midastask2h

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1 Task 2 - Part 1

Imports

[ ]:
```
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
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.optimizers import Adam
```

Extracting the imges

[ ]:
```
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.

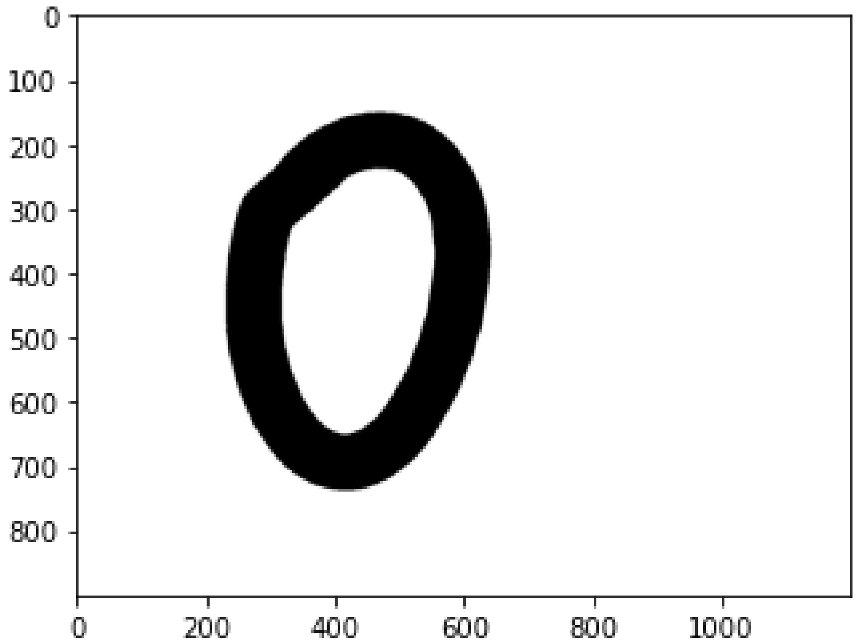
Inspecting the image to view its dimensions and colour channels

[ ]:
```
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
```

[ ]: <matplotlib.image.AxesImage at 0x7f6d8e70a2b0>



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. Scaling down the dimensions, I found that reducing the image by 20x i.e. image of dimension 45x60 has comparatively smaller number of parameters to train and the images are still recognizable from each other.

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.

[ ]:
```
train_datagen1 = ImageDataGenerator(rescale=1./255, validation_split=0.2)
```

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

[ ]:
```
BATCH_SIZE = 64
IMAGE_SIZE = (45, 60)
EPOCHS = 400
```

[ ]:
```
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.
```

[ ]:
```
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)
```

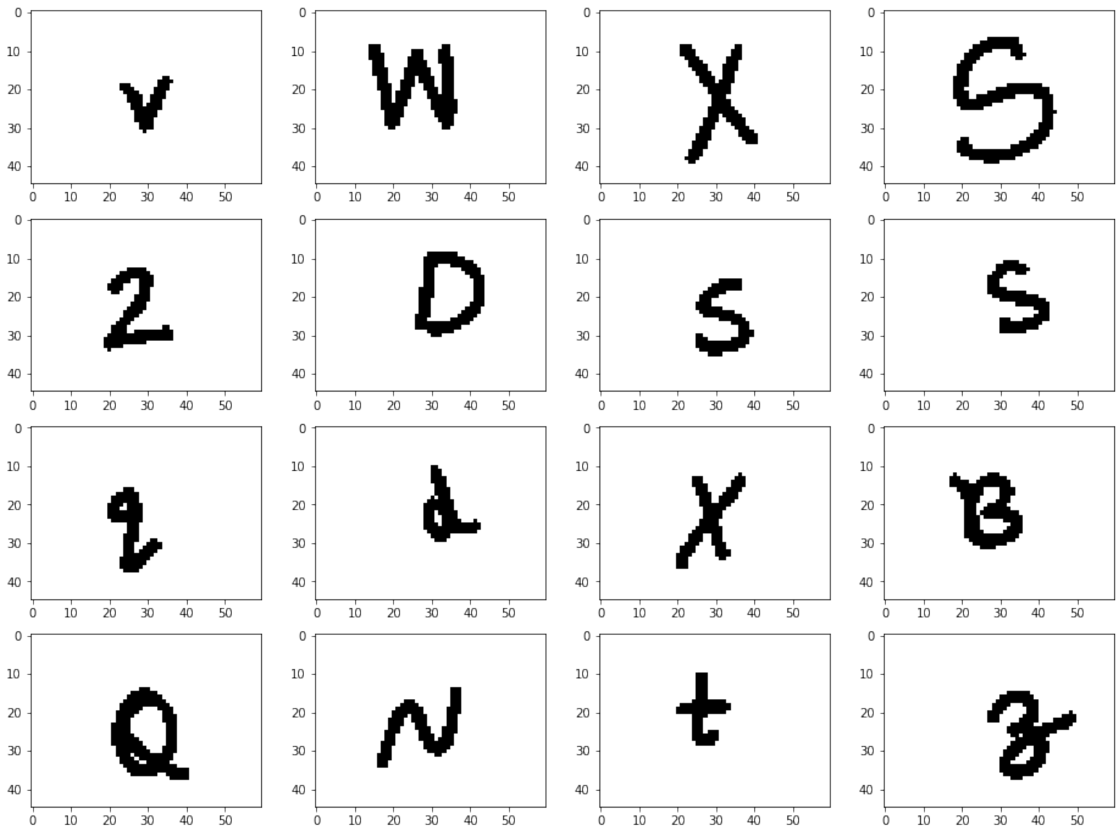
```
Found 496 images belonging to 62 classes.
```

The ImageDataGenerator class has automatically detected the 62 classes and has one-hot encoded them accordingly.

Viewing the generated samples

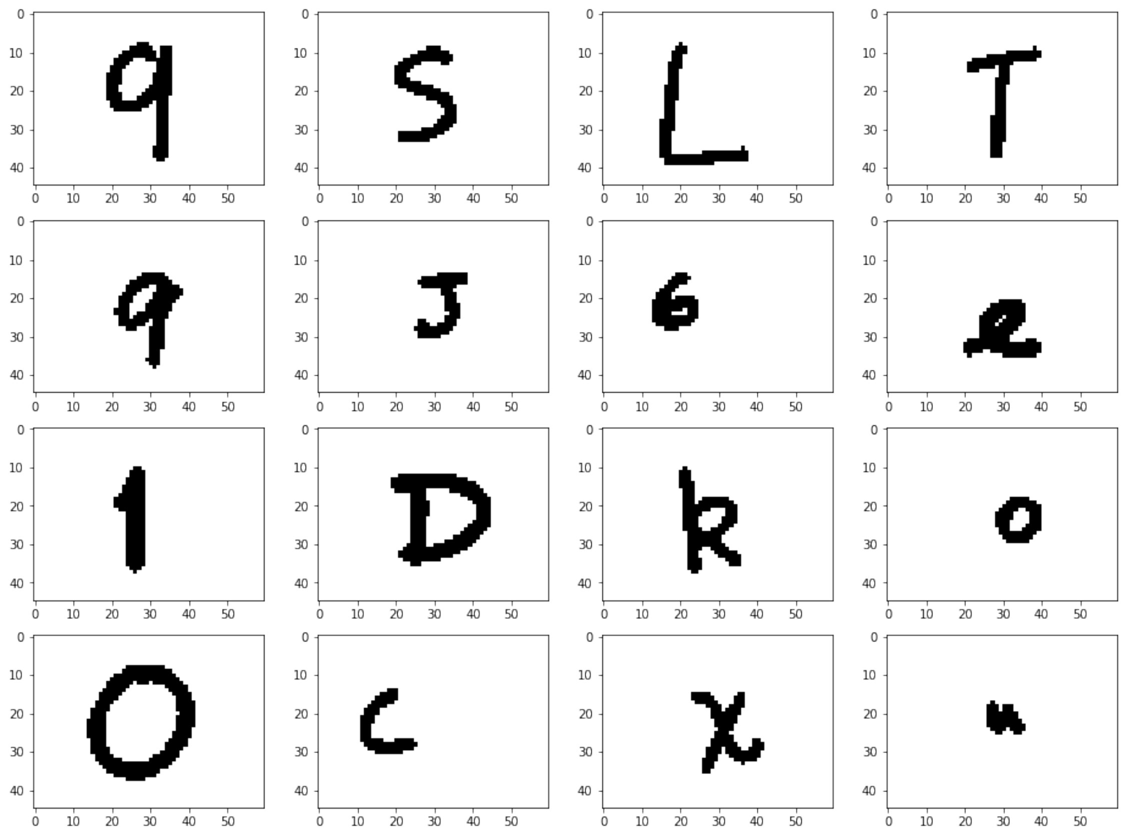
[ ]:
```
X_train_batch0, y_train_batch0 = train_generator1.next()
print(X_train_batch0.shape, y_train_batch0.shape)
print(y_train_batch0[0])
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_train_batch0[i]), cmap='gray')
plt.show()
```

```
(64, 45, 60, 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.]
```



[ ]:
```
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, 45, 60, 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

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()

# 1st Convolution Layer
model1.add(Conv2D(6, input_shape=(*IMAGE_SIZE, 1), 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))
```

```python
# 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'))
```

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

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 45, 60, 6)         156
_________________________________________________________________
batch_normalization (BatchNo (None, 45, 60, 6)         24
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 22, 30, 6)         0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 18, 26, 16)        2416
_________________________________________________________________
batch_normalization_1 (Batch (None, 18, 26, 16)        64
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 9, 13, 16)         0
_________________________________________________________________
flatten (Flatten)            (None, 1872)              0
_________________________________________________________________
dense (Dense)                (None, 256)               479488
_________________________________________________________________
batch_normalization_2 (Batch (None, 256)               1024
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
_________________________________________________________________
batch_normalization_3 (Batch (None, 128)               512
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
```

```
_________________________________________________________________
dense_2 (Dense)              (None, 62)                7998
=================================================================
Total params: 524,578
Trainable params: 523,766
Non-trainable params: 812
_________________________________________________________________
```

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

Using Early Stopping

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

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)
```

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.

[ ]:
```
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 [==============================] - 43s 1s/step - loss: 4.7297 - accuracy:
0.0399 - val_loss: 4.1328 - val_accuracy: 0.0268
Epoch 2/400
31/31 [==============================] - 34s 1s/step - loss: 3.5383 - accuracy:
0.1537 - val_loss: 4.2610 - val_accuracy: 0.0179
Epoch 3/400
```

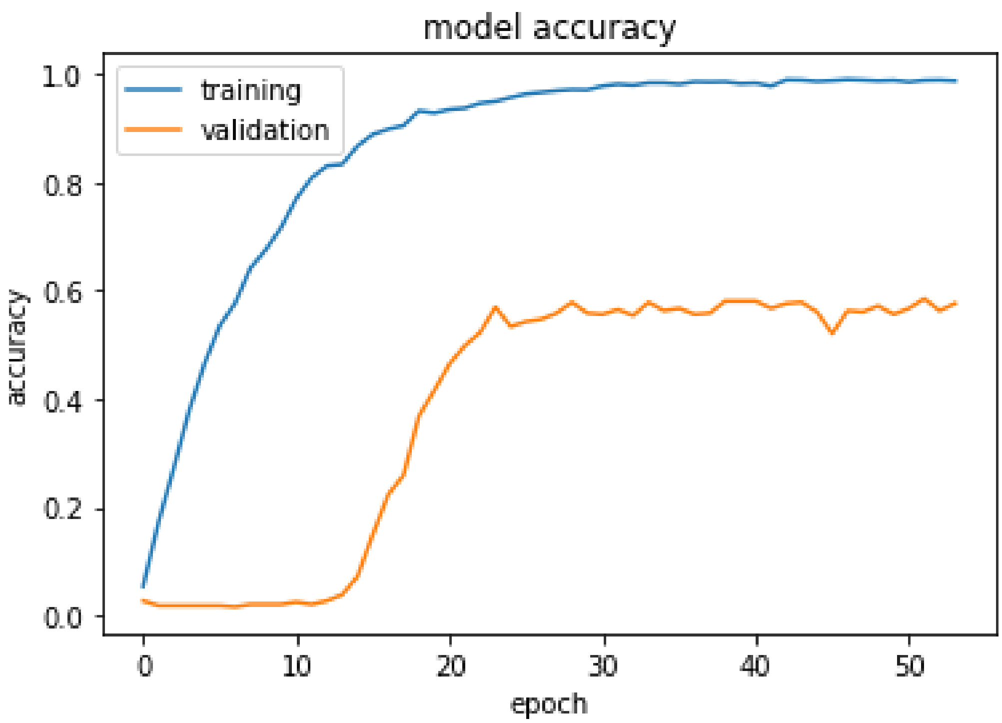
```
31/31 [==============================] - 35s 1s/step - loss: 2.9516 - accuracy:
0.2491 - val_loss: 4.5346 - val_accuracy: 0.0179
Epoch 4/400
31/31 [==============================] - 35s 1s/step - loss: 2.4749 - accuracy:
0.3632 - val_loss: 4.8323 - val_accuracy: 0.0179
Epoch 5/400
31/31 [==============================] - 34s 1s/step - loss: 2.1175 - accuracy:
0.4701 - val_loss: 5.0776 - val_accuracy: 0.0179
Epoch 6/400
31/31 [==============================] - 34s 1s/step - loss: 1.8282 - accuracy:
0.5311 - val_loss: 5.4448 - val_accuracy: 0.0179
Epoch 7/400
31/31 [==============================] - 34s 1s/step - loss: 1.6815 - accuracy:
0.5558 - val_loss: 5.6547 - val_accuracy: 0.0156
Epoch 8/400
31/31 [==============================] - 34s 1s/step - loss: 1.3730 - accuracy:
0.6490 - val_loss: 5.9653 - val_accuracy: 0.0201
Epoch 9/400
31/31 [==============================] - 34s 1s/step - loss: 1.2582 - accuracy:
0.6807 - val_loss: 6.1347 - val_accuracy: 0.0201
Epoch 10/400
31/31 [==============================] - 34s 1s/step - loss: 1.0790 - accuracy:
0.7250 - val_loss: 6.0689 - val_accuracy: 0.0201
Epoch 11/400
31/31 [==============================] - 34s 1s/step - loss: 0.9504 - accuracy:
0.7733 - val_loss: 5.8072 - val_accuracy: 0.0246
Epoch 12/400
31/31 [==============================] - 34s 1s/step - loss: 0.8048 - accuracy:
0.8265 - val_loss: 5.8509 - val_accuracy: 0.0201
Epoch 13/400
31/31 [==============================] - 34s 1s/step - loss: 0.7183 - accuracy:
0.8360 - val_loss: 5.5358 - val_accuracy: 0.0268
Epoch 14/400
31/31 [==============================] - 34s 1s/step - loss: 0.6578 - accuracy:
0.8456 - val_loss: 5.2758 - val_accuracy: 0.0379
Epoch 15/400
31/31 [==============================] - 34s 1s/step - loss: 0.5658 - accuracy:
0.8655 - val_loss: 4.6730 - val_accuracy: 0.0714
Epoch 16/400
31/31 [==============================] - 34s 1s/step - loss: 0.4676 - accuracy:
0.8971 - val_loss: 3.8975 - val_accuracy: 0.1496
Epoch 17/400
31/31 [==============================] - 34s 1s/step - loss: 0.4240 - accuracy:
0.9136 - val_loss: 3.4903 - val_accuracy: 0.2232
Epoch 18/400
31/31 [==============================] - 34s 1s/step - loss: 0.3808 - accuracy:
0.9151 - val_loss: 3.5444 - val_accuracy: 0.2589
Epoch 19/400
```

