Problem-2-CNN

March 12, 2024

CNN model for image classfication on the CIFAR-10 dataset

Model used: VGG-11 with batch normalization

[ ]:
```
import torch
import torchvision.datasets as datasets
from torchvision.transforms import v2
import torch.utils.data as dataloader
import torch.nn as nn
import torch.optim as optim
import numpy as np

import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
print(device)
```

```
cuda:0
```

[ ]:
```
# Params for wandb sweeps
PROJECT_NAME = 'cnn_vgg11_cifar10_pytorch'
PROJECT_ENTITY = 'cs20b013-bersilin'

# The 10 classes in the CIFAR-10 dataset
LABELS = {
    0: 'airplane',
    1: 'automobile',
    2: 'bird',
    3: 'cat',
    4: 'deer',
    5: 'dog',
    6: 'frog',
    7: 'horse',
    8: 'ship',
    9: 'truck'
}

# VGG - 11 Arch
```

```
ARCH = [64, 'M', 128, 'M', 256, 256, 'M', 512, 512, 'M', 512, 512, 'M']
DATA_DIR = "../data"
```

[ ]:
```
def get_transform(mean, std):
    '''
    Returns a transform to convert a CIFAR image to a tensor of type float32
    '''
    return v2.Compose([
        v2.ToImage(),
        v2.ToDtype(torch.float32, scale=True),
        v2.Normalize(mean, std)
    ])
```

[ ]:
```
def get_dataloader(batch_size: int, val_split: float = 0.2, shuffle: bool =␣
↪True):
    '''
    Load the CIFAR-10 dataset

    Normalizes the data using the mean and standard deviation of the training␣
↪data
    '''
    train_data = datasets.CIFAR10(root=DATA_DIR, train=True, download=True)
    test_data = datasets.CIFAR10(root=DATA_DIR, train=False, download=True)

    mean = np.array(train_data.data).mean(axis=(0, 1, 2)) / 255
    std = np.array(train_data.data).std(axis=(0, 1, 2)) / 255

    transform = get_transform(mean, std)
    train_data.transform = transform
    test_data.transform = transform

    train_size = int((1 - val_split) * len(train_data))
    val_size = len(train_data) - train_size

    train_data, val_data = dataloader.random_split(train_data, [train_size,␣
↪val_size])

    train_loader = dataloader.DataLoader(train_data, batch_size=batch_size,␣
↪shuffle=shuffle)
    val_loader = dataloader.DataLoader(val_data, batch_size=batch_size,␣
↪shuffle=shuffle)
    test_loader = dataloader.DataLoader(test_data, batch_size=batch_size,␣
↪shuffle=False)

    return train_data, test_data, train_loader, val_loader, test_loader, mean,␣
↪std
```

[ ]:
```python
def show_random_image(dataset: datasets.CIFAR10, index: int = None, mean: np.
↪ndarray = None, std: np.ndarray = None):
    '''
    Shows a random image from the dataset

    If the mean and standard deviation are provided, the image is denormalized
    If the index is provided, the image at that index is shown else a random␣
↪image is shown
    '''
    if index is None:
        index = np.random.randint(0, len(dataset))
    else:
        index = index

    image, label = dataset[index]

    if mean is not None and std is not None:
        # image is (3, 32, 32), std and mean are (3,)
        image = image * std[:, None, None] + mean[:, None, None]

    plot = plt.imshow(image.permute(1, 2, 0).clip(0, 1))
    plt.title(f"True Label: {LABELS[label]}")

    return plot, index, label
```

[ ]:
```python
def plot_accuracies(train_acc, val_acc):
    '''
    Plot the training and validation accuracies
    '''
    plot = plt.plot(train_acc, label='Training Accuracy')
    plt.plot(val_acc, label='Validation Accuracy')
    plt.legend()
    plt.title('Training and Validation Accuracies')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')

    return plot
```

[ ]:
```python
def plot_losses(train_loss, val_loss):
    '''
    Plot the training and validation losses
    '''
    plot = plt.plot(train_loss, label='Training Loss')
    plt.plot(val_loss, label='Validation Loss')
    plt.legend()
    plt.title('Training and Validation Losses')
    plt.xlabel('Epoch')
```

```
    plt.ylabel('Loss')

    return plot
```

