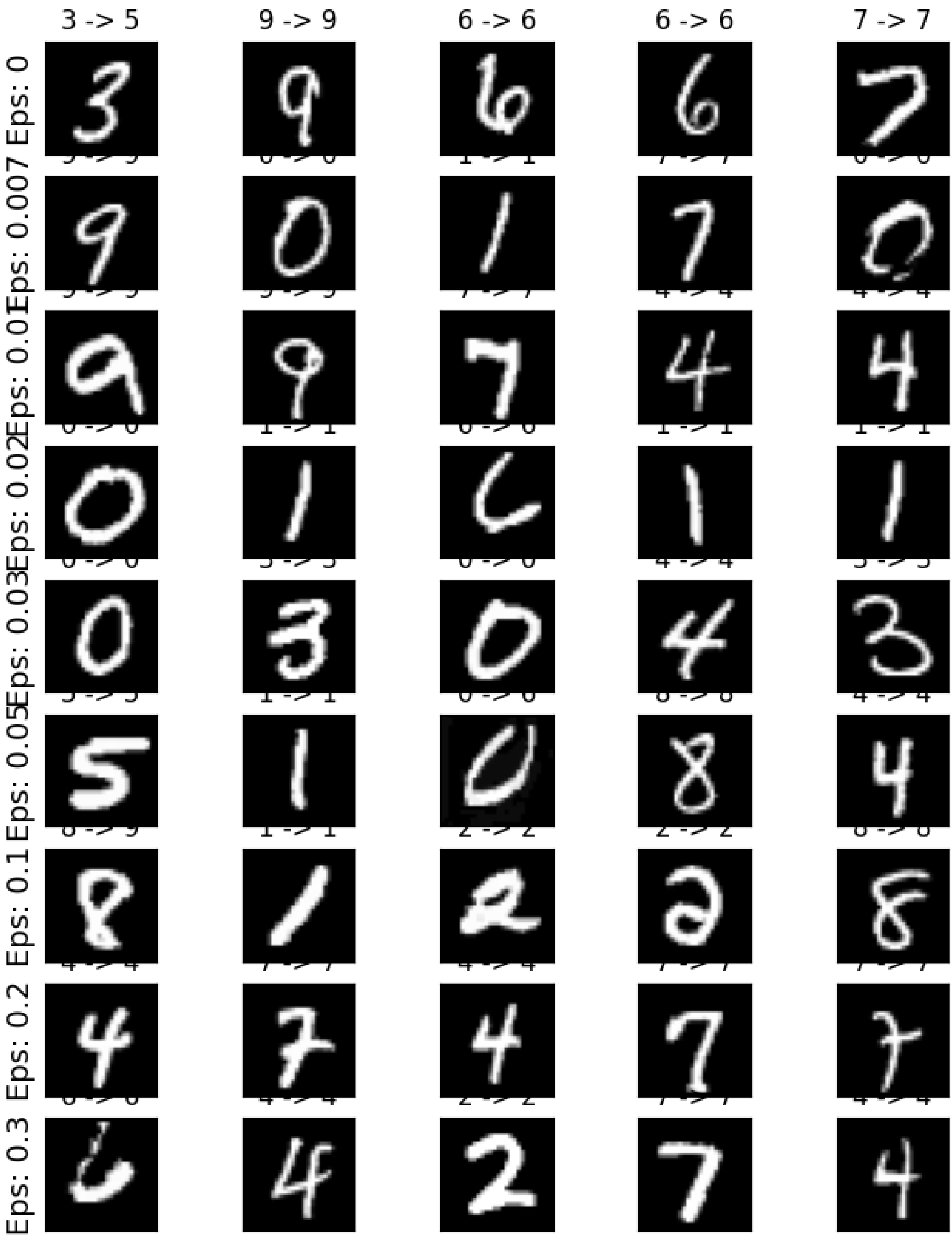


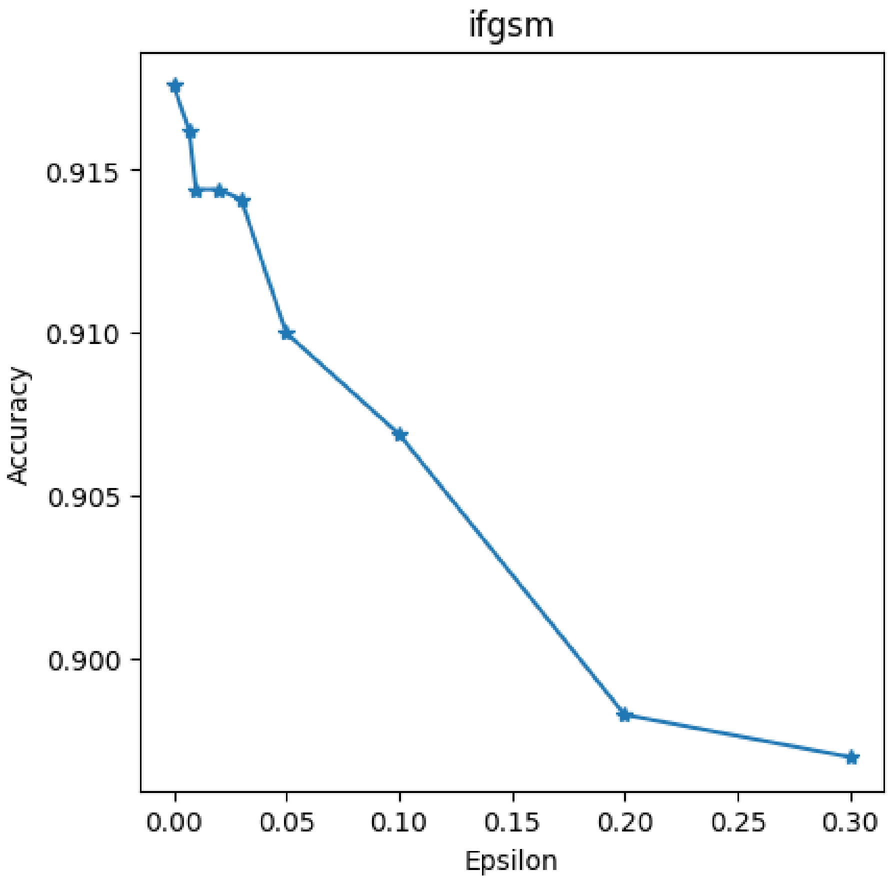

```
Epsilon: 0      Test Accuracy = 9181 / 10000 = 0.9181
Epsilon: 0.007  Test Accuracy = 9145 / 10000 = 0.9145
Epsilon: 0.01   Test Accuracy = 9169 / 10000 = 0.9169
Epsilon: 0.02   Test Accuracy = 9159 / 10000 = 0.9159
Epsilon: 0.03   Test Accuracy = 9146 / 10000 = 0.9146
Epsilon: 0.05   Test Accuracy = 9131 / 10000 = 0.9131
Epsilon: 0.1    Test Accuracy = 9092 / 10000 = 0.9092
Epsilon: 0.2    Test Accuracy = 9034 / 10000 = 0.9034
Epsilon: 0.3    Test Accuracy = 9001 / 10000 = 0.9001
```



