МИНОБРНАУКИ РОССИИ
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РТУ МИРЭА

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Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Лабораторная работа №1

по дисциплине

«Анализ защищенности систем искусственного интеллекта»

Группа:
ББМО-01-22
Выполнил:
Воронов А.И.

Проверил:
Спирин А.А.

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Выполняем импорт необходимых библиотек.

```
# импортируем 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
```

Задаем нормализующие преобразования, загружаем набор MNIST и разбиваем данные на подвыборки.

```
# задаем нормализующие преобразования, загружаем набор MNIST и разбиваем 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, 78744263.55it/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, 92329034.93it/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, 23596879.39it/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, 9835069.06it/s]Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw

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

Задаем использование GPU для вычислений, если это возможно.

```
[ ] # используем GPU если возможно
    use_cuda=True
    device = torch.device("cuda" if (use_cuda and torch.cuda.is_available()) else "cpu")
```

На основе torch создаем класс нейронной сети

```python
# создаем класс НС на основе 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
```

Проверяем работоспособность созданного класса и создаем оптимизатор, функцию потерь и трейнер сети.

```python
# проверяем работоспособность созданного класса
model = Net().to(device)
```

```python
# создаем оптимизатор, функцию потреть 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)
```

Определяем функцию обучения сети.

```python
# определяем 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
```

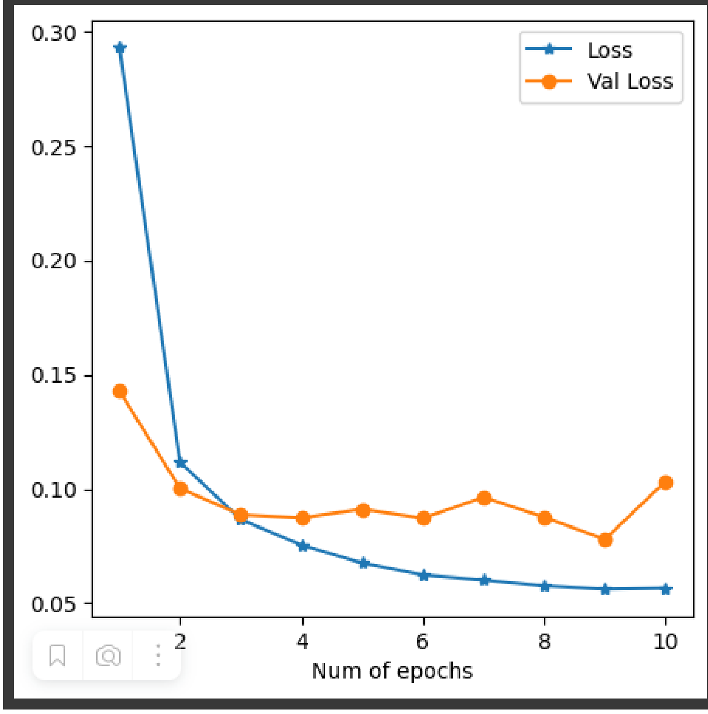
Выполним обучение модели.

```python
# обучаем 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: UserWarni
  warnings.warn(warn_msg)
Epoch: 1 Loss: 0.2929983610663845 Val_Loss: 0.14282329050162185
Epoch: 2 Loss: 0.11167306516834545 Val_Loss: 0.10023150670196206
Epoch: 3 Loss: 0.08669009416963834 Val_Loss: 0.08876393548660906
Epoch: 4 Loss: 0.07547891725945295 Val_Loss: 0.08737611839261517
Epoch: 5 Loss: 0.06766004898735753 Val_Loss: 0.09118692035006895
Epoch: 6 Loss: 0.062466110574673946 Val_Loss: 0.08722920042319367
Epoch: 7 Loss: 0.06020658712990241 Val_Loss: 0.09637939314217543
Epoch: 8 Loss: 0.05766215919957994 Val_Loss: 0.08769152700292669
Epoch: 9 Loss: 0.05625135024997346 Val_Loss: 0.07799628196370527
Epoch: 10 Loss: 0.056682715699112735 Val_Loss: 0.10335334484691157
```

Строим график.

```
# строим график
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()
```



Создаем функции атак.