[ ]:
```
# Architecture of the model

class VGG_11(nn.Module):
    def __init__(self, in_channels, num_classes):
        super(VGG_11, self).__init__()

        self.in_channels = in_channels
        self.num_classes = num_classes

        self.conv_layers = self.create_conv_layers(ARCH)

        self.fcs = nn.Sequential(
            nn.Linear(512 * 1 * 1, 4096),
            nn.ReLU(),
            nn.Dropout(p=0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(),
            nn.Dropout(p=0.5),
            nn.Linear(4096, self.num_classes)
        )

    def forward(self, x):
        x = self.conv_layers(x)
        x = x.reshape(x.shape[0], -1)
        x = self.fcs(x)

        return x

    def create_conv_layers(self, architecture):
        layers = []
        in_channels = self.in_channels

        for x in architecture:
            if type(x) == int:
                out_channels = x

                layers += [
                    nn.Conv2d(in_channels, out_channels, kernel_size=(3, 3),
 ↪stride=(1, 1), padding=(1, 1)),
                    nn.BatchNorm2d(x),
                    nn.ReLU()
                ]
```

```
                in_channels = x
            elif x == 'M':
                layers += [nn.MaxPool2d(kernel_size=(2, 2), stride=(2, 2))]

        return nn.Sequential(*layers)
```

[ ]:
```
def get_accuracy(model: nn.Module, data_loader: dataloader.DataLoader, device:␣
↪torch.device):
    '''
    Get the accuracy of the model on the data_loader
    '''
    correct, total = 0, 0

    with torch.no_grad():
        for X, y in data_loader:
            X, y = X.to(device), y.to(device)
            preds = model(X)
            _, predicted = torch.max(preds, 1)
            correct += (predicted == y).sum().item()
            total += y.size(0)

    return correct / total
```

[ ]:
```
def get_predicted_labels(model: nn.Module, data_loader: dataloader.DataLoader,␣
↪device: torch.device):
    '''
    Get the predicted labels of the model on the data_loader
    '''
    labels = []
    with torch.no_grad():
        for X, y in data_loader:
            X, y = X.to(device), y.to(device)
            preds = model(X)
            _, predicted = torch.max(preds, 1)
            labels.append(predicted)

    return torch.cat(labels)
```

[ ]:
```
# Training the model

def train(configs, train_loader: dataloader.DataLoader, val_loader: dataloader.
↪DataLoader, criterion: nn.CrossEntropyLoss,
          optimizer: optim.Optimizer, model: nn.Module, device: torch.device):
    '''
    Train the model
    '''
```

```
    if(configs['wandb_log']):
        import wandb
        wandb.init(project=PROJECT_NAME, entity=PROJECT_ENTITY)

    print('Training the model...')
    print('---------------------')

    val_accuracies, train_accuracies = [], []
    val_losses, train_losses = [], []

    for epoch in range(configs['num_epochs']):
        model.train()
        running_loss = 0.0

        total_iterations = len(train_loader)

        for i, (inputs, labels) in enumerate(train_loader):
            inputs, labels = inputs.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(inputs) # Forward pass
            loss = criterion(outputs, labels) # Calculate loss
            loss.backward() # Backward pass
            optimizer.step() # Update weights

            running_loss += loss.item()

            if (i != total_iterations-1):
                print(f'Epoch {epoch + 1}, Iteration {i + 1}/
↪{total_iterations}, Loss: {loss.item()}', end='\r')
            else:
                print(f'Epoch {epoch + 1}, Iteration {i + 1}/
↪{total_iterations}, Loss: {loss.item()}')

        print(f'Epoch {epoch + 1} done, Training Loss: {running_loss /␣
↪len(train_loader)}')
        train_losses.append(running_loss / len(train_loader))

        # Validation loss
        model.eval()
        val_loss = 0.0
        with torch.no_grad():
            for inputs, labels in val_loader:
                inputs, labels = inputs.to(device), labels.to(device)

                outputs = model(inputs)
                loss = criterion(outputs, labels)
```

```
                val_loss += loss.item()

        print(f'Epoch {epoch + 1}, Validation Loss: {val_loss /␣
↪len(val_loader)}')
        val_losses.append(val_loss / len(val_loader))

        train_accuracy = get_accuracy(model, train_loader, device)
        val_accuracy = get_accuracy(model, val_loader, device)

        train_accuracies.append(train_accuracy)
        val_accuracies.append(val_accuracy)

        print(f'Epoch {epoch + 1}, Training Accuracy: {train_accuracy},␣
↪Validation Accuracy: {val_accuracy} \n')

        if configs['wandb_log']:
            wandb.log({'Epoch:': epoch + 1,
                       'Training Loss': running_loss / len(train_loader),
                       'Validation Loss': val_loss / len(val_loader),
                       'Training Accuracy': train_accuracy,
                       'Validation Accuracy': val_accuracy})

    print('Finished Training')
    print('---------------------')

    return model, configs, train_accuracies, val_accuracies, train_losses,␣
↪val_losses
```

Used Wandb to run sweeps to find the best hyperparameters for the model from a set of hyperparameters.