Epsilon

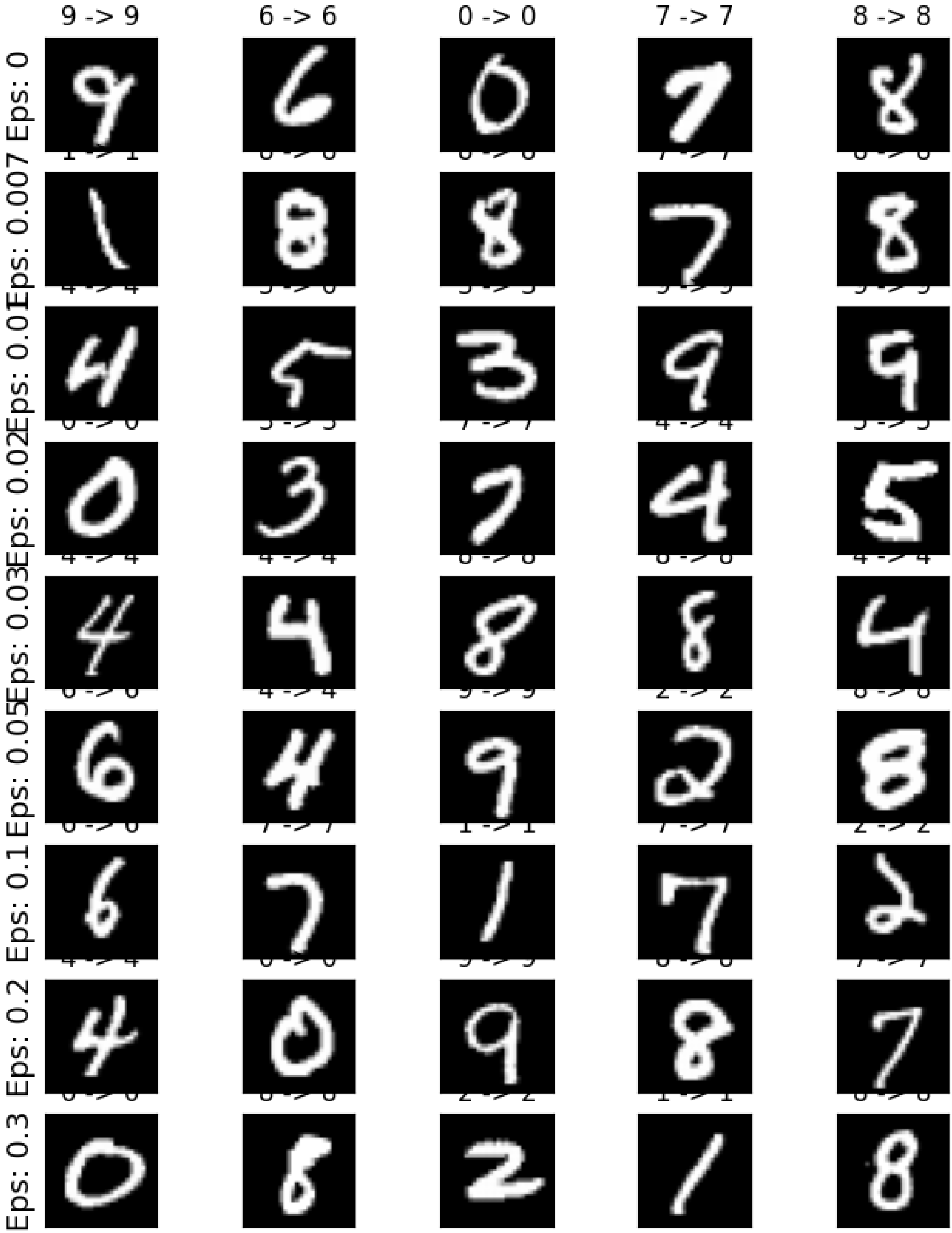
```
Epsilon: 0      Test Accuracy = 9176 / 10000 = 0.9176
Epsilon: 0.007  Test Accuracy = 9162 / 10000 = 0.9162
Epsilon: 0.01   Test Accuracy = 9144 / 10000 = 0.9144
Epsilon: 0.02   Test Accuracy = 9144 / 10000 = 0.9144
Epsilon: 0.03   Test Accuracy = 9141 / 10000 = 0.9141
Epsilon: 0.05   Test Accuracy = 9100 / 10000 = 0.91
Epsilon: 0.1    Test Accuracy = 9069 / 10000 = 0.9069
Epsilon: 0.2    Test Accuracy = 8983 / 10000 = 0.8983
Epsilon: 0.3    Test Accuracy = 8970 / 10000 = 0.897
```


