MLP - MM21B051 - Preethi

The pdf version of this notebook has all outputs and graphs, kindly refer to it We begin with loading the dataset, I have downloaded it locally We unpickle the dataset as mentioned in the official website and convert into a torch tensor, so that we can calculate the gradients and back-propagate in the later stages.

In [2]:
```
import pickle
import numpy as np
import torch

# Function to unpickle a CIFAR-10 batch file
def unpickle(file):
    with open(file, 'rb') as fo:
        data_dict = pickle.load(fo, encoding='bytes')
    return data_dict

# Load all 5 training batches
data_path = 'C:/Users/Preethi/Downloads/EE5178-Assgn1/cifar-10-python/cifar-10-b
train_data, train_labels = [], []

for i in range(1, 6):  # Load batches 1 to 5
    batch = unpickle(f"{data_path}data_batch_{i}")
    train_data.append(batch[b'data'])  # Image data (shape: (10000, 3072))
    train_labels.extend(batch[b'labels'])  # Labels

# Convert to NumPy arrays
train_data = np.vstack(train_data).astype(np.float32)  # Shape: (50000, 3072)
train_labels = np.array(train_labels)  # Shape: (50000,)

# Load test batch
test_batch = unpickle(f"{data_path}test_batch")
test_data = np.array(test_batch[b'data'], dtype=np.float32)  # Shape: (10000, 30
test_labels = np.array(test_batch[b'labels'])  # Shape: (10000,)

# Convert NumPy arrays to PyTorch tensors
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Print dataset shapes
print(f"Train data shape: {train_data.shape}, Train labels shape: {train_labels.
print(f"Test data shape: {test_data.shape}, Test labels shape: {test_labels.shap
print(f"Data stored on: {device}")
```

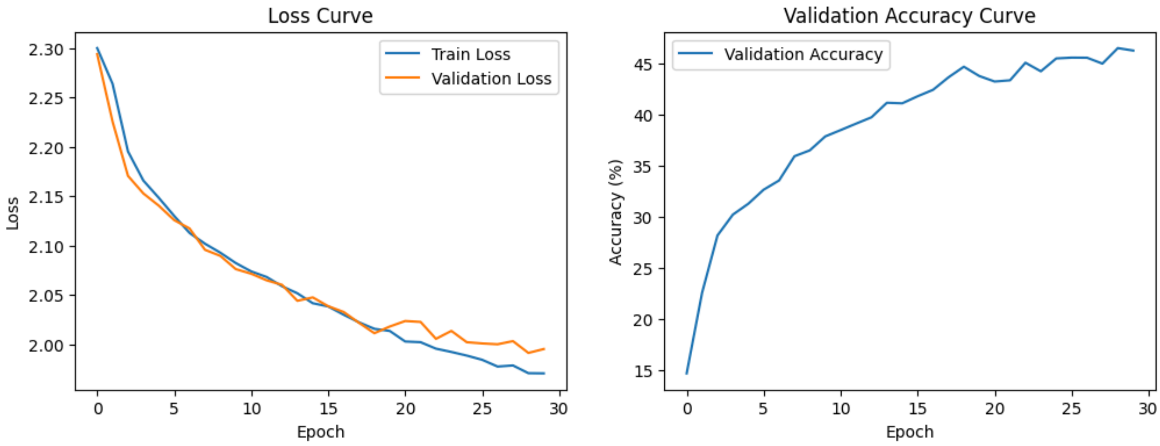
```
Train data shape: (50000, 3072), Train labels shape: (50000,)
Test data shape: (10000, 3072), Test labels shape: (10000,)
Data stored on: cpu
```

We convert the data into torch tensors and define the model with three hidden layers: h1 (500 units), h2 (250 units), and h3 (100 units), 10 units at the output layer, one for each class. The input layer is the flattened image vector. We use ReLu as the actuation function in between each layer. The loss used is cross-entropy loss, we compute the gradients wrt to this loss and optimize the weights and biases, through back-propagation.

