GMDL, Project

```
import numpy as np
import torch
import torchvision
import itertools
import matplotlib.pyplot as plt
from time import time
from torchvision import datasets, models, transforms
from torch import nn, optim
import torch.nn.functional as F
from tqdm import tqdm
from torch.optim import lr_scheduler
import copy
import os
import random
from torch.autograd import Variable
from scipy.stats import norm
from skimage.filters import threshold_sauvola, threshold_otsu
from sklearn.metrics import confusion_matrix
```

Data & Preprocessing

Random seeds for reproducibility

```
def set_seeds(seed):
     torch.manual_seed(seed)
     np.random.seed(seed * 2)
     random.seed(seed * 3)

set_seeds(seed=123)
```

Datasets, dataloaders, and transformations

When loading the dataset, we decided to add a gaussian filter to the mnist train images in order to get better results and avoid overffiting. We also tried to use Random Affine transformations but it had worse results. We have calculated the mean and std of each dataset beforehand and normalize it.

```
mnist_mean, mnist_std = 0.13, 0.31
cifar_mean, cifar_std = [0.49139968, 0.48215841, 0.44653091],
[0.24703223, 0.24348513, 0.26158784]
fash_mean, fash_std = 0.286, 0.353
```

```
mnist_transform_train = transforms.Compose([
    transforms.Resize((28, 28)),
    transforms.ToTensor(),
    transforms.Normalize(mnist_mean, mnist_std),
    transforms.GaussianBlur(kernel_size=(3,3), sigma=(0.1, 1)),
    #transforms.RandomAffine(degrees=(-20, 20), translate=(0.01,
0.15), scale=(0.9, 1.1),fill=-1)
])

mnist_transform_test = transforms.Compose([
    transforms.Resize((28, 28)),
    transforms.ToTensor(),
    transforms.Normalize(mnist_mean, mnist_std)
])

fash_transform = transforms.Compose([
    transforms.Resize((28, 28)),
    transforms.ToTensor(),
    transforms.Normalize(fash_mean, fash_std)
])

trainset_mnist = datasets.MNIST(
    root="data/MNIST",
    train=True,
    download=True,
    transform=mnist_transform_train
)

testset_mnist = datasets.MNIST(
    root="data/MNIST",
    train=False,
    download=True,
    transform=mnist_transform_test
)

testset_fash = datasets.FashionMNIST(
    root="data/FashionMNIST",
    train=False,
    download=True,
    transform=fash_transform
)

trainset_mnist, valset_mnist =
torch.utils.data.random_split(dataset=trainset_mnist, lengths=[5/6,
1/6])

batch_size = 64
# data loaders
train_mnist_loader =  torch.utils.data.DataLoader(trainset_mnist,
batch_size=batch_size,
```

```
                                                    shuffle=True,
num_workers=2)
test_mnist_loader =  torch.utils.data.DataLoader(testset_mnist,
batch_size=batch_size,
                                                  shuffle=True, num_workers=2)
val_mnist_loader =  torch.utils.data.DataLoader(valset_mnist,
batch_size=batch_size,
                                                  shuffle=True, num_workers=2)

test_fash_loader =  torch.utils.data.DataLoader(testset_fash,
batch_size=batch_size,
                                                   shuffle=True,
num_workers=2)

cifar_transform = transforms.Compose([
    transforms.Resize((28, 28)),
    transforms.ToTensor(),
    transforms.Normalize(cifar_mean, cifar_std),
    transforms.Grayscale()
])


testset_cifar = datasets.CIFAR10(
    root="data/CIFAR10",
    train=False,
    download=True,
    transform=cifar_transform
)

test_cifar_loader =  torch.utils.data.DataLoader(testset_cifar,
batch_size=batch_size,
                                                   shuffle=True,
num_workers=2)

testset_fash.targets[:] = 10
testset_cifar.targets = [10 for _ in testset_cifar.targets]

Files already downloaded and verified
```

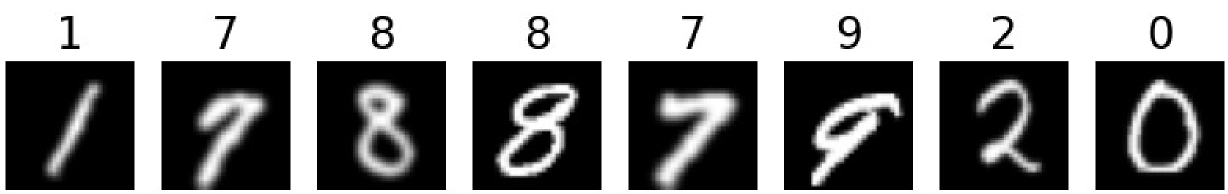
A subset of CIFAR10/FashionMNIST as OOD dataset

```
test_set_w_OOD = torch.utils.data.ConcatDataset([testset_mnist,
                                                 testset_cifar,
                                                 testset_fash
                                                  ])

test_loader_w_OOD =  torch.utils.data.DataLoader(test_set_w_OOD,
batch_size=batch_size,
                                                  shuffle=True, num_workers=2)
```

Auxiliary functions, definitions

```
def plot_images_grayscale(images, labels, mean, std, title=""):
    fig = plt.figure(figsize=(10, 10))
    pos = 1
    for i, img in enumerate(images):
        if i > 7:
            break
        fig.add_subplot(8, 8, pos)
        label = labels[i].cpu().numpy()
        img = img.cpu().numpy().transpose(1, 2, 0)
        img = std * img + mean
        plt.imshow(img, cmap='gray')
        plt.title(label, fontsize=20)
        plt.axis('off')
        pos += 1
    fig.suptitle(title, fontsize=16)
    plt.show()

def make_binary(img):
    T = threshold_otsu(img)
    binary = img > T
    return binary

def plot_images_binary(images, labels, mean, std, title=""):
    fig = plt.figure(figsize=(10, 10))
    pos = 1
    for i, img in enumerate(images):
        if i > 7:
            break
        fig.add_subplot(8, 8, pos)
        label = labels[i].cpu().numpy()
        img = img.cpu().numpy().transpose(1, 2, 0)
        img = std * img + mean
        img = make_binary(img)
        plt.imshow(img, cmap='gray')
        plt.title(label, fontsize=20)
        plt.axis('off')
        pos += 1
    fig.suptitle(title, fontsize=16)
    plt.show()

def plot_confusion_matrix(cm, classes=[i for i in range(11)],
title='Confusion matrix', cmap=plt.cm.Blues):
    # We took this function from
https://stackoverflow.com/questions/57329189/rendering-a-confusion-
matrix
    # and manipulated it for better visualization.
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
```

```
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)
    fmt = ".2f"
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]),
range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')


# visalize some images:
images, lables = next(iter(train_mnist_loader))
plot_images_grayscale(images, lables, mnist_mean, mnist_std)
```



Some images are blurry because of the Gaussian filter.

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
dataloaders={'train':train_mnist_loader, 'val': val_mnist_loader}
dataset_sizes = {'train': len(train_mnist_loader.dataset.indices),
'val':len(val_mnist_loader.dataset.indices)}
```

Models

Baseline model class

Our baseline model is a baisc convolution net that classifies the images to 10 different labels. There are 2 convolution layers and 2 fully connected layers. We decided to use dropout while training the model in order to avoid overfitting and get better generalization.

