# Training a CNN

In this lab we are going to be working with a "17 Category Flower Dataset" from Visual Geometry Group of Oxford University. We will acquire the data, split it, train multiple models and do some vizualizations.

In [1]:
```
import numpy as np
import pandas as pd
import os
import shutil
```

## 1. Data aquisition

First, let's download the data from the webpage. You could have done it manually by going to the page, but we'll do it in the script.

In [2]:
```
import urllib
```

In [3]:
```
dataset_url = "https://www.robots.ox.ac.uk/~vgg/data/flowers/17/17flowers.tgz"
split_description_url = "https://www.robots.ox.ac.uk/~vgg/data/flowers/17/datasplits.mat"
#segmentation_ground_truth_url = "https://www.robots.ox.ac.uk/~vgg/data/flowers/17/trimaps.tgz"
readme_url = "https://www.robots.ox.ac.uk/~vgg/data/flowers/17/README.txt"
```

First, let's download the README file

In [4]:
```
# create folder to store data
data_folder = "data/"
os.makedirs(data_folder, exist_ok=True)
```

In [5]:
```
# let's write a function to download data as we'll use multiple times
def get_file(file_url, target_folder=""):
    filename = os.path.basename(file_url)
    # express explicitly the filepath where data will be downloaded
    target_filepath = os.path.join(target_folder, filename)
    filepath, response = urllib.request.urlretrieve(file_url, target_filepath)

    return filepath, response
```

In [6]:
```
# download readme file
readme_filepath, response = get_file(readme_url, data_folder)
```

In [7]:
```
# Check out the README
with open(readme_filepath, 'r') as readme:
    text = readme.read()
    print(text)
```

```
17 Flower Category Database
----------------------------------------------
This set contains images of flowers belonging to 17 different categories.
The images were acquired by searching the web and taking pictures. There are
80 images for each category.

The database was used in:

Nilsback, M-E. and Zisserman, A.  A Visual Vocabulary for Flower Classification.
Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (2006)
http://www.robots.ox.ac.uk/~vgg/publications/papers/nilsback06.{pdf,ps.gz}.

The datasplits used in this paper are specified in datasplits.mat

There are 3 separate splits. The results in the paper are averaged over the 3 splits.
Each split has a training file (trn1,trn2,trn3), a validation file (val1, val2, val3)
and a testfile (tst1, tst2 or tst3).

Segmentation Ground Truth
```

```
-----------------------------------------------
The ground truth is given for a subset of the images from 13 different
categories.

More details can be found in:

Nilsback, M-E. and Zisserman, A. Delving into the whorl of flower segmentation.
Proceedings of the British Machine Vision Conference (2007)
http:www.robots.ox.ac.uk/~vgg/publications/papers/nilsback06.(pdf,ps.gz).

The ground truth file also contains the file imlist.mat, which indicated
which images in the original database that have been anotated.

Distance matrices
-----------------------------------------------

We provide two set of distance matrices:

1. distancematrices17gcfeat06.mat
- Distance matrices using the same features and segmentation as detailed in:
    Nilsback, M-E. and Zisserman, A.  A Visual Vocabulary for Flower Classification.
    Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition(2006)
    http://www.robots.ox.ac.uk/~vgg/publications/papers/nilsback06.{pdf,ps.gz}.

2. distancematrices17itfeat08.mat
- Distance matrices using the same features as described in:
    Nilsback, M-E. and Zisserman, A. Automated flower classification over a large number of classe
s.
    Proceedings of the Indian Conference on Computer Vision, Graphics and Image Processing (2008)
    http://www.robots.ox.ac.uk/~vgg/publications/papers/nilsback08.{pdf,ps.gz}.
  and the iterative segmenation scheme detailed in
    Nilsback, M-E. and Zisserman, A. Delving into the whorl of flower segmentation.
    Proceedings of the British Machine Vision Conference (2007)
    http:www.robots.ox.ac.uk/~vgg/publications/papers/nilsback06.(pdf,ps.gz).
```

Now, let's download the data

In [8]:
```python
# download the data
dataset_filepath, response = get_file(dataset_url, data_folder)
```

We have just downloaded a tar file. Let's unpack it.

In [9]:
```python
import tarfile
```

In [10]:
```python
with tarfile.open(dataset_filepath) as tar:
    tar.extractall(path=data_folder)
```

What have we extracted?

In [11]:
```python
os.listdir(data_folder)
```

Out[11]:
```
['17flowers.tgz', 'datasplits.mat', 'jpg', 'README.txt', 'training_folder']
```

We see that a new folder named *jpg* has appeared.

In [12]:
```python
os.listdir(os.path.join(data_folder, 'jpg'))[:10]
```

Out[12]:
```
['files.txt',
 'files.txt~',
 'image_0001.jpg',
 'image_0002.jpg',
 'image_0003.jpg',
 'image_0004.jpg',
 'image_0005.jpg',
 'image_0006.jpg',
 'image_0007.jpg',
 'image_0008.jpg']
```

This folder contains images of the dataset. But what about ground truth?

Based on the README, each class contains exactly 80 images. Quick check shows that images of one class are grouped together. We will use this fact later to group the images by class.

