# IEOR E4742 Assignment 2

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## Problem 1 (Convolutional Neural Networks)

**In the sample code** `example_CNN_CIFAR.ipynb`:

(a) **Add one more convolutional layer with max pooling and assess the impact of the additional convolutional layer on accuracy.**

(b) **What is the number of parameters we are trying to learn in the original code, and how does it change with the extra layer?**

## Solution to (a)

### New CNN model

- **Input Layer:** Shape (32, 32, 3)
- **Convolutional Block 1:**
  - Conv2D (32 filters, 3x3 kernel, ReLU, padding='same')
  - MaxPooling2D (2x2)
- **Convolutional Block 2:**
  - Conv2D (64 filters, 3x3 kernel, ReLU, padding='same')
  - MaxPooling2D (2x2)
- **Convolutional Block 3:**
  - Conv2D (128 filters, 3x3 kernel, ReLU, padding='same')
  - MaxPooling2D (2x2)
- **Additional Convolutional Block:**
  - **New Layer:** Conv2D (256 filters, 3x3 kernel, ReLU, padding='same')
  - MaxPooling2D (2x2)
- **Flatten Layer**

- **Dense Layer:** 128 units, ReLU
- **Dense Layer:** 64 units, ReLU
- **Output Layer:** Dense, 10 units (softmax for classification)

## Results

After adding the additional layer, we trained the model for 20 epochs with a batch size of 64. The loss and accuracy for both training and validation in original and new model settings are suggested follow:

- **Training:**
  - **Original Model:** The original model achieved an accuracy of 0.9459 and a loss of 0.1290.
  - **New Model:** The new model improved its training accuracy to 0.9698 and reduced the loss to 0.0790.

  **Explanation:** The new model demonstrated enhanced learning ability on the training set, likely due to the added layer, which increased the model's capacity to fit the training data more effectively.

- **Validation:**
  - **Original Model:** The original model's validation accuracy was 0.7231, with a loss of 1.4876.
  - **New Model:** The new model showed a slightly lower validation accuracy of 0.7336 and a higher validation loss of 1.3954.

  **Explanation:** Despite the better training performance, the new model's decrease in validation accuracy and increase in loss suggest potential overfitting, where the model learned the training data too well but struggled to generalize to unseen data.

The plots of both loss and accuracy in the original model and new model are shown as Figure 1 and Figure 2.

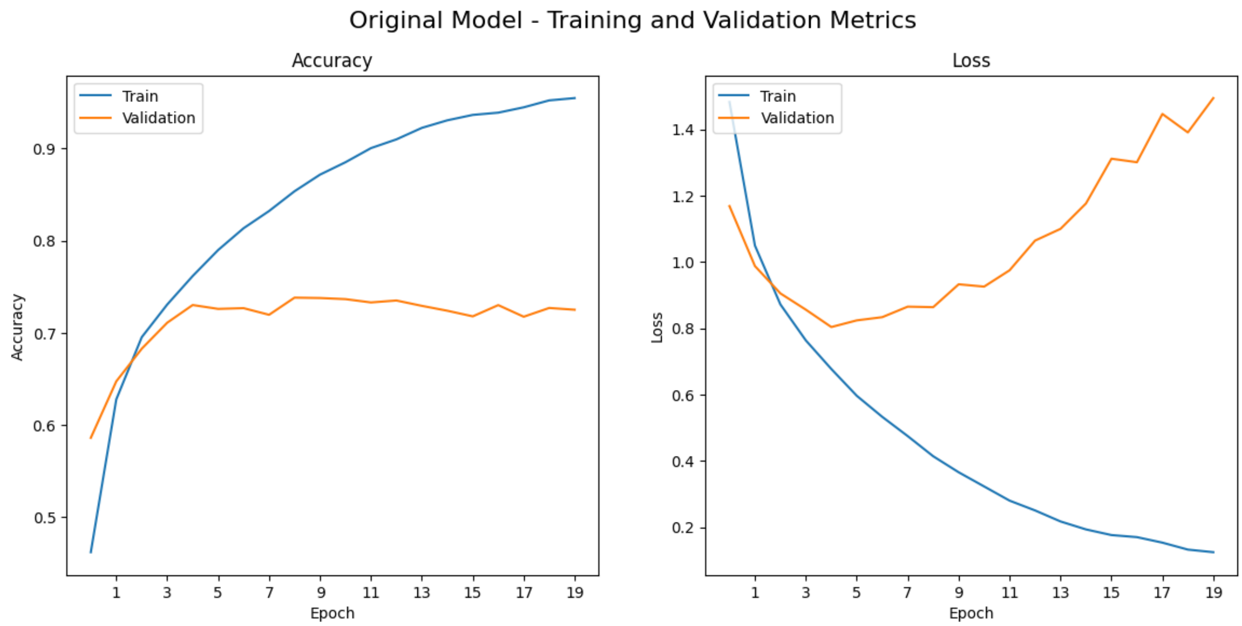


Figure 1: Training and Validation Metrics for Original Model

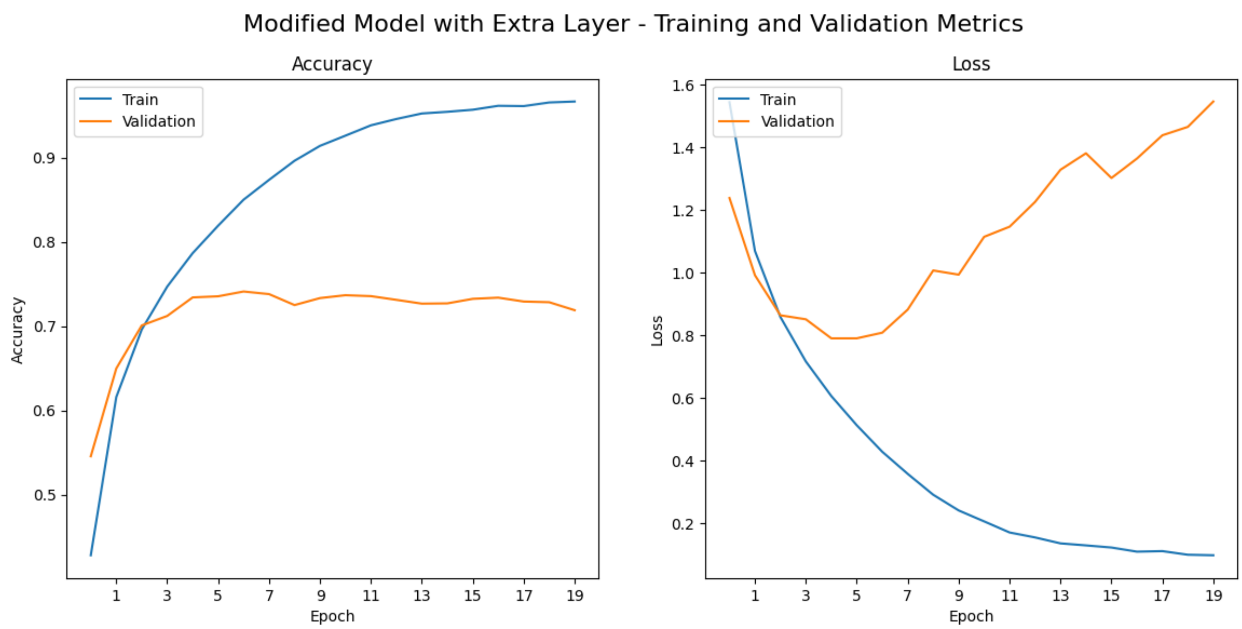


Figure 2: Training and Validation Metrics for New Model

In summary, New model performs better in the training phase, but they're quite similar in the result of validation phase.