```
class ConvNet(nn.Module):
    def __init__(self, kernel_size=3):
        super(ConvNet, self).__init__()
        self.type = 'Conv'
        self.conv1 = nn.Conv2d(in_channels=1,
                               out_channels=10,
```

```
                              kernel_size=kernel_size,
                              stride=1,
                              padding=1,
                              )

        self.conv2 = nn.Conv2d(in_channels=10,
                              out_channels=20,
                              kernel_size=kernel_size,
                              stride=1,
                              padding=1,
                              )

        image_side = 28
        padding = 1
        image_side += -2*(kernel_size//2) + 2*padding
        image_side //= 2 # maxpool
        image_side += -2*(kernel_size//2) + 2*padding
        image_side //= 2 # maxpool

        self.fc1 = nn.Linear(20 * image_side**2, 64)
        self.fc2 = nn.Linear(64, 10)

        self.dropout2d = nn.Dropout2d(p=0.5)
        self.dropout05 = nn.Dropout(p=0.5)
        self.dropout02 = nn.Dropout(p=0.2)


    def forward(self, x):
        # Max pooling over a (2, 2) window
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        if self.training:
            self.dropout2d(x)
        # adaptive_avg_pool2d with output_size=1 = simple global avg pooling
        x = F.max_pool2d(F.relu(self.conv2(x)), (2, 2))
        if self.training:
            self.dropout2d(x)
        x = torch.flatten(x, 1) # flatten all dimensions except the batch dimension
        if self.training:
            self.dropout05(x)
        x = F.relu(self.fc1(x))
        if self.training:
            self.dropout02(x)
        # note: no softmax
        x = self.fc2(x)
        return x
```

OSR model class

Our OSR model composed of 2 different models. one is the classifying net from above, and an autoencoder that learns to reconsruct images.

```
class Encoder(nn.Module):
  def __init__(self):
    super().__init__()
    self.conv = nn.Conv2d(1, 10, 5, stride=1, padding=1)
#     28*28
#     10*24*24
#     10*12*12
    self.fc1 = nn.Linear(1690, 128)
    self.fc2 = nn.Linear(128, 64)
    self.fc3 = nn.Linear(64, 32)
  def forward(self, x):
    x, max_indices = F.max_pool2d(F.relu(self.conv(x)), (2, 2),
return_indices=True)
    x = torch.flatten(x, 1)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    return x, max_indices


class Decoder(nn.Module):
  def __init__(self):
    super().__init__()
    self.fc1 = nn.Linear(32, 64)
    self.fc2 = nn.Linear(64, 128)
    self.fc3 = nn.Linear(128, 1690)
    self.deconv = nn.ConvTranspose2d(10, 1, 5, stride=1, padding=1)

  def forward(self, x, max_indices):
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    x = torch.unflatten(x, 1, (10,13,13))
    x = self.deconv(F.relu(F.max_unpool2d(x, kernel_size=(2, 2),
indices=max_indices)))
    return x



class Autoencoder(nn.Module):
  def __init__(self):
    super().__init__()
    self.encoder = Encoder()
    self.decoder = Decoder()
```

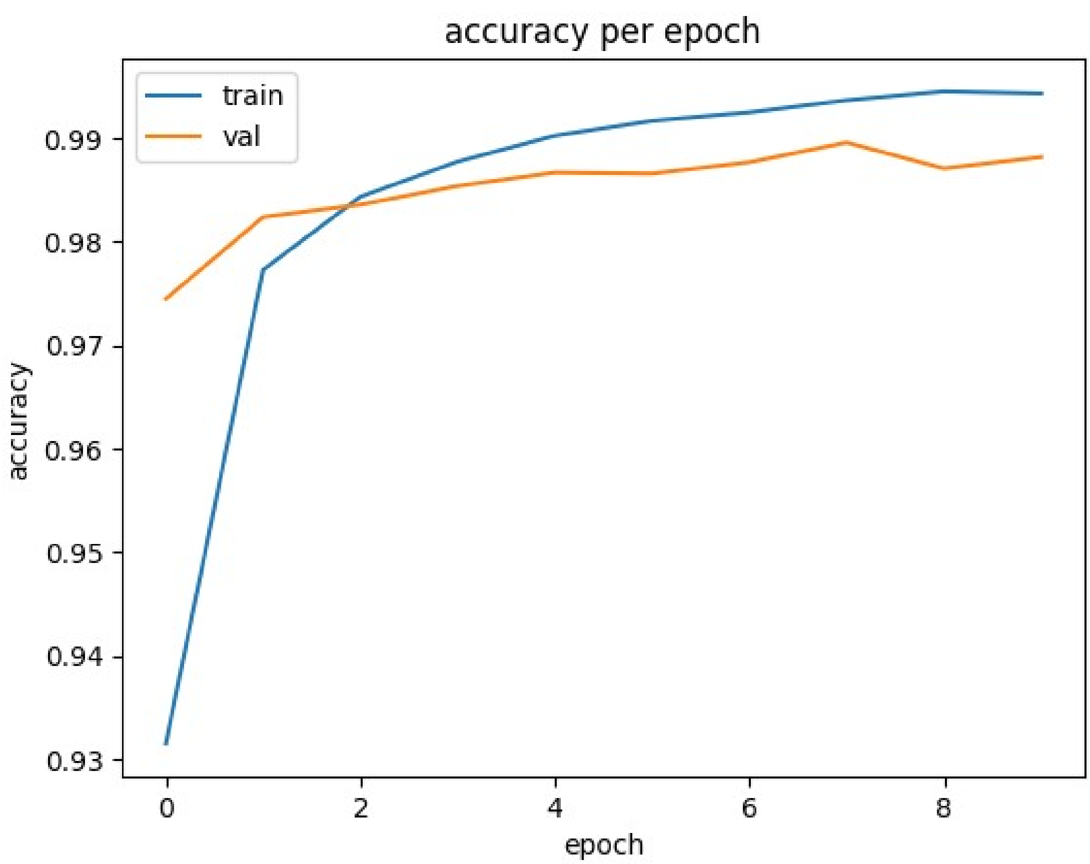
```
  def forward(self, x):
    x = self.encoder(x)
    x = self.decoder(x)
    return x

class ML_Autoencoder(Autoencoder):
    def __init__(self):
        # inhert from parent
        super(ML_Autoencoder, self).__init__()
        self.type = 'MLAE'
        self.n_classes = 11
        # Add classification head
        self.clf = ConvNet(5)

