assignment-2-brandenburg

March 31, 2024

#

DATA SCIENCE 2: ASSIGNMENT 2

###

Ian Brandenburg (2304791)

0.1 GitHub Repo

Take the alternative version of the famous "MNIST dataset", which consists of images of Zalando's articles. Your task is to correctly classify the images into one of the ten categories, such as dress or shirt. The images are in exactly the same format as we saw for the handwritten digits: 28x28 pixel grayscale images. The task is to build deep neural network models to predict the items. You can use either sklearn or keras; to get the data, go to the corresponding Kaggle page or use the fashion_mnist.load_data() function from the keras.datasets module. Make sure you split the training set into two sets: one for training your models on and one for validation and model selection. You can work with a relatively small train set if you have computational problems.

0.2 ### 1. What would be an appropriate metric to evaluate your models? Why?

An appropriate metric to evalute the models train on the Fashion MNIST data set would be the accuracy metric, since the dataset is a multi-class classification problem with balanced classes. The accuracy metric calculates the number of correctly predicted observations to the total number of observations. This provides a very straightforward assessment of the models' performance across the 10 different categories.

0.3 ### 2. Get the data and show some example images from the data.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf

# TensorFlow's Keras API
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import (BatchNormalization, Conv2D, Dense,␣
 ↪Dropout, Flatten,
```

```
                                        GlobalAveragePooling2D, MaxPooling2D,␣
↪Rescaling)
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.losses import MeanSquaredError
from tensorflow.keras.utils import to_categorical

# Scikit-learn
from sklearn.model_selection import train_test_split
```

[2]:
```
def plot_model_history(model_histories, labels):
    """Plot the training and validation accuracy and loss for multiple models.
↪"""
    if not model_histories or not labels or len(model_histories) != len(labels):
        print("The model histories and labels must be provided and match in␣
↪length.")
        return

    plt.figure(figsize=(14, 5))

    # plotting training & validation accuracy
    plt.subplot(1, 2, 1)
    for model_history, label in zip(model_histories, labels):
        epochs = range(1, len(model_history.history['accuracy']) + 1)
        plt.plot(epochs, model_history.history['accuracy'], label=f'Training␣
↪Acc {label}')
        plt.plot(epochs, model_history.history['val_accuracy'],␣
↪label=f'Validation Acc {label}', linestyle="--")
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # plotting training & validation loss
    plt.subplot(1, 2, 2)
    for model_history, label in zip(model_histories, labels):
        epochs = range(1, len(model_history.history['loss']) + 1)
        plt.plot(epochs, model_history.history['loss'], label=f'Training Loss␣
↪{label}')
        plt.plot(epochs, model_history.history['val_loss'], label=f'Validation␣
↪Loss {label}', linestyle="--")
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
```

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

[3]:
```
# loading the dataset
(train_images, train_labels), (test_images, test_labels) = fashion_mnist.
 ↪load_data()

# converting labels to one-hot encoding
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

# splitting the training data into training and validation sets
train_images, val_images, train_labels, val_labels = train_test_split(
    train_images, train_labels, test_size=0.2, random_state=20240405)

# checking the shape of the datasets
print("Training set shape:", train_images.shape)
print("Validation set shape:", val_images.shape)
print("Test set shape:", test_images.shape)
```

```
Training set shape: (48000, 28, 28)
Validation set shape: (12000, 28, 28)
Test set shape: (10000, 28, 28)
```

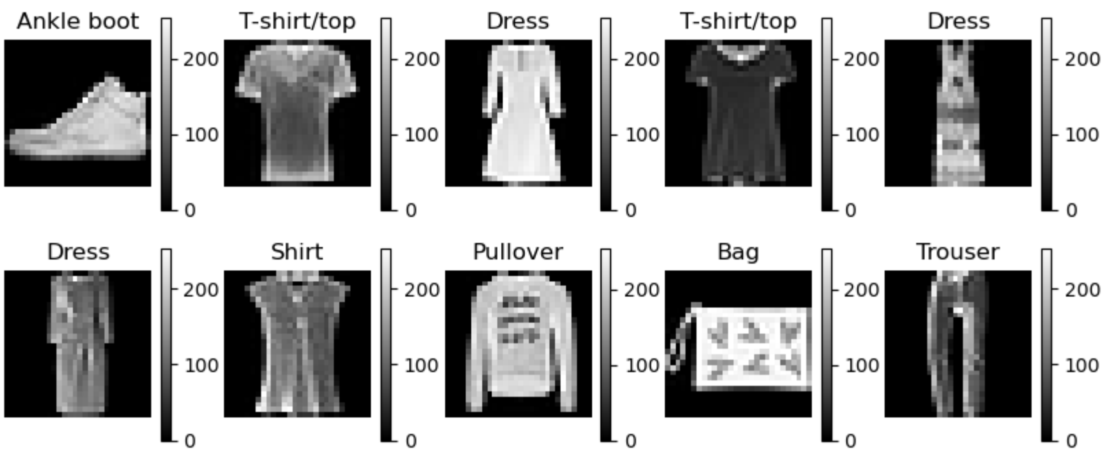
[4]:
```
print("Y Test set shape:", test_labels.shape)
```

```
Y Test set shape: (10000, 10)
```

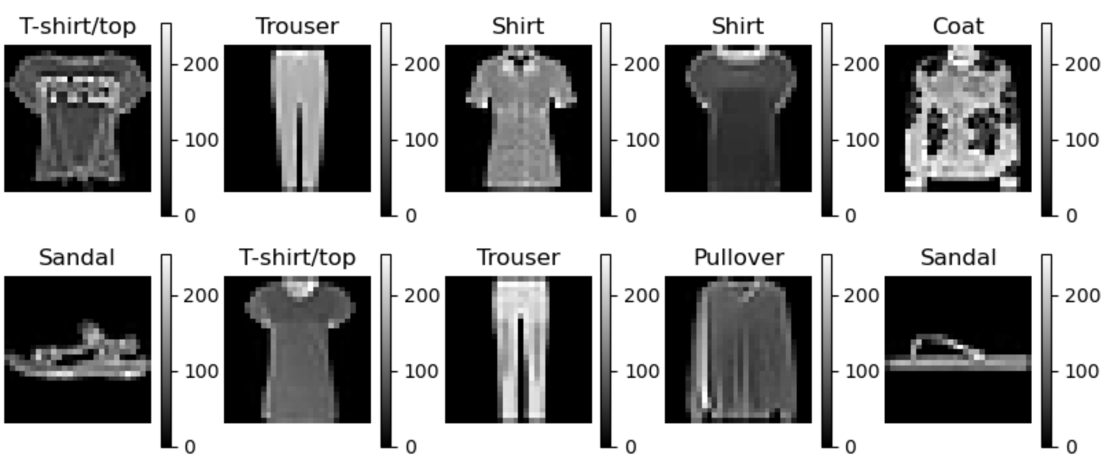
[5]:
```
def show_images(images, labels, nrows=1, ncols=5, class_names=None):
    """Display a grid of images and their labels."""
    plt.figure(figsize=(10, 2 * nrows))
    for i in range(nrows * ncols):
        plt.subplot(nrows, ncols, i + 1)
        plt.imshow(images[i], cmap='gray')
        plt.colorbar()
        if class_names is not None:
            plt.title(class_names[np.argmax(labels[i])])
        else:
            plt.title(np.argmax(labels[i]))
        plt.axis('off')
    plt.show()

class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

# Showing training images
```

```
print("Training Images:")
show_images(train_images, train_labels, nrows=2, ncols=5, class_names=class_names)

# Showing validation images
print("Validation Images:")
show_images(val_images, val_labels, nrows=2, ncols=5, class_names=class_names)

# Showing testing images
print("Test Images:")
show_images(test_images, test_labels, nrows=2, ncols=5, class_names=class_names)
```

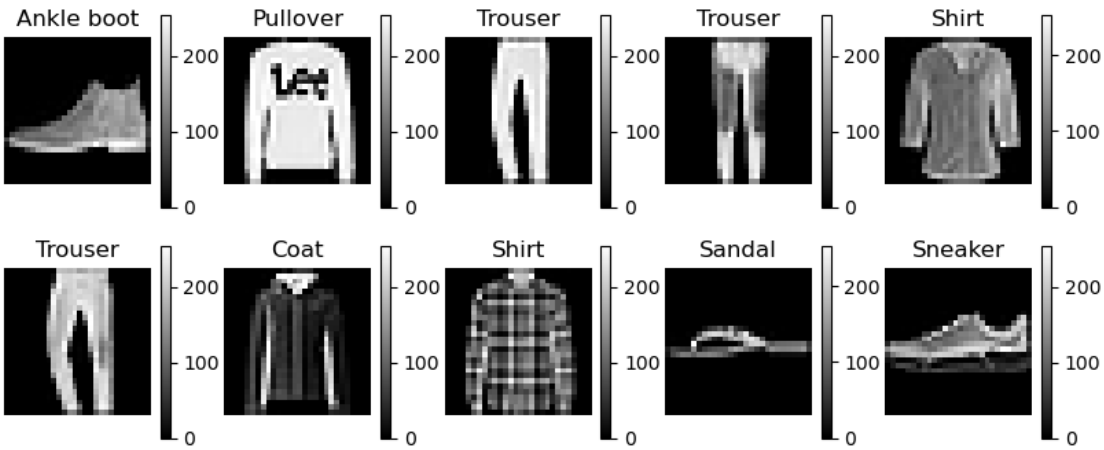
```
Training Images:
```




```
Validation Images:
```



Test Images:



0.3.1 3. Train a simple fully connected single hidden layer network to predict the items.

- Remember to normalize the data similar to what we did in class. Make sure that you use enough epochs so that the validation error begins to level off - provide a plot of the training history.

[6]:
```
model = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),  # scaling input pixels to 0-1
    Flatten(),  # converting 2D images to 1D vectors
    Dense(256, activation='relu'),  # adding hidden layer with 256 units and␣
↪ReLU activation
    Dense(10, activation='softmax')  # adding output layer with 10 units (one␣
↪for each category) and softmax activation
])

model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

print(model.summary())

history = model.fit(train_images,
                    train_labels,
                    epochs=25,
                    validation_data=(val_images, val_labels),
                    callbacks=[EarlyStopping(monitor='val_accuracy',
                                             patience=5)])
```

