Bee_Classification_1

June 29, 2021

0.1 Classification of Sub Species of Bees By Transfer Learning

0.2 Required Libraries

Necessary libraries are imported and loaded.

[2]:
```
import pandas as pd
import numpy as np
import seaborn as snsaa
import matplotlib.pyplot as plt

import skimage
import skimage.io
import skimage.transform
import random
import sys
import os
import imageio

import scipy
from sklearn.model_selection import train_test_split
from sklearn import metrics

import plotly.graph_objs as go
import plotly.figure_factory as ff
from plotly import tools
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)

import tensorflow as tf
from tensorflow import keras

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
#from tf.keras.preprocessing.image import ImageDataGenerator
```

0.3 Data Preprocessing

Data Frame is created and structured from the csv file.

[3]:
```
Img_path = 'D:/Semester_4/DL/Project/bee_imgs/bee_imgs/'
Img_width = 100
Img_height = 100
Img_channel = 3

#Random_state = 2018
```

[4]:
```
#os.listdir("D:/Semester_4/DL/Project")
bee_df = pd.read_csv('D:/Semester_4/DL/Project/bee_data.csv')
bee_df.shape
bee_df.head(n=10)
```

[4]:

	file	date	time	location	zip code	subspecies	health	pollen_carrying	caste
0	041_066.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
1	041_072.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
2	041_073.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
3	041_067.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
4	041_059.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
5	041_071.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
6	041_065.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
7	041_064.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
8	041_070.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker
9	041_058.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	hive being robbed	False	worker

[5]:
```
img_files = list(os.listdir(Img_path))
print(len(img_files))
```

```
5172
```

[6]:
```
file_names = list(bee_df['file'])
print(len(file_names))
```

```
5172
```

[7]:
```
def read_image_size(file_name):
    image = skimage.io.imread(Img_path+file_name)
```

```
    return list(image.shape)
```

[8]:
```
m = np.stack(bee_df['file'].apply(read_image_size))
df = pd.DataFrame(m,columns = ['w','h','c'])
bee_df = pd.concat([bee_df,df],axis = 1,sort=False)
bee_df.head(n=10)
```

[8]:

	file	date	time	location	zip code	subspecies	\
0	041_066.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
1	041_072.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
2	041_073.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
3	041_067.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
4	041_059.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
5	041_071.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
6	041_065.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
7	041_064.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
8	041_070.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	
9	041_058.png	8/28/18	16:07	Alvin, TX, USA	77511	-1	

	health	pollen_carrying	caste	w	h	c
0	hive being robbed	False	worker	115	164	3
1	hive being robbed	False	worker	201	90	3
2	hive being robbed	False	worker	132	167	3
3	hive being robbed	False	worker	134	97	3
4	hive being robbed	False	worker	147	106	3
5	hive being robbed	False	worker	194	135	3
6	hive being robbed	False	worker	159	170	3
7	hive being robbed	False	worker	132	95	3
8	hive being robbed	False	worker	126	190	3
9	hive being robbed	False	worker	156	189	3

0.4 Subspecies catagorization

Subspecies of bees are shown with no.of available images for each subspecies.