In [3]:
```
import pickle
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
import torch.utils.data as data
import matplotlib.pyplot as plt
from torchvision import transforms

# Normalize data to [0,1]
train_data /= 255.0
test_data /= 255.0

# Convert to PyTorch tensors
train_data = torch.tensor(train_data)
train_labels = torch.tensor(train_labels)
test_data = torch.tensor(test_data)
test_labels = torch.tensor(test_labels)

# Create PyTorch DataLoader
batch_size = 128
train_dataset = data.TensorDataset(train_data, train_labels)
test_dataset = data.TensorDataset(test_data, test_labels)
train_loader = data.DataLoader(train_dataset, batch_size=batch_size, shuffle=Tru
test_loader = data.DataLoader(test_dataset, batch_size=batch_size, shuffle=False

# Define MLP Model
class MLP(nn.Module):
    def __init__(self, input_size=3072, hidden_sizes=[500, 250, 100], output_siz
        super(MLP, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_sizes[0])
        self.fc2 = nn.Linear(hidden_sizes[0], hidden_sizes[1])
        self.fc3 = nn.Linear(hidden_sizes[1], hidden_sizes[2])
        self.fc4 = nn.Linear(hidden_sizes[2], output_size)
        self.relu = nn.ReLU()
        self.softmax = nn.Softmax(dim=1)

    def forward(self, x):
        x = self.relu(self.fc1(x))
        x = self.relu(self.fc2(x))
        x = self.relu(self.fc3(x))
        x = self.fc4(x)
        return self.softmax(x)

# Initialize model, loss, optimizer
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = MLP().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)

# Training loop
num_epochs = 30
train_losses, val_losses, val_accuracies = [], [], []

for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0

    for inputs, labels in train_loader:
```

```
        inputs, labels = inputs.to(device), labels.to(device)

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Backpropagation
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    # Compute validation loss and accuracy
    model.eval()
    val_loss = 0.0
    correct, total = 0, 0

    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            val_loss += loss.item()

            # Calculate accuracy
            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    train_losses.append(running_loss / len(train_loader))
    val_losses.append(val_loss / len(test_loader))
    val_accuracies.append(100 * correct / total)

    print(f"Epoch [{epoch+1}/{num_epochs}] - Train Loss: {train_losses[-1]:.4f},
          f"Val Loss: {val_losses[-1]:.4f}, Accuracy: {val_accuracies[-1]:.2f}%"

# Plot training & validation loss and accuracy
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(train_losses, label="Train Loss")
plt.plot(val_losses, label="Validation Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.title("Loss Curve")

plt.subplot(1, 2, 2)
plt.plot(val_accuracies, label="Validation Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy (%)")
plt.legend()
plt.title("Validation Accuracy Curve")

plt.show()
```

```
Epoch [1/30] - Train Loss: 2.3001, Val Loss: 2.2940, Accuracy: 14.72%
Epoch [2/30] - Train Loss: 2.2638, Val Loss: 2.2256, Accuracy: 22.60%
Epoch [3/30] - Train Loss: 2.1953, Val Loss: 2.1705, Accuracy: 28.21%
Epoch [4/30] - Train Loss: 2.1658, Val Loss: 2.1527, Accuracy: 30.25%
Epoch [5/30] - Train Loss: 2.1483, Val Loss: 2.1403, Accuracy: 31.31%
Epoch [6/30] - Train Loss: 2.1299, Val Loss: 2.1257, Accuracy: 32.69%
Epoch [7/30] - Train Loss: 2.1127, Val Loss: 2.1172, Accuracy: 33.59%
Epoch [8/30] - Train Loss: 2.1018, Val Loss: 2.0956, Accuracy: 35.96%
Epoch [9/30] - Train Loss: 2.0926, Val Loss: 2.0894, Accuracy: 36.54%
Epoch [10/30] - Train Loss: 2.0822, Val Loss: 2.0760, Accuracy: 37.90%
Epoch [11/30] - Train Loss: 2.0737, Val Loss: 2.0713, Accuracy: 38.52%
Epoch [12/30] - Train Loss: 2.0681, Val Loss: 2.0647, Accuracy: 39.15%
Epoch [13/30] - Train Loss: 2.0587, Val Loss: 2.0601, Accuracy: 39.77%
Epoch [14/30] - Train Loss: 2.0515, Val Loss: 2.0439, Accuracy: 41.19%
Epoch [15/30] - Train Loss: 2.0414, Val Loss: 2.0473, Accuracy: 41.14%
Epoch [16/30] - Train Loss: 2.0382, Val Loss: 2.0384, Accuracy: 41.83%
Epoch [17/30] - Train Loss: 2.0298, Val Loss: 2.0326, Accuracy: 42.46%
Epoch [18/30] - Train Loss: 2.0220, Val Loss: 2.0216, Accuracy: 43.68%
Epoch [19/30] - Train Loss: 2.0155, Val Loss: 2.0110, Accuracy: 44.72%
Epoch [20/30] - Train Loss: 2.0133, Val Loss: 2.0178, Accuracy: 43.81%
Epoch [21/30] - Train Loss: 2.0026, Val Loss: 2.0234, Accuracy: 43.27%
Epoch [22/30] - Train Loss: 2.0019, Val Loss: 2.0225, Accuracy: 43.39%
Epoch [23/30] - Train Loss: 1.9954, Val Loss: 2.0053, Accuracy: 45.11%
Epoch [24/30] - Train Loss: 1.9920, Val Loss: 2.0134, Accuracy: 44.27%
Epoch [25/30] - Train Loss: 1.9883, Val Loss: 2.0019, Accuracy: 45.53%
Epoch [26/30] - Train Loss: 1.9841, Val Loss: 2.0007, Accuracy: 45.61%
Epoch [27/30] - Train Loss: 1.9772, Val Loss: 1.9998, Accuracy: 45.60%
Epoch [28/30] - Train Loss: 1.9783, Val Loss: 2.0030, Accuracy: 45.02%
Epoch [29/30] - Train Loss: 1.9705, Val Loss: 1.9911, Accuracy: 46.54%
Epoch [30/30] - Train Loss: 1.9703, Val Loss: 1.9950, Accuracy: 46.30%
```