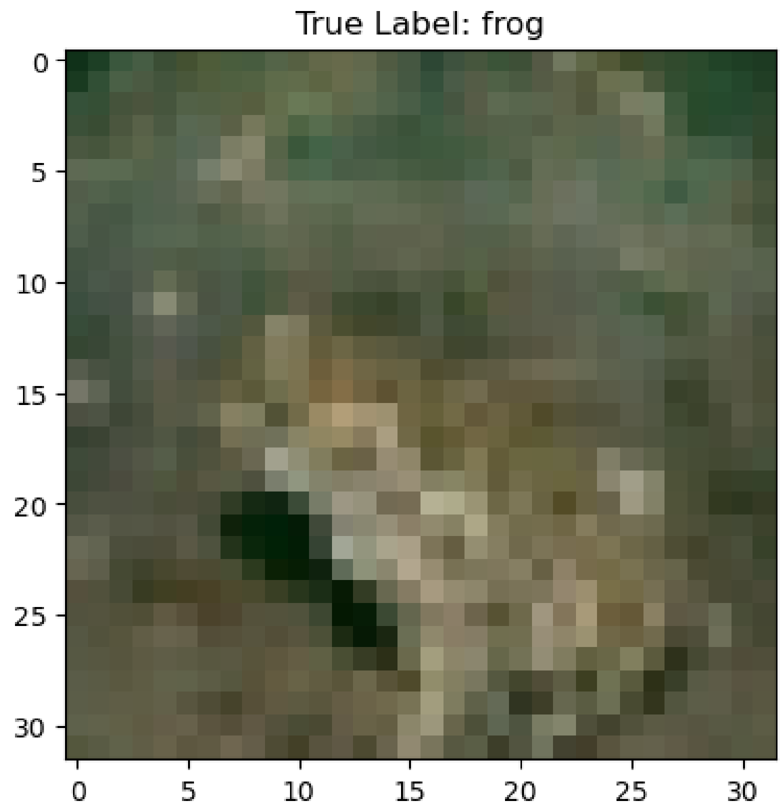
Link: CNN-Sweep

[ ]:
```
# The best hyperparameters found using wandb sweeps

best_configs = {
    'learning_rate': 0.05,
    'num_epochs': 20,
    'momentum': 0.87,
    'wandb_log': False,
    'batch_size': 100
}
```

[ ]:
```
train_data, test_data, train_loader, val_loader, test_loader, mean, std =␣
↪get_dataloader(best_configs['batch_size'])
```

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

[ ]:
```python
# Show a random image from the dataset

plot, index, label = show_random_image(train_data, mean=mean, std=std)
```



[ ]:
```python
model = VGG_11(in_channels=3, num_classes=10).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=best_configs['learning_rate'],
 ↪momentum=best_configs['momentum'])

print(model)
```

```
VGG_11(
  (conv_layers): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=(2, 2), stride=(2, 2), padding=0, dilation=1,
ceil_mode=False)
    (4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (5): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
```

```
track_running_stats=True)
    (6): ReLU()
    (7): MaxPool2d(kernel_size=(2, 2), stride=(2, 2), padding=0, dilation=1,
ceil_mode=False)
    (8): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (10): ReLU()
    (11): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (12): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (13): ReLU()
    (14): MaxPool2d(kernel_size=(2, 2), stride=(2, 2), padding=0, dilation=1,
ceil_mode=False)
    (15): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (16): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (17): ReLU()
    (18): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (19): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (20): ReLU()
    (21): MaxPool2d(kernel_size=(2, 2), stride=(2, 2), padding=0, dilation=1,
ceil_mode=False)
    (22): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (23): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (24): ReLU()
    (25): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (26): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (27): ReLU()
    (28): MaxPool2d(kernel_size=(2, 2), stride=(2, 2), padding=0, dilation=1,
ceil_mode=False)
  )
  (fcs): Sequential(
    (0): Linear(in_features=512, out_features=4096, bias=True)
    (1): ReLU()
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU()
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=10, bias=True)
  )
)
```

