midastask2part1

April 10, 2021

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1 Task 2 - Part 1

Imports

[1]:
```
import shutil
from PIL import Image
import numpy as np
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
```

Extracting the imges

[2]:
```
shutil.unpack_archive('trainPart1.zip', '../input/trainpart1zip')
```

1.1 Inspecting the image

Browsing through the dataset, we can see that there a total of 62 classes - 10 numbers from 0 to 9, 26 lowercase alphabets and 26 uppercase alphabets, having 40 examples each.

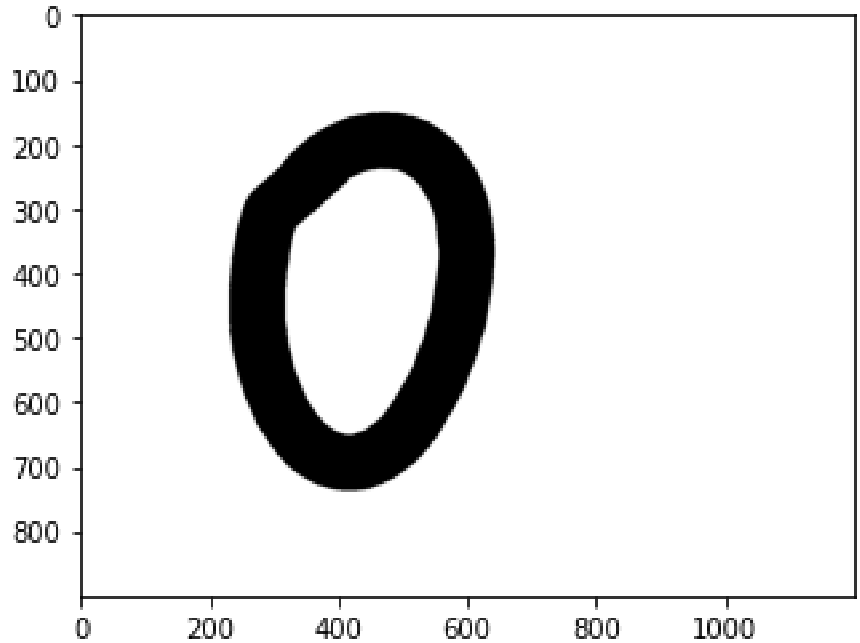
Inspecting the image to view its dimensions and colour channels

[3]:
```
image = Image.open('../input/trainpart1zip/train/Sample001/img001-001.png')
np_image = np.array(image)
print(np_image.shape)
print(image.mode)
```

```
imshow(image)
```

```
(900, 1200, 3)
RGB
```

[3]: <matplotlib.image.AxesImage at 0x7efbe2070dd0>



The image is of dimension 900x1200 with three colour channels. Looking at the images in the directory, I found that all the images are black and white and contain only handwritten digits or alphabets. We can convert them to single grayscale colour channel to reduce computations, improve speed and make the architecture less compled.

1.2 Preprossing the images to convert test and validation input and labels

NOTE: Initially, I tried to build the network on the full image dimension of 900x1200, but that just overloaded the memory with too many parameters.

Since for the later tasks, I have to downsample the images to the size of MNIST i.e. 28x28, I made all other images of this dimension.

Since the images in our dataset are not square, one way to reduce the dimension of images in this set in order to have the same input shape as the MNIST dataset can be to downscale the largest dimension to 28 and then zero-pad the shorter dimension with 0 to make it 28x28.

Also, the 0 values are displayed as black and the higher values as white, which is opposite in our case. Hence, I'll invert time in our dataset ot match to that of MNIST.

So, for our current image of 900x1200, 1200px would be scaled down to 28pxs and 900 would scale down to 900*28/1200 = 21px. Then, I would pad it with 0s in the top and bottom to make it 28x28. I'm padding it with zeros because: - 0 values don't add any extra information to the image - The MNIST images have their background values as 0

Instead of padding all the images before training, I would pad them on-the-fly with a Lambda layer in the modes, before passing it to the first convolution layer.

I noticed that after resizing down, the images are still recognizable from each other so, a conv net should be able to recognize them too.

I'll use ImageDataGenerator from Keras to preprocess and split the training images into train and validations sets.

I've normalized all pixel values to be in the range of 0 to 1 for the data to have similar range.

I split the training and validation sets in 80:20 ratio.

[4]:
```
train_datagen1 = ImageDataGenerator(rescale=1./255, validation_split=0.2,␣
↪preprocessing_function=lambda x: 1-x)
```

I create the generator object which would generate the training and validation sets. It takes the input from the images folder. I'm reducing the size of the images by 20x while taking the input, and changing the colour channel to grayscale. Each set is of batch size 64. I chose this as it's a good enough batch size for this size of dataset. The class labels are categorical and are one-hot encoded for all of the 62 classes (10 numbers + 26 lowercase alphabets + 26 uppercase alphabets).

Variables that would be used globally. I set max epochs of 400.

[5]:
```
BATCH_SIZE = 64
IMAGE_SIZE = (21, 28)
EPOCHS = 400
```

Using ImageDataGenerator, I convert the images to their one-hot encodings so that the task becomes that of classification, rather than a regression one.

[6]:
```
train_generator1 = train_datagen1.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        subset='training',
        seed=42,
        shuffle=True)
```

```
Found 1984 images belonging to 62 classes.
```

[7]:
```
validation_generator1 = train_datagen1.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=tf.squeeze(IMAGE_SIZE),
        batch_size=BATCH_SIZE,
```

```
        class_mode='categorical',
        color_mode='grayscale',
        subset='validation',
        seed=42,
        shuffle=True)
```

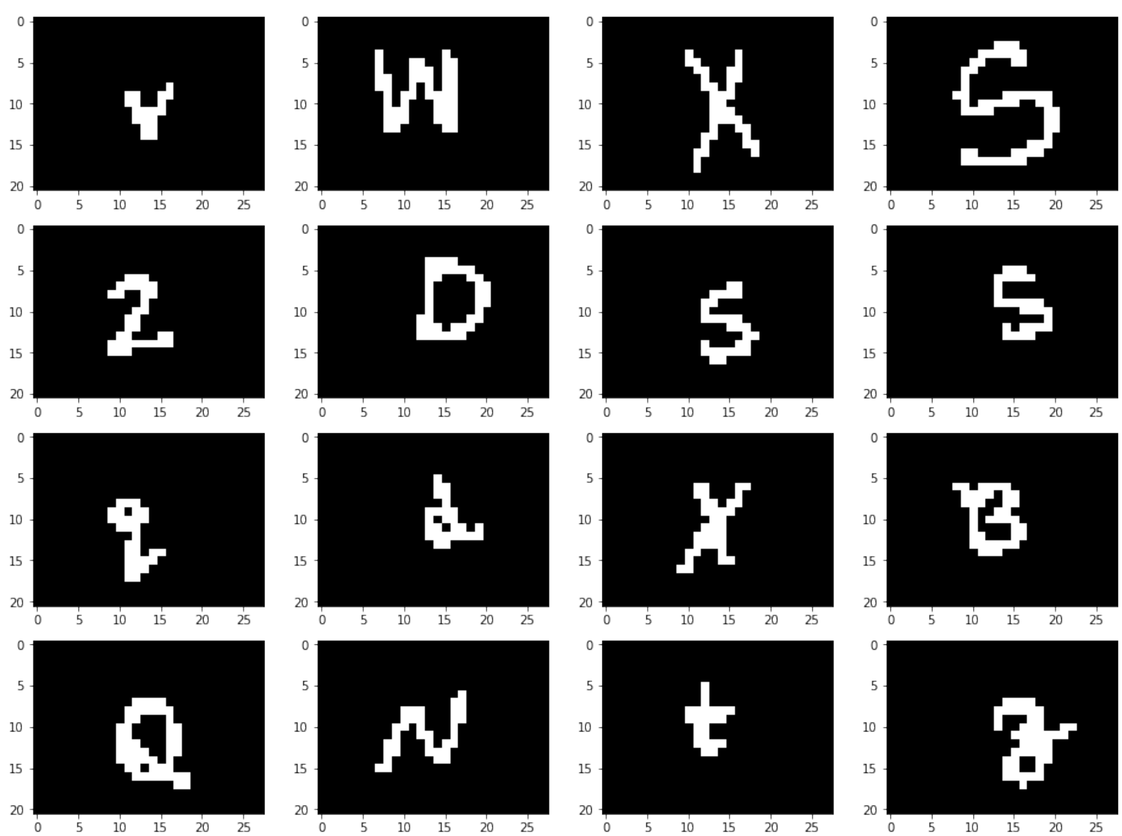
```
Found 496 images belonging to 62 classes.
```

The ImageDataGenerator class has automatically detected the 62 classes.

Viewing the generated samples

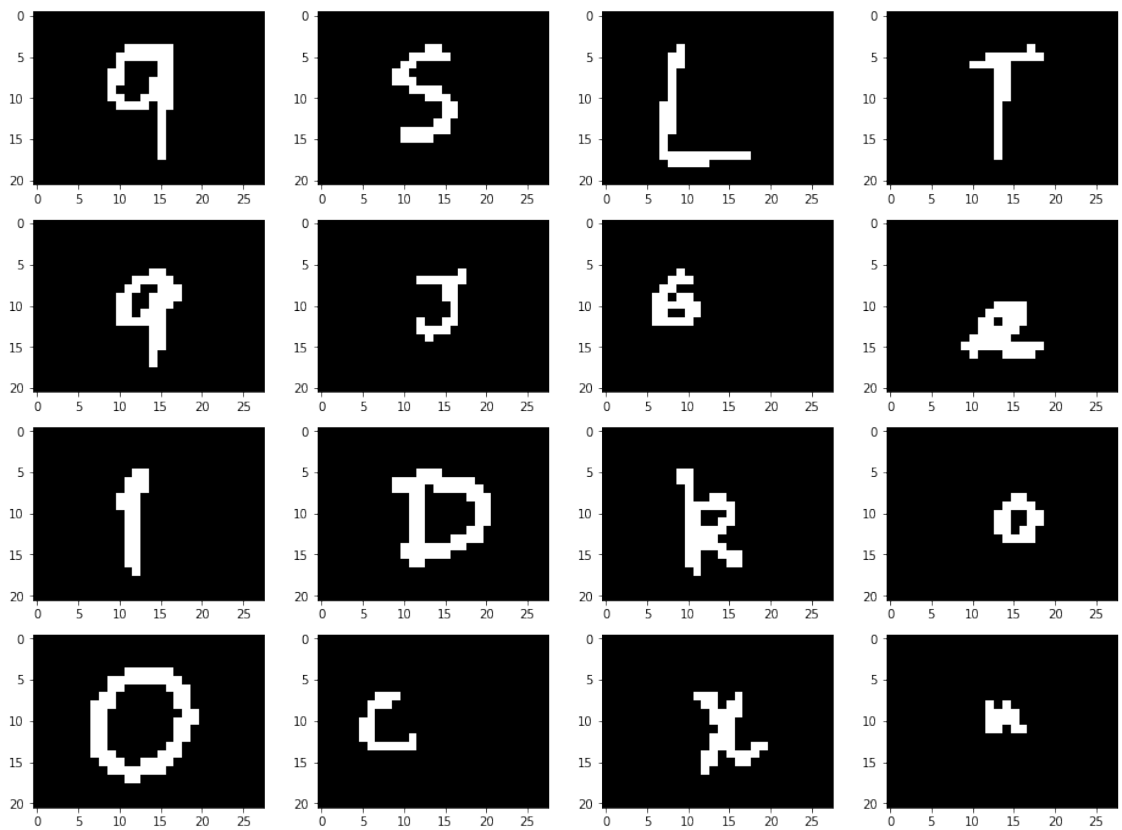
[ ]:
```
X_train_batch0, y_train_batch0 = train_generator1.next()
print(X_train_batch0.shape, y_train_batch0.shape)
print(y_train_batch0[0])
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_train_batch0[i]), cmap='gray')
plt.show()
```

```
(64, 21, 28, 1) (64, 62)
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```



[ ]:
```python
X_validation_batch0, y_validation_batch0 = validation_generator1.next()
print(X_validation_batch0.shape, y_validation_batch0.shape)
print(y_validation_batch0[0])
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_validation_batch0[i]), cmap='gray')
plt.show()
```

```
(64, 21, 28, 1) (64, 62)
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```



1.3 Building the model

I train the model for 400 epochs and use early stopping with a patience level of 20 epochs in order to prevent model from overfitting and save the best weights of the mode.

Using Early Stopping to prevent overfitting, with a patience level of 20 epochs.

[8]:
```
early_stopping_callback = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    mode='min',
    patience=20,
    restore_best_weights=True,
    verbose=1)
```

1.3.1 Experiment 1: Building the first model inspired from LeNet

I quickly build a first model, which inspired by the original LeNet, with slight modifications, to check how it performs and will then tune the hyperparameter accordingly. I also use dropouts with a probability of 0.4 for each Fully Connected Layer.

[ ]:
```
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, 1)))

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

# 2nd Convolution Layer
model1.add(Conv2D(16, kernel_size=(5,5), activation='relu'))
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(256, activation='relu'))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# 2nd Fully Connected Layer
model1.add(Dense(128, activation='relu'))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))

# Output Layer
model1.add(Dense(62, activation='softmax'))
```

[ ]:
```
model1.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_1 (Lambda)            (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 28, 28, 6)         156
_________________________________________________________________
batch_normalization_8 (Batch (None, 28, 28, 6)         24
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 14, 14, 6)         0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 10, 10, 16)        2416
_________________________________________________________________
batch_normalization_9 (Batch (None, 10, 10, 16)        64
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 5, 5, 16)          0
_________________________________________________________________
flatten_2 (Flatten)          (None, 400)               0
_________________________________________________________________
dense_6 (Dense)              (None, 256)               102656
_________________________________________________________________
batch_normalization_10 (Batc (None, 256)               1024
_________________________________________________________________
dropout_4 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_7 (Dense)              (None, 128)               32896
_________________________________________________________________
batch_normalization_11 (Batc (None, 128)               512
_________________________________________________________________
dropout_5 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_8 (Dense)              (None, 62)                7998
=================================================================
Total params: 147,746
Trainable params: 146,934
Non-trainable params: 812
_________________________________________________________________
```

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

Saving the checkpoint

[ ]:
```
checkpoint_filepath1 = 'exp1/checkpoint'
model_checkpoint_callback1 = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath1,
    save_weights_only=True,
```

```
    monitor='val_loss',
    mode='min',
    save_best_only=True)
```

[ ]:
```
history1 = model1.fit(
    train_generator1,
    epochs=EPOCHS,
    validation_data=validation_generator1,
    steps_per_epoch = train_generator1.samples // BATCH_SIZE,
    validation_steps = validation_generator1.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback1, early_stopping_callback]
)
```

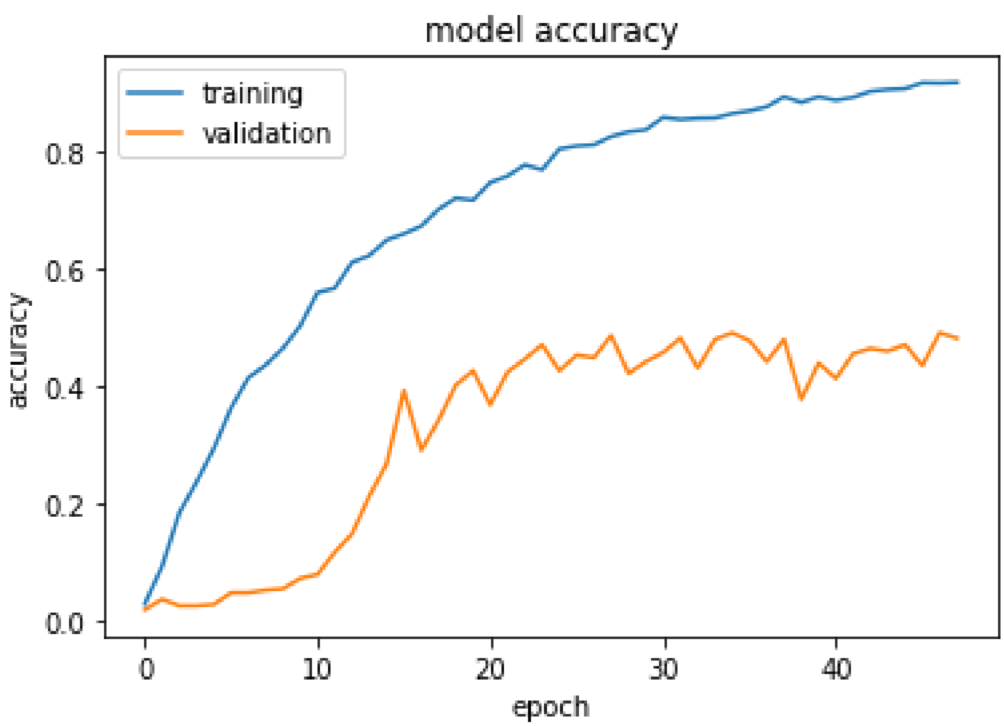
```
Epoch 1/400
31/31 [==============================] - 39s 1s/step - loss: 5.0043 - accuracy:
0.0213 - val_loss: 4.1208 - val_accuracy: 0.0179
Epoch 2/400
31/31 [==============================] - 36s 1s/step - loss: 4.0452 - accuracy:
0.0806 - val_loss: 4.1611 - val_accuracy: 0.0357
Epoch 3/400
31/31 [==============================] - 36s 1s/step - loss: 3.3932 - accuracy:
0.1817 - val_loss: 4.3968 - val_accuracy: 0.0246
Epoch 4/400
31/31 [==============================] - 36s 1s/step - loss: 3.0605 - accuracy:
0.2270 - val_loss: 4.6091 - val_accuracy: 0.0246
Epoch 5/400
31/31 [==============================] - 36s 1s/step - loss: 2.7359 - accuracy:
0.2881 - val_loss: 4.8350 - val_accuracy: 0.0268
Epoch 6/400
31/31 [==============================] - 36s 1s/step - loss: 2.4506 - accuracy:
0.3656 - val_loss: 4.8434 - val_accuracy: 0.0469
Epoch 7/400
31/31 [==============================] - 36s 1s/step - loss: 2.2959 - accuracy:
0.4072 - val_loss: 4.9224 - val_accuracy: 0.0469
Epoch 8/400
31/31 [==============================] - 36s 1s/step - loss: 2.0966 - accuracy:
0.4540 - val_loss: 4.8551 - val_accuracy: 0.0513
Epoch 9/400
31/31 [==============================] - 36s 1s/step - loss: 1.9068 - accuracy:
0.4856 - val_loss: 4.6808 - val_accuracy: 0.0536
Epoch 10/400
31/31 [==============================] - 36s 1s/step - loss: 1.7871 - accuracy:
0.5063 - val_loss: 4.6372 - val_accuracy: 0.0714
Epoch 11/400
31/31 [==============================] - 37s 1s/step - loss: 1.6535 - accuracy:
0.5538 - val_loss: 4.2520 - val_accuracy: 0.0781
Epoch 12/400
```

```
31/31 [==============================] - 37s 1s/step - loss: 1.5272 - accuracy:
0.5662 - val_loss: 3.9199 - val_accuracy: 0.1161
Epoch 13/400
31/31 [==============================] - 37s 1s/step - loss: 1.4197 - accuracy:
0.6169 - val_loss: 3.4918 - val_accuracy: 0.1473
Epoch 14/400
31/31 [==============================] - 37s 1s/step - loss: 1.3951 - accuracy:
0.6255 - val_loss: 3.1866 - val_accuracy: 0.2121
Epoch 15/400
31/31 [==============================] - 37s 1s/step - loss: 1.2665 - accuracy:
0.6570 - val_loss: 2.9442 - val_accuracy: 0.2679
Epoch 16/400
31/31 [==============================] - 37s 1s/step - loss: 1.2274 - accuracy:
0.6580 - val_loss: 2.4005 - val_accuracy: 0.3929
Epoch 17/400
31/31 [==============================] - 37s 1s/step - loss: 1.1333 - accuracy:
0.6832 - val_loss: 2.8734 - val_accuracy: 0.2902
Epoch 18/400
31/31 [==============================] - 37s 1s/step - loss: 1.0525 - accuracy:
0.7115 - val_loss: 2.5002 - val_accuracy: 0.3415
Epoch 19/400
31/31 [==============================] - 38s 1s/step - loss: 0.9996 - accuracy:
0.7156 - val_loss: 2.2576 - val_accuracy: 0.4018
Epoch 20/400
31/31 [==============================] - 37s 1s/step - loss: 0.9524 - accuracy:
0.7211 - val_loss: 2.1082 - val_accuracy: 0.4263
Epoch 21/400
31/31 [==============================] - 38s 1s/step - loss: 0.9113 - accuracy:
0.7535 - val_loss: 2.4135 - val_accuracy: 0.3683
Epoch 22/400
31/31 [==============================] - 37s 1s/step - loss: 0.8432 - accuracy:
0.7557 - val_loss: 2.1371 - val_accuracy: 0.4241
Epoch 23/400
31/31 [==============================] - 38s 1s/step - loss: 0.7570 - accuracy:
0.7891 - val_loss: 2.0216 - val_accuracy: 0.4464
Epoch 24/400
31/31 [==============================] - 38s 1s/step - loss: 0.7660 - accuracy:
0.7741 - val_loss: 1.9824 - val_accuracy: 0.4710
Epoch 25/400
31/31 [==============================] - 37s 1s/step - loss: 0.6691 - accuracy:
0.8188 - val_loss: 2.1950 - val_accuracy: 0.4263
Epoch 26/400
31/31 [==============================] - 37s 1s/step - loss: 0.6867 - accuracy:
0.8098 - val_loss: 2.2190 - val_accuracy: 0.4531
Epoch 27/400
31/31 [==============================] - 37s 1s/step - loss: 0.6584 - accuracy:
0.8170 - val_loss: 2.2322 - val_accuracy: 0.4487
Epoch 28/400
```

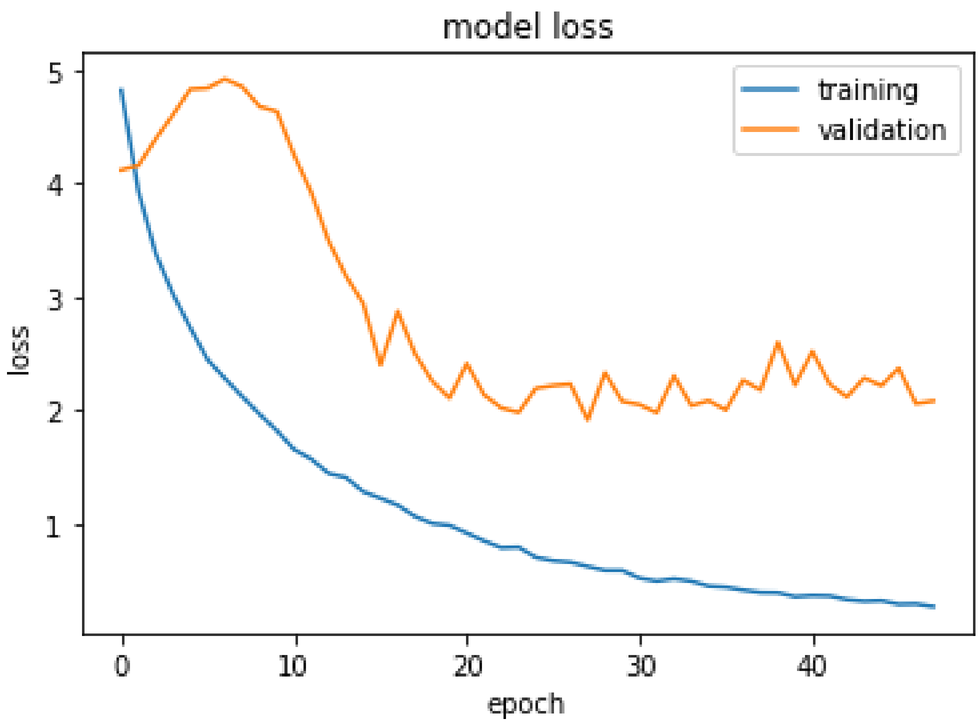
```
31/31 [==============================] - 37s 1s/step - loss: 0.6170 - accuracy:
0.8295 - val_loss: 1.9150 - val_accuracy: 0.4866
Epoch 29/400
31/31 [==============================] - 38s 1s/step - loss: 0.5531 - accuracy:
0.8508 - val_loss: 2.3321 - val_accuracy: 0.4219
Epoch 30/400
31/31 [==============================] - 37s 1s/step - loss: 0.5607 - accuracy:
0.8538 - val_loss: 2.0796 - val_accuracy: 0.4420
Epoch 31/400
31/31 [==============================] - 37s 1s/step - loss: 0.5285 - accuracy:
0.8504 - val_loss: 2.0516 - val_accuracy: 0.4576
Epoch 32/400
31/31 [==============================] - 38s 1s/step - loss: 0.4850 - accuracy:
0.8538 - val_loss: 1.9795 - val_accuracy: 0.4821
Epoch 33/400
31/31 [==============================] - 37s 1s/step - loss: 0.5016 - accuracy:
0.8662 - val_loss: 2.3053 - val_accuracy: 0.4308
Epoch 34/400
31/31 [==============================] - 37s 1s/step - loss: 0.4724 - accuracy:
0.8681 - val_loss: 2.0423 - val_accuracy: 0.4799
Epoch 35/400
31/31 [==============================] - 37s 1s/step - loss: 0.4426 - accuracy:
0.8709 - val_loss: 2.0857 - val_accuracy: 0.4911
Epoch 36/400
31/31 [==============================] - 37s 1s/step - loss: 0.4288 - accuracy:
0.8756 - val_loss: 2.0038 - val_accuracy: 0.4777
Epoch 37/400
31/31 [==============================] - 37s 1s/step - loss: 0.3914 - accuracy:
0.8919 - val_loss: 2.2656 - val_accuracy: 0.4420
Epoch 38/400
31/31 [==============================] - 36s 1s/step - loss: 0.3878 - accuracy:
0.9013 - val_loss: 2.1795 - val_accuracy: 0.4799
Epoch 39/400
31/31 [==============================] - 36s 1s/step - loss: 0.4015 - accuracy:
0.8820 - val_loss: 2.6005 - val_accuracy: 0.3772
Epoch 40/400
31/31 [==============================] - 36s 1s/step - loss: 0.3648 - accuracy:
0.8931 - val_loss: 2.2258 - val_accuracy: 0.4397
Epoch 41/400
31/31 [==============================] - 35s 1s/step - loss: 0.3648 - accuracy:
0.8867 - val_loss: 2.5196 - val_accuracy: 0.4129
Epoch 42/400
31/31 [==============================] - 36s 1s/step - loss: 0.3462 - accuracy:
0.9028 - val_loss: 2.2333 - val_accuracy: 0.4554
Epoch 43/400
31/31 [==============================] - 35s 1s/step - loss: 0.3170 - accuracy:
0.9080 - val_loss: 2.1177 - val_accuracy: 0.4643
Epoch 44/400
```

```
31/31 [==============================] - 36s 1s/step - loss: 0.3052 - accuracy:
0.9143 - val_loss: 2.2859 - val_accuracy: 0.4598
Epoch 45/400
31/31 [==============================] - 36s 1s/step - loss: 0.3035 - accuracy:
0.9181 - val_loss: 2.2188 - val_accuracy: 0.4710
Epoch 46/400
31/31 [==============================] - 36s 1s/step - loss: 0.2734 - accuracy:
0.9212 - val_loss: 2.3719 - val_accuracy: 0.4353
Epoch 47/400
31/31 [==============================] - 36s 1s/step - loss: 0.2909 - accuracy:
0.9129 - val_loss: 2.0599 - val_accuracy: 0.4911
Epoch 48/400
31/31 [==============================] - 36s 1s/step - loss: 0.2552 - accuracy:
0.9236 - val_loss: 2.0825 - val_accuracy: 0.4821
Restoring model weights from the end of the best epoch.
Epoch 00048: early stopping
```

[ ]:
```python
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.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()
```



The model performs well on the training set but goes not generalizes well on the validation set. The model is overfitting on the training data.

One reason for the overfitting can be that there's not enough training data. For this part of the task, this cannot be improved upon. So, I'll try other ways to reduce overfitting: - Data Augmentation - Regularizarion - Using different activation function - Changing the model architecture

For regularization, I'm using dropout.

1.3.2 Experiment 2: Augmenting training data

I augment the data by randomly shearing it by a range of 0.1 and rotating it by a range of 0.5 degrees.

So, these augmentation methods should help generalize better on unseen images.

Sidenote: On using other data augmentation techniques I tried other parameters tool, like horizontal and vertical shifts but, they blurred the images and the training set and they didn't really looked like the validation samples anymore (I also tested them for a small epoch and they were actually giving worse results than the first experiment). I'll show some samples to see why I did not augment much on these images, before going forward with the model building.

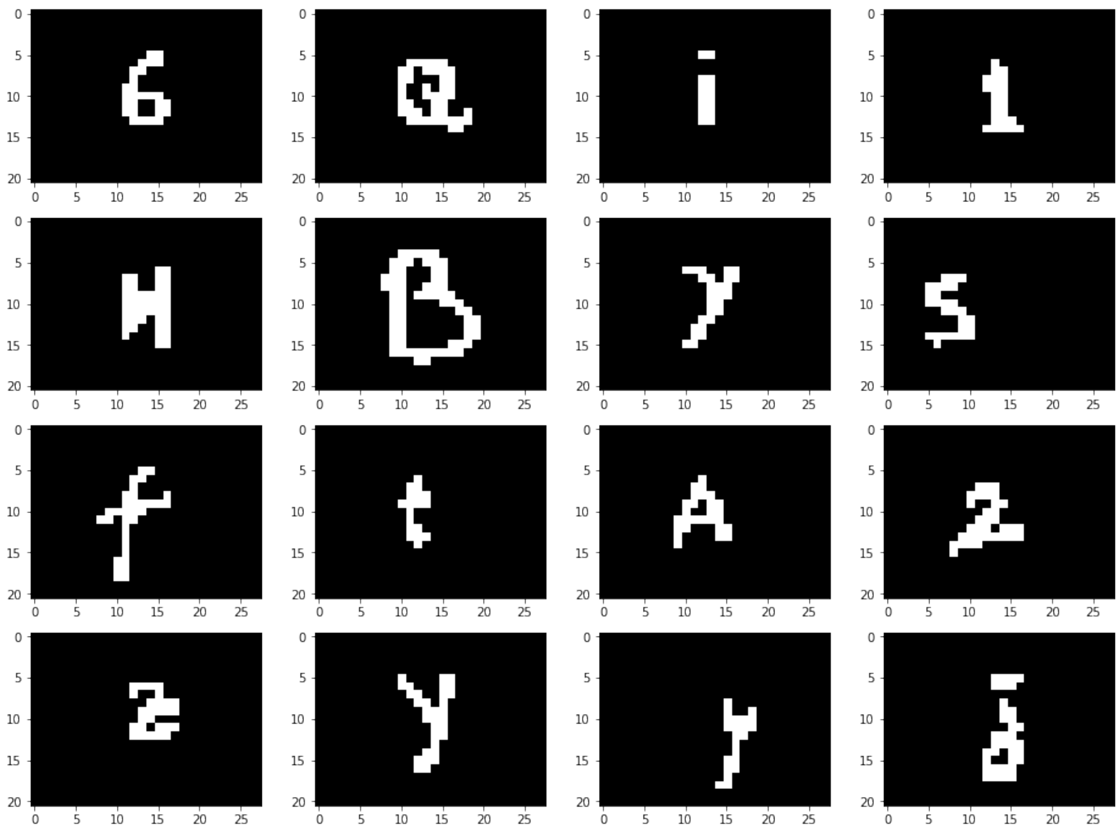
Unaugmented data

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

no_augmentation_gen = no_augmentation.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        seed=42,
        shuffle=True)

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

```
Found 2480 images belonging to 62 classes.
```



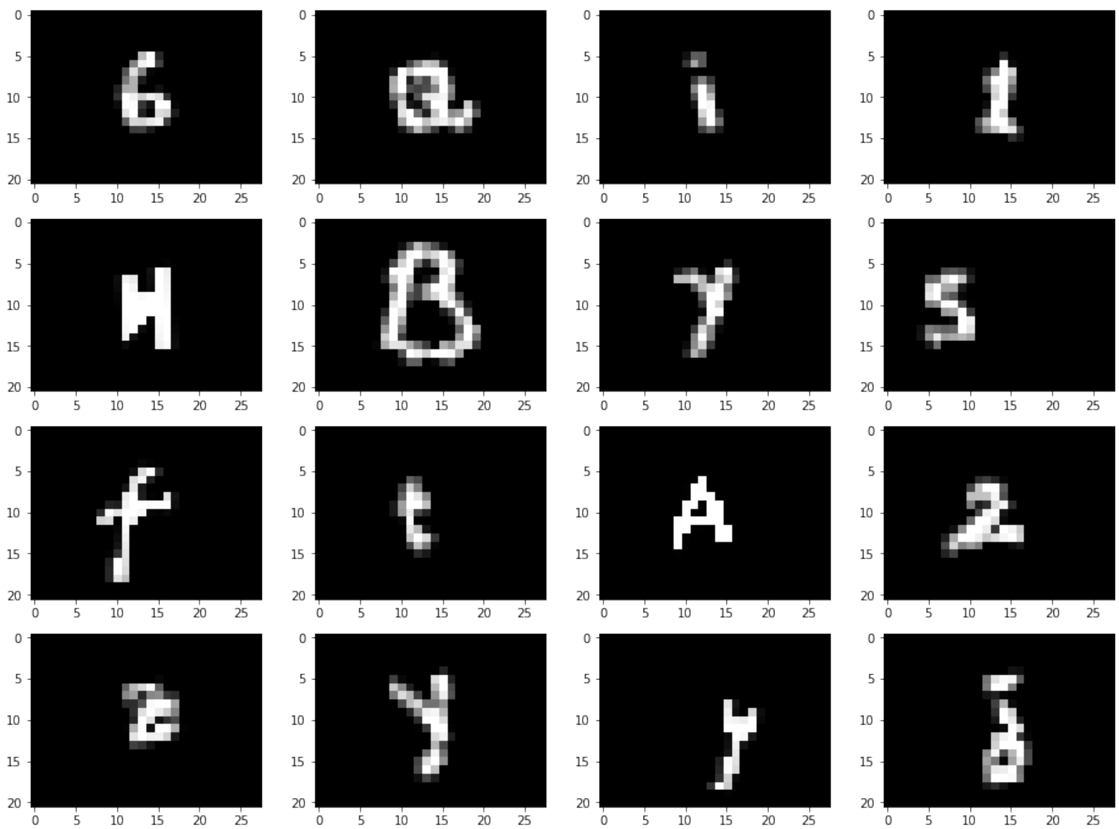
Checking rotation with max angle of 15

[ ]:
```
augmentation_test_rotation = ImageDataGenerator(rescale=1./255,␣
↪rotation_range=15, preprocessing_function=lambda x: 1-x)

augmentation_test_rotation_gen = augmentation_test_rotation.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        seed=42,
        shuffle=True)

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

```
Found 2480 images belonging to 62 classes.
```



Checking shear with max shear of 0.3

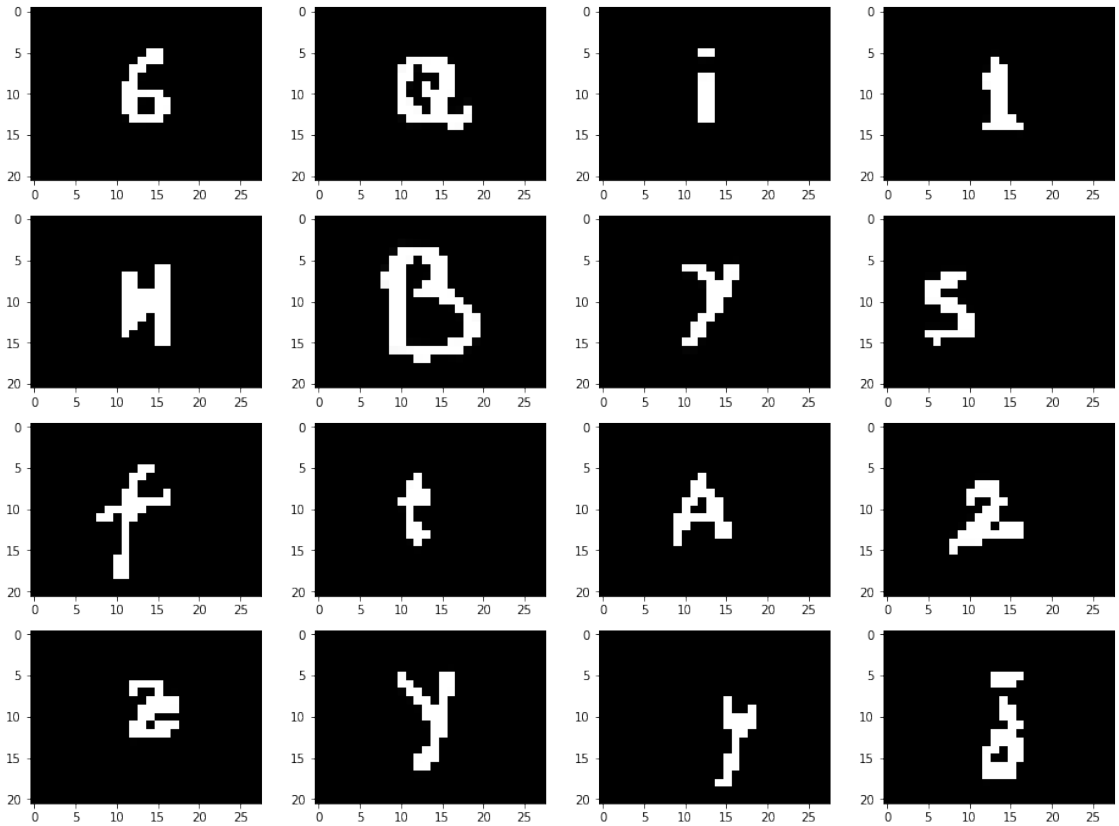
```
[ ]: augmentation_test_shear = ImageDataGenerator(rescale=1./255, shear_range=0.3,␣
     ↪preprocessing_function=lambda x: 1-x)

     augmentation_test_shear_gen = augmentation_test_shear.flow_from_directory(
             '../input/trainpart1zip/train',
             target_size=IMAGE_SIZE,
             batch_size=BATCH_SIZE,
             class_mode='categorical',
             color_mode='grayscale',
             seed=42,
             shuffle=True)

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

```
plt.show()
```

```
Found 2480 images belonging to 62 classes.
```



Checking zoom with max zoom of 0.2

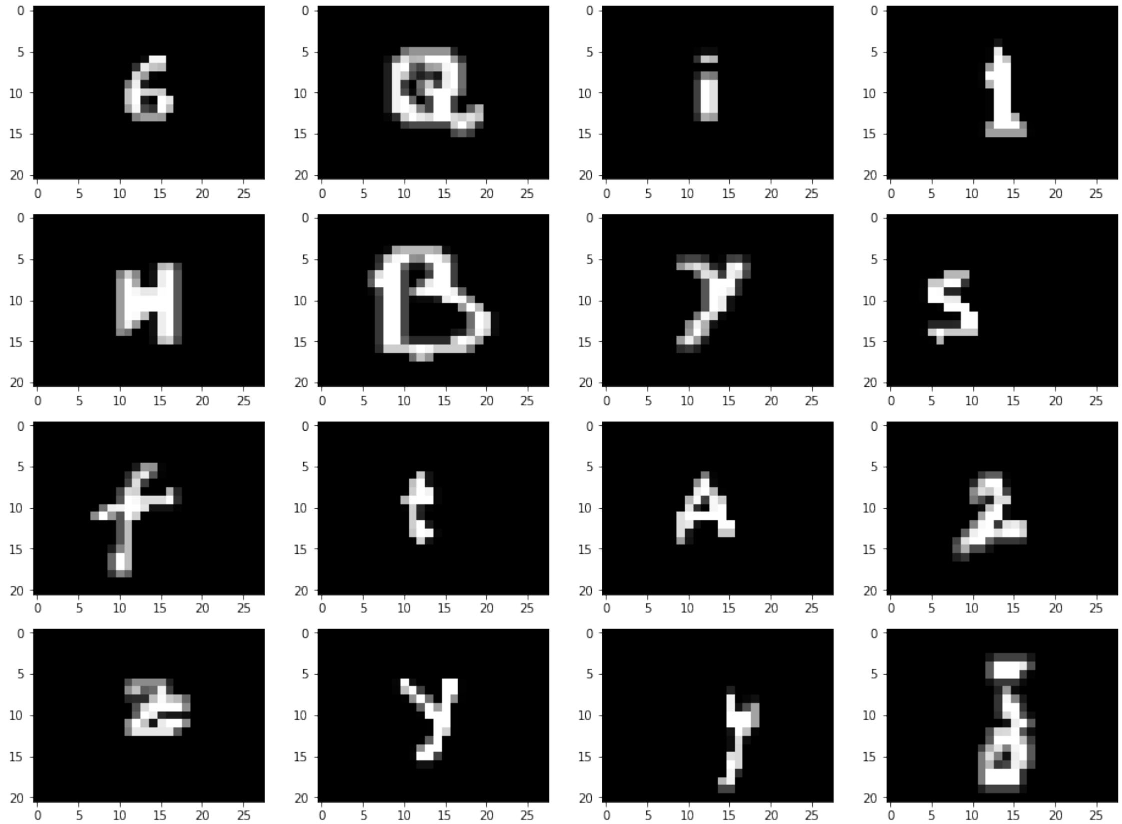
```
[ ]: augmentation_test_zoom = ImageDataGenerator(rescale=1./255, zoom_range=0.2,␣
 ↪preprocessing_function=lambda x: 1-x)

augmentation_test_zoom_gen = augmentation_test_zoom.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        seed=42,
        shuffle=True)

X_aug_zoom, _ = augmentation_test_zoom_gen.next()
plt.figure(figsize=(16,12))
for i in range(1, 17):
```

```
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_aug_zoom[i]), cmap='gray')
plt.show()
```

Found 2480 images belonging to 62 classes.



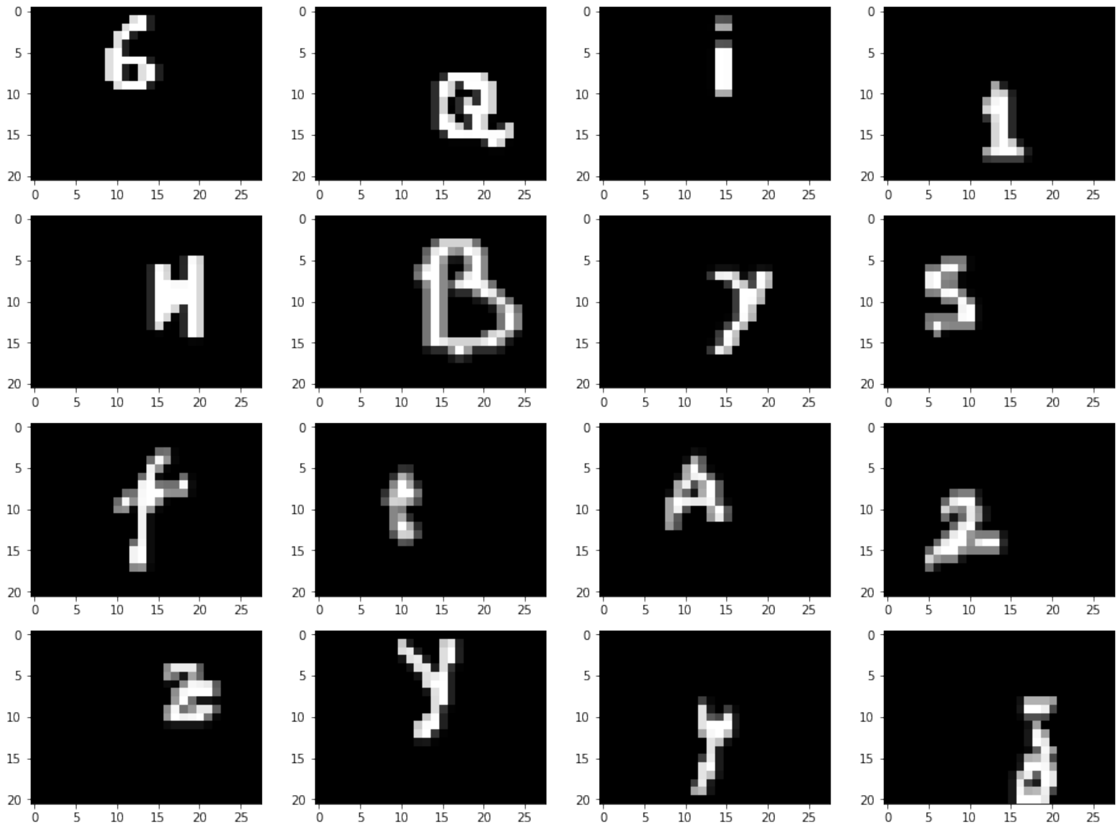
Checking with horizontal and vertical shift of 0.2

[ ]:
```
augmentation_test_shift = ImageDataGenerator(rescale=1./255,␣
↪width_shift_range=0.2, height_shift_range=0.2, preprocessing_function=lambda␣
↪x: 1-x)

augmentation_test_shift_gen = augmentation_test_shift.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        seed=42,
        shuffle=True)
```

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

```
Found 2480 images belonging to 62 classes.
```



Conclusion: On what augmentation to choose These augmentations don't turn out very well. They look very different form the training data. I think the closest is the shear, but there's no noticeable effect that I can see from the naked eye. I think I'll still go on with a little of shear and a little of rotation and see how the model performs.

[ ]:
```
train_datagen2 = ImageDataGenerator(
    rescale=1./255,
    validation_split=0.2,
    shear_range=0.1,
    rotation_range=0.5,
    preprocessing_function=lambda x: 1-x)
```

```
validation_datagen2 = ImageDataGenerator(
    rescale=1./255,
    validation_split=0.2,
    preprocessing_function=lambda x: 1-x)
```

[ ]:
```
train_generator2 = train_datagen2.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        subset='training',
        seed=42,
        shuffle=True)
```

```
Found 1984 images belonging to 62 classes.
```

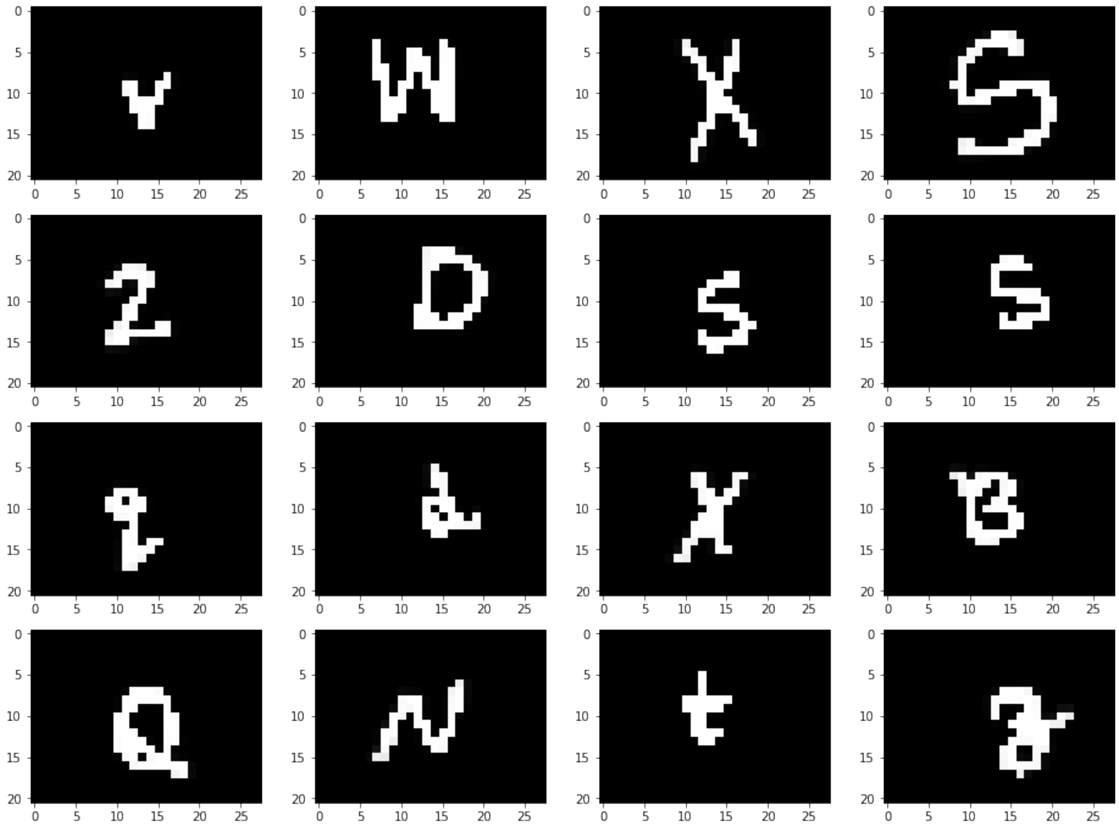
[ ]:
```
validation_generator2 = validation_datagen2.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        subset='validation',
        seed=42,
        shuffle=True)
```

```
Found 496 images belonging to 62 classes.
```

Viewing the Generated samples

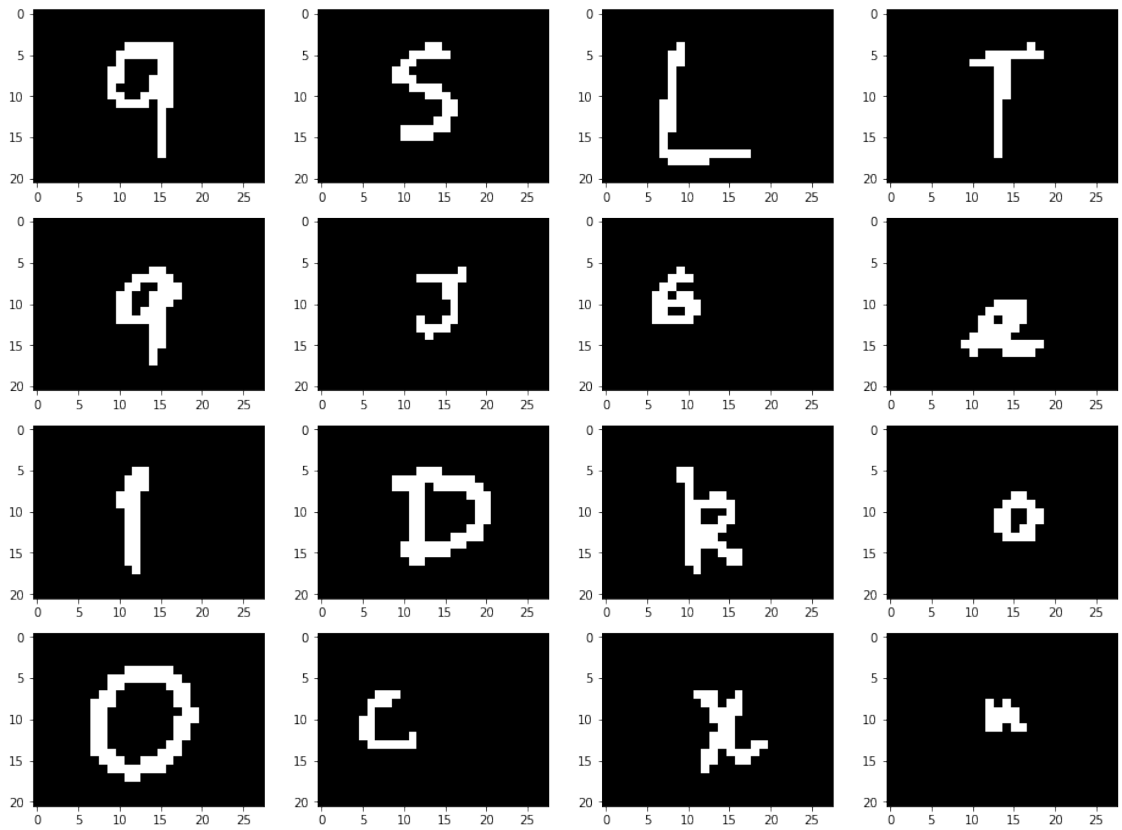
[ ]:
```
X_train_batch0, y_train_batch0 = train_generator2.next()
print(X_train_batch0.shape, y_train_batch0.shape)
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_train_batch0[i]), cmap='gray')
plt.show()
```

```
(64, 21, 28, 1) (64, 62)
```



```
[ ]: X_validation_batch0, y_validation_batch0 = validation_generator2.next()
print(X_validation_batch0.shape, y_validation_batch0.shape)
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_validation_batch0[i]), cmap='gray')
plt.show()
```

```
(64, 21, 28, 1) (64, 62)
```



Using the same architecture as before

[ ]:
```
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, 1)))

# 1st Convolution Layer
model2.add(Conv2D(6, kernel_size=(5,5), padding='same', activation='relu'))
model2.add(BatchNormalization())
model2.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
model2.add(Conv2D(16, kernel_size=(5,5), activation='relu'))
model2.add(BatchNormalization())
model2.add(MaxPooling2D(pool_size=(2,2), strides=2))

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

```
# 1st Fully Connected Layer
model2.add(Dense(256, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))

# 2nd Fully Connected Layer
model2.add(Dense(128, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.4))

# Output Layer
model2.add(Dense(62, activation='softmax'))
```

[ ]:
```
model2.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_3 (Lambda)            (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 28, 28, 6)         156
_________________________________________________________________
batch_normalization_12 (Batc (None, 28, 28, 6)         24
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 14, 14, 6)         0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 10, 10, 16)        2416
_________________________________________________________________
batch_normalization_13 (Batc (None, 10, 10, 16)        64
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 5, 5, 16)          0
_________________________________________________________________
flatten_3 (Flatten)          (None, 400)               0
_________________________________________________________________
dense_9 (Dense)              (None, 256)               102656
_________________________________________________________________
batch_normalization_14 (Batc (None, 256)               1024
_________________________________________________________________
dropout_6 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_10 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_15 (Batc (None, 128)               512
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0
_________________________________________________________________
```

```
dense_11 (Dense)              (None, 62)              7998
=================================================================
Total params: 147,746
Trainable params: 146,934
Non-trainable params: 812
_________________________________________________________________
```

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

Saving the checkpoint

```
[ ]: checkpoint_filepath2 = 'exp2/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_generator2,
         epochs=EPOCHS,
         validation_data=validation_generator2,
         steps_per_epoch = train_generator2.samples // BATCH_SIZE,
         validation_steps = validation_generator2.samples // BATCH_SIZE,
         callbacks=[model_checkpoint_callback2, early_stopping_callback]
     )
```

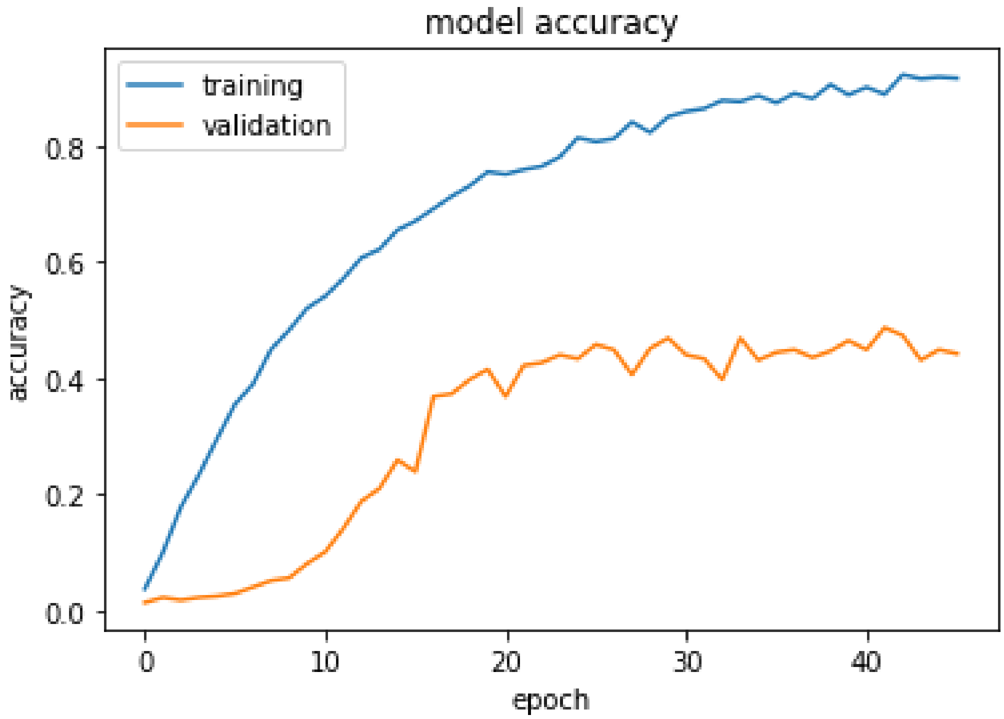
```
Epoch 1/400
31/31 [==============================] - 39s 1s/step - loss: 4.9179 - accuracy:
0.0292 - val_loss: 4.1171 - val_accuracy: 0.0134
Epoch 2/400
31/31 [==============================] - 37s 1s/step - loss: 3.9544 - accuracy:
0.0845 - val_loss: 4.2481 - val_accuracy: 0.0223
Epoch 3/400
31/31 [==============================] - 37s 1s/step - loss: 3.3298 - accuracy:
0.1834 - val_loss: 4.4117 - val_accuracy: 0.0179
Epoch 4/400
31/31 [==============================] - 37s 1s/step - loss: 2.9691 - accuracy:
0.2378 - val_loss: 4.4836 - val_accuracy: 0.0223
Epoch 5/400
31/31 [==============================] - 37s 1s/step - loss: 2.7160 - accuracy:
0.3004 - val_loss: 4.7244 - val_accuracy: 0.0246
Epoch 6/400
31/31 [==============================] - 37s 1s/step - loss: 2.4925 - accuracy:
0.3474 - val_loss: 4.7267 - val_accuracy: 0.0290
Epoch 7/400
```

```
31/31 [==============================] - 38s 1s/step - loss: 2.2964 - accuracy:
0.3897 - val_loss: 4.6166 - val_accuracy: 0.0402
Epoch 8/400
31/31 [==============================] - 38s 1s/step - loss: 2.0821 - accuracy:
0.4473 - val_loss: 4.4550 - val_accuracy: 0.0513
Epoch 9/400
31/31 [==============================] - 38s 1s/step - loss: 1.9095 - accuracy:
0.4767 - val_loss: 4.4226 - val_accuracy: 0.0558
Epoch 10/400
31/31 [==============================] - 38s 1s/step - loss: 1.7685 - accuracy:
0.5219 - val_loss: 4.1272 - val_accuracy: 0.0804
Epoch 11/400
31/31 [==============================] - 38s 1s/step - loss: 1.6479 - accuracy:
0.5503 - val_loss: 3.9994 - val_accuracy: 0.1004
Epoch 12/400
31/31 [==============================] - 38s 1s/step - loss: 1.5627 - accuracy:
0.5729 - val_loss: 3.7159 - val_accuracy: 0.1406
Epoch 13/400
31/31 [==============================] - 38s 1s/step - loss: 1.4425 - accuracy:
0.6084 - val_loss: 3.3262 - val_accuracy: 0.1875
Epoch 14/400
31/31 [==============================] - 38s 1s/step - loss: 1.3613 - accuracy:
0.6108 - val_loss: 3.2196 - val_accuracy: 0.2098
Epoch 15/400
31/31 [==============================] - 38s 1s/step - loss: 1.2495 - accuracy:
0.6619 - val_loss: 3.0782 - val_accuracy: 0.2589
Epoch 16/400
31/31 [==============================] - 38s 1s/step - loss: 1.1788 - accuracy:
0.6728 - val_loss: 3.0833 - val_accuracy: 0.2388
Epoch 17/400
31/31 [==============================] - 38s 1s/step - loss: 1.0816 - accuracy:
0.6973 - val_loss: 2.4277 - val_accuracy: 0.3683
Epoch 18/400
31/31 [==============================] - 38s 1s/step - loss: 1.0507 - accuracy:
0.7043 - val_loss: 2.5340 - val_accuracy: 0.3728
Epoch 19/400
31/31 [==============================] - 38s 1s/step - loss: 0.9735 - accuracy:
0.7281 - val_loss: 2.3432 - val_accuracy: 0.3973
Epoch 20/400
31/31 [==============================] - 38s 1s/step - loss: 0.8633 - accuracy:
0.7548 - val_loss: 2.2234 - val_accuracy: 0.4152
Epoch 21/400
31/31 [==============================] - 38s 1s/step - loss: 0.9129 - accuracy:
0.7495 - val_loss: 2.4204 - val_accuracy: 0.3683
Epoch 22/400
31/31 [==============================] - 38s 1s/step - loss: 0.8618 - accuracy:
0.7651 - val_loss: 2.1153 - val_accuracy: 0.4219
Epoch 23/400
```

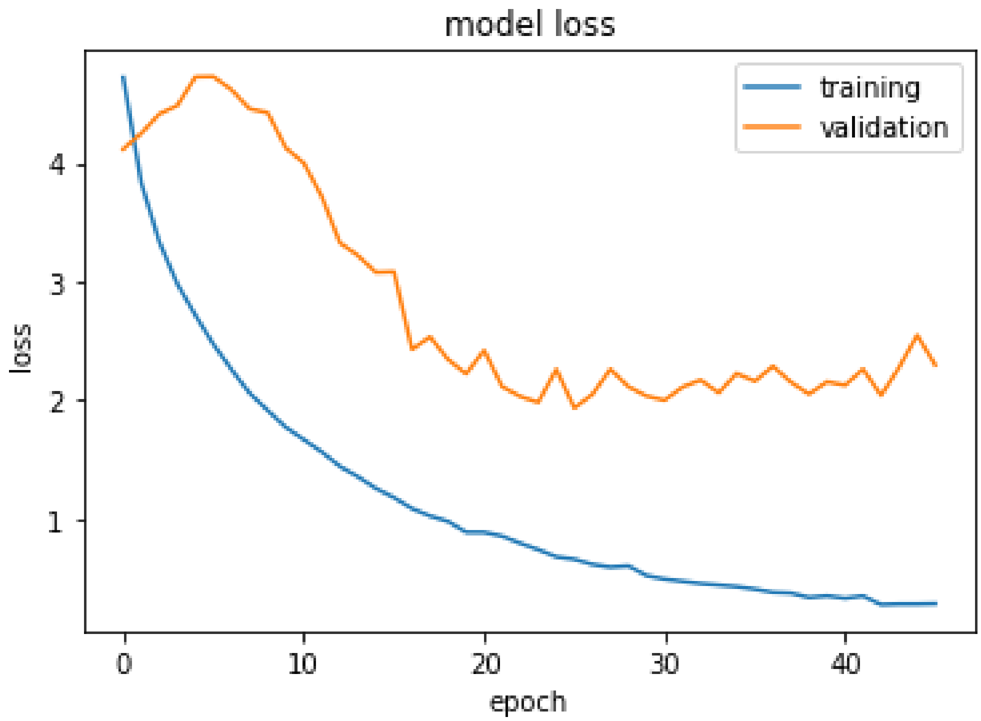
```
31/31 [==============================] - 38s 1s/step - loss: 0.7984 - accuracy:
0.7648 - val_loss: 2.0327 - val_accuracy: 0.4263
Epoch 24/400
31/31 [==============================] - 38s 1s/step - loss: 0.7360 - accuracy:
0.7823 - val_loss: 1.9827 - val_accuracy: 0.4397
Epoch 25/400
31/31 [==============================] - 38s 1s/step - loss: 0.6709 - accuracy:
0.8152 - val_loss: 2.2615 - val_accuracy: 0.4330
Epoch 26/400
31/31 [==============================] - 38s 1s/step - loss: 0.6548 - accuracy:
0.8148 - val_loss: 1.9355 - val_accuracy: 0.4576
Epoch 27/400
31/31 [==============================] - 38s 1s/step - loss: 0.5771 - accuracy:
0.8309 - val_loss: 2.0500 - val_accuracy: 0.4487
Epoch 28/400
31/31 [==============================] - 38s 1s/step - loss: 0.5515 - accuracy:
0.8555 - val_loss: 2.2629 - val_accuracy: 0.4062
Epoch 29/400
31/31 [==============================] - 38s 1s/step - loss: 0.6068 - accuracy:
0.8217 - val_loss: 2.1148 - val_accuracy: 0.4509
Epoch 30/400
31/31 [==============================] - 38s 1s/step - loss: 0.5225 - accuracy:
0.8474 - val_loss: 2.0364 - val_accuracy: 0.4688
Epoch 31/400
31/31 [==============================] - 38s 1s/step - loss: 0.4543 - accuracy:
0.8794 - val_loss: 2.0007 - val_accuracy: 0.4397
Epoch 32/400
31/31 [==============================] - 38s 1s/step - loss: 0.4583 - accuracy:
0.8642 - val_loss: 2.1119 - val_accuracy: 0.4330
Epoch 33/400
31/31 [==============================] - 38s 1s/step - loss: 0.4582 - accuracy:
0.8802 - val_loss: 2.1717 - val_accuracy: 0.3973
Epoch 34/400
31/31 [==============================] - 38s 1s/step - loss: 0.4106 - accuracy:
0.8962 - val_loss: 2.0637 - val_accuracy: 0.4688
Epoch 35/400
31/31 [==============================] - 38s 1s/step - loss: 0.4293 - accuracy:
0.8870 - val_loss: 2.2267 - val_accuracy: 0.4308
Epoch 36/400
31/31 [==============================] - 38s 1s/step - loss: 0.3922 - accuracy:
0.8794 - val_loss: 2.1612 - val_accuracy: 0.4442
Epoch 37/400
31/31 [==============================] - 38s 1s/step - loss: 0.3878 - accuracy:
0.8886 - val_loss: 2.2871 - val_accuracy: 0.4487
Epoch 38/400
31/31 [==============================] - 38s 1s/step - loss: 0.3509 - accuracy:
0.8957 - val_loss: 2.1536 - val_accuracy: 0.4353
Epoch 39/400
```

```
31/31 [==============================] - 38s 1s/step - loss: 0.3231 - accuracy:
0.9113 - val_loss: 2.0523 - val_accuracy: 0.4464
Epoch 40/400
31/31 [==============================] - 37s 1s/step - loss: 0.3275 - accuracy:
0.8947 - val_loss: 2.1564 - val_accuracy: 0.4643
Epoch 41/400
31/31 [==============================] - 37s 1s/step - loss: 0.3112 - accuracy:
0.9133 - val_loss: 2.1274 - val_accuracy: 0.4487
Epoch 42/400
31/31 [==============================] - 37s 1s/step - loss: 0.3607 - accuracy:
0.8859 - val_loss: 2.2628 - val_accuracy: 0.4866
Epoch 43/400
31/31 [==============================] - 37s 1s/step - loss: 0.2897 - accuracy:
0.9185 - val_loss: 2.0414 - val_accuracy: 0.4732
Epoch 44/400
31/31 [==============================] - 37s 1s/step - loss: 0.2757 - accuracy:
0.9142 - val_loss: 2.2787 - val_accuracy: 0.4308
Epoch 45/400
31/31 [==============================] - 38s 1s/step - loss: 0.2898 - accuracy:
0.9170 - val_loss: 2.5477 - val_accuracy: 0.4487
Epoch 46/400
31/31 [==============================] - 38s 1s/step - loss: 0.2611 - accuracy:
0.9306 - val_loss: 2.2970 - val_accuracy: 0.4420
Restoring model weights from the end of the best epoch.
Epoch 00046: early stopping
```

[ ]:
```
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.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()
```



There's no visible improvements, than the first experiment. I think this is so becuase in this case, even slightly augmenting data leads to larger variations and since we don't have a lot of training samples, it still overfits to this data and does not generalize well on the validation set. So, I'll not use regularization in further experiments.

1.3.3 Experiment 3: Using different activation function: Mish

From refs. [4] and [5], I will use the new Mish activation over ReLU. I'll use the training samples from first experiment as they gave better results than the second experiment and will use the same activation.

[11]:
```
# Mish Activation Function
def mish(x):
    return tf.keras.layers.Lambda(lambda x: x*tf.tanh(tf.math.log(1+tf.
 ↪exp(x))))(x)
```

[ ]:
```
model3 = Sequential()

# Lambda Layer for adding Padding
model3.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE, 1)))

# 1st Convolution Layer
model3.add(Conv2D(6, kernel_size=(5,5), padding='same', activation='relu'))
```

```python
model3.add(BatchNormalization())
model3.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
model3.add(Conv2D(16, kernel_size=(5,5), activation=mish))
model3.add(BatchNormalization())
model3.add(MaxPooling2D(pool_size=(2,2), strides=2))

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

# 1st Fully Connected Layer
model3.add(Dense(256, activation=mish))
model3.add(BatchNormalization())
model3.add(Dropout(0.4))

# 2nd Fully Connected Layer
model3.add(Dense(128, activation=mish))
model3.add(BatchNormalization())
model3.add(Dropout(0.4))

# Output Layer
model3.add(Dense(62, activation='softmax'))
```

[ ]:
```python
model3.summary()
```

```
Model: "sequential_9"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_7 (Lambda)            (None, 28, 28, 1)         0

_________________________________________________________________
conv2d_9 (Conv2D)            (None, 28, 28, 6)         156

_________________________________________________________________
batch_normalization_16 (Batc (None, 28, 28, 6)         24

_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 14, 14, 6)         0

_________________________________________________________________
conv2d_10 (Conv2D)           (None, 10, 10, 16)        2416

_________________________________________________________________
batch_normalization_17 (Batc (None, 10, 10, 16)        64

_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 5, 5, 16)          0

_________________________________________________________________
flatten_4 (Flatten)          (None, 400)               0

_________________________________________________________________
dense_12 (Dense)             (None, 256)               102656
```

```
_________________________________________________________________
batch_normalization_18 (Batc (None, 256)               1024
_________________________________________________________________
dropout_8 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_13 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_19 (Batc (None, 128)               512
_________________________________________________________________
dropout_9 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_14 (Dense)             (None, 62)                7998
=================================================================
Total params: 147,746
Trainable params: 146,934
Non-trainable params: 812
_________________________________________________________________
```

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

Saving the checkpoint

[ ]:
```
checkpoint_filepath3 = 'exp3/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_generator1,
    epochs=EPOCHS,
    validation_data=validation_generator1,
    steps_per_epoch = train_generator1.samples // BATCH_SIZE,
    validation_steps = validation_generator1.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback3, early_stopping_callback]
)
```

```
Epoch 1/400
31/31 [==============================] - 40s 1s/step - loss: 4.9238 - accuracy:
0.0266 - val_loss: 4.1515 - val_accuracy: 0.0134
Epoch 2/400
31/31 [==============================] - 37s 1s/step - loss: 3.8077 - accuracy:
0.0993 - val_loss: 4.2567 - val_accuracy: 0.0156
Epoch 3/400
31/31 [==============================] - 37s 1s/step - loss: 3.2195 - accuracy:
```

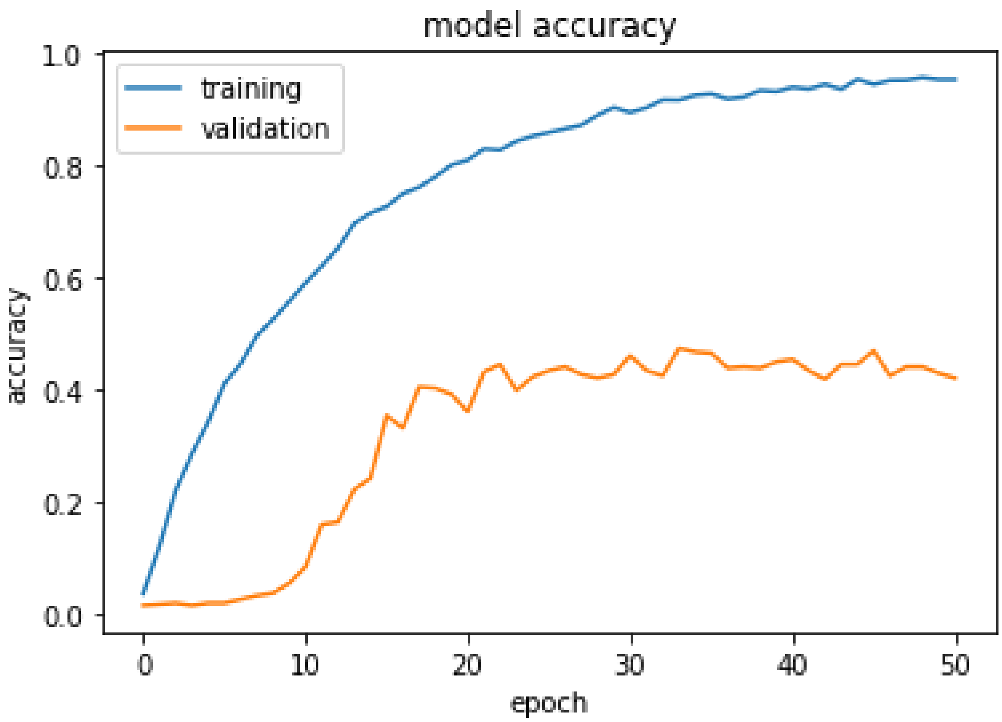
```
0.1945 - val_loss: 4.3816 - val_accuracy: 0.0179
Epoch 4/400
31/31 [==============================] - 37s 1s/step - loss: 2.8448 - accuracy:
0.2681 - val_loss: 4.4611 - val_accuracy: 0.0134
Epoch 5/400
31/31 [==============================] - 37s 1s/step - loss: 2.5315 - accuracy:
0.3386 - val_loss: 4.4283 - val_accuracy: 0.0179
Epoch 6/400
31/31 [==============================] - 37s 1s/step - loss: 2.2639 - accuracy:
0.4173 - val_loss: 4.4882 - val_accuracy: 0.0179
Epoch 7/400
31/31 [==============================] - 37s 1s/step - loss: 2.1102 - accuracy:
0.4271 - val_loss: 4.4642 - val_accuracy: 0.0246
Epoch 8/400
31/31 [==============================] - 37s 1s/step - loss: 1.9080 - accuracy:
0.4965 - val_loss: 4.4612 - val_accuracy: 0.0312
Epoch 9/400
31/31 [==============================] - 37s 1s/step - loss: 1.7929 - accuracy:
0.5288 - val_loss: 4.3792 - val_accuracy: 0.0357
Epoch 10/400
31/31 [==============================] - 37s 1s/step - loss: 1.6198 - accuracy:
0.5701 - val_loss: 4.1353 - val_accuracy: 0.0536
Epoch 11/400
31/31 [==============================] - 37s 1s/step - loss: 1.4427 - accuracy:
0.6180 - val_loss: 3.9084 - val_accuracy: 0.0826
Epoch 12/400
31/31 [==============================] - 37s 1s/step - loss: 1.3872 - accuracy:
0.6358 - val_loss: 3.5125 - val_accuracy: 0.1585
Epoch 13/400
31/31 [==============================] - 37s 1s/step - loss: 1.2686 - accuracy:
0.6511 - val_loss: 3.4489 - val_accuracy: 0.1629
Epoch 14/400
31/31 [==============================] - 37s 1s/step - loss: 1.1243 - accuracy:
0.7029 - val_loss: 3.1760 - val_accuracy: 0.2210
Epoch 15/400
31/31 [==============================] - 37s 1s/step - loss: 1.0083 - accuracy:
0.7348 - val_loss: 3.0905 - val_accuracy: 0.2411
Epoch 16/400
31/31 [==============================] - 38s 1s/step - loss: 1.0226 - accuracy:
0.7115 - val_loss: 2.5326 - val_accuracy: 0.3527
Epoch 17/400
31/31 [==============================] - 37s 1s/step - loss: 0.9417 - accuracy:
0.7337 - val_loss: 2.6130 - val_accuracy: 0.3304
Epoch 18/400
31/31 [==============================] - 37s 1s/step - loss: 0.8189 - accuracy:
0.7852 - val_loss: 2.3660 - val_accuracy: 0.4040
Epoch 19/400
31/31 [==============================] - 37s 1s/step - loss: 0.7793 - accuracy:
```

```
0.7889 - val_loss: 2.2848 - val_accuracy: 0.4018
Epoch 20/400
31/31 [==============================] - 37s 1s/step - loss: 0.7237 - accuracy:
0.8143 - val_loss: 2.3281 - val_accuracy: 0.3906
Epoch 21/400
31/31 [==============================] - 37s 1s/step - loss: 0.7046 - accuracy:
0.8139 - val_loss: 2.6179 - val_accuracy: 0.3594
Epoch 22/400
31/31 [==============================] - 37s 1s/step - loss: 0.6245 - accuracy:
0.8436 - val_loss: 2.1490 - val_accuracy: 0.4308
Epoch 23/400
31/31 [==============================] - 37s 1s/step - loss: 0.5827 - accuracy:
0.8399 - val_loss: 2.1528 - val_accuracy: 0.4442
Epoch 24/400
31/31 [==============================] - 37s 1s/step - loss: 0.5779 - accuracy:
0.8506 - val_loss: 2.3637 - val_accuracy: 0.3973
Epoch 25/400
31/31 [==============================] - 37s 1s/step - loss: 0.5390 - accuracy:
0.8463 - val_loss: 2.3321 - val_accuracy: 0.4219
Epoch 26/400
31/31 [==============================] - 37s 1s/step - loss: 0.5005 - accuracy:
0.8700 - val_loss: 2.1540 - val_accuracy: 0.4330
Epoch 27/400
31/31 [==============================] - 37s 1s/step - loss: 0.5079 - accuracy:
0.8603 - val_loss: 2.1453 - val_accuracy: 0.4397
Epoch 28/400
31/31 [==============================] - 36s 1s/step - loss: 0.4628 - accuracy:
0.8690 - val_loss: 2.2682 - val_accuracy: 0.4263
Epoch 29/400
31/31 [==============================] - 36s 1s/step - loss: 0.4201 - accuracy:
0.8810 - val_loss: 2.3403 - val_accuracy: 0.4196
Epoch 30/400
31/31 [==============================] - 36s 1s/step - loss: 0.3814 - accuracy:
0.9025 - val_loss: 2.2534 - val_accuracy: 0.4263
Epoch 31/400
31/31 [==============================] - 36s 1s/step - loss: 0.3789 - accuracy:
0.9030 - val_loss: 2.1394 - val_accuracy: 0.4598
Epoch 32/400
31/31 [==============================] - 37s 1s/step - loss: 0.3672 - accuracy:
0.9033 - val_loss: 2.4519 - val_accuracy: 0.4330
Epoch 33/400
31/31 [==============================] - 37s 1s/step - loss: 0.3402 - accuracy:
0.9130 - val_loss: 2.4075 - val_accuracy: 0.4241
Epoch 34/400
31/31 [==============================] - 37s 1s/step - loss: 0.3090 - accuracy:
0.9154 - val_loss: 2.2416 - val_accuracy: 0.4732
Epoch 35/400
31/31 [==============================] - 37s 1s/step - loss: 0.2895 - accuracy:
```

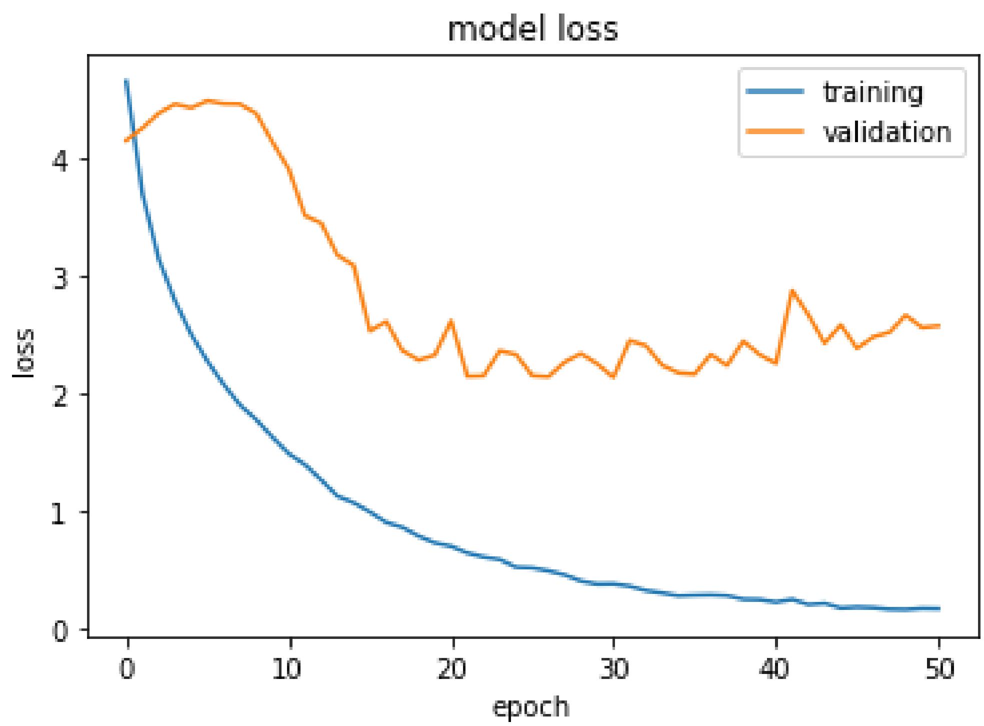
```
0.9247 - val_loss: 2.1780 - val_accuracy: 0.4665
Epoch 36/400
31/31 [==============================] - 37s 1s/step - loss: 0.3024 - accuracy:
0.9267 - val_loss: 2.1670 - val_accuracy: 0.4643
Epoch 37/400
31/31 [==============================] - 37s 1s/step - loss: 0.2943 - accuracy:
0.9190 - val_loss: 2.3336 - val_accuracy: 0.4375
Epoch 38/400
31/31 [==============================] - 37s 1s/step - loss: 0.2721 - accuracy:
0.9259 - val_loss: 2.2386 - val_accuracy: 0.4397
Epoch 39/400
31/31 [==============================] - 37s 1s/step - loss: 0.2492 - accuracy:
0.9399 - val_loss: 2.4461 - val_accuracy: 0.4375
Epoch 40/400
31/31 [==============================] - 37s 1s/step - loss: 0.2537 - accuracy:
0.9271 - val_loss: 2.3309 - val_accuracy: 0.4487
Epoch 41/400
31/31 [==============================] - 37s 1s/step - loss: 0.2149 - accuracy:
0.9474 - val_loss: 2.2564 - val_accuracy: 0.4531
Epoch 42/400
31/31 [==============================] - 37s 1s/step - loss: 0.2330 - accuracy:
0.9441 - val_loss: 2.8769 - val_accuracy: 0.4330
Epoch 43/400
31/31 [==============================] - 37s 1s/step - loss: 0.1878 - accuracy:
0.9553 - val_loss: 2.6698 - val_accuracy: 0.4174
Epoch 44/400
31/31 [==============================] - 37s 1s/step - loss: 0.2190 - accuracy:
0.9330 - val_loss: 2.4294 - val_accuracy: 0.4442
Epoch 45/400
31/31 [==============================] - 37s 1s/step - loss: 0.1724 - accuracy:
0.9581 - val_loss: 2.5843 - val_accuracy: 0.4442
Epoch 46/400
31/31 [==============================] - 36s 1s/step - loss: 0.1778 - accuracy:
0.9464 - val_loss: 2.3843 - val_accuracy: 0.4688
Epoch 47/400
31/31 [==============================] - 36s 1s/step - loss: 0.1820 - accuracy:
0.9528 - val_loss: 2.4827 - val_accuracy: 0.4241
Epoch 48/400
31/31 [==============================] - 36s 1s/step - loss: 0.1540 - accuracy:
0.9590 - val_loss: 2.5212 - val_accuracy: 0.4397
Epoch 49/400
31/31 [==============================] - 36s 1s/step - loss: 0.1612 - accuracy:
0.9595 - val_loss: 2.6670 - val_accuracy: 0.4397
Epoch 50/400
31/31 [==============================] - 36s 1s/step - loss: 0.1595 - accuracy:
0.9595 - val_loss: 2.5618 - val_accuracy: 0.4286
Epoch 51/400
31/31 [==============================] - 36s 1s/step - loss: 0.1643 - accuracy:
```

```
0.9547 - val_loss: 2.5758 - val_accuracy: 0.4196
Restoring model weights from the end of the best epoch.
Epoch 00051: early stopping
```

[ ]:
```
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.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()
```



This model performs "slightly" better than our model from Experiment 1 and also does so in less epochs. However, there is some variance as the model overfits. We used early stopping with patience level 20, so our model gives best results at around epoch 31.

1.3.4 Experiment 4: Using higher temperature in Softmax

Higher temperature in softmax helps get 'softer' weights. This can help improve accuracy further as the 'probability' is nor more evenly distributed across the classes.

[12]:
```
model4 = Sequential()

# Lambda Layer for adding Padding
model4.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE, 1)))

# 1st Convolution Layer
model4.add(Conv2D(6, kernel_size=(5,5), padding='same', activation='relu'))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
model4.add(Conv2D(16, kernel_size=(5,5), activation=mish))
model4.add(BatchNormalization())
model4.add(MaxPooling2D(pool_size=(2,2), strides=2))
```

```python
# Passing to a Fully Connected Layer
model4.add(Flatten())

# 1st Fully Connected Layer
model4.add(Dense(256, activation=mish))
model4.add(BatchNormalization())
model4.add(Dropout(0.4))

# 2nd Fully Connected Layer
model4.add(Dense(128, activation=mish))
model4.add(BatchNormalization())
model4.add(Dropout(0.4))

# Output Layer
# Increasing the softmax temperature
temp = 5
model4.add(Lambda(lambda x: x / temp))
model4.add(Dense(62, activation='softmax'))
```

[13]:
```python
model4.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_1 (Lambda)            (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 28, 28, 6)         156
_________________________________________________________________
batch_normalization_1 (Batch (None, 28, 28, 6)         24
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 6)         0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 10, 10, 16)        2416
_________________________________________________________________
batch_normalization_2 (Batch (None, 10, 10, 16)        64
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 16)          0
_________________________________________________________________
flatten (Flatten)            (None, 400)               0
_________________________________________________________________
dense (Dense)                (None, 256)               102656
_________________________________________________________________
batch_normalization_3 (Batch (None, 256)               1024
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
```

```
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
_________________________________________________________________
batch_normalization_4 (Batch (None, 128)               512
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
lambda_2 (Lambda)            (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 62)                7998
=================================================================
Total params: 147,746
Trainable params: 146,934
Non-trainable params: 812
_________________________________________________________________
```

[14]:

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

[15]:

```
checkpoint_filepath4 = 'exp4/checkpoint'
model_checkpoint_callback4 = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath4,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)
```

[16]:

```
history4 = model4.fit(
    train_generator1,
    epochs=EPOCHS,
    validation_data=validation_generator1,
    steps_per_epoch = train_generator1.samples // BATCH_SIZE,
    validation_steps = validation_generator1.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback4, early_stopping_callback]
)
```

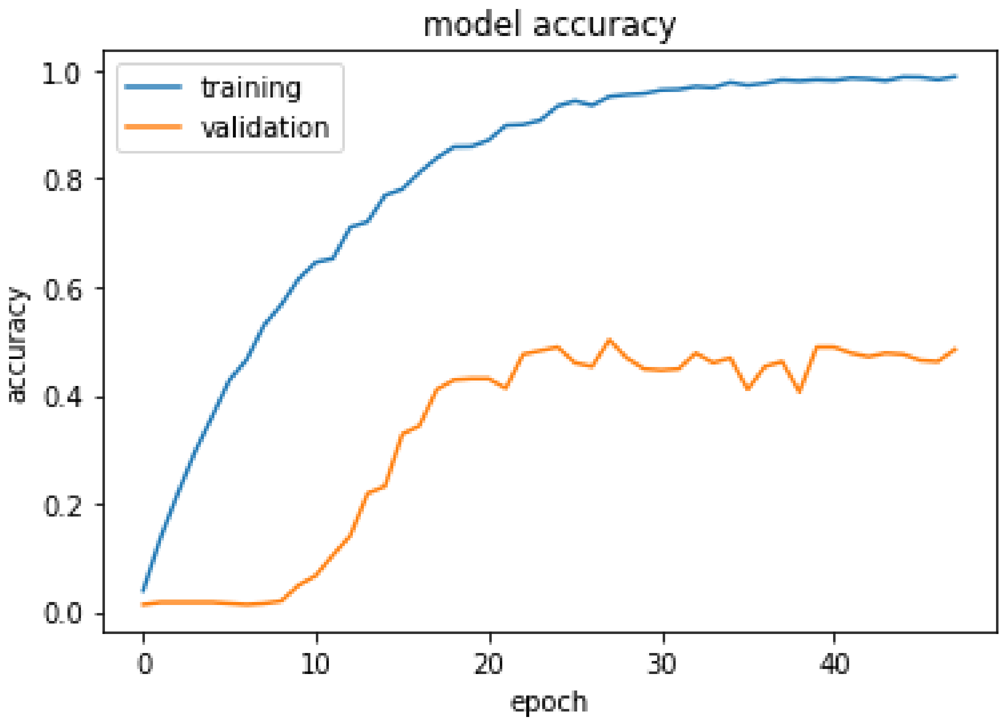
```
Epoch 1/400
31/31 [==============================] - 63s 991ms/step - loss: 4.1323 -
accuracy: 0.0277 - val_loss: 4.1238 - val_accuracy: 0.0134
Epoch 2/400
31/31 [==============================] - 30s 980ms/step - loss: 3.8507 -
accuracy: 0.1154 - val_loss: 4.1265 - val_accuracy: 0.0179
Epoch 3/400
31/31 [==============================] - 30s 974ms/step - loss: 3.6529 -
accuracy: 0.2144 - val_loss: 4.1399 - val_accuracy: 0.0179
Epoch 4/400
31/31 [==============================] - 30s 977ms/step - loss: 3.4515 -
accuracy: 0.2855 - val_loss: 4.1655 - val_accuracy: 0.0179
```

```
Epoch 5/400
31/31 [==============================] - 30s 973ms/step - loss: 3.2286 -
accuracy: 0.3662 - val_loss: 4.1651 - val_accuracy: 0.0179
Epoch 6/400
31/31 [==============================] - 30s 973ms/step - loss: 3.0389 -
accuracy: 0.4318 - val_loss: 4.1768 - val_accuracy: 0.0156
Epoch 7/400
31/31 [==============================] - 30s 976ms/step - loss: 2.8271 -
accuracy: 0.4688 - val_loss: 4.1357 - val_accuracy: 0.0134
Epoch 8/400
31/31 [==============================] - 30s 971ms/step - loss: 2.6800 -
accuracy: 0.5179 - val_loss: 4.0965 - val_accuracy: 0.0156
Epoch 9/400
31/31 [==============================] - 30s 985ms/step - loss: 2.4400 -
accuracy: 0.5749 - val_loss: 4.0263 - val_accuracy: 0.0201
Epoch 10/400
31/31 [==============================] - 30s 973ms/step - loss: 2.2798 -
accuracy: 0.6201 - val_loss: 3.9638 - val_accuracy: 0.0491
Epoch 11/400
31/31 [==============================] - 30s 975ms/step - loss: 2.0604 -
accuracy: 0.6669 - val_loss: 3.7348 - val_accuracy: 0.0670
Epoch 12/400
31/31 [==============================] - 30s 981ms/step - loss: 1.9174 -
accuracy: 0.6509 - val_loss: 3.5989 - val_accuracy: 0.1049
Epoch 13/400
31/31 [==============================] - 30s 973ms/step - loss: 1.7477 -
accuracy: 0.7129 - val_loss: 3.4710 - val_accuracy: 0.1406
Epoch 14/400
31/31 [==============================] - 30s 972ms/step - loss: 1.6214 -
accuracy: 0.7249 - val_loss: 3.1647 - val_accuracy: 0.2188
Epoch 15/400
31/31 [==============================] - 30s 974ms/step - loss: 1.4487 -
accuracy: 0.7668 - val_loss: 3.0287 - val_accuracy: 0.2321
Epoch 16/400
31/31 [==============================] - 30s 973ms/step - loss: 1.2949 -
accuracy: 0.7949 - val_loss: 2.5981 - val_accuracy: 0.3281
Epoch 17/400
31/31 [==============================] - 30s 975ms/step - loss: 1.2116 -
accuracy: 0.8257 - val_loss: 2.5388 - val_accuracy: 0.3438
Epoch 18/400
31/31 [==============================] - 30s 980ms/step - loss: 1.0757 -
accuracy: 0.8483 - val_loss: 2.3304 - val_accuracy: 0.4107
Epoch 19/400
31/31 [==============================] - 30s 982ms/step - loss: 0.9624 -
accuracy: 0.8597 - val_loss: 2.2412 - val_accuracy: 0.4286
Epoch 20/400
31/31 [==============================] - 30s 977ms/step - loss: 0.8800 -
accuracy: 0.8718 - val_loss: 2.1417 - val_accuracy: 0.4308
```

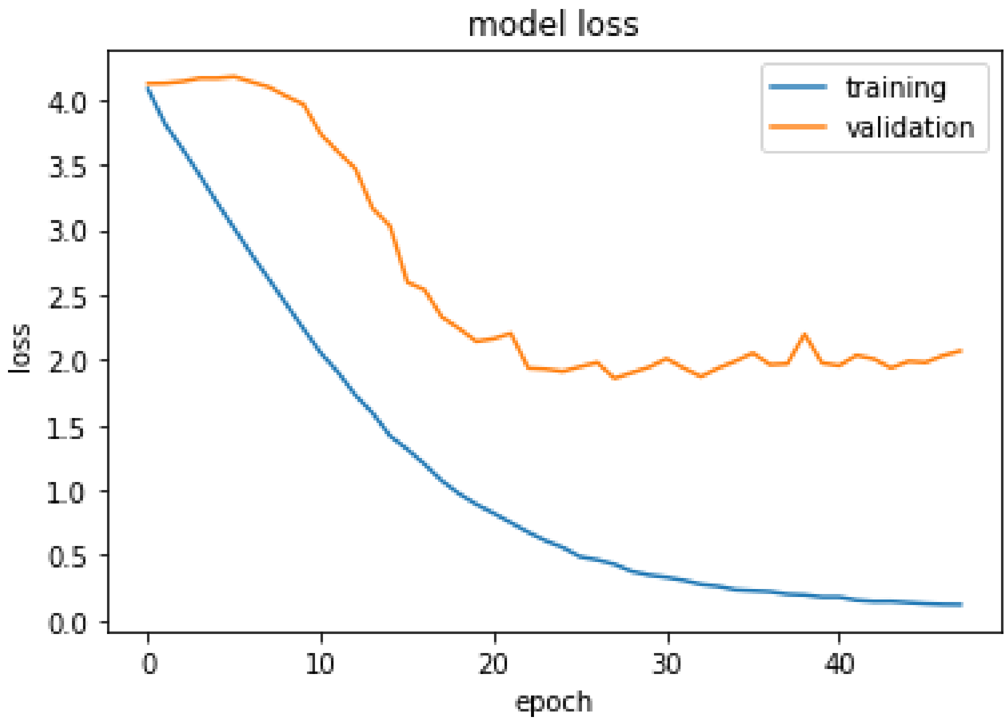
```
Epoch 21/400
31/31 [==============================] - 30s 974ms/step - loss: 0.8075 -
accuracy: 0.8760 - val_loss: 2.1626 - val_accuracy: 0.4308
Epoch 22/400
31/31 [==============================] - 30s 976ms/step - loss: 0.7716 -
accuracy: 0.8862 - val_loss: 2.2033 - val_accuracy: 0.4129
Epoch 23/400
31/31 [==============================] - 30s 976ms/step - loss: 0.6725 -
accuracy: 0.9092 - val_loss: 1.9373 - val_accuracy: 0.4754
Epoch 24/400
31/31 [==============================] - 30s 970ms/step - loss: 0.5959 -
accuracy: 0.9146 - val_loss: 1.9298 - val_accuracy: 0.4821
Epoch 25/400
31/31 [==============================] - 30s 974ms/step - loss: 0.5605 -
accuracy: 0.9423 - val_loss: 1.9122 - val_accuracy: 0.4888
Epoch 26/400
31/31 [==============================] - 30s 973ms/step - loss: 0.4715 -
accuracy: 0.9533 - val_loss: 1.9479 - val_accuracy: 0.4598
Epoch 27/400
31/31 [==============================] - 30s 970ms/step - loss: 0.4661 -
accuracy: 0.9359 - val_loss: 1.9799 - val_accuracy: 0.4531
Epoch 28/400
31/31 [==============================] - 30s 973ms/step - loss: 0.4278 -
accuracy: 0.9543 - val_loss: 1.8585 - val_accuracy: 0.5022
Epoch 29/400
31/31 [==============================] - 30s 978ms/step - loss: 0.3650 -
accuracy: 0.9591 - val_loss: 1.9026 - val_accuracy: 0.4688
Epoch 30/400
31/31 [==============================] - 30s 976ms/step - loss: 0.3498 -
accuracy: 0.9648 - val_loss: 1.9449 - val_accuracy: 0.4487
Epoch 31/400
31/31 [==============================] - 30s 973ms/step - loss: 0.3252 -
accuracy: 0.9624 - val_loss: 2.0093 - val_accuracy: 0.4464
Epoch 32/400
31/31 [==============================] - 30s 978ms/step - loss: 0.2969 -
accuracy: 0.9650 - val_loss: 1.9374 - val_accuracy: 0.4487
Epoch 33/400
31/31 [==============================] - 30s 972ms/step - loss: 0.2831 -
accuracy: 0.9660 - val_loss: 1.8723 - val_accuracy: 0.4777
Epoch 34/400
31/31 [==============================] - 30s 976ms/step - loss: 0.2665 -
accuracy: 0.9678 - val_loss: 1.9376 - val_accuracy: 0.4598
Epoch 35/400
31/31 [==============================] - 30s 972ms/step - loss: 0.2329 -
accuracy: 0.9817 - val_loss: 1.9904 - val_accuracy: 0.4688
Epoch 36/400
31/31 [==============================] - 30s 977ms/step - loss: 0.2290 -
accuracy: 0.9727 - val_loss: 2.0521 - val_accuracy: 0.4107
```

```
Epoch 37/400
31/31 [==============================] - 30s 980ms/step - loss: 0.2256 -
accuracy: 0.9739 - val_loss: 1.9637 - val_accuracy: 0.4531
Epoch 38/400
31/31 [==============================] - 30s 979ms/step - loss: 0.1992 -
accuracy: 0.9830 - val_loss: 1.9705 - val_accuracy: 0.4621
Epoch 39/400
31/31 [==============================] - 30s 983ms/step - loss: 0.1922 -
accuracy: 0.9827 - val_loss: 2.1982 - val_accuracy: 0.4062
Epoch 40/400
31/31 [==============================] - 30s 983ms/step - loss: 0.1709 -
accuracy: 0.9852 - val_loss: 1.9766 - val_accuracy: 0.4888
Epoch 41/400
31/31 [==============================] - 30s 975ms/step - loss: 0.1803 -
accuracy: 0.9800 - val_loss: 1.9562 - val_accuracy: 0.4888
Epoch 42/400
31/31 [==============================] - 30s 982ms/step - loss: 0.1542 -
accuracy: 0.9809 - val_loss: 2.0347 - val_accuracy: 0.4777
Epoch 43/400
31/31 [==============================] - 30s 978ms/step - loss: 0.1449 -
accuracy: 0.9886 - val_loss: 2.0074 - val_accuracy: 0.4710
Epoch 44/400
31/31 [==============================] - 30s 979ms/step - loss: 0.1430 -
accuracy: 0.9827 - val_loss: 1.9388 - val_accuracy: 0.4777
Epoch 45/400
31/31 [==============================] - 30s 978ms/step - loss: 0.1281 -
accuracy: 0.9916 - val_loss: 1.9889 - val_accuracy: 0.4754
Epoch 46/400
31/31 [==============================] - 30s 980ms/step - loss: 0.1262 -
accuracy: 0.9885 - val_loss: 1.9810 - val_accuracy: 0.4643
Epoch 47/400
31/31 [==============================] - 30s 983ms/step - loss: 0.1284 -
accuracy: 0.9813 - val_loss: 2.0325 - val_accuracy: 0.4621
Epoch 48/400
31/31 [==============================] - 30s 978ms/step - loss: 0.1186 -
accuracy: 0.9898 - val_loss: 2.0685 - val_accuracy: 0.4844
Restoring model weights from the end of the best epoch.
Epoch 00048: early stopping
```

[17]:
```python
plt.plot(history4.history['accuracy'])
plt.plot(history4.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



[18]:
```
plt.plot(history4.history['loss'])
plt.plot(history4.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



1.3.5 Experiment 5: Changing the Model Architecture

From ref. [1] and [2], I modify the architecture to see if it gives better results. This model is actually shown to give some very good results on the MNIST competition in Kaggle.

[19]:
```
model5 = Sequential()

# Lambda Layer for adding Padding
model5.add(Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE, 1)))

# 1st Convolution Layer
model5.add(Conv2D(32, kernel_size=3, activation=mish))
model5.add(BatchNormalization())
model5.add(Conv2D(32, kernel_size=3, activation=mish))
model5.add(BatchNormalization())
model5.add(Conv2D(32, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model5.add(BatchNormalization())
model5.add(Dropout(0.4))

# 2nd Convolution Layer
model5.add(Conv2D(64, kernel_size=3, activation=mish))
model5.add(BatchNormalization())
```

```
model5.add(Conv2D(64, kernel_size=3, activation=mish))
model5.add(BatchNormalization())
model5.add(Conv2D(64, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model5.add(BatchNormalization())
model5.add(Dropout(0.4))

# 3rd Convolution Layer
model5.add(Conv2D(128, kernel_size = 4, activation=mish))
model5.add(BatchNormalization())

# Passing to a Fully Connected Layer
model5.add(Flatten())
model5.add(Dropout(0.4))

# Output Layer
model5.add(Dense(62, activation='softmax'))
```

[20]:

```
model5.summary()
```

```
Model: "sequential_2"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda_3 (Lambda)            (None, 28, 28, 1)         0

_________________________________________________________________
conv2d_3 (Conv2D)            (None, 26, 26, 32)        320

_________________________________________________________________
batch_normalization_5 (Batch (None, 26, 26, 32)        128

_________________________________________________________________
conv2d_4 (Conv2D)            (None, 24, 24, 32)        9248

_________________________________________________________________
batch_normalization_6 (Batch (None, 24, 24, 32)        128

_________________________________________________________________
conv2d_5 (Conv2D)            (None, 12, 12, 32)        25632

_________________________________________________________________
batch_normalization_7 (Batch (None, 12, 12, 32)        128

_________________________________________________________________
dropout_2 (Dropout)          (None, 12, 12, 32)        0

_________________________________________________________________
conv2d_6 (Conv2D)            (None, 10, 10, 64)        18496

_________________________________________________________________
batch_normalization_8 (Batch (None, 10, 10, 64)        256

_________________________________________________________________
conv2d_7 (Conv2D)            (None, 8, 8, 64)          36928

_________________________________________________________________
batch_normalization_9 (Batch (None, 8, 8, 64)          256
```

```
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 4, 4, 64)          102464
_________________________________________________________________
batch_normalization_10 (Batc (None, 4, 4, 64)          256
_________________________________________________________________
dropout_3 (Dropout)          (None, 4, 4, 64)          0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 1, 1, 128)         131200
_________________________________________________________________
batch_normalization_11 (Batc (None, 1, 1, 128)         512
_________________________________________________________________
flatten_1 (Flatten)          (None, 128)               0
_________________________________________________________________
dropout_4 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 62)                7998
=================================================================
Total params: 333,950
Trainable params: 333,118
Non-trainable params: 832
_________________________________________________________________
```

[21]:
```
model5.compile(loss='categorical_crossentropy', optimizer=Adam(),␣
↪metrics=['accuracy'])
```

Saving the Checkpoint

[22]:
```
checkpoint_filepath5 = 'exp5/checkpoint'
model_checkpoint_callback5 = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath5,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)
```

[23]:
```
history5 = model5.fit(
    train_generator1,
    epochs=EPOCHS,
    validation_data=validation_generator1,
    steps_per_epoch = train_generator1.samples // BATCH_SIZE,
    validation_steps = validation_generator1.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback5, early_stopping_callback]
)
```

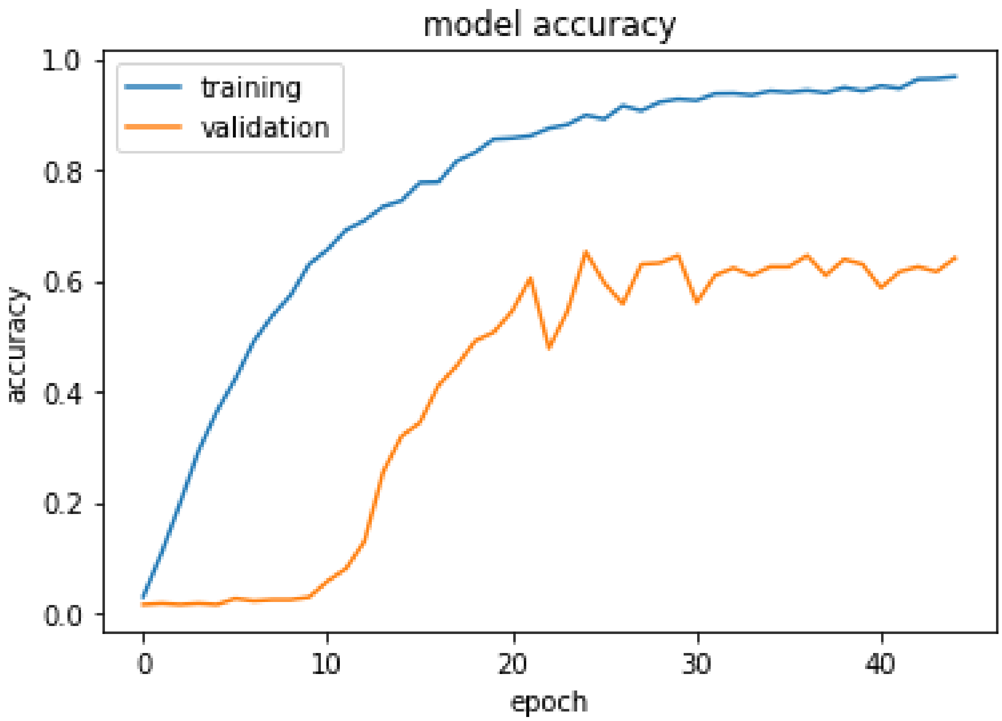
```
Epoch 1/400
31/31 [==============================] - 32s 1s/step - loss: 4.9465 - accuracy:
0.0297 - val_loss: 4.1453 - val_accuracy: 0.0156
Epoch 2/400
```

```
31/31 [==============================] - 30s 980ms/step - loss: 3.9907 -
accuracy: 0.0840 - val_loss: 4.2915 - val_accuracy: 0.0179
Epoch 3/400
31/31 [==============================] - 30s 980ms/step - loss: 3.3039 -
accuracy: 0.1876 - val_loss: 4.4831 - val_accuracy: 0.0156
Epoch 4/400
31/31 [==============================] - 30s 979ms/step - loss: 2.8396 -
accuracy: 0.2860 - val_loss: 4.6112 - val_accuracy: 0.0179
Epoch 5/400
31/31 [==============================] - 30s 977ms/step - loss: 2.4810 -
accuracy: 0.3607 - val_loss: 4.6760 - val_accuracy: 0.0156
Epoch 6/400
31/31 [==============================] - 30s 980ms/step - loss: 2.1970 -
accuracy: 0.4173 - val_loss: 4.7494 - val_accuracy: 0.0268
Epoch 7/400
31/31 [==============================] - 30s 986ms/step - loss: 1.8933 -
accuracy: 0.5047 - val_loss: 5.0638 - val_accuracy: 0.0223
Epoch 8/400
31/31 [==============================] - 30s 976ms/step - loss: 1.6094 -
accuracy: 0.5626 - val_loss: 4.9195 - val_accuracy: 0.0246
Epoch 9/400
31/31 [==============================] - 30s 975ms/step - loss: 1.5608 -
accuracy: 0.5826 - val_loss: 5.4649 - val_accuracy: 0.0246
Epoch 10/400
31/31 [==============================] - 30s 983ms/step - loss: 1.3871 -
accuracy: 0.6284 - val_loss: 5.6812 - val_accuracy: 0.0290
Epoch 11/400
31/31 [==============================] - 30s 975ms/step - loss: 1.2571 -
accuracy: 0.6602 - val_loss: 4.5095 - val_accuracy: 0.0580
Epoch 12/400
31/31 [==============================] - 30s 977ms/step - loss: 1.1079 -
accuracy: 0.7031 - val_loss: 4.4870 - val_accuracy: 0.0804
Epoch 13/400
31/31 [==============================] - 30s 978ms/step - loss: 1.0039 -
accuracy: 0.7270 - val_loss: 3.8926 - val_accuracy: 0.1295
Epoch 14/400
31/31 [==============================] - 30s 974ms/step - loss: 0.9945 -
accuracy: 0.7319 - val_loss: 3.0948 - val_accuracy: 0.2545
Epoch 15/400
31/31 [==============================] - 30s 983ms/step - loss: 0.8943 -
accuracy: 0.7375 - val_loss: 2.8344 - val_accuracy: 0.3192
Epoch 16/400
31/31 [==============================] - 30s 980ms/step - loss: 0.7943 -
accuracy: 0.7707 - val_loss: 2.4951 - val_accuracy: 0.3438
Epoch 17/400
31/31 [==============================] - 30s 983ms/step - loss: 0.7437 -
accuracy: 0.7873 - val_loss: 2.2703 - val_accuracy: 0.4107
Epoch 18/400
```

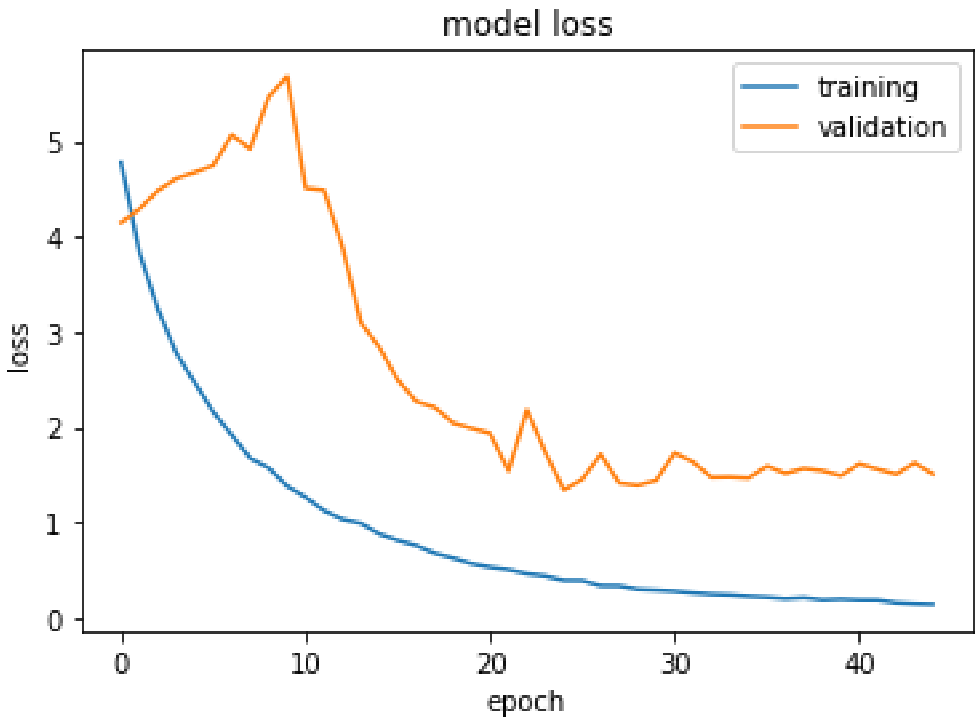
```
31/31 [==============================] - 30s 986ms/step - loss: 0.6890 -
accuracy: 0.8090 - val_loss: 2.2089 - val_accuracy: 0.4464
Epoch 19/400
31/31 [==============================] - 30s 977ms/step - loss: 0.6000 -
accuracy: 0.8392 - val_loss: 2.0425 - val_accuracy: 0.4911
Epoch 20/400
31/31 [==============================] - 30s 977ms/step - loss: 0.5414 -
accuracy: 0.8680 - val_loss: 1.9872 - val_accuracy: 0.5067
Epoch 21/400
31/31 [==============================] - 30s 980ms/step - loss: 0.5286 -
accuracy: 0.8475 - val_loss: 1.9348 - val_accuracy: 0.5446
Epoch 22/400
31/31 [==============================] - 30s 976ms/step - loss: 0.4975 -
accuracy: 0.8682 - val_loss: 1.5384 - val_accuracy: 0.6049
Epoch 23/400
31/31 [==============================] - 30s 984ms/step - loss: 0.4542 -
accuracy: 0.8780 - val_loss: 2.1819 - val_accuracy: 0.4777
Epoch 24/400
31/31 [==============================] - 30s 976ms/step - loss: 0.4386 -
accuracy: 0.8851 - val_loss: 1.7339 - val_accuracy: 0.5446
Epoch 25/400
31/31 [==============================] - 30s 978ms/step - loss: 0.3736 -
accuracy: 0.9067 - val_loss: 1.3391 - val_accuracy: 0.6518
Epoch 26/400
31/31 [==============================] - 30s 982ms/step - loss: 0.3955 -
accuracy: 0.8892 - val_loss: 1.4516 - val_accuracy: 0.5960
Epoch 27/400
31/31 [==============================] - 30s 978ms/step - loss: 0.3094 -
accuracy: 0.9266 - val_loss: 1.7136 - val_accuracy: 0.5580
Epoch 28/400
31/31 [==============================] - 30s 990ms/step - loss: 0.3048 -
accuracy: 0.9217 - val_loss: 1.4118 - val_accuracy: 0.6295
Epoch 29/400
31/31 [==============================] - 30s 978ms/step - loss: 0.2886 -
accuracy: 0.9270 - val_loss: 1.3883 - val_accuracy: 0.6317
Epoch 30/400
31/31 [==============================] - 30s 980ms/step - loss: 0.2666 -
accuracy: 0.9342 - val_loss: 1.4389 - val_accuracy: 0.6451
Epoch 31/400
31/31 [==============================] - 30s 983ms/step - loss: 0.2735 -
accuracy: 0.9240 - val_loss: 1.7285 - val_accuracy: 0.5603
Epoch 32/400
31/31 [==============================] - 30s 977ms/step - loss: 0.2552 -
accuracy: 0.9329 - val_loss: 1.6346 - val_accuracy: 0.6094
Epoch 33/400
31/31 [==============================] - 30s 979ms/step - loss: 0.2421 -
accuracy: 0.9392 - val_loss: 1.4724 - val_accuracy: 0.6228
Epoch 34/400
```

```
31/31 [==============================] - 30s 980ms/step - loss: 0.2392 -
accuracy: 0.9334 - val_loss: 1.4759 - val_accuracy: 0.6094
Epoch 35/400
31/31 [==============================] - 30s 980ms/step - loss: 0.2286 -
accuracy: 0.9384 - val_loss: 1.4647 - val_accuracy: 0.6250
Epoch 36/400
31/31 [==============================] - 30s 982ms/step - loss: 0.2094 -
accuracy: 0.9428 - val_loss: 1.5903 - val_accuracy: 0.6250
Epoch 37/400
31/31 [==============================] - 30s 982ms/step - loss: 0.1940 -
accuracy: 0.9424 - val_loss: 1.5119 - val_accuracy: 0.6451
Epoch 38/400
31/31 [==============================] - 30s 987ms/step - loss: 0.1889 -
accuracy: 0.9458 - val_loss: 1.5661 - val_accuracy: 0.6094
Epoch 39/400
31/31 [==============================] - 30s 982ms/step - loss: 0.1905 -
accuracy: 0.9473 - val_loss: 1.5409 - val_accuracy: 0.6384
Epoch 40/400
31/31 [==============================] - 30s 974ms/step - loss: 0.1942 -
accuracy: 0.9414 - val_loss: 1.4881 - val_accuracy: 0.6295
Epoch 41/400
31/31 [==============================] - 30s 979ms/step - loss: 0.1820 -
accuracy: 0.9512 - val_loss: 1.6130 - val_accuracy: 0.5871
Epoch 42/400
31/31 [==============================] - 30s 977ms/step - loss: 0.1739 -
accuracy: 0.9520 - val_loss: 1.5574 - val_accuracy: 0.6161
Epoch 43/400
31/31 [==============================] - 30s 975ms/step - loss: 0.1422 -
accuracy: 0.9701 - val_loss: 1.5035 - val_accuracy: 0.6250
Epoch 44/400
31/31 [==============================] - 30s 971ms/step - loss: 0.1379 -
accuracy: 0.9684 - val_loss: 1.6240 - val_accuracy: 0.6161
Epoch 45/400
31/31 [==============================] - 30s 983ms/step - loss: 0.1295 -
accuracy: 0.9713 - val_loss: 1.5043 - val_accuracy: 0.6406
Restoring model weights from the end of the best epoch.
Epoch 00045: early stopping
```

[24]:
```python
plt.plot(history5.history['accuracy'])
plt.plot(history5.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



[25]:
```
plt.plot(history5.history['loss'])
plt.plot(history5.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



This gives the best accuracy among all of the previous examples. Works great!

1.3.6 Experiment 6: Changing the Model Architecture even further: Using Efficient-net

Effecient Net is being used a lot nowdays so, I'll see how this architecture works for this dataset. I don't have very high hopes for this because: 1. We are not using pre-trained weights 2. We don't have a large trainign data

But I'll still give it a try to see how it does.

For this EfficientNet Model, I would use Early Stopping with larger patience value. This is so because the Keras Website says

> "Note: the accuracy will increase very slowly and may overfit."

on Training a model with EfficientNet from scratch.

Saving the Checkpoint

[ ]:
```
checkpoint_filepath6 = 'exp6/checkpoint'
model_checkpoint_callback6 = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath6,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)
```

Early Stopping Callback

[ ]:
```
early_stopping_callback2 = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    mode='min',
    patience=100,
    restore_best_weights=True,
    verbose=1)
```

[ ]:
```
from tensorflow.keras.applications import EfficientNetB0

# Initializer taken from the source code
DENSE_KERNEL_INITIALIZER = {
    'class_name': 'VarianceScaling',
    'config': {
        'scale': 1. / 3.,
        'mode': 'fan_out',
        'distribution': 'uniform'
    }
}

# Input Layer
inputs = tf.keras.layers.Input(shape=(*IMAGE_SIZE, 1))

# Lambda Layer for adding Padding
x = tf.keras.layers.Lambda(lambda image: tf.image.resize_with_crop_or_pad(
        image, 28, 28), input_shape=(*IMAGE_SIZE, 1))(inputs)

# Efficient layer except the top layer
x = EfficientNetB0(include_top=False, weights=None,
    input_shape=(48, 48, 1))(x)

# Top

# Global Average Pooling Layer
x = tf.keras.layers.GlobalAveragePooling2D(name='avg_pool')(x)
x = tf.keras.layers.Dropout(0.4, name='top_dropout')(x)

# Output Layer
outputs = tf.keras.layers.Dense(62,
    activation='softmax',
    kernel_initializer=DENSE_KERNEL_INITIALIZER,
    name='predictions')(x)

model6 = tf.keras.Model(inputs, outputs)

model6.compile(
```

```
    optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"]
)

model6.summary()
```

```
Model: "model_7"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_19 (InputLayer)        [(None, 45, 60, 1)]       0

_________________________________________________________________
efficientnetb0 (Functional)  (None, 2, 2, 1280)        4048991

_________________________________________________________________
avg_pool (GlobalAveragePooli (None, 1280)              0

_________________________________________________________________
top_dropout (Dropout)        (None, 1280)              0

_________________________________________________________________
predictions (Dense)          (None, 62)                79422
=================================================================
Total params: 4,128,413
Trainable params: 4,086,394
Non-trainable params: 42,019

_________________________________________________________________
```

[ ]:
```
history6 = model6.fit(
    train_generator1,
    epochs=EPOCHS,
    validation_data=validation_generator1,
    steps_per_epoch = train_generator1.samples // BATCH_SIZE,
    validation_steps = validation_generator1.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback6, early_stopping_callback2]
)
```

```
Epoch 1/400
31/31 [==============================] - 42s 1s/step - loss: 4.9151 - accuracy:
0.0201 - val_loss: 4.1315 - val_accuracy: 0.0179
Epoch 2/400
31/31 [==============================] - 32s 1s/step - loss: 4.4224 - accuracy:
0.0468 - val_loss: 4.1495 - val_accuracy: 0.0156
Epoch 3/400
31/31 [==============================] - 32s 1s/step - loss: 4.2469 - accuracy:
0.0709 - val_loss: 4.1952 - val_accuracy: 0.0179
Epoch 4/400
31/31 [==============================] - 32s 1s/step - loss: 3.8510 - accuracy:
0.1198 - val_loss: 4.2058 - val_accuracy: 0.0134
Epoch 5/400
31/31 [==============================] - 32s 1s/step - loss: 3.4325 - accuracy:
0.2088 - val_loss: 4.2741 - val_accuracy: 0.0156
```

```
Epoch 6/400
31/31 [==============================] - 32s 1s/step - loss: 2.8368 - accuracy:
0.3269 - val_loss: 4.3717 - val_accuracy: 0.0179
Epoch 7/400
31/31 [==============================] - 32s 1s/step - loss: 2.2589 - accuracy:
0.4527 - val_loss: 4.7584 - val_accuracy: 0.0156
Epoch 8/400
31/31 [==============================] - 32s 1s/step - loss: 1.6094 - accuracy:
0.5704 - val_loss: 5.0353 - val_accuracy: 0.0134
Epoch 9/400
31/31 [==============================] - 32s 1s/step - loss: 1.2984 - accuracy:
0.6688 - val_loss: 5.7188 - val_accuracy: 0.0179
Epoch 10/400
31/31 [==============================] - 32s 1s/step - loss: 0.9605 - accuracy:
0.7401 - val_loss: 6.1509 - val_accuracy: 0.0156
Epoch 11/400
31/31 [==============================] - 32s 1s/step - loss: 0.7479 - accuracy:
0.7929 - val_loss: 6.6623 - val_accuracy: 0.0156
Epoch 12/400
31/31 [==============================] - 32s 1s/step - loss: 0.6724 - accuracy:
0.7995 - val_loss: 7.3675 - val_accuracy: 0.0156
Epoch 13/400
31/31 [==============================] - 32s 1s/step - loss: 0.6412 - accuracy:
0.8292 - val_loss: 8.9104 - val_accuracy: 0.0156
Epoch 14/400
31/31 [==============================] - 32s 1s/step - loss: 0.4667 - accuracy:
0.8784 - val_loss: 8.4325 - val_accuracy: 0.0179
Epoch 15/400
31/31 [==============================] - 32s 1s/step - loss: 0.4531 - accuracy:
0.8752 - val_loss: 8.1772 - val_accuracy: 0.0156
Epoch 16/400
31/31 [==============================] - 32s 1s/step - loss: 0.4186 - accuracy:
0.8964 - val_loss: 8.1100 - val_accuracy: 0.0179
Epoch 17/400
31/31 [==============================] - 32s 1s/step - loss: 0.4693 - accuracy:
0.8748 - val_loss: 6.7461 - val_accuracy: 0.0268
Epoch 18/400
31/31 [==============================] - 32s 1s/step - loss: 0.4318 - accuracy:
0.8759 - val_loss: 6.5141 - val_accuracy: 0.0179
Epoch 19/400
31/31 [==============================] - 32s 1s/step - loss: 0.4297 - accuracy:
0.8865 - val_loss: 8.9487 - val_accuracy: 0.0223
Epoch 20/400
31/31 [==============================] - 32s 1s/step - loss: 0.3713 - accuracy:
0.8911 - val_loss: 9.2894 - val_accuracy: 0.0179
Epoch 21/400
31/31 [==============================] - 32s 1s/step - loss: 0.4135 - accuracy:
0.8883 - val_loss: 9.7851 - val_accuracy: 0.0179
```

```
Epoch 22/400
31/31 [==============================] - 32s 1s/step - loss: 0.3804 - accuracy:
0.8952 - val_loss: 8.2647 - val_accuracy: 0.0246
Epoch 23/400
31/31 [==============================] - 32s 1s/step - loss: 0.2838 - accuracy:
0.9314 - val_loss: 6.5974 - val_accuracy: 0.0491
Epoch 24/400
31/31 [==============================] - 32s 1s/step - loss: 0.2819 - accuracy:
0.9231 - val_loss: 7.7193 - val_accuracy: 0.0424
Epoch 25/400
31/31 [==============================] - 32s 1s/step - loss: 0.2607 - accuracy:
0.9325 - val_loss: 6.6000 - val_accuracy: 0.1183
Epoch 26/400
31/31 [==============================] - 32s 1s/step - loss: 0.2471 - accuracy:
0.9353 - val_loss: 5.7006 - val_accuracy: 0.1518
Epoch 27/400
31/31 [==============================] - 32s 1s/step - loss: 0.2334 - accuracy:
0.9373 - val_loss: 5.6679 - val_accuracy: 0.1830
Epoch 28/400
31/31 [==============================] - 32s 1s/step - loss: 0.2431 - accuracy:
0.9280 - val_loss: 5.2927 - val_accuracy: 0.1920
Epoch 29/400
31/31 [==============================] - 32s 1s/step - loss: 0.2262 - accuracy:
0.9401 - val_loss: 5.1008 - val_accuracy: 0.2366
Epoch 30/400
31/31 [==============================] - 32s 1s/step - loss: 0.2060 - accuracy:
0.9410 - val_loss: 5.3950 - val_accuracy: 0.2143
Epoch 31/400
31/31 [==============================] - 32s 1s/step - loss: 0.1982 - accuracy:
0.9356 - val_loss: 6.5190 - val_accuracy: 0.1585
Epoch 32/400
31/31 [==============================] - 32s 1s/step - loss: 0.2223 - accuracy:
0.9415 - val_loss: 5.8759 - val_accuracy: 0.2009
Epoch 33/400
31/31 [==============================] - 32s 1s/step - loss: 0.1850 - accuracy:
0.9443 - val_loss: 5.5675 - val_accuracy: 0.2076
Epoch 34/400
31/31 [==============================] - 32s 1s/step - loss: 0.1874 - accuracy:
0.9465 - val_loss: 5.6272 - val_accuracy: 0.2188
Epoch 35/400
31/31 [==============================] - 32s 1s/step - loss: 0.2202 - accuracy:
0.9338 - val_loss: 5.9353 - val_accuracy: 0.1987
Epoch 36/400
31/31 [==============================] - 32s 1s/step - loss: 0.2147 - accuracy:
0.9442 - val_loss: 6.0334 - val_accuracy: 0.1830
Epoch 37/400
31/31 [==============================] - 32s 1s/step - loss: 0.2092 - accuracy:
0.9382 - val_loss: 6.3359 - val_accuracy: 0.2188
```

```
Epoch 38/400
31/31 [==============================] - 32s 1s/step - loss: 0.2211 - accuracy:
0.9304 - val_loss: 5.9970 - val_accuracy: 0.2098
Epoch 39/400
31/31 [==============================] - 32s 1s/step - loss: 0.1915 - accuracy:
0.9412 - val_loss: 6.3312 - val_accuracy: 0.2143
Epoch 40/400
31/31 [==============================] - 32s 1s/step - loss: 0.2200 - accuracy:
0.9326 - val_loss: 6.4238 - val_accuracy: 0.2143
Epoch 41/400
31/31 [==============================] - 32s 1s/step - loss: 0.2278 - accuracy:
0.9385 - val_loss: 6.2502 - val_accuracy: 0.2031
Epoch 42/400
31/31 [==============================] - 32s 1s/step - loss: 0.2487 - accuracy:
0.9292 - val_loss: 5.7950 - val_accuracy: 0.2522
Epoch 43/400
31/31 [==============================] - 32s 1s/step - loss: 0.2104 - accuracy:
0.9415 - val_loss: 5.5785 - val_accuracy: 0.2545
Epoch 44/400
31/31 [==============================] - 32s 1s/step - loss: 0.1827 - accuracy:
0.9417 - val_loss: 6.5161 - val_accuracy: 0.2455
Epoch 45/400
31/31 [==============================] - 32s 1s/step - loss: 0.1858 - accuracy:
0.9436 - val_loss: 6.1442 - val_accuracy: 0.2031
Epoch 46/400
31/31 [==============================] - 32s 1s/step - loss: 0.1728 - accuracy:
0.9513 - val_loss: 6.6339 - val_accuracy: 0.1786
Epoch 47/400
31/31 [==============================] - 32s 1s/step - loss: 0.1473 - accuracy:
0.9556 - val_loss: 5.2963 - val_accuracy: 0.2723
Epoch 48/400
31/31 [==============================] - 32s 1s/step - loss: 0.1677 - accuracy:
0.9508 - val_loss: 6.0020 - val_accuracy: 0.2433
Epoch 49/400
31/31 [==============================] - 32s 1s/step - loss: 0.2041 - accuracy:
0.9449 - val_loss: 5.8678 - val_accuracy: 0.2500
Epoch 50/400
31/31 [==============================] - 32s 1s/step - loss: 0.1601 - accuracy:
0.9616 - val_loss: 5.5817 - val_accuracy: 0.2522
Epoch 51/400
31/31 [==============================] - 32s 1s/step - loss: 0.1253 - accuracy:
0.9651 - val_loss: 5.5550 - val_accuracy: 0.2656
Epoch 52/400
31/31 [==============================] - 32s 1s/step - loss: 0.1480 - accuracy:
0.9604 - val_loss: 5.1319 - val_accuracy: 0.2589
Epoch 53/400
31/31 [==============================] - 32s 1s/step - loss: 0.1346 - accuracy:
0.9591 - val_loss: 5.7757 - val_accuracy: 0.2455
```

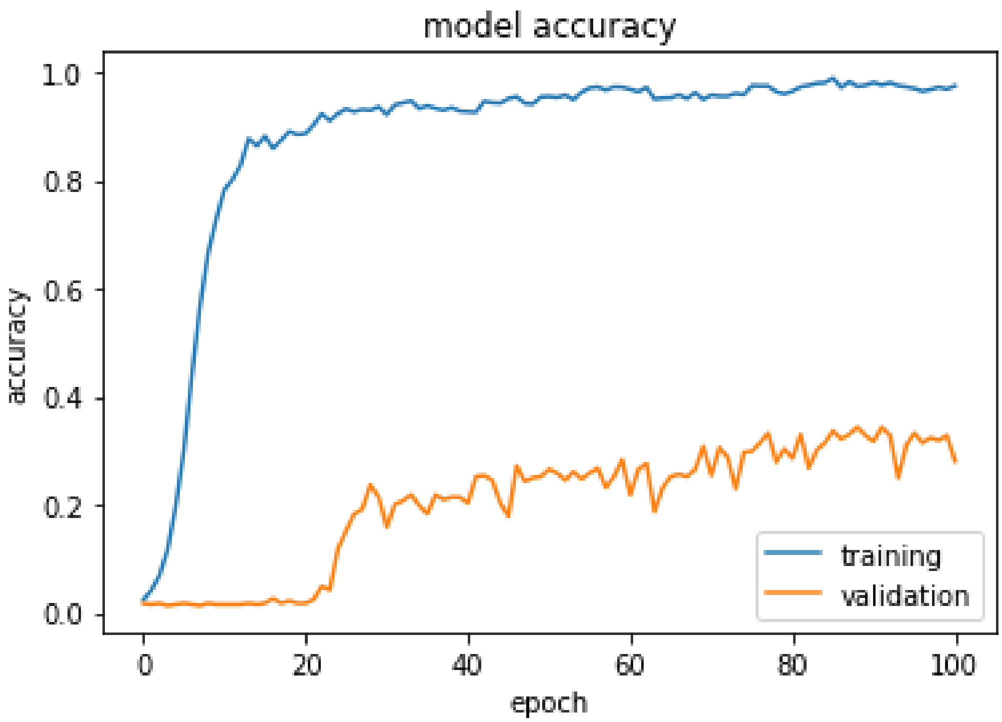
```
Epoch 54/400
31/31 [==============================] - 32s 1s/step - loss: 0.1710 - accuracy:
0.9507 - val_loss: 5.8126 - val_accuracy: 0.2612
Epoch 55/400
31/31 [==============================] - 32s 1s/step - loss: 0.1060 - accuracy:
0.9709 - val_loss: 5.4918 - val_accuracy: 0.2478
Epoch 56/400
31/31 [==============================] - 32s 1s/step - loss: 0.0894 - accuracy:
0.9723 - val_loss: 5.1332 - val_accuracy: 0.2589
Epoch 57/400
31/31 [==============================] - 32s 1s/step - loss: 0.0752 - accuracy:
0.9770 - val_loss: 5.1077 - val_accuracy: 0.2679
Epoch 58/400
31/31 [==============================] - 32s 1s/step - loss: 0.1364 - accuracy:
0.9625 - val_loss: 5.5382 - val_accuracy: 0.2321
Epoch 59/400
31/31 [==============================] - 32s 1s/step - loss: 0.0782 - accuracy:
0.9789 - val_loss: 5.3676 - val_accuracy: 0.2522
Epoch 60/400
31/31 [==============================] - 32s 1s/step - loss: 0.0827 - accuracy:
0.9771 - val_loss: 5.4748 - val_accuracy: 0.2835
Epoch 61/400
31/31 [==============================] - 32s 1s/step - loss: 0.0941 - accuracy:
0.9738 - val_loss: 5.1669 - val_accuracy: 0.2188
Epoch 62/400
31/31 [==============================] - 32s 1s/step - loss: 0.1117 - accuracy:
0.9675 - val_loss: 5.1975 - val_accuracy: 0.2656
Epoch 63/400
31/31 [==============================] - 31s 1s/step - loss: 0.0793 - accuracy:
0.9790 - val_loss: 5.4748 - val_accuracy: 0.2768
Epoch 64/400
31/31 [==============================] - 32s 1s/step - loss: 0.1675 - accuracy:
0.9548 - val_loss: 6.8398 - val_accuracy: 0.1875
Epoch 65/400
31/31 [==============================] - 32s 1s/step - loss: 0.1590 - accuracy:
0.9543 - val_loss: 6.5336 - val_accuracy: 0.2321
Epoch 66/400
31/31 [==============================] - 32s 1s/step - loss: 0.1743 - accuracy:
0.9508 - val_loss: 6.0277 - val_accuracy: 0.2522
Epoch 67/400
31/31 [==============================] - 33s 1s/step - loss: 0.1331 - accuracy:
0.9639 - val_loss: 5.5973 - val_accuracy: 0.2567
Epoch 68/400
31/31 [==============================] - 32s 1s/step - loss: 0.1496 - accuracy:
0.9551 - val_loss: 5.4199 - val_accuracy: 0.2522
Epoch 69/400
31/31 [==============================] - 32s 1s/step - loss: 0.1073 - accuracy:
0.9657 - val_loss: 5.3094 - val_accuracy: 0.2656
```

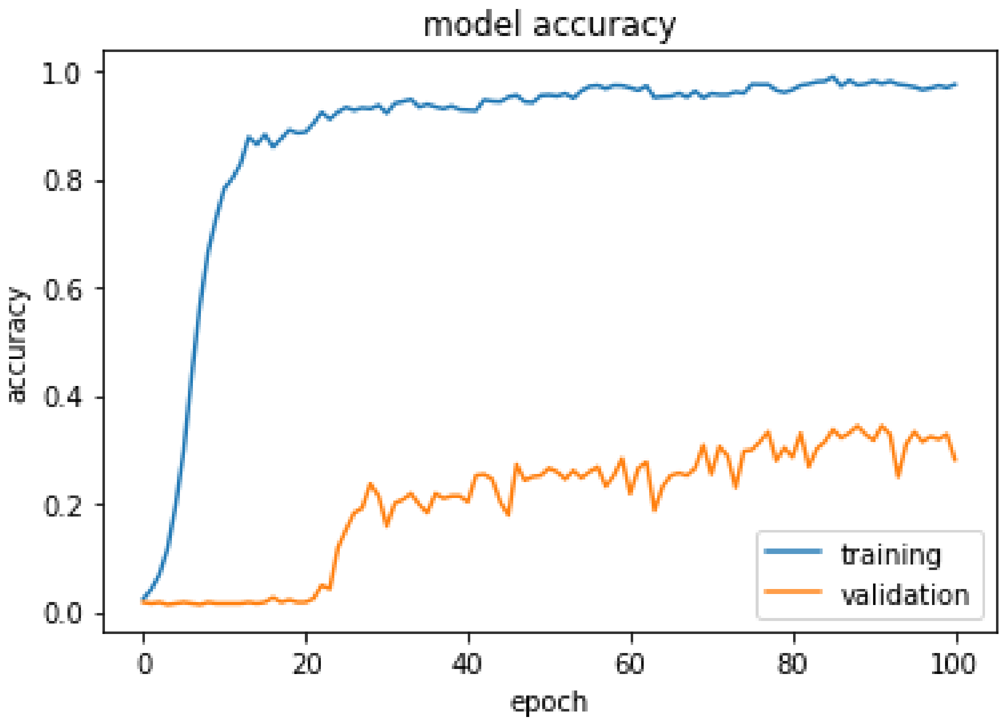
```
Epoch 70/400
31/31 [==============================] - 32s 1s/step - loss: 0.1745 - accuracy:
0.9510 - val_loss: 5.9611 - val_accuracy: 0.3080
Epoch 71/400
31/31 [==============================] - 32s 1s/step - loss: 0.1436 - accuracy:
0.9619 - val_loss: 6.7030 - val_accuracy: 0.2545
Epoch 72/400
31/31 [==============================] - 32s 1s/step - loss: 0.1382 - accuracy:
0.9589 - val_loss: 5.7207 - val_accuracy: 0.3058
Epoch 73/400
31/31 [==============================] - 32s 1s/step - loss: 0.1525 - accuracy:
0.9569 - val_loss: 5.5011 - val_accuracy: 0.2879
Epoch 74/400
31/31 [==============================] - 32s 1s/step - loss: 0.1293 - accuracy:
0.9704 - val_loss: 6.1242 - val_accuracy: 0.2299
Epoch 75/400
31/31 [==============================] - 32s 1s/step - loss: 0.1456 - accuracy:
0.9605 - val_loss: 5.5948 - val_accuracy: 0.2969
Epoch 76/400
31/31 [==============================] - 33s 1s/step - loss: 0.0789 - accuracy:
0.9792 - val_loss: 5.0845 - val_accuracy: 0.2991
Epoch 77/400
31/31 [==============================] - 33s 1s/step - loss: 0.1044 - accuracy:
0.9736 - val_loss: 5.4756 - val_accuracy: 0.3147
Epoch 78/400
31/31 [==============================] - 32s 1s/step - loss: 0.0819 - accuracy:
0.9782 - val_loss: 5.4632 - val_accuracy: 0.3326
Epoch 79/400
31/31 [==============================] - 32s 1s/step - loss: 0.1429 - accuracy:
0.9582 - val_loss: 5.0367 - val_accuracy: 0.2790
Epoch 80/400
31/31 [==============================] - 32s 1s/step - loss: 0.1364 - accuracy:
0.9656 - val_loss: 5.1341 - val_accuracy: 0.3036
Epoch 81/400
31/31 [==============================] - 32s 1s/step - loss: 0.0854 - accuracy:
0.9695 - val_loss: 5.0010 - val_accuracy: 0.2857
Epoch 82/400
31/31 [==============================] - 32s 1s/step - loss: 0.0764 - accuracy:
0.9776 - val_loss: 4.7405 - val_accuracy: 0.3304
Epoch 83/400
31/31 [==============================] - 32s 1s/step - loss: 0.0855 - accuracy:
0.9755 - val_loss: 5.2778 - val_accuracy: 0.2679
Epoch 84/400
31/31 [==============================] - 32s 1s/step - loss: 0.0981 - accuracy:
0.9753 - val_loss: 5.1260 - val_accuracy: 0.3013
Epoch 85/400
31/31 [==============================] - 32s 1s/step - loss: 0.0479 - accuracy:
0.9835 - val_loss: 4.8906 - val_accuracy: 0.3147
```

```
Epoch 86/400
31/31 [==============================] - 31s 1s/step - loss: 0.0572 - accuracy:
0.9886 - val_loss: 4.5963 - val_accuracy: 0.3371
Epoch 87/400
31/31 [==============================] - 31s 1s/step - loss: 0.0698 - accuracy:
0.9780 - val_loss: 4.7077 - val_accuracy: 0.3214
Epoch 88/400
31/31 [==============================] - 31s 1s/step - loss: 0.0604 - accuracy:
0.9848 - val_loss: 4.8737 - val_accuracy: 0.3304
Epoch 89/400
31/31 [==============================] - 31s 1s/step - loss: 0.0778 - accuracy:
0.9751 - val_loss: 4.8525 - val_accuracy: 0.3438
Epoch 90/400
31/31 [==============================] - 32s 1s/step - loss: 0.0640 - accuracy:
0.9795 - val_loss: 4.9865 - val_accuracy: 0.3281
Epoch 91/400
31/31 [==============================] - 32s 1s/step - loss: 0.0600 - accuracy:
0.9865 - val_loss: 4.9824 - val_accuracy: 0.3170
Epoch 92/400
31/31 [==============================] - 32s 1s/step - loss: 0.0794 - accuracy:
0.9811 - val_loss: 5.0791 - val_accuracy: 0.3438
Epoch 93/400
31/31 [==============================] - 31s 1s/step - loss: 0.0570 - accuracy:
0.9834 - val_loss: 5.2380 - val_accuracy: 0.3281
Epoch 94/400
31/31 [==============================] - 31s 1s/step - loss: 0.1120 - accuracy:
0.9740 - val_loss: 6.1203 - val_accuracy: 0.2500
Epoch 95/400
31/31 [==============================] - 32s 1s/step - loss: 0.0696 - accuracy:
0.9751 - val_loss: 5.0995 - val_accuracy: 0.3103
Epoch 96/400
31/31 [==============================] - 32s 1s/step - loss: 0.0898 - accuracy:
0.9723 - val_loss: 5.0952 - val_accuracy: 0.3326
Epoch 97/400
31/31 [==============================] - 32s 1s/step - loss: 0.1033 - accuracy:
0.9724 - val_loss: 5.6316 - val_accuracy: 0.3147
Epoch 98/400
31/31 [==============================] - 32s 1s/step - loss: 0.0979 - accuracy:
0.9698 - val_loss: 5.4321 - val_accuracy: 0.3237
Epoch 99/400
31/31 [==============================] - 32s 1s/step - loss: 0.0772 - accuracy:
0.9730 - val_loss: 5.2021 - val_accuracy: 0.3192
Epoch 100/400
31/31 [==============================] - 32s 1s/step - loss: 0.0845 - accuracy:
0.9761 - val_loss: 5.2520 - val_accuracy: 0.3281
Epoch 101/400
31/31 [==============================] - 32s 1s/step - loss: 0.0814 - accuracy:
0.9800 - val_loss: 5.7342 - val_accuracy: 0.2812
```

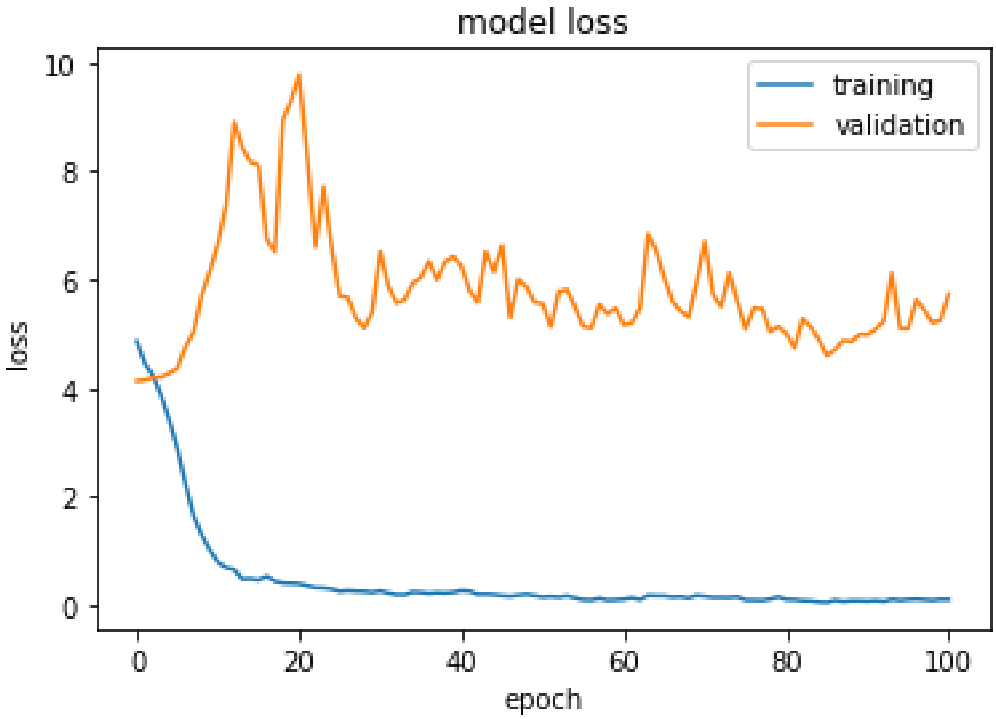
```
Restoring model weights from the end of the best epoch.
Epoch 00101: early stopping
```

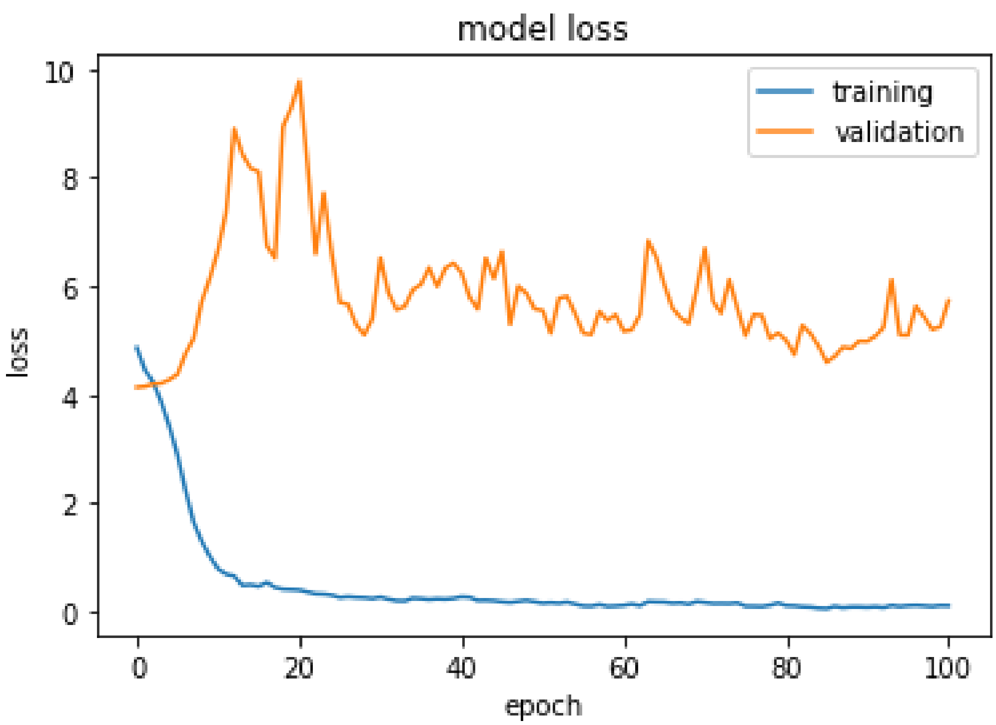
[ ]:
```
plt.plot(history6.history['accuracy'])
plt.plot(history6.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```





[ ]:
```
plt.plot(history6.history['loss'])
plt.plot(history6.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```


model loss
training
validation
loss
epoch
0
2
4
6
8
10
0
20
40
60
80
100


model loss
training
validation
loss
epoch
0
2
4
6
8
10
0
20
40
60
80
100

As expected, this does not converge. Infact, it's only half as good. This accuracy result is similar to the one shown in ref. [6] here.

1.4 Observations form these experiments

- I downscaled the images to the dimensions of that of the MNIST Images while making sure that the images are still recognizable from each other. This would reduce the number of parameters in our network. I also padded the images with 0 to maintain the aspect ratio and inverted the images so that the background now has 0 as the pixel value.
- I started with a modified version of the original LeNet, which was used to classify on the MNIST dataset, as our current dataset closely resembles it, I got an accuracy of around 50%.
- Data Augmentation did not help for this dataset as the augmented data was very different from the original data and it actually performed worse. I did not use Data augmentation for later experiments.
- I tried the Mish Activation function instead of ReLU and it reached the the same accuracy in lesser epochs, however it had some variance issues for the training accuracy in the later epochs.
- Using Softmax with greater temperature, which spreads the probabilities and it actually gave similar results in lesser epochs.
- I tried different architectures: One which is known to give pretty good accuracy on the MNIST dataset in Kaggle Competitions and one Modified EfficientNet Architecture.
  - The first of them gave very good results compared to the original LeNet and in lesser epochs, but I forgot to add the temperature of softmax to it. But still, **it gave an accuracy of 64%**!
  - The EfficientNet architecture actually gave the worst results in all of the experiments, but I think this was due to the scarcity of training data and not using a pretrained model.

1.5 Conclusions and Future Improvements

- Overall, I think the Experimet gave very good result, with around 64% accuracy, followed by LeNet with Mish and higher tenmperature Softmax. Clearly, the models were overfitting the data and I think that if trained with more data, they would perform better. For the future parts of this task, I would be using these two architectures, and would even like to try high temperature softmax for Expriment 4's architecture.
- EfficientNet can give better results than from Experiment 6 but again, it neeeds more data and some pre-trainined weights. EfficientNetV2, released recently can also be a good model, but I can't find an Open Source Implementation of it and it's a little complex to build it in this duration, so I didn not try it, but I'm sure that it would give better results than what I got from EfficientNet here.
- I have tuned the hyperparameters from what I could read online. However, I think using Weights & Biases Sweeps would give better insights. I got to know about this relatively late and there was not much time left to set it up. But it would be sweet in the future to improve the model using this.

2 References

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- [6] Image classification via fine-tuning with EfficientNet
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- [13] How does temperature affect softmax in machine learning?
- [14] Temperatured softmax · Issue #3092 · keras-team/keras
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```
[ ]:
```