trained

November 13, 2024

[1]:
```python
import tensorflow as tf
from tensorflow.keras.applications import ResNet50, MobileNetV2
from tensorflow.keras.layers import Input, Dense, Flatten, Dropout, Conv2D,␣
↪MaxPooling2D
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam, SGD
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
import numpy as np
import warnings
warnings.filterwarnings("ignore", category=UserWarning, module="keras")


# Define ResNet-18 architecture (using ResNet50 with custom layers)
def build_resnet18(input_shape=(32, 32, 3), num_classes=10):
    base_model = tf.keras.applications.ResNet50(
        input_shape=input_shape,
        include_top=False,
        weights=None  # No pretrained weights due to smaller input shape
    )
    model = Sequential([
        Input(shape=input_shape),
        base_model,
        Flatten(),
        Dense(256, activation='relu'),
        Dropout(0.5),
        Dense(num_classes, activation='softmax')
    ])
    return model

# Define MobileNetV2 architecture
def build_mobilenet(input_shape=(32, 32, 3), num_classes=10):
    base_model = MobileNetV2(input_shape=input_shape, include_top=False,␣
↪weights=None)  # No pretrained weights
    model = Sequential([
        Input(shape=input_shape),
        base_model,
```

```python
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.4),
        Dense(num_classes, activation='softmax')
    ])
    return model

# Define AlexNet architecture
def build_alexnet(input_shape=(32, 32, 3), num_classes=10):
    model = Sequential([
        Input(shape=input_shape),
        Conv2D(96, kernel_size=(3, 3), activation='relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Conv2D(256, kernel_size=(3, 3), activation='relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Flatten(),
        Dense(512, activation='relu'),
        Dropout(0.5),
        Dense(num_classes, activation='softmax')
    ])
    return model
```

[2]:
```python
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0  # Normalize pixel values to␣
 ↪[0, 1]
y_train = tf.keras.utils.to_categorical(y_train, 10)  # One-hot encode labels
y_test = tf.keras.utils.to_categorical(y_test, 10)

# Split training data into training and validation sets
x_train, x_val = x_train[:40000], x_train[40000:]
y_train, y_val = y_train[:40000], y_train[40000:]
```

[3]:
```python
# Set up data augmentation
datagen = ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True
)
datagen.fit(x_train)
```

[4]:
```python
# Function to get a new instance of an optimizer
def get_optimizer(optimizer_name):
    if optimizer_name == 'Adam':
        return Adam(learning_rate=0.0001)
    elif optimizer_name == 'SGD':
```

```
        return SGD(learning_rate=0.001, momentum=0.9)
    else:
        raise ValueError("Optimizer name must be either 'Adam' or 'SGD'")

# Function to train and evaluate each model
def train_and_evaluate(model, model_name, optimizer_name, x_train, y_train,␣
 ↪x_val, y_val):
    optimizer = get_optimizer(optimizer_name)  # Get a new optimizer instance
    model.compile(optimizer=optimizer, loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

    # Use try-except to capture any training errors and ensure cleanup
    try:
        history = model.fit(
            datagen.flow(x_train, y_train, batch_size=128),
            epochs=8,
            validation_data=(x_val, y_val),
            verbose=1
        )
    except Exception as e:
        print(f"Error during training {model_name} with {optimizer_name}: {e}")
        return None, None  # Return 8one to avoid further processing

    plot_history(history, model_name, optimizer_name)
    val_loss, val_accuracy = model.evaluate(x_val, y_val, verbose=0)
    print(f'{model_name} with {optimizer_name}: Validation Accuracy =␣
 ↪{val_accuracy:.4f}, Validation Loss = {val_loss:.4f}')
    return val_accuracy, val_loss
```

[5]:

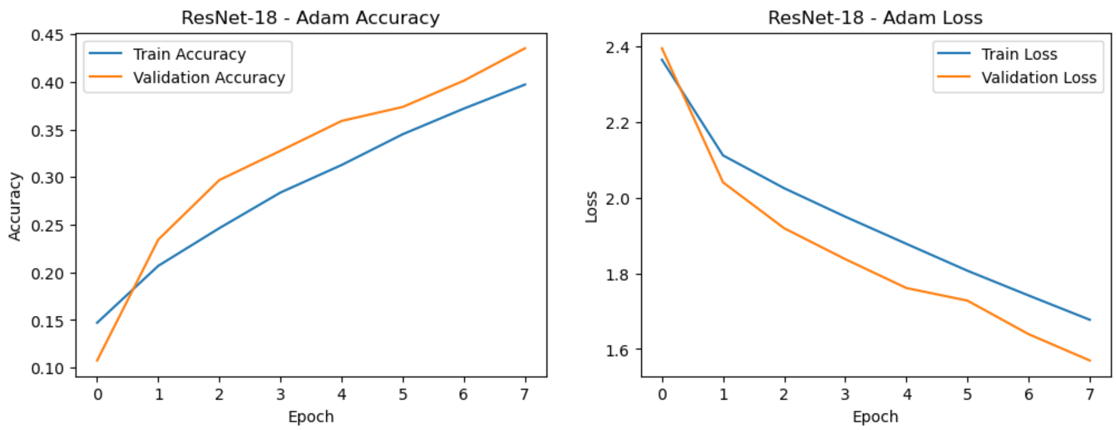
```
# Function to plot training and validation accuracy and loss
def plot_history(history, model_name, optimizer_name):
    if not history:
        return  # Skip if training was not successful

    plt.figure(figsize=(12, 4))

    # Plot accuracy
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Train Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.title(f'{model_name} - {optimizer_name} Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    # Plot loss
    plt.subplot(1, 2, 2)
```

```python
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.title(f'{model_name} - {optimizer_name} Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    plt.show()
```

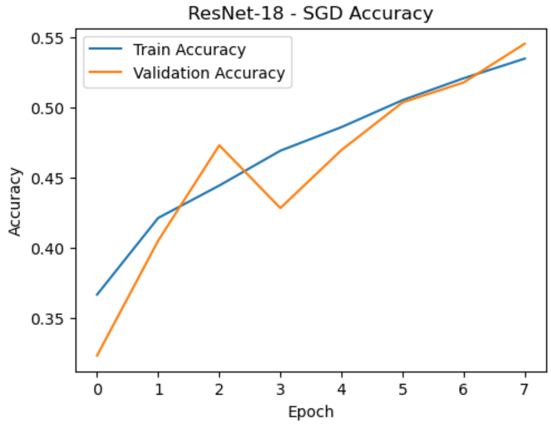
[6]:
```python
# Dictionary to hold model architectures
models = {
    'ResNet-18': build_resnet18(input_shape=(32, 32, 3), num_classes=10),
    'MobileNetV2': build_mobilenet(input_shape=(32, 32, 3), num_classes=10),
    'AlexNet': build_alexnet(input_shape=(32, 32, 3), num_classes=10)
}

# Dictionary to store results
results = {}

# Train each model with each optimizer
for model_name, model in models.items():
    for optimizer_name in ['Adam', 'SGD']:  # Specify optimizer names
        print(f'Training {model_name} with {optimizer_name} optimizer...')
        val_accuracy, val_loss = train_and_evaluate(model, model_name,␣
 ↪optimizer_name, x_train, y_train, x_val, y_val)
        if val_accuracy is not None and val_loss is not None:
            results[(model_name, optimizer_name)] = (val_accuracy, val_loss)
```

```
Training ResNet-18 with Adam optimizer…
Epoch 1/8
313/313              399s 1s/step -
accuracy: 0.1259 - loss: 2.6843 - val_accuracy: 0.1076 - val_loss: 2.3954
Epoch 2/8
313/313              392s 1s/step -
accuracy: 0.1956 - loss: 2.1391 - val_accuracy: 0.2344 - val_loss: 2.0408
Epoch 3/8
313/313              393s 1s/step -
accuracy: 0.2391 - loss: 2.0421 - val_accuracy: 0.2970 - val_loss: 1.9195
Epoch 4/8
313/313              862s 3s/step -
accuracy: 0.2751 - loss: 1.9697 - val_accuracy: 0.3277 - val_loss: 1.8377
Epoch 5/8
313/313              391s 1s/step -
accuracy: 0.3036 - loss: 1.9002 - val_accuracy: 0.3590 - val_loss: 1.7614
Epoch 6/8
313/313              391s 1s/step -
accuracy: 0.3417 - loss: 1.8170 - val_accuracy: 0.3737 - val_loss: 1.7280
Epoch 7/8
```