The split information was already provided with the dataset (otherwise we could have used train_test_split to obtain it)

In [13]:
```
# download split file
split_filepath, response = get_file(split_description_url, data_folder)
```

In [14]:
```
from scipy.io import loadmat
split = loadmat(split_filepath)
```

In [15]:
```
split.keys()
```

Out[15]:
```
dict_keys(['__header__', '__version__', '__globals__', 'trn1', 'trn2', 'trn3', 'tst1', 'tst2', 'tst
3', 'val3', 'val2', 'val1'])
```

Let's use option 1 of train/val/test split:

In [16]:
```
train = split["trn1"]
val = split["val1"]
test = split["tst1"]

print("""Train set contains {} files,
val set contains {} files,
and test set contains {} files""".format(train.shape[1], val.shape[1], test.shape[1]))
```

```
Train set contains 680 files,
val set contains 340 files,
and test set contains 340 files
```

## Excercise

Additional things to do:

- Check how many images we have downloaded.

In [17]:
```
assert(17*80==len(train[0]) + len(val[0]) + len(test[0]))
print(f"We have {17*80} images")
```

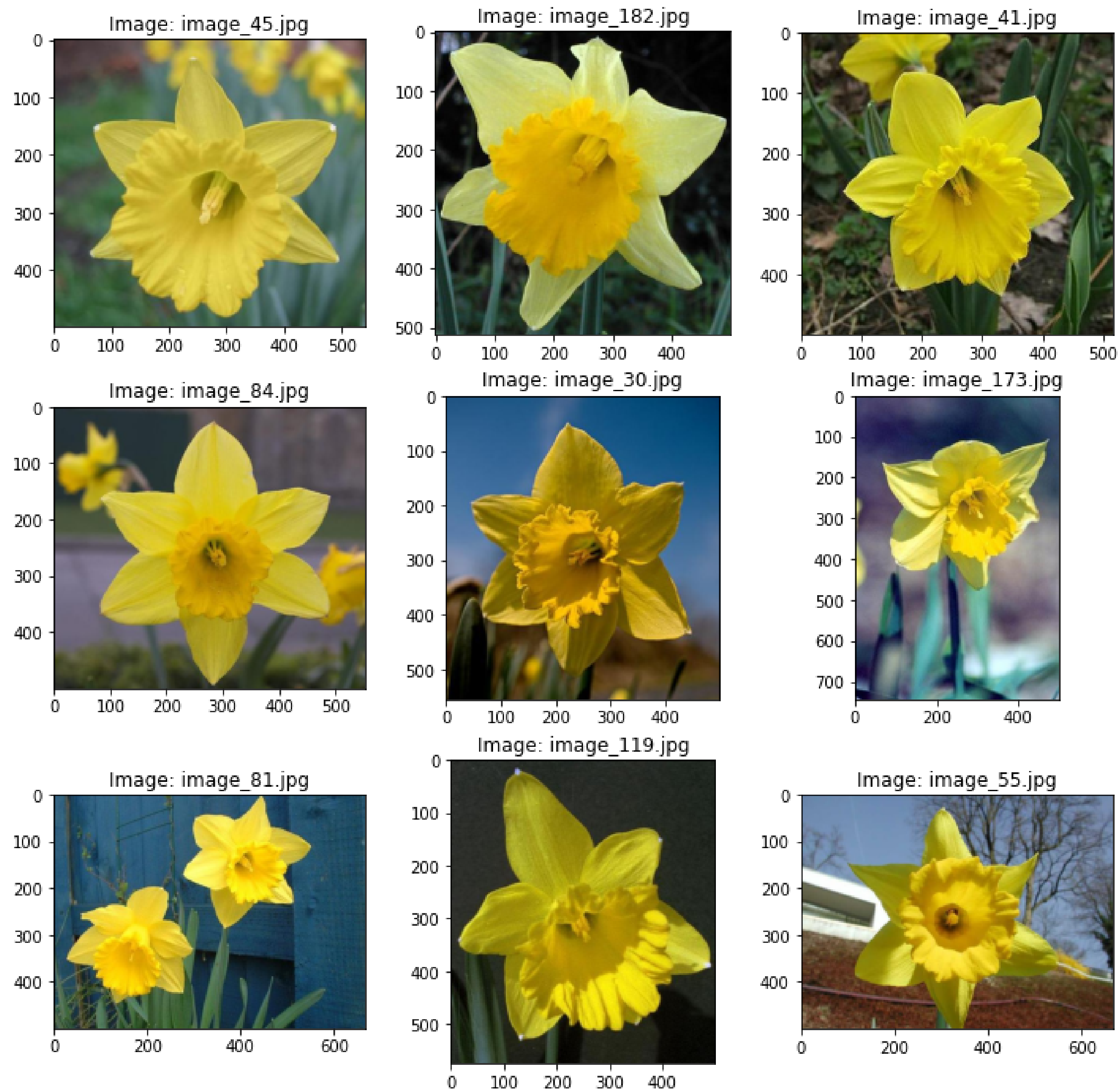
```
We have 1360 images
```

- Display some of the images.

In [18]:
```
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
img = mpimg.imread(os.path.join(data_folder,f'jpg/image_00{train[0][42]}.jpg'),)

path = os.path.join(data_folder,'jpg/image_00')

indices = np.random.randint(0,200,size=9)
fig,axes = plt.subplots(3,3,figsize=(12,12))
for ind, ax in enumerate(axes.flat):
    index = train[0][ind]
    if index<10:
        imagepath = path+'0'+str(index)+'.jpg'
    else:
        imagepath = path + str(index)+'.jpg'
    img = mpimg.imread(imagepath)
    ax.imshow(img)
    ax.set_title(f"Image: image_{indices[ind]}.jpg")
```




- Are those color images?

