Implementation of a CNN based Image Classifier using PyTorch

Downloading data and printing some sample images from the training set

In [41]:
```
import torch
import torchvision
import matplotlib.pyplot as plt
import numpy as np


# The below two lines are optional and are just there to avoid any SSL
# related errors while downloading the CIFAR-10 dataset
import ssl
ssl._create_default_https_context = ssl._create_unverified_context


#Defining plotting settings
plt.rcParams['figure.figsize'] = 14, 6


#Initializing normalizing transform for the dataset
normalize_transform = torchvision.transforms.Compose([
    torchvision.transforms.ToTensor(),
    torchvision.transforms.Normalize(mean=(0.5,), std=(0.5,))
])


#Downloading the FashionMNIST dataset into train and test sets


train_dataset = torchvision.datasets.FashionMNIST(
    root='./data',
    train=True,
    transform=normalize_transform,
    download=True
)

test_dataset = torchvision.datasets.FashionMNIST(
    root='./data',
    train=False,
    transform=normalize_transform,
    download=True
)
print(train_dataset)
print(test_dataset)
```

```python
#Generating data loaders from the corresponding datasets
batch_size = 128
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_s
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_siz


#Plotting 25 images from the 1st batch
dataiter = iter(train_loader)
images, labels = next(dataiter)
plt.imshow(np.transpose(torchvision.utils.make_grid(
images[:25], normalize=True, padding=1, nrow=5).numpy(), (1, 2, 0)))
plt.axis('off')
```

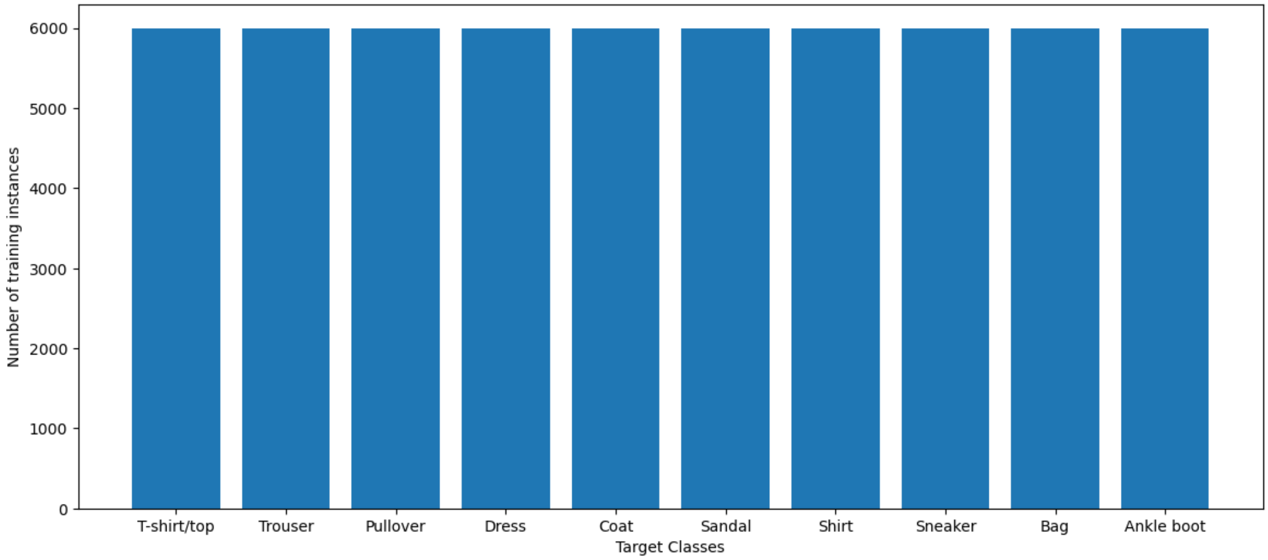
```
Dataset FashionMNIST
    Number of datapoints: 60000
    Root location: ./data
    Split: Train
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.5,), std=(0.5,))
           )
Dataset FashionMNIST
    Number of datapoints: 10000
    Root location: ./data
    Split: Test
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.5,), std=(0.5,))
           )
```