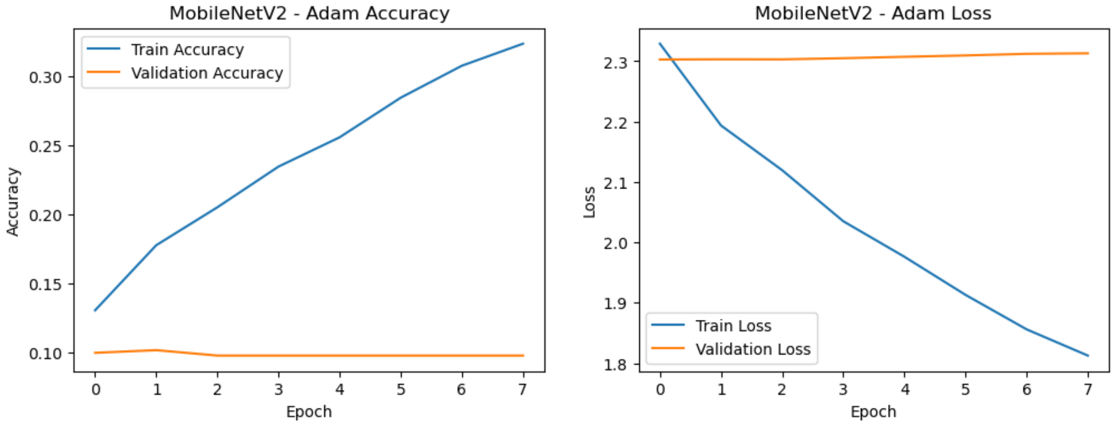
```
313/313 1248s 4s/step -
accuracy: 0.3683 - loss: 1.7584 - val_accuracy: 0.4013 - val_loss: 1.6393
Epoch 8/8
313/313 390s 1s/step -
accuracy: 0.3960 - loss: 1.6875 - val_accuracy: 0.4353 - val_loss: 1.5698
```



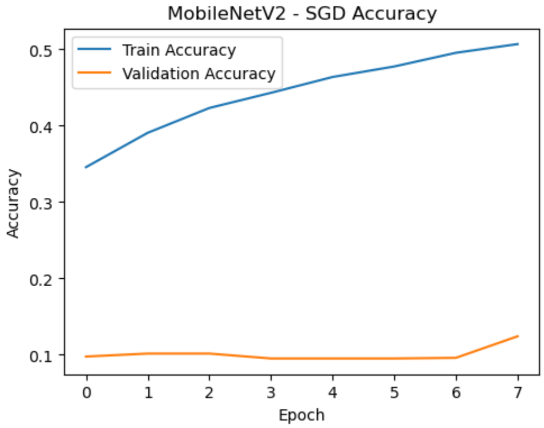

```
ResNet-18 with Adam: Validation Accuracy = 0.4353, Validation Loss = 1.5698
Training ResNet-18 with SGD optimizer…
Epoch 1/8
313/313 394s 1s/step -
accuracy: 0.3543 - loss: 1.7890 - val_accuracy: 0.3235 - val_loss: 2.0626
Epoch 2/8
313/313 389s 1s/step -
accuracy: 0.4168 - loss: 1.6101 - val_accuracy: 0.4053 - val_loss: 1.6533
Epoch 3/8
313/313 389s 1s/step -
accuracy: 0.4390 - loss: 1.5449 - val_accuracy: 0.4732 - val_loss: 1.4585
Epoch 4/8
313/313 388s 1s/step -
accuracy: 0.4668 - loss: 1.4886 - val_accuracy: 0.4285 - val_loss: 1.5386
Epoch 5/8
313/313 389s 1s/step -
accuracy: 0.4836 - loss: 1.4412 - val_accuracy: 0.4698 - val_loss: 1.5027
Epoch 6/8
313/313 6683s 21s/step -
accuracy: 0.4980 - loss: 1.4017 - val_accuracy: 0.5037 - val_loss: 1.4115
Epoch 7/8
313/313 17073s 55s/step -
accuracy: 0.5200 - loss: 1.3580 - val_accuracy: 0.5179 - val_loss: 1.3328
Epoch 8/8
313/313 6366s 20s/step -
accuracy: 0.5316 - loss: 1.3164 - val_accuracy: 0.5455 - val_loss: 1.2640
```