```
31/31 [==============================] - 35s 1s/step - loss: 0.3431 - accuracy:
0.9351 - val_loss: 2.6495 - val_accuracy: 0.3683
Epoch 20/400
31/31 [==============================] - 34s 1s/step - loss: 0.3319 - accuracy:
0.9314 - val_loss: 2.2859 - val_accuracy: 0.4152
Epoch 21/400
31/31 [==============================] - 34s 1s/step - loss: 0.3103 - accuracy:
0.9346 - val_loss: 2.2489 - val_accuracy: 0.4643
Epoch 22/400
31/31 [==============================] - 34s 1s/step - loss: 0.2913 - accuracy:
0.9393 - val_loss: 2.0367 - val_accuracy: 0.4978
Epoch 23/400
31/31 [==============================] - 34s 1s/step - loss: 0.2471 - accuracy:
0.9489 - val_loss: 1.9282 - val_accuracy: 0.5223
Epoch 24/400
31/31 [==============================] - 34s 1s/step - loss: 0.2128 - accuracy:
0.9565 - val_loss: 1.7473 - val_accuracy: 0.5692
Epoch 25/400
31/31 [==============================] - 34s 1s/step - loss: 0.2219 - accuracy:
0.9592 - val_loss: 2.0040 - val_accuracy: 0.5335
Epoch 26/400
31/31 [==============================] - 34s 1s/step - loss: 0.1746 - accuracy:
0.9658 - val_loss: 1.7587 - val_accuracy: 0.5424
Epoch 27/400
31/31 [==============================] - 34s 1s/step - loss: 0.1728 - accuracy:
0.9705 - val_loss: 1.6786 - val_accuracy: 0.5469
Epoch 28/400
31/31 [==============================] - 34s 1s/step - loss: 0.1582 - accuracy:
0.9673 - val_loss: 1.7511 - val_accuracy: 0.5580
Epoch 29/400
31/31 [==============================] - 34s 1s/step - loss: 0.1567 - accuracy:
0.9695 - val_loss: 1.7618 - val_accuracy: 0.5781
Epoch 30/400
31/31 [==============================] - 34s 1s/step - loss: 0.1358 - accuracy:
0.9740 - val_loss: 1.7916 - val_accuracy: 0.5580
Epoch 31/400
31/31 [==============================] - 35s 1s/step - loss: 0.1129 - accuracy:
0.9795 - val_loss: 1.7857 - val_accuracy: 0.5558
Epoch 32/400
31/31 [==============================] - 34s 1s/step - loss: 0.1104 - accuracy:
0.9858 - val_loss: 1.7867 - val_accuracy: 0.5647
Epoch 33/400
31/31 [==============================] - 34s 1s/step - loss: 0.1180 - accuracy:
0.9760 - val_loss: 1.7575 - val_accuracy: 0.5536
Epoch 34/400
31/31 [==============================] - 34s 1s/step - loss: 0.1020 - accuracy:
0.9823 - val_loss: 1.6768 - val_accuracy: 0.5781
Epoch 35/400
```

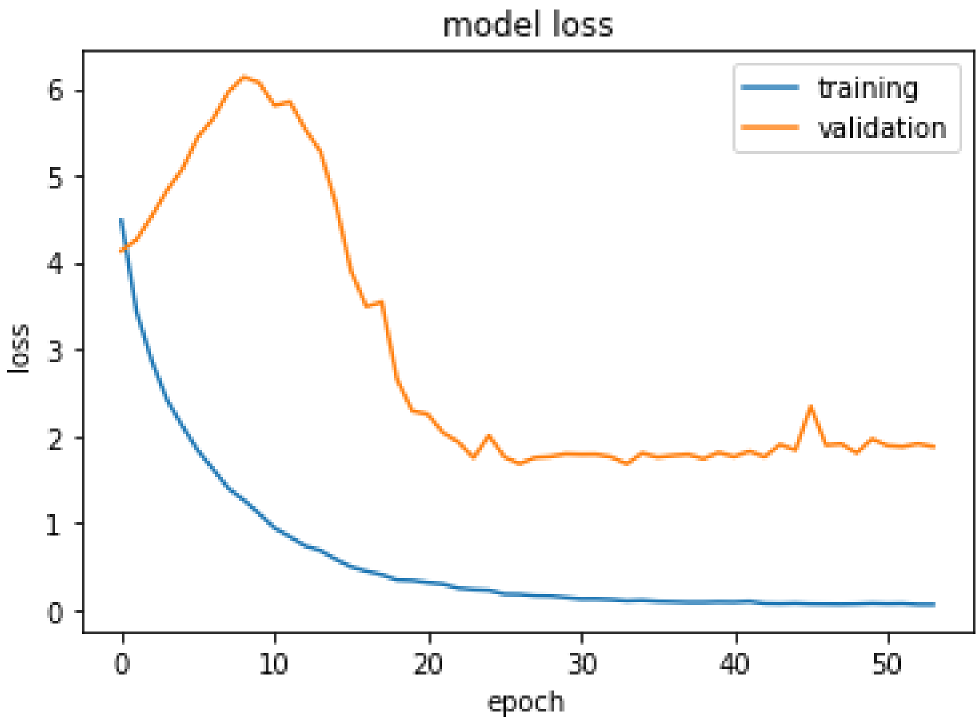
```
31/31 [==============================] - 34s 1s/step - loss: 0.1037 - accuracy:
0.9852 - val_loss: 1.8017 - val_accuracy: 0.5625
Epoch 36/400
31/31 [==============================] - 34s 1s/step - loss: 0.0904 - accuracy:
0.9817 - val_loss: 1.7548 - val_accuracy: 0.5670
Epoch 37/400
31/31 [==============================] - 34s 1s/step - loss: 0.0850 - accuracy:
0.9863 - val_loss: 1.7734 - val_accuracy: 0.5558
Epoch 38/400
31/31 [==============================] - 34s 1s/step - loss: 0.0803 - accuracy:
0.9871 - val_loss: 1.7862 - val_accuracy: 0.5580
Epoch 39/400
31/31 [==============================] - 34s 1s/step - loss: 0.0766 - accuracy:
0.9893 - val_loss: 1.7373 - val_accuracy: 0.5804
Epoch 40/400
31/31 [==============================] - 34s 1s/step - loss: 0.0851 - accuracy:
0.9844 - val_loss: 1.8073 - val_accuracy: 0.5804
Epoch 41/400
31/31 [==============================] - 34s 1s/step - loss: 0.0808 - accuracy:
0.9867 - val_loss: 1.7614 - val_accuracy: 0.5804
Epoch 42/400
31/31 [==============================] - 34s 1s/step - loss: 0.0896 - accuracy:
0.9763 - val_loss: 1.8213 - val_accuracy: 0.5670
Epoch 43/400
31/31 [==============================] - 34s 1s/step - loss: 0.0644 - accuracy:
0.9921 - val_loss: 1.7591 - val_accuracy: 0.5759
Epoch 44/400
31/31 [==============================] - 34s 1s/step - loss: 0.0647 - accuracy:
0.9889 - val_loss: 1.9004 - val_accuracy: 0.5781
Epoch 45/400
31/31 [==============================] - 34s 1s/step - loss: 0.0744 - accuracy:
0.9847 - val_loss: 1.8357 - val_accuracy: 0.5603
Epoch 46/400
31/31 [==============================] - 34s 1s/step - loss: 0.0603 - accuracy:
0.9899 - val_loss: 2.3372 - val_accuracy: 0.5201
Epoch 47/400
31/31 [==============================] - 34s 1s/step - loss: 0.0596 - accuracy:
0.9920 - val_loss: 1.8935 - val_accuracy: 0.5625
Epoch 48/400
31/31 [==============================] - 34s 1s/step - loss: 0.0561 - accuracy:
0.9887 - val_loss: 1.9065 - val_accuracy: 0.5603
Epoch 49/400
31/31 [==============================] - 34s 1s/step - loss: 0.0620 - accuracy:
0.9896 - val_loss: 1.8022 - val_accuracy: 0.5714
Epoch 50/400
31/31 [==============================] - 34s 1s/step - loss: 0.0662 - accuracy:
0.9922 - val_loss: 1.9641 - val_accuracy: 0.5558
Epoch 51/400
```

```
31/31 [==============================] - 34s 1s/step - loss: 0.0629 - accuracy:
0.9847 - val_loss: 1.8878 - val_accuracy: 0.5670
Epoch 52/400
31/31 [==============================] - 34s 1s/step - loss: 0.0588 - accuracy:
0.9910 - val_loss: 1.8750 - val_accuracy: 0.5848
Epoch 53/400
31/31 [==============================] - 34s 1s/step - loss: 0.0488 - accuracy:
0.9928 - val_loss: 1.9083 - val_accuracy: 0.5625
Epoch 54/400
31/31 [==============================] - 34s 1s/step - loss: 0.0613 - accuracy:
0.9827 - val_loss: 1.8758 - val_accuracy: 0.5759
Restoring model weights from the end of the best epoch.
Epoch 00054: 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

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.

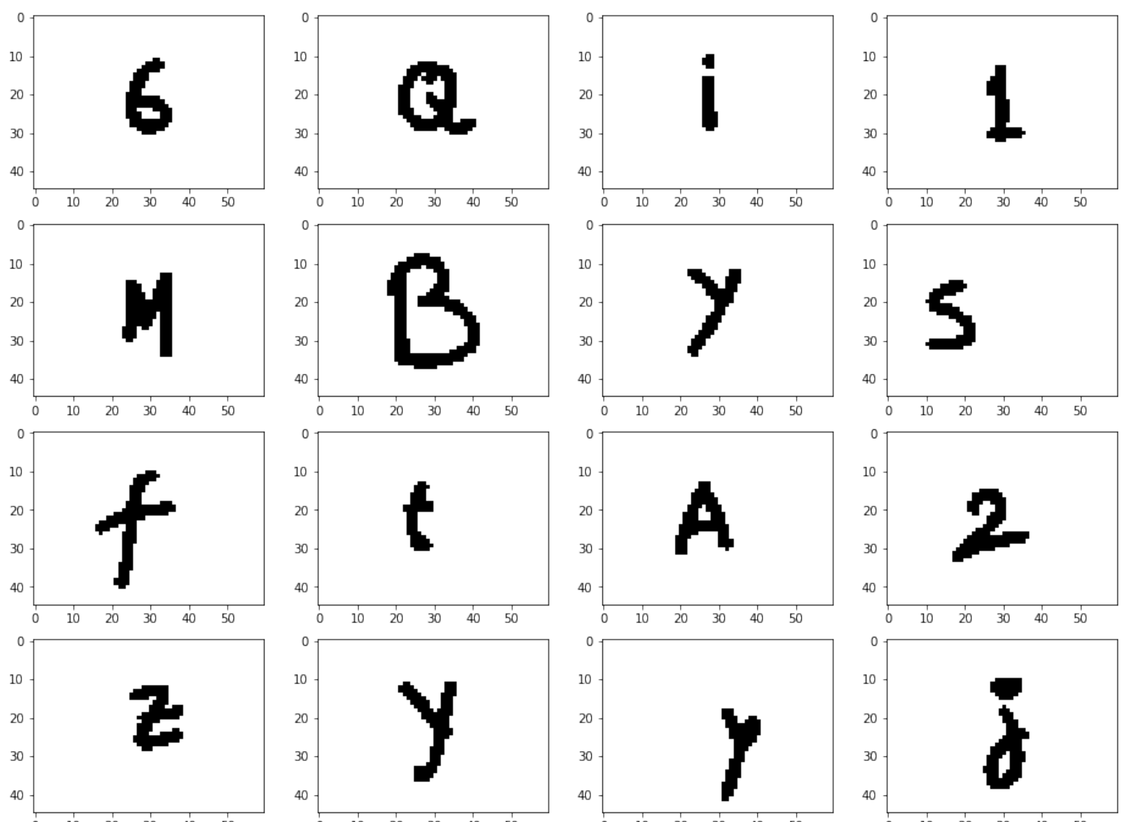
Unaugmented data

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

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.
```



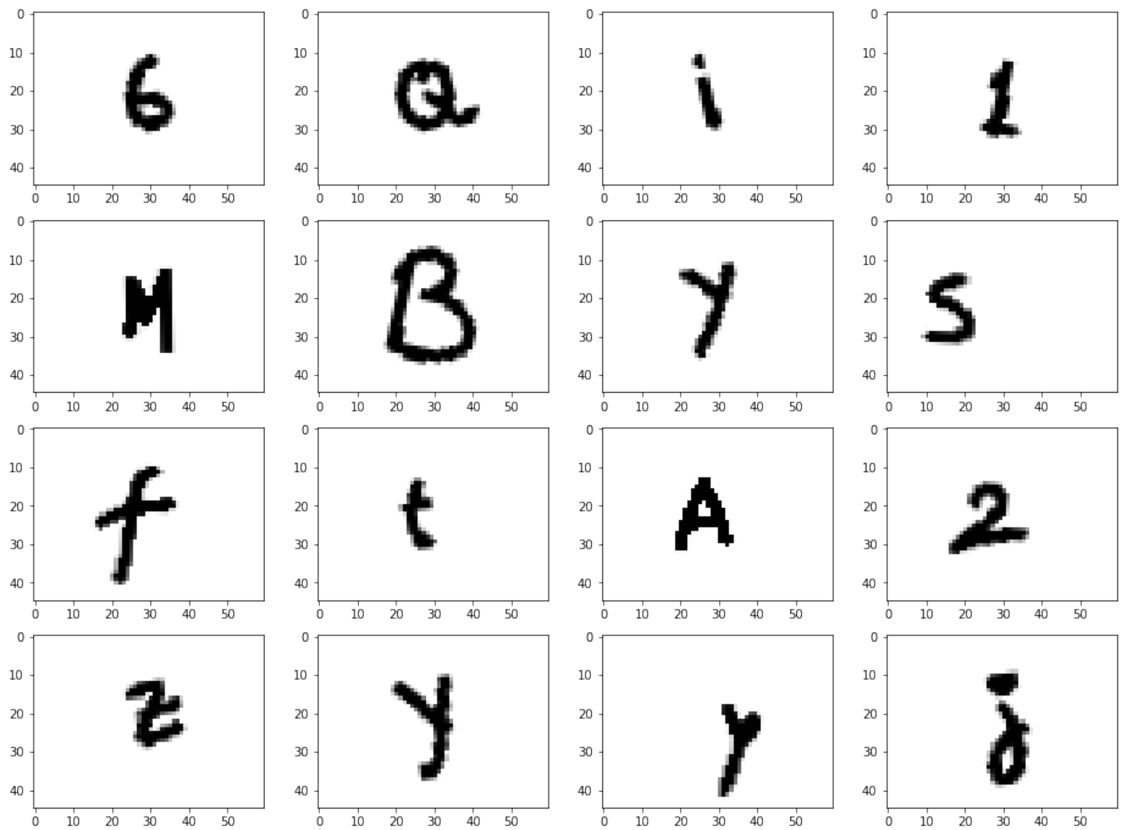
Checking rotation with max angle of 15

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

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.
```



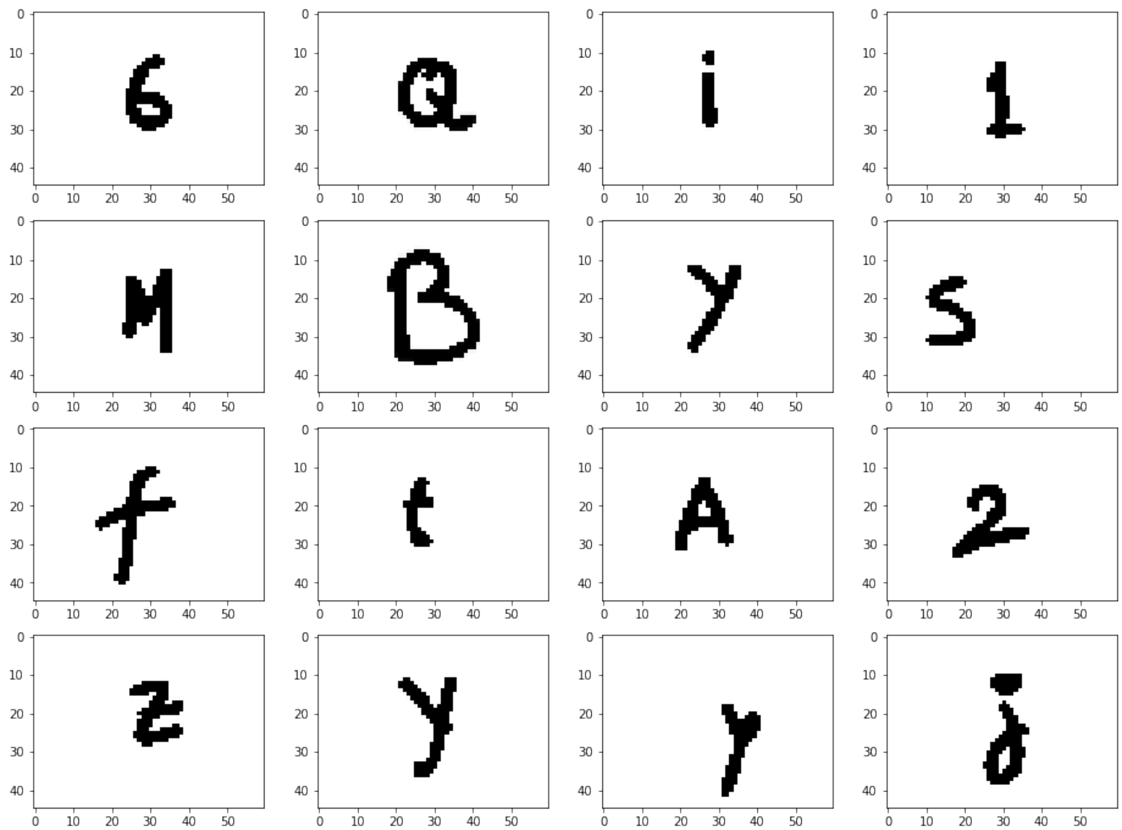
Checking shear with max shear of 0.3

[ ]:
```
augmentation_test_shear = ImageDataGenerator(rescale=1./255, shear_range=0.3)

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.
```