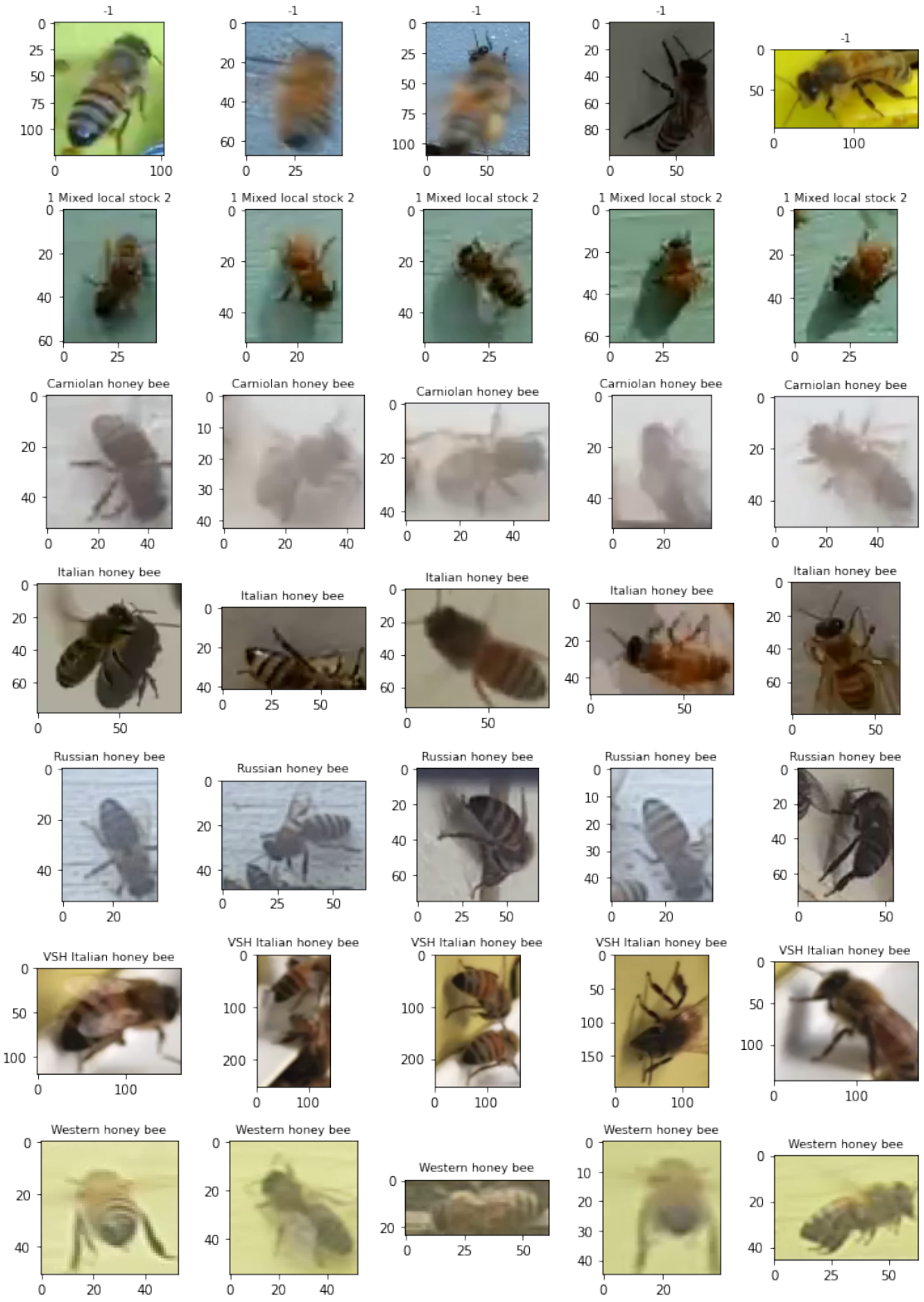
[9]:
```
temp = bee_df.groupby(['caste'])['subspecies'].value_counts()
df = pd.DataFrame(data = {'Images':temp.values}, index=temp.index)
df.reset_index()
```

[9]:

	caste	subspecies	Images
0	worker	Italian honey bee	3008
1	worker	Russian honey bee	527
2	worker	Carniolan honey bee	501
3	worker	1 Mixed local stock 2	472
4	worker	-1	428
5	worker	VSH Italian honey bee	199
6	worker	Western honey bee	37

[10]:
```
def draw_category_images(var,cols=5):
    categories = (bee_df.groupby([var])[var].nunique()).index
    f, ax = plt.subplots(nrows=len(categories),ncols=cols,␣
 ↪figsize=(2*cols,2*len(categories)))
    # draw a number of images for each location
    for i, cat in enumerate(categories):
        sample = bee_df[bee_df[var]==cat].sample(cols)
        for j in range(0,cols):
            file=Img_path + sample.iloc[j]['file']
            im=imageio.imread(file)
            ax[i, j].imshow(im, resample=True)
            ax[i, j].set_title(cat, fontsize=9)
    plt.tight_layout()
    plt.show()
```

[11]:
```
draw_category_images("subspecies")
```



Sample images of bees of different subspecies.

