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Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Практическая работа №6

по дисциплине

«Анализ защищенности систем искусственного интеллекта»

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Выполним 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
```

Загрузим набор данных (MNIST), разобьем 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, 106647046.62it/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, 42002667.76it/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, 33851480.89it/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, 17477549.33it/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

```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
```

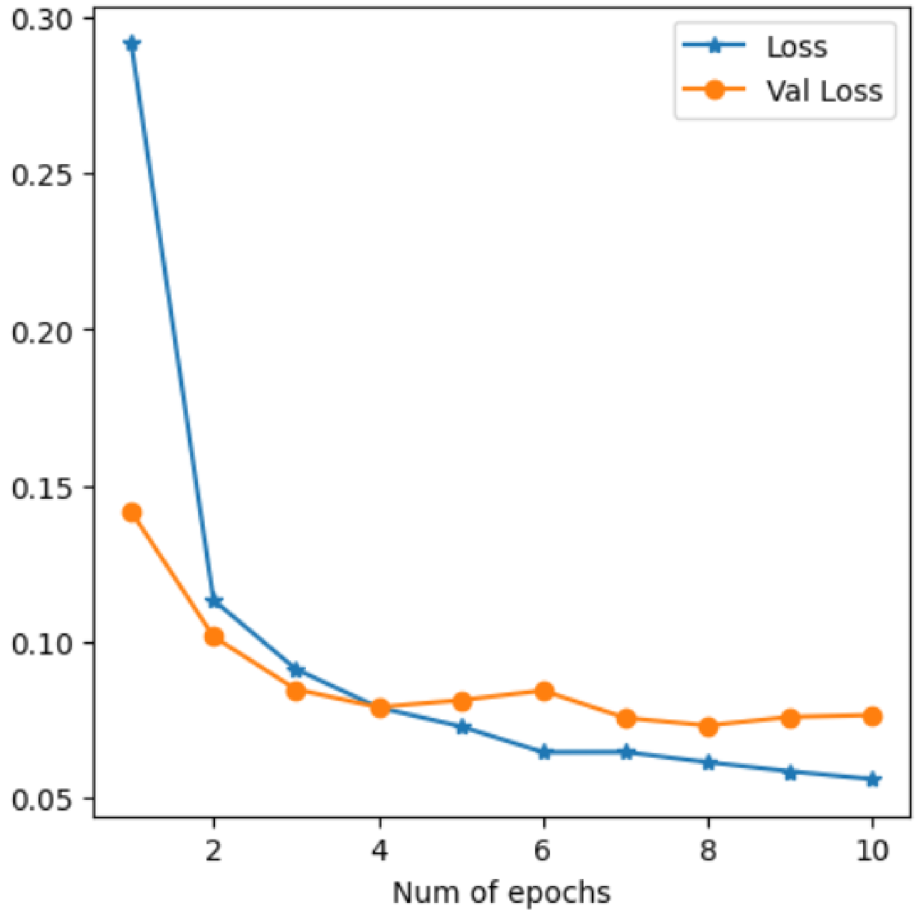
Обучим модель

```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 an error i
  warnings.warn(warn_msg)
Epoch: 1 Loss: 0.29165850282138017 Val_Loss: 0.14174661178974304
Epoch: 2 Loss: 0.1133845992699583 Val_Loss: 0.10169632793162789
Epoch: 3 Loss: 0.09130893708366651 Val_Loss: 0.08483823665866261
Epoch: 4 Loss: 0.0790467975475097 Val_Loss: 0.07914180815385971
Epoch: 5 Loss: 0.07299478122221174 Val_Loss: 0.08137973420264724
Epoch: 6 Loss: 0.06473745620841334 Val_Loss: 0.08442745800929471
Epoch: 7 Loss: 0.064776662380194 Val_Loss: 0.07570525744497564
Epoch: 8 Loss: 0.06151725916071245 Val_Loss: 0.07328030406317827
Epoch: 9 Loss: 0.05859530378177729 Val_Loss: 0.07601816120249275
Epoch: 10 Loss: 0.05611050558511743 Val_Loss: 0.07663759590508828
```

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

```python
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):
  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

