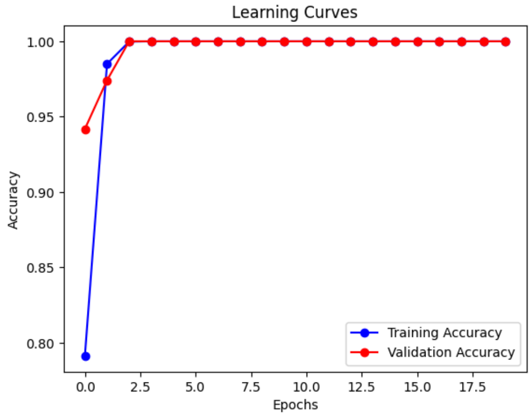
Deep Learning - Training a Simple Convolution Neural Network Model

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
import matplotlib.pyplot as plt

# Step 1: Define image dimensions, batch size, and directory paths
image_height = 100
image_width = 100
batch_size = 32

train_dir = '/content/drive/MyDrive/TrainingImages/'

# Step 2: Data generators for training
train_datagen = tf.keras.preprocessing.image.ImageDataGenerator(rescale=1./255, validation_split=0.1)

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(image_height, image_width),
    batch_size=batch_size,
    class_mode='categorical',
    subset='training'  # Use only training data
)

validation_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(image_height, image_width),
    batch_size=batch_size,
    class_mode='categorical',
    subset='validation'  # Use only validation data
)

# Step 3: Define the model architecture
model = Sequential([
    Conv2D(8, (3, 3), activation='relu', input_shape=(image_height, image_width, 3)),
    Conv2D(8, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(16, activation='relu'),
    Dense(16, activation='relu'),
    Dense(10, activation='softmax')
])

# Step 4: Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Step 5: Train the model
history = model.fit(train_generator,
                    epochs=20,
                    validation_data=validation_generator)

# Step 6(a): Plot learning curves
plt.plot(history.history['accuracy'], marker='o', label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], marker='o', label='Validation Accuracy', color='red')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Learning Curves')
plt.legend()
plt.show()
```

```
Found 4201 images belonging to 10 classes.
Found 464 images belonging to 10 classes.
Epoch 1/20
132/132 [==============================] - 1132s 9s/step - loss: 0.6253 - accuracy: 0.7912 - val_loss: 0.1014 - val_accuracy: 0.9418
Epoch 2/20
132/132 [==============================] - 43s 323ms/step - loss: 0.0557 - accuracy: 0.9850 - val_loss: 0.0454 - val_accuracy: 0.9741
Epoch 3/20
132/132 [==============================] - 42s 319ms/step - loss: 0.0071 - accuracy: 0.9998 - val_loss: 0.0182 - val_accuracy: 1.0000
Epoch 4/20
132/132 [==============================] - 42s 315ms/step - loss: 0.0024 - accuracy: 1.0000 - val_loss: 0.0120 - val_accuracy: 1.0000
Epoch 5/20
132/132 [==============================] - 42s 320ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.0060 - val_accuracy: 1.0000
Epoch 6/20
132/132 [==============================] - 45s 336ms/step - loss: 8.8531e-04 - accuracy: 1.0000 - val_loss: 0.0059 - val_accuracy: 1.0000
Epoch 7/20
132/132 [==============================] - 50s 378ms/step - loss: 5.9167e-04 - accuracy: 1.0000 - val_loss: 0.0054 - val_accuracy: 1.0000
Epoch 8/20
132/132 [==============================] - 50s 371ms/step - loss: 4.7020e-04 - accuracy: 1.0000 - val_loss: 0.0034 - val_accuracy: 1.0000
Epoch 9/20
132/132 [==============================] - 52s 392ms/step - loss: 3.3961e-04 - accuracy: 1.0000 - val_loss: 0.0031 - val_accuracy: 1.0000
Epoch 10/20
132/132 [==============================] - 47s 354ms/step - loss: 2.9397e-04 - accuracy: 1.0000 - val_loss: 0.0033 - val_accuracy: 1.0000
Epoch 11/20
132/132 [==============================] - 49s 373ms/step - loss: 2.2164e-04 - accuracy: 1.0000 - val_loss: 0.0030 - val_accuracy: 1.0000
Epoch 12/20
132/132 [==============================] - 49s 374ms/step - loss: 1.8589e-04 - accuracy: 1.0000 - val_loss: 0.0027 - val_accuracy: 1.0000
Epoch 13/20
132/132 [==============================] - 49s 369ms/step - loss: 1.5092e-04 - accuracy: 1.0000 - val_loss: 0.0026 - val_accuracy: 1.0000
Epoch 14/20
132/132 [==============================] - 46s 350ms/step - loss: 1.2612e-04 - accuracy: 1.0000 - val_loss: 0.0027 - val_accuracy: 1.0000
Epoch 15/20
132/132 [==============================] - 47s 354ms/step - loss: 1.1067e-04 - accuracy: 1.0000 - val_loss: 0.0024 - val_accuracy: 1.0000
Epoch 16/20
132/132 [==============================] - 50s 378ms/step - loss: 9.7127e-05 - accuracy: 1.0000 - val_loss: 0.0019 - val_accuracy: 1.0000
Epoch 17/20
132/132 [==============================] - 49s 368ms/step - loss: 8.1076e-05 - accuracy: 1.0000 - val_loss: 0.0013 - val_accuracy: 1.0000
Epoch 18/20
132/132 [==============================] - 47s 356ms/step - loss: 8.2567e-05 - accuracy: 1.0000 - val_loss: 0.0015 - val_accuracy: 1.0000
Epoch 19/20
132/132 [==============================] - 47s 359ms/step - loss: 6.2960e-05 - accuracy: 1.0000 - val_loss: 0.0016 - val_accuracy: 1.0000
Epoch 20/20
132/132 [==============================] - 47s 358ms/step - loss: 5.5807e-05 - accuracy: 1.0000 - val_loss: 0.0015 - val_accuracy: 1.0000
```



Transfer Learning via Feature Extraction

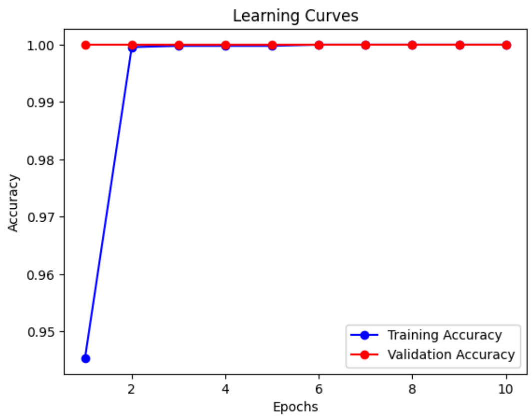
```
import torch
import torchvision
import torch.nn as nn
import torch.nn.functional as F
import matplotlib.pyplot as plt
import numpy as np
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split

# Step 1: Define configuration variables
image_height = 224  # Modified image height
image_width = 224  # Modified image width
batch_size = 32
```

```
num_classes = 10
num_epochs = 10
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Step 2: Load the dataset using ImageDataLoader and organize it on disk
train_dir = "/content/drive/MyDrive/TrainingImages/"
test_dir = "/content/drive/MyDrive/TestingImages/"

train_dataset = torchvision.datasets.ImageFolder(
    root=train_dir,
    transform=torchvision.transforms.Compose([
        torchvision.transforms.Resize((image_height, image_width)),
        torchvision.transforms.ToTensor(),
    ])
)

test_dataset = torchvision.datasets.ImageFolder(
    root=test_dir,
    transform=torchvision.transforms.Compose([
        torchvision.transforms.Resize((image_height, image_width)),
        torchvision.transforms.ToTensor(),
    ])
)

# Define data loaders for training and testing
train_loader = torch.utils.data.DataLoader(
    train_dataset,
    batch_size=batch_size,
    shuffle=True
)

test_loader = torch.utils.data.DataLoader(
    test_dataset,
    batch_size=batch_size,
    shuffle=False
)

# Define a function to calculate accuracy
def calculate_accuracy(loader, model):
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
    return correct / total

# Define the model, criterion, and optimizer
resnet18 = torchvision.models.resnet18(pretrained=True)
for param in resnet18.parameters():
    param.requires_grad = False

num_ftrs = resnet18.fc.in_features
resnet18.fc = nn.Linear(num_ftrs, num_classes)
resnet18 = resnet18.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(resnet18.parameters(), lr=0.001)

# Lists to store training and validation accuracies
train_accuracies, val_accuracies = [], []

# Train the model
for epoch in range(num_epochs):
    running_loss = 0.0
    correct_train, total_train = 0, 0
    resnet18.train()

    # Use train_loader for both training and validation
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = resnet18(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

        # Calculate training accuracy
        _, predicted = torch.max(outputs.data, 1)
```

```
        _, predicted = torch.max(outputs.data, 1)
        total_train += labels.size(0)
        correct_train += (predicted == labels).sum().item()

    # Calculate training accuracy
    train_accuracy = correct_train / total_train
    train_accuracies.append(train_accuracy)

    # Calculate validation accuracy
    val_accuracy = calculate_accuracy(train_loader, resnet18)  # Use train_loader for validation
    val_accuracies.append(val_accuracy)

    print("Epoch: {}/{}.. ".format(epoch+1, num_epochs),
          "Training Loss: {:.3f}.. ".format(running_loss/len(train_loader)),
          "Training Accuracy: {:.3f}.. ".format(train_accuracy),
          "Validation Accuracy: {:.3f}".format(val_accuracy))

# Plot learning curves
epochs = range(1, num_epochs + 1)
plt.plot(epochs, train_accuracies, marker='o', label='Training Accuracy', color='blue')
plt.plot(epochs, val_accuracies, marker='o', label='Validation Accuracy', color='red')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Learning Curves')
plt.legend()
plt.show()


# Step 6: Extract features from ResNet18 for training and test datasets
class FeatureExtractor:
    def __init__(self, model):
        self.model = model
        self.features = None
        self.hook = self.model.layer4.register_forward_hook(self.hook_fn)

    def hook_fn(self, module, input, output):
        self.features = output

    def extract(self, x):
        self.model(x)
        return self.features

train_feature_extractor = FeatureExtractor(resnet18)
test_feature_extractor = FeatureExtractor(resnet18)

train_features = []
train_labels = []

test_features = []
test_labels = []

# Extract features and labels from the training dataset
for images, labels in train_loader:
    features_batch = train_feature_extractor.extract(images.to(device))
    train_features.append(features_batch.detach().cpu().numpy())
    train_labels.append(labels.numpy())

# Extract features and labels from the test dataset
for images, labels in test_loader:
    features_batch = test_feature_extractor.extract(images.to(device))
    test_features.append(features_batch.detach().cpu().numpy())
    test_labels.append(labels.numpy())

train_features = np.concatenate(train_features)
train_labels = np.concatenate(train_labels)
test_features = np.concatenate(test_features)
test_labels = np.concatenate(test_labels)


# Flatten the features
train_features_flattened = train_features.reshape(train_features.shape[0], -1)
test_features_flattened = test_features.reshape(test_features.shape[0], -1)

# Step 7: Train SVM prediction model using extracted features
svm_model = SVC(kernel='rbf', C=10)
svm_model.fit(train_features_flattened, train_labels)

# Step 8: Evaluate SVM model
train_predictions = svm_model.predict(train_features_flattened)
test_predictions = svm_model.predict(test_features_flattened)

train_accuracy = accuracy_score(train_labels, train_predictions)
test_accuracy = accuracy_score(test_labels, test_predictions)
```

```
print("SVM Training Accuracy", train_accuracy)
print("SVM Test Accuracy", test_accuracy)
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent t
  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, 87.6MB/s]
Epoch: 1/10..  Training Loss: 0.387..  Training Accuracy: 0.945..  Validation Accuracy: 1.000
Epoch: 2/10..  Training Loss: 0.042..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 3/10..  Training Loss: 0.020..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 4/10..  Training Loss: 0.013..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 5/10..  Training Loss: 0.009..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 6/10..  Training Loss: 0.007..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 7/10..  Training Loss: 0.005..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 8/10..  Training Loss: 0.004..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 9/10..  Training Loss: 0.004..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
Epoch: 10/10..  Training Loss: 0.003..  Training Accuracy: 1.000..  Validation Accuracy: 1.000
```




```
SVM Training Accuracy 1.0
SVM Test Accuracy 1.0
```

Transfer Learning via Fine-Tuning

```
import torch
import torchvision
import torch.nn as nn
import torch.nn.functional as F
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split

# Step 1: Define configuration variables
image_height = 224  # Modified image height
image_width = 224  # Modified image width
batch_size = 32
num_classes = 10
num_epochs = 10
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Step 2: Load the dataset using ImageDataLoader and organize it on disk
train_dir = "/content/drive/MyDrive/TrainingImages/"
test_dir = "/content/drive/MyDrive/TestingImages/"

# Load the dataset without splitting
full_dataset = torchvision.datasets.ImageFolder(
    root=train_dir,
    transform=torchvision.transforms.Compose([
        torchvision.transforms.Resize((image_height, image_width)),
        torchvision.transforms.ToTensor(),
    ])
)

# Split the training dataset into training and validation sets manually
val_split = 0.1
train_size = int(len(full_dataset) * (1 - val_split))
```

```
val_size = len(full_dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(full_dataset, [train_size, val_size])

train_loader = torch.utils.data.DataLoader(
    train_dataset,
    batch_size=batch_size,
    shuffle=True
)

val_loader = torch.utils.data.DataLoader(
    val_dataset,
    batch_size=batch_size,
    shuffle=False
)

test_dataset = torchvision.datasets.ImageFolder(
    root=test_dir,
    transform=torchvision.transforms.Compose([
        torchvision.transforms.Resize((image_height, image_width)),
        torchvision.transforms.ToTensor(),
    ])
)

test_loader = torch.utils.data.DataLoader(
    test_dataset,
    batch_size=batch_size,
    shuffle=False
)

# Step 3: Build the model (fine-tuning)
resnet18 = torchvision.models.resnet18(weights=None)
num_ftrs = resnet18.fc.in_features
resnet18.fc = nn.Linear(num_ftrs, num_classes).to(device)
resnet18 = resnet18.to(device)

# Step 4: Train the model
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(resnet18.parameters(), lr=0.001)

train_accuracies, val_accuracies, test_accuracies = [], [], []

# Train the model
for epoch in range(num_epochs):
    running_loss = 0.0
    correct_train, total_train = 0, 0
    resnet18.train()
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = resnet18(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

        # Calculate training accuracy
        _, predicted = torch.max(outputs.data, 1)
        total_train += labels.size(0)
        correct_train += (predicted == labels).sum().item()

    # Calculate training accuracy
    train_accuracy = correct_train / total_train
    train_accuracies.append(train_accuracy)

    # Evaluate on validation set
    resnet18.eval()
    correct_val, total_val = 0, 0
    with torch.no_grad():
        for images, labels in val_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = resnet18(images)
            _, predicted = torch.max(outputs.data, 1)
            total_val += labels.size(0)
            correct_val += (predicted == labels).sum().item()

    val_accuracy = correct_val / total_val
    val_accuracies.append(val_accuracy)

    print("Epoch: {}/{}.. ".format(epoch+1, num_epochs),
          "Training Loss: {:.3f}.. ".format(running_loss/len(train_loader)),
          "Training Accuracy: {:.3f}.. ".format(train_accuracy),
          "Validation Accuracy: {:.3f}".format(val_accuracy))

# Step 5: Plot learning curves
```

```
epochs = range(1, num_epochs + 1)
plt.plot(epochs, train_accuracies, marker='o', label='Training Accuracy', color='blue')
plt.plot(epochs, val_accuracies, marker='o', label='Validation Accuracy', color='green')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Learning Curves')
plt.legend()
plt.show()
```

```
Epoch: 1/10..  Training Loss: 0.304..  Training Accuracy: 0.901..  Validation Accuracy: 0.989
Epoch: 2/10..  Training Loss: 0.143..  Training Accuracy: 0.956..  Validation Accuracy: 0.749
Epoch: 3/10..  Training Loss: 0.095..  Training Accuracy: 0.969..  Validation Accuracy: 1.000
Epoch: 4/10..  Training Loss: 0.050..  Training Accuracy: 0.984..  Validation Accuracy: 0.747
Epoch: 5/10..  Training Loss: 0.023..  Training Accuracy: 0.994..  Validation Accuracy: 0.987
Epoch: 6/10..  Training Loss: 0.017..  Training Accuracy: 0.995..  Validation Accuracy: 0.520
Epoch: 7/10..  Training Loss: 0.102..  Training Accuracy: 0.976..  Validation Accuracy: 0.786
Epoch: 8/10..  Training Loss: 0.113..  Training Accuracy: 0.960..  Validation Accuracy: 0.591
Epoch: 9/10..  Training Loss: 0.033..  Training Accuracy: 0.990..  Validation Accuracy: 0.756
Epoch: 10/10..  Training Loss: 0.013..  Training Accuracy: 0.998..  Validation Accuracy: 1.000
```