Importing Libraries

In [1]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, random_split
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import itertools
import numpy as np
from torchsummary import summary
from torchvision import models
import torch.nn.functional as F
#import seaborn as sns
#from sklearn.metrics import confusion_matrix
```

Set Device (GPU)

In [2]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

Out[2]:
```
device(type='cuda')
```

Data Transformations for Training and Testing

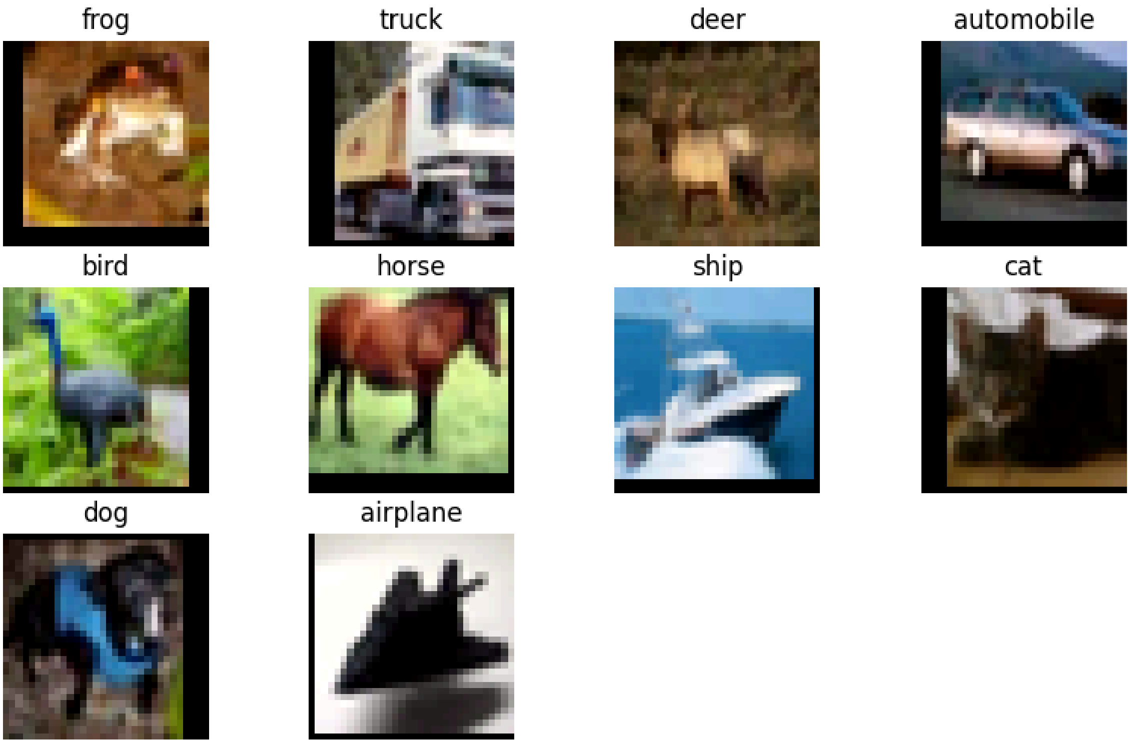
In [3]:
```
# Data Transformations
transform_train = transforms.Compose([
    transforms.RandomCrop(32, padding=4),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)),
])

transform_test = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)),
])

mean = [0.4914, 0.4822, 0.4465]
std = [0.2023, 0.1994, 0.2010]
classes = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'hors
```

Loading CIFAR-10 Dataset

In [4]:
```
# Load CIFAR-10 dataset
trainset_full = torchvision.datasets.CIFAR10(root='./data', train=True, download
testset = torchvision.datasets.CIFAR10(root='./data', train=False, download=True
```

```
# Display sample images
def show_images_from_classes(dataset, classes, mean=[0.485, 0.456, 0.406], std=[
    fig, axs = plt.subplots(3, 4, figsize=(10, 6))
    axs = axs.ravel()
    displayed_classes = set()
    for i in range(len(dataset)):
        img, label = dataset[i]
        if classes[label] not in displayed_classes:
            displayed_classes.add(classes[label])
            img = img * torch.tensor(std).view(3, 1, 1) + torch.tensor(mean).vie
            npimg = np.clip(img.numpy(), 0, 1)
            axs[len(displayed_classes)-1].imshow(np.transpose(npimg, (1, 2, 0)))
            axs[len(displayed_classes)-1].set_title(classes[label])
            axs[len(displayed_classes)-1].axis('off')

        if len(displayed_classes) == len(classes):
            break

    # Turn off any extra subplots
    for j in range(len(displayed_classes), len(axs)):
        axs[j].axis('off')

    plt.show()

# Display one sample image from each class
show_images_from_classes(trainset_full, classes)
```

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



Split Dataset into Training and Validation Sets (80-20 split)

In [5]:
```
# Split into Training and Validation Sets (80-20 split)
train_size = int(0.8 * len(trainset_full))
val_size = len(trainset_full) - train_size
trainset, valset = random_split(trainset_full, [train_size, val_size])

trainloader = DataLoader(trainset, batch_size=128, shuffle=True, num_workers=2)
valloader = DataLoader(valset, batch_size=128, shuffle=False, num_workers=2)
testloader = DataLoader(testset, batch_size=100, shuffle=False, num_workers=2)
```

Dataset Summary and Class Display

In [28]:
```
def dataset_summary():
    print("Dataset Summary:")
    print(f"Total training samples: {len(trainset_full)}")
    print(f"Training set size: {len(trainset)}")
    print(f"Validation set size: {len(valset)}")
    print(f"Test set size: {len(testset)}")
    print("Classes:", trainset_full.classes)

dataset_summary()
```

```
Dataset Summary:
Total training samples: 50000
Training set size: 40000
Validation set size: 10000
Test set size: 10000
Classes: ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'hors
e', 'ship', 'truck']
```

Plot Training and Validation Accuracy Curves

In [7]:
```
def plot_training_and_validation_accuracy(train_acc, val_acc, model_name):
    plt.plot(train_acc, label="Training Accuracy")
    plt.plot(val_acc, label="Validation Accuracy")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.title(f"Training and Validation Accuracy Curve - {model_name}")
    plt.legend()
    plt.show()
```

Evaluate Model on Test Set

In [8]:
```
def evaluate_model(model, dataloader):
    model.eval()
    correct, total = 0, 0
    with torch.no_grad():
        for inputs, labels in dataloader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            _, predicted = outputs.max(1)
            total += labels.size(0)
```

```
            correct += (predicted == labels).sum().item()
    accuracy = 100 * correct / total
    print(f"Test Accuracy: {accuracy:.2f}%")
    return accuracy
```

Training Function with Validation

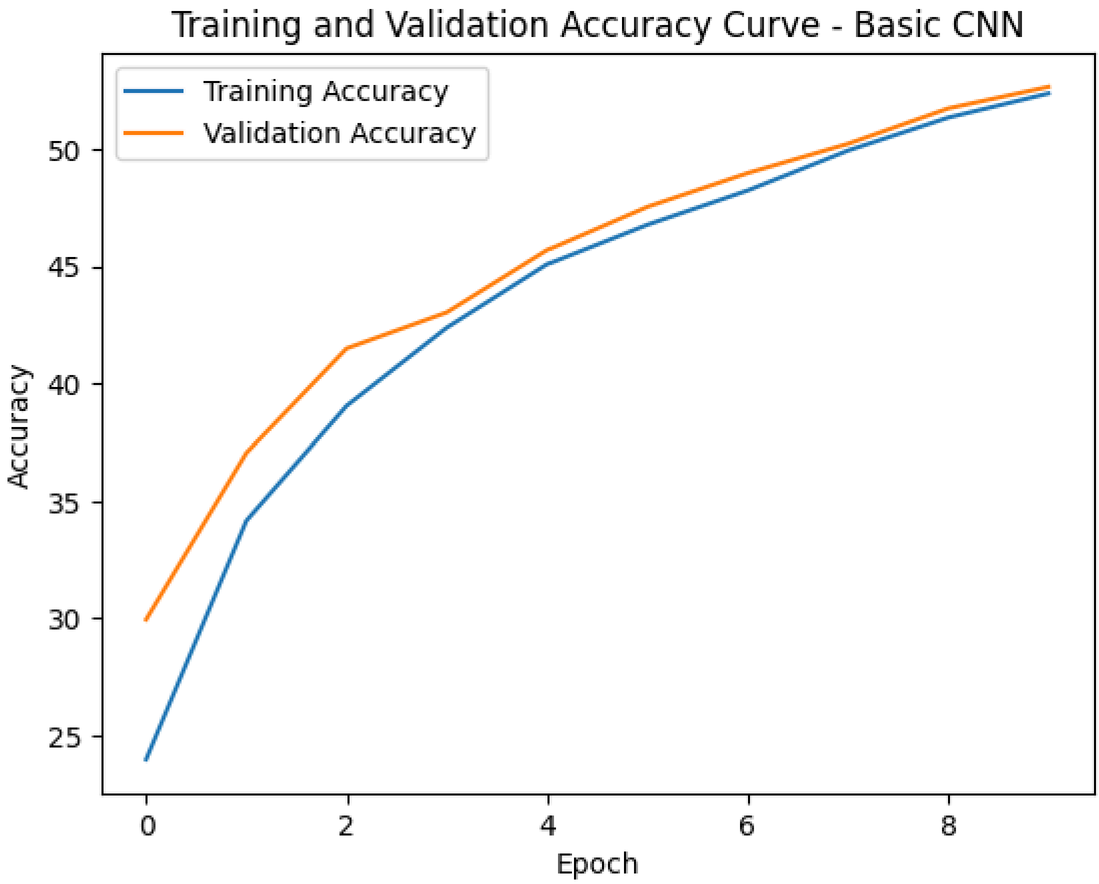
In [29]:
```
# Training function with validation
def train_model_with_validation(model, criterion, optimizer, num_epochs=10):
    train_acc, val_acc = [], []
    for epoch in range(num_epochs):
        # Training
        model.train()
        correct_train, total_train, running_loss = 0, 0, 0.0
        for inputs, labels in trainloader:
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            # Accuracy and loss tracking
            _, predicted = outputs.max(1)
            total_train += labels.size(0)
            correct_train += (predicted == labels).sum().item()
            running_loss += loss.item()