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
```

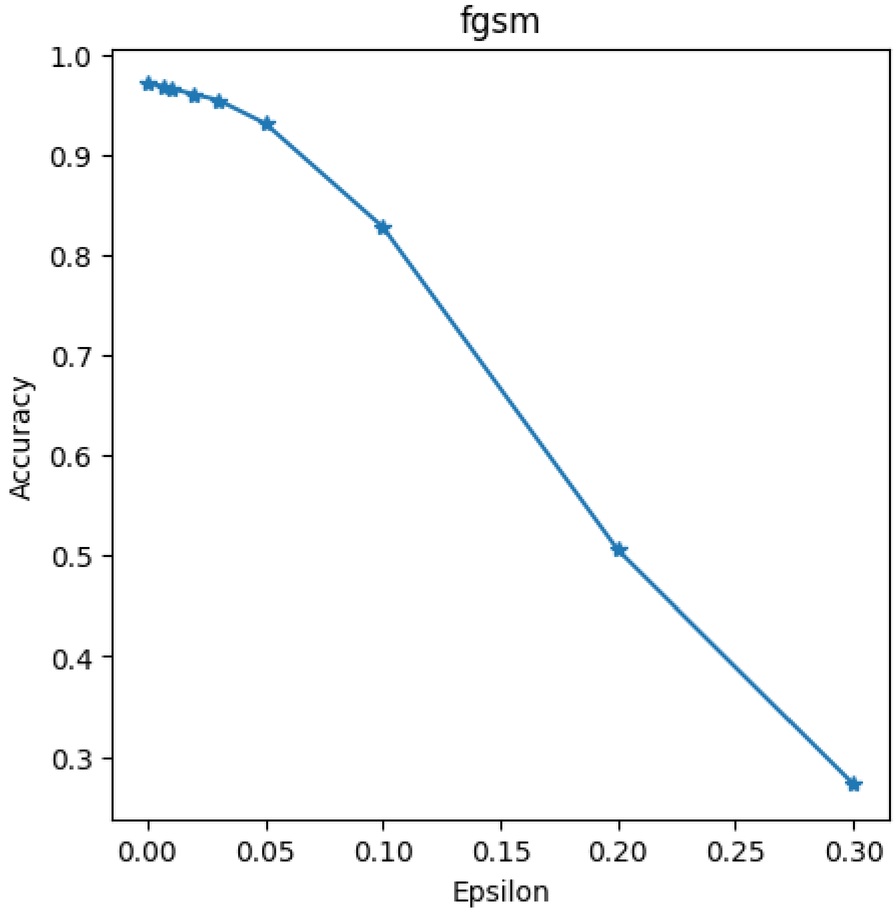
Создадим функцию проверки

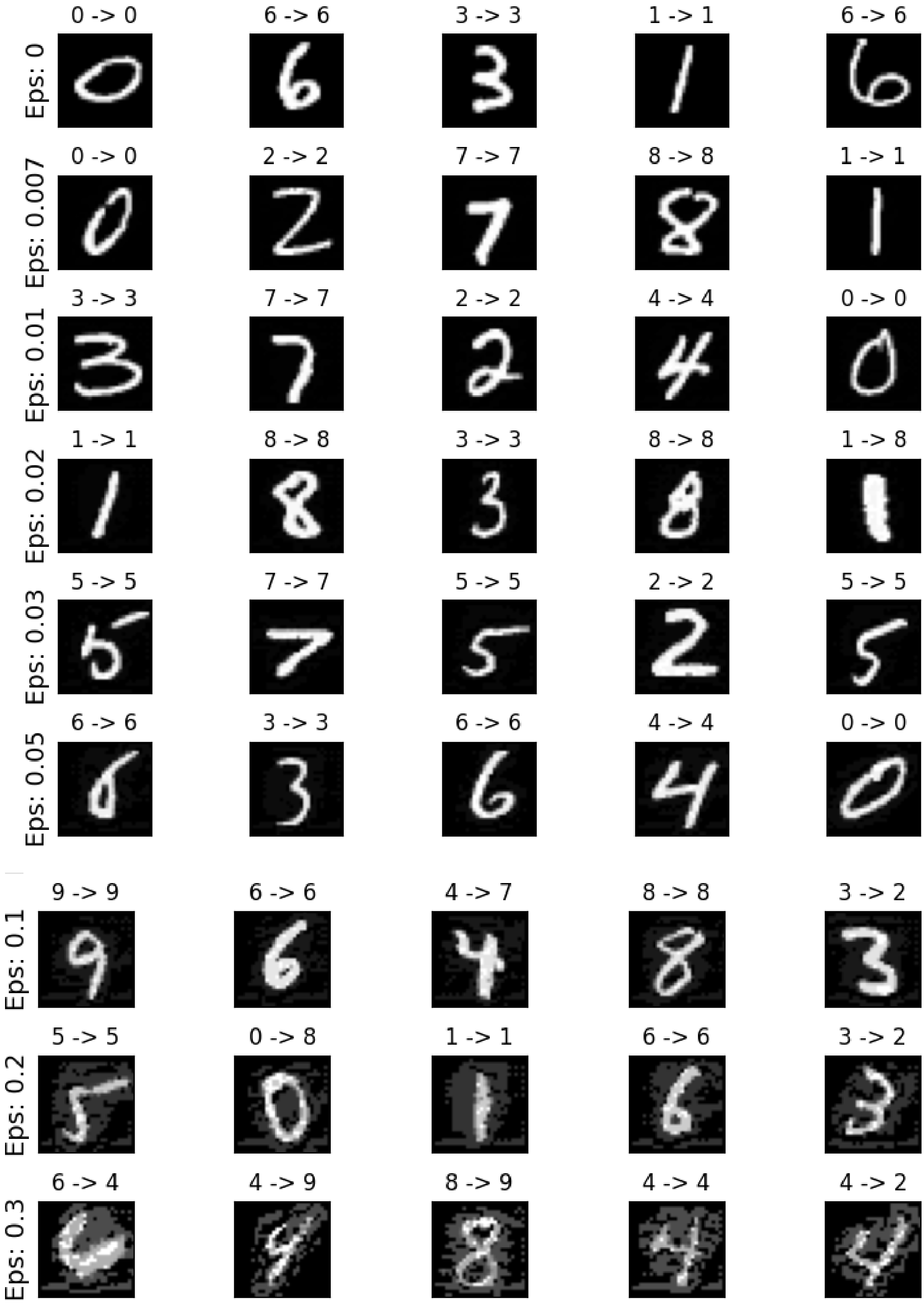
```
[ ] def test(model,device,test_loader,epsilon,attack):
      correct = 0
      adv_examples = []
      for data, target in test_loader:
        data, target = data.to(device), target.to(device)
        data.requires_grad = True
        output = model(data)
        init_pred = output.max(1, keepdim=True)[1]
        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/epsilon) и примеры выполненных атак в зависимости от степени возмущения epsilon