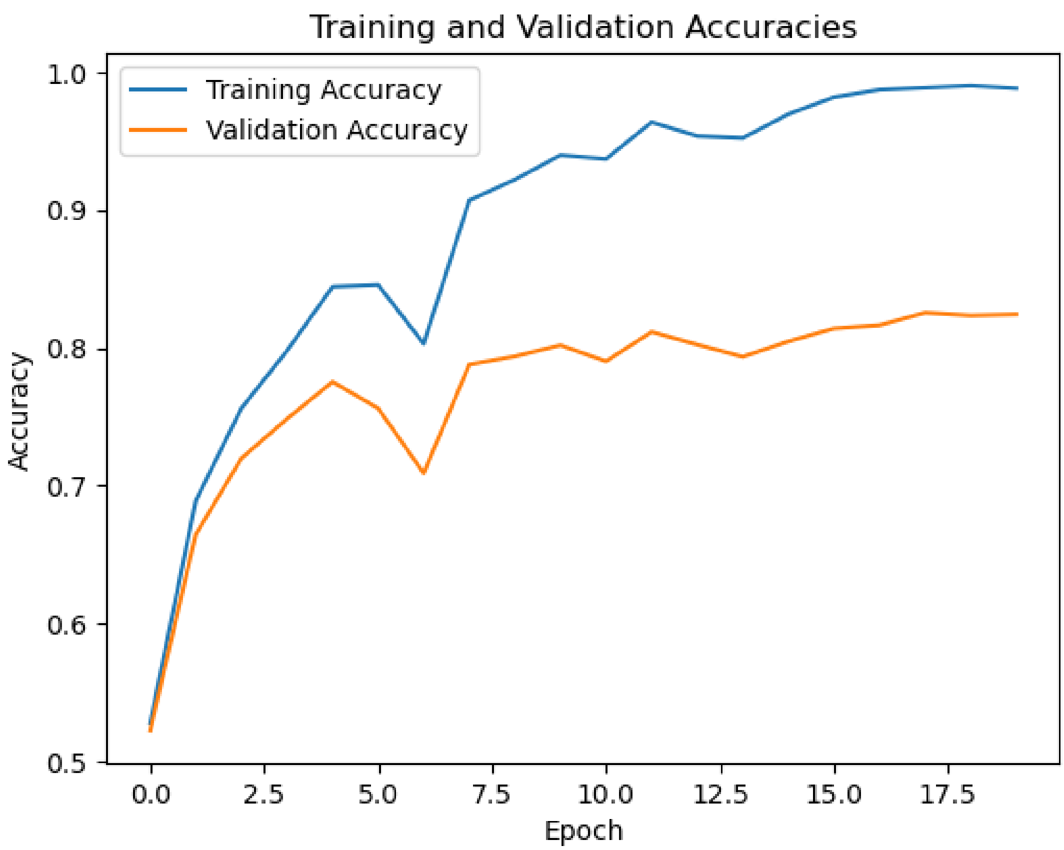
[ ]:
```
model, configs, train_acc, val_acc, train_losses, val_losses =␣
↪train(best_configs, train_loader, val_loader, criterion, optimizer, model,␣
↪device)

test_accuracy = get_accuracy(model, test_loader, device)
print(f'Test Accuracy: {test_accuracy}')
```

```
Training the model…
----------------------
Epoch 1, Iteration 400/400, Loss: 1.2897256612777713
Epoch 1 done, Training Loss: 1.5509387038648128
Epoch 1, Validation Loss: 1.379219709634781
Epoch 1, Training Accuracy: 0.52785, Validation Accuracy: 0.5224

Epoch 2, Iteration 400/400, Loss: 0.6768864989280701
Epoch 2 done, Training Loss: 1.0739452703297139
Epoch 2, Validation Loss: 0.9545514333248138
Epoch 2, Training Accuracy: 0.68905, Validation Accuracy: 0.6646

Epoch 3, Iteration 400/400, Loss: 0.8389794826507568
Epoch 3 done, Training Loss: 0.855861095637083
Epoch 3, Validation Loss: 0.8184983569383621
Epoch 3, Training Accuracy: 0.756125, Validation Accuracy: 0.7198

Epoch 4, Iteration 400/400, Loss: 0.679680407047271 73
Epoch 4 done, Training Loss: 0.6967459101974964
Epoch 4, Validation Loss: 0.7468112534284592
Epoch 4, Training Accuracy: 0.7978, Validation Accuracy: 0.7484

Epoch 5, Iteration 400/400, Loss: 0.47646436095237734
Epoch 5 done, Training Loss: 0.573146866708994
Epoch 5, Validation Loss: 0.6874427407979965
Epoch 5, Training Accuracy: 0.844275, Validation Accuracy: 0.7753

Epoch 6, Iteration 400/400, Loss: 0.40425014495849613
Epoch 6 done, Training Loss: 0.473935357965529
Epoch 6, Validation Loss: 0.7396999627351761
Epoch 6, Training Accuracy: 0.845625, Validation Accuracy: 0.7561

Epoch 7, Iteration 400/400, Loss: 0.46034678816795353
Epoch 7 done, Training Loss: 0.38997142650187017
Epoch 7, Validation Loss: 1.0155149847269058
Epoch 7, Training Accuracy: 0.802975, Validation Accuracy: 0.709

Epoch 8, Iteration 400/400, Loss: 0.30234727263450626
Epoch 8 done, Training Loss: 0.32772874131798746
Epoch 8, Validation Loss: 0.7040166458487511
Epoch 8, Training Accuracy: 0.9069, Validation Accuracy: 0.7878
```