Then, we have the confusion matrix plots, which give us more information on how the samples are classified.

- **Training:** The Modified Model outperforms the Original Model in training data classification, showing fewer misclassifications and higher accuracy. This suggests that the changes made in the Modified Model enhanced its capacity to learn from the training data more effectively.

- **Validation:** On the validation data, both the Original and Modified Models exhibit similar performance, with comparable confusion matrix patterns. This indicates that the improvements seen in training did not result in significantly better generalization for unseen data.

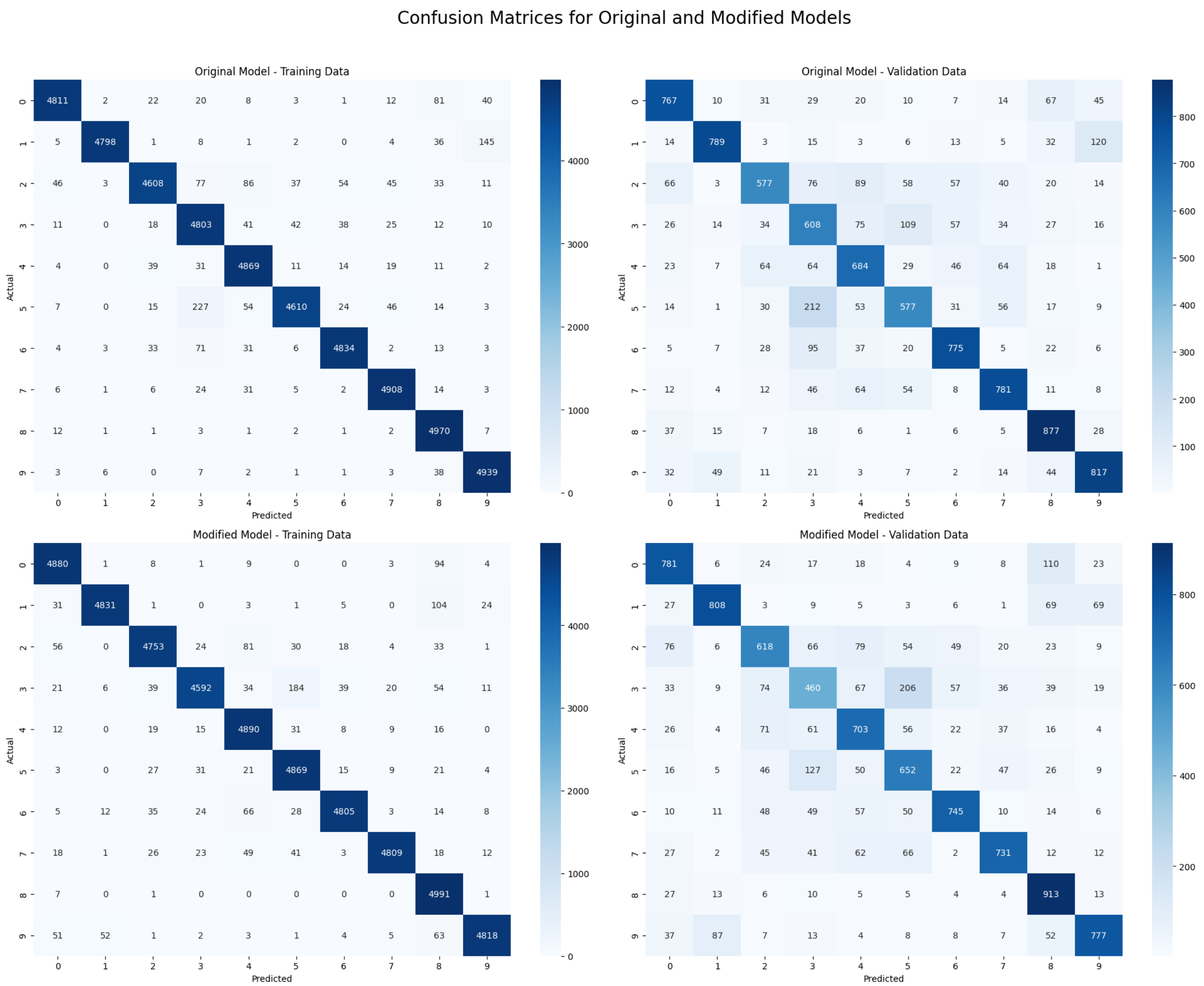


Figure 3: Confusion Matrix

Overall, while the Modified Model fits the training data better, both models show comparable effectiveness when tested on unseen data.

# Solution to (b)

# Detailed Parameter Calculation for Each Layer

## Original Model

- **Conv2D (32 filters, input shape (32, 32, 3))**:

$$(3 \times 3 \times 3 + 1) \times 32 = (27 + 1) \times 32 = 896 \text{ parameters}$$

- **MaxPooling2D**: 0 parameters
- **Conv2D (64 filters)**:

$$(3 \times 3 \times 32 + 1) \times 64 = (288 + 1) \times 64 = 18,496 \text{ parameters}$$

- **MaxPooling2D**: 0 parameters
- **Conv2D (128 filters)**:

$$(3 \times 3 \times 64 + 1) \times 128 = (576 + 1) \times 128 = 73,856 \text{ parameters}$$

- **MaxPooling2D**: 0 parameters
- **Flatten Layer**: 0 parameters
- **Dense (128 units, input 2048)**:

$$(2048 + 1) \times 128 = 262,272 \text{ parameters}$$

- **Dense (64 units)**:

$$(128 + 1) \times 64 = 8,256 \text{ parameters}$$

- **Dense (10 units)**:

$$(64 + 1) \times 10 = 650 \text{ parameters}$$

**Total Parameters for Original Model:** 364,426

## Modified Model

- **Conv2D (32 filters, input shape (32, 32, 3))**:

$$(3 \times 3 \times 3 + 1) \times 32 = (27 + 1) \times 32 = 896 \text{ parameters}$$

- **MaxPooling2D**: 0 parameters
- **Conv2D (64 filters)**:

$$(3 \times 3 \times 32 + 1) \times 64 = (288 + 1) \times 64 = 18,496 \text{ parameters}$$

- **MaxPooling2D**: 0 parameters
- **Conv2D (128 filters)**:

$$(3 \times 3 \times 64 + 1) \times 128 = (576 + 1) \times 128 = 73,856 \text{ parameters}$$

- **MaxPooling2D**: 0 parameters
- **Conv2D (256 filters)**:

$$(3 \times 3 \times 128 + 1) \times 256 = (1152 + 1) \times 256 = 295,168 \text{ parameters}$$

- **MaxPooling2D**: 0 parameters
- **Flatten Layer**: 0 parameters
- **Dense (128 units, input 1024)**:

$$(1024 + 1) \times 128 = 131,200 \text{ parameters}$$

- **Dense (64 units)**:

$$(128 + 1) \times 64 = 8,256 \text{ parameters}$$

- **Dense (10 units)**:

$$(64 + 1) \times 10 = 650 \text{ parameters}$$

**Total Parameters for Modified Model:** 528,522

The original model has a total of 364,426 trainable parameters. These parameters are distributed across three convolutional blocks and three dense layers. The Conv2D layers contribute the most to the parameter count, followed by the dense layers.