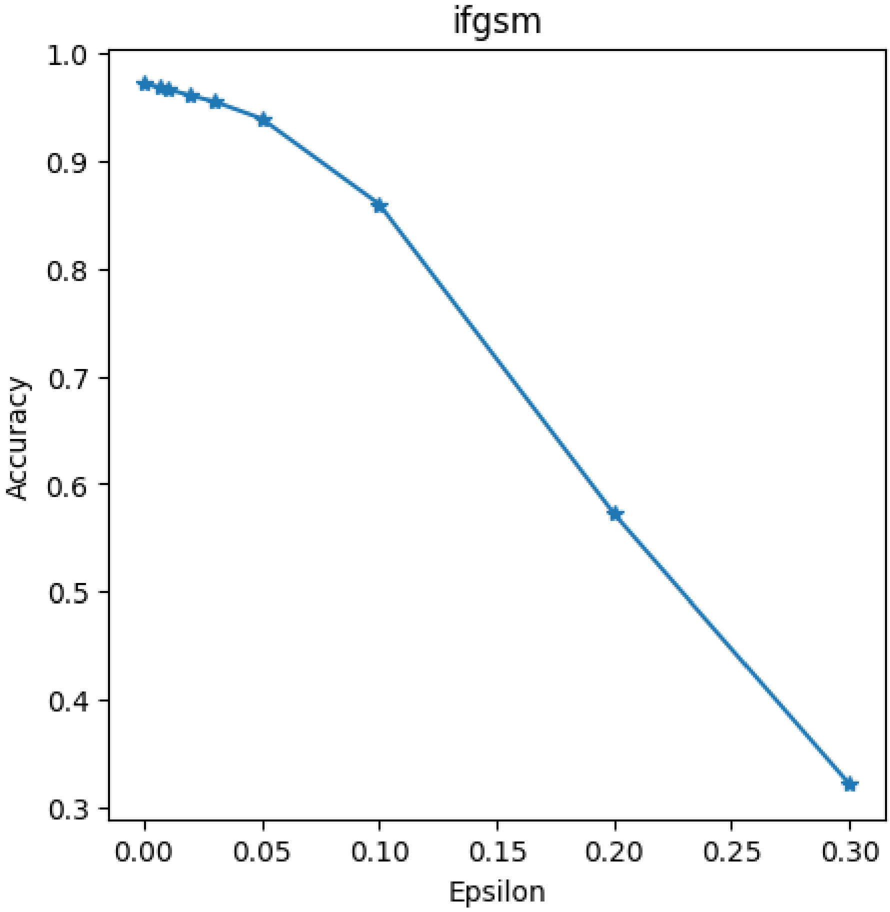
```
[ ]  epsilons = [0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
     for attack in ("fgsm","ifgsm","mifgsm"):
       accuracies = []
       examples = []
       for eps in epsilons:
         acc, ex = test(model, device,test_loader,eps,attack)
         accuracies.append(acc)
         examples.append(ex)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

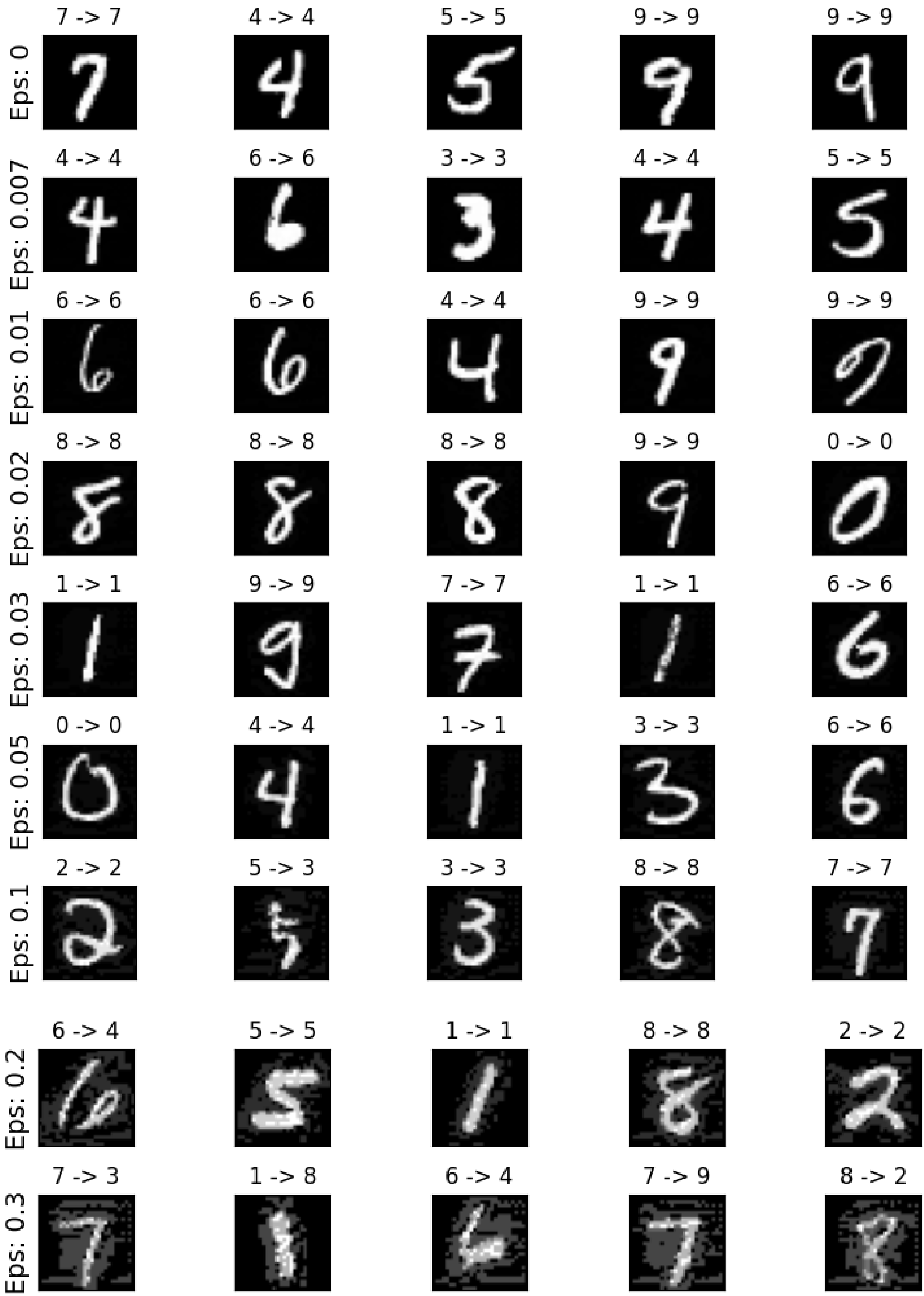
```
Epsilon: 0      Test Accuracy = 9708 / 10000 = 0.9708
Epsilon: 0.007  Test Accuracy = 9682 / 10000 = 0.9682
Epsilon: 0.01   Test Accuracy = 9657 / 10000 = 0.9657
Epsilon: 0.02   Test Accuracy = 9600 / 10000 = 0.96