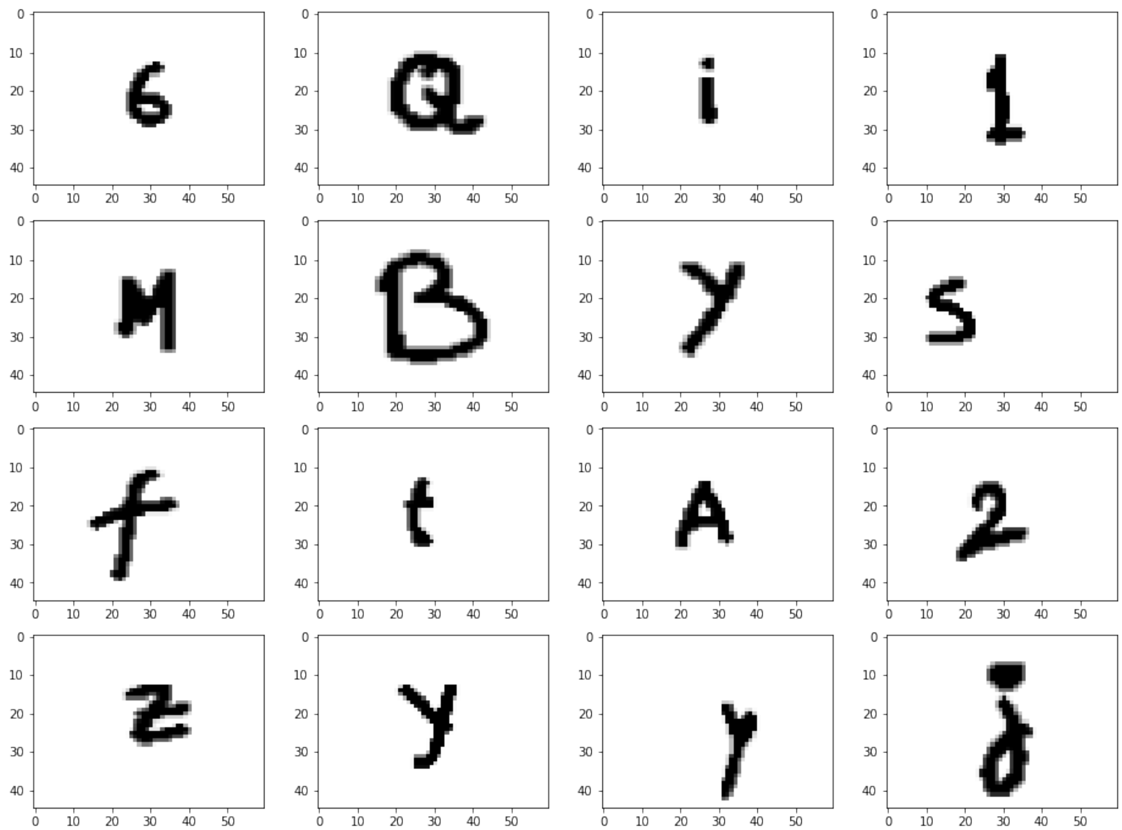
Checking zoom with max zoom of 0.2

[ ]:
```
augmentation_test_zoom = ImageDataGenerator(rescale=1./255, zoom_range=0.2)

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.
```



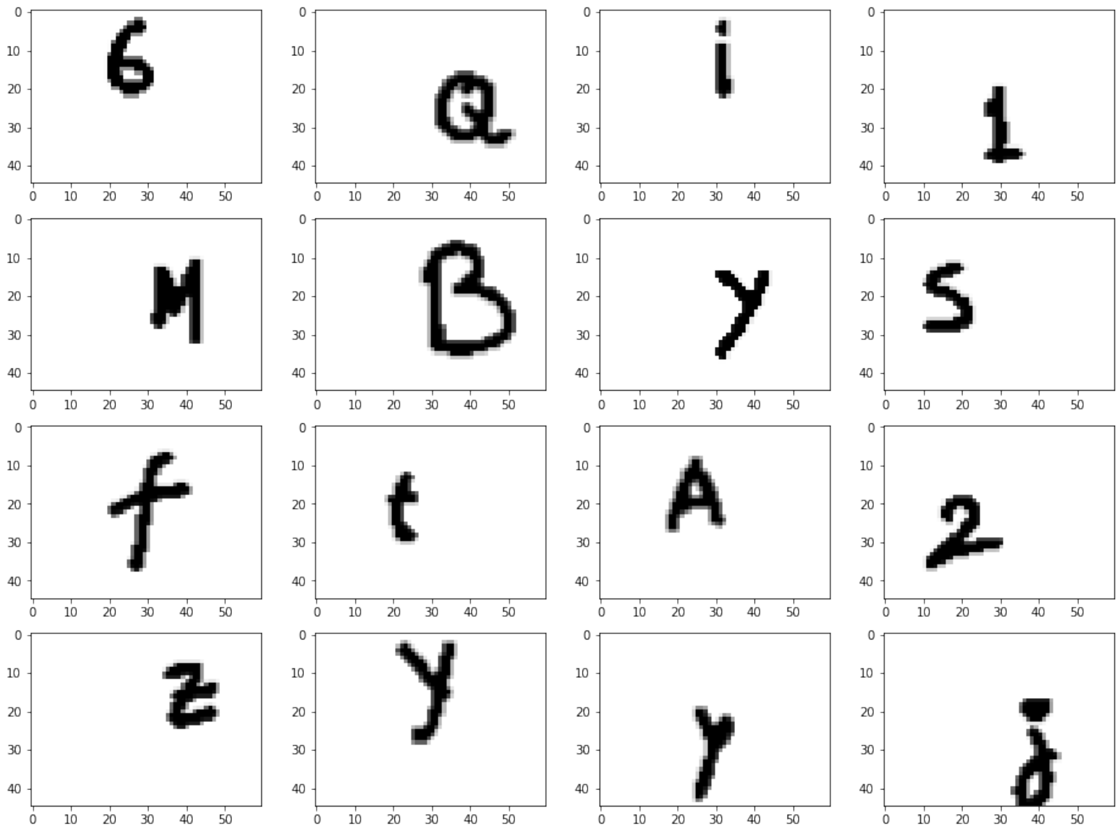
Checking with horizontal and vertical shift of 0.2

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

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)

     validation_datagen2 = ImageDataGenerator(
         rescale=1./255,
         validation_split=0.2)
```

```
[ ]: 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.
```

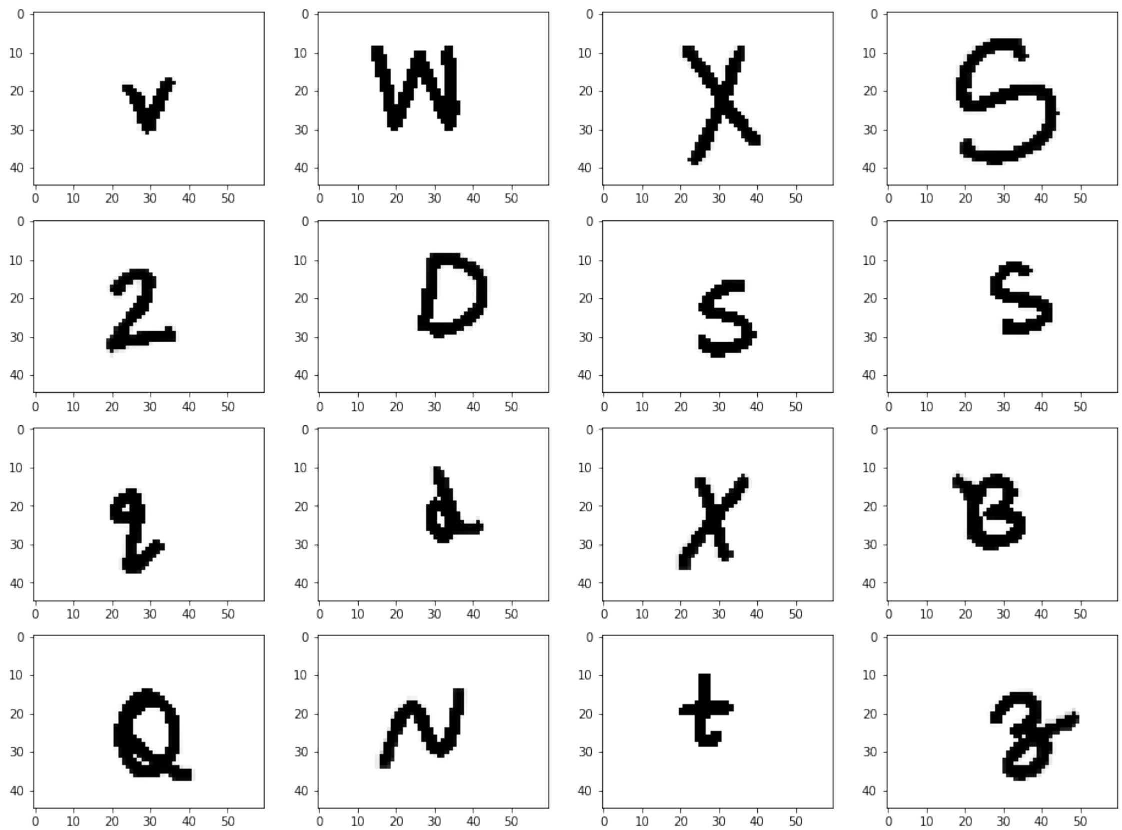
[ ]:
```
validation_generator2 = validation_datagen2.flow_from_directory(
        '../input/trainpart1zip/train',
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='categorical',
        color_mode='grayscale',
        subset='validation',
        seed=42,
        shuffle=True)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

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

Viewing the Generated samples

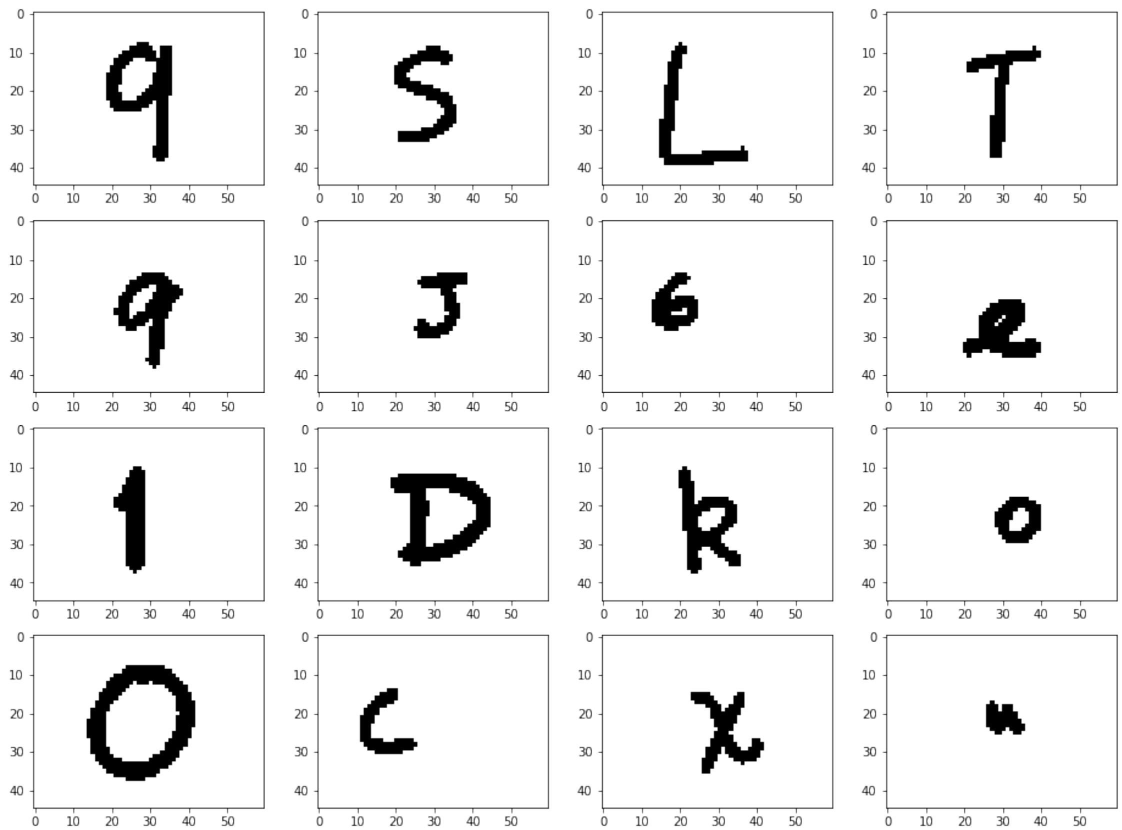
[ ]:
```
X_train_batch0, y_train_batch0 = train_generator2.next()
print(X_train_batch0.shape, y_train_batch0.shape)
plt.figure(figsize=(16,12))
for i in range(1, 17):
    plt.subplot(4,4,i)
    imshow(tf.squeeze(X_train_batch0[i]), cmap='gray')
plt.show()
```

```
(64, 45, 60, 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, 45, 60, 1) (64, 62)
```



Using the same architecture as before

[ ]:
```
model2 = Sequential()

# 1st Convolution Layer
model2.add(Conv2D(6, input_shape=(*IMAGE_SIZE, 1), 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())
```

```python
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'))
```

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

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 45, 60, 6)         156
_________________________________________________________________
batch_normalization_8 (Batch (None, 45, 60, 6)         24
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 22, 30, 6)         0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 18, 26, 16)        2416
_________________________________________________________________
batch_normalization_9 (Batch (None, 18, 26, 16)        64
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 9, 13, 16)         0
_________________________________________________________________
flatten_2 (Flatten)          (None, 1872)              0
_________________________________________________________________
dense_6 (Dense)              (None, 256)               479488
_________________________________________________________________
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: 524,578
Trainable params: 523,766
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 [==============================] - 37s 1s/step - loss: 4.8922 - accuracy:
0.0325 - val_loss: 4.1346 - val_accuracy: 0.0201
Epoch 2/400
31/31 [==============================] - 35s 1s/step - loss: 3.6093 - accuracy:
0.1459 - val_loss: 4.1228 - val_accuracy: 0.0290
Epoch 3/400
31/31 [==============================] - 35s 1s/step - loss: 3.0967 - accuracy:
0.2445 - val_loss: 4.1612 - val_accuracy: 0.0179
Epoch 4/400
31/31 [==============================] - 35s 1s/step - loss: 2.5994 - accuracy:
0.3480 - val_loss: 4.2471 - val_accuracy: 0.0223
Epoch 5/400
31/31 [==============================] - 35s 1s/step - loss: 2.3611 - accuracy:
0.3881 - val_loss: 4.4078 - val_accuracy: 0.0268
Epoch 6/400
31/31 [==============================] - 35s 1s/step - loss: 2.0162 - accuracy:
0.4768 - val_loss: 4.4157 - val_accuracy: 0.0312
Epoch 7/400
31/31 [==============================] - 35s 1s/step - loss: 1.7933 - accuracy:
0.5240 - val_loss: 4.4367 - val_accuracy: 0.0357
Epoch 8/400
31/31 [==============================] - 35s 1s/step - loss: 1.5300 - accuracy:
0.6031 - val_loss: 4.3013 - val_accuracy: 0.0402
```

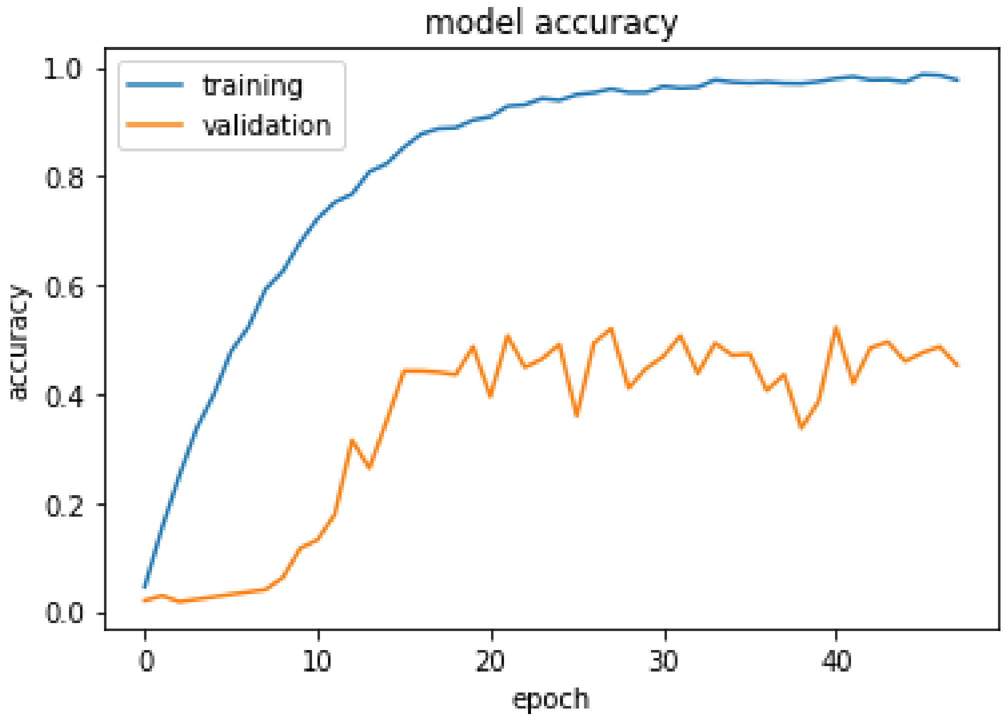
```
Epoch 9/400
31/31 [==============================] - 35s 1s/step - loss: 1.4667 - accuracy:
0.6171 - val_loss: 4.1002 - val_accuracy: 0.0625
Epoch 10/400
31/31 [==============================] - 35s 1s/step - loss: 1.2777 - accuracy:
0.6694 - val_loss: 3.8498 - val_accuracy: 0.1161
Epoch 11/400
31/31 [==============================] - 35s 1s/step - loss: 1.0951 - accuracy:
0.7186 - val_loss: 3.5382 - val_accuracy: 0.1317
Epoch 12/400
31/31 [==============================] - 35s 1s/step - loss: 0.9612 - accuracy:
0.7594 - val_loss: 3.4244 - val_accuracy: 0.1786
Epoch 13/400
31/31 [==============================] - 35s 1s/step - loss: 0.8540 - accuracy:
0.7684 - val_loss: 2.6652 - val_accuracy: 0.3147
Epoch 14/400
31/31 [==============================] - 35s 1s/step - loss: 0.7494 - accuracy:
0.8225 - val_loss: 2.8891 - val_accuracy: 0.2634
Epoch 15/400
31/31 [==============================] - 35s 1s/step - loss: 0.6920 - accuracy:
0.8349 - val_loss: 2.6686 - val_accuracy: 0.3504
Epoch 16/400
31/31 [==============================] - 35s 1s/step - loss: 0.5955 - accuracy:
0.8527 - val_loss: 2.2025 - val_accuracy: 0.4420
Epoch 17/400
31/31 [==============================] - 35s 1s/step - loss: 0.4886 - accuracy:
0.8892 - val_loss: 2.2851 - val_accuracy: 0.4420
Epoch 18/400
31/31 [==============================] - 35s 1s/step - loss: 0.4765 - accuracy:
0.8902 - val_loss: 2.1791 - val_accuracy: 0.4397
Epoch 19/400
31/31 [==============================] - 35s 1s/step - loss: 0.4340 - accuracy:
0.8955 - val_loss: 2.2505 - val_accuracy: 0.4353
Epoch 20/400
31/31 [==============================] - 35s 1s/step - loss: 0.3878 - accuracy:
0.9079 - val_loss: 1.9392 - val_accuracy: 0.4866
Epoch 21/400
31/31 [==============================] - 35s 1s/step - loss: 0.3592 - accuracy:
0.9107 - val_loss: 2.5304 - val_accuracy: 0.3951
Epoch 22/400
31/31 [==============================] - 35s 1s/step - loss: 0.3237 - accuracy:
0.9417 - val_loss: 1.8786 - val_accuracy: 0.5067
Epoch 23/400
31/31 [==============================] - 35s 1s/step - loss: 0.2836 - accuracy:
0.9400 - val_loss: 2.1518 - val_accuracy: 0.4487
Epoch 24/400
31/31 [==============================] - 35s 1s/step - loss: 0.2584 - accuracy:
0.9481 - val_loss: 1.9832 - val_accuracy: 0.4643
```