-YES

- What are their shape?

In [19]:
```
img.shape #example shape
```

Out[19]:
```
(500, 666, 3)
```

- Are they all of the same shape?

In [20]:
```
img2 = mpimg.imread(path+'47.jpg')
img2.shape
```

Out[20]:
```
(760, 500, 3)
```

-NO, the shapes are different

## 2. Data regrouping

During the training with Keras for the simplicity we are going to be using flow_from_dir method of ImageDataGenerator. However, we'll need to organize data first in the specific manner: separate train, val, test sets, and put images of each class in a designated folder.

First, let's write a function to get a class name from file index. We'll use the fact that each class has 80 images, and they are grouped together by index.

In [21]:
```
def get_image_class(file_index):
    image_class_idx = (int(file_index) - 1) // 80 + 1
    class_name = "{:02d}".format(image_class_idx)

    return class_name
```

Now let's rearrange the data

In [22]:
```
from shutil import copy
```

In [23]:
```
training_folder_name = "training_folder"
```

In [24]:
```
for filename in os.listdir(os.path.join(data_folder, 'jpg')):
    if filename.endswith('jpg'):
        ### filename 'image_0936.jpg' --> file_index 936
        file_index = int(filename[6:10])
        true_class = get_image_class(file_index)
        if file_index in train:
            split_folder = 'train'
        elif file_index in val:
            split_folder = 'val'
        elif file_index in test:
            split_folder = 'test'

        target_folder = os.path.join(data_folder, training_folder_name, split_folder, true_class)
        os.makedirs(target_folder, exist_ok=True)

        source_filepath = os.path.join(data_folder, 'jpg', filename)
        copy(source_filepath, target_folder)
    else:
        print(filename)
        print("Not a jpg file, skipping")
```

```
files.txt
Not a jpg file, skipping
files.txt~
Not a jpg file, skipping
```

## 3. CNN training

Now that we have prepared the data, we will be able to train a model.

### 3.1 Transfer learning

Let's do the transfer learning we have briefly discussed last time. We'll load one of the pretrained models from Keras library with ImageNet weights.

#### Model preparation

In [25]:
```
import tensorflow as tf
import tensorflow.keras as keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import backend as K
```

```python
import os
```

```
c:\users\eddie\kma_course\lib\site-packages\tensorflow\python\framework\dtypes.py:516: FutureWarnin
g: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, i
t will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorflow\python\framework\dtypes.py:517: FutureWarnin
g: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, i
t will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorflow\python\framework\dtypes.py:518: FutureWarnin
g: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, i
t will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorflow\python\framework\dtypes.py:519: FutureWarnin
g: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, i
t will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorflow\python\framework\dtypes.py:520: FutureWarnin
g: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, i
t will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorflow\python\framework\dtypes.py:525: FutureWarnin
g: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, i
t will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:541: Futur
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of n
umpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:542: Futur
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of n
umpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:543: Futur
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of n
umpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:544: Futur
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of n
umpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:545: Futur
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of n
umpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
c:\users\eddie\kma_course\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:550: Futur
eWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of n
umpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

In [26]:

```python
# Reproducibility!
np.random.seed(42)
tf.set_random_seed(42)
```

In [27]:

```python
# # """## GPU selection --> execute do only if you need to select a GPU / part of GPU

# os.environ["CUDA_VISIBLE_DEVICES"] = "0"

# ### Set session with share of GPU
# config_1 = tf.ConfigProto()
# # gpu_fraction_1 = float(os.environ.get('GPU_LIMIT_1', 0.45))
# # config_1.gpu_options.per_process_gpu_memory_fraction = gpu_fraction_1
# config_1.gpu_options.allow_growth = True

# sess_1 = tf.Session(config=config_1)
# sess_1.run(tf.global_variables_initializer())
# K.set_session(sess_1)
```

We'll be using VGG16 model. Together with weights, we'll also need a corresponding preprocessing function for the input images.

In [28]:
```
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.applications.vgg16 import preprocess_input as preprocess_input_vgg

from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.models import Model
```

In [29]:
```
base_model = VGG16(include_top=False, weights='imagenet', input_shape = (224,224,3))
base_model.summary()
```

```
WARNING:tensorflow:From c:\users\eddie\kma_course\lib\site-packages\tensorflow\python\ops\init_ops.
py:1251: calling VarianceScaling.__init__ (from tensorflow.python.ops.init_ops) with dtype is depre
cated 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
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0         
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792      
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928     
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0         
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856     
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584    
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0         
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168    
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080    
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080    
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0         
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160   
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808   
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808   
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0         
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808   
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808   
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808   
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0         
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

Note that we have downloaded only a convolution part of the neural network. Let's add some dense layers on top of it.

In [30]:
```
## freezing the layers
```

```
#for layer in base_model.layers:
#    layer.trainable = False
```

In [31]:
```
nb_classes = 17
```

In [32]:
```
flatten = Flatten()(base_model.output)
dropout_1 = Dropout(0.25)(flatten)
fc_1 = Dense(1000)(dropout_1)
dropout_2 = Dropout(0.5)(fc_1)
predictions = Dense(nb_classes, activation="softmax", name='predictions')(dropout_2)
```

In [33]:
```
model = Model(base_model.input, predictions)
```

In [34]:
```
model.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dropout (Dropout)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 1000)              25089000
_________________________________________________________________
dropout_1 (Dropout)          (None, 1000)              0
_________________________________________________________________
predictions (Dense)          (None, 17)                17017
=================================================================
Total params: 39,820,705
Trainable params: 39,820,705
```

```
Non-trainable params: 0
_________________________________________________________________
```

### Model training parameters

In [35]:
```
from tensorflow.keras import optimizers
```

In [36]:
```
loss = 'categorical_crossentropy'
learning_rate = 0.001
optimizer = optimizers.SGD ## optimizers.SGD ## optimizers.RMSprop ## optimizers.Adagrad ## optimiz
metrics = ['accuracy']
```

In [37]:
```
model.compile(loss=loss,
              optimizer=optimizer(learning_rate),
              metrics=metrics)
```

### Data preparation

In [38]:
```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

In [39]:
```
train_dir = os.path.join(data_folder, training_folder_name, "train")
val_dir = os.path.join(data_folder, training_folder_name, "val")
test_dir = os.path.join(data_folder, training_folder_name, "test")
```

In [40]:
```
# we'll resize images in correspondance to network input size
image_size = (224,224)
```

In [41]:
```
# apply some data augmentation
train_datagen = ImageDataGenerator(rotation_range=15,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   horizontal_flip=True,
                                   fill_mode='nearest',
                                   preprocessing_function=preprocess_input_vgg
                                  )

validation_datagen = ImageDataGenerator(preprocessing_function=preprocess_input_vgg) # for validati

train_batchsize = 30
val_batchsize = 30

# this function takes images from folders and feeds to Imagedatagenerator
train_generator = train_datagen.flow_from_directory(
        train_dir,
        target_size=image_size,
        batch_size=train_batchsize,
        class_mode='categorical')

validation_generator = validation_datagen.flow_from_directory(
        val_dir,
        target_size=image_size,
        batch_size=val_batchsize,
        class_mode='categorical',
        shuffle=False)
```

```
Found 680 images belonging to 17 classes.
Found 340 images belonging to 17 classes.
```

### Model training

In [42]:
```
epochs = 50
```

In [43]:
```
nb_train_steps = train_generator.samples // train_generator.batch_size
nb_val_steps = validation_generator.samples // validation_generator.batch_size
```

In [44]:
```python
history = model.fit_generator(
      train_generator,
      steps_per_epoch=nb_train_steps,
      epochs=epochs,
      validation_data=validation_generator,
      validation_steps=nb_val_steps,
      verbose=1, #0
)
```

```
Epoch 1/50
22/22 [==============================] - 33s 2s/step - loss: 5.1333 - acc: 0.0523 - val_loss: 2.830
7 - val_acc: 0.0758
Epoch 2/50
22/22 [==============================] - 22s 1s/step - loss: 2.8348 - acc: 0.0723 - val_loss: 2.827
7 - val_acc: 0.0727
Epoch 3/50
22/22 [==============================] - 22s 1s/step - loss: 2.8360 - acc: 0.0600 - val_loss: 2.826
5 - val_acc: 0.0424
Epoch 4/50
22/22 [==============================] - 22s 1s/step - loss: 2.8332 - acc: 0.0462 - val_loss: 2.819
6 - val_acc: 0.0788
Epoch 5/50
22/22 [==============================] - 22s 1s/step - loss: 2.8287 - acc: 0.0585 - val_loss: 2.818
7 - val_acc: 0.1000
Epoch 6/50
22/22 [==============================] - 22s 1s/step - loss: 2.8298 - acc: 0.0600 - val_loss: 2.815
7 - val_acc: 0.0818
Epoch 7/50
22/22 [==============================] - 22s 1s/step - loss: 2.8261 - acc: 0.0892 - val_loss: 2.821
4 - val_acc: 0.0697
Epoch 8/50
22/22 [==============================] - 22s 1s/step - loss: 2.8184 - acc: 0.0954 - val_loss: 2.806
9 - val_acc: 0.0879
Epoch 9/50
22/22 [==============================] - 24s 1s/step - loss: 2.7998 - acc: 0.0800 - val_loss: 2.800
9 - val_acc: 0.1061
Epoch 10/50
22/22 [==============================] - 24s 1s/step - loss: 2.8023 - acc: 0.0938 - val_loss: 2.799
0 - val_acc: 0.0818
Epoch 11/50
22/22 [==============================] - 22s 1s/step - loss: 2.8003 - acc: 0.0924 - val_loss: 2.786
8 - val_acc: 0.0848
Epoch 12/50
22/22 [==============================] - 22s 1000ms/step - loss: 2.7828 - acc: 0.0859 - val_loss:
2.7827 - val_acc: 0.1364
Epoch 13/50
22/22 [==============================] - 23s 1s/step - loss: 2.7571 - acc: 0.1246 - val_loss: 2.748
7 - val_acc: 0.1121
Epoch 14/50
22/22 [==============================] - 23s 1s/step - loss: 2.7983 - acc: 0.0815 - val_loss: 2.760
5 - val_acc: 0.1121
Epoch 15/50
22/22 [==============================] - 22s 1s/step - loss: 2.7679 - acc: 0.1138 - val_loss: 2.750
6 - val_acc: 0.1182
Epoch 16/50
22/22 [==============================] - 22s 1s/step - loss: 2.7466 - acc: 0.1242 - val_loss: 2.737
9 - val_acc: 0.1242
Epoch 17/50
22/22 [==============================] - 22s 1s/step - loss: 2.7417 - acc: 0.1231 - val_loss: 2.735
2 - val_acc: 0.1364
Epoch 18/50
22/22 [==============================] - 22s 1s/step - loss: 2.7137 - acc: 0.1123 - val_loss: 2.721
2 - val_acc: 0.1333
Epoch 19/50
22/22 [==============================] - 22s 1s/step - loss: 2.7077 - acc: 0.1492 - val_loss: 2.740
6 - val_acc: 0.1515
Epoch 20/50
22/22 [==============================] - 22s 1s/step - loss: 2.7028 - acc: 0.1415 - val_loss: 2.654
0 - val_acc: 0.1455
Epoch 21/50
22/22 [==============================] - 22s 1s/step - loss: 2.6628 - acc: 0.1585 - val_loss: 2.628
5 - val_acc: 0.1636
```