Epsilon: 0.03   Test Accuracy = 9542 / 10000 = 0.9542
Epsilon: 0.05   Test Accuracy = 9309 / 10000 = 0.9309
Epsilon: 0.1    Test Accuracy = 8277 / 10000 = 0.8277
Epsilon: 0.2    Test Accuracy = 5058 / 10000 = 0.5058
Epsilon: 0.3    Test Accuracy = 2729 / 10000 = 0.2729
```



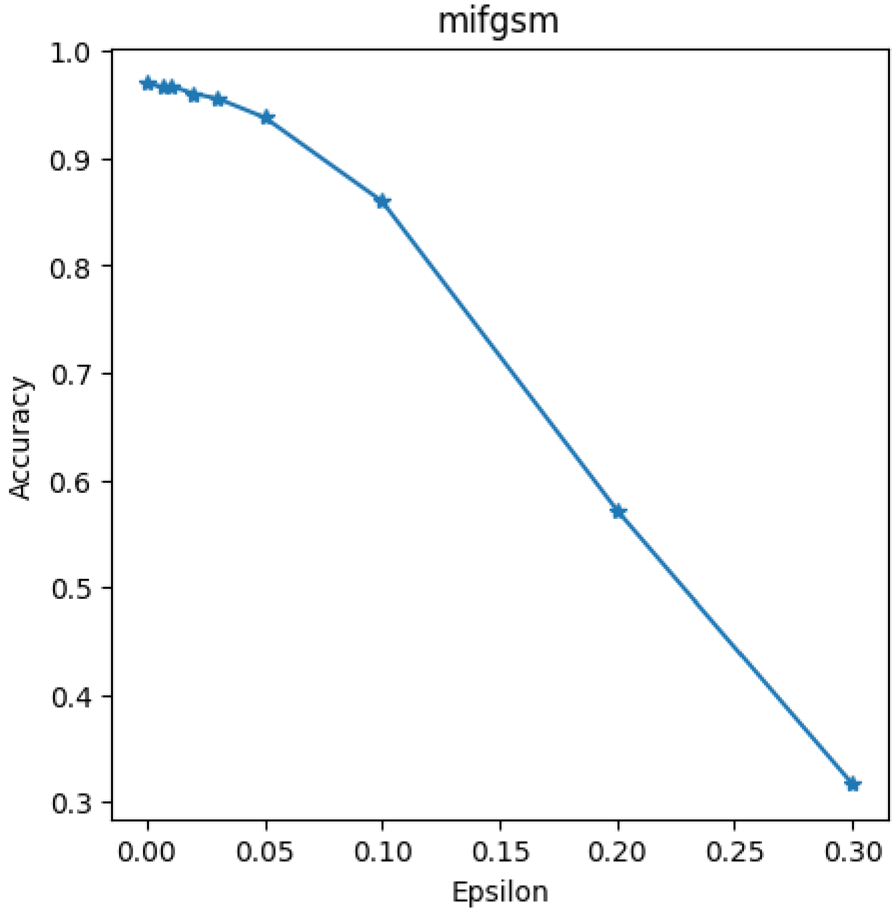

Eps: 0
0 -> 0
6 -> 6
3 -> 3
1 -> 1
6 -> 6
Eps: 0.007
0 -> 0
2 -> 2
7 -> 7
8 -> 8
1 -> 1
Eps: 0.01
3 -> 3
7 -> 7
2 -> 2
4 -> 4
0 -> 0
Eps: 0.02
1 -> 1
8 -> 8
3 -> 3
8 -> 8
1 -> 8
Eps: 0.03
5 -> 5
7 -> 7
5 -> 5
2 -> 2
5 -> 5
Eps: 0.05
6 -> 6
3 -> 3
6 -> 6
4 -> 4
0 -> 0
Eps: 0.1
9 -> 9
6 -> 6
4 -> 7