    def forward(self, x):
        encoded_vector, indices = self.encoder(x)
        recon = self.decoder(encoded_vector, indices)
        y = x.reshape((-1, 1, 28, 28))
        preds = self.clf(y)
        return recon, preds
```

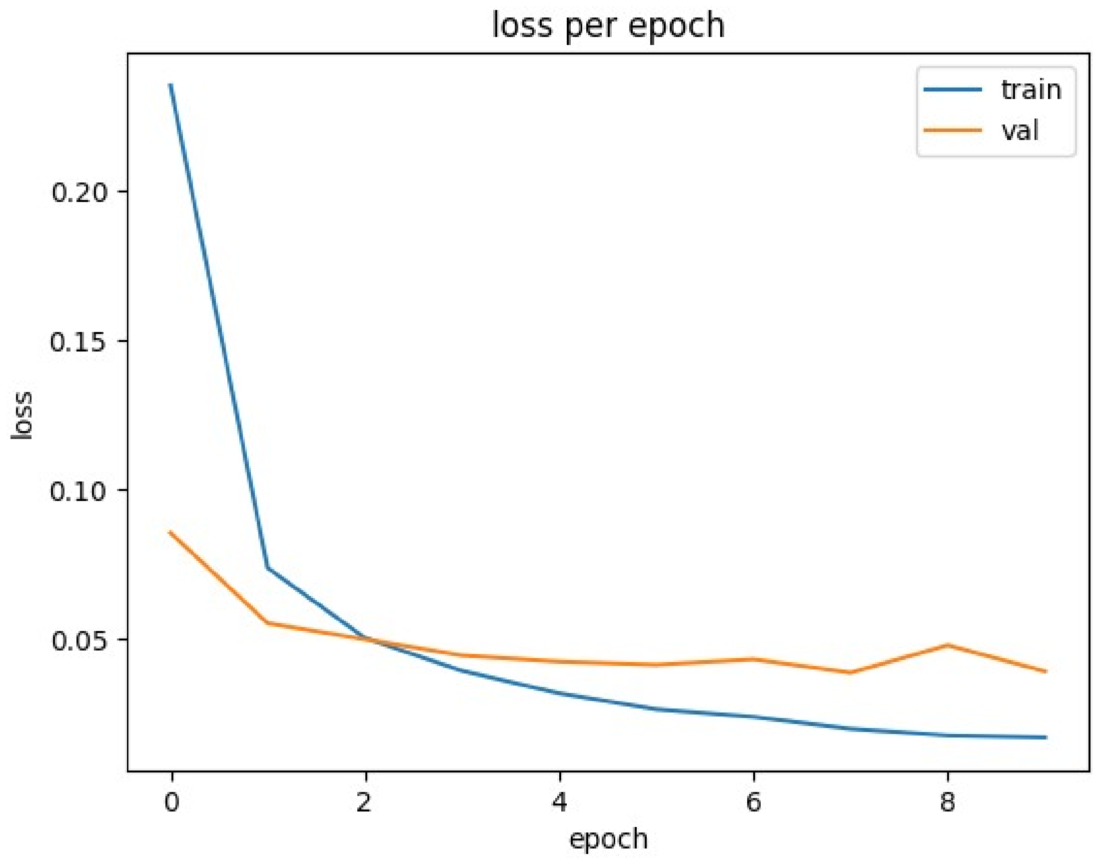
Training

```
def train_model(model, optimizer, criterion,
autoencoder_criterion=None, num_epochs=30, device='cuda'):
    since = time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0
    train_acc_per_epoch = []
    validation_acc_per_epoch = []
    train_loss_per_epoch = []
    val_loss_per_epoch = []
    model = model.to(device)
    for epoch in range(num_epochs):
        # Each epoch has a training and validation phase
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()  # Set model to training mode
            else:
                model.eval()   # Set model to evaluate mode
            running_loss = 0.0
            running_corrects = 0
            # Iterate over data.
            for inputs, labels in dataloaders[phase]:
                inputs = inputs.to(device)
                labels = torch.Tensor(labels).to(device)
                # zero the parameter gradients
                optimizer.zero_grad()
                # forward
```

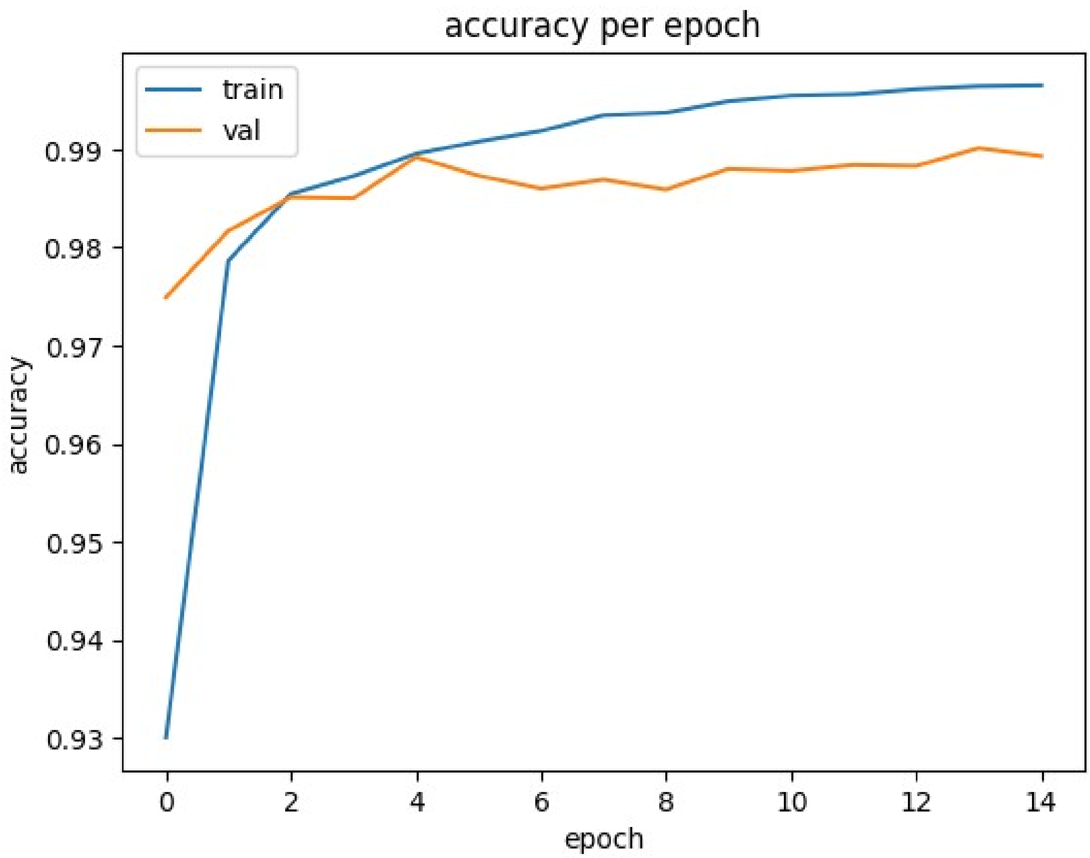
```
                # track history if only in train
                with torch.set_grad_enabled(phase == 'train'):
                    # logits: The raw predictions from the last layer
                    if model.type=='MLAE': #train both autoencoder and
conv net
                        recon, logits = model(inputs)
                        _, preds = torch.max(logits, 1)
                        loss = autoencoder_criterion(recon, inputs) +
criterion(logits, labels)

                    else:
                        logits = model(inputs)
                        _, preds = torch.max(logits, 1)
                        loss = criterion(logits, labels)
                    # backward + optimize only if in training phase
                    if phase == 'train':
                        loss.backward()
                        optimizer.step()
                # statistics
                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data)

            epoch_loss = running_loss / dataset_sizes[phase]
            epoch_acc = running_corrects.double() /
dataset_sizes[phase]


            if phase == 'train':
                train_loss_per_epoch += [epoch_loss]
                train_acc_per_epoch += [epoch_acc.item()]

