МИНОБРНАУКИ РОССИИ

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«МИРЭА – Российский технологический университет»
РТУ МИРЭА

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Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Отчет по Практическйо работе №6 и Лабораторной работе №4

по дисциплине: «Анализ защищенности систем искусственного интеллекта»

На тему: «Изучение методов защиты от атак на модели НС»

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Цель работы

Провести серию атак на НС, после чего реализовать функцию защиты и сделать выводу по полученному результату, оценив стойкость предложенного способа защиты.

Ход работы:

1. Импортируем необходимые библиотеки:

```
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. Задаем нормализующие преобразования, загружаем нбор данных и разбиваем данные на подвыборки:

```
[2] 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, 82111399.50it/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, 89465061.91it/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, 31326511.98it/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, 21821911.53it/s]Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw


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

3. Настраиваем использование графического ускорителя:

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

Создание атак на модель НС

1. Создаем класс НС на основе 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.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
```

2. Проверка работоспособности созданного класса НС:

```
[5] model = Net().to(device)
```

3. 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)
```

4. Определим функцию обучения сети:

```python
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
```

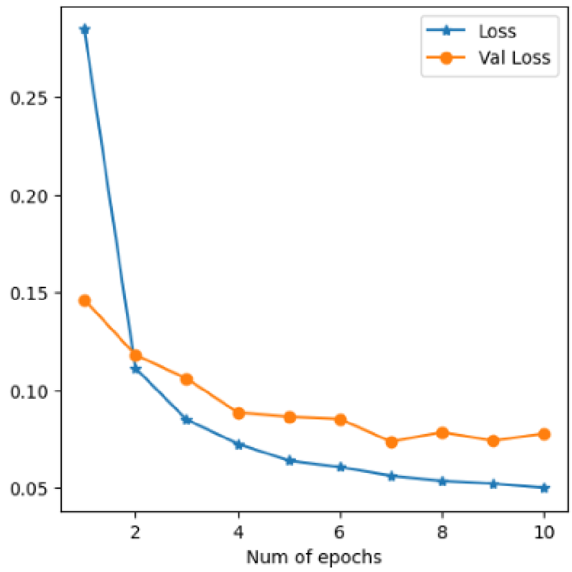
5. Обучим модель:

```python
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 ar
  warnings.warn(warn_msg)
Epoch: 1 Loss: 0.2850503676612788 Val_Loss: 0.1465472458492094
Epoch: 2 Loss: 0.11141908125931078 Val_Loss: 0.11816810167795906
Epoch: 3 Loss: 0.08508949297238538 Val_Loss: 0.10610676416118986
Epoch: 4 Loss: 0.07273402502575843 Val_Loss: 0.08871200382142519
Epoch: 5 Loss: 0.0640585860067484 Val_Loss: 0.08652106153088714
Epoch: 6 Loss: 0.0607716777421671 Val_Loss: 0.08539433175660129
Epoch: 7 Loss: 0.0562644432195245 Val_Loss: 0.07379816616976491
Epoch: 8 Loss: 0.053677760184325574 Val_Loss: 0.07861828822329812
Epoch: 9 Loss: 0.052243182574612974 Val_Loss: 0.07426569758173895
Epoch: 10 Loss: 0.050123429469401834 Val_Loss: 0.07791693960269636
```

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

```python
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()
```



7. Создаем 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
```

```
[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
```

8. Создаем функцию проверки:

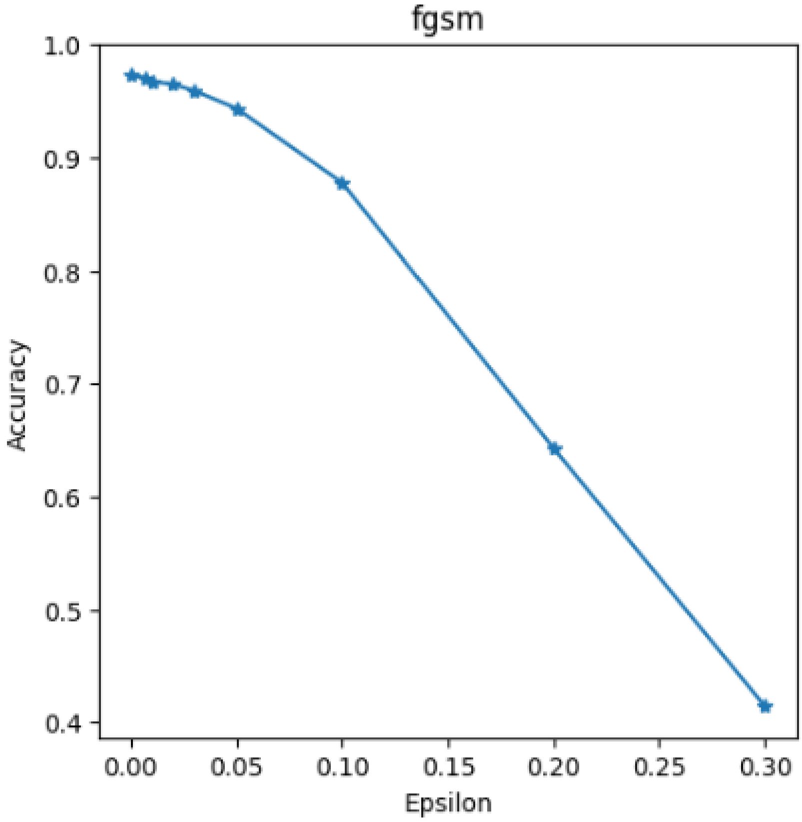
```python
def test(model,device,test_loader,epsilon,attack):
  correct = 0
  adv_examples = []
  for data, target in test_loader:
    data, target = data.to(device), target.to(device)
    data.requires_grad = True
    output = model(data)
    init_pred = output.max(1, keepdim=True)[1]
    if init_pred.item()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