```
Epoch 22/50
22/22 [==============================] - 22s 1s/step - loss: 2.6113 - acc: 0.1831 - val_loss: 2.565
2 - val_acc: 0.1818
Epoch 23/50
22/22 [==============================] - 22s 1s/step - loss: 2.5779 - acc: 0.2077 - val_loss: 2.540
1 - val_acc: 0.2000
Epoch 24/50
22/22 [==============================] - 22s 1s/step - loss: 2.4792 - acc: 0.2231 - val_loss: 2.462
2 - val_acc: 0.2455
Epoch 25/50
22/22 [==============================] - 22s 1s/step - loss: 2.3669 - acc: 0.2600 - val_loss: 2.496
9 - val_acc: 0.2606
Epoch 26/50
22/22 [==============================] - 22s 1s/step - loss: 2.4049 - acc: 0.2415 - val_loss: 2.267
0 - val_acc: 0.3030
Epoch 27/50
22/22 [==============================] - 22s 1s/step - loss: 2.2561 - acc: 0.2815 - val_loss: 2.022
4 - val_acc: 0.3636
Epoch 28/50
22/22 [==============================] - 22s 1s/step - loss: 2.1497 - acc: 0.2923 - val_loss: 2.008
0 - val_acc: 0.3758
Epoch 29/50
22/22 [==============================] - 22s 1s/step - loss: 2.2245 - acc: 0.3108 - val_loss: 1.823
8 - val_acc: 0.4182
Epoch 30/50
22/22 [==============================] - 22s 1s/step - loss: 2.0949 - acc: 0.3646 - val_loss: 1.964
8 - val_acc: 0.3636
Epoch 31/50
22/22 [==============================] - 22s 1s/step - loss: 1.9734 - acc: 0.3646 - val_loss: 1.907
4 - val_acc: 0.3788
Epoch 32/50
22/22 [==============================] - 22s 1s/step - loss: 1.8449 - acc: 0.3985 - val_loss: 1.584
1 - val_acc: 0.4788
Epoch 33/50
22/22 [==============================] - 22s 1s/step - loss: 1.7389 - acc: 0.4136 - val_loss: 1.918
3 - val_acc: 0.4030
Epoch 34/50
22/22 [==============================] - 22s 1s/step - loss: 1.6190 - acc: 0.4738 - val_loss: 1.561
2 - val_acc: 0.5000
Epoch 35/50
22/22 [==============================] - 22s 1s/step - loss: 1.9837 - acc: 0.4062 - val_loss: 1.499
7 - val_acc: 0.5152
Epoch 36/50
22/22 [==============================] - 22s 997ms/step - loss: 1.4996 - acc: 0.5188 - val_loss: 1.
3761 - val_acc: 0.5515
Epoch 37/50
22/22 [==============================] - 22s 1s/step - loss: 1.4945 - acc: 0.5030 - val_loss: 1.367
6 - val_acc: 0.5212
Epoch 38/50
22/22 [==============================] - 22s 1s/step - loss: 1.5708 - acc: 0.4815 - val_loss: 1.329
5 - val_acc: 0.5879
Epoch 39/50
22/22 [==============================] - 22s 1s/step - loss: 1.4546 - acc: 0.5308 - val_loss: 1.175
6 - val_acc: 0.6061
Epoch 40/50
22/22 [==============================] - 22s 1s/step - loss: 1.2193 - acc: 0.6062 - val_loss: 1.086
8 - val_acc: 0.6515
Epoch 41/50
22/22 [==============================] - 22s 995ms/step - loss: 1.2045 - acc: 0.6125 - val_loss: 1.
0878 - val_acc: 0.6697
Epoch 42/50
22/22 [==============================] - 22s 1s/step - loss: 1.1462 - acc: 0.6212 - val_loss: 1.018
8 - val_acc: 0.6697
Epoch 43/50
22/22 [==============================] - 22s 1s/step - loss: 1.1313 - acc: 0.6462 - val_loss: 0.990
5 - val_acc: 0.6697
Epoch 44/50
22/22 [==============================] - 22s 1s/step - loss: 1.0796 - acc: 0.6385 - val_loss: 1.051
1 - val_acc: 0.6364
Epoch 45/50
22/22 [==============================] - 22s 1s/step - loss: 0.9715 - acc: 0.6723 - val_loss: 0.888
9 - val_acc: 0.7121
```