            # deep copy the model the best accuracy based on the
validation set
            if phase == 'val':
                val_loss_per_epoch +=[epoch_loss]
                validation_acc_per_epoch += [epoch_acc.item()]
                if epoch_acc > best_acc:
                    best_acc = epoch_acc
                    best_model_wts = copy.deepcopy(model.state_dict())


    # plot accuracy per epoch
    model.load_state_dict(best_model_wts)
    plt.plot([i for i in range(num_epochs)], train_acc_per_epoch,
label="train")
    plt.plot([i for i in range(num_epochs)], validation_acc_per_epoch,
label="val")
    plt.xlabel("epoch")
    plt.ylabel("accuracy")
    plt.title("accuracy per epoch")
```

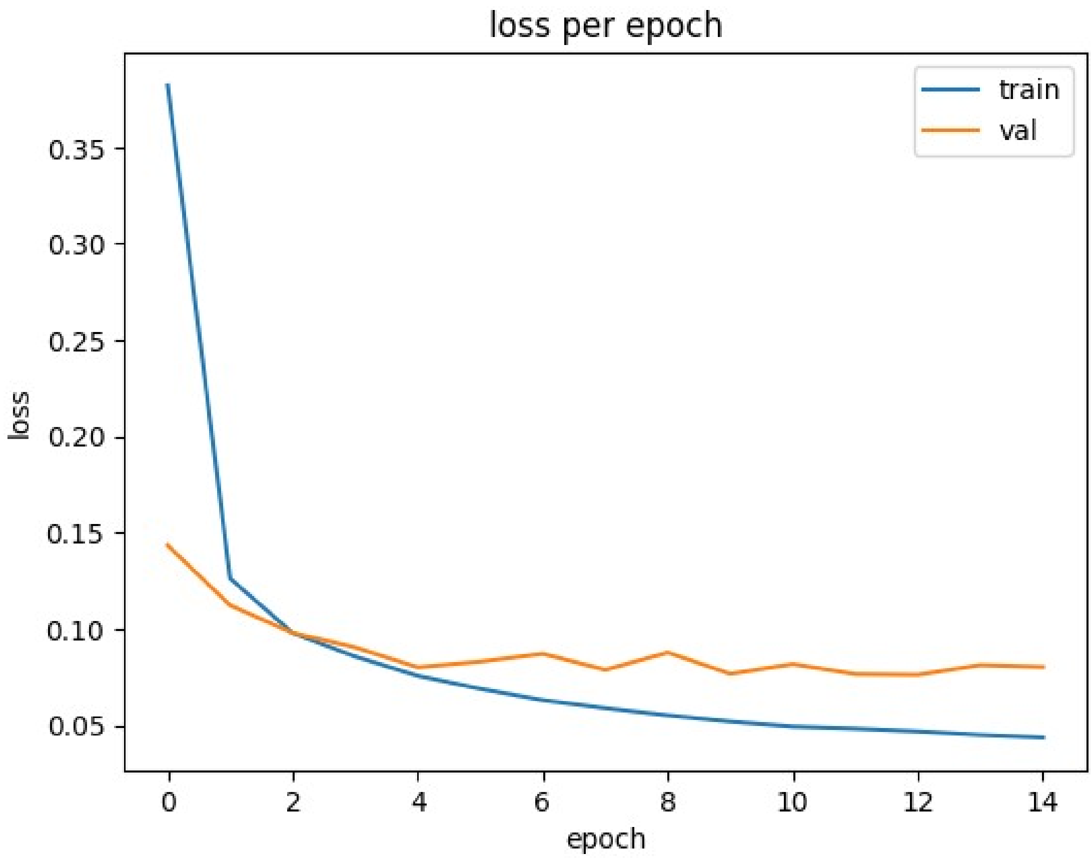
```
    plt.legend()
    plt.show()
    # plot loss per epoch
    plt.plot([i for i in range(num_epochs)], train_loss_per_epoch,
label="train")
    plt.plot([i for i in range(num_epochs)], val_loss_per_epoch,
label="val")
    plt.xlabel("epoch")
    plt.ylabel("loss")
    plt.title("loss per epoch")
    plt.legend()
    plt.show()

    # load best model weights
    return model

conv_net = ConvNet(5)

optimizer = optim.Adam(conv_net.parameters(), lr=0.001)
criterion = nn.CrossEntropyLoss()
conv_net = train_model(conv_net, optimizer, criterion,device=device,
num_epochs=10)
```






```
model = ML_Autoencoder()

optimizer = optim.Adam(model.parameters(), lr=0.001)
c1 = nn.CrossEntropyLoss()
c2 = nn.MSELoss()