```
# создаем функции атак
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
```

Создаем функцию для проверки.

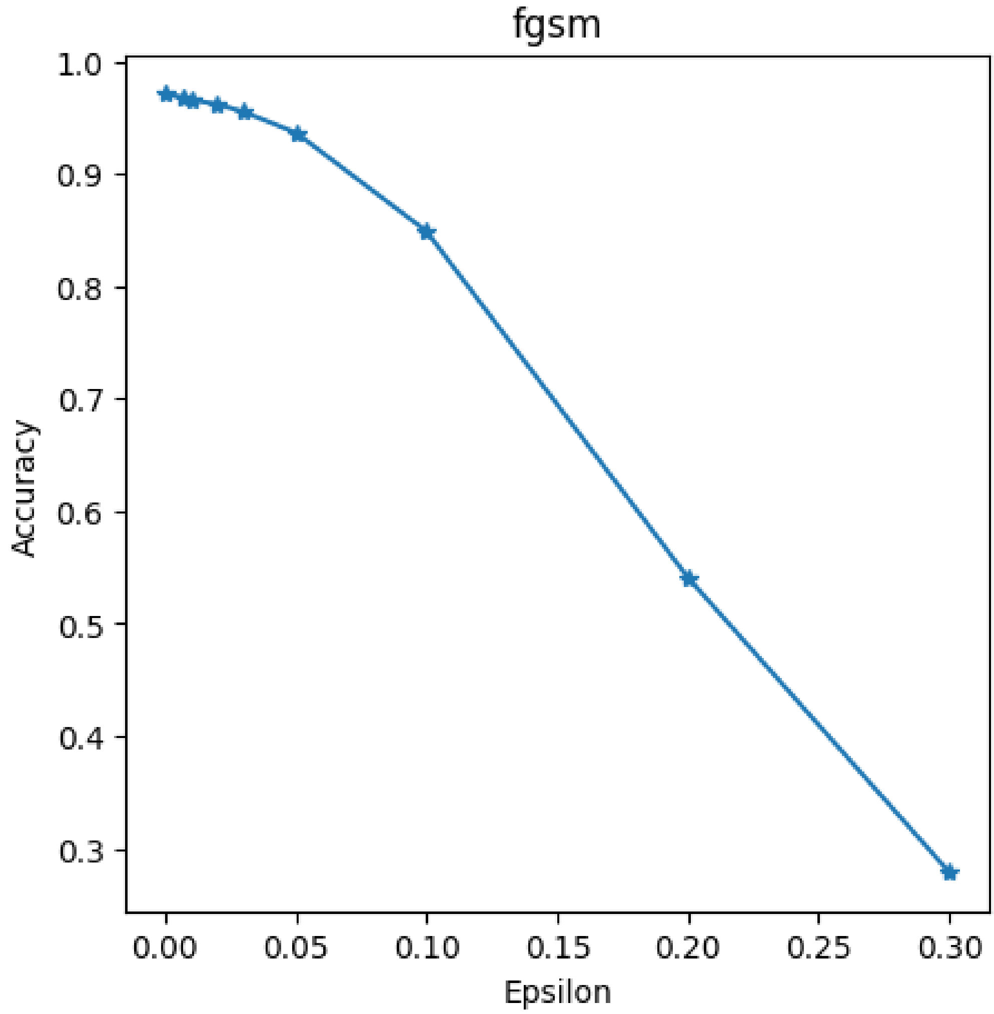
```
# создаем функци. проверки
def test(model,device,test_loader,epsilon,attack):
  correct = 0
  adv_examples = []
  for data, target in test_loader:
    data, target = data.to(device), target.to(device)
    data.requires_grad = True
    output = model(data)
    init_pred = output.max(1, keepdim=True)[1]
    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
```

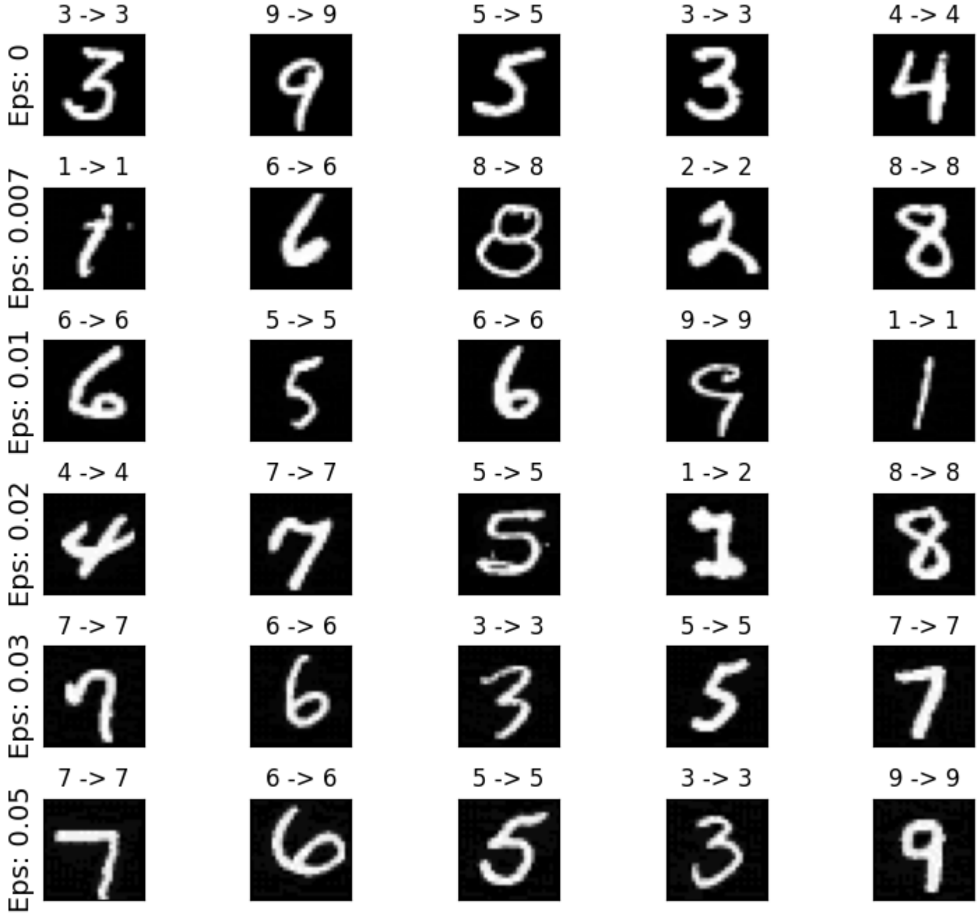
Выполним построение графиков успешности атак и примеров выполняемых атак в зависимости от степени возмущения epsilon.

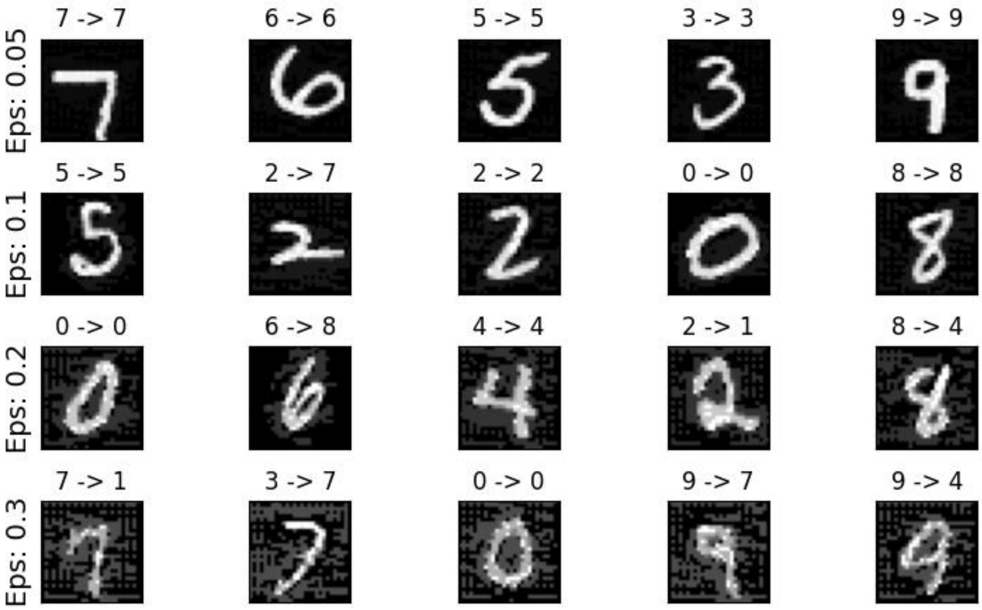
```
# строим графики успешности атак и примеры выполненых атак в зависимости от степени возмущения epsilon
epsilons = [0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
for attack in ("fgsm","ifgsm","mifgsm"):
  accuracies = []
  examples = []
  for eps in epsilons:
    acc, ex = test(model, device,test_loader,eps,attack)
    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 = 9709 / 10000 = 0.9709
Epsilon: 0.007	Test Accuracy = 9675 / 10000 = 0.9675
Epsilon: 0.01	Test Accuracy = 9654 / 10000 = 0.9654
Epsilon: 0.02	Test Accuracy = 9617 / 10000 = 0.9617
Epsilon: 0.03	Test Accuracy = 9548 / 10000 = 0.9548
Epsilon: 0.05	Test Accuracy = 9364 / 10000 = 0.9364
Epsilon: 0.1	Test Accuracy = 8487 / 10000 = 0.8487
Epsilon: 0.2	Test Accuracy = 5409 / 10000 = 0.5409
Epsilon: 0.3	Test Accuracy = 2789 / 10000 = 0.2789