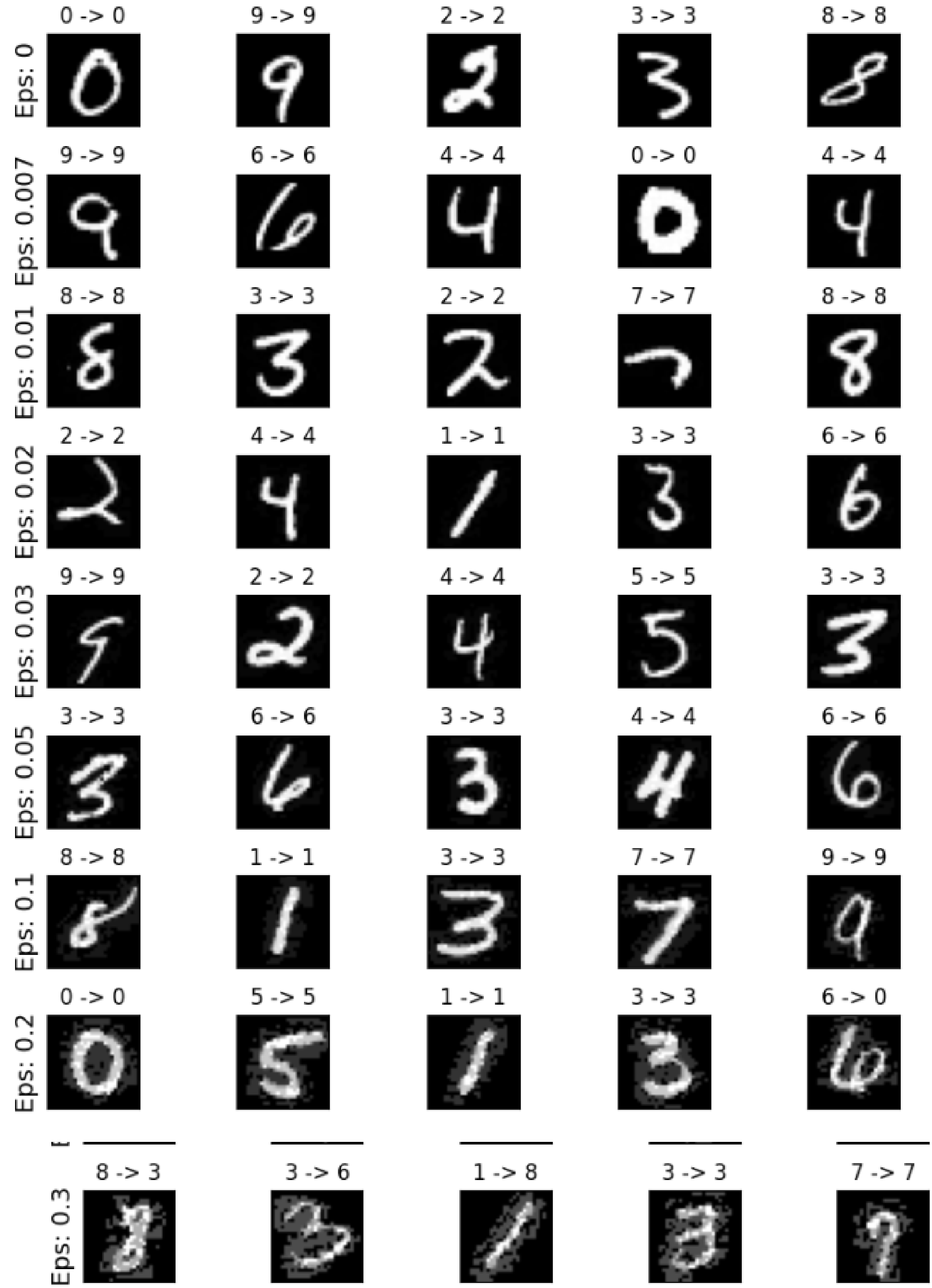
9. Построим графики успешности атак и примеры выполненных атак в зависимости от степени возмущения epsilon:

16 мин.