The modified model, which includes an additional convolutional block with 256 filters, increases the total number of trainable parameters to 528,522. This results in an increase of 164,096 parameters compared to the original model.

The addition of the extra convolutional block significantly increases the model's capacity to learn complex features:

- **Original Model:** 364,426 parameters
- **Modified Model:** 528,522 parameters
- **Increase:** 164,096 additional parameters

This increase allows the model to potentially achieve better performance, especially on more complex datasets, but it also requires more computational resources and may risk overfitting if not properly managed.

# Problem 2 (Batch Normalization)

**For Problem 1, assess the impact of batch normalization on learning speed and accuracy.**

# Solution to Problem 2

To assess the impact of batch normalization, we added batchnormalization layer after each Conv2D or Dense layer for the original model in problem 1. Then, we trained the original model and batch-normalized original model in a batch size of 64 and 20 epochs, and finally get the result of the training speed and accuracy, which are shown below:

## Training and Validation Comparison

- **Learning Speed:** From the plot below, the model with batch normalization shows quicker initial convergence, achieving higher training accuracy in the early epochs compared to the original model. This indicates that batch normalization accelerates learning by stabilizing the optimization process.

- **Accuracy:** The original model achieved a training accuracy of 0.9639 and a validation accuracy of 0.7320. In comparison, the model with batch normalization achieved a slightly higher training accuracy of 0.9749 and a validation accuracy of 0.7419. This indicates that batch normalization helps stabilize and improve generalization, as observed by the slightly better training and validation performance.

A figure showing the comparison between the original model and batch-normalized original model is as below:

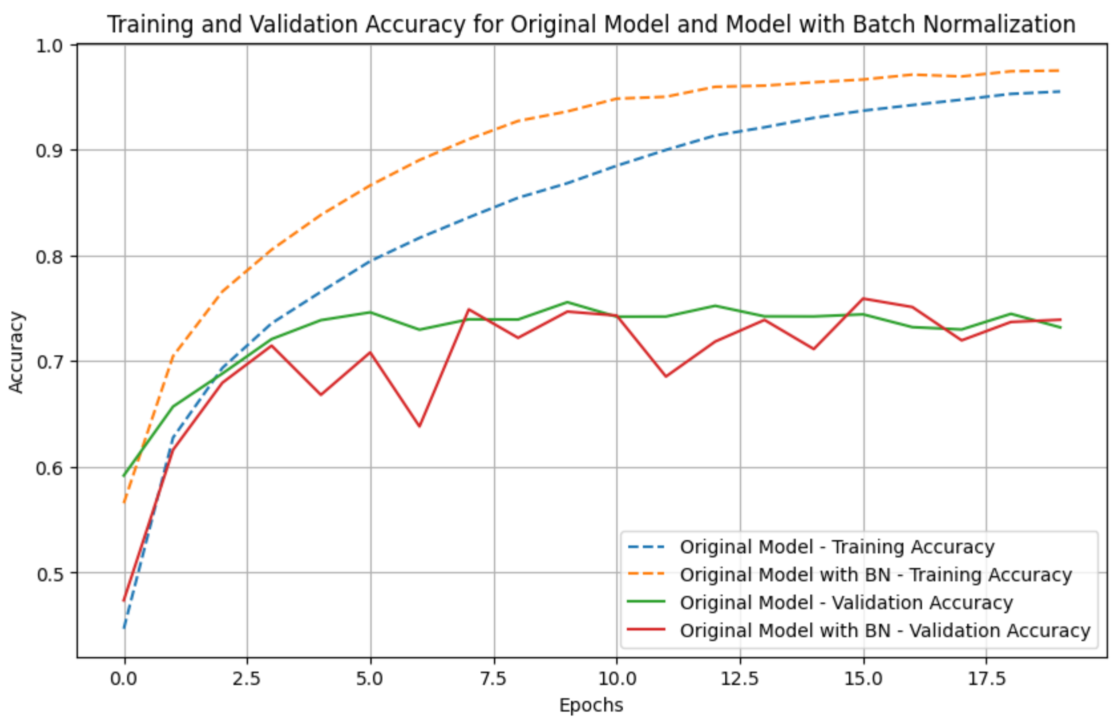


Figure 4: Accuracy Comparison

In summary, the use of batch normalization in the model enhances learning speed and generalization. The training and the validation accuracy benefits, indicating improved model robustness. This highlights the effectiveness of batch normalization in promoting faster learning and better overall performance on validation data.

# Code Appendix

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[17]:
```
from tensorflow.keras import layers, models
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

## 1 Problem 1

[18]:
```
# Load and preprocess CIFAR-10 data
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Normalize the pixel values to be between 0 and 1
x_train, x_test = x_train.astype('float32') / 255.0, x_test.astype('float32') /␣
↪255.0
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Define the original CNN model
def create_cnn_model():
    model = models.Sequential()

    # First convolutional block
    model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same',␣
↪input_shape=(32, 32, 3)))
    model.add(layers.MaxPooling2D((2, 2)))

    # Second convolutional block
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Third convolutional block
    model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten and add dense layers
```

```python
    model.add(layers.Flatten())
    model.add(layers.Dense(128, activation='relu'))
    model.add(layers.Dense(64, activation='relu'))

    # Output layer
    model.add(layers.Dense(10, activation='softmax'))  # 10 classes for CIFAR-10

    return model

# Define the modified model with an additional convolutional layer
def create_modified_cnn_model():
    model = models.Sequential()

    # First convolutional block
    model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same',␣
↪input_shape=(32, 32, 3)))
    model.add(layers.MaxPooling2D((2, 2)))

    # Second convolutional block
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Third convolutional block
    model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Additional convolutional block (added layer)
    model.add(layers.Conv2D(256, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten and add dense layers
    model.add(layers.Flatten())
    model.add(layers.Dense(128, activation='relu'))
    model.add(layers.Dense(64, activation='relu'))

    # Output layer
    model.add(layers.Dense(10, activation='softmax'))  # 10 classes for CIFAR-10

    return model
```

[19]:
```python
# Instantiate both models
original_model = create_cnn_model()
modified_model = create_modified_cnn_model()