```
Epoch 25/400
31/31 [==============================] - 35s 1s/step - loss: 0.2542 - accuracy:
0.9443 - val_loss: 2.1004 - val_accuracy: 0.4911
Epoch 26/400
31/31 [==============================] - 35s 1s/step - loss: 0.2368 - accuracy:
0.9513 - val_loss: 2.8309 - val_accuracy: 0.3594
Epoch 27/400
31/31 [==============================] - 35s 1s/step - loss: 0.2171 - accuracy:
0.9552 - val_loss: 1.9439 - val_accuracy: 0.4933
Epoch 28/400
31/31 [==============================] - 35s 1s/step - loss: 0.2030 - accuracy:
0.9621 - val_loss: 1.8581 - val_accuracy: 0.5201
Epoch 29/400
31/31 [==============================] - 35s 1s/step - loss: 0.1912 - accuracy:
0.9569 - val_loss: 2.3338 - val_accuracy: 0.4107
Epoch 30/400
31/31 [==============================] - 35s 1s/step - loss: 0.1776 - accuracy:
0.9610 - val_loss: 2.3470 - val_accuracy: 0.4464
Epoch 31/400
31/31 [==============================] - 35s 1s/step - loss: 0.1876 - accuracy:
0.9665 - val_loss: 2.1871 - val_accuracy: 0.4688
Epoch 32/400
31/31 [==============================] - 35s 1s/step - loss: 0.1733 - accuracy:
0.9631 - val_loss: 2.0909 - val_accuracy: 0.5067
Epoch 33/400
31/31 [==============================] - 35s 1s/step - loss: 0.1565 - accuracy:
0.9613 - val_loss: 2.3205 - val_accuracy: 0.4375
Epoch 34/400
31/31 [==============================] - 36s 1s/step - loss: 0.1285 - accuracy:
0.9763 - val_loss: 2.0606 - val_accuracy: 0.4933
Epoch 35/400
31/31 [==============================] - 35s 1s/step - loss: 0.1391 - accuracy:
0.9703 - val_loss: 2.0791 - val_accuracy: 0.4710
Epoch 36/400
31/31 [==============================] - 35s 1s/step - loss: 0.1356 - accuracy:
0.9708 - val_loss: 2.1052 - val_accuracy: 0.4732
Epoch 37/400
31/31 [==============================] - 35s 1s/step - loss: 0.1227 - accuracy:
0.9763 - val_loss: 2.7295 - val_accuracy: 0.4062
Epoch 38/400
31/31 [==============================] - 35s 1s/step - loss: 0.1429 - accuracy:
0.9722 - val_loss: 2.3375 - val_accuracy: 0.4353
Epoch 39/400
31/31 [==============================] - 35s 1s/step - loss: 0.1105 - accuracy:
0.9727 - val_loss: 3.5850 - val_accuracy: 0.3371
Epoch 40/400
31/31 [==============================] - 35s 1s/step - loss: 0.1190 - accuracy:
0.9701 - val_loss: 3.0252 - val_accuracy: 0.3862
```

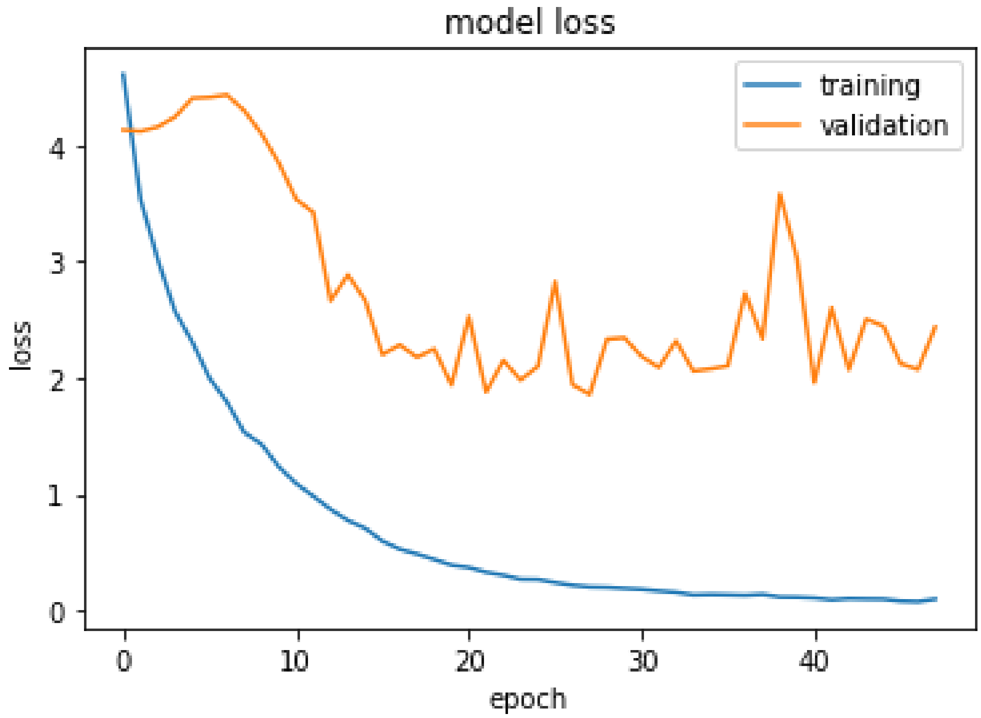
```
Epoch 41/400
31/31 [==============================] - 35s 1s/step - loss: 0.1185 - accuracy:
0.9741 - val_loss: 1.9610 - val_accuracy: 0.5223
Epoch 42/400
31/31 [==============================] - 35s 1s/step - loss: 0.0945 - accuracy:
0.9801 - val_loss: 2.6051 - val_accuracy: 0.4196
Epoch 43/400
31/31 [==============================] - 35s 1s/step - loss: 0.1067 - accuracy:
0.9750 - val_loss: 2.0708 - val_accuracy: 0.4844
Epoch 44/400
31/31 [==============================] - 35s 1s/step - loss: 0.0985 - accuracy:
0.9771 - val_loss: 2.5087 - val_accuracy: 0.4955
Epoch 45/400
31/31 [==============================] - 35s 1s/step - loss: 0.0933 - accuracy:
0.9733 - val_loss: 2.4463 - val_accuracy: 0.4598
Epoch 46/400
31/31 [==============================] - 35s 1s/step - loss: 0.0832 - accuracy:
0.9854 - val_loss: 2.1240 - val_accuracy: 0.4754
Epoch 47/400
31/31 [==============================] - 35s 1s/step - loss: 0.0771 - accuracy:
0.9873 - val_loss: 2.0747 - val_accuracy: 0.4866
Epoch 48/400
31/31 [==============================] - 35s 1s/step - loss: 0.0920 - accuracy:
0.9787 - val_loss: 2.4396 - val_accuracy: 0.4531
Restoring model weights from the end of the best epoch.
Epoch 00048: 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()
```



We see that this actually performs worse 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.

1.3.3 Experiment 3: Using different activation function

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.

[ ]:
```
# 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()

# 1st Convolution Layer
model3.add(Conv2D(6, input_shape=(*IMAGE_SIZE, 1),
                  kernel_size=(5,5), padding='same', activation=mish))
model3.add(BatchNormalization())
model3.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
```

```python
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"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 45, 60, 6)         156
_________________________________________________________________
batch_normalization (BatchNo (None, 45, 60, 6)         24
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 22, 30, 6)         0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 18, 26, 16)        2416
_________________________________________________________________
batch_normalization_1 (Batch (None, 18, 26, 16)        64
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 9, 13, 16)         0
_________________________________________________________________
flatten (Flatten)            (None, 1872)              0
_________________________________________________________________
dense (Dense)                (None, 256)               479488
_________________________________________________________________
batch_normalization_2 (Batch (None, 256)               1024
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
```

```
-----------------------------------------------------------------
batch_normalization_3 (Batch (None, 128)              512

-----------------------------------------------------------------
dropout_1 (Dropout)          (None, 128)              0

-----------------------------------------------------------------
dense_2 (Dense)              (None, 62)               7998
=================================================================
Total params: 524,578
Trainable params: 523,766
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]
)
```

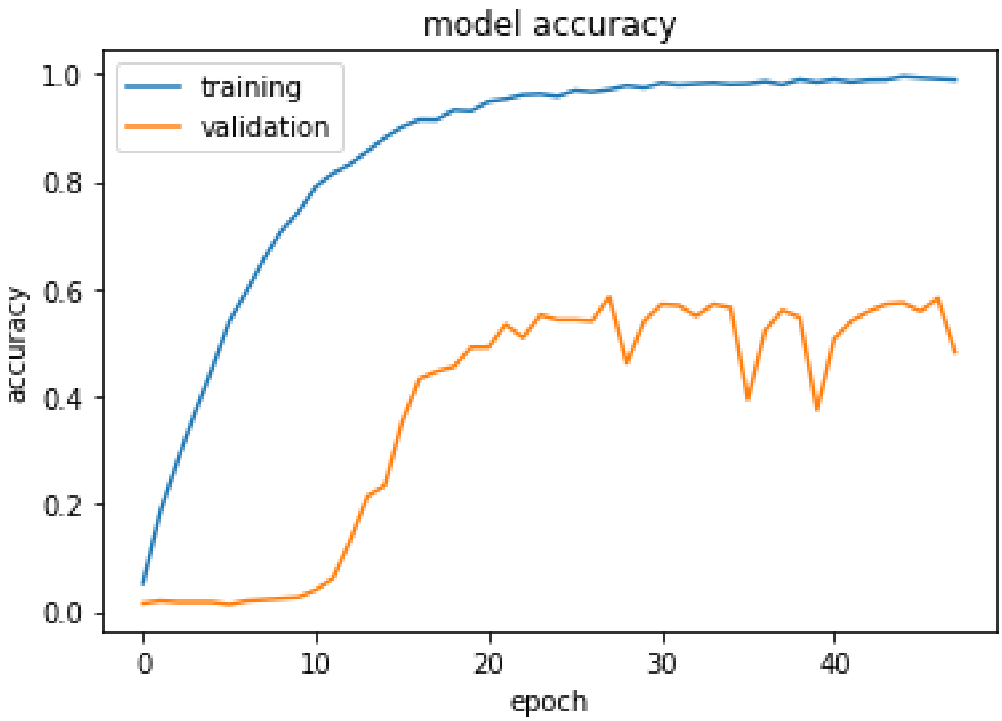
```
Epoch 1/400
31/31 [==============================] - 61s 984ms/step - loss: 4.8382 -
accuracy: 0.0325 - val_loss: 4.1591 - val_accuracy: 0.0156
Epoch 2/400
31/31 [==============================] - 30s 973ms/step - loss: 3.5108 -
accuracy: 0.1671 - val_loss: 4.4229 - val_accuracy: 0.0201
Epoch 3/400
31/31 [==============================] - 30s 974ms/step - loss: 2.8792 -
accuracy: 0.2770 - val_loss: 4.8254 - val_accuracy: 0.0179
Epoch 4/400
31/31 [==============================] - 30s 979ms/step - loss: 2.4508 -
accuracy: 0.3762 - val_loss: 5.2647 - val_accuracy: 0.0179
Epoch 5/400
31/31 [==============================] - 30s 974ms/step - loss: 2.1049 -
```