model = train_model(model,optimizer, c1, autoencoder_criterion=c2,
device=device, num_epochs=15)
```

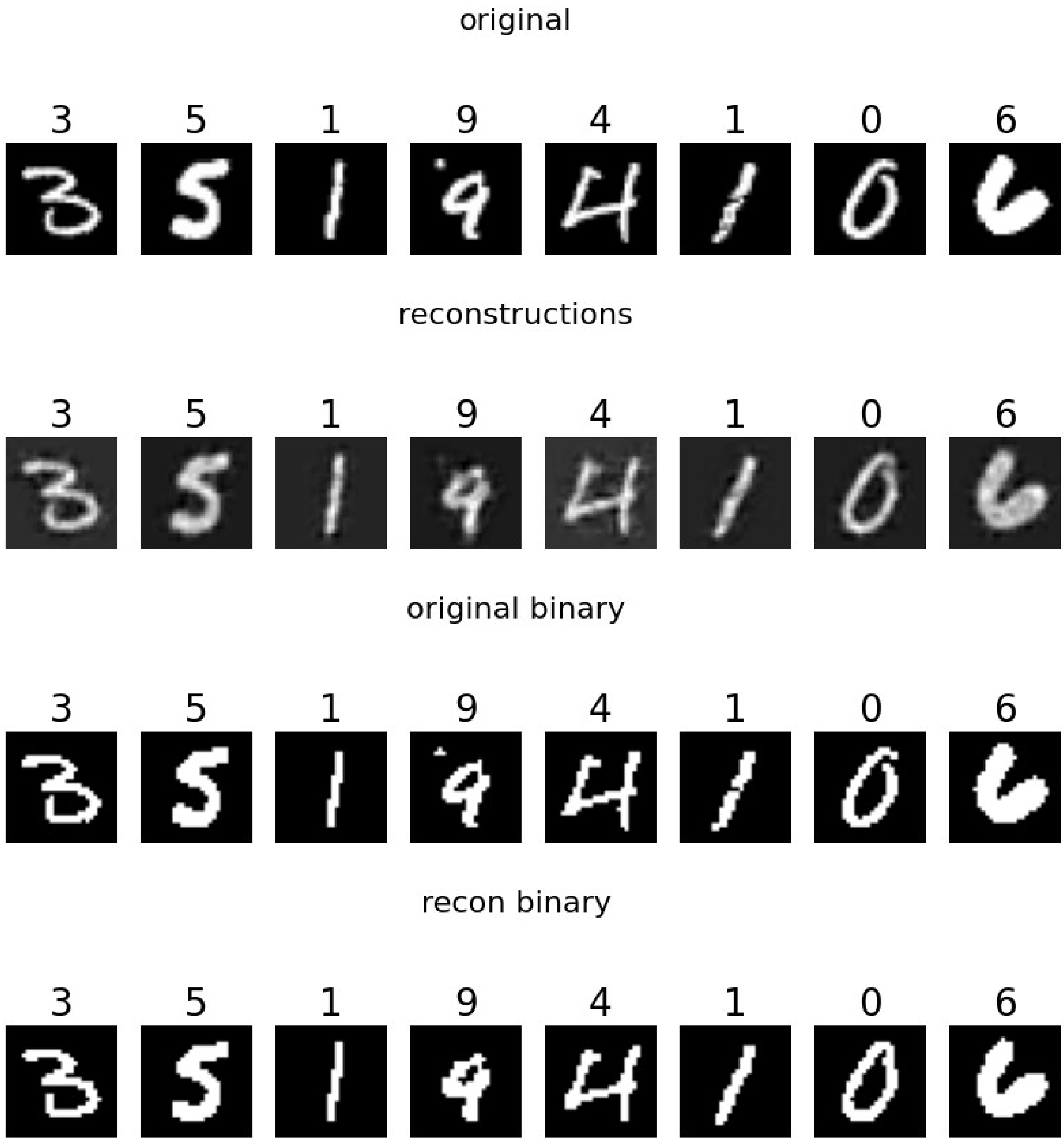

accuracy per epoch
train
val
accuracy
0.93
0.94
0.95
0.96
0.97
0.98
0.99
0
2
4
6
8
10
12
14
epoch



Based on the plot above, it seems that there is slightly overfitting in the OSR model. However, after the training phase we choose the weights that performed best on the validation set. The model does not reach higher accuracy with more epochs so we decided to use 10 epochs for the classifier and 15 for the OSR model.

```
# visualize som images and reconstructions
test_images, test_labels = next(iter(test_mnist_loader))
test_images = test_images.to(device)
test_labels = test_labels.to(device)
model.eval()

recon, preds = model(test_images)
preds = torch.max(preds, 1)
preds=preds[1]

recon = recon.detach()
plot_images_grayscale(test_images, test_labels, mnist_mean, mnist_std,
title="original")
plot_images_grayscale(recon, preds, mnist_mean, mnist_std,
title="reconstructions")
plot_images_binary(test_images, test_labels, mnist_mean, mnist_std,
title="original binary")
```

```python
plot_images_binary(recon, preds, mnist_mean, mnist_std, title="recon
binary")
```



Evaluation

```python
# This function compares between the original and reconstructed images
in terms of norm and binary differencesbased on the otsu threshold.
def norms_and_diffs(model, loader):
    norms = []
```

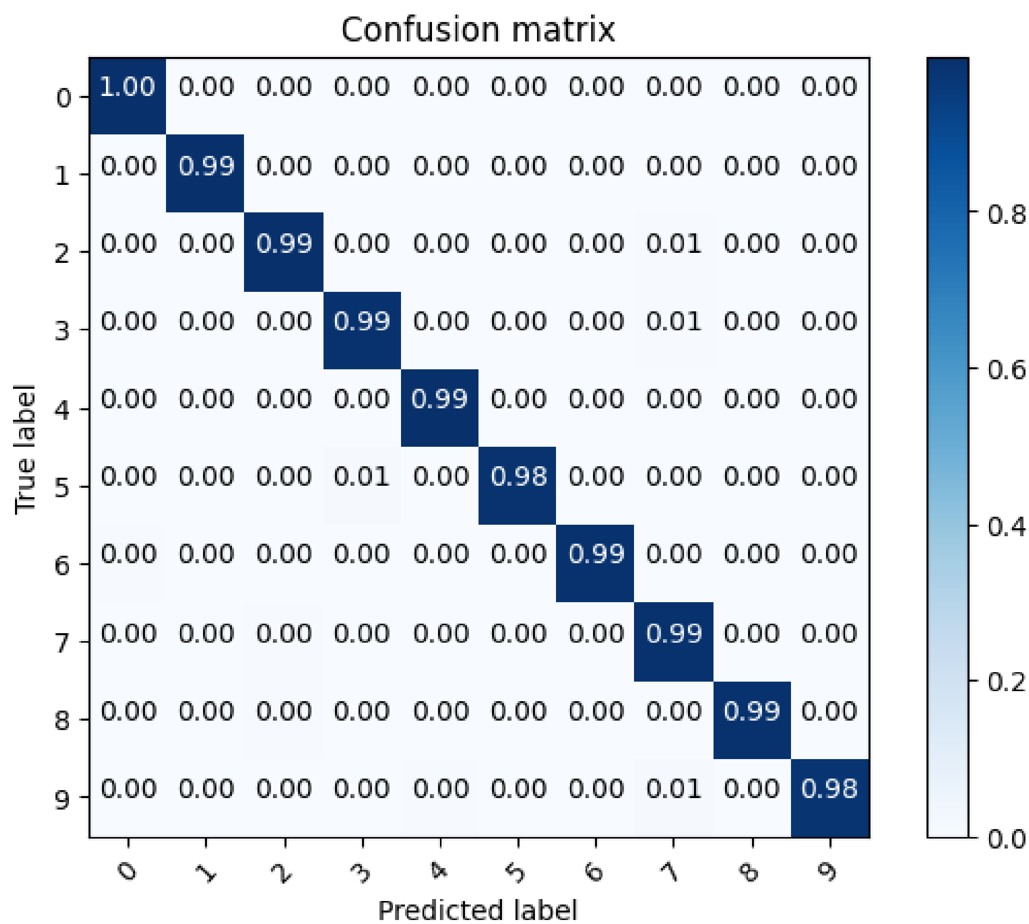
```
    diffs = []
    model.eval()
    for inputs, labels  in iter(loader):
        inputs = Variable(inputs).to(device)
        inputs = inputs.to(device)
        labels = labels.to(device)
        recons, probs = model(inputs)
        recons = recons.view(-1, 28, 28).detach().cpu().numpy()
        inputs = inputs.view(-1, 28, 28).detach().cpu().numpy()
        for i in range(len(inputs)):
            original_img = inputs[i]
            recon_img = recons[i]
            B = make_binary(recon_img)
            BO = make_binary(original_img)
            norms += [np.linalg.norm(original_img - recon_img)]
            diffs += [784 - np.sum(BO == B)]
    return norms, diffs

mnist_norms, mnist_diffs = norms_and_diffs(model, val_mnist_loader)

