monkey_species

May 13, 2019

1 Udacity Project

1.0.1 By Mayank Bhatnagar

This project is about 'Fine-Grained Categorization'. The technique is advance compared to object identification problems. We can use such techniques to recognize different species of flowers, birds or any other species. It has wider use in identifying and grouping objects and even evaluating whether we are finding a new species next existing or explored earlier.

1.1 1. Understanding Input Data and Loading Data Set

Key Import Statements

```
In [1]: ## Main Import statements
    import numpy as np
    import pandas as pd
    import cv2
    import matplotlib.pyplot as plt
    import time
    %matplotlib inline

## Loading data set
    from sklearn.datasets import load_files
    from keras.utils import np_utils
    from glob import glob
```

Using TensorFlow backend.

Summary of Data Set used in the project

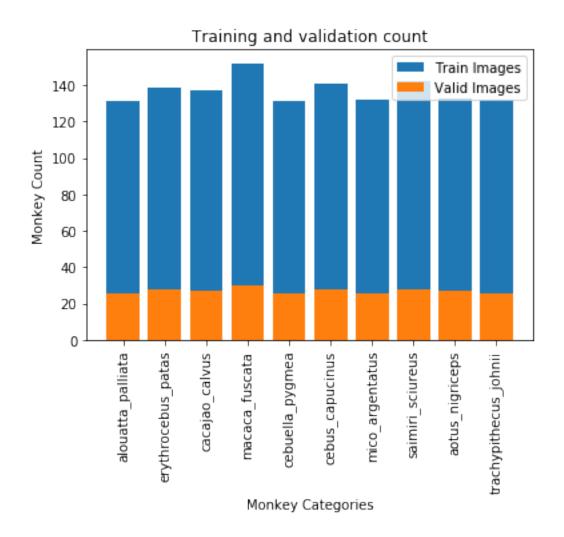
Print all the training and validation data summary print (rows)

	Label	Latin Name	Common Name	Train Images	/
0	n0	alouatta_palliata	${\tt mantled_howler}$	131	
1	n1	${ t erythrocebus_patas}$	patas_monkey	139	
2	n2	cacajao_calvus	bald_uakari	137	
3	n3	macaca_fuscata	japanese_macaque	152	
4	n4	cebuella_pygmea	$pygmy_marmoset$	131	
5	n5	cebus_capucinus	${ t white_headed_capuchin}$	141	
6	n6	${ t mico_argentatus}$	${ t silvery_marmoset}$	132	
7	n7	saimiri_sciureus	common_squirrel_monkey	142	
8	n8	aotus_nigriceps	black_headed_night_monkey	133	
9	n9	trachypithecus_johnii	nilgiri_langur	132	

```
Validation Images
0
                    26
                    28
1
                    27
2
3
                    30
4
                    26
5
                    28
6
                    26
7
                    28
8
                    27
9
                    26
```

In [4]: ## Presenting the data in a graphical format

```
plt.title('Training and validation count')
index = np.arange(len(rows))
plt.bar(index, rows['Train Images'], label='Train Images')
plt.bar(index, rows['Validation Images'], label='Valid Images')
plt.xlabel('Monkey Categories', fontsize=10)
plt.ylabel('Monkey Count', fontsize=10)
plt.xticks(index, rows['Latin Name'], fontsize=10, rotation=90)
plt.legend(loc=1)
```



Load of Data Set

```
In [5]: ## define function to load training and validation datasets
    def load_dataset(path):
        data = load_files(path)
        mon_files = np.array(data['filenames'])
        ## print(mon_files)

"""

        y = data['target']
        n = y.shape[0]
        print(y,n)
        cate = np.zeros((272,11),dtype=np.int)
        print(cate)
        print(len(cate))
        print(np.arange((n)))
```

```
print(cate[np.arange(n), y])
            cate[np.arange(n), y] = 0
            ## Check Below
            mon_targets = np_utils.to_categorical(np.array(data['target']),11)
            return mon_files, mon_targets
In [6]: ## load train and validation datasets
        train_files, train_targets = load_dataset('./training')
        valid_files, valid_targets = load_dataset('./validation')
        ## load list of monkey names
        mon_cate = [item[11:-1] for item in sorted(glob("./training/*/"))]
        mon_name = []
        for idx, item in enumerate(mon_cate):
            ## print(rows.loc[rows['Label'] == item, 'Latin Name'].iloc[0])
            mon_name.append(rows[rows['Label'] == item]['Latin Name'].iloc[0])
        ## print statistics about the dataset
        print('There are %d total monkey categories.\n' % len(mon_cate))
        print('%s \n' % rows['Latin Name'].iloc[0:len(mon_cate)])
        print('There are %s total monkey images.' % len(np.hstack([train_files, valid_files])))
        print('There are %d training monkey images.' % len(train_files))
        print('There are %d validation monkey images.' % len(valid_files))
There are 10 total monkey categories.
0
         alouatta_palliata
1
        erythrocebus_patas
2
            cacajao_calvus
3
            macaca_fuscata
4
           cebuella_pygmea
5
           cebus_capucinus
6
           mico_argentatus
7
          saimiri_sciureus
8
           aotus_nigriceps
     trachypithecus_johnii
Name: Latin Name, dtype: object
There are 1365 total monkey images.
There are 1093 training monkey images.
There are 272 validation monkey images.
```

1.2 2. Pre-Processing of Data

```
In [7]: from keras.preprocessing import image
        from tqdm import tqdm
        def path_to_tensor(img_path):
            ## loads RGB image as PIL.Image.Image type
            img = image.load_img(img_path, target_size=(224, 224))
            ## convert PIL. Image. Image type to 3D tensor with shape (224, 224, 3)
            x = image.img_to_array(img)
            ## convert 3D tensor to 4D tensor with shape (1, 224, 224, 3) and return 4D tensor
            return np.expand_dims(x, axis=0)
        def paths_to_tensor(img_paths):
            list_of_tensors = [path_to_tensor(img_path) for img_path in tqdm(img_paths)]
            return np.vstack(list_of_tensors)
In []: ## display the image, along with bounding box
        ## plt.imshow(cv_rqb)
        ## plt.show()
In [8]: ## Rescaling the images between 0 and 1
        from PIL import ImageFile
        ImageFile.LOAD_TRUNCATED_IMAGES = True
        ## pre-process the data for Keras
        train_tensors = paths_to_tensor(train_files).astype('float32')/255
        valid_tensors = paths_to_tensor(valid_files).astype('float32')/255
100%|| 1093/1093 [00:31<00:00, 34.20it/s]
100%|| 272/272 [00:08<00:00, 30.74it/s]
```