```
accuracy: 0.4616 - val_loss: 5.6886 - val_accuracy: 0.0179
Epoch 6/400
31/31 [==============================] - 30s 974ms/step - loss: 1.8642 -
accuracy: 0.5457 - val_loss: 5.7846 - val_accuracy: 0.0134
Epoch 7/400
31/31 [==============================] - 30s 969ms/step - loss: 1.5534 -
accuracy: 0.6157 - val_loss: 5.8400 - val_accuracy: 0.0201
Epoch 8/400
31/31 [==============================] - 30s 972ms/step - loss: 1.3556 -
accuracy: 0.6605 - val_loss: 5.8334 - val_accuracy: 0.0223
Epoch 9/400
31/31 [==============================] - 30s 975ms/step - loss: 1.1340 -
accuracy: 0.7309 - val_loss: 5.7567 - val_accuracy: 0.0246
Epoch 10/400
31/31 [==============================] - 30s 971ms/step - loss: 1.0382 -
accuracy: 0.7475 - val_loss: 5.3880 - val_accuracy: 0.0268
Epoch 11/400
31/31 [==============================] - 30s 975ms/step - loss: 0.8675 -
accuracy: 0.7990 - val_loss: 5.2196 - val_accuracy: 0.0402
Epoch 12/400
31/31 [==============================] - 30s 975ms/step - loss: 0.7569 -
accuracy: 0.8240 - val_loss: 4.4228 - val_accuracy: 0.0625
Epoch 13/400
31/31 [==============================] - 30s 972ms/step - loss: 0.6856 -
accuracy: 0.8373 - val_loss: 3.9223 - val_accuracy: 0.1317
Epoch 14/400
31/31 [==============================] - 30s 971ms/step - loss: 0.5931 -
accuracy: 0.8610 - val_loss: 3.3662 - val_accuracy: 0.2143
Epoch 15/400
31/31 [==============================] - 30s 973ms/step - loss: 0.5410 -
accuracy: 0.8735 - val_loss: 3.1947 - val_accuracy: 0.2344
Epoch 16/400
31/31 [==============================] - 30s 972ms/step - loss: 0.4776 -
accuracy: 0.8918 - val_loss: 2.5398 - val_accuracy: 0.3527
Epoch 17/400
31/31 [==============================] - 30s 974ms/step - loss: 0.4035 -
accuracy: 0.9192 - val_loss: 2.2641 - val_accuracy: 0.4330
Epoch 18/400
31/31 [==============================] - 30s 969ms/step - loss: 0.3627 -
accuracy: 0.9253 - val_loss: 2.1770 - val_accuracy: 0.4464
Epoch 19/400
31/31 [==============================] - 30s 976ms/step - loss: 0.3120 -
accuracy: 0.9305 - val_loss: 2.0948 - val_accuracy: 0.4554
Epoch 20/400
31/31 [==============================] - 30s 975ms/step - loss: 0.3011 -
accuracy: 0.9381 - val_loss: 2.0228 - val_accuracy: 0.4911
Epoch 21/400
31/31 [==============================] - 30s 980ms/step - loss: 0.2495 -
```

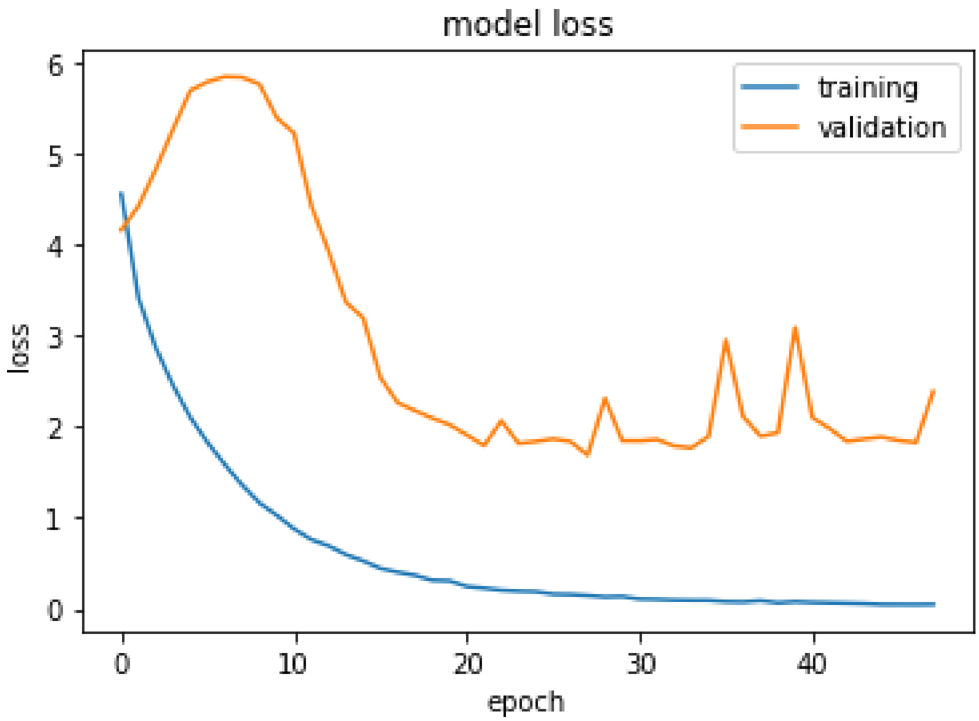
```
accuracy: 0.9470 - val_loss: 1.9106 - val_accuracy: 0.4911
Epoch 22/400
31/31 [==============================] - 30s 969ms/step - loss: 0.2261 -
accuracy: 0.9564 - val_loss: 1.7929 - val_accuracy: 0.5335
Epoch 23/400
31/31 [==============================] - 30s 973ms/step - loss: 0.2143 -
accuracy: 0.9579 - val_loss: 2.0653 - val_accuracy: 0.5089
Epoch 24/400
31/31 [==============================] - 30s 978ms/step - loss: 0.2132 -
accuracy: 0.9561 - val_loss: 1.8173 - val_accuracy: 0.5513
Epoch 25/400
31/31 [==============================] - 30s 975ms/step - loss: 0.1900 -
accuracy: 0.9605 - val_loss: 1.8378 - val_accuracy: 0.5424
Epoch 26/400
31/31 [==============================] - 30s 970ms/step - loss: 0.1631 -
accuracy: 0.9706 - val_loss: 1.8676 - val_accuracy: 0.5424
Epoch 27/400
31/31 [==============================] - 30s 972ms/step - loss: 0.1586 -
accuracy: 0.9627 - val_loss: 1.8381 - val_accuracy: 0.5402
Epoch 28/400
31/31 [==============================] - 30s 977ms/step - loss: 0.1482 -
accuracy: 0.9689 - val_loss: 1.6875 - val_accuracy: 0.5848
Epoch 29/400
31/31 [==============================] - 30s 978ms/step - loss: 0.1289 -
accuracy: 0.9766 - val_loss: 2.3107 - val_accuracy: 0.4621
Epoch 30/400
31/31 [==============================] - 30s 977ms/step - loss: 0.1297 -
accuracy: 0.9744 - val_loss: 1.8469 - val_accuracy: 0.5402
Epoch 31/400
31/31 [==============================] - 30s 982ms/step - loss: 0.1049 -
accuracy: 0.9822 - val_loss: 1.8450 - val_accuracy: 0.5714
Epoch 32/400
31/31 [==============================] - 30s 973ms/step - loss: 0.1050 -
accuracy: 0.9804 - val_loss: 1.8608 - val_accuracy: 0.5692
Epoch 33/400
31/31 [==============================] - 30s 975ms/step - loss: 0.0973 -
accuracy: 0.9831 - val_loss: 1.7893 - val_accuracy: 0.5491
Epoch 34/400
31/31 [==============================] - 30s 978ms/step - loss: 0.0946 -
accuracy: 0.9812 - val_loss: 1.7682 - val_accuracy: 0.5714
Epoch 35/400
31/31 [==============================] - 30s 973ms/step - loss: 0.0927 -
accuracy: 0.9788 - val_loss: 1.8935 - val_accuracy: 0.5647
Epoch 36/400
31/31 [==============================] - 30s 976ms/step - loss: 0.0775 -
accuracy: 0.9832 - val_loss: 2.9494 - val_accuracy: 0.3951
Epoch 37/400
31/31 [==============================] - 30s 969ms/step - loss: 0.0749 -
```

```
accuracy: 0.9908 - val_loss: 2.1115 - val_accuracy: 0.5223
Epoch 38/400
31/31 [==============================] - 30s 971ms/step - loss: 0.0970 -
accuracy: 0.9828 - val_loss: 1.8960 - val_accuracy: 0.5603
Epoch 39/400
31/31 [==============================] - 30s 976ms/step - loss: 0.0695 -
accuracy: 0.9889 - val_loss: 1.9347 - val_accuracy: 0.5469
Epoch 40/400
31/31 [==============================] - 30s 979ms/step - loss: 0.0806 -
accuracy: 0.9848 - val_loss: 3.0861 - val_accuracy: 0.3750
Epoch 41/400
31/31 [==============================] - 30s 972ms/step - loss: 0.0650 -
accuracy: 0.9918 - val_loss: 2.1020 - val_accuracy: 0.5067
Epoch 42/400
31/31 [==============================] - 30s 977ms/step - loss: 0.0664 -
accuracy: 0.9845 - val_loss: 1.9804 - val_accuracy: 0.5402
Epoch 43/400
31/31 [==============================] - 30s 968ms/step - loss: 0.0686 -
accuracy: 0.9859 - val_loss: 1.8390 - val_accuracy: 0.5580
Epoch 44/400
31/31 [==============================] - 30s 978ms/step - loss: 0.0598 -
accuracy: 0.9881 - val_loss: 1.8656 - val_accuracy: 0.5714
Epoch 45/400
31/31 [==============================] - 30s 976ms/step - loss: 0.0538 -
accuracy: 0.9946 - val_loss: 1.8879 - val_accuracy: 0.5737
Epoch 46/400
31/31 [==============================] - 30s 972ms/step - loss: 0.0532 -
accuracy: 0.9894 - val_loss: 1.8488 - val_accuracy: 0.5580
Epoch 47/400
31/31 [==============================] - 30s 975ms/step - loss: 0.0459 -
accuracy: 0.9925 - val_loss: 1.8268 - val_accuracy: 0.5826
Epoch 48/400
31/31 [==============================] - 30s 969ms/step - loss: 0.0443 -
accuracy: 0.9918 - val_loss: 2.3868 - val_accuracy: 0.4821
Restoring model weights from the end of the best epoch.
Epoch 00048: 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 28.

1.3.4 Experiment 4: Changing the Model Architecture

From ref. [1] and [2], I modify the architecture to see if it gives better results. This model actually gives very good results on the MNIST dataset.

[ ]:
```
model4 = Sequential()

# 1st Convolution Layer
model4.add(Conv2D(32, input_shape=(*IMAGE_SIZE, 1), kernel_size=3,␣
 ↪activation=mish))
model4.add(BatchNormalization())
model4.add(Conv2D(32, kernel_size=3, activation=mish))
model4.add(BatchNormalization())
model4.add(Conv2D(32, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model4.add(BatchNormalization())
model4.add(Dropout(0.4))

# 2nd Convolution Layer
model4.add(Conv2D(64, kernel_size=3, activation=mish))
```

```
model4.add(BatchNormalization())
model4.add(Conv2D(64, kernel_size=3, activation=mish))
model4.add(BatchNormalization())
model4.add(Conv2D(64, kernel_size=5, strides=2, padding='same',
 ↪activation=mish))
model4.add(BatchNormalization())
model4.add(Dropout(0.4))

# 3rd Convolution Layer
model4.add(Conv2D(128, kernel_size = 4, activation=mish))
model4.add(BatchNormalization())

# Passing to a Fully Connected Layer
model4.add(Flatten())
model4.add(Dropout(0.4))

# Output Layer
model4.add(Dense(62, activation='softmax'))
```

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

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 43, 58, 32)        320
_________________________________________________________________
batch_normalization_4 (Batch (None, 43, 58, 32)        128
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 41, 56, 32)        9248
_________________________________________________________________
batch_normalization_5 (Batch (None, 41, 56, 32)        128
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 21, 28, 32)        25632
_________________________________________________________________
batch_normalization_6 (Batch (None, 21, 28, 32)        128
_________________________________________________________________
dropout_2 (Dropout)          (None, 21, 28, 32)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 19, 26, 64)        18496
_________________________________________________________________
batch_normalization_7 (Batch (None, 19, 26, 64)        256
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 17, 24, 64)        36928
_________________________________________________________________
batch_normalization_8 (Batch (None, 17, 24, 64)        256
_________________________________________________________________
```

```
conv2d_7 (Conv2D)            (None, 9, 12, 64)         102464
_________________________________________________________________
batch_normalization_9 (Batch (None, 9, 12, 64)         256
_________________________________________________________________
dropout_3 (Dropout)          (None, 9, 12, 64)         0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 6, 9, 128)         131200
_________________________________________________________________
batch_normalization_10 (Batc (None, 6, 9, 128)         512
_________________________________________________________________
flatten_1 (Flatten)          (None, 6912)              0
_________________________________________________________________
dropout_4 (Dropout)          (None, 6912)              0
_________________________________________________________________
dense_3 (Dense)              (None, 62)                428606
=================================================================
Total params: 754,558
Trainable params: 753,726
Non-trainable params: 832
_________________________________________________________________
```

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

Saving the Checkpoint

[ ]:
```
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)
```

[ ]:
```
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]
)
```

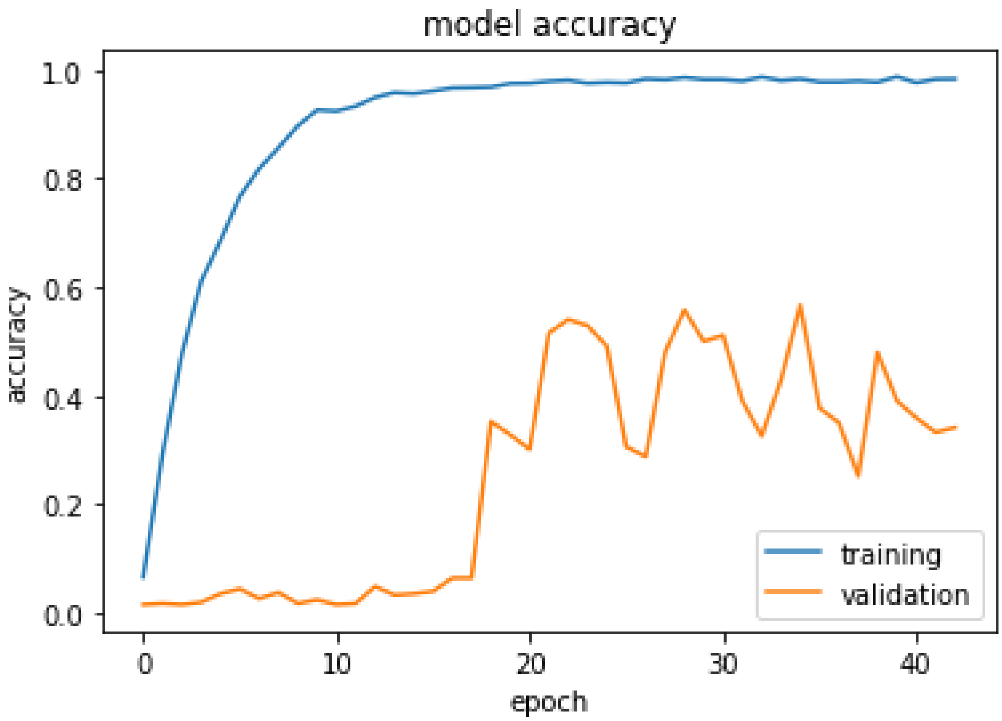
```
Epoch 1/400
31/31 [==============================] - 32s 1s/step - loss: 5.3313 - accuracy:
0.0398 - val_loss: 4.6788 - val_accuracy: 0.0156
Epoch 2/400
31/31 [==============================] - 30s 979ms/step - loss: 3.1859 -
```