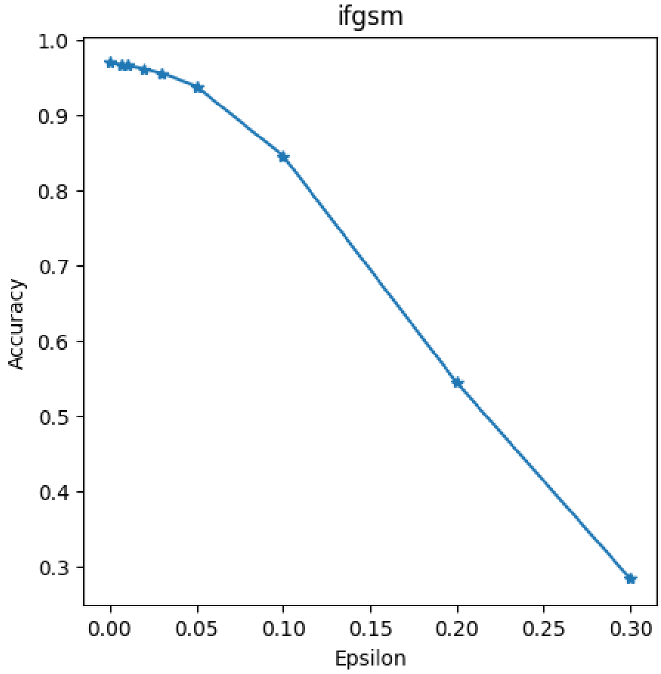


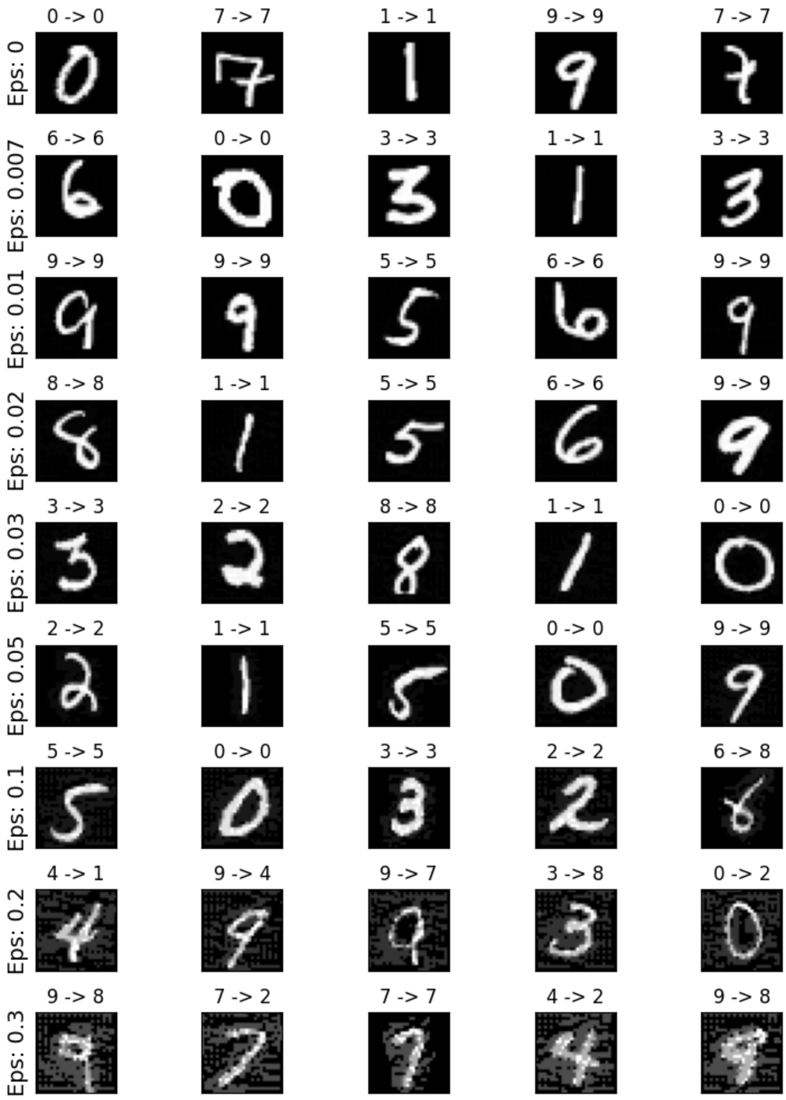




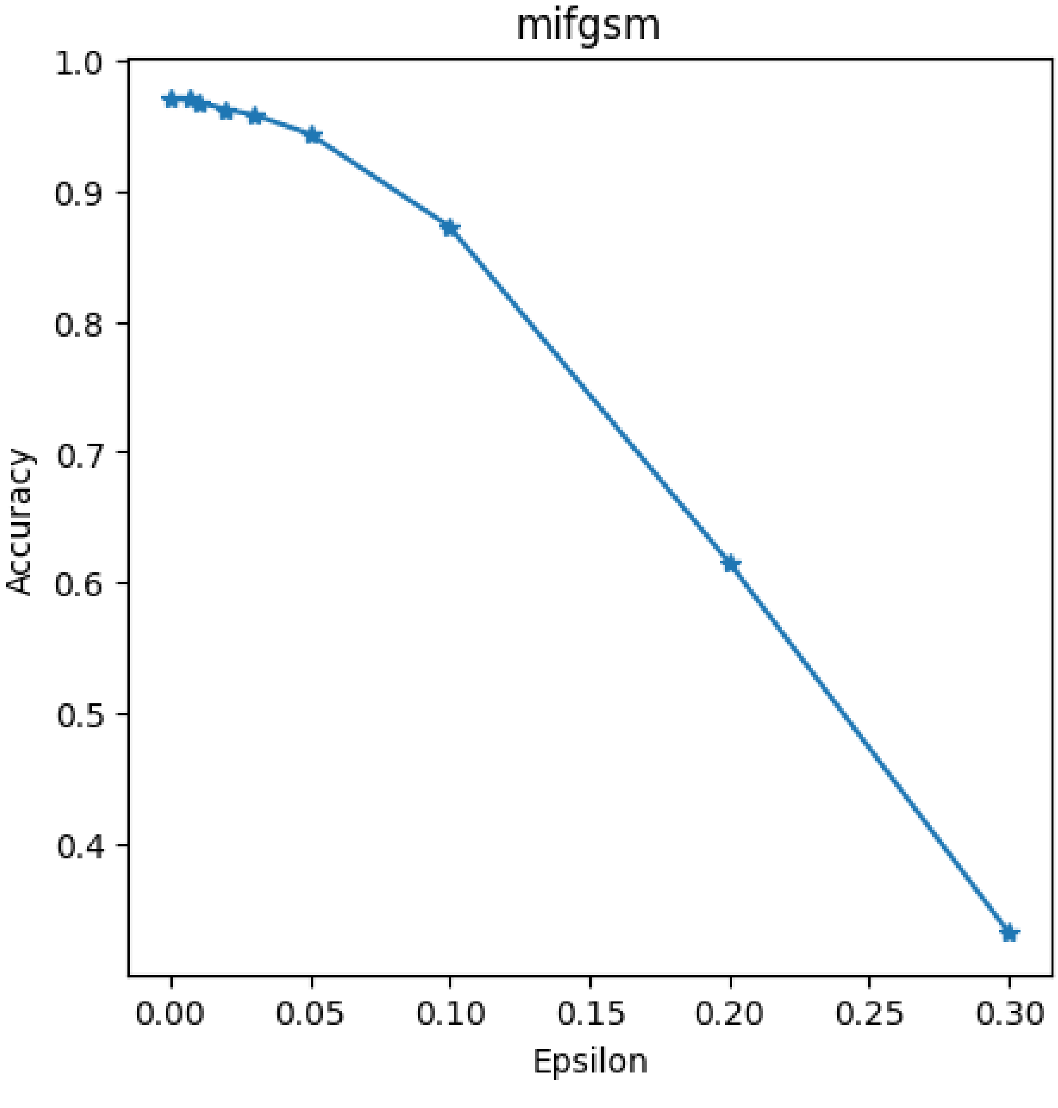
Epsilon: 0	Test Accuracy = 9708 / 10000 = 0.9708
Epsilon: 0.007	Test Accuracy = 9677 / 10000 = 0.9677
Epsilon: 0.01	Test Accuracy = 9666 / 10000 = 0.9666
Epsilon: 0.02	Test Accuracy = 9622 / 10000 = 0.9622
Epsilon: 0.03	Test Accuracy = 9563 / 10000 = 0.9563
Epsilon: 0.05	Test Accuracy = 9387 / 10000 = 0.9387
Epsilon: 0.1	Test Accuracy = 8463 / 10000 = 0.8463