1 Sub species Classification

1.1 Data preparation for Model

Creating random dataset of Train, Test and Validation.

[12]:
```
train_data, test_data = train_test_split(bee_df, test_size = 0.2, random_state␣
↪= 2018, stratify = bee_df['subspecies'] )
```

[13]:
```
train_data, val_data = train_test_split(train_data, test_size = 0.2,␣
↪random_state = 2018, stratify = train_data['subspecies'] )
```

[14]:
```
print("Train set rows: {}".format(train_data.shape[0]))
print("Test  set rows: {}".format(test_data.shape[0]))
print("Val   set rows: {}".format(val_data.shape[0]))
```

```
Train set rows: 3309
Test  set rows: 1035
Val   set rows: 828
```

1.2 Data Augumentation

[15]:
```
def read_image(file_name):
    image = skimage.io.imread(Img_path+file_name)
    image = skimage.transform.
↪resize(image,(Img_width,Img_height),mode='reflect')
    return image[:,:,:Img_channel]
```

[16]:
```
def categories_encoder(dataset, var='subspecies'):
    X = np.stack(dataset['file'].apply(read_image))
    y = pd.get_dummies(dataset[var], drop_first=False)
    return X, y
```

[17]:
```
X_train, y_train = categories_encoder(train_data)
X_val, y_val = categories_encoder(val_data)
X_test, y_test = categories_encoder(test_data)
```

[18]:
```
image_generator = tf.keras.preprocessing.image.ImageDataGenerator(
        featurewise_center=False,
        samplewise_center=False,
        featurewise_std_normalization=False,
        samplewise_std_normalization=False,
        zca_whitening=False,
        rotation_range=180,
        zoom_range = 0.1,
        width_shift_range=0.1,
        height_shift_range=0.1,
        horizontal_flip=True,
        vertical_flip=True)
```

```
image_generator.fit(X_train)
```

1.3 Transfer Learning Model

VGG19 model pre-loaded with weights trained on ImageNet. By specifying the include_top=False argument, we load a network that doesn't include the classification layers, which is ideal for feature extraction.

[19]:
```
IMG_SHAPE = (Img_width, Img_height, 3)

# Create the base model from the pre-trained model MobileNet V2
feature_extractor = tf.keras.applications.vgg19.VGG19(input_shape=IMG_SHAPE,
                                                      include_top=False,
                                                      weights= 'imagenet')
```

```
WARNING:tensorflow:From F:\Python\envs\workflowone\lib\site-
packages\tensorflow\python\ops\init_ops.py:1251: calling
VarianceScaling.__init__ (from tensorflow.python.ops.init_ops) with dtype is
deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the
constructor
```

1.4 Feature Extraction

We will freeze the layers of the VGG19 and utilize the feature extractor capabilities of this part of the network. By adding a classification layer on top of it and training the top-level classifier on our data we repurpose the pretrained model. Freezing means keeping the respective weights from updating in the weight update phase of the training process.

[20]:
```
feature_extractor.trainable = False

feature_extractor.summary()
```

```
Model: "vgg19"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 100, 100, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 100, 100, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 100, 100, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 50, 50, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 50, 50, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 50, 50, 128)       147584
```

```
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 25, 25, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 25, 25, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 25, 25, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 25, 25, 256)       590080
_________________________________________________________________
block3_conv4 (Conv2D)        (None, 25, 25, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 12, 12, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 12, 12, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 12, 12, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 12, 12, 512)       2359808
_________________________________________________________________
block4_conv4 (Conv2D)        (None, 12, 12, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 6, 6, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 6, 6, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 6, 6, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 6, 6, 512)         2359808
_________________________________________________________________
block5_conv4 (Conv2D)        (None, 6, 6, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 3, 3, 512)         0
=================================================================
Total params: 20,024,384
Trainable params: 0
Non-trainable params: 20,024,384
_________________________________________________________________
```

1. The classification layer is added here to the base model with required no of outputs. And new combined model is compiled
2. The activation function used here is softmax as we needed a probability distribution.
3. The loss function used is categorical_crossentropy as this is a multi-class classification task.
4. Optimizer used is RMSprop as it uses a moving average of squared gradients to normalize the gradient itself. That has an effect of balancing the step size — decrease the step for large gradient to avoid exploding, and increase the step for small gradient to avoid vanishing