# These are the thresholds for the reconstructed images.
# If the difference between the reconstructed image and the original
exceeds one of these thresholds,
# it is probably not in mnist!
norms_thresh = np.mean(mnist_norms) + 3 * np.std(mnist_norms)
diffs_thresh = np.mean(mnist_diffs) + 3 * np.std(mnist_diffs)

def eval_model(model, test_loader, device='cude', binary=False):
  hidden_features = []
  correct_count, all_count = 0, 0
  plot = 1
  model.eval()
  final_labels, final_preds = torch.tensor([]), torch.tensor([])
  with torch.no_grad():
    for inputs, labels in test_loader:
        inputs = inputs.to(device)
        labels = labels.to(device)
        if model.type == 'MLAE':
            recon,outputs = model(inputs)
            hidden_features.append(model.encoder(inputs)[0].detach())
            X = recon - inputs
            X = X.detach()
            norms = torch.linalg.norm(X, dim=( 2, 3)).view((-1))
            recon = recon.detach().cpu().numpy().reshape((-1, 28, 28))
            recon_binary = make_binary(recon)
            original_binary =
make_binary(inputs.detach().cpu().numpy().reshape((-1, 28, 28)))
            diffs = np.sum(recon_binary != original_binary, axis=(1,
2))
            diffs = torch.from_numpy(diffs)
```

```
            _, preds = torch.max(outputs, 1)
            # change prediction if norm or diff is over the threshold
            preds[diffs > diffs_thresh] = 10
            preds[norms > norms_thresh] = 10
        else:
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
        if binary:
            preds[preds<10] = 0
            preds[preds>9] = 1
            labels[labels < 10] = 0
            labels[labels > 9] = 1
        final_labels = torch.cat((final_labels, labels.cpu()), 0)
        final_preds = torch.cat((final_preds, preds.cpu()), 0)
        correct_pred = torch.eq(labels, preds).cpu()
        correct_count += correct_pred.numpy().sum()
        all_count += len(labels)
  print("Number Of Images Tested =", all_count)
  print("\nModel Accuracy =", (correct_count/all_count))
  cf_matrix = confusion_matrix(final_labels, final_preds)
  plot_confusion_matrix(cf_matrix, classes=[i for i in
range(1+int(final_labels.max()))])
  return final_preds, final_labels, hidden_features
```

Baseline results

```
_ = eval_model(conv_net, test_mnist_loader, device=device)
```

```
Number Of Images Tested = 10000

Model Accuracy = 0.989
```



OSR rational

The idea:

The mnist dataset samples have very specific visual qualities, which for a human makes it easy to differentiate from images with other semantic meanings. To make use of these qualities for the task at hand, we wanted to train a model that could reconstruct mnist images very well from a context-vector embedding, with the idea being that it would fail to reconstruct images outside the mnist dataset. That would allow us to use a measurement of dissimilarity between a reconstruction of an image and the original sample to identify images outside the closed set, and for the images identified as coming from the mnist samples-distribution, we would use the baseline model for classification.

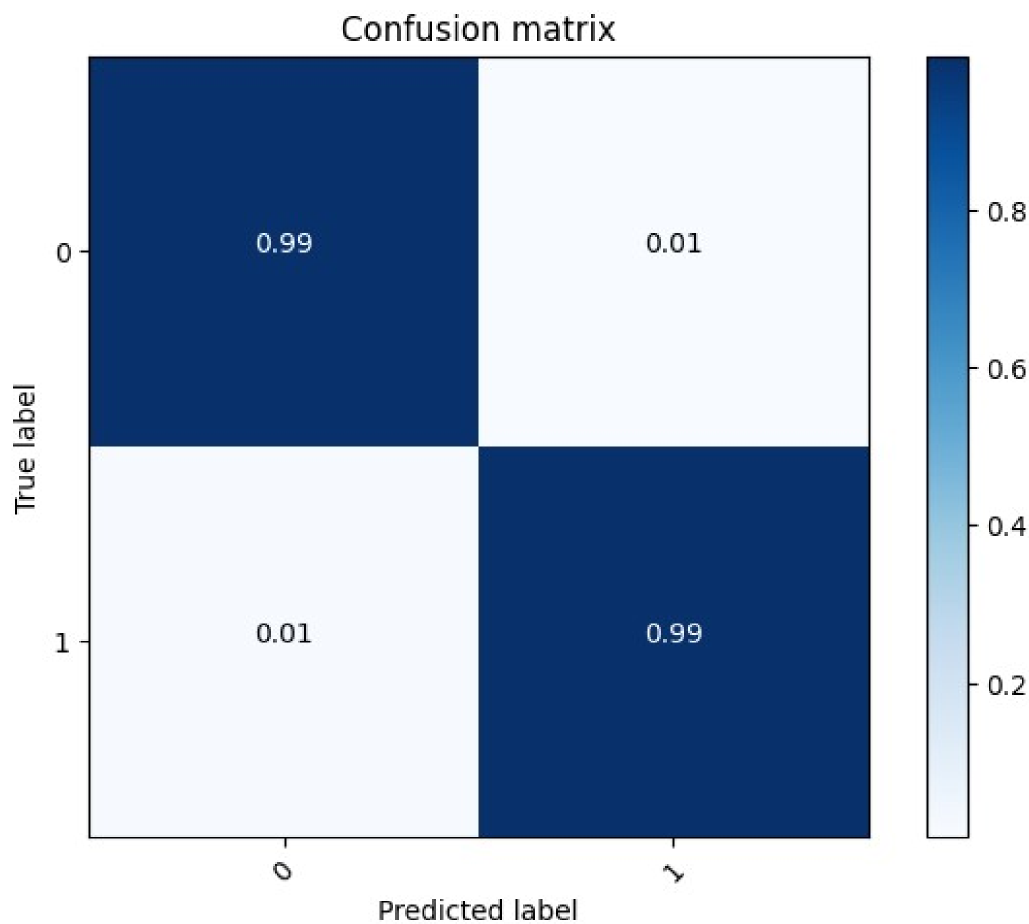
The implementation:

To classify a sample, we embed it to a context vector using convolutional layers (convolution, maxpool, relu), and several fully connected layers, reconstruct it using an architecture which is supposed to represent the mirroring of the embedding architecture, make the reconstruction black-and-white, and measure the dissimilarity of the reconstructed image from the original. The measurement is made using the norm of pixel-wise difference. If the measurement taken is above a certain threshold we conclude that the sample is from OOD, otherwise we conclude that the sample is from MNIST distribution, and use the baseline model to determine which digit it represents. We defined the threshold to be the mean plus 3 times the standard deviation of the dissimilarity measurements over the mnist evaluation set. The model is trained only on MNIST data, and only OOD data is only present during evaluation stages.

OOD results

