Comp 472 Project 1

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Load the data

Importing dataset to devite it between train and test datasets.

```
from keras.datasets import cifar10

(X_train, y_train), (X_test, y_test) = cifar10.load_data()

print("Training data shape:", X_train.shape, y_train.shape)
print("Test data shape:", X_test.shape, y_test.shape)
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 4s 0us/step
Training data shape: (50000, 32, 32, 3) (50000, 1)
Test data shape: (10000, 32, 32, 3) (10000, 1)
```

Using first 500 training images and the first 100 test images of each class

```
import numpy as np

X_train_filtered = []
y_train_filtered = []
X_test_filtered = []
y_test_filtered = []

# Loop through each class
for class_label in range(10):
    train_indices = np.where(y_train.flatten() == class_label)[0][:500] # 500 images for each class for training purposes
    test_indices = np.where(y_test.flatten() == class_label)[0][:100] # 100 images for each class for test purposes.

    #data to the filtered arrays
    X_train_filtered.append(X_train[train_indices])
    y_train_filtered.append(y_train[train_indices])
    X_test_filtered.append(X_test[test_indices])
    y_test_filtered.append(y_test[test_indices])

# print("X_train: " , X_train_filtered)
# print("y_train: " , y_train_filtered)
# print("X_test: " , X_test_filtered)
# print("y_test: " , y_test_filtered)

# concatenating lists to form final arrays
X_train_filtered = np.concatenate(X_train_filtered)
y_train_filtered = np.concatenate(y_train_filtered)
X_test_filtered = np.concatenate(X_test_filtered)
y_test_filtered = np.concatenate(y_test_filtered)

# the shapes of the filtered datasets
print("training data shape:", X_train_filtered.shape, y_train_filtered.shape)
print("test data shape:", X_test_filtered.shape, y_test_filtered.shape)
```

```
training data shape: (5000, 32, 32, 3) (5000, 1)
test data shape: (1000, 32, 32, 3) (1000, 1)
```

Here we do:

1. Resizing and

2. Normalizing

** imageNet means and std were taken from: stack-overflow

```
import torch
import torchvision.transforms as transforms

transform = transforms.Compose([
    transforms.ToPILImage(),  # Convert to PIL image
    transforms.Resize((224, 224)),  # Resize to 224x224
    transforms.ToTensor(),  # Convert to tensor
    transforms.Normalize(mean=[0.485, 0.456, 0.406],  # ImageNet means
                         std=[0.229, 0.224, 0.225])   # ImageNet stds
])

# now appling the transformation to the training and test sets
X_train_normalized = torch.stack([transform(img) for img in X_train_filtered])
X_test_normalized = torch.stack([transform(img) for img in X_test_filtered])

print("Training data shape after transformation:", X_train_normalized.shape)
print("Test data shape after transformation:", X_test_normalized.shape)
```

```
Training data shape after transformation: torch.Size([5000, 3, 224, 224])
Test data shape after transformation: torch.Size([1000, 3, 224, 224])
```

Now we can extract features using ResNet-18

device will be selected based on GPU and CPU. original code: Pytorch website

how to use pretrained resnet and evalute it, was taken from Stack-Overflow

```
from torch.utils.data import DataLoader, TensorDataset
from torchvision.models import resnet18

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu') # taken from pytorch

resnet18 = resnet18(pretrained=True).to(device)
resnet18.eval()  # stackoverflow code


batch_size = 32 # with higher batch size, my colab environment crashes...
train_dataset = TensorDataset(X_train_normalized)
test_dataset = TensorDataset(X_test_normalized)
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

# Function to extract features in batches
def extract_features_in_batches(model, loader):
    all_features = []
    for batch in loader:
        data = batch[0].to(device)  # Move data to the same device as the model
        with torch.no_grad():  # No gradient computation for inference
            features = model(data).squeeze()  # Extract features
        all_features.append(features.cpu())  # Move to CPU to free GPU memory
    return torch.cat(all_features)

# Now we extract features for training and test sets
X_train_features = extract_features_in_batches(resnet18, train_loader)
X_test_features = extract_features_in_batches(resnet18, test_loader)

print("Feature extraction complete with batch processing.")
print("Training features shape:", X_train_features.shape)
print("Test features shape:", X_test_features.shape)
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:00<00:00, 63.4MB/s]
```

Final task for Dataset overview, PCA Dimensionality Reduction

```
from sklearn.decomposition import PCA

pca = PCA(n_components=50)

# Appling PCA on the training and test feature sets
X_train_pca = pca.fit_transform(X_train_features.cpu().numpy())
X_test_pca = pca.transform(X_test_features.cpu().numpy())

print("Training features shape after PCA:", X_train_pca.shape)
print("Test features shape after PCA:", X_test_pca.shape)
```

Naive Bayes:

Custom Gaussian Naive Bayes Implementation

idea was taken from:

1. StackOverflow
2. Scikit-learn's naive_bayes class

** Also Google GEMINI Suggeted some codes(like co-pilot) while writing it on colab environment.

```
import numpy as np

class GaussianNaiveBayes:
    def __init__(self) -> None:
        self.means = None
        self.variances = None
        self.priors = None

    def fit(self, X, y) -> None:
        self.classes = np.unique(y)
        n_features = X.shape[1]
        n_classes = len(self.classes)

        self.means = np.zeros((n_classes, n_features))
        self.variances = np.zeros((n_classes, n_features))
        self.priors = np.zeros(n_classes)

        for idx, cls in enumerate(self.classes):
            X_cls = X[y == cls]
            self.means[idx, :] = X_cls.mean(axis=0)
            self.variances[idx, :] = X_cls.var(axis=0) + 1e-9  # Added small value to avoid division by zero ** This idea is from GOOGLE GEM
            self.priors[idx] = X_cls.shape[0] / X.shape[0]

    def predict(self, X) -> np.ndarray:
        posteriors = np.zeros((X.shape[0], len(self.classes)))

        for idx, cls in enumerate(self.classes):
            prior = np.log(self.priors[idx])
            likelihood = -0.5 * np.sum(np.log(2 * np.pi * self.variances[idx, :]))
            likelihood -= 0.5 * np.sum(((X - self.means[idx, :]) ** 2) / self.variances[idx, :], axis=1)
            posteriors[:, idx] = prior + likelihood

        return self.classes[np.argmax(posteriors, axis=1)]

gnb_custom = GaussianNaiveBayes()
gnb_custom.fit(X_train_pca, y_train_filtered.flatten())  # Flatten y_train for compatibility


y_pred_custom = gnb_custom.predict(X_test_pca)
print("Custom Gaussian Naive Bayes completed.")
```

```
Custom Gaussian Naive Bayes completed.
```

Gaussian Naive Bayes Using Scikit-Learn

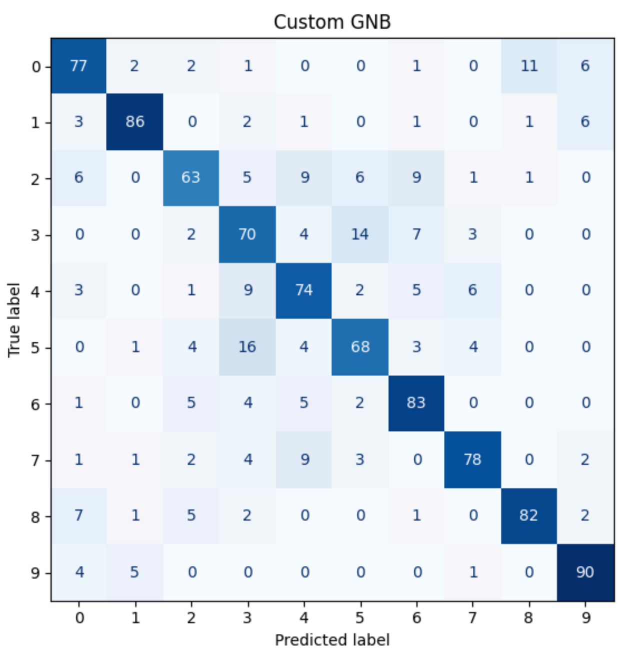
```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score

gnb_sklearn = GaussianNB()
gnb_sklearn.fit(X_train_pca, y_train_filtered.flatten())

y_pred_sklearn = gnb_sklearn.predict(X_test_pca)
print("Scikit-learn Gaussian Naive Bayes completed.")
```

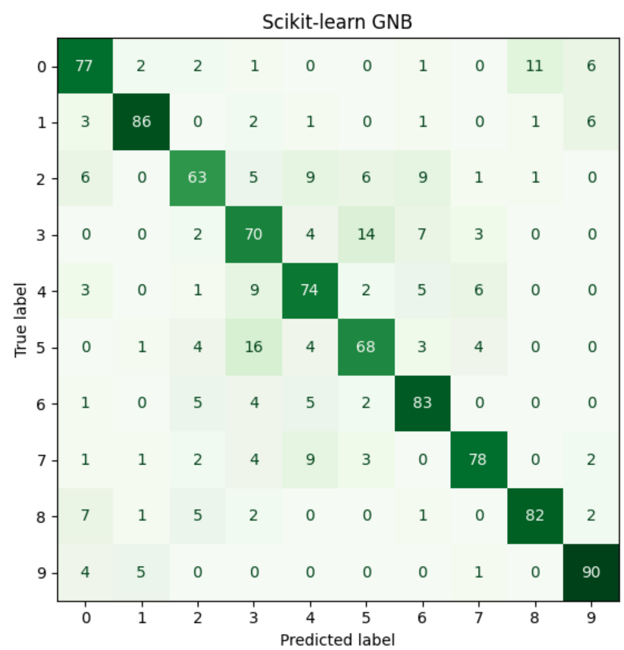
```
Scikit-learn Gaussian Naive Bayes completed.
```

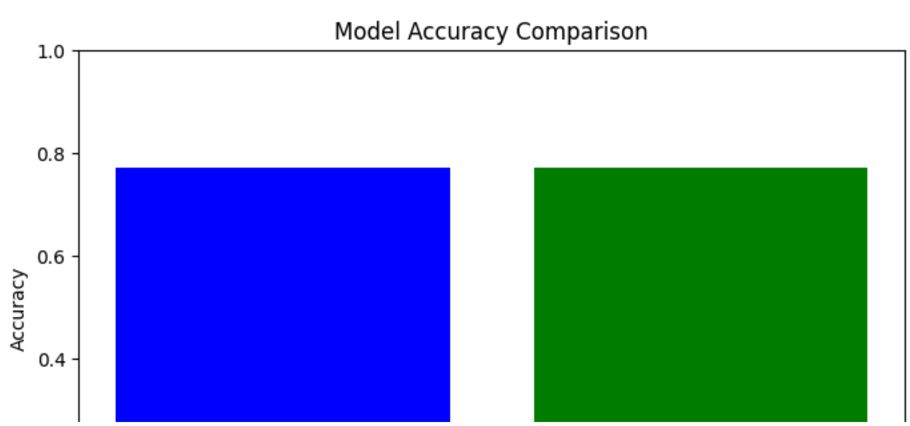
Evaluate both of these models on the test set.