# Compile both models
original_model.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
```

```
modified_model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

# Print model summaries to compare parameter counts
print("Original Model Summary:")
original_model.summary()
```

```
Original Model Summary:
```

**Model: "sequential_4"**

```
 Layer (type)                          Output Shape                          ␣
↪Param #

 conv2d_13 (Conv2D)                    (None, 32, 32, 32)                       ␣
↪896

 max_pooling2d_13 (MaxPooling2D)       (None, 16, 16, 32)                       ␣
↪  0

 conv2d_14 (Conv2D)                    (None, 16, 16, 64)                     ␣
↪18,496

 max_pooling2d_14 (MaxPooling2D)       (None, 8, 8, 64)                         ␣
↪  0

 conv2d_15 (Conv2D)                    (None, 8, 8, 128)                      ␣
↪73,856

 max_pooling2d_15 (MaxPooling2D)       (None, 4, 4, 128)                        ␣
↪  0

 flatten_4 (Flatten)                   (None, 2048)                             ␣
↪  0

 dense_12 (Dense)                      (None, 128)                           ␣
↪262,272

 dense_13 (Dense)                      (None, 64)                              ␣
↪8,256

 dense_14 (Dense)                      (None, 10)                               ␣
↪650
```

**Total params:** 364,426 (1.39 MB)

**Trainable params:** 364,426 (1.39 MB)

**Non-trainable params:** 0 (0.00 B)

[20]:
```
print("\nModified Model Summary (with extra layer):")
modified_model.summary()
```

```
Modified Model Summary (with extra layer):
```

**Model: "sequential_5"**

```
Layer (type)                           Output Shape                         ␣
↪Param #

conv2d_16 (Conv2D)                     (None, 32, 32, 32)                       ␣
↪896

max_pooling2d_16 (MaxPooling2D)        (None, 16, 16, 32)                       ␣
↪  0

conv2d_17 (Conv2D)                     (None, 16, 16, 64)                     ␣
↪18,496

max_pooling2d_17 (MaxPooling2D)        (None, 8, 8, 64)                         ␣
↪  0

conv2d_18 (Conv2D)                     (None, 8, 8, 128)                      ␣
↪73,856

max_pooling2d_18 (MaxPooling2D)        (None, 4, 4, 128)                        ␣
↪  0

conv2d_19 (Conv2D)                     (None, 4, 4, 256)                    ␣
↪295,168

max_pooling2d_19 (MaxPooling2D)        (None, 2, 2, 256)                        ␣
↪  0

flatten_5 (Flatten)                    (None, 1024)                             ␣
↪  0
```

```
 dense_15 (Dense)                     (None, 128)                      ␣
↪131,200

 dense_16 (Dense)                     (None, 64)                        ␣
↪8,256

 dense_17 (Dense)                     (None, 10)                          ␣
↪650
```

**Total params:** 528,522 (2.02 MB)

**Trainable params:** 528,522 (2.02 MB)

**Non-trainable params:** 0 (0.00 B)

[21]:
```
# Train both models
print("Training original model...")
history_original = original_model.fit(x_train, y_train, epochs=20,␣
 ↪batch_size=64, validation_data=(x_test, y_test))

print("\nTraining modified model with extra layer...")
history_modified = modified_model.fit(x_train, y_train, epochs=20,␣
 ↪batch_size=64, validation_data=(x_test, y_test))

# Final evaluation of both models
original_train_loss, original_train_accuracy = original_model.evaluate(x_train,␣
 ↪y_train, verbose=0)
original_test_loss, original_test_accuracy = original_model.evaluate(x_test,␣
 ↪y_test, verbose=0)

modified_train_loss, modified_train_accuracy = modified_model.evaluate(x_train,␣
 ↪y_train, verbose=0)
modified_test_loss, modified_test_accuracy = modified_model.evaluate(x_test,␣
 ↪y_test, verbose=0)

print(f"\nOriginal Model - Training Accuracy: {original_train_accuracy * 100:.
 ↪2f}%, Validation Accuracy: {original_test_accuracy * 100:.2f}%")
print(f"Modified Model - Training Accuracy: {modified_train_accuracy * 100:.
 ↪2f}%, Validation Accuracy: {modified_test_accuracy * 100:.2f}%")
```

```
Training original model…
Epoch 1/20
782/782              8s 7ms/step -
accuracy: 0.3675 - loss: 1.7192 - val_accuracy: 0.5833 - val_loss: 1.1669
```

```
Epoch 2/20
782/782            3s 4ms/step -
accuracy: 0.6146 - loss: 1.0810 - val_accuracy: 0.6660 - val_loss: 0.9457
Epoch 3/20
782/782            3s 4ms/step -
accuracy: 0.6929 - loss: 0.8788 - val_accuracy: 0.6971 - val_loss: 0.8663
Epoch 4/20
782/782            6s 5ms/step -
accuracy: 0.7366 - loss: 0.7561 - val_accuracy: 0.7114 - val_loss: 0.8464
Epoch 5/20
782/782            3s 4ms/step -
accuracy: 0.7653 - loss: 0.6681 - val_accuracy: 0.7060 - val_loss: 0.8413
Epoch 6/20
782/782            3s 4ms/step -
accuracy: 0.7929 - loss: 0.5953 - val_accuracy: 0.7247 - val_loss: 0.8239
Epoch 7/20
782/782            6s 4ms/step -
accuracy: 0.8160 - loss: 0.5192 - val_accuracy: 0.7338 - val_loss: 0.7769
Epoch 8/20
782/782            3s 4ms/step -
accuracy: 0.8372 - loss: 0.4650 - val_accuracy: 0.7081 - val_loss: 0.8968
Epoch 9/20
782/782            5s 4ms/step -
accuracy: 0.8542 - loss: 0.4124 - val_accuracy: 0.7441 - val_loss: 0.8293
Epoch 10/20
782/782            6s 5ms/step -
accuracy: 0.8745 - loss: 0.3531 - val_accuracy: 0.7388 - val_loss: 0.8725
Epoch 11/20
782/782            3s 4ms/step -
accuracy: 0.8887 - loss: 0.3138 - val_accuracy: 0.7350 - val_loss: 0.8881
Epoch 12/20
782/782            5s 4ms/step -
accuracy: 0.9053 - loss: 0.2687 - val_accuracy: 0.7264 - val_loss: 1.0087
Epoch 13/20
782/782            6s 5ms/step -
accuracy: 0.9137 - loss: 0.2409 - val_accuracy: 0.7304 - val_loss: 1.0467
Epoch 14/20
782/782            5s 4ms/step -
accuracy: 0.9251 - loss: 0.2102 - val_accuracy: 0.7312 - val_loss: 1.0711
Epoch 15/20
782/782            3s 4ms/step -
accuracy: 0.9372 - loss: 0.1771 - val_accuracy: 0.7285 - val_loss: 1.1660
Epoch 16/20
782/782            4s 5ms/step -
accuracy: 0.9371 - loss: 0.1743 - val_accuracy: 0.7397 - val_loss: 1.1625
Epoch 17/20
782/782            5s 4ms/step -
accuracy: 0.9479 - loss: 0.1455 - val_accuracy: 0.7301 - val_loss: 1.2991
```