```
accuracy: 0.2657 - val_loss: 5.6807 - val_accuracy: 0.0179
Epoch 3/400
31/31 [==============================] - 30s 979ms/step - loss: 2.0750 -
accuracy: 0.4680 - val_loss: 6.7425 - val_accuracy: 0.0156
Epoch 4/400
31/31 [==============================] - 30s 974ms/step - loss: 1.4255 -
accuracy: 0.6142 - val_loss: 5.9356 - val_accuracy: 0.0201
Epoch 5/400
31/31 [==============================] - 30s 974ms/step - loss: 1.0759 -
accuracy: 0.6824 - val_loss: 5.0072 - val_accuracy: 0.0357
Epoch 6/400
31/31 [==============================] - 30s 983ms/step - loss: 0.7809 -
accuracy: 0.7552 - val_loss: 5.1140 - val_accuracy: 0.0446
Epoch 7/400
31/31 [==============================] - 30s 973ms/step - loss: 0.5856 -
accuracy: 0.8184 - val_loss: 9.4351 - val_accuracy: 0.0268
Epoch 8/400
31/31 [==============================] - 30s 975ms/step - loss: 0.4152 -
accuracy: 0.8653 - val_loss: 10.7215 - val_accuracy: 0.0379
Epoch 9/400
31/31 [==============================] - 30s 973ms/step - loss: 0.3180 -
accuracy: 0.8919 - val_loss: 17.2575 - val_accuracy: 0.0179
Epoch 10/400
31/31 [==============================] - 30s 976ms/step - loss: 0.2462 -
accuracy: 0.9311 - val_loss: 15.8880 - val_accuracy: 0.0246
Epoch 11/400
31/31 [==============================] - 30s 977ms/step - loss: 0.2204 -
accuracy: 0.9266 - val_loss: 19.3261 - val_accuracy: 0.0156
Epoch 12/400
31/31 [==============================] - 30s 976ms/step - loss: 0.2188 -
accuracy: 0.9283 - val_loss: 23.3252 - val_accuracy: 0.0179
Epoch 13/400
31/31 [==============================] - 30s 982ms/step - loss: 0.1608 -
accuracy: 0.9534 - val_loss: 17.8566 - val_accuracy: 0.0491
Epoch 14/400
31/31 [==============================] - 30s 977ms/step - loss: 0.1251 -
accuracy: 0.9622 - val_loss: 20.5541 - val_accuracy: 0.0335
Epoch 15/400
31/31 [==============================] - 30s 973ms/step - loss: 0.1106 -
accuracy: 0.9626 - val_loss: 21.3762 - val_accuracy: 0.0357
Epoch 16/400
31/31 [==============================] - 30s 986ms/step - loss: 0.1038 -
accuracy: 0.9697 - val_loss: 21.3300 - val_accuracy: 0.0402
Epoch 17/400
31/31 [==============================] - 30s 977ms/step - loss: 0.0934 -
accuracy: 0.9725 - val_loss: 14.5734 - val_accuracy: 0.0647
Epoch 18/400
31/31 [==============================] - 30s 977ms/step - loss: 0.1067 -
```

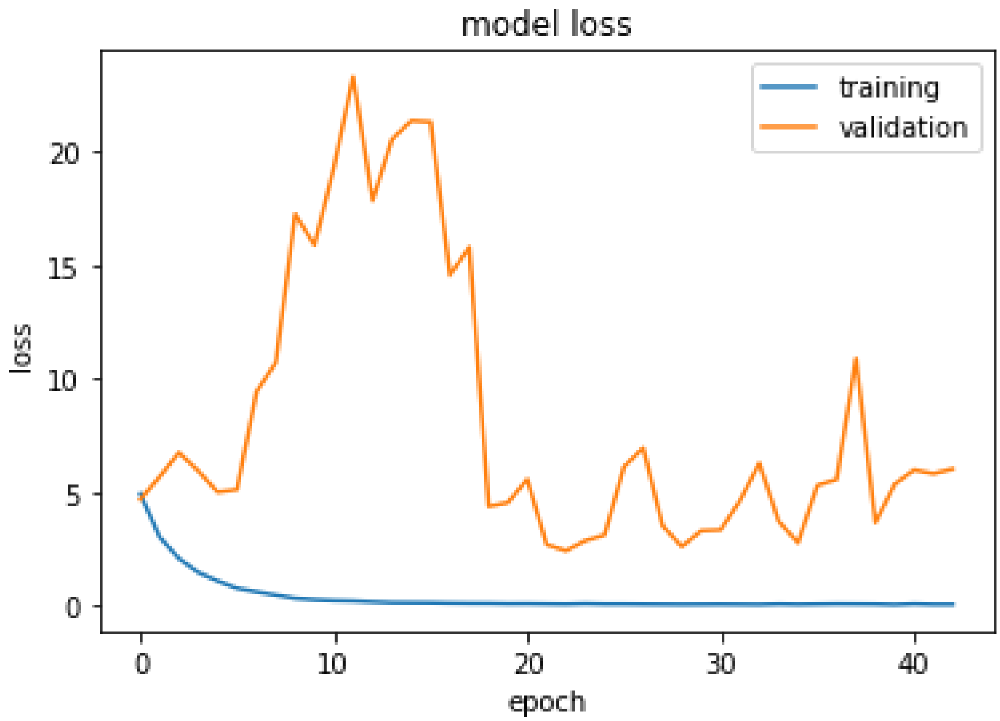
```
accuracy: 0.9654 - val_loss: 15.8007 - val_accuracy: 0.0647
Epoch 19/400
31/31 [==============================] - 30s 982ms/step - loss: 0.0960 -
accuracy: 0.9675 - val_loss: 4.3696 - val_accuracy: 0.3527
Epoch 20/400
31/31 [==============================] - 30s 975ms/step - loss: 0.0761 -
accuracy: 0.9714 - val_loss: 4.5411 - val_accuracy: 0.3281
Epoch 21/400
31/31 [==============================] - 30s 974ms/step - loss: 0.0832 -
accuracy: 0.9721 - val_loss: 5.5686 - val_accuracy: 0.3013
Epoch 22/400
31/31 [==============================] - 30s 979ms/step - loss: 0.0728 -
accuracy: 0.9794 - val_loss: 2.6852 - val_accuracy: 0.5156
Epoch 23/400
31/31 [==============================] - 30s 981ms/step - loss: 0.0759 -
accuracy: 0.9789 - val_loss: 2.4136 - val_accuracy: 0.5402
Epoch 24/400
31/31 [==============================] - 30s 978ms/step - loss: 0.0938 -
accuracy: 0.9717 - val_loss: 2.8570 - val_accuracy: 0.5290
Epoch 25/400
31/31 [==============================] - 30s 975ms/step - loss: 0.0530 -
accuracy: 0.9822 - val_loss: 3.1094 - val_accuracy: 0.4911
Epoch 26/400
31/31 [==============================] - 30s 983ms/step - loss: 0.0754 -
accuracy: 0.9716 - val_loss: 6.1126 - val_accuracy: 0.3058
Epoch 27/400
31/31 [==============================] - 30s 986ms/step - loss: 0.0537 -
accuracy: 0.9881 - val_loss: 6.9506 - val_accuracy: 0.2879
Epoch 28/400
31/31 [==============================] - 30s 974ms/step - loss: 0.0515 -
accuracy: 0.9836 - val_loss: 3.5170 - val_accuracy: 0.4799
Epoch 29/400
31/31 [==============================] - 30s 979ms/step - loss: 0.0497 -
accuracy: 0.9872 - val_loss: 2.5949 - val_accuracy: 0.5580
Epoch 30/400
31/31 [==============================] - 30s 979ms/step - loss: 0.0498 -
accuracy: 0.9833 - val_loss: 3.3020 - val_accuracy: 0.5000
Epoch 31/400
31/31 [==============================] - 30s 977ms/step - loss: 0.0497 -
accuracy: 0.9860 - val_loss: 3.3340 - val_accuracy: 0.5112
Epoch 32/400
31/31 [==============================] - 30s 977ms/step - loss: 0.0562 -
accuracy: 0.9750 - val_loss: 4.6205 - val_accuracy: 0.3906
Epoch 33/400
31/31 [==============================] - 30s 980ms/step - loss: 0.0493 -
accuracy: 0.9863 - val_loss: 6.2758 - val_accuracy: 0.3259
Epoch 34/400
31/31 [==============================] - 30s 978ms/step - loss: 0.0728 -
```

```
accuracy: 0.9810 - val_loss: 3.7161 - val_accuracy: 0.4286
Epoch 35/400
31/31 [==============================] - 30s 979ms/step - loss: 0.0449 -
accuracy: 0.9850 - val_loss: 2.7671 - val_accuracy: 0.5670
Epoch 36/400
31/31 [==============================] - 30s 982ms/step - loss: 0.0508 -
accuracy: 0.9801 - val_loss: 5.3039 - val_accuracy: 0.3772
Epoch 37/400
31/31 [==============================] - 30s 986ms/step - loss: 0.0696 -
accuracy: 0.9793 - val_loss: 5.5649 - val_accuracy: 0.3504
Epoch 38/400
31/31 [==============================] - 30s 977ms/step - loss: 0.0804 -
accuracy: 0.9757 - val_loss: 10.8941 - val_accuracy: 0.2522
Epoch 39/400
31/31 [==============================] - 30s 976ms/step - loss: 0.0624 -
accuracy: 0.9783 - val_loss: 3.6520 - val_accuracy: 0.4799
Epoch 40/400
31/31 [==============================] - 30s 973ms/step - loss: 0.0436 -
accuracy: 0.9890 - val_loss: 5.3549 - val_accuracy: 0.3906
Epoch 41/400
31/31 [==============================] - 30s 976ms/step - loss: 0.0637 -
accuracy: 0.9812 - val_loss: 5.9832 - val_accuracy: 0.3594
Epoch 42/400
31/31 [==============================] - 30s 976ms/step - loss: 0.0414 -
accuracy: 0.9890 - val_loss: 5.8161 - val_accuracy: 0.3326
Epoch 43/400
31/31 [==============================] - 30s 978ms/step - loss: 0.0526 -
accuracy: 0.9824 - val_loss: 6.0260 - val_accuracy: 0.3415
Restoring model weights from the end of the best epoch.
Epoch 00043: early stopping
```

[ ]:
```
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()
```



[ ]:
```
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()
```



This is is actually worse than all other experiments we have done so far. Though the training accuracy converges fast, the validation accuracy and loss have too much variance.

1.3.5 Experiment 5: 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_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)
```

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))

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

# 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)

model5 = tf.keras.Model(inputs, outputs)

model5.compile(
    optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"]
)
```

```
model5.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
_________________________________________________________________
```

[ ]:
```
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_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:
```

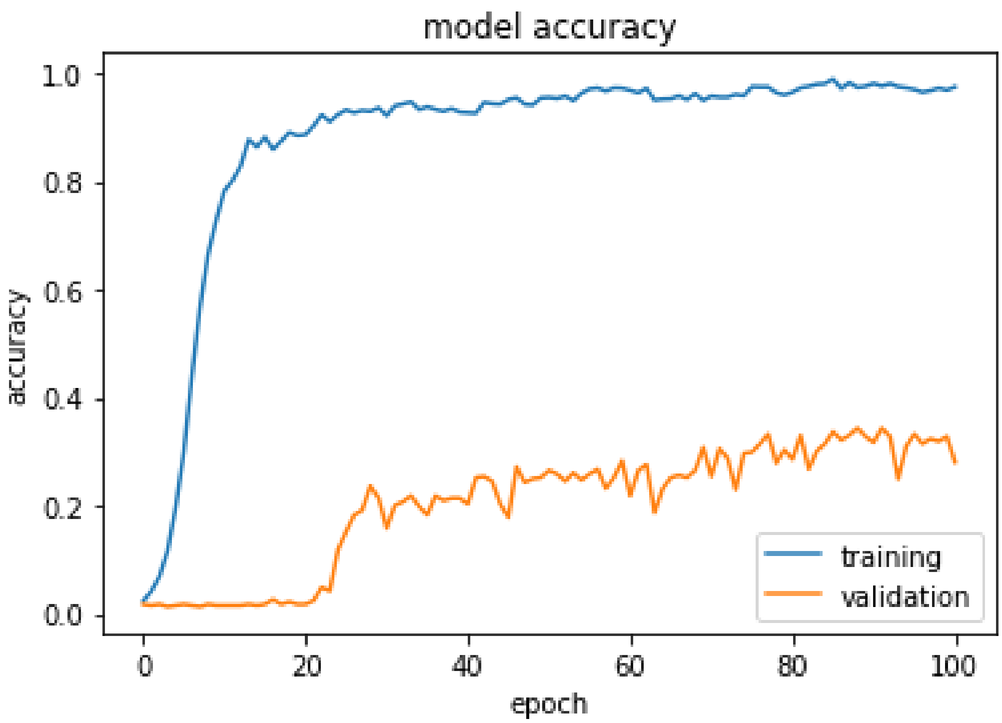
```
0.9304 - val_loss: 5.9970 - val_accuracy: 0.2098
Epoch 39/400
31/31 [==============================] - 32s 1s/step - loss: 0.1915 - accuracy:
0.9412 - val_loss: 6.3312 - val_accuracy: 0.2143
Epoch 40/400
31/31 [==============================] - 32s 1s/step - loss: 0.2200 - accuracy:
0.9326 - val_loss: 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:
```

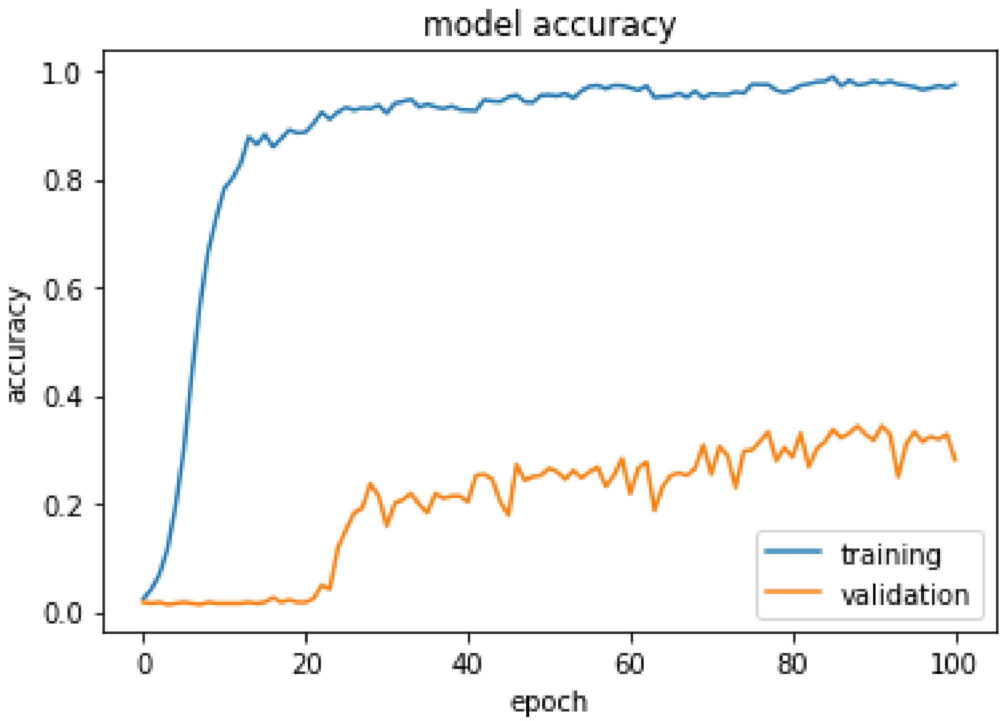
```
0.9507 - val_loss: 5.8126 - val_accuracy: 0.2612
Epoch 55/400
31/31 [==============================] - 32s 1s/step - loss: 0.1060 - accuracy:
0.9709 - val_loss: 5.4918 - val_accuracy: 0.2478
Epoch 56/400
31/31 [==============================] - 32s 1s/step - loss: 0.0894 - accuracy:
0.9723 - val_loss: 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:
```

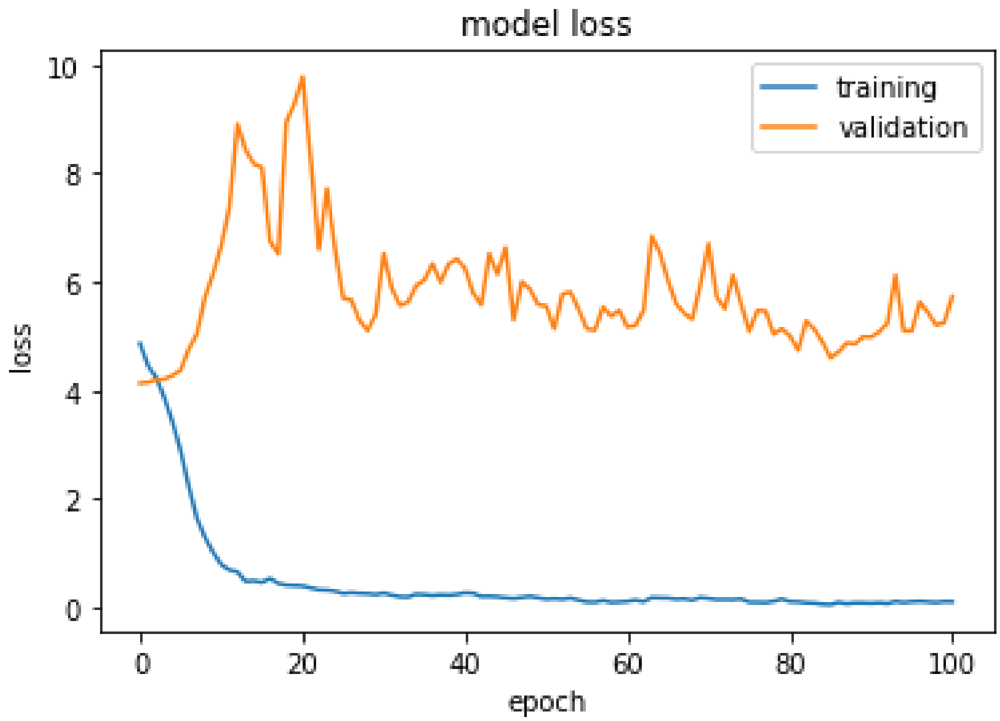
```
0.9886 - val_loss: 4.5963 - val_accuracy: 0.3371
Epoch 87/400
31/31 [==============================] - 31s 1s/step - loss: 0.0698 - accuracy:
0.9780 - val_loss: 4.7077 - val_accuracy: 0.3214
Epoch 88/400
31/31 [==============================] - 31s 1s/step - loss: 0.0604 - accuracy:
0.9848 - val_loss: 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
```

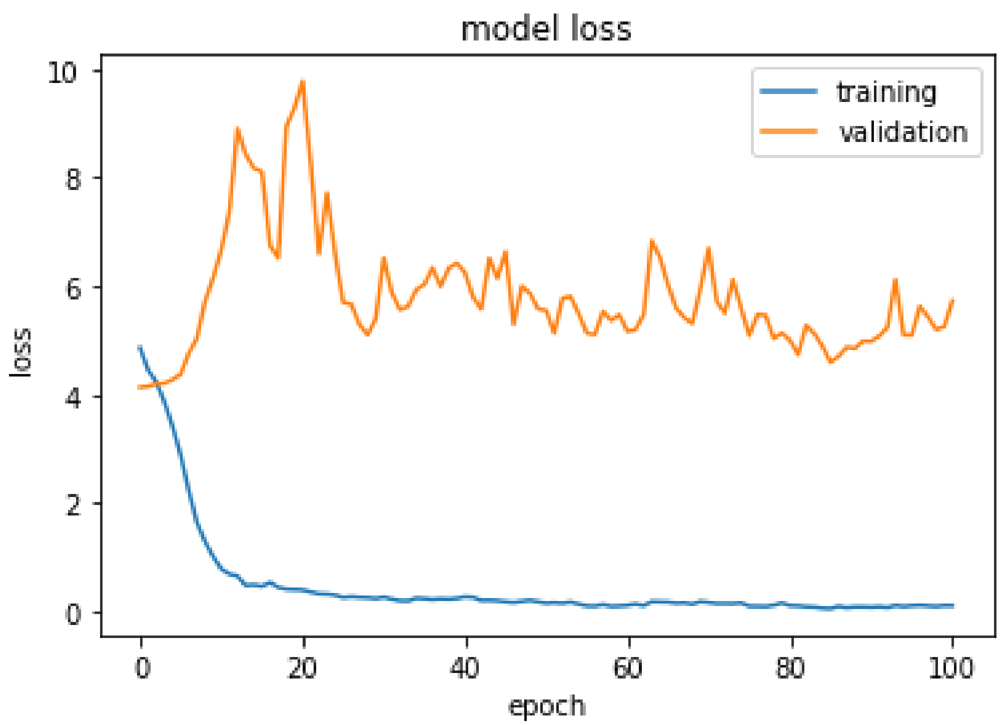
[ ]:
```
plt.plot(history5.history['accuracy'])
plt.plot(history5.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```






```
[ ]: 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()
```


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


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

As expected, this does not converge. Infact, it's not even reaching a 50% accuracy. This accuracy result is similar to the one shown in ref. [6] here.

