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DDA Lab 7 Report

In [1]:

```
import torch
from torch.nn import Module
from torch import nn
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader, Dataset
from torch.utils.tensorboard import SummaryWriter
import torch.nn.functional as F
import matplotlib.pyplot as plt
import numpy as np
```

Network Analysis: Image Classification - Part 2

The Network has three convolution layer, two max pool and three fully connected layers with ReLU as activation function. Since the Loss here used is CrossEntropy so there wasn't any need for the softmax layer. The input and output channels are selected after some experiments.

In [2]:

```
class CNNetwork(Module):
    def __init__(self, input_channels):
        super(CNNetwork, self).__init__()
        self.conv1 = nn.Conv2d(input_channels, 10, kernel_size = 5)
        self.pool1 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.conv2 = nn.Conv2d(10, 30, kernel_size = 5)
        self.conv3 = nn.Conv2d(30, 60, kernel_size = 5)
        self.pool2 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.fc1 = nn.Linear(540, 270)
        self.fc2 = nn.Linear(270, 130)
        self.fc3 = nn.Linear(130, 10)


    def forward(self, x):
        y = F.relu(self.conv1(x))
        y = self.pool1(y)
        y = F.relu(self.conv2(y))
        y = F.relu(self.conv3(y))
        y = self.pool2(y)
        y = y.view(-1, 60*3*3)
        y = F.relu(self.fc1(y))
        y = F.relu(self.fc2(y))
        y = self.fc3(y)
        return y
```

In [3]:

```
CifarTrain = torchvision.datasets.CIFAR10(root = './data', train = True, transform = transf
CifarTest = torchvision.datasets.CIFAR10(root = './data', train = False, transform = transf
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [6]:

```
batch_size = 128
epochs = 10
learning_rate = 10**(-3)
CifarTrainHalf = torch.utils.data.Subset(CifarTrain, range(len(CifarTrain)//2))
```

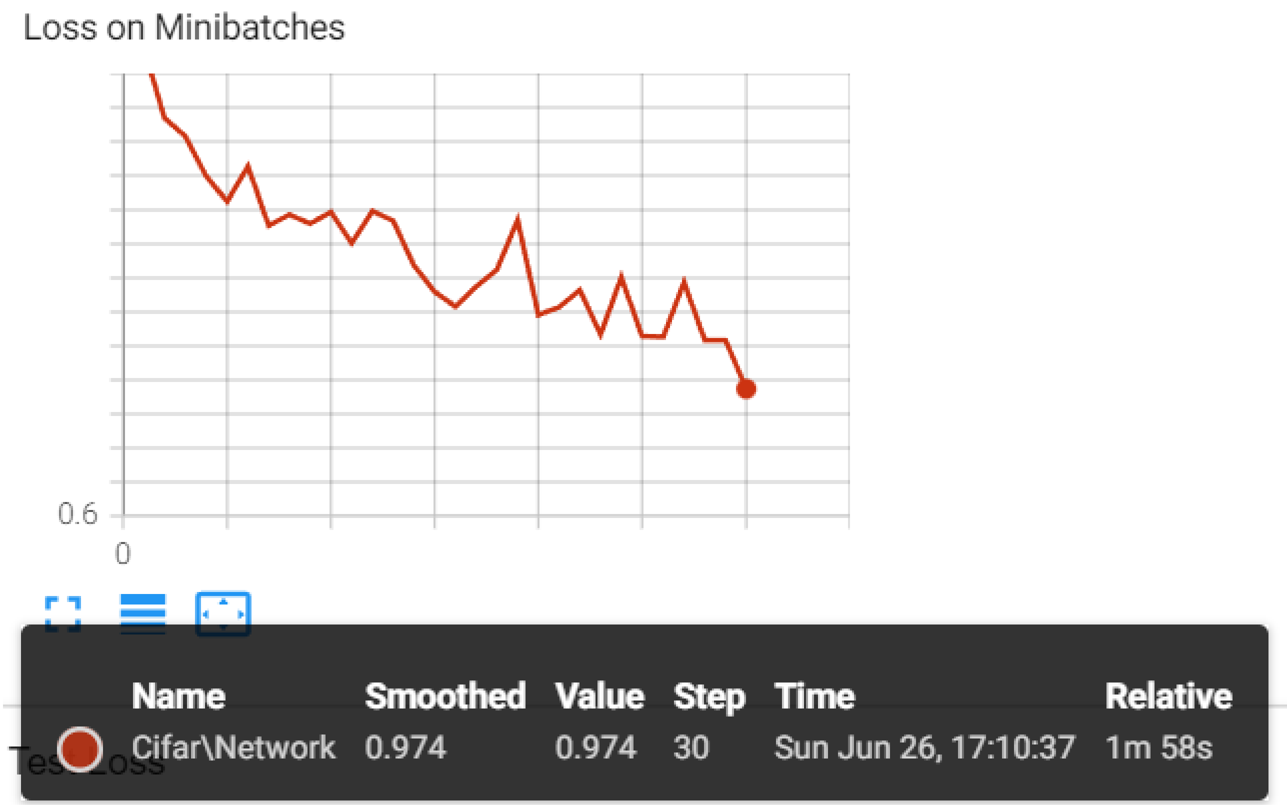
In [7]:

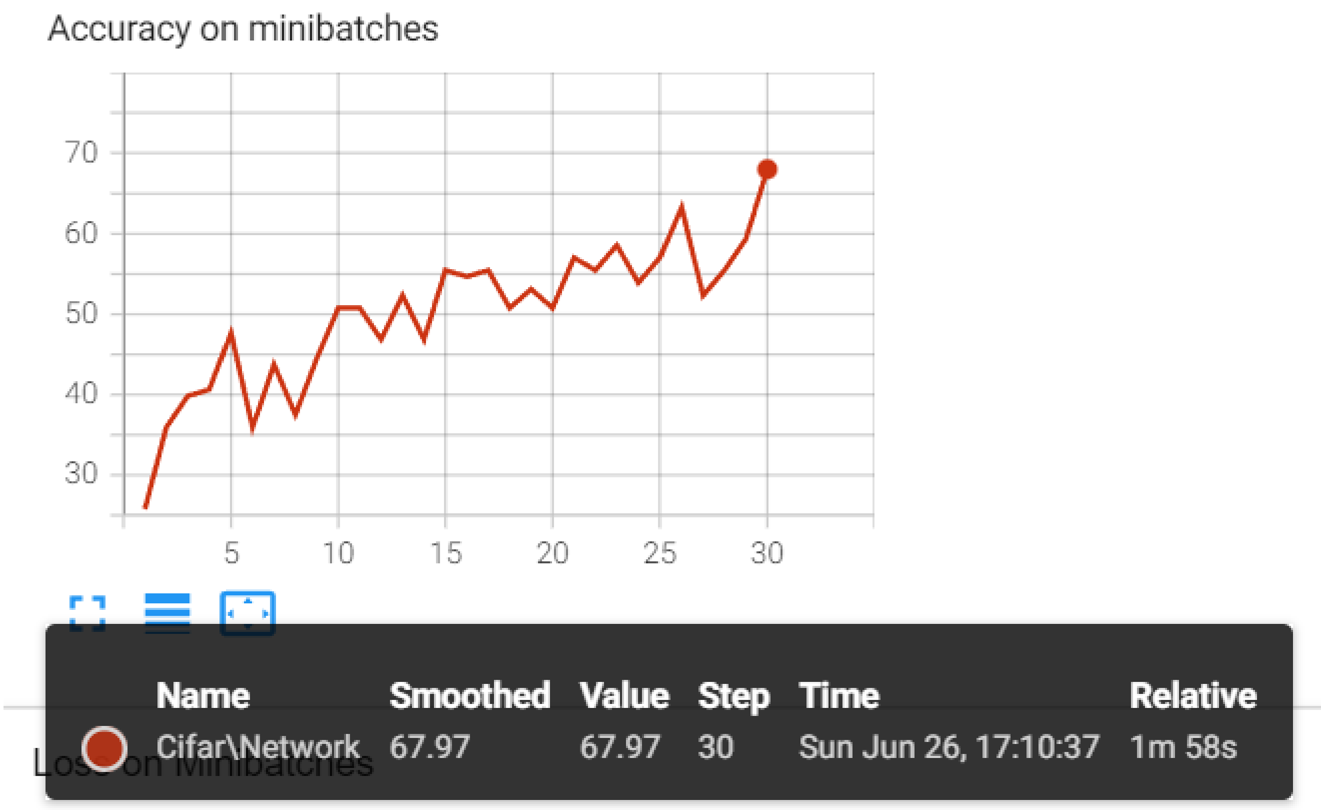
```
train_loader = DataLoader(CifarTrainHalf, batch_size = batch_size, shuffle=True)
test_loader = DataLoader(CifarTest, batch_size = 64, shuffle = True)
```

In [ ]:

```
ModelCNN = CNNetwork(3)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(ModelCNN.parameters(),lr = learning_rate)
writer = SummaryWriter(f'runs/Cifar/Network')
step = 0
for epoch in range(epochs):
    total_loss = 0
    correct_pred = 0
    sample_size = 0
    for i, batch in enumerate(train_loader):
        optimizer.zero_grad()
        yhat = ModelCNN(batch[0])
        loss = criterion(yhat.squeeze(), batch[1].squeeze())
        total_loss += loss.item()
        pred = torch.max(yhat.data, 1)[1]
        sample_size = batch[1].size(0)
        correct_pred += (pred == batch[1]).sum().item()
        loss.backward()
        optimizer.step()
        if (i + 1) % 50 == 0:
            writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
            writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item()/sa
                              step + 1)
            step += 1
    accuracy = (correct_pred/len(CifarTrainHalf))*100
    writer.add_scalar('Train Loss', np.sqrt(total_loss/len(CifarTrainHalf)), epoch + 1)
    writer.add_scalar('Train accuracy', accuracy, epoch + 1)

    with torch.no_grad():
        test_pred = 0
        test_loss = 0
        for i, (img, label) in enumerate(test_loader):
            optimizer.zero_grad()
            output = ModelCNN(img)
            loss = criterion(output.squeeze(), label.squeeze())
            test_loss += loss.item()
            pred = torch.max(output.data, 1)[1]
            test_pred += (pred == label).sum().item()
        accuracy = (test_pred/len(CifarTest))*100
        writer.add_scalar('Test Loss', np.sqrt(test_loss/len(CifarTest)), epoch + 1)
        writer.add_scalar('Test accuracy', accuracy, epoch + 1)

writer.close()
writer.flush()
```

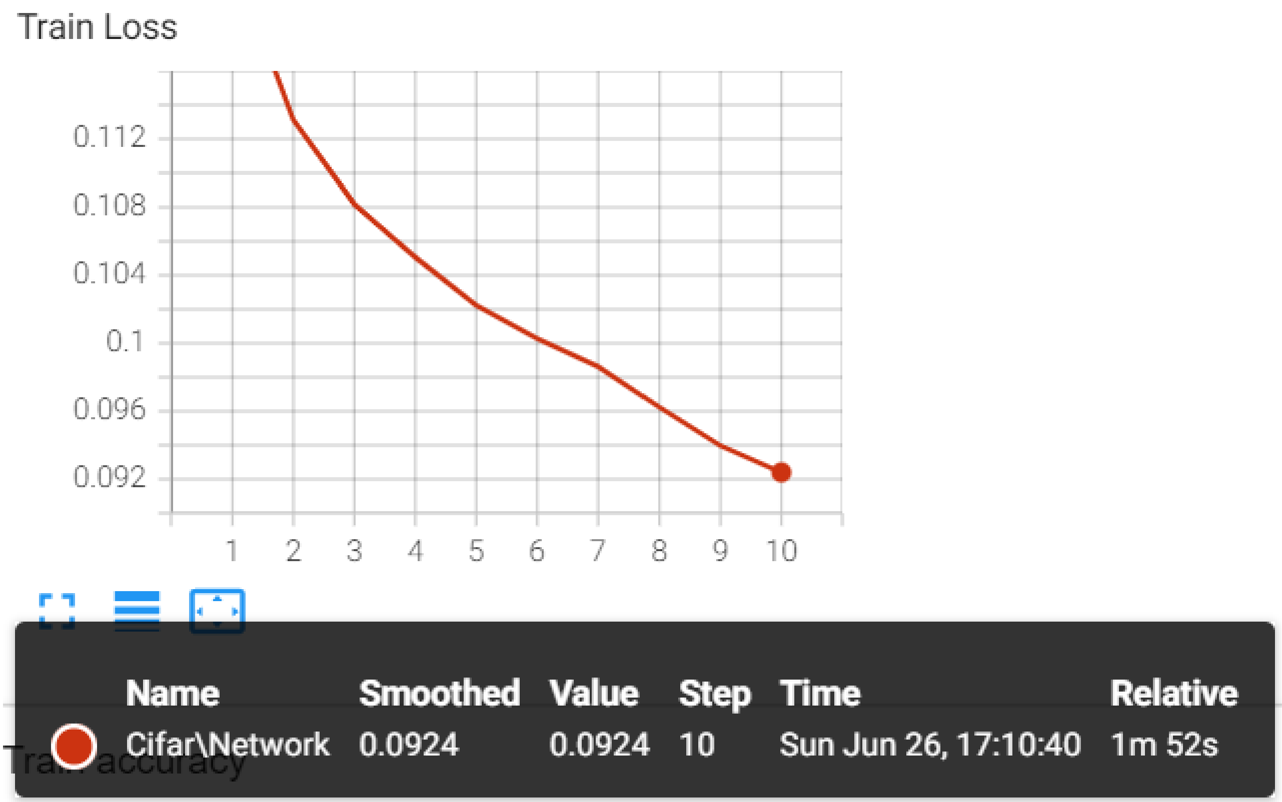
For batches we can see see the trend in loss and accuracy, as the model sees more and more data, loss is decreased and accuracy is increased.

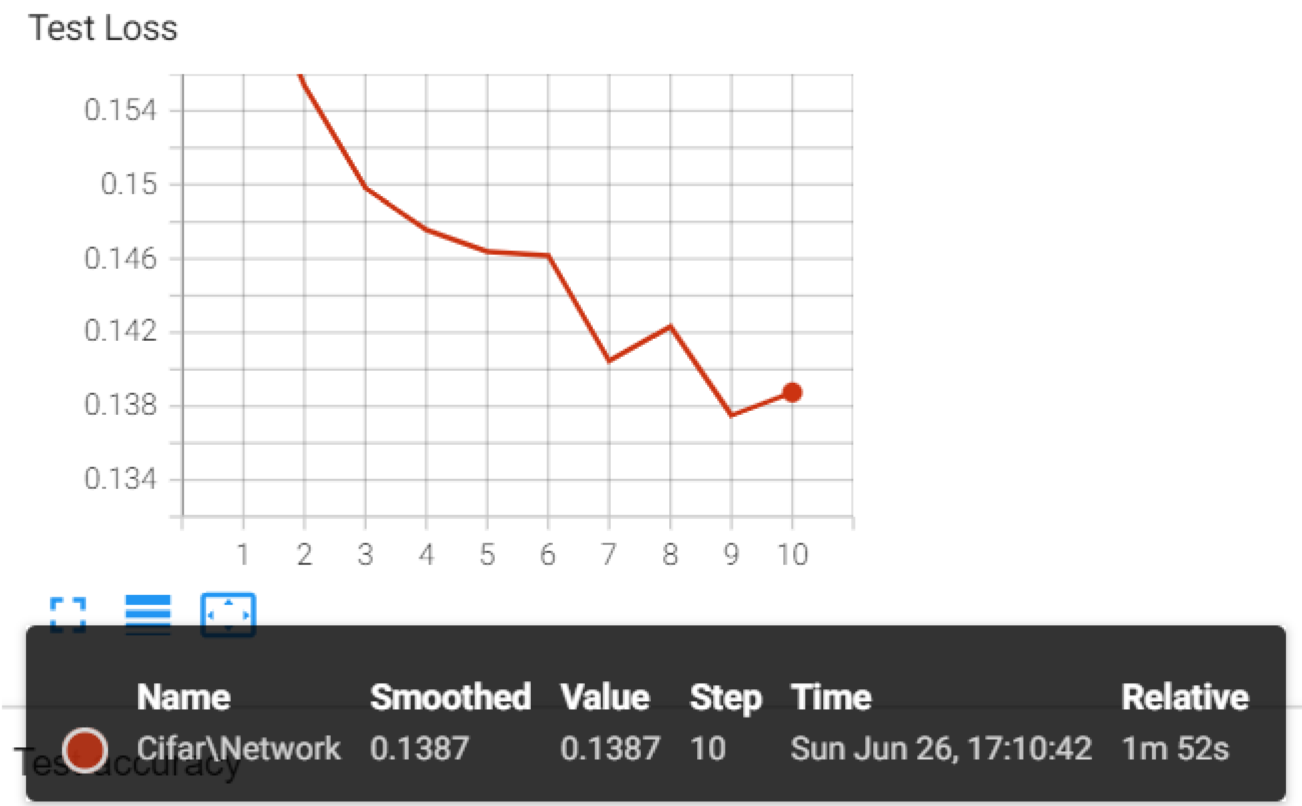




Training and Test Loss

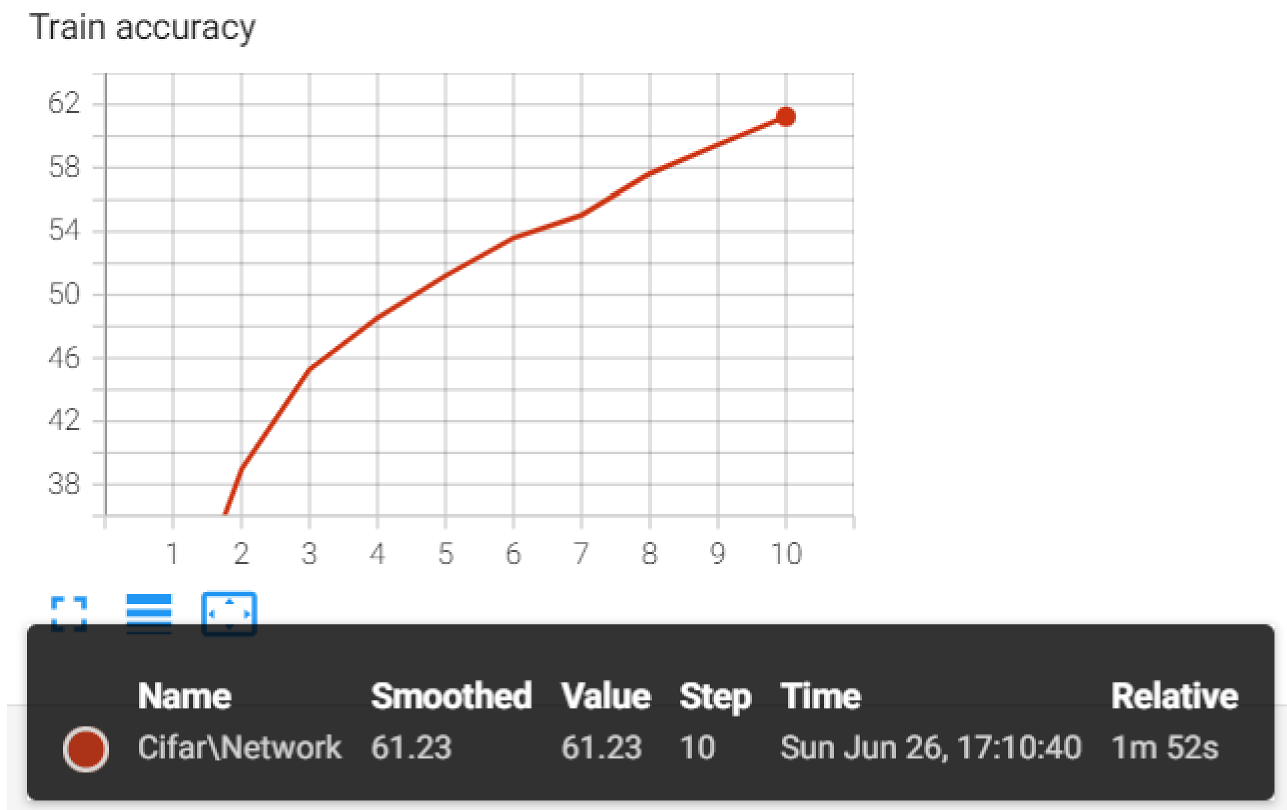
For the 10th epoch, the test loss as seen below is very high (0.14) as compared to the training loss which is 0.09

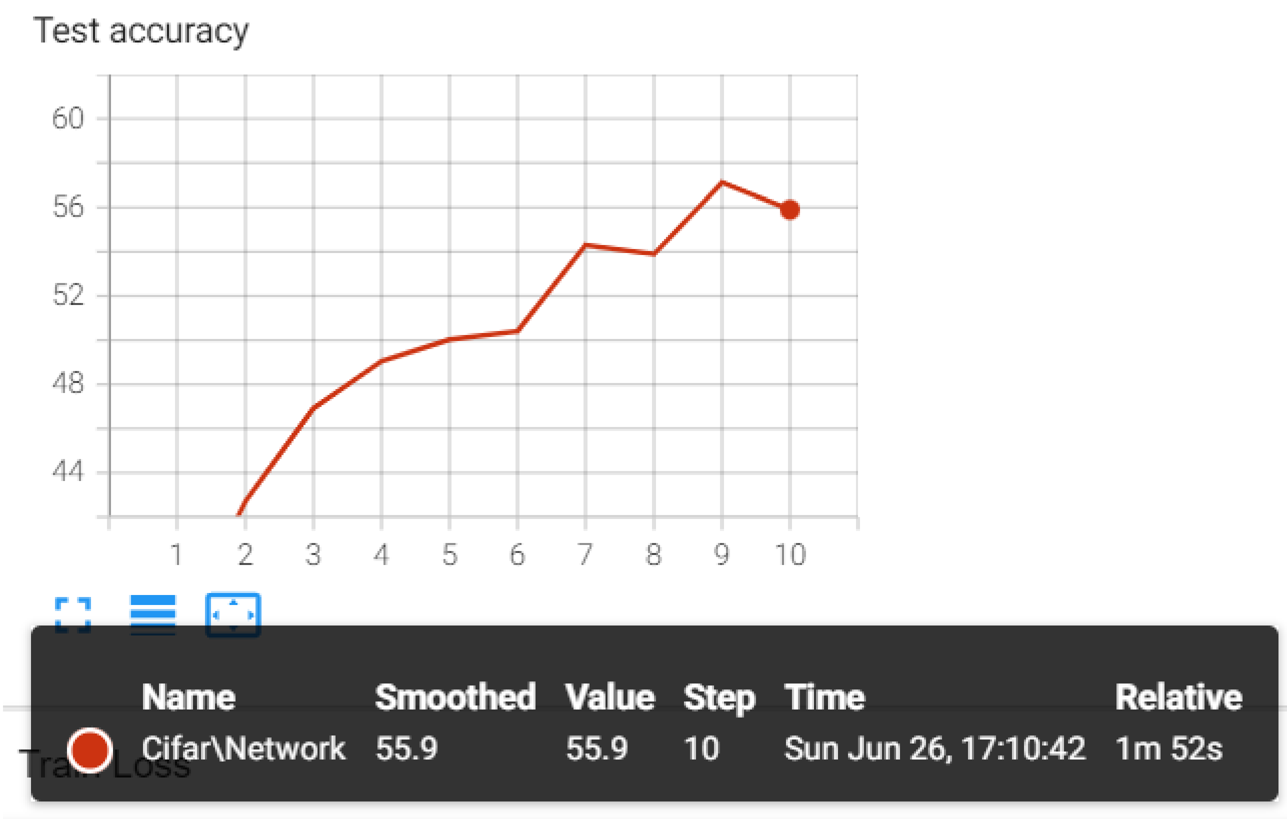




Training and Test Accuracy

Also on comparing accuracy we see that training accuracy is more than the test accuracy





Now we will see approaches to deal with overfiting as seen above

Normalization Effect

mean and standard deviation for Normalization

In [8]:

```
R_total_mean, G_total_mean, B_total_mean = 0, 0, 0
R_total_std, G_total_std, B_total_std = 0, 0, 0
for img, label in CifarTrain:
    R_mean, G_mean ,B_mean = torch.mean(img, dim = [1,2])
    R_std, G_std ,B_std = torch.std(img, dim = [1,2])
    R_total_mean += R_mean
    G_total_mean += G_mean
    B_total_mean += B_mean
    R_total_std += R_std
    G_total_std += G_std
    B_total_std += B_std
print(R_total_mean/len(CifarTrain), G_total_mean/len(CifarTrain), B_total_mean/len(CifarTra
print(R_total_std/len(CifarTrain), G_total_std/len(CifarTrain), B_total_std/len(CifarTrain)
```

```
tensor(0.4914) tensor(0.4822) tensor(0.4465)
tensor(0.2023) tensor(0.1994) tensor(0.2010)
```

Transformations defined for augmentation, normalization and both as below

In [ ]:

```
transformAug = transforms.Compose([transforms.Resize((32,32)),
                                      transforms.RandomHorizontalFlip(),
                                      transforms.RandomRotation(10),
                                      transforms.ColorJitter(brightness=0.3, contrast=0.2,
                                      transforms.ToTensor()
                               ])

transformNorm = transforms.Compose([transforms.Resize((32,32)),
                                      transforms.ToTensor(),
                                      transforms.Normalize((0.4914, 0.4822, 0.4465), (0.202
                               ])

transformBoth = transforms.Compose([transforms.Resize((32,32)),
                                      transforms.RandomHorizontalFlip(),
                                      transforms.RandomRotation(10),
                                      transforms.ColorJitter(brightness=0.3, contrast=0.2,
                                      transforms.ToTensor(),
                                      transforms.Normalize((0.4914, 0.4822, 0.4465), (0.202
                               ])
```

1. Augmentation

The general idea is to increase dataset by appending more images with some changes such as change in contrast, rotation etc.

In [ ]:

```
CifarTrainAug = torchvision.datasets.CIFAR10(root = './data', train = True,
                                             transform = transformAug, download = True)
CifarTestAug = torchvision.datasets.CIFAR10(root = './data', train = False,
                                            transform = transformAug, download = True)
```

In [ ]:

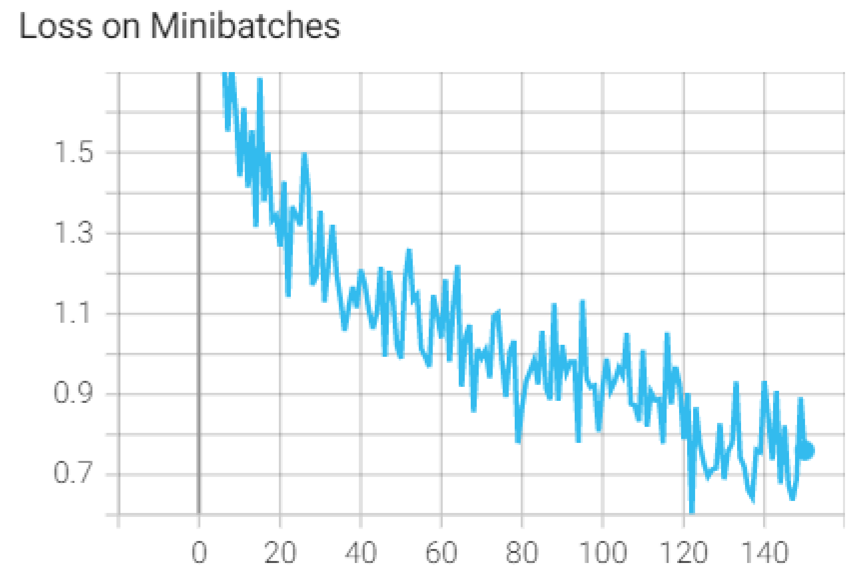
```
AugmentedDataTrain = torch.utils.data.ConcatDataset([CifarTrain, CifarTrainAug])
AugmentedDataTest = torch.utils.data.ConcatDataset([CifarTest, CifarTestAug])
```

In [ ]:

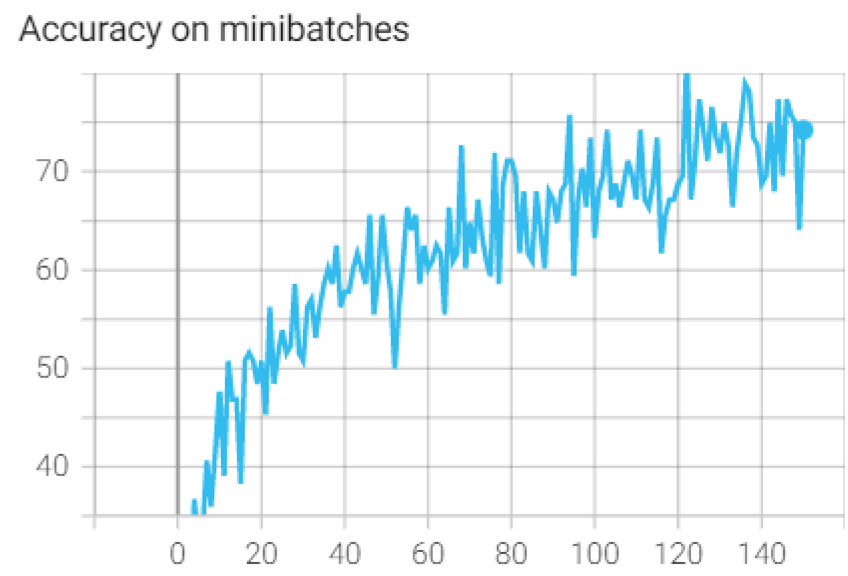
```
train_loaderAug = DataLoader(AugmentedDataTrain, batch_size = batch_size, shuffle=True)
test_loaderAug = DataLoader(AugmentedDataTest, batch_size = 64, shuffle = True)
```

In [ ]:

```
ModelCNNAug = CNNetwork(3)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(ModelCNNAug.parameters(),lr = learning_rate)
writer = SummaryWriter(f'runs/Cifar/Augmentation')
step = 0
for epoch in range(epochs):
    total_loss = 0
    correct_pred = 0
    sample_size = 0
    for i, batch in enumerate(train_loaderAug):
        optimizer.zero_grad()
        yhat = ModelCNNAug(batch[0])
        loss = criterion(yhat.squeeze(), batch[1].squeeze())
        total_loss += loss.item()
        pred = torch.max(yhat.data, 1)[1]
        sample_size = batch[1].size(0)
        correct_pred += (pred == batch[1]).sum().item()
        loss.backward()
        optimizer.step()
        if (i + 1) % 50 == 0:
            writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
            writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item()/sa
                              step + 1)
            step += 1
    accuracy = (correct_pred/len(AugmentedDataTrain))*100
    writer.add_scalar('Train Loss', np.sqrt(total_loss/len(AugmentedDataTrain)), epoch + 1)
    writer.add_scalar('Train accuracy', accuracy, epoch + 1)

    with torch.no_grad():
        test_pred = 0
        test_loss = 0
        for i, (img, label) in enumerate(test_loaderAug):
            optimizer.zero_grad()
            output = ModelCNNAug(img)
            loss = criterion(output.squeeze(), label.squeeze())
            test_loss += loss.item()
            pred = torch.max(output.data, 1)[1]
            test_pred += (pred == label).sum().item()
        accuracy = (test_pred/len(AugmentedDataTest))*100
        writer.add_scalar('Test Loss', np.sqrt(test_loss/len(AugmentedDataTest)), epoch + 1
        writer.add_scalar('Test accuracy', accuracy, epoch + 1)

writer.close()
writer.flush()
```



Name	Smoothed	Value	Step	Time	Relative
Cifar\Augmentation	0.76	0.76	150	Sun Jun 26, 17:32:34	11m 46s

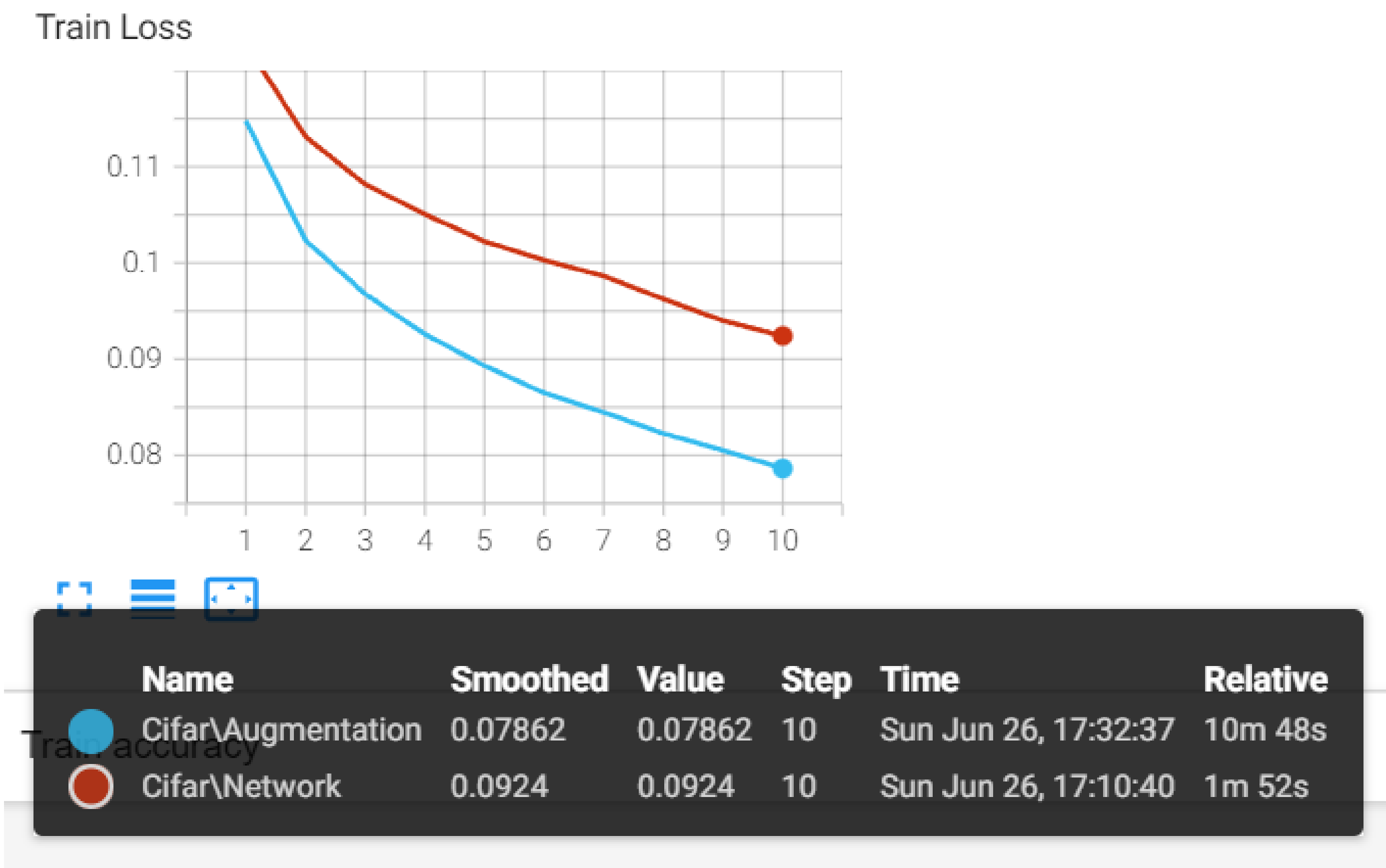


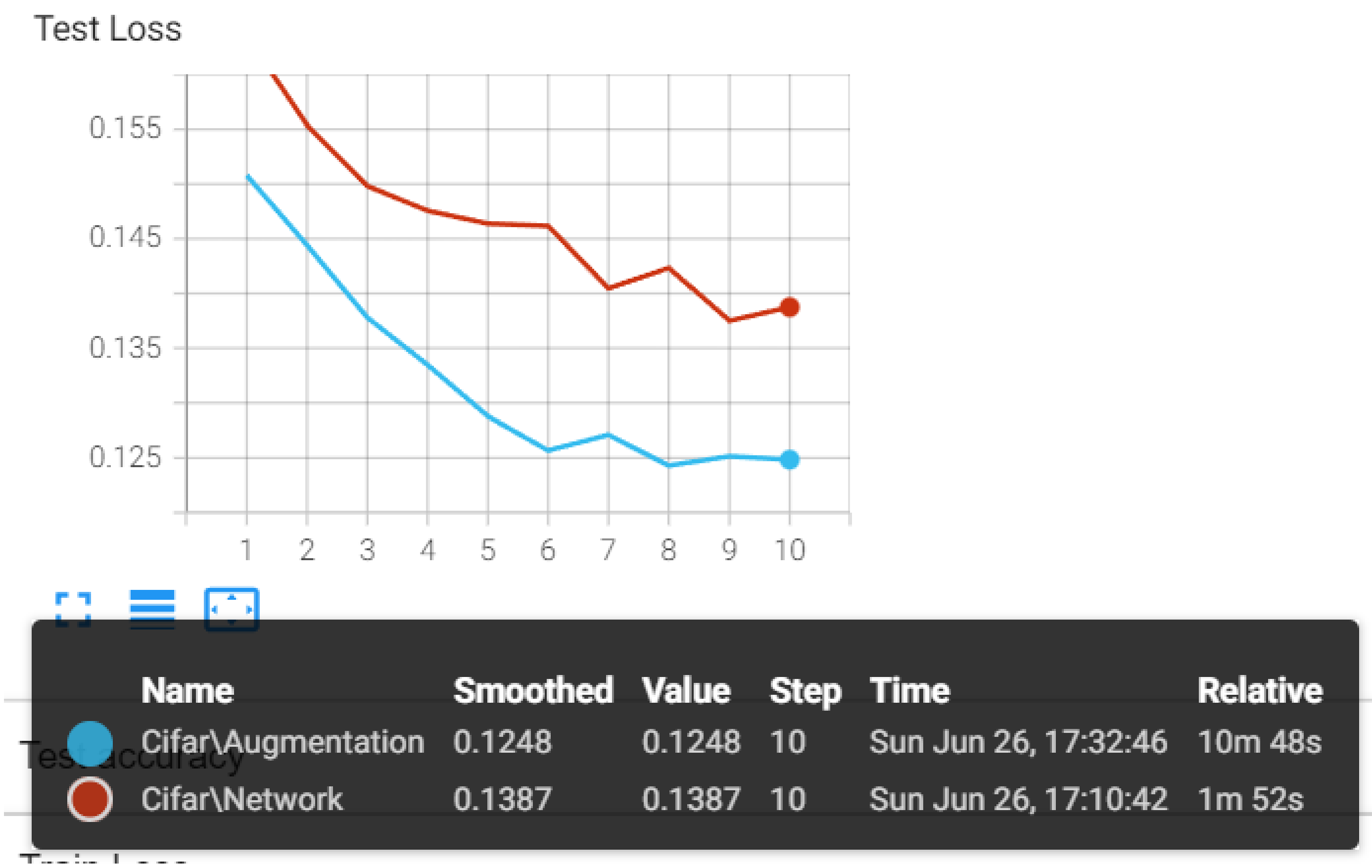
Name	Smoothed	Value	Step	Time	Relative
Cifar\Augmentation	74.22	74.22	150	Sun Jun 26, 17:32:34	11m 46s

Training and Test Loss

Comparison with baseline

The Network seems to work even better after Augmentation to the dataset. Not only the loss on training has decreased but also on the test itself.





Training and test accuracy

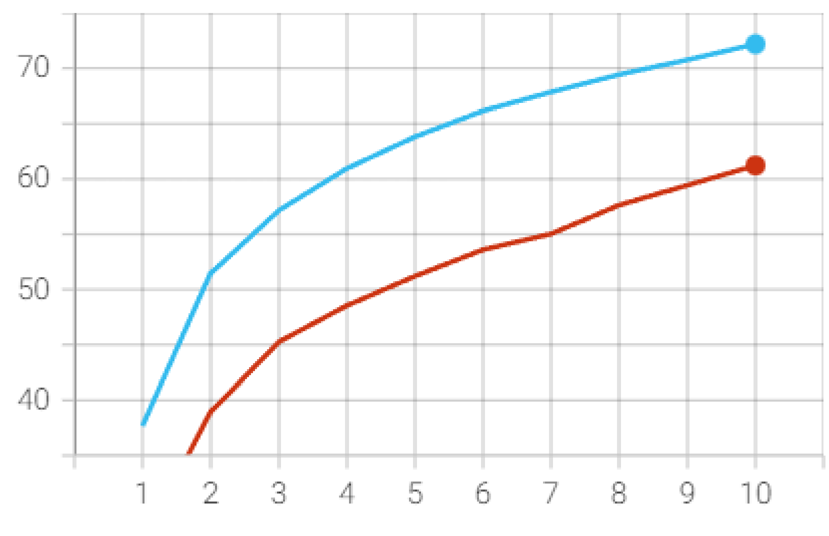
comparison with baseline

After augmentation, the training and test accuracy have both risen.

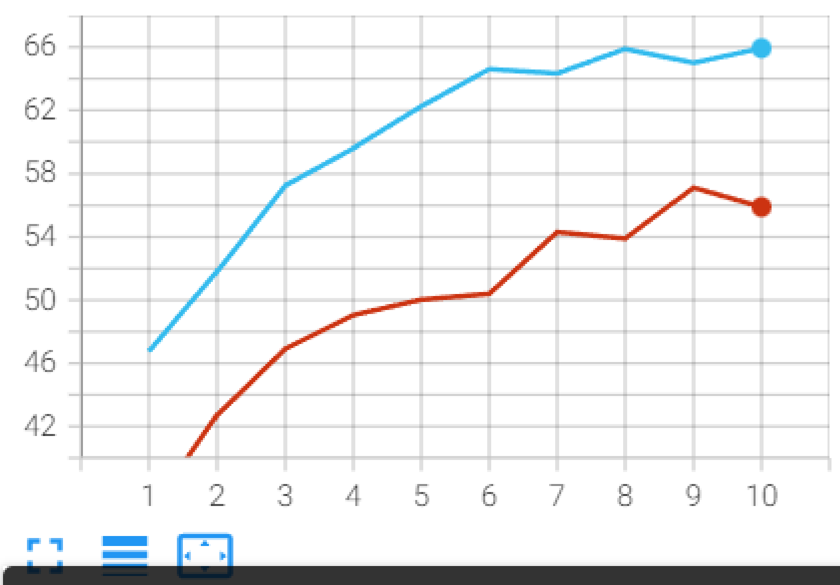
Train Loss

	Name	Smoothed	Value	Step	Time	Relative
●	Cifar\Augmentation	72.18	72.18	10	Sun Jun 26, 17:32:37	10m 48s
●	Cifar\Network	61.23	61.23	10	Sun Jun 26, 17:10:40	1m 52s

Train accuracy



Test accuracy



	Name	Smoothed	Value	Step	Time	Relative
●	Cifar\Augmentation	65.93	65.93	10	Sun Jun 26, 17:32:46	10m 48s
●	Cifar\Network	55.9	55.9	10	Sun Jun 26, 17:10:42	1m 52s

Train Loss

Normalization

Normalizing dataset also has huge impact on the performance of the model.

In [ ]:

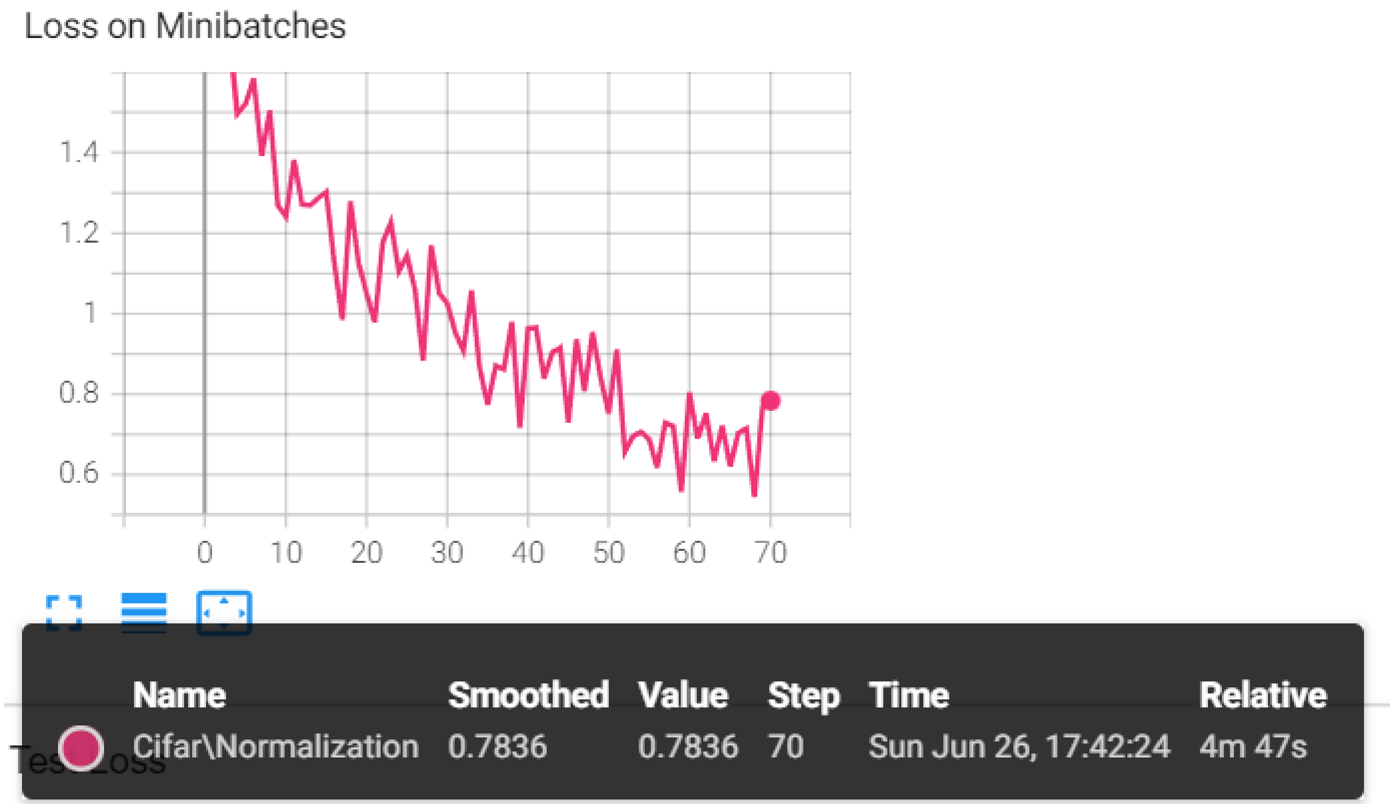
```
CifarTrainNorm = torchvision.datasets.CIFAR10(root = './data', train = True,
                                              transform = transformNorm, download = True)
CifarTestNorm = torchvision.datasets.CIFAR10(root = './data', train = False,
                                             transform = transformNorm, download = True)
```

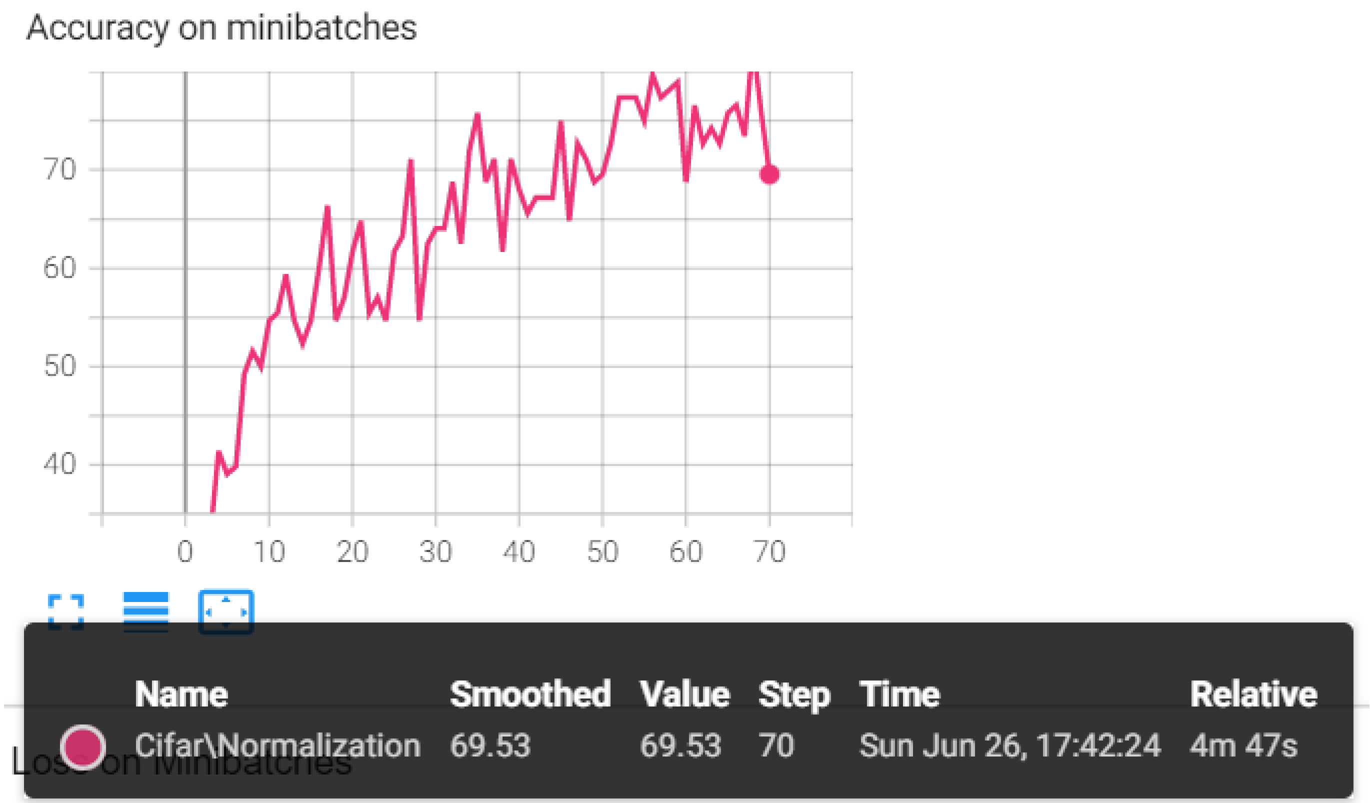
In [ ]:

```
train_loaderNorm = DataLoader(CifarTrainNorm, batch_size = batch_size, shuffle=True)
test_loaderNorm = DataLoader(CifarTestNorm, batch_size = 64, shuffle = True)
```

In [ ]:

```
ModelCNNnorm = CNNetwork(3)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(ModelCNNnorm.parameters(),lr = learning_rate)
writer = SummaryWriter(f'runs/Cifar/Normalization')
step = 0
for epoch in range(epochs):
    total_loss = 0
    correct_pred = 0
    sample_size = 0
    for i, batch in enumerate(train_loaderNorm):
        optimizer.zero_grad()
        yhat = ModelCNNnorm(batch[0])
        loss = criterion(yhat.squeeze(), batch[1].squeeze())
        total_loss += loss.item()
        pred = torch.max(yhat.data, 1)[1]
        sample_size = batch[1].size(0)
        correct_pred += (pred == batch[1]).sum().item()
        loss.backward()
        optimizer.step()
        if (i + 1) % 50 == 0:
            writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
            writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item()/sa
                              step + 1)
            step += 1
    accuracy = (correct_pred/len(CifarTrainNorm))*100
    writer.add_scalar('Train Loss', np.sqrt(total_loss/len(CifarTrainNorm)), epoch + 1)
    writer.add_scalar('Train accuracy', accuracy, epoch + 1)

    with torch.no_grad():
        test_pred = 0
        test_loss = 0
        for i, (img, label) in enumerate(test_loaderNorm):
            optimizer.zero_grad()
            output = ModelCNNnorm(img)
            loss = criterion(output.squeeze(), label.squeeze())
            test_loss += loss.item()
            pred = torch.max(output.data, 1)[1]
            test_pred += (pred == label).sum().item()
        accuracy = (test_pred/len(CifarTestNorm))*100
        writer.add_scalar('Test Loss', np.sqrt(test_loss/len(CifarTestNorm)), epoch + 1)
        writer.add_scalar('Test accuracy', accuracy, epoch + 1)

writer.close()
writer.flush()
```



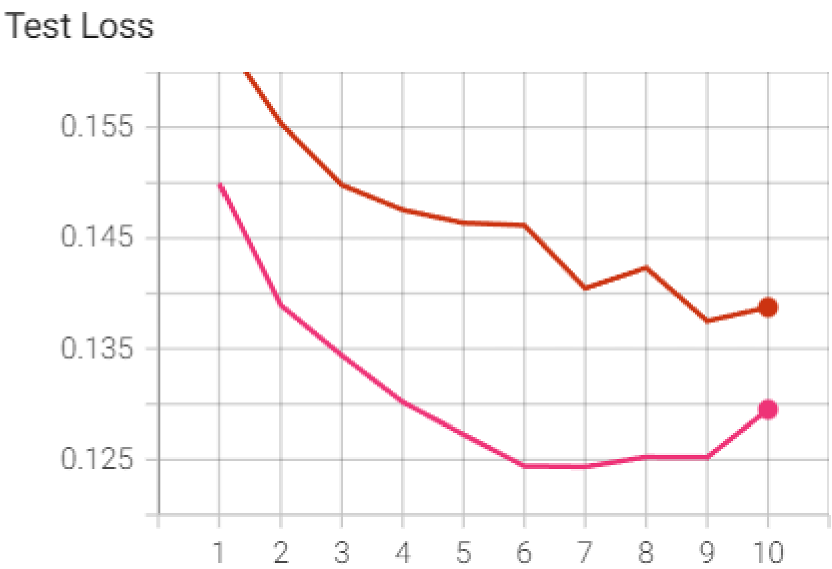


Training and Test Loss

Comparison with baseline

After normalization both training and test loss has decreased as can be seen below.

	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Network	0.0924	0.0924	10	Sun Jun 26, 17:10:40	1m 52s
	Cifar\Normalization	0.07022	0.07022	10	Sun Jun 26, 17:42:27	4m 26s



	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Network	0.1387	0.1387	10	Sun Jun 26, 17:10:42	1m 52s
	Cifar\Normalization	0.1295	0.1295	10	Sun Jun 26, 17:42:30	4m 26s

Training and test accuracy

comparison with baseline

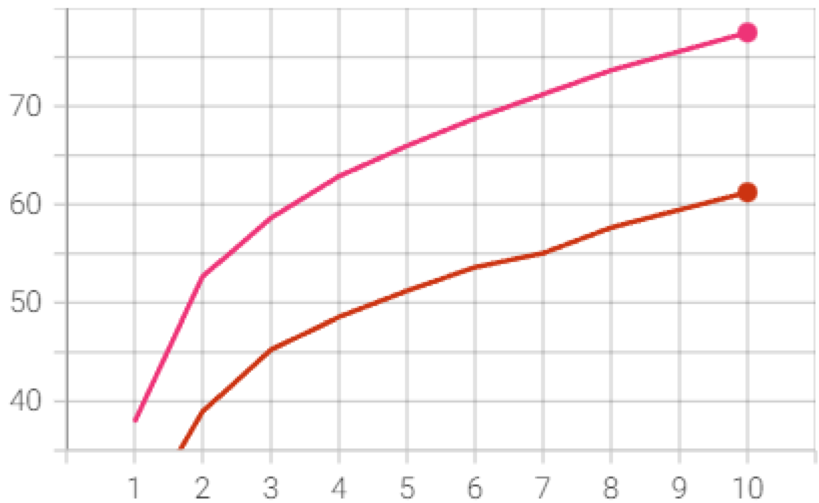
The training accuracy has increased from around 60% to 77.5% while the test accuracy from 60% to 66% over a range of 10 epochs.

rain Loss

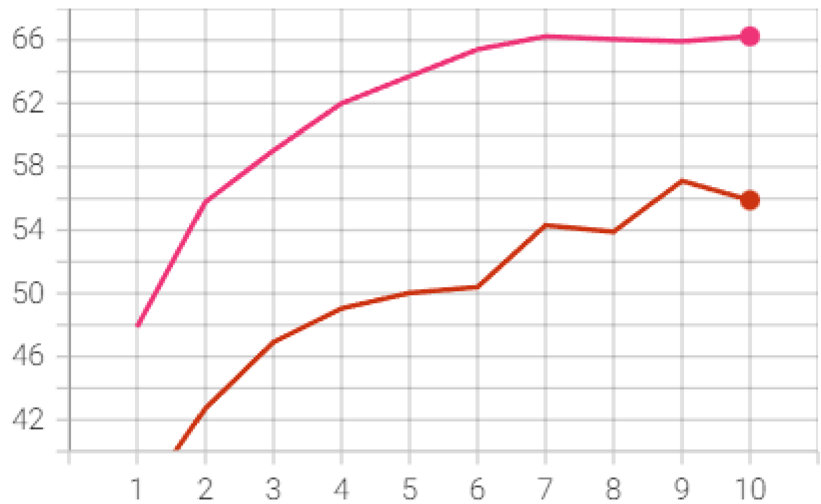
rain accuracy

	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Network	61.23	61.23	10	Sun Jun 26, 17:10:40	1m 52s
	Cifar\Normalization	77.5	77.5	10	Sun Jun 26, 17:42:27	4m 26s

Train accuracy



Test accuracy



	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Network	55.9	55.9	10	Sun Jun 26, 17:10:42	1m 52s
	Cifar\Normalization	66.24	66.24	10	Sun Jun 26, 17:42:30	4m 26s

Train Loss

Augmentation + Normalization

Now both the Augmentation and normalization has been applied to the dataset.

In [ ]:

```
CifarTrainAugNorm = torchvision.datasets.CIFAR10(root = './data', train = True,
                                                 transform = transformBoth, download = True)
CifarTestAugNorm = torchvision.datasets.CIFAR10(root = './data', train = False,
                                                transform = transformBoth, download = True)
```

In [ ]:

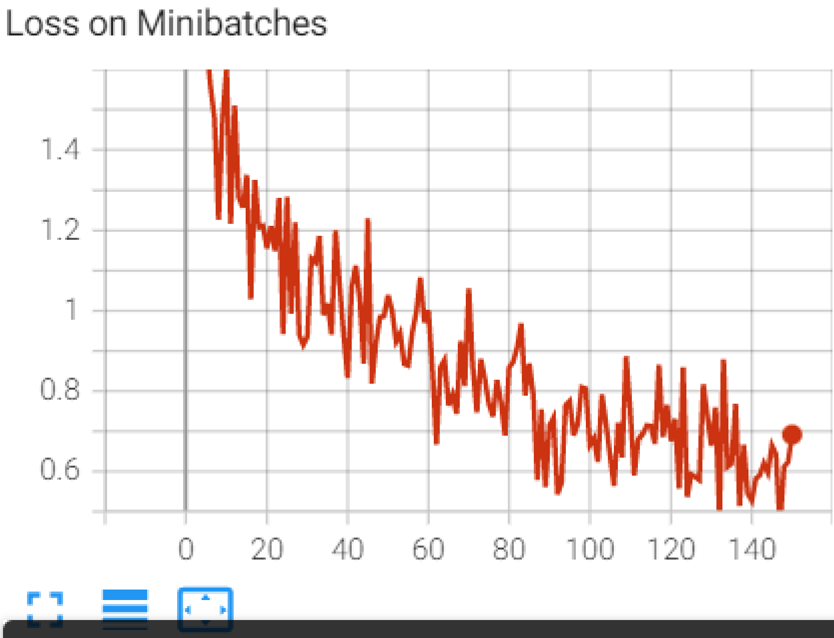
```
AugmentedTrain = torch.utils.data.ConcatDataset([CifarTrainAugNorm, CifarTrainNorm])
AugmentedTest = torch.utils.data.ConcatDataset([CifarTestAugNorm, CifarTestNorm])
```

In [ ]:

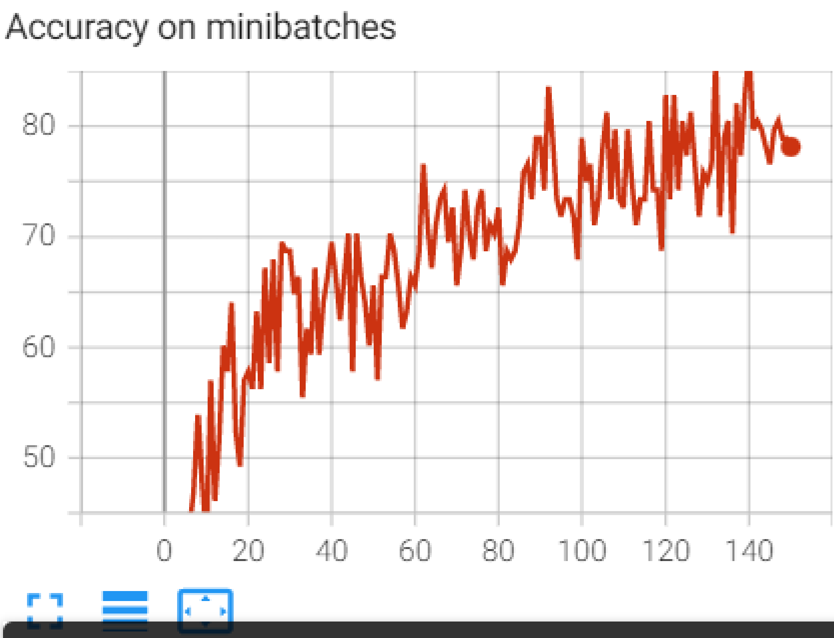
```
train_loaderAugNorm = DataLoader(AugmentedTrain, batch_size = batch_size, shuffle=True)
test_loaderAugNorm = DataLoader(AugmentedTest, batch_size = 64, shuffle = True)
```

In [ ]:

```
Model = CNNetwork(3)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(Model.parameters(),lr = learning_rate)
writer = SummaryWriter(f'runs/Cifar/Norm_Aug')
step = 0
for epoch in range(epochs):
    total_loss = 0
    correct_pred = 0
    sample_size = 0
    for i, batch in enumerate(train_loaderAugNorm):
        optimizer.zero_grad()
        yhat = Model(batch[0])
        loss = criterion(yhat.squeeze(), batch[1].squeeze())
        total_loss += loss.item()
        pred = torch.max(yhat.data, 1)[1]
        sample_size = batch[1].size(0)
        correct_pred += (pred == batch[1]).sum().item()
        loss.backward()
        optimizer.step()
        if (i + 1) % 50 == 0:
            writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
            writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item()/sa
                              step + 1)
            step += 1
    accuracy = (correct_pred/len(AugmentedTrain))*100
    writer.add_scalar('Train Loss', np.sqrt(total_loss/len(AugmentedTrain)), epoch + 1)
    writer.add_scalar('Train accuracy', accuracy, epoch + 1)

    with torch.no_grad():
        test_pred = 0
        test_loss = 0
        for i, (img, label) in enumerate(test_loaderAugNorm):
            optimizer.zero_grad()
            output = Model(img)
            loss = criterion(output.squeeze(), label.squeeze())
            test_loss += loss.item()
            pred = torch.max(output.data, 1)[1]
            test_pred += (pred == label).sum().item()
        accuracy = (test_pred/len(AugmentedTest))*100
        writer.add_scalar('Test Loss', np.sqrt(test_loss/len(AugmentedTest)), epoch + 1)
        writer.add_scalar('Test accuracy', accuracy, epoch + 1)

writer.close()
writer.flush()
```



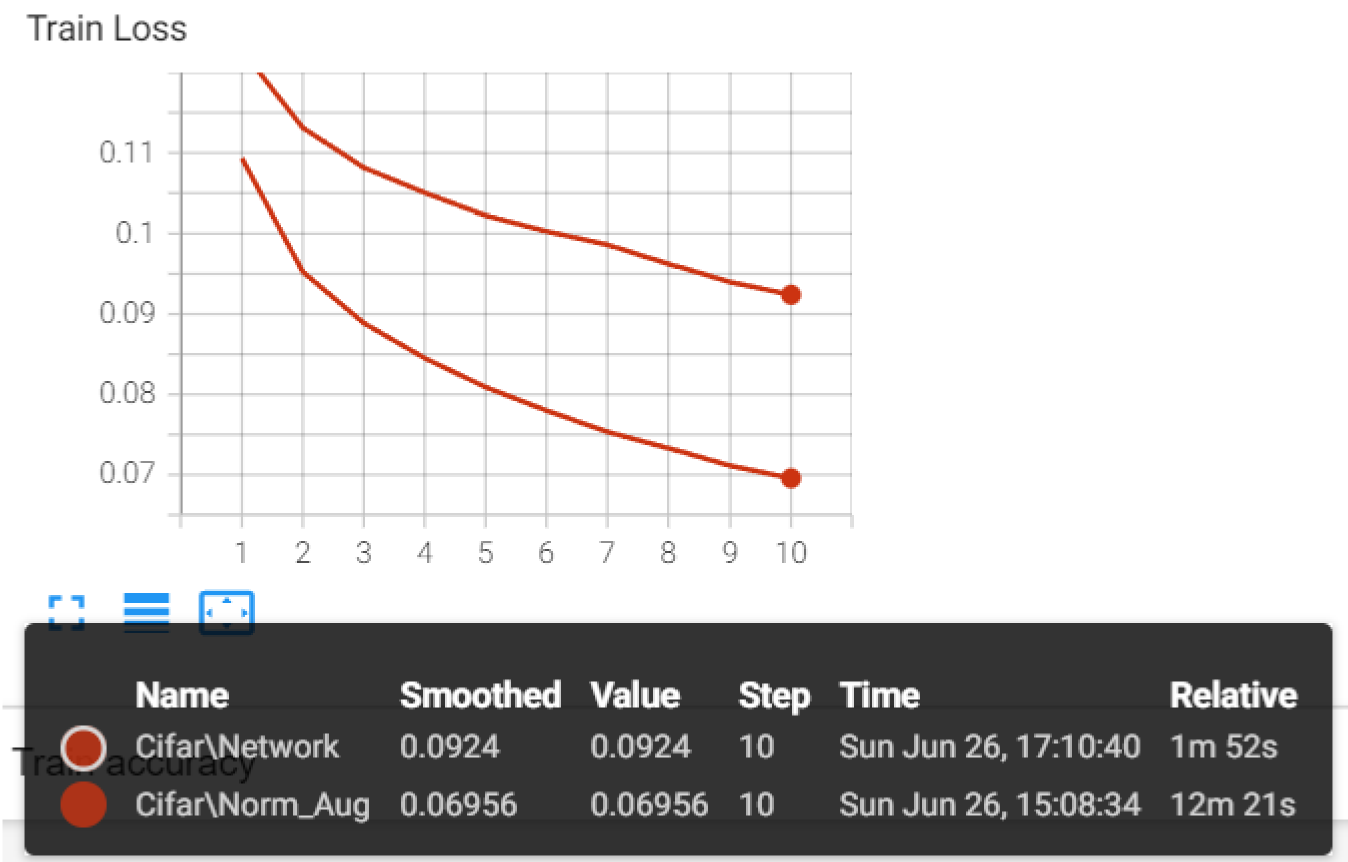
	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Norm_Aug	0.6916	0.6916	150	Sun Jun 26, 15:08:31	13m 25s

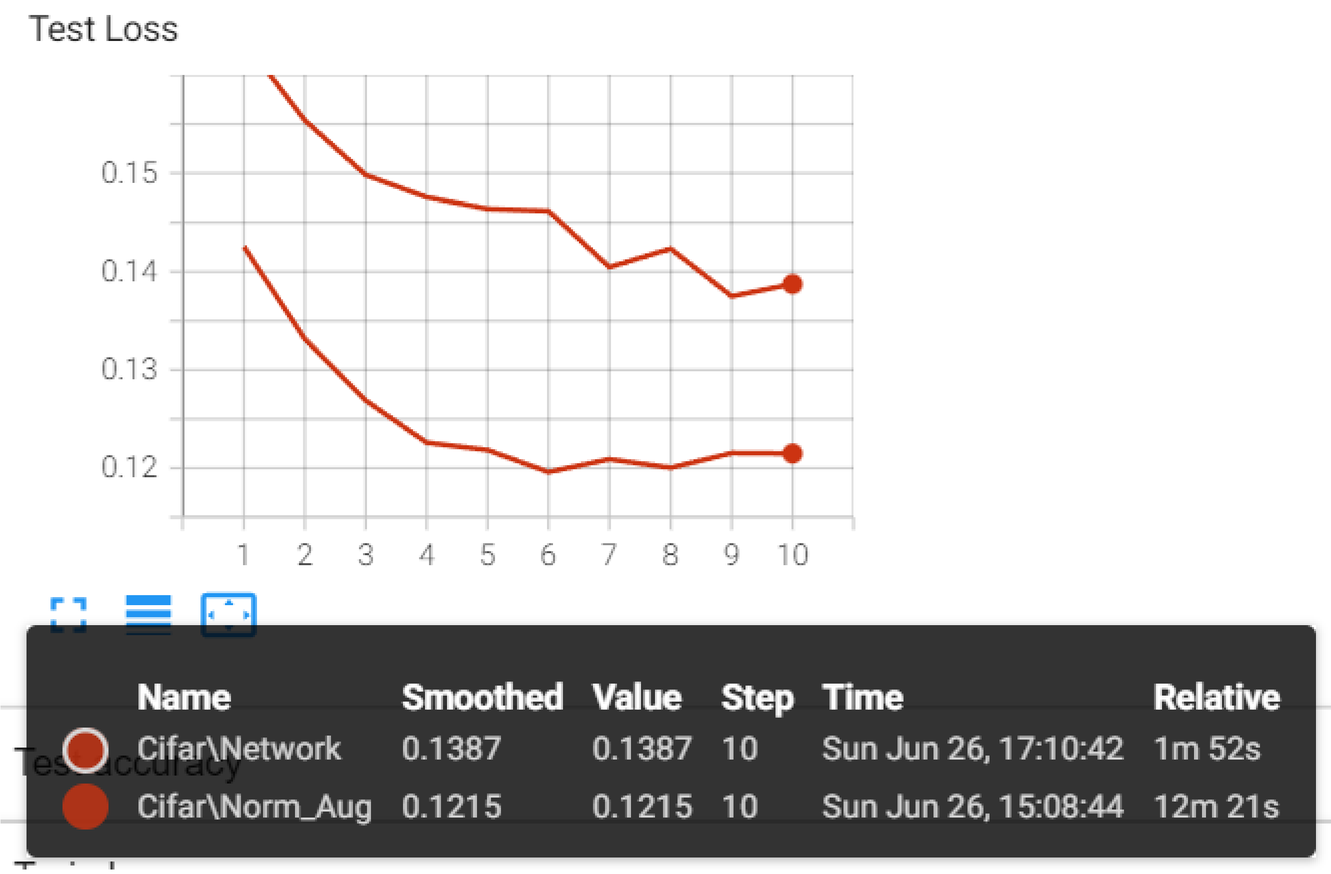


	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Norm_Aug	78.13	78.13	150	Sun Jun 26, 15:08:31	13m 25s

Training and Test Loss

Comparison with baseline

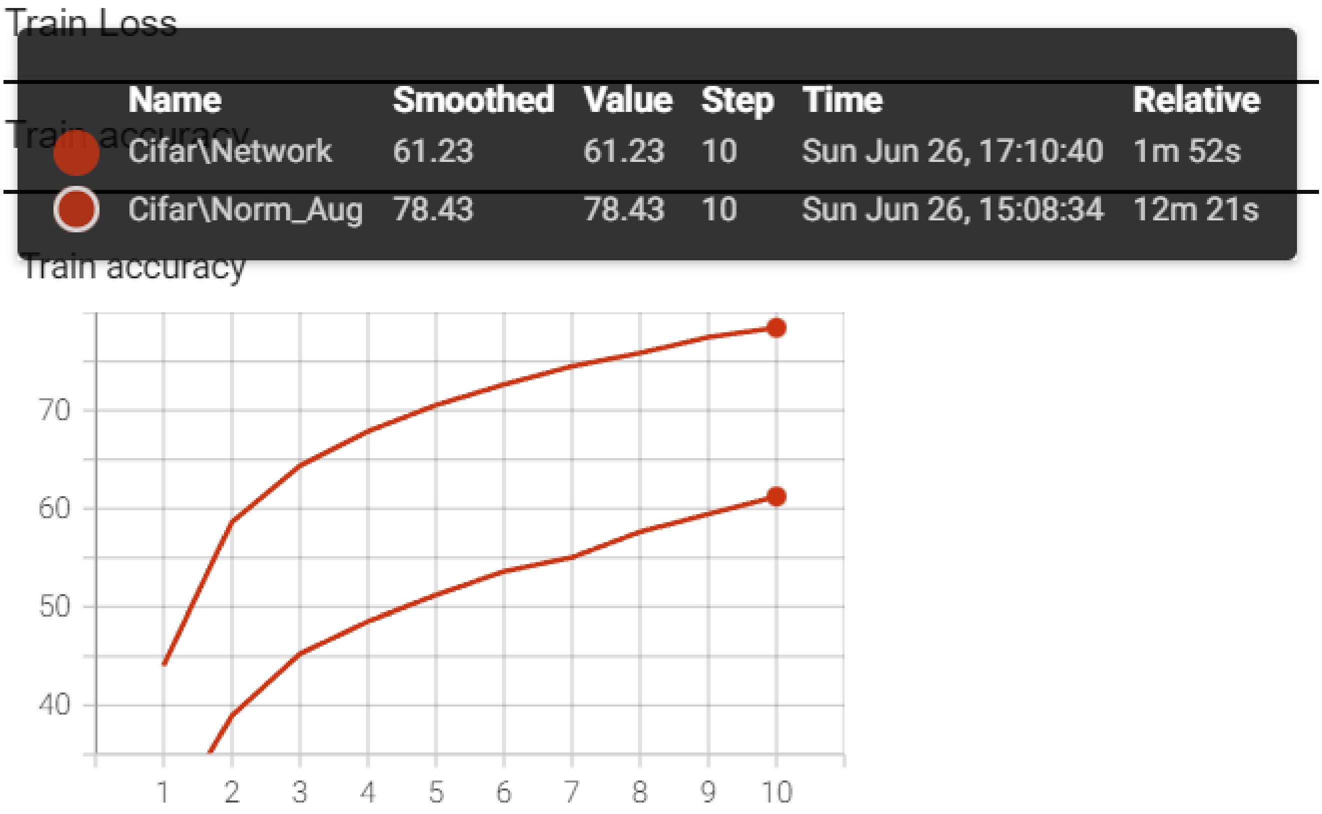


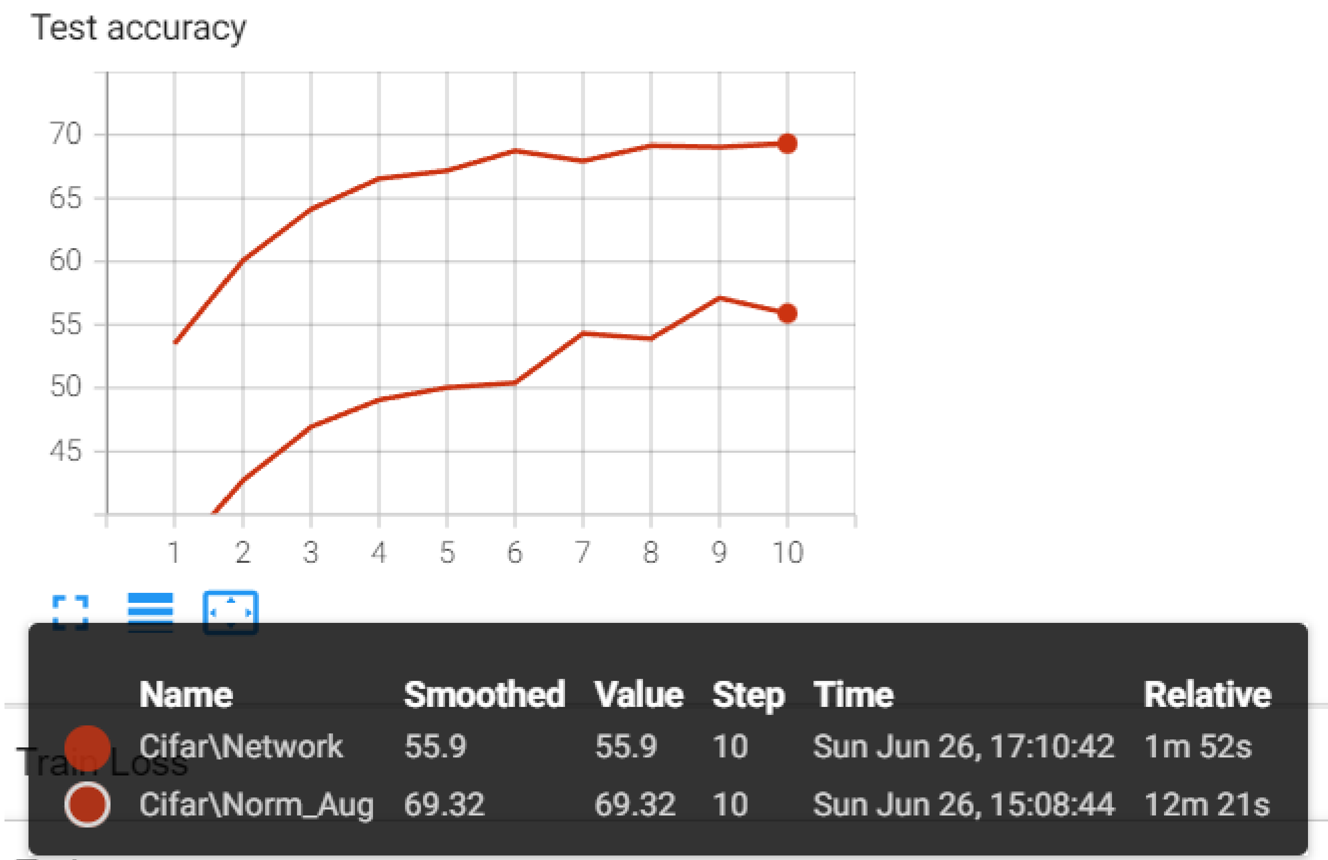


Training and Test accuracy

Comparison with baseline

This has resulted in the higher accuracy increase so far with train accuracy around 79% and test accuracy 70% over a range of 10 epochs.





Network Regularization

So far the modification to the dataset has resulted in the increase in the model accuracy as well as decrease in the loss. These all modification changes from model to model as well as the amount of training data available. Now we will see how can we make changes in the model itself, by dropping some neurons or by penalising the weights associated with them to improve model efficiency.

Dropout

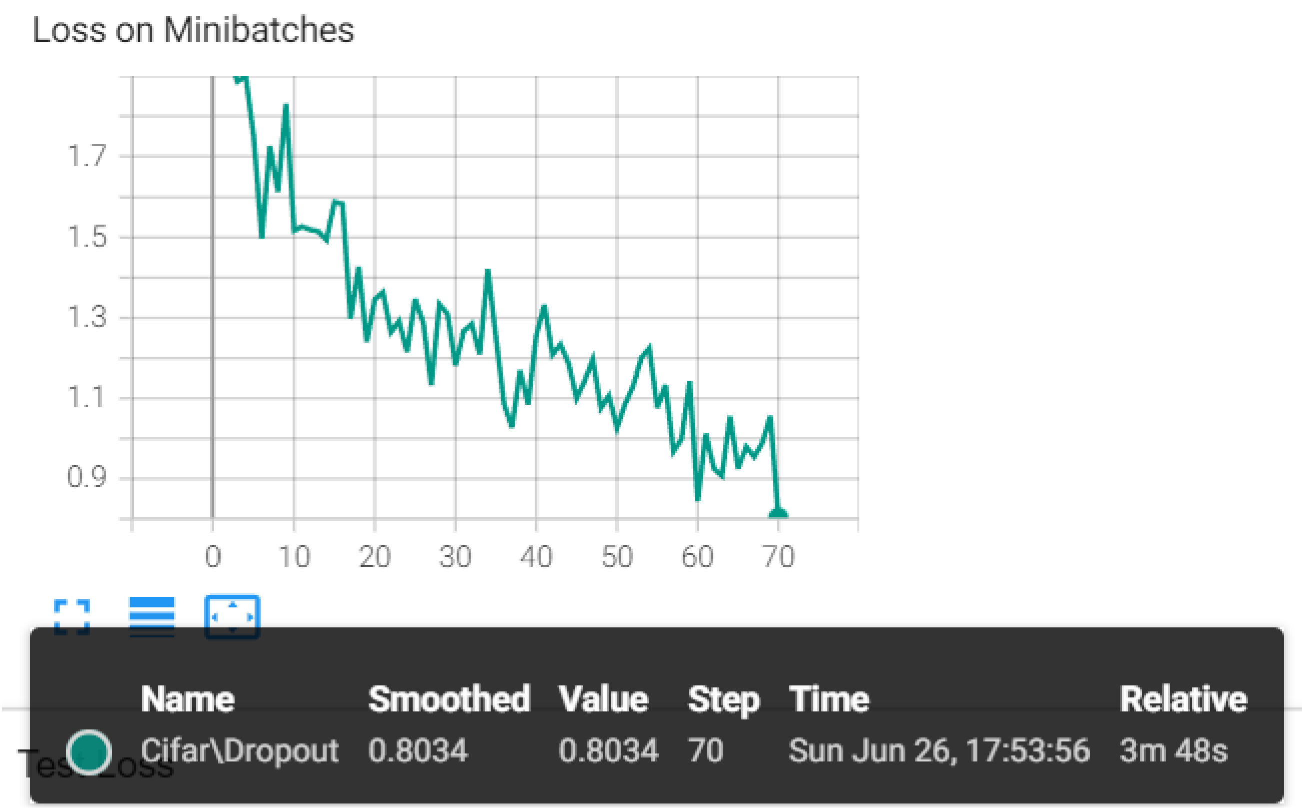
For the fully connected layers, we give a probability for the number of neurons that can be dropped that the model over training finds to be not that important in order to reduce complexity as well as increase efficiency.

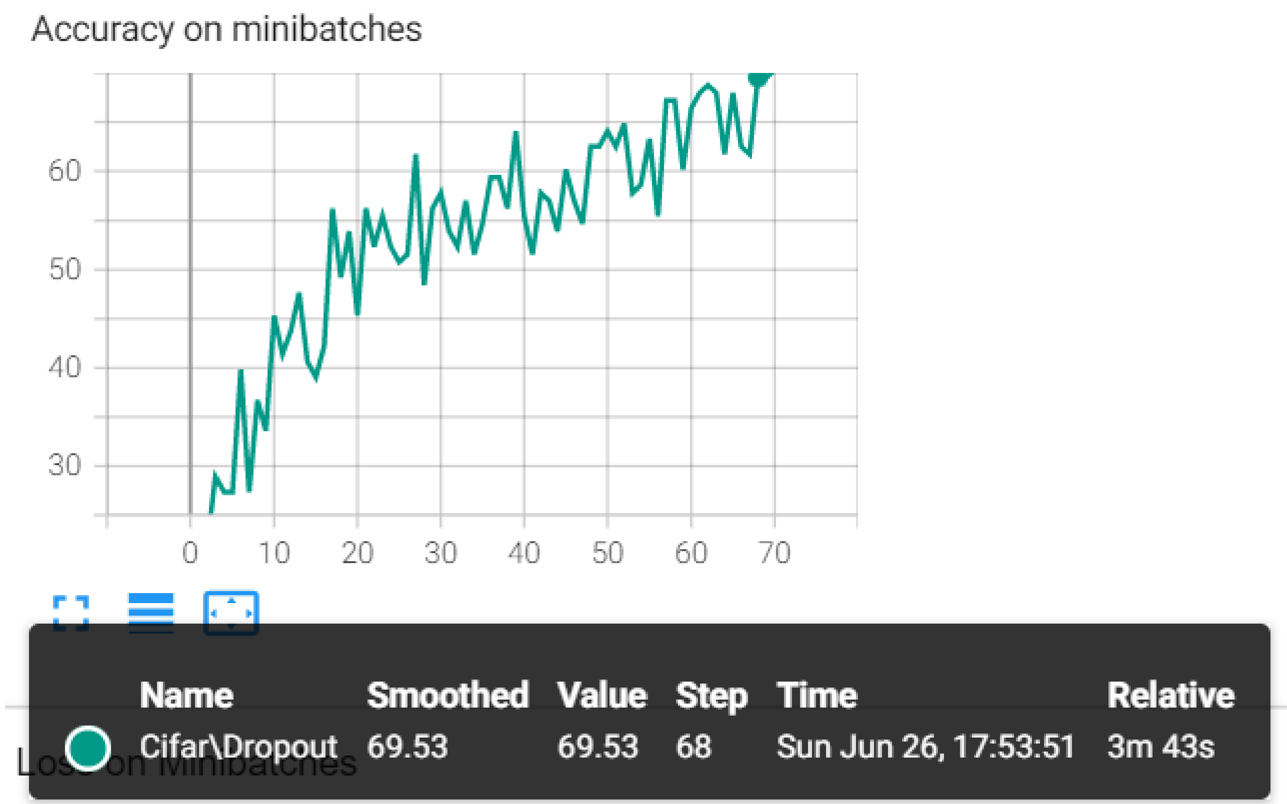
In [ ]:

```
class CNNDropout(Module):
    def __init__(self, input_channels, dropProb1, dropProb2):
        super(CNNetwork, self).__init__()
        self.conv1 = nn.Conv2d(input_channels, 10, kernel_size = 5)
        self.pool1 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.conv2 = nn.Conv2d(10, 30, kernel_size = 5)
        self.conv3 = nn.Conv2d(30, 60, kernel_size = 5)
        self.pool2 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.fc1 = nn.Linear(540, 270)
        self.dropout1 = nn.Dropout(dropProb1)
        self.fc2 = nn.Linear(270, 130)
        self.dropout2 = nn.Dropout(dropProb2)
        self.fc3 = nn.Linear(130, 10)


    def forward(self, x):
        y = F.relu(self.conv1(x))
        y = self.pool1(y)
        y = F.relu(self.conv2(y))
        y = F.relu(self.conv3(y))
        y = self.pool2(y)
        y = y.view(-1, 60*3*3)
        y = F.relu(self.fc1(y))
        y = self.dropout1(y)
        y = F.relu(self.fc2(y))
        y = self.dropout2(y)
        y = self.fc3(y)
        return y
```

In [ ]:

```
ModelD = CNNDropout(3, 0.3, 0.2)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(ModelD.parameters(),lr = learning_rate)
writer = SummaryWriter(f'runs/Cifar/Dropout')
step = 0
for epoch in range(epochs):
    total_loss = 0
    correct_pred = 0
    sample_size = 0
    for i, batch in enumerate(train_loader):
        optimizer.zero_grad()
        yhat = ModelD(batch[0])
        loss = criterion(yhat.squeeze(), batch[1].squeeze())
        total_loss += loss.item()
        pred = torch.max(yhat.data, 1)[1]
        sample_size = batch[1].size(0)
        correct_pred += (pred == batch[1]).sum().item()
        loss.backward()
        optimizer.step()
        if (i + 1) % 50 == 0:
            writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
            writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item()/sa
                              step + 1)
            step += 1
    accuracy = (correct_pred/len(CifarTrain))*100
    writer.add_scalar('Train Loss', np.sqrt(total_loss/len(CifarTrain)), epoch + 1)
    writer.add_scalar('Train accuracy', accuracy, epoch + 1)

    with torch.no_grad():
        test_pred = 0
        test_loss = 0
        for i, (img, label) in enumerate(test_loader):
            optimizer.zero_grad()
            output = ModelD(img)
            loss = criterion(output.squeeze(), label.squeeze())
            test_loss += loss.item()
            pred = torch.max(output.data, 1)[1]
            test_pred += (pred == label).sum().item()
        accuracy = (test_pred/len(CifarTest))*100
        writer.add_scalar('Test Loss', np.sqrt(test_loss/len(CifarTest)), epoch + 1)
        writer.add_scalar('Test accuracy', accuracy, epoch + 1)

writer.close()
writer.flush()
```



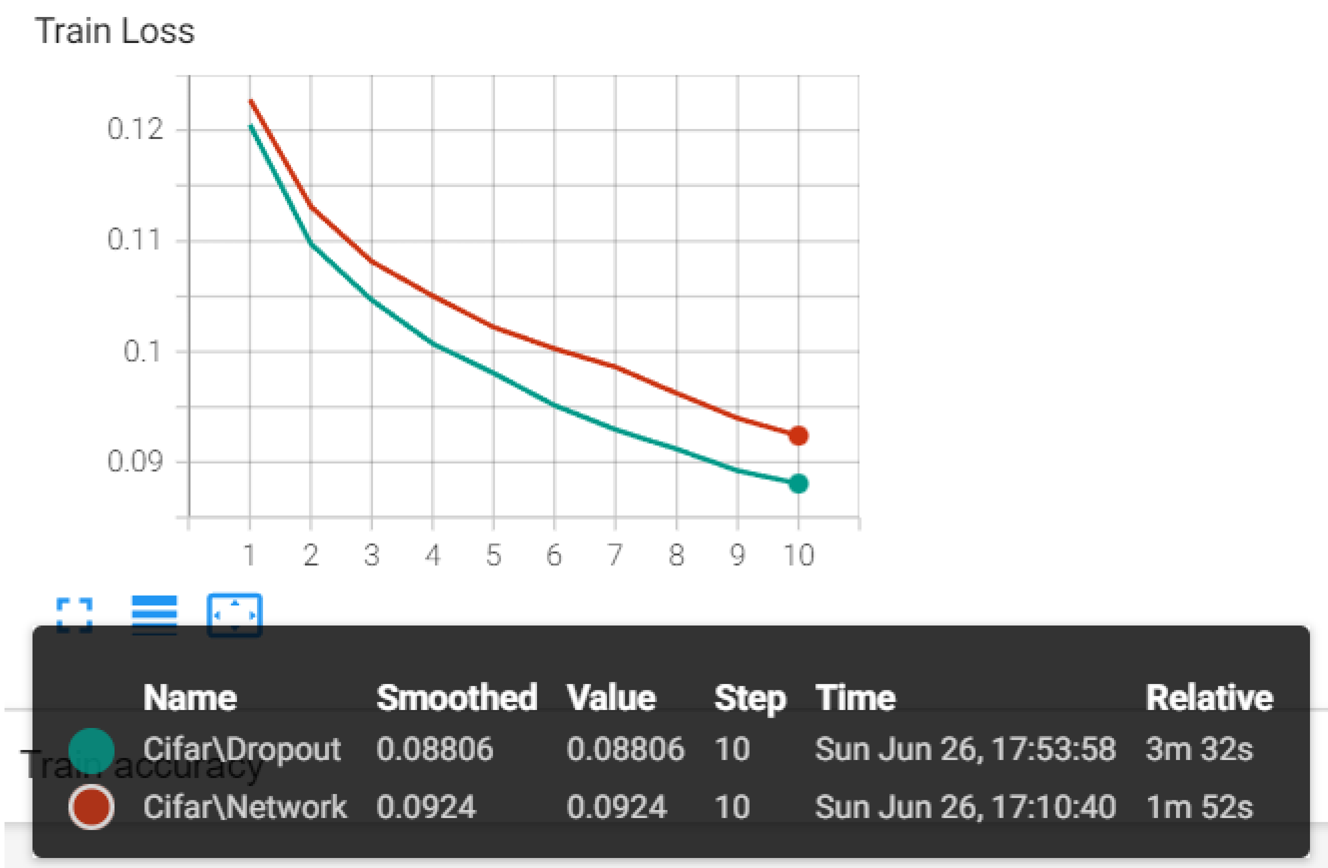


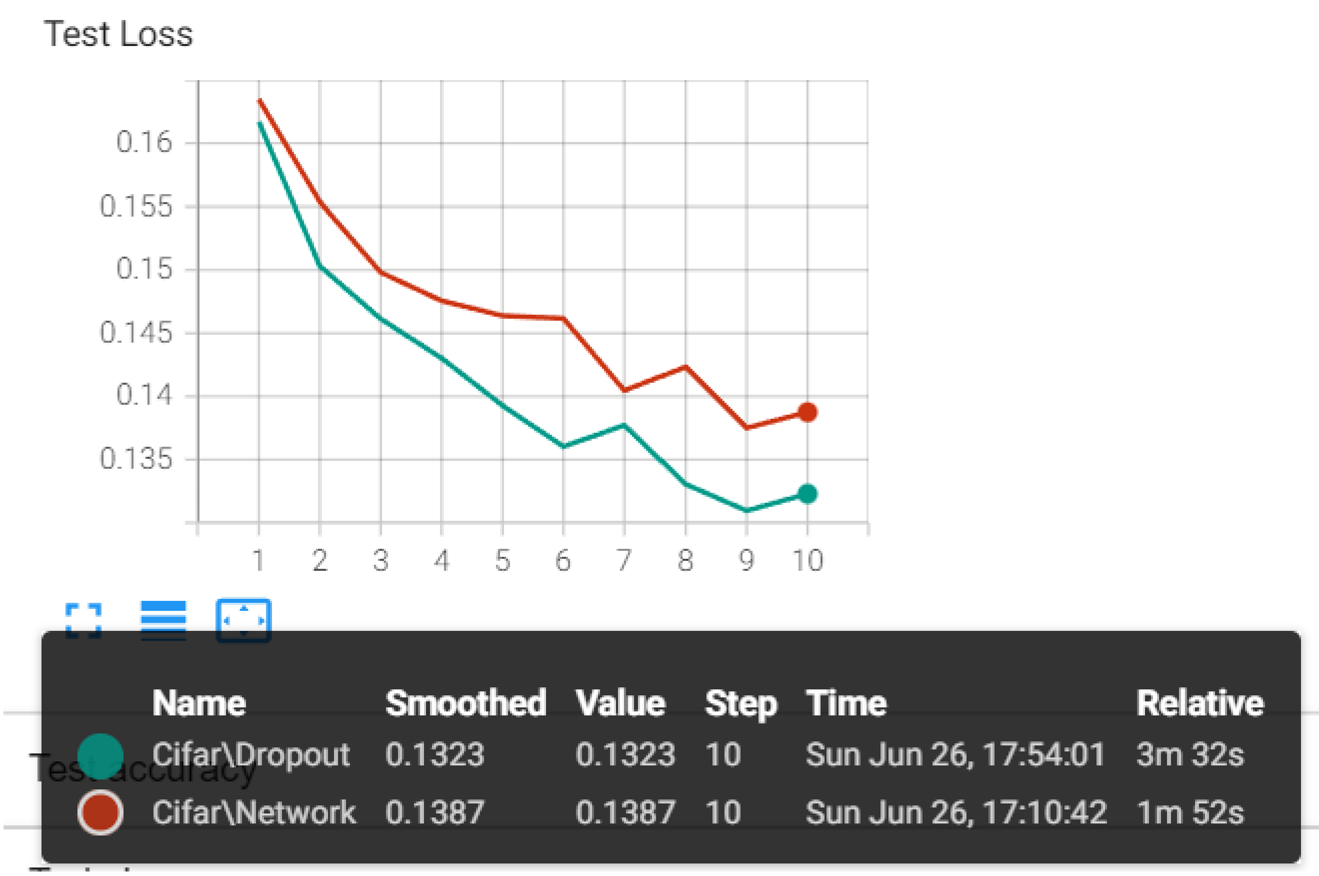
Training and Test Loss

Comparison with baseline

Since the probabilities chosen here are random, the efficiency can be increased more by adjusting them. For the case, we can still see the decrease in the

more by adjusting them. For this case, we can still see the decrease in the training and test loss as compared to the baseline.

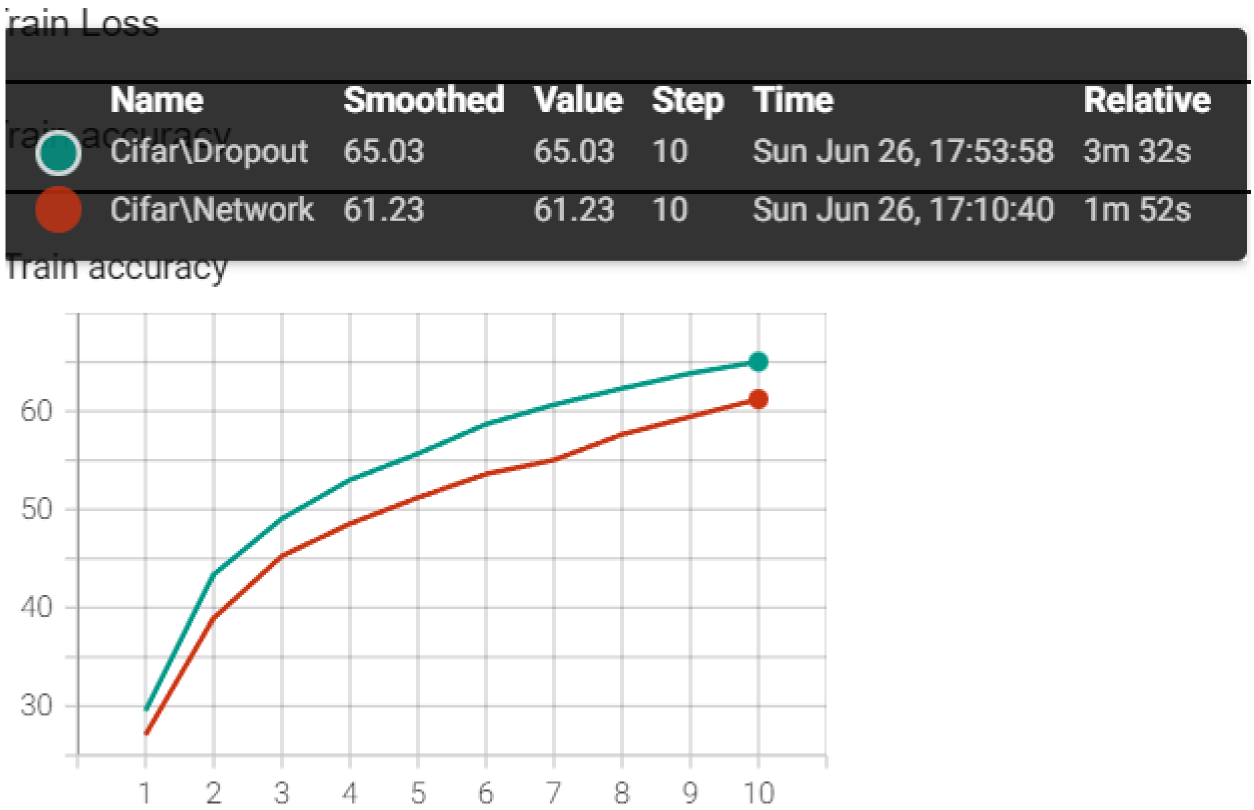


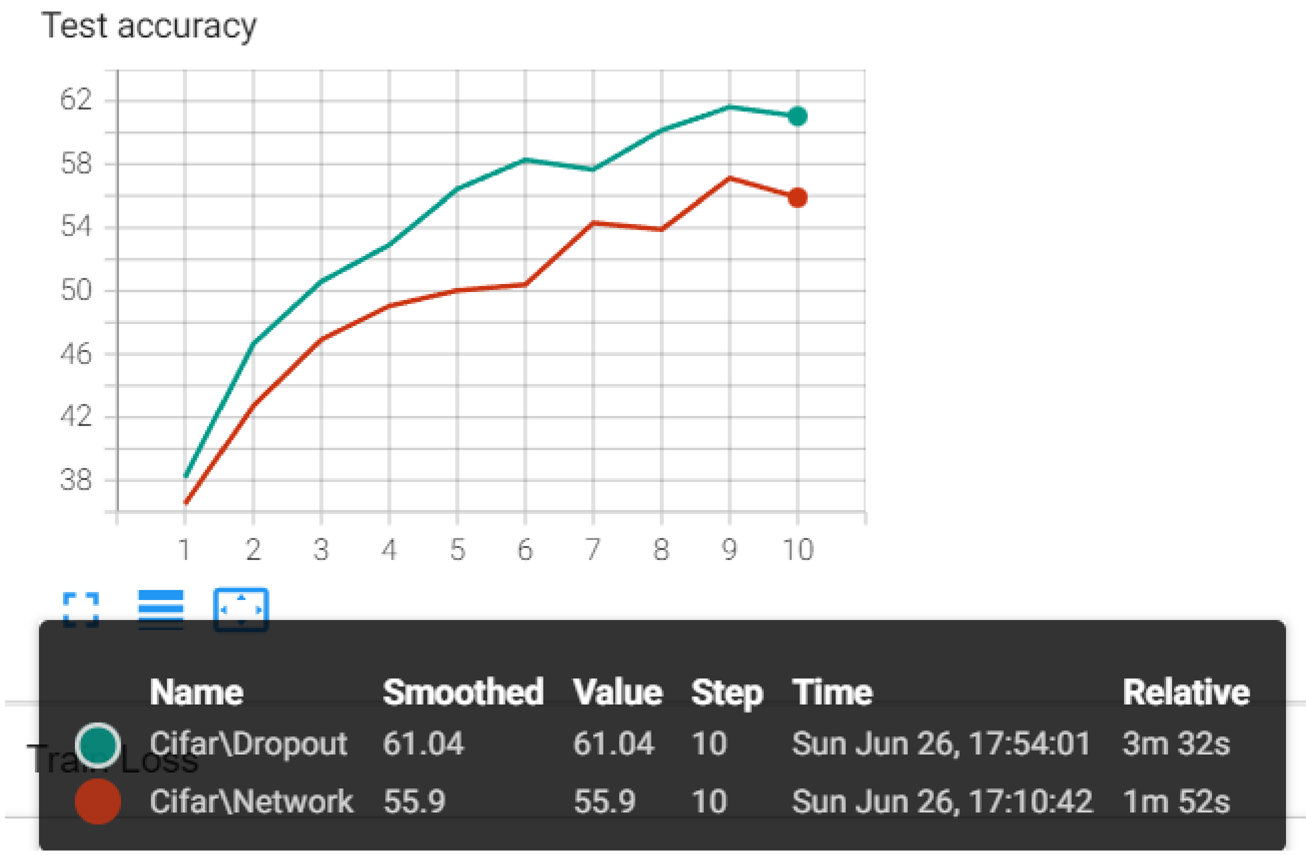


Training and Test accuracy

Comparison with baseline

The accuracy is though not as good as the one after Aigmentation+Normalization but it is better than the baseline.





L1 Regularization

After the first fully connected layer, L1 regularization is applied to the parameters obtained from that layer. Since this layer has the maximum input among other FC layers and thus it is chosen randomly. The results may be better by using it on other or all layers. For the experiment part I have chosen this particular layer.

In [ ]:

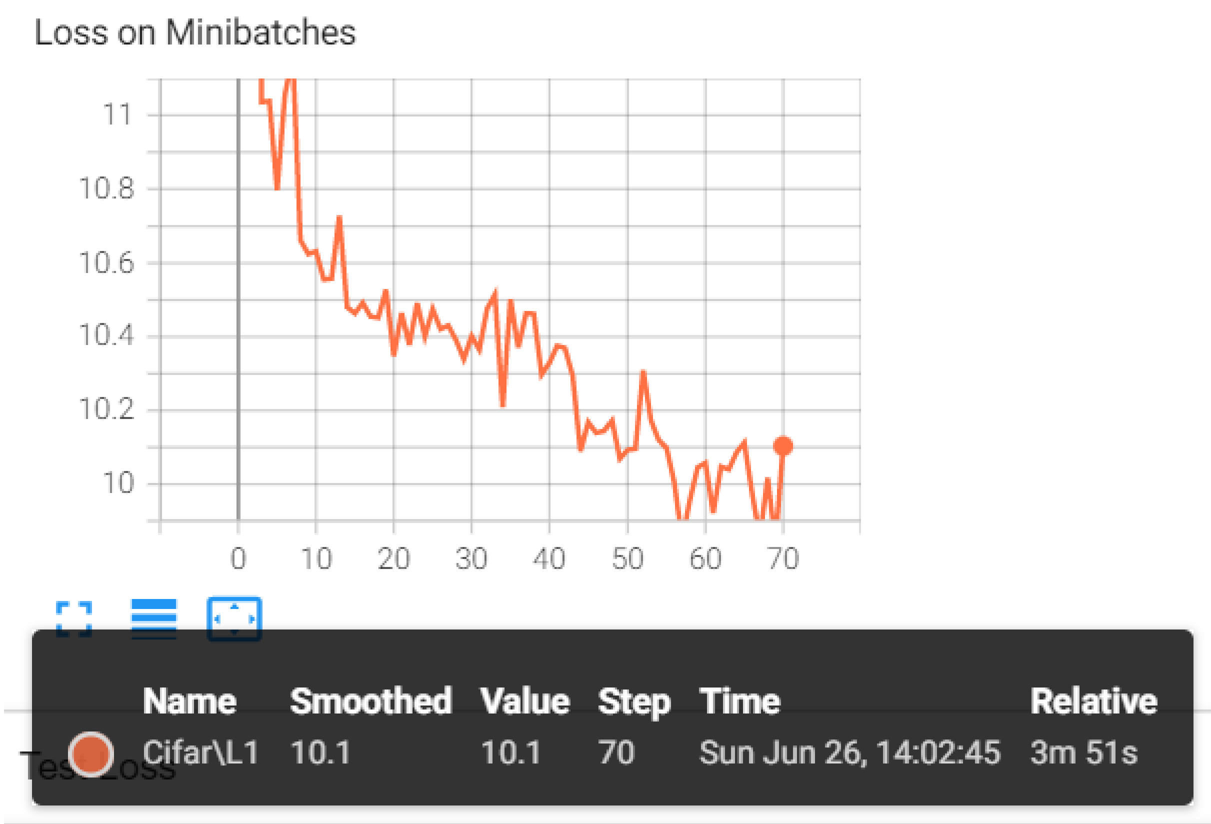
```
lambda1, lambda2 = 0.5, 0.5
```

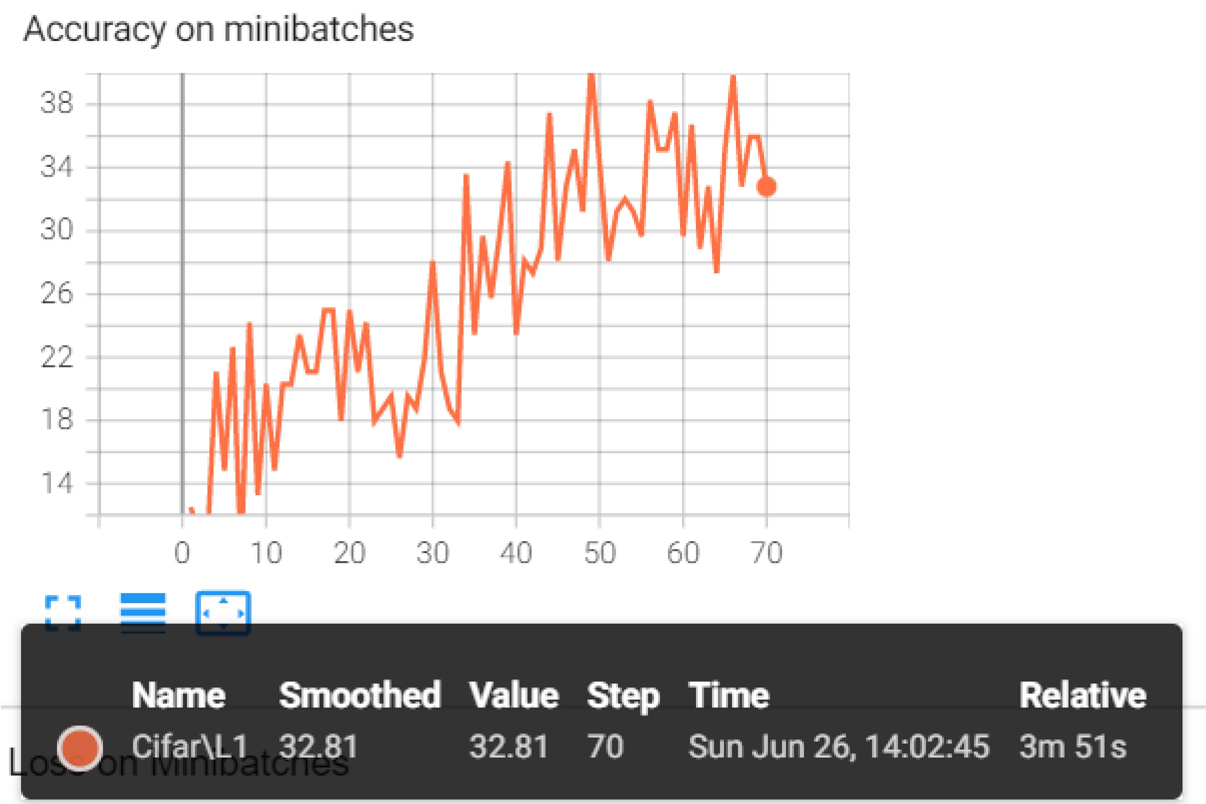
In [ ]:

```
class CNNL1(Module):
    def __init__(self, input_channels):
        super(CNNL1, self).__init__()
        self.conv1 = nn.Conv2d(input_channels, 10, kernel_size = 5)
        self.pool1 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.conv2 = nn.Conv2d(10, 30, kernel_size = 5)
        self.conv3 = nn.Conv2d(30, 60, kernel_size = 5)
        self.pool2 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.fc1 = nn.Linear(540, 270)
        self.fc2 = nn.Linear(270, 130)
        self.fc3 = nn.Linear(130, 10)


    def forward(self, x):
        y = F.relu(self.conv1(x))
        y = self.pool1(y)
        y = F.relu(self.conv2(y))
        y = F.relu(self.conv3(y))
        y = self.pool2(y)
        y = y.view(-1, 60*3*3)
        y1 = F.relu(self.fc1(y))
        y2 = F.relu(self.fc2(y1))
        out = self.fc3(y2)
        return out, y1
```

In [ ]:

```
ModelL1 = CNNL1(3)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(ModelL1.parameters(),lr = learning_rate)
writer = SummaryWriter(f'runs/Cifar/L1')
step = 0
for epoch in range(epochs):
    total_loss = 0
    correct_pred = 0
    sample_size = 0
    for i, batch in enumerate(train_loader):
        optimizer.zero_grad()
        yhat, y1 = ModelL1(batch[0])
        entropyloss = criterion(yhat.squeeze(), batch[1].squeeze())
        y1_params = torch.cat([x.view(-1) for x in ModelL1.fc1.parameters()])
        l1_regularization = lambda1*torch.norm(y1_params, 1)
        loss = entropyloss + l1_regularization
        total_loss += loss.item()
        pred = torch.max(yhat.data, 1)[1]
        sample_size = batch[1].size(0)
        correct_pred += (pred == batch[1]).sum().item()
        loss.backward()
        optimizer.step()
        if (i + 1) % 50 == 0:
            writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
            writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item()/sa
                              step + 1)
            step += 1
    accuracy = (correct_pred/len(CifarTrain))*100
    writer.add_scalar('Train Loss', np.sqrt(total_loss/len(CifarTrain)), epoch + 1)
    writer.add_scalar('Train accuracy', accuracy, epoch + 1)

    with torch.no_grad():
        test_pred = 0
        test_loss = 0
        for i, (img, label) in enumerate(test_loader):
            optimizer.zero_grad()
            output, _ = ModelL1(img)
            loss = criterion(output.squeeze(), label.squeeze())
            test_loss += loss.item()
            pred = torch.max(output.data, 1)[1]
            test_pred += (pred == label).sum().item()
        accuracy = (test_pred/len(CifarTest))*100
        writer.add_scalar('Test Loss', np.sqrt(test_loss/len(CifarTest)), epoch + 1)
        writer.add_scalar('Test accuracy', accuracy, epoch + 1)

writer.close()
writer.flush()
```





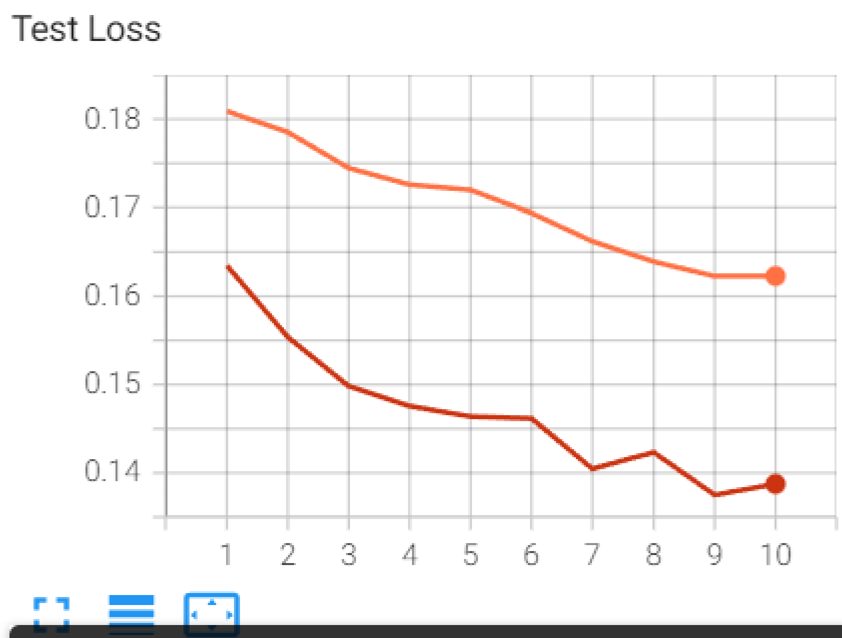
Training and Test Loss

comparison with baseline

Which technique is to be chosen for increasing model efficiency depends on so

many factors and thus can be varied from model to model. Here we can see after applying L1 regularization the training and test loss has increased as compared to the baseline. This is may be due to the fact that the model has penalized parameters more as lambda1 is 0.5 and thus the model is performing worse now. Due to lack of time, other values of lambda cannot be experimented.

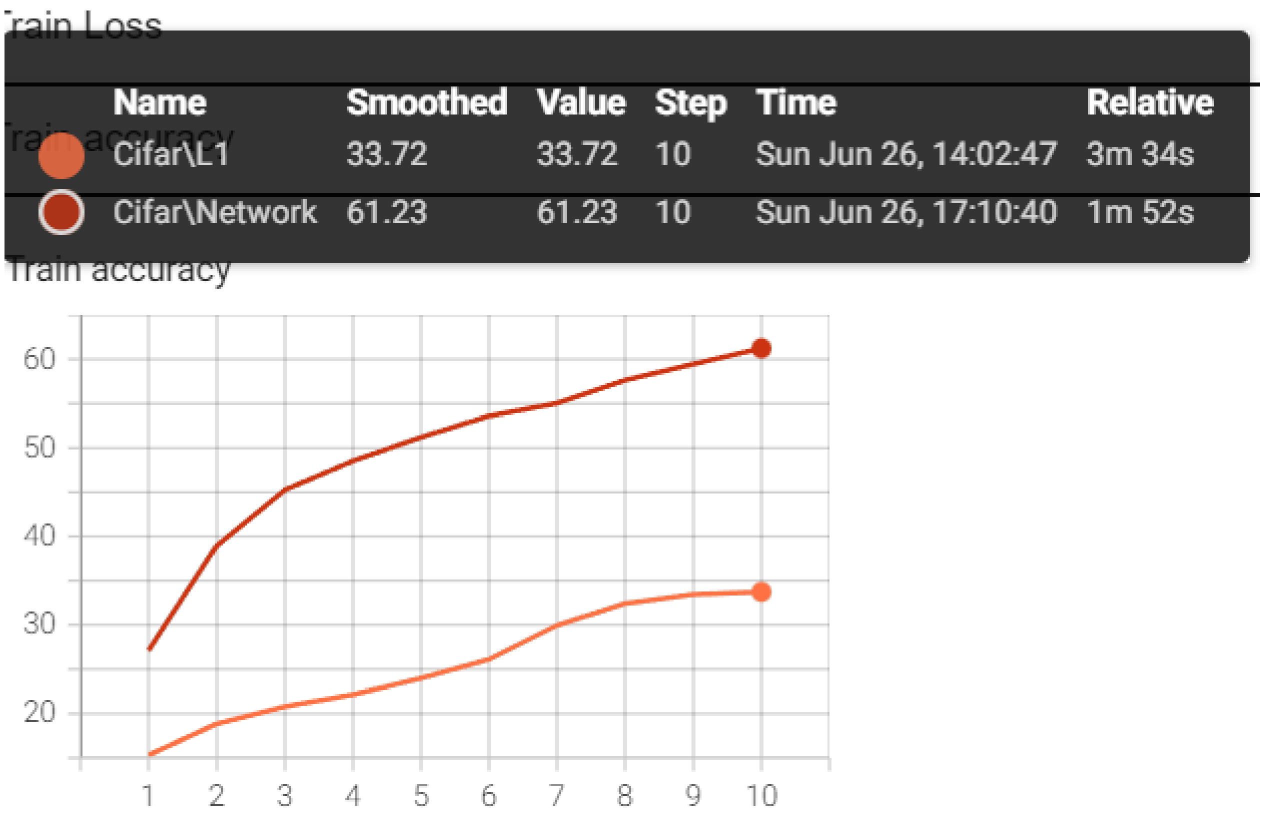
	Name	Smoothed	Value	Step	Time	Relative
	Cifar\L1	0.2801	0.2801	10	Sun Jun 26, 14:02:47	3m 34s
	Cifar\Network	0.0924	0.0924	10	Sun Jun 26, 17:10:40	1m 52s

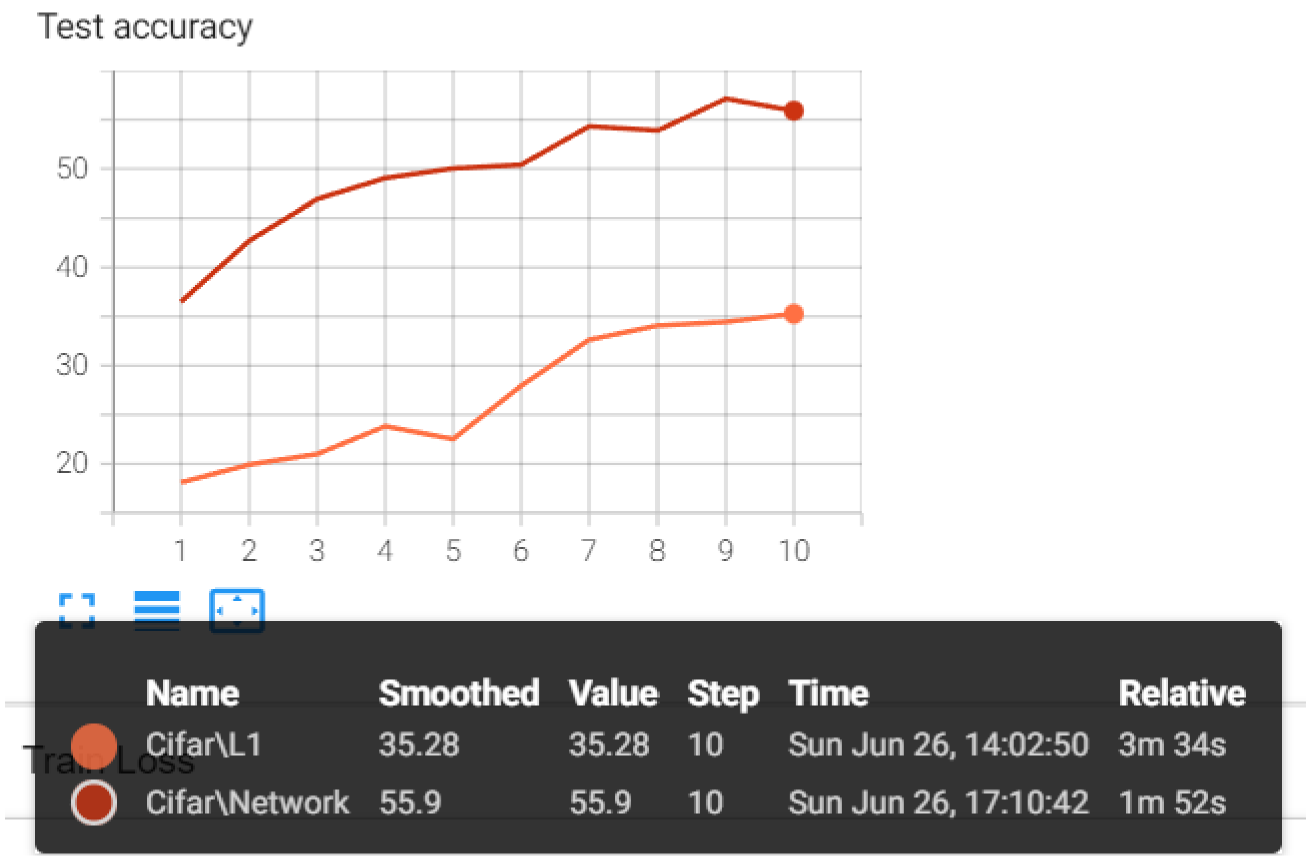


	Name	Smoothed	Value	Step	Time	Relative
	Cifar\L1	0.1623	0.1623	10	Sun Jun 26, 14:02:50	3m 34s
	Cifar\Network	0.1387	0.1387	10	Sun Jun 26, 17:10:42	1m 52s

Training and Test Accuracy

comparison with baseline





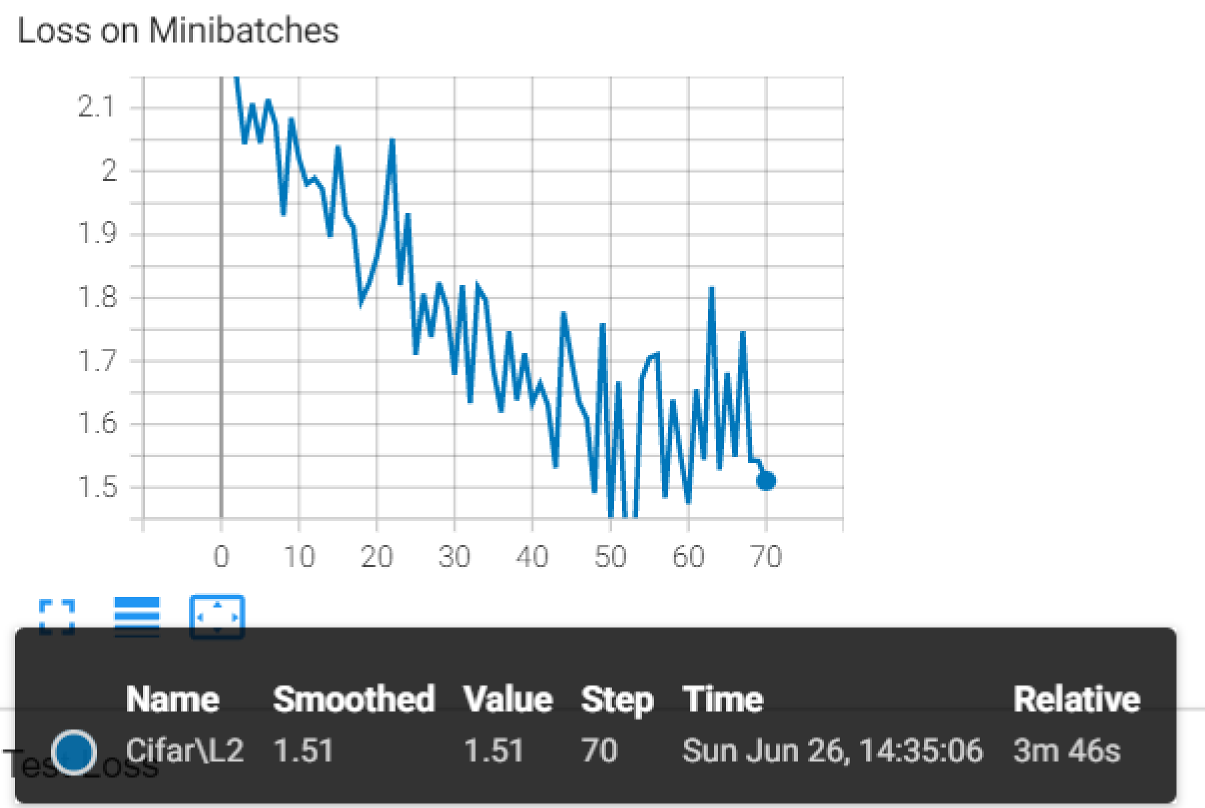
L2 Regularization

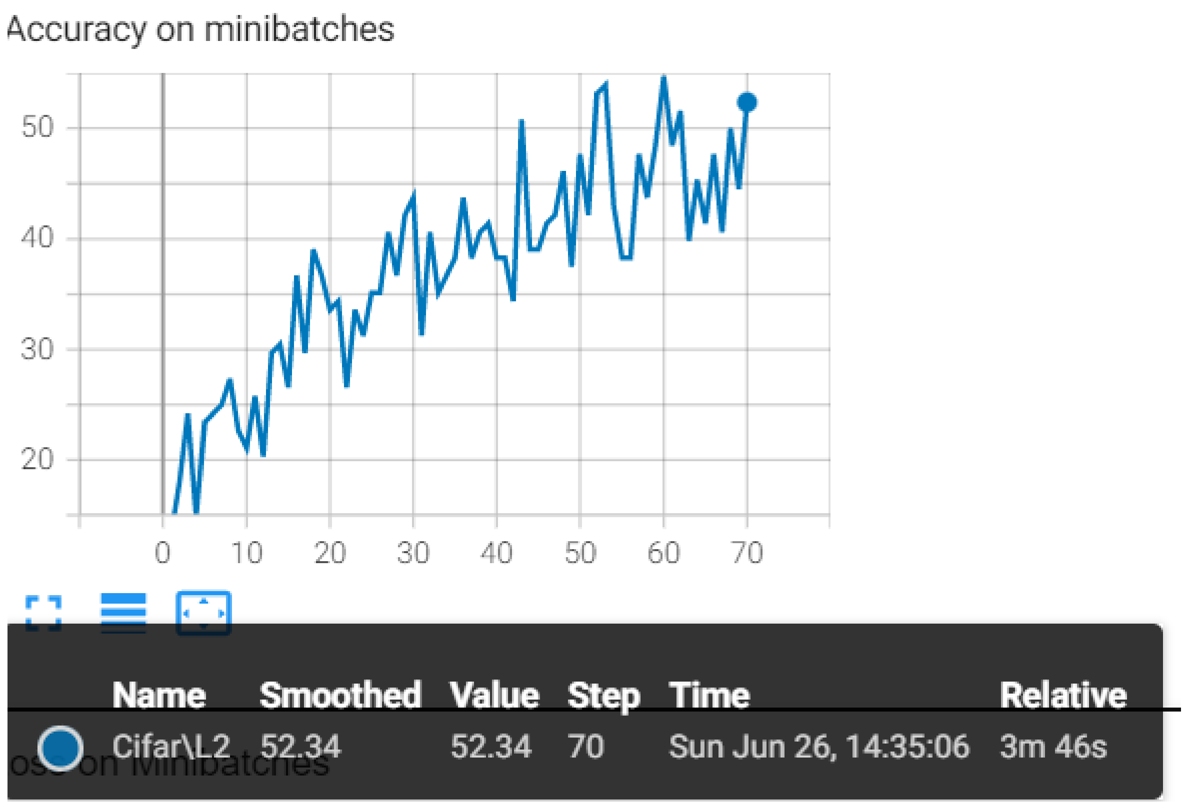
In [ ]:

```
class CNNL2(Module):
    def __init__(self, input_channels):
        super(CNNL2, self).__init__()
        self.conv1 = nn.Conv2d(input_channels, 10, kernel_size = 5)
        self.pool1 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.conv2 = nn.Conv2d(10, 30, kernel_size = 5)
        self.conv3 = nn.Conv2d(30, 60, kernel_size = 5)
        self.pool2 = nn.MaxPool2d(kernel_size = 2, stride = 2)
        self.fc1 = nn.Linear(540, 270)
        self.fc2 = nn.Linear(270, 130)
        self.fc3 = nn.Linear(130, 10)


    def forward(self, x):
        y = F.relu(self.conv1(x))
        y = self.pool1(y)
        y = F.relu(self.conv2(y))
        y = F.relu(self.conv3(y))
        y = self.pool2(y)
        y = y.view(-1, 60*3*3)
        y1 = F.relu(self.fc1(y))
        y2 = F.relu(self.fc2(y1))
        out = self.fc3(y2)
        return out, y1
```

In [ ]:

```
ModelL2 = CNNL2(3)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(ModelL2.parameters(),lr = learning_rate)
writer = SummaryWriter(f'runs/Cifar/L2')
step = 0
for epoch in range(epochs):
    total_loss = 0
    correct_pred = 0
    sample_size = 0
    for i, batch in enumerate(train_loader):
        optimizer.zero_grad()
        yhat, y1 = ModelL2(batch[0])
        entropyloss = criterion(yhat.squeeze(), batch[1].squeeze())
        y1_params = torch.cat([x.view(-1) for x in ModelL2.fc1.parameters()])
        l2_regularization = lambda2*torch.norm(y1_params, 2)
        loss = entropyloss + l2_regularization
        total_loss += loss.item()
        pred = torch.max(yhat.data, 1)[1]
        sample_size = batch[1].size(0)
        correct_pred += (pred == batch[1]).sum().item()
        loss.backward()
        optimizer.step()
        if (i + 1) % 50 == 0:
            writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
            writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item()/sa
                              step + 1)
            step += 1
    accuracy = (correct_pred/len(CifarTrain))*100
    writer.add_scalar('Train Loss', np.sqrt(total_loss/len(CifarTrain)), epoch + 1)
    writer.add_scalar('Train accuracy', accuracy, epoch + 1)

    with torch.no_grad():
        test_pred = 0
        test_loss = 0
        for i, (img, label) in enumerate(test_loader):
            optimizer.zero_grad()
            output, _ = ModelL2(img)
            loss = criterion(output.squeeze(), label.squeeze())
            test_loss += loss.item()
            pred = torch.max(output.data, 1)[1]
            test_pred += (pred == label).sum().item()
        accuracy = (test_pred/len(CifarTest))*100
        writer.add_scalar('Test Loss', np.sqrt(test_loss/len(CifarTest)), epoch + 1)
        writer.add_scalar('Test accuracy', accuracy, epoch + 1)

writer.close()
writer.flush()
```





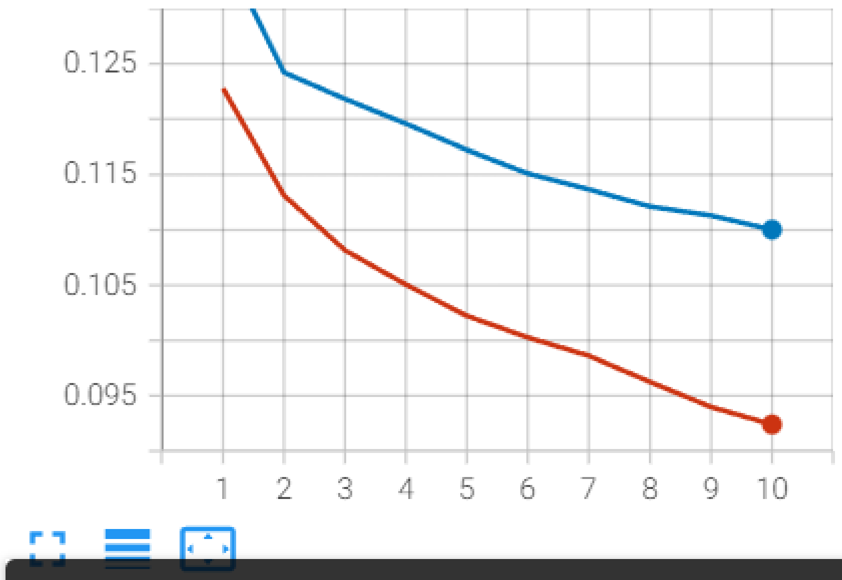
Training and Test loss

Comparison with baseline

As seen above for the L1 regularization, same is observed for the L2

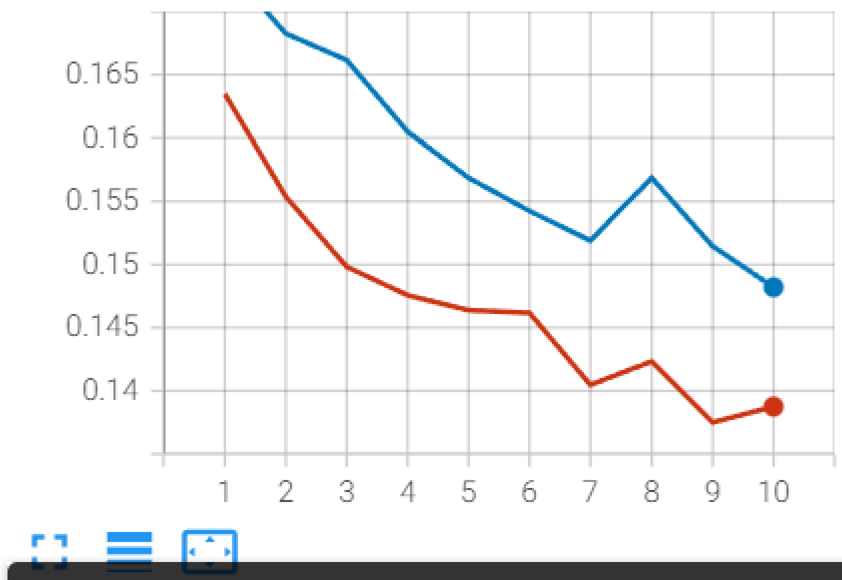
regularization. There has been an increase in the loss and decrease in the accuracy as compared to the baseline.

Train Loss



	Name	Smoothed	Value	Step	Time	Relative
●	Cifar\L2	0.11	0.11	10	Sun Jun 26, 14:35:09	3m 29s
●	Cifar\Network	0.0924	0.0924	10	Sun Jun 26, 17:10:40	1m 52s

Test Loss



	Name	Smoothed	Value	Step	Time	Relative
●	Cifar\L2	0.1482	0.1482	10	Sun Jun 26, 14:35:11	3m 29s
●	Cifar\Network	0.1387	0.1387	10	Sun Jun 26, 17:10:42	1m 52s

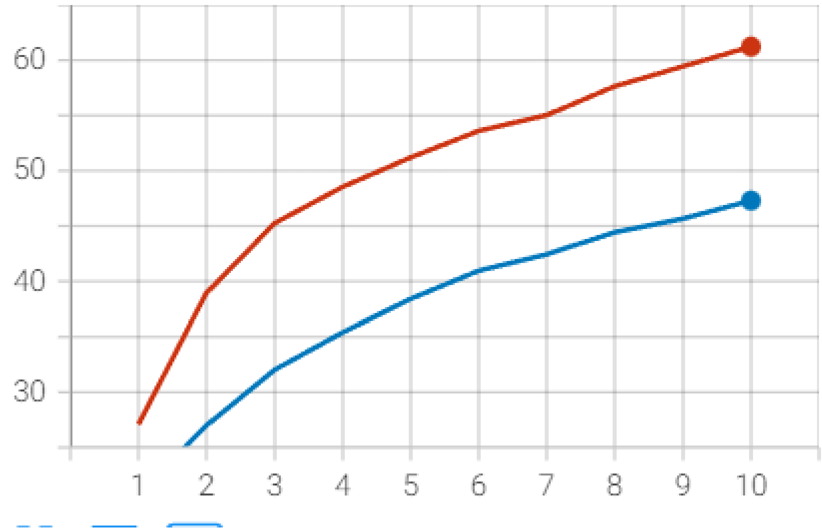
training and Test Accuracy

comparison with baseline

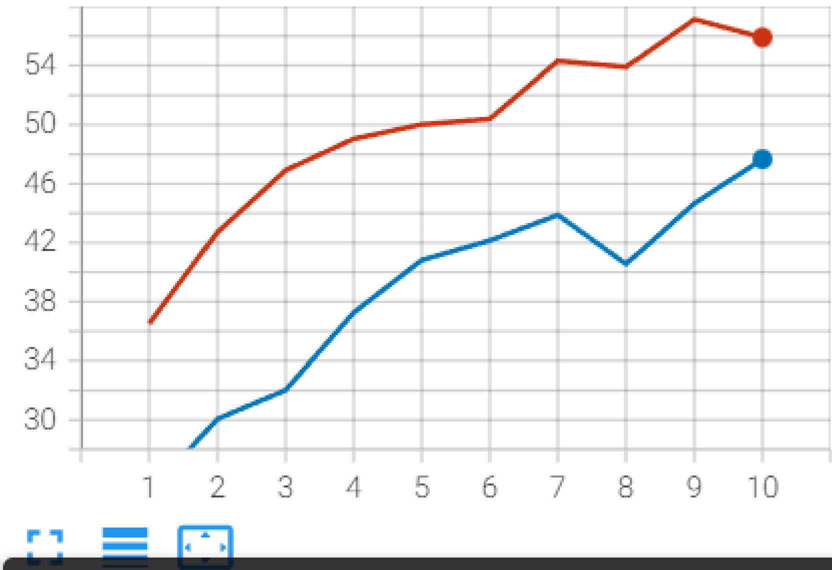
rain Loss

Name	Smoothed	Value	Step	Time	Relative
Cifar\L2	47.3	47.3	10	Sun Jun 26, 14:35:09	3m 29s
Cifar\Network	61.23	61.23	10	Sun Jun 26, 17:10:40	1m 52s

Train accuracy



Test accuracy



Name	Smoothed	Value	Step	Time	Relative
Cifar\L2	47.67	47.67	10	Sun Jun 26, 14:35:11	3m 29s
Cifar\Network	55.9	55.9	10	Sun Jun 26, 17:10:42	1m 52s

Train Loss

Optimizers

Now we will be experimenting with two optimizers and how they response the

different learning rates.

In [ ]:

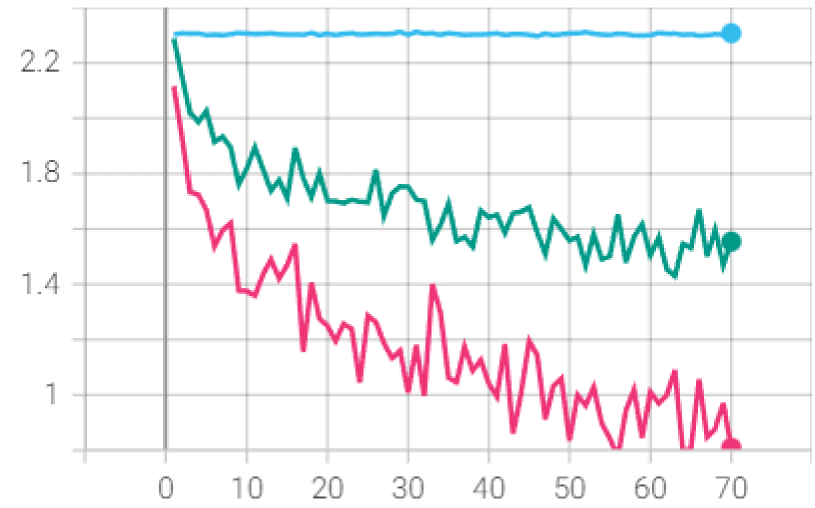
```
learningRate = [0.01, 0.001, 0.0001]
```

Adam Optimizer

In [ ]:

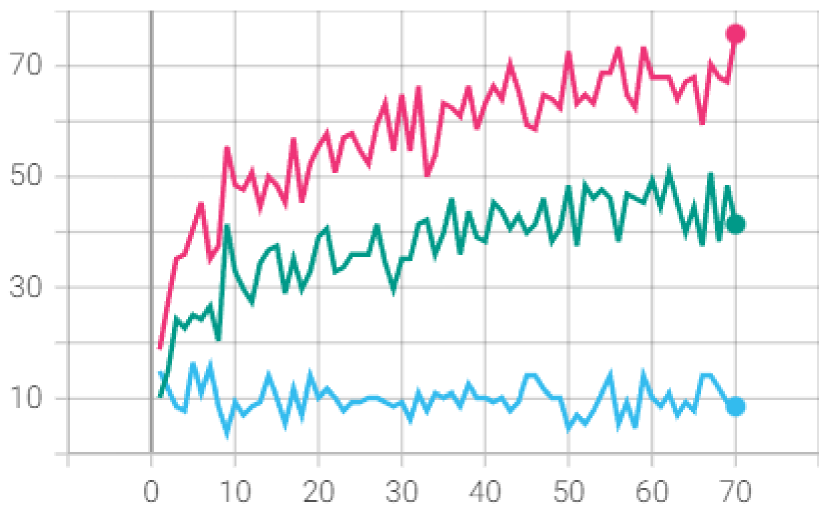
```
for learning_rate in learningRate:
    Model = CNNetwork(3)
    criterion = nn.CrossEntropyLoss()
    optimizer = torch.optim.Adam(Model.parameters(),lr = learning_rate)
    writer = SummaryWriter(f'runs/Cifar/Adam {+ learning_rate}')
    step = 0
    for epoch in range(epochs):
        total_loss = 0
        correct_pred = 0
        sample_size = 0
        for i, batch in enumerate(train_loader):
            optimizer.zero_grad()
            yhat = Model(batch[0])
            loss = criterion(yhat.squeeze(), batch[1].squeeze())
            total_loss += loss.item()
            pred = torch.max(yhat.data, 1)[1]
            sample_size = batch[1].size(0)
            correct_pred += (pred == batch[1]).sum().item()
            loss.backward()
            optimizer.step()
            if (i + 1) % 50 == 0:
                writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
                writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item(
                                  step + 1)
                step += 1

        accuracy = (correct_pred/len(CifarTrain))*100
        writer.add_scalar('Train Loss', np.sqrt(total_loss/len(CifarTrain)), epoch + 1)
        writer.add_scalar('Train accuracy', accuracy, epoch + 1)

        with torch.no_grad():
            test_pred = 0
            test_loss = 0
            for i, (img, label) in enumerate(test_loader):
                optimizer.zero_grad()
                output = Model(img)
                loss = criterion(output.squeeze(), label.squeeze())
                test_loss += loss.item()
                pred = torch.max(output.data, 1)[1]
                test_pred += (pred == label).sum().item()
            accuracy = (test_pred/len(CifarTest))*100
            writer.add_scalar('Test Loss', np.sqrt(test_loss/len(CifarTest)), epoch + 1)
            writer.add_scalar('Test accuracy', accuracy, epoch + 1)