1.3 3. Creating a Benchmark ResNet50 and VGG16 model

```
In [9]: ## Common functions for Creating Benchmarking

from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D
from keras.layers import Dropout, Flatten, Dense
from keras.models import Sequential
from keras import backend

from keras.models import Sequential, Model
from keras.optimizers import Adam, SGD

from keras.applications.resnet50 import ResNet50
from keras.applications.vgg16 import VGG16
```

1.3.1 Creating ResNET50 model using three modularized functions

ResNet50_mod => Create ResNet50 model
 train_model => Train the created model
 create_graph => Plot Accuracy and Loss functions

```
In [10]: ## Creating a ResNet50 Model after clearing session
         def ResNet50_mod():
             ## To clear memory from the model. Remove the comment and run.
             backend.clear session()
             ## To create a new model
             ResNet50_model = ResNet50(weights='imagenet',include_top=False,input_shape=(224,224
             x = ResNet50_model.output
             x = Dense(512, activation='relu')(x)
             x = Dropout(0.5)(x)
             x = Dense(512, activation='relu')(x)
             x = Dropout(0.5)(x)
             output = Dense(11, activation='softmax', name='custom_output')(x) ## Need to check
             ResNet50_T_model = Model(inputs=ResNet50_model.input, outputs = output)
             ## Suppressing retraining of already trained model
             for layer in ResNet50_model.layers:
                 layer.trainable = False
             ## Compiling the model
             ResNet50_T_model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metr
             ## Checking how does the complie process work with Adm optimizer
             ## ResNet50_T_model.compile(Adam(lr=0.001), loss='categorical_crossentropy', metric
             return ResNet50_T_model
In [11]: ## This is an additional logic
         def train_model(model, epochs_val, batch_val):
             acc = []
             val_acc = []
             loss = []
             val_loss = []
             test_accu = []
             time_taken = []
             for e_val in epochs_val:
                 for b_val in batch_val:
                     print (e_val, ' ', b_val)
                     ## Calling function to create the model
                     #monkey_model = monkey_mod()
```

```
## Start tracking the time
                     start_time = time.time()
                     ## Training the model and capturing the history
                     model_history = model.fit(train_tensors, train_targets,
                                         validation_data=(valid_tensors, valid_targets),
                                         epochs=e_val, batch_size=b_val, callbacks=None, verbose
                     ## Stop tracking the time
                     end_time = time.time()
                     time_taken.append(end_time - start_time)
                     ## Capture accuracy and loss information
                     acc.append(model_history.history['acc'])
                     val_acc.append(model_history.history['val_acc'])
                     loss.append(model_history.history['loss'])
                     val_loss.append(model_history.history['val_loss'])
                     ## Getting prediction and accuracy details
                     mon_predictions = [np.argmax(model.predict(np.expand_dims(tensor, axis=0)))
                     ## report test accuracy
                     test_accuracy = 100*np.sum(np.array(mon_predictions)==np.argmax(valid_targe
                     print('Test accuracy: %.4f%%' % test_accuracy)
                     test_accu.append(test_accuracy)
                     ## Printing the training time taken
                     print('Training Time: %s sec' % time_taken)
             ## Create Plot for the model
             ## create_graph(epochs_val, batch_val, acc, val_acc, loss, val_loss, test_accu)
             return (acc, val_acc, loss, val_loss, test_accu, time_taken)
In [12]: ## Plotting all the graphs together as a generic function
         def create_graph(epochs_val, batch_val, acc, val_acc, loss, val_loss, test_acc, time_ta
             x = 0
             ## Iterate for all the values for each epochs
             for e_val in epochs_val:
                 for b_val in batch_val:
                     plt.title('Training and validation accuracy: Epoch (' + str(e_val) + '), Ba
                     plt.plot(range(1,e_val+1), acc[x], 'red', label='Training acc')
                     plt.plot(range(1,e_val+1), val_acc[x], 'blue', label='Validation acc')
                     plt.xlabel('No. of Epochs')
                     plt.ylabel('Accuracy Value')
                     plt.legend()
```

```
plt.title('Training and validation loss: Epoch (' + str(e_val) + '), Batch
            plt.plot(range(1,e_val+1), loss[x], 'red', label='Training loss')
            plt.plot(range(1,e_val+1), val_loss[x], 'blue', label='Validation loss')
            plt.xlabel('No. of Epochs')
            plt.ylabel('Loss Value')
            plt.legend()
            plt.show()
            ## Printing accuracy information for each batch run
            print('Test Accuracy: %.4f%%' % test_accu[x])
            ## Printing the training time taken
            print('Training Time: %s sec' % time_taken[x])
            x += 1
In [13]: ### Create model and train
     ## Submitting with below
     epochs_val = [10, 20, 40]
     batch_val = [16,32]
     ## Test with below
     \#epochs\_val = [10]
     #batch_val = [32]
     ## Create and train the model
     model = ResNet50_mod()
     (acc, val_acc, loss, val_loss, test_accu, time_taken) = train_model(model, epochs_val,
Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.2/re
Train on 1093 samples, validate on 272 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
```

plt.figure()

```
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Test accuracy: 26.8382%
Training Time: [170.2390956878662] sec
10
Train on 1093 samples, validate on 272 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Test accuracy: 94.4853%
Training Time: [170.2390956878662, 142.29511785507202] sec
Train on 1093 samples, validate on 272 samples
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
```

```
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
Test accuracy: 95.9559%
Training Time: [170.2390956878662, 142.29511785507202, 333.946396112442] sec
20
Train on 1093 samples, validate on 272 samples
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
```

```
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
Test accuracy: 95.5882%
Training Time: [170.2390956878662, 142.29511785507202, 333.946396112442, 284.02110266685486] sec
Train on 1093 samples, validate on 272 samples
Epoch 1/40
Epoch 2/40
Epoch 3/40
Epoch 4/40
Epoch 5/40
Epoch 6/40
Epoch 7/40
Epoch 8/40
Epoch 9/40
Epoch 10/40
```