```
C:\Users\iandr\anaconda3\Lib\site-
```

```
packages\keras\src\layers\preprocessing\tf_data_layer.py:19: 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__(**kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 28, 28, 1)	0
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 256)	200,960
dense_1 (Dense)	(None, 10)	2,570

Total params: 203,530 (795.04 KB)

Trainable params: 203,530 (795.04 KB)

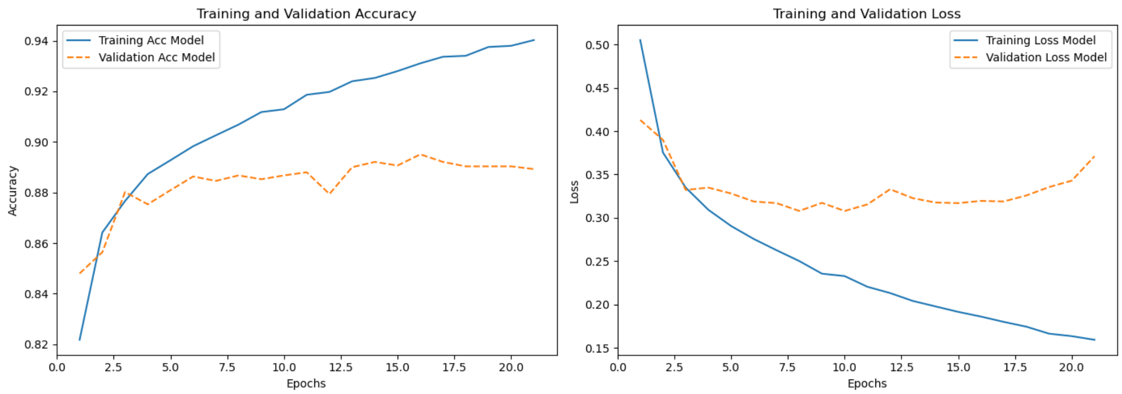
Non-trainable params: 0 (0.00 B)

```
None
Epoch 1/25
1500/1500              6s 3ms/step -
accuracy: 0.7840 - loss: 0.6230 - val_accuracy: 0.8480 - val_loss: 0.4129
Epoch 2/25
1500/1500              5s 3ms/step -
accuracy: 0.8607 - loss: 0.3831 - val_accuracy: 0.8564 - val_loss: 0.3899
Epoch 3/25
1500/1500              5s 4ms/step -
accuracy: 0.8763 - loss: 0.3332 - val_accuracy: 0.8802 - val_loss: 0.3322
Epoch 4/25
1500/1500              5s 3ms/step -
accuracy: 0.8868 - loss: 0.3078 - val_accuracy: 0.8753 - val_loss: 0.3348
Epoch 5/25
1500/1500              5s 3ms/step -
accuracy: 0.8918 - loss: 0.2933 - val_accuracy: 0.8809 - val_loss: 0.3281
Epoch 6/25
1500/1500              5s 3ms/step -
accuracy: 0.8995 - loss: 0.2721 - val_accuracy: 0.8863 - val_loss: 0.3188
Epoch 7/25
```

```
1500/1500            5s 3ms/step -
accuracy: 0.9045 - loss: 0.2536 - val_accuracy: 0.8846 - val_loss: 0.3169
Epoch 8/25
1500/1500            5s 3ms/step -
accuracy: 0.9069 - loss: 0.2472 - val_accuracy: 0.8867 - val_loss: 0.3079
Epoch 9/25
1500/1500            5s 3ms/step -
accuracy: 0.9127 - loss: 0.2329 - val_accuracy: 0.8852 - val_loss: 0.3172
Epoch 10/25
1500/1500            5s 3ms/step -
accuracy: 0.9146 - loss: 0.2298 - val_accuracy: 0.8867 - val_loss: 0.3079
Epoch 11/25
1500/1500            4s 3ms/step -
accuracy: 0.9203 - loss: 0.2139 - val_accuracy: 0.8880 - val_loss: 0.3154
Epoch 12/25
1500/1500            4s 3ms/step -
accuracy: 0.9215 - loss: 0.2076 - val_accuracy: 0.8794 - val_loss: 0.3329
Epoch 13/25
1500/1500            5s 3ms/step -
accuracy: 0.9255 - loss: 0.2020 - val_accuracy: 0.8900 - val_loss: 0.3227
Epoch 14/25
1500/1500            4s 3ms/step -
accuracy: 0.9270 - loss: 0.1975 - val_accuracy: 0.8921 - val_loss: 0.3176
Epoch 15/25
1500/1500            4s 3ms/step -
accuracy: 0.9312 - loss: 0.1847 - val_accuracy: 0.8907 - val_loss: 0.3169
Epoch 16/25
1500/1500            5s 3ms/step -
accuracy: 0.9335 - loss: 0.1811 - val_accuracy: 0.8951 - val_loss: 0.3195
Epoch 17/25
1500/1500            5s 3ms/step -
accuracy: 0.9353 - loss: 0.1763 - val_accuracy: 0.8921 - val_loss: 0.3189
Epoch 18/25
1500/1500            4s 3ms/step -
accuracy: 0.9378 - loss: 0.1654 - val_accuracy: 0.8903 - val_loss: 0.3258
Epoch 19/25
1500/1500            4s 3ms/step -
accuracy: 0.9387 - loss: 0.1658 - val_accuracy: 0.8903 - val_loss: 0.3355
Epoch 20/25
1500/1500            4s 3ms/step -
accuracy: 0.9399 - loss: 0.1609 - val_accuracy: 0.8903 - val_loss: 0.3429
Epoch 21/25
1500/1500            4s 3ms/step -
accuracy: 0.9412 - loss: 0.1558 - val_accuracy: 0.8892 - val_loss: 0.3710
```

The model above flattens the data, since we are looking at developing a fully connected hidden layer, subsequently converting the 2D images to 1D vectors. A hidden layer with 128 units was created, using ReLU activation. Finally, the moodel sets the output layer to 10 units (one for each category), and uses softmax activation on the output. 25 epochs were used to ensure the accuracy metric would level off. This was tested by using the EarlyStopping function with a patience of 5. It stops at 21 epochs with a validation accuracy of 0.8892. There is still room for improvement, so we will try various other models to attempt to improve the accuracy and decrease the loss without overfitting.

[7]:
```
plot_model_history([history], ['Model'])
```



Here, both the loss and accuracy metrics for the validation set level off before the training loss and accuracy. The training loss seems to still be decreasing while the accuracy increasing, at the time that the EarlyStopping function stops the epochs from running further. Visually, it seems like the training set does not predict the validation model very well; however, they are not very far off in their accuracy and loss metrics, so this model my not be bad.

0.4 ### 4. Experiment with different network architectures and settings (number of hidden layers, number of nodes, regularization, etc.)

- Train at least 3 models. Explain what you have tried and how it worked.

Model 1: Nodes Increased The first model developed to try different network architextures and settings increases the number of nodes to 512. Increasing the number of nodes allows for the model to capture the relationship between images and labels more clearly. A larger number of nodes can capture more complex patterns in the data, while also improving the learning ability of the model. The addition of nodes can also lead to overfitting, which makes generalizing the results of the data less feasible. Furthermore, additional nodes leads to longer training times, requiring more memory and processing power.