        # Calculate training accuracy
        epoch_loss = running_loss / len(trainloader)
        epoch_accuracy = 100 * correct_train / total_train
        train_acc.append(epoch_accuracy)

        # Validation
        model.eval()
        correct_val, total_val = 0, 0
        with torch.no_grad():
            for inputs, labels in valloader:
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = model(inputs)
                _, predicted = outputs.max(1)
                total_val += labels.size(0)
                correct_val += (predicted == labels).sum().item()

        val_accuracy = 100 * correct_val / total_val
        val_acc.append(val_accuracy)

        # Print epoch results
        print(f"Epoch [{epoch + 1}/{num_epochs}], Loss: {epoch_loss:.4f}, Train

    return train_acc, val_acc
```

Basic CNN

In [39]:
```
class BasicCNN(nn.Module):
    def __init__(self):
        super(BasicCNN, self).__init__()

        self.conv1 = nn.Conv2d(3, 32, kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=3, padding=1)
        self.pool = nn.MaxPool2d(2, 2)
        self.fc1 = nn.Linear(64 * 8 * 8, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 64 * 8 * 8)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x
```

In [40]:
```
# Instantiate the model, define the loss function and optimizer
model = BasicCNN().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

# Train the model and track accuracy
train_acc, val_acc = train_model_with_validation(model, criterion, optimizer, nu

# Plot the training and validation accuracy
plot_training_and_validation_accuracy(train_acc, val_acc, "Basic CNN")

# Evaluate the model on the test set
test_accuracy = evaluate_model(model, testloader)
print(f"Test Accuracy for Basic CNN: {test_accuracy:.2f}%")
```

```
Epoch [1/10], Loss: 2.1246, Train Accuracy: 23.98%, Validation Accuracy: 29.95%
Epoch [2/10], Loss: 1.8434, Train Accuracy: 34.16%, Validation Accuracy: 37.05%
Epoch [3/10], Loss: 1.6887, Train Accuracy: 39.05%, Validation Accuracy: 41.50%
Epoch [4/10], Loss: 1.5935, Train Accuracy: 42.39%, Validation Accuracy: 43.04%
Epoch [5/10], Loss: 1.5270, Train Accuracy: 45.09%, Validation Accuracy: 45.70%
Epoch [6/10], Loss: 1.4768, Train Accuracy: 46.78%, Validation Accuracy: 47.55%
Epoch [7/10], Loss: 1.4347, Train Accuracy: 48.25%, Validation Accuracy: 48.99%
Epoch [8/10], Loss: 1.3982, Train Accuracy: 49.95%, Validation Accuracy: 50.24%
Epoch [9/10], Loss: 1.3604, Train Accuracy: 51.36%, Validation Accuracy: 51.75%
Epoch [10/10], Loss: 1.3310, Train Accuracy: 52.39%, Validation Accuracy: 52.67%
```




```
Test Accuracy: 55.45%
Test Accuracy for Basic CNN: 55.45%
```

Hyperparameter Tuning for Basic CNN

In [41]:
```
class OptimizedCNN(nn.Module):
    def __init__(self):
        super(OptimizedCNN, self).__init__()

        # Convolutional Layers with Batch Normalization and Dropout
        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, padding=1)
        self.bn1 = nn.BatchNorm2d(64)

        self.conv2 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
        self.bn2 = nn.BatchNorm2d(128)

        self.conv3 = nn.Conv2d(128, 128, kernel_size=3, padding=1)
        self.bn3 = nn.BatchNorm2d(128)

        # Pooling and Dropout Layers
        self.pool = nn.MaxPool2d(2, 2)
        self.dropout = nn.Dropout(0.3)

        # Fully Connected Layers
        self.fc1 = nn.Linear(128 * 4 * 4, 256)
        self.fc2 = nn.Linear(256, 128)
        self.fc3 = nn.Linear(128, 10)

    def forward(self, x):
        # Convolutional Layer 1
        x = self.pool(F.relu(self.bn1(self.conv1(x))))
```

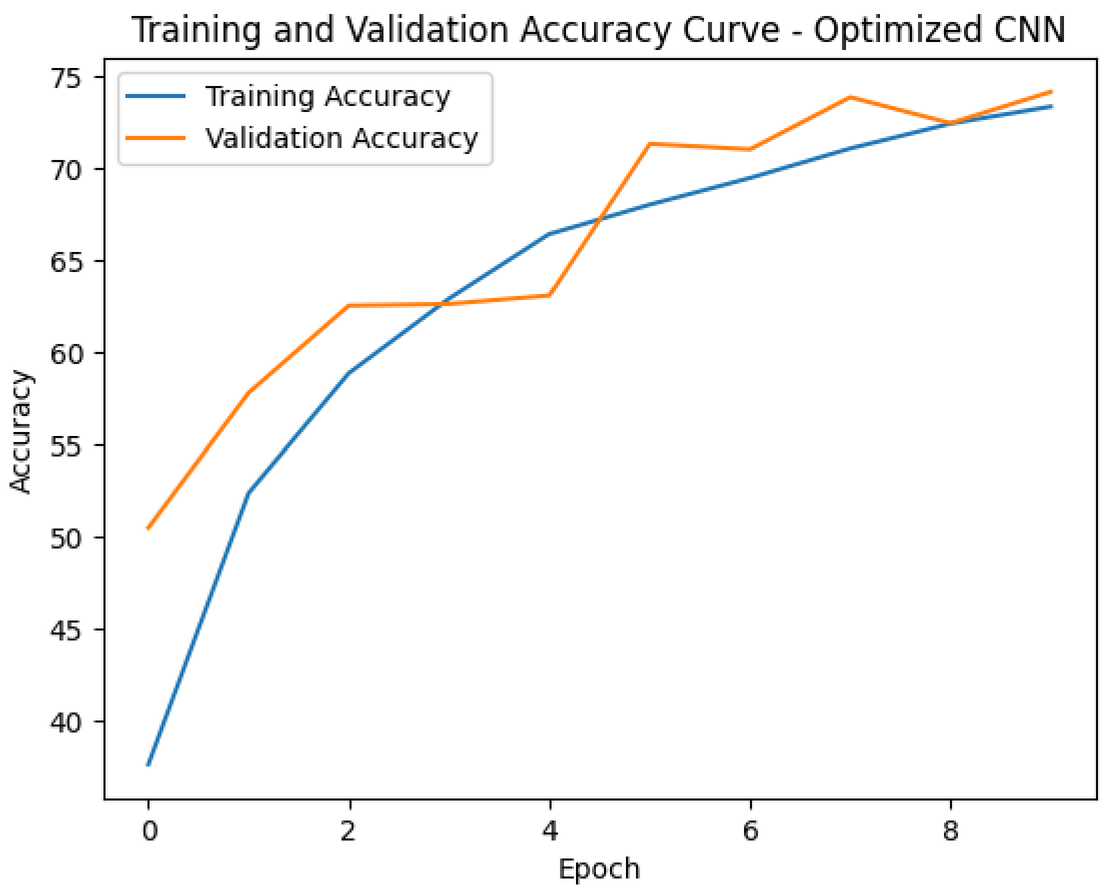
```
        # Convolutional Layer 2
        x = self.pool(F.relu(self.bn2(self.conv2(x))))

        # Convolutional Layer 3
        x = self.pool(F.relu(self.bn3(self.conv3(x))))

        # Flatten for Fully Connected Layers
        x = x.view(-1, 128 * 4 * 4)

        # Fully Connected Layers with Dropout
        x = F.relu(self.fc1(x))
        x = self.dropout(x)

        x = F.relu(self.fc2(x))
        x = self.dropout(x)

        # Output Layer
        x = self.fc3(x)

        return x
```

In [42]:
```
# Instantiate the model, define the loss function and optimizer
model_optimized = OptimizedCNN().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model_optimized.parameters(), lr=0.01, momentum=0.9,
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='max', pa
```

