```
# Import libraries
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import time
from queue import PriorityQueue
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA

# Device configuration
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
device
```

```
device(type='cuda', index=0)
```

```
# CIFAR10 dataset
whole_train_dataset = torchvision.datasets.CIFAR10(root="./data", train=True, trans
                                          download=True)
test_dataset = torchvision.datasets.CIFAR10(root="./data", train=False, transform=t
train_dataset, valid_dataset = torch.utils.data.random_split(whole_train_dataset, [
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', '
```

Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./da

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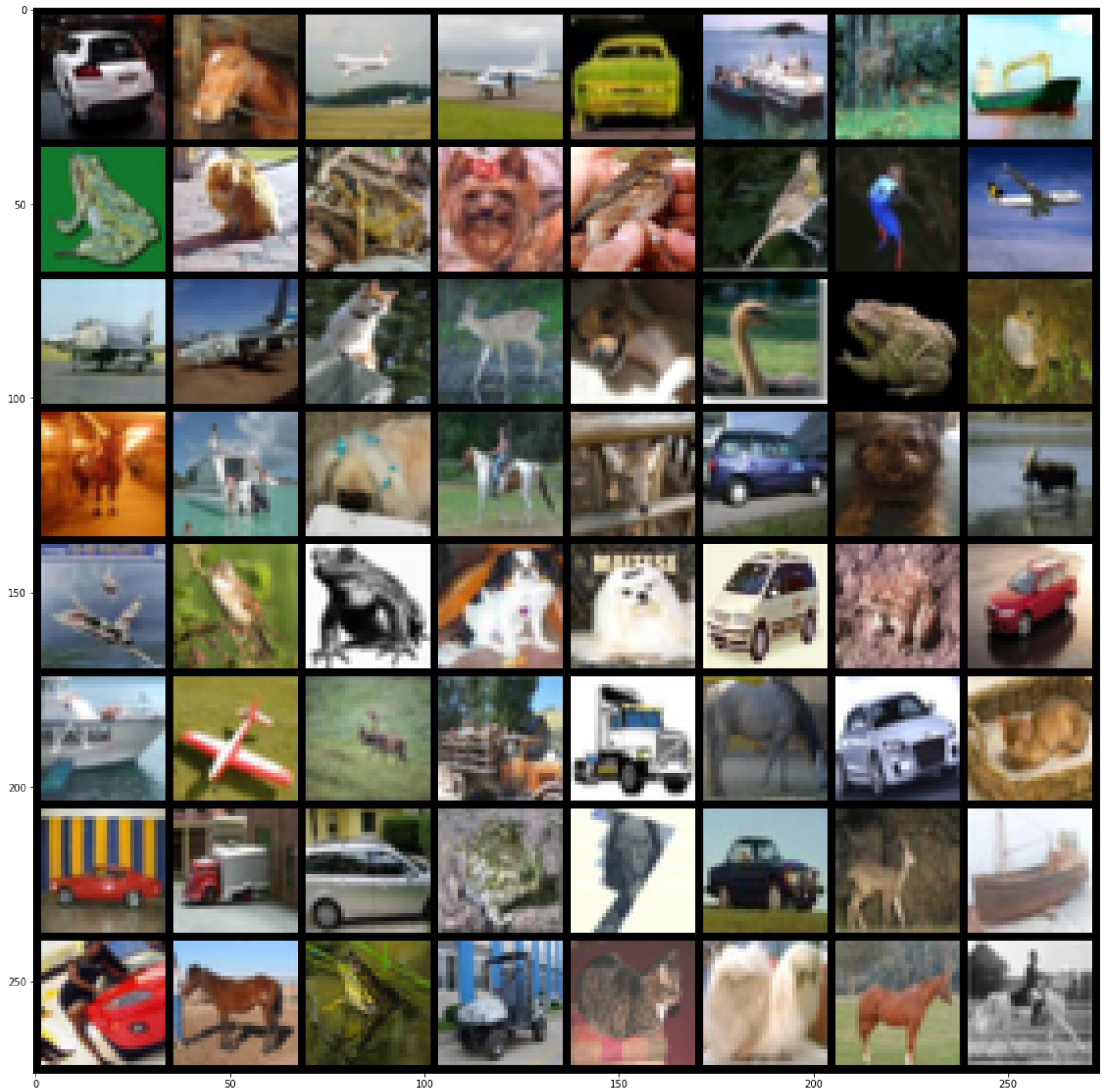
13555463.82it/s]

```
# Batch size of the dataset
batch_size = 64
# Data loader
train_loader = torch.utils.data.DataLoader(dataset=train_dataset, batch_size=batch_
                                          shuffle=True)
valid_loader = torch.utils.data.DataLoader(dataset=valid_dataset, batch_size=batch_
                                          shuffle=True)
test_loader = torch.utils.data.DataLoader(dataset=test_dataset, batch_size=batch_si
                                          shuffle=True)
```

```
# Visualise a batch of images
plt.subplots(1,1,figsize=[20,20])
image, label = iter(train_loader).next()
grid_image = torchvision.utils.make_grid(image)
permuted_image = torch.permute(grid_image, (1,2,0))
plt.imshow(permuted_image)
plt.show()
```


0
50
100
150
200
250
0
50
100
150
200
250

```
# Original CNN
num_class = 10
class ConvNet(nn.Module):
    def __init__(self, num_class=10):
        super(ConvNet, self).__init__()
        self._layer1 = nn.Sequential(
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, stride=1, padd
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (32, 16, 16)
        self._layer2 = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, pad
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (64, 8, 8)
        self._layer3 = nn.Sequential(
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, stride=1, pa
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (128, 4, 4)
        self._layer4 = nn.Sequential(
            nn.Conv2d(in_channels=128, out_channels=2048, kernel_size=4, stride=1,
            nn.ReLU()
        ) # Output size = (2048, 1, 1)
        self._layer5 = nn.Linear(in_features=2048*1*1, out_features=4096)
        self._layer6 = nn.Linear(in_features=4096, out_features=num_class)

        self._layer1_out = None
        self._layer2_out = None
        self._layer3_out = None
        self._layer4_out = None
        self._layer5_out = None
        self._layer6_out = None

    def forward(self, x):
        self._layer1_out = self._layer1(x)
        self._layer2_out = self._layer2(self._layer1_out)
        self._layer3_out = self._layer3(self._layer2_out)
        self._layer4_out = self._layer4(self._layer3_out)
        self._layer5_out = self._layer5(self._layer4_out.reshape(self._layer4_out.s
        self._layer6_out = self._layer6(self._layer5_out)
        return self._layer6_out

    def get_layer(self, num_layer):
      if num_layer == 1:
        return self._layer1_out
      elif num_layer == 2:
        return self._layer2_out
      elif num_layer == 3:
        return self._layer3_out
      elif num_layer == 4:
        return self._layer4_out
```

```
      elif num_layer == 5:
        return self._layer5_out
      else:
        return self._layer6_out


# CNN with 1 convolutional block
num_class = 10
class ConvNet1layer(nn.Module):
    def __init__(self, num_class=10):
        super(ConvNet1layer, self).__init__()
        self._layer1 = nn.Sequential(
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, stride=1, padd
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (32, 16, 16)
        self._layer2 = nn.Linear(in_features=32*16*16, out_features=4096)
        self._layer3 = nn.Linear(in_features=4096, out_features=num_class)

        self._layer1_out = None
        self._layer2_out = None
        self._layer3_out = None

    def forward(self, x):
        self._layer1_out = self._layer1(x)
        self._layer2_out = self._layer2(self._layer1_out.reshape(self._layer1_out.s
        self._layer3_out = self._layer3(self._layer2_out)
        return self._layer3_out

    def get_layer(self, num_layer):
      if num_layer == 1:
        return self._layer1_out
      elif num_layer == 2:
        return self._layer2_out
      elif num_layer == 3:
        return self._layer3_out


# CNN with 2 convolutional block
num_class = 10
class ConvNet2layer(nn.Module):
    def __init__(self, num_class=10):
        super(ConvNet2layer, self).__init__()
        self._layer1 = nn.Sequential(
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, stride=1, padd
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (32, 16, 16)
        self._layer2 = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, pad
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (64, 8, 8)
        self._layer3 = nn.Linear(in_features=64*8*8, out_features=4096)
        self._layer4 = nn.Linear(in_features=4096, out_features=num_class)
```

```
        self._layer1_out = None
        self._layer2_out = None
        self._layer3_out = None
        self._layer4_out = None

    def forward(self, x):
        self._layer1_out = self._layer1(x)
        self._layer2_out = self._layer2(self._layer1_out)
        self._layer3_out = self._layer3(self._layer2_out.reshape(self._layer2_out.s
        self._layer4_out = self._layer4(self._layer3_out)
        return self._layer4_out

    def get_layer(self, num_layer):
      if num_layer == 1:
        return self._layer1_out
      elif num_layer == 2:
        return self._layer2_out
      elif num_layer == 3:
        return self._layer3_out
      elif num_layer == 4:
        return self._layer4_out


# CNN with 1 convolutional block
num_class = 10
class ConvNet3layer(nn.Module):
    def __init__(self, num_class=10):
        super(ConvNet3layer, self).__init__()
        self._layer1 = nn.Sequential(
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, stride=1, padd
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (32, 16, 16)
        self._layer2 = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, pad
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (64, 8, 8)
        self._layer3 = nn.Sequential(
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, stride=1, pa
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        ) # Output size = (128, 4, 4)
        self._layer4 = nn.Linear(in_features=128*4*4, out_features=4096)
        self._layer5 = nn.Linear(in_features=4096, out_features=num_class)

        self._layer1_out = None
        self._layer2_out = None
        self._layer3_out = None
        self._layer4_out = None
        self._layer5_out = None

    def forward(self, x):
        self._layer1_out = self._layer1(x)
```