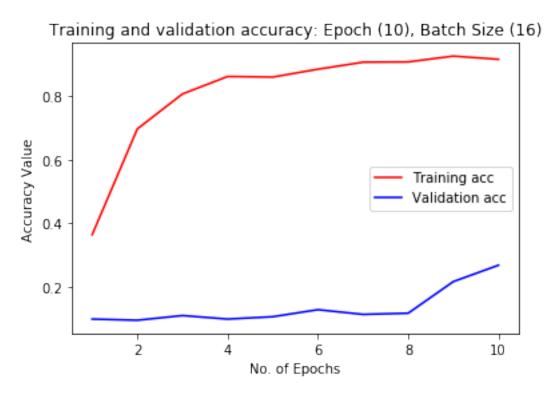
```
Epoch 11/40
Epoch 12/40
Epoch 13/40
Epoch 14/40
Epoch 15/40
Epoch 16/40
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
Epoch 29/40
Epoch 30/40
Epoch 31/40
Epoch 32/40
Epoch 33/40
Epoch 34/40
```

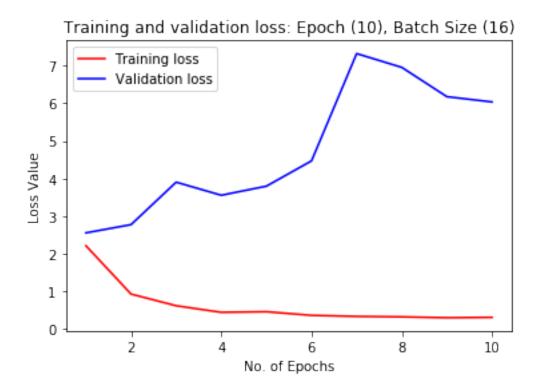
```
Epoch 35/40
Epoch 36/40
Epoch 37/40
Epoch 38/40
Epoch 39/40
Epoch 40/40
Test accuracy: 95.2206%
Training Time: [170.2390956878662, 142.29511785507202, 333.946396112442, 284.02110266685486, 666
Train on 1093 samples, validate on 272 samples
Epoch 1/40
Epoch 2/40
Epoch 3/40
Epoch 4/40
Epoch 5/40
Epoch 6/40
Epoch 7/40
Epoch 8/40
Epoch 9/40
Epoch 10/40
Epoch 11/40
Epoch 12/40
Epoch 13/40
Epoch 14/40
Epoch 15/40
Epoch 16/40
```

```
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
Epoch 29/40
Epoch 30/40
Epoch 31/40
Epoch 32/40
Epoch 33/40
Epoch 34/40
Epoch 35/40
Epoch 36/40
Epoch 37/40
Epoch 38/40
Epoch 39/40
Epoch 40/40
```

Test accuracy: 94.8529%

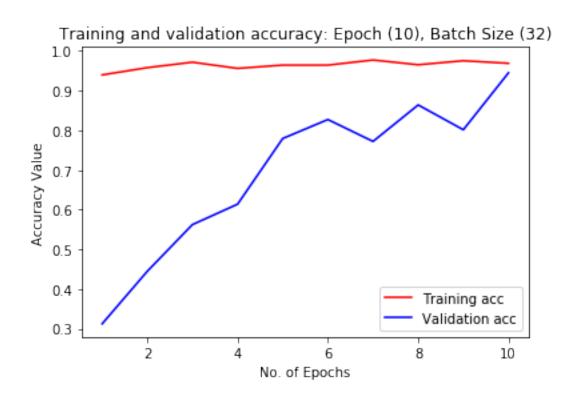
Training Time: [170.2390956878662, 142.29511785507202, 333.946396112442, 284.02110266685486, 666

