midastask2part2-3

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1 Task 2 Part 2

Imports

[48]:
```
import shutil
from PIL import Image
import numpy as np
import scipy
import matplotlib.pyplot as plt
from matplotlib.pyplot import imshow
%matplotlib inline
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, Lambda
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import load_model
from tensorflow.keras.datasets import mnist
from tensorflow.keras.utils import to_categorical
```

1.1 Preprocessing the image

Extracting the images

[4]:
```
shutil.unpack_archive('trainPart1.zip', 'input/part2')
```

Delete all other samples except images from 0-9

[5]:
```
for i in range(11, 63):
    shutil.rmtree(f'input/part2/train/Sample0{i}')
```

1.2 Generating the dataset for pre-training

As with part 1 of this task, I'm converting all the images to the dimension of the MNIST images by first resizing the largest dimension to 28 and then zer-padding them to make it a square. The background in the MNIST dtaset have 0 value so, I'm inverting our daatset images to make it similar to MNIST

Some global variables

[6]:
```
BATCH_SIZE = 64
IMAGE_SIZE_BEFORE_PADDING = (21, 28)
EPOCHS = 400
IMAGE_SIZE = (28, 28)
```

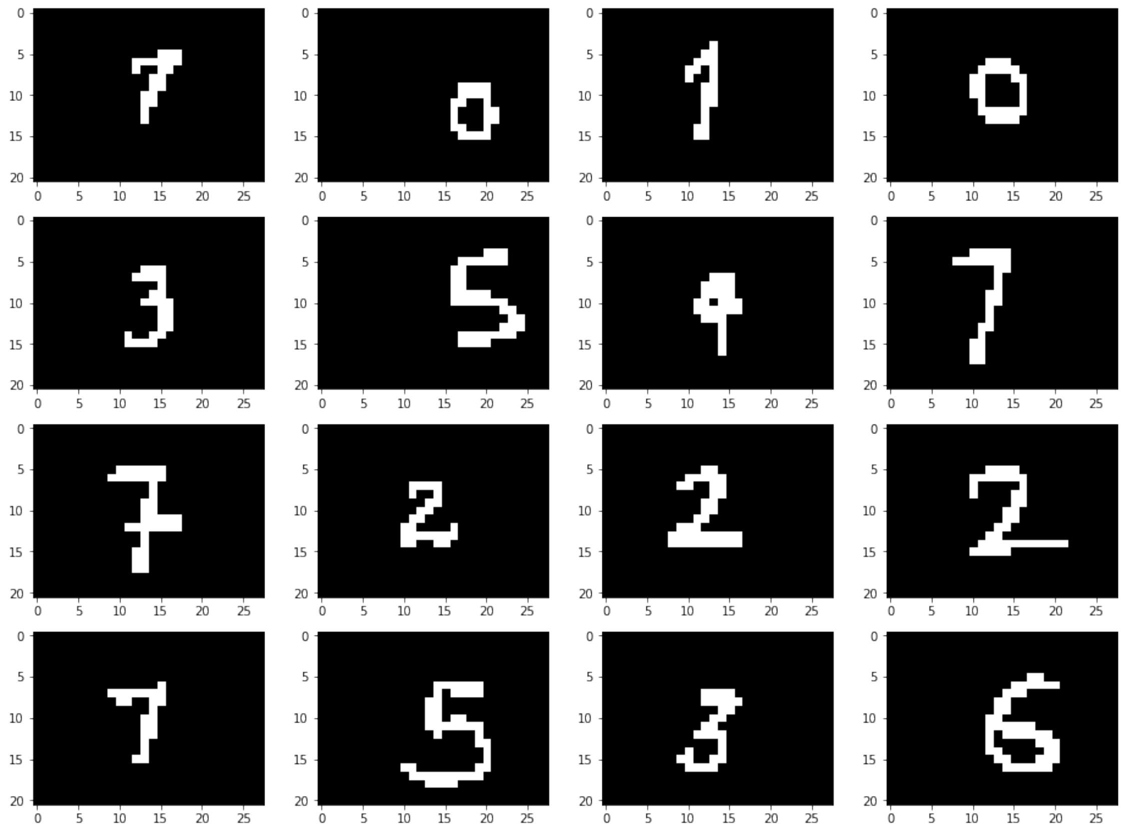
Using ImageDataGenerator to generate the samples form the dataset

[43]:
```
train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2,␣
↪preprocessing_function=lambda x: 1-x)
```

[44]:
```
train_generator = train_datagen.flow_from_directory(
    'input/part2/train',
    target_size=IMAGE_SIZE_BEFORE_PADDING,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    color_mode='grayscale',
    subset='training',
    seed=42,
    shuffle=True)

validation_generator = train_datagen.flow_from_directory(
    'input/part2/train',
    target_size=IMAGE_SIZE_BEFORE_PADDING,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    color_mode='grayscale',
    subset='validation',
    seed=42,
    shuffle=True)

X_train_batch0, y_train_batch0 = train_generator.next()
print(X_train_batch0.shape, y_train_batch0.shape)
print(y_train_batch0[0])
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_train_batch0[i]), cmap='gray')
plt.show()
```

```
Found 320 images belonging to 10 classes.
```

```
Found 80 images belonging to 10 classes.
(64, 21, 28, 1) (64, 10)
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

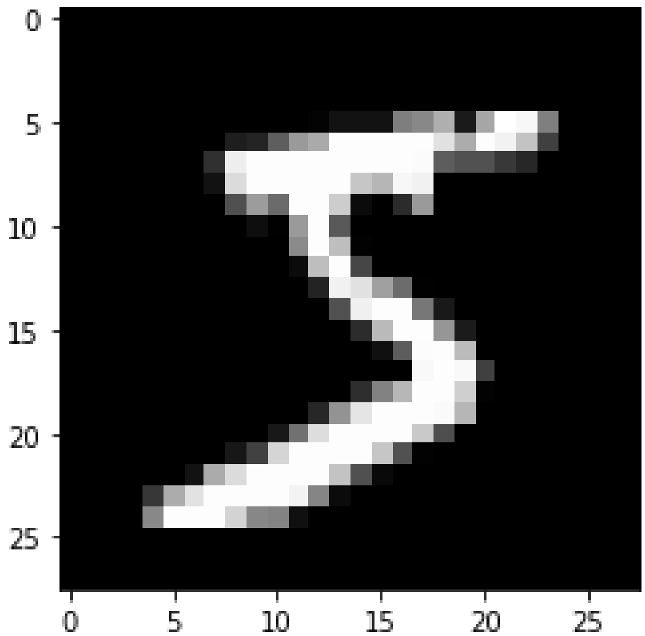


1.3 Loading the MNIST Dataset

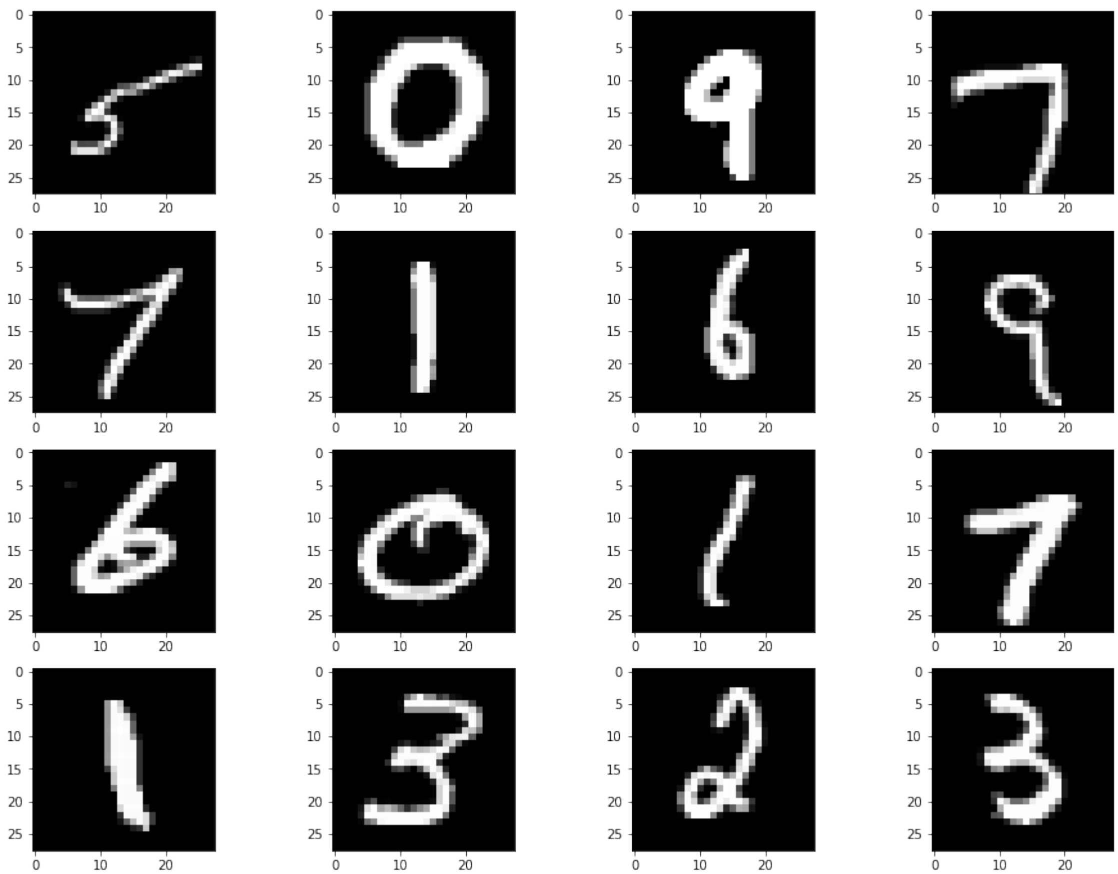
[58]:
```python
(x_train, y_train), (x_test, y_test) = mnist.load_data(path="mnist.npz")
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

x_train = x_train.reshape(x_train.shape[0], x_train.shape[1], x_train.shape[2],␣
 ↪1)
x_test = x_test.reshape(x_test.shape[0], x_test.shape[1], x_test.shape[2], 1)


print(x_train.shape, y_train.shape)
print(x_test.shape, y_test.shape)
imshow(tf.squeeze(x_train[0]), cmap='gray')
```

```
(60000, 28, 28, 1) (60000, 10)
(10000, 28, 28, 1) (10000, 10)
```

[58]: <matplotlib.image.AxesImage at 0x7fa8e459e990>



[60]:
```
mnist_datagen = ImageDataGenerator(rescale=1.0/255.0)

# prepare an iterators to scale images
mnist_train_gen = mnist_datagen.flow(x_train, y_train, batch_size=BATCH_SIZE)
mnist_test_gen = mnist_datagen.flow(x_test, y_test, batch_size=BATCH_SIZE)

mnist_x_train, _ = mnist_train_gen.next()
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(mnist_x_train[i]), cmap='gray')
plt.show()
```



1.4 Building the Model

From my results from Part 1 of this task, Architecture from Kaggle and the original performed good. I'll use them both with Mish Activation and higher temperature for the Softmax and see how both of them perform.

[96]:

```python
# Early Stopping callback
early_stopping_callback = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    mode='min',
    patience=10,
    restore_best_weights=True,
    verbose=1)

early_stopping_callback2 = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    mode='min',
    patience=50,
    restore_best_weights=True,
    verbose=1)
```

[62]:
```
# Softmax Temperature
temp = 5
```

[63]:
```
# Mish Activation function
def mish(x):
    return tf.keras.layers.Lambda(lambda x: x*tf.tanh(tf.math.log(1+tf.
 ↪exp(x))))(x)
```

1.4.1 Modified LeNet Architecture

Pre-training on our dataset

[72]:
```
model1 = Sequential()

# Lambda Layer for adding Padding
model1.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE_BEFORE_PADDING, 1)))

# 1st Convolution Layer
model1.add(Conv2D(6, input_shape=(*IMAGE_SIZE, 1),
                  kernel_size=(5,5), padding='same', activation=mish))
model1.add(BatchNormalization())
model1.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
model1.add(Conv2D(16, kernel_size=(5,5), activation=mish))
model1.add(BatchNormalization())
model1.add(MaxPooling2D(pool_size=(2,2), strides=2))

# Passing to a Fully Connected Layer
model1.add(Flatten())

# 1st Fully Connected Layer
model1.add(Dense(120, activation=mish))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# 2nd Fully Connected Layer
model1.add(Dense(84, activation=mish))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# Output Layer
# Increasing the softmax temperature
model1.add(Lambda(lambda x: x / temp))
model1.add(Dense(10, activation='softmax'))

model1.summary()
```

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

```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_18 (Lambda)           (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_38 (Conv2D)           (None, 28, 28, 6)         156
_________________________________________________________________
batch_normalization_48 (Batc (None, 28, 28, 6)         24
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 14, 14, 6)         0
_________________________________________________________________
conv2d_39 (Conv2D)           (None, 10, 10, 16)        2416
_________________________________________________________________
batch_normalization_49 (Batc (None, 10, 10, 16)        64
_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 5, 5, 16)          0
_________________________________________________________________
flatten_9 (Flatten)          (None, 400)               0
_________________________________________________________________
dense_19 (Dense)             (None, 120)               48120
_________________________________________________________________
batch_normalization_50 (Batc (None, 120)               480
_________________________________________________________________
dropout_22 (Dropout)         (None, 120)               0
_________________________________________________________________
dense_20 (Dense)             (None, 84)                10164
_________________________________________________________________
batch_normalization_51 (Batc (None, 84)                336
_________________________________________________________________
dropout_23 (Dropout)         (None, 84)                0
_________________________________________________________________
lambda_19 (Lambda)           (None, 84)                0
_________________________________________________________________
dense_21 (Dense)             (None, 10)                850
=================================================================
Total params: 62,610
Trainable params: 62,158
Non-trainable params: 452
_________________________________________________________________
```

[73]:
```
checkpoint_filepath1 = 'part2_pretrained/checkpoint'
model_checkpoint_callback1 = tf.keras.callbacks.ModelCheckpoint(
```

```python
    filepath=checkpoint_filepath1,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)

history1 = model1.fit(
    train_generator,
    epochs=EPOCHS,
    validation_data=validation_generator,
    steps_per_epoch = train_generator.samples // BATCH_SIZE,
    validation_steps = validation_generator.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback1, early_stopping_callback]
)
```

```
Epoch 1/400
5/5 [==============================] - 7s 1s/step - loss: 2.3350 - accuracy:
0.1408 - val_loss: 2.3025 - val_accuracy: 0.1250
Epoch 2/400
5/5 [==============================] - 5s 1s/step - loss: 2.1667 - accuracy:
0.1862 - val_loss: 2.3019 - val_accuracy: 0.1562
Epoch 3/400
5/5 [==============================] - 5s 1s/step - loss: 2.0587 - accuracy:
0.3332 - val_loss: 2.2992 - val_accuracy: 0.2500
Epoch 4/400
5/5 [==============================] - 5s 1s/step - loss: 1.9465 - accuracy:
0.4384 - val_loss: 2.3031 - val_accuracy: 0.0938
Epoch 5/400
5/5 [==============================] - 5s 1s/step - loss: 1.8744 - accuracy:
0.5266 - val_loss: 2.2950 - val_accuracy: 0.1250
Epoch 6/400
5/5 [==============================] - 5s 1s/step - loss: 1.7995 - accuracy:
0.5392 - val_loss: 2.2947 - val_accuracy: 0.0938
Epoch 7/400
5/5 [==============================] - 5s 1s/step - loss: 1.7303 - accuracy:
0.6256 - val_loss: 2.2930 - val_accuracy: 0.0938
Epoch 8/400
5/5 [==============================] - 5s 1s/step - loss: 1.6355 - accuracy:
0.6813 - val_loss: 2.2916 - val_accuracy: 0.0938
Epoch 9/400
5/5 [==============================] - 5s 1s/step - loss: 1.5828 - accuracy:
0.7044 - val_loss: 2.2957 - val_accuracy: 0.0781
Epoch 10/400
5/5 [==============================] - 5s 1s/step - loss: 1.5233 - accuracy:
0.7276 - val_loss: 2.2877 - val_accuracy: 0.1094
Epoch 11/400
5/5 [==============================] - 5s 1s/step - loss: 1.4812 - accuracy:
```

```
0.7599 - val_loss: 2.2909 - val_accuracy: 0.0938
Epoch 12/400
5/5 [==============================] - 5s 1s/step - loss: 1.3877 - accuracy:
0.7908 - val_loss: 2.2846 - val_accuracy: 0.1094
Epoch 13/400
5/5 [==============================] - 5s 1s/step - loss: 1.3261 - accuracy:
0.7970 - val_loss: 2.2914 - val_accuracy: 0.0781
Epoch 14/400
5/5 [==============================] - 5s 1s/step - loss: 1.2805 - accuracy:
0.8424 - val_loss: 2.2885 - val_accuracy: 0.0938
Epoch 15/400
5/5 [==============================] - 5s 1s/step - loss: 1.2517 - accuracy:
0.8400 - val_loss: 2.2887 - val_accuracy: 0.1250
Epoch 16/400
5/5 [==============================] - 5s 1s/step - loss: 1.1849 - accuracy:
0.8377 - val_loss: 2.2985 - val_accuracy: 0.0781
Epoch 17/400
5/5 [==============================] - 5s 1s/step - loss: 1.1716 - accuracy:
0.8437 - val_loss: 2.3015 - val_accuracy: 0.0625
Epoch 18/400
5/5 [==============================] - 5s 1s/step - loss: 1.1299 - accuracy:
0.8556 - val_loss: 2.2902 - val_accuracy: 0.0938
Epoch 19/400
5/5 [==============================] - 5s 1s/step - loss: 1.0983 - accuracy:
0.8705 - val_loss: 2.2715 - val_accuracy: 0.1094
Epoch 20/400
5/5 [==============================] - 5s 1s/step - loss: 1.0094 - accuracy:
0.9096 - val_loss: 2.3084 - val_accuracy: 0.0625
Epoch 21/400
5/5 [==============================] - 5s 1s/step - loss: 0.9620 - accuracy:
0.9091 - val_loss: 2.2951 - val_accuracy: 0.0938
Epoch 22/400
5/5 [==============================] - 5s 1s/step - loss: 0.8908 - accuracy:
0.9303 - val_loss: 2.2915 - val_accuracy: 0.0938
Epoch 23/400
5/5 [==============================] - 5s 1s/step - loss: 0.8682 - accuracy:
0.9439 - val_loss: 2.2891 - val_accuracy: 0.0938
Epoch 24/400
5/5 [==============================] - 5s 1s/step - loss: 0.8186 - accuracy:
0.9275 - val_loss: 2.2630 - val_accuracy: 0.1094
Epoch 25/400
5/5 [==============================] - 5s 1s/step - loss: 0.7741 - accuracy:
0.9478 - val_loss: 2.2757 - val_accuracy: 0.0781
Epoch 26/400
5/5 [==============================] - 5s 1s/step - loss: 0.7337 - accuracy:
0.9551 - val_loss: 2.2845 - val_accuracy: 0.0938
Epoch 27/400
5/5 [==============================] - 5s 1s/step - loss: 0.7269 - accuracy:
```

```
0.9504 - val_loss: 2.2639 - val_accuracy: 0.1094
Epoch 28/400
5/5 [==============================] - 5s 1s/step - loss: 0.6759 - accuracy:
0.9553 - val_loss: 2.2978 - val_accuracy: 0.0938
Epoch 29/400
5/5 [==============================] - 5s 1s/step - loss: 0.6449 - accuracy:
0.9685 - val_loss: 2.2644 - val_accuracy: 0.0938
Epoch 30/400
5/5 [==============================] - 5s 1s/step - loss: 0.6143 - accuracy:
0.9737 - val_loss: 2.2837 - val_accuracy: 0.1250
Epoch 31/400
5/5 [==============================] - 5s 1s/step - loss: 0.5540 - accuracy:
0.9898 - val_loss: 2.2901 - val_accuracy: 0.0938
Epoch 32/400
5/5 [==============================] - 5s 1s/step - loss: 0.5415 - accuracy:
0.9746 - val_loss: 2.2707 - val_accuracy: 0.1250
Epoch 33/400
5/5 [==============================] - 5s 1s/step - loss: 0.5386 - accuracy:
0.9858 - val_loss: 2.2405 - val_accuracy: 0.1562
Epoch 34/400
5/5 [==============================] - 5s 1s/step - loss: 0.4734 - accuracy:
0.9863 - val_loss: 2.2529 - val_accuracy: 0.1406
Epoch 35/400
5/5 [==============================] - 5s 1s/step - loss: 0.5061 - accuracy:
0.9815 - val_loss: 2.3207 - val_accuracy: 0.0938
Epoch 36/400
5/5 [==============================] - 5s 1s/step - loss: 0.4500 - accuracy:
0.9918 - val_loss: 2.2306 - val_accuracy: 0.1562
Epoch 37/400
5/5 [==============================] - 5s 1s/step - loss: 0.4188 - accuracy:
0.9874 - val_loss: 2.2606 - val_accuracy: 0.1250
Epoch 38/400
5/5 [==============================] - 5s 1s/step - loss: 0.4009 - accuracy:
0.9884 - val_loss: 2.2462 - val_accuracy: 0.1094
Epoch 39/400
5/5 [==============================] - 5s 1s/step - loss: 0.3854 - accuracy:
0.9832 - val_loss: 2.2524 - val_accuracy: 0.1250
Epoch 40/400
5/5 [==============================] - 5s 1s/step - loss: 0.3878 - accuracy:
0.9944 - val_loss: 2.2173 - val_accuracy: 0.1406
Epoch 41/400
5/5 [==============================] - 5s 1s/step - loss: 0.3504 - accuracy:
0.9990 - val_loss: 2.2385 - val_accuracy: 0.1094
Epoch 42/400
5/5 [==============================] - 5s 1s/step - loss: 0.3115 - accuracy:
0.9990 - val_loss: 2.2221 - val_accuracy: 0.1719
Epoch 43/400
5/5 [==============================] - 5s 1s/step - loss: 0.3233 - accuracy:
```

```
1.0000 - val_loss: 2.2036 - val_accuracy: 0.1719
Epoch 44/400
5/5 [==============================] - 5s 1s/step - loss: 0.2786 - accuracy:
1.0000 - val_loss: 2.2289 - val_accuracy: 0.1719
Epoch 45/400
5/5 [==============================] - 5s 1s/step - loss: 0.2823 - accuracy:
0.9919 - val_loss: 2.2786 - val_accuracy: 0.1406
Epoch 46/400
5/5 [==============================] - 5s 1s/step - loss: 0.2678 - accuracy:
1.0000 - val_loss: 2.1884 - val_accuracy: 0.2344
Epoch 47/400
5/5 [==============================] - 5s 1s/step - loss: 0.2516 - accuracy:
0.9944 - val_loss: 2.1898 - val_accuracy: 0.2031
Epoch 48/400
5/5 [==============================] - 5s 1s/step - loss: 0.2470 - accuracy:
1.0000 - val_loss: 2.1143 - val_accuracy: 0.2656
Epoch 49/400
5/5 [==============================] - 5s 1s/step - loss: 0.2421 - accuracy:
1.0000 - val_loss: 2.1382 - val_accuracy: 0.2812
Epoch 50/400
5/5 [==============================] - 5s 1s/step - loss: 0.2127 - accuracy:
0.9983 - val_loss: 2.1238 - val_accuracy: 0.2812
Epoch 51/400
5/5 [==============================] - 5s 1s/step - loss: 0.2142 - accuracy:
1.0000 - val_loss: 2.1230 - val_accuracy: 0.2812
Epoch 52/400
5/5 [==============================] - 5s 1s/step - loss: 0.2120 - accuracy:
1.0000 - val_loss: 2.1204 - val_accuracy: 0.2656
Epoch 53/400
5/5 [==============================] - 5s 1s/step - loss: 0.2052 - accuracy:
0.9974 - val_loss: 2.0434 - val_accuracy: 0.2812
Epoch 54/400
5/5 [==============================] - 5s 1s/step - loss: 0.1759 - accuracy:
1.0000 - val_loss: 2.1185 - val_accuracy: 0.2656
Epoch 55/400
5/5 [==============================] - 5s 1s/step - loss: 0.1805 - accuracy:
1.0000 - val_loss: 2.1326 - val_accuracy: 0.2500
Epoch 56/400
5/5 [==============================] - 5s 1s/step - loss: 0.1809 - accuracy:
1.0000 - val_loss: 2.1546 - val_accuracy: 0.2500
Epoch 57/400
5/5 [==============================] - 5s 1s/step - loss: 0.1725 - accuracy:
1.0000 - val_loss: 2.0024 - val_accuracy: 0.3281
Epoch 58/400
5/5 [==============================] - 5s 1s/step - loss: 0.1708 - accuracy:
0.9961 - val_loss: 2.0347 - val_accuracy: 0.3125
Epoch 59/400
5/5 [==============================] - 5s 1s/step - loss: 0.1589 - accuracy:
```

```
1.0000 - val_loss: 1.9952 - val_accuracy: 0.3594
Epoch 60/400
5/5 [==============================] - 5s 1s/step - loss: 0.1594 - accuracy:
1.0000 - val_loss: 1.9768 - val_accuracy: 0.3438
Epoch 61/400
5/5 [==============================] - 5s 1s/step - loss: 0.1380 - accuracy:
1.0000 - val_loss: 1.9830 - val_accuracy: 0.3438
Epoch 62/400
5/5 [==============================] - 5s 1s/step - loss: 0.1325 - accuracy:
0.9974 - val_loss: 1.9374 - val_accuracy: 0.3438
Epoch 63/400
5/5 [==============================] - 5s 1s/step - loss: 0.1380 - accuracy:
1.0000 - val_loss: 1.9140 - val_accuracy: 0.3906
Epoch 64/400
5/5 [==============================] - 5s 1s/step - loss: 0.1334 - accuracy:
1.0000 - val_loss: 2.0197 - val_accuracy: 0.3438
Epoch 65/400
5/5 [==============================] - 5s 1s/step - loss: 0.1328 - accuracy:
1.0000 - val_loss: 1.8738 - val_accuracy: 0.4375
Epoch 66/400
5/5 [==============================] - 5s 1s/step - loss: 0.1142 - accuracy:
1.0000 - val_loss: 1.8837 - val_accuracy: 0.3594
Epoch 67/400
5/5 [==============================] - 5s 1s/step - loss: 0.1263 - accuracy:
1.0000 - val_loss: 1.8314 - val_accuracy: 0.4531
Epoch 68/400
5/5 [==============================] - 5s 1s/step - loss: 0.1217 - accuracy:
1.0000 - val_loss: 1.8422 - val_accuracy: 0.4219
Epoch 69/400
5/5 [==============================] - 5s 1s/step - loss: 0.1003 - accuracy:
1.0000 - val_loss: 1.8616 - val_accuracy: 0.4062
Epoch 70/400
5/5 [==============================] - 5s 1s/step - loss: 0.0995 - accuracy:
1.0000 - val_loss: 1.7578 - val_accuracy: 0.4844
Epoch 71/400
5/5 [==============================] - 5s 1s/step - loss: 0.1037 - accuracy:
1.0000 - val_loss: 1.8136 - val_accuracy: 0.4062
Epoch 72/400
5/5 [==============================] - 5s 1s/step - loss: 0.1030 - accuracy:
1.0000 - val_loss: 1.7199 - val_accuracy: 0.4375
Epoch 73/400
5/5 [==============================] - 5s 1s/step - loss: 0.0939 - accuracy:
1.0000 - val_loss: 1.7787 - val_accuracy: 0.4375
Epoch 74/400
5/5 [==============================] - 5s 1s/step - loss: 0.0881 - accuracy:
1.0000 - val_loss: 1.7015 - val_accuracy: 0.4375
Epoch 75/400
5/5 [==============================] - 5s 1s/step - loss: 0.0795 - accuracy:
```

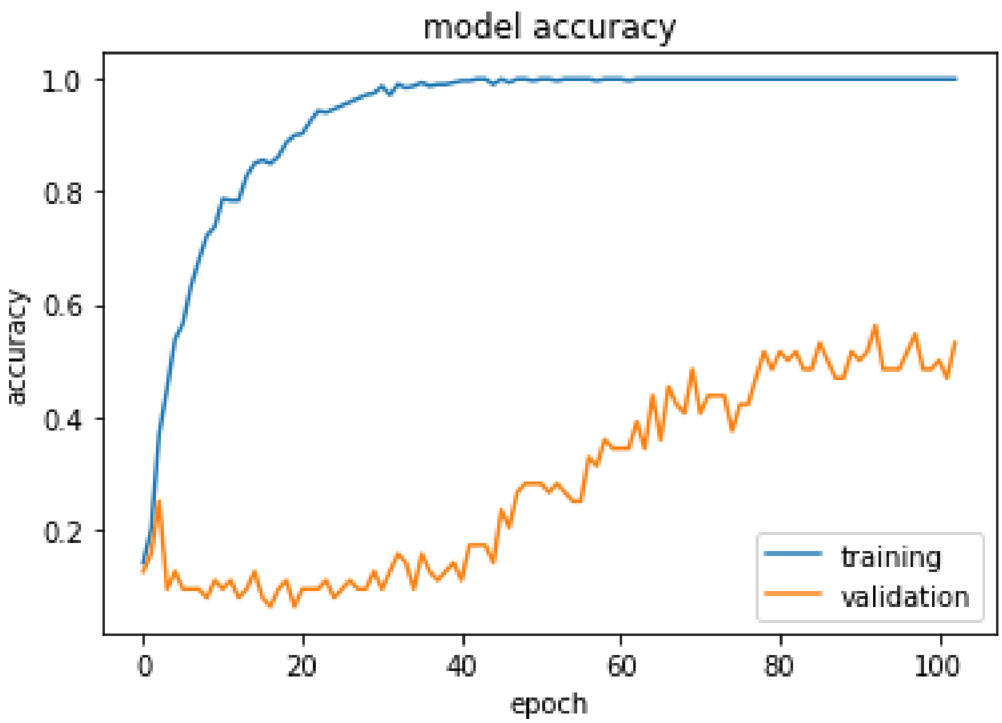
```
1.0000 - val_loss: 1.7746 - val_accuracy: 0.3750
Epoch 76/400
5/5 [==============================] - 5s 1s/step - loss: 0.0826 - accuracy:
1.0000 - val_loss: 1.6884 - val_accuracy: 0.4219
Epoch 77/400
5/5 [==============================] - 5s 1s/step - loss: 0.0821 - accuracy:
1.0000 - val_loss: 1.7874 - val_accuracy: 0.4219
Epoch 78/400
5/5 [==============================] - 5s 1s/step - loss: 0.0844 - accuracy:
1.0000 - val_loss: 1.6324 - val_accuracy: 0.4688
Epoch 79/400
5/5 [==============================] - 5s 1s/step - loss: 0.0875 - accuracy:
1.0000 - val_loss: 1.6147 - val_accuracy: 0.5156
Epoch 80/400
5/5 [==============================] - 5s 1s/step - loss: 0.0747 - accuracy:
1.0000 - val_loss: 1.6822 - val_accuracy: 0.4844
Epoch 81/400
5/5 [==============================] - 5s 1s/step - loss: 0.0756 - accuracy:
1.0000 - val_loss: 1.5401 - val_accuracy: 0.5156
Epoch 82/400
5/5 [==============================] - 5s 1s/step - loss: 0.0680 - accuracy:
1.0000 - val_loss: 1.4624 - val_accuracy: 0.5000
Epoch 83/400
5/5 [==============================] - 5s 1s/step - loss: 0.0690 - accuracy:
1.0000 - val_loss: 1.5235 - val_accuracy: 0.5156
Epoch 84/400
5/5 [==============================] - 5s 1s/step - loss: 0.0722 - accuracy:
1.0000 - val_loss: 1.5455 - val_accuracy: 0.4844
Epoch 85/400
5/5 [==============================] - 5s 1s/step - loss: 0.0737 - accuracy:
1.0000 - val_loss: 1.4869 - val_accuracy: 0.4844
Epoch 86/400
5/5 [==============================] - 5s 1s/step - loss: 0.0702 - accuracy:
1.0000 - val_loss: 1.5180 - val_accuracy: 0.5312
Epoch 87/400
5/5 [==============================] - 5s 1s/step - loss: 0.0675 - accuracy:
1.0000 - val_loss: 1.4989 - val_accuracy: 0.5000
Epoch 88/400
5/5 [==============================] - 5s 1s/step - loss: 0.0680 - accuracy:
1.0000 - val_loss: 1.5496 - val_accuracy: 0.4688
Epoch 89/400
5/5 [==============================] - 5s 1s/step - loss: 0.0653 - accuracy:
1.0000 - val_loss: 1.5138 - val_accuracy: 0.4688
Epoch 90/400
5/5 [==============================] - 5s 1s/step - loss: 0.0614 - accuracy:
1.0000 - val_loss: 1.4448 - val_accuracy: 0.5156
Epoch 91/400
5/5 [==============================] - 5s 1s/step - loss: 0.0684 - accuracy:
```

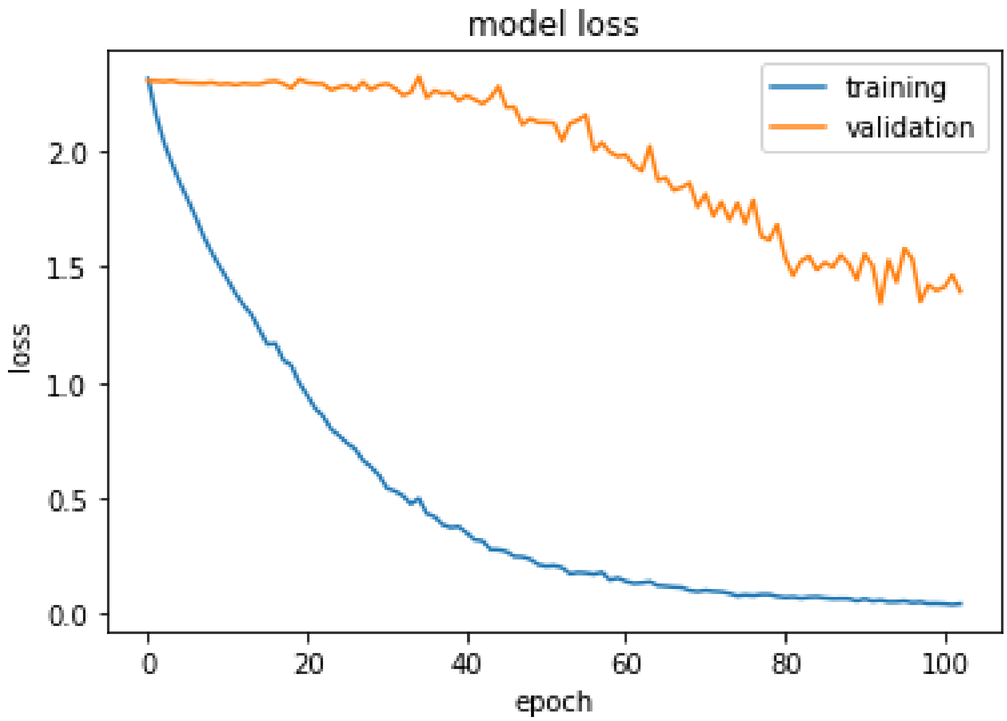
```
1.0000 - val_loss: 1.5538 - val_accuracy: 0.5000
Epoch 92/400
5/5 [==============================] - 5s 1s/step - loss: 0.0565 - accuracy:
1.0000 - val_loss: 1.5061 - val_accuracy: 0.5156
Epoch 93/400
5/5 [==============================] - 5s 1s/step - loss: 0.0626 - accuracy:
1.0000 - val_loss: 1.3431 - val_accuracy: 0.5625
Epoch 94/400
5/5 [==============================] - 5s 1s/step - loss: 0.0518 - accuracy:
1.0000 - val_loss: 1.5286 - val_accuracy: 0.4844
Epoch 95/400
5/5 [==============================] - 5s 1s/step - loss: 0.0546 - accuracy:
1.0000 - val_loss: 1.4344 - val_accuracy: 0.4844
Epoch 96/400
5/5 [==============================] - 5s 1s/step - loss: 0.0594 - accuracy:
1.0000 - val_loss: 1.5791 - val_accuracy: 0.4844
Epoch 97/400
5/5 [==============================] - 5s 1s/step - loss: 0.0468 - accuracy:
1.0000 - val_loss: 1.5325 - val_accuracy: 0.5156
Epoch 98/400
5/5 [==============================] - 5s 1s/step - loss: 0.0552 - accuracy:
1.0000 - val_loss: 1.3494 - val_accuracy: 0.5469
Epoch 99/400
5/5 [==============================] - 5s 1s/step - loss: 0.0459 - accuracy:
1.0000 - val_loss: 1.4215 - val_accuracy: 0.4844
Epoch 100/400
5/5 [==============================] - 5s 1s/step - loss: 0.0448 - accuracy:
1.0000 - val_loss: 1.3978 - val_accuracy: 0.4844
Epoch 101/400
5/5 [==============================] - 5s 1s/step - loss: 0.0435 - accuracy:
1.0000 - val_loss: 1.4117 - val_accuracy: 0.5000
Epoch 102/400
5/5 [==============================] - 5s 1s/step - loss: 0.0421 - accuracy:
1.0000 - val_loss: 1.4643 - val_accuracy: 0.4688
Epoch 103/400
5/5 [==============================] - 5s 1s/step - loss: 0.0439 - accuracy:
1.0000 - val_loss: 1.3935 - val_accuracy: 0.5312
Restoring model weights from the end of the best epoch.
Epoch 00103: early stopping
```

[74]:

```
plt.figure(1)
plt.plot(history1.history['accuracy'])
plt.plot(history1.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
```

```
plt.show()

plt.figure(2)
plt.plot(history1.history['loss'])
plt.plot(history1.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```





This is the expected performance, but it actually gives good results after some more epochs. I think this is becasue now we have lesst samples to train with (only numbers).

Training on MNIST with pre-trained weights

[75]:
```
model1 = Sequential()

# Lambda Layer for adding Padding
model1.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE_BEFORE_PADDING, 1)))

# 1st Convolution Layer
model1.add(Conv2D(6, input_shape=(*IMAGE_SIZE, 1),
                  kernel_size=(5,5), padding='same', activation=mish))
model1.add(BatchNormalization())
model1.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
model1.add(Conv2D(16, kernel_size=(5,5), activation=mish))
model1.add(BatchNormalization())
model1.add(MaxPooling2D(pool_size=(2,2), strides=2))

# Passing to a Fully Connected Layer
model1.add(Flatten())
```

```python
# 1st Fully Connected Layer
model1.add(Dense(120, activation=mish))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# 2nd Fully Connected Layer
model1.add(Dense(84, activation=mish))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# Output Layer
# Increasing the softmax temperature
model1.add(Lambda(lambda x: x / temp))
model1.add(Dense(10, activation='softmax'))

model1.summary()

model1.load_weights('part2_pretrained/checkpoint')

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

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_20 (Lambda)           (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_40 (Conv2D)           (None, 28, 28, 6)         156
_________________________________________________________________
batch_normalization_52 (Batc (None, 28, 28, 6)         24
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 14, 14, 6)         0
_________________________________________________________________
conv2d_41 (Conv2D)           (None, 10, 10, 16)        2416
_________________________________________________________________
batch_normalization_53 (Batc (None, 10, 10, 16)        64
_________________________________________________________________
max_pooling2d_13 (MaxPooling (None, 5, 5, 16)          0
_________________________________________________________________
flatten_10 (Flatten)         (None, 400)               0
_________________________________________________________________
dense_22 (Dense)             (None, 120)               48120
_________________________________________________________________
batch_normalization_54 (Batc (None, 120)               480
_________________________________________________________________
```

```
dropout_24 (Dropout)         (None, 120)               0
_________________________________________________________________
dense_23 (Dense)             (None, 84)                10164
_________________________________________________________________
batch_normalization_55 (Batc (None, 84)                336
_________________________________________________________________
dropout_25 (Dropout)         (None, 84)                0
_________________________________________________________________
lambda_21 (Lambda)           (None, 84)                0
_________________________________________________________________
dense_24 (Dense)             (None, 10)                850
=================================================================
Total params: 62,610
Trainable params: 62,158
Non-trainable params: 452
_________________________________________________________________
```

[76]:

```
checkpoint_filepath1_after = 'part2_after_training/checkpoint'
model_checkpoint_callback1_after = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath1_after,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)

history1_after = model1.fit(
    mnist_train_gen,
    epochs=EPOCHS,
    validation_data=mnist_test_gen,
    steps_per_epoch = len(x_train) // BATCH_SIZE,
    validation_steps = len(x_test) // BATCH_SIZE,
    callbacks=[model_checkpoint_callback1_after, early_stopping_callback]
)
```

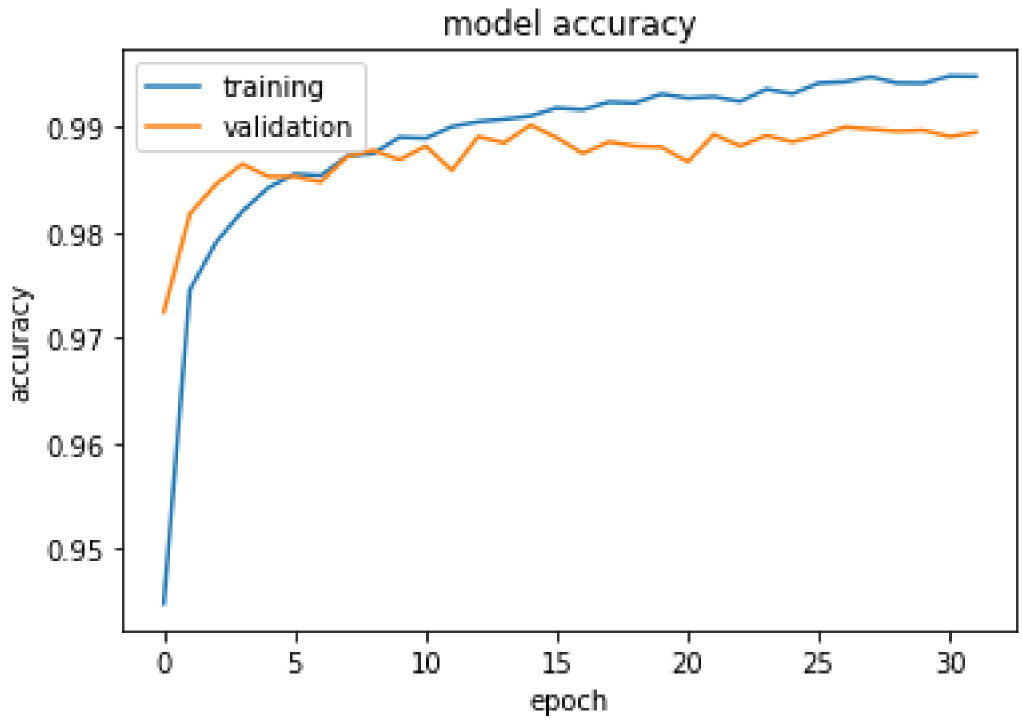
```
Epoch 1/400
937/937 [==============================] - 7s 7ms/step - loss: 0.3721 -
accuracy: 0.8970 - val_loss: 0.0916 - val_accuracy: 0.9725
Epoch 2/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0984 -
accuracy: 0.9727 - val_loss: 0.0605 - val_accuracy: 0.9818
Epoch 3/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0753 -
accuracy: 0.9784 - val_loss: 0.0475 - val_accuracy: 0.9846
Epoch 4/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0618 -
accuracy: 0.9826 - val_loss: 0.0421 - val_accuracy: 0.9865
Epoch 5/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0529 -
```

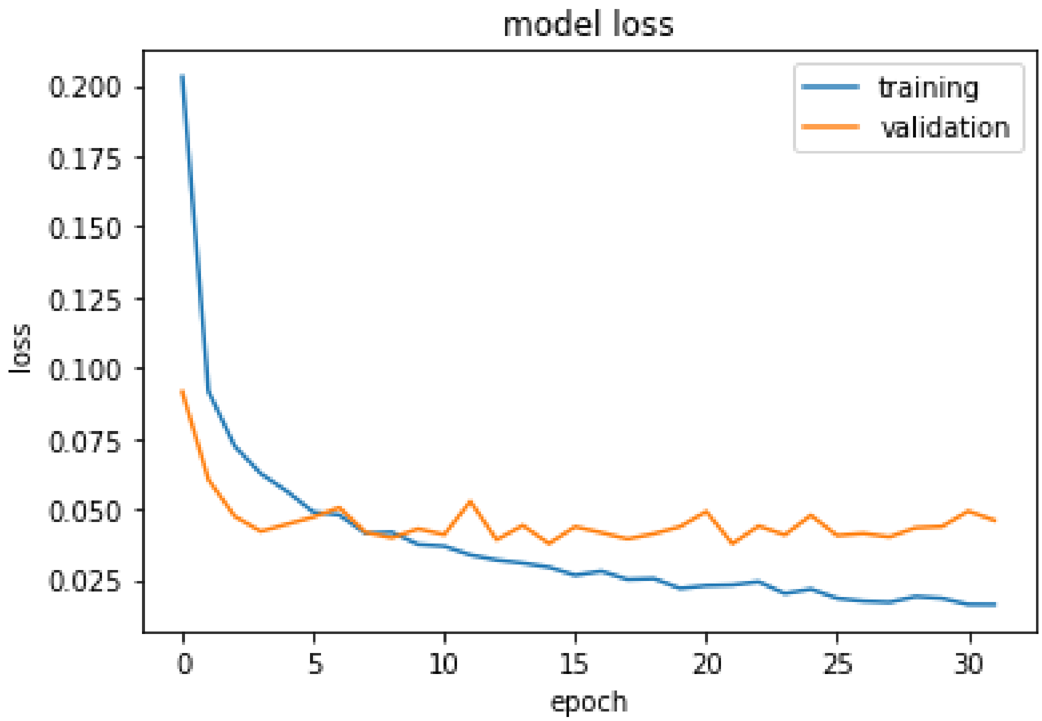
```
accuracy: 0.9849 - val_loss: 0.0447 - val_accuracy: 0.9853
Epoch 6/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0482 -
accuracy: 0.9858 - val_loss: 0.0472 - val_accuracy: 0.9853
Epoch 7/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0456 -
accuracy: 0.9857 - val_loss: 0.0505 - val_accuracy: 0.9848
Epoch 8/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0393 -
accuracy: 0.9880 - val_loss: 0.0418 - val_accuracy: 0.9872
Epoch 9/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0423 -
accuracy: 0.9871 - val_loss: 0.0398 - val_accuracy: 0.9878
Epoch 10/400
937/937 [==============================] - 6s 7ms/step - loss: 0.0358 -
accuracy: 0.9893 - val_loss: 0.0430 - val_accuracy: 0.9869
Epoch 11/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0328 -
accuracy: 0.9899 - val_loss: 0.0410 - val_accuracy: 0.9882
Epoch 12/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0315 -
accuracy: 0.9904 - val_loss: 0.0527 - val_accuracy: 0.9859
Epoch 13/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0307 -
accuracy: 0.9914 - val_loss: 0.0391 - val_accuracy: 0.9891
Epoch 14/400
937/937 [==============================] - 6s 7ms/step - loss: 0.0307 -
accuracy: 0.9911 - val_loss: 0.0442 - val_accuracy: 0.9885
Epoch 15/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0287 -
accuracy: 0.9913 - val_loss: 0.0378 - val_accuracy: 0.9902
Epoch 16/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0262 -
accuracy: 0.9919 - val_loss: 0.0438 - val_accuracy: 0.9890
Epoch 17/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0259 -
accuracy: 0.9921 - val_loss: 0.0417 - val_accuracy: 0.9875
Epoch 18/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0262 -
accuracy: 0.9920 - val_loss: 0.0394 - val_accuracy: 0.9886
Epoch 19/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0235 -
accuracy: 0.9925 - val_loss: 0.0413 - val_accuracy: 0.9882
Epoch 20/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0195 -
accuracy: 0.9937 - val_loss: 0.0438 - val_accuracy: 0.9881
Epoch 21/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0215 -
```

```
accuracy: 0.9928 - val_loss: 0.0491 - val_accuracy: 0.9867
Epoch 22/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0214 -
accuracy: 0.9935 - val_loss: 0.0377 - val_accuracy: 0.9893
Epoch 23/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0227 -
accuracy: 0.9929 - val_loss: 0.0440 - val_accuracy: 0.9882
Epoch 24/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0218 -
accuracy: 0.9932 - val_loss: 0.0409 - val_accuracy: 0.9892
Epoch 25/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0213 -
accuracy: 0.9934 - val_loss: 0.0478 - val_accuracy: 0.9886
Epoch 26/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0180 -
accuracy: 0.9942 - val_loss: 0.0406 - val_accuracy: 0.9892
Epoch 27/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0147 -
accuracy: 0.9953 - val_loss: 0.0414 - val_accuracy: 0.9900
Epoch 28/400
937/937 [==============================] - 7s 7ms/step - loss: 0.0163 -
accuracy: 0.9948 - val_loss: 0.0402 - val_accuracy: 0.9898
Epoch 29/400
937/937 [==============================] - 6s 7ms/step - loss: 0.0172 -
accuracy: 0.9946 - val_loss: 0.0434 - val_accuracy: 0.9896
Epoch 30/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0183 -
accuracy: 0.9941 - val_loss: 0.0438 - val_accuracy: 0.9897
Epoch 31/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0136 -
accuracy: 0.9958 - val_loss: 0.0493 - val_accuracy: 0.9891
Epoch 32/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0155 -
accuracy: 0.9948 - val_loss: 0.0460 - val_accuracy: 0.9895
Restoring model weights from the end of the best epoch.
Epoch 00032: early stopping
```

[78]:
```
plt.figure(1)
plt.plot(history1_after.history['accuracy'])
plt.plot(history1_after.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()

plt.figure(2)
```

```
plt.plot(history1_after.history['loss'])
plt.plot(history1_after.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```





This performs really good on the MNIST dataset adn converges fast.

Untrained network with random initializations

[81]:
```
model1 = Sequential()

# Lambda Layer for adding Padding
model1.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE_BEFORE_PADDING, 1)))

# 1st Convolution Layer
model1.add(Conv2D(6, input_shape=(*IMAGE_SIZE, 1),
                  kernel_size=(5,5), padding='same', activation=mish))
model1.add(BatchNormalization())
model1.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
model1.add(Conv2D(16, kernel_size=(5,5), activation=mish))
model1.add(BatchNormalization())
model1.add(MaxPooling2D(pool_size=(2,2), strides=2))

# Passing to a Fully Connected Layer
model1.add(Flatten())
```

```python
# 1st Fully Connected Layer
model1.add(Dense(120, activation=mish))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# 2nd Fully Connected Layer
model1.add(Dense(84, activation=mish))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# Output Layer
# Increasing the softmax temperature
model1.add(Lambda(lambda x: x / temp))
model1.add(Dense(10, activation='softmax'))

model1.summary()

model1.compile(loss='categorical_crossentropy', optimizer=Adam(),
 metrics=['accuracy'])
```

```
Model: "sequential_12"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_24 (Lambda)           (None, 28, 28, 1)         0

_________________________________________________________________
conv2d_44 (Conv2D)           (None, 28, 28, 6)         156

_________________________________________________________________
batch_normalization_60 (Batc (None, 28, 28, 6)         24

_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 14, 14, 6)         0

_________________________________________________________________
conv2d_45 (Conv2D)           (None, 10, 10, 16)        2416

_________________________________________________________________
batch_normalization_61 (Batc (None, 10, 10, 16)        64

_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 5, 5, 16)          0

_________________________________________________________________
flatten_12 (Flatten)         (None, 400)               0

_________________________________________________________________
dense_28 (Dense)             (None, 120)               48120

_________________________________________________________________
batch_normalization_62 (Batc (None, 120)               480

_________________________________________________________________
dropout_28 (Dropout)         (None, 120)               0

_________________________________________________________________
dense_29 (Dense)             (None, 84)                10164
```

```
-----------------------------------------------------------------
batch_normalization_63 (Batc (None, 84)                336

-----------------------------------------------------------------
dropout_29 (Dropout)         (None, 84)                0

-----------------------------------------------------------------
lambda_25 (Lambda)           (None, 84)                0

-----------------------------------------------------------------
dense_30 (Dense)             (None, 10)                850
=================================================================
Total params: 62,610
Trainable params: 62,158
Non-trainable params: 452

-----------------------------------------------------------------
```

[82]:

```
checkpoint_filepath1_un = 'part2_untrained/checkpoint'
model_checkpoint_callback1_un = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath1_un,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)

history1_un = model1.fit(
    mnist_train_gen,
    epochs=EPOCHS,
    validation_data=mnist_test_gen,
    steps_per_epoch = len(x_train) // BATCH_SIZE,
    validation_steps = len(x_test) // BATCH_SIZE,
    callbacks=[model_checkpoint_callback1_un, early_stopping_callback]
)
```

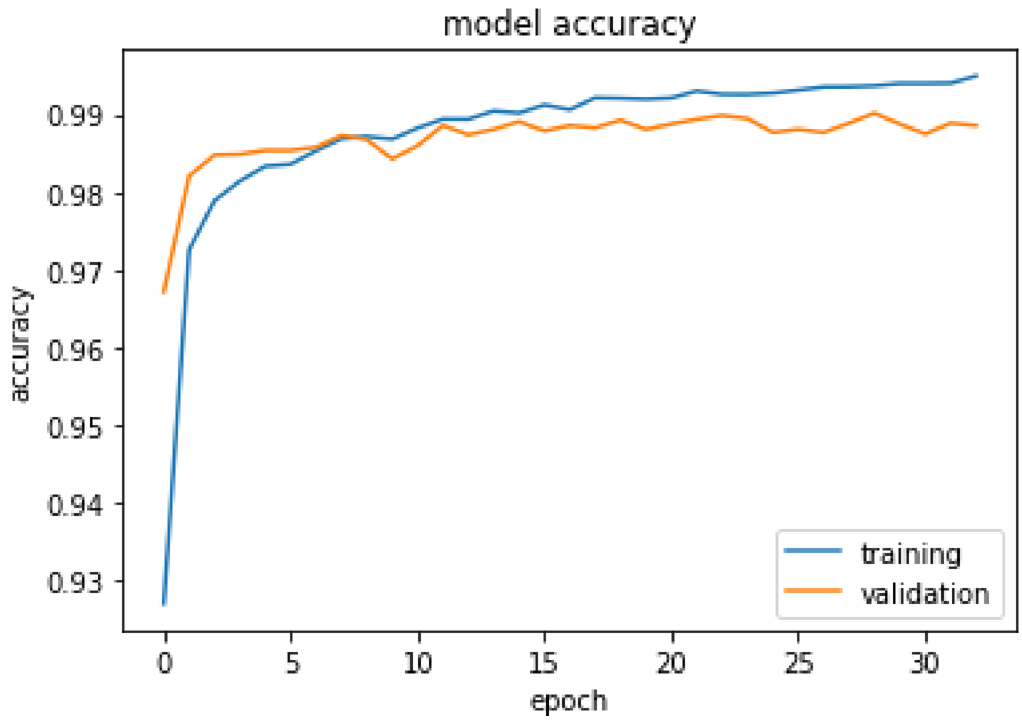
```
Epoch 1/400
937/937 [==============================] - 7s 7ms/step - loss: 0.7657 -
accuracy: 0.8426 - val_loss: 0.1065 - val_accuracy: 0.9671
Epoch 2/400
937/937 [==============================] - 6s 7ms/step - loss: 0.1026 -
accuracy: 0.9714 - val_loss: 0.0564 - val_accuracy: 0.9821
Epoch 3/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0768 -
accuracy: 0.9788 - val_loss: 0.0495 - val_accuracy: 0.9848
Epoch 4/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0648 -
accuracy: 0.9809 - val_loss: 0.0486 - val_accuracy: 0.9849
Epoch 5/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0569 -
accuracy: 0.9834 - val_loss: 0.0466 - val_accuracy: 0.9854
Epoch 6/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0544 -
```

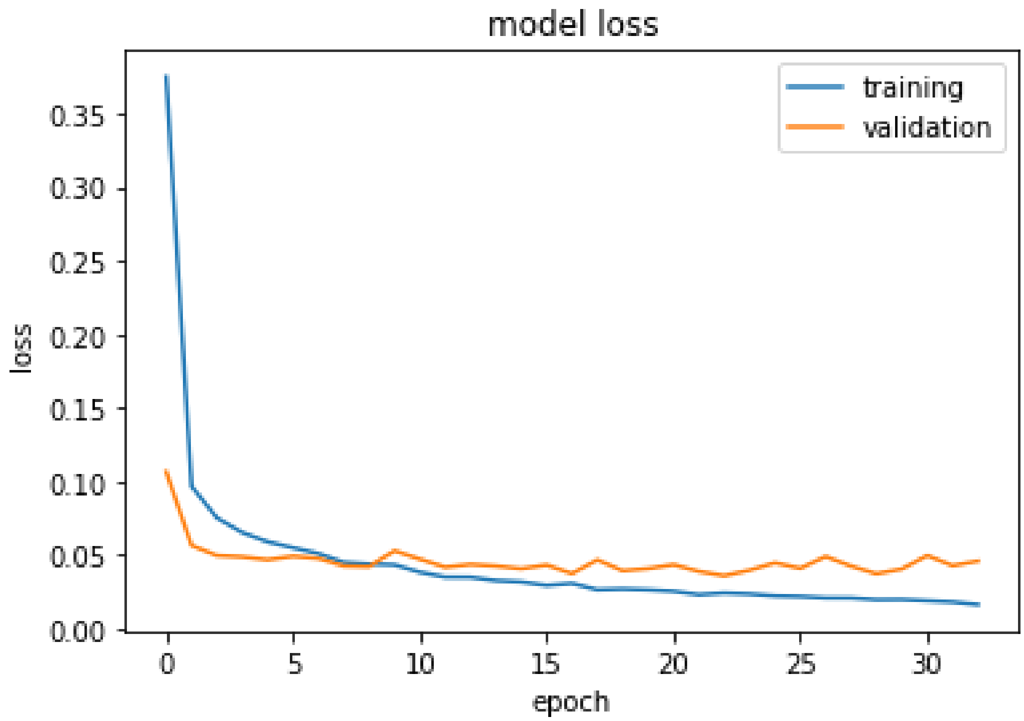
```
accuracy: 0.9834 - val_loss: 0.0490 - val_accuracy: 0.9854
Epoch 7/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0533 -
accuracy: 0.9844 - val_loss: 0.0476 - val_accuracy: 0.9858
Epoch 8/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0425 -
accuracy: 0.9870 - val_loss: 0.0424 - val_accuracy: 0.9873
Epoch 9/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0412 -
accuracy: 0.9877 - val_loss: 0.0420 - val_accuracy: 0.9868
Epoch 10/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0429 -
accuracy: 0.9868 - val_loss: 0.0527 - val_accuracy: 0.9843
Epoch 11/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0374 -
accuracy: 0.9888 - val_loss: 0.0470 - val_accuracy: 0.9860
Epoch 12/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0326 -
accuracy: 0.9896 - val_loss: 0.0416 - val_accuracy: 0.9886
Epoch 13/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0355 -
accuracy: 0.9896 - val_loss: 0.0434 - val_accuracy: 0.9874
Epoch 14/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0311 -
accuracy: 0.9908 - val_loss: 0.0423 - val_accuracy: 0.9881
Epoch 15/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0304 -
accuracy: 0.9904 - val_loss: 0.0405 - val_accuracy: 0.9891
Epoch 16/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0305 -
accuracy: 0.9909 - val_loss: 0.0430 - val_accuracy: 0.9879
Epoch 17/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0275 -
accuracy: 0.9913 - val_loss: 0.0372 - val_accuracy: 0.9886
Epoch 18/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0256 -
accuracy: 0.9923 - val_loss: 0.0465 - val_accuracy: 0.9883
Epoch 19/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0260 -
accuracy: 0.9924 - val_loss: 0.0391 - val_accuracy: 0.9893
Epoch 20/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0237 -
accuracy: 0.9926 - val_loss: 0.0406 - val_accuracy: 0.9881
Epoch 21/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0234 -
accuracy: 0.9929 - val_loss: 0.0433 - val_accuracy: 0.9888
Epoch 22/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0212 -
```

```
accuracy: 0.9936 - val_loss: 0.0387 - val_accuracy: 0.9894
Epoch 23/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0241 -
accuracy: 0.9925 - val_loss: 0.0357 - val_accuracy: 0.9899
Epoch 24/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0207 -
accuracy: 0.9934 - val_loss: 0.0395 - val_accuracy: 0.9895
Epoch 25/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0206 -
accuracy: 0.9930 - val_loss: 0.0445 - val_accuracy: 0.9877
Epoch 26/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0213 -
accuracy: 0.9934 - val_loss: 0.0408 - val_accuracy: 0.9881
Epoch 27/400
937/937 [==============================] - 6s 7ms/step - loss: 0.0205 -
accuracy: 0.9937 - val_loss: 0.0488 - val_accuracy: 0.9877
Epoch 28/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0195 -
accuracy: 0.9942 - val_loss: 0.0423 - val_accuracy: 0.9889
Epoch 29/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0175 -
accuracy: 0.9941 - val_loss: 0.0371 - val_accuracy: 0.9902
Epoch 30/400
937/937 [==============================] - 6s 7ms/step - loss: 0.0187 -
accuracy: 0.9939 - val_loss: 0.0403 - val_accuracy: 0.9888
Epoch 31/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0188 -
accuracy: 0.9942 - val_loss: 0.0495 - val_accuracy: 0.9875
Epoch 32/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0165 -
accuracy: 0.9944 - val_loss: 0.0426 - val_accuracy: 0.9889
Epoch 33/400
937/937 [==============================] - 6s 6ms/step - loss: 0.0160 -
accuracy: 0.9953 - val_loss: 0.0457 - val_accuracy: 0.9886
Restoring model weights from the end of the best epoch.
Epoch 00033: early stopping
```

[83]:
```
plt.figure(1)
plt.plot(history1_un.history['accuracy'])
plt.plot(history1_un.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()

plt.figure(2)
```

```
plt.plot(history1_un.history['loss'])
plt.plot(history1_un.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



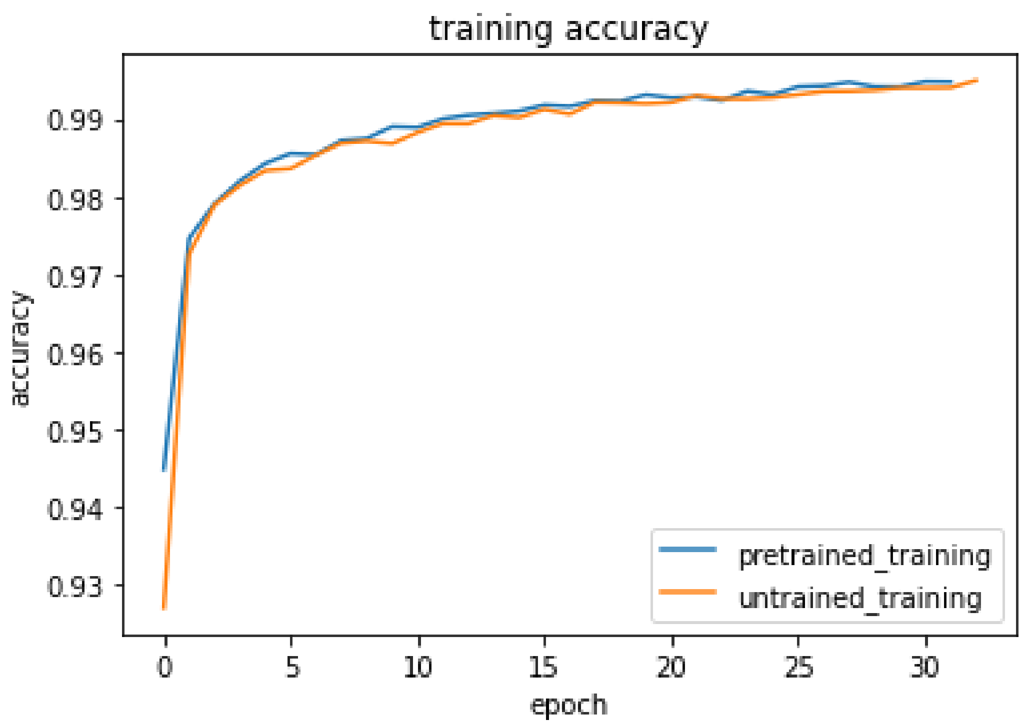


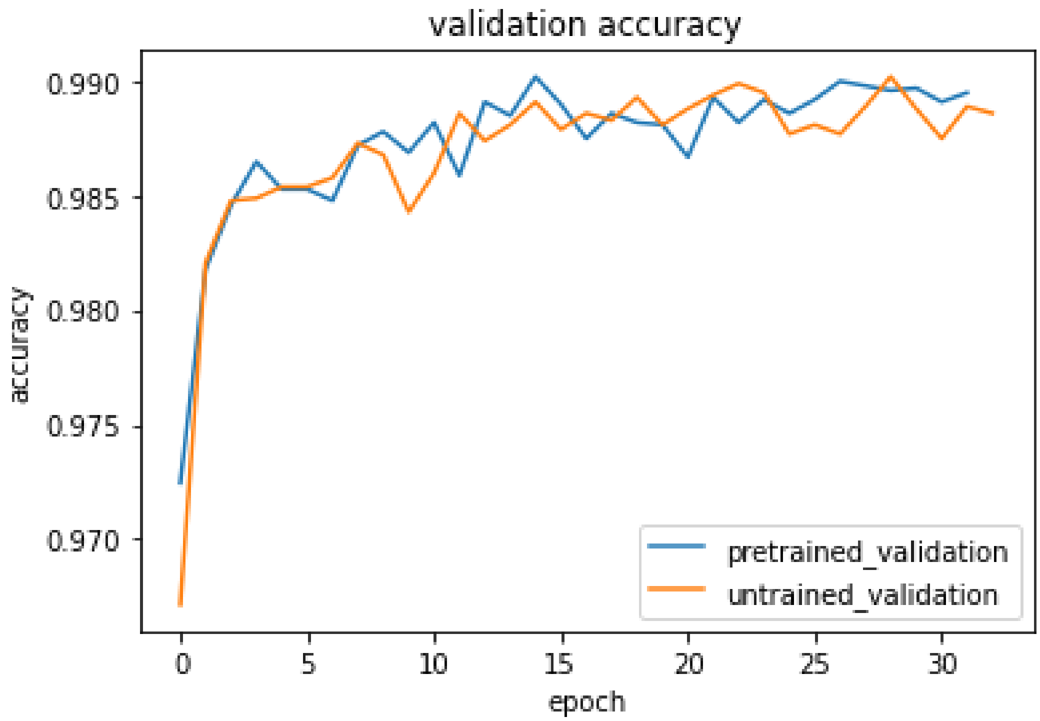
This has similar performance to that of the pretrained model. Let's compare the plots more closely.

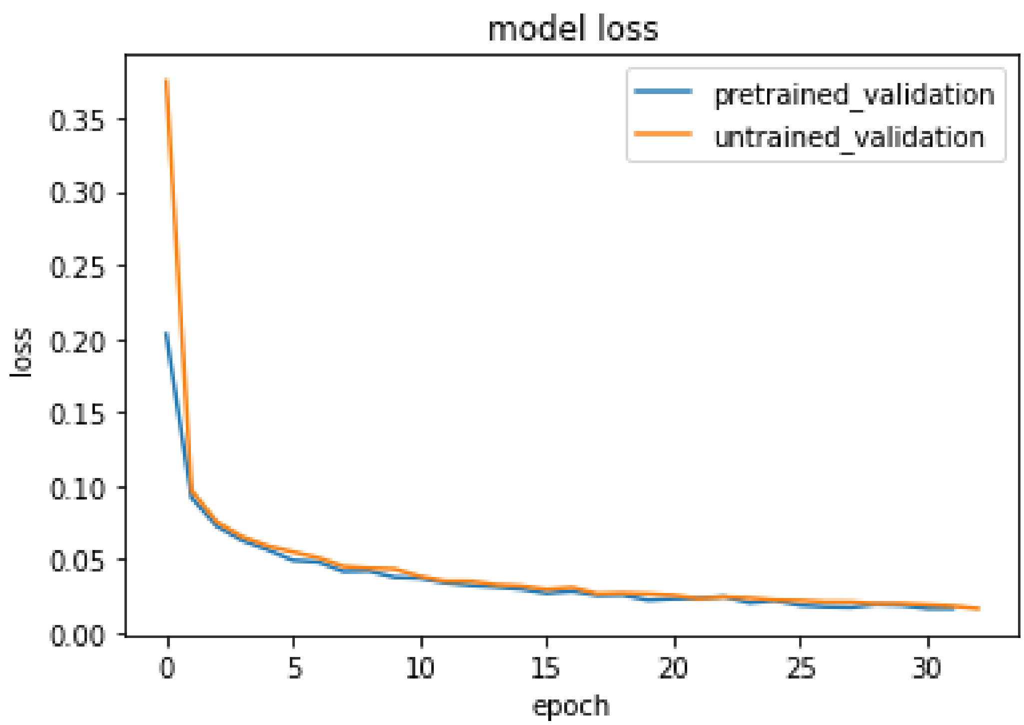
Observations and results

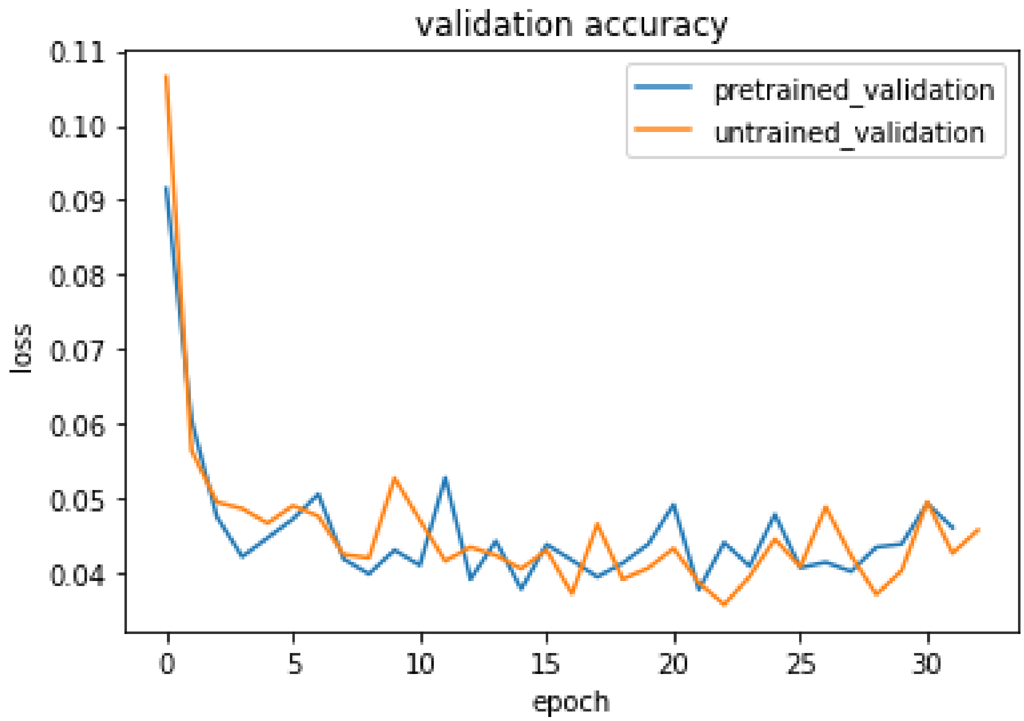
[86]:
```
plt.figure(1)
plt.plot(history1_after.history['accuracy'])
plt.plot(history1_un.history['accuracy'])
plt.title('training accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['pretrained_training', 'untrained_training'], loc='best')
plt.show()

plt.figure(2)
plt.plot(history1_after.history['val_accuracy'])
plt.plot(history1_un.history['val_accuracy'])
plt.title('validation accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['pretrained_validation', 'untrained_validation'], loc='best')
plt.show()

plt.figure(3)
plt.plot(history1_after.history['loss'])
```

```
plt.plot(history1_un.history['loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['pretrained_validation', 'untrained_validation'], loc='best')
plt.show()

plt.figure(4)
plt.plot(history1_after.history['val_loss'])
plt.plot(history1_un.history['val_loss'])
plt.title('validation accuracy')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['pretrained_validation', 'untrained_validation'], loc='best')
plt.show()
```




validation accuracy
0.990
0.985
0.980
0.975
0.970
accuracy
0
5
10
15
20
25
30
epoch
pretrained_validation
untrained_validation


model loss
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
loss
0
5
10
15
20
25
30
epoch
pretrained_validation
untrained_validation



We can see that although both the models perform at-par with each other, the pretrained model performs 'slightly' better. The reasons are: - The pretrained accuracy for both the test and validation sets start higher than the randomly initialized models. - During the training phase, the pretrained overall performs better. - The same can be said for the loss, which starts lower for both the training and validation set for the pretrained model and for most part, stays lower. - **Overall, the pre-trained network ahs higher final accuracy and lower final loss and also has converged faster**

1.4.2 2nd Architecture from Kaggle

Pre-training on our dataset

[97]:
```
model2 = Sequential()

# Lambda Layer for adding Padding
model2.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE_BEFORE_PADDING, 1)))

# 1st Convolution Layer
model2.add(Conv2D(32, input_shape=(*IMAGE_SIZE, 1), kernel_size=3,␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(32, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
```

```python
model2.add(Conv2D(32, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))

# 2nd Convolution Layer
model2.add(Conv2D(64, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(64, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(64, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))

# 3rd Convolution Layer
model2.add(Conv2D(128, kernel_size = 4, activation=mish))
model2.add(BatchNormalization())

# Passing to a Fully Connected Layer
model2.add(Flatten())
model2.add(Dropout(0.4))

# Output Layer

# Increasing the softmax temperature
model2.add(Lambda(lambda x: x / temp))
model2.add(Dense(10, activation='softmax'))

model2.summary()

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

```
Model: "sequential_16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_32 (Lambda)           (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_67 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
batch_normalization_85 (Batc (None, 26, 26, 32)        128
_________________________________________________________________
conv2d_68 (Conv2D)           (None, 24, 24, 32)        9248
_________________________________________________________________
batch_normalization_86 (Batc (None, 24, 24, 32)        128
```

```
_________________________________________________________________
conv2d_69 (Conv2D)           (None, 12, 12, 32)        25632
_________________________________________________________________
batch_normalization_87 (Batc (None, 12, 12, 32)        128
_________________________________________________________________
dropout_39 (Dropout)         (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_70 (Conv2D)           (None, 10, 10, 64)        18496
_________________________________________________________________
batch_normalization_88 (Batc (None, 10, 10, 64)        256
_________________________________________________________________
conv2d_71 (Conv2D)           (None, 8, 8, 64)          36928
_________________________________________________________________
batch_normalization_89 (Batc (None, 8, 8, 64)          256
_________________________________________________________________
conv2d_72 (Conv2D)           (None, 4, 4, 64)          102464
_________________________________________________________________
batch_normalization_90 (Batc (None, 4, 4, 64)          256
_________________________________________________________________
dropout_40 (Dropout)         (None, 4, 4, 64)          0
_________________________________________________________________
conv2d_73 (Conv2D)           (None, 1, 1, 128)         131200
_________________________________________________________________
batch_normalization_91 (Batc (None, 1, 1, 128)         512
_________________________________________________________________
flatten_16 (Flatten)         (None, 128)               0
_________________________________________________________________
dropout_41 (Dropout)         (None, 128)               0
_________________________________________________________________
lambda_33 (Lambda)           (None, 128)               0
_________________________________________________________________
dense_34 (Dense)             (None, 10)                1290
=================================================================
Total params: 327,242
Trainable params: 326,410
Non-trainable params: 832
_________________________________________________________________
```

[98]:

```
checkpoint_filepath2 = 'part2_pretrained2/checkpoint'
model_checkpoint_callback2 = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath2,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)

history2 = model2.fit(
```

```
    train_generator,
    epochs=EPOCHS,
    validation_data=validation_generator,
    steps_per_epoch = train_generator.samples // BATCH_SIZE,
    validation_steps = validation_generator.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback2, early_stopping_callback2]
)
```

```
Epoch 1/400
5/5 [==============================] - 7s 1s/step - loss: 2.3138 - accuracy:
0.1182 - val_loss: 2.3023 - val_accuracy: 0.1250
Epoch 2/400
5/5 [==============================] - 5s 1s/step - loss: 2.1094 - accuracy:
0.2765 - val_loss: 2.3019 - val_accuracy: 0.1094
Epoch 3/400
5/5 [==============================] - 5s 1s/step - loss: 1.8971 - accuracy:
0.4526 - val_loss: 2.3014 - val_accuracy: 0.0938
Epoch 4/400
5/5 [==============================] - 5s 1s/step - loss: 1.7170 - accuracy:
0.5365 - val_loss: 2.2995 - val_accuracy: 0.1094
Epoch 5/400
5/5 [==============================] - 5s 1s/step - loss: 1.5864 - accuracy:
0.6230 - val_loss: 2.2963 - val_accuracy: 0.1094
Epoch 6/400
5/5 [==============================] - 5s 1s/step - loss: 1.4425 - accuracy:
0.6797 - val_loss: 2.3012 - val_accuracy: 0.1094
Epoch 7/400
5/5 [==============================] - 5s 1s/step - loss: 1.3561 - accuracy:
0.6646 - val_loss: 2.2970 - val_accuracy: 0.1250
Epoch 8/400
5/5 [==============================] - 5s 1s/step - loss: 1.2197 - accuracy:
0.7739 - val_loss: 2.3238 - val_accuracy: 0.0781
Epoch 9/400
5/5 [==============================] - 5s 1s/step - loss: 1.0814 - accuracy:
0.7930 - val_loss: 2.3032 - val_accuracy: 0.1250
Epoch 10/400
5/5 [==============================] - 5s 1s/step - loss: 1.0078 - accuracy:
0.8230 - val_loss: 2.3186 - val_accuracy: 0.0625
Epoch 11/400
5/5 [==============================] - 5s 1s/step - loss: 0.9029 - accuracy:
0.8525 - val_loss: 2.3191 - val_accuracy: 0.1250
Epoch 12/400
5/5 [==============================] - 5s 1s/step - loss: 0.8383 - accuracy:
0.8854 - val_loss: 2.3288 - val_accuracy: 0.1250
Epoch 13/400
5/5 [==============================] - 5s 1s/step - loss: 0.7853 - accuracy:
0.8871 - val_loss: 2.3276 - val_accuracy: 0.0781
```

```
Epoch 14/400
5/5 [==============================] - 5s 1s/step - loss: 0.6906 - accuracy:
0.9464 - val_loss: 2.3178 - val_accuracy: 0.1094
Epoch 15/400
5/5 [==============================] - 5s 1s/step - loss: 0.6484 - accuracy:
0.9485 - val_loss: 2.3706 - val_accuracy: 0.1094
Epoch 16/400
5/5 [==============================] - 5s 1s/step - loss: 0.5745 - accuracy:
0.9457 - val_loss: 2.4311 - val_accuracy: 0.0938
Epoch 17/400
5/5 [==============================] - 5s 1s/step - loss: 0.5378 - accuracy:
0.9681 - val_loss: 2.4543 - val_accuracy: 0.1250
Epoch 18/400
5/5 [==============================] - 5s 1s/step - loss: 0.4636 - accuracy:
0.9917 - val_loss: 2.4655 - val_accuracy: 0.1094
Epoch 19/400
5/5 [==============================] - 5s 1s/step - loss: 0.4483 - accuracy:
0.9838 - val_loss: 2.6810 - val_accuracy: 0.0938
Epoch 20/400
5/5 [==============================] - 5s 1s/step - loss: 0.4116 - accuracy:
0.9829 - val_loss: 2.6248 - val_accuracy: 0.1250
Epoch 21/400
5/5 [==============================] - 5s 1s/step - loss: 0.3498 - accuracy:
1.0000 - val_loss: 2.6185 - val_accuracy: 0.1250
Epoch 22/400
5/5 [==============================] - 5s 1s/step - loss: 0.3386 - accuracy:
0.9897 - val_loss: 2.7297 - val_accuracy: 0.1094
Epoch 23/400
5/5 [==============================] - 5s 1s/step - loss: 0.2743 - accuracy:
0.9990 - val_loss: 2.7349 - val_accuracy: 0.1094
Epoch 24/400
5/5 [==============================] - 5s 1s/step - loss: 0.2714 - accuracy:
0.9897 - val_loss: 2.7203 - val_accuracy: 0.1094
Epoch 25/400
5/5 [==============================] - 5s 1s/step - loss: 0.2513 - accuracy:
1.0000 - val_loss: 2.8316 - val_accuracy: 0.1094
Epoch 26/400
5/5 [==============================] - 5s 1s/step - loss: 0.2315 - accuracy:
1.0000 - val_loss: 2.7348 - val_accuracy: 0.1250
Epoch 27/400
5/5 [==============================] - 5s 1s/step - loss: 0.2211 - accuracy:
0.9961 - val_loss: 2.8925 - val_accuracy: 0.1094
Epoch 28/400
5/5 [==============================] - 5s 1s/step - loss: 0.2223 - accuracy:
1.0000 - val_loss: 2.8186 - val_accuracy: 0.1094
Epoch 29/400
5/5 [==============================] - 5s 1s/step - loss: 0.1764 - accuracy:
1.0000 - val_loss: 2.9625 - val_accuracy: 0.0938
```

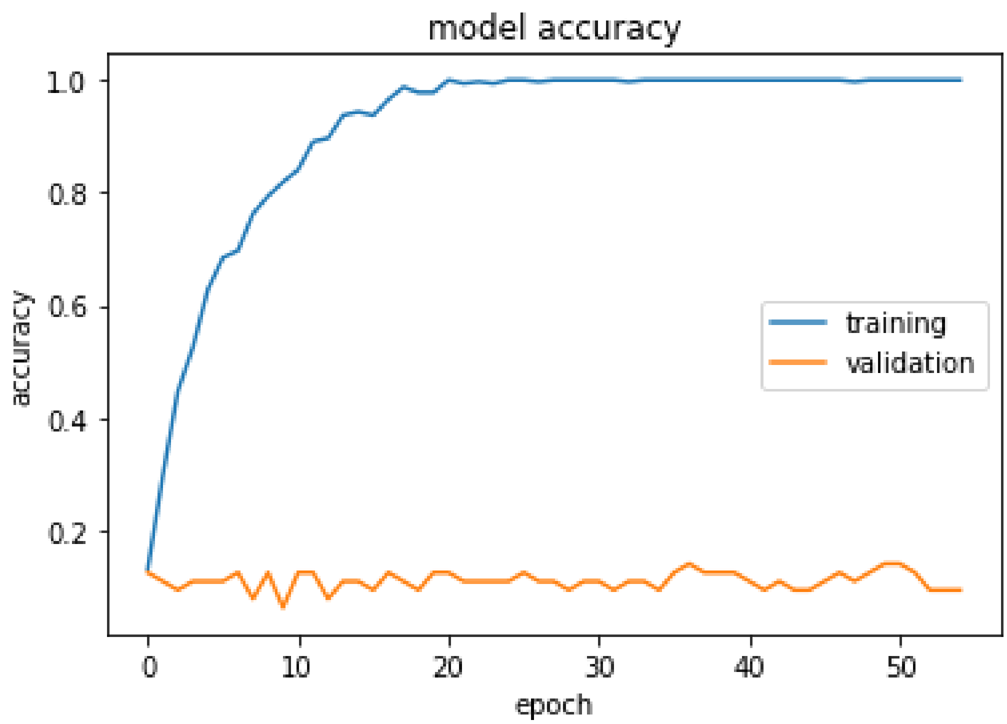
```
Epoch 30/400
5/5 [==============================] - 5s 1s/step - loss: 0.1890 - accuracy:
1.0000 - val_loss: 2.9418 - val_accuracy: 0.1094
Epoch 31/400
5/5 [==============================] - 5s 1s/step - loss: 0.1569 - accuracy:
1.0000 - val_loss: 3.0047 - val_accuracy: 0.1094
Epoch 32/400
5/5 [==============================] - 5s 1s/step - loss: 0.1630 - accuracy:
1.0000 - val_loss: 2.9697 - val_accuracy: 0.0938
Epoch 33/400
5/5 [==============================] - 5s 1s/step - loss: 0.1461 - accuracy:
0.9990 - val_loss: 2.9317 - val_accuracy: 0.1094
Epoch 34/400
5/5 [==============================] - 5s 1s/step - loss: 0.1385 - accuracy:
1.0000 - val_loss: 3.0667 - val_accuracy: 0.1094
Epoch 35/400
5/5 [==============================] - 5s 1s/step - loss: 0.1221 - accuracy:
1.0000 - val_loss: 2.9470 - val_accuracy: 0.0938
Epoch 36/400
5/5 [==============================] - 5s 1s/step - loss: 0.1207 - accuracy:
1.0000 - val_loss: 2.9738 - val_accuracy: 0.1250
Epoch 37/400
5/5 [==============================] - 5s 1s/step - loss: 0.1099 - accuracy:
1.0000 - val_loss: 3.0589 - val_accuracy: 0.1406
Epoch 38/400
5/5 [==============================] - 5s 1s/step - loss: 0.0955 - accuracy:
1.0000 - val_loss: 3.0744 - val_accuracy: 0.1250
Epoch 39/400
5/5 [==============================] - 5s 1s/step - loss: 0.1074 - accuracy:
1.0000 - val_loss: 3.1594 - val_accuracy: 0.1250
Epoch 40/400
5/5 [==============================] - 5s 1s/step - loss: 0.0911 - accuracy:
1.0000 - val_loss: 3.1274 - val_accuracy: 0.1250
Epoch 41/400
5/5 [==============================] - 5s 1s/step - loss: 0.0868 - accuracy:
1.0000 - val_loss: 3.0317 - val_accuracy: 0.1094
Epoch 42/400
5/5 [==============================] - 5s 1s/step - loss: 0.0772 - accuracy:
1.0000 - val_loss: 3.1888 - val_accuracy: 0.0938
Epoch 43/400
5/5 [==============================] - 5s 1s/step - loss: 0.0826 - accuracy:
1.0000 - val_loss: 3.1052 - val_accuracy: 0.1094
Epoch 44/400
5/5 [==============================] - 5s 1s/step - loss: 0.0763 - accuracy:
1.0000 - val_loss: 3.1776 - val_accuracy: 0.0938
Epoch 45/400
5/5 [==============================] - 5s 1s/step - loss: 0.0668 - accuracy:
1.0000 - val_loss: 3.3263 - val_accuracy: 0.0938
```

```
Epoch 46/400
5/5 [==============================] - 5s 1s/step - loss: 0.0709 - accuracy:
1.0000 - val_loss: 3.2739 - val_accuracy: 0.1094
Epoch 47/400
5/5 [==============================] - 5s 1s/step - loss: 0.0714 - accuracy:
1.0000 - val_loss: 3.0664 - val_accuracy: 0.1250
Epoch 48/400
5/5 [==============================] - 5s 1s/step - loss: 0.0720 - accuracy:
0.9961 - val_loss: 3.0611 - val_accuracy: 0.1094
Epoch 49/400
5/5 [==============================] - 5s 1s/step - loss: 0.0548 - accuracy:
1.0000 - val_loss: 3.0912 - val_accuracy: 0.1250
Epoch 50/400
5/5 [==============================] - 5s 1s/step - loss: 0.0572 - accuracy:
1.0000 - val_loss: 3.0163 - val_accuracy: 0.1406
Epoch 51/400
5/5 [==============================] - 5s 1s/step - loss: 0.0587 - accuracy:
1.0000 - val_loss: 3.1670 - val_accuracy: 0.1406
Epoch 52/400
5/5 [==============================] - 5s 1s/step - loss: 0.0546 - accuracy:
1.0000 - val_loss: 3.1523 - val_accuracy: 0.1250
Epoch 53/400
5/5 [==============================] - 5s 1s/step - loss: 0.0555 - accuracy:
1.0000 - val_loss: 3.2594 - val_accuracy: 0.0938
Epoch 54/400
5/5 [==============================] - 5s 1s/step - loss: 0.0506 - accuracy:
1.0000 - val_loss: 3.2338 - val_accuracy: 0.0938
Epoch 55/400
5/5 [==============================] - 5s 1s/step - loss: 0.0495 - accuracy:
1.0000 - val_loss: 3.2775 - val_accuracy: 0.0938
Restoring model weights from the end of the best epoch.
Epoch 00055: early stopping
```

[100]:

```
plt.figure(1)
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()

plt.figure(2)
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
```

```
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



THis actually performs worse in pre-training, than the modified LeNet used before.

I think the reason for thi smight be that this model has more parameters and is more complex so, it does not does well with these small trainign set.

Let's see how it performtms on the MNIST dataset.

Training on MNIST with pre-trained weights

[103]:
```
model2 = Sequential()

# Lambda Layer for adding Padding
model2.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE_BEFORE_PADDING, 1)))

# 1st Convolution Layer
model2.add(Conv2D(32, input_shape=(*IMAGE_SIZE, 1), kernel_size=3,␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(32, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(32, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))
```

```
# 2nd Convolution Layer
model2.add(Conv2D(64, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(64, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(64, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))

# 3rd Convolution Layer
model2.add(Conv2D(128, kernel_size = 4, activation=mish))
model2.add(BatchNormalization())

# Passing to a Fully Connected Layer
model2.add(Flatten())
model2.add(Dropout(0.4))

# Output Layer

# Increasing the softmax temperature
model2.add(Lambda(lambda x: x / temp))
model2.add(Dense(10, activation='softmax'))

model2.summary()

model2.load_weights('part2_pretrained2/checkpoint')

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

```
Model: "sequential_18"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_36 (Lambda)           (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_81 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
batch_normalization_99 (Batc (None, 26, 26, 32)        128
_________________________________________________________________
conv2d_82 (Conv2D)           (None, 24, 24, 32)        9248
_________________________________________________________________
batch_normalization_100 (Bat (None, 24, 24, 32)        128
_________________________________________________________________
conv2d_83 (Conv2D)           (None, 12, 12, 32)        25632
```

```
_________________________________________________________________
batch_normalization_101 (Bat (None, 12, 12, 32)        128
_________________________________________________________________
dropout_45 (Dropout)         (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_84 (Conv2D)           (None, 10, 10, 64)        18496
_________________________________________________________________
batch_normalization_102 (Bat (None, 10, 10, 64)        256
_________________________________________________________________
conv2d_85 (Conv2D)           (None, 8, 8, 64)          36928
_________________________________________________________________
batch_normalization_103 (Bat (None, 8, 8, 64)          256
_________________________________________________________________
conv2d_86 (Conv2D)           (None, 4, 4, 64)          102464
_________________________________________________________________
batch_normalization_104 (Bat (None, 4, 4, 64)          256
_________________________________________________________________
dropout_46 (Dropout)         (None, 4, 4, 64)          0
_________________________________________________________________
conv2d_87 (Conv2D)           (None, 1, 1, 128)         131200
_________________________________________________________________
batch_normalization_105 (Bat (None, 1, 1, 128)         512
_________________________________________________________________
flatten_18 (Flatten)         (None, 128)               0
_________________________________________________________________
dropout_47 (Dropout)         (None, 128)               0
_________________________________________________________________
lambda_37 (Lambda)           (None, 128)               0
_________________________________________________________________
dense_36 (Dense)             (None, 10)                1290
=================================================================
Total params: 327,242
Trainable params: 326,410
Non-trainable params: 832
_________________________________________________________________
```

[104]:

```
checkpoint_filepath2_after = 'part2_after_training2/checkpoint'
model_checkpoint_callback2_after = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath2_after,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)

history2_after = model2.fit(
    mnist_train_gen,
    epochs=EPOCHS,
```

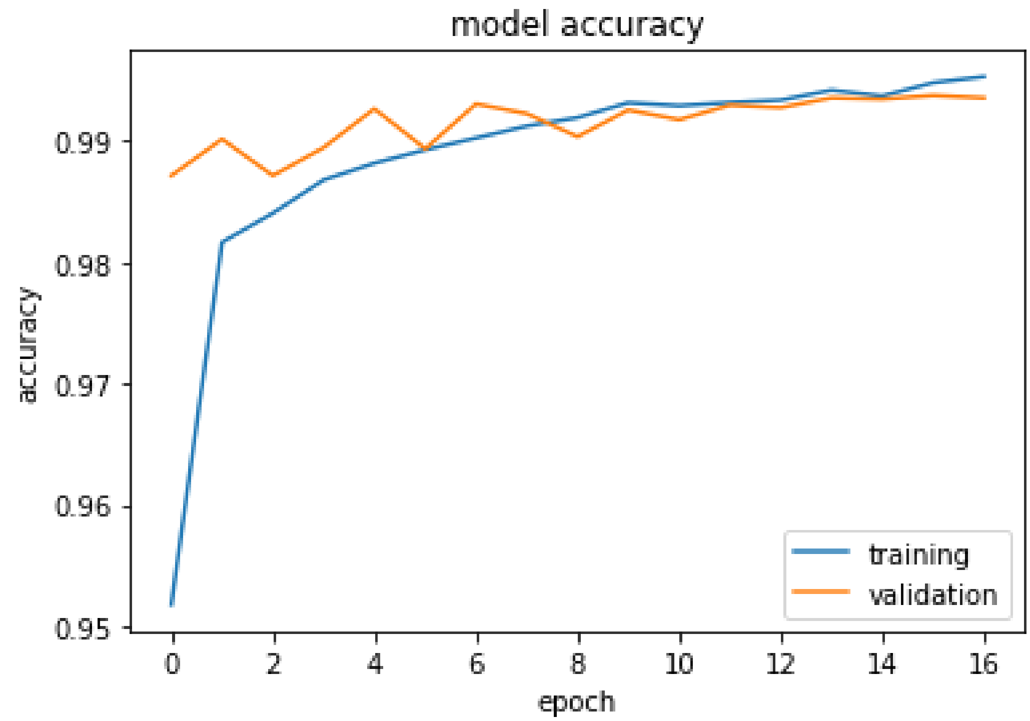
```
    validation_data=mnist_test_gen,
    steps_per_epoch = len(x_train) // BATCH_SIZE,
    validation_steps = len(x_test) // BATCH_SIZE,
    callbacks=[model_checkpoint_callback2_after, early_stopping_callback]
)
```

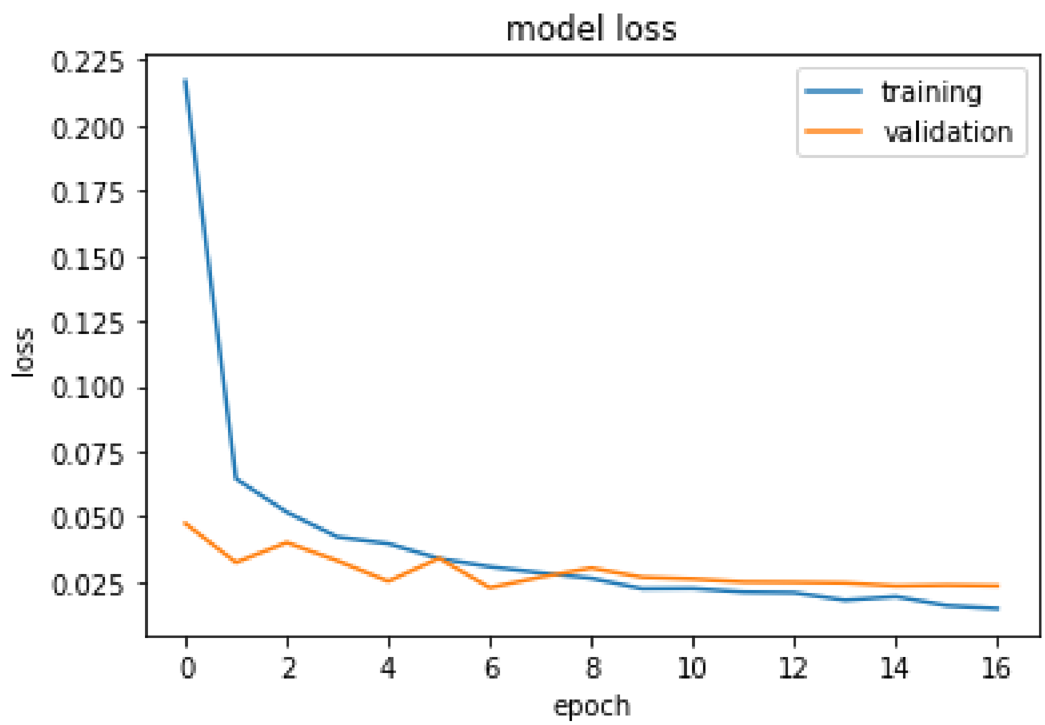
```
Epoch 1/400
937/937 [==============================] - 12s 12ms/step - loss: 0.4861 -
accuracy: 0.8868 - val_loss: 0.0475 - val_accuracy: 0.9872
Epoch 2/400
937/937 [==============================] - 11s 11ms/step - loss: 0.0653 -
accuracy: 0.9817 - val_loss: 0.0325 - val_accuracy: 0.9902
Epoch 3/400
937/937 [==============================] - 11s 11ms/step - loss: 0.0515 -
accuracy: 0.9841 - val_loss: 0.0401 - val_accuracy: 0.9872
Epoch 4/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0401 -
accuracy: 0.9874 - val_loss: 0.0331 - val_accuracy: 0.9895
Epoch 5/400
937/937 [==============================] - 11s 11ms/step - loss: 0.0385 -
accuracy: 0.9884 - val_loss: 0.0253 - val_accuracy: 0.9927
Epoch 6/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0311 -
accuracy: 0.9906 - val_loss: 0.0341 - val_accuracy: 0.9894
Epoch 7/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0308 -
accuracy: 0.9904 - val_loss: 0.0228 - val_accuracy: 0.9931
Epoch 8/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0268 -
accuracy: 0.9917 - val_loss: 0.0269 - val_accuracy: 0.9923
Epoch 9/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0247 -
accuracy: 0.9921 - val_loss: 0.0303 - val_accuracy: 0.9904
Epoch 10/400
937/937 [==============================] - 11s 11ms/step - loss: 0.0201 -
accuracy: 0.9939 - val_loss: 0.0268 - val_accuracy: 0.9926
Epoch 11/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0205 -
accuracy: 0.9939 - val_loss: 0.0261 - val_accuracy: 0.9918
Epoch 12/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0215 -
accuracy: 0.9933 - val_loss: 0.0250 - val_accuracy: 0.9930
Epoch 13/400
937/937 [==============================] - 11s 11ms/step - loss: 0.0203 -
accuracy: 0.9939 - val_loss: 0.0249 - val_accuracy: 0.9928
Epoch 14/400
937/937 [==============================] - 11s 11ms/step - loss: 0.0192 -
```

```
accuracy: 0.9939 - val_loss: 0.0246 - val_accuracy: 0.9936
Epoch 15/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0170 -
accuracy: 0.9946 - val_loss: 0.0234 - val_accuracy: 0.9935
Epoch 16/400
937/937 [==============================] - 11s 11ms/step - loss: 0.0146 -
accuracy: 0.9951 - val_loss: 0.0237 - val_accuracy: 0.9938
Epoch 17/400
937/937 [==============================] - 11s 12ms/step - loss: 0.0147 -
accuracy: 0.9951 - val_loss: 0.0235 - val_accuracy: 0.9936
Restoring model weights from the end of the best epoch.
Epoch 00017: early stopping
```

[105]:

```
plt.figure(1)
plt.plot(history2_after.history['accuracy'])
plt.plot(history2_after.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()

plt.figure(2)
plt.plot(history2_after.history['loss'])
plt.plot(history2_after.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```


model accuracy
accuracy
0.99
0.98
0.97
0.96
0.95
0
2
4
6
8
10
12
14
16
epoch
training
validation


model loss
loss
0.225
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0
2
4
6
8
10
12
14
16
epoch
training
validation

This is pretty good! It achieves higher accuracy than the LeNet, and in almost half the time.

Untrained network with random initializations

[109]:
```
model2 = Sequential()

# Lambda Layer for adding Padding
model2.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE_BEFORE_PADDING, 1)))

# 1st Convolution Layer
model2.add(Conv2D(32, input_shape=(*IMAGE_SIZE, 1), kernel_size=3,␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(32, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(32, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))

# 2nd Convolution Layer
model2.add(Conv2D(64, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(64, kernel_size=3, activation=mish))
model2.add(BatchNormalization())
model2.add(Conv2D(64, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))

# 3rd Convolution Layer
model2.add(Conv2D(128, kernel_size = 4, activation=mish))
model2.add(BatchNormalization())

# Passing to a Fully Connected Layer
model2.add(Flatten())
model2.add(Dropout(0.4))

# Output Layer

# Increasing the softmax temperature
model2.add(Lambda(lambda x: x / temp))
model2.add(Dense(10, activation='softmax'))

model2.summary()
```

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

```
Model: "sequential_20"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_40 (Lambda)           (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_95 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
batch_normalization_113 (Bat (None, 26, 26, 32)        128
_________________________________________________________________
conv2d_96 (Conv2D)           (None, 24, 24, 32)        9248
_________________________________________________________________
batch_normalization_114 (Bat (None, 24, 24, 32)        128
_________________________________________________________________
conv2d_97 (Conv2D)           (None, 12, 12, 32)        25632
_________________________________________________________________
batch_normalization_115 (Bat (None, 12, 12, 32)        128
_________________________________________________________________
dropout_51 (Dropout)         (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_98 (Conv2D)           (None, 10, 10, 64)        18496
_________________________________________________________________
batch_normalization_116 (Bat (None, 10, 10, 64)        256
_________________________________________________________________
conv2d_99 (Conv2D)           (None, 8, 8, 64)          36928
_________________________________________________________________
batch_normalization_117 (Bat (None, 8, 8, 64)          256
_________________________________________________________________
conv2d_100 (Conv2D)          (None, 4, 4, 64)          102464
_________________________________________________________________
batch_normalization_118 (Bat (None, 4, 4, 64)          256
_________________________________________________________________
dropout_52 (Dropout)         (None, 4, 4, 64)          0
_________________________________________________________________
conv2d_101 (Conv2D)          (None, 1, 1, 128)         131200
_________________________________________________________________
batch_normalization_119 (Bat (None, 1, 1, 128)         512
_________________________________________________________________
flatten_20 (Flatten)         (None, 128)               0
_________________________________________________________________
dropout_53 (Dropout)         (None, 128)               0
_________________________________________________________________
lambda_41 (Lambda)           (None, 128)               0
_________________________________________________________________
```

```
dense_38 (Dense)             (None, 10)                1290
=================================================================
Total params: 327,242
Trainable params: 326,410
Non-trainable params: 832
_________________________________________________________________
```

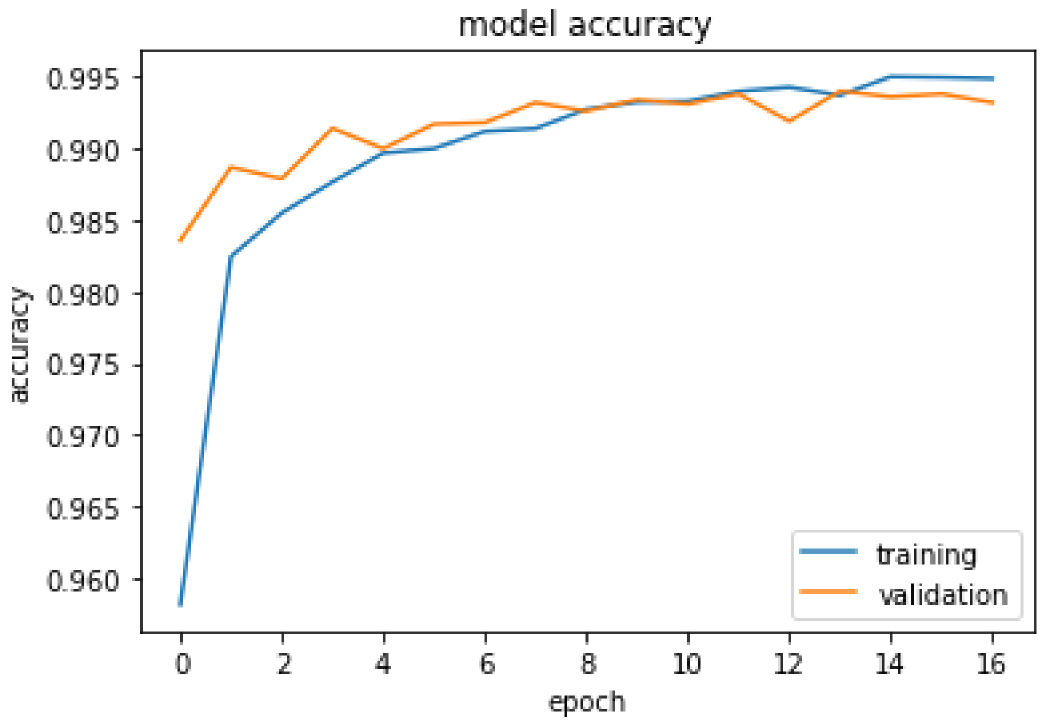
[110]:

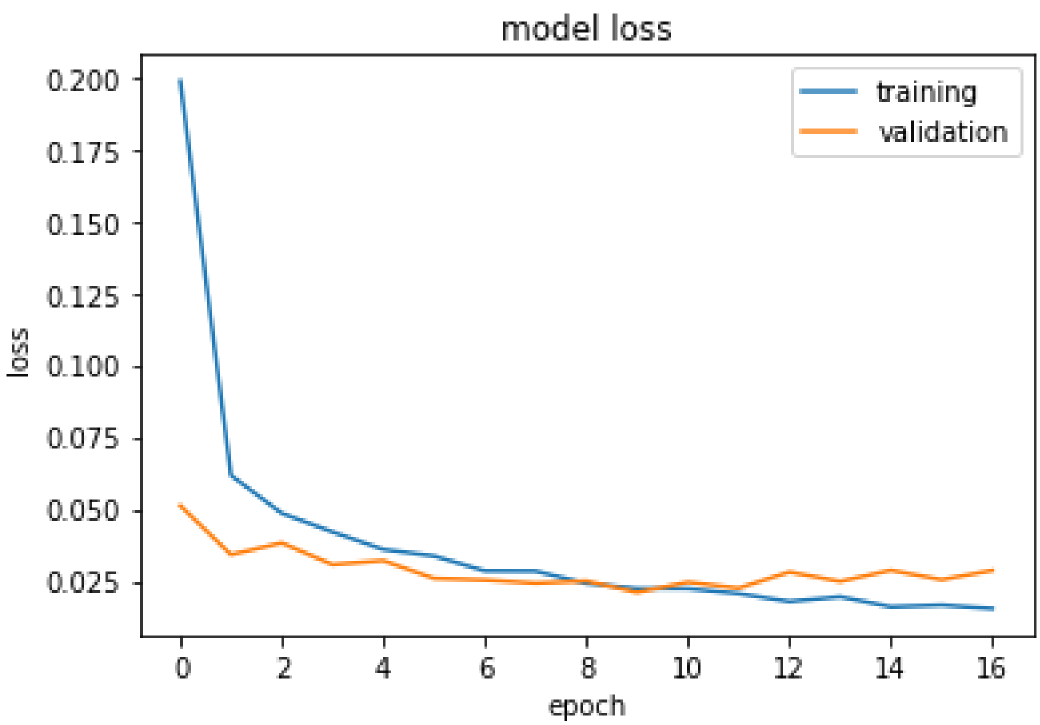
```
checkpoint_filepath2_un = 'part2_untrained2/checkpoint'
model_checkpoint_callback2_un = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath2_un,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)

history2_un = model2.fit(
    train_generator3,
    epochs=17,
    validation_data=mnist_test_gen,
    steps_per_epoch = len(x_train) // BATCH_SIZE,
    validation_steps = len(x_test) // BATCH_SIZE,
    callbacks=[model_checkpoint_callback2_un, early_stopping_callback]
)
```

```
Epoch 1/17
937/937 [==============================] - 12s 12ms/step - loss: 0.4512 -
accuracy: 0.9017 - val_loss: 0.0512 - val_accuracy: 0.9836
Epoch 2/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0633 -
accuracy: 0.9817 - val_loss: 0.0342 - val_accuracy: 0.9887
Epoch 3/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0458 -
accuracy: 0.9865 - val_loss: 0.0382 - val_accuracy: 0.9879
Epoch 4/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0421 -
accuracy: 0.9878 - val_loss: 0.0307 - val_accuracy: 0.9914
Epoch 5/17
937/937 [==============================] - 11s 12ms/step - loss: 0.0341 -
accuracy: 0.9899 - val_loss: 0.0321 - val_accuracy: 0.9900
Epoch 6/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0332 -
accuracy: 0.9898 - val_loss: 0.0259 - val_accuracy: 0.9917
Epoch 7/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0294 -
accuracy: 0.9908 - val_loss: 0.0253 - val_accuracy: 0.9918
Epoch 8/17
937/937 [==============================] - 11s 12ms/step - loss: 0.0294 -
accuracy: 0.9913 - val_loss: 0.0243 - val_accuracy: 0.9932
```

```
Epoch 9/17
937/937 [==============================] - 11s 12ms/step - loss: 0.0257 -
accuracy: 0.9924 - val_loss: 0.0250 - val_accuracy: 0.9926
Epoch 10/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0210 -
accuracy: 0.9935 - val_loss: 0.0211 - val_accuracy: 0.9934
Epoch 11/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0212 -
accuracy: 0.9934 - val_loss: 0.0246 - val_accuracy: 0.9931
Epoch 12/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0193 -
accuracy: 0.9943 - val_loss: 0.0225 - val_accuracy: 0.9938
Epoch 13/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0190 -
accuracy: 0.9940 - val_loss: 0.0281 - val_accuracy: 0.9919
Epoch 14/17
937/937 [==============================] - 11s 12ms/step - loss: 0.0200 -
accuracy: 0.9937 - val_loss: 0.0249 - val_accuracy: 0.9940
Epoch 15/17
937/937 [==============================] - 11s 12ms/step - loss: 0.0134 -
accuracy: 0.9959 - val_loss: 0.0287 - val_accuracy: 0.9936
Epoch 16/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0169 -
accuracy: 0.9948 - val_loss: 0.0254 - val_accuracy: 0.9938
Epoch 17/17
937/937 [==============================] - 11s 11ms/step - loss: 0.0148 -
accuracy: 0.9950 - val_loss: 0.0287 - val_accuracy: 0.9932
```

[111]:
```
plt.figure(1)
plt.plot(history2_un.history['accuracy'])
plt.plot(history2_un.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()

plt.figure(2)
plt.plot(history2_un.history['loss'])
plt.plot(history2_un.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```

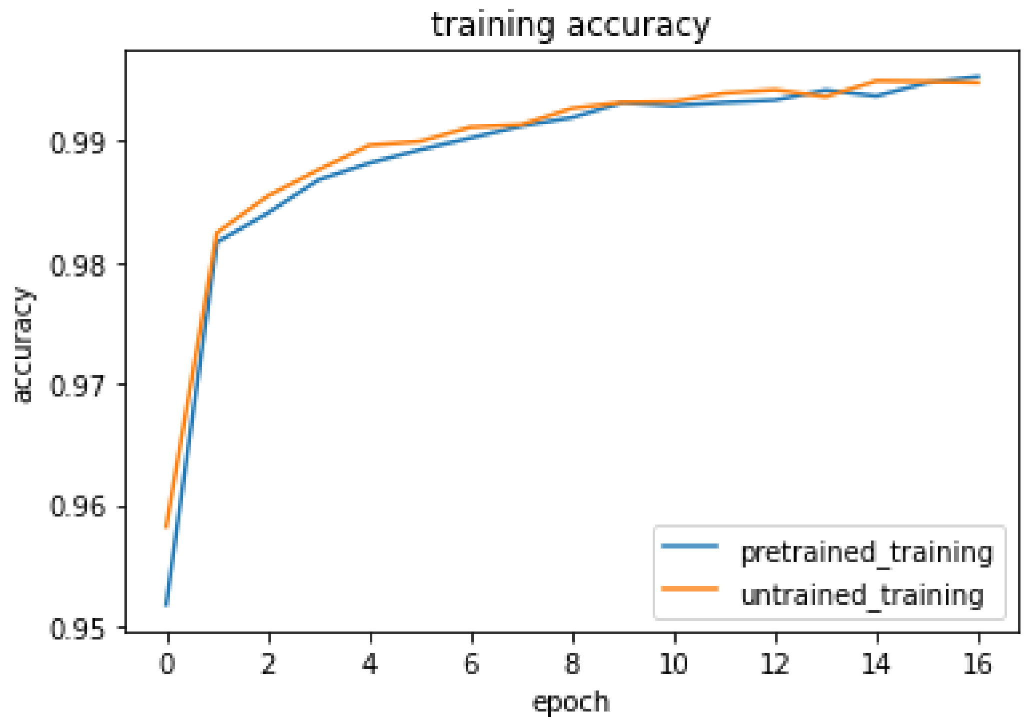

model accuracy
accuracy
epoch
training
validation
0.995
0.990
0.985
0.980
0.975
0.970
0.965
0.960
0
2
4
6
8
10
12
14
16

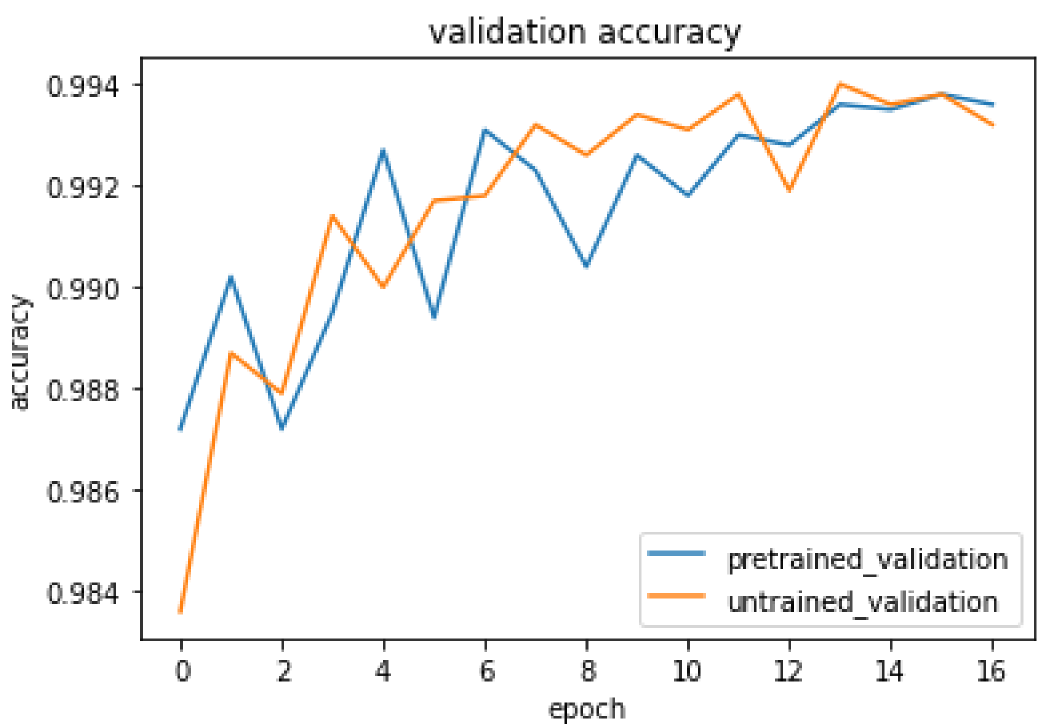

model loss
loss
epoch
training
validation
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0
2
4
6
8
10
12
14
16

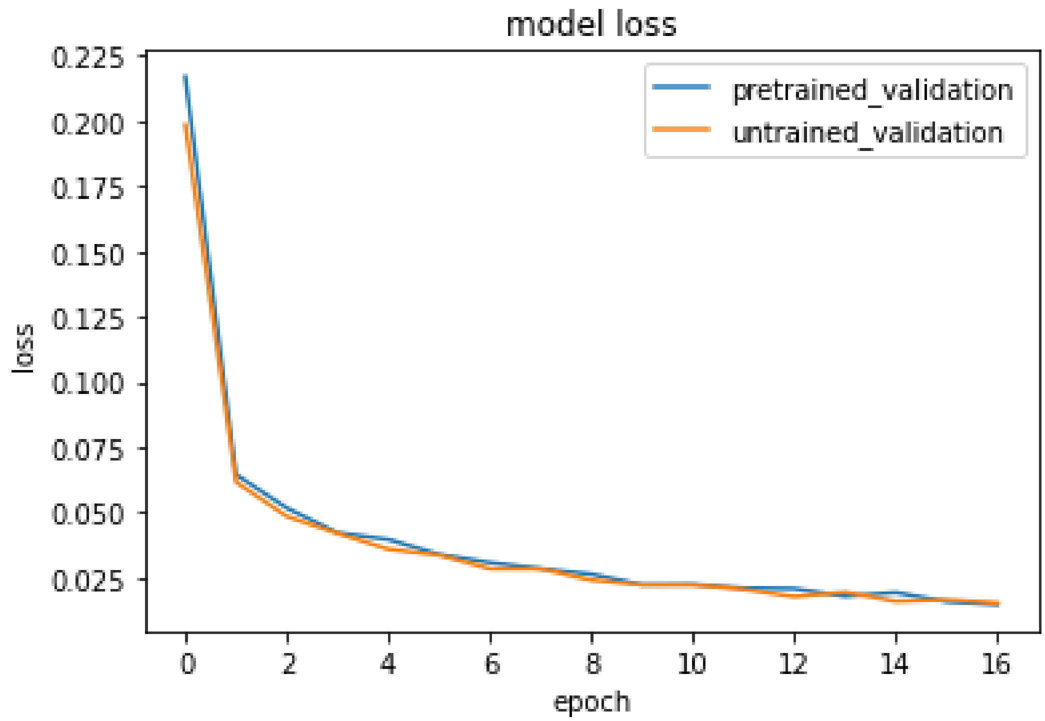
This performs the same as before. Let's see them together to notice the difference.

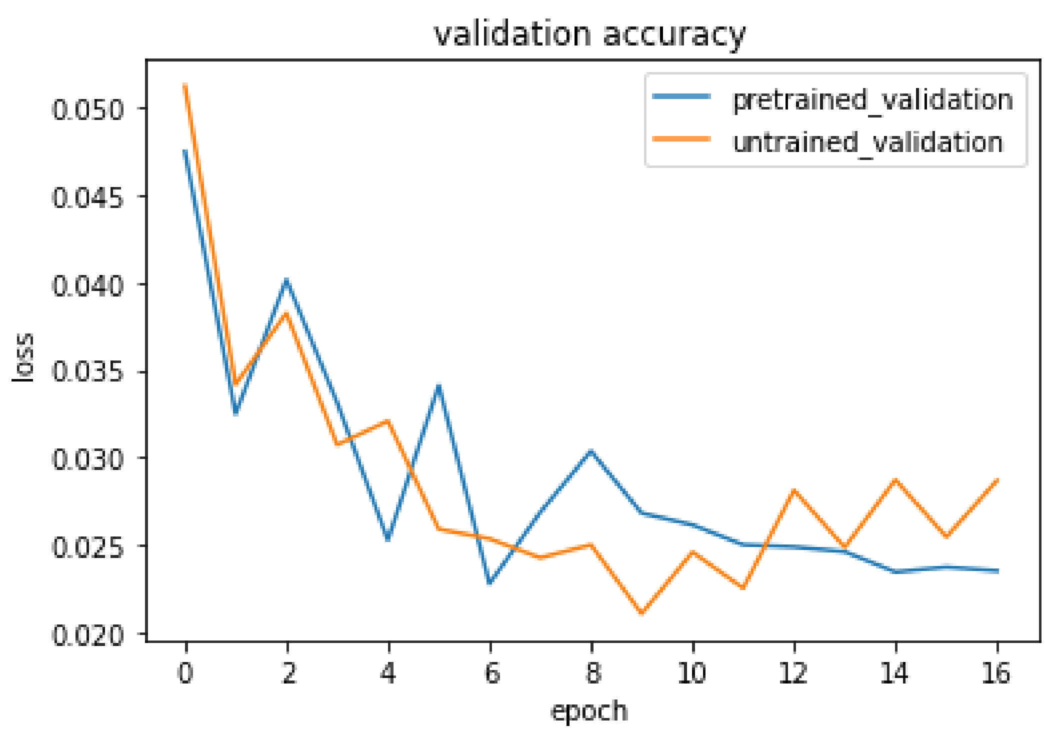
Observations and results

[112]:
```python
plt.figure(1)
plt.plot(history2_after.history['accuracy'])
plt.plot(history2_un.history['accuracy'])
plt.title('training accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['pretrained_training', 'untrained_training'], loc='best')
plt.show()

plt.figure(2)
plt.plot(history2_after.history['val_accuracy'])
plt.plot(history2_un.history['val_accuracy'])
plt.title('validation accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['pretrained_validation', 'untrained_validation'], loc='best')
plt.show()

plt.figure(3)
plt.plot(history2_after.history['loss'])
plt.plot(history2_un.history['loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['pretrained_validation', 'untrained_validation'], loc='best')
plt.show()

plt.figure(4)
plt.plot(history2_after.history['val_loss'])
plt.plot(history2_un.history['val_loss'])
plt.title('validation accuracy')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['pretrained_validation', 'untrained_validation'], loc='best')
plt.show()
```


training accuracy
accuracy
0.95
0.96
0.97
0.98
0.99
0
2
4
6
8
10
12
14
16
epoch
pretrained_training
untrained_training


validation accuracy
accuracy
0.984
0.986
0.988
0.990
0.992
0.994
0
2
4
6
8
10
12
14
16
epoch
pretrained_validation
untrained_validation


model loss
pretrained_validation
untrained_validation
loss
epoch
0.225
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0
2
4
6
8
10
12
14
16


validation accuracy
pretrained_validation
untrained_validation
loss
epoch
0.050
0.045
0.040
0.035
0.030
0.025
0.020
0
2
4
6
8
10
12
14
16

This is interesting. For this case, the untrained model performs 'slightly' better than the pretrained one during the initial epochs but the pretrained model does better in the end.

As seen before, it did not perform well during pre-training. This may be due to the more complex nature of the architecture and less availability of the pretraining data.

It is to be noted that this architecture achieved very good accuracy in almost half the epochs of the original LeNet.

Some observations: - The untrained accuracy for both the test and validation sets start higher than the pretrianed models. - During the training phase, the pretrained overall performs better in the end. - The same can be said for the loss, which starts lower for both the training and validation set for the pretrained model and for most part, stays lower. - **Overall, the pre-trained network ahs higher final accuracy and lower final loss.**

2 Task 2 Part 3

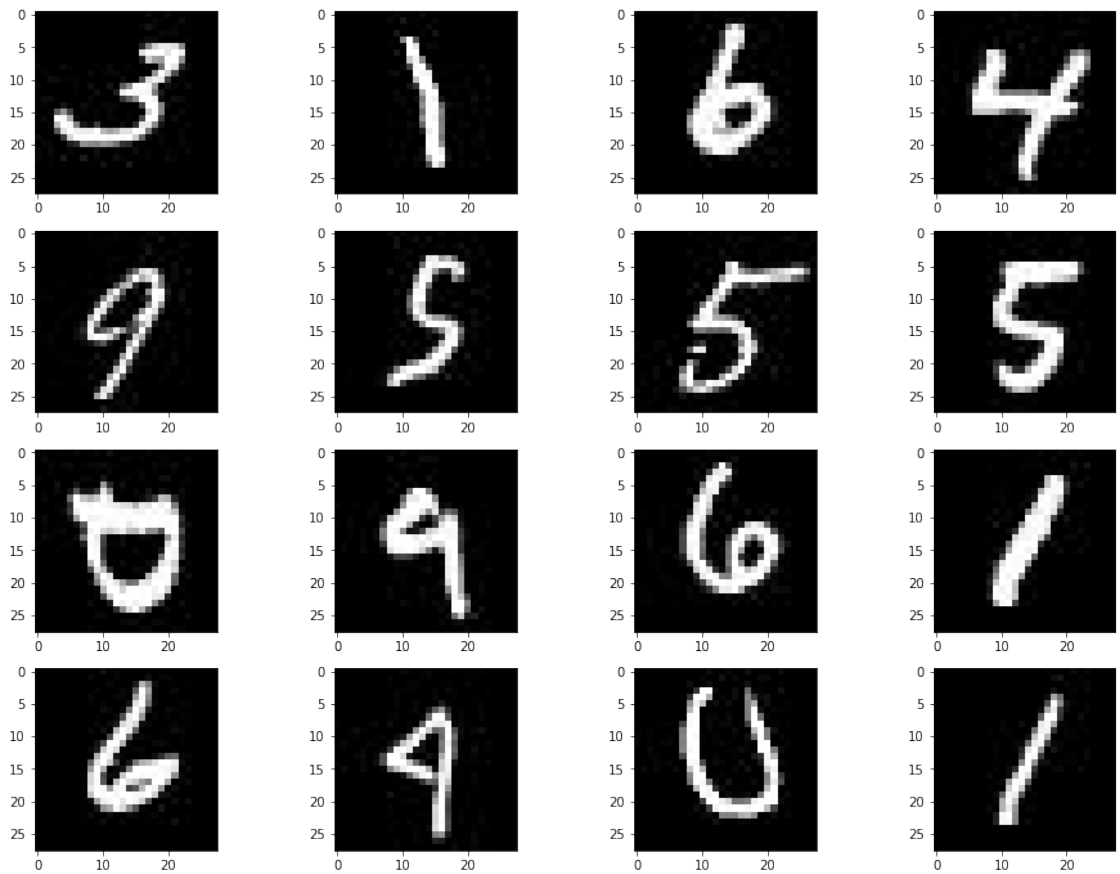
2.1 Extracting the dataset

[115]:
```
shutil.unpack_archive('mnistTask3.zip', 'input/part3')
```

[117]:
```
train_datagen3 = ImageDataGenerator(rescale=1./255)
```

[118]:
```
train_generator3 = train_datagen3.flow_from_directory(
    'input/part3/mnistTask',
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    color_mode='grayscale',
    subset='training',
    seed=42,
    shuffle=True)

X_train_batch3, y_train_batch3 = train_generator3.next()
print(X_train_batch3.shape, y_train_batch3.shape)
print(y_train_batch3[0])
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_train_batch3[i]), cmap='gray')
plt.show()
```

```
Found 60000 images belonging to 10 classes.
(64, 28, 28, 1) (64, 10)
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
```



2.2 Building the Model

I've used the 2nd Architecture for faster convergence

[124]:
```
model3 = Sequential()

# 1st Convolution Layer
model3.add(Conv2D(32, input_shape=(*IMAGE_SIZE, 1), kernel_size=3,␣
 ↪activation=mish))
model3.add(BatchNormalization())
model3.add(Conv2D(32, kernel_size=3, activation=mish))
model3.add(BatchNormalization())
model3.add(Conv2D(32, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model3.add(BatchNormalization())
model3.add(Dropout(0.4))

# 2nd Convolution Layer
model3.add(Conv2D(64, kernel_size=3, activation=mish))
model3.add(BatchNormalization())
```

```
model3.add(Conv2D(64, kernel_size=3, activation=mish))
model3.add(BatchNormalization())
model3.add(Conv2D(64, kernel_size=5, strides=2, padding='same',␣
↪activation=mish))
model3.add(BatchNormalization())
model3.add(Dropout(0.4))

# 3rd Convolution Layer
model3.add(Conv2D(128, kernel_size = 4, activation=mish))
model3.add(BatchNormalization())

# Passing to a Fully Connected Layer
model3.add(Flatten())
model3.add(Dropout(0.4))

# Output Layer

# Increasing the softmax temperature
model3.add(Lambda(lambda x: x / temp))
model3.add(Dense(10, activation='softmax'))

model3.summary()

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

```
Model: "sequential_23"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_116 (Conv2D)          (None, 26, 26, 32)        320
_________________________________________________________________
batch_normalization_134 (Bat (None, 26, 26, 32)        128
_________________________________________________________________
conv2d_117 (Conv2D)          (None, 24, 24, 32)        9248
_________________________________________________________________
batch_normalization_135 (Bat (None, 24, 24, 32)        128
_________________________________________________________________
conv2d_118 (Conv2D)          (None, 12, 12, 32)        25632
_________________________________________________________________
batch_normalization_136 (Bat (None, 12, 12, 32)        128
_________________________________________________________________
dropout_60 (Dropout)         (None, 12, 12, 32)        0
_________________________________________________________________
conv2d_119 (Conv2D)          (None, 10, 10, 64)        18496
_________________________________________________________________
batch_normalization_137 (Bat (None, 10, 10, 64)        256
```

```
_________________________________________________________________
conv2d_120 (Conv2D)          (None, 8, 8, 64)          36928
_________________________________________________________________
batch_normalization_138 (Bat (None, 8, 8, 64)          256
_________________________________________________________________
conv2d_121 (Conv2D)          (None, 4, 4, 64)          102464
_________________________________________________________________
batch_normalization_139 (Bat (None, 4, 4, 64)          256
_________________________________________________________________
dropout_61 (Dropout)         (None, 4, 4, 64)          0
_________________________________________________________________
conv2d_122 (Conv2D)          (None, 1, 1, 128)         131200
_________________________________________________________________
batch_normalization_140 (Bat (None, 1, 1, 128)         512
_________________________________________________________________
flatten_23 (Flatten)         (None, 128)               0
_________________________________________________________________
dropout_62 (Dropout)         (None, 128)               0
_________________________________________________________________
lambda_44 (Lambda)           (None, 128)               0
_________________________________________________________________
dense_41 (Dense)             (None, 10)                1290
=================================================================
Total params: 327,242
Trainable params: 326,410
Non-trainable params: 832
_________________________________________________________________
```

[125]:

```
checkpoint_filepath3 = 'part3/checkpoint'
model_checkpoint_callback3 = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath3,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)

history3 = model3.fit(
    train_generator3,
    epochs=EPOCHS,
    validation_data=mnist_test_gen,
    steps_per_epoch = train_generator3.samples // BATCH_SIZE // BATCH_SIZE,
    validation_steps = len(x_test) // BATCH_SIZE,
    callbacks=[model_checkpoint_callback3, early_stopping_callback2]
)
```

```
Epoch 1/400
14/14 [==============================] - 2s 101ms/step - loss: 2.3510 -
accuracy: 0.0999 - val_loss: 2.3044 - val_accuracy: 0.0980
```

```
Epoch 2/400
14/14 [==============================] - 1s 74ms/step - loss: 2.3570 - accuracy:
0.0996 - val_loss: 2.3115 - val_accuracy: 0.0320
Epoch 3/400
14/14 [==============================] - 1s 75ms/step - loss: 2.3429 - accuracy:
0.1234 - val_loss: 2.3213 - val_accuracy: 0.0281
Epoch 4/400
14/14 [==============================] - 1s 76ms/step - loss: 2.3446 - accuracy:
0.1220 - val_loss: 2.3289 - val_accuracy: 0.0449
Epoch 5/400
14/14 [==============================] - 1s 77ms/step - loss: 2.3509 - accuracy:
0.1131 - val_loss: 2.3544 - val_accuracy: 0.0759
Epoch 6/400
14/14 [==============================] - 1s 74ms/step - loss: 2.3196 - accuracy:
0.0975 - val_loss: 2.3816 - val_accuracy: 0.0830
Epoch 7/400
14/14 [==============================] - 1s 74ms/step - loss: 2.3376 - accuracy:
0.1117 - val_loss: 2.4043 - val_accuracy: 0.0136
Epoch 8/400
14/14 [==============================] - 1s 74ms/step - loss: 2.3185 - accuracy:
0.1045 - val_loss: 2.4284 - val_accuracy: 0.0071
Epoch 9/400
14/14 [==============================] - 1s 76ms/step - loss: 2.3078 - accuracy:
0.1117 - val_loss: 2.4550 - val_accuracy: 0.0021
Epoch 10/400
14/14 [==============================] - 1s 72ms/step - loss: 2.3338 - accuracy:
0.1025 - val_loss: 2.4787 - val_accuracy: 0.0034
Epoch 11/400
14/14 [==============================] - 1s 79ms/step - loss: 2.2805 - accuracy:
0.1182 - val_loss: 2.4759 - val_accuracy: 0.0022
Epoch 12/400
14/14 [==============================] - 1s 77ms/step - loss: 2.2976 - accuracy:
0.1117 - val_loss: 2.4692 - val_accuracy: 0.0033
Epoch 13/400
14/14 [==============================] - 1s 74ms/step - loss: 2.3046 - accuracy:
0.1338 - val_loss: 2.4820 - val_accuracy: 0.0038
Epoch 14/400
14/14 [==============================] - 1s 76ms/step - loss: 2.3112 - accuracy:
0.1189 - val_loss: 2.5052 - val_accuracy: 0.0045
Epoch 15/400
14/14 [==============================] - 1s 79ms/step - loss: 2.3051 - accuracy:
0.0873 - val_loss: 2.5120 - val_accuracy: 0.0067
Epoch 16/400
14/14 [==============================] - 1s 79ms/step - loss: 2.2678 - accuracy:
0.1159 - val_loss: 2.5398 - val_accuracy: 0.0154
Epoch 17/400
14/14 [==============================] - 1s 77ms/step - loss: 2.3158 - accuracy:
0.0986 - val_loss: 2.5383 - val_accuracy: 0.0194
```

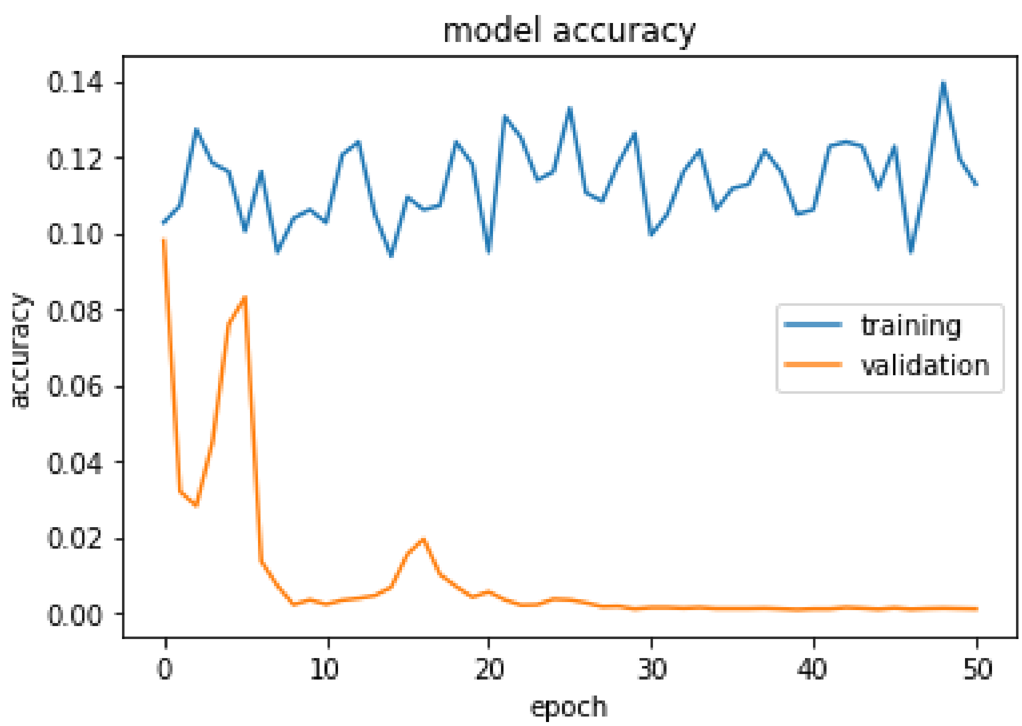
```
Epoch 18/400
14/14 [==============================] - 1s 78ms/step - loss: 2.3276 - accuracy:
0.1075 - val_loss: 2.5549 - val_accuracy: 0.0101
Epoch 19/400
14/14 [==============================] - 1s 76ms/step - loss: 2.2674 - accuracy:
0.1251 - val_loss: 2.6085 - val_accuracy: 0.0069
Epoch 20/400
14/14 [==============================] - 1s 74ms/step - loss: 2.2903 - accuracy:
0.1255 - val_loss: 2.6486 - val_accuracy: 0.0041
Epoch 21/400
14/14 [==============================] - 1s 72ms/step - loss: 2.3012 - accuracy:
0.0824 - val_loss: 2.6632 - val_accuracy: 0.0055
Epoch 22/400
14/14 [==============================] - 1s 74ms/step - loss: 2.2887 - accuracy:
0.1316 - val_loss: 2.7288 - val_accuracy: 0.0034
Epoch 23/400
14/14 [==============================] - 1s 76ms/step - loss: 2.2791 - accuracy:
0.1210 - val_loss: 2.8443 - val_accuracy: 0.0020
Epoch 24/400
14/14 [==============================] - 1s 74ms/step - loss: 2.2848 - accuracy:
0.1181 - val_loss: 2.8780 - val_accuracy: 0.0021
Epoch 25/400
14/14 [==============================] - 1s 76ms/step - loss: 2.2925 - accuracy:
0.1133 - val_loss: 2.8934 - val_accuracy: 0.0036
Epoch 26/400
14/14 [==============================] - 1s 76ms/step - loss: 2.2695 - accuracy:
0.1257 - val_loss: 2.9376 - val_accuracy: 0.0034
Epoch 27/400
14/14 [==============================] - 1s 76ms/step - loss: 2.2827 - accuracy:
0.1016 - val_loss: 2.9933 - val_accuracy: 0.0026
Epoch 28/400
14/14 [==============================] - 1s 78ms/step - loss: 2.2814 - accuracy:
0.1156 - val_loss: 3.0169 - val_accuracy: 0.0016
Epoch 29/400
14/14 [==============================] - 1s 77ms/step - loss: 2.2619 - accuracy:
0.1196 - val_loss: 3.0630 - val_accuracy: 0.0017
Epoch 30/400
14/14 [==============================] - 1s 78ms/step - loss: 2.2639 - accuracy:
0.1162 - val_loss: 3.0653 - val_accuracy: 0.0010
Epoch 31/400
14/14 [==============================] - 1s 79ms/step - loss: 2.2968 - accuracy:
0.1126 - val_loss: 3.0272 - val_accuracy: 0.0014
Epoch 32/400
14/14 [==============================] - 1s 78ms/step - loss: 2.2856 - accuracy:
0.0937 - val_loss: 2.9784 - val_accuracy: 0.0014
Epoch 33/400
14/14 [==============================] - 1s 80ms/step - loss: 2.2682 - accuracy:
0.1064 - val_loss: 2.9511 - val_accuracy: 0.0012
```

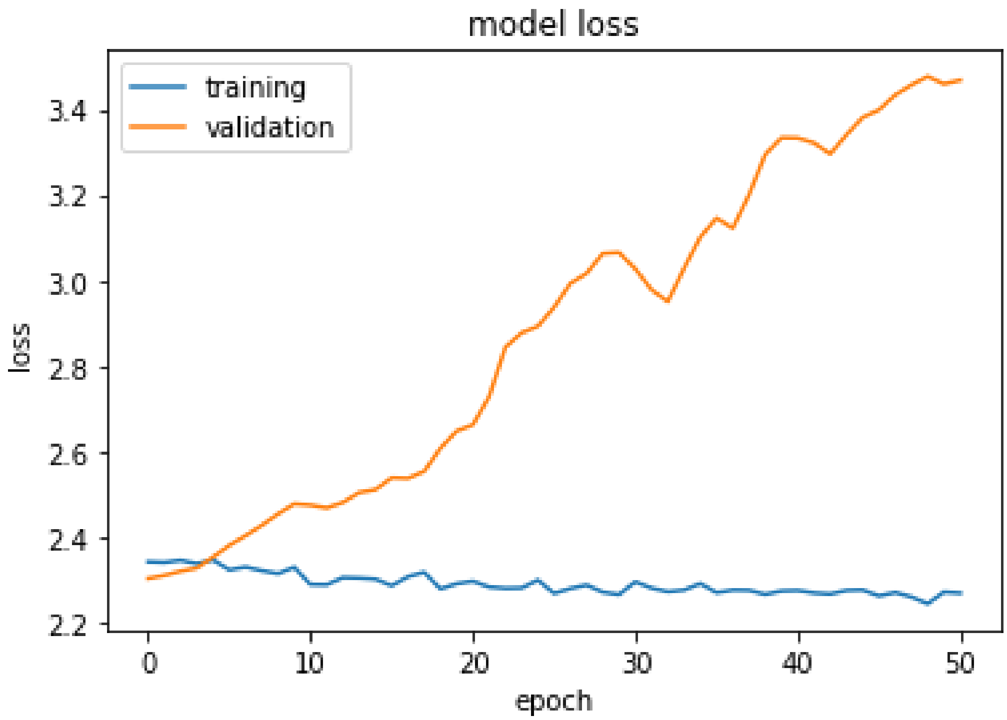
```
Epoch 34/400
14/14 [==============================] - 1s 76ms/step - loss: 2.2701 - accuracy:
0.1189 - val_loss: 3.0290 - val_accuracy: 0.0014
Epoch 35/400
14/14 [==============================] - 1s 74ms/step - loss: 2.2918 - accuracy:
0.1029 - val_loss: 3.1015 - val_accuracy: 0.0011
Epoch 36/400
14/14 [==============================] - 1s 79ms/step - loss: 2.2663 - accuracy:
0.1232 - val_loss: 3.1458 - val_accuracy: 0.0011
Epoch 37/400
14/14 [==============================] - 1s 74ms/step - loss: 2.2737 - accuracy:
0.1216 - val_loss: 3.1219 - val_accuracy: 0.0011
Epoch 38/400
14/14 [==============================] - 1s 77ms/step - loss: 2.2712 - accuracy:
0.1120 - val_loss: 3.2004 - val_accuracy: 0.0012
Epoch 39/400
14/14 [==============================] - 1s 73ms/step - loss: 2.2763 - accuracy:
0.1092 - val_loss: 3.2946 - val_accuracy: 0.0010
Epoch 40/400
14/14 [==============================] - 1s 75ms/step - loss: 2.2807 - accuracy:
0.0910 - val_loss: 3.3334 - val_accuracy: 8.0128e-04
Epoch 41/400
14/14 [==============================] - 1s 76ms/step - loss: 2.2733 - accuracy:
0.0990 - val_loss: 3.3329 - val_accuracy: 0.0010
Epoch 42/400
14/14 [==============================] - 1s 73ms/step - loss: 2.2750 - accuracy:
0.1250 - val_loss: 3.3215 - val_accuracy: 0.0010
Epoch 43/400
14/14 [==============================] - 1s 77ms/step - loss: 2.2670 - accuracy:
0.1212 - val_loss: 3.2956 - val_accuracy: 0.0014
Epoch 44/400
14/14 [==============================] - 1s 74ms/step - loss: 2.2843 - accuracy:
0.1118 - val_loss: 3.3403 - val_accuracy: 0.0012
Epoch 45/400
14/14 [==============================] - 1s 72ms/step - loss: 2.2787 - accuracy:
0.1134 - val_loss: 3.3808 - val_accuracy: 9.0144e-04
Epoch 46/400
14/14 [==============================] - 1s 72ms/step - loss: 2.2654 - accuracy:
0.1215 - val_loss: 3.3984 - val_accuracy: 0.0013
Epoch 47/400
14/14 [==============================] - 1s 74ms/step - loss: 2.2865 - accuracy:
0.0950 - val_loss: 3.4335 - val_accuracy: 9.0144e-04
Epoch 48/400
14/14 [==============================] - 1s 77ms/step - loss: 2.2580 - accuracy:
0.1302 - val_loss: 3.4568 - val_accuracy: 0.0011
Epoch 49/400
14/14 [==============================] - 1s 73ms/step - loss: 2.2504 - accuracy:
0.1384 - val_loss: 3.4763 - val_accuracy: 0.0012
```

```
Epoch 50/400
14/14 [==============================] - 1s 75ms/step - loss: 2.2606 - accuracy:
0.1233 - val_loss: 3.4587 - val_accuracy: 0.0011
Epoch 51/400
14/14 [==============================] - 1s 75ms/step - loss: 2.2736 - accuracy:
0.1243 - val_loss: 3.4676 - val_accuracy: 0.0010
Restoring model weights from the end of the best epoch.
Epoch 00051: early stopping
```

[126]:

```
plt.figure(1)
plt.plot(history3.history['accuracy'])
plt.plot(history3.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()

plt.figure(2)
plt.plot(history3.history['loss'])
plt.plot(history3.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```





I've used higher early stopping patience level for this as this had so much variance.

2.2.1 Observation and results

This model does not perform any good. This is because of the data provided, as we have seen pretty good results with this model.

I think this dataset comes from the MNIST distribution, but has been randomly shiuffled, so the labels no more correspond to the correct image. SInce this was tested on the correctly labelled MNIST dataset, it performed very badly as it had learned the wrong weights.

This is a classic example of how we should alwasy check and verify that the data that we have is cleaned, properly labelled and unbiased as even good models give very bad and biased predictions if the data is incorrect.

[ ]:

```
```