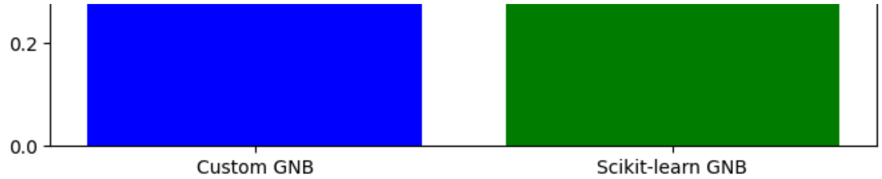
```
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay

accuracy_custom = accuracy_score(y_test_filtered.flatten(), y_pred_custom)
accuracy_sklearn = accuracy_score(y_test_filtered.flatten(), y_pred_sklearn)

print("\nCustom GNB Classification Report:")
print(classification_report(y_test_filtered.flatten(), y_pred_custom))

print("\nScikit-learn GNB Classification Report:")
print(classification_report(y_test_filtered.flatten(), y_pred_sklearn))


fig, axes = plt.subplots(1, 2, figsize=(14, 6)) # confussion matrix

ConfusionMatrixDisplay.from_predictions(
    y_test_filtered.flatten(),
    y_pred_custom,
    ax=axes[0],
    cmap="Blues",
    colorbar=False
)
axes[0].set_title("Custom GNB")

ConfusionMatrixDisplay.from_predictions(
    y_test_filtered.flatten(),
    y_pred_sklearn,
    ax=axes[1],
    cmap="Greens",
    colorbar=False
)
axes[1].set_title("Scikit-learn GNB")

plt.tight_layout()
plt.show()

models = ['Custom GNB', 'Scikit-learn GNB']
accuracies = [accuracy_custom, accuracy_sklearn]

plt.figure(figsize=(8, 5))
plt.bar(models, accuracies, color=['blue', 'green'])
plt.title('Model Accuracy Comparison')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.show()


# now i save the naive_bayes_model::
import pickle
with open('naive_bayes_model.pkl', 'wb') as f:
    pickle.dump(gnb_custom, f)
    print("Model saved to naive_bayes_model.pkl")
from google.colab import files
files.download('naive_bayes_model.pkl')
```

```
Custom GNB Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.77      0.76       100
           1       0.90      0.86      0.88       100
           2       0.75      0.63      0.68       100
           3       0.62      0.70      0.66       100
           4       0.70      0.74      0.72       100
           5       0.72      0.68      0.70       100
           6       0.75      0.83      0.79       100
           7       0.84      0.78      0.81       100
           8       0.86      0.82      0.84       100
           9       0.85      0.90      0.87       100

    accuracy                           0.77      1000
   macro avg       0.77      0.77      0.77      1000
weighted avg       0.77      0.77      0.77      1000


Scikit-learn GNB Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.77      0.76       100
           1       0.90      0.86      0.88       100
           2       0.75      0.63      0.68       100
           3       0.62      0.70      0.66       100
           4       0.70      0.74      0.72       100
           5       0.72      0.68      0.70       100
           6       0.75      0.83      0.79       100
           7       0.84      0.78      0.81       100
           8       0.86      0.82      0.84       100
           9       0.85      0.90      0.87       100

    accuracy                           0.77      1000
   macro avg       0.77      0.77      0.77      1000
weighted avg       0.77      0.77      0.77      1000
```










```
Model saved to naive_bayes_model.pkl
```

Section 4: Decision Tree.

Custom Decision Tree Classifier (Gini Index, Max Depth = 50)

the idea was taken from: [Ander Fernandez's blog] and [Medium.com]

```
import numpy as np

class DecisionTreeClassifier:
    def __init__(self, max_depth=50):
        self.max_depth = max_depth
        self.tree = None

    def gini(self, y):
        m = len(y)
        if m == 0:
            return 0
        _, counts = np.unique(y, return_counts=True)
        probabilities = counts / m
        return 1 - np.sum(probabilities ** 2)

    def split(self, X, y, feature, threshold):
        left_indices = X[:, feature] < threshold
        right_indices = ~left_indices
        return X[left_indices], y[left_indices], X[right_indices], y[right_indices]

    def best_split(self, X, y):
        m, n = X.shape
        if m <= 1:
            return None, None
        parent_gini = self.gini(y)
        best_gain = 0
        best_split_feature, best_split_threshold = None, None
        for feature in range(n):
            thresholds = np.unique(X[:, feature])
            for threshold in thresholds:
                X_left, y_left, X_right, y_right = self.split(X, y, feature, threshold)
                if len(y_left) == 0 or len(y_right) == 0:
                    continue
                n_left, n_right = len(y_left), len(y_right)
                child_gini = (n_left / m) * self.gini(y_left) + (n_right / m) * self.gini(y_right)
                gain = parent_gini - child_gini
                if gain > best_gain:
                    best_gain = gain
                    best_split_feature, best_split_threshold = feature, threshold
        return best_split_feature, best_split_threshold

    def build_tree(self, X, y, depth=0):
        if depth >= self.max_depth or len(np.unique(y)) == 1:
            return np.argmax(np.bincount(y))
        feature, threshold = self.best_split(X, y)
        if feature is None:
            return np.argmax(np.bincount(y))
        X_left, y_left, X_right, y_right = self.split(X, y, feature, threshold)
        return {
            'feature': feature,
            'threshold': threshold,
```

```
            'left': self.build_tree(X_left, y_left, depth + 1),
            'right': self.build_tree(X_right, y_right, depth + 1),
        }

    def fit(self, X, y):
        self.tree = self.build_tree(X, y)

    def predict_sample(self, sample, tree):
        if isinstance(tree, dict):
            if sample[tree['feature']] < tree['threshold']:
                return self.predict_sample(sample, tree['left'])
            else:
                return self.predict_sample(sample, tree['right'])
        else:
            return tree

    def predict(self, X):
        return np.array([self.predict_sample(sample, self.tree) for sample in X])
```

Train the tree:

```
custom_tree = DecisionTreeClassifier(max_depth=50)
custom_tree.fit(X_train_pca, y_train_filtered.flatten())
```

Save the model:

** code suggested by GOOGLE GEMINI. propt was: I want to download my custom dicision tree.

```
import cloudpickle

# Save the custom tree model using cloudpickle
with open('dtc_cloudpickle.pkl', 'wb') as f:
    cloudpickle.dump(custom_tree, f)

print("Model saved to dtc_cloudpickle.pkl")

# Download the model file
from google.colab import files
files.download('dtc_cloudpickle.pkl')
```

```
Model saved to dtc_cloudpickle.pkl
```

Predict on Test Set:

```
y_pred_custom_tree = custom_tree.predict(X_test_pca)
```

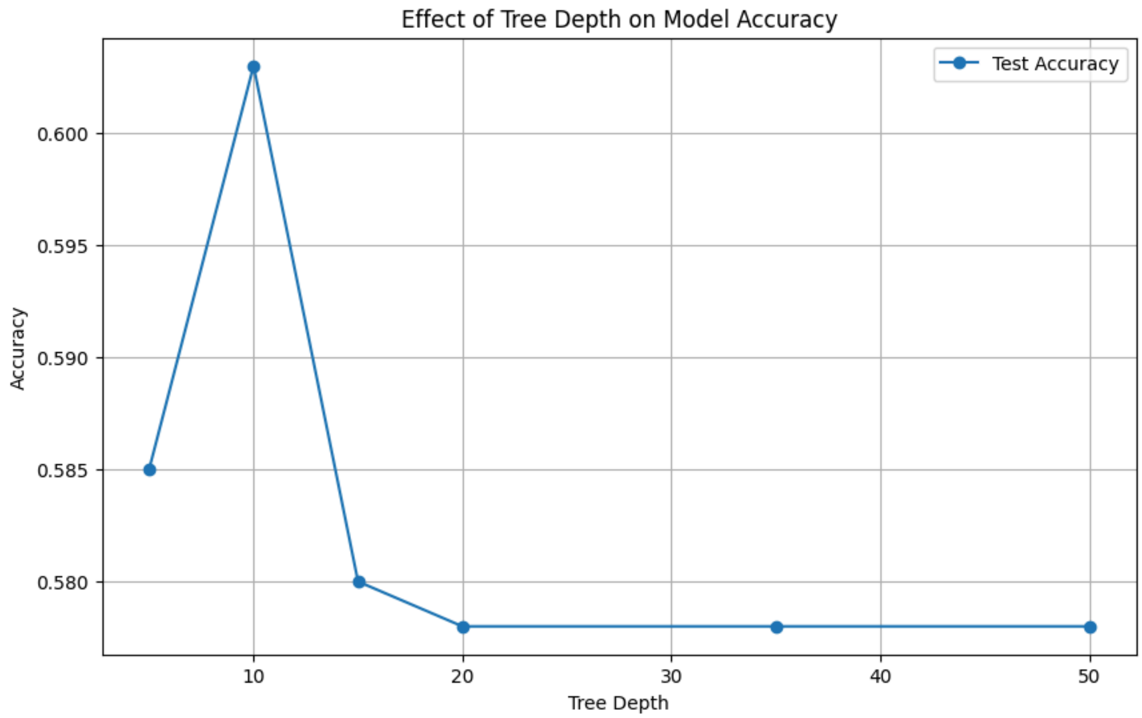
Experimenting with Different Depths

```
depths = [5, 10, 15, 20, 35, 50]  # We will experiment with 6 depts from 5 to 50
accuracies_for_custome_tree = []

for depth in depths:
    custom_tree = DecisionTreeClassifier(max_depth=depth)
    custom_tree.fit(X_train_pca, y_train_filtered.flatten())

    y_pred = custom_tree.predict(X_test_pca)
    #print(y_pred)

    accuracy = np.mean(y_pred == y_test_filtered.flatten())

    accuracies_for_custome_tree.append(accuracy)
    print(f"Tree Depth: {depth}, Accuracy: {accuracy:.4f}")
```

```
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(10, 6))
plt.plot(depths, accuracies_for_custome_tree, marker='o', label='Test Accuracy')
plt.title("Effect of Tree Depth on Model Accuracy")
plt.xlabel("Tree Depth")
plt.ylabel("Accuracy")
plt.grid(True)
plt.legend()
plt.show()
```

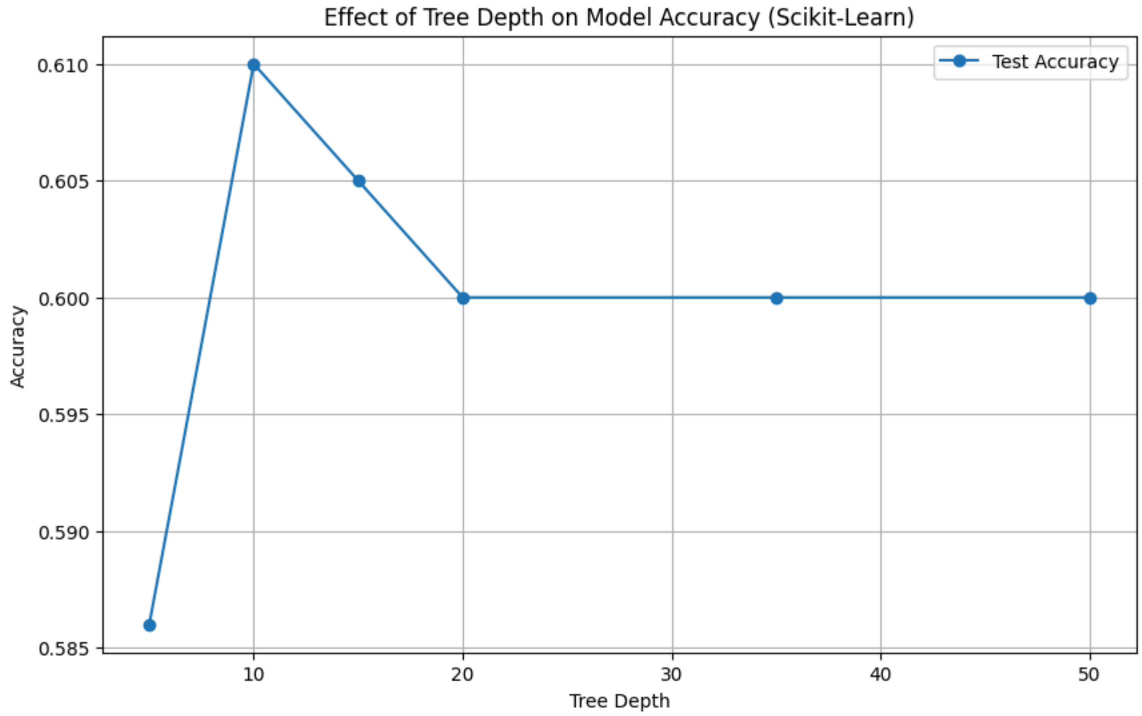
```
Tree Depth: 5, Accuracy: 0.5850
Tree Depth: 10, Accuracy: 0.6030
Tree Depth: 15, Accuracy: 0.5800
Tree Depth: 20, Accuracy: 0.5780
Tree Depth: 35, Accuracy: 0.5780
Tree Depth: 50, Accuracy: 0.5780
```