As we can see from the graphs, the validation and training losses progressively deacrease with each epoch, and the accuracy is 46% at the end of 30 epochs, and val loss is 1.99.

We will now test the model's performance on the test data set.

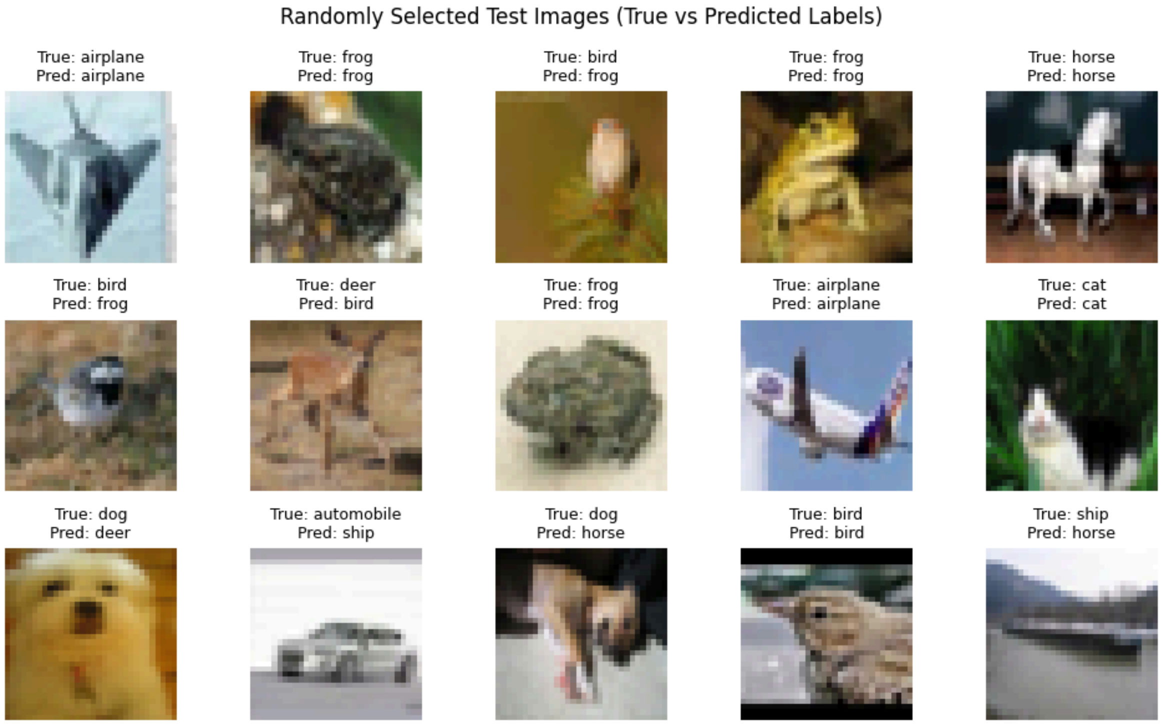
In [5]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
```