```
Epoch 18/20
782/782              3s 4ms/step -
accuracy: 0.9557 - loss: 0.1266 - val_accuracy: 0.7257 - val_loss: 1.3095
Epoch 19/20
782/782              3s 4ms/step -
accuracy: 0.9558 - loss: 0.1253 - val_accuracy: 0.7281 - val_loss: 1.3956
Epoch 20/20
782/782              3s 4ms/step -
accuracy: 0.9540 - loss: 0.1290 - val_accuracy: 0.7231 - val_loss: 1.4876

Training modified model with extra layer…
Epoch 1/20
782/782              10s 9ms/step -
accuracy: 0.3286 - loss: 1.8056 - val_accuracy: 0.5919 - val_loss: 1.1287
Epoch 2/20
782/782              6s 5ms/step -
accuracy: 0.6081 - loss: 1.0840 - val_accuracy: 0.6652 - val_loss: 0.9514
Epoch 3/20
782/782              6s 5ms/step -
accuracy: 0.7041 - loss: 0.8353 - val_accuracy: 0.6772 - val_loss: 0.9418
Epoch 4/20
782/782              4s 5ms/step -
accuracy: 0.7581 - loss: 0.6899 - val_accuracy: 0.7352 - val_loss: 0.7802
Epoch 5/20
782/782              5s 5ms/step -
accuracy: 0.7986 - loss: 0.5678 - val_accuracy: 0.7387 - val_loss: 0.7886
Epoch 6/20
782/782              5s 5ms/step -
accuracy: 0.8321 - loss: 0.4727 - val_accuracy: 0.7475 - val_loss: 0.7569
Epoch 7/20
782/782              5s 5ms/step -
accuracy: 0.8653 - loss: 0.3860 - val_accuracy: 0.7434 - val_loss: 0.8130
Epoch 8/20
782/782              6s 6ms/step -
accuracy: 0.8911 - loss: 0.3119 - val_accuracy: 0.7436 - val_loss: 0.9003
Epoch 9/20
782/782              4s 5ms/step -
accuracy: 0.9121 - loss: 0.2498 - val_accuracy: 0.7461 - val_loss: 0.8984
Epoch 10/20
782/782              5s 5ms/step -
accuracy: 0.9313 - loss: 0.2011 - val_accuracy: 0.7321 - val_loss: 1.0650
Epoch 11/20
782/782              4s 5ms/step -
accuracy: 0.9363 - loss: 0.1824 - val_accuracy: 0.7425 - val_loss: 1.0817
Epoch 12/20
782/782              4s 5ms/step -
accuracy: 0.9512 - loss: 0.1411 - val_accuracy: 0.7470 - val_loss: 1.1716
Epoch 13/20
```

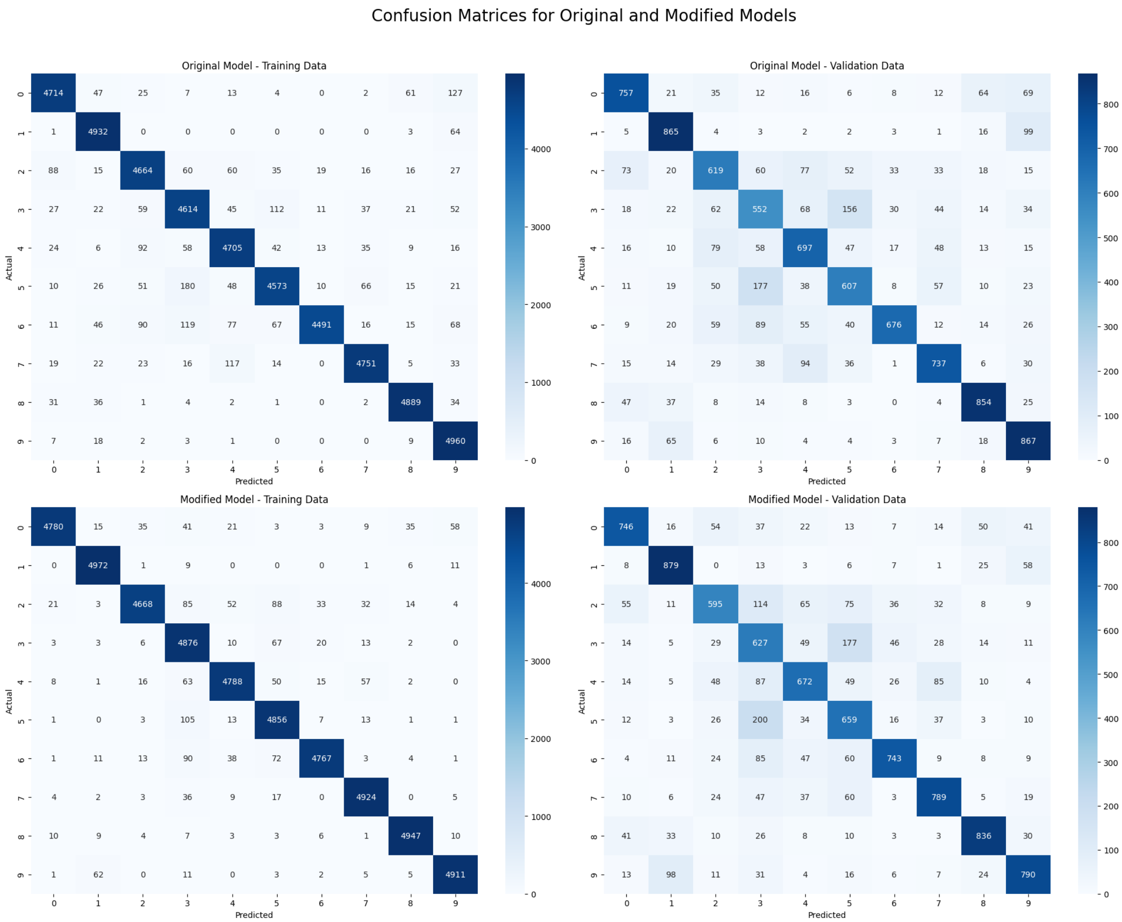
```
782/782            4s 5ms/step -
accuracy: 0.9534 - loss: 0.1338 - val_accuracy: 0.7447 - val_loss: 1.2081
Epoch 14/20
782/782            4s 6ms/step -
accuracy: 0.9618 - loss: 0.1075 - val_accuracy: 0.7412 - val_loss: 1.2350
Epoch 15/20
782/782            4s 5ms/step -
accuracy: 0.9642 - loss: 0.1027 - val_accuracy: 0.7350 - val_loss: 1.2969
Epoch 16/20
782/782            4s 5ms/step -
accuracy: 0.9653 - loss: 0.1012 - val_accuracy: 0.7422 - val_loss: 1.3481
Epoch 17/20
782/782            6s 5ms/step -
accuracy: 0.9675 - loss: 0.0923 - val_accuracy: 0.7394 - val_loss: 1.2960
Epoch 18/20
782/782            5s 5ms/step -
accuracy: 0.9704 - loss: 0.0847 - val_accuracy: 0.7387 - val_loss: 1.5074
Epoch 19/20
782/782            4s 5ms/step -
accuracy: 0.9709 - loss: 0.0835 - val_accuracy: 0.7412 - val_loss: 1.5056
Epoch 20/20
782/782            6s 5ms/step -
accuracy: 0.9740 - loss: 0.0790 - val_accuracy: 0.7336 - val_loss: 1.3954