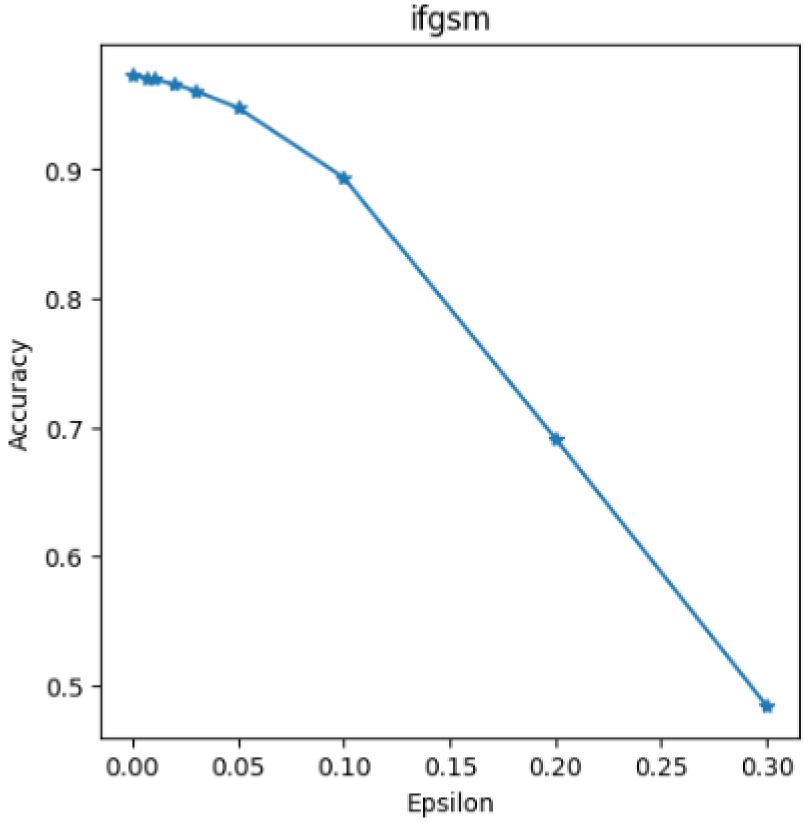
```
epsilons = [0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
for attack in ("fgsm","ifgsm","mifgsm"):
  accuracies = []
  examples = []
  for eps in epsilons:
    acc, ex = test(model, device,test_loader,eps,attack)
    accuracies.append(acc)
    examples.append(ex)
  plt.figure(figsize=(5,5))
  plt.plot(epsilons, 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()
```

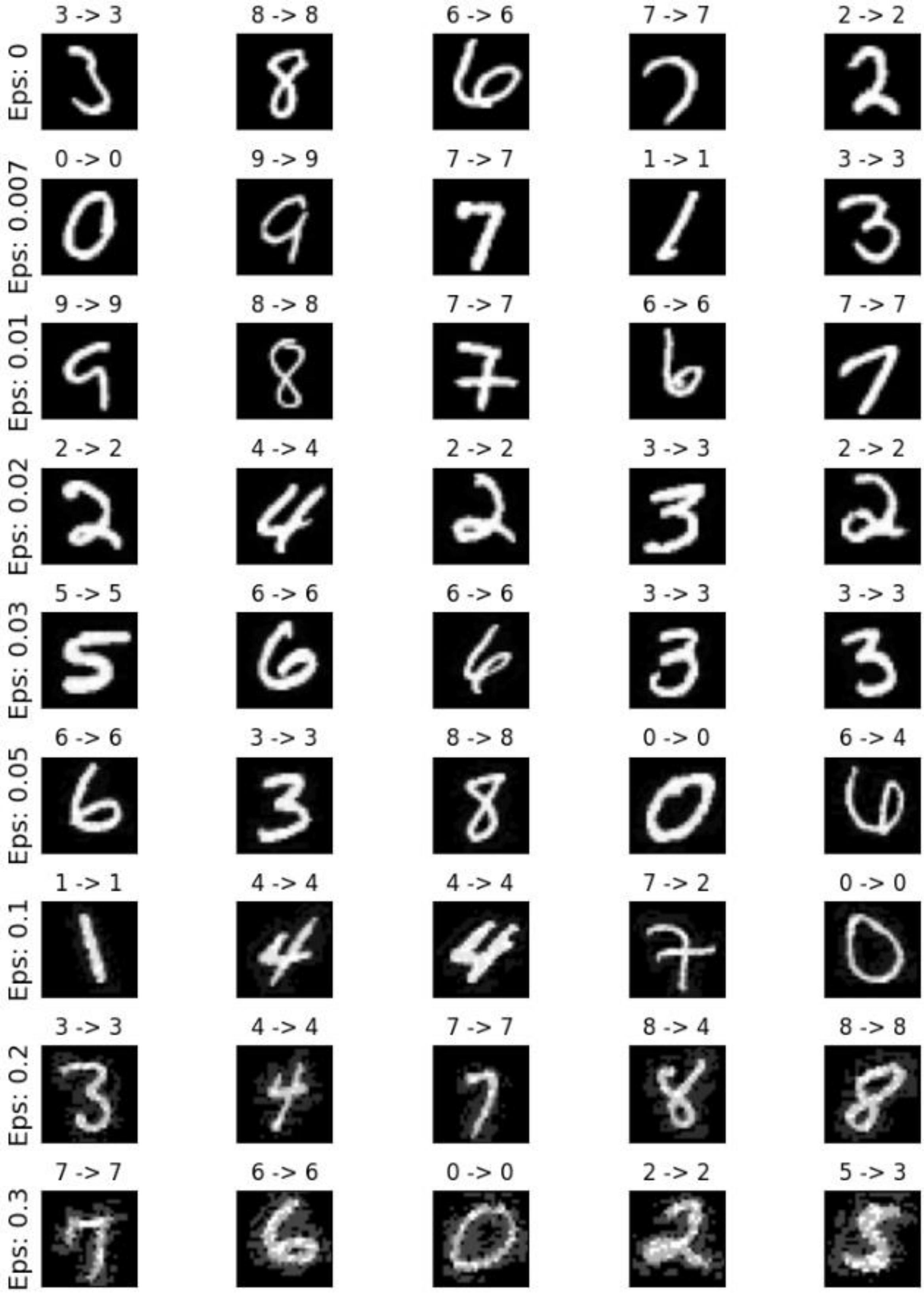
```
Epsilon: 0      Test Accuracy = 9730 / 10000 = 0.973
Epsilon: 0.007  Test Accuracy = 9706 / 10000 = 0.9706
Epsilon: 0.01   Test Accuracy = 9674 / 10000 = 0.9674
Epsilon: 0.02   Test Accuracy = 9650 / 10000 = 0.965
Epsilon: 0.03   Test Accuracy = 9592 / 10000 = 0.9592
Epsilon: 0.05   Test Accuracy = 9436 / 10000 = 0.9436
Epsilon: 0.1    Test Accuracy = 8778 / 10000 = 0.8778
Epsilon: 0.2    Test Accuracy = 6428 / 10000 = 0.6428
Epsilon: 0.3    Test Accuracy = 4143 / 10000 = 0.4143
```