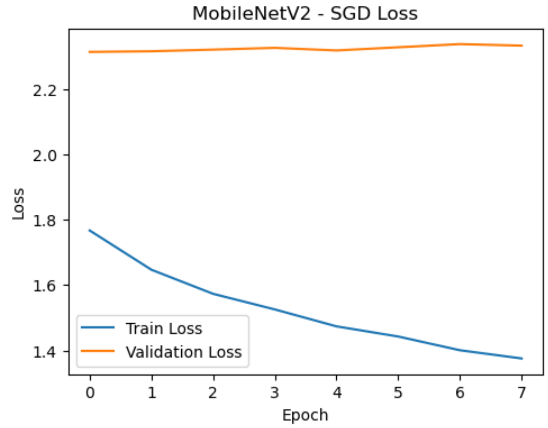



```
ResNet-18 with SGD: Validation Accuracy = 0.5455, Validation Loss = 1.2640
Training MobileNetV2 with Adam optimizer…
Epoch 1/8
313/313              34s 89ms/step -
accuracy: 0.1184 - loss: 2.4307 - val_accuracy: 0.0997 - val_loss: 2.3028
Epoch 2/8
313/313              29s 91ms/step -
accuracy: 0.1651 - loss: 2.2193 - val_accuracy: 0.1016 - val_loss: 2.3031
Epoch 3/8
313/313              28s 89ms/step -
accuracy: 0.1993 - loss: 2.1410 - val_accuracy: 0.0977 - val_loss: 2.3030
Epoch 4/8
313/313              28s 89ms/step -
accuracy: 0.2284 - loss: 2.0500 - val_accuracy: 0.0977 - val_loss: 2.3049
Epoch 5/8
313/313              28s 89ms/step -
accuracy: 0.2500 - loss: 1.9932 - val_accuracy: 0.0977 - val_loss: 2.3073
Epoch 6/8
313/313              27s 88ms/step -
accuracy: 0.2796 - loss: 1.9192 - val_accuracy: 0.0977 - val_loss: 2.3095
Epoch 7/8
313/313              27s 86ms/step -
accuracy: 0.3029 - loss: 1.8687 - val_accuracy: 0.0977 - val_loss: 2.3122
Epoch 8/8
313/313              27s 86ms/step -
accuracy: 0.3169 - loss: 1.8245 - val_accuracy: 0.0977 - val_loss: 2.3130
```