    writer.close()
    writer.flush()
```

Loss on Minibatches



Name	Smoothed	Value	Step	Time	Relative
Cifar\Adam 0.0001	1.554	1.554	70	Sun Jun 26, 16:33:55	3m 34s
Cifar\Adam 0.001	0.8094	0.8094	70	Sun Jun 26, 16:30:15	3m 34s
Cifar\Adam 0.01	2.307	2.307	70	Sun Jun 26, 16:26:34	2m 57s

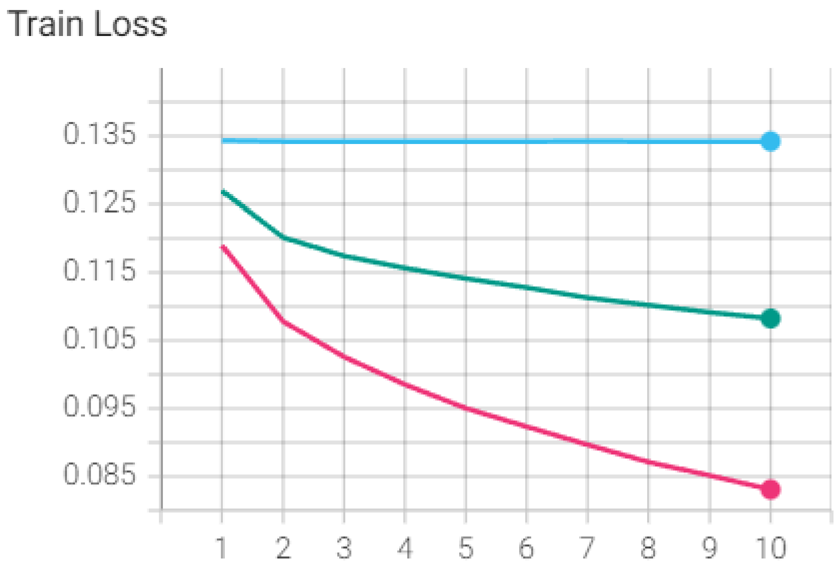
Accuracy on minibatches



Name	Smoothed	Value	Step	Time	Relative
Cifar\Adam 0.0001	41.41	41.41	70	Sun Jun 26, 16:33:55	3m 34s
Cifar\Adam 0.001	75.78	75.78	70	Sun Jun 26, 16:30:15	3m 34s
Cifar\Adam 0.01	8.594	8.594	70	Sun Jun 26, 16:26:34	2m 57s

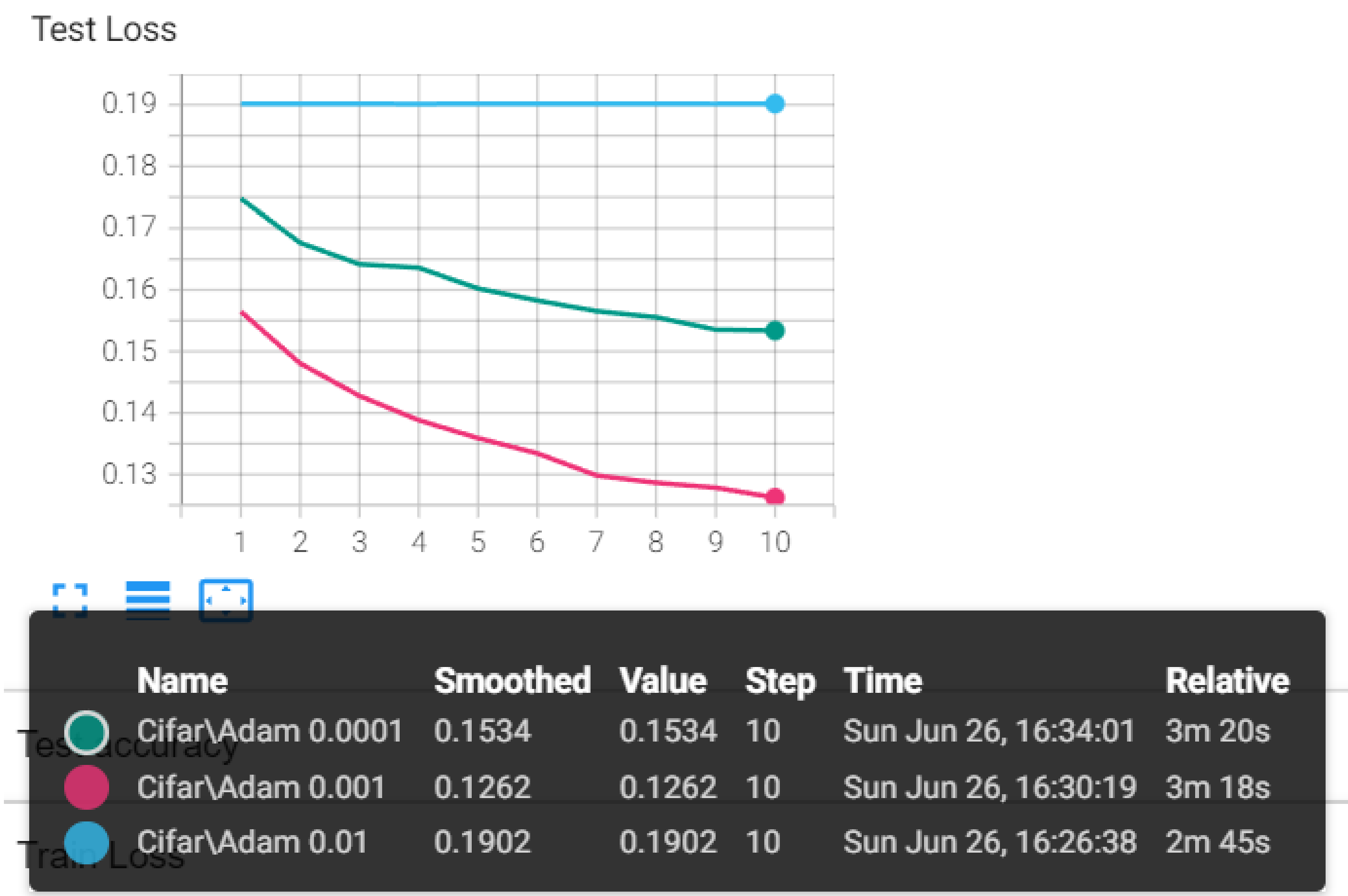
Training and Test Loss

As can be seen below, both the training and test loss has decreased more faster when the initial learning rate is neither too big nor too small. For example here three different learning rates were experimented and the results have been found best for learning rate 0.001.



Name	Smoothed	Value	Step	Time	Relative
Cifar\Adam 0.0001	0.1082	0.1082	10	Sun Jun 26, 16:33:58	3m 19s
Cifar\Adam 0.001	0.08308	0.08308	10	Sun Jun 26, 16:30:17	3m 18s
Cifar\Adam 0.01	0.1342	0.1342	10	Sun Jun 26, 16:26:36	2m 45s

Train accuracy



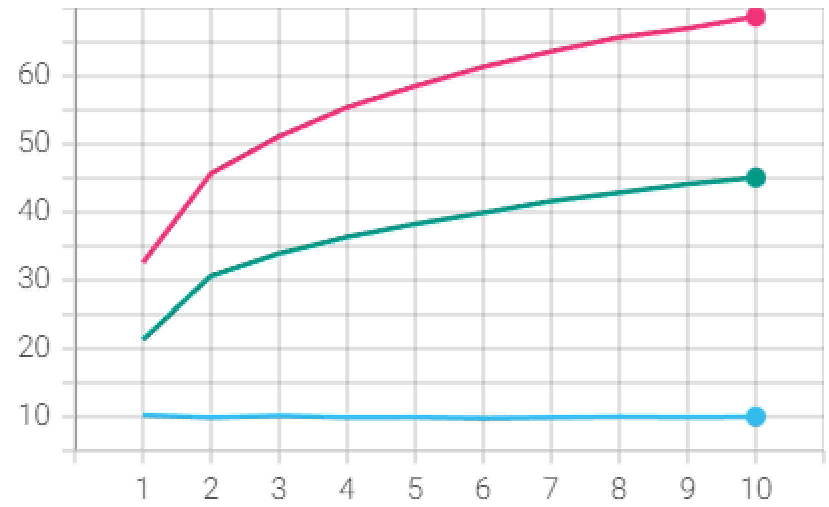
Training and Test Accuracy

since the learning rate that has resulted in maximum decrease in loss has also increased the accuracy most.

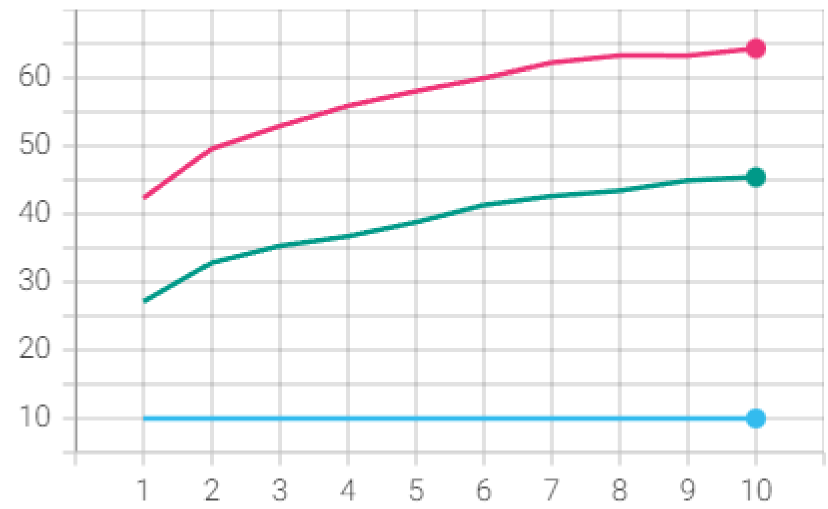
Train Loss

	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Adam 0.0001	45.06	45.06	10	Sun Jun 26, 16:33:58	3m 19s
	Cifar\Adam 0.001	68.74	68.74	10	Sun Jun 26, 16:30:17	3m 18s
	Cifar\Adam 0.01	10.01	10.01	10	Sun Jun 26, 16:26:36	2m 45s

Train accuracy



Test accuracy

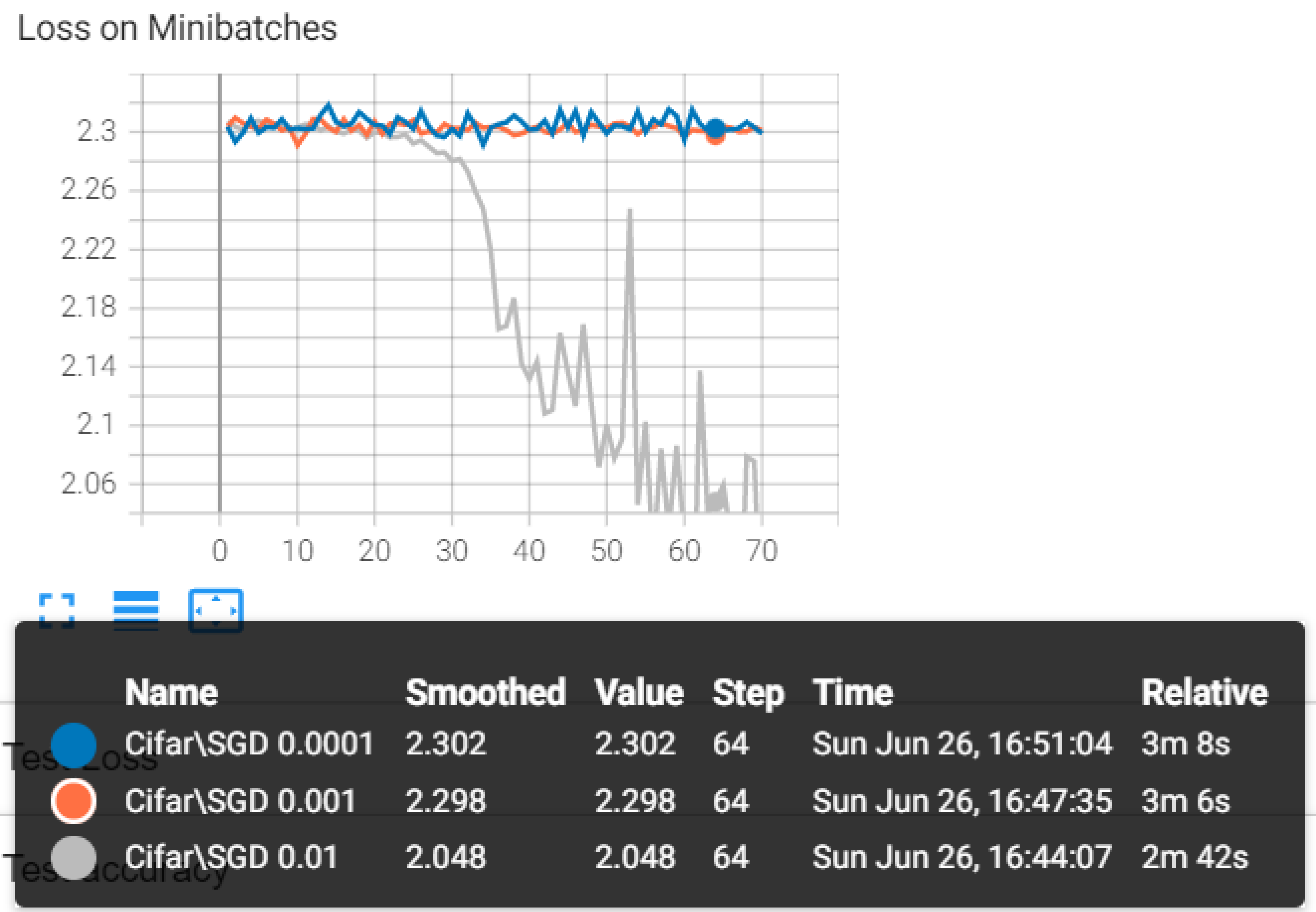


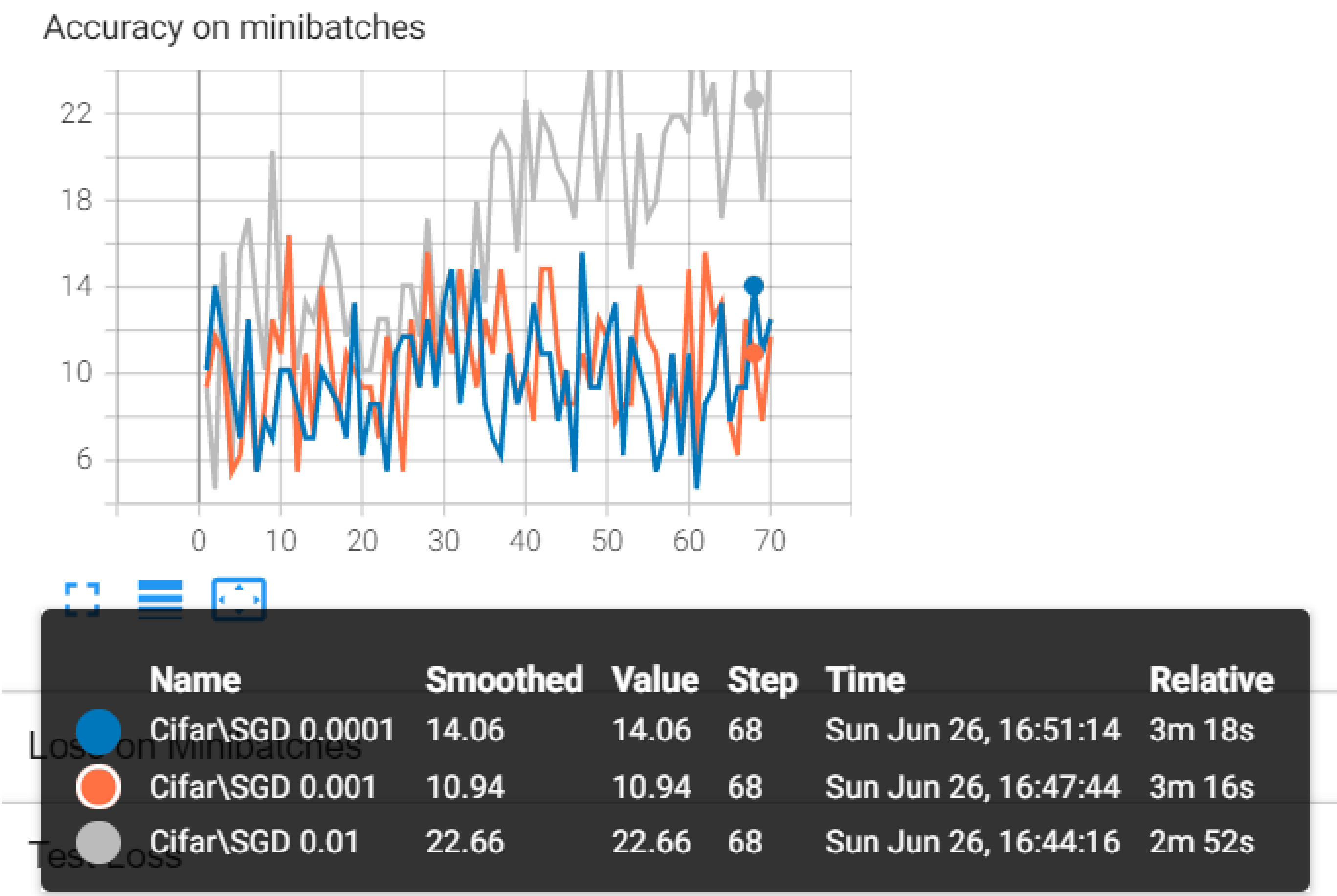
	Name	Smoothed	Value	Step	Time	Relative
	Cifar\Adam 0.0001	45.41	45.41	10	Sun Jun 26, 16:34:01	3m 20s
	Cifar\Adam 0.001	64.26	64.26	10	Sun Jun 26, 16:30:19	3m 18s
	Cifar\Adam 0.01	10	10	10	Sun Jun 26, 16:26:38	2m 45s

SGD Optimizer

In [ ]:

```
for learning_rate in learningRate:
    Model = CNNetwork(3)
    criterion = nn.CrossEntropyLoss()
    optimizer = torch.optim.SGD(Model.parameters(),lr = learning_rate)
    writer = SummaryWriter(f'runs/Cifar/SGD {+ learning_rate}')
    step = 0
    for epoch in range(epochs):
        total_loss = 0
        correct_pred = 0
        sample_size = 0
        for i, batch in enumerate(train_loader):
            optimizer.zero_grad()
            yhat = Model(batch[0])
            loss = criterion(yhat.squeeze(), batch[1].squeeze())
            total_loss += loss.item()
            pred = torch.max(yhat.data, 1)[1]
            sample_size = batch[1].size(0)
            correct_pred += (pred == batch[1]).sum().item()
            loss.backward()
            optimizer.step()
            if (i + 1) % 50 == 0:
                writer.add_scalar('Loss on Minibatches', loss.item(), step + 1)
                writer.add_scalar('Accuracy on minibatches',((pred == batch[1]).sum().item(
                                  step + 1)
                step += 1

        accuracy = (correct_pred/len(CifarTrain))*100
        writer.add_scalar('Train Loss', np.sqrt(total_loss/len(CifarTrain)), epoch + 1)
        writer.add_scalar('Train accuracy', accuracy, epoch + 1)

        with torch.no_grad():
            test_pred = 0
            test_loss = 0
            for i, (img, label) in enumerate(test_loader):
                optimizer.zero_grad()
                output = Model(img)
                loss = criterion(output.squeeze(), label.squeeze())
                test_loss += loss.item()
                pred = torch.max(output.data, 1)[1]
                test_pred += (pred == label).sum().item()
            accuracy = (test_pred/len(CifarTest))*100
            writer.add_scalar('Test Loss', np.sqrt(test_loss/len(CifarTest)), epoch + 1)
            writer.add_scalar('Test accuracy', accuracy, epoch + 1)

    writer.close()
    writer.flush()
```

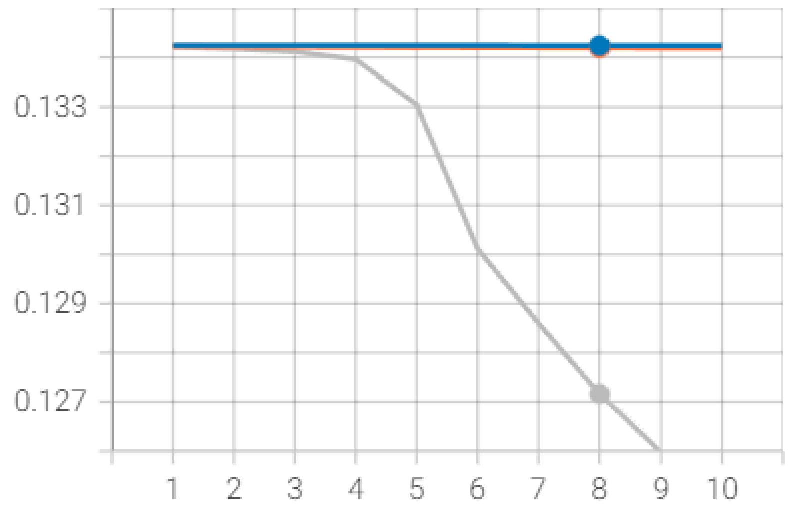




Training and Test Loss

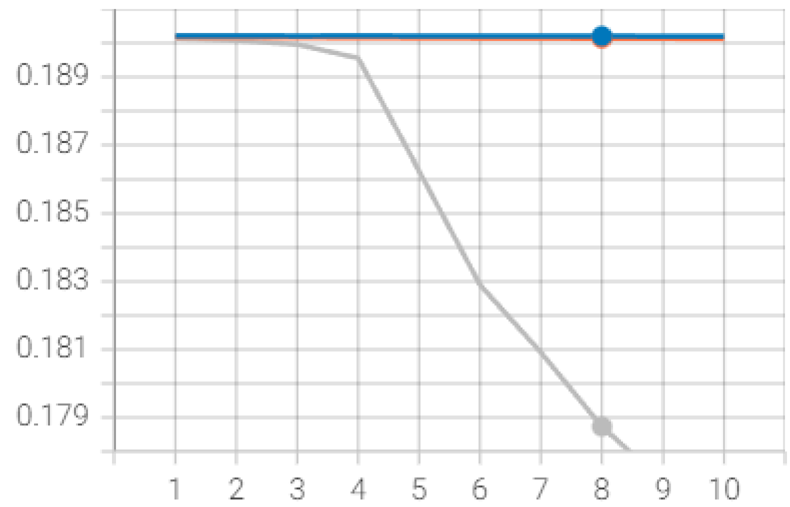
SGD seems to work better with not too small initial learning rate and afterwards a small learning rate there is hardly any much declination in the loss.

Train Loss



	Name	Smoothed	Value	Step	Time	Relative
	Cifar\SGD 0.0001	0.1342	0.1342	8	Sun Jun 26, 16:50:39	2m 26s
	Cifar\SGD 0.001	0.1342	0.1342	8	Sun Jun 26, 16:47:10	2m 25s
	Cifar\SGD 0.01	0.1272	0.1272	8	Sun Jun 26, 16:43:44	2m 5s

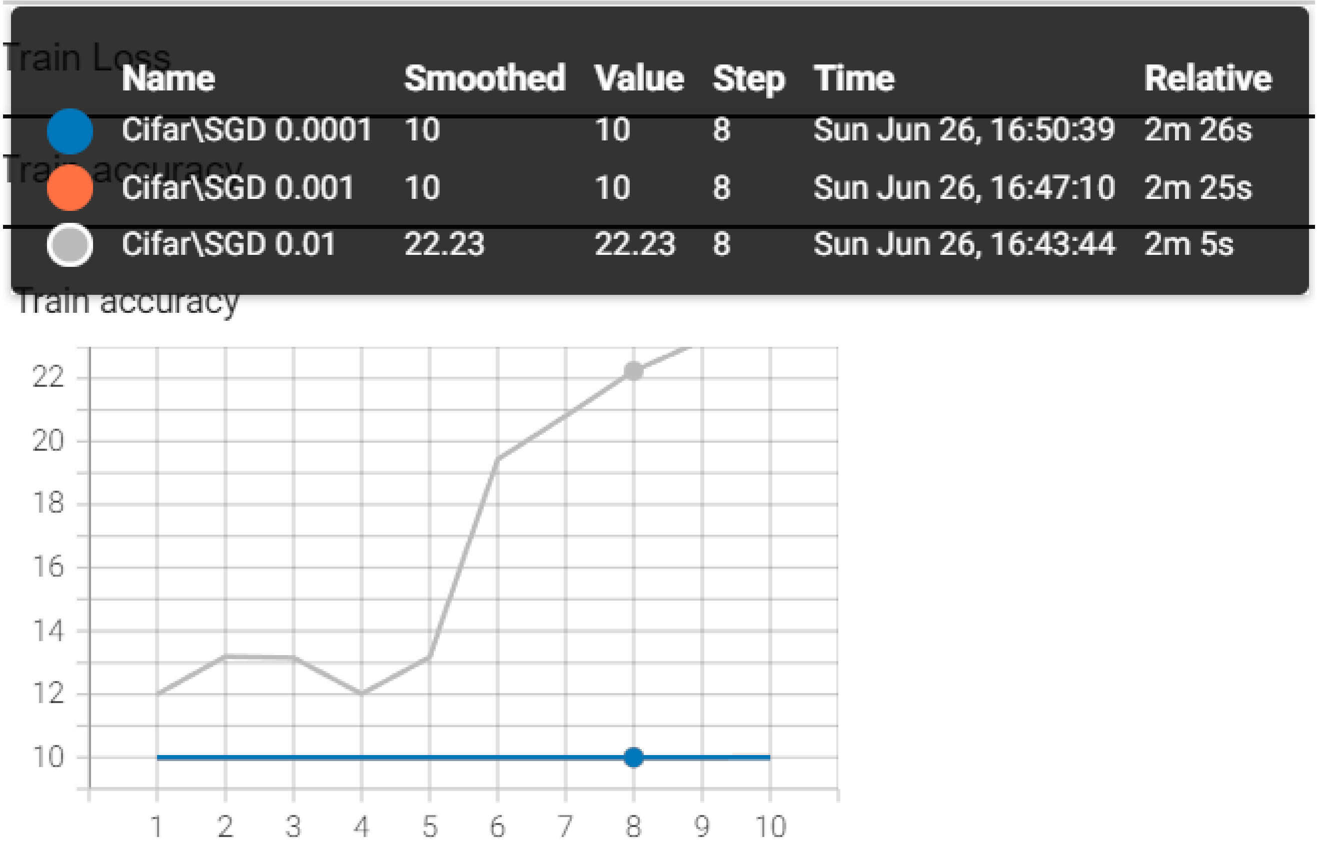
Test Loss



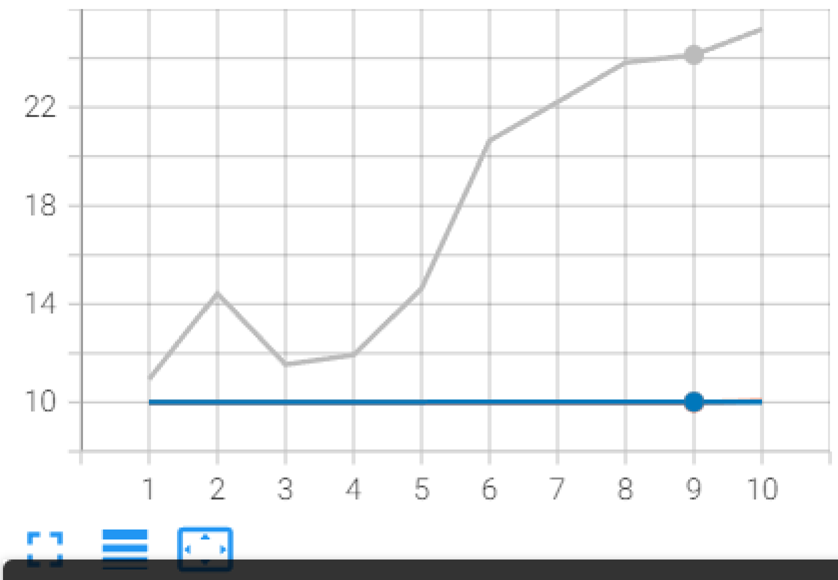
	Name	Smoothed	Value	Step	Time	Relative
	Cifar\SGD 0.0001	0.1902	0.1902	8	Sun Jun 26, 16:50:41	2m 26s
	Cifar\SGD 0.001	0.1901	0.1901	8	Sun Jun 26, 16:47:12	2m 25s
	Cifar\SGD 0.01	0.1787	0.1787	8	Sun Jun 26, 16:43:46	2m 5s

Training and Test Accuracy

As seen above for loss same applies to accuracy.



Test accuracy



	Name	Smoothed	Value	Step	Time	Relative
	Cifar\SGD 0.0001	10.02	10.02	9	Sun Jun 26, 16:51:02	2m 47s
	Cifar\SGD 0.001	10	10	9	Sun Jun 26, 16:47:32	2m 46s
	Cifar\SGD 0.01	24.13	24.13	9	Sun Jun 26, 16:44:05	2m 24s

In [ ]:

```

```