Scikit-learn's DecisionTreeClassifier

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

accuracies_for_sklearn_tree = []

for depth in depths:
    sk_tree = DecisionTreeClassifier(criterion="gini", max_depth=depth, random_state=42)
    sk_tree.fit(X_train_pca, y_train_filtered.flatten())

    y_pred_sklearn_tree = sk_tree.predict(X_test_pca)

    accuracy = accuracy_score(y_test_filtered.flatten(), y_pred_sklearn_tree)
    accuracies_for_sklearn_tree.append(accuracy)
    print(f"Tree Depth: {depth}, Accuracy: {accuracy:.4f}")

plt.figure(figsize=(10, 6))
plt.plot(depths, accuracies_for_sklearn_tree, marker='o', label='Test Accuracy')
plt.title("Effect of Tree Depth on Model Accuracy (Scikit-Learn)")
plt.xlabel("Tree Depth")
plt.ylabel("Accuracy")
plt.grid(True)
plt.legend()
plt.show()
```

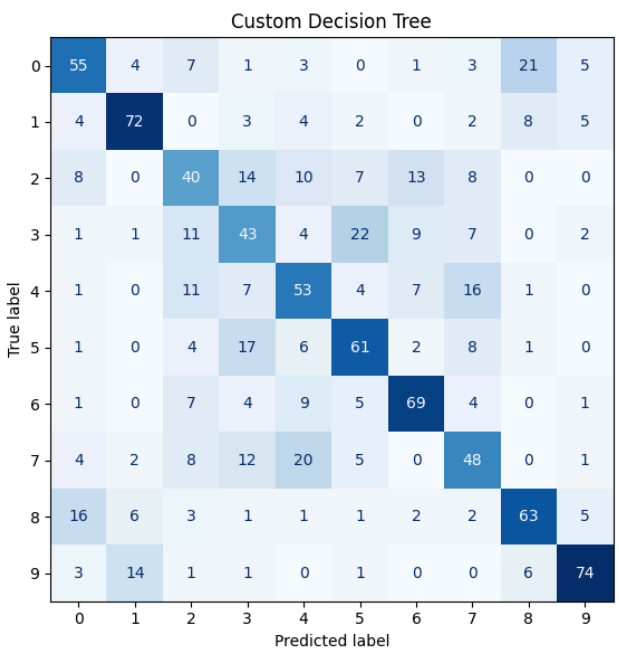
```
Tree Depth: 5, Accuracy: 0.5860
Tree Depth: 10, Accuracy: 0.6100
Tree Depth: 15, Accuracy: 0.6050
Tree Depth: 20, Accuracy: 0.6000
Tree Depth: 35, Accuracy: 0.6000
Tree Depth: 50, Accuracy: 0.6000
```

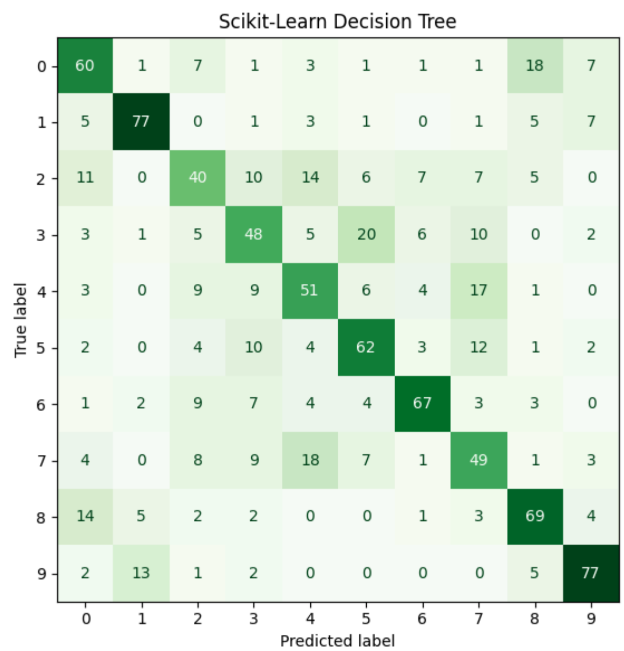


Evaluation and Graphical Comparison

```
from sklearn.metrics import classification_report, ConfusionMatrixDisplay

print("Custom Decision Tree Classification Report:")
print(classification_report(y_test_filtered.flatten(), y_pred_custom_tree))

print("\nScikit-Learn Decision Tree Classification Report:")
print(classification_report(y_test_filtered.flatten(), y_pred_sklearn_tree))

fig, axes = plt.subplots(1, 2, figsize=(14, 6)) # for plotting confussion matrix

ConfusionMatrixDisplay.from_predictions(
    y_test_filtered.flatten(),
    y_pred_custom_tree,
    ax=axes[0],
    cmap="Blues",
    colorbar=False
)
axes[0].set_title("Custom Decision Tree")

# Scikit-Learn Decision Tree confusion matrix
ConfusionMatrixDisplay.from_predictions(
    y_test_filtered.flatten(),
    y_pred_sklearn_tree,
    ax=axes[1],
    cmap="Greens",
    colorbar=False
)
axes[1].set_title("Scikit-Learn Decision Tree")

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

```
Custom Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.59      0.55      0.57       100
           1       0.73      0.72      0.72       100
           2       0.43      0.40      0.42       100
           3       0.42      0.43      0.42       100
           4       0.48      0.53      0.50       100
           5       0.56      0.61      0.59       100
           6       0.67      0.69      0.68       100
           7       0.49      0.48      0.48       100
           8       0.63      0.63      0.63       100
           9       0.80      0.74      0.77       100

    accuracy                           0.58      1000
   macro avg       0.58      0.58      0.58      1000
weighted avg       0.58      0.58      0.58      1000


Scikit-Learn Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.60      0.59       100
           1       0.78      0.77      0.77       100
           2       0.47      0.40      0.43       100
           3       0.48      0.48      0.48       100
           4       0.50      0.51      0.50       100
           5       0.58      0.62      0.60       100
           6       0.74      0.67      0.71       100
           7       0.48      0.49      0.48       100
           8       0.64      0.69      0.66       100
           9       0.75      0.77      0.76       100

    accuracy                           0.60      1000
   macro avg       0.60      0.60      0.60      1000
weighted avg       0.60      0.60      0.60      1000
```





MLP

Implementation of the specified three-layer MLP using PyTorch:

Help taken from: [pytorch discussion] and [medium.com]

I just ignored the layers part. as we need to implement three-layerd MLP.

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

class MLP(nn.Module):
    def __init__(self):
        super(MLP, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(50, 512),
            nn.ReLU(),
            nn.Linear(512, 512),
            nn.BatchNorm1d(512),
            nn.ReLU(),
            nn.Linear(512, 10)
        )

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

batch_size = 32

train_dataset = TensorDataset(torch.tensor(X_train_pca, dtype=torch.float32),
                               torch.tensor(y_train_filtered.flatten(), dtype=torch.long))
test_dataset = TensorDataset(torch.tensor(X_test_pca, dtype=torch.float32),
                              torch.tensor(y_test_filtered.flatten(), dtype=torch.long))

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

# device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

mlp_model = MLP().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(mlp_model.parameters(), lr=0.01, momentum=0.9)

num_epochs = 100
for epoch in range(num_epochs):
    mlp_model.train()
    running_loss = 0.0
    for inputs, labels in train_loader:
        inputs, labels = inputs.to(device), labels.to(device)

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

        # Backward pass and optimization
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader):.4f}")


mlp_model.eval()
correct = 0
total = 0

with torch.no_grad():
    for inputs, labels in test_loader:
        inputs, labels = inputs.to(device), labels.to(device)
        outputs = mlp_model(inputs)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

accuracy = correct / total
print(f"Test Accuracy: {accuracy:.4f}")

#now we save the model:
## Code suggested by Google GEMINI.
```

```
torch.save(mlp_model.state_dict(), 'mlp_model.pth')
print("Model saved to mlp_model.pth")
# Download the model file
from google.colab import files
files.download('mlp_model.pth')
```

```
Epoch [44/100], Loss: 0.0040
Epoch [45/100], Loss: 0.0051
Epoch [46/100], Loss: 0.0099
Epoch [47/100], Loss: 0.0074
Epoch [48/100], Loss: 0.0063
Epoch [49/100], Loss: 0.0185
Epoch [50/100], Loss: 0.0187
Epoch [51/100], Loss: 0.0241
Epoch [52/100], Loss: 0.0331
Epoch [53/100], Loss: 0.0168
Epoch [54/100], Loss: 0.0379
Epoch [55/100], Loss: 0.0282
Epoch [56/100], Loss: 0.0279
Epoch [57/100], Loss: 0.0195
Epoch [58/100], Loss: 0.0117
Epoch [59/100], Loss: 0.0112
Epoch [60/100], Loss: 0.0066
Epoch [61/100], Loss: 0.0037
Epoch [62/100], Loss: 0.0031
Epoch [63/100], Loss: 0.0065
Epoch [64/100], Loss: 0.0033
Epoch [65/100], Loss: 0.0029
Epoch [66/100], Loss: 0.0028
Epoch [67/100], Loss: 0.0020
Epoch [68/100], Loss: 0.0030
Epoch [69/100], Loss: 0.0020
Epoch [70/100], Loss: 0.0012
Epoch [71/100], Loss: 0.0014
Epoch [72/100], Loss: 0.0011
Epoch [73/100], Loss: 0.0028
Epoch [74/100], Loss: 0.0190
Epoch [75/100], Loss: 0.0384
Epoch [76/100], Loss: 0.0116
Epoch [77/100], Loss: 0.0041
Epoch [78/100], Loss: 0.0034
Epoch [79/100], Loss: 0.0024
Epoch [80/100], Loss: 0.0031
Epoch [81/100], Loss: 0.0021
Epoch [82/100], Loss: 0.0028
Epoch [83/100], Loss: 0.0166
Epoch [84/100], Loss: 0.0468
Epoch [85/100], Loss: 0.0418
Epoch [86/100], Loss: 0.0263
Epoch [87/100], Loss: 0.0159
Epoch [88/100], Loss: 0.0096
Epoch [89/100], Loss: 0.0045
Epoch [90/100], Loss: 0.0044
Epoch [91/100], Loss: 0.0119
Epoch [92/100], Loss: 0.0043
Epoch [93/100], Loss: 0.0028
Epoch [94/100], Loss: 0.0021
Epoch [95/100], Loss: 0.0017
Epoch [96/100], Loss: 0.0018
Epoch [97/100], Loss: 0.0028
Epoch [98/100], Loss: 0.0026
Epoch [99/100], Loss: 0.0018
Epoch [100/100], Loss: 0.0023
Test Accuracy: 0.8070
```

experiment by varying the depth of the MLP and document the influence on performance:

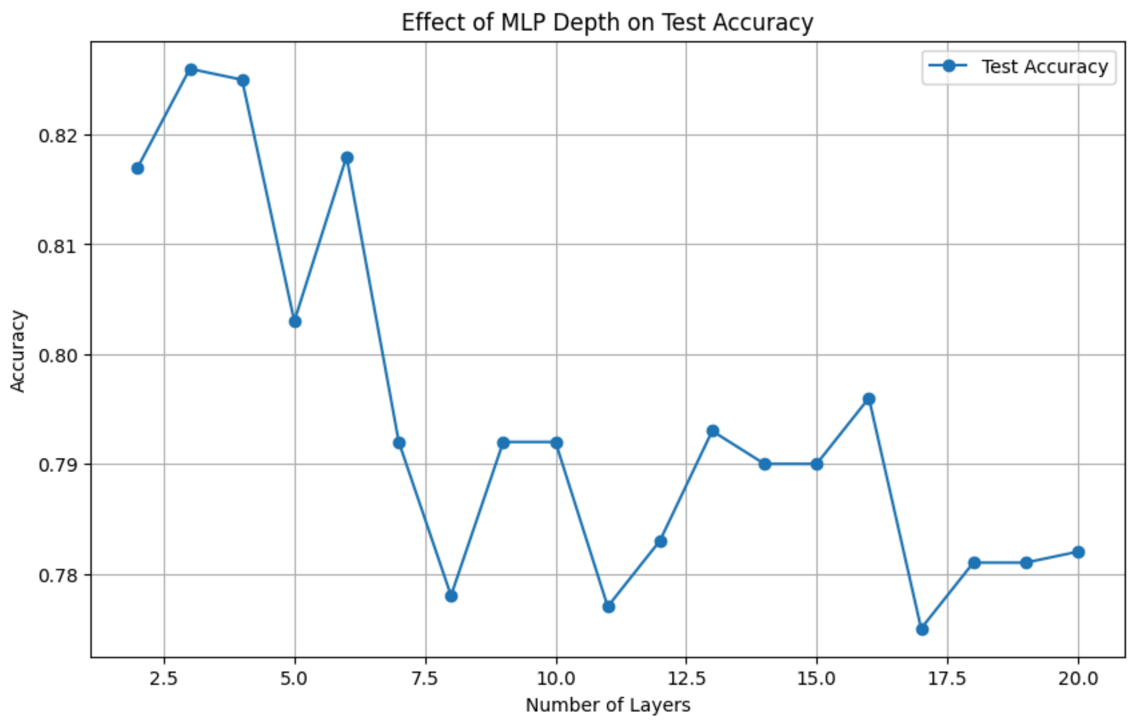
```
class MLPVariant(nn.Module):
    def __init__(self, depth):
        super(MLPVariant, self).__init__()
        layers = []


        layers.append(nn.Linear(50, 512))
        layers.append(nn.ReLU())


        for _ in range(depth - 2):  # -2 to account for input and output layers
            layers.append(nn.Linear(512, 512))
```