```
test_batch = unpickle('C:/Users/Preethi/Downloads/EE5178-Assgn1/cifar-10-python/
test_data = test_batch[b'data'].reshape(-1, 3, 32, 32).astype(np.float32) / 255.
test_labels = np.array(test_batch[b'labels'])

# Convert to PyTorch tensors
test_data = torch.tensor(test_data).float()
test_labels = torch.tensor(test_labels).long()

# Create DataLoader
test_loader = torch.utils.data.DataLoader(torch.utils.data.TensorDataset(test_da

# ----------- Evaluate the Model (Average Test Accuracy) -----------
model.eval()
correct, total = 0, 0

with torch.no_grad():
    for images, labels in test_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images.view(images.size(0), -1))  # Flatten the input
        _, predicted = outputs.max(1)
        correct += (predicted == labels).sum().item()
        total += labels.size(0)

test_accuracy = 100 * correct / total
print(f"\nAverage Test Accuracy: {test_accuracy:.2f}%")
```

```
Average Test Accuracy: 46.30%
```

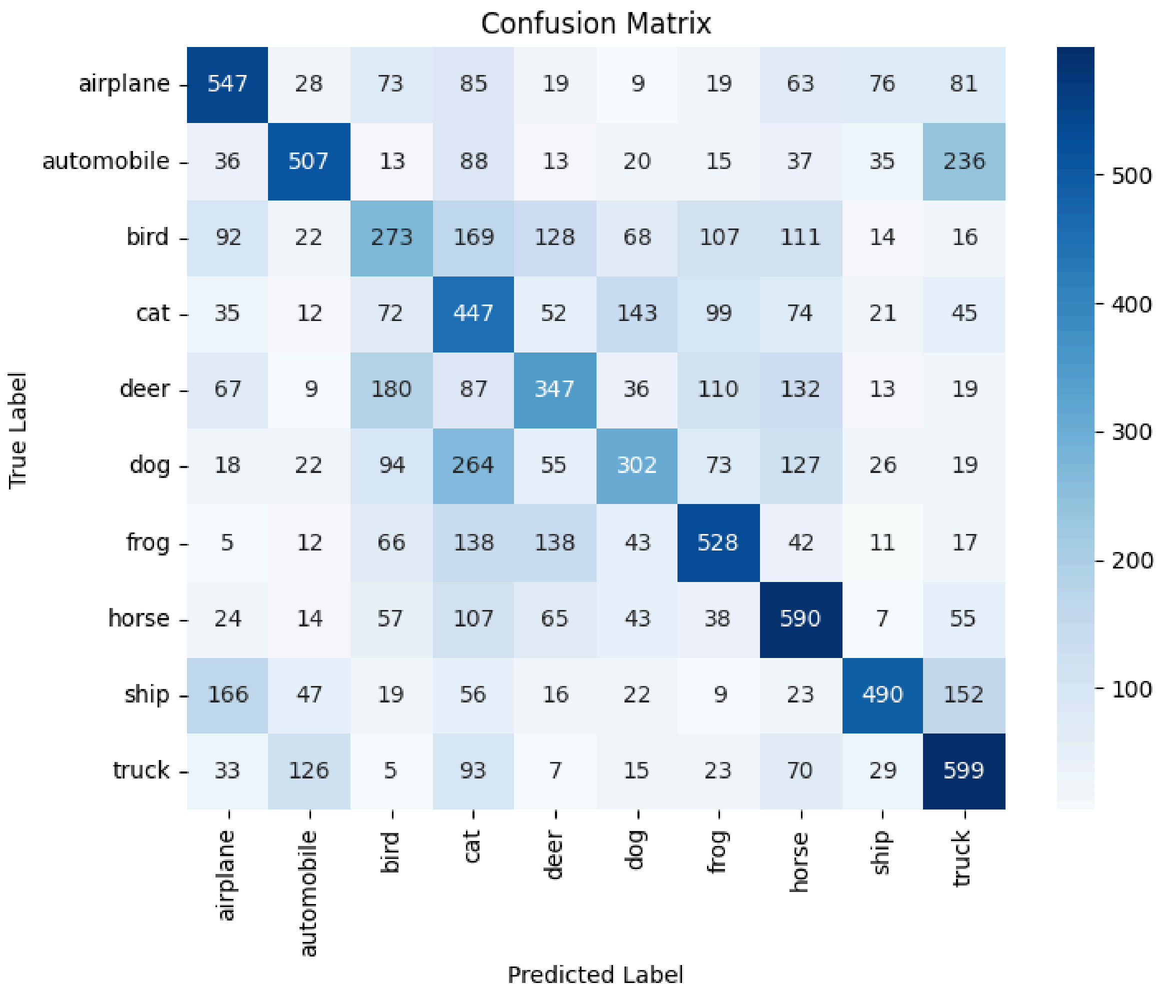
Next, we randomly visualise the prediction of the model on a few images

In [7]:
```
# ----------- Display Random Test Images with Predictions -----------
import random