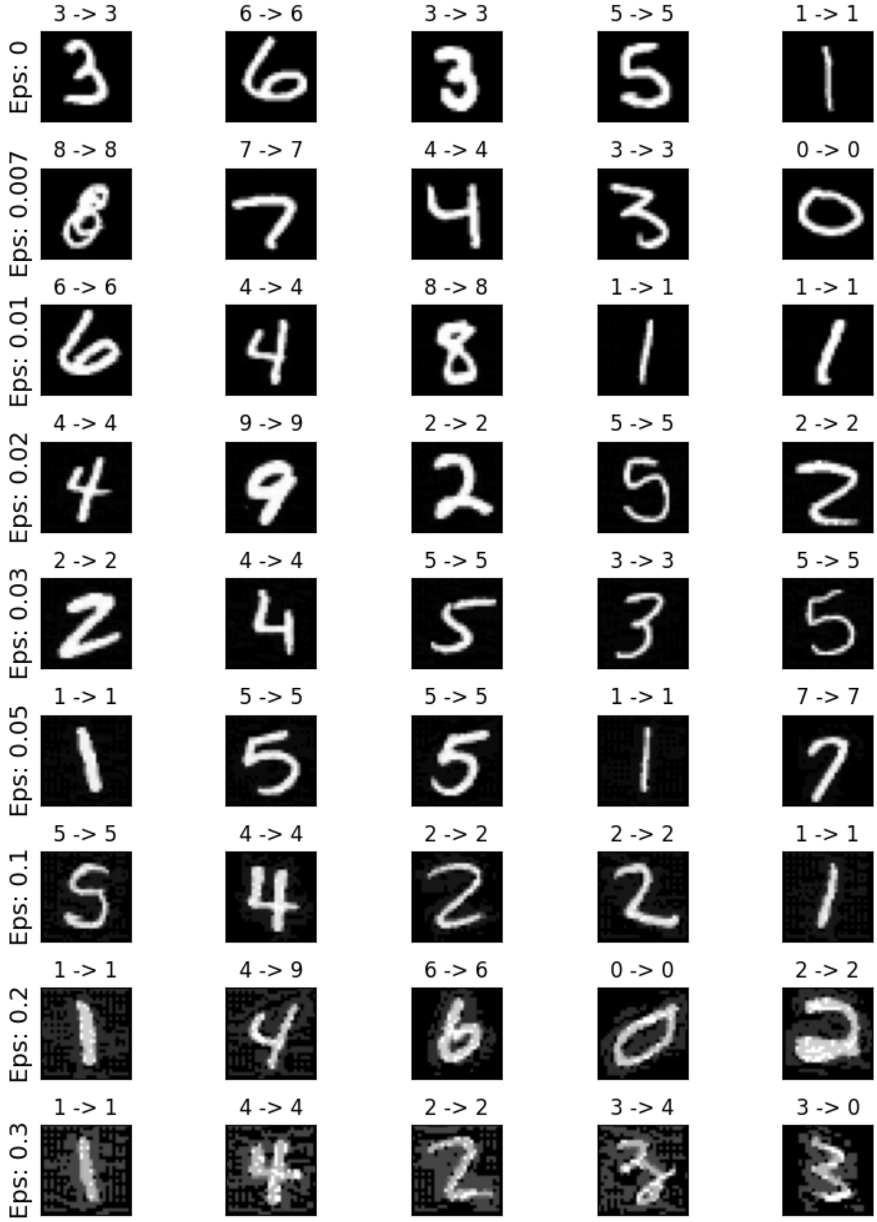
Epsilon: 0.2 Test Accuracy = 5445 / 10000 = 0.5445
Epsilon: 0.3 Test Accuracy = 2837 / 10000 = 0.2837





Epsilon: 0	Test Accuracy = 9700 / 10000 = 0.97
Epsilon: 0.007	Test Accuracy = 9696 / 10000 = 0.9696
Epsilon: 0.01	Test Accuracy = 9676 / 10000 = 0.9676
Epsilon: 0.02	Test Accuracy = 9621 / 10000 = 0.9621
Epsilon: 0.03	Test Accuracy = 9579 / 10000 = 0.9579
Epsilon: 0.05	Test Accuracy = 9432 / 10000 = 0.9432
Epsilon: 0.1	Test Accuracy = 8723 / 10000 = 0.8723
Epsilon: 0.2	Test Accuracy = 6155 / 10000 = 0.6155
Epsilon: 0.3	Test Accuracy = 3324 / 10000 = 0.3324





Создадим два класса нейросети.

```python
# создаем два 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
```