[21]:
```
model = tf.keras.Sequential([
  feature_extractor,
  tf.keras.layers.GlobalAveragePooling2D(),
  tf.keras.layers.Dense(y_train.columns.size, activation='softmax')
])
#'''By doing a global average we make the convolution invariant to where the␣
 ↪object of interest is and this acts as a data augmentaiton of moving the␣
 ↪object around to different regions. This prevents overfitting of the fc␣
 ↪layers.'''
model.compile(optimizer=tf.keras.optimizers.RMSprop(lr=0.01),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg19 (Model)                (None, 3, 3, 512)         20024384
_________________________________________________________________
global_average_pooling2d (Gl (None, 512)               0
_________________________________________________________________
dense (Dense)                (None, 7)                 3591
=================================================================
Total params: 20,027,975
Trainable params: 3,591
Non-trainable params: 20,024,384
_________________________________________________________________
```

1. Epochs is selected as 50 as the model seems to perform well with increased epochs.
2. Batch size is decided to be 32 as batch size plays an influential role. Batch size when it is more the learning process seems to be quick and there is drop in performance and similarly when too low it learns before processing and tend to predict wrongly.

[22]:
```
EPOCHS = 50
BATCH_SIZE = 32

train_model1  = model.fit_generator(image_generator.flow(X_train, y_train,␣
 ↪batch_size= BATCH_SIZE),
                        epochs= EPOCHS,
                        verbose = 2,
                        validation_data=image_generator.flow(X_val, y_val),
                        steps_per_epoch= len(X_train)/BATCH_SIZE)
```

```
Epoch 1/50
104/103 - 139s - loss: 1.0010 - acc: 0.6546 - val_loss: 0.9005 - val_acc: 0.6715
Epoch 2/50
104/103 - 135s - loss: 0.7356 - acc: 0.7350 - val_loss: 0.6760 - val_acc: 0.7500
```

```
Epoch 3/50
104/103 - 135s - loss: 0.6586 - acc: 0.7610 - val_loss: 0.6362 - val_acc: 0.7886
Epoch 4/50
104/103 - 137s - loss: 0.6140 - acc: 0.7761 - val_loss: 0.5430 - val_acc: 0.7850
Epoch 5/50
104/103 - 135s - loss: 0.5822 - acc: 0.7770 - val_loss: 0.5623 - val_acc: 0.7850
Epoch 6/50
104/103 - 135s - loss: 0.5664 - acc: 0.7897 - val_loss: 0.4723 - val_acc: 0.8152
Epoch 7/50
104/103 - 135s - loss: 0.5479 - acc: 0.7936 - val_loss: 0.5349 - val_acc: 0.7959
Epoch 8/50
104/103 - 135s - loss: 0.5400 - acc: 0.8033 - val_loss: 0.4732 - val_acc: 0.8200
Epoch 9/50
104/103 - 135s - loss: 0.5166 - acc: 0.8042 - val_loss: 0.4629 - val_acc: 0.8357
Epoch 10/50
104/103 - 138s - loss: 0.5094 - acc: 0.8093 - val_loss: 0.5025 - val_acc: 0.8128
Epoch 11/50
104/103 - 138s - loss: 0.5132 - acc: 0.8090 - val_loss: 0.4705 - val_acc: 0.8345
Epoch 12/50
104/103 - 137s - loss: 0.5108 - acc: 0.8135 - val_loss: 0.4647 - val_acc: 0.8261
Epoch 13/50
104/103 - 135s - loss: 0.5037 - acc: 0.8163 - val_loss: 0.5185 - val_acc: 0.7971
Epoch 14/50
104/103 - 134s - loss: 0.4998 - acc: 0.8075 - val_loss: 0.4936 - val_acc: 0.8176
Epoch 15/50
104/103 - 135s - loss: 0.4801 - acc: 0.8105 - val_loss: 0.4826 - val_acc: 0.8249
Epoch 16/50