class_names = unpickle('C:/Users/Preethi/Downloads/EE5178-Assgn1/cifar-10-python
class_names = [name.decode('utf-8') for name in class_names]

fig, axes = plt.subplots(3, 5, figsize=(10, 6))
fig.suptitle("Randomly Selected Test Images (True vs Predicted Labels)", fontsiz

model.eval()
for i in range(3):
    for j in range(5):
        idx = random.randint(0, len(test_data) - 1)
        image = test_data[idx].numpy().transpose(1, 2, 0)
        true_label = class_names[test_labels[idx].item()]

        with torch.no_grad():
            output = model(test_data[idx].view(1, -1).to(device))  # Flatten bef
            pred_label = class_names[output.argmax().item()]

        axes[i, j].imshow(image)
        axes[i, j].set_title(f"True: {true_label}\nPred: {pred_label}", fontsize
        axes[i, j].axis('off')

plt.tight_layout()
plt.show()
```



Confusion matrix for the true vs predicted labels of the model on the test dataset, we see that truck, horse, airplane and automobile have the best predictions, while bird, dog and deer are lesser accurate.

In [8]:
```
# ----------- Compute and Display Confusion Matrix -----------
all_preds, all_labels = [], []

with torch.no_grad():
    for images, labels in test_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images.view(images.size(0), -1))  # Flatten the input
        _, predicted = outputs.max(1)
        all_preds.extend(predicted.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

conf_matrix = confusion_matrix(all_labels, all_preds)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=class_na
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```



	airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck
airplane	547	28	73	85	19	9	19	63	76	81
automobile	36	507	13	88	13	20	15	37	35	236
bird	92	22	273	169	128	68	107	111	14	16
cat	35	12	72	447	52	143	99	74	21	45
deer	67	9	180	87	347	36	110	132	13	19
dog	18	22	94	264	55	302	73	127	26	19
frog	5	12	66	138	138	43	528	42	11	17
horse	24	14	57	107	65	43	38	590	7	55
ship	166	47	19	56	16	22	9	23	490	152
truck	33	126	5	93	7	15	23	70	29	599