```
Epoch 46/50
22/22 [==============================] - 22s 1s/step - loss: 0.9197 - acc: 0.7138 - val_loss: 1.507
6 - val_acc: 0.5606
Epoch 47/50
22/22 [==============================] - 22s 1s/step - loss: 0.9764 - acc: 0.6954 - val_loss: 0.880
8 - val_acc: 0.7121
Epoch 48/50
22/22 [==============================] - 22s 1s/step - loss: 0.7899 - acc: 0.7379 - val_loss: 0.798
1 - val_acc: 0.7667
Epoch 49/50
22/22 [==============================] - 22s 998ms/step - loss: 0.8021 - acc: 0.7312 - val_loss: 0.
8964 - val_acc: 0.7000
Epoch 50/50
22/22 [==============================] - 22s 1s/step - loss: 0.7591 - acc: 0.7631 - val_loss: 0.804
1 - val_acc: 0.7818
```

In [45]:

```
print('training acc.:',history.history['acc'][-1])
print('val acc.:', (history.history['val_acc'])[-1])
```

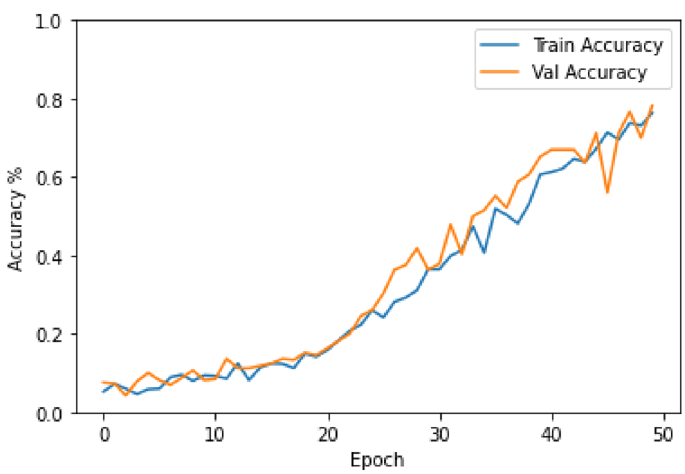
```
training acc.: 0.7630769
val acc.: 0.7818182
```

In [46]:

```
import matplotlib.pyplot as plt
%matplotlib inline
def plot_history(history):
    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy %')
    plt.plot(history.epoch, np.array(history.history['acc']),
    label='Train Accuracy')
    plt.plot(history.epoch, np.array(history.history['val_acc']),
    label = 'Val Accuracy')
    plt.legend()
    plt.ylim([0, 1])
```

In [47]:

```
plot_history(history)
```




### Save model

In [48]:

```
weights_folder = "weights"
os.makedirs(weights_folder, exist_ok=True)

model_name = 'vgg16_transfer_weights.h5'
model_path = os.path.join(weights_folder, model_name)
```

In [49]:

```
# uncomment to save model
# model.save(model_path)
```

### Do the test on images

```
from tensorflow.keras.preprocessing import image
```

In [50]:
```
from tensorflow.keras.models import load_model
```

In [51]:
```
# model = load_model(model_path, compile=False)
```

Single image prediction

In [52]:
```
#test_dir = "data/training_folder/test"
#image_size = (224,224)
```

In [53]:
```
class_idx = '08'
image_name = os.listdir(os.path.join(test_dir, class_idx))[0]
image_path = os.path.join(test_dir, class_idx, image_name)
```

In [54]:
```
image_path
```

Out[54]:
```
'data/training_folder\\test\\08\\image_0564.jpg'
```

In [55]:
```
# predicting image: getting the output vector
img = image.load_img(image_path, target_size=image_size)
img_array = image.img_to_array(img)
img_expanded = np.expand_dims(img_array, axis=0)
preprocessed_image = preprocess_input_vgg(img_expanded)

pred = model.predict(preprocessed_image)
print(pred)
```

```
[[2.5455248e-01 1.2235704e-06 4.3765303e-07 2.1682472e-05 1.9703209e-06
  9.0924817e-07 1.5998894e-05 7.3553097e-01 2.3544788e-05 3.9512652e-04
  1.7409110e-06 3.0837407e-05 1.4433003e-04 2.6464569e-03 6.3373023e-03
  4.6452965e-07 2.9449983e-04]]
```

In [56]:
```
img_expanded.shape
```

Out[56]:
```
(1, 224, 224, 3)
```

In [57]:
```
img_array.shape
```

Out[57]:
```
(224, 224, 3)
```

In [58]:
```
classes = ["{:02d}".format(i) for i in range(1, 18)]
pred_class_idx = np.argmax(pred, axis=1)
classes[pred_class_idx[0]]
```

Out[58]:
```
'08'
```

In [59]:
```
pred[0][pred_class_idx]
```

Out[59]:
```
array([0.735531], dtype=float32)
```

Multiple image predictions

In [60]:
```
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns; sns.set()
```

In [61]:
```
test_datagen = ImageDataGenerator(preprocessing_function=preprocess_input_vgg)
```

In [62]:
```
test_generator = test_datagen.flow_from_directory(
        test_dir,
        target_size=image_size,
        shuffle = False,
        class_mode='categorical',
        batch_size=1)

filenames = test_generator.filenames
```

```
nb_samples = len(filenames)