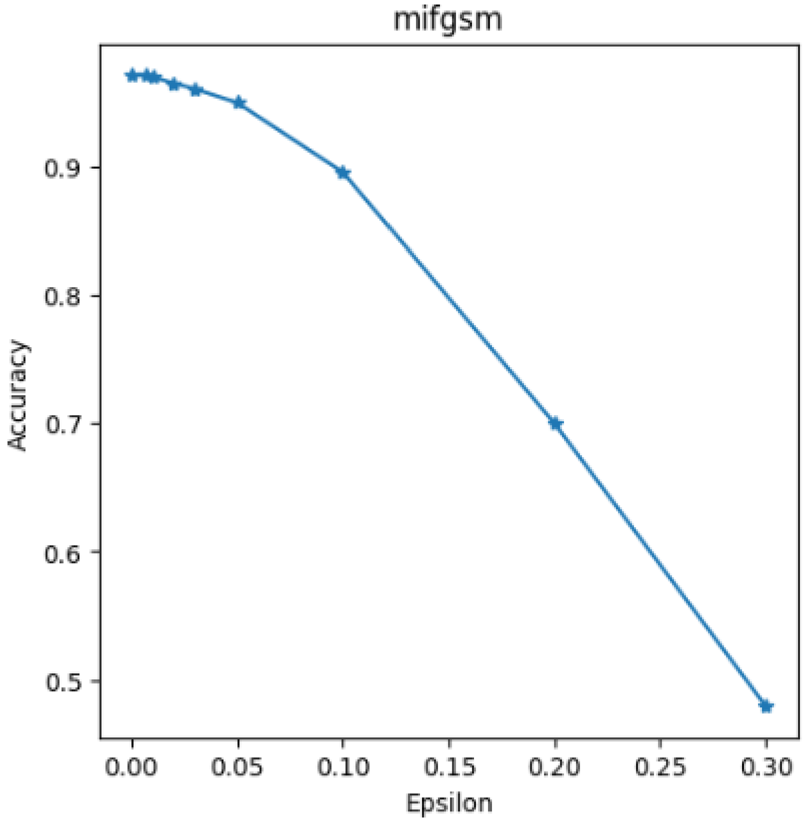

Eps: 0
0 -> 0
9 -> 9
2 -> 2
3 -> 3
8 -> 8
Eps: 0.007
9 -> 9
6 -> 6
4 -> 4
0 -> 0
4 -> 4
Eps: 0.01
8 -> 8
3 -> 3
2 -> 2
7 -> 7
8 -> 8
Eps: 0.02
2 -> 2
4 -> 4
1 -> 1
3 -> 3
6 -> 6
Eps: 0.03
9 -> 9
2 -> 2
4 -> 4
5 -> 5
3 -> 3
Eps: 0.05
3 -> 3
6 -> 6
3 -> 3
4 -> 4
6 -> 6
Eps: 0.1
8 -> 8
1 -> 1
3 -> 3
7 ->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

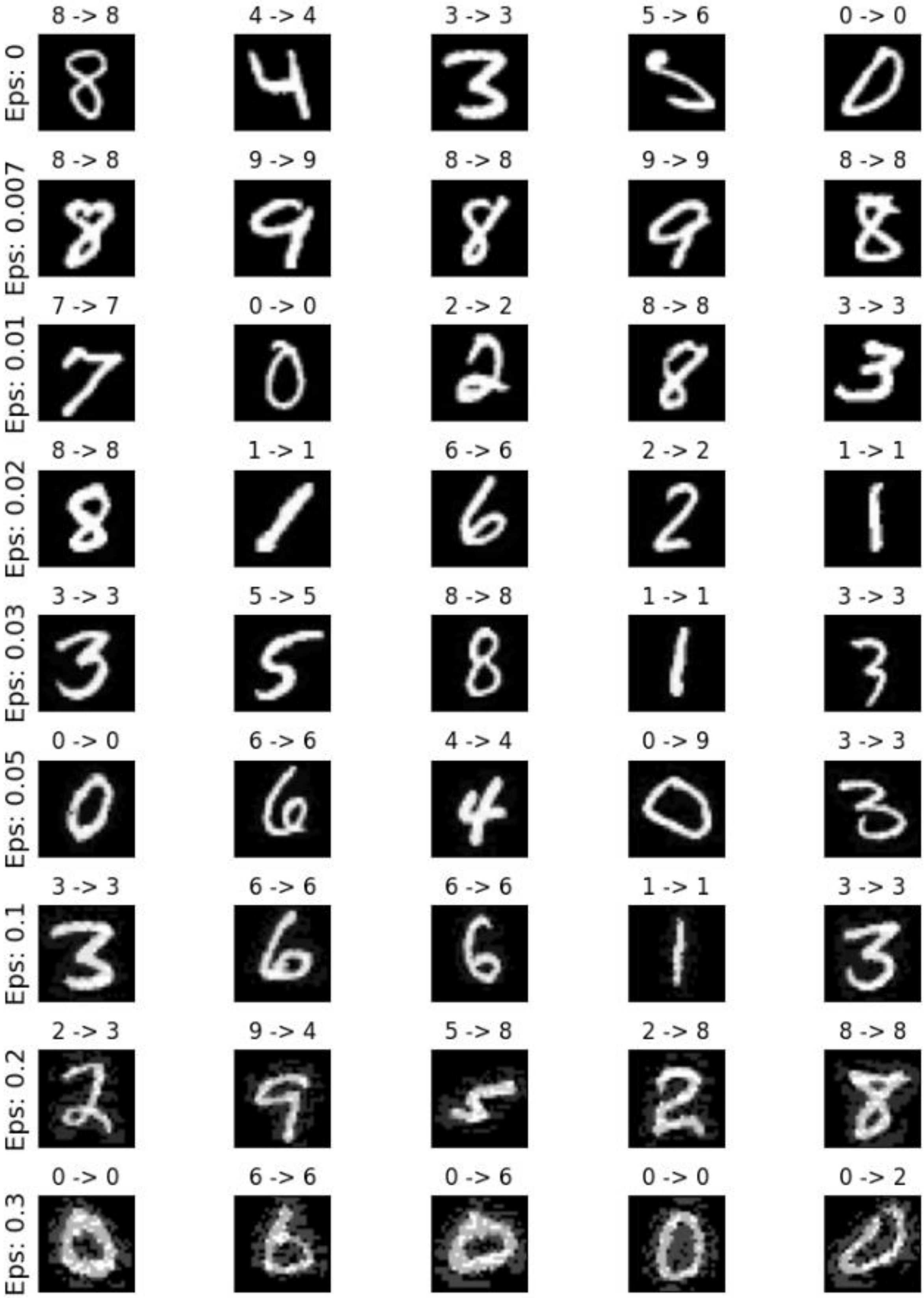
```
Epsilon: 0      Test Accuracy = 9729 / 10000 = 0.9729
Epsilon: 0.007  Test Accuracy = 9709 / 10000 = 0.9709
Epsilon: 0.01   Test Accuracy = 9699 / 10000 = 0.9699
Epsilon: 0.02   Test Accuracy = 9659 / 10000 = 0.9659
Epsilon: 0.03   Test Accuracy = 9606 / 10000 = 0.9606
Epsilon: 0.05   Test Accuracy = 9477 / 10000 = 0.9477
Epsilon: 0.1    Test Accuracy = 8936 / 10000 = 0.8936
Epsilon: 0.2    Test Accuracy = 6912 / 10000 = 0.6912
Epsilon: 0.3    Test Accuracy = 4839 / 10000 = 0.4839
```