104/103 - 135s - loss: 0.4615 - acc: 0.8268 - val_loss: 0.4436 - val_acc: 0.8309
Epoch 17/50
104/103 - 139s - loss: 0.4920 - acc: 0.8205 - val_loss: 0.4662 - val_acc: 0.8333
Epoch 18/50
104/103 - 138s - loss: 0.4689 - acc: 0.8223 - val_loss: 0.4167 - val_acc: 0.8418
Epoch 19/50
104/103 - 141s - loss: 0.4593 - acc: 0.8220 - val_loss: 0.4669 - val_acc: 0.8176
Epoch 20/50
104/103 - 135s - loss: 0.4467 - acc: 0.8274 - val_loss: 0.5771 - val_acc: 0.7862
Epoch 21/50
104/103 - 135s - loss: 0.4621 - acc: 0.8335 - val_loss: 0.5367 - val_acc: 0.7874
Epoch 22/50
104/103 - 138s - loss: 0.4785 - acc: 0.8274 - val_loss: 0.4738 - val_acc: 0.8249
Epoch 23/50
104/103 - 137s - loss: 0.4530 - acc: 0.8253 - val_loss: 0.4162 - val_acc: 0.8527
Epoch 24/50
104/103 - 135s - loss: 0.4434 - acc: 0.8386 - val_loss: 0.4850 - val_acc: 0.8309
Epoch 25/50
104/103 - 135s - loss: 0.4517 - acc: 0.8256 - val_loss: 0.4116 - val_acc: 0.8490
Epoch 26/50
104/103 - 138s - loss: 0.4466 - acc: 0.8365 - val_loss: 0.4467 - val_acc: 0.8551
```

```
Epoch 27/50
104/103 - 141s - loss: 0.4610 - acc: 0.8314 - val_loss: 0.4925 - val_acc: 0.8309
Epoch 28/50
104/103 - 134s - loss: 0.4554 - acc: 0.8302 - val_loss: 0.4043 - val_acc: 0.8478
Epoch 29/50
104/103 - 136s - loss: 0.4614 - acc: 0.8238 - val_loss: 0.4848 - val_acc: 0.8237
Epoch 30/50
104/103 - 135s - loss: 0.4543 - acc: 0.8377 - val_loss: 0.4514 - val_acc: 0.8502
Epoch 31/50
104/103 - 135s - loss: 0.4373 - acc: 0.8317 - val_loss: 0.4225 - val_acc: 0.8478
Epoch 32/50
104/103 - 135s - loss: 0.4540 - acc: 0.8299 - val_loss: 0.4493 - val_acc: 0.8418
Epoch 33/50
104/103 - 135s - loss: 0.4322 - acc: 0.8395 - val_loss: 0.4892 - val_acc: 0.8345
Epoch 34/50
104/103 - 136s - loss: 0.4346 - acc: 0.8365 - val_loss: 0.4006 - val_acc: 0.8623
Epoch 35/50
104/103 - 135s - loss: 0.4394 - acc: 0.8344 - val_loss: 0.4564 - val_acc: 0.8333
Epoch 36/50
104/103 - 135s - loss: 0.4382 - acc: 0.8429 - val_loss: 0.4323 - val_acc: 0.8466
Epoch 37/50
104/103 - 135s - loss: 0.4204 - acc: 0.8429 - val_loss: 0.5136 - val_acc: 0.8213
Epoch 38/50
104/103 - 135s - loss: 0.4337 - acc: 0.8365 - val_loss: 0.4348 - val_acc: 0.8539
Epoch 39/50
104/103 - 135s - loss: 0.4329 - acc: 0.8419 - val_loss: 0.5114 - val_acc: 0.8345
Epoch 40/50
104/103 - 135s - loss: 0.4288 - acc: 0.8377 - val_loss: 0.3800 - val_acc: 0.8587
Epoch 41/50
104/103 - 135s - loss: 0.4150 - acc: 0.8450 - val_loss: 0.4405 - val_acc: 0.8309
Epoch 42/50
104/103 - 135s - loss: 0.4323 - acc: 0.8426 - val_loss: 0.5274 - val_acc: 0.8043
Epoch 43/50
104/103 - 135s - loss: 0.4331 - acc: 0.8302 - val_loss: 0.4849 - val_acc: 0.8333
Epoch 44/50
104/103 - 134s - loss: 0.4345 - acc: 0.8450 - val_loss: 0.4673 - val_acc: 0.8418
Epoch 45/50
104/103 - 133s - loss: 0.4225 - acc: 0.8386 - val_loss: 0.5166 - val_acc: 0.8056
Epoch 46/50
104/103 - 132s - loss: 0.4498 - acc: 0.8386 - val_loss: 0.4342 - val_acc: 0.8490
Epoch 47/50
104/103 - 129s - loss: 0.4232 - acc: 0.8422 - val_loss: 0.4491 - val_acc: 0.8394
Epoch 48/50
104/103 - 128s - loss: 0.4156 - acc: 0.8422 - val_loss: 0.4555 - val_acc: 0.8370
Epoch 49/50
104/103 - 128s - loss: 0.4133 - acc: 0.8525 - val_loss: 0.4649 - val_acc: 0.8394
Epoch 50/50
104/103 - 128s - loss: 0.4401 - acc: 0.8413 - val_loss: 0.5091 - val_acc: 0.8176
```