predict = model.predict_generator(test_generator,steps=nb_samples)
```

```
Found 340 images belonging to 17 classes.
```

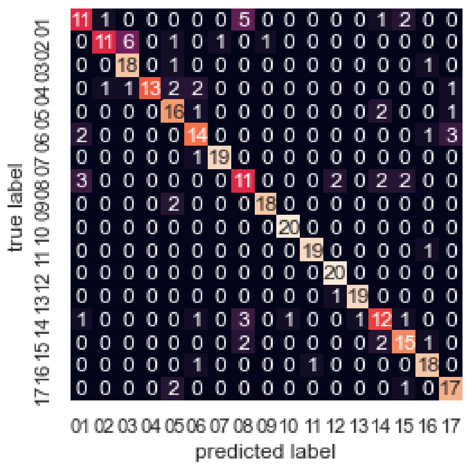
In [63]:
```
predict.shape
```

Out[63]:
```
(340, 17)
```

In [64]:
```
y_pred = np.argmax(predict, axis=1)
print('Confusion Matrix')

mat = confusion_matrix(test_generator.classes, y_pred)
sns.heatmap(mat, square=True, annot=True, fmt='d', cbar=False,
            xticklabels=classes,
            yticklabels=classes)
plt.xlabel('predicted label')
plt.ylabel('true label');
```

```
Confusion Matrix
```




In [65]:
```
#my results - lesser batch size
#results heavily depend on seed - acc varies in range 0.2 - 0.9
print(classification_report(test_generator.classes + 1, y_pred + 1))  ## adding 1 to preserve the c
```

```
              precision    recall  f1-score   support

           1       0.65      0.55      0.59        20
           2       0.85      0.55      0.67        20
           3       0.72      0.90      0.80        20
           4       1.00      0.65      0.79        20
           5       0.67      0.80      0.73        20
           6       0.70      0.70      0.70        20
           7       0.95      0.95      0.95        20
           8       0.52      0.55      0.54        20
           9       0.95      0.90      0.92        20
          10       0.95      1.00      0.98        20
          11       0.95      0.95      0.95        20
          12       0.87      1.00      0.93        20
          13       0.95      0.95      0.95        20
          14       0.63      0.60      0.62        20
          15       0.71      0.75      0.73        20
          16       0.82      0.90      0.86        20
          17       0.77      0.85      0.81        20

    accuracy                           0.80       340
   macro avg       0.80      0.80      0.79       340
weighted avg       0.80      0.80      0.79       340
```

In [66]:
```
##original results
print(classification_report(test_generator.classes + 1, y_pred + 1))  ## adding 1 to preserve the c
```

```
              precision    recall  f1-score   support

           1       0.65      0.55      0.59        20
           2       0.85      0.55      0.67        20
           3       0.72      0.90      0.80        20
           4       1.00      0.65      0.79        20
           5       0.67      0.80      0.73        20
           6       0.70      0.70      0.70        20
           7       0.95      0.95      0.95        20
           8       0.52      0.55      0.54        20
           9       0.95      0.90      0.92        20
          10       0.95      1.00      0.98        20
          11       0.95      0.95      0.95        20
          12       0.87      1.00      0.93        20
          13       0.95      0.95      0.95        20
          14       0.63      0.60      0.62        20
          15       0.71      0.75      0.73        20
          16       0.82      0.90      0.86        20
          17       0.77      0.85      0.81        20

    accuracy                           0.80       340
   macro avg       0.80      0.80      0.79       340
weighted avg       0.80      0.80      0.79       340
```

Things to do

- Check some of incorrectly classified images
- Experiment with other models available in Keras
- Build your own network
- Optimize one or several training hyperparameters

### 3.2 Training enhancement

There are multiple ways to improve the quality of the model. Have a look at these papers that provide some heuristics for training a classification or object detection model.

I've done the following:

- used resnet50 with smaller images
- added custom LR Scheduler and EarlyStopping

In [67]:

```
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input, decode_predictions
```

In [68]:

```
base_model = ResNet50(include_top=False, weights='imagenet', input_shape = (112,112,3))
# base_model.summary()

#Note that we have downloaded only a convolution part of the neural network. Let's add some dense l

nb_classes = 17

flatten = Flatten()(base_model.output)
dropout_1 = Dropout(0.25)(flatten)
fc_1 = Dense(1000)(dropout_1)
dropout_2 = Dropout(0.5)(fc_1)
predictions = Dense(nb_classes, activation="softmax", name='predictions')(dropout_2)

model = Model(base_model.input, predictions)

# model.summary()
```

```
c:\users\eddie\kma_course\lib\site-packages\keras_applications\resnet50.py:265: UserWarning: The ou
tput shape of `ResNet50(include_top=False)` has been changed since Keras 2.2.0.
  warnings.warn('The output shape of `ResNet50(include_top=False)` '
```

In [69]:
```python
# we'll resize images in correspondance to network input size
image_size = (112,112)
```

In [70]:
```python
# apply some data augmentation
train_datagen = ImageDataGenerator(rotation_range=15,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   horizontal_flip=True,
                                   fill_mode='nearest',
                                   preprocessing_function=preprocess_input_vgg
                                  )

validation_datagen = ImageDataGenerator(preprocessing_function=preprocess_input_vgg) # for validati

train_batchsize = 30
val_batchsize = 30

# this function takes images from folders and feeds to Imagedatagenerator
train_generator = train_datagen.flow_from_directory(
        train_dir,
        target_size=image_size,
        batch_size=train_batchsize,
        class_mode='categorical')

validation_generator = validation_datagen.flow_from_directory(
        val_dir,
        target_size=image_size,
        batch_size=val_batchsize,
        class_mode='categorical',
        shuffle=False)
```