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

```
Epsilon: 0      Test Accuracy = 9708 / 10000 = 0.9708
Epsilon: 0.007  Test Accuracy = 9706 / 10000 = 0.9706
Epsilon: 0.01   Test Accuracy = 9694 / 10000 = 0.9694
Epsilon: 0.02   Test Accuracy = 9646 / 10000 = 0.9646
Epsilon: 0.03   Test Accuracy = 9601 / 10000 = 0.9601
Epsilon: 0.05   Test Accuracy = 9494 / 10000 = 0.9494
Epsilon: 0.1    Test Accuracy = 8953 / 10000 = 0.8953
Epsilon: 0.2    Test Accuracy = 6999 / 10000 = 0.6999
Epsilon: 0.3    Test Accuracy = 4797 / 10000 = 0.4797
```





Защита от атак

1. Создаем 2 класса НС

```python
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
```

[16]
```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
```

2. Переопределяем функцию обучения и тестирования:

```
[17] 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
```

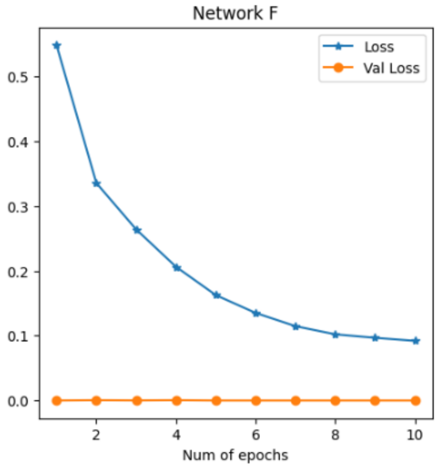
3. Создаем функцию защиты методом дистиляции:

```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,"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()
```

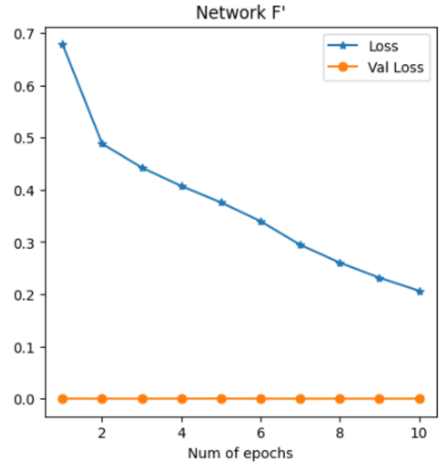
4. Получаем результаты оценки защиты сетей:

```python
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)
```