```
_ = eval_model(model, test_loader_w_OOD, device=device, binary=True)
```

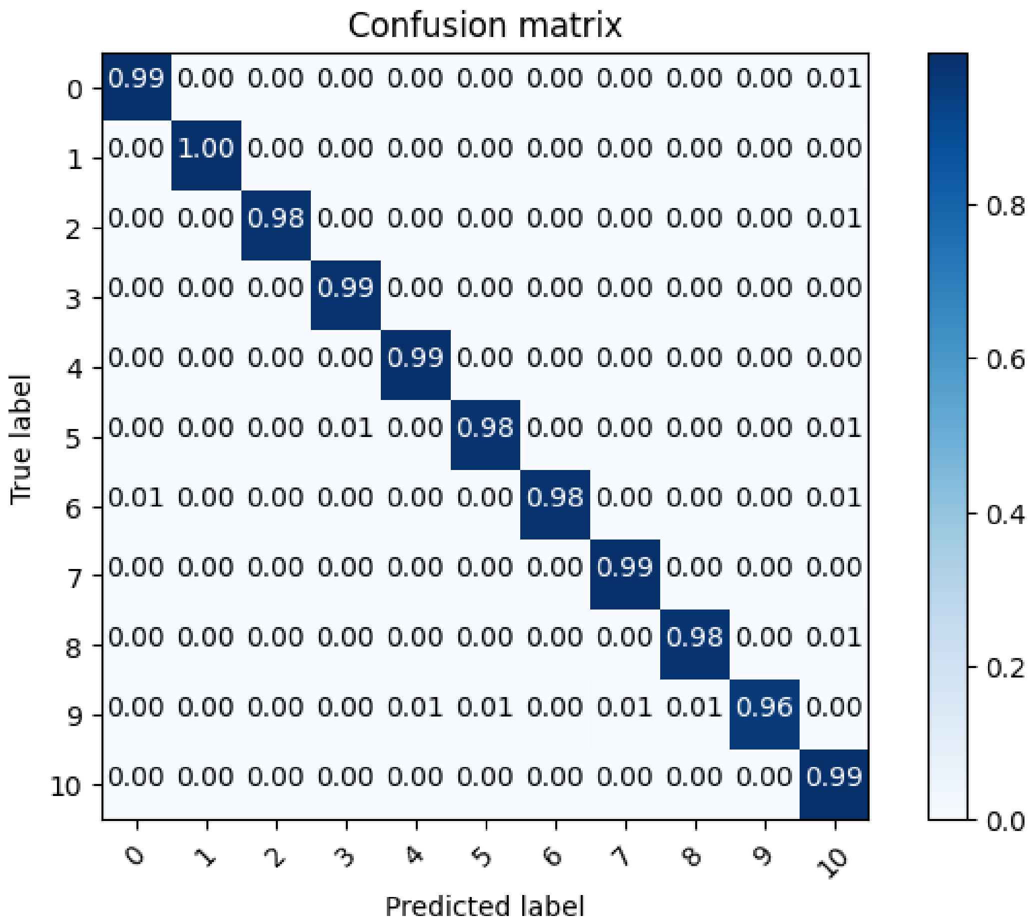
```
Number Of Images Tested = 30000

Model Accuracy = 0.9911333333333333
```



OSR results

```
final_preds, _, hidden_features = eval_model(model, test_loader_w_OOD,
device=device, binary=False)
```

```
Number Of Images Tested = 30000

Model Accuracy = 0.9879333333333333
```



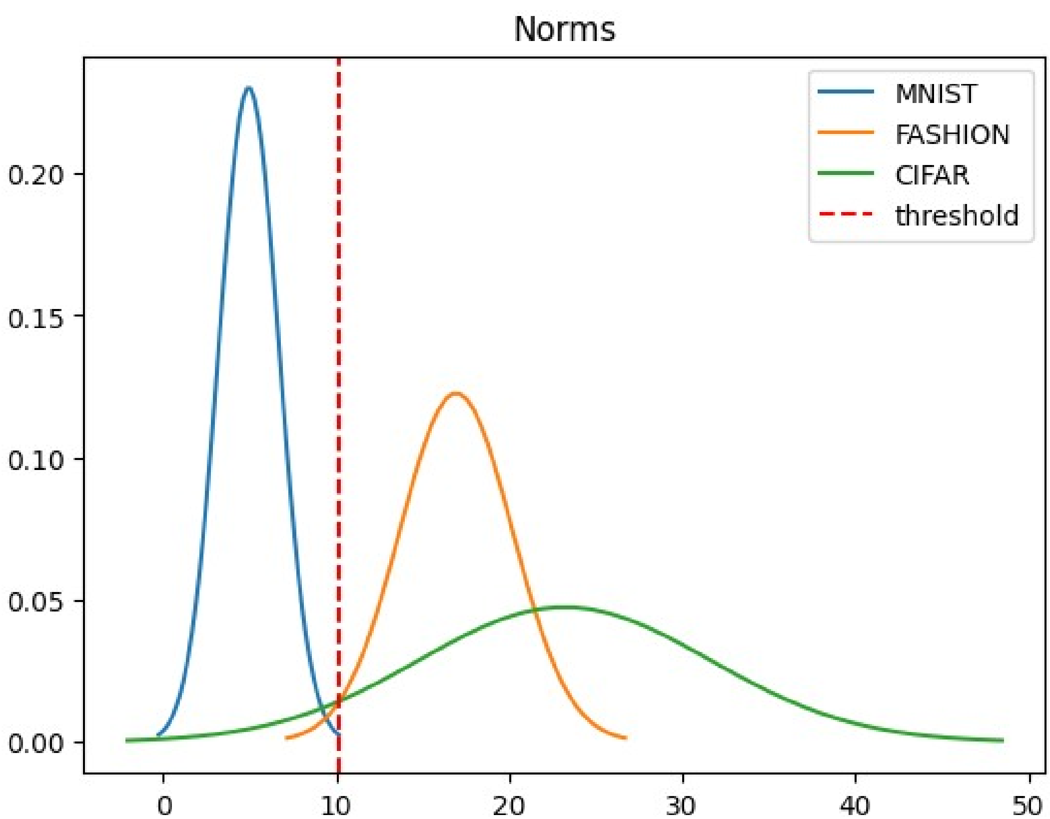
Results:

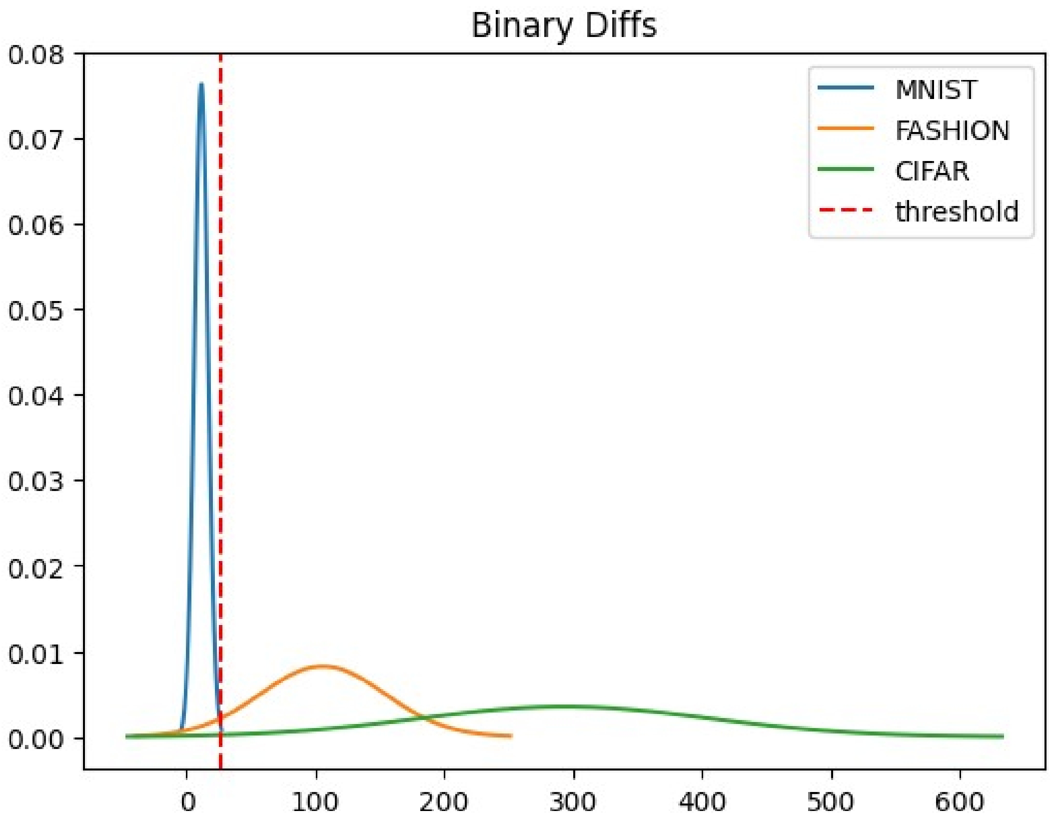
As we can see above, the digits classifier was able to get 98.9% accuracy over the test set of mnist. The OSR model reached 99.1% accuracy when needed to decide if an image is part of MNIST or not. in general case, the accuracy of the model, including classifying the digits, is 98.7%.

If we assume that the differences between the original and reconstructed images are distributed normally, we can see below how the different datasets gaussians are seperated.