8 ->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

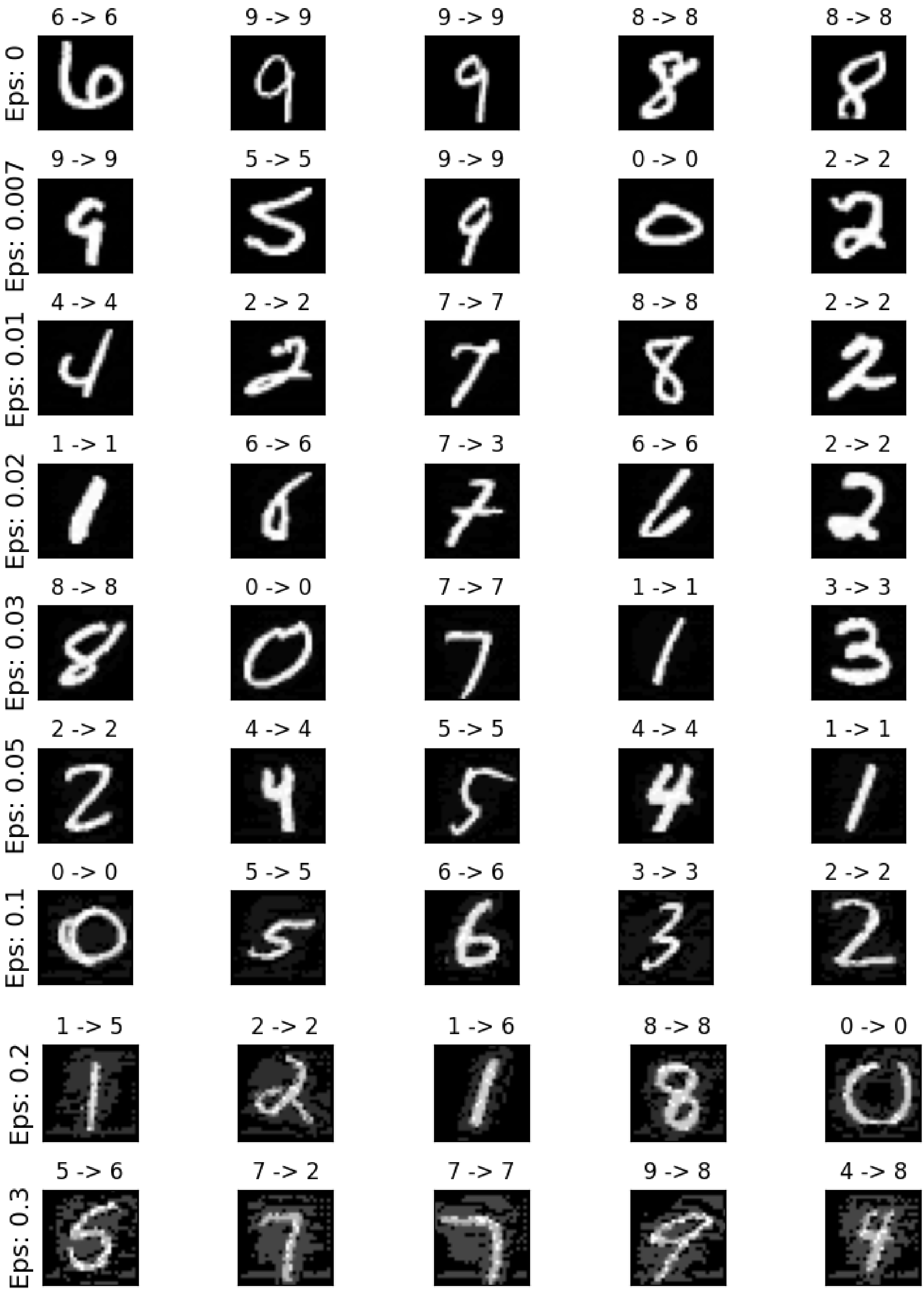
```
Epsilon: 0      Test Accuracy = 9722 / 10000 = 0.9722
Epsilon: 0.007  Test Accuracy = 9687 / 10000 = 0.9687
Epsilon: 0.01   Test Accuracy = 9669 / 10000 = 0.9669
Epsilon: 0.02   Test Accuracy = 9610 / 10000 = 0.961
Epsilon: 0.03   Test Accuracy = 9553 / 10000 = 0.9553
Epsilon: 0.05   Test Accuracy = 9395 / 10000 = 0.9395
Epsilon: 0.1    Test Accuracy = 8601 / 10000 = 0.8601
Epsilon: 0.2    Test Accuracy = 5723 / 10000 = 0.5723
Epsilon: 0.3    Test Accuracy = 3215 / 10000 = 0.3215
```




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