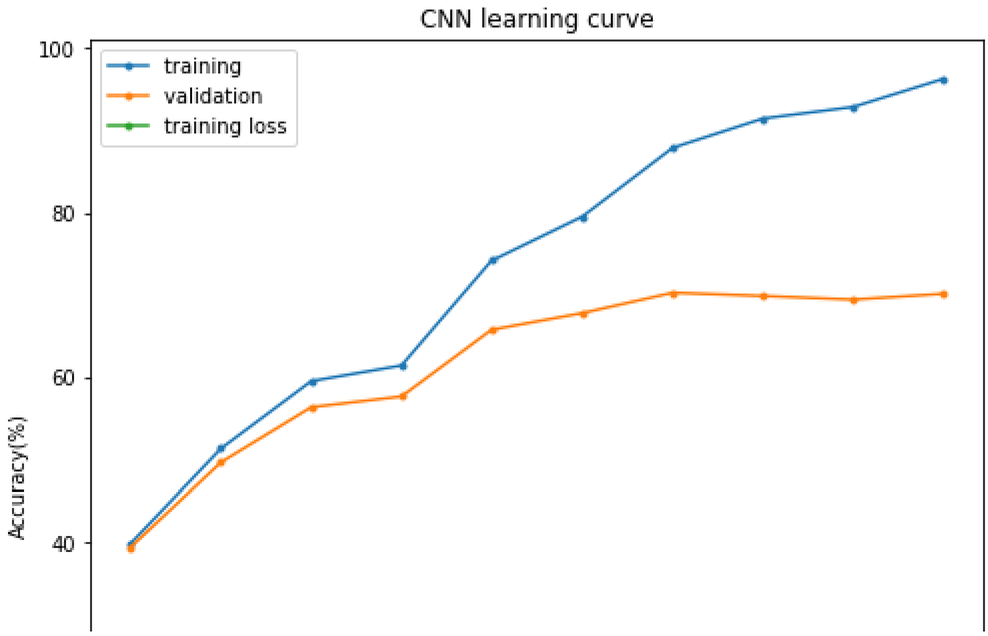
```
        self._layer2_out = self._layer2(self._layer1_out)
        self._layer3_out = self._layer3(self._layer2_out)
        self._layer4_out = self._layer4(self._layer3_out.reshape(self._layer3_out.s
        self._layer5_out = self._layer5(self._layer4_out)
        return self._layer5_out

    def get_layer(self, num_layer):
      if num_layer == 1:
        return self._layer1_out
      elif num_layer == 2:
        return self._layer2_out
      elif num_layer == 3:
        return self._layer3_out
      elif num_layer == 4:
        return self._layer4_out
      elif num_layer == 5:
        return self._layer5_out


# CNN with no max pooling layers
num_class = 10
class ConvNetNoMax(nn.Module):
    def __init__(self, num_class=10):
        super(ConvNetNoMax, self).__init__()
        self._layer1 = nn.Sequential(
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, stride=1, padd
            nn.ReLU()
        ) # Output size = (32, 32, 32)
        self._layer2 = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, pad
            nn.ReLU()
        ) # Output size = (64, 32, 32)
        self._layer3 = nn.Linear(in_features=64*32*32, out_features=4096)
        self._layer4 = nn.Linear(in_features=4096, out_features=num_class)

        self._layer1_out = None
        self._layer2_out = None
        self._layer3_out = None
        self._layer4_out = None

    def forward(self, x):
        self._layer1_out = self._layer1(x)
        self._layer2_out = self._layer2(self._layer1_out)
        self._layer3_out = self._layer3(self._layer2_out.reshape(self._layer2_out.s
        self._layer4_out = self._layer4(self._layer3_out)
        return self._layer4_out

    def get_layer(self, num_layer):
      if num_layer == 1:
        return self._layer1_out
      elif num_layer == 2:
        return self._layer2_out
      elif num_layer == 3:
        return self._layer3_out
```

```
      elif num_layer == 4:
        return self._layer4_out

  # DNN
  num_class = 10
  class DenseNet(nn.Module):
      def __init__(self, num_class=10):
          super(DenseNet, self).__init__()

          self._layer1 = nn.Sequential(
              nn.Linear(in_features=32*32*3, out_features=512),
              nn.ReLU()
          ) # Output size = (1, 512)
          self._layer2 = nn.Sequential(
              nn.Linear(in_features=512, out_features=1024),
              nn.ReLU()
          ) # Output size = (1, 1024)
          self._layer3 = nn.Sequential(
              nn.Linear(in_features=1024, out_features=2048),
              nn.ReLU()
          ) # Output size = (1, 2048)
          self._layer4 = nn.Sequential(
              nn.Linear(in_features=2048, out_features=4096),
              nn.ReLU()
          ) # Output size = (1,4096)
          self._layer5 = nn.Linear(in_features=4096, out_features=num_class)

          self._layer1_out = None
          self._layer2_out = None
          self._layer3_out = None
          self._layer4_out = None
          self._layer5_out = None

      def forward(self, x):
        x = x.reshape(-1, 32*32*3)
        self._layer1_out = self._layer1(x)
        self._layer2_out = self._layer2(self._layer1_out)
        self._layer3_out = self._layer3(self._layer2_out)
        self._layer4_out = self._layer4(self._layer3_out)
        self._layer5_out = self._layer5(self._layer4_out)
        return self._layer5_out

      def get_layer(self, num_layer):
        if num_layer == 1:
          return self._layer1_out
        elif num_layer == 2:
          return self._layer2_out
        elif num_layer == 3:
          return self._layer3_out
        elif num_layer == 4:
          return self._layer4_out
        else:
          return self._layer5_out
```

```
# Train function for neural networks
def train(model, criterion, learning_rate, optimizer, train_loader, valid_loader, n
  # Parameters to be defined
  total_steps = len(train_loader)
  train_accuracy = 0
  train_accuracy_list = []
  valid_accuracy = 0
  best_valid_accuracy = 0
  no_improvement = 0
  valid_accuracy_list = []
  loss_list = []
  # Forward feed and Optimization
  for epoch in range(num_epoch):
      for i, (image, label) in enumerate(train_loader):
        # Load a batch of data
        image = image.to(device)
        label = label.to(device)

        # Put data into the neural network
        output = model(image)
        # Evaluate the loss
        loss = criterion(output, label)
        # Backpropagation and optimization
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
      # Save loss into a list for the learning curve
      loss_list.append(loss.item())

      # Neural network evaluation in the training set
      model.eval()
      with torch.no_grad():
          train_correct = 0
          train_total = 0
          for image, label in train_loader:
              image = image.to(device)
              label = label.to(device)

              output = model(image)
              _, predicted = torch.max(output.data, 1)
              train_total += label.size(0)
              train_correct += (predicted == label).sum().item()

      # Save training set accuracy for the learning curve
      train_accuracy = train_correct/train_total*100
      train_accuracy_list.append(train_accuracy)

      # Neural network evaluation in the validation set
      with torch.no_grad():
          valid_correct = 0
          valid_total = 0
          for image, label in valid_loader:
              image = image.to(device)
              label = label.to(device)
```

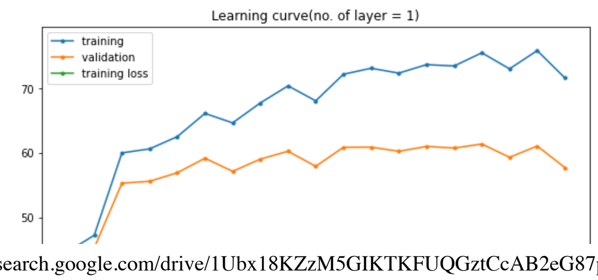
```
                output = model(image)
                _, predicted = torch.max(output.data, 1)
                valid_total += label.size(0)
                valid_correct += (predicted == label).sum().item()

        # Save training set accuracy for the learning curve
        valid_accuracy = valid_correct/valid_total*100
        valid_accuracy_list.append(valid_accuracy)
        print(f"Epoch[{epoch+1}/{num_epoch}], Loss:{loss.item()}, Training Accuracy:

        # Early stopping
        if valid_accuracy > best_valid_accuracy:
          best_valid_accuracy = valid_accuracy
          no_improvement = 0
        else:
          no_improvement += 1
        if no_improvement == n_no_improvement:
          break
    return model, loss_list, train_accuracy_list, valid_accuracy_list

# Learning curve function
def learning_curve(save=False, path=None, title=None, train_accuracy_list=None, val
    fig, ax = plt.subplots(1,1,figsize=[8,8])
    ax.plot([i for i in range(len(train_accuracy_list))], train_accuracy_list, mark
    ax.plot([i for i in range(len(valid_accuracy_list))], valid_accuracy_list, mark
    ax.plot([i for i in range(len(loss_list))], loss_list, marker=".", label="train
    ax.set_title(title)
    ax.set_xlabel("Epoch")
    ax.set_ylabel("Accuracy(%)")
    plt.legend()
    if save == True:
      fig.savefig(path)

# Train an original CNN
cnn_model = ConvNet(num_class=10).to(device)
criterion = nn.CrossEntropyLoss()
learning_rate = 0.1
optimizer = torch.optim.SGD(params=cnn_model.parameters(), lr=learning_rate)
train_loader = train_loader
valid_loader = valid_loader
num_epoch = 30
n_no_improvement = 3
cnn_model, loss_list, train_accuracy_list, valid_accuracy_list = train(cnn_model, c
learning_curve(save=True, path="cnn_model_original_lc", train_accuracy_list=train_a
```

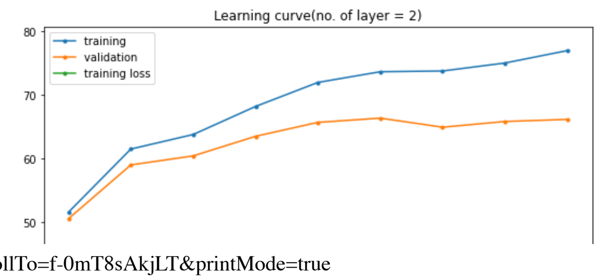
```
Epoch[1/30], Loss:1.834172248840332, Training Accuracy: 39.9075%, Validatio
Epoch[2/30], Loss:1.1700890064239502, Training Accuracy: 51.370000000000005
Epoch[3/30], Loss:1.1501590013504028, Training Accuracy: 59.545%, Validatio
Epoch[4/30], Loss:1.097917914390564, Training Accuracy: 61.4425%, Validatio
Epoch[5/30], Loss:0.8922512531280518, Training Accuracy: 74.21%, Validation
Epoch[6/30], Loss:0.5716832876205444, Training Accuracy: 79.535%, Validatio
Epoch[7/30], Loss:0.49166393280029297, Training Accuracy: 87.88%, Validatio
Epoch[8/30], Loss:0.6343632936477661, Training Accuracy: 91.435%, Validatio
Epoch[9/30], Loss:0.3750077486038208, Training Accuracy: 92.8425%, Validati
Epoch[10/30], Loss:0.22277632355690002, Training Accuracy: 96.2525%, Valida
```

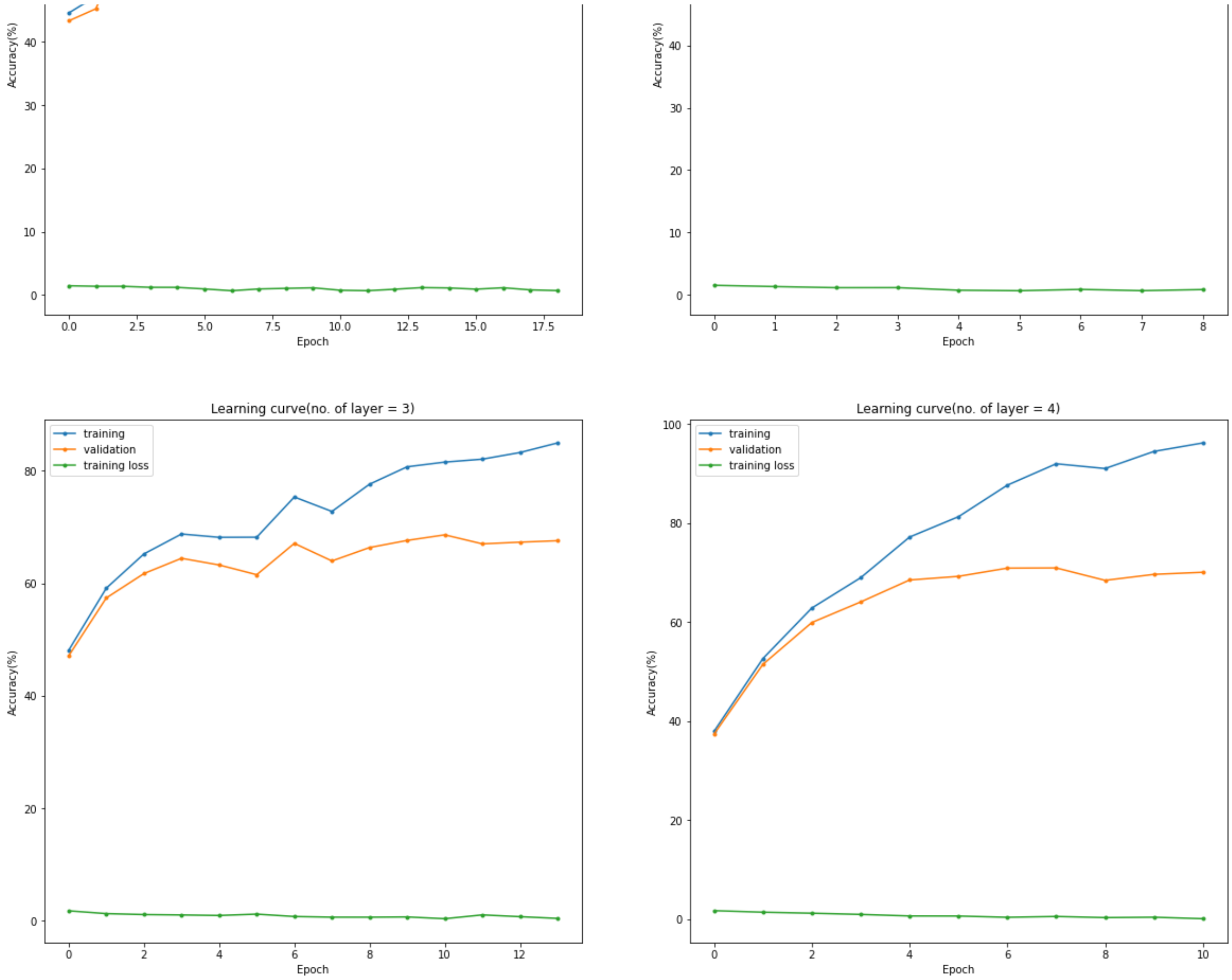



```
# Train CNNs with 1, 2, 3, 4 convolutional blocks
fig, ax = plt.subplots(2,2,figsize=[20,20])
axis = [(0,0),(0,1),(1,0),(1,1)]
train_accuracy_max = []
valid_accuracy_max = []
loss_min = []
for index, CNN in enumerate([ConvNet1layer, ConvNet2layer, ConvNet2layer, ConvNet])
  cnn_model = CNN(num_class=10).to(device)
  criterion = nn.CrossEntropyLoss()
  learning_rate = 0.1
  optimizer = torch.optim.SGD(params=cnn_model.parameters(), lr=learning_rate)
  train_loader = train_loader
  valid_loader = valid_loader
  num_epoch = 30
  n_no_improvement = 3
  cnn_model, loss_list, train_accuracy_list, valid_accuracy_list = train(cnn_model,
  train_accuracy_max.append(max(train_accuracy_list))
  valid_accuracy_max.append(max(valid_accuracy_list))
  loss_min.append(min(loss_list))
  row, column = axis[index]
  ax[row][column].plot([i for i in range(len(train_accuracy_list))], train_accuracy
  ax[row][column].plot([i for i in range(len(valid_accuracy_list))], valid_accuracy
  ax[row][column].plot([i for i in range(len(loss_list))], loss_list, marker=".", l
  ax[row][column].set_title(f"Learning curve(no. of layer = {index+1})")
  ax[row][column].set_xlabel("Epoch")
  ax[row][column].set_ylabel("Accuracy(%)")
  ax[row][column].legend()
```

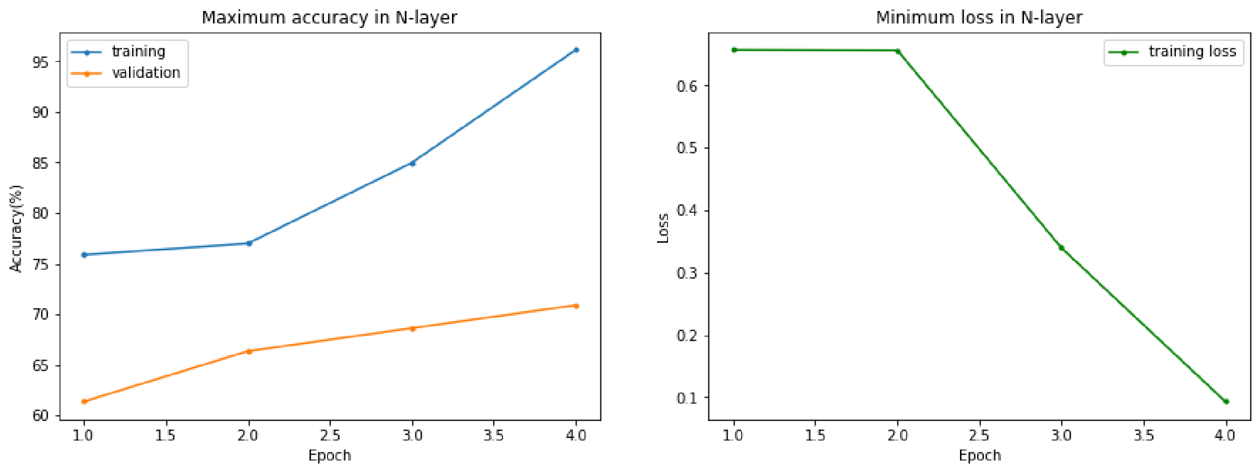
```
Epoch[1/30], Loss:1.4435992240905762, Training Accuracy: 44.5575%, Validati
Epoch[2/30], Loss:1.36066472530365, Training Accuracy: 47.2025%, Validation
Epoch[3/30], Loss:1.3569222688674927, Training Accuracy: 59.99250000000001%
Epoch[4/30], Loss:1.1947115659713745, Training Accuracy: 60.614999999999995
Epoch[5/30], Loss:1.1874756813049316, Training Accuracy: 62.517500000000005
Epoch[6/30], Loss:0.9373486042022705, Training Accuracy: 66.1225%, Validati
Epoch[7/30], Loss:0.6569656729698181, Training Accuracy: 64.6525%, Validati
Epoch[8/30], Loss:0.9363547563552856, Training Accuracy: 67.755%, Validatio
Epoch[9/30], Loss:1.0311768054962158, Training Accuracy: 70.4025%, Validati
Epoch[10/30], Loss:1.120340347290039, Training Accuracy: 68.07%, Validation
Epoch[11/30], Loss:0.7297576069831848, Training Accuracy: 72.1975%, Validat
Epoch[12/30], Loss:0.6615102291107178, Training Accuracy: 73.1325%, Validat
Epoch[13/30], Loss:0.8888604044914246, Training Accuracy: 72.3725%, Validat
Epoch[14/30], Loss:1.1530753374099731, Training Accuracy: 73.69250000000001
Epoch[15/30], Loss:1.0986626148223877, Training Accuracy: 73.4825%, Validat
Epoch[16/30], Loss:0.9024112820625305, Training Accuracy: 75.53%, Validatio
Epoch[17/30], Loss:1.1285609006881714, Training Accuracy: 73.0375%, Validat
Epoch[18/30], Loss:0.7884595990180969, Training Accuracy: 75.8725%, Validat
Epoch[19/30], Loss:0.6789387464523315, Training Accuracy: 71.6275%, Validat
Epoch[1/30], Loss:1.5265092849731445, Training Accuracy: 51.5375%, Validati
Epoch[2/30], Loss:1.3237429857254028, Training Accuracy: 61.482499999999995
Epoch[3/30], Loss:1.1452070474624634, Training Accuracy: 63.77%, Validation
Epoch[4/30], Loss:1.154433250427246, Training Accuracy: 68.1875%, Validatio
Epoch[5/30], Loss:0.737276554107666, Training Accuracy: 71.9725%, Validatio
Epoch[6/30], Loss:0.6562880277633667, Training Accuracy: 73.6575%, Validati
Epoch[7/30], Loss:0.869956374168396, Training Accuracy: 73.775%, Validation
Epoch[8/30], Loss:0.6633521318435669, Training Accuracy: 75.0325%, Validati
Epoch[9/30], Loss:0.845159649848938, Training Accuracy: 76.9875%, Validatio
Epoch[1/30], Loss:1.732466697692871, Training Accuracy: 48.089999999999996%
Epoch[2/30], Loss:1.2401726245880127, Training Accuracy: 59.137499999999996
Epoch[3/30], Loss:1.074942708015442, Training Accuracy: 65.225%, Validation
Epoch[4/30], Loss:1.0060639381408691, Training Accuracy: 68.77%, Validation
Epoch[5/30], Loss:0.914389967918396, Training Accuracy: 68.1825%, Validatio
Epoch[6/30], Loss:1.1533972024917603, Training Accuracy: 68.2%, Validation
Epoch[7/30], Loss:0.7320619821548462, Training Accuracy: 75.3525%, Validati
Epoch[8/30], Loss:0.613974928855896, Training Accuracy: 72.7825%, Validatio
Epoch[9/30], Loss:0.6109513640403748, Training Accuracy: 77.63250000000001%
Epoch[10/30], Loss:0.6543534994125366, Training Accuracy: 80.72749999999999
Epoch[11/30], Loss:0.33957940340042114, Training Accuracy: 81.5625%, Valida
Epoch[12/30], Loss:1.0179082155227661, Training Accuracy: 82.0825%, Validat
Epoch[13/30], Loss:0.7025007009506226, Training Accuracy: 83.265%, Validati
Epoch[14/30], Loss:0.394182026386261, Training Accuracy: 84.9675%, Validati
Epoch[1/30], Loss:1.7090626955032349, Training Accuracy: 37.9%, Validation
Epoch[2/30], Loss:1.396533489227295, Training Accuracy: 52.5975%, Validatio
Epoch[3/30], Loss:1.1965198516845703, Training Accuracy: 62.7925%, Validati
Epoch[4/30], Loss:0.9559071660041809, Training Accuracy: 68.92%, Validation
Epoch[5/30], Loss:0.6474428176879883, Training Accuracy: 77.125%, Validatio
Epoch[6/30], Loss:0.6329729557037354, Training Accuracy: 81.2325%, Validati
Epoch[7/30], Loss:0.3778480291366577, Training Accuracy: 87.605%, Validatio
Epoch[8/30], Loss:0.5472712516784668, Training Accuracy: 91.92%, Validation
Epoch[9/30], Loss:0.3155595660209656, Training Accuracy: 90.96%, Validation
Epoch[10/30], Loss:0.3944661617279053, Training Accuracy: 94.415%, Validati
Epoch[11/30], Loss:0.09311220794916153, Training Accuracy: 96.1225%, Valida
```






Accuracy(%)
Epoch
Accuracy(%)
Epoch
Learning curve(no. of layer = 3)
training
validation
training loss
Accuracy(%)
Epoch
Learning curve(no. of layer = 4)
training
validation
training loss
Accuracy(%)
Epoch

```
# Plot the maximum accuracy in traiing set, validation set and minimum loss of CNN
fig, ax = plt.subplots(1,2,figsize=[15,5])
ax[0].plot([i+1 for i in range(len(train_accuracy_max))], train_accuracy_max, marke
ax[0].plot([i+1 for i in range(len(valid_accuracy_max))], valid_accuracy_max, marke
ax[1].plot([i+1 for i in range(len(loss_min))], loss_min, marker=".", label="traini
ax[0].set_title(f"Maximum accuracy in N-layer")
ax[0].set_xlabel("Epoch")
ax[0].set_ylabel("Accuracy(%)")
ax[0].legend()
ax[1].set_title(f"Minimum loss in N-layer")
ax[1].set_xlabel("Epoch")
ax[1].set_ylabel("Loss")
ax[1].legend()
fig.savefig("cnn_layer_summary.png")
```




```
# Train CNNs with 10^-5 to 10^0 L2 regularization
fig, ax = plt.subplots(2,3, figsize=[15,15])
row_column = [(0,0), (0,1), (0,2), (1,0), (1,1), (1,2)]
index = 0
for index, alpha in enumerate([-5, -4, -3, -2, -1, 0]):
  cnn_model = ConvNet(num_class=10).to(device)
  criterion = nn.CrossEntropyLoss()
  learning_rate = 0.1
  optimizer = torch.optim.SGD(params=cnn_model.parameters(), lr=learning_rate, weig
  train_loader = train_loader
  valid_loader = valid_loader
  num_epoch = 50
  n_no_improvement = 5
  cnn_model, loss_list, train_accuracy_list, valid_accuracy_list = train(cnn_model,
  row, column = row_column[index]
  ax[row][column].plot([i for i in range(len(train_accuracy_list))], train_accuracy
  ax[row][column].plot([i for i in range(len(valid_accuracy_list))], valid_accuracy
  ax[row][column].plot([i for i in range(len(loss_list))], loss_list, marker=".", l
  ax[row][column].set_title(f"Learning curve(L2:10^{alpha})")
  ax[row][column].set_xlabel("Epoch")
```

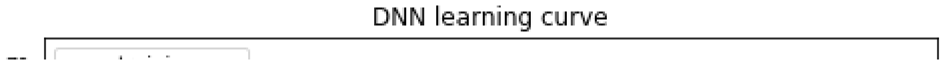
```
    ax[row][column].set_ylabel("Accuracy(%)")
    ax[row][column].legend()
```

```
Epoch[1/50], Loss:1.7979432344436646, Training Accuracy: 37.0%, Validation
Epoch[2/50], Loss:1.31745183467865, Training Accuracy: 51.127500000000005%,
Epoch[3/50], Loss:1.158024549484253, Training Accuracy: 60.540000000000006%
Epoch[4/50], Loss:1.2576788663864136, Training Accuracy: 64.7175%, Validati
Epoch[5/50], Loss:0.8490377068519592, Training Accuracy: 73.165%, Validatio
Epoch[6/50], Loss:0.7441189885139465, Training Accuracy: 80.825%, Validatio
Epoch[7/50], Loss:0.517412066459658, Training Accuracy: 86.1275%, Validati
Epoch[8/50], Loss:0.5251293778419495, Training Accuracy: 90.3725%, Validati
Epoch[9/50], Loss:0.39576414227485657, Training Accuracy: 94.1575%, Validat
Epoch[10/50], Loss:0.3887689113616943, Training Accuracy: 95.705%, Validat
Epoch[11/50], Loss:0.12799574434757233, Training Accuracy: 95.6%, Validatio
Epoch[12/50], Loss:0.30046820640563965, Training Accuracy: 97.1475%, Valida
Epoch[13/50], Loss:0.050701528787612915, Training Accuracy: 98.7025%, Valid
Epoch[14/50], Loss:0.0922823622822761, Training Accuracy: 98.105%, Validat
Epoch[15/50], Loss:0.040415484458208084, Training Accuracy: 98.507500000000
Epoch[16/50], Loss:0.05204831808805466, Training Accuracy: 98.3275%, Valida
Epoch[17/50], Loss:0.004636985715478659, Training Accuracy: 98.304999999999
Epoch[18/50], Loss:0.04442549496891144, Training Accuracy: 97.6%, Validati
Epoch[1/50], Loss:1.7394925355911255, Training Accuracy: 40.527499999999996
Epoch[2/50], Loss:1.2872847318649292, Training Accuracy: 54.1025%, Validati
Epoch[3/50], Loss:1.3444874286651611, Training Accuracy: 62.822500000000005
Epoch[4/50], Loss:0.895442605018615 7, Training Accuracy: 70.21%, Validation
Epoch[5/50], Loss:1.1714483499526978, Training Accuracy: 73.33%, Validation
Epoch[6/50], Loss:0.5379042029380798, Training Accuracy: 81.38250000000001%
Epoch[7/50], Loss:0.4790600538253784, Training Accuracy: 85.66749999999999%
Epoch[8/50], Loss:0.7279185652732849, Training Accuracy: 86.13%, Validation
Epoch[9/50], Loss:0.34353113174438477, Training Accuracy: 93.63%, Validatio
Epoch[10/50], Loss:0.25099027156829834, Training Accuracy: 96.1425%, Valida
Epoch[11/50], Loss:0.1391584575176239, Training Accuracy: 96.76%, Validatio
Epoch[12/50], Loss:0.1813632696866989, Training Accuracy: 94.2975%, Validat
Epoch[13/50], Loss:0.10117306560277939, Training Accuracy: 97.08%, Validati
Epoch[14/50], Loss:0.15188603103160858, Training Accuracy: 98.3524999999999
Epoch[1/50], Loss:1.7536437511444092, Training Accuracy: 38.0525%, Validati
Epoch[2/50], Loss:1.5623881816864014, Training Accuracy: 48.52%, Validation
Epoch[3/50], Loss:1.3785285949707031, Training Accuracy: 59.565%, Validatio
Epoch[4/50], Loss:0.9560930132865906, Training Accuracy: 67.09%, Validation
Epoch[5/50], Loss:0.8478828072547913, Training Accuracy: 70.635%, Validatio
Epoch[6/50], Loss:0.9023010730743408, Training Accuracy: 72.795%, Validatio
Epoch[7/50], Loss:0.9888664484024048, Training Accuracy: 81.765%, Validatio
Epoch[8/50], Loss:0.646549642086029, Training Accuracy: 84.125%, Validation
Epoch[9/50], Loss:0.5904465317726135, Training Accuracy: 85.065%, Validatio
Epoch[10/50], Loss:0.500035285949707, Training Accuracy: 92.335%, Validatio
Epoch[11/50], Loss:0.29693758487701416, Training Accuracy: 94.6875%, Valida
Epoch[12/50], Loss:0.12369435280561447, Training Accuracy: 96.6125%, Valida
Epoch[13/50], Loss:0.18576504290103912, Training Accuracy: 97.0425%, Valida
Epoch[14/50], Loss:0.2875842750072479, Training Accuracy: 93.10249999999999
Epoch[15/50], Loss:0.12597142159938812, Training Accuracy: 97.5675%, Valida
Epoch[16/50], Loss:0.07494053989648819, Training Accuracy: 97.7225%, Valida
Epoch[1/50], Loss:1.8838781118392944, Training Accuracy: 27.665%, Validatio
Epoch[2/50], Loss:1.6017838716506958, Training Accuracy: 38.57%, Validation
Epoch[3/50], Loss:1.831206202507019, Training Accuracy: 42.4975%, Validatio
Epoch[4/50], Loss:1.821392297744751, Training Accuracy: 43.64%, Validation
Epoch[5/50], Loss:1.3605544567108154, Training Accuracy: 46.612500000000004
Epoch[6/50], Loss:1.265623688697815, Training Accuracy: 49.5325%, Validatio
Epoch[7/50], Loss:1.4581109285354614, Training Accuracy: 51.2625%, Validati
Epoch[8/50], Loss:1.4398549795150757, Training Accuracy: 53.0725%, Validati
Epoch[9/50], Loss:1.205130696296692, Training Accuracy: 56.9975%, Validatio
Epoch[10/50], Loss:1.4654110670089722, Training Accuracy: 58.19499999999999
Epoch[11/50], Loss:1.29230797290802, Training Accuracy: 55.925000000000004%
Epoch[12/50], Loss:1.4419119358062744, Training Accuracy: 57.4225%, Validat
```

```
Epoch[13/50], Loss:1.3823338747024536, Training Accuracy: 60.785%, Validati
Epoch[14/50], Loss:1.020607352256775, Training Accuracy: 61.845000000000006
Epoch[15/50], Loss:0.9119833707809448, Training Accuracy: 63.295%, Validati
Epoch[16/50], Loss:1.155288577079773, Training Accuracy: 65.9375%, Validati
Epoch[17/50], Loss:0.9489369988441467, Training Accuracy: 67.32249999999999
Epoch[18/50], Loss:0.8850423097610474, Training Accuracy: 63.34999999999999
Epoch[19/50], Loss:1.0125056505203247, Training Accuracy: 64.02250000000001
Epoch[20/50], Loss:1.0995625257492065, Training Accuracy: 65.59%, Validatio
Epoch[21/50], Loss:1.2184432744979858, Training Accuracy: 61.5725%, Validat
Epoch[22/50], Loss:1.0323705673217773, Training Accuracy: 59.89499999999999
Epoch[1/50], Loss:2.2986488342285156, Training Accuracy: 9.945%, Validation
Epoch[2/50], Loss:2.3053767681121826, Training Accuracy: 9.950000000000001%
Epoch[3/50], Loss:2.3015899658203125, Training Accuracy: 9.950000000000001%
Epoch[4/50], Loss:2.3033056259155273, Training Accuracy: 10.127500000000001
Epoch[5/50], Loss:2.300581455230713, Training Accuracy: 10.0025%, Validatio
Epoch[6/50], Loss:2.3043503761291504, Training Accuracy: 10.0025%, Validati
Epoch[1/50], Loss:2.3018782138824463, Training Accuracy: 9.950000000000001%
Epoch[2/50], Loss:2.3026883602142334, Training Accuracy: 10.055%, Validatio
Epoch[3/50], Loss:2.300522804260254, Training Accuracy: 9.945%, Validation
```

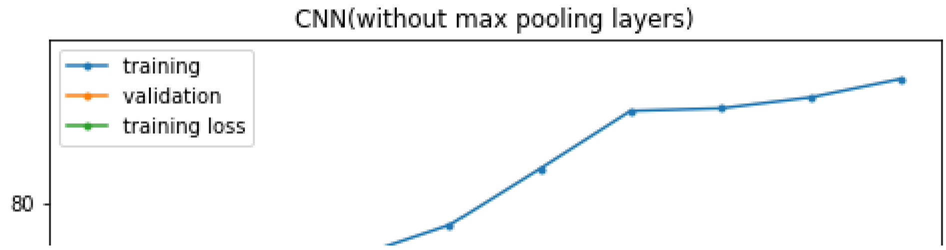
```python
# Train a dense neural network
dense_model = DenseNet(num_class=10).to(device)
criterion = nn.CrossEntropyLoss()
learning_rate = 0.1
optimizer = torch.optim.SGD(params=dense_model.parameters(), lr=learning_rate)
train_loader = train_loader
valid_loader = valid_loader
num_epoch = 30
n_no_improvement = 5
dense_model, loss_list, train_accuracy_list, valid_accuracy_list = train(dense_mode
learning_curve(save=True, path="dense_model_lc", title="DNN learning curve", train_
```

```
Epoch[1/30], Loss:1.726396918296814, Training Accuracy: 30.885%, Validation
Epoch[2/30], Loss:1.938817024230957, Training Accuracy: 37.28%, Validation
Epoch[3/30], Loss:1.8413617610931396, Training Accuracy: 39.1475%, Validati
Epoch[4/30], Loss:1.6248738765716553, Training Accuracy: 42.78%, Validation
Epoch[5/30], Loss:1.7452144622802734, Training Accuracy: 41.4825%, Validati
Epoch[6/30], Loss:1.5426400899887085, Training Accuracy: 49.075%, Validatio
Epoch[7/30], Loss:1.4607850313186646, Training Accuracy: 47.557500000000005
Epoch[8/30], Loss:1.3142403364181519, Training Accuracy: 52.68000000000001%
Epoch[9/30], Loss:1.5302914381027222, Training Accuracy: 52.845%, Validatio
Epoch[10/30], Loss:1.3847599029541016, Training Accuracy: 55.75499999999999
Epoch[11/30], Loss:1.596746802330017, Training Accuracy: 53.86%, Validation
Epoch[12/30], Loss:1.2815014123916626, Training Accuracy: 56.645%, Validati
Epoch[13/30], Loss:1.1623497009277344, Training Accuracy: 58.34249999999999
Epoch[14/30], Loss:1.1158604621887207, Training Accuracy: 60.5%, Validation
Epoch[15/30], Loss:1.0876585245132446, Training Accuracy: 62.57%, Validatio
Epoch[16/30], Loss:1.1641464233398438, Training Accuracy: 61.4425%, Validat
Epoch[17/30], Loss:1.0584123134613037, Training Accuracy: 66.9775%, Validat
Epoch[18/30], Loss:1.0207831859588623, Training Accuracy: 67.6225%, Validat
Epoch[19/30], Loss:1.0777592658996582, Training Accuracy: 68.93%, Validatio
Epoch[20/30], Loss:0.8432711958885193, Training Accuracy: 65.66%, Validatio
```



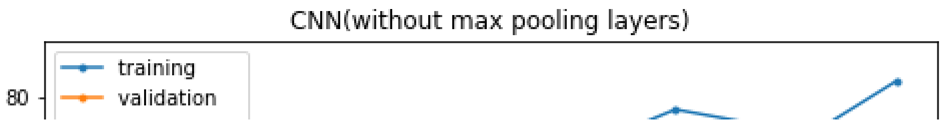

```
# Train a CNN with no max pooling layers
start_time = time.time() # Calculate the execution time
cnn_model_nomax = ConvNetNoMax(num_class=10).to(device)
criterion = nn.CrossEntropyLoss()
learning_rate = 0.1
optimizer = torch.optim.SGD(params=cnn_model_nomax.parameters(), lr=learning_rate)
train_loader = train_loader
valid_loader = valid_loader
num_epoch = 30
n_no_improvement = 3
cnn_model_nomax, loss_list, train_accuracy_list, valid_accuracy_list = train(cnn_mo
print("--- %s seconds ---" % (time.time() - start_time)) # Calculate the execution
learning_curve(save=False, path="cnn_model_nomax_lc", title="CNN(without max poolin
```

```
Epoch[1/30], Loss:1.4803636074066162, Training Accuracy: 45.81%, Validation
Epoch[2/30], Loss:1.0424985885620117, Training Accuracy: 63.375%, Validatio
Epoch[3/30], Loss:1.00474214553833, Training Accuracy: 68.5975%, Validation
Epoch[4/30], Loss:0.9432967305183411, Training Accuracy: 73.85249999999999%
Epoch[5/30], Loss:1.0646564960479736, Training Accuracy: 77.47749999999999%
Epoch[6/30], Loss:0.7092303037643433, Training Accuracy: 84.22500000000001%
Epoch[7/30], Loss:0.39393460750579834, Training Accuracy: 91.13250000000001
Epoch[8/30], Loss:0.4810178279876709, Training Accuracy: 91.44%, Validation
Epoch[9/30], Loss:0.31664401292800903, Training Accuracy: 92.7525%, Validat
Epoch[10/30], Loss:0.21612733602523804, Training Accuracy: 94.965%, Validat
--- 548.0471804141998 seconds ---
```




```
# Train a CNN with 2 convolutional blocks
start_time = time.time() # Calculate the execution time
cnn_model2layer = ConvNet2layer(num_class=10).to(device)
criterion = nn.CrossEntropyLoss()
learning_rate = 0.1
optimizer = torch.optim.SGD(params=cnn_model2layer.parameters(), lr=learning_rate)
train_loader = train_loader
valid_loader = valid_loader
num_epoch = 30
n_no_improvement = 3
cnn_model2layer, loss_list, train_accuracy_list, valid_accuracy_list = train(cnn_mo
print("--- %s seconds ---" % (time.time() - start_time))
learning_curve(save=False, path="cnn_model_nomax_lc", title="CNN(without max poolin
```

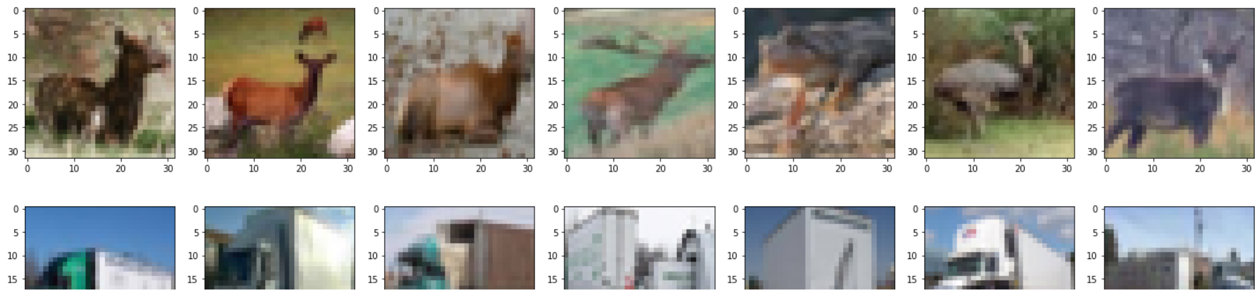
```
Epoch[1/30], Loss:1.5683300495147705, Training Accuracy: 47.745%, Validatio
Epoch[2/30], Loss:1.3041530847549438, Training Accuracy: 52.66%, Validation
Epoch[3/30], Loss:1.1676266193389893, Training Accuracy: 66.1675%, Validati
Epoch[4/30], Loss:0.9332227110862732, Training Accuracy: 68.95750000000001%
Epoch[5/30], Loss:0.9660124778747559, Training Accuracy: 70.08%, Validation
Epoch[6/30], Loss:1.0733729600906372, Training Accuracy: 71.9425%, Validati
Epoch[7/30], Loss:0.9733961820602417, Training Accuracy: 75.78%, Validation
Epoch[8/30], Loss:0.7123333811759949, Training Accuracy: 75.605%, Validatio
Epoch[9/30], Loss:0.8251937031745911, Training Accuracy: 78.7025%, Validati
Epoch[10/30], Loss:0.8192508220672607, Training Accuracy: 77.345%, Validati
Epoch[11/30], Loss:0.7416654825210571, Training Accuracy: 76.9525%, Validat
Epoch[12/30], Loss:0.7831147313117981, Training Accuracy: 81.6325%, Validat
--- 145.25149631500244 seconds ---
```




```
# Finding the images with highest similarity(lowest Euclidean distance) to the targ
# in term of the output of second fully connected layer
fig, ax = plt.subplots(5,7,figsize=[25,20])
train_image = 0
row = 0
while train_image < 5: # 5 target images
  selected_image, selected_target = train_dataset.__getitem__(train_image) # get th
  selected_image = torch.unsqueeze(selected_image, 0) # Unsqueeze to add an axis to
  selected_image = selected_image.to(device)
  _ = cnn_model(selected_image) # Forward feed
  selected_image_flatten = cnn_model.get_layer(5) # Extract the 1x4096 vector
  print(classes[selected_target]) # Print and check the true class


  cnn_model.eval()
  index_nn_pq = PriorityQueue() # A priority queue to sort the similarity
  with torch.no_grad():
    for index, num_image  in enumerate(range(len(valid_dataset))):
      image, target = valid_dataset.__getitem__(num_image)
      image = torch.unsqueeze(image, 0)
      image = image.to(device)
      _ = cnn_model(image)
      image_flatten = cnn_model.get_layer(5)
      # Calculate the Euclidean distance between the target image and the current i
      n_n = torch.sum((selected_image_flatten - image_flatten)**2)
      # Put the Euclidean distance and image index into the pirority queue
      index_nn_pq.put((n_n, index))

# Display the image
  for column in range(7):
    # Display the target image
    if column == 0:
      selected_image, selected_target = train_dataset.__getitem__(train_image)
      ax[row][column].imshow(torch.permute(selected_image, (1,2,0)))
      continue
    # Display the image with the highest similarity
    n_n, index = index_nn_pq.get() # Dequeue the pirority queue
    image, target = valid_dataset.__getitem__(index) # Get the image
    ax[row][column].imshow(torch.permute(image, (1,2,0))) # Plot the image
```

```
      print(classes[target], n_n) # Check the class and the similarity(Euclidean dist
    row += 1
    train_image += 1
```