```
fash_norms, fash_diffs = norms_and_diffs(model, test_fash_loader)
cifar_norms, cifar_diffs = norms_and_diffs(model, test_cifar_loader)

def plot_gaussian(mean, std, label=""):
    X = np.linspace(mean- 3 * std, mean+3*std, 50)
    plt.plot(X, norm.pdf(X, mean, std), label=label)

plot_gaussian(np.mean(mnist_norms), np.std(mnist_norms),
label="MNIST")
plot_gaussian(np.mean(fash_norms), np.std(fash_norms),
label="FASHION")
```

```
plot_gaussian(np.mean(cifar_norms), np.std(cifar_norms),
label="CIFAR")
plt.axvline(norms_thresh, ls='--', color='r', label="threshold")
plt.legend()
plt.title("Norms")
plt.show()

plot_gaussian(np.mean(mnist_diffs), np.std(mnist_diffs),
label="MNIST")
plot_gaussian(np.mean(fash_diffs), np.std(fash_diffs),
label="FASHION")
plot_gaussian(np.mean(cifar_diffs), np.std(cifar_diffs),
label="CIFAR")
plt.axvline(diffs_thresh,ls='--', color='r', label="threshold")
plt.legend()
plt.title("Binary Diffs")
plt.show()
```

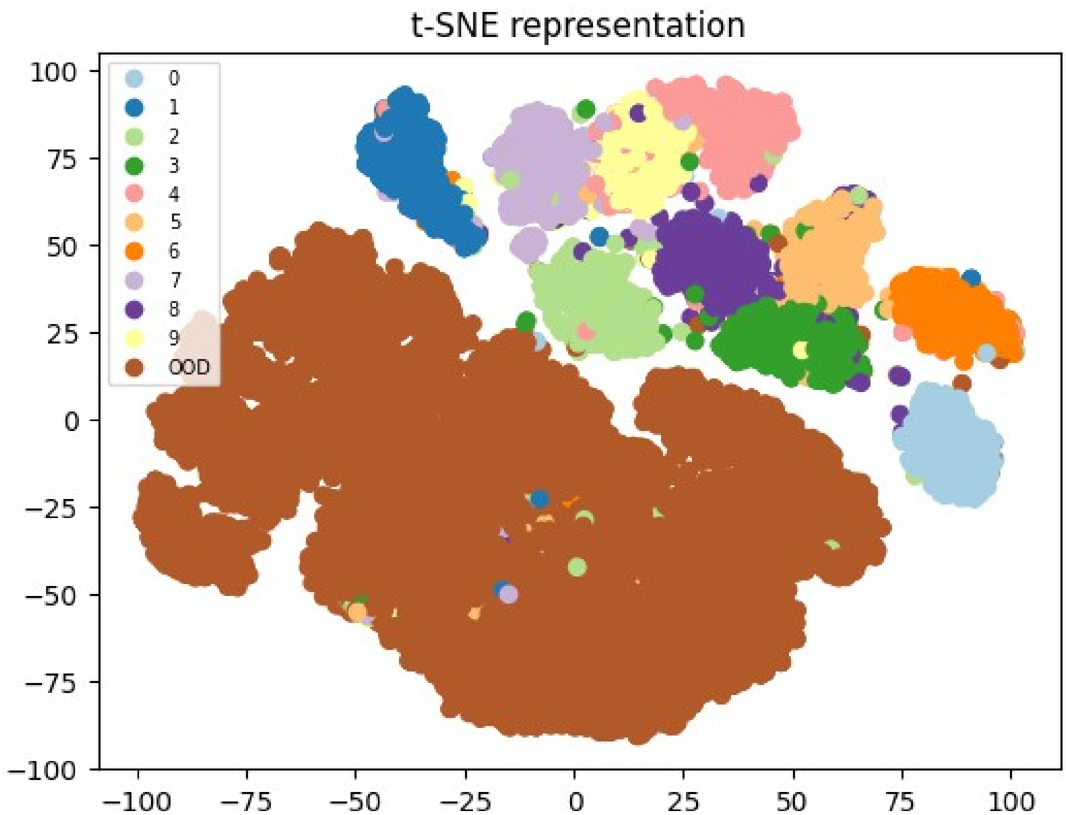





```
torch.save(model.state_dict(), "./ML_autoencoder_W.pth")
torch.save(conv_net.state_dict(), "./conv_net_W.pth")
```

t-SNE visualization of embedded layer of the test data

```
from sklearn.manifold import TSNE
from torchvision.models.feature_extraction import
create_feature_extractor

model.eval()
with torch.no_grad():
    tsned_embedded_points = TSNE(n_components=2, learning_rate='auto',
init='random').fit_transform(torch.cat(hidden_features).cpu())


hidden_scatter  = plt.scatter(tsned_embedded_points[:,0],
tsned_embedded_points[:,1], c=final_preds, cmap="Paired")
handles, _ = hidden_scatter.legend_elements()
legend = plt.legend(handles = handles, labels = [*range(0,10),
"OOD"],fontsize="7")
plt.title("t-SNE representation")
plt.show()
```



T-SNE is an algorithm for reduce dimentions of hig dimentional data. This helps to visualize the distribution of the data in high dimentions. we can see above how the encoder distributes the different classes and the OOD data. There is some overlap between the classes so its not perfect. We can see that the overlap fits the results from the confusion matrix (for example, the classes of 9 and 4 are very close).