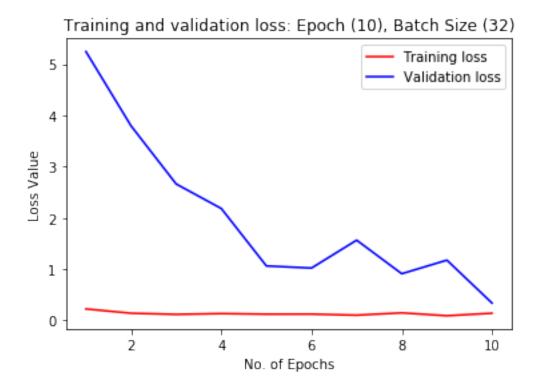




Test Accuracy: 26.8382%

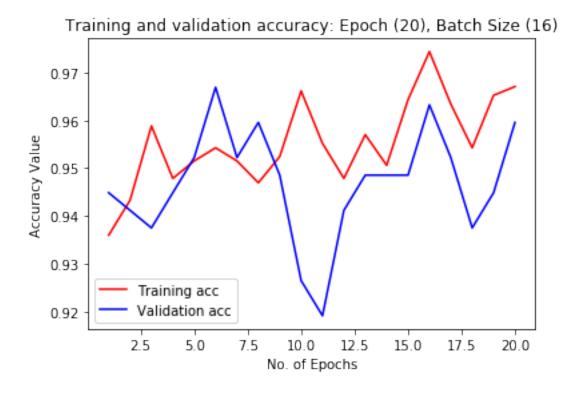
Training Time: 170.2390956878662 sec

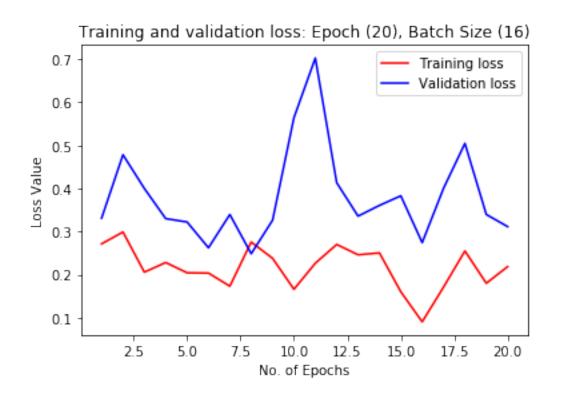




Test Accuracy: 94.4853%

Training Time: 142.29511785507202 sec

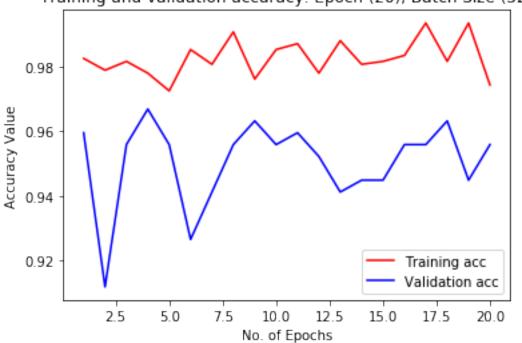


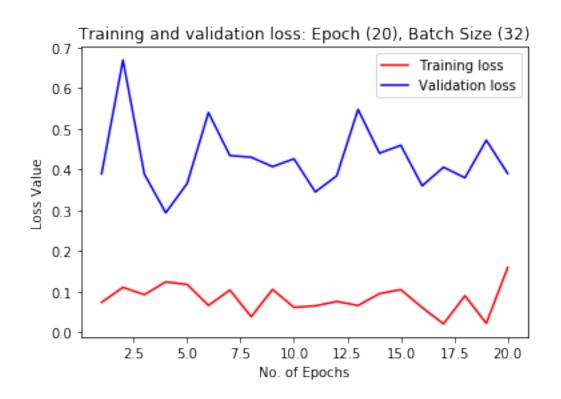


Test Accuracy: 95.9559%

Training Time: 333.946396112442 sec

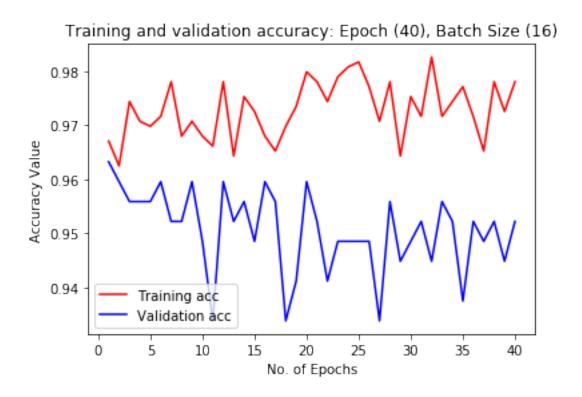


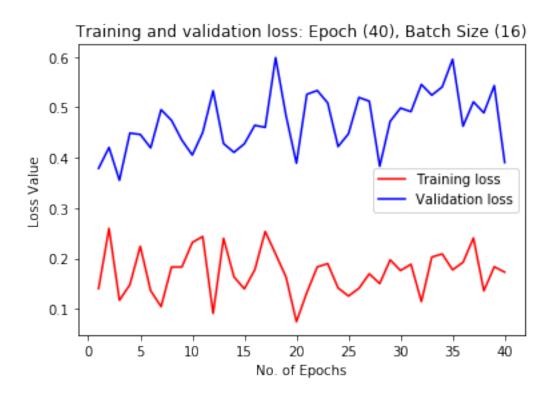




Test Accuracy: 95.5882%

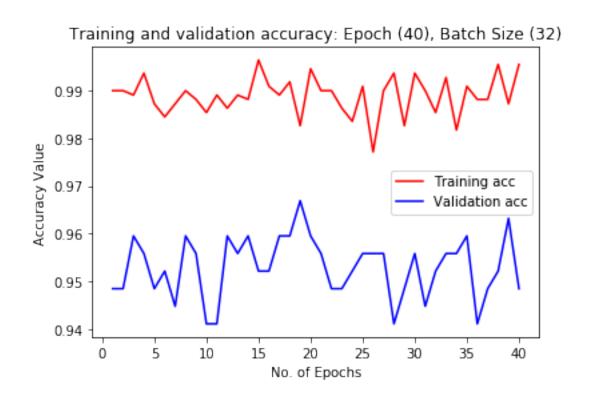
Training Time: 284.02110266685486 sec

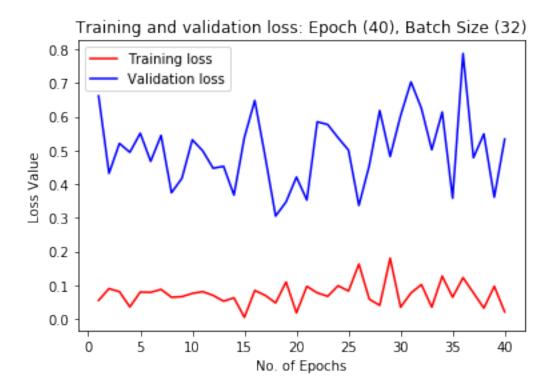




Test Accuracy: 95.2206%

Training Time: 666.5932734012604 sec





Test Accuracy: 94.8529%

Training Time: 566.6708428859711 sec

1.3.2 Creating VGG16 model using three modularized functions

Created New Function

1. VGG16_mod => Create VGG16 model

Used Existing Function

- 2. train_model => Train the created model
- 3. create_graph => Plot Accuracy and Loss functions

To clear memory from the model. Remove the comment and run.
backend.clear_session()

To create a new model

```
x = Dense(512, activation='relu')(x)
         x = Dropout(0.5)(x)
         x = Dense(512, activation='relu')(x)
         x = Dropout(0.5)(x)
         output = Dense(11, activation='softmax', name='custom_output')(x) ## Check why it of
         VGG16_T_model = Model(inputs=VGG16_model.input, outputs = output)
         ## Suppressing retraining of already trained model
         for layer in VGG16_model.layers:
            layer.trainable = False
         ## Compiling the model
         VGG16_T_model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics
         ## Checking how does the complie process work with Adm optimizer
         ## ResNet50_T_model.compile(Adam(lr=0.001), loss='categorical_crossentropy', metric
         return VGG16_T_model
In [16]: ### Create model and train
      ## Submitting with below
      epochs_val = [10, 20, 40]
      batch_val = [16,32]
      ## Test with below
      \#epochs\_val = [10]
      #batch_val = [32]
      ## Create and train model
      model = VGG16_mod()
      (acc, val_acc, loss, val_loss, test_accu, time_taken) = train_model(model, epochs_val,
Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.1/vg
58892288/58889256 [============= ] - 1s Ous/step
10
Train on 1093 samples, validate on 272 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
```