```
E:\Codes_data\try\envs\ai\lib\site-packages\torch\optim\lr_scheduler.py:62: UserW
arning: The verbose parameter is deprecated. Please use get_last_lr() to access t
he learning rate.
  warnings.warn(
```

In [44]:
```
# Train the model and track accuracy
train_acc_optimized, val_acc_optimized = train_model_with_validation(
    model_optimized, criterion, optimizer,  num_epochs=10
)

# Plot the training and validation accuracy for the optimized model
plot_training_and_validation_accuracy(train_acc_optimized, val_acc_optimized, "C

# Evaluate the optimized model on the test set
test_accuracy_optimized = evaluate_model(model_optimized, testloader)
print(f"Test Accuracy for Optimized CNN: {test_accuracy_optimized:.2f}%")
```

```
Epoch [1/10], Loss: 1.6762, Train Accuracy: 37.65%, Validation Accuracy: 50.49%
Epoch [2/10], Loss: 1.3045, Train Accuracy: 52.37%, Validation Accuracy: 57.79%
Epoch [3/10], Loss: 1.1461, Train Accuracy: 58.85%, Validation Accuracy: 62.52%
Epoch [4/10], Loss: 1.0446, Train Accuracy: 62.90%, Validation Accuracy: 62.61%
Epoch [5/10], Loss: 0.9651, Train Accuracy: 66.41%, Validation Accuracy: 63.07%
Epoch [6/10], Loss: 0.9112, Train Accuracy: 68.00%, Validation Accuracy: 71.30%
Epoch [7/10], Loss: 0.8651, Train Accuracy: 69.45%, Validation Accuracy: 71.00%
Epoch [8/10], Loss: 0.8311, Train Accuracy: 71.05%, Validation Accuracy: 73.83%
Epoch [9/10], Loss: 0.7943, Train Accuracy: 72.39%, Validation Accuracy: 72.42%
Epoch [10/10], Loss: 0.7704, Train Accuracy: 73.32%, Validation Accuracy: 74.12%
```




```
Test Accuracy: 75.94%
Test Accuracy for Optimized CNN: 75.94%
```

In [50]:
```
# Function to define and summarise ResNet-18
def resnet18_summary():
    print("\nResNet-18 Model Summary:")
    model = models.resnet18(weights=None)
    model.fc = nn.Linear(model.fc.in_features, 10)
    model = model.to(device)
    summary(model, (3, 32, 32))

# Function to define and summarise AlexNet
def alexnet_summary():
    print("\nAlexNet Model Summary:")
    model = models.alexnet(weights=None)
    model.features[0] = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1)
    model.classifier[6] = nn.Linear(model.classifier[6].in_features, 10)
    model = model.to(device)
    summary(model, (3, 32, 32))

# Function to define and summarise MobileNetV2
def mobilenet_v2_summary():
    print("\nMobileNetV2 Model Summary:")
    model = models.mobilenet_v2(weights=None)
    model.classifier[1] = nn.Linear(model.classifier[1].in_features, 10)
    model = model.to(device)
    summary(model, (3, 32, 32))
```

Define ResNet-18 & MobileNetV2 Model

In [31]:
```
def get_resnet18():
    model = torchvision.models.resnet18(weights=None)
    num_features = model.fc.in_features
    model.fc = nn.Linear(model.fc.in_features, 10)

    model.fc = nn.Sequential(
        nn.Dropout(0.5),  # Add dropout with 50% probability
        nn.Linear(num_features, 10)
    )

    return model.to(device)


def get_mobilenet_v2():
    model = torchvision.models.mobilenet_v2(weights=None)
    model.classifier[1] = nn.Linear(model.classifier[1].in_features, 10)
    return model.to(device)
```

In [45]:
```
# Display resnet18 model summaries
resnet18_summary()
```

```
ResNet-18 Model Summary:
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 16, 16]           9,408
       BatchNorm2d-2           [-1, 64, 16, 16]             128
              ReLU-3           [-1, 64, 16, 16]               0
         MaxPool2d-4             [-1, 64, 8, 8]               0
            Conv2d-5             [-1, 64, 8, 8]          36,864
       BatchNorm2d-6             [-1, 64, 8, 8]             128
              ReLU-7             [-1, 64, 8, 8]               0
            Conv2d-8             [-1, 64, 8, 8]          36,864
       BatchNorm2d-9             [-1, 64, 8, 8]             128
             ReLU-10             [-1, 64, 8, 8]               0
       BasicBlock-11             [-1, 64, 8, 8]               0
           Conv2d-12             [-1, 64, 8, 8]          36,864
      BatchNorm2d-13             [-1, 64, 8, 8]             128
             ReLU-14             [-1, 64, 8, 8]               0
           Conv2d-15             [-1, 64, 8, 8]          36,864
      BatchNorm2d-16             [-1, 64, 8, 8]             128
             ReLU-17             [-1, 64, 8, 8]               0
       BasicBlock-18             [-1, 64, 8, 8]               0
           Conv2d-19            [-1, 128, 4, 4]          73,728
      BatchNorm2d-20            [-1, 128, 4, 4]             256
             ReLU-21            [-1, 128, 4, 4]               0
           Conv2d-22            [-1, 128, 4, 4]         147,456
      BatchNorm2d-23            [-1, 128, 4, 4]             256
           Conv2d-24            [-1, 128, 4, 4]           8,192
      BatchNorm2d-25            [-1, 128, 4, 4]             256
             ReLU-26            [-1, 128, 4, 4]               0
       BasicBlock-27            [-1, 128, 4, 4]               0
           Conv2d-28            [-1, 128, 4, 4]         147,456
      BatchNorm2d-29            [-1, 128, 4, 4]             256
             ReLU-30            [-1, 128, 4, 4]               0
           Conv2d-31            [-1, 128, 4, 4]         147,456
      BatchNorm2d-32            [-1, 128, 4, 4]             256
             ReLU-33            [-1, 128, 4, 4]               0
       BasicBlock-34            [-1, 128, 4, 4]               0
           Conv2d-35            [-1, 256, 2, 2]         294,912
      BatchNorm2d-36            [-1, 256, 2, 2]             512
             ReLU-37            [-1, 256, 2, 2]               0
           Conv2d-38            [-1, 256, 2, 2]         589,824
      BatchNorm2d-39            [-1, 256, 2, 2]             512
           Conv2d-40            [-1, 256, 2, 2]          32,768
      BatchNorm2d-41            [-1, 256, 2, 2]             512
             ReLU-42            [-1, 256, 2, 2]               0
       BasicBlock-43            [-1, 256, 2, 2]               0
           Conv2d-44            [-1, 256, 2, 2]         589,824
      BatchNorm2d-45            [-1, 256, 2, 2]             512
             ReLU-46            [-1, 256, 2, 2]               0
           Conv2d-47            [-1, 256, 2, 2]         589,824
      BatchNorm2d-48            [-1, 256, 2, 2]             512
             ReLU-49            [-1, 256, 2, 2]               0
       BasicBlock-50            [-1, 256, 2, 2]               0
           Conv2d-51            [-1, 512, 1, 1]       1,179,648
      BatchNorm2d-52            [-1, 512, 1, 1]           1,024
             ReLU-53            [-1, 512, 1, 1]               0
           Conv2d-54            [-1, 512, 1, 1]       2,359,296
      BatchNorm2d-55            [-1, 512, 1, 1]           1,024
           Conv2d-56            [-1, 512, 1, 1]         131,072
```

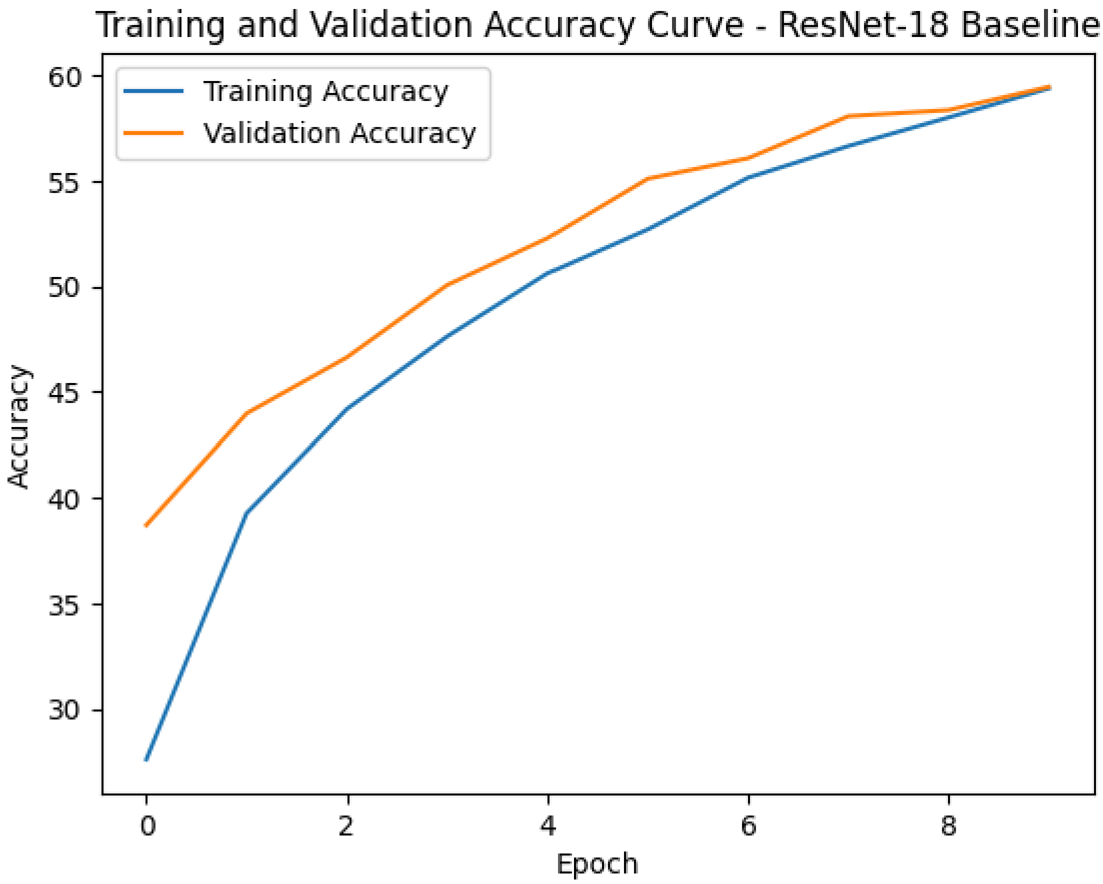
```
       BatchNorm2d-57             [-1, 512, 1, 1]           1,024
              ReLU-58             [-1, 512, 1, 1]               0
        BasicBlock-59             [-1, 512, 1, 1]               0
            Conv2d-60             [-1, 512, 1, 1]       2,359,296
       BatchNorm2d-61             [-1, 512, 1, 1]           1,024
              ReLU-62             [-1, 512, 1, 1]               0
            Conv2d-63             [-1, 512, 1, 1]       2,359,296
       BatchNorm2d-64             [-1, 512, 1, 1]           1,024
              ReLU-65             [-1, 512, 1, 1]               0
        BasicBlock-66             [-1, 512, 1, 1]               0
AdaptiveAvgPool2d-67             [-1, 512, 1, 1]               0
            Linear-68                    [-1, 10]           5,130
================================================================
Total params: 11,181,642
Trainable params: 11,181,642
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 1.29
Params size (MB): 42.65
Estimated Total Size (MB): 43.95
----------------------------------------------------------------
```

Baseline Training for ResNet-18

In [32]:

```
# Baseline Training for ResNet-18
print("Training ResNet-18 Baseline...")
resnet18_baseline = get_resnet18()
criterion = nn.CrossEntropyLoss()
optimizer_resnet18 = optim.SGD(resnet18_baseline.parameters(), lr=0.001, momentu
train_acc_resnet18, val_acc_resnet18 = train_model_with_validation(resnet18_base
plot_training_and_validation_accuracy(train_acc_resnet18, val_acc_resnet18, "Res
print("Evaluating ResNet-18 Baseline Model on Test Set...")
evaluate_model(resnet18_baseline, testloader)
```

```
Training ResNet-18 Baseline...
Epoch [1/10], Loss: 2.0058, Train Accuracy: 27.62%, Validation Accuracy: 38.71%
Epoch [2/10], Loss: 1.6376, Train Accuracy: 39.27%, Validation Accuracy: 43.98%
Epoch [3/10], Loss: 1.5117, Train Accuracy: 44.18%, Validation Accuracy: 46.63%
Epoch [4/10], Loss: 1.4286, Train Accuracy: 47.62%, Validation Accuracy: 50.05%
Epoch [5/10], Loss: 1.3560, Train Accuracy: 50.60%, Validation Accuracy: 52.27%
Epoch [6/10], Loss: 1.3019, Train Accuracy: 52.69%, Validation Accuracy: 55.09%
Epoch [7/10], Loss: 1.2435, Train Accuracy: 55.14%, Validation Accuracy: 56.06%
Epoch [8/10], Loss: 1.2073, Train Accuracy: 56.63%, Validation Accuracy: 58.05%
Epoch [9/10], Loss: 1.1672, Train Accuracy: 57.99%, Validation Accuracy: 58.34%
Epoch [10/10], Loss: 1.1338, Train Accuracy: 59.37%, Validation Accuracy: 59.44%
```




```
Evaluating ResNet-18 Baseline Model on Test Set...
Test Accuracy: 61.84%
```

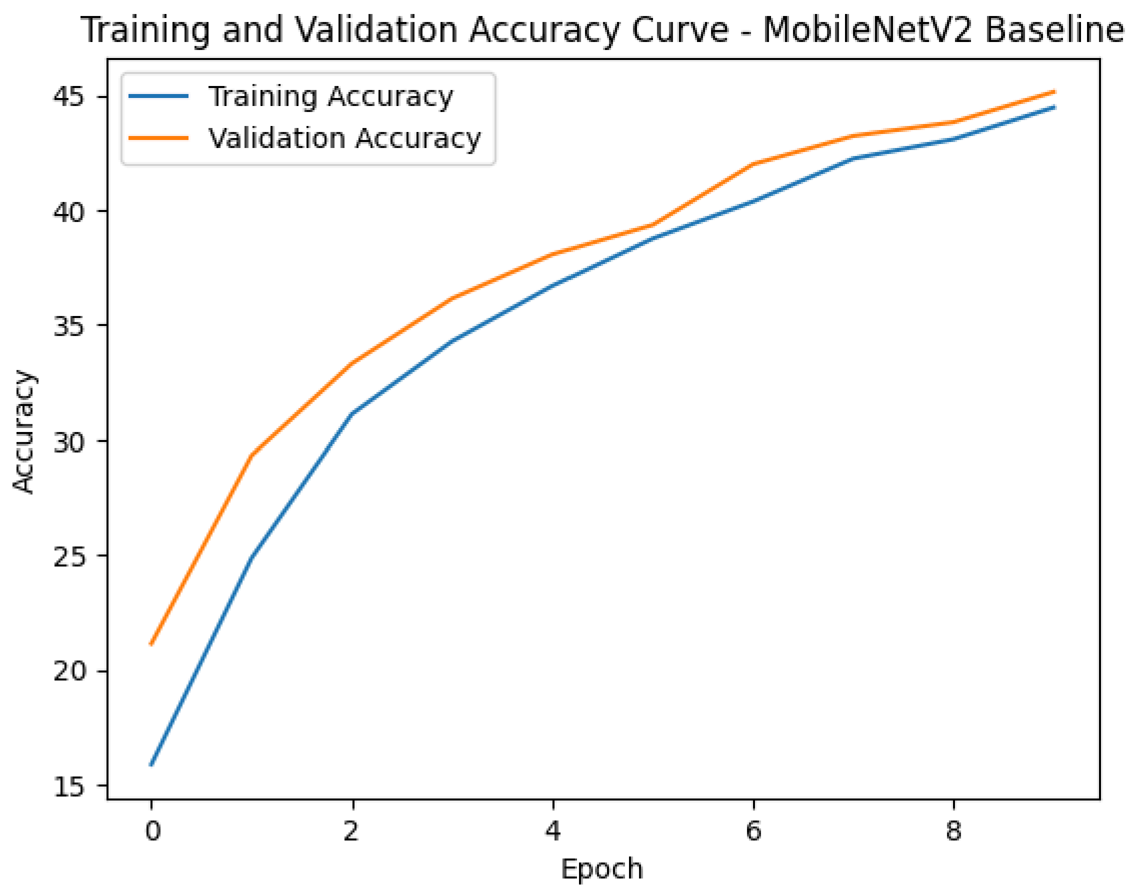
Out[32]: 61.84

Baseline Training for MobileNetV2

In [33]:

```
print("\nTraining MobileNetV2 Baseline...")
mobilenet_v2_baseline = get_mobilenet_v2()
optimizer_mobilenet_v2 = optim.SGD(mobilenet_v2_baseline.parameters(), lr=0.001,
train_acc_mobilenet_v2, val_acc_mobilenet_v2 = train_model_with_validation(mobil
plot_training_and_validation_accuracy(train_acc_mobilenet_v2, val_acc_mobilenet_
print("Evaluating MobileNetV2 Baseline Model on Test Set...")
evaluate_model(mobilenet_v2_baseline, testloader)
```

```
Training MobileNetV2 Baseline...
Epoch [1/10], Loss: 2.2174, Train Accuracy: 15.89%, Validation Accuracy: 21.15%
Epoch [2/10], Loss: 1.9694, Train Accuracy: 24.87%, Validation Accuracy: 29.33%
Epoch [3/10], Loss: 1.8321, Train Accuracy: 31.12%, Validation Accuracy: 33.32%
Epoch [4/10], Loss: 1.7515, Train Accuracy: 34.29%, Validation Accuracy: 36.15%
Epoch [5/10], Loss: 1.6960, Train Accuracy: 36.70%, Validation Accuracy: 38.07%
Epoch [6/10], Loss: 1.6461, Train Accuracy: 38.77%, Validation Accuracy: 39.36%
Epoch [7/10], Loss: 1.6018, Train Accuracy: 40.38%, Validation Accuracy: 42.00%
Epoch [8/10], Loss: 1.5622, Train Accuracy: 42.24%, Validation Accuracy: 43.23%
Epoch [9/10], Loss: 1.5325, Train Accuracy: 43.09%, Validation Accuracy: 43.83%
Epoch [10/10], Loss: 1.5072, Train Accuracy: 44.47%, Validation Accuracy: 45.15%
```




```
Evaluating MobileNetV2 Baseline Model on Test Set...
Test Accuracy: 46.82%
```

Out[33]: 46.82

In [46]:
```
# Model's summary
mobilenet_v2_summary()
```

```
MobileNetV2 Model Summary:
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 16, 16]             864
       BatchNorm2d-2           [-1, 32, 16, 16]              64
             ReLU6-3           [-1, 32, 16, 16]               0
            Conv2d-4           [-1, 32, 16, 16]             288
       BatchNorm2d-5           [-1, 32, 16, 16]              64
             ReLU6-6           [-1, 32, 16, 16]               0
            Conv2d-7           [-1, 16, 16, 16]             512
       BatchNorm2d-8           [-1, 16, 16, 16]              32
  InvertedResidual-9           [-1, 16, 16, 16]               0
           Conv2d-10           [-1, 96, 16, 16]           1,536
      BatchNorm2d-11           [-1, 96, 16, 16]             192
            ReLU6-12           [-1, 96, 16, 16]               0
           Conv2d-13             [-1, 96, 8, 8]             864
      BatchNorm2d-14             [-1, 96, 8, 8]             192
            ReLU6-15             [-1, 96, 8, 8]               0
           Conv2d-16             [-1, 24, 8, 8]           2,304
      BatchNorm2d-17             [-1, 24, 8, 8]              48
 InvertedResidual-18             [-1, 24, 8, 8]               0
           Conv2d-19            [-1, 144, 8, 8]           3,456
      BatchNorm2d-20            [-1, 144, 8, 8]             288
            ReLU6-21            [-1, 144, 8, 8]               0
           Conv2d-22            [-1, 144, 8, 8]           1,296
      BatchNorm2d-23            [-1, 144, 8, 8]             288
            ReLU6-24            [-1, 144, 8, 8]               0
           Conv2d-25             [-1, 24, 8, 8]           3,456
      BatchNorm2d-26             [-1, 24, 8, 8]              48
 InvertedResidual-27             [-1, 24, 8, 8]               0
           Conv2d-28            [-1, 144, 8, 8]           3,456
      BatchNorm2d-29            [-1, 144, 8, 8]             288
            ReLU6-30            [-1, 144, 8, 8]               0
           Conv2d-31            [-1, 144, 4, 4]           1,296
      BatchNorm2d-32            [-1, 144, 4, 4]             288
            ReLU6-33            [-1, 144, 4, 4]               0
           Conv2d-34             [-1, 32, 4, 4]           4,608
      BatchNorm2d-35             [-1, 32, 4, 4]              64
 InvertedResidual-36             [-1, 32, 4, 4]               0
           Conv2d-37            [-1, 192, 4, 4]           6,144
      BatchNorm2d-38            [-1, 192, 4, 4]             384
            ReLU6-39            [-1, 192, 4, 4]               0
           Conv2d-40            [-1, 192, 4, 4]           1,728
      BatchNorm2d-41            [-1, 192, 4, 4]             384
            ReLU6-42            [-1, 192, 4, 4]               0
           Conv2d-43             [-1, 32, 4, 4]           6,144
      BatchNorm2d-44             [-1, 32, 4, 4]              64
 InvertedResidual-45             [-1, 32, 4, 4]               0
           Conv2d-46            [-1, 192, 4, 4]           6,144
      BatchNorm2d-47            [-1, 192, 4, 4]             384
            ReLU6-48            [-1, 192, 4, 4]               0
           Conv2d-49            [-1, 192, 4, 4]           1,728
      BatchNorm2d-50            [-1, 192, 4, 4]             384
            ReLU6-51            [-1, 192, 4, 4]               0
           Conv2d-52             [-1, 32, 4, 4]           6,144
      BatchNorm2d-53             [-1, 32, 4, 4]              64
 InvertedResidual-54             [-1, 32, 4, 4]               0
           Conv2d-55            [-1, 192, 4, 4]           6,144
      BatchNorm2d-56            [-1, 192, 4, 4]             384
```

```
           ReLU6-57           [-1, 192, 4, 4]               0
          Conv2d-58           [-1, 192, 2, 2]           1,728
     BatchNorm2d-59           [-1, 192, 2, 2]             384
           ReLU6-60           [-1, 192, 2, 2]               0
          Conv2d-61            [-1, 64, 2, 2]          12,288
     BatchNorm2d-62            [-1, 64, 2, 2]             128
InvertedResidual-63            [-1, 64, 2, 2]               0
          Conv2d-64           [-1, 384, 2, 2]          24,576
     BatchNorm2d-65           [-1, 384, 2, 2]             768
           ReLU6-66           [-1, 384, 2, 2]               0
          Conv2d-67           [-1, 384, 2, 2]           3,456
     BatchNorm2d-68           [-1, 384, 2, 2]             768
           ReLU6-69           [-1, 384, 2, 2]               0
          Conv2d-70            [-1, 64, 2, 2]          24,576
     BatchNorm2d-71            [-1, 64, 2, 2]             128
InvertedResidual-72            [-1, 64, 2, 2]               0
          Conv2d-73           [-1, 384, 2, 2]          24,576
     BatchNorm2d-74           [-1, 384, 2, 2]             768
           ReLU6-75           [-1, 384, 2, 2]               0
          Conv2d-76           [-1, 384, 2, 2]           3,456
     BatchNorm2d-77           [-1, 384, 2, 2]             768
           ReLU6-78           [-1, 384, 2, 2]               0
          Conv2d-79            [-1, 64, 2, 2]          24,576
     BatchNorm2d-80            [-1, 64, 2, 2]             128
InvertedResidual-81            [-1, 64, 2, 2]               0
          Conv2d-82           [-1, 384, 2, 2]          24,576
     BatchNorm2d-83           [-1, 384, 2, 2]             768
           ReLU6-84           [-1, 384, 2, 2]               0
          Conv2d-85           [-1, 384, 2, 2]           3,456
     BatchNorm2d-86           [-1, 384, 2, 2]             768
           ReLU6-87           [-1, 384, 2, 2]               0
          Conv2d-88            [-1, 64, 2, 2]          24,576
     BatchNorm2d-89            [-1, 64, 2, 2]             128
InvertedResidual-90            [-1, 64, 2, 2]               0
          Conv2d-91           [-1, 384, 2, 2]          24,576
     BatchNorm2d-92           [-1, 384, 2, 2]             768
           ReLU6-93           [-1, 384, 2, 2]               0
          Conv2d-94           [-1, 384, 2, 2]           3,456
     BatchNorm2d-95           [-1, 384, 2, 2]             768
           ReLU6-96           [-1, 384, 2, 2]               0
          Conv2d-97            [-1, 96, 2, 2]          36,864
     BatchNorm2d-98            [-1, 96, 2, 2]             192
InvertedResidual-99            [-1, 96, 2, 2]               0
         Conv2d-100           [-1, 576, 2, 2]          55,296
    BatchNorm2d-101           [-1, 576, 2, 2]           1,152
          ReLU6-102           [-1, 576, 2, 2]               0
         Conv2d-103           [-1, 576, 2, 2]           5,184
    BatchNorm2d-104           [-1, 576, 2, 2]           1,152
          ReLU6-105           [-1, 576, 2, 2]               0
         Conv2d-106            [-1, 96, 2, 2]          55,296
    BatchNorm2d-107            [-1, 96, 2, 2]             192
InvertedResidual-108           [-1, 96, 2, 2]               0
         Conv2d-109           [-1, 576, 2, 2]          55,296
    BatchNorm2d-110           [-1, 576, 2, 2]           1,152
          ReLU6-111           [-1, 576, 2, 2]               0
         Conv2d-112           [-1, 576, 2, 2]           5,184
    BatchNorm2d-113           [-1, 576, 2, 2]           1,152
          ReLU6-114           [-1, 576, 2, 2]               0
         Conv2d-115            [-1, 96, 2, 2]          55,296
    BatchNorm2d-116            [-1, 96, 2, 2]             192
```