```
Epsilon: 0      Test Accuracy = 9704 / 10000 = 0.9704
Epsilon: 0.007  Test Accuracy = 9665 / 10000 = 0.9665
Epsilon: 0.01   Test Accuracy = 9678 / 10000 = 0.9678
Epsilon: 0.02   Test Accuracy = 9605 / 10000 = 0.9605
Epsilon: 0.03   Test Accuracy = 9559 / 10000 = 0.9559
Epsilon: 0.05   Test Accuracy = 9382 / 10000 = 0.9382
Epsilon: 0.1    Test Accuracy = 8600 / 10000 = 0.86
Epsilon: 0.2    Test Accuracy = 5718 / 10000 = 0.5718
Epsilon: 0.3    Test Accuracy = 3169 / 10000 = 0.3169
```





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
```

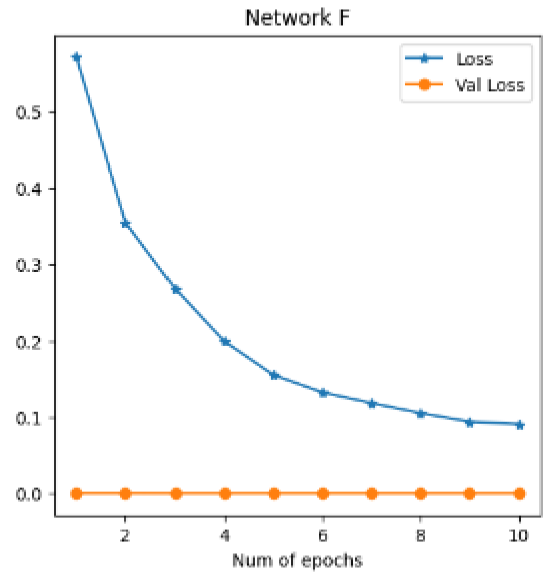
Создадим функцию защиты методом дистилляции

```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,"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()
```