VGG16_model = VGG16(weights='imagenet',include_top=False,input_shape=(224,224,3),

x = VGG16_model.output

```
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Test accuracy: 65.8088%
Training Time: [261.41396284103394] sec
Train on 1093 samples, validate on 272 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Test accuracy: 74.2647%
Training Time: [261.41396284103394, 230.02988648414612] sec
20
Train on 1093 samples, validate on 272 samples
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
```

```
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
Test accuracy: 81.2500%
Training Time: [261.41396284103394, 230.02988648414612, 516.8229987621307] sec
Train on 1093 samples, validate on 272 samples
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
```

```
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
Test accuracy: 83.0882%
Training Time: [261.41396284103394, 230.02988648414612, 516.8229987621307, 454.4341125488281] se
40
Train on 1093 samples, validate on 272 samples
Epoch 1/40
Epoch 2/40
Epoch 3/40
Epoch 4/40
Epoch 5/40
Epoch 6/40
Epoch 7/40
Epoch 8/40
Epoch 9/40
Epoch 10/40
```

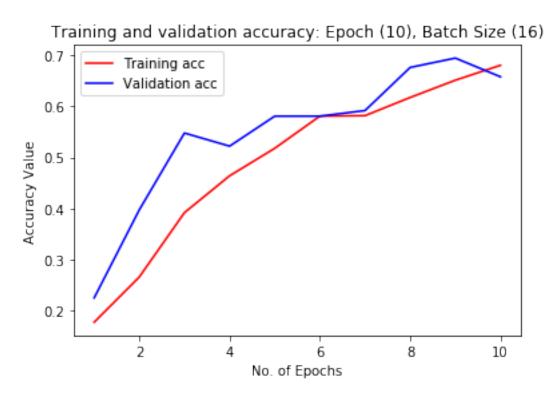
```
Epoch 11/40
Epoch 12/40
Epoch 13/40
Epoch 14/40
Epoch 15/40
Epoch 16/40
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
Epoch 29/40
Epoch 30/40
Epoch 31/40
Epoch 32/40
Epoch 33/40
Epoch 34/40
```

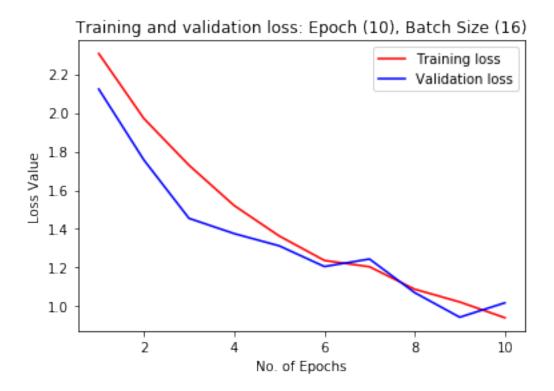
```
Epoch 35/40
Epoch 36/40
Epoch 37/40
Epoch 38/40
Epoch 39/40
Epoch 40/40
Test accuracy: 85.2941%
Training Time: [261.41396284103394, 230.02988648414612, 516.8229987621307, 454.4341125488281, 10
Train on 1093 samples, validate on 272 samples
Epoch 1/40
Epoch 2/40
Epoch 3/40
Epoch 4/40
Epoch 5/40
Epoch 6/40
Epoch 7/40
Epoch 8/40
Epoch 9/40
Epoch 10/40
Epoch 11/40
Epoch 12/40
Epoch 13/40
Epoch 14/40
Epoch 15/40
Epoch 16/40
```

```
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
Epoch 29/40
Epoch 30/40
Epoch 31/40
Epoch 32/40
Epoch 33/40
Epoch 34/40
Epoch 35/40
Epoch 36/40
Epoch 37/40
Epoch 38/40
Epoch 39/40
Epoch 40/40
```

Test accuracy: 85.6618%

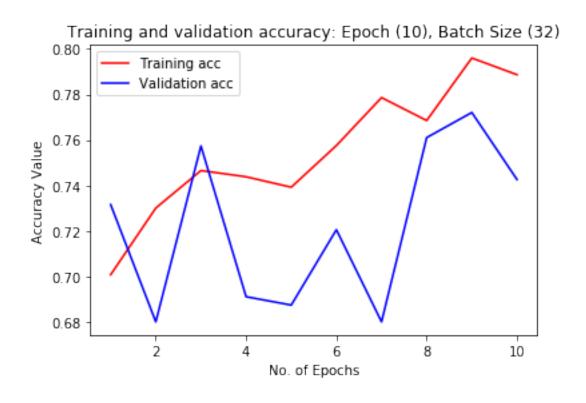
Training Time: [261.41396284103394, 230.02988648414612, 516.8229987621307, 454.4341125488281, 10