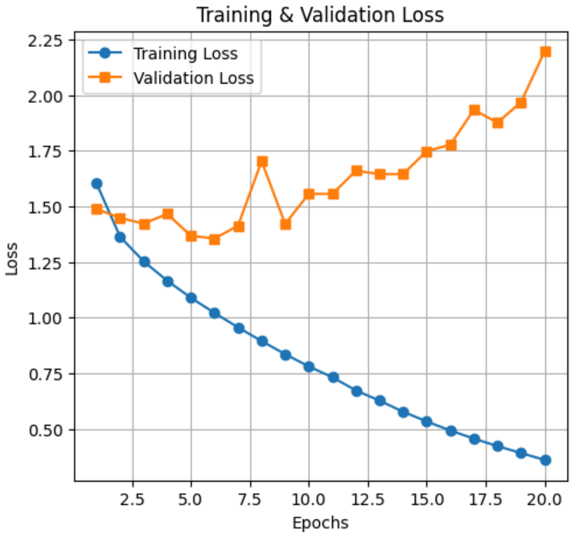
We next train the model with batch normalisation layers added. Batch normalisation, normalises the outputs of each layer before they are passed onto the subsequent layer. WE further plot the training and validation losses, accuracy for the batch normalised model.

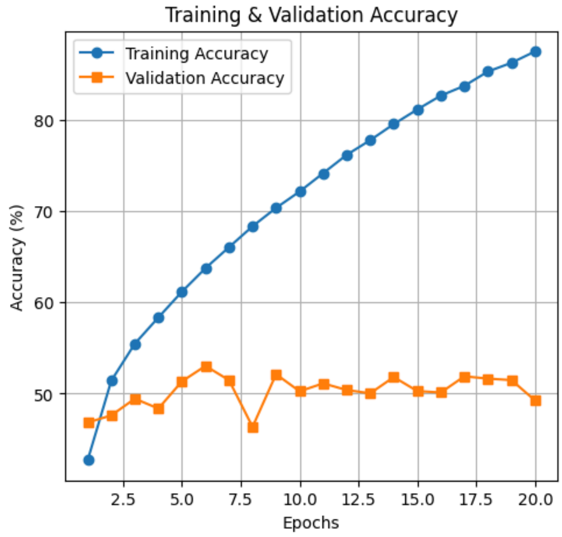
In [ ]:
```
# Define MLP Model with Batch Normalization
class MLP_CIFAR10_bnorm(nn.Module):
    def __init__(self):
        super(MLP_CIFAR10_bnorm, self).__init__()
        self.fc1 = nn.Linear(3072, 500)
        self.bn1 = nn.BatchNorm1d(500)  # Batch Normalization
        self.fc2 = nn.Linear(500, 250)
        self.bn2 = nn.BatchNorm1d(250)  # Batch Normalization
        self.fc3 = nn.Linear(250, 100)
        self.bn3 = nn.BatchNorm1d(100)  # Batch Normalization
        self.fc4 = nn.Linear(100, 10)
        self.relu = nn.ReLU()
        self.softmax = nn.Softmax(dim=1)

    def forward(self, x):
        x = x.view(x.size(0), -1)  # Flatten input (32x32x3 → 3072)
        x = self.relu(self.bn1(self.fc1(x)))
        x = self.relu(self.bn2(self.fc2(x)))
        x = self.relu(self.bn3(self.fc3(x)))
        x = self.fc4(x)  # No activation for final logits
        return x  # Softmax applied in loss function

# 3. Train the model
```

```
model = MLP_CIFAR10_bnorm().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)

num_epochs = 20
train_losses, val_losses, train_accuracies, val_accuracies = [], [], [], []

for epoch in range(num_epochs):
    model.train()
    running_loss, correct, total = 0.0, 0, 0

    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
        _, predicted = outputs.max(1)
        correct += (predicted == labels).sum().item()
        total += labels.size(0)

    train_loss = running_loss / len(train_loader)
    train_acc = 100 * correct / total
    train_losses.append(train_loss)
    train_accuracies.append(train_acc)

    # Validation Loop
    model.eval()
    val_loss, correct, total = 0.0, 0, 0

    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            loss = criterion(outputs, labels)
            val_loss += loss.item()
            _, predicted = outputs.max(1)
            correct += (predicted == labels).sum().item()
            total += labels.size(0)

    val_loss /= len(test_loader)
    val_acc = 100 * correct / total
    val_losses.append(val_loss)
    val_accuracies.append(val_acc)

    print(f"Epoch {epoch+1}/{num_epochs} - Train Loss: {train_loss:.4f}, Val Los

# 4. Plot Loss and Accuracy
epochs = np.arange(1, num_epochs + 1)

plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(epochs, train_losses, label="Training Loss", marker="o")