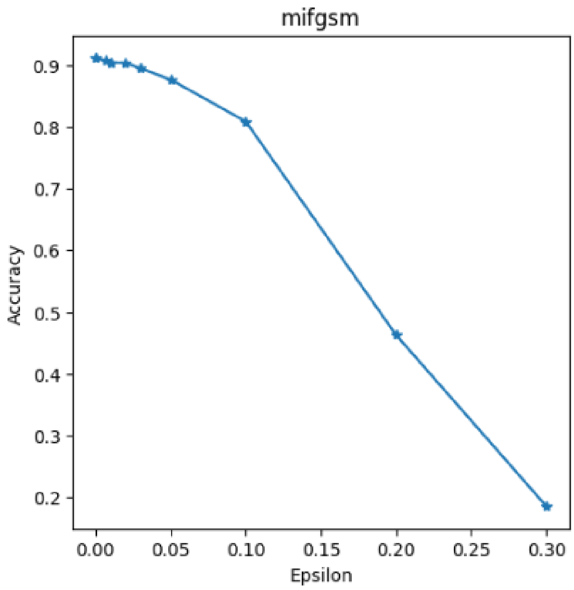
```
Fitting the model...
Epoch: 1 Loss: 0.5481338738800597 Val_Loss: 1.003228621557355e-05
Epoch: 2 Loss: 0.3353229173747994 Val_Loss: 0.00045950331687927244
Epoch: 3 Loss: 0.26381421273058636 Val_Loss: 0.00011647366284596501
Epoch: 4 Loss: 0.2061726351569701 Val_Loss: 0.00046973809078335765
Epoch: 5 Loss: 0.16251364960605083 Val_Loss: 4.2924879031488676e-06
Epoch: 6 Loss: 0.13502419098830928 Val_Loss: 1.265520486049354e-06
Epoch: 7 Loss: 0.11464148852530506 Val_Loss: 1.9935742660891264e-06
Epoch: 8 Loss: 0.10202881376955898 Val_Loss: 8.956958248745651e-06
Epoch: 9 Loss: 0.09666660607148457 Val_Loss: 1.391292948028422e-07
Epoch: 10 Loss: 0.09198299259128082 Val_Loss: 2.5270764308515935e-08
```