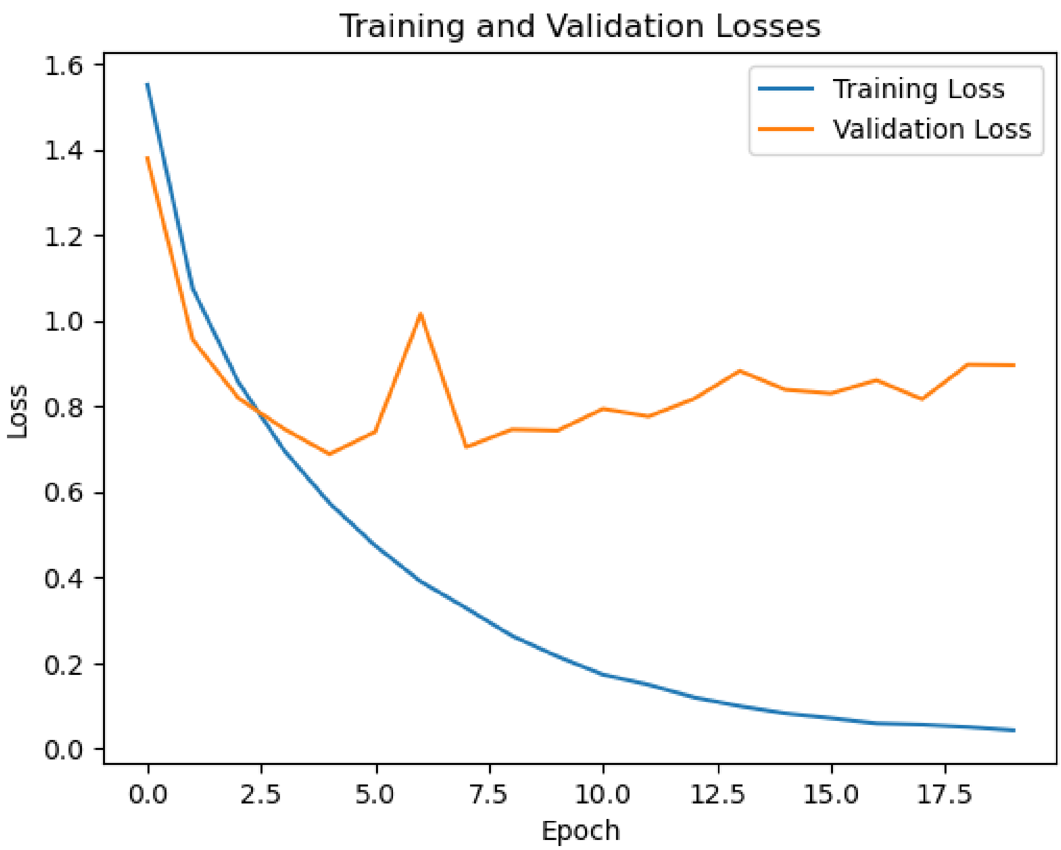
```
Epoch 9, Iteration 400/400, Loss: 0.13178446888923645
Epoch 9 done, Training Loss: 0.2631975689344108
Epoch 9, Validation Loss: 0.745115105509758
Epoch 9, Training Accuracy: 0.922, Validation Accuracy: 0.7938

Epoch 10, Iteration 400/400, Loss: 0.22050194442272186
Epoch 10 done, Training Loss: 0.21479833325371145
Epoch 10, Validation Loss: 0.7424911978840828
Epoch 10, Training Accuracy: 0.93965, Validation Accuracy: 0.8018

Epoch 11, Iteration 400/400, Loss: 0.178242772817611754
Epoch 11 done, Training Loss: 0.17240080697461962
Epoch 11, Validation Loss: 0.7936042732000351
Epoch 11, Training Accuracy: 0.9369, Validation Accuracy: 0.7902

Epoch 12, Iteration 400/400, Loss: 0.240711897611618045
Epoch 12 done, Training Loss: 0.14870931839104742
Epoch 12, Validation Loss: 0.7757334208488464
Epoch 12, Training Accuracy: 0.96365, Validation Accuracy: 0.8115

Epoch 13, Iteration 400/400, Loss: 0.248021468520164572
Epoch 13 done, Training Loss: 0.11912807707674801
Epoch 13, Validation Loss: 0.8170935362577438
Epoch 13, Training Accuracy: 0.9536, Validation Accuracy: 0.8023

Epoch 14, Iteration 400/400, Loss: 0.075590349733829554
Epoch 14 done, Training Loss: 0.09882449768250808
Epoch 14, Validation Loss: 0.8821187806129456
Epoch 14, Training Accuracy: 0.95215, Validation Accuracy: 0.7935

Epoch 15, Iteration 400/400, Loss: 0.122518017888069155
Epoch 15 done, Training Loss: 0.08191141835413873
Epoch 15, Validation Loss: 0.8383062526583671
Epoch 15, Training Accuracy: 0.969475, Validation Accuracy: 0.8046

Epoch 16, Iteration 400/400, Loss: 0.028977606445550928
Epoch 16 done, Training Loss: 0.07070228560944088
Epoch 16, Validation Loss: 0.829431443810463
Epoch 16, Training Accuracy: 0.981725, Validation Accuracy: 0.814

Epoch 17, Iteration 400/400, Loss: 0.062961481511592865
Epoch 17 done, Training Loss: 0.058448616773239336
Epoch 17, Validation Loss: 0.860380944609642
Epoch 17, Training Accuracy: 0.987225, Validation Accuracy: 0.8164

Epoch 18, Iteration 400/400, Loss: 0.0164760611951351174
Epoch 18 done, Training Loss: 0.055438797994866035
```

```
Epoch 18, Validation Loss: 0.8160173261165619
Epoch 18, Training Accuracy: 0.988725, Validation Accuracy: 0.8254

Epoch 19, Iteration 400/400, Loss: 0.0302005391567945485
Epoch 19 done, Training Loss: 0.049988452923862496
Epoch 19, Validation Loss: 0.8966067013144493
Epoch 19, Training Accuracy: 0.9902, Validation Accuracy: 0.8234

Epoch 20, Iteration 400/400, Loss: 0.0224803499877452855
Epoch 20 done, Training Loss: 0.04224968572962098
Epoch 20, Validation Loss: 0.895276209115982
Epoch 20, Training Accuracy: 0.9883, Validation Accuracy: 0.8242

Finished Training
---------------------
Test Accuracy: 0.815
```