plt.plot(epochs, val_losses, label="Validation Loss", marker="s")
plt.xlabel("Epochs")
```

```
plt.ylabel("Loss")
plt.title("Training & Validation Loss")
plt.legend()
plt.grid()

plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracies, label="Training Accuracy", marker="o")
plt.plot(epochs, val_accuracies, label="Validation Accuracy", marker="s")
plt.xlabel("Epochs")
plt.ylabel("Accuracy (%)")
plt.title("Training & Validation Accuracy")
plt.legend()
plt.grid()

plt.show()
```

```
Epoch 1/20 - Train Loss: 1.6034, Val Loss: 1.4885, Train Acc: 42.73%, Val Acc: 4
6.83%
Epoch 2/20 - Train Loss: 1.3632, Val Loss: 1.4481, Train Acc: 51.42%, Val Acc: 4
7.61%
Epoch 3/20 - Train Loss: 1.2526, Val Loss: 1.4225, Train Acc: 55.47%, Val Acc: 4
9.44%
Epoch 4/20 - Train Loss: 1.1657, Val Loss: 1.4664, Train Acc: 58.34%, Val Acc: 4
8.36%
Epoch 5/20 - Train Loss: 1.0892, Val Loss: 1.3679, Train Acc: 61.17%, Val Acc: 5
1.34%
Epoch 6/20 - Train Loss: 1.0211, Val Loss: 1.3553, Train Acc: 63.75%, Val Acc: 5
3.03%
Epoch 7/20 - Train Loss: 0.9560, Val Loss: 1.4133, Train Acc: 66.05%, Val Acc: 5
1.47%
Epoch 8/20 - Train Loss: 0.8944, Val Loss: 1.7035, Train Acc: 68.34%, Val Acc: 4
6.35%
Epoch 9/20 - Train Loss: 0.8355, Val Loss: 1.4213, Train Acc: 70.35%, Val Acc: 5
2.12%
Epoch 10/20 - Train Loss: 0.7804, Val Loss: 1.5562, Train Acc: 72.15%, Val Acc: 5
0.25%
Epoch 11/20 - Train Loss: 0.7319, Val Loss: 1.5561, Train Acc: 74.16%, Val Acc: 5
1.12%
Epoch 12/20 - Train Loss: 0.6725, Val Loss: 1.6603, Train Acc: 76.17%, Val Acc: 5
0.39%
Epoch 13/20 - Train Loss: 0.6266, Val Loss: 1.6450, Train Acc: 77.78%, Val Acc: 5
0.03%
Epoch 14/20 - Train Loss: 0.5767, Val Loss: 1.6451, Train Acc: 79.54%, Val Acc: 5
1.81%
Epoch 15/20 - Train Loss: 0.5329, Val Loss: 1.7485, Train Acc: 81.15%, Val Acc: 5
0.27%
Epoch 16/20 - Train Loss: 0.4923, Val Loss: 1.7770, Train Acc: 82.67%, Val Acc: 5
0.12%
Epoch 17/20 - Train Loss: 0.4560, Val Loss: 1.9341, Train Acc: 83.74%, Val Acc: 5
1.89%
Epoch 18/20 - Train Loss: 0.4221, Val Loss: 1.8769, Train Acc: 85.31%, Val Acc: 5
1.64%
Epoch 19/20 - Train Loss: 0.3911, Val Loss: 1.9682, Train Acc: 86.26%, Val Acc: 5
1.48%
Epoch 20/20 - Train Loss: 0.3601, Val Loss: 2.1968, Train Acc: 87.51%, Val Acc: 4
9.25%
```





Batch normalization doesn't seem to be useful in this case as it seems to be leading to overfitting. The training losses are progressively decreasing, however the validation loss increases and the same can be seen with accuracy too; training accuracy increases drastically, while not much improvement is seen on the validation set.