1.3.6 Experiment 6: Reducing Batch Size

Smaller batch sizes tend to converge faster [12]. Hence, I'll reduce the batch size to 32 to see the performance. I'll use the two best models I have achieved form the past experiments 3 and 4.

Architecture from Experiment 3

[ ]:
```
BATCH_SIZE = 32
```

[ ]:
```
train_generator3 = 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)

validation_generator3 = 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 1984 images belonging to 62 classes.
Found 496 images belonging to 62 classes.
```

[ ]:
```
model6_1 = Sequential()

# 1st Convolution Layer
model6_1.add(Conv2D(6, input_shape=(*IMAGE_SIZE, 1),
                  kernel_size=(5,5), padding='same', activation=mish))
model6_1.add(BatchNormalization())
model6_1.add(MaxPooling2D(pool_size=(2,2), strides=2))

# 2nd Convolution Layer
model6_1.add(Conv2D(16, kernel_size=(5,5), activation=mish))
model6_1.add(BatchNormalization())
model6_1.add(MaxPooling2D(pool_size=(2,2), strides=2))
```

```python
# Passing to a Fully Connected Layer
model6_1.add(Flatten())

# 1st Fully Connected Layer
model6_1.add(Dense(256, activation=mish))
model6_1.add(BatchNormalization())
model6_1.add(Dropout(0.4))

# 2nd Fully Connected Layer
model6_1.add(Dense(128, activation=mish))
model6_1.add(BatchNormalization())
model6_1.add(Dropout(0.4))

# Output Layer
model6_1.add(Dense(62, activation='softmax'))
```

[ ]:
```python
model6_1.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_13 (Conv2D)           (None, 45, 60, 6)         156
_________________________________________________________________
batch_normalization_19 (Batc (None, 45, 60, 6)         24
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 22, 30, 6)         0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 18, 26, 16)        2416
_________________________________________________________________
batch_normalization_20 (Batc (None, 18, 26, 16)        64
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 9, 13, 16)         0
_________________________________________________________________
flatten_4 (Flatten)          (None, 1872)              0
_________________________________________________________________
dense_10 (Dense)             (None, 256)               479488
_________________________________________________________________
batch_normalization_21 (Batc (None, 256)               1024
_________________________________________________________________
dropout_9 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_11 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_22 (Batc (None, 128)               512
_________________________________________________________________
dropout_10 (Dropout)         (None, 128)               0
```

```
-----------------------------------------------------------------
dense_12 (Dense)             (None, 62)               7998
=================================================================
Total params: 524,578
Trainable params: 523,766
Non-trainable params: 812
-----------------------------------------------------------------
```

```
[ ]: model6_1.compile(loss='categorical_crossentropy', optimizer=Adam(),␣
      ↪metrics=['accuracy'])
```

Saving the Model Checkpoint

```
[ ]: checkpoint_filepath6_1 = 'exp6_1/checkpoint'
     model_checkpoint_callback6_1 = tf.keras.callbacks.ModelCheckpoint(
         filepath=checkpoint_filepath6_1,
         save_weights_only=True,
         monitor='val_loss',
         mode='min',
         save_best_only=True)
```

```
[ ]: history6_1 = model6_1.fit(
         train_generator3,
         epochs=EPOCHS,
         validation_data=validation_generator3,
         steps_per_epoch = train_generator3.samples // BATCH_SIZE,
         validation_steps = validation_generator3.samples // BATCH_SIZE,
         callbacks=[model_checkpoint_callback6_1, early_stopping_callback]
     )
```

```
Epoch 1/400
62/62 [==============================] - 33s 513ms/step - loss: 4.6588 -
accuracy: 0.0335 - val_loss: 4.3612 - val_accuracy: 0.0167
Epoch 2/400
62/62 [==============================] - 31s 499ms/step - loss: 3.3342 -
accuracy: 0.1942 - val_loss: 4.6904 - val_accuracy: 0.0250
Epoch 3/400
62/62 [==============================] - 31s 495ms/step - loss: 2.6940 -
accuracy: 0.3107 - val_loss: 4.8908 - val_accuracy: 0.0208
Epoch 4/400
62/62 [==============================] - 31s 501ms/step - loss: 2.2589 -
accuracy: 0.4113 - val_loss: 4.9160 - val_accuracy: 0.0083
Epoch 5/400
62/62 [==============================] - 30s 493ms/step - loss: 1.8811 -
accuracy: 0.5197 - val_loss: 4.5471 - val_accuracy: 0.0354
Epoch 6/400
62/62 [==============================] - 31s 494ms/step - loss: 1.5784 -
accuracy: 0.5897 - val_loss: 3.7062 - val_accuracy: 0.1250
```

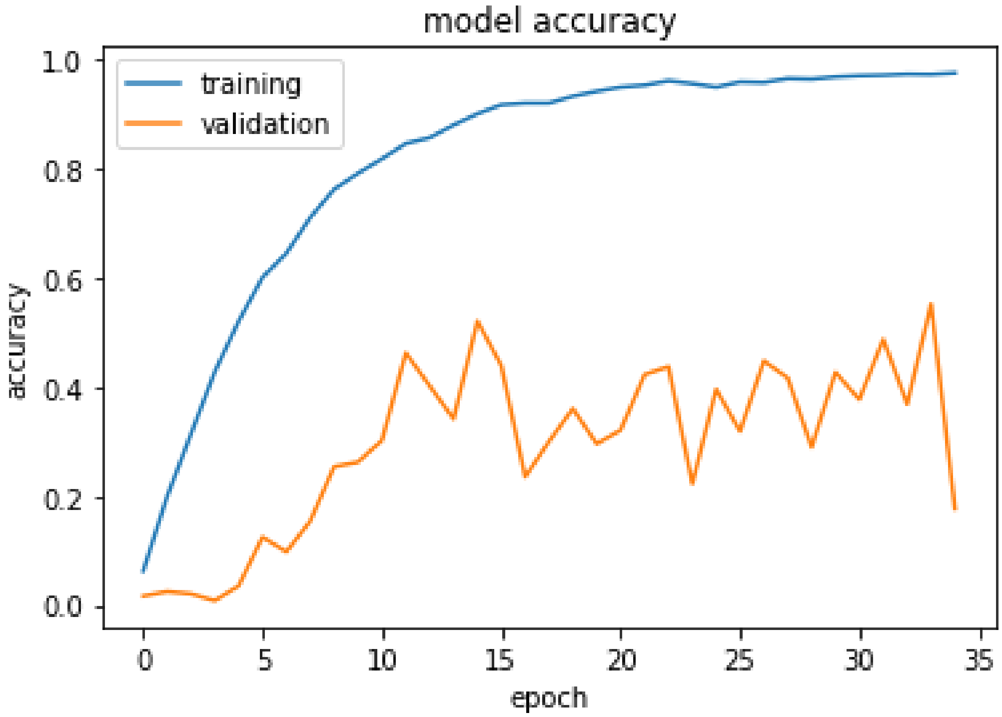
```
Epoch 7/400
62/62 [==============================] - 31s 496ms/step - loss: 1.3584 -
accuracy: 0.6500 - val_loss: 4.0543 - val_accuracy: 0.0979
Epoch 8/400
62/62 [==============================] - 30s 492ms/step - loss: 1.1313 -
accuracy: 0.7136 - val_loss: 3.6911 - val_accuracy: 0.1542
Epoch 9/400
62/62 [==============================] - 31s 494ms/step - loss: 0.9335 -
accuracy: 0.7652 - val_loss: 2.9963 - val_accuracy: 0.2542
Epoch 10/400
62/62 [==============================] - 31s 502ms/step - loss: 0.8233 -
accuracy: 0.7817 - val_loss: 3.0014 - val_accuracy: 0.2625
Epoch 11/400
62/62 [==============================] - 31s 498ms/step - loss: 0.6886 -
accuracy: 0.8157 - val_loss: 2.9491 - val_accuracy: 0.3021
Epoch 12/400
62/62 [==============================] - 31s 503ms/step - loss: 0.5739 -
accuracy: 0.8549 - val_loss: 2.0746 - val_accuracy: 0.4625
Epoch 13/400
62/62 [==============================] - 31s 498ms/step - loss: 0.5214 -
accuracy: 0.8688 - val_loss: 2.4844 - val_accuracy: 0.4021
Epoch 14/400
62/62 [==============================] - 31s 504ms/step - loss: 0.4385 -
accuracy: 0.8842 - val_loss: 2.7843 - val_accuracy: 0.3417
Epoch 15/400
62/62 [==============================] - 31s 503ms/step - loss: 0.3956 -
accuracy: 0.9032 - val_loss: 1.7987 - val_accuracy: 0.5208
Epoch 16/400
62/62 [==============================] - 31s 503ms/step - loss: 0.3296 -
accuracy: 0.9288 - val_loss: 2.1770 - val_accuracy: 0.4396
Epoch 17/400
62/62 [==============================] - 31s 508ms/step - loss: 0.3260 -
accuracy: 0.9238 - val_loss: 4.9160 - val_accuracy: 0.2354
Epoch 18/400
62/62 [==============================] - 31s 502ms/step - loss: 0.2988 -
accuracy: 0.9266 - val_loss: 4.9212 - val_accuracy: 0.3000
Epoch 19/400
62/62 [==============================] - 31s 501ms/step - loss: 0.2539 -
accuracy: 0.9368 - val_loss: 3.1581 - val_accuracy: 0.3604
Epoch 20/400
62/62 [==============================] - 31s 501ms/step - loss: 0.2521 -
accuracy: 0.9353 - val_loss: 3.8498 - val_accuracy: 0.2958
Epoch 21/400
62/62 [==============================] - 31s 504ms/step - loss: 0.2160 -
accuracy: 0.9512 - val_loss: 3.2776 - val_accuracy: 0.3208
Epoch 22/400
62/62 [==============================] - 31s 507ms/step - loss: 0.2002 -
accuracy: 0.9499 - val_loss: 2.2856 - val_accuracy: 0.4229
```

```
Epoch 23/400
62/62 [==============================] - 31s 505ms/step - loss: 0.2160 -
accuracy: 0.9587 - val_loss: 2.4635 - val_accuracy: 0.4375
Epoch 24/400
62/62 [==============================] - 31s 507ms/step - loss: 0.1797 -
accuracy: 0.9628 - val_loss: 8.9669 - val_accuracy: 0.2229
Epoch 25/400
62/62 [==============================] - 31s 502ms/step - loss: 0.1637 -
accuracy: 0.9541 - val_loss: 2.8599 - val_accuracy: 0.3958
Epoch 26/400
62/62 [==============================] - 31s 503ms/step - loss: 0.1494 -
accuracy: 0.9656 - val_loss: 4.0128 - val_accuracy: 0.3187
Epoch 27/400
62/62 [==============================] - 31s 505ms/step - loss: 0.1535 -
accuracy: 0.9597 - val_loss: 2.5226 - val_accuracy: 0.4479
Epoch 28/400
62/62 [==============================] - 32s 512ms/step - loss: 0.1725 -
accuracy: 0.9620 - val_loss: 2.6662 - val_accuracy: 0.4167
Epoch 29/400
62/62 [==============================] - 32s 524ms/step - loss: 0.1454 -
accuracy: 0.9656 - val_loss: 5.0952 - val_accuracy: 0.2896
Epoch 30/400
62/62 [==============================] - 32s 519ms/step - loss: 0.1288 -
accuracy: 0.9682 - val_loss: 2.9926 - val_accuracy: 0.4271
Epoch 31/400
62/62 [==============================] - 31s 504ms/step - loss: 0.1090 -
accuracy: 0.9715 - val_loss: 3.3791 - val_accuracy: 0.3771
Epoch 32/400
62/62 [==============================] - 32s 518ms/step - loss: 0.1163 -
accuracy: 0.9706 - val_loss: 2.4737 - val_accuracy: 0.4875
Epoch 33/400
62/62 [==============================] - 32s 517ms/step - loss: 0.0936 -
accuracy: 0.9808 - val_loss: 3.3878 - val_accuracy: 0.3688
Epoch 34/400
62/62 [==============================] - 31s 510ms/step - loss: 0.1080 -
accuracy: 0.9750 - val_loss: 1.9445 - val_accuracy: 0.5521
Epoch 35/400
62/62 [==============================] - 32s 510ms/step - loss: 0.1041 -
accuracy: 0.9722 - val_loss: 7.3934 - val_accuracy: 0.1771
Restoring model weights from the end of the best epoch.
Epoch 00035: early stopping
```

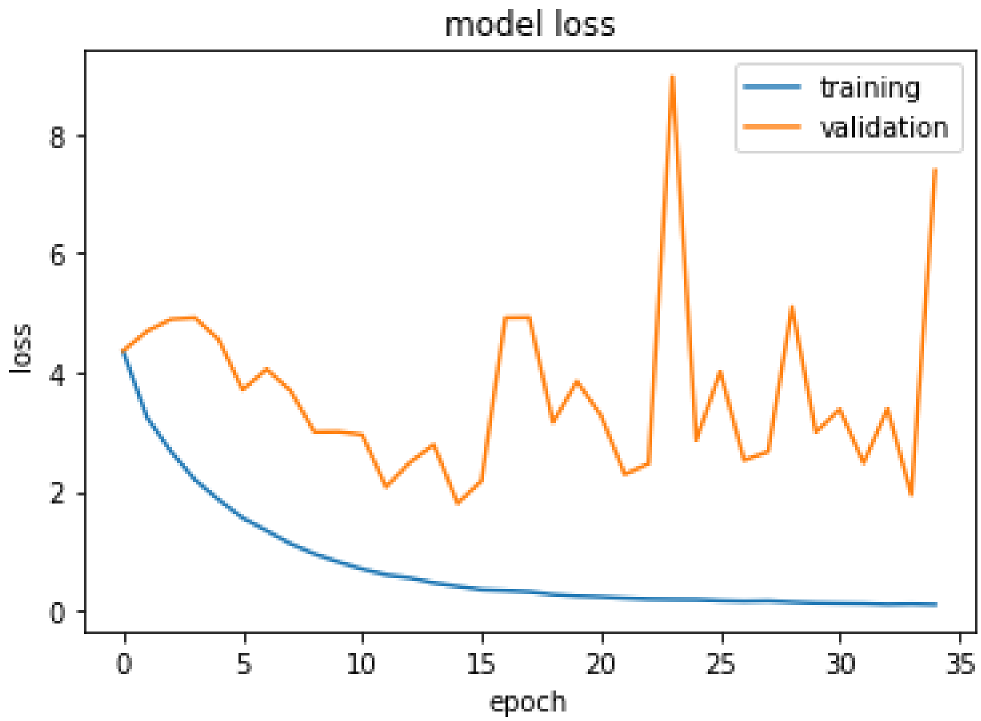
[ ]:

```
plt.plot(history6_1.history['accuracy'])
plt.plot(history6_1.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
```

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




```
[ ]: plt.plot(history6_1.history['loss'])
     plt.plot(history6_1.history['val_loss'])
     plt.title('model loss')
     plt.ylabel('loss')
     plt.xlabel('epoch')
     plt.legend(['training', 'validation'], loc='best')
     plt.show()
```



Architecture from Experiment 4

[ ]:
```
model6_2 = Sequential()

# 1st Convolution Layer
model6_2.add(Conv2D(32, input_shape=(*IMAGE_SIZE, 1), kernel_size=3,␣
 ↪activation=mish))
model6_2.add(BatchNormalization())
model6_2.add(Conv2D(32, kernel_size=3, activation=mish))
model6_2.add(BatchNormalization())
model6_2.add(Conv2D(32, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model6_2.add(BatchNormalization())
model6_2.add(Dropout(0.4))

# 2nd Convolution Layer
model6_2.add(Conv2D(64, kernel_size=3, activation=mish))
model6_2.add(BatchNormalization())
model6_2.add(Conv2D(64, kernel_size=3, activation=mish))
model6_2.add(BatchNormalization())
model6_2.add(Conv2D(64, kernel_size=5, strides=2, padding='same',␣
 ↪activation=mish))
model6_2.add(BatchNormalization())
```

```
model6_2.add(Dropout(0.4))

# 3rd Convolution Layer
model6_2.add(Conv2D(128, kernel_size = 4, activation=mish))
model6_2.add(BatchNormalization())

# Passing to a Fully Connected Layer
model6_2.add(Flatten())
model6_2.add(Dropout(0.4))

# Output Layer
model6_2.add(Dense(62, activation='softmax'))
```