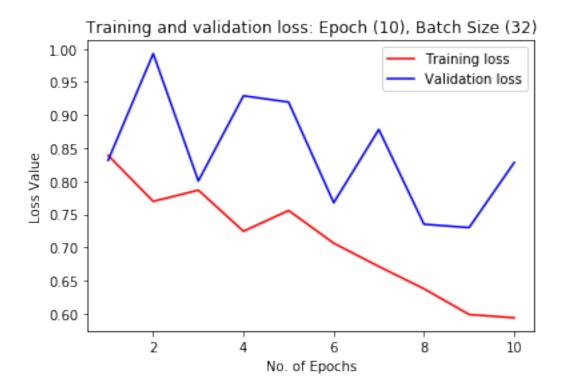




Test Accuracy: 65.8088%

Training Time: 261.41396284103394 sec

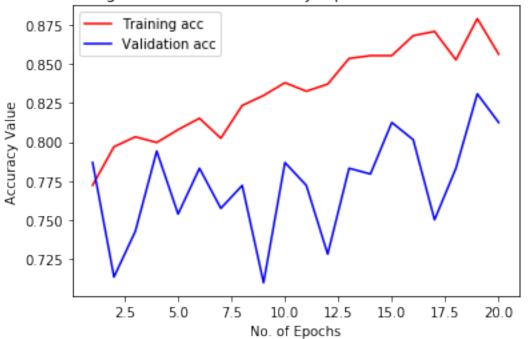


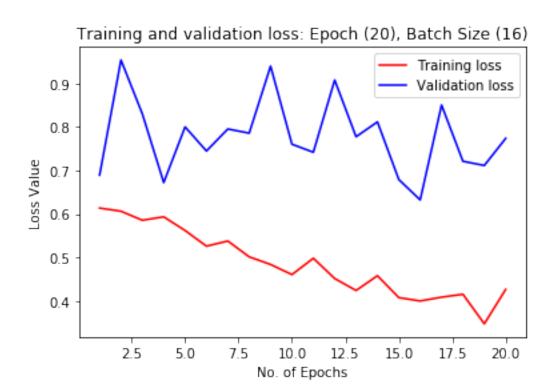


Test Accuracy: 74.2647%

Training Time: 230.02988648414612 sec

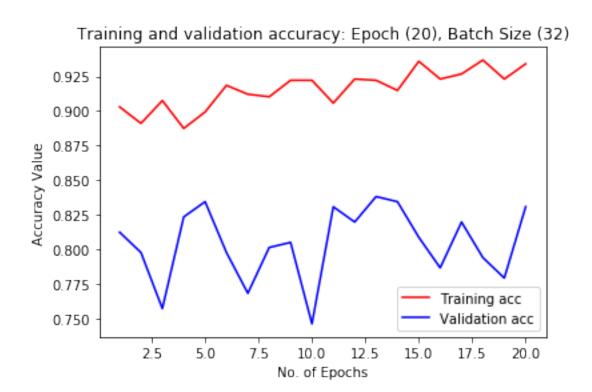


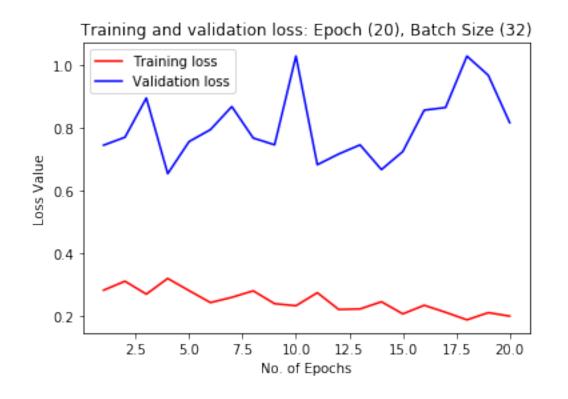




Test Accuracy: 81.2500%

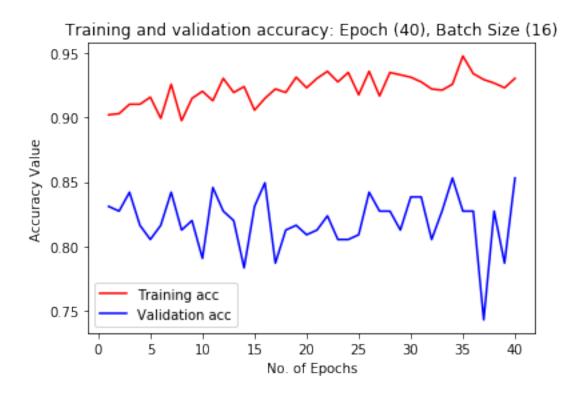
Training Time: 516.8229987621307 sec

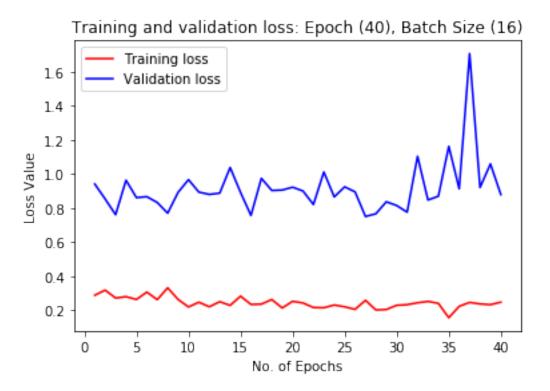




Test Accuracy: 83.0882%

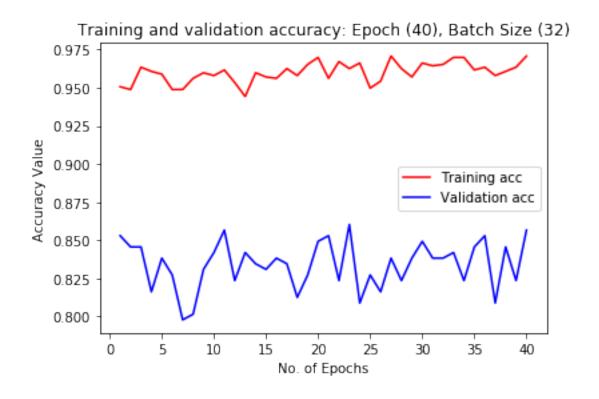
Training Time: 454.4341125488281 sec

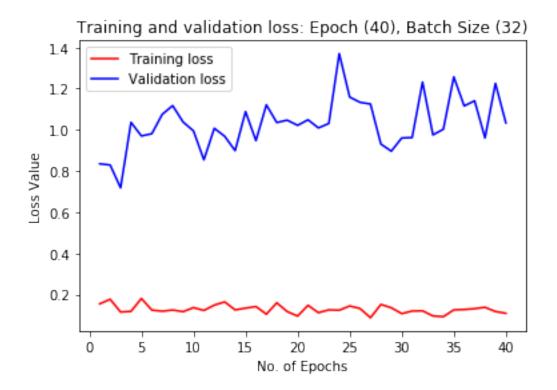




Test Accuracy: 85.2941%

Training Time: 1033.9515569210052 sec





Test Accuracy: 85.6618%

Training Time: 907.8175492286682 sec

1.4 4. Creating a CNN Model from Scratch

Create a CNN model with initial size of 224, 224, 3. CNN model would consist of following steps:

- a. Convolutional Layer with initial Input (244, 224, 3)
- b. Max Pooling to reduce special dimension
- c. Convolutional Layer
- d. Max Pooling
- e. Dropout
- f. Dense
- g. Softmax