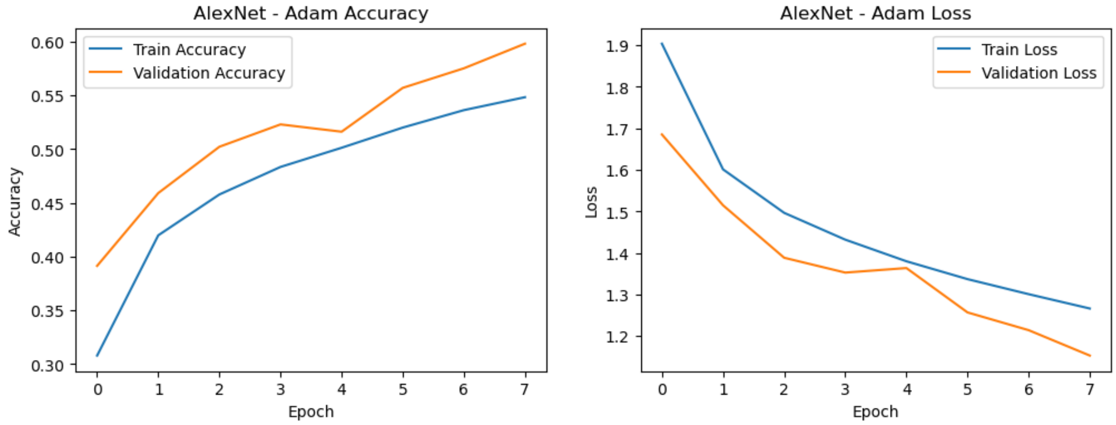



```
MobileNetV2 with Adam: Validation Accuracy = 0.0977, Validation Loss = 2.3130
Training MobileNetV2 with SGD optimizer…
Epoch 1/8
313/313              30s 83ms/step -
accuracy: 0.3335 - loss: 1.8000 - val_accuracy: 0.0977 - val_loss: 2.3131
Epoch 2/8
313/313              26s 84ms/step -
accuracy: 0.3776 - loss: 1.6747 - val_accuracy: 0.1016 - val_loss: 2.3152
Epoch 3/8
313/313              27s 86ms/step -
accuracy: 0.4191 - loss: 1.5798 - val_accuracy: 0.1016 - val_loss: 2.3202
Epoch 4/8
313/313              27s 85ms/step -
accuracy: 0.4362 - loss: 1.5464 - val_accuracy: 0.0952 - val_loss: 2.3256
Epoch 5/8
313/313              27s 86ms/step -
accuracy: 0.4633 - loss: 1.4713 - val_accuracy: 0.0952 - val_loss: 2.3176
Epoch 6/8
313/313              27s 87ms/step -
accuracy: 0.4779 - loss: 1.4452 - val_accuracy: 0.0952 - val_loss: 2.3273
Epoch 7/8
313/313              27s 86ms/step -
accuracy: 0.4992 - loss: 1.3990 - val_accuracy: 0.0960 - val_loss: 2.3371
Epoch 8/8
313/313              27s 87ms/step -
accuracy: 0.5061 - loss: 1.3814 - val_accuracy: 0.1242 - val_loss: 2.3324
```