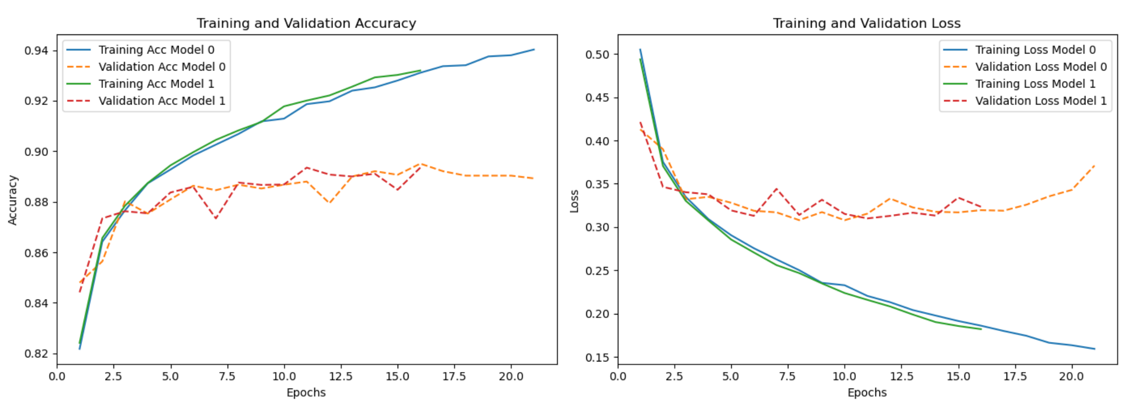
[8]:
```
model1 = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),
    Flatten(),
    Dense(512, activation='relu'),  # adding an increased number of nodes
    Dense(10, activation='softmax')
])
```

```python
model1.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])

print(model1.summary())

history1 = model1.fit(train_images, train_labels, epochs=25,␣
↪validation_data=(val_images, val_labels),␣
↪callbacks=[EarlyStopping(monitor='val_accuracy', patience=5)])
```

```
Model: "sequential_1"


 Layer (type)                      Output Shape                  Param #

 rescaling_1 (Rescaling)           (None, 28, 28, 1)                   0

 flatten_1 (Flatten)               (None, 784)                         0

 dense_2 (Dense)                   (None, 512)                   401,920

 dense_3 (Dense)                   (None, 10)                      5,130


 Total params: 407,050 (1.55 MB)

 Trainable params: 407,050 (1.55 MB)

 Non-trainable params: 0 (0.00 B)

None
Epoch 1/25
1500/1500             7s 4ms/step -
accuracy: 0.7835 - loss: 0.6177 - val_accuracy: 0.8442 - val_loss: 0.4214
Epoch 2/25
1500/1500             6s 4ms/step -
accuracy: 0.8644 - loss: 0.3758 - val_accuracy: 0.8734 - val_loss: 0.3464
Epoch 3/25
1500/1500             6s 4ms/step -
accuracy: 0.8813 - loss: 0.3242 - val_accuracy: 0.8763 - val_loss: 0.3402
Epoch 4/25
1500/1500             6s 4ms/step -
accuracy: 0.8897 - loss: 0.3046 - val_accuracy: 0.8754 - val_loss: 0.3378
Epoch 5/25
1500/1500             6s 4ms/step -
accuracy: 0.8932 - loss: 0.2873 - val_accuracy: 0.8837 - val_loss: 0.3192
```

```
Epoch 6/25
1500/1500          6s 4ms/step -
accuracy: 0.8997 - loss: 0.2708 - val_accuracy: 0.8859 - val_loss: 0.3129
Epoch 7/25
1500/1500          7s 5ms/step -
accuracy: 0.9051 - loss: 0.2530 - val_accuracy: 0.8734 - val_loss: 0.3441
Epoch 8/25
1500/1500          6s 4ms/step -
accuracy: 0.9084 - loss: 0.2483 - val_accuracy: 0.8876 - val_loss: 0.3139
Epoch 9/25
1500/1500          6s 4ms/step -
accuracy: 0.9138 - loss: 0.2309 - val_accuracy: 0.8867 - val_loss: 0.3315
Epoch 10/25
1500/1500          6s 4ms/step -
accuracy: 0.9195 - loss: 0.2192 - val_accuracy: 0.8868 - val_loss: 0.3151
Epoch 11/25
1500/1500          8s 5ms/step -
accuracy: 0.9189 - loss: 0.2203 - val_accuracy: 0.8935 - val_loss: 0.3099
Epoch 12/25
1500/1500          8s 5ms/step -
accuracy: 0.9233 - loss: 0.2039 - val_accuracy: 0.8907 - val_loss: 0.3129
Epoch 13/25
1500/1500          7s 4ms/step -
accuracy: 0.9265 - loss: 0.1950 - val_accuracy: 0.8900 - val_loss: 0.3165
Epoch 14/25
1500/1500          6s 4ms/step -
accuracy: 0.9300 - loss: 0.1863 - val_accuracy: 0.8911 - val_loss: 0.3132
Epoch 15/25
1500/1500          6s 4ms/step -
accuracy: 0.9293 - loss: 0.1866 - val_accuracy: 0.8848 - val_loss: 0.3340
Epoch 16/25
1500/1500          8s 5ms/step -
accuracy: 0.9331 - loss: 0.1787 - val_accuracy: 0.8935 - val_loss: 0.3234
```

[9]:
```
plot_model_history([history, history1], ['Model 0', 'Model 1'])
```



The initial model, `Model 0`, performs better since the performance metric results are quite similar to the increased nodes model. The increased number of nodes did not seem to have a significant influence on increasing the validation accuracy or decreasing the validation loss. `Model 1: Increased Nodes` yeilded very similar results to `Model 0`

0.5 #### Model 2: Added Dropout and Increased Nodes

The second model maintains the increased number of nodes, while added a Dropout. The dropout is intended to help mitigate the risk of overfitting by randomly setting a portion of the network's neurons to 0 during the training the process.

[10]:
```
model2 = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),
    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.5),  # adding dropout
    Dense(10, activation='softmax')
])

model2.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

print(model2.summary())

history2 = model2.fit(train_images, train_labels, epochs=25,␣
 ↪validation_data=(val_images, val_labels),␣
 ↪callbacks=[EarlyStopping(monitor='val_accuracy', patience=5)])
```

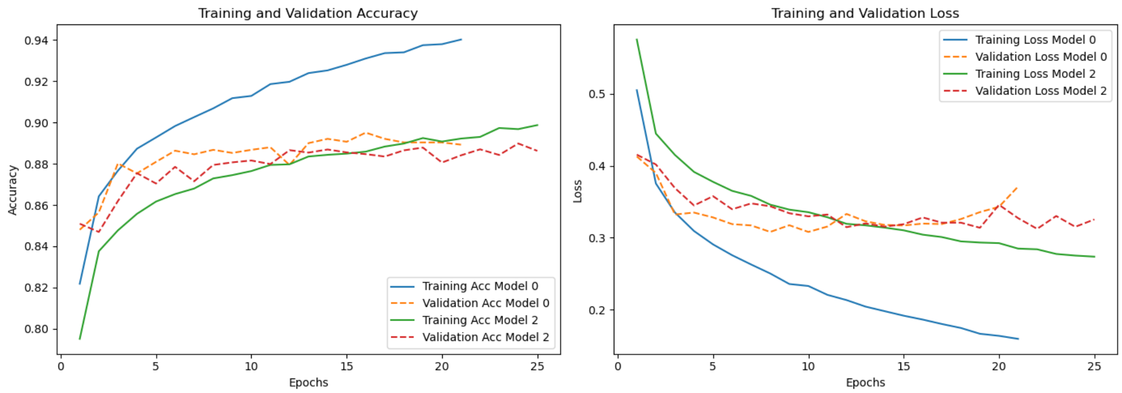
```
Model: "sequential_2"


 Layer (type)                    Output Shape                  Param #

 rescaling_2 (Rescaling)         (None, 28, 28, 1)                   0

 flatten_2 (Flatten)             (None, 784)                         0

 dense_4 (Dense)                 (None, 512)                   401,920

 dropout (Dropout)               (None, 512)                         0

 dense_5 (Dense)                 (None, 10)                      5,130
```

```
 Total params: 407,050 (1.55 MB)

 Trainable params: 407,050 (1.55 MB)

 Non-trainable params: 0 (0.00 B)

None
Epoch 1/25
1500/1500            8s 5ms/step -
accuracy: 0.7467 - loss: 0.7183 - val_accuracy: 0.8509 - val_loss: 0.4154
Epoch 2/25
1500/1500            7s 5ms/step -
accuracy: 0.8360 - loss: 0.4514 - val_accuracy: 0.8469 - val_loss: 0.4018
Epoch 3/25
1500/1500            7s 5ms/step -
accuracy: 0.8469 - loss: 0.4199 - val_accuracy: 0.8619 - val_loss: 0.3689
Epoch 4/25
1500/1500            7s 4ms/step -
accuracy: 0.8573 - loss: 0.3877 - val_accuracy: 0.8754 - val_loss: 0.3447
Epoch 5/25
1500/1500            7s 5ms/step -
accuracy: 0.8613 - loss: 0.3788 - val_accuracy: 0.8704 - val_loss: 0.3576
Epoch 6/25
1500/1500            7s 5ms/step -
accuracy: 0.8643 - loss: 0.3685 - val_accuracy: 0.8785 - val_loss: 0.3394
Epoch 7/25
1500/1500            7s 5ms/step -
accuracy: 0.8663 - loss: 0.3596 - val_accuracy: 0.8715 - val_loss: 0.3476
Epoch 8/25
1500/1500            7s 4ms/step -
accuracy: 0.8744 - loss: 0.3443 - val_accuracy: 0.8794 - val_loss: 0.3436
Epoch 9/25
1500/1500            7s 5ms/step -
accuracy: 0.8715 - loss: 0.3421 - val_accuracy: 0.8807 - val_loss: 0.3339
Epoch 10/25
1500/1500            7s 4ms/step -
accuracy: 0.8763 - loss: 0.3344 - val_accuracy: 0.8816 - val_loss: 0.3296
Epoch 11/25
1500/1500            6s 4ms/step -
accuracy: 0.8793 - loss: 0.3276 - val_accuracy: 0.8798 - val_loss: 0.3321
Epoch 12/25
1500/1500            7s 4ms/step -
accuracy: 0.8793 - loss: 0.3182 - val_accuracy: 0.8866 - val_loss: 0.3145
Epoch 13/25
1500/1500            11s 5ms/step -
accuracy: 0.8840 - loss: 0.3190 - val_accuracy: 0.8854 - val_loss: 0.3197
```

```
Epoch 14/25
1500/1500              7s 4ms/step -
accuracy: 0.8878 - loss: 0.3053 - val_accuracy: 0.8869 - val_loss: 0.3152
Epoch 15/25
1500/1500              6s 4ms/step -
accuracy: 0.8882 - loss: 0.3066 - val_accuracy: 0.8855 - val_loss: 0.3187
Epoch 16/25
1500/1500              6s 4ms/step -
accuracy: 0.8868 - loss: 0.3031 - val_accuracy: 0.8847 - val_loss: 0.3281
Epoch 17/25
1500/1500              6s 4ms/step -
accuracy: 0.8892 - loss: 0.2986 - val_accuracy: 0.8835 - val_loss: 0.3208
Epoch 18/25
1500/1500              7s 4ms/step -
accuracy: 0.8913 - loss: 0.2925 - val_accuracy: 0.8865 - val_loss: 0.3208
Epoch 19/25
1500/1500              7s 4ms/step -
accuracy: 0.8911 - loss: 0.2917 - val_accuracy: 0.8878 - val_loss: 0.3137
Epoch 20/25
1500/1500              6s 4ms/step -
accuracy: 0.8923 - loss: 0.2901 - val_accuracy: 0.8806 - val_loss: 0.3456
Epoch 21/25
1500/1500              7s 4ms/step -
accuracy: 0.8916 - loss: 0.2863 - val_accuracy: 0.8841 - val_loss: 0.3271
Epoch 22/25
1500/1500              6s 4ms/step -
accuracy: 0.8910 - loss: 0.2899 - val_accuracy: 0.8870 - val_loss: 0.3122
Epoch 23/25
1500/1500              7s 4ms/step -
accuracy: 0.8958 - loss: 0.2757 - val_accuracy: 0.8842 - val_loss: 0.3300
Epoch 24/25
1500/1500              7s 4ms/step -
accuracy: 0.8958 - loss: 0.2706 - val_accuracy: 0.8898 - val_loss: 0.3150
Epoch 25/25
1500/1500              7s 4ms/step -
accuracy: 0.8994 - loss: 0.2698 - val_accuracy: 0.8863 - val_loss: 0.3252
```

[11]:

```
plot_model_history([history, history2], ['Model 0', 'Model 2'])
```



The model seems to have improved the overfitting issue by narrowing the gap between the training and validation accuracy metric; nevertheless, `Model 0` still performs better as it is more simple and does not have a very large overfitting issue, and has higher scores than `Model 2: Dropout`

0.6 #### Model 3: Adding a hidden layer

The idea behind adding a hidden layer is backed by increasing the model complexity in order to improve the model's generalization capabilities. Furthermore, adding a hidden layer increases the model's depth, which can also enhance the model's abilities to be trained on more complex data.

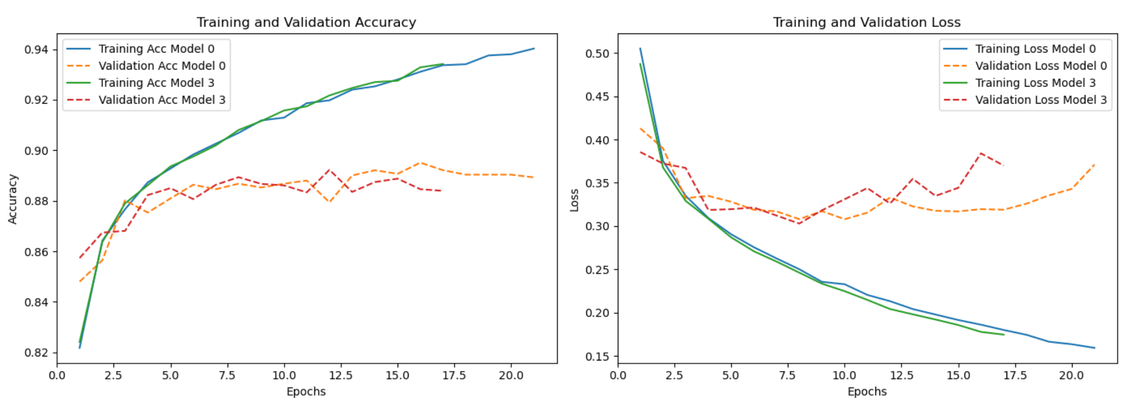
[12]:
```python
model3 = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),
    Flatten(),
    Dense(256, activation='relu'),
    Dense(256, activation='relu'),  # adding additional hidden layer
    Dense(10, activation='softmax')
])

model3.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

print(model3.summary())

history3 = model3.fit(train_images, train_labels, epochs=25,␣
 ↪validation_data=(val_images, val_labels),␣
 ↪callbacks=[EarlyStopping(monitor='val_accuracy', patience=5)])
```

```
Model: "sequential_3"


 Layer (type)                    Output Shape                 Param #

 rescaling_3 (Rescaling)         (None, 28, 28, 1)                  0
```

```
 flatten_3 (Flatten)              (None, 784)                    0

 dense_6 (Dense)                  (None, 256)              200,960

 dense_7 (Dense)                  (None, 256)               65,792

 dense_8 (Dense)                  (None, 10)                 2,570


 Total params: 269,322 (1.03 MB)

 Trainable params: 269,322 (1.03 MB)

 Non-trainable params: 0 (0.00 B)

None
Epoch 1/25
1500/1500             7s 4ms/step -
accuracy: 0.7781 - loss: 0.6186 - val_accuracy: 0.8573 - val_loss: 0.3855
Epoch 2/25
1500/1500             5s 3ms/step -
accuracy: 0.8612 - loss: 0.3776 - val_accuracy: 0.8674 - val_loss: 0.3722
Epoch 3/25
1500/1500             5s 4ms/step -
accuracy: 0.8772 - loss: 0.3362 - val_accuracy: 0.8681 - val_loss: 0.3671
Epoch 4/25
1500/1500             5s 3ms/step -
accuracy: 0.8892 - loss: 0.3048 - val_accuracy: 0.8823 - val_loss: 0.3186
Epoch 5/25
1500/1500             4s 3ms/step -
accuracy: 0.8948 - loss: 0.2836 - val_accuracy: 0.8850 - val_loss: 0.3195
Epoch 6/25
1500/1500             5s 3ms/step -
accuracy: 0.8994 - loss: 0.2665 - val_accuracy: 0.8807 - val_loss: 0.3213
Epoch 7/25
1500/1500             5s 3ms/step -
accuracy: 0.9046 - loss: 0.2550 - val_accuracy: 0.8863 - val_loss: 0.3121
Epoch 8/25
1500/1500             5s 3ms/step -
accuracy: 0.9087 - loss: 0.2433 - val_accuracy: 0.8893 - val_loss: 0.3028
Epoch 9/25
1500/1500             5s 3ms/step -
accuracy: 0.9117 - loss: 0.2322 - val_accuracy: 0.8867 - val_loss: 0.3182
Epoch 10/25
1500/1500             5s 3ms/step -
```

```
accuracy: 0.9173 - loss: 0.2193 - val_accuracy: 0.8861 - val_loss: 0.3310
Epoch 11/25
1500/1500          5s 3ms/step -
accuracy: 0.9187 - loss: 0.2121 - val_accuracy: 0.8833 - val_loss: 0.3439
Epoch 12/25
1500/1500          5s 3ms/step -
accuracy: 0.9221 - loss: 0.2008 - val_accuracy: 0.8923 - val_loss: 0.3260
Epoch 13/25
1500/1500          5s 3ms/step -
accuracy: 0.9241 - loss: 0.1963 - val_accuracy: 0.8835 - val_loss: 0.3545
Epoch 14/25
1500/1500          5s 3ms/step -
accuracy: 0.9287 - loss: 0.1894 - val_accuracy: 0.8874 - val_loss: 0.3348
Epoch 15/25
1500/1500          4s 3ms/step -
accuracy: 0.9298 - loss: 0.1799 - val_accuracy: 0.8888 - val_loss: 0.3441
Epoch 16/25
1500/1500          5s 3ms/step -
accuracy: 0.9333 - loss: 0.1751 - val_accuracy: 0.8846 - val_loss: 0.3840
Epoch 17/25
1500/1500          5s 3ms/step -
accuracy: 0.9376 - loss: 0.1675 - val_accuracy: 0.8839 - val_loss: 0.3699
```

[13]:
```
plot_model_history([history, history3], ['Model 0', 'Model 3'])
```



The addition of the hidden layer did not seem to drastically improve the accuracy or loss metrics in the model. This model seems to perform very similarly to `Model 0`, but as a result of `Model 0` being simpler than `Model 4: Additional Layer`, `Model 0` would still be preferred.

0.7 #### Model 4: Extra Layer, Dropout, and Increased Nodes

The following model now incorporates components from the previous three models to experiment and see how adding an additional layer, additional dropout, and increasing the nodes in both layers will influence the accuracy and loss of the model.

[14]:
```
model4 = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),
    Flatten(),
    Dense(512, activation='relu'),  # increasing number of nodes
    Dropout(0.5),  # adding dropout
    Dense(512, activation='relu'),  # increasing number of nodes...again
    Dropout(0.5),  # adding dropout...again
    Dense(10, activation='softmax')
])

model4.compile(optimizer='adam', loss='categorical_crossentropy',
 ↪metrics=['accuracy'])

print(model4.summary())

history4 = model4.fit(train_images, train_labels, epochs=25,
 ↪validation_data=(val_images, val_labels),
 ↪callbacks=[EarlyStopping(monitor='val_accuracy', patience=5)])
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
rescaling_4 (Rescaling)	(None, 28, 28, 1)	0
flatten_4 (Flatten)	(None, 784)	0
dense_9 (Dense)	(None, 512)	401,920
dropout_1 (Dropout)	(None, 512)	0
dense_10 (Dense)	(None, 512)	262,656
dropout_2 (Dropout)	(None, 512)	0
dense_11 (Dense)	(None, 10)	5,130

Total params: 669,706 (2.55 MB)

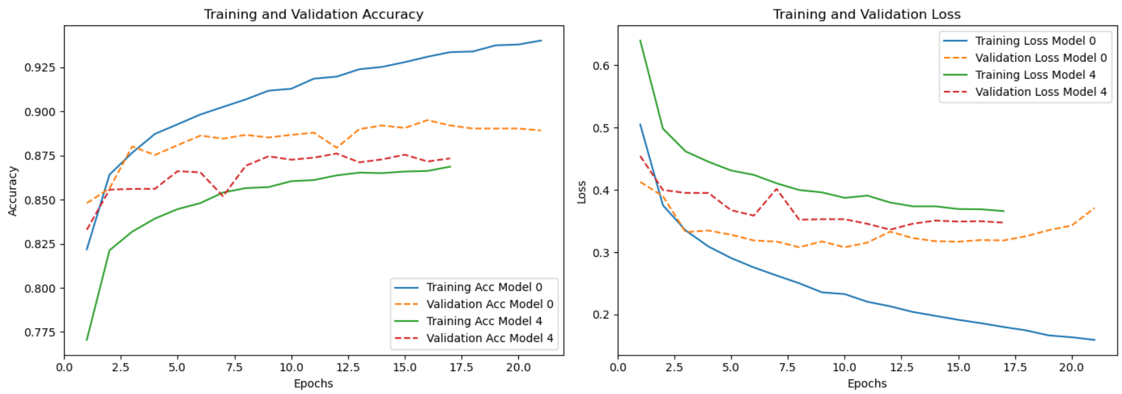
Trainable params: 669,706 (2.55 MB)

Non-trainable params: 0 (0.00 B)

```
None
Epoch 1/25
1500/1500              11s 6ms/step -
accuracy: 0.7086 - loss: 0.8055 - val_accuracy: 0.8329 - val_loss: 0.4545
Epoch 2/25
1500/1500              10s 6ms/step -
accuracy: 0.8165 - loss: 0.5076 - val_accuracy: 0.8557 - val_loss: 0.3998
Epoch 3/25
1500/1500              10s 6ms/step -
accuracy: 0.8326 - loss: 0.4605 - val_accuracy: 0.8561 - val_loss: 0.3952
Epoch 4/25
1500/1500              9s 6ms/step -
accuracy: 0.8408 - loss: 0.4429 - val_accuracy: 0.8562 - val_loss: 0.3951
Epoch 5/25
1500/1500              9s 6ms/step -
accuracy: 0.8445 - loss: 0.4307 - val_accuracy: 0.8662 - val_loss: 0.3674
Epoch 6/25
1500/1500              10s 6ms/step -
accuracy: 0.8473 - loss: 0.4257 - val_accuracy: 0.8655 - val_loss: 0.3587
Epoch 7/25
1500/1500              10s 7ms/step -
accuracy: 0.8523 - loss: 0.4101 - val_accuracy: 0.8519 - val_loss: 0.4016
Epoch 8/25
1500/1500              10s 6ms/step -
accuracy: 0.8588 - loss: 0.3935 - val_accuracy: 0.8692 - val_loss: 0.3522
Epoch 9/25
1500/1500              10s 6ms/step -
accuracy: 0.8587 - loss: 0.3866 - val_accuracy: 0.8746 - val_loss: 0.3529
Epoch 10/25
1500/1500              10s 6ms/step -
accuracy: 0.8610 - loss: 0.3855 - val_accuracy: 0.8727 - val_loss: 0.3529
Epoch 11/25
1500/1500              10s 6ms/step -
accuracy: 0.8595 - loss: 0.3917 - val_accuracy: 0.8738 - val_loss: 0.3455
Epoch 12/25
1500/1500              10s 7ms/step -
accuracy: 0.8660 - loss: 0.3736 - val_accuracy: 0.8762 - val_loss: 0.3362
Epoch 13/25
1500/1500              10s 6ms/step -
accuracy: 0.8670 - loss: 0.3698 - val_accuracy: 0.8712 - val_loss: 0.3457
Epoch 14/25
1500/1500              10s 7ms/step -
accuracy: 0.8607 - loss: 0.3754 - val_accuracy: 0.8728 - val_loss: 0.3508
Epoch 15/25
1500/1500              10s 7ms/step -
accuracy: 0.8665 - loss: 0.3695 - val_accuracy: 0.8755 - val_loss: 0.3491
Epoch 16/25
1500/1500              10s 7ms/step -
```

```
accuracy: 0.8641 - loss: 0.3715 - val_accuracy: 0.8717 - val_loss: 0.3497
Epoch 17/25
1500/1500              10s 6ms/step -
accuracy: 0.8695 - loss: 0.3641 - val_accuracy: 0.8734 - val_loss: 0.3474
```

[15]:
```python
plot_model_history([history, history4], ['Model 0', 'Model 4'])
```



`Model 4` does show improvement on the overfitting issue, with both the training and validation sets having very similar accuracy and loss scores. This suggests that the dropout does help mitigate overfitting successfully in this dataset. However, since `Model 0` is so simple, it is still the preferred model at this time.

0.8 #### Model 5: Batch Normalization

The following model incorporates batch normalization, a technique aimed at improving the speed, performance, and stability of neural networks. Batch Normalization normlizes the output of a previous layer by subtracting the batch mean and dividing by the batch standard deviation. This methods operates per-feature, ensuring that they have a mean of 0 and a standard deviation of 1. This method is aimed at improving the performance of the model, reducing the overfitting, and decreasing the training time.

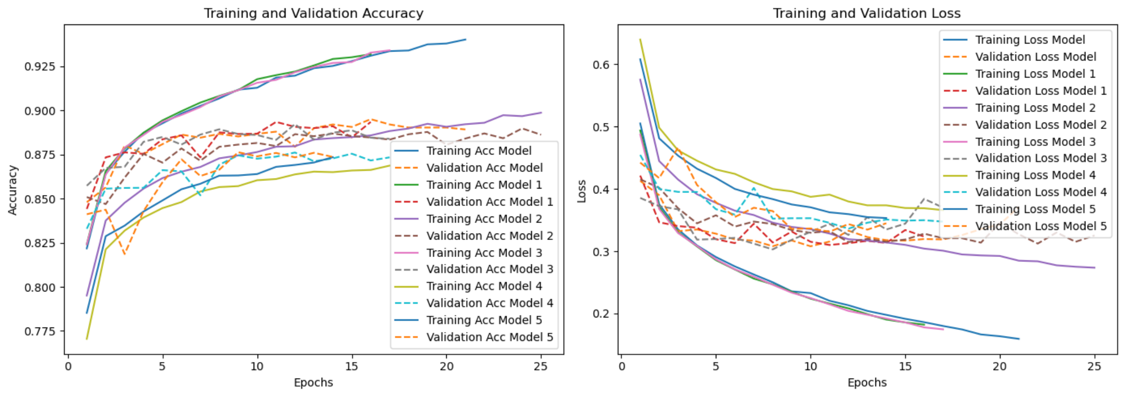
[16]:
```python
model5 = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),
    Flatten(),
    Dense(256, activation='relu'),  # reducing number of nodes
    BatchNormalization(),  # adding batch normalization
    Dropout(0.3),  # reducing dropout rate
    Dense(256, activation='relu'),  # reducing number of nodes...again
    BatchNormalization(),  # adding batch normalization...again
    Dropout(0.3),  # reducing dropout rate...again
    Dense(10, activation='softmax')
])
```

```python
model5.compile(optimizer=Adam(learning_rate=0.001),  # adjusting the learning␣
 ↪rate
              loss='categorical_crossentropy',
              metrics=['accuracy'])

print(model5.summary())

history5 = model5.fit(train_images, train_labels, epochs=25,␣
 ↪validation_data=(val_images, val_labels),
                      callbacks=[EarlyStopping(monitor='val_accuracy',␣
 ↪patience=5)])
```

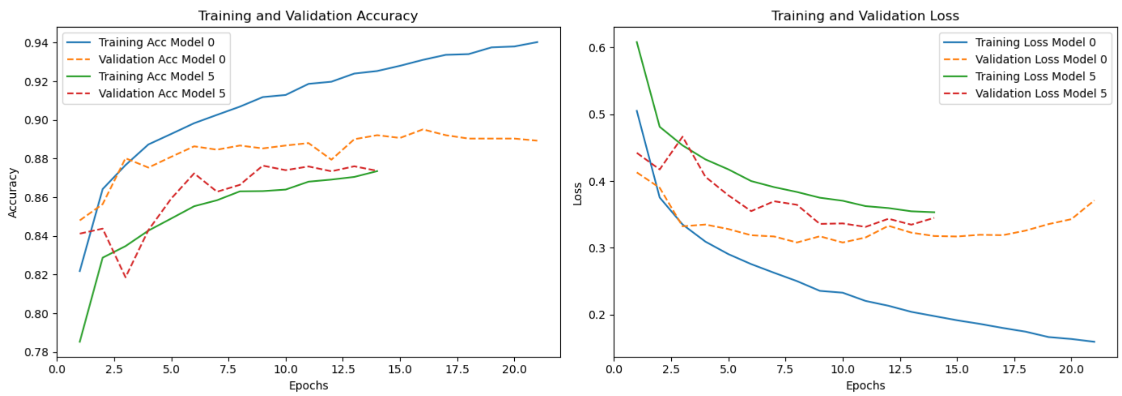
```
Model: "sequential_5"

 Layer (type)                     Output Shape                  Param #

 rescaling_5 (Rescaling)          (None, 28, 28, 1)                   0

 flatten_5 (Flatten)              (None, 784)                         0

 dense_12 (Dense)                 (None, 256)                   200,960

 batch_normalization              (None, 256)                     1,024
 (BatchNormalization)

 dropout_3 (Dropout)              (None, 256)                         0

 dense_13 (Dense)                 (None, 256)                    65,792

 batch_normalization_1            (None, 256)                     1,024
 (BatchNormalization)

 dropout_4 (Dropout)              (None, 256)                         0

 dense_14 (Dense)                 (None, 10)                      2,570


 Total params: 271,370 (1.04 MB)

 Trainable params: 270,346 (1.03 MB)

 Non-trainable params: 1,024 (4.00 KB)

None
```

```
Epoch 1/25
1500/1500               9s 4ms/step -
accuracy: 0.7489 - loss: 0.7371 - val_accuracy: 0.8412 - val_loss: 0.4422
Epoch 2/25
1500/1500               5s 4ms/step -
accuracy: 0.8262 - loss: 0.4875 - val_accuracy: 0.8438 - val_loss: 0.4173
Epoch 3/25
1500/1500               6s 4ms/step -
accuracy: 0.8320 - loss: 0.4584 - val_accuracy: 0.8186 - val_loss: 0.4665
Epoch 4/25
1500/1500               6s 4ms/step -
accuracy: 0.8411 - loss: 0.4388 - val_accuracy: 0.8430 - val_loss: 0.4063
Epoch 5/25
1500/1500               5s 4ms/step -
accuracy: 0.8482 - loss: 0.4222 - val_accuracy: 0.8593 - val_loss: 0.3786
Epoch 6/25
1500/1500               6s 4ms/step -
accuracy: 0.8539 - loss: 0.4031 - val_accuracy: 0.8723 - val_loss: 0.3549
Epoch 7/25
1500/1500               7s 4ms/step -
accuracy: 0.8616 - loss: 0.3836 - val_accuracy: 0.8628 - val_loss: 0.3697
Epoch 8/25
1500/1500               6s 4ms/step -
accuracy: 0.8607 - loss: 0.3865 - val_accuracy: 0.8664 - val_loss: 0.3644
Epoch 9/25
1500/1500               6s 4ms/step -
accuracy: 0.8657 - loss: 0.3676 - val_accuracy: 0.8763 - val_loss: 0.3358
Epoch 10/25
1500/1500               6s 4ms/step -
accuracy: 0.8659 - loss: 0.3641 - val_accuracy: 0.8740 - val_loss: 0.3365
Epoch 11/25
1500/1500               7s 5ms/step -
accuracy: 0.8690 - loss: 0.3596 - val_accuracy: 0.8759 - val_loss: 0.3313
Epoch 12/25
1500/1500               7s 5ms/step -
accuracy: 0.8708 - loss: 0.3517 - val_accuracy: 0.8734 - val_loss: 0.3435
Epoch 13/25
1500/1500               7s 5ms/step -
accuracy: 0.8701 - loss: 0.3576 - val_accuracy: 0.8760 - val_loss: 0.3346
Epoch 14/25
1500/1500               7s 5ms/step -
accuracy: 0.8714 - loss: 0.3578 - val_accuracy: 0.8737 - val_loss: 0.3448
```

[17]:
```
plot_model_history([history, history1, history2, history3, history4, history5],
 ['Model', 'Model 1', 'Model 2', 'Model 3', 'Model 4', 'Model 5'])
```



[18]:
```
plot_model_history([history, history5], ['Model 0', 'Model 5'])
```



0.9 ### 5. Try to improve the accuracy of your model by using convolution

- Train at least two different models (you can vary the number of convolutional and pooling layers or whether you include a fully connected layer before the output, etc.).

Model 6: Adding Convolution, Pooling, and Fully Connected Layer This model adds a convolutional layer, pooling layer, and a fully connected hidden layer before the output.

The purpose of the convolutional layer is to better learn spatial hierarchies of features from the images. This is done by applying learnable filters to the images. These filters can capture various aspects of the images, such as edges, tectures, or patterns, and can improve the accuracy of the model. This can easily lead to overfitting.

The purpose of pooling layers is to reduce the spatial dimensions of the images for the next convolutional layer.

[19]:
```
model6 = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),
```

```
    Conv2D(32, (3, 3), activation='relu'),  # Convolutional layer
    MaxPooling2D((2, 2)),  # Pooling layer
    Flatten(),  # converting 3D feature maps to 1D feature vectors
    Dense(256, activation='relu'),
    Dense(10, activation='softmax')
])

model6.compile(optimizer='adam',
               loss='categorical_crossentropy',
               metrics=['accuracy'])

print(model6.summary())

history6 = model6.fit(train_images, train_labels, epochs=25,
                      validation_data=(val_images, val_labels),
                      callbacks=[EarlyStopping(monitor='val_accuracy', 
 ↪patience=5)])
```

```
Model: "sequential_6"
```

Layer (type)	Output Shape	Param #
rescaling_6 (Rescaling)	(None, 28, 28, 1)	0
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
flatten_6 (Flatten)	(None, 5408)	0
dense_15 (Dense)	(None, 256)	1,384,704
dense_16 (Dense)	(None, 10)	2,570

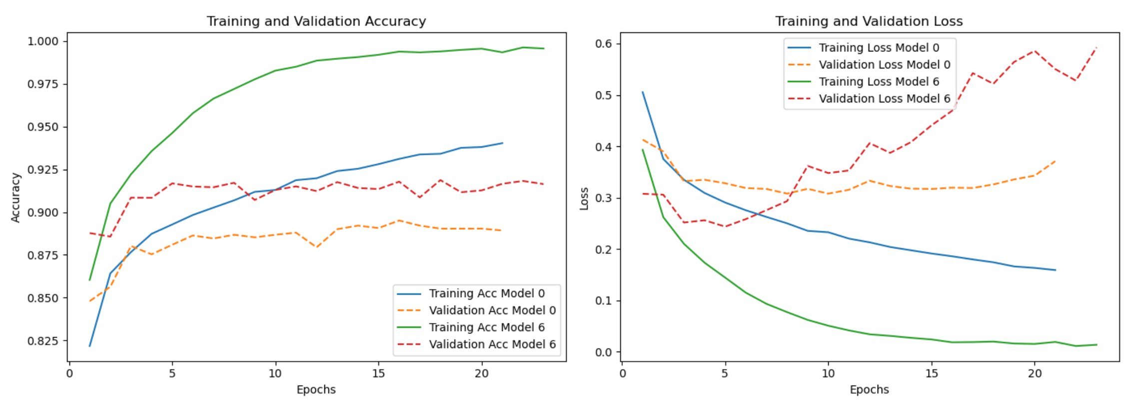
```
 Total params: 1,387,594 (5.29 MB)

 Trainable params: 1,387,594 (5.29 MB)

 Non-trainable params: 0 (0.00 B)

None
Epoch 1/25
1500/1500             27s 17ms/step -
```

```
accuracy: 0.8118 - loss: 0.5292 - val_accuracy: 0.8878 - val_loss: 0.3075
Epoch 2/25
1500/1500            24s 16ms/step -
accuracy: 0.9032 - loss: 0.2654 - val_accuracy: 0.8857 - val_loss: 0.3058
Epoch 3/25
1500/1500            26s 17ms/step -
accuracy: 0.9230 - loss: 0.2116 - val_accuracy: 0.9084 - val_loss: 0.2516
Epoch 4/25
1500/1500            28s 19ms/step -
accuracy: 0.9357 - loss: 0.1751 - val_accuracy: 0.9083 - val_loss: 0.2561
Epoch 5/25
1500/1500            30s 20ms/step -
accuracy: 0.9482 - loss: 0.1396 - val_accuracy: 0.9168 - val_loss: 0.2437
Epoch 6/25
1500/1500            27s 18ms/step -
accuracy: 0.9607 - loss: 0.1104 - val_accuracy: 0.9149 - val_loss: 0.2583
Epoch 7/25
1500/1500            27s 18ms/step -
accuracy: 0.9684 - loss: 0.0888 - val_accuracy: 0.9145 - val_loss: 0.2757
Epoch 8/25
1500/1500            26s 18ms/step -
accuracy: 0.9738 - loss: 0.0726 - val_accuracy: 0.9171 - val_loss: 0.2933
Epoch 9/25
1500/1500            27s 18ms/step -
accuracy: 0.9786 - loss: 0.0597 - val_accuracy: 0.9071 - val_loss: 0.3618
Epoch 10/25
1500/1500            26s 18ms/step -
accuracy: 0.9842 - loss: 0.0481 - val_accuracy: 0.9129 - val_loss: 0.3479
Epoch 11/25
1500/1500            30s 20ms/step -
accuracy: 0.9861 - loss: 0.0388 - val_accuracy: 0.9150 - val_loss: 0.3530
Epoch 12/25
1500/1500            25s 17ms/step -
accuracy: 0.9910 - loss: 0.0298 - val_accuracy: 0.9122 - val_loss: 0.4061
Epoch 13/25
1500/1500            24s 16ms/step -
accuracy: 0.9909 - loss: 0.0276 - val_accuracy: 0.9175 - val_loss: 0.3872
Epoch 14/25
1500/1500            26s 18ms/step -
accuracy: 0.9920 - loss: 0.0238 - val_accuracy: 0.9141 - val_loss: 0.4080
Epoch 15/25
1500/1500            33s 22ms/step -
accuracy: 0.9938 - loss: 0.0197 - val_accuracy: 0.9134 - val_loss: 0.4407
Epoch 16/25
1500/1500            29s 19ms/step -
accuracy: 0.9938 - loss: 0.0180 - val_accuracy: 0.9178 - val_loss: 0.4692
Epoch 17/25
1500/1500            25s 17ms/step -
```

```
accuracy: 0.9949 - loss: 0.0151 - val_accuracy: 0.9086 - val_loss: 0.5424
Epoch 18/25
1500/1500              24s 16ms/step -
accuracy: 0.9932 - loss: 0.0218 - val_accuracy: 0.9187 - val_loss: 0.5216
Epoch 19/25
1500/1500              27s 18ms/step -
accuracy: 0.9958 - loss: 0.0133 - val_accuracy: 0.9116 - val_loss: 0.5639
Epoch 20/25
1500/1500              26s 18ms/step -
accuracy: 0.9952 - loss: 0.0152 - val_accuracy: 0.9127 - val_loss: 0.5857
Epoch 21/25
1500/1500              25s 17ms/step -
accuracy: 0.9947 - loss: 0.0154 - val_accuracy: 0.9165 - val_loss: 0.5502
Epoch 22/25
1500/1500              26s 17ms/step -
accuracy: 0.9977 - loss: 0.0076 - val_accuracy: 0.9182 - val_loss: 0.5278
Epoch 23/25
1500/1500              26s 17ms/step -
accuracy: 0.9965 - loss: 0.0114 - val_accuracy: 0.9163 - val_loss: 0.5923
```

[20]:

```
plot_model_history([history, history6], ['Model 0', 'Model 6'])
```



`Model 6` shows a significant increase in the accuracy scores and decrease in loss score in the training model; however, this is not reflected in the validation metrics. This suggests the model is drastically overfitting, and `Model 0` would still be preferred. Earlier, we saw the improvement Dropouts made to the overfitting issue, so perhaps that will help us here. The next model will attempt to decrease the overfitting issue using dropouts.

0.10 #### Model 7: Convolution, Pooling, and Fully Connected Layers with Dropouts to improve Overfitting

This model builds on the previous model by including a dropout to improve the overfitting issue. Additionally, multiple convolutional and pooling layers are added, including a fully connected layer.

[21]:
```
model7 = Sequential([
    Rescaling(1./255, input_shape=(28, 28, 1)),
    Conv2D(64, (3, 3), activation='relu'),  # increasing the number of filters
    MaxPooling2D((2, 2)),
    Dropout(0.3), # adding dropout
    Conv2D(64, (3, 3), activation='relu'),  # adding additional convolutional␣
 ↪layer
    MaxPooling2D((2, 2)),
    Dropout(0.3), # adding another dropout
    Flatten(),
    Dense(256, activation='relu'),  # adding smaller dense layer before output
    Dropout(0.5), # aaaaaand anotha one
    Dense(10, activation='softmax')
])

model7.compile(optimizer='adam',
               loss='categorical_crossentropy',
               metrics=['accuracy'])

print(model7.summary())

history7 = model7.fit(train_images, train_labels, epochs=25,
                      validation_data=(val_images, val_labels),
                      callbacks=[EarlyStopping(monitor='val_accuracy',␣
 ↪patience=5)])
```

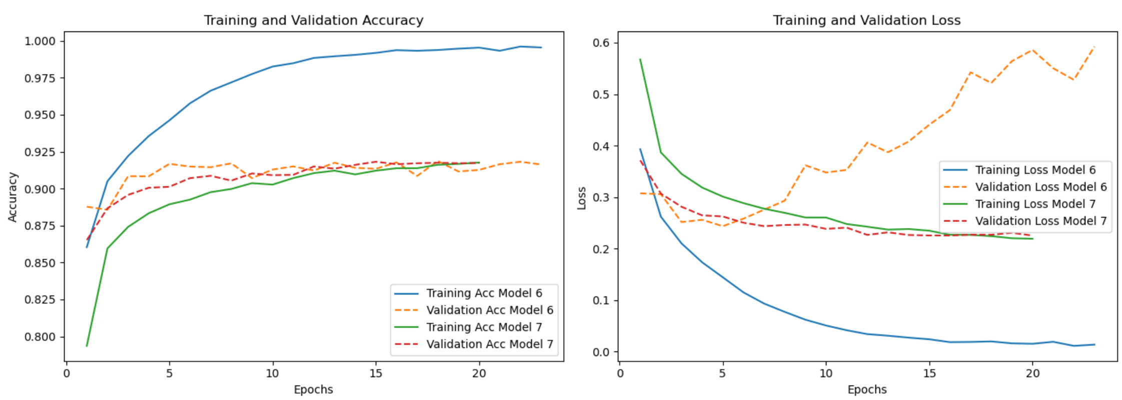
Model: "sequential_7"

Layer (type)	Output Shape	Param #
rescaling_7 (Rescaling)	(None, 28, 28, 1)	0
conv2d_1 (Conv2D)	(None, 26, 26, 64)	640
max_pooling2d_1 (MaxPooling2D)	(None, 13, 13, 64)	0
dropout_5 (Dropout)	(None, 13, 13, 64)	0
conv2d_2 (Conv2D)	(None, 11, 11, 64)	36,928
max_pooling2d_2 (MaxPooling2D)	(None, 5, 5, 64)	0
dropout_6 (Dropout)	(None, 5, 5, 64)	0
flatten_7 (Flatten)	(None, 1600)	0

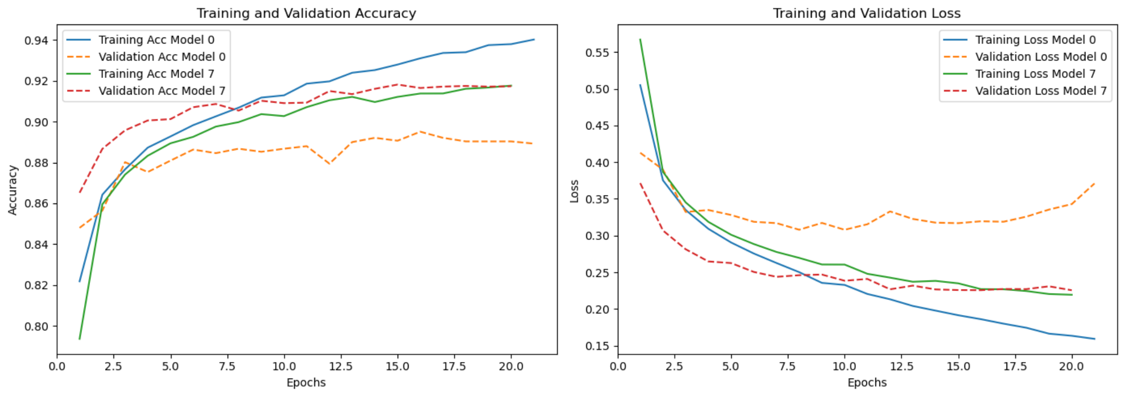
```
 dense_17 (Dense)                (None, 256)                  409,856

 dropout_7 (Dropout)             (None, 256)                        0

 dense_18 (Dense)                (None, 10)                     2,570


 Total params: 449,994 (1.72 MB)

 Trainable params: 449,994 (1.72 MB)

 Non-trainable params: 0 (0.00 B)

None
Epoch 1/25
1500/1500             26s 16ms/step -
accuracy: 0.7191 - loss: 0.7696 - val_accuracy: 0.8652 - val_loss: 0.3715
Epoch 2/25
1500/1500             23s 15ms/step -
accuracy: 0.8569 - loss: 0.3958 - val_accuracy: 0.8867 - val_loss: 0.3069
Epoch 3/25
1500/1500             23s 15ms/step -
accuracy: 0.8747 - loss: 0.3501 - val_accuracy: 0.8957 - val_loss: 0.2814
Epoch 4/25
1500/1500             24s 16ms/step -
accuracy: 0.8826 - loss: 0.3208 - val_accuracy: 0.9006 - val_loss: 0.2647
Epoch 5/25
1500/1500             26s 17ms/step -
accuracy: 0.8904 - loss: 0.2976 - val_accuracy: 0.9013 - val_loss: 0.2625
Epoch 6/25
1500/1500             24s 16ms/step -
accuracy: 0.8936 - loss: 0.2826 - val_accuracy: 0.9071 - val_loss: 0.2504
Epoch 7/25
1500/1500             23s 15ms/step -
accuracy: 0.8980 - loss: 0.2756 - val_accuracy: 0.9087 - val_loss: 0.2437
Epoch 8/25
1500/1500             22s 15ms/step -
accuracy: 0.9000 - loss: 0.2735 - val_accuracy: 0.9054 - val_loss: 0.2460
Epoch 9/25
1500/1500             25s 17ms/step -
accuracy: 0.9047 - loss: 0.2583 - val_accuracy: 0.9103 - val_loss: 0.2468
Epoch 10/25
1500/1500             22s 15ms/step -
accuracy: 0.9033 - loss: 0.2567 - val_accuracy: 0.9091 - val_loss: 0.2384
Epoch 11/25
1500/1500             25s 17ms/step -
```

```
accuracy: 0.9071 - loss: 0.2479 - val_accuracy: 0.9093 - val_loss: 0.2408
Epoch 12/25
1500/1500          24s 16ms/step -
accuracy: 0.9099 - loss: 0.2440 - val_accuracy: 0.9150 - val_loss: 0.2267
Epoch 13/25
1500/1500          23s 15ms/step -
accuracy: 0.9118 - loss: 0.2357 - val_accuracy: 0.9135 - val_loss: 0.2317
Epoch 14/25
1500/1500          21s 14ms/step -
accuracy: 0.9097 - loss: 0.2364 - val_accuracy: 0.9161 - val_loss: 0.2266
Epoch 15/25
1500/1500          21s 14ms/step -
accuracy: 0.9131 - loss: 0.2275 - val_accuracy: 0.9182 - val_loss: 0.2257
Epoch 16/25
1500/1500          22s 14ms/step -
accuracy: 0.9145 - loss: 0.2274 - val_accuracy: 0.9165 - val_loss: 0.2255
Epoch 17/25
1500/1500          23s 15ms/step -
accuracy: 0.9145 - loss: 0.2254 - val_accuracy: 0.9172 - val_loss: 0.2271
Epoch 18/25
1500/1500          24s 16ms/step -
accuracy: 0.9157 - loss: 0.2241 - val_accuracy: 0.9175 - val_loss: 0.2270
Epoch 19/25
1500/1500          23s 15ms/step -
accuracy: 0.9188 - loss: 0.2155 - val_accuracy: 0.9172 - val_loss: 0.2308
Epoch 20/25
1500/1500          22s 15ms/step -
accuracy: 0.9182 - loss: 0.2166 - val_accuracy: 0.9173 - val_loss: 0.2254
```

[22]:
```
plot_model_history([history6, history7], ['Model 6', 'Model 7'])
```

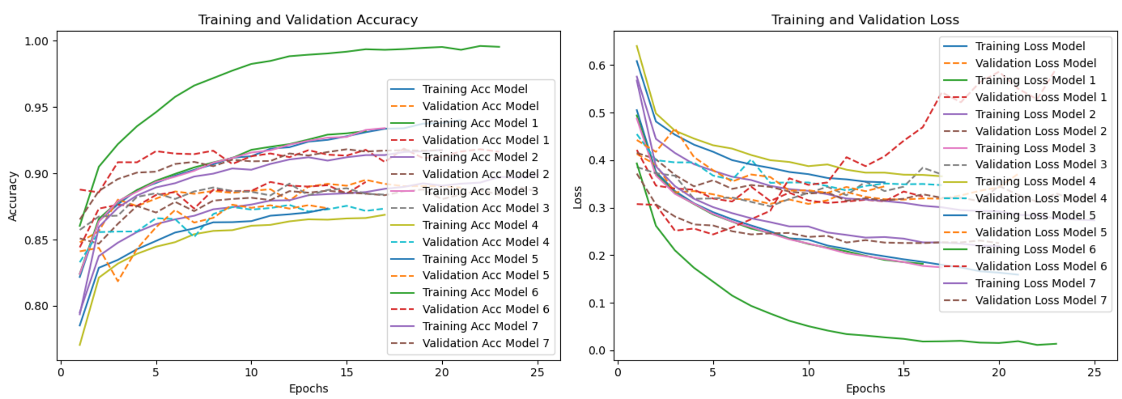


[23]:
```
plot_model_history([history, history7], ['Model 0', 'Model 7'])
```



Model 7 shows improvement in the overfitting issue as seen in Model 6. As a result in this improvement to overfitting, Model 7's metrics seem to be performing better than Model 0 as a result of the convolutional and pooling layers. This is the preferred model for predicting the categories of the images.

[24]:
```
plot_model_history([history, history1, history2, history3, history4, history5,␣
↪history6, history7], ['Model', 'Model 1', 'Model 2', 'Model 3', 'Model 4',␣
↪'Model 5', 'Model 6', 'Model 7'])
```



0.11 ### 6. Try to use a pre-trained network to improve accuracy.

The following procedure attempts to use the MobileNetV2 pretrained image dataset to predict on our image dataset. There was an issue with the differences in image size when setting up the model. To fix this, padding was added to our image set. This can cause issues in the predictive power of the model, as this padding will add additional noise to the images.

[25]:
```
def pad_images(images):

    if images.ndim == 3:
```

```
        images = images[..., tf.newaxis]

    # 2 pixels on top, bottom, left, and right, and no padding on the batch and␣
↪channels
    padding = [[0, 0], [2, 2], [2, 2], [0, 0]]

    # applying constant padding
    images_padded = tf.pad(images, paddings=padding, mode='CONSTANT',␣
↪constant_values=0)
    return images_padded

train_images_padded = pad_images(train_images)
val_images_padded = pad_images(val_images)
```

[26]:
```
# loading MobileNetV2 without the top layer to use as a base model
base_model = MobileNetV2(weights='imagenet', include_top=False,␣
↪input_shape=(32, 32, 3), alpha=1.0)

# freezing the base model layers
base_model.trainable = False

model8 = Sequential([
    base_model,
    GlobalAveragePooling2D(),  # Reduces each feature map to a single value
    BatchNormalization(),
    Dense(1024, activation='relu'), # high number of nodes
    Dropout(0.5),
    Dense(512, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])

print(model8.summary())

# compiling the enhanced model
model8.compile(optimizer='adam',
                        loss='categorical_crossentropy',
                        metrics=['accuracy'])
```

```
C:\Users\iandr\AppData\Local\Temp\ipykernel_17864\2767747608.py:2: UserWarning:
`input_shape` is undefined or non-square, or `rows` is not in [96, 128, 160,
192, 224]. Weights for input shape (224, 224) will be loaded as the default.
  base_model = MobileNetV2(weights='imagenet', include_top=False,
input_shape=(32, 32, 3), alpha=1.0)
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_224 (Functional)	?	2,257,984
global_average_pooling2d (GlobalAveragePooling2D)	?	0 (unbuilt)
batch_normalization_2 (BatchNormalization)	?	0 (unbuilt)
dense_19 (Dense)	?	0 (unbuilt)
dropout_8 (Dropout)	?	0
dense_20 (Dense)	?	0 (unbuilt)
dropout_9 (Dropout)	?	0
dense_21 (Dense)	?	0 (unbuilt)

Total params: 2,257,984 (8.61 MB)

Trainable params: 0 (0.00 B)

Non-trainable params: 2,257,984 (8.61 MB)

None

[27]:
```python
# converting images to rgb
def convert_to_rgb(images):
    images_rgb = tf.repeat(images, 3, axis=-1)
    return images_rgb

train_images_rgb = convert_to_rgb(train_images_padded)
val_images_rgb = convert_to_rgb(val_images_padded)
```

[28]:
```python
# fitting the model
history8 = model8.fit(
    train_images_rgb, train_labels,
    epochs=10,
    validation_data=(val_images_rgb, val_labels),
    callbacks=[EarlyStopping(monitor='val_accuracy', patience=3)])
```

```
Epoch 1/10
1500/1500              75s 44ms/step -
accuracy: 0.4477 - loss: 1.4920 - val_accuracy: 0.5298 - val_loss: 1.2593
Epoch 2/10
1500/1500              63s 42ms/step -
accuracy: 0.5122 - loss: 1.3160 - val_accuracy: 0.5375 - val_loss: 1.2592
Epoch 3/10
1500/1500              65s 44ms/step -
accuracy: 0.5238 - loss: 1.2805 - val_accuracy: 0.5350 - val_loss: 1.2326
Epoch 4/10
1500/1500              67s 45ms/step -
accuracy: 0.5278 - loss: 1.2652 - val_accuracy: 0.5441 - val_loss: 1.2235
Epoch 5/10
1500/1500              59s 40ms/step -
accuracy: 0.5308 - loss: 1.2592 - val_accuracy: 0.5466 - val_loss: 1.2126
Epoch 6/10
1500/1500              64s 43ms/step -
accuracy: 0.5355 - loss: 1.2400 - val_accuracy: 0.5505 - val_loss: 1.1992
Epoch 7/10
1500/1500              59s 39ms/step -
accuracy: 0.5416 - loss: 1.2348 - val_accuracy: 0.5520 - val_loss: 1.1974
Epoch 8/10
1500/1500              61s 41ms/step -
accuracy: 0.5433 - loss: 1.2281 - val_accuracy: 0.5605 - val_loss: 1.1943
Epoch 9/10
1500/1500              67s 45ms/step -
accuracy: 0.5399 - loss: 1.2277 - val_accuracy: 0.5569 - val_loss: 1.2001
Epoch 10/10
1500/1500              49s 33ms/step -
accuracy: 0.5472 - loss: 1.2117 - val_accuracy: 0.5610 - val_loss: 1.2021
```

This model does not seem to fit our data very well at all. With an accuracy of 0.54 and a loss over 1, this model is basically guessing. This could be a result of the added padding, but it is also a testimate to how difficult it is to create a pretrained dataset that is able to be applied on other datasets for image prediction.

0.12 ### 7. Select a final model and evaluate it on the test set. How does the test error compare to the validation error?

The model selected was the 7th model, with the added convolutional, pooling, dropout, and fully connected hidden layers. This model had the best combination of accuracy and loss scores while reducing overfitting.

[31]:
```python
from tensorflow.keras.losses import MeanSquaredError
import pandas as pd

models = [model, model1, model2, model3, model4, model5, model6, model7]
```

```
model_histories = [history, history1, history2, history3, history4, history5,␣
↪history6, history7]
results = []

mse = MeanSquaredError()

# looping through each model, its history, and evaluating it on the test set
for i, (model, history) in enumerate(zip(models, model_histories)):
    # test set evaluation
    test_loss, test_accuracy = model.evaluate(test_images, test_labels,␣
↪verbose=0)

    # predictions for MSE calculation
    test_predictions = model.predict(test_images)
    # assuming test_labels are one-hot encoded, converting predictions for MSE␣
↪calculation
    test_mse = mse(test_labels, test_predictions).numpy()

    # extracting training and validation loss and accuracy from the model's␣
↪history
    training_loss = history.history['loss'][-1]
    training_accuracy = history.history['accuracy'][-1]
    validation_loss = history.history['val_loss'][-1]
    validation_accuracy = history.history['val_accuracy'][-1]

    # appending the results
    results.append({
        'Model': f'Model{i}',
        'Training Loss': training_loss,
        'Training Accuracy': training_accuracy,
        'Validation Loss': validation_loss,
        'Validation Accuracy': validation_accuracy,
        'Test Loss': test_loss,
        'Test Accuracy': test_accuracy,
        'Test MSE': test_mse
    })

results_df = pd.DataFrame(results)
```

```
313/313              1s 3ms/step
313/313              0s 1ms/step
313/313              0s 1ms/step
313/313              1s 2ms/step
313/313              1s 1ms/step
313/313              0s 1ms/step
313/313              1s 2ms/step
313/313              1s 4ms/step
```

[32]:
```
results_df
```

[32]:

	Model	Training Loss	Training Accuracy	Validation Loss
0	Model0	0.159150	0.940229	0.370988
1	Model1	0.181970	0.931938	0.323383
2	Model2	0.273494	0.898729	0.325238
3	Model3	0.174464	0.934125	0.369907
4	Model4	0.365952	0.868729	0.347417
5	Model5	0.353225	0.873500	0.344833
6	Model6	0.013830	0.995500	0.592348
7	Model7	0.219290	0.917646	0.225436

	Validation Accuracy	Test Loss	Test Accuracy	Test MSE
0	0.889250	0.241583	0.9139	0.012384
1	0.893500	0.349837	0.8900	0.016377
2	0.886250	0.344006	0.8829	0.016931
3	0.883917	0.394902	0.8829	0.017341
4	0.873417	0.368259	0.8689	0.018789
5	0.873667	0.365301	0.8701	0.018734
6	0.916333	0.628959	0.9151	0.015001
7	0.917333	0.241583	0.9139	0.012384

Here, the best model was determined to be `Model 7`. This is as a result of having very similar scores in the validation metrics as compared to the training metrics, while maintaining the highest validation accuracy. This is reflected in having the best test MSE as well.

[33]:
```
# calculating the MSE on the validation and test set for comparison
mse = MeanSquaredError()

# predicting on the validation set
val_predictions = model7.predict(val_images)
validation_mse = mse(val_labels, val_predictions).numpy()

# predicting on the test set
test_predictions = model7.predict(test_images)
test_mse = mse(test_labels, test_predictions).numpy()

print(f"Test MSE: {test_mse:.4f}")
print(f"Validation MSE: {validation_mse:.4f}")
```

```
375/375             1s 3ms/step
313/313             1s 3ms/step
Test MSE: 0.0124
Validation MSE: 0.0120
```

Here, we used the MSE as an error score to best interpret the model. When set to predict the test set, model 7 performs very well by having a very similar test MSE score to the validation MSE. This suggests that this model can generalize quite well, and that there are not overfitting issues in this model.