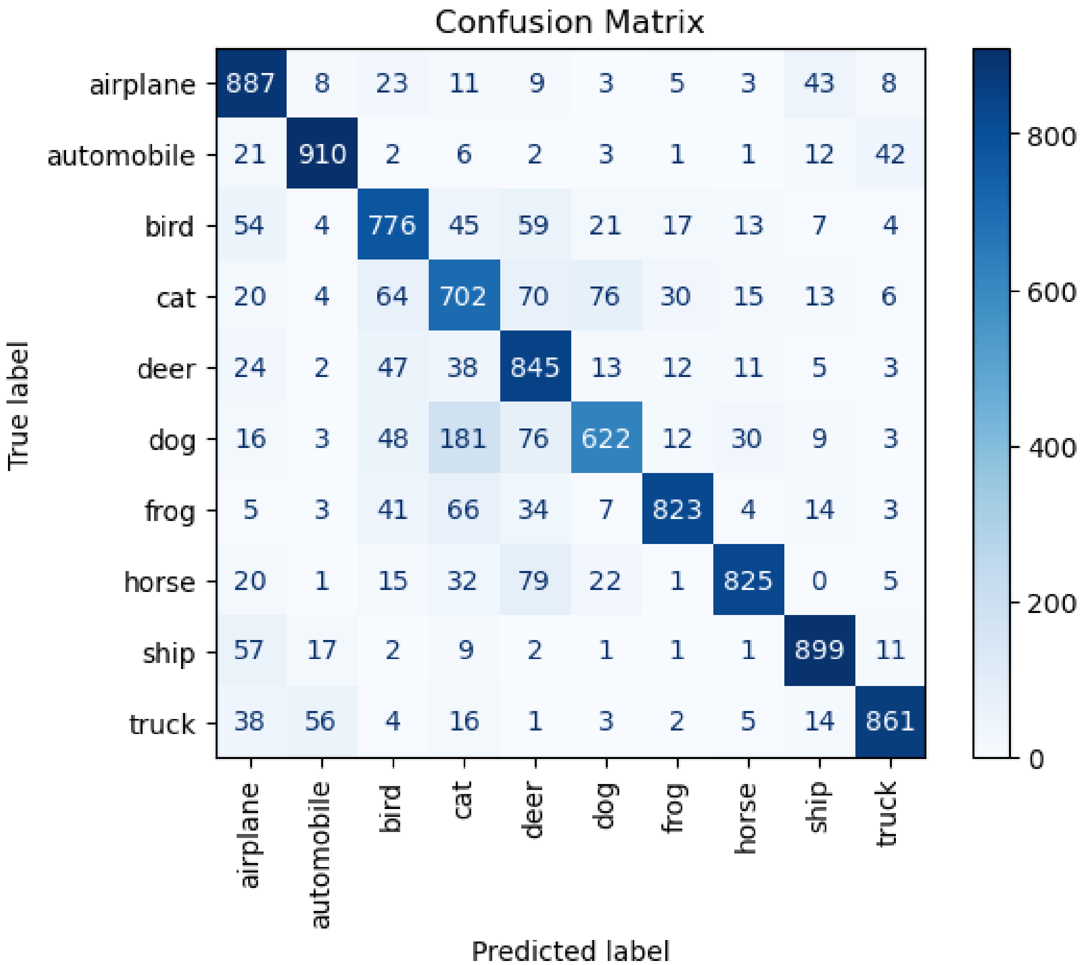
[ ]:
```
plot = plot_accuracies(train_acc, val_acc)
plt.show()
```



[ ]:
```python
plot2 = plot_losses(train_losses, val_losses)
plt.show()
```

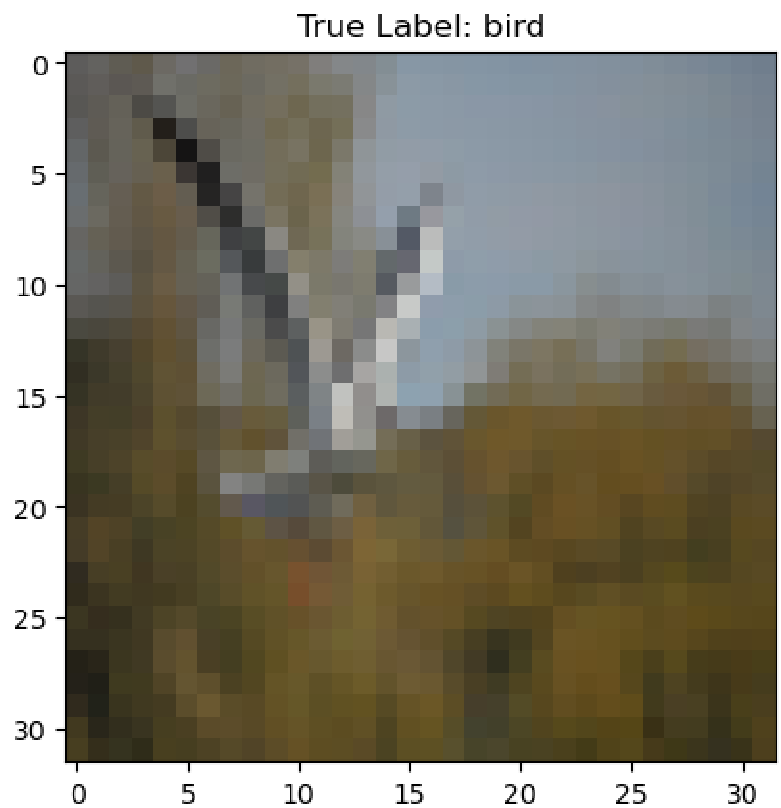


[ ]:
```python
# Confusion Matrix

predicted_labels = get_predicted_labels(model, test_loader, device)
true_labels = test_data.targets

cm = confusion_matrix(true_labels, predicted_labels.cpu().numpy())
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=LABELS.
 ↪values())
disp.plot(cmap='Blues', xticks_rotation='vertical')

plt.title('Confusion Matrix')
plt.show()
```