Получаем результаты оценки защищенных сетей

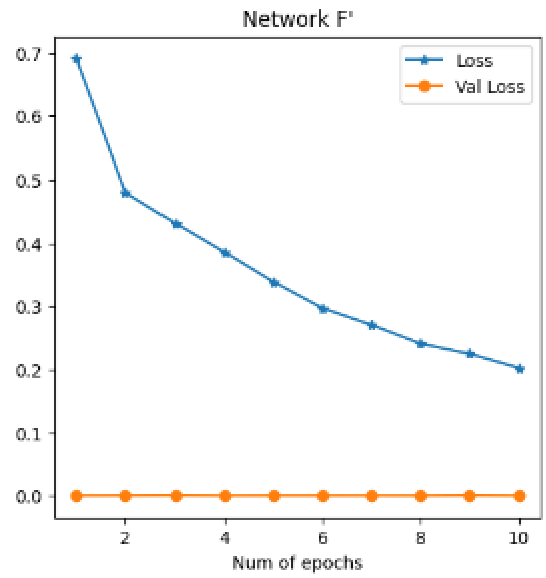
```python
Temp=100
epochs=10
epsilons=[0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons)
```

```
Fitting the model...
Epoch: 1 Loss: 0.5706202287519799 Val_Loss: 8.249447653070093e-05
Epoch: 2 Loss: 0.3545042174551342 Val_Loss: 7.158523872494697e-05
Epoch: 3 Loss: 0.2684014369479434 Val_Loss: 6.209565556491725e-06
Epoch: 4 Loss: 0.1991503801513177 Val_Loss: 4.936715587973594e-07
Epoch: 5 Loss: 0.15499293439917233 Val_Loss: 2.1840261667966843e-05
Epoch: 6 Loss: 0.13230935157652426 Val_Loss: 2.0522175317455548e-05
Epoch: 7 Loss: 0.1182749427824363 Val_Loss: 1.0402818582952022e-05
Epoch: 8 Loss: 0.10521015077048566 Val_Loss: 7.633360641193577e-07
Epoch: 9 Loss: 0.09395652426495998 Val_Loss: 4.768370942542788e-11
Epoch: 10 Loss: 0.09073624960929061 Val_Loss: 2.0621534349629655e-08
```