```
                layers.append(nn.BatchNorm1d(512))
                layers.append(nn.ReLU())


            layers.append(nn.Linear(512, 10))

            self.model = nn.Sequential(*layers)

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

    depths = [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12 , 13 , 14 , 15 , 16 , 17 , 18 , 19 , 20]
    accuracies = []

    for depth in depths:
        model = MLPVariant(depth).to(device)
        criterion = nn.CrossEntropyLoss()
        optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

        num_epochs = 10
        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)


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


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

                running_loss += loss.item()

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

            accuracy = correct / total
            print(f"Epoch [{epoch+1}/{num_epochs}], Depth: {depth}, Loss: {running_loss/len(train_loader):.4f}, Accuracy: {accuracy:.4f}")

        accuracies.append(accuracy)
        print(f"Final Depth: {depth}, Test Accuracy: {accuracy:.4f}")

    import matplotlib.pyplot as plt

    plt.figure(figsize=(10, 6))
    plt.plot(depths, accuracies, marker='o', label="Test Accuracy")
    plt.title("Effect of MLP Depth on Test Accuracy")
    plt.xlabel("Number of Layers")
    plt.ylabel("Accuracy")
    plt.grid(True)
    plt.legend()
    plt.show()
```

```
Epoch [1/10], Depth: 2, Loss: 0.8791, Accuracy: 0.7740
Epoch [2/10], Depth: 2, Loss: 0.5201, Accuracy: 0.7740
Epoch [3/10], Depth: 2, Loss: 0.4757, Accuracy: 0.8060
Epoch [4/10], Depth: 2, Loss: 0.4122, Accuracy: 0.8180
Epoch [5/10], Depth: 2, Loss: 0.3724, Accuracy: 0.8050
Epoch [6/10], Depth: 2, Loss: 0.3435, Accuracy: 0.7980
Epoch [7/10], Depth: 2, Loss: 0.3285, Accuracy: 0.8240
Epoch [8/10], Depth: 2, Loss: 0.2791, Accuracy: 0.8160
Epoch [9/10], Depth: 2, Loss: 0.2768, Accuracy: 0.8160
Epoch [10/10], Depth: 2, Loss: 0.2468, Accuracy: 0.8170
Final Depth: 2, Test Accuracy: 0.8170
Epoch [1/10], Depth: 3, Loss: 1.1277, Accuracy: 0.7630
Epoch [2/10], Depth: 3, Loss: 0.6654, Accuracy: 0.7840
Epoch [3/10], Depth: 3, Loss: 0.5618, Accuracy: 0.8000
Epoch [4/10], Depth: 3, Loss: 0.5083, Accuracy: 0.8140
Epoch [5/10], Depth: 3, Loss: 0.4646, Accuracy: 0.8180
Epoch [6/10], Depth: 3, Loss: 0.4313, Accuracy: 0.8170
Epoch [7/10], Depth: 3, Loss: 0.4111, Accuracy: 0.8290
Epoch [8/10], Depth: 3, Loss: 0.3851, Accuracy: 0.8240
Epoch [9/10], Depth: 3, Loss: 0.3543, Accuracy: 0.8340
Epoch [10/10], Depth: 3, Loss: 0.3375, Accuracy: 0.8260
Final Depth: 3, Test Accuracy: 0.8260
Epoch [1/10], Depth: 4, Loss: 1.0506, Accuracy: 0.7750
Epoch [2/10], Depth: 4, Loss: 0.6120, Accuracy: 0.7990
Epoch [3/10], Depth: 4, Loss: 0.5097, Accuracy: 0.8050
Epoch [4/10], Depth: 4, Loss: 0.4436, Accuracy: 0.8230
Epoch [5/10], Depth: 4, Loss: 0.3906, Accuracy: 0.8140
Epoch [6/10], Depth: 4, Loss: 0.3548, Accuracy: 0.8160
Epoch [7/10], Depth: 4, Loss: 0.3017, Accuracy: 0.8160
Epoch [8/10], Depth: 4, Loss: 0.2657, Accuracy: 0.8170
Epoch [9/10], Depth: 4, Loss: 0.2329, Accuracy: 0.8270
Epoch [10/10], Depth: 4, Loss: 0.2087, Accuracy: 0.8250
Final Depth: 4, Test Accuracy: 0.8250
Epoch [1/10], Depth: 5, Loss: 1.0724, Accuracy: 0.7640
Epoch [2/10], Depth: 5, Loss: 0.5944, Accuracy: 0.7970
Epoch [3/10], Depth: 5, Loss: 0.4743, Accuracy: 0.7950
Epoch [4/10], Depth: 5, Loss: 0.3942, Accuracy: 0.8010
Epoch [5/10], Depth: 5, Loss: 0.3372, Accuracy: 0.8140
Epoch [6/10], Depth: 5, Loss: 0.2822, Accuracy: 0.8140
Epoch [7/10], Depth: 5, Loss: 0.2283, Accuracy: 0.8180
Epoch [8/10], Depth: 5, Loss: 0.1916, Accuracy: 0.8160
Epoch [9/10], Depth: 5, Loss: 0.1601, Accuracy: 0.8110
Epoch [10/10], Depth: 5, Loss: 0.1341, Accuracy: 0.8030
Final Depth: 5, Test Accuracy: 0.8030
Epoch [1/10], Depth: 6, Loss: 1.0474, Accuracy: 0.7830
Epoch [2/10], Depth: 6, Loss: 0.5766, Accuracy: 0.8040
Epoch [3/10], Depth: 6, Loss: 0.4514, Accuracy: 0.8270
Epoch [4/10], Depth: 6, Loss: 0.3532, Accuracy: 0.8260
Epoch [5/10], Depth: 6, Loss: 0.2859, Accuracy: 0.8150
Epoch [6/10], Depth: 6, Loss: 0.2239, Accuracy: 0.8050
Epoch [7/10], Depth: 6, Loss: 0.1905, Accuracy: 0.8170
Epoch [8/10], Depth: 6, Loss: 0.1373, Accuracy: 0.8160
Epoch [9/10], Depth: 6, Loss: 0.1131, Accuracy: 0.8240
Epoch [10/10], Depth: 6, Loss: 0.0866, Accuracy: 0.8180
Final Depth: 6, Test Accuracy: 0.8180
Epoch [1/10], Depth: 7, Loss: 1.0998, Accuracy: 0.7700
Epoch [2/10], Depth: 7, Loss: 0.5950, Accuracy: 0.8020
Epoch [3/10], Depth: 7, Loss: 0.4404, Accuracy: 0.7970
Epoch [4/10], Depth: 7, Loss: 0.3441, Accuracy: 0.8010
Epoch [5/10], Depth: 7, Loss: 0.2635, Accuracy: 0.8070
Epoch [6/10], Depth: 7, Loss: 0.2077, Accuracy: 0.7970
Epoch [7/10], Depth: 7, Loss: 0.1668, Accuracy: 0.8020
Epoch [8/10], Depth: 7, Loss: 0.1409, Accuracy: 0.8060
Epoch [9/10], Depth: 7, Loss: 0.1035, Accuracy: 0.8090
Epoch [10/10], Depth: 7, Loss: 0.0936, Accuracy: 0.7920
Final Depth: 7, Test Accuracy: 0.7920
Epoch [1/10], Depth: 8, Loss: 1.1075, Accuracy: 0.7770
Epoch [2/10], Depth: 8, Loss: 0.5813, Accuracy: 0.8060
Epoch [3/10], Depth: 8, Loss: 0.4488, Accuracy: 0.7930
Epoch [4/10], Depth: 8, Loss: 0.3531, Accuracy: 0.7980
Epoch [5/10], Depth: 8, Loss: 0.2727, Accuracy: 0.8170
Epoch [6/10], Depth: 8, Loss: 0.2053, Accuracy: 0.8030
Epoch [7/10], Depth: 8, Loss: 0.1717, Accuracy: 0.8100
Epoch [8/10], Depth: 8, Loss: 0.1378, Accuracy: 0.7910
Epoch [9/10], Depth: 8, Loss: 0.1021, Accuracy: 0.8040
Epoch [10/10], Depth: 8, Loss: 0.0955, Accuracy: 0.7780
Final Depth: 8, Test Accuracy: 0.7780
Epoch [1/10], Depth: 9, Loss: 1.1652, Accuracy: 0.7780
Epoch [2/10], Depth: 9, Loss: 0.6125, Accuracy: 0.7930
Epoch [3/10], Depth: 9, Loss: 0.4748, Accuracy: 0.7940
Epoch [4/10], Depth: 9, Loss: 0.3843, Accuracy: 0.7920
Epoch [5/10], Depth: 9, Loss: 0.3149, Accuracy: 0.7940
Epoch [6/10], Depth: 9, Loss: 0.2581, Accuracy: 0.7980
Epoch [7/10], Depth: 9, Loss: 0.2038, Accuracy: 0.7790
```

```
Epoch [8/10], Depth: 9, Loss: 0.1580, Accuracy: 0.7960
Epoch [9/10], Depth: 9, Loss: 0.1297, Accuracy: 0.7990
Epoch [10/10], Depth: 9, Loss: 0.1210, Accuracy: 0.7920
Final Depth: 9, Test Accuracy: 0.7920
Epoch [1/10], Depth: 10, Loss: 1.1944, Accuracy: 0.7610
Epoch [2/10], Depth: 10, Loss: 0.6291, Accuracy: 0.7810
Epoch [3/10], Depth: 10, Loss: 0.5185, Accuracy: 0.7940
Epoch [4/10], Depth: 10, Loss: 0.4026, Accuracy: 0.7940
Epoch [5/10], Depth: 10, Loss: 0.3081, Accuracy: 0.8040
Epoch [6/10], Depth: 10, Loss: 0.2585, Accuracy: 0.8020
Epoch [7/10], Depth: 10, Loss: 0.2237, Accuracy: 0.7890
Epoch [8/10], Depth: 10, Loss: 0.1936, Accuracy: 0.7930
Epoch [9/10], Depth: 10, Loss: 0.1809, Accuracy: 0.7860
Epoch [10/10], Depth: 10, Loss: 0.1597, Accuracy: 0.7920
Final Depth: 10, Test Accuracy: 0.7920
Epoch [1/10], Depth: 11, Loss: 1.2556, Accuracy: 0.7610
Epoch [2/10], Depth: 11, Loss: 0.6739, Accuracy: 0.7750
Epoch [3/10], Depth: 11, Loss: 0.5504, Accuracy: 0.7870
Epoch [4/10], Depth: 11, Loss: 0.4378, Accuracy: 0.7890
Epoch [5/10], Depth: 11, Loss: 0.3626, Accuracy: 0.7900
Epoch [6/10], Depth: 11, Loss: 0.3331, Accuracy: 0.7710
Epoch [7/10], Depth: 11, Loss: 0.2650, Accuracy: 0.7730
Epoch [8/10], Depth: 11, Loss: 0.2382, Accuracy: 0.7830
Epoch [9/10], Depth: 11, Loss: 0.2303, Accuracy: 0.7730
Epoch [10/10], Depth: 11, Loss: 0.1731, Accuracy: 0.7770
Final Depth: 11, Test Accuracy: 0.7770
Epoch [1/10], Depth: 12, Loss: 1.2609, Accuracy: 0.7580
Epoch [2/10], Depth: 12, Loss: 0.7062, Accuracy: 0.7960
Epoch [3/10], Depth: 12, Loss: 0.5665, Accuracy: 0.7820
Epoch [4/10], Depth: 12, Loss: 0.4741, Accuracy: 0.8050
Epoch [5/10], Depth: 12, Loss: 0.3988, Accuracy: 0.7990
Epoch [6/10], Depth: 12, Loss: 0.3563, Accuracy: 0.7930
Epoch [7/10], Depth: 12, Loss: 0.3437, Accuracy: 0.7820
Epoch [8/10], Depth: 12, Loss: 0.2991, Accuracy: 0.7870
Epoch [9/10], Depth: 12, Loss: 0.2615, Accuracy: 0.7830
Epoch [10/10], Depth: 12, Loss: 0.2095, Accuracy: 0.7830
Final Depth: 12, Test Accuracy: 0.7830
Epoch [1/10], Depth: 13, Loss: 1.3126, Accuracy: 0.7460
Epoch [2/10], Depth: 13, Loss: 0.7417, Accuracy: 0.7930
Epoch [3/10], Depth: 13, Loss: 0.6067, Accuracy: 0.7850
Epoch [4/10], Depth: 13, Loss: 0.5189, Accuracy: 0.7970
Epoch [5/10], Depth: 13, Loss: 0.4776, Accuracy: 0.7820
Epoch [6/10], Depth: 13, Loss: 0.3934, Accuracy: 0.7850
Epoch [7/10], Depth: 13, Loss: 0.3609, Accuracy: 0.7960
Epoch [8/10], Depth: 13, Loss: 0.2942, Accuracy: 0.7800
Epoch [9/10], Depth: 13, Loss: 0.2840, Accuracy: 0.7930
Epoch [10/10], Depth: 13, Loss: 0.2312, Accuracy: 0.7930
Final Depth: 13, Test Accuracy: 0.7930
Epoch [1/10], Depth: 14, Loss: 1.4029, Accuracy: 0.7370
Epoch [2/10], Depth: 14, Loss: 0.8240, Accuracy: 0.7380
Epoch [3/10], Depth: 14, Loss: 0.6595, Accuracy: 0.7810
Epoch [4/10], Depth: 14, Loss: 0.5575, Accuracy: 0.7820
Epoch [5/10], Depth: 14, Loss: 0.4876, Accuracy: 0.7790
Epoch [6/10], Depth: 14, Loss: 0.4465, Accuracy: 0.7680
Epoch [7/10], Depth: 14, Loss: 0.3720, Accuracy: 0.7830
Epoch [8/10], Depth: 14, Loss: 0.3673, Accuracy: 0.7860
Epoch [9/10], Depth: 14, Loss: 0.3379, Accuracy: 0.7720
Epoch [10/10], Depth: 14, Loss: 0.2710, Accuracy: 0.7900
Final Depth: 14, Test Accuracy: 0.7900
Epoch [1/10], Depth: 15, Loss: 1.4646, Accuracy: 0.6920
Epoch [2/10], Depth: 15, Loss: 0.8482, Accuracy: 0.7560
Epoch [3/10], Depth: 15, Loss: 0.7074, Accuracy: 0.7530
Epoch [4/10], Depth: 15, Loss: 0.5971, Accuracy: 0.7750
Epoch [5/10], Depth: 15, Loss: 0.5412, Accuracy: 0.7670
Epoch [6/10], Depth: 15, Loss: 0.4928, Accuracy: 0.7850
Epoch [7/10], Depth: 15, Loss: 0.4288, Accuracy: 0.7870
Epoch [8/10], Depth: 15, Loss: 0.3843, Accuracy: 0.7740
Epoch [9/10], Depth: 15, Loss: 0.3346, Accuracy: 0.7850
Epoch [10/10], Depth: 15, Loss: 0.3120, Accuracy: 0.7900
Final Depth: 15, Test Accuracy: 0.7900
Epoch [1/10], Depth: 16, Loss: 1.4949, Accuracy: 0.7010
Epoch [2/10], Depth: 16, Loss: 0.9126, Accuracy: 0.7460
Epoch [3/10], Depth: 16, Loss: 0.7441, Accuracy: 0.7650
Epoch [4/10], Depth: 16, Loss: 0.6435, Accuracy: 0.7750
Epoch [5/10], Depth: 16, Loss: 0.5903, Accuracy: 0.7750
Epoch [6/10], Depth: 16, Loss: 0.5088, Accuracy: 0.7870
Epoch [7/10], Depth: 16, Loss: 0.4231, Accuracy: 0.7720
Epoch [8/10], Depth: 16, Loss: 0.4119, Accuracy: 0.7950
Epoch [9/10], Depth: 16, Loss: 0.3846, Accuracy: 0.7600
Epoch [10/10], Depth: 16, Loss: 0.3504, Accuracy: 0.7960
Final Depth: 16, Test Accuracy: 0.7960
Epoch [1/10], Depth: 17, Loss: 1.5057, Accuracy: 0.6760
Epoch [2/10], Depth: 17, Loss: 0.9184, Accuracy: 0.7430
Epoch [3/10], Depth: 17, Loss: 0.7862, Accuracy: 0.7630
Epoch [4/10], Depth: 17, Loss: 0.7013, Accuracy: 0.7600
```

```
Epoch [5/10], Depth: 17, Loss: 0.6005, Accuracy: 0.7810
Epoch [6/10], Depth: 17, Loss: 0.5717, Accuracy: 0.7830
Epoch [7/10], Depth: 17, Loss: 0.5315, Accuracy: 0.7850
Epoch [8/10], Depth: 17, Loss: 0.4548, Accuracy: 0.7900
Epoch [9/10], Depth: 17, Loss: 0.4219, Accuracy: 0.7790
Epoch [10/10], Depth: 17, Loss: 0.3731, Accuracy: 0.7750
Final Depth: 17, Test Accuracy: 0.7750
Epoch [1/10], Depth: 18, Loss: 1.5274, Accuracy: 0.6720
Epoch [2/10], Depth: 18, Loss: 0.9520, Accuracy: 0.7440
Epoch [3/10], Depth: 18, Loss: 0.8378, Accuracy: 0.7480
Epoch [4/10], Depth: 18, Loss: 0.7235, Accuracy: 0.7720
Epoch [5/10], Depth: 18, Loss: 0.6389, Accuracy: 0.7740
Epoch [6/10], Depth: 18, Loss: 0.5854, Accuracy: 0.7860
Epoch [7/10], Depth: 18, Loss: 0.5511, Accuracy: 0.7840
Epoch [8/10], Depth: 18, Loss: 0.4824, Accuracy: 0.7820
Epoch [9/10], Depth: 18, Loss: 0.4674, Accuracy: 0.7760
Epoch [10/10], Depth: 18, Loss: 0.4163, Accuracy: 0.7810
Final Depth: 18, Test Accuracy: 0.7810
Epoch [1/10], Depth: 19, Loss: 1.5800, Accuracy: 0.6720
Epoch [2/10], Depth: 19, Loss: 0.9795, Accuracy: 0.7290
Epoch [3/10], Depth: 19, Loss: 0.8651, Accuracy: 0.7270
Epoch [4/10], Depth: 19, Loss: 0.7578, Accuracy: 0.7560
Epoch [5/10], Depth: 19, Loss: 0.7010, Accuracy: 0.7730
Epoch [6/10], Depth: 19, Loss: 0.6043, Accuracy: 0.7790
Epoch [7/10], Depth: 19, Loss: 0.5818, Accuracy: 0.7710
Epoch [8/10], Depth: 19, Loss: 0.5522, Accuracy: 0.7760
Epoch [9/10], Depth: 19, Loss: 0.4883, Accuracy: 0.7940
Epoch [10/10], Depth: 19, Loss: 0.4717, Accuracy: 0.7810
Final Depth: 19, Test Accuracy: 0.7810
Epoch [1/10], Depth: 20, Loss: 1.6040, Accuracy: 0.6650
Epoch [2/10], Depth: 20, Loss: 1.0489, Accuracy: 0.7140
Epoch [3/10], Depth: 20, Loss: 0.9209, Accuracy: 0.7380
Epoch [4/10], Depth: 20, Loss: 0.8057, Accuracy: 0.7740
Epoch [5/10], Depth: 20, Loss: 0.7087, Accuracy: 0.7640
Epoch [6/10], Depth: 20, Loss: 0.6947, Accuracy: 0.7670
Epoch [7/10], Depth: 20, Loss: 0.6226, Accuracy: 0.7680
Epoch [8/10], Depth: 20, Loss: 0.5601, Accuracy: 0.7820
Epoch [9/10], Depth: 20, Loss: 0.5433, Accuracy: 0.7890
Epoch [10/10], Depth: 20, Loss: 0.5273, Accuracy: 0.7820
Final Depth: 20, Test Accuracy: 0.7820
```

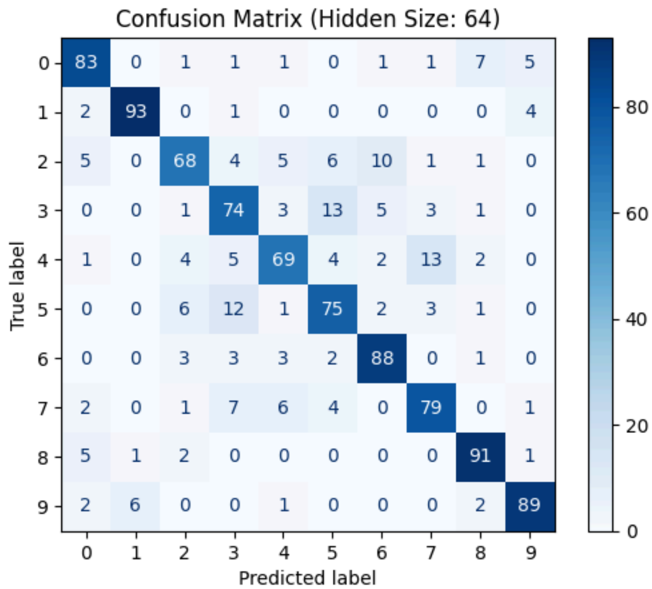


This time we vary the sizes of the hidden layers. And experiment with larger and smaller sizes. And then we analyze the trade-offs in computational cost and performance of the model.

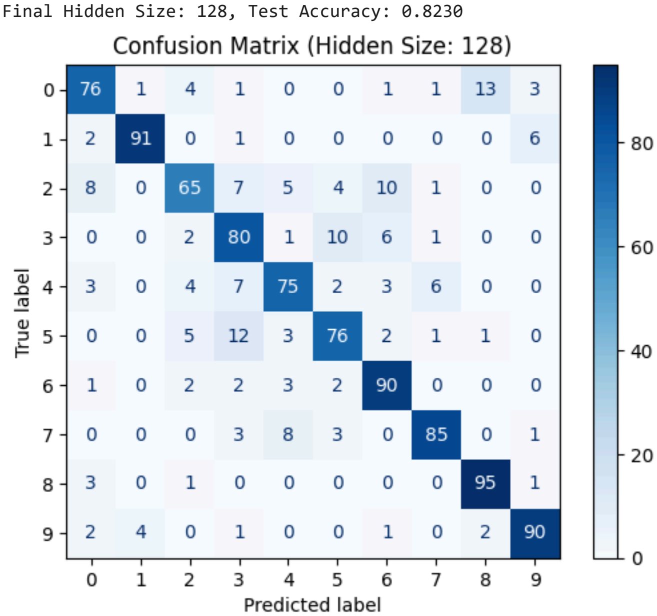
```
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classification_report
import matplotlib.pyplot as plt

class MLPVariableHidden(nn.Module):
    def __init__(self, hidden_size):
        super(MLPVariableHidden, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(50, hidden_size),
            nn.ReLU(),
            nn.Linear(hidden_size, hidden_size),
            nn.BatchNorm1d(hidden_size),
            nn.ReLU(),
            nn.Linear(hidden_size, 10)
        )

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


hidden_sizes = [64, 128, 256, 512, 1024]
accuracies = []


for hidden_size in hidden_sizes:

    model = MLPVariableHidden(hidden_size).to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

    num_epochs = 10
    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)

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

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            running_loss += loss.item()

        print(f"Epoch [{epoch+1}/{num_epochs}], Hidden Size: {hidden_size}, Loss: {running_loss/len(train_loader):.4f}")

    model.eval()
    correct = 0
    total = 0
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    accuracy = correct / total
    accuracies.append(accuracy)
    print(f"Final Hidden Size: {hidden_size}, Test Accuracy: {accuracy:.4f}")

    # Plot confusion matrix
```

```
        cm = confusion_matrix(all_labels, all_preds)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[str(i) for i in range(10)])
        disp.plot(cmap=plt.cm.Blues)
        plt.title(f'Confusion Matrix (Hidden Size: {hidden_size})')
        plt.show()

    plt.figure(figsize=(10, 6))
    plt.plot(hidden_sizes, accuracies, marker='o', label='Test Accuracy')
    plt.title('Effect of Hidden Layer Size on Test Accuracy')
    plt.xlabel('Hidden Layer Size')
    plt.ylabel('Accuracy')
    plt.grid(True)
    plt.legend()
    plt.show()
```

```
Epoch [1/10], Hidden Size: 64, Loss: 1.7655
Epoch [2/10], Hidden Size: 64, Loss: 1.1582
Epoch [3/10], Hidden Size: 64, Loss: 0.9146
Epoch [4/10], Hidden Size: 64, Loss: 0.7936
Epoch [5/10], Hidden Size: 64, Loss: 0.7111
Epoch [6/10], Hidden Size: 64, Loss: 0.6553
Epoch [7/10], Hidden Size: 64, Loss: 0.6075
Epoch [8/10], Hidden Size: 64, Loss: 0.5684
Epoch [9/10], Hidden Size: 64, Loss: 0.5492
Epoch [10/10], Hidden Size: 64, Loss: 0.5329
Final Hidden Size: 64, Test Accuracy: 0.8090
```

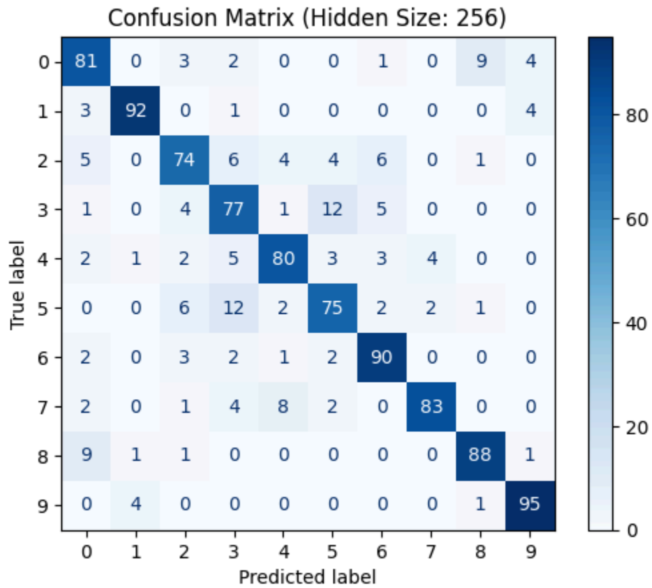



```
Epoch [1/10], Hidden Size: 128, Loss: 1.6121
Epoch [2/10], Hidden Size: 128, Loss: 0.9727
Epoch [3/10], Hidden Size: 128, Loss: 0.7769
Epoch [4/10], Hidden Size: 128, Loss: 0.6800
Epoch [5/10], Hidden Size: 128, Loss: 0.6201
Epoch [6/10], Hidden Size: 128, Loss: 0.5801
Epoch [7/10], Hidden Size: 128, Loss: 0.5453
Epoch [8/10], Hidden Size: 128, Loss: 0.5121
Epoch [9/10], Hidden Size: 128, Loss: 0.4885
Epoch [10/10], Hidden Size: 128, Loss: 0.4663
Final Hidden Size: 128, Test Accuracy: 0.8230
```

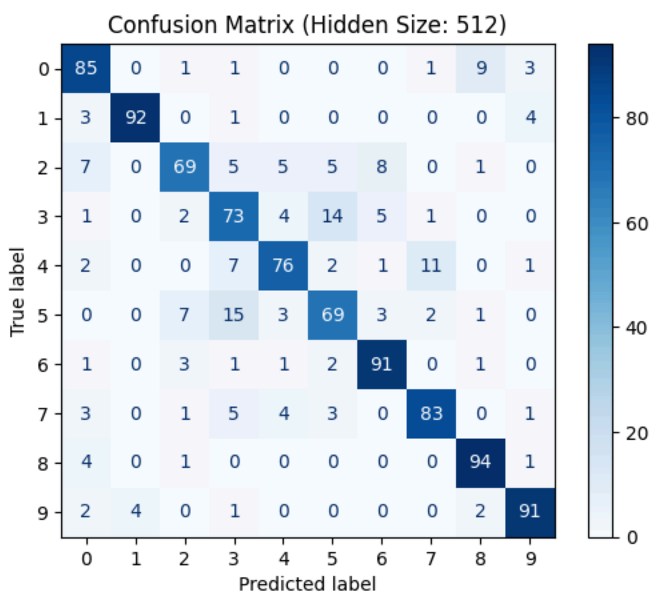



```
Epoch [1/10], Hidden Size: 256, Loss: 1.3531
Epoch [2/10], Hidden Size: 256, Loss: 0.7951
Epoch [3/10], Hidden Size: 256, Loss: 0.6702
Epoch [4/10], Hidden Size: 256, Loss: 0.5941
Epoch [5/10], Hidden Size: 256, Loss: 0.5484
Epoch [6/10], Hidden Size: 256, Loss: 0.5146
Epoch [7/10], Hidden Size: 256, Loss: 0.4852
Epoch [8/10], Hidden Size: 256, Loss: 0.4521
Epoch [9/10], Hidden Size: 256, Loss: 0.4314
Epoch [10/10], Hidden Size: 256, Loss: 0.4128
```

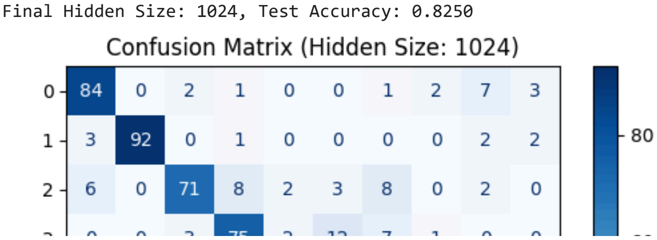
```
Final Hidden Size: 256, Test Accuracy: 0.8350
```

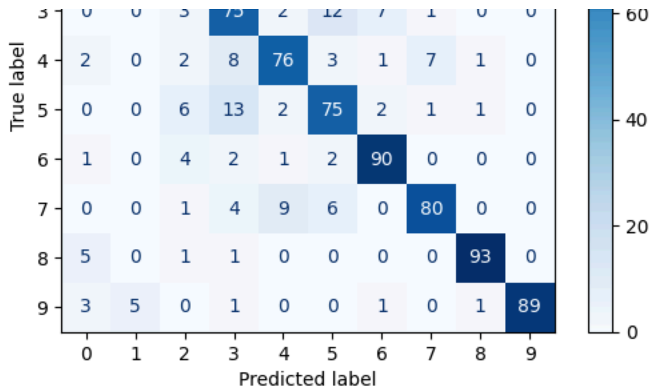


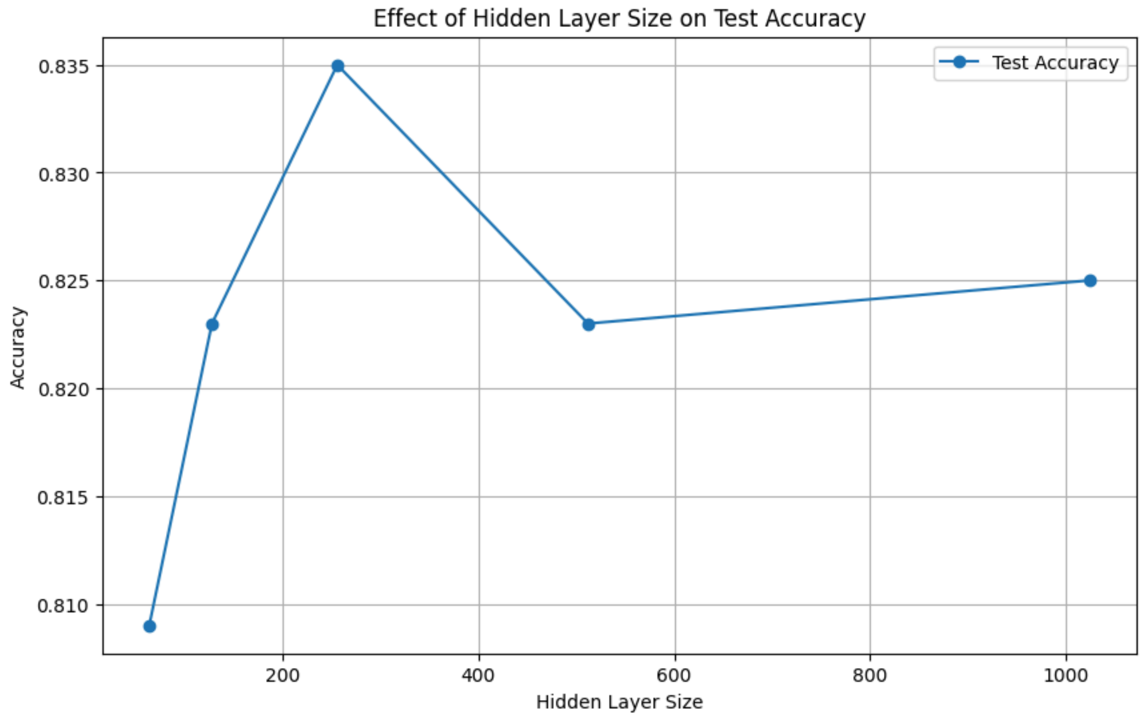

```
Epoch [1/10], Hidden Size: 512, Loss: 1.1041
Epoch [2/10], Hidden Size: 512, Loss: 0.6558
Epoch [3/10], Hidden Size: 512, Loss: 0.5735
Epoch [4/10], Hidden Size: 512, Loss: 0.5151
Epoch [5/10], Hidden Size: 512, Loss: 0.4691
Epoch [6/10], Hidden Size: 512, Loss: 0.4321
Epoch [7/10], Hidden Size: 512, Loss: 0.4069
Epoch [8/10], Hidden Size: 512, Loss: 0.3768
Epoch [9/10], Hidden Size: 512, Loss: 0.3569
Epoch [10/10], Hidden Size: 512, Loss: 0.3398
Final Hidden Size: 512, Test Accuracy: 0.8230
```




```
Epoch [1/10], Hidden Size: 1024, Loss: 0.9168
Epoch [2/10], Hidden Size: 1024, Loss: 0.5627
Epoch [3/10], Hidden Size: 1024, Loss: 0.4777
Epoch [4/10], Hidden Size: 1024, Loss: 0.4304
Epoch [5/10], Hidden Size: 1024, Loss: 0.3947
Epoch [6/10], Hidden Size: 1024, Loss: 0.3561
Epoch [7/10], Hidden Size: 1024, Loss: 0.3336
Epoch [8/10], Hidden Size: 1024, Loss: 0.2983
Epoch [9/10], Hidden Size: 1024, Loss: 0.2810
Epoch [10/10], Hidden Size: 1024, Loss: 0.2595
Final Hidden Size: 1024, Test Accuracy: 0.8250
```




True label
4 2 0 2 8 76 3 1 7 1 0
5 0 0 6 13 2 75 2 1 1 0
6 1 0 4 2 1 2 90 0 0 0
7 0 0 1 4 9 6 0 80 0 0
8 5 0 1 1 0 0 0 0 93 0
9 3 5 0 1 0 0 1 0 1 89
0 1 2 3 4 5 6 7 8 9
Predicted label
60
40
20
0


Effect of Hidden Layer Size on Test Accuracy
Test Accuracy
0.835
0.830
0.825
0.820
0.815
0.810
Accuracy
200
400
600
800
1000
Hidden Layer Size

CNN

Define the VGG11 Class

idea taken from: debugger cafe

```
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision.datasets as datasets
from torch.utils.data import DataLoader

class VGG11(nn.Module):
    def __init__(self):
        super(VGG11, self).__init__()
        self.features = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),

            nn.Conv2d(64, 128, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),

            nn.Conv2d(128, 256, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(),
            nn.Conv2d(256, 256, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),

            nn.Conv2d(256, 512, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(),
            nn.Conv2d(512, 512, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),

            nn.Conv2d(512, 512, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(),
            nn.Conv2d(512, 512, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )

        self._to_linear = nn.Sequential(
            nn.Flatten(),
            nn.Linear(512 * 1 * 1, 4096)
        )

        self.classifier = nn.Sequential(
            nn.Linear(512 * 1 * 1, 4096),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(4096, 10)
        )

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)  # Flatten the tensor
        x = self.classifier(x)
```

```
        return x
```

Data Loading and Preprocessing

```
import numpy as np

def cifar_loader(batch_size, num_train_per_class=500, num_test_per_class=100):
    normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])

    train_set = datasets.CIFAR10('./data', train=True, download=True,
                                 transform=transforms.Compose([transforms.RandomHorizontalFlip(),
                                                               transforms.RandomCrop(32, 4),
                                                               transforms.ToTensor(), normalize]))

    test_set = datasets.CIFAR10('./data', train=False, download=True,
                                transform=transforms.Compose([transforms.ToTensor(), normalize]))

    # only include the first 500 images per class for training and 100 for testing
    train_indices = []
    test_indices = []

    for class_label in range(10):
        train_class_indices = np.where(np.array(train_set.targets) == class_label)[0][:num_train_per_class]
        test_class_indices = np.where(np.array(test_set.targets) == class_label)[0][:num_test_per_class]

        train_indices.extend(train_class_indices)
        test_indices.extend(test_class_indices)

    train_subset = torch.utils.data.Subset(train_set, train_indices)
    test_subset = torch.utils.data.Subset(test_set, test_indices)

    train_loader = DataLoader(train_subset, batch_size=batch_size, shuffle=True, pin_memory=True)
    test_loader = DataLoader(test_subset, batch_size=batch_size, shuffle=False, pin_memory=True)

    return train_loader, test_loader

batch_size = 64
train_loader, test_loader = cifar_loader(batch_size)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./data/cifar-10-python.tar.gz
100%|██████████| 170M/170M [00:05<00:00, 31.1MB/s]
Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```

Inititialize the model.

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = VGG11().to(device)

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

Training the model

```
import matplotlib.pyplot as plt

train_losses = []
train_accuracies = []

num_epochs = 30

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

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

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

        # Backward pass
        loss.backward()
        optimizer.step()

        running_loss += loss.item()


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

    avg_loss = running_loss / len(train_loader)
    accuracy = 100 * correct / total
    train_losses.append(avg_loss)
    train_accuracies.append(accuracy)

    print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {avg_loss:.4f}, Accuracy: {accuracy:.2f}%')
```

```
Epoch [1/30], Loss: 2.0166, Accuracy: 24.54%
Epoch [2/30], Loss: 1.7939, Accuracy: 34.16%
Epoch [3/30], Loss: 1.6040, Accuracy: 39.38%
Epoch [4/30], Loss: 1.4678, Accuracy: 46.26%
Epoch [5/30], Loss: 1.3800, Accuracy: 50.10%
Epoch [6/30], Loss: 1.3180, Accuracy: 52.98%
Epoch [7/30], Loss: 1.2758, Accuracy: 55.14%
Epoch [8/30], Loss: 1.2064, Accuracy: 57.48%
Epoch [9/30], Loss: 1.1799, Accuracy: 59.04%
Epoch [10/30], Loss: 1.1493, Accuracy: 59.76%
Epoch [11/30], Loss: 1.0154, Accuracy: 63.98%
Epoch [12/30], Loss: 0.9843, Accuracy: 64.96%
Epoch [13/30], Loss: 0.9507, Accuracy: 66.84%
Epoch [14/30], Loss: 0.9103, Accuracy: 68.16%
Epoch [15/30], Loss: 0.8894, Accuracy: 69.92%
Epoch [16/30], Loss: 0.8477, Accuracy: 70.50%
Epoch [17/30], Loss: 0.7918, Accuracy: 73.24%
Epoch [18/30], Loss: 0.8004, Accuracy: 73.38%
Epoch [19/30], Loss: 0.7673, Accuracy: 73.24%
Epoch [20/30], Loss: 0.7453, Accuracy: 74.86%
Epoch [21/30], Loss: 0.7467, Accuracy: 74.86%
Epoch [22/30], Loss: 0.6601, Accuracy: 77.96%
Epoch [23/30], Loss: 0.6852, Accuracy: 77.26%
Epoch [24/30], Loss: 0.6190, Accuracy: 78.86%
Epoch [25/30], Loss: 0.5778, Accuracy: 80.08%
Epoch [26/30], Loss: 0.5913, Accuracy: 80.20%
Epoch [27/30], Loss: 0.6047, Accuracy: 79.58%
Epoch [28/30], Loss: 0.5404, Accuracy: 81.78%
Epoch [29/30], Loss: 0.5140, Accuracy: 83.20%
Epoch [30/30], Loss: 0.5256, Accuracy: 81.72%
```

Save the model:

code suggested by Google Gemini.

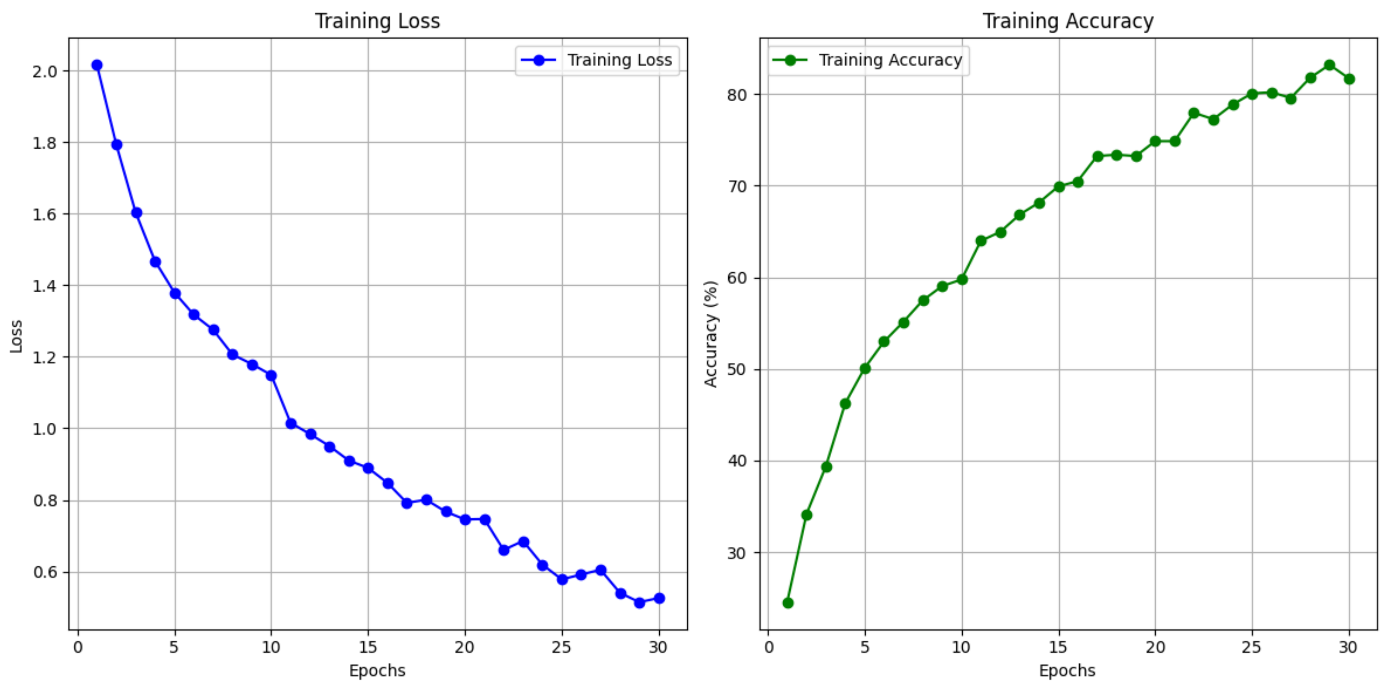
```
torch.save(model, 'vgg11_full_model.pth')
print("Full model saved to vgg11_full_model.pth")
from google.colab import files
files.download('vgg11_full_model.pth')
```

```
Full model saved to vgg11_full_model.pth
```

Training loss and accuracy:

```
epochs = range(1, num_epochs + 1)

plt.figure(figsize=(12, 6))
```

```
plt.subplot(1, 2, 1)
plt.plot(epochs, train_losses, marker='o', color='b', label='Training Loss')
plt.title('Training Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid(True)
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracies, marker='o', color='g', label='Training Accuracy')
plt.title('Training Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy (%)')
plt.grid(True)
plt.legend()

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

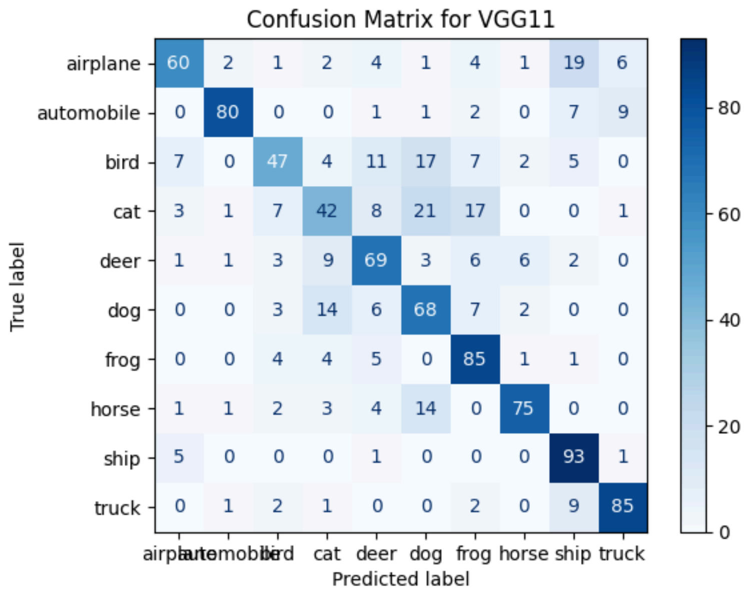


Evalute the model:

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

model.eval()
correct = 0
total = 0
all_preds = []
all_labels = []

with torch.no_grad():
    for inputs, labels in test_loader:
        inputs, labels = inputs.to(device), labels.to(device)
        outputs = model(inputs)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
        all_preds.extend(predicted.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

accuracy = correct / total
print(f"Test Accuracy: {accuracy:.4f}")
```

```
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']


cm = confusion_matrix(all_labels, all_preds)
cm_display = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)


cm_display.plot(cmap='Blues')
plt.title('Confusion Matrix for VGG11')
plt.show()
```

```
Test Accuracy: 0.7040
```



Experiment with the model by adding and removing laters.

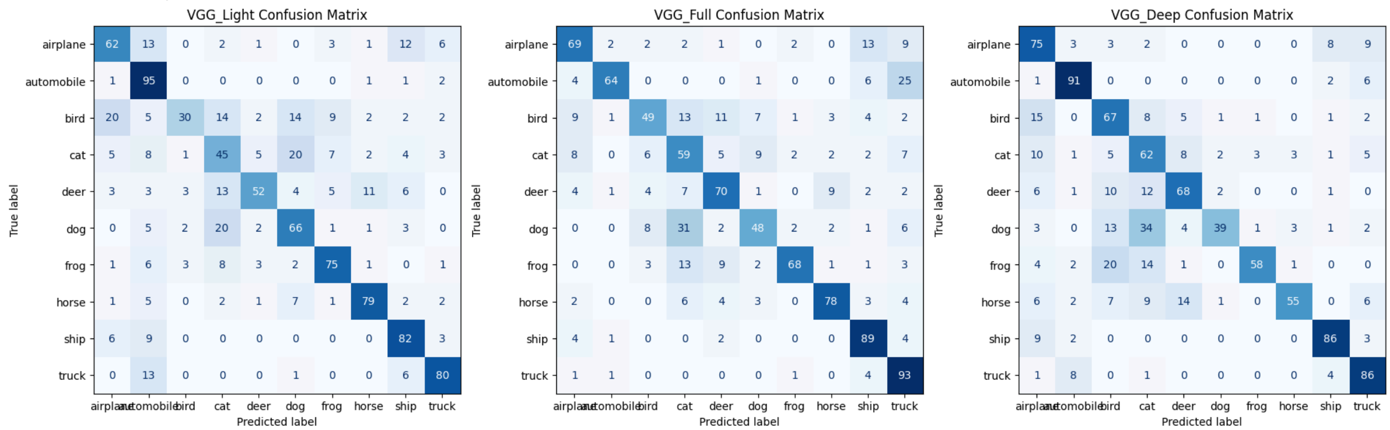
we will define a custome VG11 class for this.

```
# modified VGG architectures (idea from : https://debuggercafe.com/implementing-vgg11-from-scratch-using-pytorch/)
class ModifiedVGG(nn.Module):
    def __init__(self, layers_config):
        super(ModifiedVGG, self).__init__()
        layers = []
        in_channels = 3
        for config in layers_config:
            if config == 'M':
                layers += [nn.MaxPool2d(kernel_size=2, stride=2)]
            else:
                layers += [
                    nn.Conv2d(in_channels, config, kernel_size=3, padding=1),
                    nn.BatchNorm2d(config),
                    nn.ReLU(inplace=True)
                ]
                in_channels = config
        self.features = nn.Sequential(*layers)

        def compute_fc_input_size(x):
            x = self.features(x)
            return x.view(x.size(0), -1)


        dummy_input = torch.zeros(1, 3, 32, 32)
        self.fc_input_size = compute_fc_input_size(dummy_input).size(1)

        self.classifier = nn.Sequential(
            nn.Linear(self.fc_input_size, 4096),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(),
```

```
            nn.Dropout(0.5),
            nn.Linear(4096, 10)
        )

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.classifier(x)
        return x


layer_configs = {
    "VGG_Light": [64, 'M', 128, 'M', 256, 'M', 512, 'M'],
    "VGG_Full": [64, 'M', 128, 'M', 256, 256, 'M', 512, 512, 'M', 512, 512, 'M'],
    "VGG_Deep": [64, 64, 'M', 128, 128, 'M', 256, 256, 256, 'M', 512, 512, 512, 'M']
}


results = {}
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')


batch_size = 64
train_loader, test_loader = cifar_loader(batch_size)

for name, config in layer_configs.items():
    print(f"\nTraining {name}...")
    model = ModifiedVGG(config).to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)

    num_epochs = 30
    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)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()
        print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader):.4f}")

    model.eval()
    all_preds = []
    all_labels = []
    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            _, predicted = torch.max(outputs, 1)
            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    acc = sum(1 for x, y in zip(all_preds, all_labels) if x == y) / len(all_labels)
    cm = confusion_matrix(all_labels, all_preds)
    results[name] = {'accuracy': acc, 'confusion_matrix': cm}
    print(f"{name} Accuracy: {acc:.4f}")


fig, axes = plt.subplots(1, 3, figsize=(18, 6))
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
for ax, (name, result) in zip(axes, results.items()):
    cm_display = ConfusionMatrixDisplay(confusion_matrix=result['confusion_matrix'], display_labels=class_names)
    cm_display.plot(ax=ax, cmap='Blues', colorbar=False)
    ax.set_title(f"{name} Confusion Matrix")
plt.tight_layout()
plt.show()


results
```

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

Training VGG_Light...
Epoch [1/30], Loss: 2.0073
Epoch [2/30], Loss: 1.7059
Epoch [3/30], Loss: 1.6278
Epoch [4/30], Loss: 1.5147
Epoch [5/30], Loss: 1.4475
Epoch [6/30], Loss: 1.3815
Epoch [7/30], Loss: 1.3442
Epoch [8/30], Loss: 1.2764
Epoch [9/30], Loss: 1.2258
Epoch [10/30], Loss: 1.2398
Epoch [11/30], Loss: 1.1812
Epoch [12/30], Loss: 1.1641
Epoch [13/30], Loss: 1.0954
Epoch [14/30], Loss: 1.0569
Epoch [15/30], Loss: 1.0449
Epoch [16/30], Loss: 0.9909
Epoch [17/30], Loss: 0.9842
Epoch [18/30], Loss: 0.9685
Epoch [19/30], Loss: 0.9411
Epoch [20/30], Loss: 0.9059
Epoch [21/30], Loss: 0.8828
Epoch [22/30], Loss: 0.8675
Epoch [23/30], Loss: 0.8615
Epoch [24/30], Loss: 0.8204
Epoch [25/30], Loss: 0.7983
Epoch [26/30], Loss: 0.7795
Epoch [27/30], Loss: 0.7742
Epoch [28/30], Loss: 0.7298
Epoch [29/30], Loss: 0.7288
Epoch [30/30], Loss: 0.7435
VGG_Light Accuracy: 0.6660

Training VGG_Full...
Epoch [1/30], Loss: 2.0195
Epoch [2/30], Loss: 1.7245
Epoch [3/30], Loss: 1.5631
Epoch [4/30], Loss: 1.4857
Epoch [5/30], Loss: 1.3918
Epoch [6/30], Loss: 1.3131
Epoch [7/30], Loss: 1.2621
Epoch [8/30], Loss: 1.1862
Epoch [9/30], Loss: 1.1328
Epoch [10/30], Loss: 1.0784
Epoch [11/30], Loss: 1.0115
Epoch [12/30], Loss: 0.9916
Epoch [13/30], Loss: 0.9212
Epoch [14/30], Loss: 0.8869
Epoch [15/30], Loss: 0.8839
Epoch [16/30], Loss: 0.8476
Epoch [17/30], Loss: 0.7727
Epoch [18/30], Loss: 0.7865
Epoch [19/30], Loss: 0.7636
Epoch [20/30], Loss: 0.7167
Epoch [21/30], Loss: 0.7518
Epoch [22/30], Loss: 0.6855
Epoch [23/30], Loss: 0.6588
Epoch [24/30], Loss: 0.6342
Epoch [25/30], Loss: 0.6024
Epoch [26/30], Loss: 0.5678
Epoch [27/30], Loss: 0.5377
Epoch [28/30], Loss: 0.5390
Epoch [29/30], Loss: 0.5025
Epoch [30/30], Loss: 0.5374
VGG_Full Accuracy: 0.6870

Training VGG_Deep...
Epoch [1/30], Loss: 2.0425
Epoch [2/30], Loss: 1.7501
Epoch [3/30], Loss: 1.6213
Epoch [4/30], Loss: 1.5043
Epoch [5/30], Loss: 1.4728
Epoch [6/30], Loss: 1.3740
Epoch [7/30], Loss: 1.3240
Epoch [8/30], Loss: 1.2165
Epoch [9/30], Loss: 1.1592
Epoch [10/30], Loss: 1.0765
Epoch [11/30], Loss: 1.1188
Epoch [12/30], Loss: 0.9757
Epoch [13/30], Loss: 0.9426
Epoch [14/30], Loss: 0.9410
```

```
Epoch [15/30], Loss: 0.8962
Epoch [16/30], Loss: 0.8201
Epoch [17/30], Loss: 0.7881
Epoch [18/30], Loss: 0.7345
Epoch [19/30], Loss: 0.7307
Epoch [20/30], Loss: 0.7081
Epoch [21/30], Loss: 0.7032
Epoch [22/30], Loss: 0.6438
Epoch [23/30], Loss: 0.6428
Epoch [24/30], Loss: 0.6424
Epoch [25/30], Loss: 0.5928
Epoch [26/30], Loss: 0.5356
Epoch [27/30], Loss: 0.6016
Epoch [28/30], Loss: 0.4859
Epoch [29/30], Loss: 0.5100
Epoch [30/30], Loss: 0.4892
VGG_Deep Accuracy: 0.6870
```




```
{'VGG_Light': {'accuracy': 0.666,
  'confusion_matrix': array([[62, 13,  0,  2,  1,  0,  3,  1, 12,  6],
        [ 1, 95,  0,  0,  0,  0,  0,  1,  1,  2],
        [20,  5, 30, 14,  2, 14,  9,  2,  2,  2],
        [ 5,  8,  1, 45,  5, 20,  7,  2,  4,  3],
        [ 3,  3,  3, 13, 52,  4,  5, 11,  6,  0],
        [ 0,  5,  2, 20,  2, 66,  1,  1,  3,  0],
        [ 1,  6,  3,  8,  3,  2, 75,  1,  0,  1],
        [ 1,  5,  0,  2,  1,  7,  1, 79,  2,  2],
        [ 6,  9,  0,  0,  0,  0,  0,  0, 82,  3],
        [ 0, 13,  0,  0,  0,  1,  0,  0,  6, 80]])},
 'VGG_Full': {'accuracy': 0.687,
  'confusion_matrix': array([[69,  2,  2,  2,  1,  0,  2,  0, 13,  9],
        [ 4, 64,  0,  0,  0,  1,  0,  0,  6, 25],
        [ 9,  1, 49, 13, 11,  7,  1,  3,  4,  2],
        [ 8,  0,  6, 59,  5,  9,  2,  2,  2,  7],
        [ 4,  1,  4,  7, 70,  1,  0,  9,  2,  2],
        [ 0,  0,  8, 31,  2, 48,  2,  2,  1,  6],
        [ 0,  0,  3, 13,  9,  2, 68,  1,  1,  3],
        [ 2,  0,  0,  6,  4,  3,  0, 78,  3,  4],
        [ 4,  1,  0,  0,  2,  0,  0,  0, 89,  4],
        [ 1,  1,  0,  0,  0,  0,  1,  0,  4, 93]])},
 'VGG_Deep': {'accuracy': 0.687,
  'confusion_matrix': array([[75,  3,  3,  2,  0,  0,  0,  0,  8,  9],
        [ 1, 91,  0,  0,  0,  0,  0,  0,  2,  6],
        [15,  0, 67,  8,  5,  1,  1,  0,  1,  2],
        [10,  1,  5, 62,  8,  2,  3,  3,  1,  5],
        [ 6,  1, 10, 12, 68,  2,  0,  0,  1,  0],
        [ 3,  0, 13, 34,  4, 39,  1,  3,  1,  2],
        [ 4,  2, 20, 14,  1,  0, 58,  1,  0,  0],
        [ 6,  2,  7,  9, 14,  1,  0, 55,  0,  6],
        [ 9,  2,  0,  0,  0,  0,  0,  0, 86,  3],
        [ 1,  8,  0,  1,  0,  0,  0,  0,  4, 86]])}}
```

Double-click (or enter) to edit

Modified VGG Class with Adjustable Kernel Sizes:

```
class ModifiedVGGWithKernels(nn.Module):
    def __init__(self, layers_config, kernel_size=3):
        super(ModifiedVGGWithKernels, self).__init__()
        layers = []
        in_channels = 3
        for config in layers_config:
            if config == 'M':
                layers += [nn.MaxPool2d(kernel_size=2, stride=2)]
            else:
                layers += [
                    nn.Conv2d(in_channels, config, kernel_size=kernel_size, padding=kernel_size//2),
                    nn.BatchNorm2d(config),
                    nn.ReLU(inplace=True)
                ]
                in_channels = config
        self.features = nn.Sequential(*layers)


        def compute_fc_input_size(x):
            x = self.features(x)
            return x.view(x.size(0), -1)

        dummy_input = torch.zeros(1, 3, 32, 32)
        self.fc_input_size = compute_fc_input_size(dummy_input).size(1)

        self.classifier = nn.Sequential(
            nn.Linear(self.fc_input_size, 4096),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(4096, 10)
        )

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.classifier(x)
        return x
```

Experiment with different Kernel sizes:

```
kernel_sizes = [2, 3, 5, 7]
results_kernel_sizes = {}


for kernel_size in kernel_sizes:
    print(f"\nTraining with kernel size {kernel_size}x{kernel_size}...")

    model = ModifiedVGGWithKernels([64, 'M', 128, 'M', 256, 'M', 512, 'M'], kernel_size).to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)

    num_epochs = 30
    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)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()
```

```
            print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader):.4f}")

        model.eval()
        all_preds = []
        all_labels = []
        with torch.no_grad():
            for inputs, labels in test_loader:
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = model(inputs)
                _, predicted = torch.max(outputs, 1)
                all_preds.extend(predicted.cpu().numpy())
                all_labels.extend(labels.cpu().numpy())

        acc = sum(1 for x, y in zip(all_preds, all_labels) if x == y) / len(all_labels)
        cm = confusion_matrix(all_labels, all_preds)
        results_kernel_sizes[kernel_size] = {'accuracy': acc, 'confusion_matrix': cm}
        print(f"Kernel size {kernel_size}x{kernel_size} Accuracy: {acc:.4f}")


    fig, axes = plt.subplots(1, len(kernel_sizes), figsize=(18, 6))
    class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
    for ax, (kernel_size, result) in zip(axes, results_kernel_sizes.items()):
        cm_display = ConfusionMatrixDisplay(confusion_matrix=result['confusion_matrix'], display_labels=class_names)
        cm_display.plot(ax=ax, cmap='Blues', colorbar=False)
        ax.set_title(f"Kernel {kernel_size}x{kernel_size}")
    plt.tight_layout()
    plt.show()

    results_kernel_sizes
```