```
InvertedResidual-117          [-1, 96, 2, 2]               0
          Conv2d-118         [-1, 576, 2, 2]          55,296
     BatchNorm2d-119         [-1, 576, 2, 2]           1,152
           ReLU6-120         [-1, 576, 2, 2]               0
          Conv2d-121         [-1, 576, 1, 1]           5,184
     BatchNorm2d-122         [-1, 576, 1, 1]           1,152
           ReLU6-123         [-1, 576, 1, 1]               0
          Conv2d-124         [-1, 160, 1, 1]          92,160
     BatchNorm2d-125         [-1, 160, 1, 1]             320
InvertedResidual-126         [-1, 160, 1, 1]               0
          Conv2d-127         [-1, 960, 1, 1]         153,600
     BatchNorm2d-128         [-1, 960, 1, 1]           1,920
           ReLU6-129         [-1, 960, 1, 1]               0
          Conv2d-130         [-1, 960, 1, 1]           8,640
     BatchNorm2d-131         [-1, 960, 1, 1]           1,920
           ReLU6-132         [-1, 960, 1, 1]               0
          Conv2d-133         [-1, 160, 1, 1]         153,600
     BatchNorm2d-134         [-1, 160, 1, 1]             320
InvertedResidual-135         [-1, 160, 1, 1]               0
          Conv2d-136         [-1, 960, 1, 1]         153,600
     BatchNorm2d-137         [-1, 960, 1, 1]           1,920
           ReLU6-138         [-1, 960, 1, 1]               0
          Conv2d-139         [-1, 960, 1, 1]           8,640
     BatchNorm2d-140         [-1, 960, 1, 1]           1,920
           ReLU6-141         [-1, 960, 1, 1]               0
          Conv2d-142         [-1, 160, 1, 1]         153,600
     BatchNorm2d-143         [-1, 160, 1, 1]             320
InvertedResidual-144         [-1, 160, 1, 1]               0
          Conv2d-145         [-1, 960, 1, 1]         153,600
     BatchNorm2d-146         [-1, 960, 1, 1]           1,920
           ReLU6-147         [-1, 960, 1, 1]               0
          Conv2d-148         [-1, 960, 1, 1]           8,640
     BatchNorm2d-149         [-1, 960, 1, 1]           1,920
           ReLU6-150         [-1, 960, 1, 1]               0
          Conv2d-151         [-1, 320, 1, 1]         307,200
     BatchNorm2d-152         [-1, 320, 1, 1]             640
InvertedResidual-153         [-1, 320, 1, 1]               0
          Conv2d-154        [-1, 1280, 1, 1]         409,600
     BatchNorm2d-155        [-1, 1280, 1, 1]           2,560
           ReLU6-156        [-1, 1280, 1, 1]               0
         Dropout-157              [-1, 1280]               0
          Linear-158                [-1, 10]          12,810
================================================================
Total params: 2,236,682
Trainable params: 2,236,682
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 3.13
Params size (MB): 8.53
Estimated Total Size (MB): 11.67
----------------------------------------------------------------
```

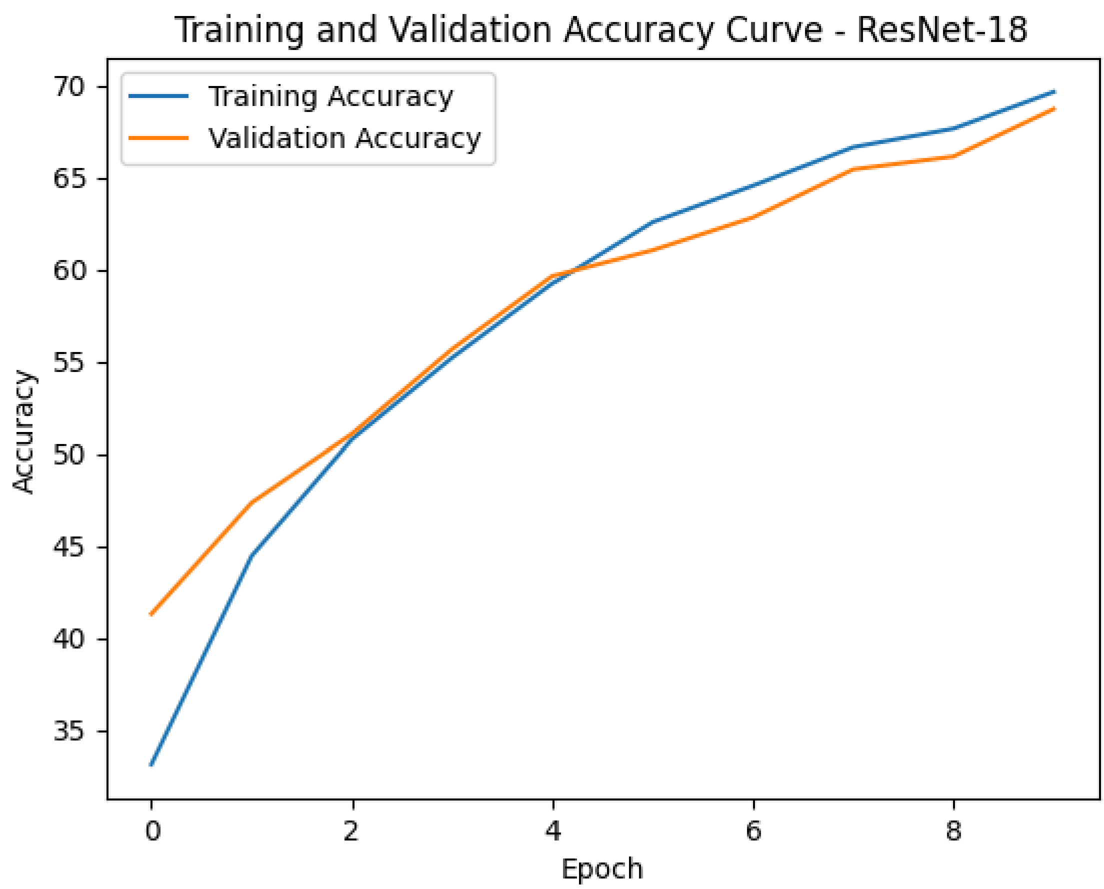
Hyperparameter Tuning for ResNet-18

In [34]:
```
# Hyperparameters taken
learning_rate = 0.01
weight_decay = 0.0001
```

```python
optimizer_type = 'Adam'

# Function to set optimiser with updated hyperparameters
def get_optimizer(model):
    return optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9, weight_

# Improved training function for ResNet-18 with dropout
def improved_training(model_fn, model_name, num_epochs=10):
    print(f"\nTraining {model_name} with adjusted configuration: lr={learning_ra
    model = model_fn()  # Use the modified ResNet-18 with dropout
    optimizer = get_optimizer(model)
    criterion = nn.CrossEntropyLoss()
    train_acc, val_acc = train_model_with_validation(model, criterion, optimizer
    test_accuracy = evaluate_model(model, testloader)
    plot_training_and_validation_accuracy(train_acc, val_acc, f"{model_name}")
    print(f"Test Accuracy for {model_name}: {test_accuracy:.2f}%")
```

In [36]:
```python
print("Optimisation for ResNet-18 ")
improved_training(get_resnet18, "ResNet-18")
```

```
Optimisation for ResNet-18

Training ResNet-18 with adjusted configuration: lr=0.01, optimizer=Adam, weight_d
ecay=0.0005
Epoch [1/10], Loss: 1.8988, Train Accuracy: 33.11%, Validation Accuracy: 41.29%
Epoch [2/10], Loss: 1.5775, Train Accuracy: 44.43%, Validation Accuracy: 47.33%
Epoch [3/10], Loss: 1.4215, Train Accuracy: 50.75%, Validation Accuracy: 51.05%
Epoch [4/10], Loss: 1.2880, Train Accuracy: 55.18%, Validation Accuracy: 55.65%
Epoch [5/10], Loss: 1.1726, Train Accuracy: 59.22%, Validation Accuracy: 59.62%
Epoch [6/10], Loss: 1.0730, Train Accuracy: 62.56%, Validation Accuracy: 61.03%
Epoch [7/10], Loss: 1.0177, Train Accuracy: 64.54%, Validation Accuracy: 62.81%
Epoch [8/10], Loss: 0.9590, Train Accuracy: 66.63%, Validation Accuracy: 65.42%
Epoch [9/10], Loss: 0.9172, Train Accuracy: 67.64%, Validation Accuracy: 66.12%
Epoch [10/10], Loss: 0.8687, Train Accuracy: 69.64%, Validation Accuracy: 68.70%
Test Accuracy: 69.71%
```