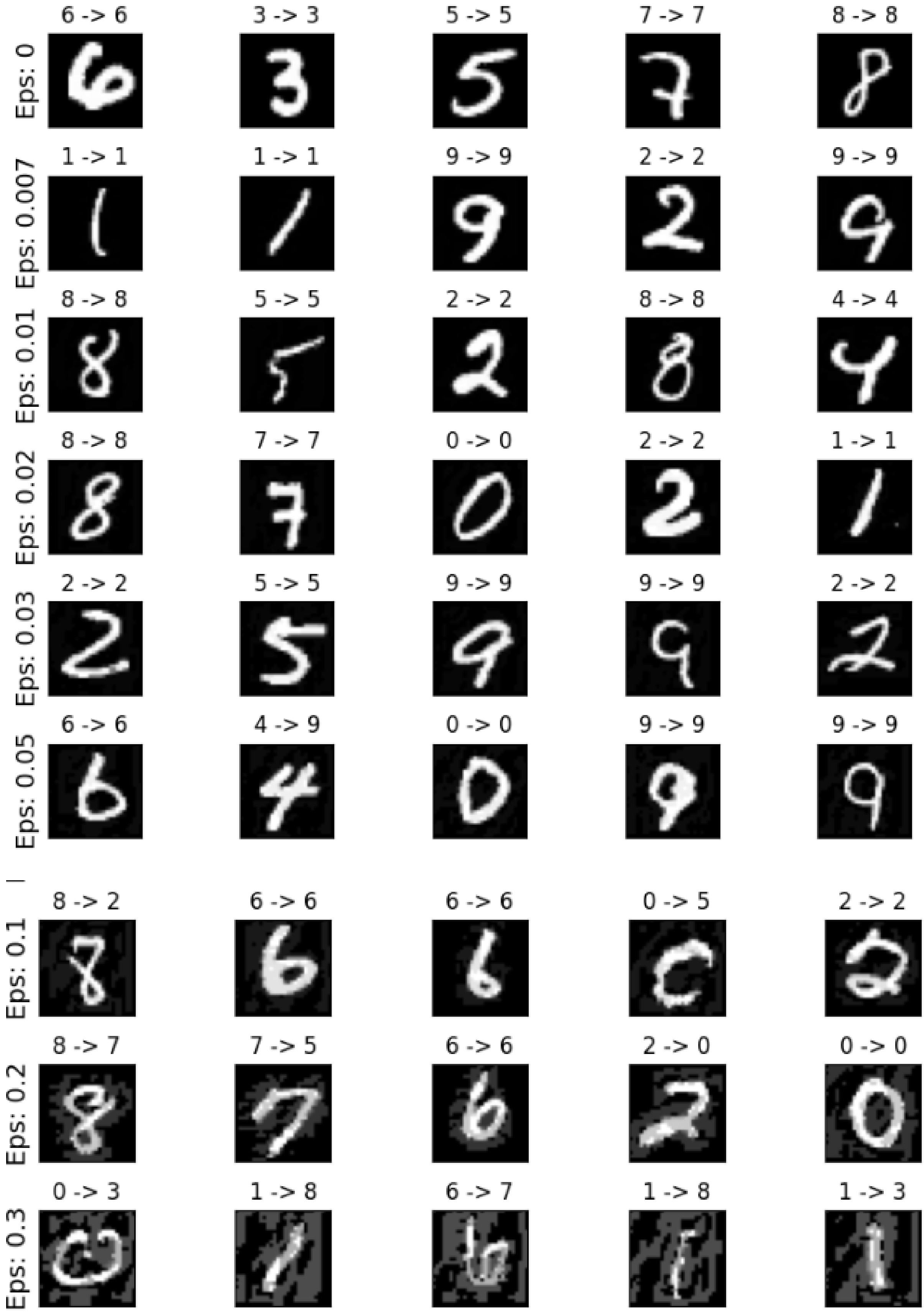



```
Fitting the model...
Epoch: 1 Loss: 0.6784468315404466 Val_Loss: 7.445180974900722e-05
Epoch: 2 Loss: 0.4882124064700297 Val_Loss: 1.9082169979810715e-05
Epoch: 3 Loss: 0.4424660353774885 Val_Loss: 1.618420109152794e-05
Epoch: 4 Loss: 0.40715175550074595 Val_Loss: 6.557496637105942e-05
Epoch: 5 Loss: 0.3757558067303607 Val_Loss: 0.00021618845984339714
Epoch: 6 Loss: 0.3397686602646741 Val_Loss: 2.1136321491212584e-05
Epoch: 7 Loss: 0.2946280665979756 Val_Loss: 7.914992245787288e-06
Epoch: 8 Loss: 0.260406978453543 Val_Loss: 2.318001270759850e-06
Epoch: 9 Loss: 0.23156262885010914 Val_Loss: 2.070512989848794e-06
Epoch: 10 Loss: 0.20667021672648633 Val_Loss: 1.3112946021465177e-09
```




```
Epsilon: 0      Test Accuracy = 9119 / 10000 = 0.9119
Epsilon: 0.007  Test Accuracy = 9147 / 10000 = 0.9147
Epsilon: 0.01   Test Accuracy = 9026 / 10000 = 0.9026
Epsilon: 0.02   Test Accuracy = 9036 / 10000 = 0.9036
Epsilon: 0.03   Test Accuracy = 8931 / 10000 = 0.8931
Epsilon: 0.05   Test Accuracy = 8782 / 10000 = 0.8782
Epsilon: 0.1    Test Accuracy = 8024 / 10000 = 0.8024
Epsilon: 0.2    Test Accuracy = 4639 / 10000 = 0.4639
Epsilon: 0.3    Test Accuracy = 1817 / 10000 = 0.1817
Epsilon: 0      Test Accuracy = 9119 / 10000 = 0.9119
Epsilon: 0.007  Test Accuracy = 9063 / 10000 = 0.9063
Epsilon: 0.01   Test Accuracy = 9114 / 10000 = 0.9114
Epsilon: 0.02   Test Accuracy = 8996 / 10000 = 0.8996
Epsilon: 0.03   Test Accuracy = 8926 / 10000 = 0.8926
Epsilon: 0.05   Test Accuracy = 8778 / 10000 = 0.8778
Epsilon: 0.1    Test Accuracy = 7991 / 10000 = 0.7991
Epsilon: 0.2    Test Accuracy = 4662 / 10000 = 0.4662
Epsilon: 0.3    Test Accuracy = 1852 / 10000 = 0.1852
Epsilon: 0      Test Accuracy = 9113 / 10000 = 0.9113
Epsilon: 0.007  Test Accuracy = 9069 / 10000 = 0.9069
Epsilon: 0.01   Test Accuracy = 9041 / 10000 = 0.9041
Epsilon: 0.02   Test Accuracy = 9033 / 10000 = 0.9033
Epsilon: 0.03   Test Accuracy = 8945 / 10000 = 0.8945
Epsilon: 0.05   Test Accuracy = 8763 / 10000 = 0.8763
Epsilon: 0.1    Test Accuracy = 8084 / 10000 = 0.8084
Epsilon: 0.2    Test Accuracy = 4628 / 10000 = 0.4628
Epsilon: 0.3    Test Accuracy = 1853 / 10000 = 0.1853
```




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

Заключение

В ходе выполнения лабораторной и практической работы были успешно реализованы атаки на защищенные и незащищенные модели НС, показавшие разную эффективность. Способ дистилляционной защиты смог предоставить достаточно высокий уровень безопасности в сравнении с незащищенными моделями. Так, точность оказалась на уровне 91%.