Создадим функции 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
```

Зададим функцию защиты сетей.

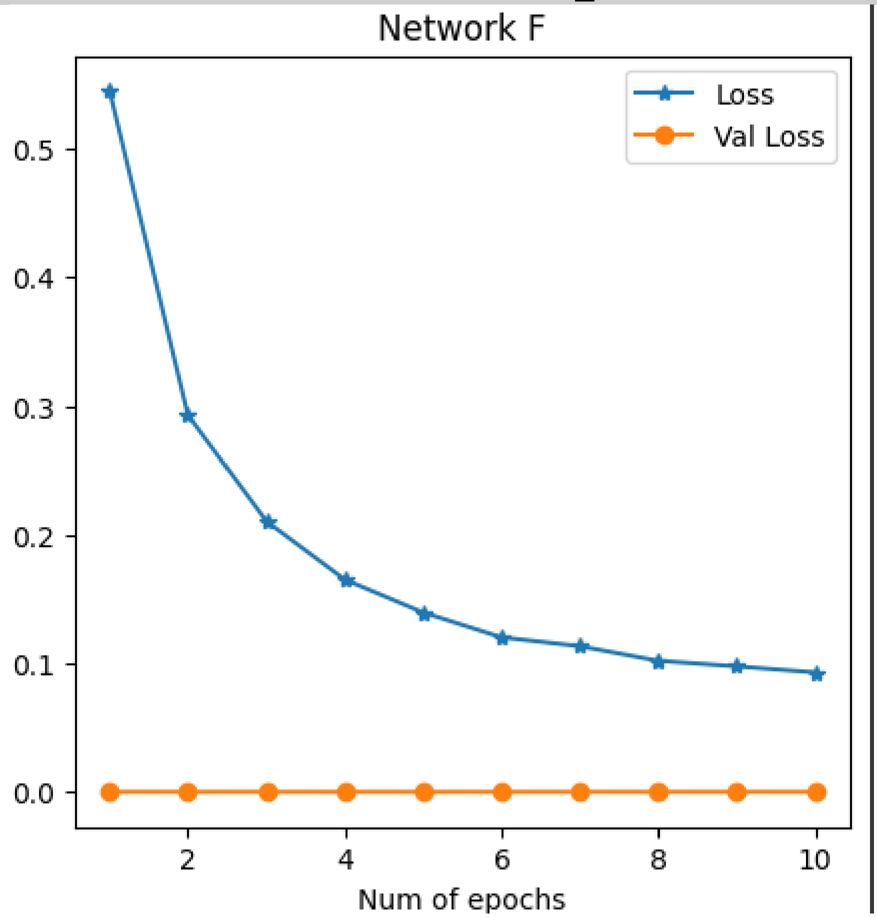
```
def defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons):
  modelF = NetF().to(device)
  optimizerF = optim.Adam(modelF.parameters(),lr=0.0001, betas=(0.9, 0.999))
  schedulerF = optim.lr_scheduler.ReduceLROnPlateau(optimizerF, mode='min', factor=0.1, patience=3)
  modelF1 = NetF1().to(device)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

Получим результаты оценки защищенных сетей.

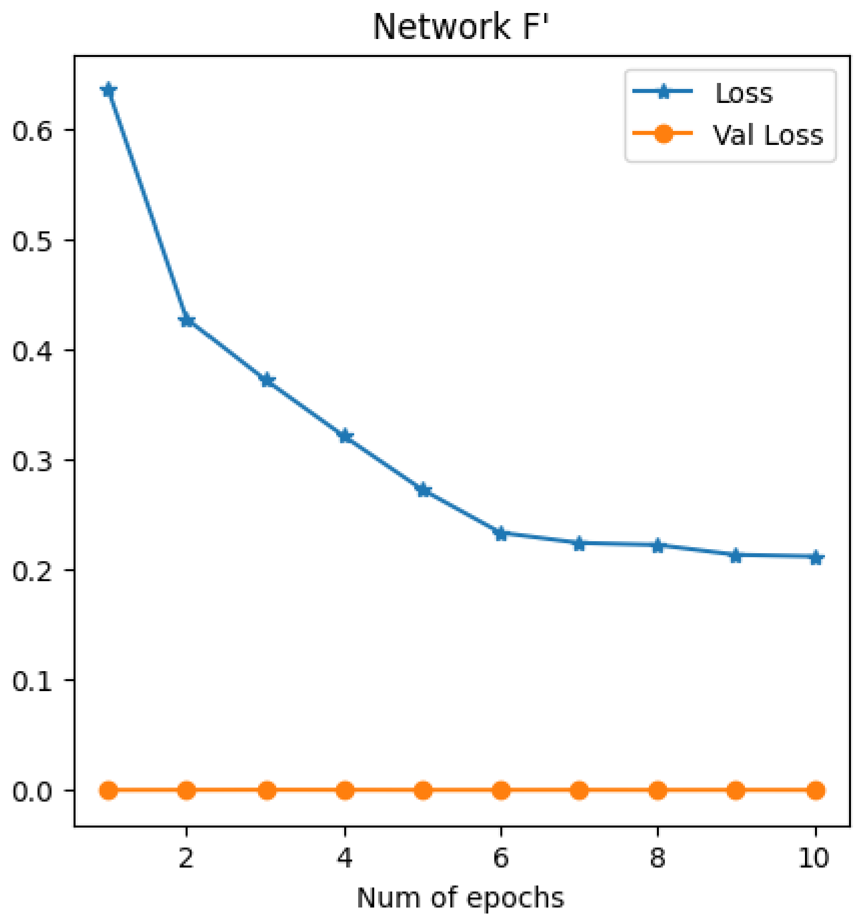
```
# получаем результаты оценки защищеных сетей
Temp=100
epochs=10
epsilons=[0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons)
```

Fitting the model...
Epoch: 1 Loss: 0.5448293192800642 Val_Loss: 7.73291103541851e-06
Epoch: 2 Loss: 0.2927316698674613 Val_Loss: 1.0102411732077599e-06
Epoch: 3 Loss: 0.2102989830346451 Val_Loss: 6.601312197744847e-07
Epoch: 4 Loss: 0.16505023587049214 Val_Loss: 7.533462459105067e-06
Epoch: 5 Loss: 0.13952160401099645 Val_Loss: 4.494635201990604e-06
Epoch: 6 Loss: 0.12023352776694962 Val_Loss: 1.9566755509003998e-07
Epoch: 7 Loss: 0.11333786990761777 Val_Loss: 1.9792682214756497e-06
Epoch: 8 Loss: 0.1019939355488022 Val_Loss: 4.203413613140583e-07
Epoch: 9 Loss: 0.0976399402378025 Val_Loss: 2.3648618487641217e-06
Epoch: 10 Loss: 0.09295012344814668 Val_Loss: 7.459939115506131e-08