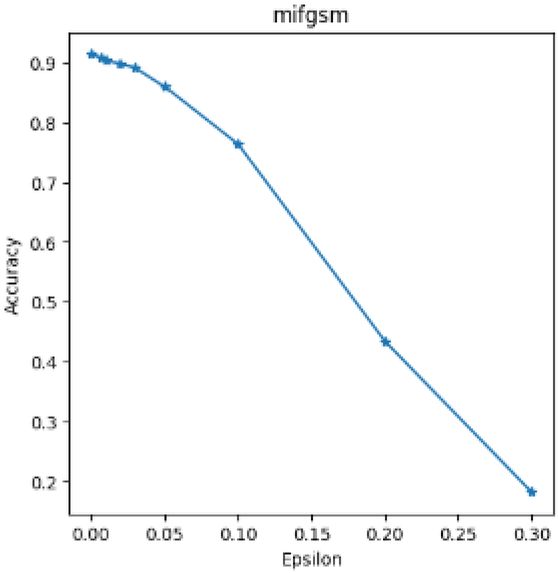


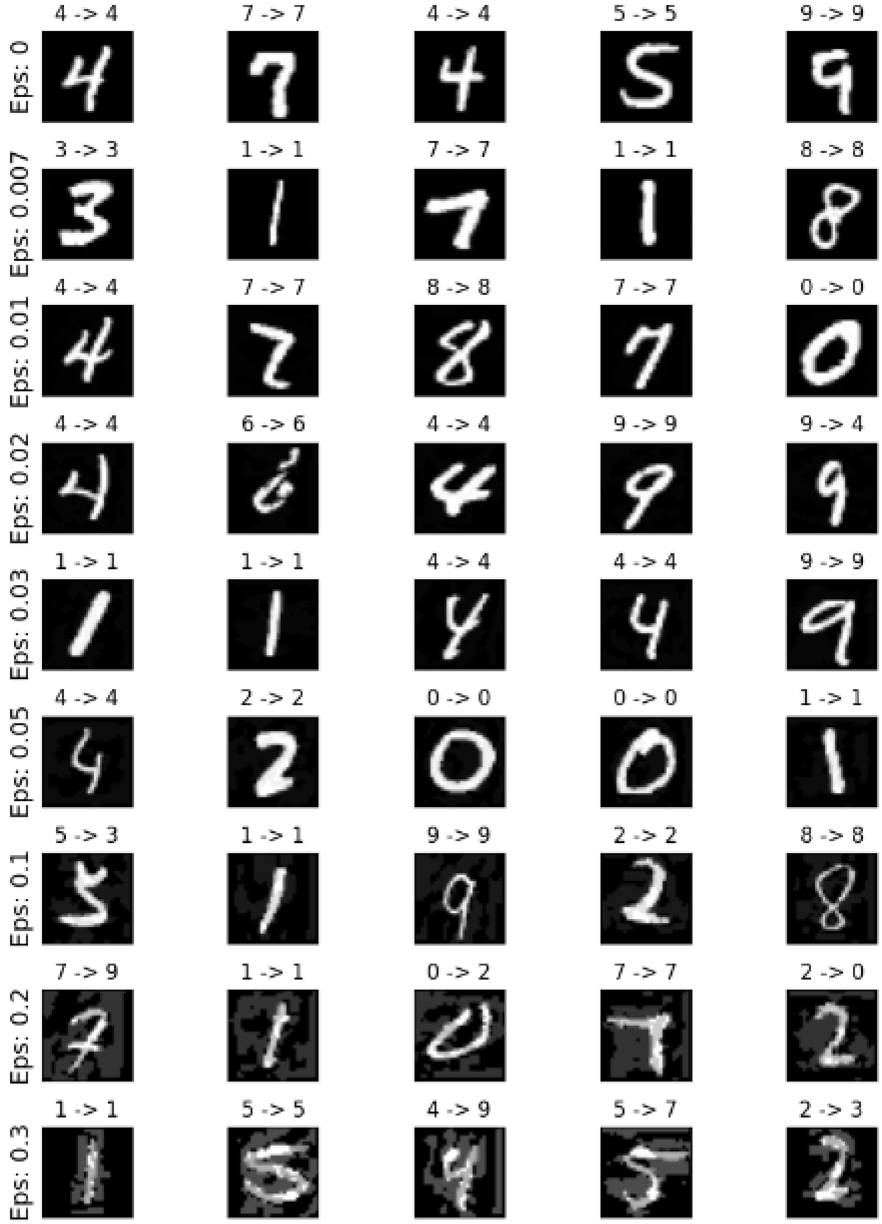
.

```
Fitting the model...
Epoch: 1 Loss: 0.6908011980243247 Val_Loss: 5.4475905746221544e-05
Epoch: 2 Loss: 0.47934048698511544 Val_Loss: 0.00015452935751527548
Epoch: 3 Loss: 0.43145106536227606 Val_Loss: 0.00043453699350357055
Epoch: 4 Loss: 0.38570553604473884 Val_Loss: 1.327155469916761e-05
Epoch: 5 Loss: 0.33855904813294896 Val_Loss: 0.00010562587110325694
Epoch: 6 Loss: 0.2970336308658502 Val_Loss: 7.979812920093536e-05
Epoch: 7 Loss: 0.2704591011468641 Val_Loss: 2.7051750384271144e-05
Epoch: 8 Loss: 0.2409409079124368 Val_Loss: 3.921909950577174e-09
Epoch: 9 Loss: 0.22466166278708538 Val_Loss: 0.00040194199084753565
Epoch: 10 Loss: 0.20263305166835704 Val_Loss: 9.179073458653875e-10
```



```
Epsilon: 0      Test Accuracy = 9149 / 10000 = 0.9149
Epsilon: 0.007  Test Accuracy = 9098 / 10000 = 0.9098
Epsilon: 0.01   Test Accuracy = 9055 / 10000 = 0.9055
Epsilon: 0.02   Test Accuracy = 8978 / 10000 = 0.8978
Epsilon: 0.03   Test Accuracy = 8898 / 10000 = 0.8898
Epsilon: 0.05   Test Accuracy = 8599 / 10000 = 0.8599
Epsilon: 0.1    Test Accuracy = 7632 / 10000 = 0.7632
Epsilon: 0.2    Test Accuracy = 4428 / 10000 = 0.4428
Epsilon: 0.3    Test Accuracy = 1825 / 10000 = 0.1825
Epsilon: 0      Test Accuracy = 9125 / 10000 = 0.9125
Epsilon: 0.007  Test Accuracy = 9112 / 10000 = 0.9112
Epsilon: 0.01   Test Accuracy = 9119 / 10000 = 0.9119
Epsilon: 0.02   Test Accuracy = 8984 / 10000 = 0.8984
Epsilon: 0.03   Test Accuracy = 8875 / 10000 = 0.8875
Epsilon: 0.05   Test Accuracy = 8629 / 10000 = 0.8629
Epsilon: 0.1    Test Accuracy = 7678 / 10000 = 0.7678
Epsilon: 0.2    Test Accuracy = 4413 / 10000 = 0.4413
Epsilon: 0.3    Test Accuracy = 1901 / 10000 = 0.1901
Epsilon: 0      Test Accuracy = 9146 / 10000 = 0.9146
Epsilon: 0.007  Test Accuracy = 9082 / 10000 = 0.9082
Epsilon: 0.01   Test Accuracy = 9036 / 10000 = 0.9036
Epsilon: 0.02   Test Accuracy = 8987 / 10000 = 0.8987
Epsilon: 0.03   Test Accuracy = 8917 / 10000 = 0.8917
Epsilon: 0.05   Test Accuracy = 8601 / 10000 = 0.8601
Epsilon: 0.1    Test Accuracy = 7638 / 10000 = 0.7638
Epsilon: 0.2    Test Accuracy = 4343 / 10000 = 0.4343
Epsilon: 0.3    Test Accuracy = 1817 / 10000 = 0.1817
```





Защитная дистилляция, как метод, способствует упрощению структуры нейронных сетей, улучшению их обучаемости и ускорению выполнения задач. Однако, его эффективность может зависеть от ряда факторов, включая сложность начального модели, качество обучения и размер обучающего набора данных.