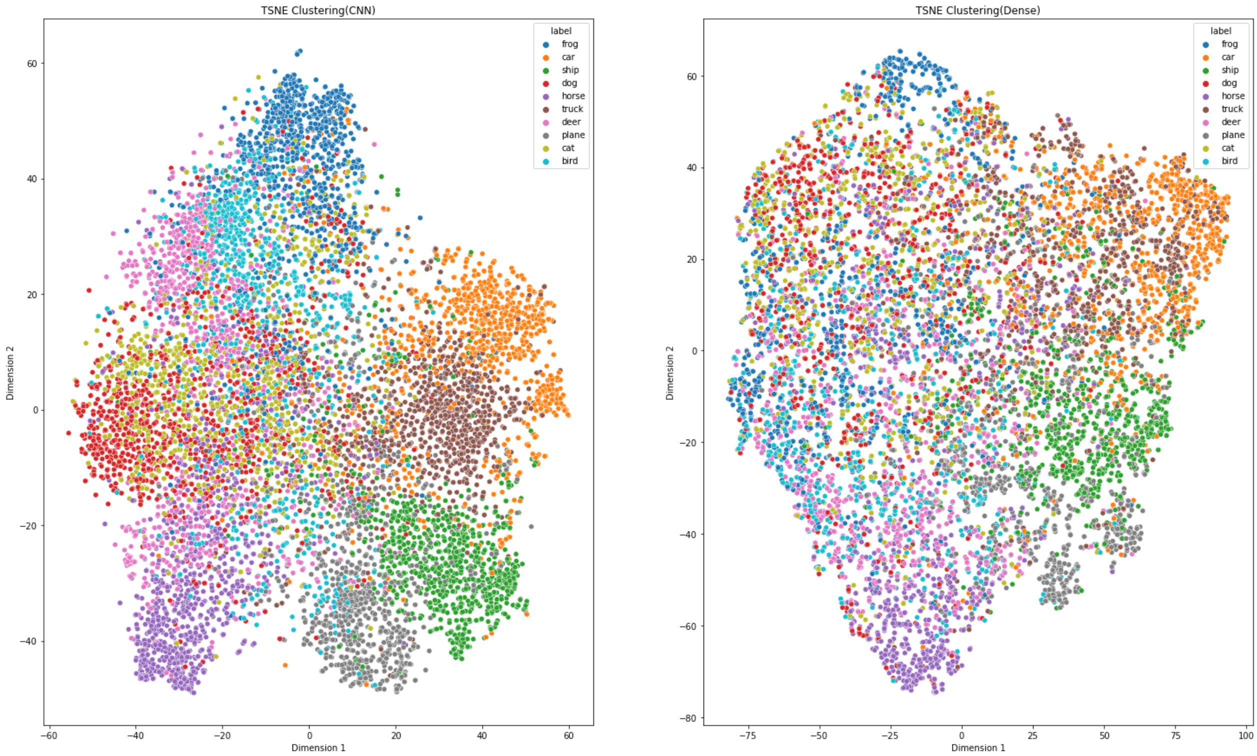
```
deer
deer tensor(63.7309, device='cuda:0')
deer tensor(65.1599, device='cuda:0')
deer tensor(69.8398, device='cuda:0')
frog tensor(72.1103, device='cuda:0')
bird tensor(72.1882, device='cuda:0')
deer tensor(72.5016, device='cuda:0')
truck
truck tensor(122.3137, device='cuda:0')
truck tensor(140.6585, device='cuda:0')
truck tensor(152.1940, device='cuda:0')
truck tensor(152.5486, device='cuda:0')
truck tensor(152.6234, device='cuda:0')
truck tensor(157.1622, device='cuda:0')
truck
car tensor(85.6006, device='cuda:0')
truck tensor(92.2293, device='cuda:0')
truck tensor(94.0501, device='cuda:0')
bird tensor(96.6377, device='cuda:0')
truck tensor(97.7937, device='cuda:0')
plane tensor(97.9414, device='cuda:0')
horse
horse tensor(159.9772, device='cuda:0')
horse tensor(168.3970, device='cuda:0')
horse tensor(176.3793, device='cuda:0')
bird tensor(178.8043, device='cuda:0')
cat tensor(182.6591, device='cuda:0')
dog tensor(184.1456, device='cuda:0')
deer
deer tensor(40.5932, device='cuda:0')
deer tensor(42.6102, device='cuda:0')
deer tensor(42.6633, device='cuda:0')
deer tensor(43.4705, device='cuda:0')
deer tensor(43.9916, device='cuda:0')
deer tensor(44.8067, device='cuda:0')
```



```
# Dimension reduction by T-SNE of all 1x4096 vectors from all images
fig, ax = plt.subplots(1,2,figsize=[25,15])
i = 0
for model in [cnn_model, dense_model]:
  # Put all 1x4096 vectors and their label from all images into a list
  flatten_vectors = []
  with torch.no_grad():
    for index, num_image  in enumerate(range(len(valid_dataset))):
      image, target = valid_dataset.__getitem__(num_image)
      image = torch.unsqueeze(image, 0)
      image = image.to(device)
      _ = model(image)
      image_flatten = model.get_layer(5)
      flatten_vectors.append((image_flatten, target))
```

```
# Separate 1x4096 vectors and their labels into two list
vectors = []
target_vector = []
with torch.no_grad():
  for vector in flatten_vectors:
    flatten_image, target = vector
    flatten_image = flatten_image.detach().cpu().numpy().ravel()
    vectors.append(flatten_image)
    target_vector.append(target)
vectors = np.array(vectors)

# Perform T-SNE for all 1x4096 vectors to reduce them into 1x2 vectors
tsne_matrix = TSNE(n_components=2, learning_rate="auto", init="pca").fit_transfor

# Put T-SNE results and the labels into dataframe for plotting
tsne_matrix_df = pd.DataFrame(tsne_matrix, columns=["dim1", "dim2"])
tsne_matrix_df["label"] = target_vector
tsne_matrix_df["label"] = tsne_matrix_df["label"].apply(lambda x: classes[x]) # M
sns.scatterplot(x=tsne_matrix_df["dim1"], y=tsne_matrix_df["dim2"], hue=tsne_matr
if model == cnn_model:
  ax[i].set_title(f"TSNE Clustering(CNN)")
else:
  ax[i].set_title(f"TSNE Clustering(Dense)")
ax[i].set_xlabel("Dimension 1")
ax[i].set_ylabel("Dimension 2")
i += 1
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:986: Futu
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:986: Futu
  FutureWarning,
```




```python
# Overall evaluation of the testing set
cnn_model.eval()
with torch.no_grad():
  correct = 0
  total = 0
  for image, label in test_loader:
      image = image.to(device)
      label = label.to(device)

      output = cnn_model(image)
      _, predicted = torch.max(output.data, 1)
      total += label.size(0)
      correct += (predicted == label).sum().item()
  print(f"Accuracy: {correct/total*100}%")
```

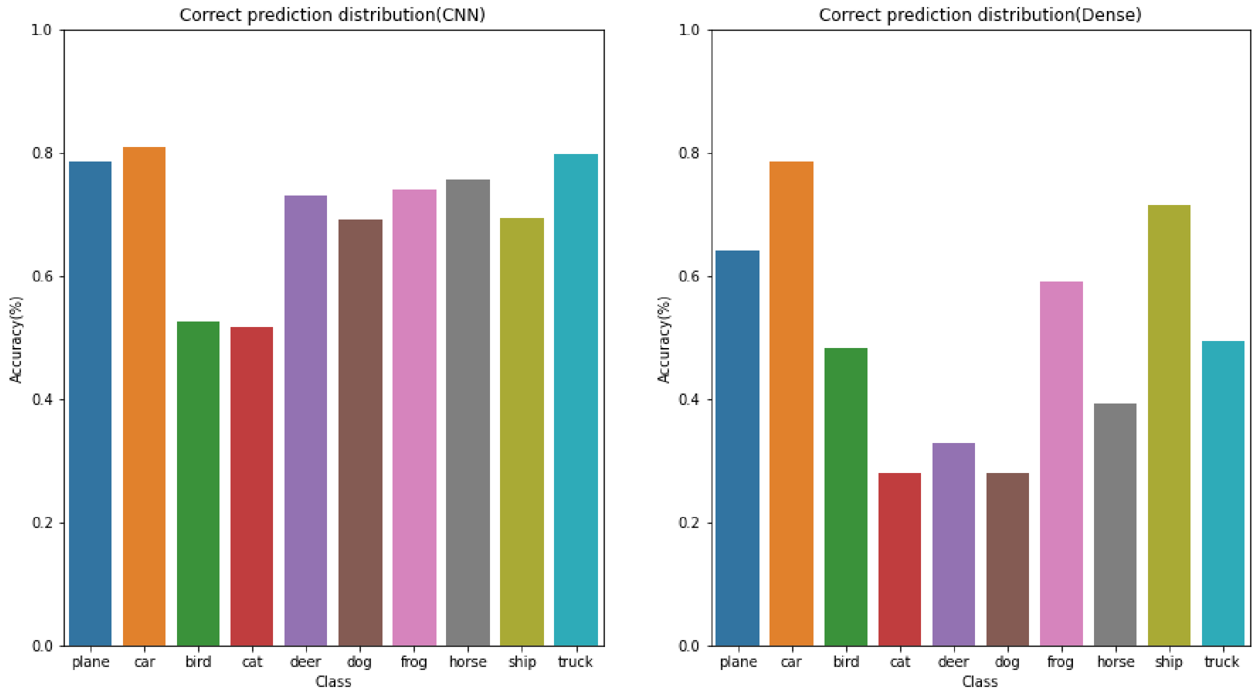
```
Accuracy: 69.74000000000001%
```

```python
# Evaluation function for a distribution of correct predictions in each class
def evaluation_class(model, dataset):
  correct_array = np.zeros(10) # Correc count for 10 classes
  total_array = np.zeros(10) # Total count for 10 classes
  with torch.no_grad():
    for i in range(len(test_dataset)):
      image, label = test_dataset.__getitem__(i)
      total_array[label] += 1
      image = torch.unsqueeze(image, 0)
      image = image.to(device)
      output = model(image)
      _, predicted = torch.max(output.data, 1) # Get the index of the highest score
```

```
      if predicted == label: # Count correct predictions
        correct_array[predicted] += 1
  return correct_array, total_array
```

```
# Plot the distribution
fig, ax = plt.subplots(1,2,figsize=[15,8])
correct_array_cnn, total_array_cnn = evaluation_class(cnn_model, test_dataset)
correct_array_dense, total_array_dense = evaluation_class(dense_model, test_dataset
sns.barplot(x=classes, y=correct_array_cnn/total_array_cnn, ax=ax[0])
sns.barplot(x=classes, y=correct_array_dense/total_array_dense, ax=ax[1])
ax[0].set_title("Correct prediction distribution(CNN)")
ax[0].set_xlabel("Class")
ax[0].set_ylabel("Accuracy(%)")
ax[0].set_ylim([0, 1])
ax[1].set_title("Correct prediction distribution(Dense)")
ax[1].set_xlabel("Class")
ax[1].set_ylabel("Accuracy(%)")
ax[1].set_ylim([0, 1])
```

```
(0.0, 1.0)
```




```
# Plot the distribution of predicting cat images
prediction = np.zeros(10)
total = np.zeros(10)
with torch.no_grad():
  for i in range(len(test_dataset)):
```