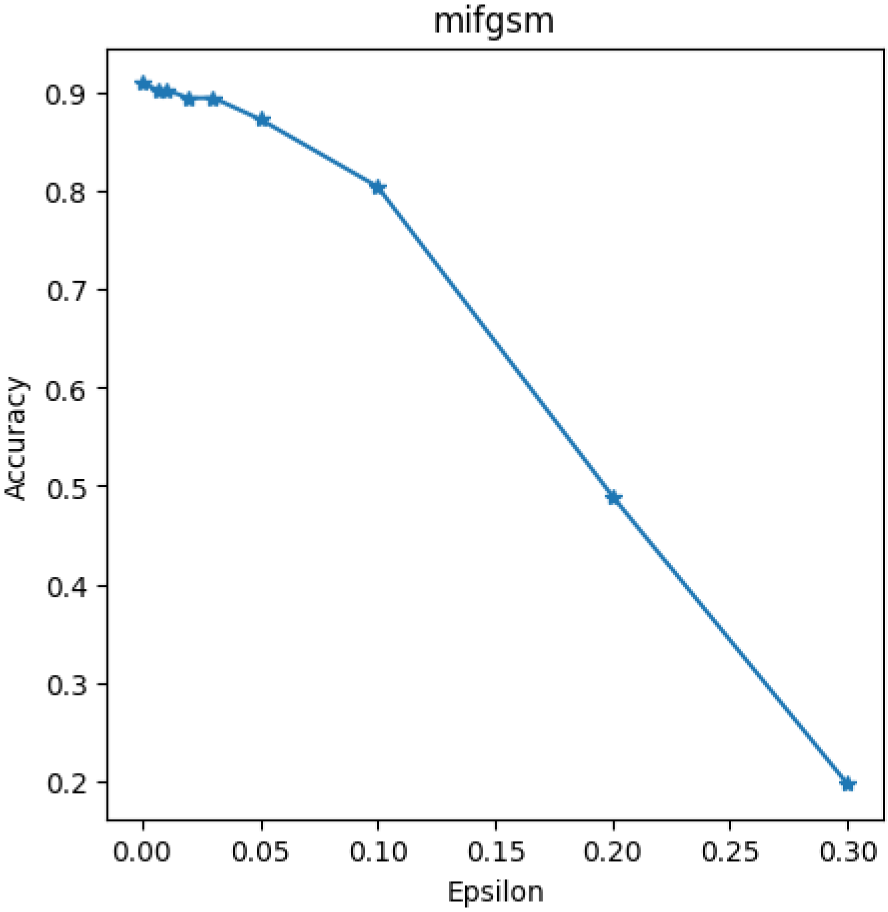
Fitting the model...
Epoch: 1 Loss: 0.6363280130847226 Val_Loss: 4.991228529252112e-06
Epoch: 2 Loss: 0.42811888280111854 Val_Loss: 6.821165650617332e-05
Epoch: 3 Loss: 0.3726626193641786 Val_Loss: 0.00015932790189981 46
Epoch: 4 Loss: 0.3215511648770174 Val_Loss: 9.6123790089041e-05
Epoch: 5 Loss: 0.2729614160263343 Val_Loss: 1.9890321791172028e-05