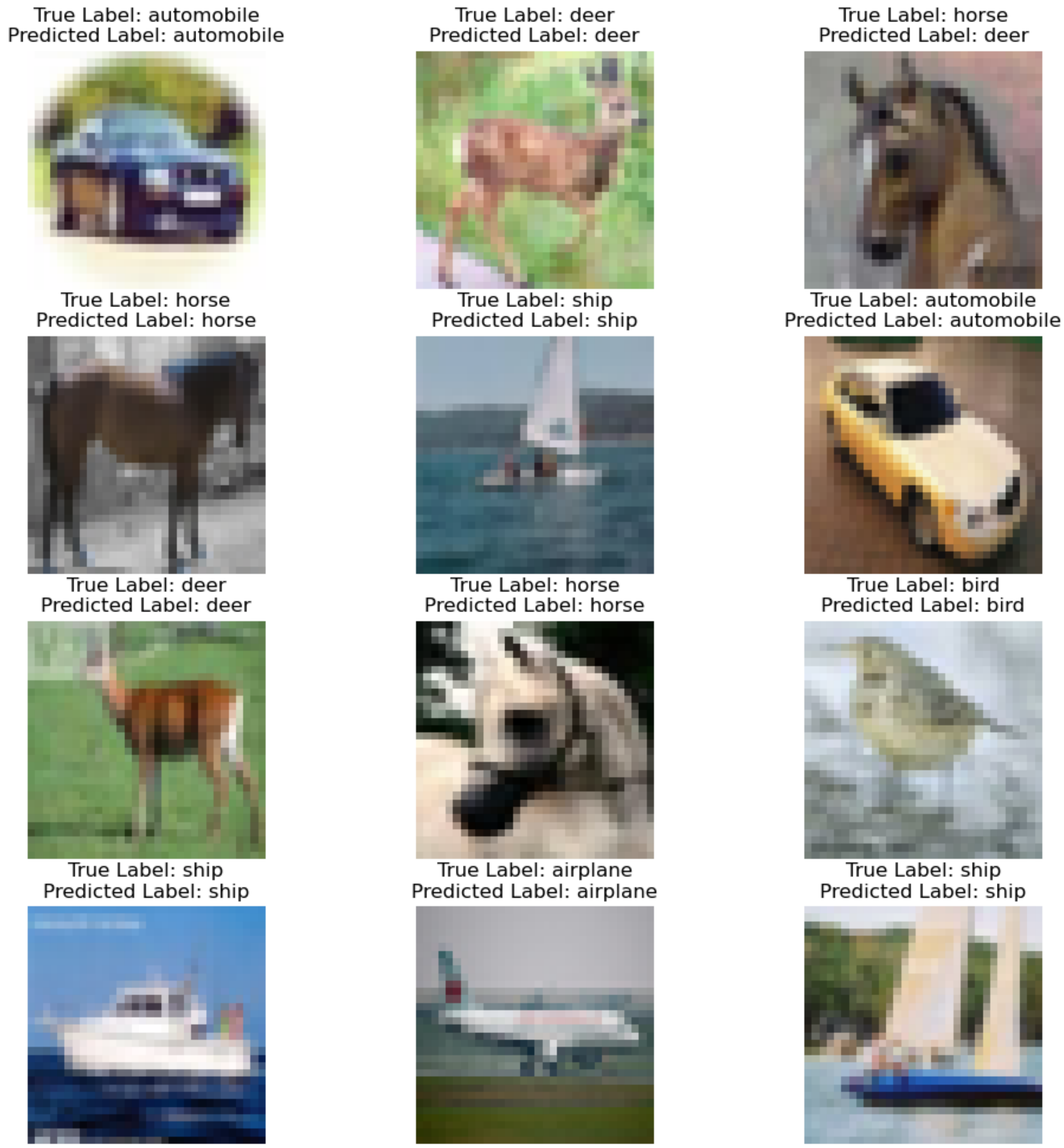


[ ]:
```
# Show an random image and its predicted label

plot, index, label = show_random_image(test_data, mean=mean, std=std)

predicted_label = predicted_labels[index].item()
print(f'True Label: {LABELS[label]}')
print(f'Predicted Label: {LABELS[predicted_label]}')
```

```
True Label: bird
Predicted Label: bird
```



[ ]:
```
# Take a random 10 images and show their true and predicted labels in a 5*2 grid

fig, ax = plt.subplots(4, 3, figsize=(12, 12))
axes = ax.flatten()

for i in range(12):
    plot, index, label = show_random_image(test_data, mean=mean, std=std)
    predicted_label = predicted_labels[index].item()
    axes[i].set_title(f'True Label: {LABELS[label]}\nPredicted Label:␣
 ↪{LABELS[predicted_label]}')
    axes[i].axis('off')
    axes[i].imshow(plot.get_array().clip(0, 1))
```


True Label: automobile
Predicted Label: automobile
True Label: deer
Predicted Label: deer
True Label: horse
Predicted Label: deer
True Label: horse
Predicted Label: horse
True Label: ship
Predicted Label: ship
True Label: automobile
Predicted Label: automobile
True Label: deer
Predicted Label: deer
True Label: horse
Predicted Label: horse
True Label: bird
Predicted Label: bird
True Label: ship
Predicted Label: ship
True Label: airplane
Predicted Label: airplane
True Label: ship
Predicted Label: ship