Out[41]:
```
(-0.5, 145.5, 145.5, -0.5)
```

Plotting class distribution of the dataset

In [42]:
```
#Iterating over the training dataset and storing the target class for each s
classes = []
for batch_idx, data in enumerate(train_loader, 0):
        x, y = data
        classes.extend(y.tolist())

#Calculating the unique classes and the respective counts and plotting them
unique, counts = np.unique(classes, return_counts=True)
names = list(test_dataset.class_to_idx.keys())
plt.bar(names, counts)
plt.xlabel("Target Classes")
plt.ylabel("Number of training instances")
```

Out[42]:
```
Text(0, 0.5, 'Number of training instances')
```



Implementing the CNN architecture with removing Conv2d, ReLU layers.

In [43]:
```
class CNN(torch.nn.Module):
        def __init__(self):
                super().__init__()
                self.model = torch.nn.Sequential(


                        #Input = 1 x 28 x 28, Output = 32 x 28 x 28
                        torch.nn.Conv2d(in_channels=1, out_channels=32, kern
                        torch.nn.ReLU(),
                        #Input = 32 x 28 x 28, Output = 32 x 14 x 14
                        torch.nn.MaxPool2d(kernel_size=2),

                        #Input = 32 x 14 x 14, Output = 64 x 14 x 14
                        torch.nn.Conv2d(in_channels=32, out_channels=64, ker
                        torch.nn.ReLU(),
                        #Input = 64 x 14 x 14, Output = 64 x 7 x 7
                        torch.nn.MaxPool2d(kernel_size=2),



                        #Input = 64 x 7 x 7, Output = 128 x 7 x 7
                        torch.nn.Conv2d(in_channels=64, out_channels=128, ke
                        torch.nn.ReLU(),
                        #Input = 128 x 7 x 7, Output = 128 x 3 x 3
                        torch.nn.MaxPool2d(kernel_size=2),

                        torch.nn.Flatten(),
                        torch.nn.Linear(128 * 3 * 3, 512),
                        torch.nn.ReLU(),
                        torch.nn.Linear(512, 10)


                )

        def forward(self, x):
                return self.model(x)
```

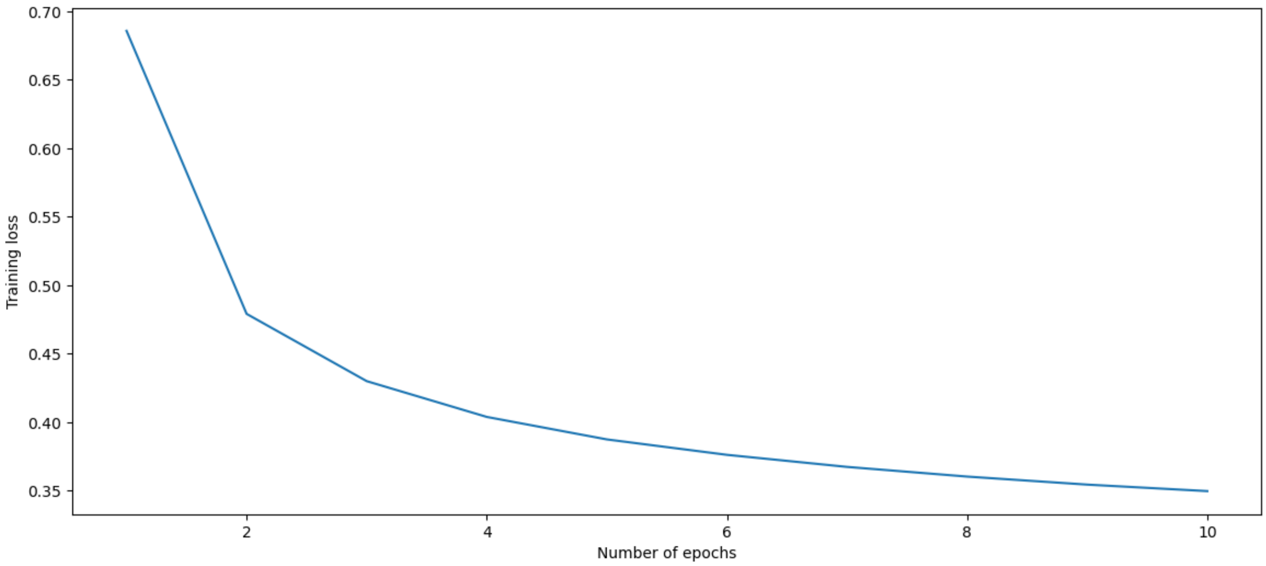
Defining the training parameters and beginning the training process