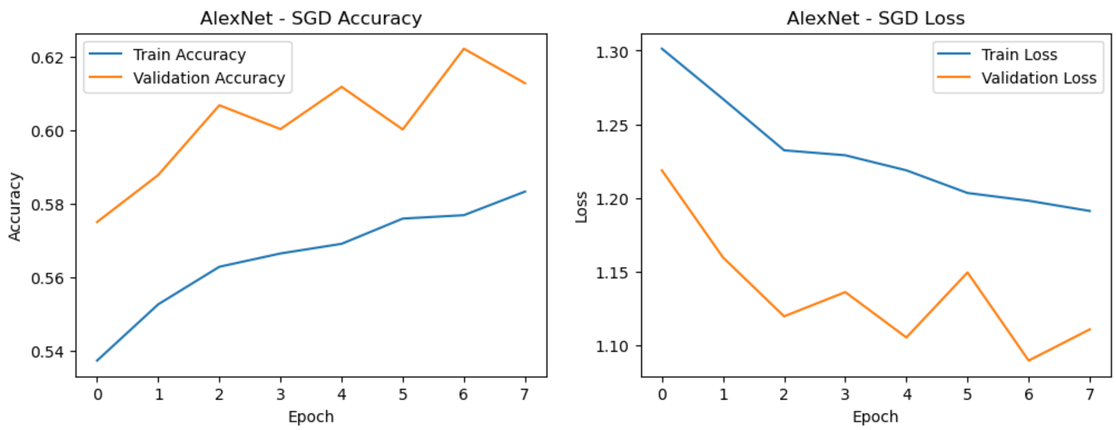





```
MobileNetV2 with SGD: Validation Accuracy = 0.1242, Validation Loss = 2.3324
Training AlexNet with Adam optimizer…
Epoch 1/8
313/313              27s 84ms/step -
accuracy: 0.2394 - loss: 2.0681 - val_accuracy: 0.3915 - val_loss: 1.6855
Epoch 2/8
313/313              27s 85ms/step -
accuracy: 0.4034 - loss: 1.6423 - val_accuracy: 0.4592 - val_loss: 1.5150
Epoch 3/8
313/313              27s 85ms/step -
accuracy: 0.4521 - loss: 1.5130 - val_accuracy: 0.5023 - val_loss: 1.3888
Epoch 4/8
313/313              26s 84ms/step -
accuracy: 0.4798 - loss: 1.4487 - val_accuracy: 0.5231 - val_loss: 1.3531
Epoch 5/8
313/313              26s 83ms/step -
accuracy: 0.4998 - loss: 1.3921 - val_accuracy: 0.5163 - val_loss: 1.3640
Epoch 6/8
313/313              26s 83ms/step -
accuracy: 0.5165 - loss: 1.3449 - val_accuracy: 0.5571 - val_loss: 1.2572
Epoch 7/8
313/313              26s 83ms/step -
accuracy: 0.5368 - loss: 1.3021 - val_accuracy: 0.5753 - val_loss: 1.2145
Epoch 8/8
313/313              26s 83ms/step -
accuracy: 0.5425 - loss: 1.2810 - val_accuracy: 0.5982 - val_loss: 1.1534
```




```
AlexNet with Adam: Validation Accuracy = 0.5982, Validation Loss = 1.1534
Training AlexNet with SGD optimizer…
Epoch 1/8
313/313              25s 80ms/step -
accuracy: 0.5293 - loss: 1.3198 - val_accuracy: 0.5751 - val_loss: 1.2186
Epoch 2/8
313/313              25s 80ms/step -
accuracy: 0.5474 - loss: 1.2747 - val_accuracy: 0.5879 - val_loss: 1.1595
Epoch 3/8
313/313              25s 80ms/step -
accuracy: 0.5612 - loss: 1.2352 - val_accuracy: 0.6069 - val_loss: 1.1196
Epoch 4/8
313/313              25s 81ms/step -
accuracy: 0.5664 - loss: 1.2376 - val_accuracy: 0.6004 - val_loss: 1.1360
Epoch 5/8
313/313              25s 81ms/step -
accuracy: 0.5676 - loss: 1.2242 - val_accuracy: 0.6119 - val_loss: 1.1052
Epoch 6/8
313/313              25s 81ms/step -
accuracy: 0.5697 - loss: 1.2130 - val_accuracy: 0.6003 - val_loss: 1.1494
Epoch 7/8
313/313              26s 82ms/step -
accuracy: 0.5747 - loss: 1.1983 - val_accuracy: 0.6223 - val_loss: 1.0896
Epoch 8/8
313/313              25s 81ms/step -
accuracy: 0.5800 - loss: 1.1951 - val_accuracy: 0.6129 - val_loss: 1.1107
```




```
AlexNet with SGD: Validation Accuracy = 0.6129, Validation Loss = 1.1107
```

[7]:
```python
# Find the best model and optimizer based on validation accuracy
if results:
    best_model_info = max(results, key=lambda x: results[x][0])
    best_model_name, best_optimizer_name = best_model_info
    best_model = models[best_model_name]
    best_optimizer = get_optimizer(best_optimizer_name)

    print(f"\nBest Model: {best_model_name} with {best_optimizer_name} optimizer")

    # Recompile best model with best optimizer and evaluate on the test set
    best_model.compile(optimizer=best_optimizer, loss='categorical_crossentropy', metrics=['accuracy'])
    test_loss, test_accuracy = best_model.evaluate(x_test, y_test, verbose=0)
    print(f'\nTest Accuracy of Best Model ({best_model_name} with {best_optimizer_name}): {test_accuracy:.4f}')
else:
    print("No valid results to display.")
```

```
Best Model: AlexNet with SGD optimizer

Test Accuracy of Best Model (AlexNet with SGD): 0.6115
```

[ ]:

[ ]:
```
]
```

[ ]: