

In [1]:

```
Collecting tfa-nightly
  Downloading tfa_nightly-0.15.0.dev20210910145451-cp37-cp37m-many
  linux_2_12_x86_64.manylinux2010_x86_64.whl (1.1 MB)
    |██████████| 1.1 MB 11.8 MB/s eta 0:00:01
Requirement already satisfied: typeguard>=2.7 in /usr/local/lib/python3.7/dist-packages (from tfa-nightly) (2.7.1)
Installing collected packages: tfa-nightly
Successfully installed tfa-nightly-0.15.0.dev20210910145451
```

In [96]:

```
import tensorflow as tf
import os
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)

import tensorflow.keras as keras
import tensorflow_addons as tfa
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import pandas as pd
from scipy.interpolate import interp1d
from scipy.ndimage.interpolation import rotate, shift
import PIL
from PIL import Image
from imgaug import augmenters as iaa
from skimage import util as sku
import random
from itertools import chain
from itertools import permutations
from itertools import combinations
from itertools import cycle
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Input, Conv2D, Activation, MaxPooling2D
import json
from keras.preprocessing import image
import warnings
warnings.filterwarnings('ignore')

%load_ext tensorboard

print("Tensorflow version is: ", tf.__version__)
assert tf.__version__[0] == '2'
```

The tensorflow extension is already loaded. To reload it, use:
%reload_ext tensorboard
Tensorflow version is: 2.6.0

In [3]:

```
Archive:  drive/MyDrive/A1_data.zip
  inflating: A1_data/Images.zip
  inflating: A1_data/README.md
  inflating: A1_data/_MACOSX/._README.md
  inflating: A1_data/S40AR_test_data.csv
```

In [4]:

```
Streaming output truncated to the last 5000 lines.
```

```
inflating: A1_data/Images/Img_4611.jpg
inflating: A1_data/Images/Img_789.jpg
inflating: A1_data/Images/Img_7318.jpg
inflating: A1_data/Images/Img_6006.jpg
inflating: A1_data/Images/Img_9335.jpg
inflating: A1_data/Images/Img_1769.jpg
inflating: A1_data/Images/Img_8995.jpg
inflating: A1_data/Images/Img_6760.jpg
inflating: A1_data/Images/Img_9453.jpg
inflating: A1_data/Images/Img_3618.jpg
inflating: A1_data/Images/Img_4177.jpg
inflating: A1_data/Images/Img_5269.jpg
inflating: A1_data/Images/Img_2506.jpg
inflating: A1_data/Images/Img_4163.jpg
inflating: A1_data/Images/Img_2512.jpg
inflating: A1_data/Images/Img_8981.jpg
inflating: A1_data/Images/Img_6774.jpg
inflating: A1_data/Images/Img_9447.jpg
```

In [4]:

Exploratory Data Analysis

Strategy

- Load the images and visualize a sample. Check the differences in dimensions of the images
- Getting the minimum and maximum values for the dimensions of images
- Look at the basic information of the dataframe, and check for missing values
- Checking the distribution of the action_classes and actions

In [5]:

```
img_dir = "A1_data/Images/"

data_df = pd.read_csv('A1_data/S40AR_train_data.csv')
```

Out[5]:

	FileName	action	action_class
0	Img_1000.jpg	walking_the_dog	Interacting_with_animal
1	Img_1001.jpg	riding_a_bike	other_activity
2	Img_1002.jpg	gardening	domestic_work
3	Img_1008.jpg	cooking	domestic_work
4	Img_1010.jpg	jumping	other_activity

In [5]:

Now we can visualize the images to see if they've loaded correctly

```
In [6]: for i in range(5):
    img=mpimg.imread(img_dir+data_df.head(5) ['FileName'][i])
    print(data_df.head(5) ['action'][i])
    print(data_df.head(5) ['action_class'][i])
    imgplot = plt.imshow(img)
```

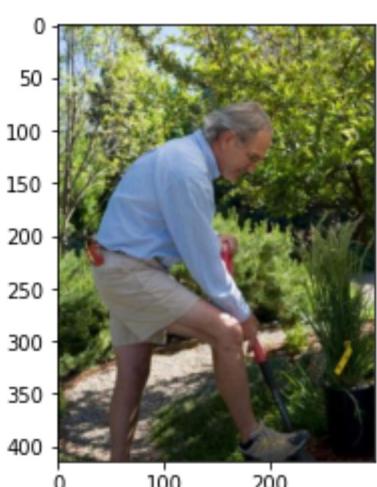
walking_the_dog
Interacting_with_animal



riding_a_bike
other_activity



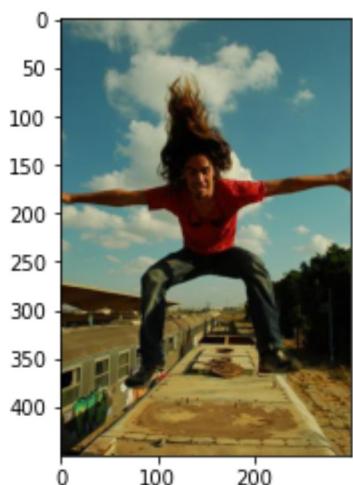
gardening
domestic_work



cooking
domestic_work



jumping
other_activity



✓ Observations:

- Images loaded in correctly
- The images are all of different dimensions, resizing might be required
- Images are coloured, so there will be a 3-channel input into the model

In [6]:



Getting the max and min x and y values from each image

In [7]:



```
max_x = 0
max_y = 0
min_x = 1000
min_y = 1000

for i in range(len(data_df)):
    img=mpimg.imread(img_dir+data_df['FileName'][i])
    imgplot = plt.imshow(img)
    img_size = imgplot.get_size()
```

```
    img_x = img_size[1]
    img_y = img_size[0]

    if(img_x > max_x):
        max_x = img_x

    if(img_y > max_y):
        max_y = img_y

    if(img_x < min_x):
        min_x = img_x

    if(img_y < min_y):
        min_y = img_y

print("Max X: "+str(max_x))
print("Max Y: "+str(max_y))
print("Min X: "+str(min_x))
print("Min Y: "+str(min_y))
```

```
Max X: 961
Max Y: 960
Min X: 200
Min Y: 200
```



✓ Observations:

- The images vary quite greatly in dimensions, and for our model we want them all to have the same dimensions, while also retaining the characteristics of each image that makes them have an associated image. There are two major techniques for handling this, as pointed out over here - <https://wandb.ai/ayush-thakur/dl-question-bank/reports/How-to-Handle-Images-of-Different-Sizes-in-a-Convolutional-Neural-Network--VmldzoyMDk3NzQ> (<https://wandb.ai/ayush-thakur/dl-question-bank/reports/How-to-Handle-Images-of-Different-Sizes-in-a-Convolutional-Neural-Network--VmldzoyMDk3NzQ>)
- Either an average size compromise or a definitive size based on the baseline model will be used

In [10]:

Basic information from data frame

In [8]:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3030 entries, 0 to 3029
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   FileName    3030 non-null    object  
 1   action      3030 non-null    object  
 2   action_class 3030 non-null    object  
dtypes: object(3)
memory usage: 71.1+ KB
```

✓ Observations:

- There are no missing values in the dataset, so we don't have to do anything to deal with it

In [8]:

Class Distribution

Now we can look at the distribution of the different action classes, and each subclass within the action classes

In [9]:

```
# printing out the value counts for each column
for column in data_df.columns:
    print(column + ": " + str(data_df[column].unique()))
    print(data_df[column].value_counts())
    . . .
```

```
FileName: ['Img_1000.jpg' 'Img_1001.jpg' 'Img_1002.jpg' ... 'Img_987.jpg'
           'Img_988.jpg' 'Img_995.jpg']
Img_4955.jpg      1
Img_7844.jpg      1
Img_1804.jpg      1
Img_3158.jpg      1
Img_5582.jpg      1
...
Img_8929.jpg      1
Img_5588.jpg      1
Img_4866.jpg      1
Img_2934.jpg      1
Img_1691.jpg      1
Name: FileName, Length: 3030, dtype: int64

action: ['walking_the_dog' 'riding_a_bike' 'gardening' 'cooking' '
         'jumping'
         'cutting_vegetables' 'watching_TV' 'cleaning_the_floor'
         'shooting_an_arrow' 'texting_message' 'playing_violin' 'feeding_a
         _horse'
         'taking_photos' 'washing_dishes' 'riding_a_horse' 'rowing_a_boat'
         'playing_guitar' 'climbing' 'running' 'phoning' 'using_a_computer
         '']
riding_a_horse      196
jumping              195
climbing              195
riding_a_bike        193
walking_the_dog       193
playing_guitar        189
cooking              100
```

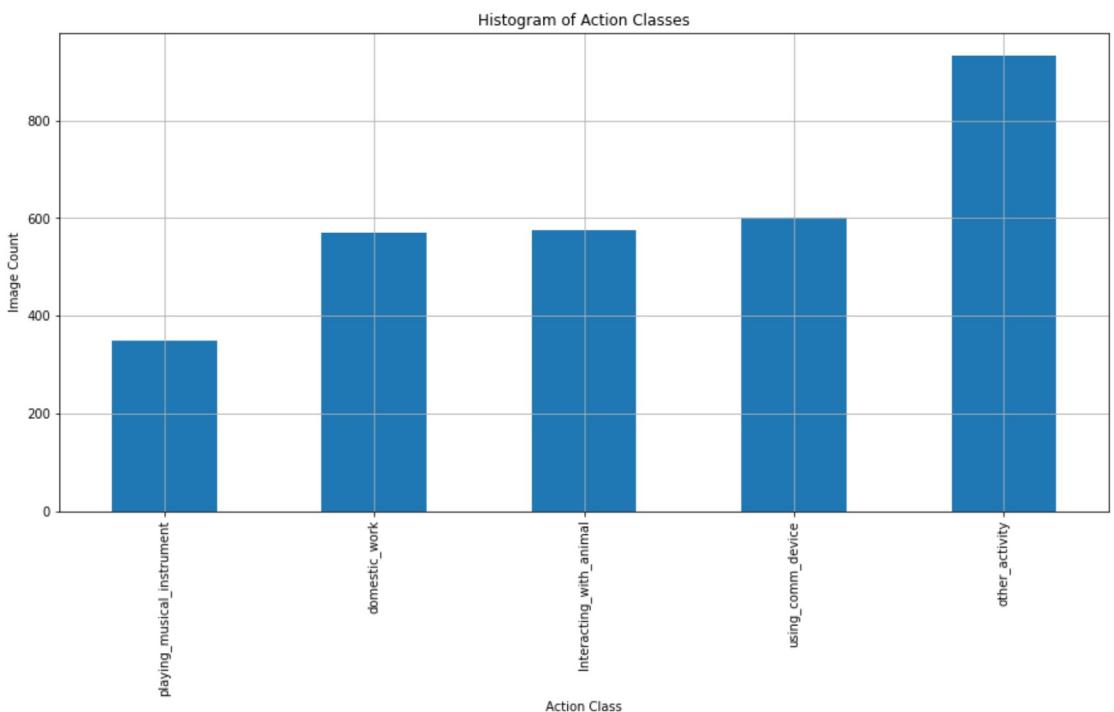
✓ Observations:

- There seems to be an uneven distribution, it's worth plotting this out to visualize the differences better

In [9]: ➤

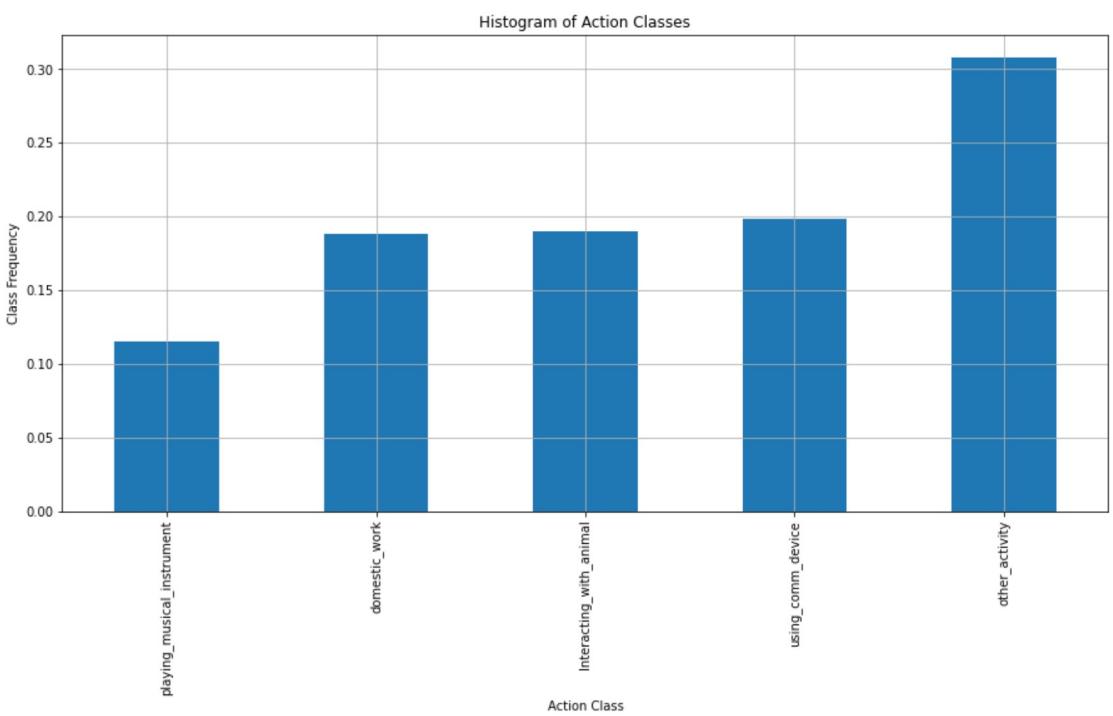
Distribution of Action Class

```
In [10]: plt.figure(figsize=(15, 7))
data_df.action_class.value_counts(ascending=True).plot(kind='bar',
plt.xlabel("Action Class")
plt.ylabel("Image Count")
plt.title("Histogram of Action Classes")
plt.show()
```



```
playing_musical_instrument      349
domestic_work                   570
Interacting_with_animal        576
using_comm_device               602
other_activity                  933
Name: action_class, dtype: int64
```

```
In [11]: plt.figure(figsize=(15, 7))
data_df.action_class.value_counts(normalize=True, ascending=True).p
plt.xlabel("Action Class")
plt.ylabel("Class Frequency")
plt.title("Histogram of Action Classes")
plt.show()
```



```
playing_musical_instrument      0.115182
domestic_work                  0.188119
Interacting_with_animal       0.190099
using_comm_device              0.198680
other_activity                 0.307921
Name: action_class, dtype: float64
```

✓ Observations:

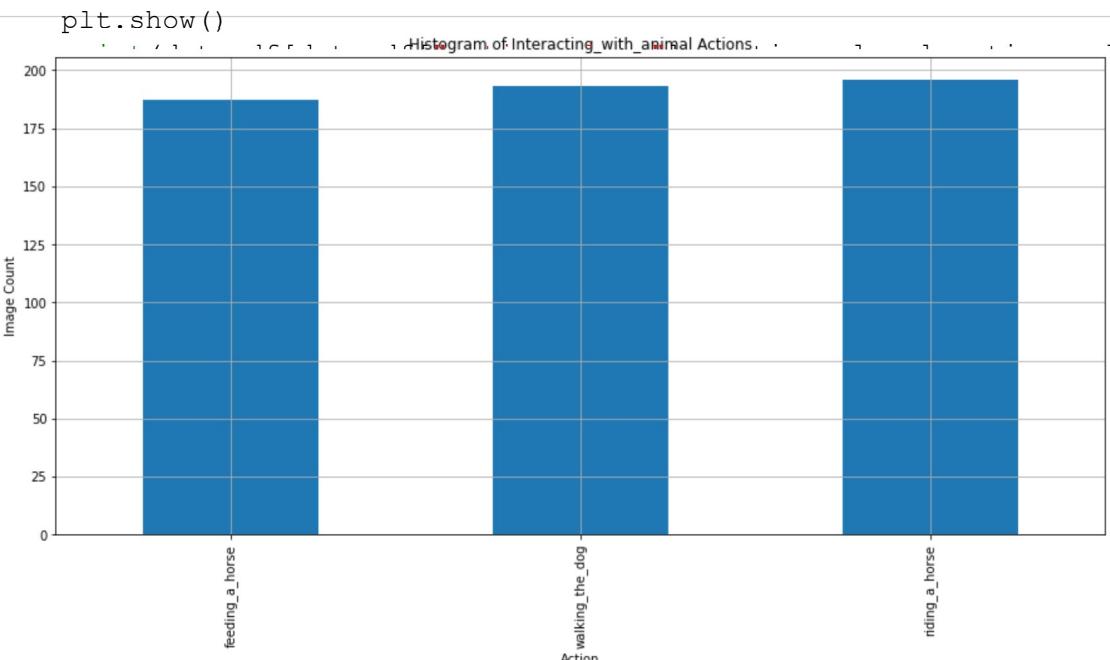
- There definitely is a class imbalance in this dataset, with "other_activity" having as many as 3 times the number of images as "playing musical instrument"
- The classes "domestic work", "interacting with animal" and "using_comm_device" are nearly evenly represented in this dataset

```
In [11]:
```

Distribution of Action

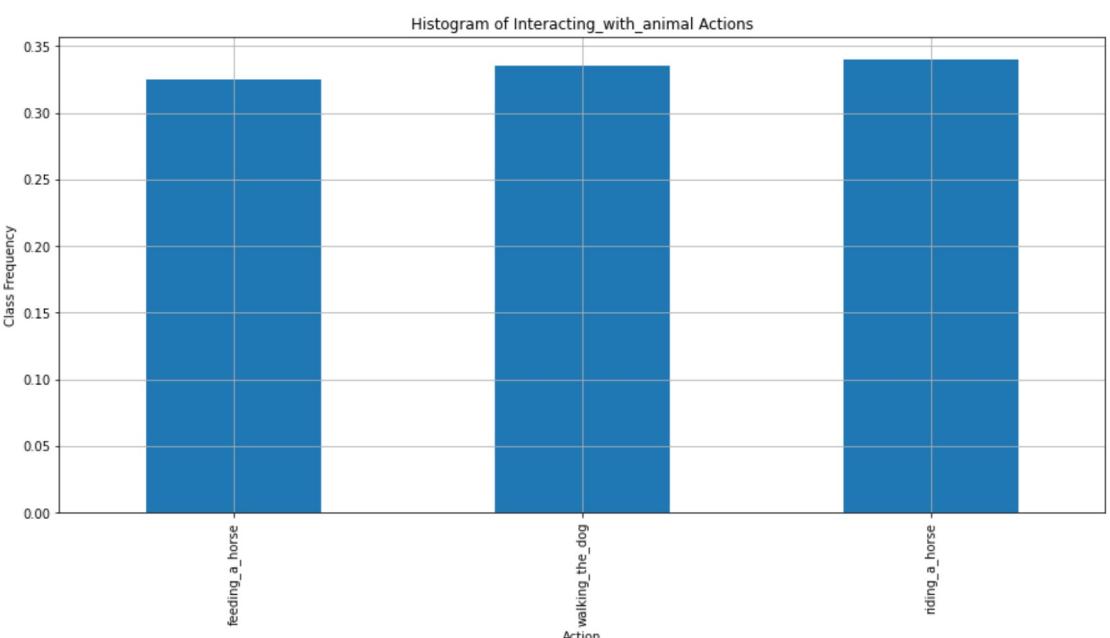
```
In [12]: for action_class in data_df['action_class'].unique():

    plt.figure(figsize=(15, 7))
    data_df[data_df["action_class"]==action_class].action.value_cou
    plt.xlabel("Action")
    #plt.xticks(rotation=35)
    plt.ylabel("Image Count")
    plt.title("Histogram of " + action_class + " Actions")
```



```
In [13]: for action_class in data_df['action_class'].unique():

    plt.figure(figsize=(15,7))
    data_df[data_df["action_class"]==action_class].action.value_counts()
    plt.xlabel("Action")
    #plt.xticks(rotation=35)
    plt.ylabel("Class Frequency")
    plt.title("Histogram of " + action_class + " Actions")
    plt.show()
    print(data_df[data_df["action_class"]==action_class].action.val
```



✓ Observations:

- Actions of action classes "playing_musical_instrument" and "interacting_with_animal" are well balanced
- The other 3 action classes have a lot of imbalance with their sub actions

In [13]:

Performance metric choice

- action_class: **Accuracy**. Even though there is an imbalance in class distribution, this is something we can accommodate for with data augmentation. Moreover, if we consider the distribution ignoring "other_activity", it is not too imbalanced. "other_activity" is a generic action_class for arguably a more diverse set of actions than the other action_classes. Thus, the standard accuracy metric should be good enough.
- action: **Top 5 Categorical Accuracy**. Chosen because there are 21 classes in total, with a wide variety of different actions, that can sometimes be interpreted differently. For example, "cooking", "washing dishes", and "cutting vegetables" are 3 activites that tend to have the person doing them in a similar posture. Our deep learning model may interpret this posture to be the primary determinant of classifying these. Moreover, sometimes there is overlap in the images themselves. For example, a person may be cutting vegetables, but have the stove on with food cooking and dishes in the sink all simultaneously. This can confuse the model, so having a "top 5" seems more appropriate.

Data Loader

Strategy

- Resize all the images to a unified size, and save to a new dataframe
- Take a sample of images, and try different augmentations on them, visualizing all the augmentations
- Determine the parameters (or range of parameters) for each augmentation within which the image is still usable
- Write a function to generate permutations and combinations of each of the augmentations for each image, preserving the label

In [14]:

Out[14]:

	FileName	action	action_class
0	Img_1000.jpg	walking_the_dog	Interacting_with_animal
1	Img_1001.jpg	riding_a_bike	other_activity
2	Img_1002.jpg	gardening	domestic_work
3	Img_1008.jpg	cooking	domestic_work
4	Img_1010.jpg	jumping	other_activity
...
3025	Img_977.jpg	texting_message	using_comm_device
3026	Img_980.jpg	feeding_a_horse	Interacting_with_animal
3027	Img_987.jpg	riding_a_bike	other_activity
3028	Img_988.jpg	jumping	other_activity
3029	Img_995.jpg	playing_guitar	playing_musical_instrument

3030 rows × 3 columns

In [14]:

Image Resizing

- 224x224 was chosen as it is a common image size to input for images that convey more complex data
- Furthermore, upsizing smaller images to a higher resolution might make them lose some details due to fuzziness
- Higher resolution images will also require a lot more computational time for network

In [15]:

```
# UNCOMMENT THE LINE BELOW TO CREATE THE NEW DIRECTORY
!mkdir "images_scaled"
for i in range(len(data_df)):
    img=mpimg.imread(img_dir+data_df['FileName'][i])
    #imgplot = plt.imshow(img)
    image_scaled = tf.image.convert_image_dtype(img, tf.float32)
    image_scaled = tf.image.resize(image_scaled, (224, 224))
```

In [16]:

```
data_df.action = pd.Categorical(data_df.action)
data_df["action_num"] = data_df.action.cat.codes

data_df.action_class = pd.Categorical(data_df.action_class)
data_df["action_class_num"] = data_df.action_class.cat.codes

data_df["FileName_scaled"] = "images_scaled/" + data_df['FileName']
```

In [17]:

Out[17]:

	FileName	action	action_class	action_num	action_class_nu
0	Img_1000.jpg	walking_the_dog	Interacting_with_animal	18	
1	Img_1001.jpg	riding_a_bike	other_activity	10	
2	Img_1002.jpg	gardening	domestic_work	5	
3	Img_1008.jpg	cooking	domestic_work	2	
4	Img_1010.jpg	jumping	other_activity	6	
...
3025	Img_977.jpg	texting_message	using_comm_device	16	
3026	Img_980.jpg	feeding_a_horse	Interacting_with_animal	4	
3027	Img_987.jpg	riding_a_bike	other_activity	10	
3028	Img_988.jpg	jumping	other_activity	6	
3029	Img_995.jpg	playing_guitar	playing_musical_instrument	8	

3030 rows × 6 columns

Image augmentations

Strategy

- The best parameters were picked from each observation, and then combinations of all of them were looked at on images to see if the images still held up to being what they're supposed to look like as per the label

Horizontal/Vertical flipping

```
In [18]: ┌─ for i in range(5):
    #plt.subplots(1,3)
    plt.figure(1)
    plt.figure(figsize=(12,5))
    plt.subplot(231)
    plt.title("Original")
    img=mpimg.imread(data_df.head(5) ['FileName_scaled'][i])
    print(data_df.head(5) ['action'][i])
    print(data_df.head(5) ['action_class'][i])
    plt.imshow(img)

    #plt.show()

    #Horizontally flipped
    hflip= iaa.Fliplr(p=1.0)
    hflipped_image= hflip.augment_image(img)

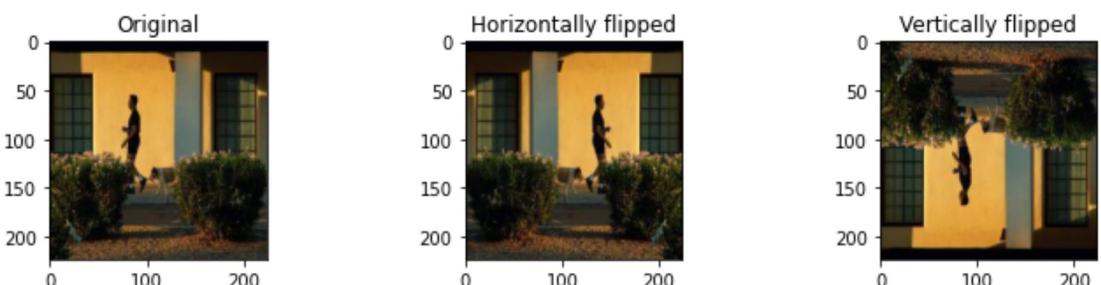
    #Vertically flipped
    vflip= iaa.Flipud(p=1.0)
    vflipped_image= vflip.augment_image(img)

    plt.subplot(232)
    plt.title("Horizontally flipped")
    plt.imshow(hflipped_image)
    plt.subplot(233)
    plt.imshow(vflipped_image)
    plt.title("Vertically flipped")
    plt.show()

    print("-----")
    #plt.show()
```

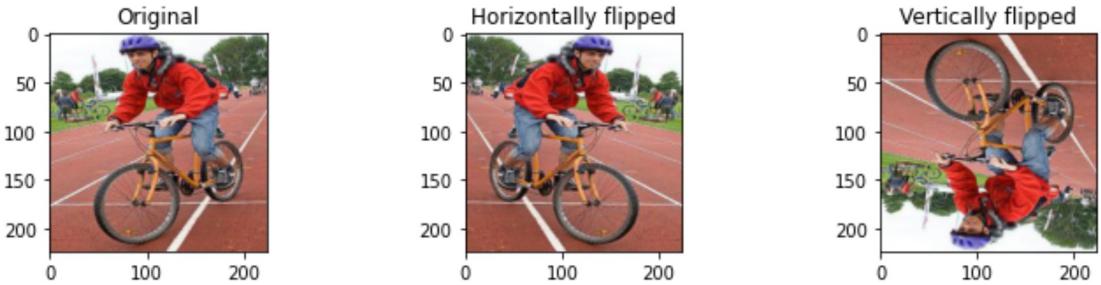
walking_the_dog
Interacting_with_animal

<Figure size 432x288 with 0 Axes>



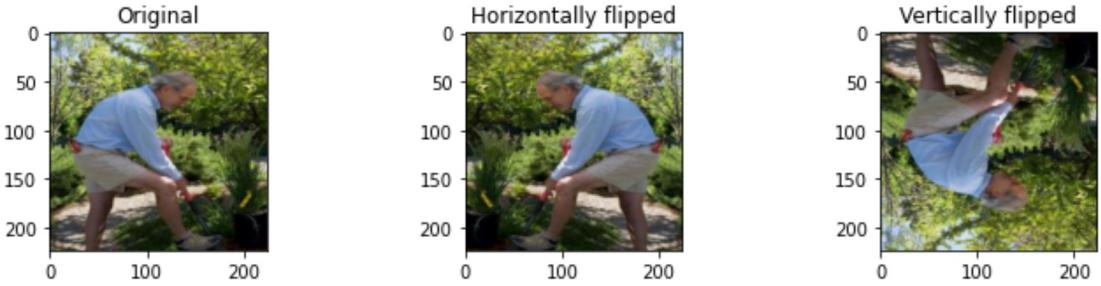
riding_a_bike
other_activity

<Figure size 432x288 with 0 Axes>



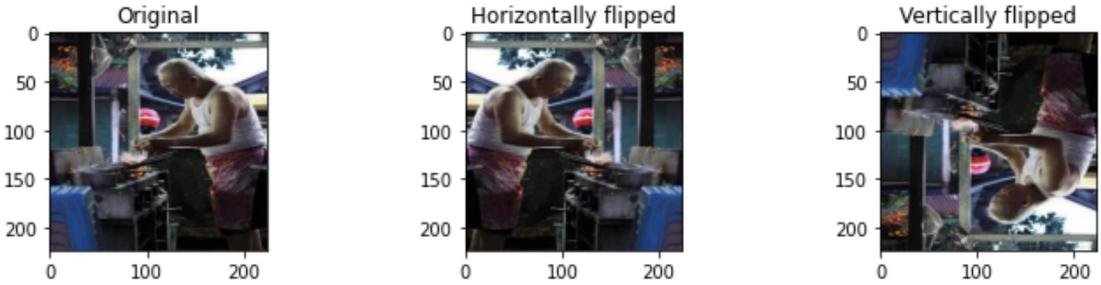
gardening
domestic_work

<Figure size 432x288 with 0 Axes>



cooking
domestic_work

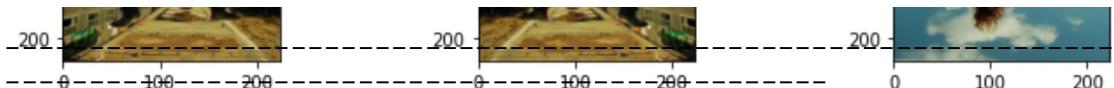
<Figure size 432x288 with 0 Axes>



jumping
other_activity

<Figure size 432x288 with 0 Axes>





In [18]:

Rotation

In [19]:

```

rotation_degree = 20
for i in range(5):
    #plt.subplots(1,3)
    plt.figure(1)
    plt.figure(figsize=(12,5))
    plt.subplot(231)
    plt.title("Original")
    img=mpimg.imread(data_df.head(5) ['FileName_scaled'][i])
    print(data_df.head(5) ['action'][i])
    print(data_df.head(5) ['action_class'][i])
    plt.imshow(img)

    #plt.show()

    # clockwise rotation
    rot = iaa.Affine(rotate=(rotation_degree,rotation_degree))
    rot_clockwise_image_right = rot.augment_image(img)

    # clockwise rotation
    rot2 = iaa.Affine(rotate=(-rotation_degree,-rotation_degree))
    rot_clockwise_image_left = rot2.augment_image(img)

    plt.subplot(232)
    plt.title(str(rotation_degree)+"-degree right rotation")
    plt.imshow(rot_clockwise_image_right)

    plt.subplot(233)
    plt.imshow(rot_clockwise_image_left)
    plt.title(str(rotation_degree)+"-degree left rotation")
    plt.show()

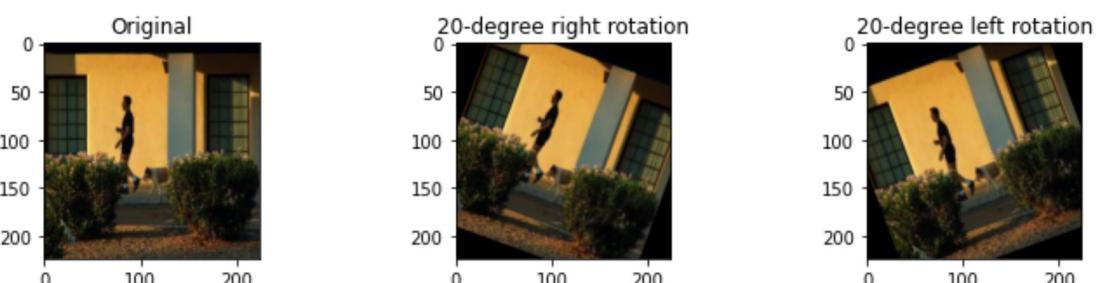
    print("-----")

    #plt.show()

```

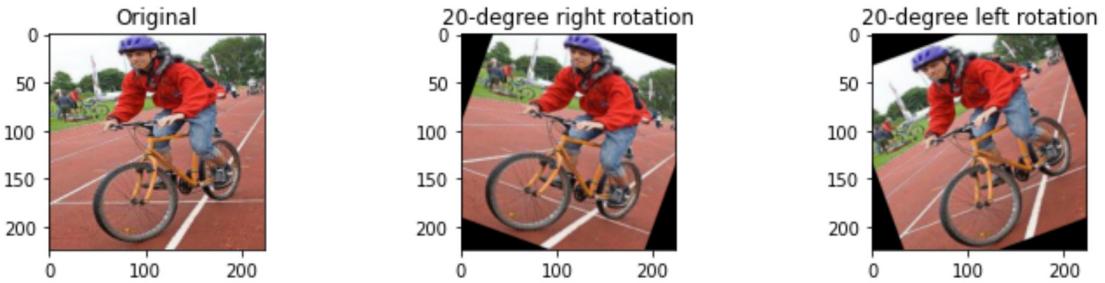
walking_the_dog
Interacting_with_animal

<Figure size 432x288 with 0 Axes>



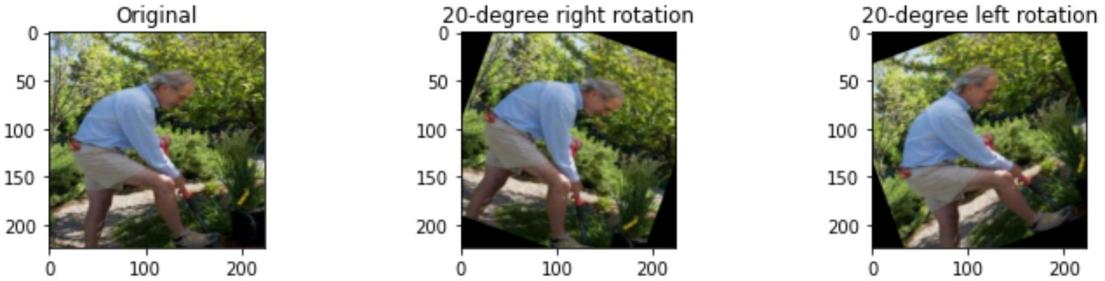
riding_a_bike
other_activity

<Figure size 432x288 with 0 Axes>



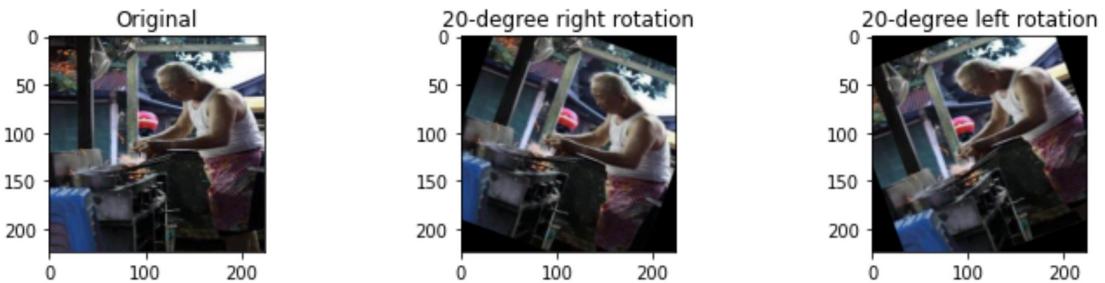
gardening
domestic_work

<Figure size 432x288 with 0 Axes>



cooking
domestic_work

<Figure size 432x288 with 0 Axes>



jumping
other_activity

<Figure size 432x288 with 0 Axes>





In [19]:

Image cropping

In [20]:

```
for i in range(5):

    plt.figure(1)
    plt.figure(figsize=(12,5))
    plt.subplot(231)
    plt.title("Original")
    img=mpimg.imread(data_df.head(5) ['FileName_scaled'][i])
    print(data_df.head(5) ['action'][i])
    print(data_df.head(5) ['action_class'][i])
    plt.imshow(img)

    crop = iaa.Crop(percent=(0.1, 0.1)) # crop image
    crop_image1=crop.augment_image(img)

    crop = iaa.Crop(percent=(0.1, 0.2)) # crop image
    crop_image2=crop.augment_image(img)

    plt.subplot(232)
    plt.title("Cropped image")
    plt.imshow(crop_image1)

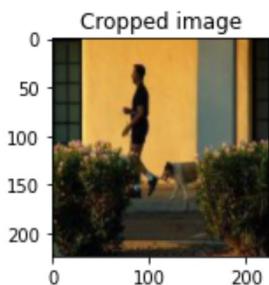
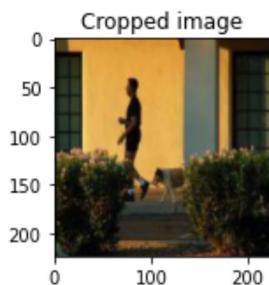
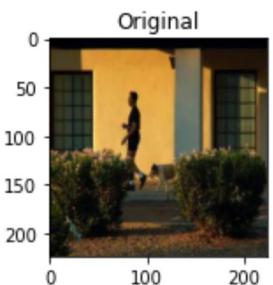
    plt.subplot(233)
    plt.title("Cropped image")
    plt.imshow(crop_image2)

    plt.show()

print("-----")
#plt.show()
```

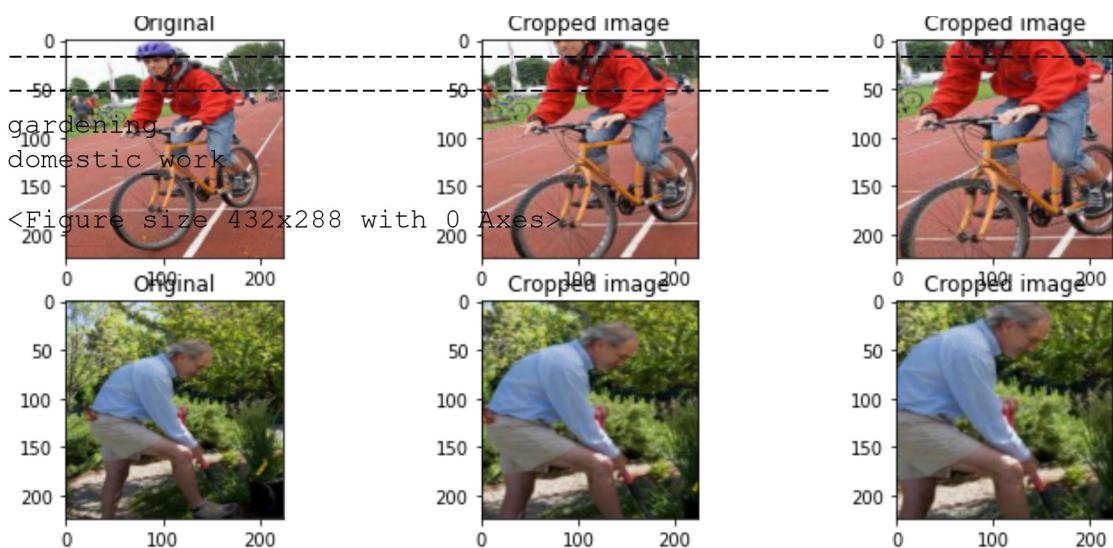
walking_the_dog
Interacting_with_animal

<Figure size 432x288 with 0 Axes>



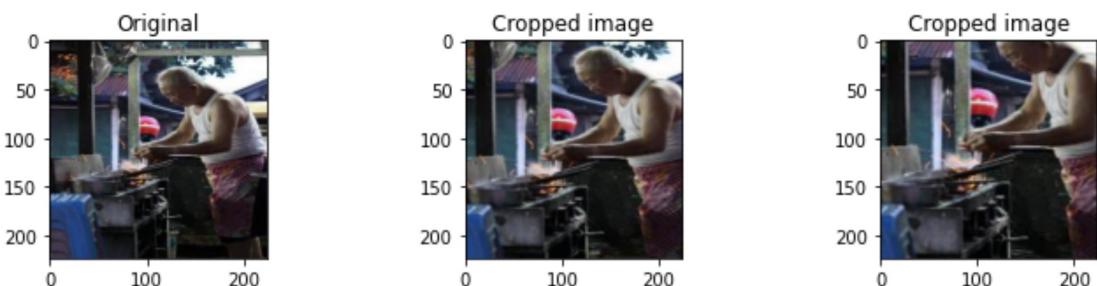
riding_a_bike
other_activity

<Figure size 432x288 with 0 Axes>



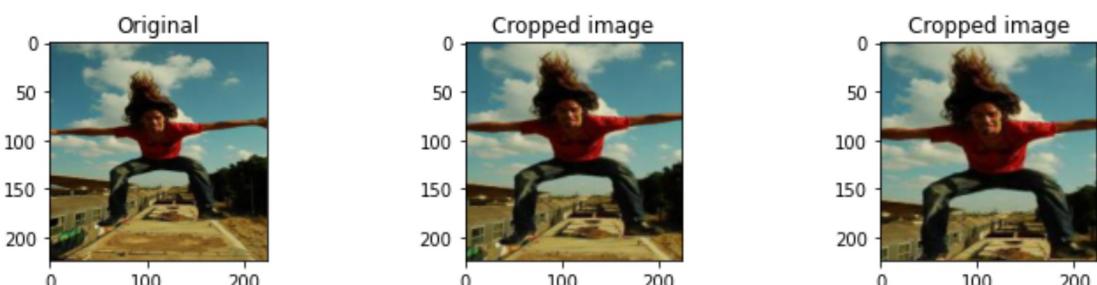
gardening
domestic_work

<Figure size 432x288 with 0 Axes>



cooking
domestic_work

<Figure size 432x288 with 0 Axes>



In [20]:

Gamma adjustment (brightening and darkening)

In [21]:

```

for i in range(5):

    plt.figure(1)
    plt.figure(figsize=(12,5))
    plt.subplot(231)
    plt.title("Original")
    img=mpimg.imread(data_df.head(5) ['FileName_scaled'][i])
    print(data_df.head(5) ['action'][i])
    print(data_df.head(5) ['action_class'][i])
    plt.imshow(img)

    # bright
    contrast1=iaa.GammaContrast(gamma=0.5)
    brightened_image = contrast1.augment_image(img)

    #dark
    contrast2=iaa.GammaContrast(gamma=1.3)
    darkened_image = contrast2.augment_image(img)

    plt.subplot(232)
    plt.title("Brightened image")
    plt.imshow(brightened_image)

    plt.subplot(233)
    plt.title("Darkened image")
    plt.imshow(darkened_image)

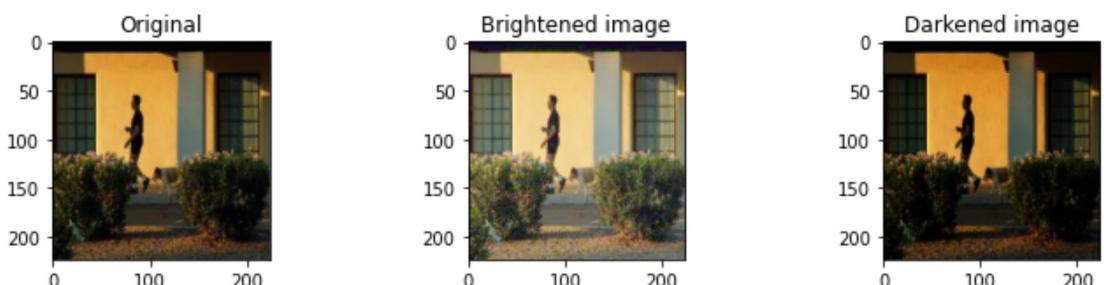
    plt.show()

print("-----")
# plt.show()

```

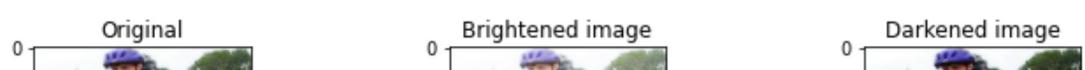
walking_the_dog
Interacting_with_animal

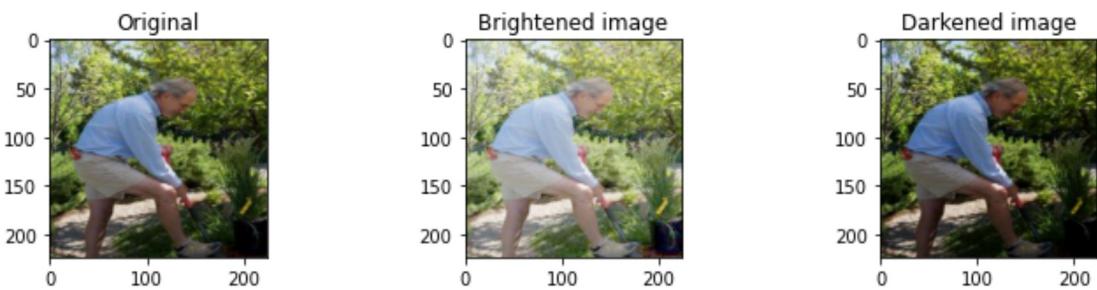
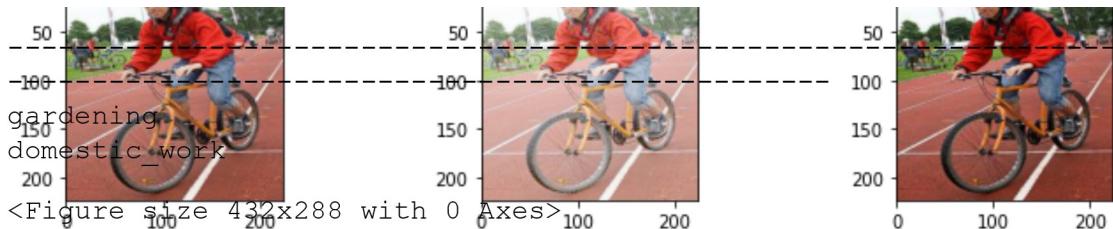
<Figure size 432x288 with 0 Axes>



riding_a_bike
other_activity

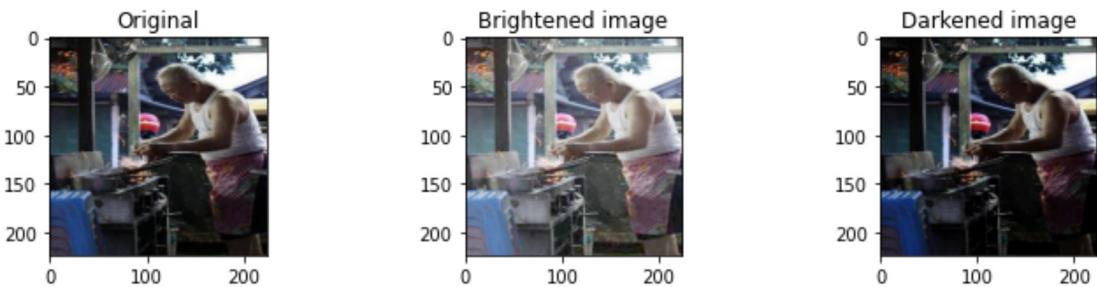
<Figure size 432x288 with 0 Axes>





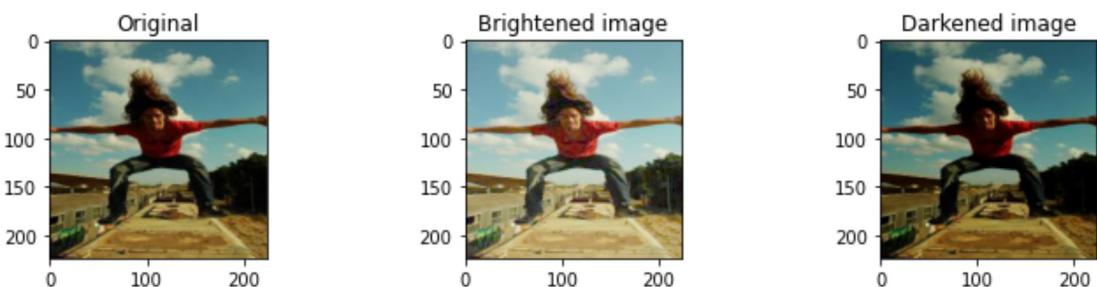
cooking
domestic_work

<Figure size 432x288 with 0 Axes>



jumping
other_activity

<Figure size 432x288 with 0 Axes>



In [21]:



Adding random noise

In [22]:



```
for i in range(5):

    plt.figure(1)
    plt.figure(figsize=(12,5))
    plt.subplot(221)
    plt.title("Original")
    img=mpimg.imread(data_df.head(5) ['FileName_scaled'][i])
    print(data_df.head(5) ['action'][i])
    print(data_df.head(5) ['action_class'][i])
    plt.imshow(img)

    noisy_image= sku.random_noise(img)

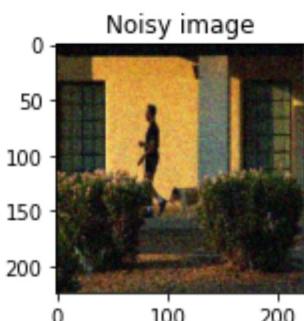
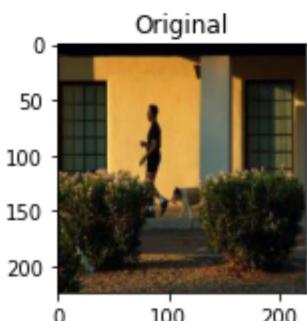
    plt.subplot(222)
    plt.title("Noisy image")
    plt.imshow(noisy_image)

    plt.show()

print("-----")
```

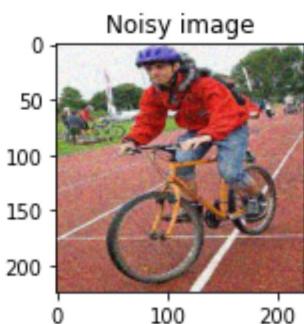
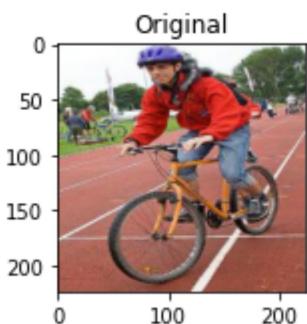
walking_the_dog
Interacting_with_animal

<Figure size 432x288 with 0 Axes>



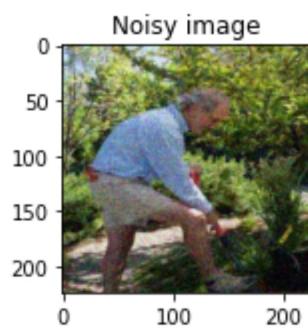
riding_a_bike
other_activity

<Figure size 432x288 with 0 Axes>



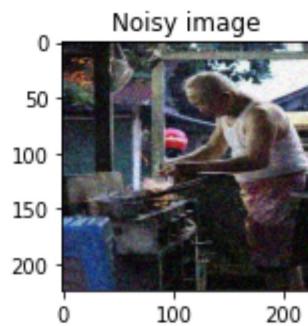
gardening
domestic_work

<Figure size 432x288 with 0 Axes>



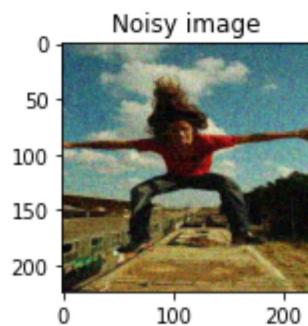
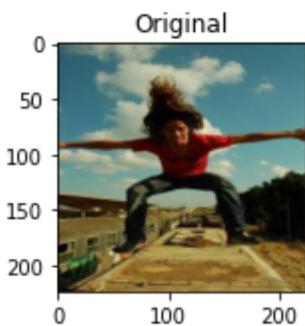
cooking
domestic_work

<Figure size 432x288 with 0 Axes>



jumping
other_activity

<Figure size 432x288 with 0 Axes>



In [22]:

Trying random combinations together

In [23]:

```
for i in range(5):

    plt.figure(1)
    plt.figure(figsize=(12,5))
    plt.subplot(221)
    plt.title("Original")
    img=mpimg.imread(data_df.head(5) ['FileName_scaled'][i])
    print(data_df.head(5) ['action'][i])
    print(data_df.head(5) ['action_class'][i])
    plt.imshow(img)

    # add noise
    noisy_image= sku.random_noise(img)

    # brighten
    contrast1=iaa.GammaContrast(gamma=0.5)
    brightened_image = contrast1.augment_image(noisy_image)

    # rotate
    rot = iaa.Affine(rotate=(rotation_degree, rotation_degree))
    rot_clockwise_image_right = rot.augment_image(brightened_image)

    # crop
    crop = iaa.Crop(percent=(0.1, 0.1))
    crop_image1=crop.augment_image(rot_clockwise_image_right)

    # flip horizontally
    hflip= iaa.Fliplr(p=1.0)
    hflipped_image=hflip.augment_image(crop_image1)

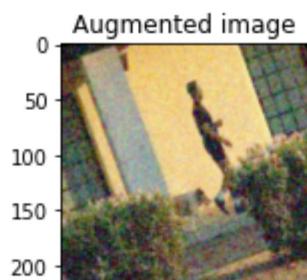
    plt.subplot(222)
    plt.title("Augmented image")
    plt.imshow(hflipped_image)

    plt.show()

print("-----")
# plt.show()
```

walking_the_dog
Interacting_with_animal

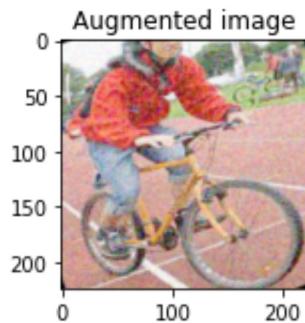
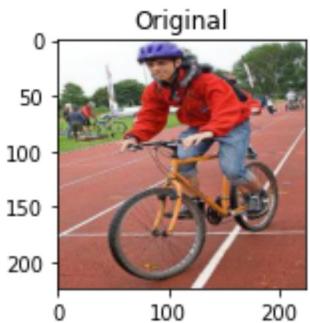
<Figure size 432x288 with 0 Axes>



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

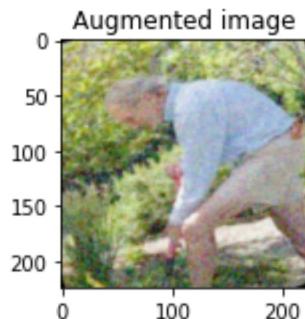
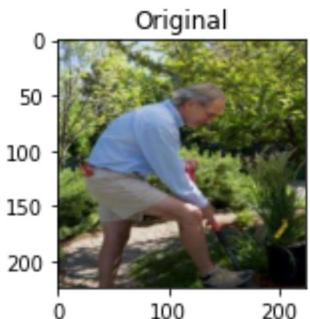
riding_a_bike
other_activity

<Figure size 432x288 with 0 Axes>



gardening
domestic_work

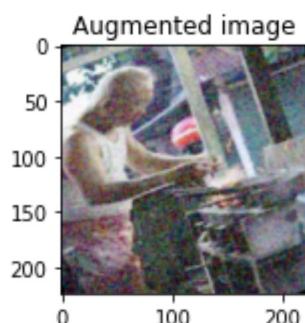
<Figure size 432x288 with 0 Axes>



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

cooking
domestic_work

<Figure size 432x288 with 0 Axes>



```
jumping
other_activity
<Figure size 432x288 with 0 Axes>
```



✓ Observations:

- The images seem to retain their essence in terms of their classification label, while still being different to the original, as we want the augmentations to be

In [23]:



Putting it all together

In [24]:



Out[24]:

	FileName	action	action_class	action_num	action_class_nu
0	Img_1000.jpg	walking_the_dog	Interacting_with_animal	18	
1	Img_1001.jpg	riding_a_bike	other_activity	10	
2	Img_1002.jpg	gardening	domestic_work	5	
3	Img_1008.jpg	cooking	domestic_work	2	
4	Img_1010.jpg	jumping	other_activity	6	
...
3025	Img_977.jpg	texting_message	using_comm_device	16	
3026	Img_980.jpg	feeding_a_horse	Interacting_with_animal	4	
3027	Img_987.jpg	riding_a_bike	other_activity	10	
3028	Img_988.jpg	jumping	other_activity	6	
3029	Img_995.jpg	playing_guitar	playing_musical_instrument	8	

3030 rows × 6 columns

First we split the data into train, test, and validation sets

In [25]:



```
train_data_df, test_data_df = train_test_split(data_df, test_size=0)
train_data_df, val_data_df = train_test_split(train_data_df, test_s...
```

In [26]:

Out[26]:

	FileName	action	action_class	action_num	action_class_num
1494	Img_5261.jpg	feeding_a_horse	Interacting_with_animal	4	0
483	Img_2455.jpg	feeding_a_horse	Interacting_with_animal	4	0
1052	Img_4043.jpg	cooking	domestic_work	2	1
2695	Img_8659.jpg	climbing	other_activity	1	2
2702	Img_868.jpg	running	other_activity	13	2
...
1804	Img_6122.jpg	feeding_a_horse	Interacting_with_animal	4	0
2606	Img_8406.jpg	cooking	domestic_work	2	1
33	Img_1098.jpg	climbing	other_activity	1	2
1635	Img_5642.jpg	watching_TV	using_comm_device	20	4
687	Img_2982.jpg	watching_TV	using_comm_device	20	4

1704 rows × 6 columns

In [27]:

Out[27]:

	FileName	action	action_class	action_num	action_class_num
2704	Img_8683.jpg	shooting_an_arrow	other_activity	14	2
1095	Img_419.jpg	climbing	other_activity	1	2
2969	Img_9398.jpg	cooking	domestic_work	2	1
1316	Img_4789.jpg	walking_the_dog	Interacting_with_animal	18	0
881	Img_3555.jpg	walking_the_dog	Interacting_with_animal	18	0
...
2486	Img_808.jpg	riding_a_horse	Interacting_with_animal	11	0
2175	Img_7183.jpg	cooking	domestic_work	2	1
551	Img_2611.jpg	riding_a_horse	Interacting_with_animal	11	0
2666	Img_8559.jpg	washing_dishes	domestic_work	19	1
2964	Img_9389.jpg	running	other_activity	13	2

568 rows × 6 columns

In [28]:

Out[28]:

	FileName	action	action_class	action_num	action_class_n
535	Img_257.jpg	rowing_a_boat	other_activity	12	
1369	Img_4929.jpg	riding_a_bike	other_activity	10	
1171	Img_4372.jpg	climbing	other_activity	1	
2921	Img_9279.jpg	walking_the_dog	Interacting_with_animal	18	
736	Img_3148.jpg	texting_message	using_comm_device	16	
...

	FileName	action	action_class	action_num	action_class_n
1076	Img_4112.jpg	riding_a_horse	Interacting_with_animal	11	
545	Img_2596.jpg	cleaning_the_floor	domestic_work	0	
1645	Img_5672.jpg	jumping	other_activity	6	
894	Img_3588.jpg	cooking	domestic_work	2	
1387	Img_4963.jpg	playing_violin	playing_musical_instrument	9	

In [29]: augmentations = ['hflip', 'rotate', 'crop', 'gamma', 'noise']

In [30]:

```
Out[30]: [('hflip',),
           ('rotate',),
           ('crop',),
           ('gamma',),
           ('noise',),
           ('hflip', 'rotate'),
           ('hflip', 'crop'),
           ('hflip', 'gamma'),
           ('hflip', 'noise'),
           ('rotate', 'crop'),
           ('rotate', 'gamma'),
           ('rotate', 'noise'),
           ('crop', 'gamma'),
           ('crop', 'noise'),
           ('gamma', 'noise'),
           ('hflip', 'rotate', 'crop'),
           ('hflip', 'rotate', 'gamma'),
           ('hflip', 'rotate', 'noise'),
           ('hflip', 'crop', 'gamma'),
           ('hflip', 'crop', 'noise'),
           ('hflip', 'gamma', 'noise'),
           ('rotate', 'crop', 'gamma'),
           ('rotate', 'crop', 'noise'),
           ('rotate', 'gamma', 'noise'),
           ('crop', 'gamma', 'noise'),
           ('hflip', 'rotate', 'crop', 'gamma'),
           ('hflip', 'rotate', 'crop', 'noise'),
           ('hflip', 'rotate', 'gamma', 'noise'),
           ('hflip', 'crop', 'gamma', 'noise'),
           ('rotate', 'crop', 'gamma', 'noise'),
           ('hflip', 'rotate', 'crop', 'gamma', 'noise')]
```

✓ Observations:

- There are 32 variations for each image, excluding the original

In [30]:

Writing the generator

For this assignment I wrote a custom data generator, with a modified data loading mechanism from the class in the week 5 lab, as well as the custom generator found [here](#)

(<https://stanford.edu/~shervine/blog/keras-how-to-generate-data-on-the-fly>.)

The data generator has the capability to augment the images, as well as load the images with the two classes, to be fed into our Multi-Task learning model.

```
In [66]: ┌─ class DataGenerator(keras.utils.Sequence):  
    # Initializer  
    def __init__(self, data_frame, batch_size = 32, dim = (224, 224,  
        shuffle = True, create_folder = False,  
        augment = False, file_name = '', data_mean=0, data_std=1):  
        self.batch_size = batch_size  
        self.shuffle = shuffle  
        self.create_folder = create_folder  
        self.file_name = file_name  
        self.augment = augment  
        self.dim = dim  
        self.n_channels = n_channels  
        self.data_frame = data_frame  
        self.image_column = image_column  
  
        # if the data is to be augmented, we call the augment function  
        if self.augment == True:  
            self.data_frame = self.__augment()  
        # otherwise read the dataframe as is  
        else:  
            self.data_frame = data_frame  
  
        # We have 2 labels since we're going to be doing multi-class  
        self.action_class_label = data_frame['action_class_num'].values  
        self.action_class_ids = np.arange(len(self.action_class_label))  
  
        self.action_label = data_frame['action_num'].values.tolist()  
        self.action_ids = np.arange(len(self.action_label)).tolist()  
  
        # Data normalization parameters  
        self.data_mean = data_mean  
        self.data_std = data_std  
  
        self.on_epoch_end()  
  
    def __len__(self):  
        'Denotes the number of batches per epoch'  
        return int(np.floor(len(self.action_class_ids) / self.batch_size))  
  
    def __augment(self):  
        'Augmentation function'  
  
        rows_list = []  
        if self.create_folder == True:  
            !mkdir "images_augmented"  
  
        # Augmentation parameters  
        rotation_degree = 20  
        augmentations = ['hflip', 'rotate', 'crop', 'gamma', 'noise']  
        augmentation_combinations = list(chain(*[combinations(augmentations, r) for r in range(1, len(augmentations)+1)]))  
  
        for index, row in self.data_frame.iterrows():
```

```
# Reading in the image file
img=mpimg.imread(row['FileName_scaled'])
og_filename = "images_augmented/" + (row['FileName_scaled'])
dict_line = {"FileName": og_filename, "action":row["action"]}
rows_list.append(dict_line)
tf.keras.preprocessing.image.save_img(og_filename, img)

# Looping over each augmentation combination from above
for augmentation in augmentation_combinations:

    img=mpimg.imread(row['FileName_scaled'])

    # Horizontal flip
    if 'hflip' in augmentation:

        hflip = iaa.Fliplr(p=1.0)
        img = hflip.augment_image(img)

    # Rotation
    if 'rotate' in augmentation:

        # randomly selects clockwise or anti-clockwise
        rotation_orientation = random.choice([(rotation,
        rot = iaa.Affine(rotate=rotation_orientation)
        img = rot.augment_image(img)

    # Cropping
    if 'crop' in augmentation:

        crop = iaa.Crop(percent=(0.1, 0.1))
        img = crop.augment_image(img)

    # Gamma
    if 'gamma' in augmentation:

        # randomly selects brightening or darkening
        gamma = random.choice([0.5, 1.3])
        contrast_brighten = iaa.GammaContrast(gamma=gamma)
        img = contrast_brighten.augment_image(img)

    # Adding noise
    if 'noise' in augmentation:

        img = sku.random_noise(img)

    # Saving the augmented image
    augmented_filename = "images_augmented/" + (row['FileName'])
    tf.keras.preprocessing.image.save_img(augmented_filename, img)
    dict_line = {"FileName": augmented_filename, "action":row["action"]}
    rows_list.append(dict_line)

# Creating a new dataframe from the augmented images and saving it
augmented_df = pd.DataFrame(rows_list)
augmented_df.to_csv(self.file_name, index = False)

# Changing the dataframe's labels to categorical numbers
augmented_df.action = pd.Categorical(augmented_df.action)
augmented_df["action_num"] = augmented_df.action.cat.codes

augmented_df.action_class = pd.Categorical(augmented_df.act...
```

```
augmented_df["action_class_num"] = augmented_df.action_class

return augmented_df

def __getitem__(self, index):
    'Generate one batch of data for the given index'
    # Generate indexes of the batch
    indexes = self.indexes[index * self.batch_size:(index+1) * self.batch_size]

    # Find list of IDs
    data_ids_temp = [self.action_class_ids[k] for k in indexes]

    action_class_label_temp = [self.action_class_label[k] for k in indexes]
    action_label_temp = [self.action_label[k] for k in indexes]

    # Generate data
    X, [action_class, action] = self.__data_generation(data_ids_temp)

    return X, [keras.utils.to_categorical(action_class, num_classes=self.n_classes),
               action_label_temp]
    #return X, [action_class, action]

def on_epoch_end(self):
    'Updates indexes after each epoch'
    self.indexes = np.arange(len(self.action_ids))
    if self.shuffle == True:
        np.random.shuffle(self.indexes)

def __data_generation(self, data_ids_temp, action_class_label_temp):
    'Generates data containing batch_size samples'

    # Initialization
    X = np.empty((self.batch_size, *self.dim))#, self.n_channel)
    action_class = np.empty((self.batch_size), dtype=int)
    action = np.empty((self.batch_size), dtype=int)

    # Generate data
    for i, ids in enumerate(data_ids_temp):

        X[i,] = self.__read_data_instance(data_ids_temp[i])
        action_class[i] = action_class_label_temp[i]
        action[i] = action_label_temp[i]

    #return X, keras.utils.to_categorical(y, num_classes=self.n_classes)
    return X, [action_class, action]

def __read_data_instance(self, pid):
    # Read an image
    filepath = self.data_frame.iloc[pid][self.image_column]

    data = Image.open(filepath)

    data = np.asarray(data)

    X = data

    # Input normalization
    X = (X - self.data_mean) / self.data_std
```

```
    return X
```

In []: █

In []: █

```
'''  
BATCH_SIZE = 64  
  
data_mean = 0.  
data_std = 255.0  
  
training_generator = DataGenerator(  
    data_frame = train_data_df,  
    batch_size = BATCH_SIZE,  
    data_mean = data_mean,  
    data_std = data_std,  
    create_folder = True,  
    dim = (224, 224, 3),  
    shuffle = True,  
    augment = True,  
    file_name = 'drive/MyDrive/train')  
  
'''
```

In [31]: █ # If the augmentation is already done, since it's a lengthy process

Streaming output truncated to the last 5000 lines.

```
inflating: images_augmented/Img_8696_('hflip', 'rotate').jpg  
inflating: images_augmented/Img_4638_('hflip', 'gamma', 'noise')  
.jpg  
inflating: images_augmented/Img_4754_('crop',).jpg  
inflating: images_augmented/Img_3117_('gamma', 'noise').jpg  
inflating: images_augmented/Img_1669_('rotate', 'gamma', 'noise')  
.jpg  
inflating: images_augmented/Img_5405_('gamma', 'noise').jpg  
inflating: images_augmented/Img_8563.jpg  
inflating: images_augmented/Img_1752_('crop', 'noise').jpg  
inflating: images_augmented/Img_6834_('rotate', 'crop', 'gamma')  
.jpg  
inflating: images_augmented/Img_269_('crop',).jpg  
inflating: images_augmented/Img_5529.jpg  
inflating: images_augmented/Img_9022_('hflip', 'gamma', 'noise')  
.jpg  
inflating: images_augmented/Img_3594_('noise',).jpg  
inflating: images_augmented/Img_6376_('rotate', 'crop', 'noise')  
.jpg  
'''
```

In [32]: █

In [33]: █

```
train_data_df.action = pd.Categorical(train_data_df.action)  
train_data_df["action_num"] = train_data_df.action.cat.codes  
  
train_data_df.action_class = pd.Categorical(train_data_df.action_cl
```

In [34]: █

Out[34]:

	FileName	action	action_class	act
0	images_augmented/Img_5261.jpg	feeding_a_horse	Interacting_with_animal	

		FileName	action	action_class	act
1	images_augmented/Img_5261_(‘hflip’).jpg	feeding_a_horse	Interacting_with_animal		
2	images_augmented/Img_5261_(‘rotate’).jpg	feeding_a_horse	Interacting_with_animal		
3	images_augmented/Img_5261_(‘crop’).jpg	feeding_a_horse	Interacting_with_animal		
4	images_augmented/Img_5261_(‘gamma’).jpg	feeding_a_horse	Interacting_with_animal		
...
54523	images_augmented/Img_2982_(‘hflip’, ‘rotate’, ...)	watching_TV	using_comm_device		
54524	images_augmented/Img_2982_(‘hflip’, ‘rotate’, ...)	watching_TV	using_comm_device		
54525	images_augmented/Img_2982_(‘hflip’, ‘crop’, ‘g...’)	watching_TV	using_comm_device		
54526	images_augmented/Img_2982_(‘rotate’, ‘crop’, ‘...’)	watching_TV	using_comm_device		
54527	images_augmented/Img_2982_(‘hflip’, ‘rotate’, ...)	watching_TV	using_comm_device		

In []: ➞

Multi-task Learning Model

Strategy

- We first create an evaluation pipeline
- Then we find a baseline model from previous research, and add the aspect of multi-task learning to it

Model Evaluation Setup

```
In [39]: ➞ class Logger(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        action_class_accuracy = logs.get('action_class_accuracy')
        action_accuracy = logs.get('action_accuracy')
        val_action_class_accuracy = logs.get('val_action_class_accuracy')
        val_action_accuracy = logs.get('val_action_accuracy')

        action_class_top_k = logs.get('action_class_top_k_categorical_accuracy')
        action_top_k = logs.get('action_top_k_categorical_accuracy')
        val_action_class_top_k = logs.get('val_action_class_top_k_categorical_accuracy')
        val_action_top_k = logs.get('val_action_top_k_categorical_accuracy')

        print('*30, epoch + 1, '*30)
        print("")
        print(f'action_class_accuracy: {action_class_accuracy:.2f},')
        print(f'val_action_class_accuracy: {val_action_class_accuracy:.2f}')
        print("")
        print(f'action_class_top_k_categorical_accuracy : {action_class_top_k}')
        print(f'val_action_class_top_k_categorical_accuracy : {val_action_top_k}'
```

```
    print("")
```

```
In [40]: ┌ def get_callbacks(model_name):  
  checkpoint_path = model_name + "/cp.ckpt"  
  
  all_callbacks = [  
      tf.keras.callbacks.EarlyStopping(  
          monitor="val_action_top_k_categorical_accuracy"  
          min_delta=0,  
          patience=5,  
          verbose=1,  
          restore_best_weights=True,  
      ),  
      tf.keras.callbacks.EarlyStopping(  
          monitor="val_action_class_accuracy",  
          min_delta=0,  
          patience=5,  
          verbose=1,  
          restore_best_weights=True,  
      ),  
  
      tf.keras.callbacks.ModelCheckpoint(checkpoint_path  
          save_weights_only=True,  
          verbose=1,  
          save_best_only = True),  
      Logger(),  
      tf.keras.callbacks.TensorBoard(log_dir = './logs')  
  ]
```

```
In [41]: ┌ def plotter(history_hold, metric = 'accuracy', loss='loss', ylim_metric=100)  
  cycol = cycle('bgrcmk')  
  plt.figure(figsize=(10,5))  
  for name, item in history_hold.items():  
      metric_train = item[metric]  
      metric_val = item['val_' + metric]  
      loss_train = item[loss]  
      loss_val = item['val_' + loss]  
  
      x_train = np.arange(0,len(loss_val))  
  
      c=next(cycol)  
      plt.style.use("ggplot")  
      plt.subplot(1,2,1)  
      plt.plot(x_train, metric_train, c+'-', label=name+'_train')  
      plt.plot(x_train, metric_val, c+'--', label=name+'_val')  
  
      plt.legend()  
      plt.xlim([1, xlim_max])  
      plt.ylim(ylim_metric)  
      plt.xlabel('Epoch')  
      plt.ylabel(metric)  
      plt.grid(True)  
      plt.title(metric)  
  
      plt.subplot(1,2,2)
```

```
plt.plot(x_train, loss_train, c+'-', label=name+'_train')
plt.plot(x_train, loss_val, c+'--', label=name+'_val')

plt.legend()
plt.xlim([1, xlim_max])
# plt.ylim(ylim_loss)
plt.xlabel('Epoch')
plt.ylabel(loss)
plt.grid(True)
```

In []: █

In []: █

Resnet Implementation

Implementation taken mostly as-is from the week 6 lab, with a few minor tweaks to add additional flexibility with parameters

```
In [ ]: █ class ResidualBlock(tf.keras.layers.Layer):

    # Initialize components of the model
    def __init__(self, filter_num, stride=1, reg_lambda=0.0, kernel_initializer='he_normal', kernel_regularizer='l2', kernel_size=3, padding='same'):
        super(ResidualBlock, self).__init__()
        self.conv1 = tf.keras.layers.Conv2D(filters=filter_num,
                                           kernel_size=kernel_size,
                                           strides=stride,
                                           kernel_initializer=kernel_initializer,
                                           kernel_regularizer=kernel_regularizer,
                                           padding=padding)

        self.bn1 = tf.keras.layers.BatchNormalization(momentum=momentum)
        self.conv2 = tf.keras.layers.Conv2D(filters=filter_num,
                                           kernel_size=kernel_size,
                                           strides=1,
                                           kernel_initializer=kernel_initializer,
                                           kernel_regularizer=kernel_regularizer,
                                           padding=padding)

        self.bn2 = tf.keras.layers.BatchNormalization(momentum=momentum)
        if stride != 1:
            self.downsample = tf.keras.Sequential()
            self.downsample.add(tf.keras.layers.Conv2D(filters=filter_num,
                                                       kernel_size=kernel_size,
                                                       kernel_initializer=kernel_initializer,
                                                       kernel_regularizer=kernel_regularizer,
                                                       strides=stride))
            self.downsample.add(tf.keras.layers.BatchNormalization(momentum=momentum))
        else:
            self.downsample = lambda x: x

    # Define the forward function
    def call(self, inputs, training=None, **kwargs):
        residual = self.downsample(inputs)

        x = self.conv1(inputs)
        x = self.bn1(x, training=training)
        x = tf.nn.relu(x)
        x = self.conv2(x)
        x = self.bn2(x, training=training)
```

```
        output = tf.nn.relu(tf.keras.layers.add([residual, x]))\n\n    return output\n\n\ndef get_config(self):\n\n    config = super().get_config().copy()\n    config.update({\n        'conv1': self.conv1,\n        'bn1': self.bn1,\n        'conv2': self.conv2,\n        'bn2': self.bn2,\n        'downsample': self.downsample,\n    })\n\n    return config
```

In []: █

In []: █

Baseline Model

The baseline model selected is the original ResNet paper used on ImageNet. This was selected to test whether the original architecture can generalize well to other image recognition problems, and with a limited set of data

```
In [ ]: █ BATCH_SIZE = 64\n\n\ndef train_data_generator(\n    data_frame, batch_size, data_mean, data_std,\n    create_folder=False, dim=(224, 224, 3),\n    shuffle=True, augment=False,\n    file_name='drive/MyDrive/train'):\n\n    data_mean = 0.\n    data_std = 255.0\n    prefix = ''\n\n    generator = DataGenerator(\n        data_mean=data_mean,\n        data_std=data_std,\n        data_frame=data_frame,\n        batch_size=batch_size,\n        create_folder=create_folder,\n        dim=dim,\n        shuffle=shuffle,\n        augment=augment,\n        file_name=file_name)\n\n    return generator\n\n\ndef val_data_generator(\n    data_frame, batch_size, data_mean, data_std,\n    create_folder=False, dim=(224, 224, 3),\n    shuffle=True, augment=False,\n    file_name='drive/MyDrive/validation'):\n\n    data_mean = 0.\n    data_std = 255.0\n    prefix = ''\n\n    generator = DataGenerator(\n        data_mean=data_mean,\n        data_std=data_std,\n        data_frame=data_frame,\n        batch_size=batch_size,\n        create_folder=create_folder,\n        dim=dim,\n        shuffle=shuffle,\n        augment=augment,\n        file_name=file_name,\n        image_column='FileName_scaled')\n\n    return generator
```

In []: █ filters = [64, 128, 256, 512]

```
block_size = [3, 4, 6, 3]
reg_lambda = 0.00

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

In []: █ first_time = True

```
input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7, 7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
                name = "conv_1")(input_)

bn_1 = BatchNormalization(momentum=0.9)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                        kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                        kernel_initializer= tf.keras.initializers.RandomNormal(),
                        name = "action_class")(flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                  kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                  kernel_initializer= tf.keras.initializers.RandomNormal(),
                  name = "action")(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
```

```
loss = {
    'action_class': 'categorical_crossentropy',
    'action': 'categorical_crossentropy'
},
optimizer = optimizer_,
metrics = [
    'accuracy',
    tf.keras.metrics.TopKCategoricalAccuracy(
        k=5,
        name="top_k_categorical_accuracy",
        dtype=None
    )

] #tf.keras.metrics.F1Score(num_classes = 5, average="weighted")

)

Model: "model_1"
```

Layer (type)	Output Shape	Param #	C
connected to			
input (InputLayer)	[None, 224, 224, 3]	0	i
conv_1 (Conv2D) input[0][0]	(None, 224, 224, 64)	9472	c
batch_normalization_37 (BatchNo conv_1[0][0]	(None, 224, 224, 64)	256	b
residual_block_16 (ResidualBloc atch_normalization_37[0][0]	(None, 112, 112, 64)	78784	r
residual_block_17 (ResidualBloc esidual_block_16[0][0]	(None, 112, 112, 64)	74368	r
residual_block_18 (ResidualBloc esidual_block_17[0][0]	(None, 112, 112, 64)	74368	r
residual_block_19 (ResidualBloc esidual_block_18[0][0]	(None, 56, 56, 128)	231296	r
residual_block_20 (ResidualBloc esidual_block_19[0][0]	(None, 56, 56, 128)	296192	r
residual_block_21 (ResidualBloc esidual_block_20[0][0]	(None, 56, 56, 128)	296192	r

residual_block_22 (ResidualBloc	(None, 56, 56, 128)	296192	r
esidual_block_21[0][0]			
residual_block_23 (ResidualBloc	(None, 28, 28, 256)	921344	r
esidual_block_22[0][0]			
residual_block_24 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_23[0][0]			
residual_block_25 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_24[0][0]			
residual_block_26 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_25[0][0]			
residual_block_27 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_26[0][0]			
residual_block_28 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_27[0][0]			
residual_block_29 (ResidualBloc	(None, 14, 14, 512)	3677696	r
esidual_block_28[0][0]			
residual_block_30 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_29[0][0]			
residual_block_31 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_30[0][0]			
gap_1 (GlobalAveragePooling2D)	(None, 512)	0	r
esidual_block_31[0][0]			
flat_1 (Flatten)	(None, 512)	0	g
ap_1[0][0]			
action_class (Dense)	(None, 5)	2565	f
lat_1[0][0]			
action (Dense)	(None, 21)	10773	f
lat_1[0][0]			
<hr/>			
Total params: 21,327,962			
Trainable params: 21,310,810			

```
Non-trainable params: 17,152
```

```
In [ ]: █
```

```
In [ ]: █
```

```
<IPython.core.display.Javascript object>
```

```
In [ ]: █
```

```
In [ ]: █ model_name = "baseline"
```

```
model_results[model_name] = model.fit(  
    training_generator,  
    validation_data = validation_generator,  
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,  
    validation_steps = len(val_data_df)//BATCH_SIZE,  
    epochs = 200,  
    callbacks = get_callbacks(model_name),  
    verbose = True
```

```
Epoch 1/200
```

```
6/852 [........................] - ETA: 8:12 - loss: 12.25  
21 - action_class_loss: 8.1074 - action_loss: 4.1447 - action_clas  
s_accuracy: 0.2396 - action_class_top_k_categorical_accuracy: 1.00  
00 - action_accuracy: 0.0885 - action_top_k_categorical_accuracy:  
0.3047WARNING:tensorflow:Callback method `on_train_batch_end` is s  
low compared to the batch time (batch time: 0.1595s vs `on_train_b  
atch_end` time: 0.2643s). Check your callbacks.  
852/852 [=====] - 349s 384ms/step - loss:  
3.9387 - action_class_loss: 1.3736 - action_loss: 2.5651 - action_  
class_accuracy: 0.4430 - action_class_top_k_categorical_accuracy:  
1.0000 - action_accuracy: 0.2137 - action_top_k_categorical_accur  
acy: 0.5898 - val_loss: 3.7318 - val_action_class_loss: 1.2612 - va  
l_action_loss: 2.4705 - val_action_class_accuracy: 0.4961 - val_ac  
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac  
y: 0.2559 - val_action_top_k_categorical_accuracy: 0.6406
```

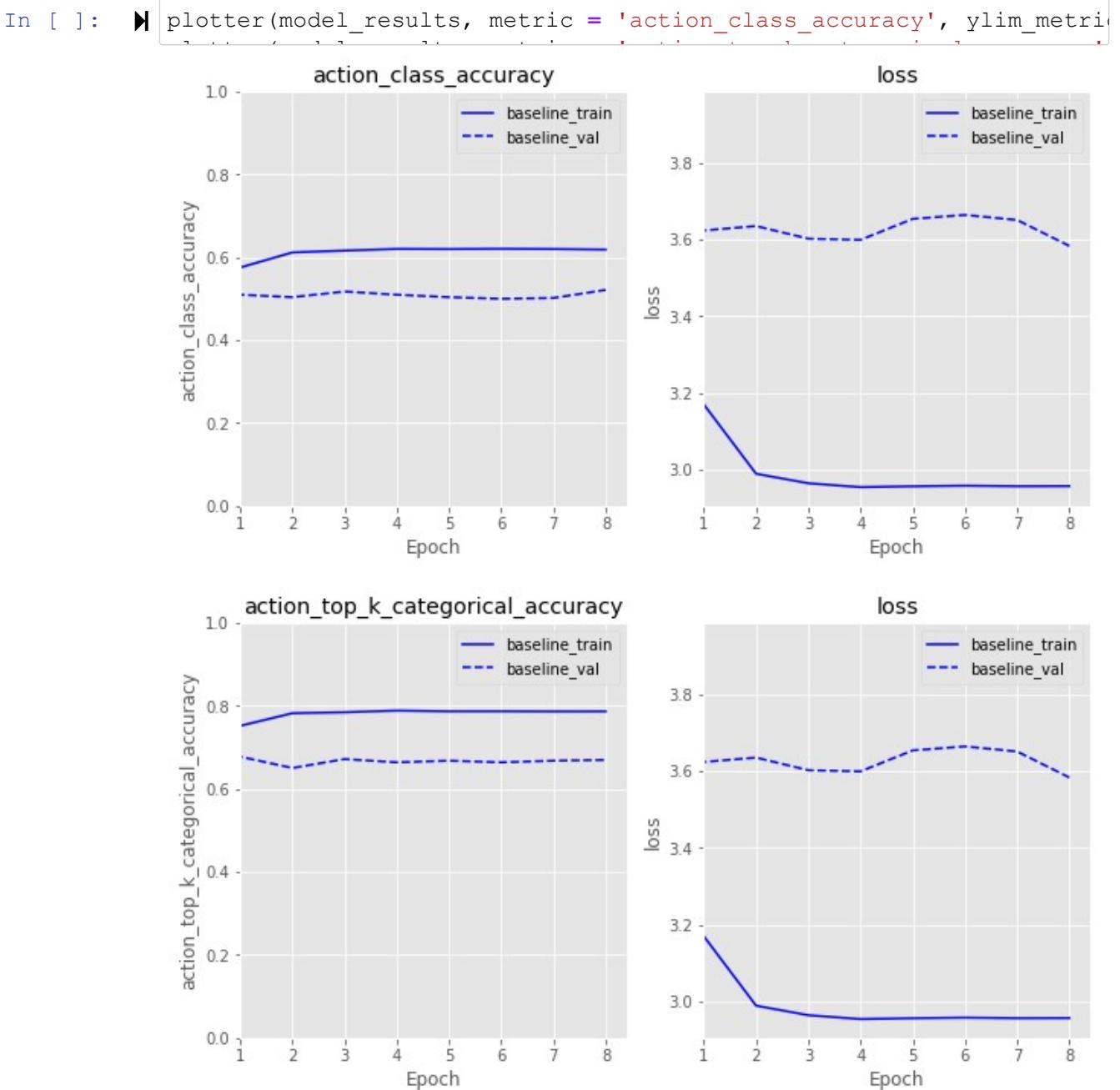
```
Epoch 00001: val_loss improved from inf to 3.73177, saving model t  
o baseline/cp.ckpt
```

```
In [ ]: █
```

```
# Save model results  
model_results[model_name] = model_results[model_name].history  
  
with open("drive/MyDrive/model_results.json", "w") as fp:
```

```
In [ ]: █
```

```
# Save model weights
```



✓ Observations:

- Action_class seems to be underfitting
- Action seems to be overfitting
- The model performance plateaus very quickly
- Momentum might be too high which is why it's having difficulty estimating the unknown target function. Decreasing the momentum and ensuring the optimization happens in smaller steps might be useful

In []: ⏷

Experimentation - Momentum

Strategy

- First, we do a random search and halve the momentum to 0.4. Then we do a semi-grid search based on the performance evaluations

Halving the momentum to 0.4

```
In [ ]: BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train',
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation',
    image_column = "FileName_scaled"
)
```

```
In [ ]: filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.00

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

```
In [ ]: first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
```

```
        name = "conv_1") (input_)

bn_1 = BatchNormalization(momentum=0.4) (conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2)) (bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2)) (res_x)

#reshape_1 = Reshape(res_x.shape[1:], name="reshape_1") (res_x)

gap_1 = GlobalAveragePooling2D(name = "gap_1") (res_x)

flat_1 = Flatten(name = "flat_1") (gap_1)

action_class = Dense(5, activation=tf.nn.softmax,
                     kernel_regularizer=tf.keras.regularizers.l2(
                     kernel_initializer=tf.keras.initializers.RandomUniform(
                     name = "action_class")) (flat_1)

action = Dense(21, activation=tf.nn.softmax,
               kernel_regularizer=tf.keras.regularizers.l2(
               kernel_initializer=tf.keras.initializers.RandomUniform(
               name = "action")) (flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
loss = {
    'action_class': 'categorical_crossentropy',
    'action': 'categorical_crossentropy'
},
optimizer = optimizer_,
metrics = [
    'accuracy',
    tf.keras.metrics.TopKCategoricalAccuracy(
        k=5,
        name="top_k_categorical_accuracy",
        dtype=None
    )
]
)

)
```

Model: "model_2"

Layer (type)	Output Shape	Param #	C
connected to			
input (InputLayer)	[(None, 224, 224, 3) 0		
=====			
conv_1 (Conv2D) input[0][0]	(None, 224, 224, 64) 9472		i
=====			
batch_normalization_74 (BatchNo conv_1[0][0]	(None, 224, 224, 64) 256		c
=====			
residual_block_32 (ResidualBloc atch_normalization_74[0][0]	(None, 112, 112, 64) 78784		b
=====			
residual_block_33 (ResidualBloc esidual_block_32[0][0]	(None, 112, 112, 64) 74368		r
=====			
residual_block_34 (ResidualBloc esidual_block_33[0][0]	(None, 112, 112, 64) 74368		r
=====			
residual_block_35 (ResidualBloc esidual_block_34[0][0]	(None, 56, 56, 128) 231296		r
=====			
residual_block_36 (ResidualBloc esidual_block_35[0][0]	(None, 56, 56, 128) 296192		r
=====			
residual_block_37 (ResidualBloc esidual_block_36[0][0]	(None, 56, 56, 128) 296192		r
=====			
residual_block_38 (ResidualBloc esidual_block_37[0][0]	(None, 56, 56, 128) 296192		r
=====			
residual_block_39 (ResidualBloc esidual_block_38[0][0]	(None, 28, 28, 256) 921344		r
=====			
residual_block_40 (ResidualBloc esidual_block_39[0][0]	(None, 28, 28, 256) 1182208		r
=====			
residual_block_41 (ResidualBloc esidual_block_40[0][0]	(None, 28, 28, 256) 1182208		r
=====			
residual_block_42 (ResidualBloc esidual_block_41[0][0]	(None, 28, 28, 256) 1182208		r

```
esidual_block_41[0][0]
```

```
residual_block_43 (ResidualBloc (None, 28, 28, 256) 1182208 r  
esidual_block_42[0][0]
```

```
residual_block_44 (ResidualBloc (None, 28, 28, 256) 1182208 r  
esidual_block_43[0][0]
```

```
residual_block_45 (ResidualBloc (None, 14, 14, 512) 3677696 r  
esidual_block_44[0][0]
```

```
residual_block_46 (ResidualBloc (None, 14, 14, 512) 4723712 r  
esidual_block_45[0][0]
```

```
residual_block_47 (ResidualBloc (None, 14, 14, 512) 4723712 r  
esidual_block_46[0][0]
```

```
gap_1 (GlobalAveragePooling2D) (None, 512) 0 r  
esidual_block_47[0][0]
```

```
flat_1 (Flatten) (None, 512) 0 g  
ap_1[0][0]
```

```
action_class (Dense) (None, 5) 2565 f  
lat_1[0][0]
```

```
action (Dense) (None, 21) 10773 f  
lat_1[0][0]
```

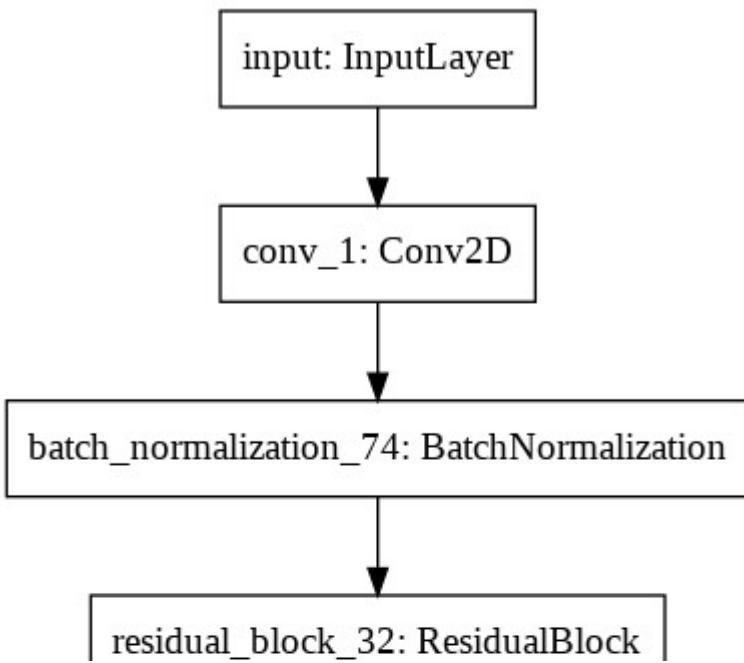
```
Total params: 21,327,962
```

```
Trainable params: 21,310,810
```

```
Non-trainable params: 17,152
```

In []:

Out[43]:



In []:

In []:

```
Reusing TensorBoard on port 6006 (pid 413), started 0:59:46 ago.  
(Use '!kill 413' to kill it.)
```

```
<IPython.core.display.Javascript object>
```

In []:

```
model_name = "momentum_04"

model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True
```

```
Epoch 1/200
```

```
6/852 [........................] - ETA: 8:19 - loss: 8.170
6 - action_class_loss: 4.0014 - action_loss: 4.1692 - action_class_accuracy: 0.2604 - action_class_top_k_categorical_accuracy: 1.000
0 - action_accuracy: 0.0391 - action_top_k_categorical_accuracy: 0.2708
WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time (batch time: 0.1584s vs `on_train_batch_end` time: 0.3354s). Check your callbacks.
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time (batch time: 0.1584s vs `on_train_batch_end` time: 0.3354s). Check your callbacks.
```

```
852/852 [=====] - 332s 384ms/step - loss: 3.8758 - action_class_loss: 1.3360 - action_loss: 2.5398 - action_class_accuracy: 0.4518 - action_class_top_k_categorical_accuracy:
```

```
In [ ]: # Save model results
model_results[model_name] = model_results[model_name].history

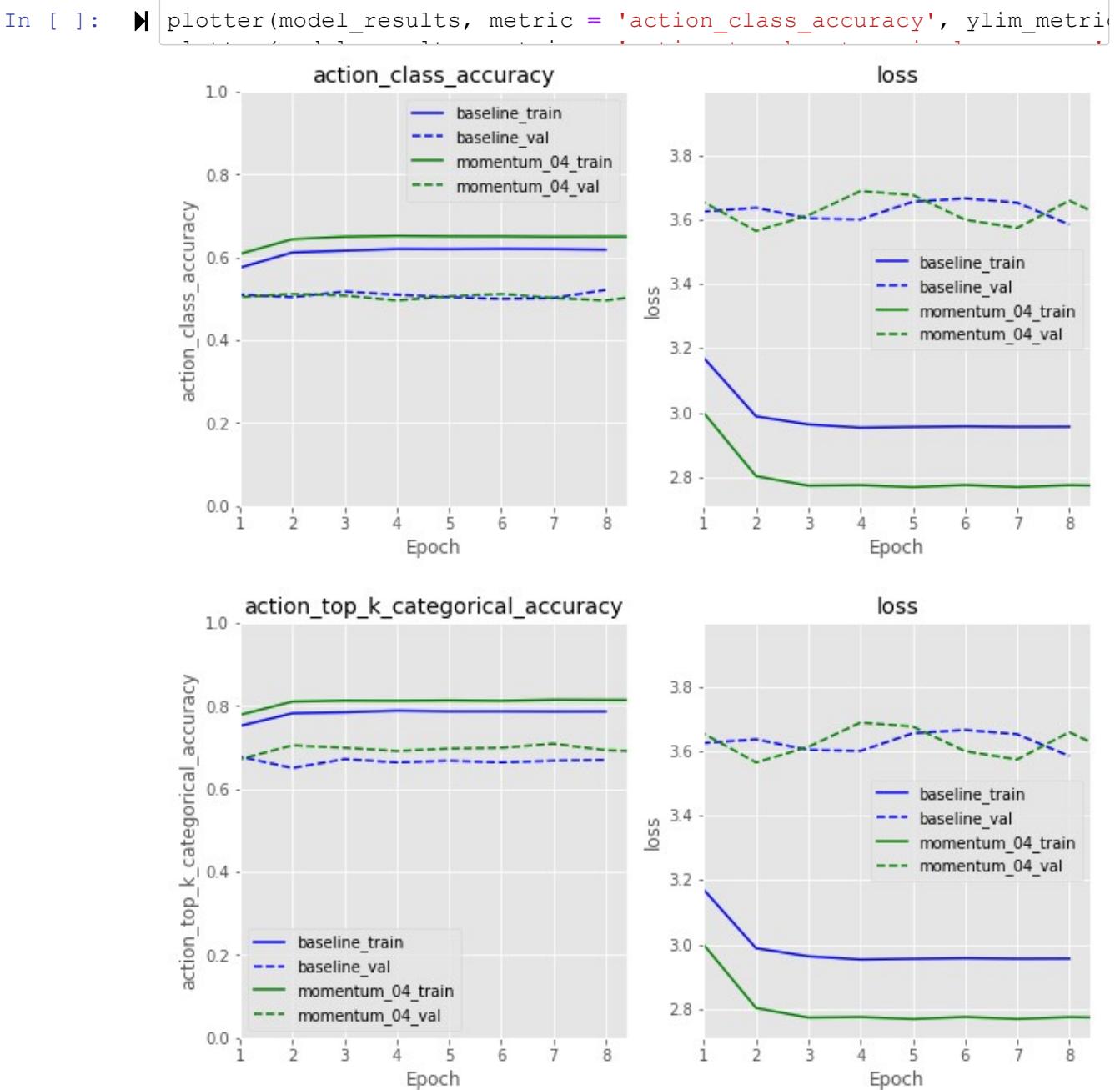
!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

```
In [ ]: # Save model weights
```

```
WARNING:absl:Found untraced functions such as conv2d_72_layer_call_and_return_conditional_losses, conv2d_72_layer_call_fn, conv2d_73_layer_call_and_return_conditional_losses, conv2d_73_layer_call_fn, conv2d_75_layer_call_and_return_conditional_losses while saving (showing 5 of 160). These functions will not be directly callable after loading.
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/momentum_04_model/assets
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/momentum_04_model/assets
```



✓ Observations:

- Action_class is still underfitting in general, and is overfitting when compared to validation set.
- Slight increase in action metric, but it is still overfitting
- Might need to reduce the momentum even further

In []:

In []:

Reducing the momentum further to 0.1

In []: file_ = open('drive/MyDrive/model_results.json')
model_results = json.load(file_)

```
In [ ]: BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train',
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation',
    image_column = "FileName_scaled"
)
```

```
In [ ]: filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.00

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

```
In [ ]: first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
                name = "conv_1")(input_)

bn_1 = BatchNormalization(momentum=0.1)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)
```

```

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
                               first_time = False)
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                         kernel_initializer=tf.keras.initializers.RandomUniform(
                             name = "action_class"))(flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                   kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                   kernel_initializer=tf.keras.initializers.RandomUniform(
                       name = "action"))(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
            name="top_k_categorical_accuracy",
            dtype=None
        )
    ]
)

```

Model: "model"

Layer (type)	Output Shape	Param #	C
connected to			
=====			
input (InputLayer)	[None, 224, 224, 3]	0	

conv_1 (Conv2D) nput[0][0]	(None, 224, 224, 64)	9472	i
batch_normalization (BatchNorma conv_1[0][0]	(None, 224, 224, 64)	256	c
residual_block (ResidualBlock) batch_normalization[0][0]	(None, 112, 112, 64)	78784	b
residual_block_1 (ResidualBlock) residual_block[0][0]	(None, 112, 112, 64)	74368	r
residual_block_2 (ResidualBlock) residual_block_1[0][0]	(None, 112, 112, 64)	74368	r
residual_block_3 (ResidualBlock) residual_block_2[0][0]	(None, 56, 56, 128)	231296	r
residual_block_4 (ResidualBlock) residual_block_3[0][0]	(None, 56, 56, 128)	296192	r
residual_block_5 (ResidualBlock) residual_block_4[0][0]	(None, 56, 56, 128)	296192	r
residual_block_6 (ResidualBlock) residual_block_5[0][0]	(None, 56, 56, 128)	296192	r
residual_block_7 (ResidualBlock) residual_block_6[0][0]	(None, 28, 28, 256)	921344	r
residual_block_8 (ResidualBlock) residual_block_7[0][0]	(None, 28, 28, 256)	1182208	r
residual_block_9 (ResidualBlock) residual_block_8[0][0]	(None, 28, 28, 256)	1182208	r
residual_block_10 (ResidualBloc residual_block_9[0][0]	(None, 28, 28, 256)	1182208	r
residual_block_11 (ResidualBloc residual_block_10[0][0]	(None, 28, 28, 256)	1182208	r
residual_block_12 (ResidualBloc residual_block_11[0][0]	(None, 28, 28, 256)	1182208	r

```
residual_block_13 (ResidualBloc (None, 14, 14, 512) 3677696 r
esidual_block_12[0][0]

residual_block_14 (ResidualBloc (None, 14, 14, 512) 4723712 r
esidual_block_13[0][0]

residual_block_15 (ResidualBloc (None, 14, 14, 512) 4723712 r
esidual_block_14[0][0]

gap_1 (GlobalAveragePooling2D) (None, 512) 0 r
esidual_block_15[0][0]

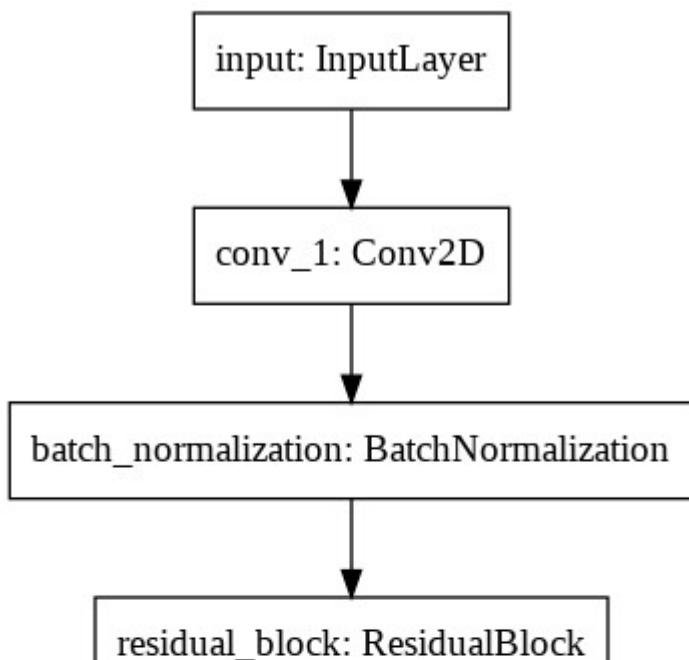
flat_1 (Flatten) (None, 512) 0 g
ap_1[0][0]

action_class (Dense) (None, 5) 2565 f
lat_1[0][0]

action (Dense) (None, 21) 10773 f
lat_1[0][0]
=====
=====
Total params: 21,327,962
Trainable params: 21,310,810
Non-trainable params: 17,152
```

In []:

Out[34]:



In []:

<IPython.core.display.Javascript object>

In []:

```
model_name = "momentum_01"

model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True
```

Epoch 1/200
6/852 [........................] - ETA: 7:51 - loss: 12.81
90 - action_class_loss: 7.9169 - action_loss: 4.9021 - action_classes_accuracy: 0.2214 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.0677 - action_top_k_categorical_accuracy: 0.3151WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time (batch time: 0.1481s vs `on_train_batch_end` time: 0.2650s). Check your callbacks.
852/852 [=====] - 346s 381ms/step - loss: 3.9843 - action_class_loss: 1.3938 - action_loss: 2.5905 - action_classes_accuracy: 0.4361 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.2065 - action_top_k_categorical_accuracy: 0.5865 - val_loss: 3.9198 - val_action_class_loss: 1.3370 - val_action_loss: 2.5828 - val_action_classes_accuracy: 0.4277 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_action_accuracy: 0.2344 - val_action_top_k_categorical_accuracy: 0.6055

Epoch 00001: val_loss improved from inf to 3.91979, saving model to momentum_01/cp.ckpt

In []:

```
# Save model results
model_results[model_name] = model_results[model_name].history

!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

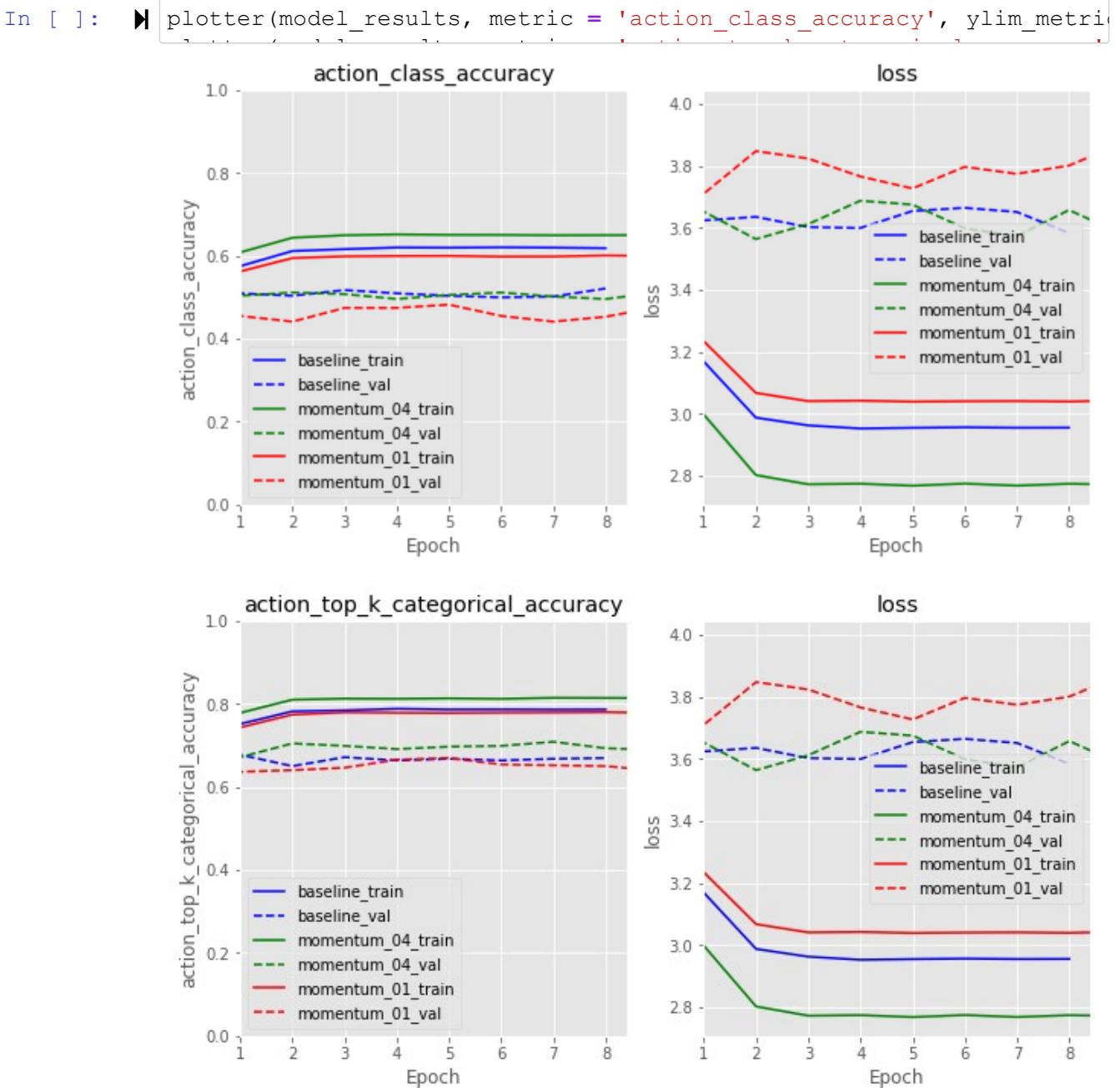
In []:

Save model weights

WARNING:absl:Found untraced functions such as conv2d_layer_call_fn, conv2d_layer_call_and_return_conditional_losses, conv2d_1_layer_call_fn, conv2d_1_layer_call_and_return_conditional_losses, conv2d_3_layer_call_fn while saving (showing 5 of 160). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: drive/MyDrive/momentum_01_model/assets

INFO:tensorflow:Assets written to: drive/MyDrive/momentum_01_model/assets



✓ Observations:

- Performance overall is worse than the baseline model
- It might not be the case that there is a problem with the optimization step size.
- We might need to increase the overall complexity of the model

In []:

In []:

Experimentation - Increasing Model Complexity

Strategy

- First we try adding more hidden layers to the MLP

- Then we add more ResNet blocks to the model architecture
- Then we evaluate the performance from both of these and continue to tune

Adding more hidden layers to the MLP

- 4 hidden layers are added to the MLP, with 4096 neurons each. While this may be a lot of additional hidden layers to add to an already complex model, it is done in order to test the approach. It is expected from this that the model will perform well on the training data and not on the validation data, overfitting significantly

```
In [ ]: BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train'
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation'
    image_column = "FileName_scaled"
)
```

```
In [ ]: filters = [64, 128, 256, 512]
block_size = [3, 4, 6, 3]
reg_lambda = 0.00

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df) // BATCH_SIZE,
    staircase=False)
```

```
In [ ]: first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")
```

```
conv_1 = Conv2D(filters = 64,
                 kernel_size = (7, 7),
                 strides = 1,
                 kernel_initializer = tf.keras.initializers.RandomNormal(),
                 kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                 padding = "same",
                 name = "conv_1") (input_)

bn_1 = BatchNormalization(momentum=0.4) (conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2)) (bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):
        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2)) (res_x)

#reshape_1 = Reshape(res_x.shape[1:], name="reshape_1") (res_x)

gap_1 = GlobalAveragePooling2D(name = "gap_1") (res_x)

flat_1 = Flatten(name = "flat_1") (gap_1)
hidden_1 = Dense(4096, activation = tf.nn.relu, name = "hidden_1") (flat_1)
hidden_2 = Dense(4096, activation = tf.nn.relu, name = "hidden_2") (hidden_1)
hidden_3 = Dense(4096, activation = tf.nn.relu, name = "hidden_3") (hidden_2)
hidden_4 = Dense(4096, activation = tf.nn.relu, name = "hidden_4") (hidden_3)

action_class = Dense(5, activation=tf.nn.softmax,
                     kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                     kernel_initializer= tf.keras.initializers.RandomNormal(),
                     name = "action_class") (hidden_4)

action = Dense(21, activation= tf.nn.softmax,
               kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
               kernel_initializer= tf.keras.initializers.RandomNormal(),
               name = "action") (hidden_4)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
```

```
        name="top_k_categorical_accuracy",
        dtype=None
    )
]

)
)
```

Model: "model_3"

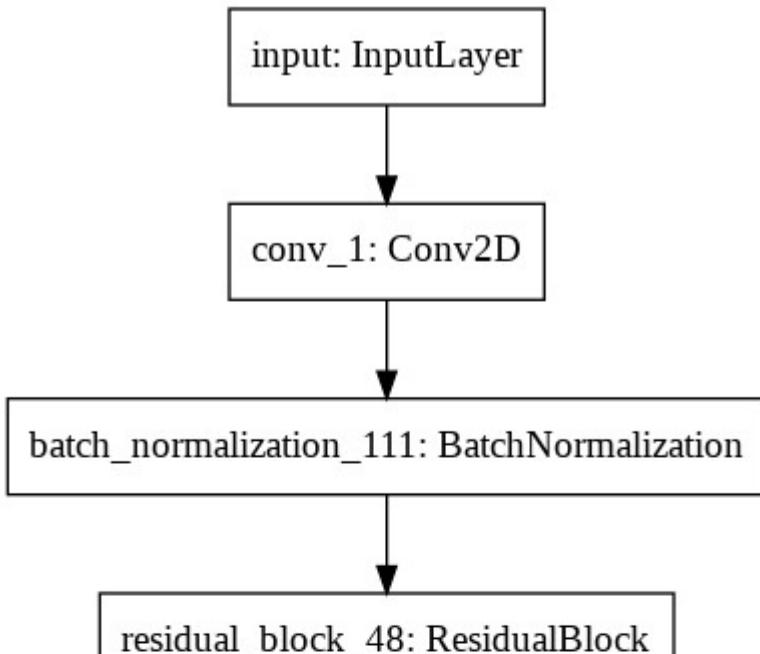
Layer (type)	Output Shape	Param #	C
connected to			
input (InputLayer)	[(None, 224, 224, 3) 0		i
nput[0][0]			
conv_1 (Conv2D)	(None, 224, 224, 64) 9472		c
conv_1[0][0]			
batch_normalization_111 (BatchN	(None, 224, 224, 64) 256		c
conv_1[0][0]			
residual_block_48 (ResidualBloc	(None, 112, 112, 64) 78784		b
atch_normalization_111[0][0]			
residual_block_49 (ResidualBloc	(None, 112, 112, 64) 74368		r
esidual_block_48[0][0]			
residual_block_50 (ResidualBloc	(None, 112, 112, 64) 74368		r
esidual_block_49[0][0]			
residual_block_51 (ResidualBloc	(None, 56, 56, 128) 231296		r
esidual_block_50[0][0]			
residual_block_52 (ResidualBloc	(None, 56, 56, 128) 296192		r
esidual_block_51[0][0]			
residual_block_53 (ResidualBloc	(None, 56, 56, 128) 296192		r
esidual_block_52[0][0]			
residual_block_54 (ResidualBloc	(None, 56, 56, 128) 296192		r
esidual_block_53[0][0]			
residual_block_55 (ResidualBloc	(None, 28, 28, 256) 921344		r
esidual_block_54[0][0]			

residual_block_56 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_55[0][0]			
residual_block_57 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_56[0][0]			
residual_block_58 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_57[0][0]			
residual_block_59 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_58[0][0]			
residual_block_60 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_59[0][0]			
residual_block_61 (ResidualBloc	(None, 14, 14, 512)	3677696	r
esidual_block_60[0][0]			
residual_block_62 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_61[0][0]			
residual_block_63 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_62[0][0]			
gap_1 (GlobalAveragePooling2D)	(None, 512)	0	r
esidual_block_63[0][0]			
flat_1 (Flatten)	(None, 512)	0	g
ap_1[0][0]			
hidden_1 (Dense)	(None, 4096)	2101248	f
lat_1[0][0]			
hidden_2 (Dense)	(None, 4096)	16781312	h
idden_1[0][0]			
hidden_3 (Dense)	(None, 4096)	16781312	h
idden_2[0][0]			
hidden_4 (Dense)	(None, 4096)	16781312	h
idden_3[0][0]			
action_class (Dense)	(None, 5)	20485	h
idden_4[0][0]			

```
action (Dense)           (None, 21)      86037      h
hidden_4[0][0]
=====
=====
Total params: 73,866,330
Trainable params: 73,849,178
Non-trainable params: 17,152
```

In []:

Out[52]:



In []:

<IPython.core.display.Javascript object>

In []:

file_ = open('drive/MyDrive/model_results.json')

In []:

model_name = "hidden_dense"

```
model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True
```

```
Epoch 1/200
6/852 [........................] - ETA: 7:40 - loss: 10.62
26 - action_class_loss: 5.8698 - action_loss: 4.7528 - action_class_accuracy: 0.2292 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.0651 - action_top_k_categorical_accuracy: 0.2474WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time (batch time: 0.1427s vs `on_train_batch_end` time: 0.3201s). Check your callbacks.
852/852 [=====] - 330s 383ms/step - loss: 4.0414 - action_class_loss: 1.3721 - action_loss: 2.6693 - action_class_accuracy: 0.4243 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.1750 - action_top_k_categorical_accuracy: 0.5425 - val_loss: 3.7942 - val_action_class_loss: 1.2537 - val_action_loss: 2.5405 - val_action_class_accuracy: 0.4883 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_accuracy: 0.2539 - val_action_top_k_categorical_accuracy: 0.6309

Epoch 00001: val_loss improved from inf to 3.79417, saving model to hidden_dense/cp.ckpt
=====
action_class_accuracy: 0.42, action_accuracy: 0.18
val_action_class_accuracy: 0.49, val_action_accuracy: 0.25

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.54
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.63

Epoch 2/200
852/852 [=====] - 325s 381ms/step - loss: 3.3543 - action_class_loss: 1.0980 - action_loss: 2.2563 - action_class_accuracy: 0.5486 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.2863 - action_top_k_categorical_accuracy: 0.7050 - val_loss: 3.7631 - val_action_class_loss: 1.2700 - val_action_loss: 2.4932 - val_action_class_accuracy: 0.4824 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_accuracy: 0.2500 - val_action_top_k_categorical_accuracy: 0.6367

Epoch 00002: val_loss improved from 3.79417 to 3.76314, saving model to hidden_dense/cp.ckpt
=====
action_class_accuracy: 0.55, action_accuracy: 0.29
val_action_class_accuracy: 0.48, val_action_accuracy: 0.25

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.71
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.64

Epoch 3/200
852/852 [=====] - 325s 381ms/step - loss: 3.1527 - action_class_loss: 1.0153 - action_loss: 2.1374 - action_class_accuracy: 0.5896 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.3182 - action_top_k_categorical_accuracy: 0.7414 - val_loss: 3.8034 - val_action_class_loss: 1.2880 - val_action_loss: 2.5154 - val_action_class_accuracy: 0.4824 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_accuracy: 0.2520 - val_action_top_k_categorical_accuracy: 0.6484
```

```
Epoch 00003: val_loss did not improve from 3.76314
=====
action_class_accuracy: 0.59, action_accuracy: 0.32
val_action_class_accuracy: 0.48, val_action_accuracy: 0.25

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.74
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.65

Epoch 4/200
852/852 [=====] - 325s 381ms/step - loss: 3.1197 - action_class_loss: 1.0010 - action_loss: 2.1186 - action_class_accuracy: 0.5937 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.3207 - action_top_k_categorical_accuracy: 0.7483 - val_loss: 3.8821 - val_action_class_loss: 1.3183 - val_action_loss: 2.5637 - val_action_class_accuracy: 0.4727 - val_action_top_k_categorical_accuracy: 1.0000 - val_accuracy: 0.2461 - val_action_top_k_categorical_accuracy: 0.6367
Restoring model weights from the end of the best epoch.

Epoch 00004: val_loss did not improve from 3.76314
===== 4 =====
```

```
In [ ]: # Save model results
model_results[model_name] = model_results[model_name].history

!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

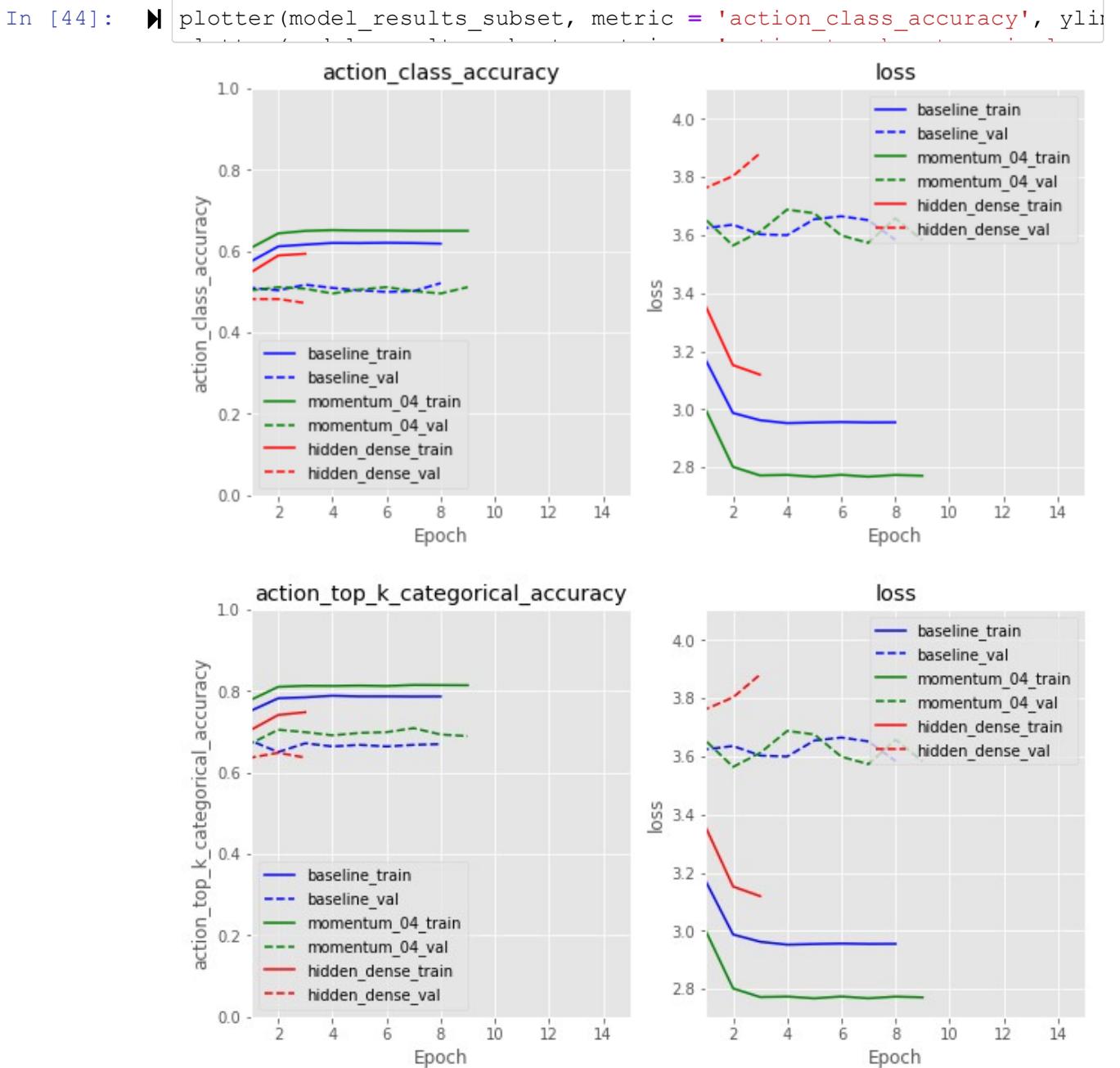
```
In [ ]: # Save model weights
WARNING:absl:Found untraced functions such as conv2d_108_layer_call_and_return_conditional_losses, conv2d_108_layer_call_fn, conv2d_109_layer_call_and_return_conditional_losses, conv2d_109_layer_call_fn, conv2d_111_layer_call_and_return_conditional_losses while saving (showing 5 of 160). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: drive/MyDrive/hidden_dense_mode1/assets

INFO:tensorflow:Assets written to: drive/MyDrive/hidden_dense_mode1/assets
```

```
In [42]: file_ = open('drive/MyDrive/model_results.json')
```

```
In [43]: names = { 'baseline', 'momentum_04', 'hidden_dense'}
```



✓ Observations:

- The model surprisingly did not perform any better on the training set, let alone the validation set. Perhaps the complexity of the MLP is just right for this task already.
- We might have more luck adding more ResNet blocks

In [44]:

In [44]:

Adding more ResNet blocks

In []:

```
BATCH_SIZE = 64
data_mean = 0.
```

```
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train'
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation'
    image_column = "FileName_scaled"
)
```

In []: █

```
filters = [64, 128, 256, 512]
block_size = [6,6,6,6]
reg_lambda = 0.00

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

In []: █

```
first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
                name = "conv_1")(input_)

bn_1 = BatchNormalization(momentum=0.4)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)(bn_1)
    else:
```

```
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)(res_x)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)(res_x)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                         kernel_initializer=tf.keras.initializers.RandomUniform(
                             name = "action_class"))(flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                  kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                  kernel_initializer=tf.keras.initializers.RandomUniform(
                      name = "action"))(flat_1)

    model = tf.keras.models.Model(input_, [action_class, action])

    model.compile(
        loss = {
            'action_class': 'categorical_crossentropy',
            'action': 'categorical_crossentropy'
        },
        optimizer = optimizer_,
        metrics = [
            'accuracy',
            tf.keras.metrics.TopKCategoricalAccuracy(
                k=5,
                name="top_k_categorical_accuracy",
                dtype=None
            )
        ]
    )

)
```

Model: "model_7"

Layer (type) connected to	Output Shape	Param #	C
<hr/>			
input (InputLayer)	[None, 224, 224, 3]	0	

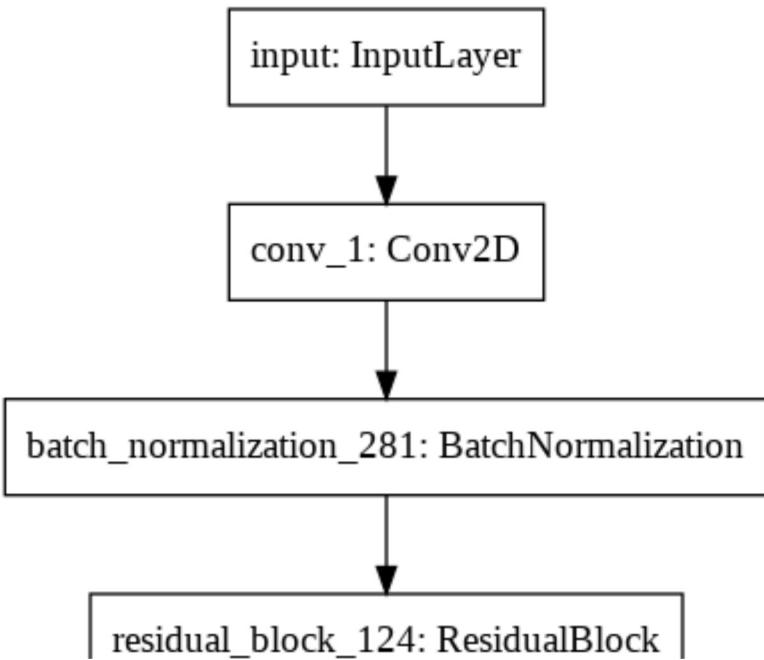
conv_1 (Conv2D) nput[0][0]	(None, 224, 224, 64) 9472	i
batch_normalization_281 (BatchN conv_1[0][0]	(None, 224, 224, 64) 256	c
residual_block_124 (ResidualBlo atch_normalization_281[0][0]	(None, 112, 112, 64) 78784	b
residual_block_125 (ResidualBlo esidual_block_124[0][0]	(None, 112, 112, 64) 74368	r
residual_block_126 (ResidualBlo esidual_block_125[0][0]	(None, 112, 112, 64) 74368	r
residual_block_127 (ResidualBlo esidual_block_126[0][0]	(None, 112, 112, 64) 74368	r
residual_block_128 (ResidualBlo esidual_block_127[0][0]	(None, 112, 112, 64) 74368	r
residual_block_129 (ResidualBlo esidual_block_128[0][0]	(None, 112, 112, 64) 74368	r
residual_block_130 (ResidualBlo esidual_block_129[0][0]	(None, 56, 56, 128) 231296	r
residual_block_131 (ResidualBlo esidual_block_130[0][0]	(None, 56, 56, 128) 296192	r
residual_block_132 (ResidualBlo esidual_block_131[0][0]	(None, 56, 56, 128) 296192	r
residual_block_133 (ResidualBlo esidual_block_132[0][0]	(None, 56, 56, 128) 296192	r
residual_block_134 (ResidualBlo esidual_block_133[0][0]	(None, 56, 56, 128) 296192	r
residual_block_135 (ResidualBlo esidual_block_134[0][0]	(None, 56, 56, 128) 296192	r
residual_block_136 (ResidualBlo esidual_block_135[0][0]	(None, 28, 28, 256) 921344	r

residual_block_137 (ResidualBlo	(None, 28, 28, 256)	1182208	r
esidual_block_136[0][0]			
residual_block_138 (ResidualBlo	(None, 28, 28, 256)	1182208	r
esidual_block_137[0][0]			
residual_block_139 (ResidualBlo	(None, 28, 28, 256)	1182208	r
esidual_block_138[0][0]			
residual_block_140 (ResidualBlo	(None, 28, 28, 256)	1182208	r
esidual_block_139[0][0]			
residual_block_141 (ResidualBlo	(None, 28, 28, 256)	1182208	r
esidual_block_140[0][0]			
residual_block_142 (ResidualBlo	(None, 14, 14, 512)	3677696	r
esidual_block_141[0][0]			
residual_block_143 (ResidualBlo	(None, 14, 14, 512)	4723712	r
esidual_block_142[0][0]			
residual_block_144 (ResidualBlo	(None, 14, 14, 512)	4723712	r
esidual_block_143[0][0]			
residual_block_145 (ResidualBlo	(None, 14, 14, 512)	4723712	r
esidual_block_144[0][0]			
residual_block_146 (ResidualBlo	(None, 14, 14, 512)	4723712	r
esidual_block_145[0][0]			
residual_block_147 (ResidualBlo	(None, 14, 14, 512)	4723712	r
esidual_block_146[0][0]			
gap_1 (GlobalAveragePooling2D)	(None, 512)	0	r
esidual_block_147[0][0]			
flat_1 (Flatten)	(None, 512)	0	g
ap_1[0][0]			
action_class (Dense)	(None, 5)	2565	f
lat_1[0][0]			
action (Dense)	(None, 21)	10773	f
lat_1[0][0]			
=====			
=====			

```
Total params: 36,314,586  
Trainable params: 36,289,498  
Non-trainable params: 25,088
```

In []: █

Out[81]:



In []: █

In []: █

```
Reusing TensorBoard on port 6006 (pid 2517), started 0:03:00 ago.  
(Use '!kill 2517' to kill it.)
```

```
<IPython.core.display.Javascript object>
```

In []: █

```
model_name = "hidden_conv"
```

```
model_results[model_name] = model.fit(  
    training_generator,  
    validation_data = validation_generator,  
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,  
    validation_steps = len(val_data_df)//BATCH_SIZE,  
    epochs = 200,  
    callbacks = get_callbacks(model_name),  
    verbose = True
```

```
Epoch 1/200
```

```
6/852 [........................] - ETA: 12:37 - loss: 20.4  
095 - action_class_loss: 11.5818 - action_loss: 8.8276 - action_cl  
ass_accuracy: 0.2188 - action_class_top_k_categorical_accuracy: 1.  
0000 - action_accuracy: 0.0573 - action_top_k_categorical_accurac  
y: 0.2656WARNING:tensorflow:Callback method `on_train_batch_end` i  
s slow compared to the batch time (batch time: 0.1997s vs `on_trai  
n_batch_end` time: 0.5794s). Check your callbacks.
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow co  
mpared to the batch time=batch_time=0.199435s vs step_batch_time=0.199435s vs step_batch_size=128 and action_loss: 2.7813 - action_  
class_accuracy: 0.3974 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.1687 - action_top_k_categorical_accuracy: 0.5147 - val_loss: 3.8341 - val_action_class_loss: 1.2881 - val_ action_loss: 2.5460 - val_action_class_accuracy: 0.4727 - val_ac  
tion class top k categorical accuracy: 1.0000 - val action accurac
```

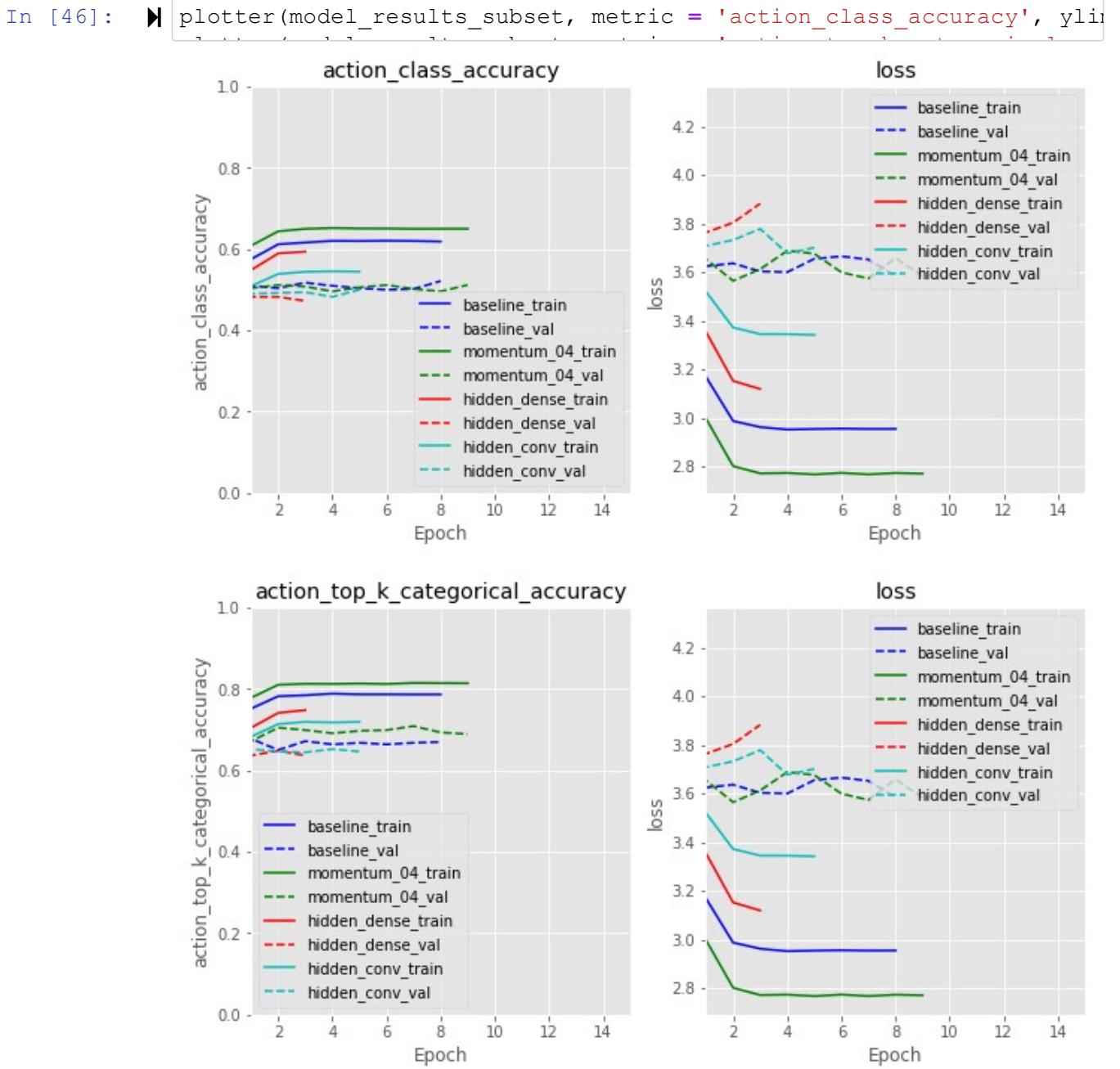
```
In [ ]: # Save model results  
model_results[model_name] = model_results[model_name].history  
  
!rm -r "drive/MyDrive/model_results.json"  
with open("drive/MyDrive/model_results.json", "w") as fp:
```

```
In [ ]: # Save model weights
```

```
In [ ]:
```

```
In [ ]: file_ = open('drive/MyDrive/model_results.json')
```

```
In [45]: names = { 'baseline', 'momentum_04', 'hidden_dense', 'hidden_conv'}
```



✓ Observations:

- Again, there doesn't seem to be any positive impact on the performance. It is actually performance worse now.
- Increasing the model complexity may not be what's needed here to boost performance. It might be worth trying to tune the model to use different optimizers

In []:

In []:

Experimentation - Changing Optimizers

Strategy

- Testing two additional optimizers: Adam and RMSprop. Both are **adaptive** optimizers that don't need a learning rate schedule specified. Adam is also used commonly for image classification

Optimizer - Adam

```
In [ ]: ┌ BATCH_SIZE = 64
          data_mean = 0.
          data_std = 255.0
          prefix=' '
          training_generator = DataGenerator(
              data_frame = train_data_df,
              batch_size = BATCH_SIZE,
              data_mean = data_mean,
              data_std = data_std,
              create_folder = False,
              dim = (224, 224, 3),
              shuffle = True,
              augment = False,
              file_name = 'drive/MyDrive/train'
          )

          validation_generator = DataGenerator(
              data_frame = val_data_df,
              batch_size = BATCH_SIZE,
              data_mean = data_mean,
              data_std = data_std,
              create_folder = False,
              dim = (224, 224, 3),
              shuffle = True,
              augment = False,
              file_name = 'drive/MyDrive/validation'
              image_column = "FileName_scaled"
          )
```

```
In [ ]: ┌ filters = [64, 128, 256, 512]
          block_size = [3,4,6,3]
          reg_lambda = 0.00

          #lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
          #    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BA
          #    staircase=False)
```

```
In [ ]: ┌ first_time = True

          input_ = Input(shape = (224, 224, 3), name = "input")

          conv_1 = Conv2D(filters = 64,
                          kernel_size = (7,7),
                          strides = 1,
                          kernel_initializer = tf.keras.initializers.RandomNo
                          kernel_regularizer=tf.keras.regularizers.l2(reg_lam
```

```
padding = "same",
name = "conv_1") (input_)

bn_1 = BatchNormalization(momentum=0.4) (conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2)) (bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

        #maxpool_x = MaxPool2D(pool_size = (2,2)) (res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1") (res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1") (res_x)

    flat_1 = Flatten(name = "flat_1") (gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer=tf.keras.regularizers.l2(
                             reg_lambda),
                         kernel_initializer=tf.keras.initializers.RandomNormal(
                             mean=0.0, stddev=0.01, seed=None),
                         name = "action_class") (flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                   kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                   kernel_initializer=tf.keras.initializers.RandomNormal(
                       mean=0.0, stddev=0.01, seed=None),
                   name = "action") (flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
            name="top_k_categorical_accuracy",
            dtype=None
        )
    ]
)

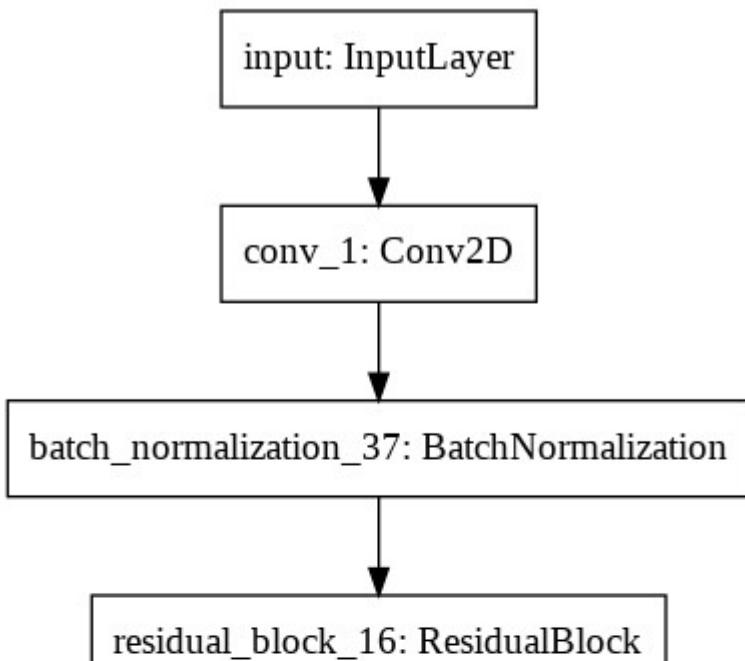
model.summary()
Model: "model_1"
```

Layer (type)	Output Shape	Param #	C
connected to			
=====			
input (InputLayer)	[(None, 224, 224, 3) 0		
=====			
conv_1 (Conv2D) input[0][0]	(None, 224, 224, 64) 9472		i
=====			
batch_normalization_37 (BatchNo conv_1[0][0]	(None, 224, 224, 64) 256		c
=====			
residual_block_16 (ResidualBloc atch_normalization_37[0][0]	(None, 112, 112, 64) 78784		b
=====			
residual_block_17 (ResidualBloc esidual_block_16[0][0]	(None, 112, 112, 64) 74368		r
=====			
residual_block_18 (ResidualBloc esidual_block_17[0][0]	(None, 112, 112, 64) 74368		r
=====			
residual_block_19 (ResidualBloc esidual_block_18[0][0]	(None, 56, 56, 128) 231296		r
=====			
residual_block_20 (ResidualBloc esidual_block_19[0][0]	(None, 56, 56, 128) 296192		r
=====			
residual_block_21 (ResidualBloc esidual_block_20[0][0]	(None, 56, 56, 128) 296192		r
=====			
residual_block_22 (ResidualBloc esidual_block_21[0][0]	(None, 56, 56, 128) 296192		r
=====			
residual_block_23 (ResidualBloc esidual_block_22[0][0]	(None, 28, 28, 256) 921344		r
=====			
residual_block_24 (ResidualBloc esidual_block_23[0][0]	(None, 28, 28, 256) 1182208		r
=====			
residual_block_25 (ResidualBloc esidual_block_24[0][0]	(None, 28, 28, 256) 1182208		r
=====			
residual_block_26 (ResidualBloc esidual_block_25[0][0]	(None, 28, 28, 256) 1182208		r
=====			

residual_block_27 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_26[0][0]			
residual_block_28 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_27[0][0]			
residual_block_29 (ResidualBloc	(None, 14, 14, 512)	3677696	r
esidual_block_28[0][0]			
residual_block_30 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_29[0][0]			
residual_block_31 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_30[0][0]			
gap_1 (GlobalAveragePooling2D)	(None, 512)	0	r
esidual_block_31[0][0]			
flat_1 (Flatten)	(None, 512)	0	g
ap_1[0][0]			
action_class (Dense)	(None, 5)	2565	f
lat_1[0][0]			
action (Dense)	(None, 21)	10773	f
lat_1[0][0]			
=====			
=====			
Total params: 21,327,962			
Trainable params: 21,310,810			
Non-trainable params: 17,152			

In []:

Out[45]:



In []:

In []:

```
Reusing TensorBoard on port 6006 (pid 441), started 1:25:52 ago.  
(Use '!kill 441' to kill it.)
```

```
<IPython.core.display.Javascript object>
```

In []:

```
model_name = "optimizer_adam_no_lr"

model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True
```

```
Epoch 1/200
```

```
6/852 [........................] - ETA: 12:55 - loss: 5.39  
44 - action_class_loss: 2.0331 - action_loss: 3.3613 - action_clas  
s_accuracy: 0.2370 - action_class_top_k_categorical_accuracy: 1.00  
00 - action_accuracy: 0.0599 - action_top_k_categorical_accuracy:  
0.3125WARNING:tensorflow:Callback method `on_train_batch_end` is s  
low compared to the batch time (batch time: 0.2252s vs `on_train_b  
atch_end` time: 0.5962s). Check your callbacks.
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow co  
mpared to the batch time (batch time: 0.2252s vs `on_train_batch_e  
nd` time: 0.5962s). Check your callbacks.
```

```
852/852 [=====] - 554s 645ms/step - loss: 3.7163 - action_class_loss: 1.2757 - action_loss: 2.4406 - action_class_accuracy: 0.4728 - action_class_top_k_categorical_accuracy:
```

```
In [ ]: # Save model results
model_results[model_name] = model_results[model_name].history
!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

```
In [ ]: # Save model weights
```

```
WARNING:absl:Found untraced functions such as conv2d_36_layer_call_and_return_conditional_losses, conv2d_36_layer_call_fn, conv2d_37_layer_call_and_return_conditional_losses, conv2d_37_layer_call_fn, conv2d_39_layer_call_and_return_conditional_losses while saving (showing 5 of 160). These functions will not be directly callable after loading.
```

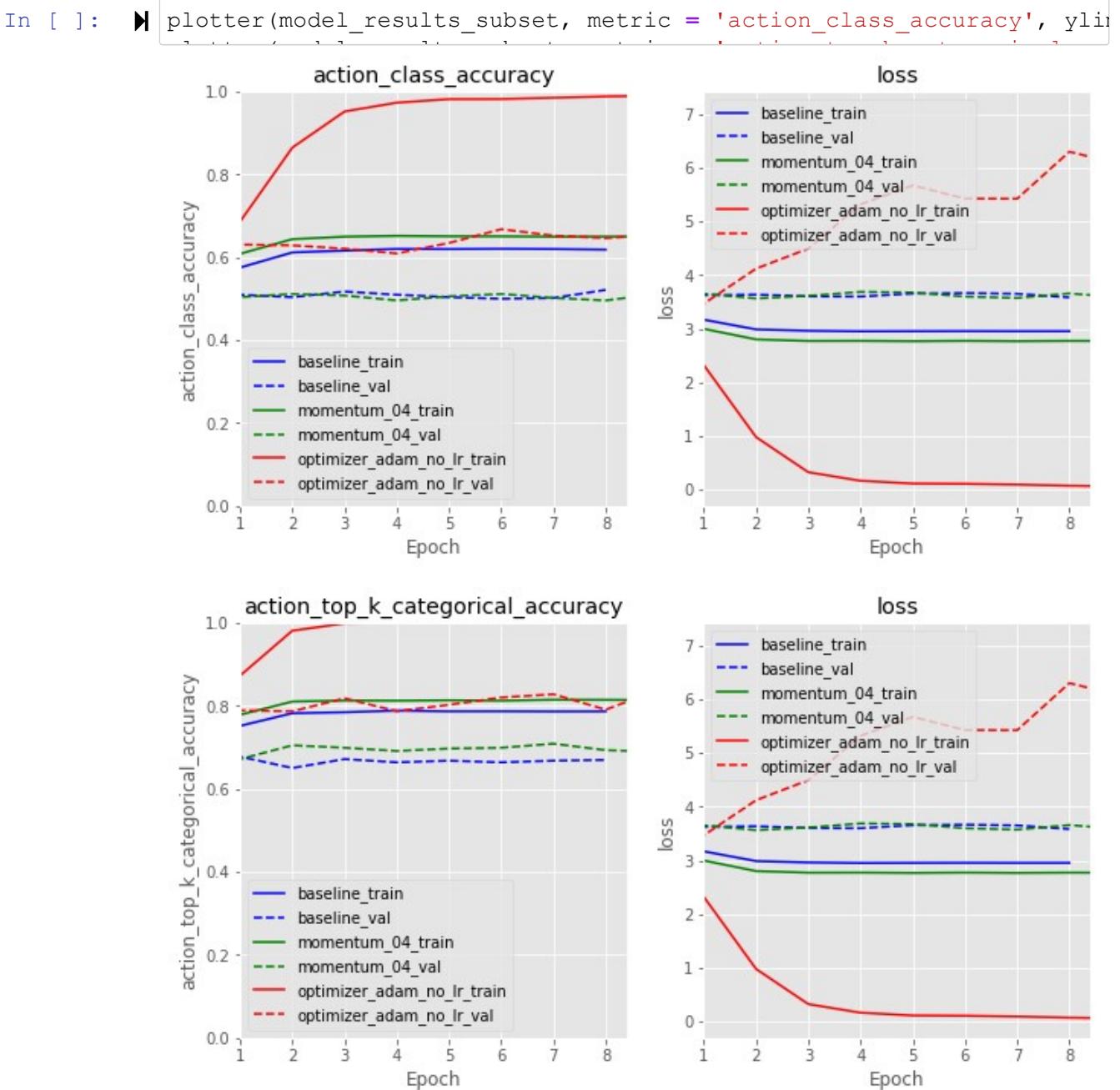
```
INFO:tensorflow:Assets written to: drive/MyDrive/optimizer_adam_no_lr_model/assets
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/optimizer_adam_no_lr_model/assets
```

```
In [ ]: 
```

```
Out[52]: dict_keys(['baseline', 'momentum_04', 'momentum_01', 'momentum_02', 'hidden_dense', 'hidden_conv', 'optimizer_adam', 'optimizer_adam_no_lr'])
```

```
In [ ]: names = { 'baseline', 'momentum_04', 'optimizer_adam_no_lr' }
```



In []: ⏷

✓ Observations:

- The model seems to be overfitting for both tasks, but more so for action_class than action_top_k.
- Regularization can potentially help here.

Optimizer - RMSProp

In []: ⏷

```
BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
```

```
batch_size = BATCH_SIZE,
data_mean = data_mean,
data_std = data_std,
create_folder = False,
dim = (224, 224, 3),
shuffle = True,
augment = False,
file_name = 'drive/MyDrive/train'
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation'
    image_column = "FileName_scaled"
)
```

```
In [ ]: filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.00

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

```
In [ ]: first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                 kernel_size = (7,7),
                 strides = 1,
                 kernel_initializer = tf.keras.initializers.RandomNormal(),
                 kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                 padding = "same",
                 name = "conv_1")(input_)

bn_1 = BatchNormalization(momentum=0.4)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)
```

```
for _ in range(1, nBlocks):

    res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)(res_x)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                         kernel_initializer=tf.keras.initializers.RandomNormal(
                             name = "action_class"))(flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                   kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                   kernel_initializer=tf.keras.initializers.RandomNormal(
                       name = "action"))(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
            name="top_k_categorical_accuracy",
            dtype=None
        )
    ]
)
```

Model: "model_1"

Layer (type) connected to	Output Shape	Param #	C
<hr/>			
input (InputLayer)	[None, 224, 224, 3]	0	
<hr/>			
conv_1 (Conv2D) input[0][0]	(None, 224, 224, 64)	9472	i
<hr/>			
batch_normalization_37 (BatchNo conv_1[0][0]	(None, 224, 224, 64)	256	c

residual_block_16 (ResidualBloc (None, 112, 112, 64) 78784 atch_normalization_37[0][0]	b
residual_block_17 (ResidualBloc (None, 112, 112, 64) 74368 esidual_block_16[0][0]	r
residual_block_18 (ResidualBloc (None, 112, 112, 64) 74368 esidual_block_17[0][0]	r
residual_block_19 (ResidualBloc (None, 56, 56, 128) 231296 esidual_block_18[0][0]	r
residual_block_20 (ResidualBloc (None, 56, 56, 128) 296192 esidual_block_19[0][0]	r
residual_block_21 (ResidualBloc (None, 56, 56, 128) 296192 esidual_block_20[0][0]	r
residual_block_22 (ResidualBloc (None, 56, 56, 128) 296192 esidual_block_21[0][0]	r
residual_block_23 (ResidualBloc (None, 28, 28, 256) 921344 esidual_block_22[0][0]	r
residual_block_24 (ResidualBloc (None, 28, 28, 256) 1182208 esidual_block_23[0][0]	r
residual_block_25 (ResidualBloc (None, 28, 28, 256) 1182208 esidual_block_24[0][0]	r
residual_block_26 (ResidualBloc (None, 28, 28, 256) 1182208 esidual_block_25[0][0]	r
residual_block_27 (ResidualBloc (None, 28, 28, 256) 1182208 esidual_block_26[0][0]	r
residual_block_28 (ResidualBloc (None, 28, 28, 256) 1182208 esidual_block_27[0][0]	r
residual_block_29 (ResidualBloc (None, 14, 14, 512) 3677696 esidual_block_28[0][0]	r
residual_block_30 (ResidualBloc (None, 14, 14, 512) 4723712 esidual_block_29[0][0]	r

```

residual_block_31 (ResidualBlock) (None, 14, 14, 512) 4723712      r
esidual_block_30[0][0]

gap_1 (GlobalAveragePooling2D)   (None, 512)           0          r
esidual_block_31[0][0]

flat_1 (Flatten)               (None, 512)           0          g
ap_1[0][0]

action_class (Dense)          (None, 5)              2565      f
lat_1[0][0]

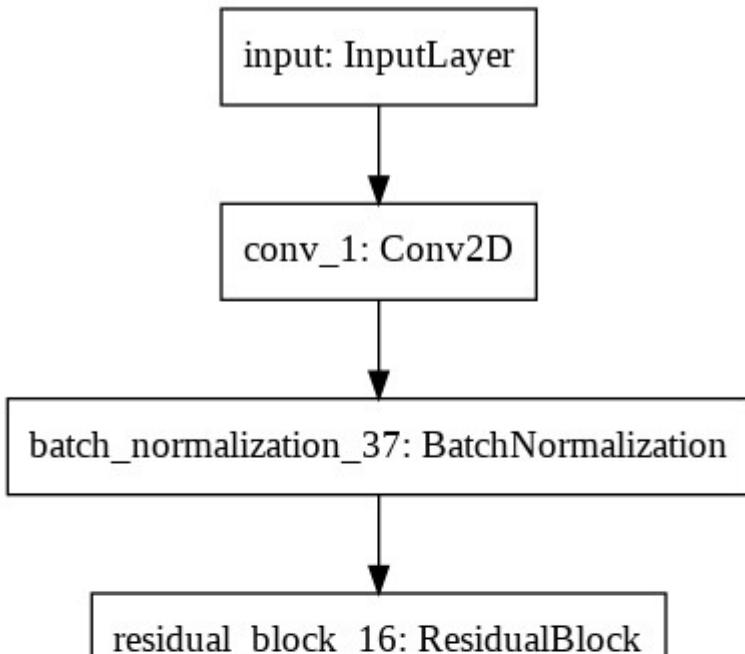
action (Dense)                (None, 21)             10773     f
lat_1[0][0]
=====
=====

Total params: 21,327,962
Trainable params: 21,310,810
Non-trainable params: 17,152

```

In []:

Out[42]:



In []:

<IPython.core.display.Javascript object>

In []:

#file_ = open('drive/MyDrive/model_results.json')

In []:

model_name = "optimizer_rmsprop"

model_results[model_name] = model.fit(

```
        training_generator,
        validation_data = validation_generator,
        steps_per_epoch = len(train_data_df)//BATCH_SIZE,
        validation_steps = len(val_data_df)//BATCH_SIZE,
        epochs = 200,
        callbacks = get_callbacks(model_name),
        verbose = True

Epoch 1/200
 6/852 [........................] - ETA: 11:59 - loss: 6.33
42 - action_class_loss: 2.5594 - action_loss: 3.7748 - action_clas
s_accuracy: 0.1927 - action_class_top_k_categorical_accuracy: 1.00
00 - action_accuracy: 0.0495 - action_top_k_categorical_accuracy:
0.2552WARNING:tensorflow:Callback method `on_train_batch_end` is s
low compared to the batch time (batch time: 0.3248s vs `on_train_b
atch_end` time: 0.3766s). Check your callbacks.
852/852 [=====] - 580s 651ms/step - loss:
3.9282 - action_class_loss: 1.3556 - action_loss: 2.5726 - action_
class_accuracy: 0.4317 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.2093 - action_top_k_categorical_accur
acy: 0.5857 - val_loss: 4.1435 - val_action_class_loss: 1.5091 - va
l_action_loss: 2.6344 - val_action_class_accuracy: 0.4434 - val_ac
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac
y: 0.2793 - val_action_top_k_categorical_accuracy: 0.6523

Epoch 00001: val_loss improved from inf to 4.14350, saving model t
o optimizer_rmsprop/cp.ckpt
```

```
In [ ]: # Save model results
model_results[model_name] = model_results[model_name].history

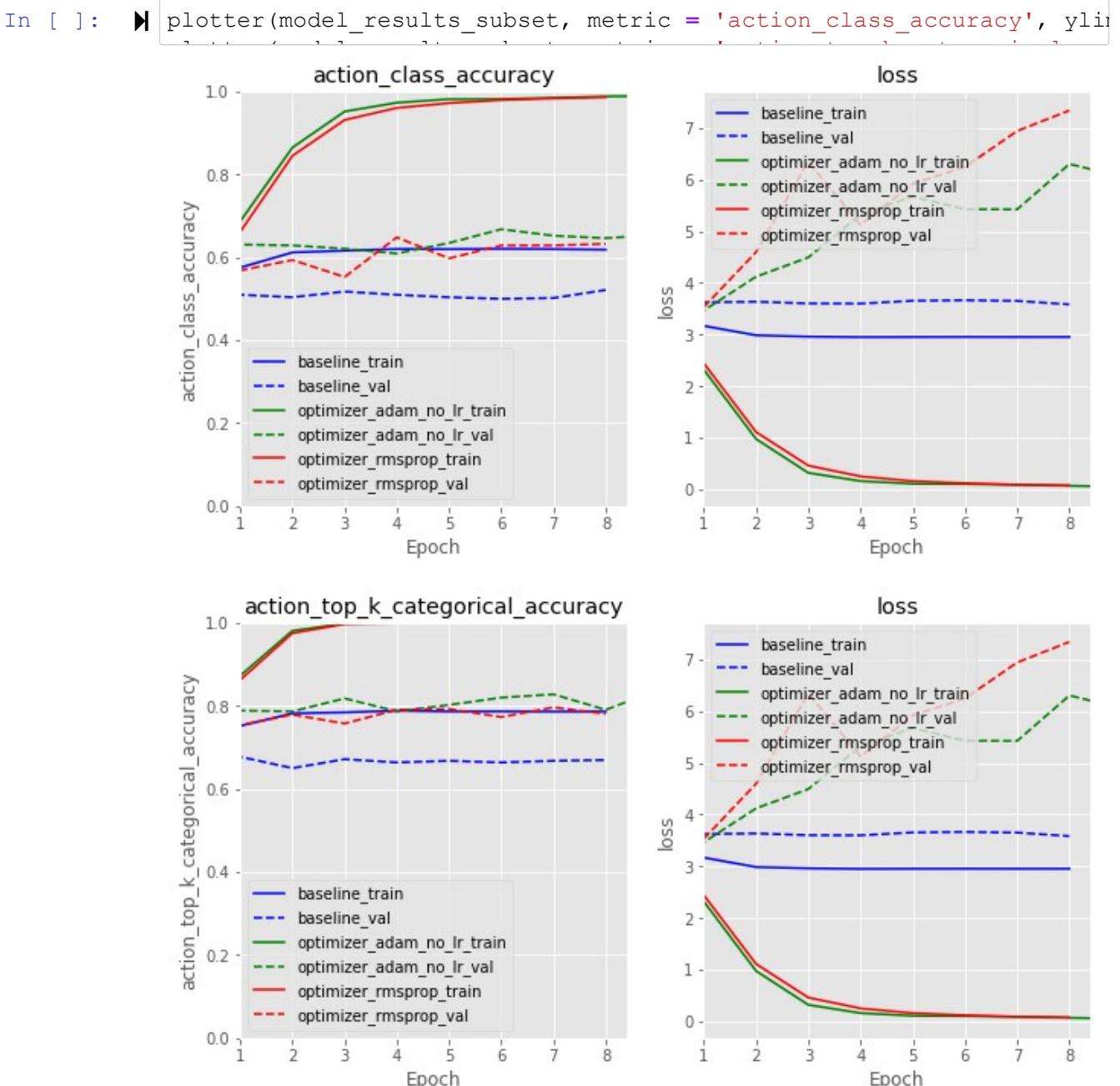
!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

```
In [ ]: # Save model weights
WARNING:absl:Found untraced functions such as conv2d_36_layer_call
_and_return_conditional_losses, conv2d_36_layer_call_fn, conv2d_37
_layer_call_and_return_conditional_losses, conv2d_37_layer_call_f
n, conv2d_39_layer_call_and_return_conditional_losses while saving
(showing 5 of 160). These functions will not be directly callable
after loading.

INFO:tensorflow:Assets written to: drive/MyDrive/optimizer_rmsprop
_model/assets

INFO:tensorflow:Assets written to: drive/MyDrive/optimizer_rmsprop
_model/assets
```

```
In [ ]: names = { 'optimizer_adam_no_lr', 'optimizer_rmsprop', 'baseline'
```



In []: ⏪

✓ Observations:

- Just like Adamn, the model is overfitting
- In terms of relative performance, RMSprop is almost on par with adam, however we will stick to adamm because as mentioned before it is used more commonly for image classification

In []: ⏪

In []: ⏪

In []: ⏪

In []:

In []:

Experimentation - Regularization

Strategy

- First we will try to reduce the batch size, since that tends to have a regularizing effect on the model
- Then we will try to use L1 and L2 regularization, and do some tuning to the lambda parameter

Reducing the batch size

In []:

```
BATCH_SIZE = 16

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train',
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation',
    image_column = "FileName_scaled"
)
```

In []:

```
filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.00

optimizer_ = tf.keras.optimizers.Adam()
```

In []:

```
first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
                name = "conv_1")(input_)

bn_1 = BatchNormalization(momentum=0.4)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):
        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                         kernel_initializer= tf.keras.initializers.RandomNormal(),
                         name = "action_class")(flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                  kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                  kernel_initializer= tf.keras.initializers.RandomNormal(),
                  name = "action")(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
```

```
'accuracy',
tf.keras.metrics.TopKCategoricalAccuracy(
    k=5,
    name="top_k_categorical_accuracy",
    dtype=None
)
]

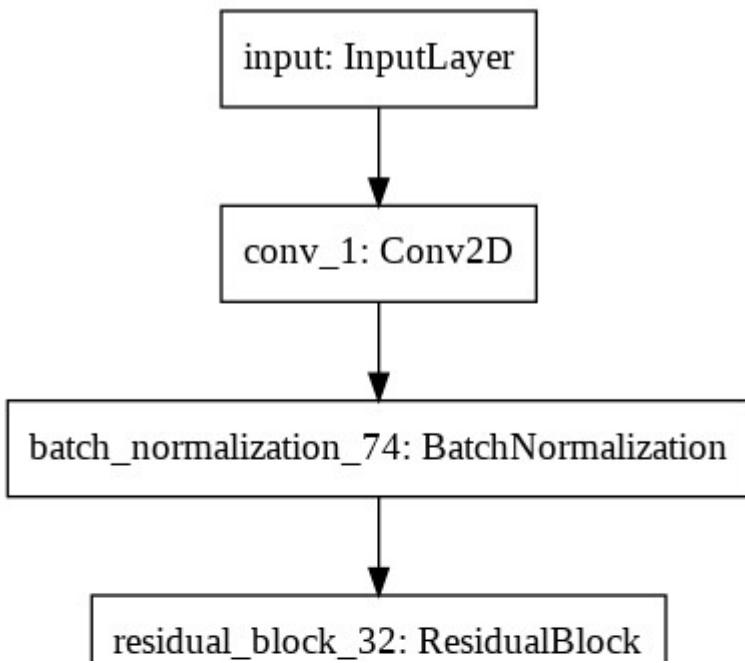
)
Model: "model_2"
```

Layer (type) connected to	Output Shape	Param #	C
input (InputLayer)	[None, 224, 224, 3]	0	i
conv_1 (Conv2D) input[0][0]	(None, 224, 224, 64)	9472	c
batch_normalization_74 (BatchNo conv_1[0][0]	(None, 224, 224, 64)	256	b
residual_block_32 (ResidualBloc atch_normalization_74[0][0]	(None, 112, 112, 64)	78784	r
residual_block_33 (ResidualBloc esidual_block_32[0][0]	(None, 112, 112, 64)	74368	r
residual_block_34 (ResidualBloc esidual_block_33[0][0]	(None, 112, 112, 64)	74368	r
residual_block_35 (ResidualBloc esidual_block_34[0][0]	(None, 56, 56, 128)	231296	r
residual_block_36 (ResidualBloc esidual_block_35[0][0]	(None, 56, 56, 128)	296192	r
residual_block_37 (ResidualBloc esidual_block_36[0][0]	(None, 56, 56, 128)	296192	r
residual_block_38 (ResidualBloc esidual_block_37[0][0]	(None, 56, 56, 128)	296192	r

residual_block_39 (ResidualBloc	(None, 28, 28, 256)	921344	r
esidual_block_38[0][0]			
residual_block_40 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_39[0][0]			
residual_block_41 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_40[0][0]			
residual_block_42 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_41[0][0]			
residual_block_43 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_42[0][0]			
residual_block_44 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_43[0][0]			
residual_block_45 (ResidualBloc	(None, 14, 14, 512)	3677696	r
esidual_block_44[0][0]			
residual_block_46 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_45[0][0]			
residual_block_47 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_46[0][0]			
gap_1 (GlobalAveragePooling2D)	(None, 512)	0	r
esidual_block_47[0][0]			
flat_1 (Flatten)	(None, 512)	0	g
ap_1[0][0]			
action_class (Dense)	(None, 5)	2565	f
lat_1[0][0]			
action (Dense)	(None, 21)	10773	f
lat_1[0][0]			
Total params: 21,327,962			
Trainable params: 21,310,810			
Non-trainable params: 17,152			

In []:

Out[60]:



In []:

In []:

```
Reusing TensorBoard on port 6006 (pid 441), started 3:24:52 ago.  
(Use '!kill 441' to kill it.)
```

```
<IPython.core.display.Javascript object>
```

In []:

```
model_name = "reg_batch_size"

model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True
```

```
Epoch 1/200
```

```
6/3408 [........................] - ETA: 21:55 - loss: 6.  
3666 - action_class_loss: 2.4174 - action_loss: 3.9492 - action_cl  
ass_accuracy: 0.1979 - action_class_top_k_categorical_accuracy: 1.  
0000 - action_accuracy: 0.0625 - action_top_k_categorical_accurac  
y: 0.2708WARNING:tensorflow:Callback method `on_train_batch_end` i  
s slow compared to the batch time (batch time: 0.0733s vs `on_trai  
n_batch_end` time: 0.2167s). Check your callbacks.
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow co  
mpared to the batch time (batch time: 0.0733s vs `on_train_batch_e  
nd` time: 0.2167s). Check your callbacks.
```

```
3408/3408 [=====] - 623s 181ms/step - los  
s: 3.9137 - action_class_loss: 1.3422 - action_loss: 2.5715 - acti  
on_class_accuracy: 0.4344 - action_class_top_k_categorical_accurac
```

```
In [ ]: # Save model results  
model_results[model_name] = model_results[model_name].history  
  
!rm -r "drive/MyDrive/model_results.json"  
with open("drive/MyDrive/model_results.json", "w") as fp:  
    fp.write(model_results[model_name].to_json())
```

```
In [ ]: # Save model weights
```

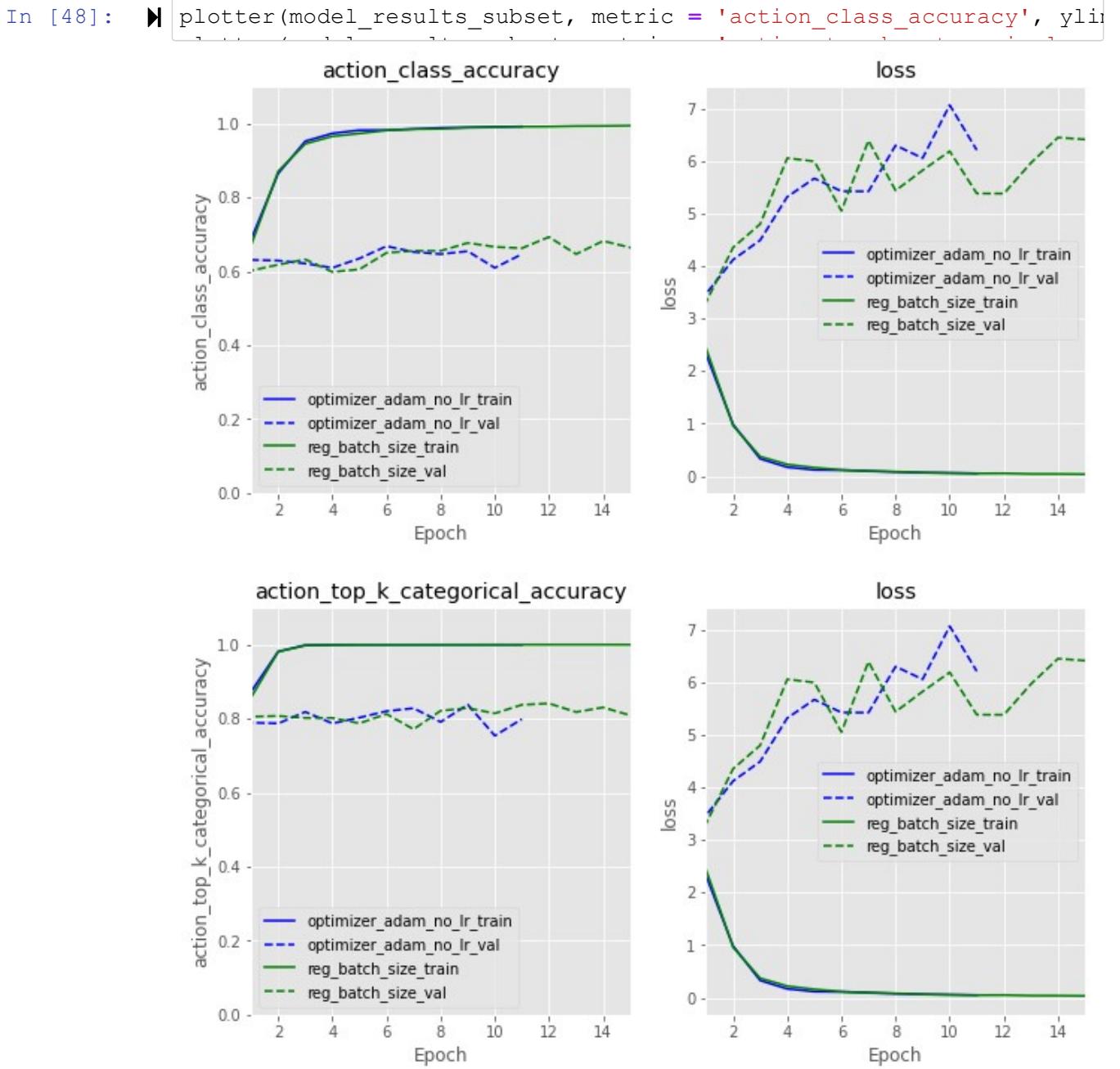
```
WARNING:absl:Found untraced functions such as conv2d_72_layer_call  
_and_return_conditional_losses, conv2d_72_layer_call_fn, conv2d_73  
_layer_call_and_return_conditional_losses, conv2d_73_layer_call_f  
n, conv2d_75_layer_call_and_return_conditional_losses while saving  
(showing 5 of 160). These functions will not be directly callable  
after loading.
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/reg_batch_size_mo  
del/assets
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/reg_batch_size_mo  
del/assets
```

```
In [ ]: file_ = open('drive/MyDrive/model_results.json')
```

```
In [47]: names = { 'optimizer_adam_no_lr', 'reg_batch_size' }
```



✓ Observations:

- The reduction of the batch size 4x from 64 to 16 results in a much longer training time because the number of steps for training increase by a factor of the same amount
- There is no considerable difference in performance

Regularization - L2 with lambda = 0.01

Strategy

- We start with default value of 0.01 from the [documentation] (https://www.tensorflow.org/api_docs/python/tf/keras/regularizers/L2)
- We then do a semi-grid search based on the performance

```
In [ ]: █ BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/training',
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation',
    image_column = "FileName_scaled"
)
```

```
In [ ]: █ filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.01
```

```
In [ ]: █ first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
                name = "conv_1")(input_)

bn_1 = BatchNormalization(momentum=0.4)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)

for nFilters, nBlocks in zip(filters, block_size):
```

```

if first_time == True:
    res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)
    first_time = False
else:
    res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

for _ in range(1, nBlocks):
    res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

#maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

#reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

flat_1 = Flatten(name = "flat_1")(gap_1)

action_class = Dense(5, activation=tf.nn.softmax,
                     kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                     kernel_initializer=tf.keras.initializers.RandomUniform(
                         name = "action_class"))(flat_1)

action = Dense(21, activation=tf.nn.softmax,
               kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
               kernel_initializer=tf.keras.initializers.RandomUniform(
                   name = "action"))(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
            name="top_k_categorical_accuracy",
            dtype=None
        )
    ]
)

```

Model: "model_3"

Layer (type)	Output Shape	Param #	C
connected to			
=====			
input (InputLayer)	[(None, 224, 224, 3) 0		

conv_1 (Conv2D) nput[0][0]	(None, 224, 224, 64) 9472	i
batch_normalization_111 (BatchN conv_1[0][0])	(None, 224, 224, 64) 256	c
residual_block_48 (ResidualBloc atch_normalization_111[0][0])	(None, 112, 112, 64) 78784	b
residual_block_49 (ResidualBloc esidual_block_48[0][0])	(None, 112, 112, 64) 74368	r
residual_block_50 (ResidualBloc esidual_block_49[0][0])	(None, 112, 112, 64) 74368	r
residual_block_51 (ResidualBloc esidual_block_50[0][0])	(None, 56, 56, 128) 231296	r
residual_block_52 (ResidualBloc esidual_block_51[0][0])	(None, 56, 56, 128) 296192	r
residual_block_53 (ResidualBloc esidual_block_52[0][0])	(None, 56, 56, 128) 296192	r
residual_block_54 (ResidualBloc esidual_block_53[0][0])	(None, 56, 56, 128) 296192	r
residual_block_55 (ResidualBloc esidual_block_54[0][0])	(None, 28, 28, 256) 921344	r
residual_block_56 (ResidualBloc esidual_block_55[0][0])	(None, 28, 28, 256) 1182208	r
residual_block_57 (ResidualBloc esidual_block_56[0][0])	(None, 28, 28, 256) 1182208	r
residual_block_58 (ResidualBloc esidual_block_57[0][0])	(None, 28, 28, 256) 1182208	r
residual_block_59 (ResidualBloc esidual_block_58[0][0])	(None, 28, 28, 256) 1182208	r
residual_block_60 (ResidualBloc esidual_block_59[0][0])	(None, 28, 28, 256) 1182208	r

```
residual_block_61 (ResidualBlok (None, 14, 14, 512) 3677696      r
esidual_block_60[0][0]

=====
residual_block_62 (ResidualBlok (None, 14, 14, 512) 4723712      r
esidual_block_61[0][0]

=====
residual_block_63 (ResidualBlok (None, 14, 14, 512) 4723712      r
esidual_block_62[0][0]

=====
gap_1 (GlobalAveragePooling2D)   (None, 512)          0      r
esidual_block_63[0][0]

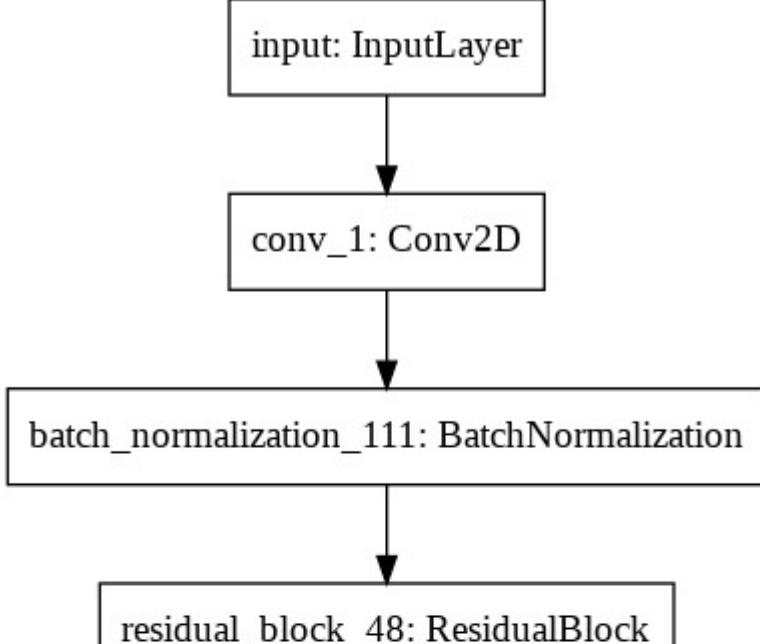
=====
flat_1 (Flatten)                (None, 512)          0      g
ap_1[0][0]

=====
action_class (Dense)            (None, 5)           2565      f
lat_1[0][0]

=====
action (Dense)                  (None, 21)          10773     f
lat_1[0][0]
=====
=====
Total params: 21,327,962
Trainable params: 21,310,810
Non-trainable params: 17,152
```

In []:

Out[58]:



In []:

rm: cannot remove 'logs': No such file or directory

In []:

```
Reusing TensorBoard on port 6006 (pid 619), started 1:43:17 ago.  
(Use '!kill 619' to kill it.)  
<IPython.core.display.Javascript object>
```

In []:

```
model_name = "reg_labmda_0p01"  
  
model_results[model_name] = model.fit(  
    training_generator,  
    validation_data = validation_generator,  
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,  
    validation_steps = len(val_data_df)//BATCH_SIZE,  
    epochs = 200,  
    callbacks = get_callbacks(model_name),  
    verbose = True  
,
```

```
Epoch 1/200
```

```
6/852 [........................] - ETA: 12:16 - loss: 504.  
7764 - action_class_loss: 1.9089 - action_loss: 3.4557 - action_cl  
ass_accuracy: 0.1849 - action_class_top_k_categorical_accuracy: 1.  
0000 - action_accuracy: 0.0495 - action_top_k_categorical_accurac  
y: 0.2943WARNING:tensorflow:Callback method `on_train_batch_end` i  
s slow compared to the batch time (batch time: 0.2301s vs `on_trai  
n_batch_end` time: 0.5500s). Check your callbacks.
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow co  
mpared to the batch time (batch time: 0.2301s vs `on_train_batch_e  
nd` time: 0.5500s). Check your callbacks.
```

```
852/852 [=====] - 554s 646ms/step - loss: 29.3000 - action_class_loss: 1.4761 - action_loss: 2.8556 - action  
_class_accuracy: 0.3638 - action_class_top_k_categorical_accuracy:  
1.0000 - action_accuracy: 0.1309 - action_top_k_categorical_accura  
cy: 0.4613 - val_loss: 5.3385 - val_action_class_loss: 1.6575 - va  
l_action_loss: 2.9781 - val_action_class_accuracy: 0.3027 - val_ac  
tion class top k categorical accuracy: 1.0000 - val action accurac
```

In []:

```
# Save model results  
model_results[model_name] = model_results[model_name].history  
  
!rm -r "drive/MyDrive/model_results.json"  
with open("drive/MyDrive/model_results.json", "w") as fp:
```

In []:

```
# Save model weights
```

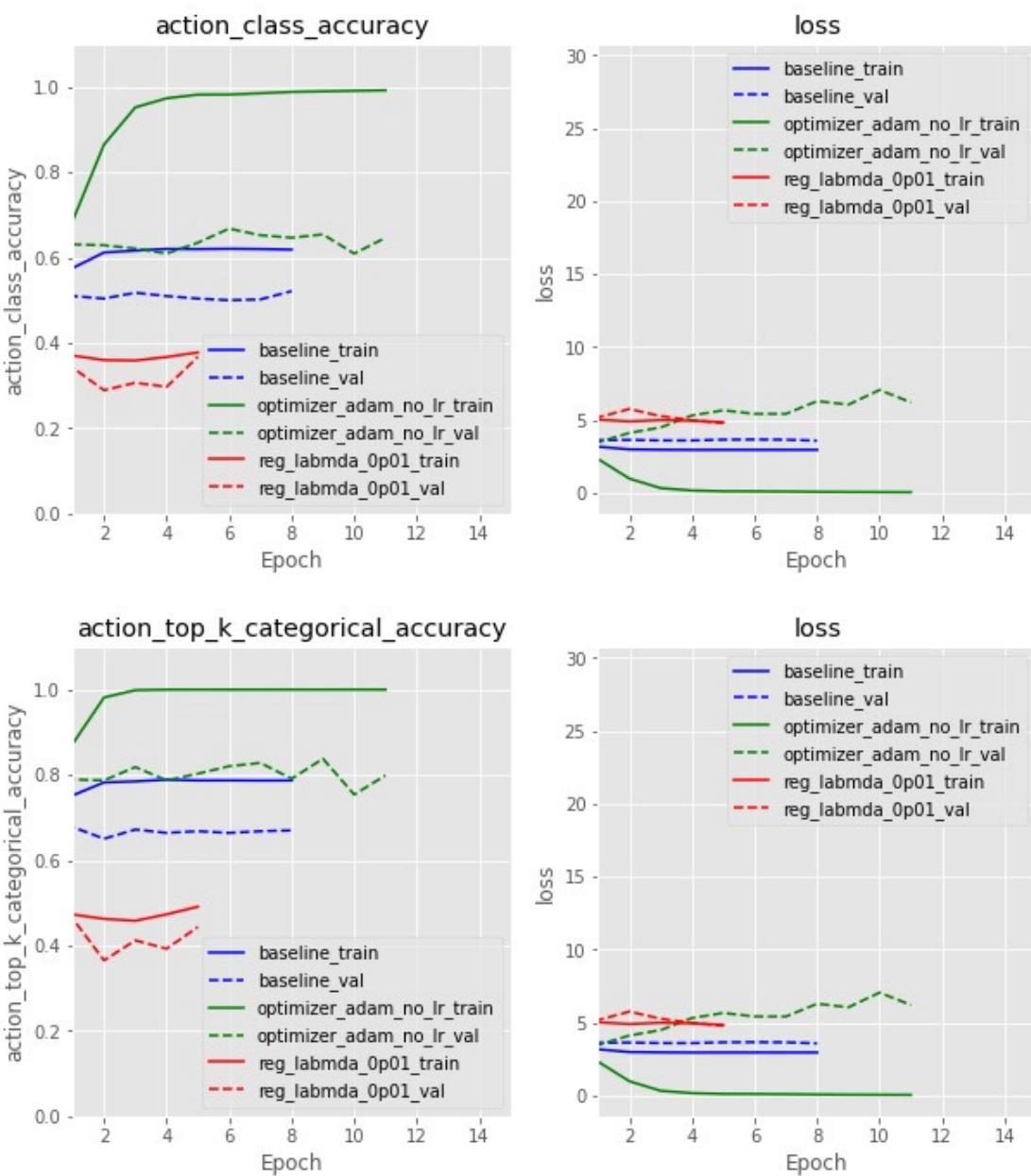
```
WARNING:absl:Found untraced functions such as conv2d_108_layer_c  
al_and_return_conditional_losses, conv2d_108_layer_call_fn, conv2d_  
109_layer_call_and_return_conditional_losses, conv2d_109_layer_c  
al_fn, conv2d_111_layer_call_and_return_conditional_losses while sa  
ving (showing 5 of 160). These functions will not be directly call  
able after loading.
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/reg_labmda_0p01_m  
odel/assets
```

```
TensorFlow+TensorFlow-Addons written to: /drive/Music/drive/notebooks/Desktop/Projects/Human-Action-Reco...
```

```
In [49]: names = { 'baseline', 'optimizer_adam_no_lr', 'reg_lambda_0p01' }
```

```
In [50]: plotter(model_results_subset, metric = 'action_class_accuracy', ylim = (0.0, 1.0))
```



✓ Observations:

- Performance is considerably worse, even more than baseline.
- This means that we need to decrease the lambda parameter further to minimize the regularizing impact

```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```

In []: █

In []: █

Regularization - L2 with lambda = 0.001

- The lambda value is decreased ten-fold to assess if that increases performance

In []: █ BATCH_SIZE = 64

```
data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train'
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation'
    image_column = "FileName_scaled"
)
```

In []: █ filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.001

In []: █

```
first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7, 7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNo.
```

```
        kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
        padding = "same",
        name = "conv_1"))(input_)

bn_1 = BatchNormalization(momentum=0.4)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
        first_time = False)
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer=tf.keras.regularizers.l2(
                         kernel_initializer=tf.keras.initializers.RandomUniform(
                         name = "action_class"))(flat_1))

    action = Dense(21, activation=tf.nn.softmax,
                   kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                   kernel_initializer=tf.keras.initializers.RandomUniform(
                   name = "action"))(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
loss = {
    'action_class': 'categorical_crossentropy',
    'action': 'categorical_crossentropy'
},
optimizer = optimizer_,
metrics = [
    'accuracy',
    tf.keras.metrics.TopKCategoricalAccuracy(
        k=5,
        name="top_k_categorical_accuracy",
        dtype=None
    )
]
)

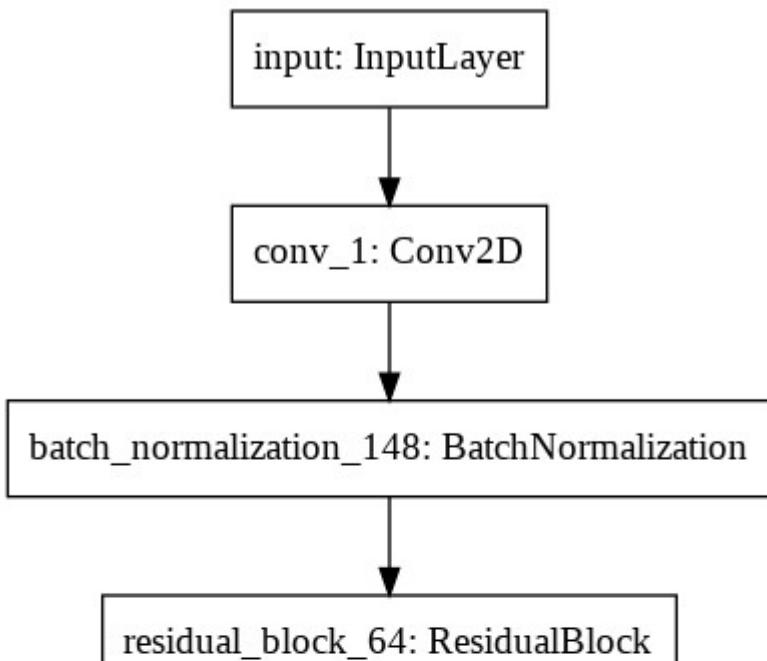
Model = "model_A"
```

Layer (type)	Output Shape	Param #	C
connected to			
input (InputLayer)	[(None, 224, 224, 3) 0		
conv_1 (Conv2D) input[0][0]	(None, 224, 224, 64) 9472	i	
batch_normalization_148 (BatchN conv_1[0][0]	(None, 224, 224, 64) 256	c	
residual_block_64 (ResidualBloc atch_normalization_148[0][0]	(None, 112, 112, 64) 78784	b	
residual_block_65 (ResidualBloc esidual_block_64[0][0]	(None, 112, 112, 64) 74368	r	
residual_block_66 (ResidualBloc esidual_block_65[0][0]	(None, 112, 112, 64) 74368	r	
residual_block_67 (ResidualBloc esidual_block_66[0][0]	(None, 56, 56, 128) 231296	r	
residual_block_68 (ResidualBloc esidual_block_67[0][0]	(None, 56, 56, 128) 296192	r	
residual_block_69 (ResidualBloc esidual_block_68[0][0]	(None, 56, 56, 128) 296192	r	
residual_block_70 (ResidualBloc esidual_block_69[0][0]	(None, 56, 56, 128) 296192	r	
residual_block_71 (ResidualBloc esidual_block_70[0][0]	(None, 28, 28, 256) 921344	r	
residual_block_72 (ResidualBloc esidual_block_71[0][0]	(None, 28, 28, 256) 1182208	r	
residual_block_73 (ResidualBloc esidual_block_72[0][0]	(None, 28, 28, 256) 1182208	r	
residual_block_74 (ResidualBloc esidual_block_73[0][0]	(None, 28, 28, 256) 1182208	r	

residual_block_75 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_74[0][0]			
residual_block_76 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_75[0][0]			
residual_block_77 (ResidualBloc	(None, 14, 14, 512)	3677696	r
esidual_block_76[0][0]			
residual_block_78 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_77[0][0]			
residual_block_79 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_78[0][0]			
gap_1 (GlobalAveragePooling2D)	(None, 512)	0	r
esidual_block_79[0][0]			
flat_1 (Flatten)	(None, 512)	0	g
ap_1[0][0]			
action_class (Dense)	(None, 5)	2565	f
lat_1[0][0]			
action (Dense)	(None, 21)	10773	f
lat_1[0][0]			
=====			
=====			
Total params: 21,327,962			
Trainable params: 21,310,810			
Non-trainable params: 17,152			

In []:

Out[70]:



In []:

In []:

<IPython.core.display.Javascript object>

In []:

```
model_name = "reg_lambda_0p001"

model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True
)
```

Epoch 1/200

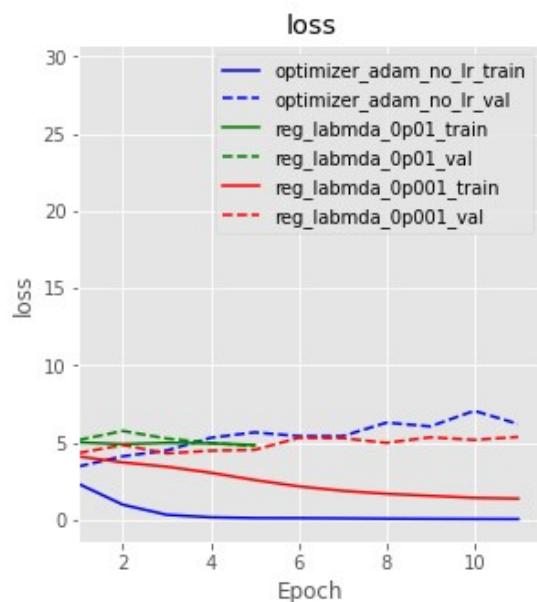
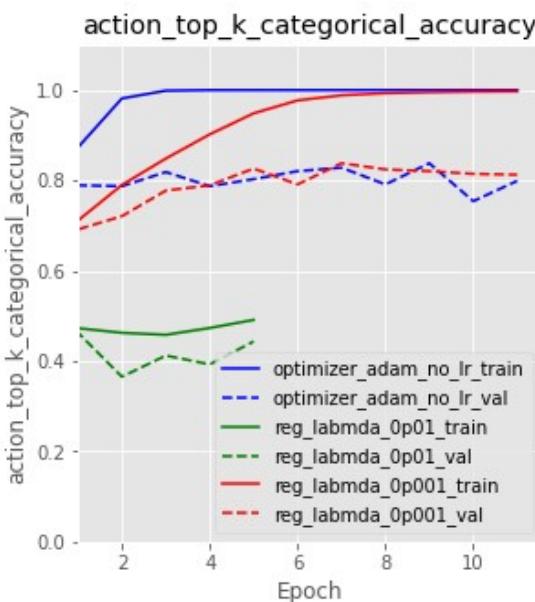
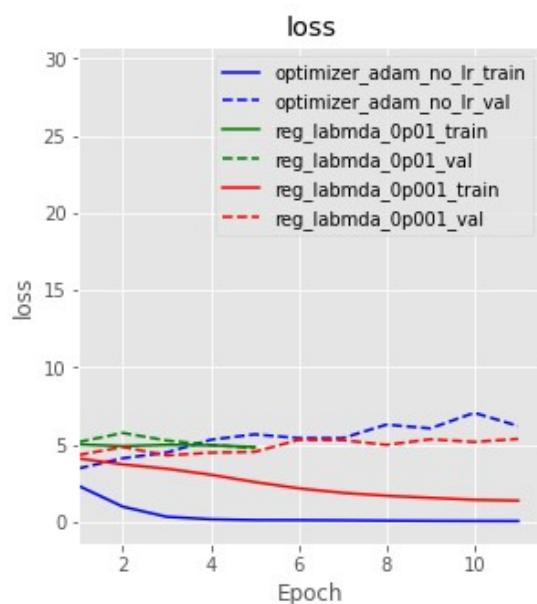
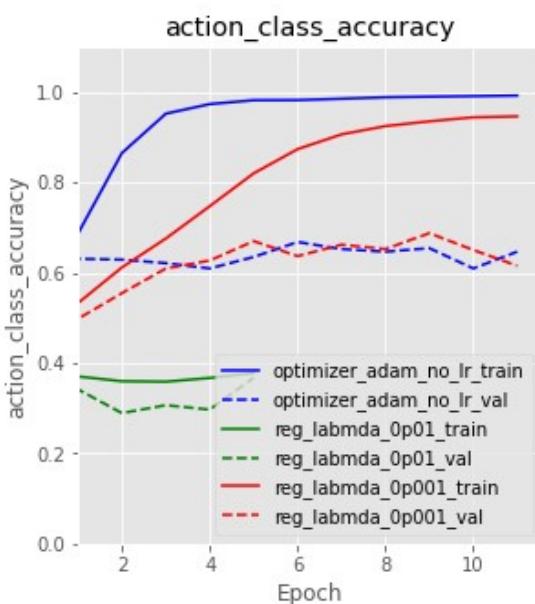
```
6/852 [........................] - ETA: 12:21 - loss: 58.0
462 - action_class_loss: 2.0803 - action_loss: 3.6221 - action_class_accuracy: 0.2370 - action_class_top_k_categorical_accuracy: 1.0
000 - action_accuracy: 0.0521 - action_top_k_categorical_accuracy: 0.2526WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time (batch time: 0.2306s vs `on_train_batch_end` time: 0.5522s). Check your callbacks.
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time (batch time: 0.2306s vs `on_train_batch_end` time: 0.5522s). Check your callbacks.
```

```
In [ ]: file_ = open('drive/MyDrive/model_results.json')
```

```
In [51]: names = { 'optimizer_adam_no_lr', 'reg_labmda_0p01', 'reg_labmda_0p001' }
```

```
In [ ]: plotter(model_results_subset, metric = 'action_class_accuracy', ylim = (0.0, 1.0))
```



```
In [ ]: 
```

✓ Observations:

- While the model is overfitting, and performance evaluation is still around the same value at the end of the epochs, it is not overfitting as quickly, as can be seen from the plots. We can try to increase the lambda value from here

```
In [ ]: 
```

Regularization - L2 with lambda = 0.005

- We increase the value of lambda to approximately halfway between 0.01 and 0.001

```
In [ ]: ┌ BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''
training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train'
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation'
    image_column = "FileName_scaled"
)
```

```
In [ ]: ┌ filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.005

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

```
In [ ]: ┌
first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
```

```
        name = "conv_1") (input_)

bn_1 = BatchNormalization(momentum=0.4) (conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2)) (bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2)) (res_x)

#reshape_1 = Reshape(res_x.shape[1:], name="reshape_1") (res_x)

gap_1 = GlobalAveragePooling2D(name = "gap_1") (res_x)

flat_1 = Flatten(name = "flat_1") (gap_1)

action_class = Dense(5, activation=tf.nn.softmax,
                     kernel_regularizer=tf.keras.regularizers.l2(
                     kernel_initializer=tf.keras.initializers.RandomNormal(
                     name = "action_class")) (flat_1)

action = Dense(21, activation=tf.nn.softmax,
               kernel_regularizer=tf.keras.regularizers.l2(
               kernel_initializer=tf.keras.initializers.RandomNormal(
               name = "action")) (flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
loss = {
    'action_class': 'categorical_crossentropy',
    'action': 'categorical_crossentropy'
},
optimizer = optimizer_,
metrics = [
    'accuracy',
    tf.keras.metrics.TopKCategoricalAccuracy(
        k=5,
        name="top_k_categorical_accuracy",
        dtype=None
    )
]
)

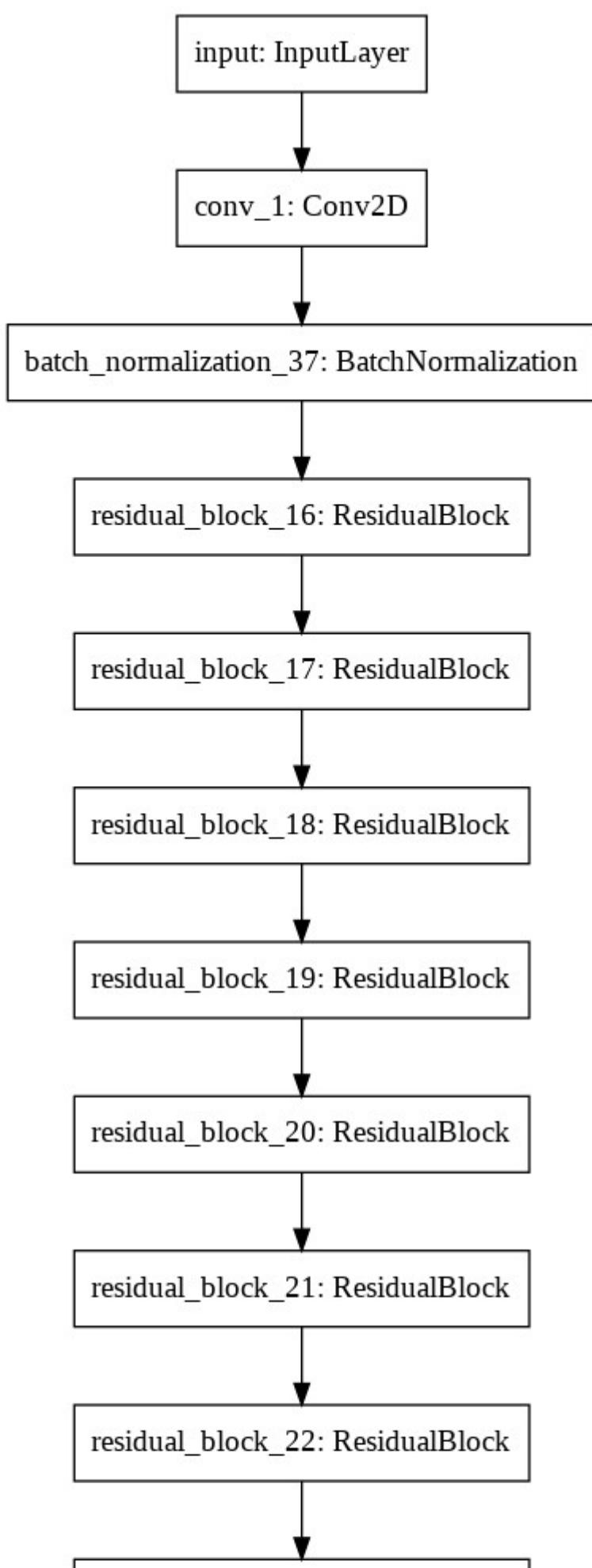
Model: "model_1"
```

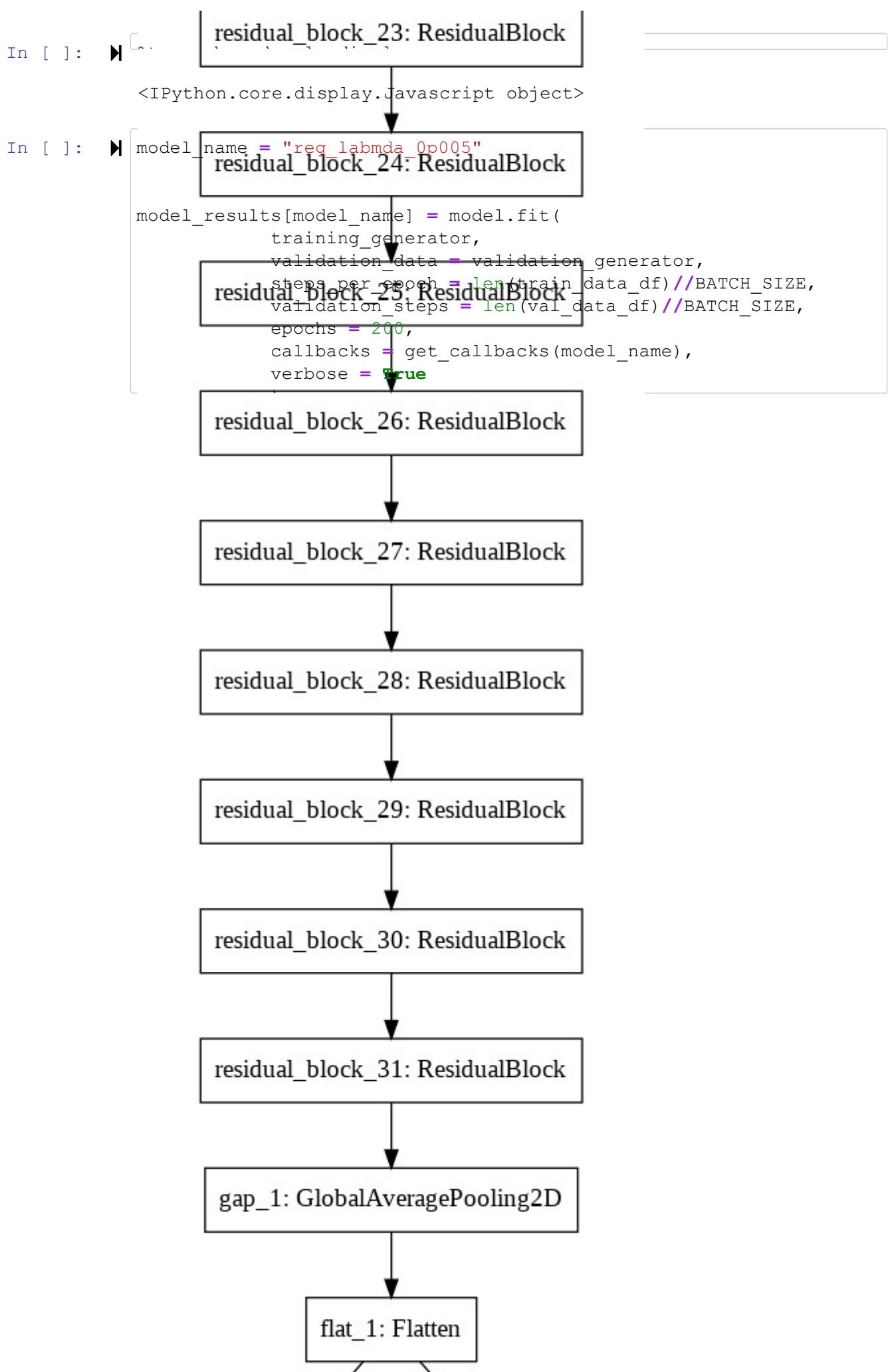
Layer (type)	Output Shape	Param #	C
connected to			
=====	=====	=====	=====
input (InputLayer)	[(None, 224, 224, 3) 0		
conv_1 (Conv2D)	(None, 224, 224, 64) 9472	i	
input[0][0]			
batch_normalization_37 (BatchNo	(None, 224, 224, 64) 256	c	
conv_1[0][0]			
residual_block_16 (ResidualBloc	(None, 112, 112, 64) 78784	b	
atch_normalization_37[0][0]			
residual_block_17 (ResidualBloc	(None, 112, 112, 64) 74368	r	
esidual_block_16[0][0]			
residual_block_18 (ResidualBloc	(None, 112, 112, 64) 74368	r	
esidual_block_17[0][0]			
residual_block_19 (ResidualBloc	(None, 56, 56, 128) 231296	r	
esidual_block_18[0][0]			
residual_block_20 (ResidualBloc	(None, 56, 56, 128) 296192	r	
esidual_block_19[0][0]			
residual_block_21 (ResidualBloc	(None, 56, 56, 128) 296192	r	
esidual_block_20[0][0]			
residual_block_22 (ResidualBloc	(None, 56, 56, 128) 296192	r	
esidual_block_21[0][0]			
residual_block_23 (ResidualBloc	(None, 28, 28, 256) 921344	r	
esidual_block_22[0][0]			
residual_block_24 (ResidualBloc	(None, 28, 28, 256) 1182208	r	
esidual_block_23[0][0]			
residual_block_25 (ResidualBloc	(None, 28, 28, 256) 1182208	r	
esidual_block_24[0][0]			
residual_block_26 (ResidualBloc	(None, 28, 28, 256) 1182208	r	
esidual_block_25[0][0]			

residual_block_27 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_26[0][0]			
residual_block_28 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_27[0][0]			
residual_block_29 (ResidualBloc	(None, 14, 14, 512)	3677696	r
esidual_block_28[0][0]			
residual_block_30 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_29[0][0]			
residual_block_31 (ResidualBloc	(None, 14, 14, 512)	4723712	r
esidual_block_30[0][0]			
gap_1 (GlobalAveragePooling2D)	(None, 512)	0	r
esidual_block_31[0][0]			
flat_1 (Flatten)	(None, 512)	0	g
ap_1[0][0]			
action_class (Dense)	(None, 5)	2565	f
lat_1[0][0]			
action (Dense)	(None, 21)	10773	f
lat_1[0][0]			
=====			
=====			
Total params:	21,327,962		
Trainable params:	21,310,810		
Non-trainable params:	17,152		

In []:

Out[44]:





Epoch 1/200
6/852 [.....] - ETA: 11:57 - loss: 258.
5840 - action_class_loss: 2.0877 - action_loss: 3.3607 - action_cl
ass_accuracy: 0.2552 - action_top_k_categorical_accuracy: 1.
0000 - action_accuracy: 0.0833 - action_top_k_categorical_accurac
y: 0.2839WARNING:tensorflow:Callback method `on_train_batch_end` i
s slow compared to the batch time (batch time: 0.2316s vs `on_trai
n_batch_end` time: 0.5309s). Check your callbacks.
852/852 [=====] - 555s 645ms/step - loss:
20.0061 - action_class_loss: 1.4455 - action_loss: 2.7996 - action
_class_accuracy: 0.3857 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.1410 - action_top_k_categorical_accura
cy: 0.4905 - val_loss: 5.0512 - val_action_class_loss: 1.4840 - va
l_action_loss: 2.8109 - val_action_class_accuracy: 0.4062 - val_ac
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac
y: 0.1562 - val_action_top_k_categorical_accuracy: 0.5059

Epoch 00001: val_loss improved from inf to 5.05122, saving model t
o reg_lambda_0p005/cp.ckpt
===== 1 =====

action_class_accuracy: 0.39, action_accuracy: 0.14
val_action_class_accuracy: 0.41, val_action_accuracy: 0.16

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ
orical_accuracy: 0.49
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top
_k_categorical_accuracy: 0.51

Epoch 2/200
852/852 [=====] - 547s 641ms/step - loss:
4.7475 - action_class_loss: 1.3766 - action_loss: 2.6712 - action_
class_accuracy: 0.4220 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.1791 - action_top_k_categorical_accura
cy: 0.5529 - val_loss: 4.7240 - val_action_class_loss: 1.3553 - va
l_action_loss: 2.6988 - val_action_class_accuracy: 0.4219 - val_ac
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac
y: 0.1816 - val_action_top_k_categorical_accuracy: 0.5547

Epoch 00002: val_loss improved from 5.05122 to 4.72398, saving mod
el to reg_lambda_0p005/cp.ckpt
===== 2 =====

action_class_accuracy: 0.42, action_accuracy: 0.18
val_action_class_accuracy: 0.42, val_action_accuracy: 0.18

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ
orical_accuracy: 0.55
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top
_k_categorical_accuracy: 0.55

Epoch 3/200
852/852 [=====] - 547s 641ms/step - loss:
4.7074 - action_class_loss: 1.3358 - action_loss: 2.5851 - action_
class_accuracy: 0.4386 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.2033 - action_top_k_categorical_accura
cy: 0.5916 - val_loss: 5.5277 - val_action_class_loss: 1.4949 - va
l_action_loss: 3.1532 - val_action_class_accuracy: 0.4492 - val_ac
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac
y: 0.1875 - val_action_top_k_categorical_accuracy: 0.5918

```
Epoch 00003: val_loss did not improve from 4.72398
=====
action_class_accuracy: 0.44, action_accuracy: 0.20
val_action_class_accuracy: 0.45, val_action_accuracy: 0.19

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.59
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.59

Epoch 4/200
852/852 [=====] - 546s 641ms/step - loss: 4.5361 - action_class_loss: 1.2779 - action_loss: 2.4679 - action_class_accuracy: 0.4689 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.2368 - action_top_k_categorical_accuracy: 0.6375 - val_loss: 4.7931 - val_action_class_loss: 1.3704 - val_action_loss: 2.5901 - val_action_class_accuracy: 0.4805 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_action_accuracy: 0.1973 - val_action_top_k_categorical_accuracy: 0.6230

Epoch 00004: val_loss did not improve from 4.72398
=====
action_class_accuracy: 0.47, action_accuracy: 0.24
val_action_class_accuracy: 0.48, val_action_accuracy: 0.20

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.64
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.62

Epoch 5/200
852/852 [=====] - 546s 641ms/step - loss: 4.4434 - action_class_loss: 1.2331 - action_loss: 2.3782 - action_class_accuracy: 0.4932 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.2688 - action_top_k_categorical_accuracy: 0.6693 - val_loss: 5.1668 - val_action_class_loss: 1.2840 - val_action_loss: 3.0444 - val_action_class_accuracy: 0.5234 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_action_accuracy: 0.2441 - val_action_top_k_categorical_accuracy: 0.6484

Epoch 00005: val_loss did not improve from 4.72398
=====
action_class_accuracy: 0.49, action_accuracy: 0.27
val_action_class_accuracy: 0.52, val_action_accuracy: 0.24

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.67
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.65

Epoch 6/200
852/852 [=====] - 546s 641ms/step - loss: 4.3312 - action_class_loss: 1.1765 - action_loss: 2.2861 - action_class_accuracy: 0.5231 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.2941 - action_top_k_categorical_accuracy: 0.6989 - val_loss: 4.3686 - val_action_class_loss: 1.1855 - va
```

```
l_action_loss: 2.3582 - val_action_class_accuracy: 0.5332 - val_ac-
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac-
y: 0.2754 - val_action_top_k_categorical_accuracy: 0.7070

Epoch 00006: val_loss improved from 4.72398 to 4.36861, saving mod-
el to reg_labmda_0p005/cp.ckpt
===== 6 =====

action_class_accuracy: 0.52, action_accuracy: 0.29
val_action_class_accuracy: 0.53, val_action_accuracy: 0.28

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ-
orical_accuracy: 0.70
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top-
_k_categorical_accuracy: 0.71

Epoch 7/200
852/852 [=====] - 546s 641ms/step - loss:
4.0793 - action_class_loss: 1.0901 - action_loss: 2.1365 - action_
class_accuracy: 0.5682 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.3383 - action_top_k_categorical_accur-
acy: 0.7404 - val_loss: 7.2998 - val_action_class_loss: 2.5582 - va-
l_action_loss: 3.9758 - val_action_class_accuracy: 0.5137 - val_ac-
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac-
y: 0.2715 - val_action_top_k_categorical_accuracy: 0.6680

Epoch 00007: val_loss did not improve from 4.36861
===== 7 =====

action_class_accuracy: 0.57, action_accuracy: 0.34
val_action_class_accuracy: 0.51, val_action_accuracy: 0.27

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ-
orical_accuracy: 0.74
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top-
_k_categorical_accuracy: 0.67

Epoch 8/200
852/852 [=====] - 546s 641ms/step - loss:
3.8462 - action_class_loss: 1.0092 - action_loss: 1.9899 - action_
class_accuracy: 0.6085 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.3795 - action_top_k_categorical_accur-
acy: 0.7794 - val_loss: 4.4414 - val_action_class_loss: 1.2581 - va-
l_action_loss: 2.3576 - val_action_class_accuracy: 0.5664 - val_ac-
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac-
y: 0.3301 - val_action_top_k_categorical_accuracy: 0.7285

Epoch 00008: val_loss did not improve from 4.36861
===== 8 =====

action_class_accuracy: 0.61, action_accuracy: 0.38
val_action_class_accuracy: 0.57, val_action_accuracy: 0.33

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ-
orical_accuracy: 0.78
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top-
_k_categorical_accuracy: 0.73

Epoch 9/200
852/852 [=====] - 547s 642ms/step - loss:
```

```
3.5843 - action_class_loss: 0.9269 - action_loss: 1.8304 - action_
class_accuracy: 0.6456 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.4273 - action_top_k_categorical_accur
acy: 0.8142 - val_loss: 3.8903 - val_action_class_loss: 1.0697 - va
l_action_loss: 2.0367 - val_action_class_accuracy: 0.5977 - val_ac
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac
y: 0.3809 - val_action_top_k_categorical_accuracy: 0.7520
```

```
Epoch 00009: val_loss improved from 4.36861 to 3.89027, saving mod
el to reg_labmda_0p005/cp.ckpt
```

```
===== 9 =====
```

```
action_class_accuracy: 0.65, action_accuracy: 0.43
val_action_class_accuracy: 0.60, val_action_accuracy: 0.38
```

```
action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ
orical_accuracy: 0.81
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top
_k_categorical_accuracy: 0.75
```

```
Epoch 10/200
```

```
852/852 [=====] - 547s 642ms/step - loss:
3.2859 - action_class_loss: 0.8257 - action_loss: 1.6408 - action_
class_accuracy: 0.6898 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.4823 - action_top_k_categorical_accur
acy: 0.8528 - val_loss: 4.0846 - val_action_class_loss: 1.1509 - va
l_action_loss: 2.1007 - val_action_class_accuracy: 0.6113 - val_ac
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac
y: 0.3965 - val_action_top_k_categorical_accuracy: 0.7715
```

```
Epoch 00010: val_loss did not improve from 3.89027
```

```
===== 10 =====
```

```
action_class_accuracy: 0.69, action_accuracy: 0.48
val_action_class_accuracy: 0.61, val_action_accuracy: 0.40
```

```
action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ
orical_accuracy: 0.85
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top
_k_categorical_accuracy: 0.77
```

```
Epoch 11/200
```

```
852/852 [=====] - 547s 642ms/step - loss:
3.0195 - action_class_loss: 0.7200 - action_loss: 1.4553 - action_
class_accuracy: 0.7306 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.5357 - action_top_k_categorical_accur
acy: 0.8855 - val_loss: 4.1522 - val_action_class_loss: 1.1711 - va
l_action_loss: 2.1416 - val_action_class_accuracy: 0.6094 - val_ac
tion_class_top_k_categorical_accuracy: 1.0000 - val_action_accurac
y: 0.4277 - val_action_top_k_categorical_accuracy: 0.7539
```

```
Epoch 00011: val_loss did not improve from 3.89027
```

```
===== 11 =====
```

```
action_class_accuracy: 0.73, action_accuracy: 0.54
val_action_class_accuracy: 0.61, val_action_accuracy: 0.43
```

```
action_class_top_k_categorical_accuracy : 1.00, action_top_k_categ
orical_accuracy: 0.89
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top
```

```
_k_categorical_accuracy: 0.75

Epoch 12/200
852/852 [=====] - 547s 642ms/step - loss: 2.7886 - action_class_loss: 0.6177 - action_loss: 1.2914 - action_class_accuracy: 0.7729 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.5858 - action_top_k_categorical_accuracy: 0.9139 - val_loss: 4.1367 - val_action_class_loss: 1.1699 - val_action_loss: 2.0520 - val_action_class_accuracy: 0.6602 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_action_accuracy: 0.4297 - val_action_top_k_categorical_accuracy: 0.8047

Epoch 00012: val_loss did not improve from 3.89027
=====
action_class_accuracy: 0.77, action_accuracy: 0.59
val_action_class_accuracy: 0.66, val_action_accuracy: 0.43

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.91
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.80

Epoch 13/200
852/852 [=====] - 547s 642ms/step - loss: 2.5758 - action_class_loss: 0.5281 - action_loss: 1.1375 - action_class_accuracy: 0.8072 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.6330 - action_top_k_categorical_accuracy: 0.9356 - val_loss: 4.5365 - val_action_class_loss: 1.3630 - val_action_loss: 2.2372 - val_action_class_accuracy: 0.6250 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_action_accuracy: 0.4160 - val_action_top_k_categorical_accuracy: 0.7812

Epoch 00013: val_loss did not improve from 3.89027
=====
action_class_accuracy: 0.81, action_accuracy: 0.63
val_action_class_accuracy: 0.62, val_action_accuracy: 0.42

action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.94
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.78

Epoch 14/200
852/852 [=====] - 547s 642ms/step - loss: 2.4293 - action_class_loss: 0.4631 - action_loss: 1.0249 - action_class_accuracy: 0.8316 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.6688 - action_top_k_categorical_accuracy: 0.9505 - val_loss: 4.4483 - val_action_class_loss: 1.2791 - val_action_loss: 2.1966 - val_action_class_accuracy: 0.5996 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_action_accuracy: 0.4199 - val_action_top_k_categorical_accuracy: 0.7812

Epoch 00014: val_loss did not improve from 3.89027
=====
action_class_accuracy: 0.83, action_accuracy: 0.67
val_action_class_accuracy: 0.60, val_action_accuracy: 0.42
```

```
action_class_top_k_categorical_accuracy : 1.00, action_top_k_categorical_accuracy: 0.95
val_action_class_top_k_categorical_accuracy : 1.00, val_action_top_k_categorical_accuracy: 0.78
```

Epoch 15/200

```
In [ ]: # Save model results
model_results[model_name] = model_results[model_name].history

!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

```
In [ ]: # Save model weights
```

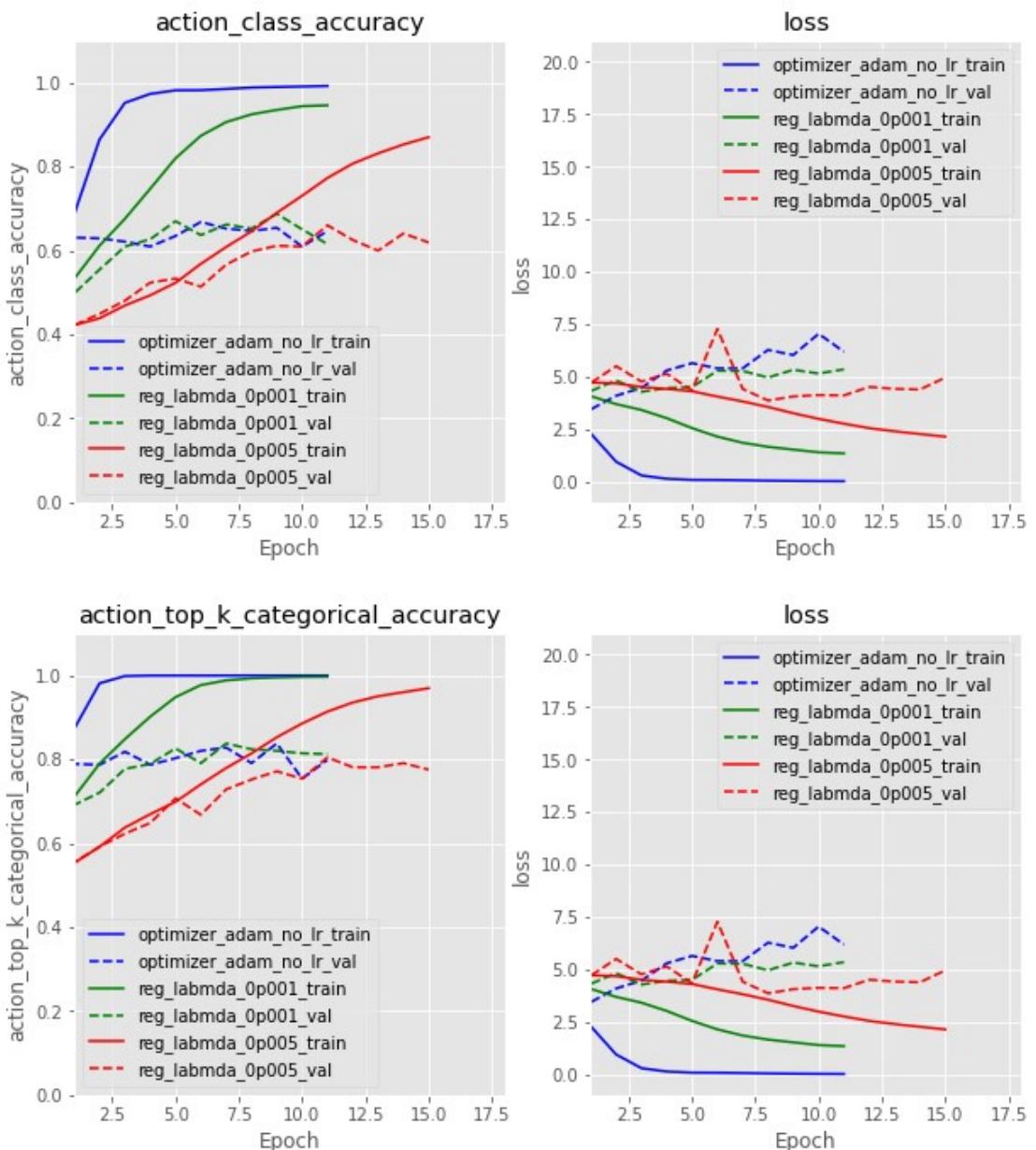
```
WARNING:absl:Found untraced functions such as conv2d_36_layer_call_fn, conv2d_36_layer_call_and_return_conditional_losses, conv2d_37_layer_call_fn, conv2d_37_layer_call_and_return_conditional_losses, conv2d_39_layer_call_fn while saving (showing 5 of 160). These functions will not be directly callable after loading.
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/reg_labmda_0p005_model/assets
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/reg_labmda_0p005_model/assets
```

```
In [52]: names = { 'optimizer_adam_no_lr', 'reg_labmda_0p005' , 'reg_labmda_
```

```
In [53]: plotter(model_results_subset, metric = 'action_class_accuracy', ylim = (0.0, 1.0))
plotter(model_results_subset, metric = 'action_top_k_categorical_accuracy', ylim = (0.0, 1.0))
```



```
In [ ]:
```

✓ Observations:

- There is less overfitting, but it still does overfit towards the end. Might need to increase the reg_lambda parameter, as well as give the model a higher patience parameter in the early stopping in the callbacks

```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```

Regularization - L2 with lambda = 0.0075

```
In [ ]: █ BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train',
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation',
    image_column = "FileName_scaled"
)
```

```
In [ ]: █ filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.0075

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

```
In [ ]: █ first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer= tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
                name = "conv_1")(input_)
```

```

bn_1 = BatchNormalization(momentum=0.4)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
        first_time = False
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

#reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

flat_1 = Flatten(name = "flat_1")(gap_1)

action_class = Dense(5, activation=tf.nn.softmax,
                     kernel_regularizer=tf.keras.regularizers.l2(
                     kernel_initializer=tf.keras.initializers.RandomNormal(
                     name = "action_class"))(flat_1)

action = Dense(21, activation=tf.nn.softmax,
               kernel_regularizer=tf.keras.regularizers.l2(
               kernel_initializer=tf.keras.initializers.RandomNormal(
               name = "action"))(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
            name="top_k_categorical_accuracy",
            dtype=None
        )
    ]
)

```

Model: "model_4"

Layer (type)	Output Shape	Param #	C
connected to			

=====			
input (InputLayer)	[None, 224, 224, 3]	0	i
conv_1 (Conv2D) nput[0][0]	(None, 224, 224, 64)	9472	i
batch_normalization_148 (BatchN conv_1[0][0]	(None, 224, 224, 64)	256	c
residual_block_64 (ResidualBloc atch_normalization_148[0][0]	(None, 112, 112, 64)	78784	b
residual_block_65 (ResidualBloc esidual_block_64[0][0]	(None, 112, 112, 64)	74368	r
residual_block_66 (ResidualBloc esidual_block_65[0][0]	(None, 112, 112, 64)	74368	r
residual_block_67 (ResidualBloc esidual_block_66[0][0]	(None, 56, 56, 128)	231296	r
residual_block_68 (ResidualBloc esidual_block_67[0][0]	(None, 56, 56, 128)	296192	r
residual_block_69 (ResidualBloc esidual_block_68[0][0]	(None, 56, 56, 128)	296192	r
residual_block_70 (ResidualBloc esidual_block_69[0][0]	(None, 56, 56, 128)	296192	r
residual_block_71 (ResidualBloc esidual_block_70[0][0]	(None, 28, 28, 256)	921344	r
residual_block_72 (ResidualBloc esidual_block_71[0][0]	(None, 28, 28, 256)	1182208	r
residual_block_73 (ResidualBloc esidual_block_72[0][0]	(None, 28, 28, 256)	1182208	r
residual_block_74 (ResidualBloc esidual_block_73[0][0]	(None, 28, 28, 256)	1182208	r
residual_block_75 (ResidualBloc esidual_block_74[0][0]	(None, 28, 28, 256)	1182208	r

```
residual_block_76 (ResidualBlok (None, 28, 28, 256) 1182208 r
esidual_block_75[0][0]

=====
residual_block_77 (ResidualBlok (None, 14, 14, 512) 3677696 r
esidual_block_76[0][0]

=====
residual_block_78 (ResidualBlok (None, 14, 14, 512) 4723712 r
esidual_block_77[0][0]

=====
residual_block_79 (ResidualBlok (None, 14, 14, 512) 4723712 r
esidual_block_78[0][0]

=====
gap_1 (GlobalAveragePooling2D) (None, 512) 0 r
esidual_block_79[0][0]

=====
flat_1 (Flatten) (None, 512) 0 g
ap_1[0][0]

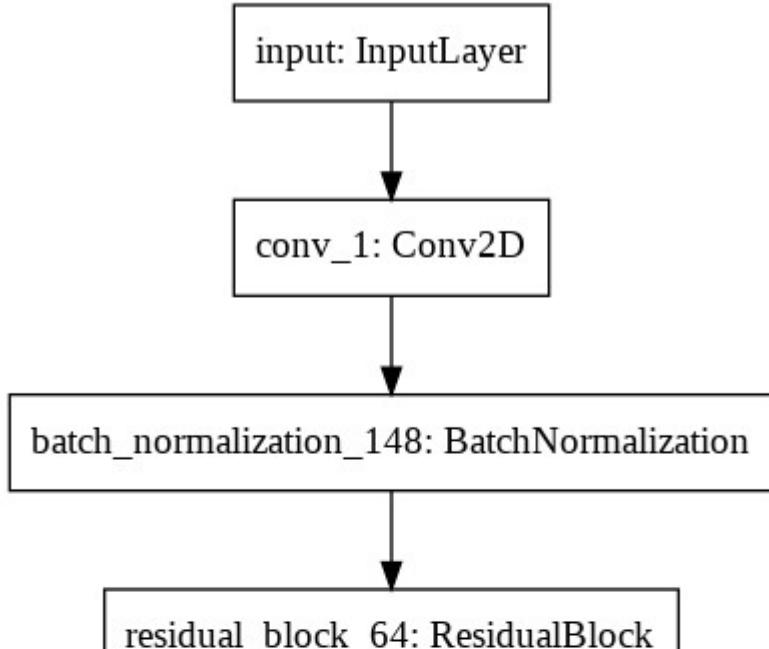
=====
action_class (Dense) (None, 5) 2565 f
lat_1[0][0]
=====
=====

action (Dense) (None, 21) 10773 f
lat_1[0][0]
=====
=====

Total params: 21,327,962
Trainable params: 21,310,810
Non-trainable params: 17,152
```

In []:

Out[72]:



```
In [ ]: █ .
```

```
In [ ]: █ .
```

```
<IPython.core.display.Javascript object>
```

```
In [ ]: █ model_name = "reg_labmda_0p0075"

model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True
)

Epoch 1/200
  6/852 [........................] - ETA: 11:42 - loss: 382.
1844 - action_class_loss: 1.9836 - action_loss: 3.3542 - action_cl
ass_accuracy: 0.2734 - action_class_top_k_categorical_accuracy: 1.
0000 - action_accuracy: 0.0625 - action_top_k_categorical_accurac
y: 0.2943WARNING:tensorflow:Callback method `on_train_batch_end` i
s slow compared to the batch time (batch time: 0.2292s vs `on_trai
n_batch_end` time: 0.5163s). Check your callbacks.

WARNING:tensorflow:Callback method `on_train_batch_end` is slow co
mpared to the batch time (batch time: 0.2292s vs `on_train_batch_e
nd` time: 0.5163s). Check your callbacks.

852/852 [=====] - 554s 644ms/step - loss:
24.5107 - action_class_loss: 1.4761 - action_loss: 2.8614 - action
_class_accuracy: 0.3681 - action_class_top_k_categorical_accuracy:
1.0000 - action_accuracy: 0.1234 - action_top_k_categorical_accura
cy: 0.4584 - val_loss: 5.1680 - val_action_class_loss: 1.4663 - va
l_action_loss: 2.8688 - val_action_class_accuracy: 0.3809 - val_ac
tion class top k categorical accuracy: 1.0000 - val action accurac
```

```
In [ ]: █ # Save model results
model_results[model_name] = model_results[model_name].history

!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

```
In [ ]: █ # Save model weights
```

```
WARNING:absl:Found untraced functions such as conv2d_144_layer_c
all_fn, conv2d_144_layer_call_and_return_conditional_losses, conv2d_
145_layer_call_fn, conv2d_145_layer_call_and_return_conditional_lo
sses, conv2d_147_layer_call_fn while saving (showing 5 of 160). Th
ese functions will not be directly callable after loading.

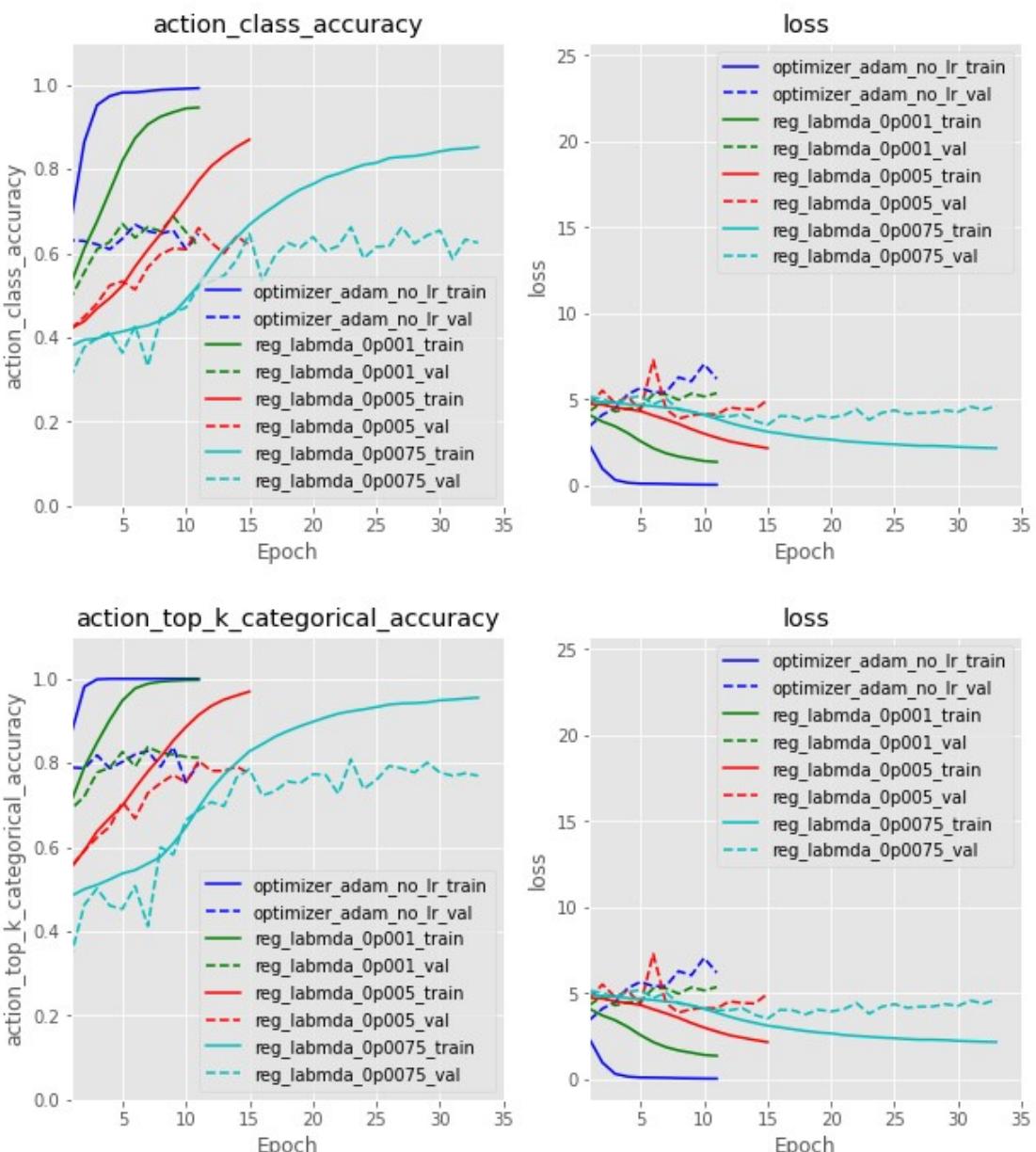
INFO:tensorflow:Assets written to: drive/MyDrive/reg_labmda_0p0075
_model/assets

INFO:tensorflow:Assets written to: drive/MyDrive/reg_labmda_0p0075
_model/assets
```

```
In [ ]: file_ = open('drive/MyDrive/model_results.json')
```

```
In [ ]: names = { 'optimizer_adam_no_lr', 'reg_labmda_0p005' , 'reg_labmda_0p001' , 'reg_labmda_0p0075' }
```

```
In [ ]: plotter(model_results_subset, metric = 'action_class_accuracy', ylim = (0.0, 1.0))
plotter(model_results_subset, metric = 'action_top_k_categorical_accuracy', ylim = (0.0, 1.0))
```



✓ Observations:

- Still overfitting with lots of epochs, and performance plateaus with approximately the same values.
- Might be worth trying a different regularization technique like L1

```
In [ ]: 
```

```
In [ ]: 
```

Regularization - L1 with lambda = 0.001

In []:

```
class ResidualBlock(tf.keras.layers.Layer):

    # Initialize components of the model
    def __init__(self, filter_num, stride=1, reg_lambda=0.0, kernel_initializer='he_normal', kernel_regularizer='l1'):
        super(ResidualBlock, self).__init__()
        self.conv1 = tf.keras.layers.Conv2D(filters=filter_num,
                                           kernel_size=kernel_size,
                                           strides=stride,
                                           kernel_initializer=kernel_initializer,
                                           kernel_regularizer=kernel_regularizer,
                                           padding="same")
        self.bn1 = tf.keras.layers.BatchNormalization(momentum=momentum)
        self.conv2 = tf.keras.layers.Conv2D(filters=filter_num,
                                           kernel_size=kernel_size,
                                           strides=1,
                                           kernel_initializer=kernel_initializer,
                                           kernel_regularizer=kernel_regularizer,
                                           padding="same")
        self.bn2 = tf.keras.layers.BatchNormalization(momentum=momentum)
        if stride != 1:
            self.downsample = tf.keras.Sequential()
            self.downsample.add(tf.keras.layers.Conv2D(filters=filter_num,
                                                       kernel_size=kernel_size,
                                                       kernel_initializer=kernel_initializer,
                                                       kernel_regularizer=kernel_regularizer,
                                                       strides=stride))
            self.downsample.add(tf.keras.layers.BatchNormalization())
        else:
            self.downsample = lambda x: x

    # Define the forward function
    def call(self, inputs, training=None, **kwargs):
        residual = self.downsample(inputs)

        x = self.conv1(inputs)
        x = self.bn1(x, training=training)
        x = tf.nn.relu(x)
        x = self.conv2(x)
        x = self.bn2(x, training=training)

        output = tf.nn.relu(tf.keras.layers.add([residual, x]))

        return output

    def get_config(self):

        config = super().get_config().copy()
        config.update({
            'conv1': self.conv1,
            'bn1': self.bn1,
            'conv2': self.conv2,
            'bn2': self.bn2,
            'downsample': self.downsample,
        })
```

```
        })  
In [ ]: BATCH_SIZE = 64  
  
data_mean = 0.  
data_std = 255.0  
prefix=''  
training_generator = DataGenerator(  
    data_frame = train_data_df,  
    batch_size = BATCH_SIZE,  
    data_mean = data_mean,  
    data_std = data_std,  
    create_folder = False,  
    dim = (224, 224, 3),  
    shuffle = True,  
    augment = False,  
    file_name = 'drive/MyDrive/train/  
)  
  
validation_generator = DataGenerator(  
    data_frame = val_data_df,  
    batch_size = BATCH_SIZE,  
    data_mean = data_mean,  
    data_std = data_std,  
    create_folder = False,  
    dim = (224, 224, 3),  
    shuffle = True,  
    augment = False,  
    file_name = 'drive/MyDrive/validation/  
image_column = "FileName_scaled"  
)
```

```
In [ ]: filters = [64, 128, 256, 512]  
block_size = [3,4,6,3]  
reg_lambda = 0.001  
  
lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(  
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,  
    staircase=False)
```

```
In [ ]: first_time = True  
  
input_ = Input(shape = (224, 224, 3), name = "input")  
  
conv_1 = Conv2D(filters = 64,  
                kernel_size = (7,7),  
                strides = 1,  
                kernel_initializer = tf.keras.initializers.RandomNormal(),  
                kernel_regularizer= tf.keras.regularizers.l1(reg_lambda),  
                padding = "same",  
                name = "conv_1")(input_)  
  
bn_1 = BatchNormalization(momentum=0.4)(conv_1)  
  