Original Model - Training Accuracy: 94.59%, Validation Accuracy: 72.31%
Modified Model - Training Accuracy: 96.98%, Validation Accuracy: 73.36%
```

[22]:
```
def plot_confusion_matrices(model1, model2, x_train, y_train, x_test, y_test):
    fig, axes = plt.subplots(2, 2, figsize=(20, 16))
    fig.suptitle('Confusion Matrices for Original and Modified Models',␣
 ↪fontsize=20)

    # Original Model - Training Data
    y_pred_train_orig = model1.predict(x_train)
    y_pred_classes_train_orig = np.argmax(y_pred_train_orig, axis=1)
    y_true_train = np.argmax(y_train, axis=1)
    cm_train_orig = confusion_matrix(y_true_train, y_pred_classes_train_orig)

    sns.heatmap(cm_train_orig, annot=True, fmt='d', cmap='Blues', ax=axes[0,␣
 ↪0], xticklabels=range(10), yticklabels=range(10))
    axes[0, 0].set_title('Original Model - Training Data')
    axes[0, 0].set_xlabel('Predicted')
    axes[0, 0].set_ylabel('Actual')

    # Original Model - Validation Data
    y_pred_test_orig = model1.predict(x_test)
    y_pred_classes_test_orig = np.argmax(y_pred_test_orig, axis=1)
```

```python
    y_true_test = np.argmax(y_test, axis=1)
    cm_test_orig = confusion_matrix(y_true_test, y_pred_classes_test_orig)

    sns.heatmap(cm_test_orig, annot=True, fmt='d', cmap='Blues', ax=axes[0, 1],␣
↪xticklabels=range(10), yticklabels=range(10))
    axes[0, 1].set_title('Original Model - Validation Data')
    axes[0, 1].set_xlabel('Predicted')
    axes[0, 1].set_ylabel('Actual')

    # Modified Model - Training Data
    y_pred_train_mod = model2.predict(x_train)
    y_pred_classes_train_mod = np.argmax(y_pred_train_mod, axis=1)
    cm_train_mod = confusion_matrix(y_true_train, y_pred_classes_train_mod)

    sns.heatmap(cm_train_mod, annot=True, fmt='d', cmap='Blues', ax=axes[1, 0],␣
↪xticklabels=range(10), yticklabels=range(10))
    axes[1, 0].set_title('Modified Model - Training Data')
    axes[1, 0].set_xlabel('Predicted')
    axes[1, 0].set_ylabel('Actual')

    # Modified Model - Validation Data
    y_pred_test_mod = model2.predict(x_test)
    y_pred_classes_test_mod = np.argmax(y_pred_test_mod, axis=1)
    cm_test_mod = confusion_matrix(y_true_test, y_pred_classes_test_mod)

    sns.heatmap(cm_test_mod, annot=True, fmt='d', cmap='Blues', ax=axes[1, 1],␣
↪xticklabels=range(10), yticklabels=range(10))
    axes[1, 1].set_title('Modified Model - Validation Data')
    axes[1, 1].set_xlabel('Predicted')
    axes[1, 1].set_ylabel('Actual')

    plt.tight_layout(rect=[0, 0, 1, 0.96])
    plt.show()
```

[23]:
```python
plot_confusion_matrices(original_model, modified_model, x_train, y_train,␣
↪x_test, y_test)
```

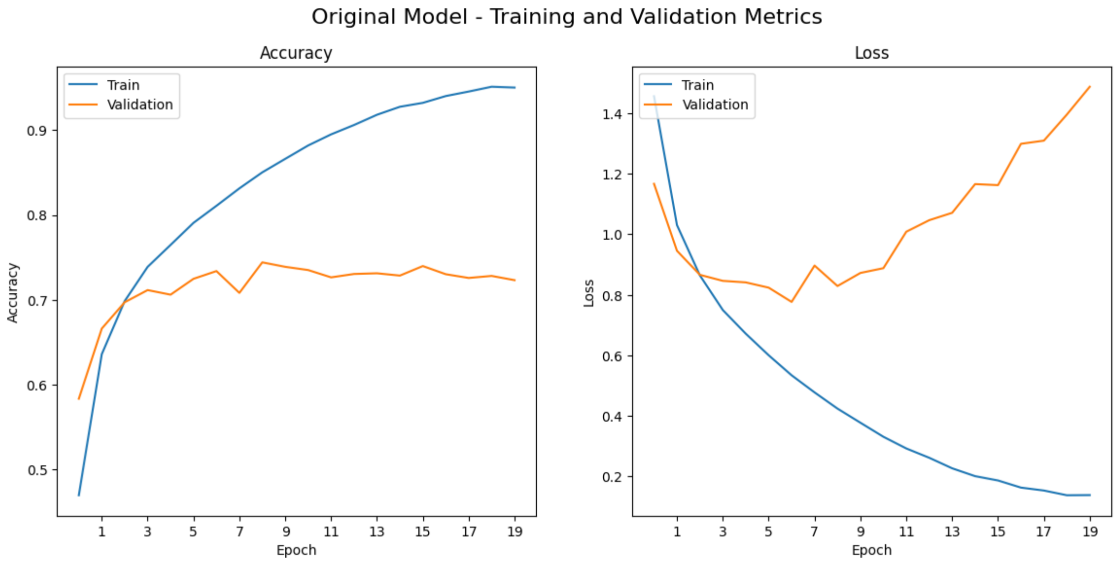
```
1563/1563              3s 2ms/step
313/313              1s 2ms/step
1563/1563              3s 2ms/step
313/313              1s 2ms/step
```

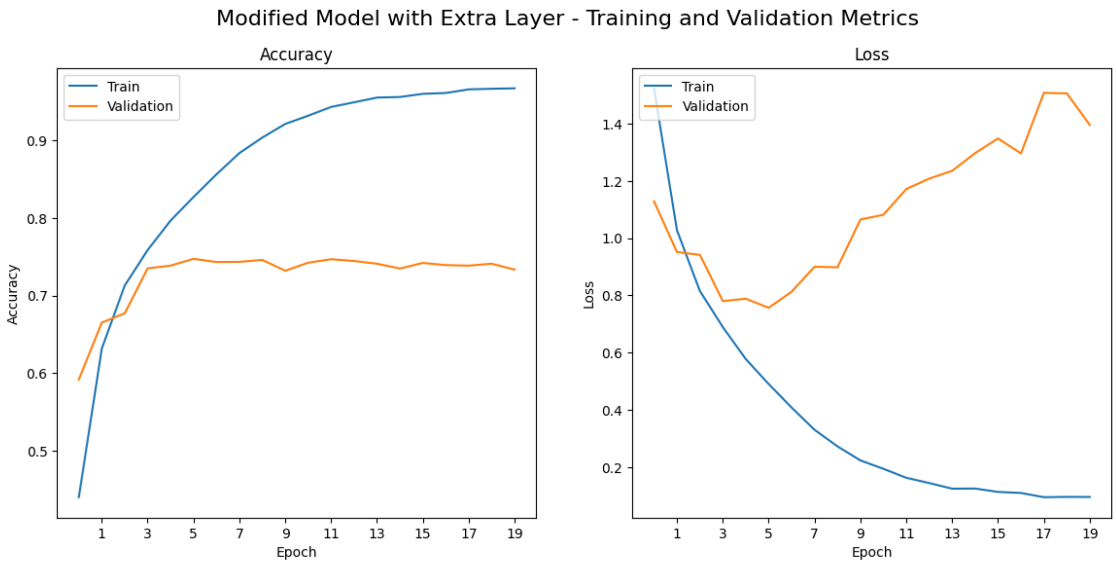