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

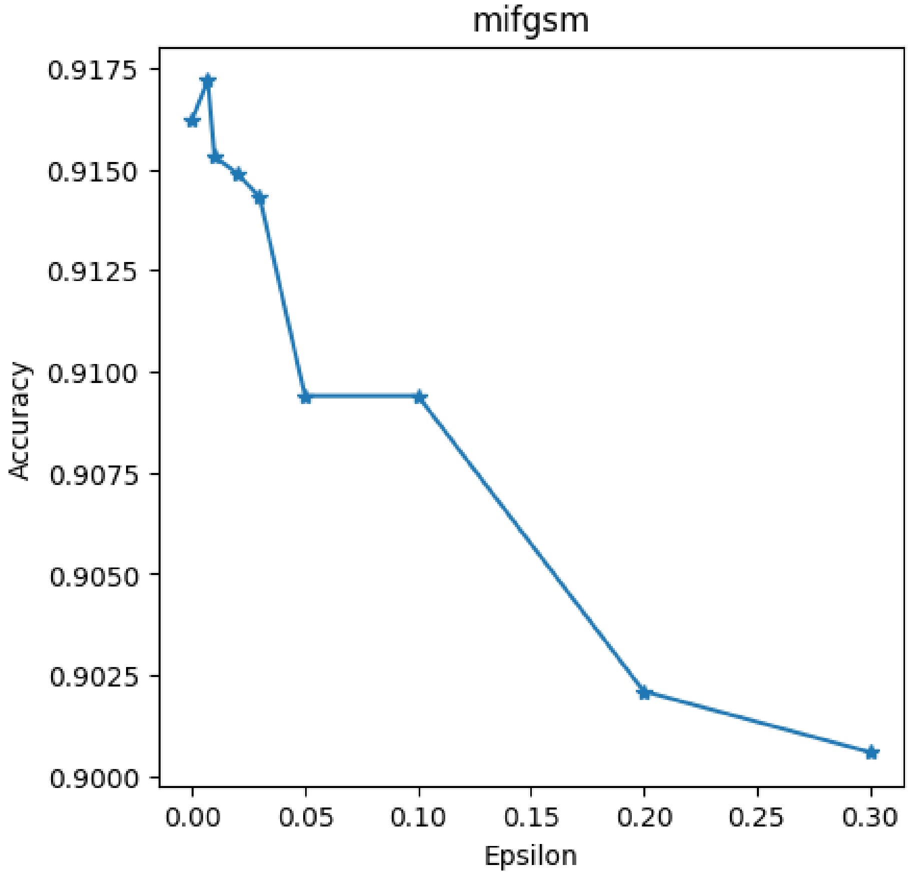


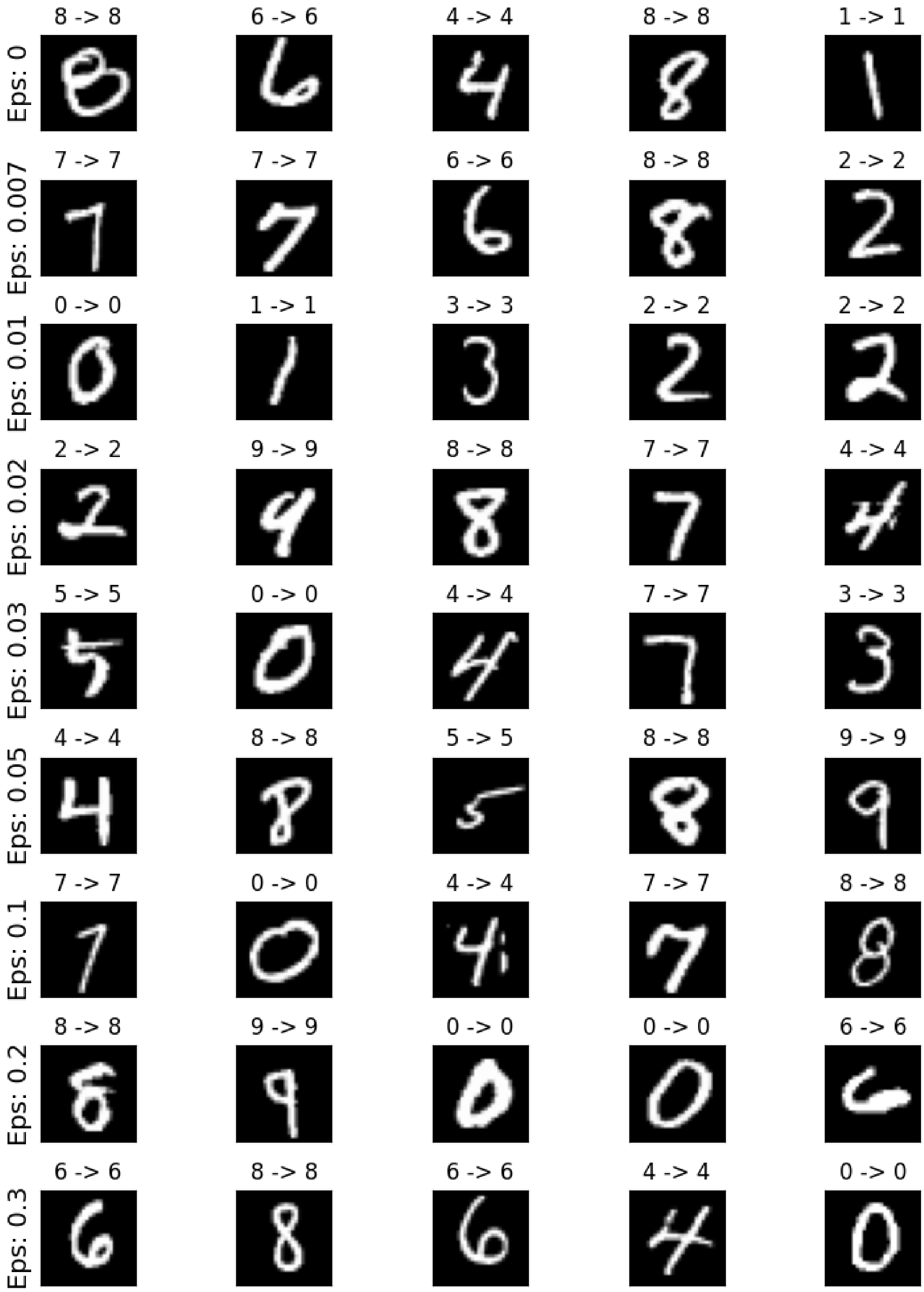
Epsilon

```
Epsilon: 0      Test Accuracy = 9162 / 10000 = 0.9162
Epsilon: 0.007  Test Accuracy = 9172 / 10000 = 0.9172
Epsilon: 0.01   Test Accuracy = 9153 / 10000 = 0.9153
Epsilon: 0.02   Test Accuracy = 9149 / 10000 = 0.9149
Epsilon: 0.03   Test Accuracy = 9143 / 10000 = 0.9143
Epsilon: 0.05   Test Accuracy = 9094 / 10000 = 0.9094
Epsilon: 0.1    Test Accuracy = 9094 / 10000 = 0.9094
Epsilon: 0.2    Test Accuracy = 9021 / 10000 = 0.9021
Epsilon: 0.3    Test Accuracy = 9006 / 10000 = 0.9006
```



9 -> 9
6 -> 6
0 -> 0
7 -> 7
8 -> 8
Eps: 0
Eps: 0.007
Eps: 0.01
Eps: 0.02
Eps: 0.03
Eps: 0.05
Eps: 0.1
Eps: 0.2
Eps: 0.3


mifgsm
0.9175
0.9150
0.9125
0.9100
0.9075
0.9050
0.9025
0.9000
Accuracy
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Epsilon



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

17. Сделать выводы по полученным результатам, оценить стойкость предложенного способа защиты моделей НС

Защитная дистилляция (Defensive Distillation) является методом защиты модели машинного обучения от атак, основанных на использовании обратных атак или атак переноса. Этот метод был предложен в 2016 году Филемми Шайи и Юрием Янгом.

Основная идея защитной дистилляции заключается в повторном обучении модели с использованием двух процессов: дистилляции и обучения защитного классификатора.

В процессе дистилляции:

1. Исходная модель, называемая учителем, обучается на исходных данных.

2. Затем полученные предсказания учителя используются для учебника, построенного на основе этих предсказаний. Учебник является более компактной и менее сложной моделью, называемой учеником.

3. Ученик затем обучается всему набору данных с учителем, используя предсказания учителя в качестве дополнительной информации.

В процессе обучения защитного классификатора:

1. Используется учебник, полученный из первого шага дистилляции, а также оригинальный набор данных исходной модели.

2. Защитный классификатор обучается на этом наборе данных, используя учебник как дополнительный вход для повышения устойчивости модели к атакам.

Цель защитной дистилляции заключается в том, чтобы сделать модель более устойчивой к атакам, например, к обратному инжинирингу или к атакам переноса, обеспечивая стройную и компактную модель, которая может сохранить высокую производительность.

Итог по увеличению стойкости модели:

атака fgsm снизила точность для обычной модели до - 22%, для защищенной - до - 90%;

атака ifgsm снизила точность не защищенных данных до - 25%, защищенных - до - 90%; атака

mifgsm снизила точность не защищенных данных до - 24%, защищенных - до - 90%.