#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)
```

```

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
                               first_time = False)
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer=tf.keras.regularizers.l1(l1),
                         kernel_initializer=tf.keras.initializers.RandomUniform(
                             name = "action_class"))(flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                   kernel_regularizer=tf.keras.regularizers.l1(l1),
                   kernel_initializer=tf.keras.initializers.RandomUniform(
                       name = "action"))(flat_1)

model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
            name="top_k_categorical_accuracy",
            dtype=None
        )
    ]
)

```

Model: "model_1"

Layer (type)	Output Shape	Param #	C
connected to			

input (InputLayer)	[(None, 224, 224, 3) 0	
conv_1 (Conv2D) nput[0][0]	(None, 224, 224, 64) 9472	i
batch_normalization_37 (BatchNo conv_1[0][0]	(None, 224, 224, 64) 256	c
residual_block_16 (ResidualBloc atch_normalization_37[0][0]	(None, 112, 112, 64) 78784	b
residual_block_17 (ResidualBloc esidual_block_16[0][0]	(None, 112, 112, 64) 74368	r
residual_block_18 (ResidualBloc esidual_block_17[0][0]	(None, 112, 112, 64) 74368	r
residual_block_19 (ResidualBloc esidual_block_18[0][0]	(None, 56, 56, 128) 231296	r
residual_block_20 (ResidualBloc esidual_block_19[0][0]	(None, 56, 56, 128) 296192	r
residual_block_21 (ResidualBloc esidual_block_20[0][0]	(None, 56, 56, 128) 296192	r
residual_block_22 (ResidualBloc esidual_block_21[0][0]	(None, 56, 56, 128) 296192	r
residual_block_23 (ResidualBloc esidual_block_22[0][0]	(None, 28, 28, 256) 921344	r
residual_block_24 (ResidualBloc esidual_block_23[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_25 (ResidualBloc esidual_block_24[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_26 (ResidualBloc esidual_block_25[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_27 (ResidualBloc esidual_block_26[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_28 (ResidualBloc esidual_block_27[0][0]	(None, 28, 28, 256) 1182208	r

```
esidual_block_27[0][0]
```

```
residual_block_29 (ResidualBloc (None, 14, 14, 512) 3677696 r  
esidual_block_28[0][0]
```

```
residual_block_30 (ResidualBloc (None, 14, 14, 512) 4723712 r  
esidual_block_29[0][0]
```

```
residual_block_31 (ResidualBloc (None, 14, 14, 512) 4723712 r  
esidual_block_30[0][0]
```

```
gap_1 (GlobalAveragePooling2D) (None, 512) 0 r  
esidual_block_31[0][0]
```

```
flat_1 (Flatten) (None, 512) 0 g  
ap_1[0][0]
```

```
action_class (Dense) (None, 5) 2565 f  
lat_1[0][0]
```

```
action (Dense) (None, 21) 10773 f  
lat_1[0][0]
```

```
=====
```

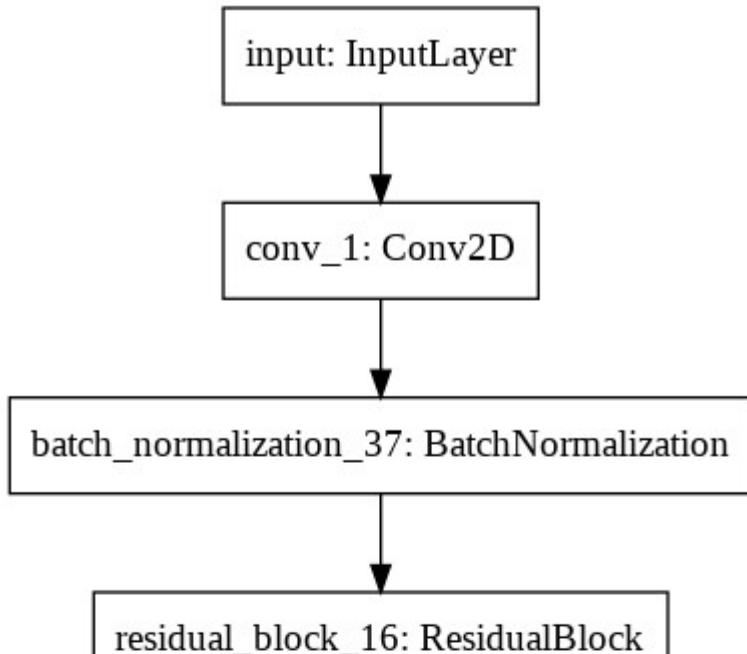
```
Total params: 21,327,962
```

```
Trainable params: 21,310,810
```

```
Non-trainable params: 17,152
```

In []:

Out[46]:



In []:

<IPython.core.display.Javascript object>

In []:

```
model_name = "l1_reg_labmda_0p001"

model_results[model_name] = model.fit(
    training_generator,
    validation_data = validation_generator,
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,
    validation_steps = len(val_data_df)//BATCH_SIZE,
    epochs = 200,
    callbacks = get_callbacks(model_name),
    verbose = True

Epoch 1/200
 6/852 [........................] - ETA: 8:24 - loss: 810.7
603 - action_class_loss: 1.8098 - action_loss: 3.2528 - action_class_accuracy: 0.2344 - action_class_top_k_categorical_accuracy: 1.0
000 - action_accuracy: 0.0729 - action_top_k_categorical_accuracy: 0.3203WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time (batch time: 0.1450s vs `on_train_batch_end` time: 0.3557s). Check your callbacks.
852/852 [=====] - 329s 381ms/step - loss: 57.5056 - action_class_loss: 1.5573 - action_loss: 2.9903 - action_class_accuracy: 0.3186 - action_class_top_k_categorical_accuracy: 1.0000 - action_accuracy: 0.0948 - action_top_k_categorical_accuracy: 0.3894 - val_loss: 17.6507 - val_action_class_loss: 1.6043 - val_action_loss: 2.9364 - val_action_class_accuracy: 0.3418 - val_action_class_top_k_categorical_accuracy: 1.0000 - val_action_accuracy: 0.1191 - val_action_top_k_categorical_accuracy: 0.4062

Epoch 00001: val_loss improved from inf to 17.65068, saving model to l1_reg_labmda_0p001/cp.ckpt
```

In []:

```
# Save model results
model_results[model_name] = model_results[model_name].history

!rm -r "drive/MyDrive/model_results.json"
with open("drive/MyDrive/model_results.json", "w") as fp:
```

In []:

Save model weights

```
WARNING:absl:Found untraced functions such as conv2d_36_layer_call_fn, conv2d_36_layer_call_and_return_conditional_losses, conv2d_37_layer_call_fn, conv2d_37_layer_call_and_return_conditional_losses, conv2d_39_layer_call_fn while saving (showing 5 of 160). These functions will not be directly callable after loading.
```

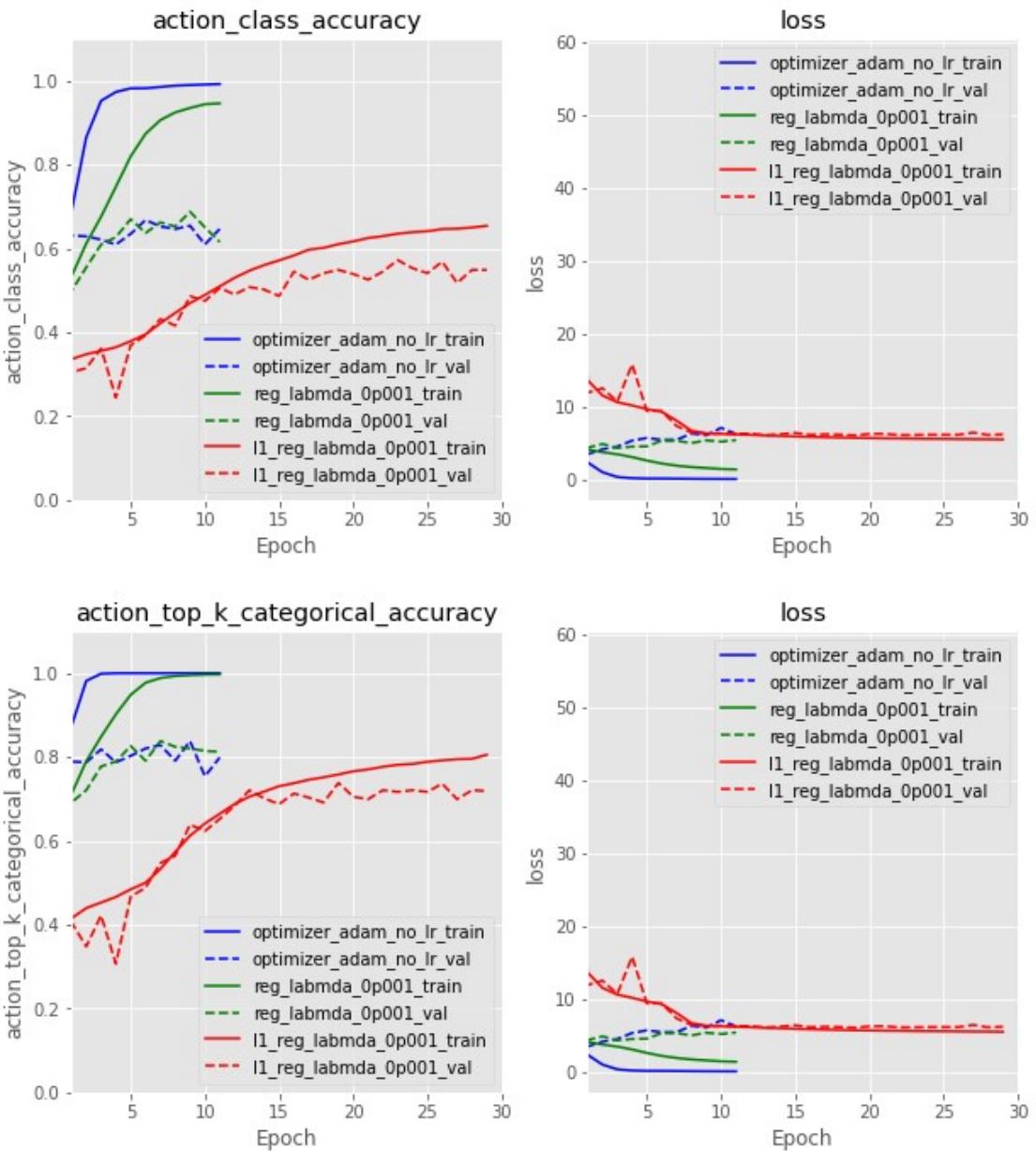
```
INFO:tensorflow:Assets written to: drive/MyDrive/l1_reg_labmda_0p01_model/assets
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/l1_reg_labmda_0p01_model/assets
```

In []:

```
names = { 'optimizer_adam_no_lr', 'l1_reg_labmda_0p001', 'reg_labmda' }
model_results_subset = { key:value for key,value in model_results.i
```

```
In [ ]: plotter(model_results_subset, metric = 'action_class_accuracy', ylim = (0.0, 1.0))
plotter(model_results_subset, metric = 'action_top_k_categorical_accuracy', ylim = (0.0, 1.0))
```



```
In [ ]: 
```

✓ Observations:

- The model is significantly underfitting
- We might have to try to tune a different parameter, since the model's performance seems to be hitting a ceiling

```
In [ ]: 
```

```
In [ ]: 
```

Experimentation - Activation Function

- We try Leaky ReLU, which has a small slope for negative values instead of a flat slope

like ReLU. It is used more commonly for image classification tasks and tends to have better performance

```
In [ ]: █ # add kernel size and momentum as parameters here, then remove this

class ResidualBlock(tf.keras.layers.Layer):

    # Initialize components of the model
    def __init__(self, filter_num, stride=1, reg_lambda=0.0, kernel_size=3, momentum=0.9):
        super(ResidualBlock, self).__init__()
        self.conv1 = tf.keras.layers.Conv2D(filters=filter_num,
                                           kernel_size=kernel_size,
                                           strides=stride,
                                           kernel_initializer=tf.keras.initializers.he_normal(),
                                           kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                                           padding="same")
        self.bn1 = tf.keras.layers.BatchNormalization(momentum=momentum)
        self.conv2 = tf.keras.layers.Conv2D(filters=filter_num,
                                           kernel_size=kernel_size,
                                           strides=1,
                                           kernel_initializer=tf.keras.initializers.he_normal(),
                                           kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                                           padding="same")
        self.bn2 = tf.keras.layers.BatchNormalization(momentum=momentum)
        if stride != 1:
            self.downsample = tf.keras.Sequential()
            self.downsample.add(tf.keras.layers.Conv2D(filters=filter_num,
                                                       kernel_size=kernel_size,
                                                       kernel_initializer=tf.keras.initializers.he_normal(),
                                                       kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                                                       strides=stride))
            self.downsample.add(tf.keras.layers.BatchNormalization(momentum=momentum))
        else:
            self.downsample = lambda x: x

    # Define the forward function
    def call(self, inputs, training=None, **kwargs):
        residual = self.downsample(inputs)

        x = self.conv1(inputs)
        x = self.bn1(x, training=training)
        x = tf.nn.leaky_relu(x)
        x = self.conv2(x)
        x = self.bn2(x, training=training)

        output = tf.nn.leaky_relu(tf.keras.layers.add([residual, x]))

        return output

    def get_config(self):

        config = super().get_config().copy()
        config.update({
            'conv1': self.conv1,
            'bn1': self.bn1,
            'conv2': self.conv2,
            'bn2': self.bn2,
            'downsample': self.downsample,
        })
    
```

```
In [ ]: BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
prefix=''

training_generator = DataGenerator(
    data_frame = train_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/train',
)

validation_generator = DataGenerator(
    data_frame = val_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/validation',
    image_column = "FileName_scaled"
)
```

```
In [ ]: filters = [64, 128, 256, 512]
block_size = [3,4,6,3]
reg_lambda = 0.005

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate = 0.1, decay_steps = len(train_data_df)//BATCH_SIZE,
    staircase=False)
```

```
In [ ]: first_time = True

input_ = Input(shape = (224, 224, 3), name = "input")

conv_1 = Conv2D(filters = 64,
                kernel_size = (7,7),
                strides = 1,
                kernel_initializer = tf.keras.initializers.RandomNormal(),
                kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                padding = "same",
                name = "conv_1")(input_)

bn_1 = BatchNormalization(momentum=0.4)(conv_1)

#maxpool_1 = MaxPool2D(pool_size = (2,2))(bn_1)
```

```

for nFilters, nBlocks in zip(filters, block_size):

    if first_time == True:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda,
                               first_time = False)
    else:
        res_x = ResidualBlock(nFilters, stride = 2, reg_lambda = reg_lambda)

    for _ in range(1, nBlocks):

        res_x = ResidualBlock(nFilters, stride = 1, reg_lambda = reg_lambda)

    #maxpool_x = MaxPool2D(pool_size = (2,2))(res_x)

    #reshape_1 = Reshape(res_x.shape[1:], name="reshape_1")(res_x)

    gap_1 = GlobalAveragePooling2D(name = "gap_1")(res_x)

    flat_1 = Flatten(name = "flat_1")(gap_1)

    action_class = Dense(5, activation=tf.nn.softmax,
                         kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                         kernel_initializer=tf.keras.initializers.RandomUniform(
                             name = "action_class"))(flat_1)

    action = Dense(21, activation=tf.nn.softmax,
                   kernel_regularizer=tf.keras.regularizers.l2(reg_lambda),
                   kernel_initializer=tf.keras.initializers.RandomUniform(
                       name = "action"))(flat_1)

    model = tf.keras.models.Model(input_, [action_class, action])

model.compile(
    loss = {
        'action_class': 'categorical_crossentropy',
        'action': 'categorical_crossentropy'
    },
    optimizer = optimizer_,
    metrics = [
        'accuracy',
        tf.keras.metrics.TopKCategoricalAccuracy(
            k=5,
            name="top_k_categorical_accuracy",
            dtype=None
        )
    ]
)

```

Model: "model_2"

Layer (type)	Output Shape	Param #	C
connected to			
=====			

input (InputLayer)	[None, 224, 224, 3] 0	
conv_1 (Conv2D) nput[0][0]	(None, 224, 224, 64) 9472	i
batch_normalization_74 (BatchNo conv_1[0][0]	(None, 224, 224, 64) 256	c
residual_block_32 (ResidualBloc atch_normalization_74[0][0]	(None, 112, 112, 64) 78784	b
residual_block_33 (ResidualBloc esidual_block_32[0][0]	(None, 112, 112, 64) 74368	r
residual_block_34 (ResidualBloc esidual_block_33[0][0]	(None, 112, 112, 64) 74368	r
residual_block_35 (ResidualBloc esidual_block_34[0][0]	(None, 56, 56, 128) 231296	r
residual_block_36 (ResidualBloc esidual_block_35[0][0]	(None, 56, 56, 128) 296192	r
residual_block_37 (ResidualBloc esidual_block_36[0][0]	(None, 56, 56, 128) 296192	r
residual_block_38 (ResidualBloc esidual_block_37[0][0]	(None, 56, 56, 128) 296192	r
residual_block_39 (ResidualBloc esidual_block_38[0][0]	(None, 28, 28, 256) 921344	r
residual_block_40 (ResidualBloc esidual_block_39[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_41 (ResidualBloc esidual_block_40[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_42 (ResidualBloc esidual_block_41[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_43 (ResidualBloc esidual_block_42[0][0]	(None, 28, 28, 256) 1182208	r
residual_block_44 (ResidualBloc esidual_block_43[0][0]	(None, 28, 28, 256) 1182208	r

```
esidual_block_43[0][0]
```

```
residual_block_45 (ResidualBloc (None, 14, 14, 512) 3677696 r  
esidual_block_44[0][0]
```

```
residual_block_46 (ResidualBloc (None, 14, 14, 512) 4723712 r  
esidual_block_45[0][0]
```

```
residual_block_47 (ResidualBloc (None, 14, 14, 512) 4723712 r  
esidual_block_46[0][0]
```

```
gap_1 (GlobalAveragePooling2D) (None, 512) 0 r  
esidual_block_47[0][0]
```

```
flat_1 (Flatten) (None, 512) 0 g  
ap_1[0][0]
```

```
action_class (Dense) (None, 5) 2565 f  
lat_1[0][0]
```

```
action (Dense) (None, 21) 10773 f  
lat_1[0][0]
```

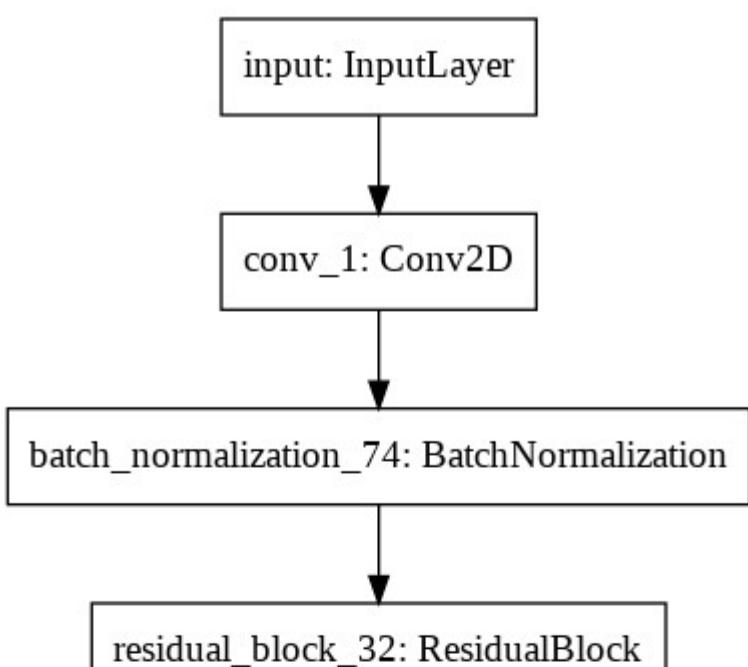
```
Total params: 21,327,962
```

```
Trainable params: 21,310,810
```

```
Non-trainable params: 17,152
```

In []: ►

Out[69]:



In []: ► !rm -r logs

In []:

```
Reusing TensorBoard on port 6006 (pid 830), started 2:57:48 ago.  
(Use '!kill 830' to kill it.)  
<IPython.core.display.Javascript object>
```

In []:

```
model_name = "activation_leaky_relu"  
  
model_results[model_name] = model.fit(  
    training_generator,  
    validation_data = validation_generator,  
    steps_per_epoch = len(train_data_df)//BATCH_SIZE,  
    validation_steps = len(val_data_df)//BATCH_SIZE,  
    epochs = 200,  
    callbacks = get_callbacks(model_name),  
    verbose = True  
,
```

Epoch 1/200

```
6/852 [........................] - ETA: 8:34 - loss: 259.1  
831 - action_class_loss: 2.0968 - action_loss: 3.5281 - action_cla  
ss_accuracy: 0.2708 - action_class_top_k_categorical_accuracy: 1.0  
000 - action_accuracy: 0.0755 - action_top_k_categorical_accuracy:  
0.3229WARNING:tensorflow:Callback method `on_train_batch_end` is s  
low compared to the batch time (batch time: 0.1472s vs `on_train_b  
atch_end` time: 0.3634s). Check your callbacks.
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow co  
mpared to the batch time (batch time: 0.1472s vs `on_train_batch_e  
nd` time: 0.3634s). Check your callbacks.
```

```
852/852 [=====] - 331s 383ms/step - loss: 19.2723 - action_class_loss: 1.4481 - action_loss: 2.8004 - action  
_class_accuracy: 0.3799 - action_class_top_k_categorical_accuracy:  
1.0000 - action_accuracy: 0.1463 - action_top_k_categorical_accura  
cy: 0.4914 - val_loss: 4.7852 - val_action_class_loss: 1.3889 - va  
l_action_loss: 2.7201 - val_action_class_accuracy: 0.4043 - val_ac  
tion class top k categorical accuracy: 1.0000 - val action accurac
```

In []:

```
# Save model results  
model_results[model_name] = model_results[model_name].history  
  
!rm -r "drive/MyDrive/model_results.json"  
with open("drive/MyDrive/model_results.json", "w") as fp:
```

In []:

```
# Save model weights
```

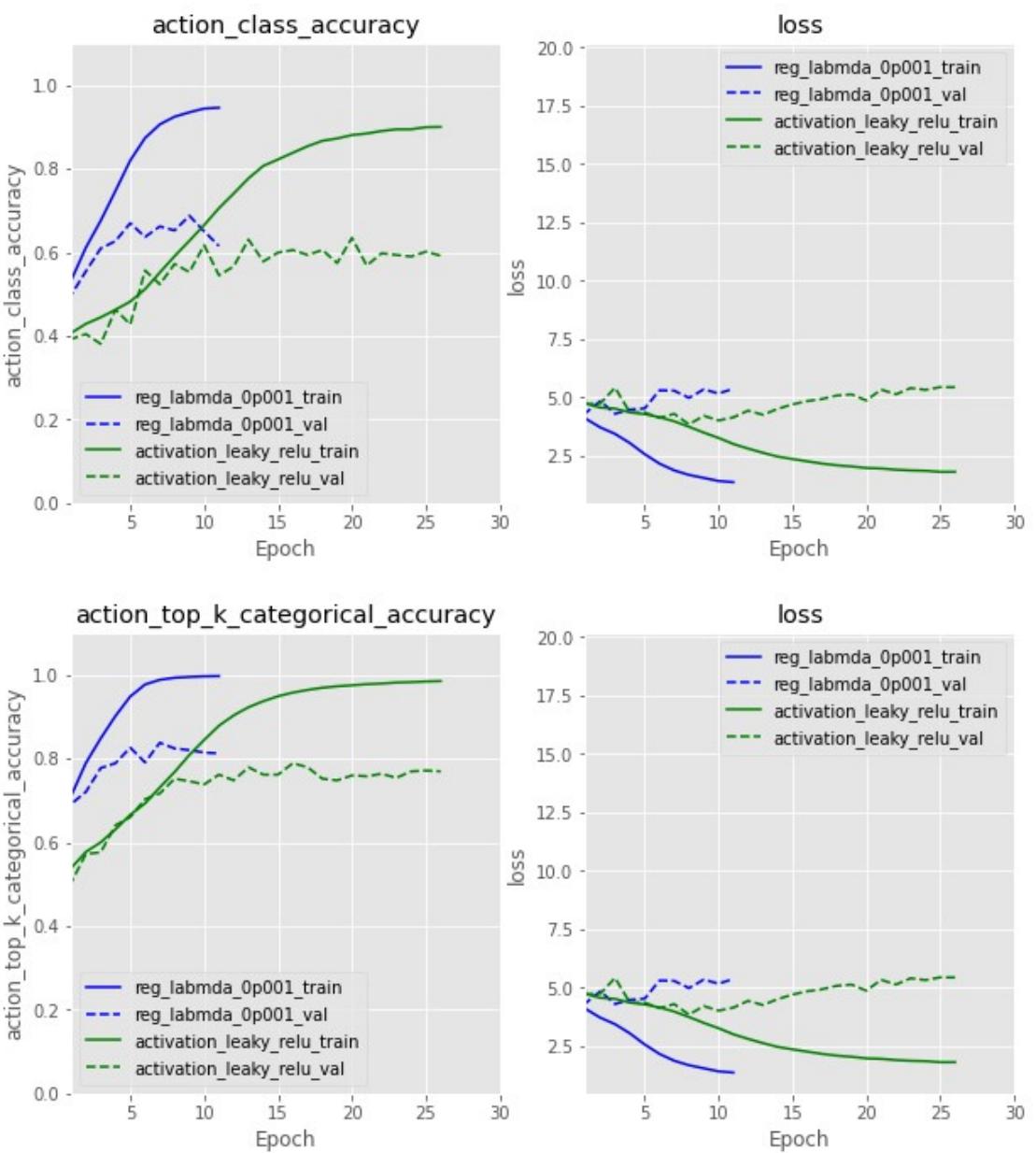
```
WARNING:absl:Found untraced functions such as conv2d_72_layer_call  
_fn, conv2d_72_layer_call_and_return_conditional_losses, conv2d_73  
_layer_call_fn, conv2d_73_layer_call_and_return_conditional_lasse  
s, conv2d_75_layer_call_fn while saving (showing 5 of 160). These  
functions will not be directly callable after loading.
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/activation_leaky_  
relu_model/assets
```

```
INFO:tensorflow:Assets written to: drive/MyDrive/activation_leaky_  
relu_model/assets
```

```
In [60]: names = { 'reg_lambda_0p001', 'activation_leaky_relu'}
```

```
In [61]: plotter(model_results_subset, metric = 'action_class_accuracy', ylim = (0.0, 1.0))
plotter(model_results_subset, metric = 'action_top_k_categorical_accuracy', ylim = (0.0, 1.0))
```



✓ Observations:

- There is no improvement in performance, in fact it does slightly worse

```
In [141]:
```

```
In [ ]:
```

```
In [ ]:
```

Test Data Evaluation

In [62]:

Out[62]:

	FileName	action	action_class	action_num	action_class_n
535	Img_257.jpg	rowing_a_boat	other_activity	12	
1369	Img_4929.jpg	riding_a_bike	other_activity	10	
1171	Img_4372.jpg	climbing	other_activity	1	
2921	Img_9279.jpg	walking_the_dog	Interacting_with_animal	18	
736	Img_3148.jpg	texting_message	using_comm_device	16	
...
1076	Img_4112.jpg	riding_a_horse	Interacting_with_animal	11	
545	Img_2596.jpg	cleaning_the_floor	domestic_work	0	
1645	Img_5672.jpg	jumping	other_activity	6	
894	Img_3588.jpg	cooking	domestic_work	2	
1387	Img_4963.jpg	playing_violin	playing_musical_instrument	9	

758 rows × 6 columns

In [63]:

```
best_model = tf.keras.models.load_model("drive/MyDrive/reg_lambda_0")
best_model.summary()
```

Model: "model_4"

Layer (type)	Output Shape	Param #	C
connected to			
input (InputLayer)	[None, 224, 224, 3]	0	i
conv_1 (Conv2D)	(None, 224, 224, 64)	9472	c
batch_normalization_148 (BatchN	(None, 224, 224, 64)	256	c
conv_1[0][0]			
residual_block_64 (ResidualBloc	(None, 112, 112, 64)	78784	b
atch_normalization_148[0][0]			
residual_block_65 (ResidualBloc	(None, 112, 112, 64)	74368	r
esidual_block_64[0][0]			
residual_block_66 (ResidualBloc	(None, 112, 112, 64)	74368	r
esidual_block_65[0][0]			
residual_block_67 (ResidualBloc	(None, 56, 56, 128)	231296	r
esidual_block_66[0][0]			
residual_block_68 (ResidualBloc	(None, 56, 56, 128)	296192	r
esidual_block_67[0][0]			
residual_block_69 (ResidualBloc	(None, 56, 56, 128)	296192	r
esidual_block_68[0][0]			
residual_block_70 (ResidualBloc	(None, 56, 56, 128)	296192	r
esidual_block_69[0][0]			
residual_block_71 (ResidualBloc	(None, 28, 28, 256)	921344	r
esidual_block_70[0][0]			
residual_block_72 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_71[0][0]			
residual_block_73 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_72[0][0]			
residual_block_74 (ResidualBloc	(None, 28, 28, 256)	1182208	r
esidual_block_73[0][0]			

```
residual_block_75 (ResidualBloc (None, 28, 28, 256) 1182208 r
esidual_block_74[0][0]

residual_block_76 (ResidualBloc (None, 28, 28, 256) 1182208 r
esidual_block_75[0][0]

residual_block_77 (ResidualBloc (None, 14, 14, 512) 3677696 r
esidual_bloc 76[0][0]
```

In [69]:

```
BATCH_SIZE = 64

data_mean = 0.
data_std = 255.0
testing_generator = DataGenerator(
    data_frame = test_data_df,
    batch_size = BATCH_SIZE,
    data_mean = data_mean,
    data_std = data_std,
    create_folder = False,
    dim = (224, 224, 3),
    shuffle = True,
    augment = False,
    file_name = 'drive/MyDrive/test',
    image_column = "FileName_scaled")
```

In [142]:

```
results = best_model.evaluate(testing_generator, batch_size = BATCH_SIZE)

11/11 [=====] - 2s 152ms/step - loss: 4.8
139 - action_class_loss: 1.4272 - action_loss: 2.2995 - action_class_accuracy: 0.6406 - action_class_top_k_categorical_accuracy: 1.0
000 - action_accuracy: 0.4915 - action_top_k_categorical_accuracy: 0.8281
```

In [143]:

```
Out[143]: [4.813885688781738,
1.4271916151046753,
2.299529790878296,
0.640625,
1.0,
0.49147728085517883,
0.828125]
```

In [144]:

```
In [146]: for i in range(len(results)):
    print(metrics[i] + ":" + str(results[i]))
```

```
loss: 4.813885688781738
action class loss: 1 1271916151016753
```

✓ Observations:

- This matches the validation set performance

In []: █

In []: █

Making Predictions

In [77]: █

In [78]: █

Out[78]:

	FileName
0	Img_1005.jpg
1	Img_1012.jpg
2	Img_1014.jpg
3	Img_1015.jpg
4	Img_102.jpg
...	...
2094	Img_985.jpg
2095	Img_986.jpg
2096	Img_993.jpg
2097	Img_994.jpg
2098	Img_996.jpg

2099 rows × 1 columns

First we need to resize all the images to 224x224

In [79]: █

```
!mkdir "predict_images_scaled"
for i in range(len(predict_df)):
    img=mpimg.imread(img_dir+predict_df['FileName'][i])
    #imgplot = plt.imshow(img)
    image_scaled = tf.image.convert_image_dtype(img, tf.float32)
    image_scaled = tf.image.resize(image_scaled, (224, 224))
```

In [80]: █

In [81]: █

Out[81]:

FileName

FileName_scaled

	FileName	FileName_scaled
0	Img_1005.jpg	predict_images_scaled/Img_1005.jpg
1	Img_1012.jpg	predict_images_scaled/Img_1012.jpg
2	Img_1014.jpg	predict_images_scaled/Img_1014.jpg
3	Img_1015.jpg	predict_images_scaled/Img_1015.jpg
4	Img_102.jpg	predict_images_scaled/Img_102.jpg
...
2094	Img_985.jpg	predict_images_scaled/Img_985.jpg
2095	Img_986.jpg	predict_images_scaled/Img_986.jpg
2096	Img_993.jpg	predict_images_scaled/Img_993.jpg
2097	Img_994.jpg	predict_images_scaled/Img_994.jpg
2098	Img_996.jpg	predict_images_scaled/Img_996.jpg

Now we need to link the prediction values with their associated class labels for both tasks

```
In [165]: action_labels = {}
for i in range(21):
    action_labels[i] = train_data_df["action"][train_data_df["action"] == i].values[0]

action_class_labels = {}
for i in range(5):
```

```
In [166]: . . . . .
```

```
Out[166]: {0: 'cleaning_the_floor',
 1: 'climbing',
 2: 'cooking',
 3: 'cutting_vegetables',
 4: 'feeding_a_horse',
 5: 'gardening',
 6: 'jumping',
 7: 'phoning',
 8: 'playing_guitar',
 9: 'playing_violin',
 10: 'riding_a_bike',
 11: 'riding_a_horse',
 12: 'rowing_a_boat',
 13: 'running',
 14: 'shooting_an_arrow',
 15: 'taking_photos',
 16: 'texting_message',
 17: 'using_a_computer',
 18: 'walking_the_dog',
 19: 'washing_dishes',
 20: 'watching_TV'}
```

```
In [167]: . . . . .
```

```
Out[167]:
```

```
{0: 'Interacting_with_animal',
```

Now we can make the predictions

```
In [168]: █ rows_list = []
for i in range(len(predict_df)):
    img = image.load_img(predict_df['FileName_scaled'][i])
    x = image.img_to_array(img)
    x = np.expand_dims(x, axis=0)
    x /= 255
    #images = np.vstack([x])

    prediction = best_model.predict(x)

    dict_line = {"FileName": predict_df['FileName_scaled'][i], "act."
rows_list.append(dict_line)

predictions_df = pd.DataFrame(rows_list)
predictions_df.to_csv("predictions.csv", index = False)
```

```
In [ ]: █
```

```
In [171]: █
```

```
In [ ]: █
```