```
[24]: def plot_training_history(history, title="Model"):
          # Plot training & validation accuracy values
          plt.figure(figsize=(14, 6))
          plt.suptitle(f'{title} - Training and Validation Metrics', fontsize=16)

          plt.subplot(1, 2, 1)
          plt.plot(history.history['accuracy'])
          plt.plot(history.history['val_accuracy'])
          plt.title('Accuracy')
          plt.ylabel('Accuracy')
          plt.xlabel('Epoch')
          plt.xticks(np.arange(1, len(history.history['accuracy'])+1, 2))
          plt.legend(['Train', 'Validation'], loc='upper left')

          # Plot training & validation loss values
          plt.subplot(1, 2, 2)
          plt.plot(history.history['loss'])
          plt.plot(history.history['val_loss'])
```

```
    plt.title('Loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.xticks(np.arange(1, len(history.history['accuracy'])+1, 2))
    plt.legend(['Train', 'Validation'], loc='upper left')

    plt.show()
```

[25]:
```
# Plot training history for both models
plot_training_history(history_original, title="Original Model")
plot_training_history(history_modified, title="Modified Model with Extra Layer")
```



## 2 Problem 2

[26]:
```
# Load and preprocess CIFAR-10 data
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Normalize the pixel values to be between 0 and 1
x_train, x_test = x_train.astype('float32') / 255.0, x_test.astype('float32') /
↪255.0
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Define the original CNN model without batch normalization
def create_original_cnn_model():
    model = models.Sequential()

    # First convolutional block
    model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same',
↪input_shape=(32, 32, 3)))
    model.add(layers.MaxPooling2D((2, 2)))

    # Second convolutional block
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Third convolutional block
    model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten and add dense layers
    model.add(layers.Flatten())
    model.add(layers.Dense(128, activation='relu'))
    model.add(layers.Dense(64, activation='relu'))

    # Output layer
    model.add(layers.Dense(10, activation='softmax'))  # 10 classes for CIFAR-10

    return model

# Define the original CNN model with batch normalization
def create_cnn_model_with_batch_norm():
    model = models.Sequential()

    # First convolutional block
```

```
    model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same',␣
↪input_shape=(32, 32, 3)))
    model.add(layers.BatchNormalization())
    model.add(layers.MaxPooling2D((2, 2)))

    # Second convolutional block
    model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
    model.add(layers.BatchNormalization())
    model.add(layers.MaxPooling2D((2, 2)))

    # Third convolutional block
    model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
    model.add(layers.BatchNormalization())
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten and add dense layers
    model.add(layers.Flatten())
    model.add(layers.Dense(128, activation='relu'))
    model.add(layers.BatchNormalization())
    model.add(layers.Dense(64, activation='relu'))
    model.add(layers.BatchNormalization())

    # Output layer
    model.add(layers.Dense(10, activation='softmax'))  # 10 classes for CIFAR-10

    return model
```

[27]:
```
# Instantiate both models
original_model = create_original_cnn_model()
original_model_bn = create_cnn_model_with_batch_norm()

# Compile both models
original_model.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
original_model_bn.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
```