```
Test Accuracy for ResNet-18: 69.71%
```

Hyperparameter Tuning for MobileNetV2

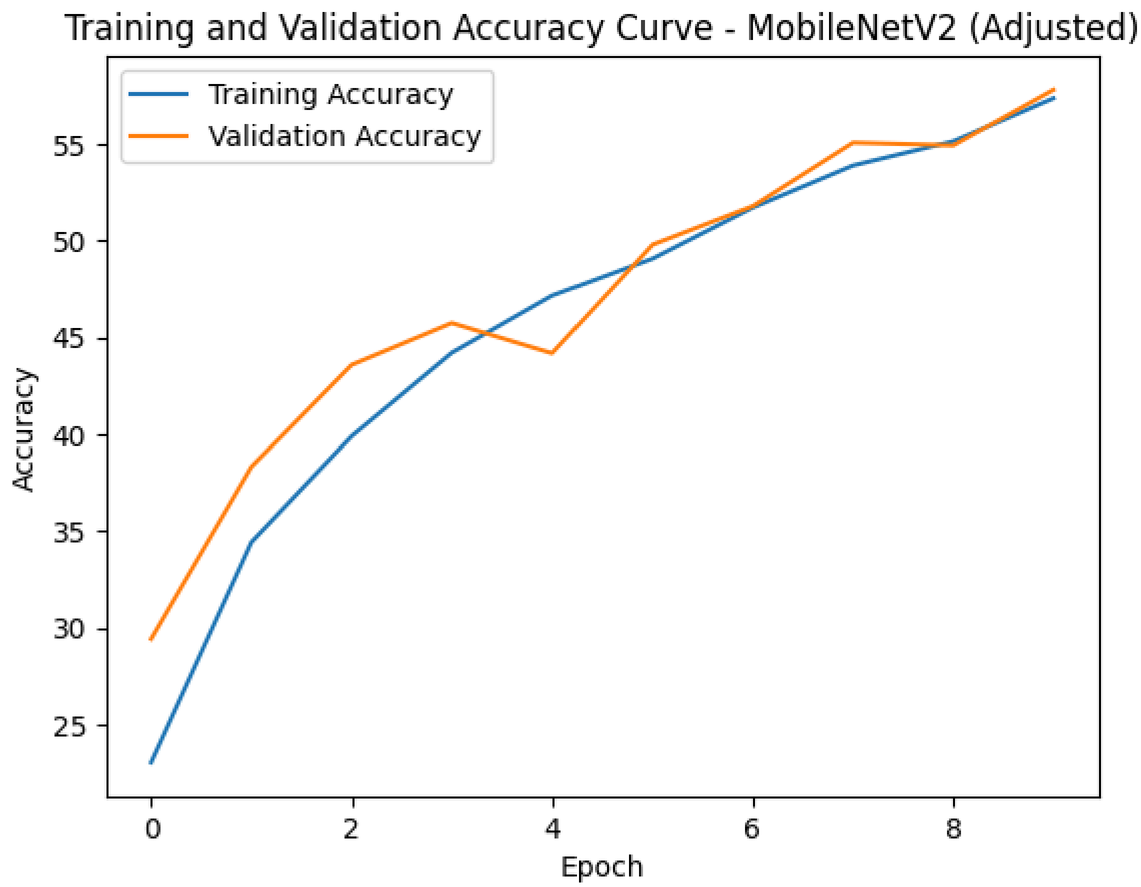
In [37]:

```
# Hyperparameters chosen for MobileNetV2
learning_rate = 0.01
weight_decay =  0.0005
optimizer_type = 'Adam'

# Improved training function for MobileNetV2
def improved_training_for_MobileNetV2(model_fn, model_name, num_epochs=10):
    print(f"\nTraining {model_name} with Hyperparameters chosen: lr={learning_ra
    model = model_fn()
    optimizer = get_optimizer(model)
    criterion = nn.CrossEntropyLoss()
    train_acc, val_acc = train_model_with_validation(model, criterion, optimizer
    test_accuracy = evaluate_model(model, testloader)
    plot_training_and_validation_accuracy(train_acc, val_acc, f"{model_name} (Ad
    print(f"Test Accuracy for {model_name}: {test_accuracy:.2f}%")
```

In [38]:

```
print("\n Optimisation for MobileNetV2")
improved_training_for_MobileNetV2(get_mobilenet_v2, "MobileNetV2")
```

```
 Optimisation for MobileNetV2

Training MobileNetV2 with Hyperparameters chosen: lr=0.01, optimizer=Adam, weight
_decay=0.0005
Epoch [1/10], Loss: 2.1105, Train Accuracy: 23.05%, Validation Accuracy: 29.43%
Epoch [2/10], Loss: 1.7821, Train Accuracy: 34.42%, Validation Accuracy: 38.31%
Epoch [3/10], Loss: 1.6389, Train Accuracy: 39.89%, Validation Accuracy: 43.57%
Epoch [4/10], Loss: 1.5379, Train Accuracy: 44.20%, Validation Accuracy: 45.73%
Epoch [5/10], Loss: 1.4644, Train Accuracy: 47.15%, Validation Accuracy: 44.17%
Epoch [6/10], Loss: 1.4023, Train Accuracy: 49.05%, Validation Accuracy: 49.78%
Epoch [7/10], Loss: 1.3377, Train Accuracy: 51.70%, Validation Accuracy: 51.77%
Epoch [8/10], Loss: 1.2863, Train Accuracy: 53.87%, Validation Accuracy: 55.05%
Epoch [9/10], Loss: 1.2491, Train Accuracy: 55.12%, Validation Accuracy: 54.91%
Epoch [10/10], Loss: 1.1934, Train Accuracy: 57.34%, Validation Accuracy: 57.78%
Test Accuracy: 60.23%
```




```
Test Accuracy for MobileNetV2: 60.23%
```

In [47]:

```
# Model's summary
alexnet_summary()
```

```
AlexNet Model Summary:
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 32, 32]           1,792
              ReLU-2           [-1, 64, 32, 32]               0
         MaxPool2d-3           [-1, 64, 15, 15]               0
            Conv2d-4          [-1, 192, 15, 15]         307,392
              ReLU-5          [-1, 192, 15, 15]               0
         MaxPool2d-6            [-1, 192, 7, 7]               0
            Conv2d-7            [-1, 384, 7, 7]         663,936
              ReLU-8            [-1, 384, 7, 7]               0
            Conv2d-9            [-1, 256, 7, 7]         884,992
             ReLU-10            [-1, 256, 7, 7]               0
           Conv2d-11            [-1, 256, 7, 7]         590,080
             ReLU-12            [-1, 256, 7, 7]               0
        MaxPool2d-13            [-1, 256, 3, 3]               0
AdaptiveAvgPool2d-14            [-1, 256, 6, 6]               0
          Dropout-15                 [-1, 9216]               0
           Linear-16                 [-1, 4096]      37,752,832
             ReLU-17                 [-1, 4096]               0
          Dropout-18                 [-1, 4096]               0
           Linear-19                 [-1, 4096]      16,781,312
             ReLU-20                 [-1, 4096]               0
           Linear-21                   [-1, 10]          40,970
================================================================
Total params: 57,023,306
Trainable params: 57,023,306
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 2.83
Params size (MB): 217.53
Estimated Total Size (MB): 220.36
----------------------------------------------------------------
```

Define AlexNet

In [24]:

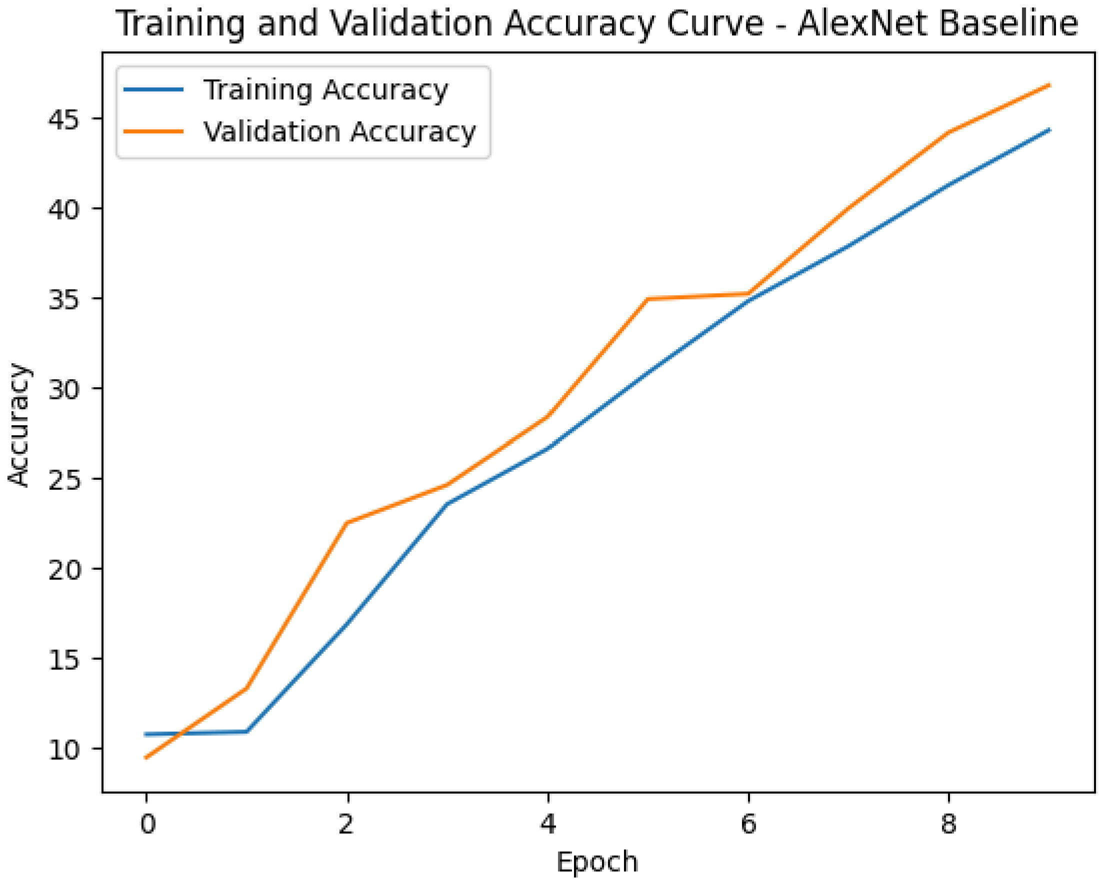
```python
# Define the AlexNet model and move to the device
def get_alexnet():
    model = models.alexnet(pretrained=False)
    model.features[0] = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1)
    model.classifier[6] = nn.Linear(model.classifier[6].in_features, 10)  # 10 c
    return model.to(device)

# Training function with accuracy tracking
def train_model_with_accuracy_tracking(model, criterion, optimizer, trainloader,
    train_acc, val_acc = [], []

    for epoch in range(num_epochs):
        # Training phase
        model.train()
        correct_train, total_train = 0, 0

        for inputs, labels in trainloader:
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(inputs)
```

```
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            # Track accuracy
            _, predicted = outputs.max(1)
            total_train += labels.size(0)
            correct_train += predicted.eq(labels).sum().item()

        train_accuracy = 100 * correct_train / total_train
        train_acc.append(train_accuracy)

        # Validation phase
        model.eval()
        correct_val, total_val = 0, 0
        with torch.no_grad():
            for inputs, labels in valloader:
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = model(inputs)
                _, predicted = outputs.max(1)
                total_val += labels.size(0)
                correct_val += predicted.eq(labels).sum().item()

        val_accuracy = 100 * correct_val / total_val
        val_acc.append(val_accuracy)

        # Print epoch results
        print(f"Epoch [{epoch+1}/{num_epochs}], Train Accuracy: {train_accuracy:

    return train_acc, val_acc
```

Baseline Training for AlexNet

In [25]:
```
# Load model, criterion, and optimizer
model = get_alexnet()
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

# Assuming trainloader, valloader, and testloader are defined
# Train the model
train_acc, val_acc = train_model_with_accuracy_tracking(model, criterion, optimi

# Plot training and validation accuracy
plot_training_and_validation_accuracy(train_acc, val_acc, "AlexNet Baseline")

# Evaluate model on the test set
print("Evaluating AlexNet Baseline Model on Test Set...")
evaluate_model(model, testloader)
```

```
Epoch [1/10], Train Accuracy: 10.78%, Validation Accuracy: 9.50%
Epoch [2/10], Train Accuracy: 10.92%, Validation Accuracy: 13.33%
Epoch [3/10], Train Accuracy: 16.89%, Validation Accuracy: 22.52%
Epoch [4/10], Train Accuracy: 23.56%, Validation Accuracy: 24.63%
Epoch [5/10], Train Accuracy: 26.63%, Validation Accuracy: 28.38%
Epoch [6/10], Train Accuracy: 30.83%, Validation Accuracy: 34.93%
Epoch [7/10], Train Accuracy: 34.81%, Validation Accuracy: 35.22%
Epoch [8/10], Train Accuracy: 37.87%, Validation Accuracy: 39.96%
Epoch [9/10], Train Accuracy: 41.26%, Validation Accuracy: 44.18%
Epoch [10/10], Train Accuracy: 44.31%, Validation Accuracy: 46.80%
```



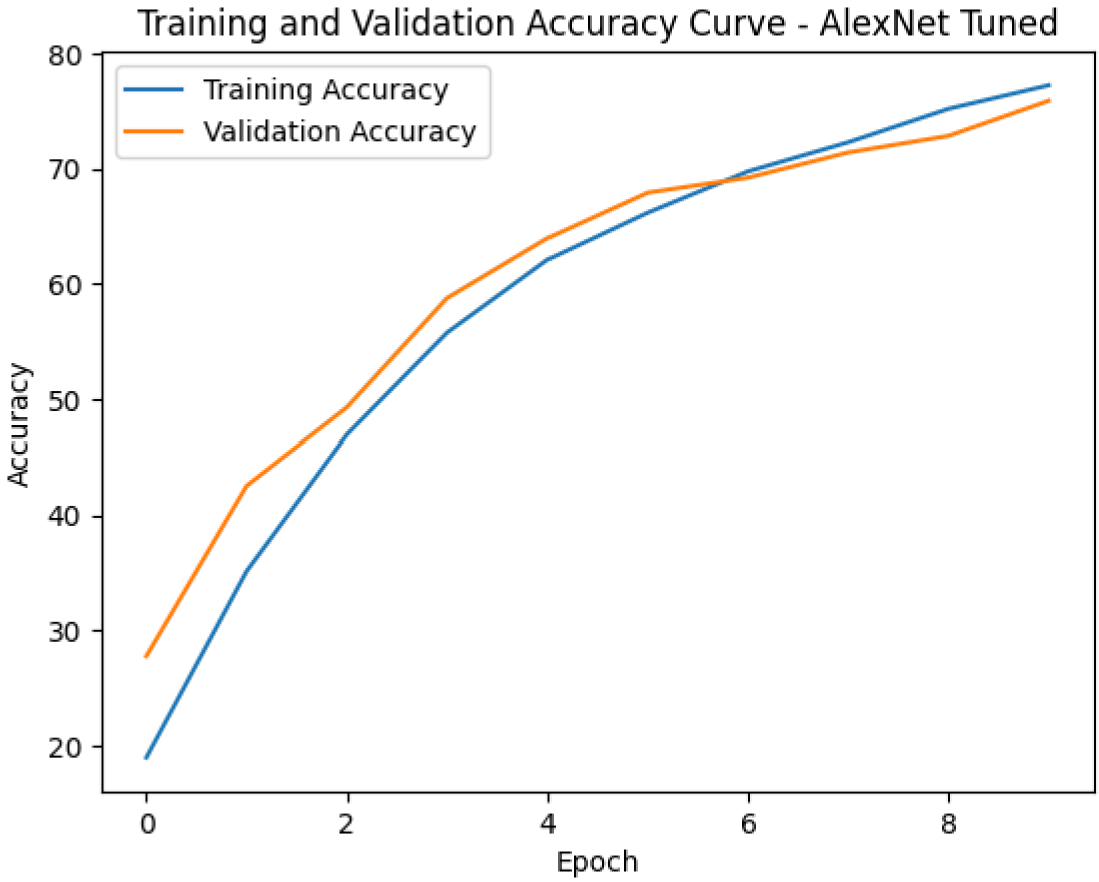

```
Evaluating AlexNet Baseline Model on Test Set...
Test Accuracy: 48.54%
```

Out[25]: 48.54

Hyperparameter Tuning for AlexNet

In [27]:
```
# Hyperparameter tuning with different learning rate and weight decay
print("\nHyperparameter Tuning: lr=0.01, weight_decay=0.0005")
model_tuned = get_alexnet()  # Instantiate a fresh model
optimizer_tuned = optim.SGD(model_tuned.parameters(), lr=0.01, momentum=0.9, wei

# Train the model with tuned hyperparameters
train_acc_tuned, val_acc_tuned = train_model_with_accuracy_tracking(model_tuned,

# Plot training and validation accuracy for tuned model
plot_training_and_validation_accuracy(train_acc_tuned, val_acc_tuned, "AlexNet T

# Evaluate tuned model on the test set
print("Evaluating AlexNet Tuned Model on Test Set...")
evaluate_model(model_tuned, testloader)
```

```
Hyperparameter Tuning: lr=0.01, weight_decay=0.0005
Epoch [1/10], Train Accuracy: 18.94%, Validation Accuracy: 27.75%
Epoch [2/10], Train Accuracy: 35.12%, Validation Accuracy: 42.53%
Epoch [3/10], Train Accuracy: 46.94%, Validation Accuracy: 49.29%
Epoch [4/10], Train Accuracy: 55.76%, Validation Accuracy: 58.77%
Epoch [5/10], Train Accuracy: 62.10%, Validation Accuracy: 63.97%
Epoch [6/10], Train Accuracy: 66.19%, Validation Accuracy: 67.93%
Epoch [7/10], Train Accuracy: 69.78%, Validation Accuracy: 69.23%
Epoch [8/10], Train Accuracy: 72.31%, Validation Accuracy: 71.42%
Epoch [9/10], Train Accuracy: 75.21%, Validation Accuracy: 72.86%
Epoch [10/10], Train Accuracy: 77.26%, Validation Accuracy: 75.91%
```




```
Evaluating AlexNet Tuned Model on Test Set...
Test Accuracy: 77.66%
```

Out[27]: 77.66

In [49]:
```
torch.cuda.empty_cache()
# print(torch.cuda.memory_summary(device=None, abbreviated=True))
```