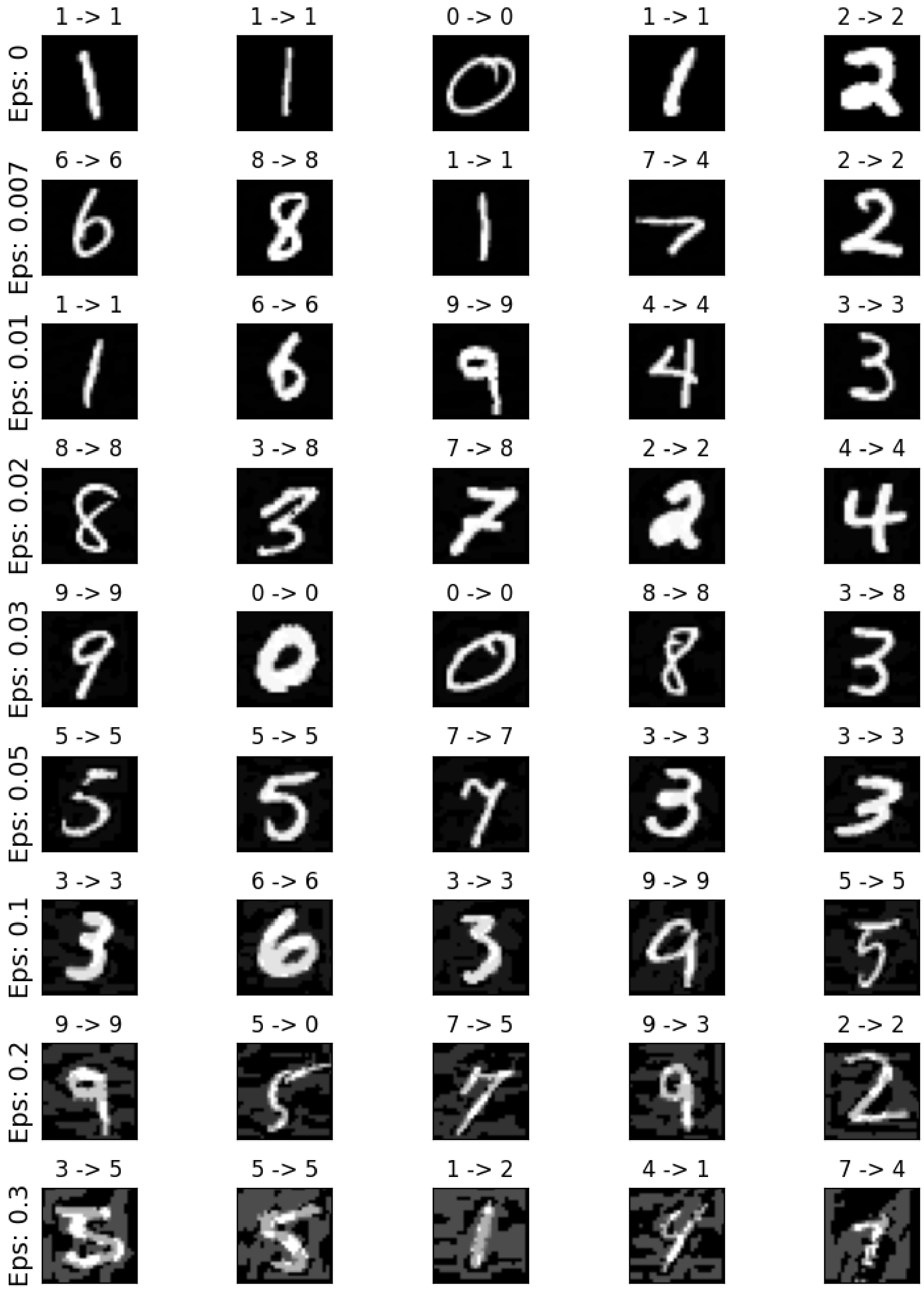
```
Epoch: 6 Loss: 0.2336730380693122 Val_Loss: 1.4186868444085125e-05
Epoch: 7 Loss: 0.22432161142330115 Val_Loss: 5.9460494473751167e-05
Epoch: 8 Loss: 0.22250396553932653 Val_Loss: 2.616085112094879e-07
Epoch: 9 Loss: 0.21347470993006776 Val_Loss: 2.3429323930758982e-05
Epoch: 10 Loss: 0.21204543162817313 Val_Loss: 1.9299010455142708e-08
```




```
Epsilon: 0      Test Accuracy = 9114 / 10000 = 0.9114
Epsilon: 0.007  Test Accuracy = 9015 / 10000 = 0.9015
Epsilon: 0.01   Test Accuracy = 9007 / 10000 = 0.9007
Epsilon: 0.02   Test Accuracy = 8973 / 10000 = 0.8973
Epsilon: 0.03   Test Accuracy = 8935 / 10000 = 0.8935
Epsilon: 0.05   Test Accuracy = 8718 / 10000 = 0.8718
Epsilon: 0.1    Test Accuracy = 8046 / 10000 = 0.8046
Epsilon: 0.2    Test Accuracy = 4897 / 10000 = 0.4897
Epsilon: 0.3    Test Accuracy = 2008 / 10000 = 0.2008
Epsilon: 0      Test Accuracy = 9128 / 10000 = 0.9128
Epsilon: 0.007  Test Accuracy = 9018 / 10000 = 0.9018
Epsilon: 0.01   Test Accuracy = 9038 / 10000 = 0.9038
Epsilon: 0.02   Test Accuracy = 8954 / 10000 = 0.8954
Epsilon: 0.03   Test Accuracy = 8897 / 10000 = 0.8897
Epsilon: 0.05   Test Accuracy = 8735 / 10000 = 0.8735
Epsilon: 0.1    Test Accuracy = 8077 / 10000 = 0.8077
Epsilon: 0.2    Test Accuracy = 4935 / 10000 = 0.4935
```

Epsilon: 0.3   Test Accuracy = 1992 / 10000 = 0.1992
Epsilon: 0   Test Accuracy = 9102 / 10000 = 0.9102
Epsilon: 0.007 Test Accuracy = 9030 / 10000 = 0.903
Epsilon: 0.01   Test Accuracy = 9034 / 10000 = 0.9034
Epsilon: 0.02   Test Accuracy = 8948 / 10000 = 0.8948
Epsilon: 0.03   Test Accuracy = 8951 / 10000 = 0.8951
Epsilon: 0.05   Test Accuracy = 8733 / 10000 = 0.8733
Epsilon: 0.1   Test Accuracy = 8047 / 10000 = 0.8047
Epsilon: 0.2   Test Accuracy = 4898 / 10000 = 0.4898
Epsilon: 0.3   Test Accuracy = 1969 / 10000 = 0.1969





Вывод

Без использования защитных механизмов (при eps=0) точность модели высока, и она составляет 91.28%.

С увеличением значения eps точность модели ухудшается, особенно при больших значениях. Это свидетельствует о том, что модель чувствительна к атакам с добавлением шума (например, FGSM, iFGSM, MI-FGSM).

После применения механизма защиты (путем обучения модели на защищенных данных) наблюдается улучшение в стойкости модели к атакам.

Точность модели при различных значениях eps становится выше по сравнению с беззащитным вариантом. Особенно заметно улучшение на больших значениях eps. Однако, даже с использованием защиты, модель не обладает абсолютной стойкостью к атакам, и точность все равно снижается с увеличением eps.

Графики показывают, как меняется точность модели в зависимости от степени атаки (eps) для различных методов (FGSM, iFGSM, MI-FGSM). С увеличением eps точность модели снижается, что является ожидаемым результатом при увеличении степени атаки.

Визуализация примеров атак позволяет увидеть, как изменяется внешний вид изображений после атаки для различных значений eps.

Можно заметить, что с увеличением eps изображения становятся все более искаженными и трудными для классификации моделью.