[ ]:
```
model6_2.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_6 (Conv2D)            (None, 43, 58, 32)        320
_________________________________________________________________
batch_normalization_12 (Batc (None, 43, 58, 32)        128
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 41, 56, 32)        9248
_________________________________________________________________
batch_normalization_13 (Batc (None, 41, 56, 32)        128
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 21, 28, 32)        25632
_________________________________________________________________
batch_normalization_14 (Batc (None, 21, 28, 32)        128
_________________________________________________________________
dropout_6 (Dropout)          (None, 21, 28, 32)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 19, 26, 64)        18496
_________________________________________________________________
batch_normalization_15 (Batc (None, 19, 26, 64)        256
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 17, 24, 64)        36928
_________________________________________________________________
batch_normalization_16 (Batc (None, 17, 24, 64)        256
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 9, 12, 64)         102464
_________________________________________________________________
batch_normalization_17 (Batc (None, 9, 12, 64)         256
_________________________________________________________________
dropout_7 (Dropout)          (None, 9, 12, 64)         0
_________________________________________________________________
```

```
conv2d_12 (Conv2D)           (None, 6, 9, 128)         131200
_________________________________________________________________
batch_normalization_18 (Batc (None, 6, 9, 128)         512
_________________________________________________________________
flatten_3 (Flatten)          (None, 6912)              0
_________________________________________________________________
dropout_8 (Dropout)          (None, 6912)              0
_________________________________________________________________
dense_9 (Dense)              (None, 62)                428606
=================================================================
Total params: 754,558
Trainable params: 753,726
Non-trainable params: 832
_________________________________________________________________
```

[ ]:
```
model6_2.compile(loss='categorical_crossentropy', optimizer=Adam(),␣
 ↪metrics=['accuracy'])
```

Saving the Model Checkpoint

[ ]:
```
checkpoint_filepath6_2 = 'exp6_2/checkpoint'
model_checkpoint_callback6_2 = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_filepath6_2,
    save_weights_only=True,
    monitor='val_loss',
    mode='min',
    save_best_only=True)
```

[ ]:
```
history6_2 = model6_2.fit(
    train_generator3,
    epochs=EPOCHS,
    validation_data=validation_generator3,
    steps_per_epoch = train_generator3.samples // BATCH_SIZE,
    validation_steps = validation_generator3.samples // BATCH_SIZE,
    callbacks=[model_checkpoint_callback6_2, early_stopping_callback]
)
```

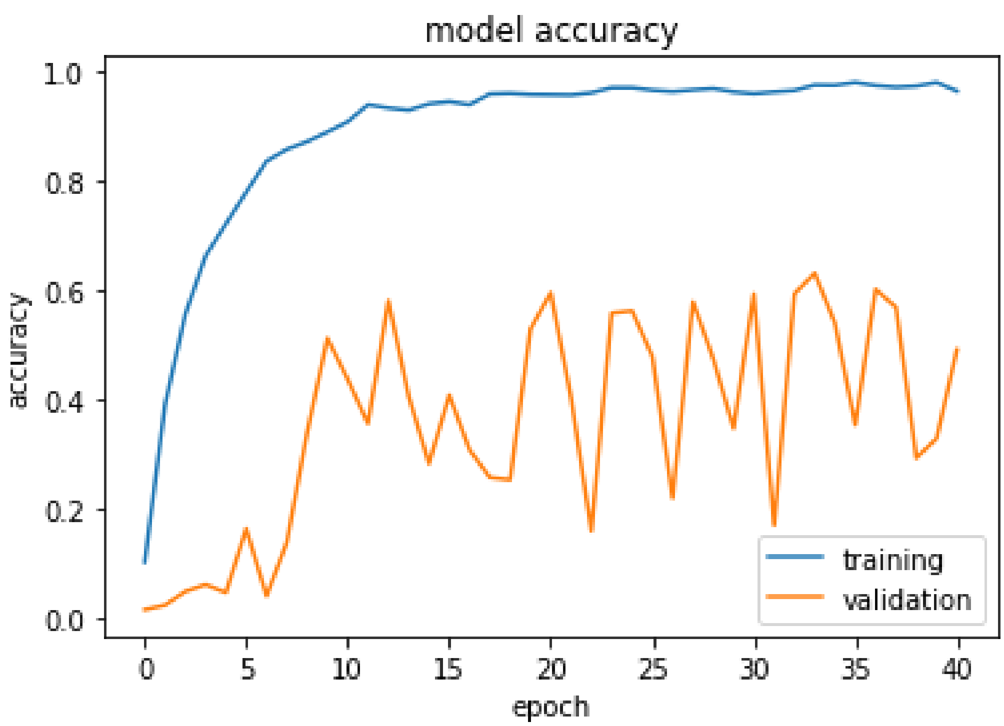
```
Epoch 1/400
62/62 [==============================] - 33s 506ms/step - loss: 5.2828 -
accuracy: 0.0535 - val_loss: 5.1547 - val_accuracy: 0.0167
Epoch 2/400
62/62 [==============================] - 31s 499ms/step - loss: 2.6122 -
accuracy: 0.3701 - val_loss: 6.4788 - val_accuracy: 0.0250
Epoch 3/400
62/62 [==============================] - 31s 499ms/step - loss: 1.6781 -
accuracy: 0.5677 - val_loss: 6.7860 - val_accuracy: 0.0500
Epoch 4/400
62/62 [==============================] - 31s 498ms/step - loss: 1.2515 -
```

```
accuracy: 0.6698 - val_loss: 7.6091 - val_accuracy: 0.0625
Epoch 5/400
62/62 [==============================] - 31s 501ms/step - loss: 1.0160 -
accuracy: 0.7232 - val_loss: 11.6267 - val_accuracy: 0.0479
Epoch 6/400
62/62 [==============================] - 31s 498ms/step - loss: 0.7533 -
accuracy: 0.7794 - val_loss: 6.4720 - val_accuracy: 0.1646
Epoch 7/400
62/62 [==============================] - 31s 497ms/step - loss: 0.5145 -
accuracy: 0.8392 - val_loss: 14.5081 - val_accuracy: 0.0417
Epoch 8/400
62/62 [==============================] - 31s 499ms/step - loss: 0.4077 -
accuracy: 0.8741 - val_loss: 7.0863 - val_accuracy: 0.1396
Epoch 9/400
62/62 [==============================] - 31s 498ms/step - loss: 0.3797 -
accuracy: 0.8741 - val_loss: 4.7880 - val_accuracy: 0.3396
Epoch 10/400
62/62 [==============================] - 31s 497ms/step - loss: 0.3910 -
accuracy: 0.8966 - val_loss: 2.4809 - val_accuracy: 0.5125
Epoch 11/400
62/62 [==============================] - 31s 500ms/step - loss: 0.2723 -
accuracy: 0.9176 - val_loss: 3.2420 - val_accuracy: 0.4375
Epoch 12/400
62/62 [==============================] - 31s 496ms/step - loss: 0.2342 -
accuracy: 0.9413 - val_loss: 4.5787 - val_accuracy: 0.3562
Epoch 13/400
62/62 [==============================] - 31s 498ms/step - loss: 0.2054 -
accuracy: 0.9412 - val_loss: 2.6093 - val_accuracy: 0.5813
Epoch 14/400
62/62 [==============================] - 31s 495ms/step - loss: 0.2238 -
accuracy: 0.9324 - val_loss: 4.7339 - val_accuracy: 0.4062
Epoch 15/400
62/62 [==============================] - 30s 493ms/step - loss: 0.2045 -
accuracy: 0.9379 - val_loss: 8.2359 - val_accuracy: 0.2833
Epoch 16/400
62/62 [==============================] - 31s 495ms/step - loss: 0.1736 -
accuracy: 0.9482 - val_loss: 4.0421 - val_accuracy: 0.4083
Epoch 17/400
62/62 [==============================] - 31s 493ms/step - loss: 0.2080 -
accuracy: 0.9468 - val_loss: 5.7639 - val_accuracy: 0.3083
Epoch 18/400
62/62 [==============================] - 31s 493ms/step - loss: 0.1215 -
accuracy: 0.9621 - val_loss: 7.6276 - val_accuracy: 0.2583
Epoch 19/400
62/62 [==============================] - 30s 491ms/step - loss: 0.1403 -
accuracy: 0.9562 - val_loss: 6.9810 - val_accuracy: 0.2542
Epoch 20/400
62/62 [==============================] - 31s 495ms/step - loss: 0.1488 -
```

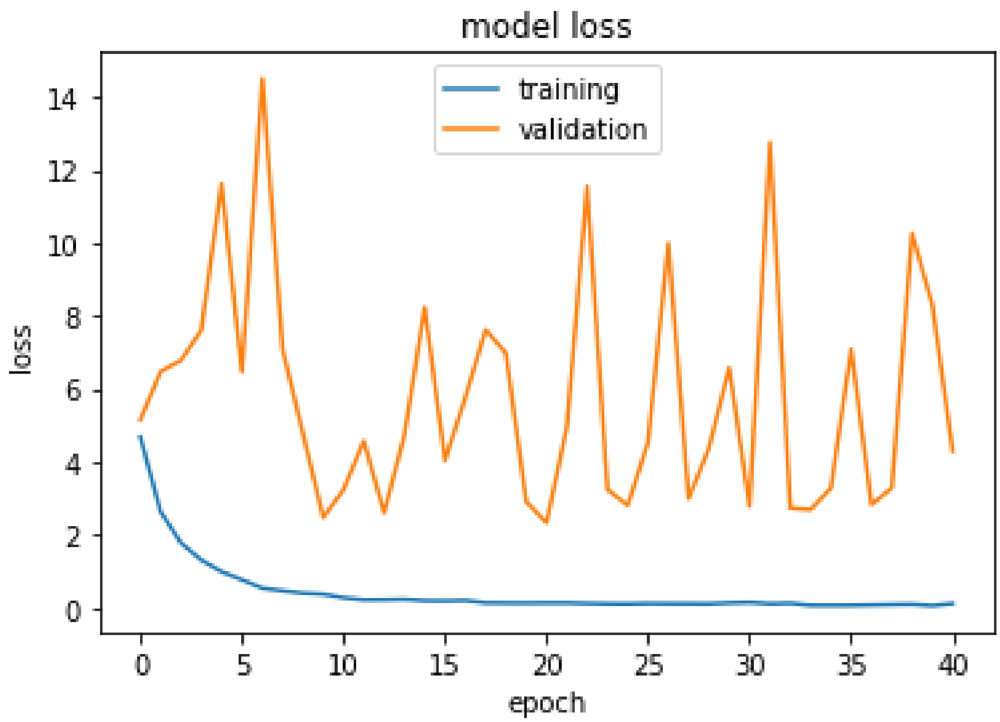
```
accuracy: 0.9545 - val_loss: 2.9153 - val_accuracy: 0.5292
Epoch 21/400
62/62 [==============================] - 32s 518ms/step - loss: 0.1313 -
accuracy: 0.9593 - val_loss: 2.3372 - val_accuracy: 0.5958
Epoch 22/400
62/62 [==============================] - 32s 521ms/step - loss: 0.1090 -
accuracy: 0.9694 - val_loss: 4.9452 - val_accuracy: 0.4042
Epoch 23/400
62/62 [==============================] - 32s 511ms/step - loss: 0.1232 -
accuracy: 0.9624 - val_loss: 11.5529 - val_accuracy: 0.1604
Epoch 24/400
62/62 [==============================] - 32s 514ms/step - loss: 0.0993 -
accuracy: 0.9700 - val_loss: 3.2483 - val_accuracy: 0.5583
Epoch 25/400
62/62 [==============================] - 31s 497ms/step - loss: 0.1000 -
accuracy: 0.9740 - val_loss: 2.8103 - val_accuracy: 0.5625
Epoch 26/400
62/62 [==============================] - 31s 494ms/step - loss: 0.1198 -
accuracy: 0.9633 - val_loss: 4.5392 - val_accuracy: 0.4792
Epoch 27/400
62/62 [==============================] - 31s 498ms/step - loss: 0.1238 -
accuracy: 0.9620 - val_loss: 9.9924 - val_accuracy: 0.2208
Epoch 28/400
62/62 [==============================] - 31s 494ms/step - loss: 0.1024 -
accuracy: 0.9735 - val_loss: 2.9984 - val_accuracy: 0.5792
Epoch 29/400
62/62 [==============================] - 31s 498ms/step - loss: 0.0960 -
accuracy: 0.9717 - val_loss: 4.3783 - val_accuracy: 0.4750
Epoch 30/400
62/62 [==============================] - 31s 496ms/step - loss: 0.1184 -
accuracy: 0.9671 - val_loss: 6.5769 - val_accuracy: 0.3479
Epoch 31/400
62/62 [==============================] - 31s 503ms/step - loss: 0.1328 -
accuracy: 0.9623 - val_loss: 2.7831 - val_accuracy: 0.5938
Epoch 32/400
62/62 [==============================] - 31s 502ms/step - loss: 0.1031 -
accuracy: 0.9680 - val_loss: 12.7633 - val_accuracy: 0.1708
Epoch 33/400
62/62 [==============================] - 31s 497ms/step - loss: 0.1445 -
accuracy: 0.9608 - val_loss: 2.7398 - val_accuracy: 0.5938
Epoch 34/400
62/62 [==============================] - 31s 498ms/step - loss: 0.0686 -
accuracy: 0.9757 - val_loss: 2.6970 - val_accuracy: 0.6313
Epoch 35/400
62/62 [==============================] - 31s 496ms/step - loss: 0.0559 -
accuracy: 0.9780 - val_loss: 3.2838 - val_accuracy: 0.5396
Epoch 36/400
62/62 [==============================] - 31s 498ms/step - loss: 0.0626 -
```

```
accuracy: 0.9802 - val_loss: 7.0936 - val_accuracy: 0.3542
Epoch 37/400
62/62 [==============================] - 31s 504ms/step - loss: 0.0741 -
accuracy: 0.9786 - val_loss: 2.8313 - val_accuracy: 0.6021
Epoch 38/400
62/62 [==============================] - 31s 500ms/step - loss: 0.0796 -
accuracy: 0.9741 - val_loss: 3.2906 - val_accuracy: 0.5688
Epoch 39/400
62/62 [==============================] - 31s 500ms/step - loss: 0.0906 -
accuracy: 0.9743 - val_loss: 10.2623 - val_accuracy: 0.2937
Epoch 40/400
62/62 [==============================] - 31s 502ms/step - loss: 0.0475 -
accuracy: 0.9831 - val_loss: 8.2991 - val_accuracy: 0.3292
Epoch 41/400
62/62 [==============================] - 31s 504ms/step - loss: 0.0958 -
accuracy: 0.9667 - val_loss: 4.2879 - val_accuracy: 0.4917
Restoring model weights from the end of the best epoch.
Epoch 00041: early stopping
```

[ ]:
```
plt.plot(history6_2.history['accuracy'])
plt.plot(history6_2.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



[ ]:
```
plt.plot(history6_2.history['loss'])
plt.plot(history6_2.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training', 'validation'], loc='best')
plt.show()
```



We see that batch size of 32 actually performs worse than that of 64.

1.4 Observations form these experiments

- I downscaled the images by 20x while making sure that the images are still recognizable from each other. This would reduce the number of parameters in our network.
- 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 a little below 60%.
- 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 didn 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.
- 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 similar result to the original LeNet and in lesser epochs, but had larger variance in training accuracy in the later epochs.
  - 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.
- I tried reducing Batch size form 64 to 32, but it gave worse results than 64.

1.5 Conclusions

- Overall, I think the original LeNet with Mish activation and the Model Architecture from Experiment 4 gave good results. 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.
- EfficientNet can give better results than from Experiment 5 but again, it neeeds more data and some pre-trained weights.

2 References

- [1] EMNIST handwritten character recognition with Deep Learning
- [2] How to choose CNN Architecture MNIST
- [3] Swish Vs Mish: Latest Activation Functions
- [4] Mish Class Definition in Keras
- [5] Mnist_EfficientNet Kaggle Notebook
- [6] Image classification via fine-tuning with EfficientNet
- [7] Keras EfficientNet Implementation Source Code
- [8] Keras ModelCheckpoint Documentaion
- [9] Keras EarlyStopping Documentaion
- [10] Keras ImageDataGenerator Documentation
- [11] Keras EfficientNetB0 Documentation
- [12] Effect of Batch Size on Neural Net Training


```
[ ]:
```