1.5 Model Evaluation

[23]:
```
def create_trace(x,y,ylabel,color):
        trace = go.Scatter(
            x = x,y = y,
            name=ylabel,
            marker=dict(color=color),
            mode = "markers+lines",
            text=x
        )
        return trace

def plot_accuracy_and_loss(train_model):
    hist = train_model.history
    acc = hist['acc']
    val_acc = hist['val_acc']
    loss = hist['loss']
    val_loss = hist['val_loss']
    epochs = list(range(1,len(acc)+1))
    #define the traces
    trace_ta = create_trace(epochs,acc,"Training accuracy", "Green")
    trace_va = create_trace(epochs,val_acc,"Validation accuracy", "Red")
    trace_tl = create_trace(epochs,loss,"Training loss", "Blue")
    trace_vl = create_trace(epochs,val_loss,"Validation loss", "Magenta")
    fig = tools.make_subplots(rows=1,cols=2, subplot_titles=('Training and␣
 ↪validation accuracy',
                                                             'Training and␣
 ↪validation loss'))
    #add traces to the figure
    fig.append_trace(trace_ta,1,1)
    fig.append_trace(trace_va,1,1)
    fig.append_trace(trace_tl,1,2)
    fig.append_trace(trace_vl,1,2)
    #set the layout for the figure
    fig['layout']['xaxis'].update(title = 'Epoch')
    fig['layout']['xaxis2'].update(title = 'Epoch')
    fig['layout']['yaxis'].update(title = 'Accuracy', range=[0,1])
    fig['layout']['yaxis2'].update(title = 'Loss', range=[0,1])
    #plot
    iplot(fig, filename='accuracy-loss')
```

[24]:
```
plot_accuracy_and_loss(train_model1)
```

As expected, the error on the training and validation set is high in the beginning and both start to decline as we increase the epoch.

1.6 Test Results

[25]:
```
score = model.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.5848645467113182
Test accuracy: 0.8125604
```

1.7 Test accuracy Report

[26]:
```
def test_accuracy_report(model):
    predicted = model.predict(X_test)
    test_predicted = np.argmax(predicted, axis=1)
    test_truth = np.argmax(y_test.values, axis=1)
    print(metrics.classification_report(test_truth, test_predicted,␣
 ↪target_names=y_test.columns))
    test_res = model.evaluate(X_test, y_test.values, verbose=0)
    print('Loss function: %s, accuracy:' % test_res[0], test_res[1])
```

[27]:
```
test_accuracy_report(model)
```

```
                     precision    recall  f1-score   support

                 -1       1.00      0.30      0.46        86
1 Mixed local stock 2       0.94      0.17      0.29        94
  Carniolan honey bee       0.94      0.98      0.96       100
    Italian honey bee       0.78      0.98      0.87       602
    Russian honey bee       0.92      0.80      0.86       106
VSH Italian honey bee       0.65      0.65      0.65        40
    Western honey bee       1.00      0.29      0.44         7

             accuracy                           0.81      1035
            macro avg       0.89      0.60      0.65      1035
         weighted avg       0.84      0.81      0.78      1035

Loss function: 0.5848645467113182, accuracy: 0.8125604
```