1.4.1 Creating New model using three modularized functions

Created a New Function

1. monkey_mod => Creat new CNN model

Used Existing Functions

2. train model => Train the created model

Submitting with below

3. create_graph => Plot Accuracy and Loss functions

```
In [18]: ## Creating a Model from scratch after clearing session
         def monkey_mod():
             ## To clear memory from the model. Remove the comment and run.
             backend.clear session()
             ## To create a new model
             model = Sequential()
             model.add(Conv2D(filters=16, kernel_size=2, padding='same', activation='relu', inpu
             model.add(MaxPooling2D(pool_size=2))
             model.add(Conv2D(filters=32, kernel_size=2, padding='same', activation='relu'))
             model.add(MaxPooling2D(pool_size=2))
             model.add(Conv2D(filters=64, kernel_size=2, padding='same', activation='relu'))
             model.add(MaxPooling2D(pool_size=2))
             model.add(Conv2D(filters=128, kernel_size=2, padding='same', activation='relu'))
             model.add(MaxPooling2D(pool_size=2))
             model.add(Dropout(0.3))
             model.add(Dense(256, activation='relu'))
             ## Following doesn't make model efficient
             #model.add(Dropout(0.3))
             #model.add(Dense(128, activation='relu'))
             #model.add(Dropout(0.3))
             #model.add(Dense(64, activation='relu'))
             #model.add(Dropout(0.3))
             #model.add(Dense(32, activation='relu'))
             model.add(Flatten())
             model.add(Dense(11, activation='relu'))
             model.add(Dropout(0.3))
             model.add(Dense(11, activation='softmax'))
             ## Compiling the model
             model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accur
             return model
In [19]: ### Create model and train
```

```
epochs_val = [10, 20, 40]
  batch_val = [16,32]
  ## Test with below
  \#epochs\_val = [10]
  #batch_val = [32]
  model = monkey_mod()
  (acc, val_acc, loss, val_loss, test_accu, time_taken) = train_model(model, epochs_val,
10
Train on 1093 samples, validate on 272 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Test accuracy: 41.9118%
Training Time: [44.07009315490723] sec
Train on 1093 samples, validate on 272 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
```

```
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Test accuracy: 49.2647%
Training Time: [44.07009315490723, 40.20986723899841] sec
20
Train on 1093 samples, validate on 272 samples
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
```

```
Epoch 19/20
Epoch 20/20
Test accuracy: 52.2059%
Training Time: [44.07009315490723, 40.20986723899841, 85.70699787139893] sec
Train on 1093 samples, validate on 272 samples
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
```

```
Test accuracy: 53.6765%
Training Time: [44.07009315490723, 40.20986723899841, 85.70699787139893, 80.04647326469421] sec
Train on 1093 samples, validate on 272 samples
Epoch 1/40
Epoch 2/40
Epoch 3/40
Epoch 4/40
Epoch 5/40
Epoch 6/40
Epoch 7/40
Epoch 8/40
Epoch 9/40
Epoch 10/40
Epoch 11/40
Epoch 12/40
Epoch 13/40
Epoch 14/40
Epoch 15/40
Epoch 16/40
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
```

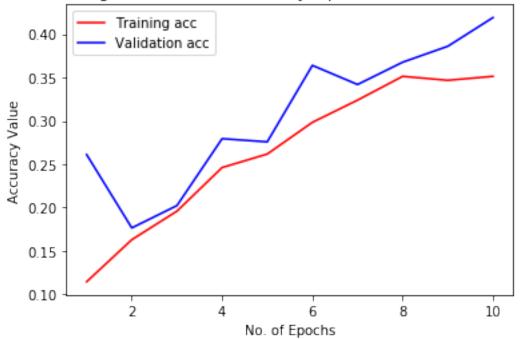
```
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
Epoch 29/40
Epoch 30/40
Epoch 31/40
Epoch 32/40
Epoch 33/40
Epoch 34/40
Epoch 35/40
Epoch 36/40
Epoch 37/40
Epoch 38/40
Epoch 39/40
Epoch 40/40
Test accuracy: 53.6765%
Training Time: [44.07009315490723, 40.20986723899841, 85.70699787139893, 80.04647326469421, 172.
40
Train on 1093 samples, validate on 272 samples
Epoch 1/40
Epoch 2/40
Epoch 3/40
Epoch 4/40
```

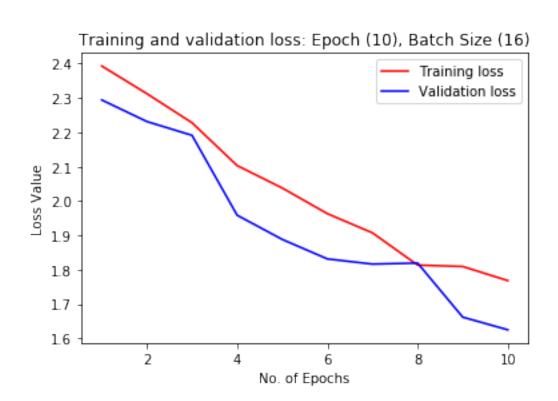
```
Epoch 5/40
Epoch 6/40
Epoch 7/40
Epoch 8/40
Epoch 9/40
Epoch 10/40
Epoch 11/40
Epoch 12/40
Epoch 13/40
Epoch 14/40
Epoch 15/40
Epoch 16/40
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
```

```
Epoch 30/40
Epoch 31/40
Epoch 32/40
Epoch 33/40
Epoch 34/40
Epoch 35/40
Epoch 36/40
Epoch 37/40
Epoch 38/40
Epoch 39/40
Epoch 40/40
Test accuracy: 55.5147%
Training Time: [44.07009315490723, 40.20986723899841, 85.70699787139893, 80.04647326469421, 172.
```

Epoch 29/40

Training and validation accuracy: Epoch (10), Batch Size (16)

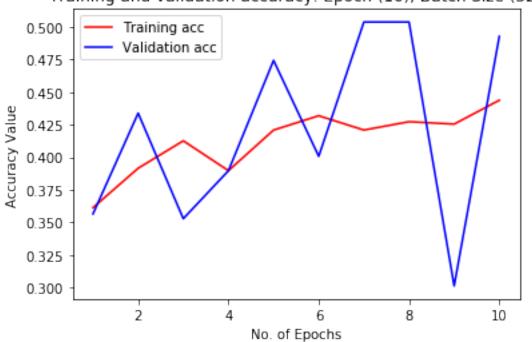




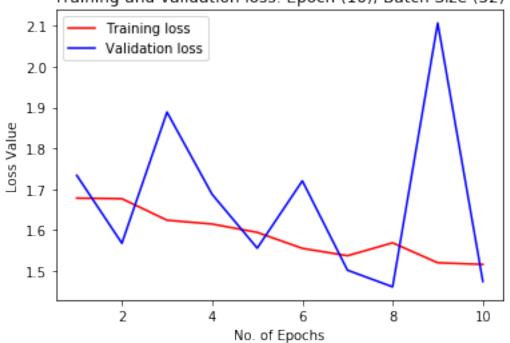
Test Accuracy: 41.9118%

Training Time: 44.07009315490723 sec





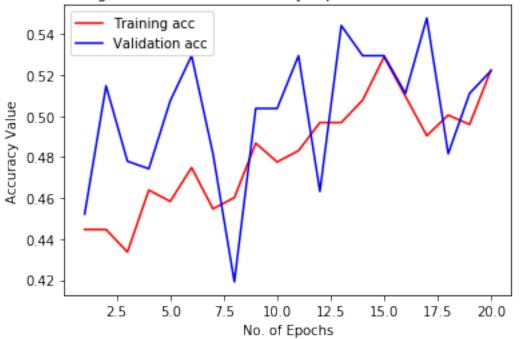
Training and validation loss: Epoch (10), Batch Size (32)