```
/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

[28]:
```
# Train both models and record training time
import time
```

```python
print("Training original model...")
start_time = time.time()
history_original = original_model.fit(x_train, y_train, epochs=20,␣
    ↪batch_size=64, validation_data=(x_test, y_test))
end_time = time.time()
original_training_time = end_time - start_time
print(f"Original model training completed in {original_training_time:.2f}␣
    ↪seconds.")

print("\nTraining original model with batch normalization...")
start_time = time.time()
history_original_bn = original_model_bn.fit(x_train, y_train, epochs=20,␣
    ↪batch_size=64, validation_data=(x_test, y_test))
end_time = time.time()
original_bn_training_time = end_time - start_time
print(f"Original model with batch normalization training completed in␣
    ↪{original_bn_training_time:.2f} seconds.")
```

```
Training original model…
Epoch 1/20
782/782              7s 6ms/step -
accuracy: 0.3347 - loss: 1.7947 - val_accuracy: 0.5533 - val_loss: 1.2140
Epoch 2/20
782/782              8s 4ms/step -
accuracy: 0.5932 - loss: 1.1288 - val_accuracy: 0.6531 - val_loss: 0.9881
Epoch 3/20
782/782              5s 4ms/step -
accuracy: 0.6836 - loss: 0.8978 - val_accuracy: 0.6830 - val_loss: 0.9038
Epoch 4/20
782/782              4s 5ms/step -
accuracy: 0.7292 - loss: 0.7706 - val_accuracy: 0.7093 - val_loss: 0.8360
Epoch 5/20
782/782              3s 4ms/step -
accuracy: 0.7592 - loss: 0.6844 - val_accuracy: 0.7167 - val_loss: 0.8283
Epoch 6/20
782/782              3s 4ms/step -
accuracy: 0.7927 - loss: 0.5953 - val_accuracy: 0.7377 - val_loss: 0.7625
Epoch 7/20
782/782              6s 4ms/step -
accuracy: 0.8137 - loss: 0.5381 - val_accuracy: 0.7426 - val_loss: 0.7707
Epoch 8/20
782/782              5s 4ms/step -
accuracy: 0.8365 - loss: 0.4649 - val_accuracy: 0.7516 - val_loss: 0.7567
Epoch 9/20
782/782              3s 4ms/step -
accuracy: 0.8594 - loss: 0.4066 - val_accuracy: 0.7440 - val_loss: 0.8107
Epoch 10/20
```

```
782/782              3s 4ms/step -
accuracy: 0.8726 - loss: 0.3576 - val_accuracy: 0.7460 - val_loss: 0.8099
Epoch 11/20
782/782              4s 5ms/step -
accuracy: 0.8888 - loss: 0.3185 - val_accuracy: 0.7395 - val_loss: 0.9044
Epoch 12/20
782/782              5s 4ms/step -
accuracy: 0.9049 - loss: 0.2757 - val_accuracy: 0.7388 - val_loss: 0.9443
Epoch 13/20
782/782              5s 4ms/step -
accuracy: 0.9150 - loss: 0.2426 - val_accuracy: 0.7483 - val_loss: 0.9468
Epoch 14/20
782/782              4s 4ms/step -
accuracy: 0.9283 - loss: 0.2037 - val_accuracy: 0.7400 - val_loss: 0.9998
Epoch 15/20
782/782              3s 4ms/step -
accuracy: 0.9362 - loss: 0.1821 - val_accuracy: 0.7358 - val_loss: 1.1077
Epoch 16/20
782/782              3s 4ms/step -
accuracy: 0.9418 - loss: 0.1684 - val_accuracy: 0.7370 - val_loss: 1.2159
Epoch 17/20
782/782              5s 6ms/step -
accuracy: 0.9500 - loss: 0.1451 - val_accuracy: 0.7367 - val_loss: 1.2360
Epoch 18/20
782/782              8s 4ms/step -
accuracy: 0.9484 - loss: 0.1448 - val_accuracy: 0.7335 - val_loss: 1.3886
Epoch 19/20
782/782              3s 4ms/step -
accuracy: 0.9530 - loss: 0.1311 - val_accuracy: 0.7265 - val_loss: 1.3616
Epoch 20/20
782/782              5s 4ms/step -
accuracy: 0.9562 - loss: 0.1264 - val_accuracy: 0.7320 - val_loss: 1.3932
Original model training completed in 92.96 seconds.

Training original model with batch normalization…
Epoch 1/20
782/782              13s 9ms/step -
accuracy: 0.4834 - loss: 1.4602 - val_accuracy: 0.4436 - val_loss: 1.7126
Epoch 2/20
782/782              4s 5ms/step -
accuracy: 0.6974 - loss: 0.8734 - val_accuracy: 0.6940 - val_loss: 0.8784
Epoch 3/20
782/782              6s 6ms/step -
accuracy: 0.7659 - loss: 0.6795 - val_accuracy: 0.6957 - val_loss: 0.8805
Epoch 4/20
782/782              4s 5ms/step -
accuracy: 0.8128 - loss: 0.5520 - val_accuracy: 0.7225 - val_loss: 0.8184
Epoch 5/20
```

```
782/782              6s 5ms/step -
accuracy: 0.8470 - loss: 0.4398 - val_accuracy: 0.7223 - val_loss: 0.8515
Epoch 6/20
782/782              4s 5ms/step -
accuracy: 0.8808 - loss: 0.3489 - val_accuracy: 0.7451 - val_loss: 0.8040
Epoch 7/20
782/782              5s 5ms/step -
accuracy: 0.8993 - loss: 0.2917 - val_accuracy: 0.7352 - val_loss: 0.9167
Epoch 8/20
782/782              4s 5ms/step -
accuracy: 0.9260 - loss: 0.2203 - val_accuracy: 0.6903 - val_loss: 1.1059
Epoch 9/20
782/782              5s 5ms/step -
accuracy: 0.9378 - loss: 0.1810 - val_accuracy: 0.7003 - val_loss: 1.1159
Epoch 10/20
782/782              5s 5ms/step -
accuracy: 0.9443 - loss: 0.1606 - val_accuracy: 0.7254 - val_loss: 1.0847
Epoch 11/20
782/782              6s 5ms/step -
accuracy: 0.9523 - loss: 0.1402 - val_accuracy: 0.7341 - val_loss: 1.0977
Epoch 12/20
782/782              4s 5ms/step -
accuracy: 0.9565 - loss: 0.1224 - val_accuracy: 0.6926 - val_loss: 1.3914
Epoch 13/20
782/782              5s 5ms/step -
accuracy: 0.9581 - loss: 0.1191 - val_accuracy: 0.7357 - val_loss: 1.1727
Epoch 14/20
782/782              5s 5ms/step -
accuracy: 0.9652 - loss: 0.0982 - val_accuracy: 0.7436 - val_loss: 1.1696
Epoch 15/20
782/782              5s 5ms/step -
accuracy: 0.9716 - loss: 0.0845 - val_accuracy: 0.7512 - val_loss: 1.1373
Epoch 16/20
782/782              4s 6ms/step -
accuracy: 0.9694 - loss: 0.0876 - val_accuracy: 0.7448 - val_loss: 1.1655
Epoch 17/20
782/782              4s 5ms/step -
accuracy: 0.9707 - loss: 0.0846 - val_accuracy: 0.6923 - val_loss: 1.6226
Epoch 18/20
782/782              5s 5ms/step -
accuracy: 0.9712 - loss: 0.0830 - val_accuracy: 0.7434 - val_loss: 1.2910
Epoch 19/20
782/782              5s 5ms/step -
accuracy: 0.9752 - loss: 0.0694 - val_accuracy: 0.7393 - val_loss: 1.3204
Epoch 20/20
782/782              4s 5ms/step -
accuracy: 0.9756 - loss: 0.0712 - val_accuracy: 0.7419 - val_loss: 1.2885
Original model with batch normalization training completed in 105.26 seconds.
```

[29]:
```python
# Final evaluation of both models
original_train_loss, original_train_accuracy = original_model.evaluate(x_train,␣
↪y_train, verbose=0)
original_test_loss, original_test_accuracy = original_model.evaluate(x_test,␣
↪y_test, verbose=0)

original_bn_train_loss, original_bn_train_accuracy = original_model_bn.
↪evaluate(x_train, y_train, verbose=0)
original_bn_test_loss, original_bn_test_accuracy = original_model_bn.
↪evaluate(x_test, y_test, verbose=0)

# Print training and validation accuracy
print(f"\nOriginal Model - Training Accuracy: {original_train_accuracy:.4f},␣
↪Validation Accuracy: {original_test_accuracy:.4f}")
print(f"Original Model with Batch Normalization - Training Accuracy:␣
↪{original_bn_train_accuracy:.4f}, Validation Accuracy:␣
↪{original_bn_test_accuracy:.4f}")

# Print training times
print(f"Original Model Training Time: {original_training_time:.2f} seconds")
print(f"Original Model with Batch Normalization Training Time:␣
↪{original_bn_training_time:.2f} seconds")
```

```
Original Model - Training Accuracy: 0.9639, Validation Accuracy: 0.7320
Original Model with Batch Normalization - Training Accuracy: 0.9749, Validation
Accuracy: 0.7419
Original Model Training Time: 92.96 seconds
Original Model with Batch Normalization Training Time: 105.26 seconds
```

[30]:
```python
# Plot training and validation accuracy for both models on the same plot
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))

# Plot training accuracy
plt.plot(history_original.history['accuracy'], label='Original Model - Training␣
↪Accuracy', linestyle='--')
plt.plot(history_original_bn.history['accuracy'], label='Original Model with BN␣
↪- Training Accuracy', linestyle='--')

# Plot validation accuracy
plt.plot(history_original.history['val_accuracy'], label='Original Model -␣
↪Validation Accuracy')
plt.plot(history_original_bn.history['val_accuracy'], label='Original Model␣
↪with BN - Validation Accuracy')
```

```
plt.title('Training and Validation Accuracy for Original Model and Model with␣
↪Batch Normalization')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```