In [44]:
```
#Selecting the appropriate training device
#from torch.optim.lr_scheduler import StepLR

from torch.optim.lr_scheduler import MultiStepLR


device = 'cuda' if torch.cuda.is_available() else 'cpu'
model = CNN().to(device)

#Defining the model hyper parameters
num_epochs = 10
learning_rate = 0.001
weight_decay = 0.01
```

```
criterion = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate, weight_de
#scheduler = StepLR(optimizer, step_size=2, gamma=0.1)

scheduler = MultiStepLR(optimizer,
                        milestones=[4, 7], # List of epoch indices
                        gamma =0.5) # Multiplicative factor of learning rate

#Training process begins
train_loss_list = []
for epoch in range(num_epochs):
        print(f'Epoch {epoch+1}/{num_epochs}:', end = ' ')
        train_loss = 0

        #Iterating over the training dataset in batches
        model.train()
        for i, (images, labels) in enumerate(train_loader):

                #Extracting images and target labels for the batch being ite
                images = images.to(device)
                labels = labels.to(device)

                #Calculating the model output and the cross entropy loss
                outputs = model(images)
                loss = criterion(outputs, labels)

                #Updating weights according to calculated loss
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()
                scheduler.step()
                train_loss += loss.item()

        #Printing loss for each epoch
        train_loss_list.append(train_loss/len(train_loader))
        print(f"Training loss = {train_loss_list[-1]}")

#Plotting loss for all epochs
plt.plot(range(1,num_epochs+1), train_loss_list)
plt.xlabel("Number of epochs")
plt.ylabel("Training loss")
```

```
Epoch 1/10: Training loss = 0.6858297149255586
Epoch 2/10: Training loss = 0.4790012387832853
Epoch 3/10: Training loss = 0.42983509962365574
Epoch 4/10: Training loss = 0.4036899660823188
Epoch 5/10: Training loss = 0.38725589390502557
Epoch 6/10: Training loss = 0.3759850684259492
Epoch 7/10: Training loss = 0.3671678291010196
Epoch 8/10: Training loss = 0.3600924234591059
Epoch 9/10: Training loss = 0.3542242176306527
Epoch 10/10: Training loss = 0.3494821182890996
```

Out[44]:
```
Text(0, 0.5, 'Training loss')
```



Calculating the model's accuracy on the test set

In [45]:
```
test_acc=0
model.eval()

with torch.no_grad():
        #Iterating over the training dataset in batches
        for i, (images, labels) in enumerate(test_loader):

                images = images.to(device)
                y_true = labels.to(device)

                #Calculating outputs for the batch being iterated
                outputs = model(images)

                #Calculated prediction labels from models
                _, y_pred = torch.max(outputs.data, 1)

                #Comparing predicted and true labels
                test_acc += (y_pred == y_true).sum().item()

        print(f"Test set accuracy = {100 * test_acc / len(test_dataset)} %")
```

```
Test set accuracy = 85.55 %
```

Generating predictions for sample images in the test set

In [46]:
```
#Generating predictions for 'num_images' amount of images from the last batc
num_images = 5
y_true_name = [names[y_true[idx]] for idx in range(num_images)]
y_pred_name = [names[y_pred[idx]] for idx in range(num_images)]

#Generating the title for the plot
title = f"Actual labels: {y_true_name}, Predicted labels: {y_pred_name}"

#Finally plotting the images with their actual and predicted labels in the t
plt.imshow(np.transpose(torchvision.utils.make_grid(images[:num_images].cpu(
plt.title(title)
plt.axis("off")
```

Out[46]:
```
(-0.5, 145.5, 29.5, -0.5)
```

Actual labels: ['Dress', 'Pullover', 'Sneaker', 'Sandal', 'Bag'], Predicted labels: ['Dress', 'T-shirt/top', 'Sneaker', 'Sandal', 'Bag']