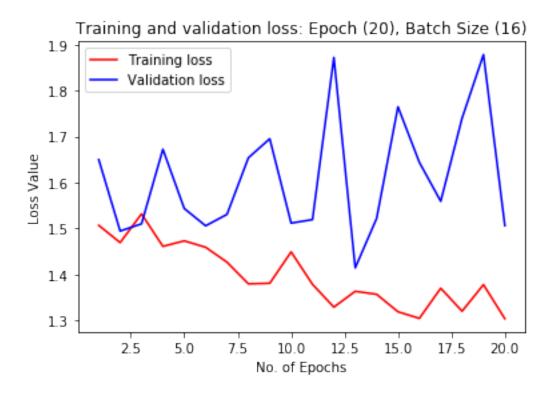


Test Accuracy: 49.2647%

Training Time: 40.20986723899841 sec

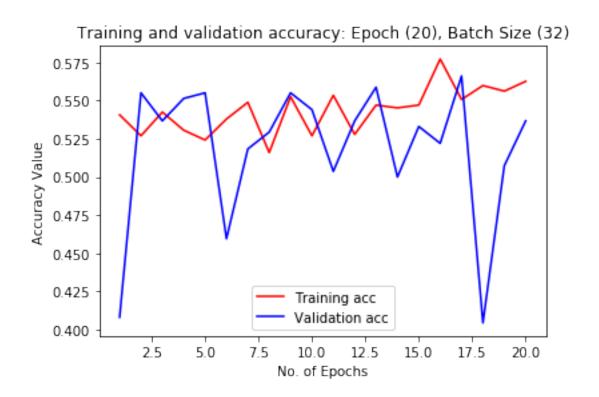


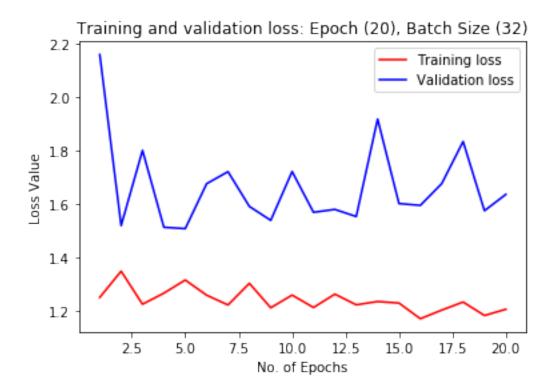




Test Accuracy: 52.2059%

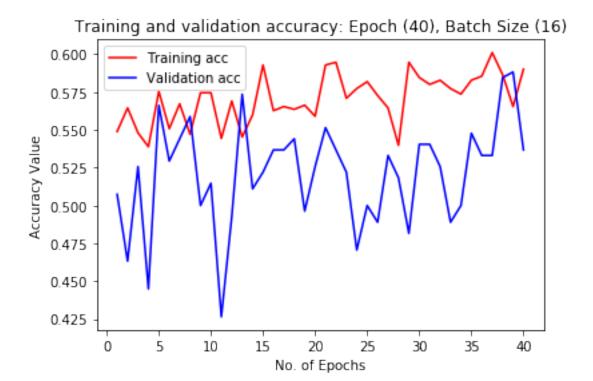
Training Time: 85.70699787139893 sec

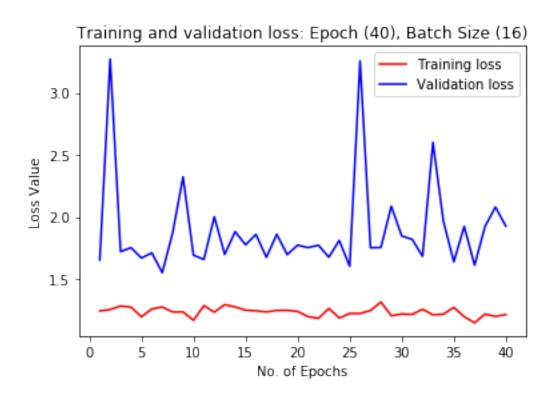




Test Accuracy: 53.6765%

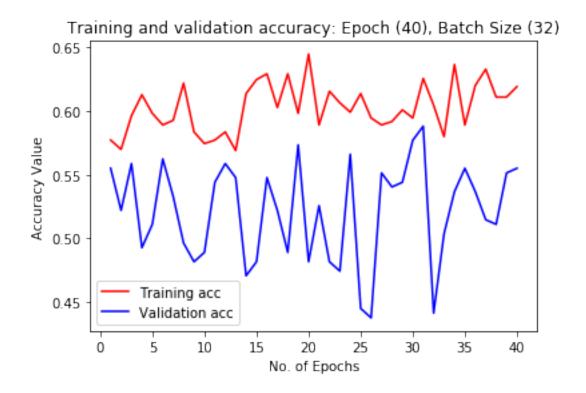
Training Time: 80.04647326469421 sec

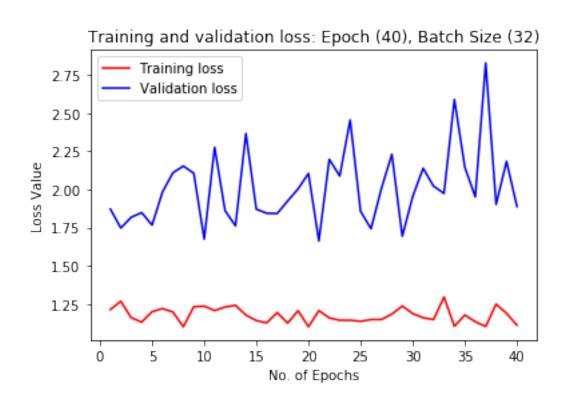




Test Accuracy: 53.6765%

Training Time: 172.35104942321777 sec





Test Accuracy: 55.5147%

Training Time: 159.63770246505737 sec

1.5 #### End of Project