```
Found 680 images belonging to 17 classes.
Found 340 images belonging to 17 classes.
```

### Model training parameters

In [74]:
```python
loss = 'categorical_crossentropy'
learning_rate = 0.001
optimizer = optimizers.SGD ## optimizers.SGD ## optimizers.RMSprop ## optimizers.Adagrad ## optimiz
metrics = ['accuracy']
epochs = 50
model.compile(loss=loss,
              optimizer=optimizer(learning_rate),
              metrics=metrics)
```

In [72]:
```python
nb_train_steps = train_generator.samples // train_generator.batch_size
nb_val_steps = validation_generator.samples // validation_generator.batch_size
```

In [73]:
```python
def step_decay(epoch,lr):
    decay_rate = 0.9
    decay_step = 10
    if epoch% decay_step ==0 and epoch:
        return lr * decay_rate
    return lr
```

In [75]:
```python
history = model.fit_generator(
      train_generator,
      steps_per_epoch=nb_train_steps,
      epochs=epochs,
      validation_data=validation_generator,
      validation_steps=nb_val_steps,
      verbose=1, #0
      callbacks=[tf.keras.callbacks.EarlyStopping(patience=5,monitor='loss',restore_best_weights=Tr
)
```

```
Epoch 00001: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 1/50
```

```
22/22 [==============================] - 15s 691ms/step - loss: 5.6794 - acc: 0.2000 - val_loss: 2.
5075 - val_acc: 0.4909

Epoch 00002: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 2/50
22/22 [==============================] - 7s 313ms/step - loss: 2.7803 - acc: 0.4600 - val_loss: 2.3
152 - val_acc: 0.6273

Epoch 00003: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 3/50
22/22 [==============================] - 7s 310ms/step - loss: 1.8465 - acc: 0.6154 - val_loss: 1.4
151 - val_acc: 0.7212

Epoch 00004: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 4/50
22/22 [==============================] - 7s 306ms/step - loss: 1.3209 - acc: 0.7123 - val_loss: 1.1
988 - val_acc: 0.7576

Epoch 00005: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 5/50
22/22 [==============================] - 7s 300ms/step - loss: 0.9997 - acc: 0.7615 - val_loss: 0.8
386 - val_acc: 0.8152

Epoch 00006: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 6/50
22/22 [==============================] - 7s 303ms/step - loss: 0.8266 - acc: 0.7909 - val_loss: 0.7
991 - val_acc: 0.8303

Epoch 00007: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 7/50
22/22 [==============================] - 7s 298ms/step - loss: 0.7493 - acc: 0.8062 - val_loss: 0.7
146 - val_acc: 0.8303

Epoch 00008: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 8/50
22/22 [==============================] - 7s 301ms/step - loss: 0.6125 - acc: 0.8431 - val_loss: 0.6
688 - val_acc: 0.8515

Epoch 00009: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 9/50
22/22 [==============================] - 7s 301ms/step - loss: 0.6446 - acc: 0.8364 - val_loss: 0.6
411 - val_acc: 0.8606

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0010000000474974513.
Epoch 10/50
22/22 [==============================] - 7s 299ms/step - loss: 0.3959 - acc: 0.8859 - val_loss: 0.5
546 - val_acc: 0.8636

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 11/50
22/22 [==============================] - 7s 310ms/step - loss: 0.3257 - acc: 0.9000 - val_loss: 0.6
239 - val_acc: 0.8303

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 12/50
22/22 [==============================] - 7s 299ms/step - loss: 0.4195 - acc: 0.8831 - val_loss: 0.5
133 - val_acc: 0.8636

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 13/50
22/22 [==============================] - 7s 299ms/step - loss: 0.3431 - acc: 0.8969 - val_loss: 0.5
840 - val_acc: 0.8606

Epoch 00014: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 14/50
22/22 [==============================] - 7s 305ms/step - loss: 0.2808 - acc: 0.9200 - val_loss: 0.5
779 - val_acc: 0.8727

Epoch 00015: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 15/50
22/22 [==============================] - 7s 302ms/step - loss: 0.3569 - acc: 0.8938 - val_loss: 0.5
916 - val_acc: 0.8636
```

```
Epoch 00016: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 16/50
22/22 [==============================] - 7s 306ms/step - loss: 0.2395 - acc: 0.9277 - val_loss: 0.5
232 - val_acc: 0.8727

Epoch 00017: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 17/50
22/22 [==============================] - 7s 306ms/step - loss: 0.2294 - acc: 0.9400 - val_loss: 0.5
014 - val_acc: 0.8758

Epoch 00018: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 18/50
22/22 [==============================] - 7s 309ms/step - loss: 0.1513 - acc: 0.9515 - val_loss: 0.5
535 - val_acc: 0.8818

Epoch 00019: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 19/50
22/22 [==============================] - 7s 304ms/step - loss: 0.2212 - acc: 0.9462 - val_loss: 0.5
148 - val_acc: 0.8788

Epoch 00020: LearningRateScheduler reducing learning rate to 0.0009000000427477062.
Epoch 20/50
22/22 [==============================] - 7s 304ms/step - loss: 0.1786 - acc: 0.9492 - val_loss: 0.5
076 - val_acc: 0.8879

Epoch 00021: LearningRateScheduler reducing learning rate to 0.0008100000384729356.
Epoch 21/50
22/22 [==============================] - 7s 304ms/step - loss: 0.1766 - acc: 0.9569 - val_loss: 0.5
503 - val_acc: 0.8848

Epoch 00022: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 22/50
22/22 [==============================] - 7s 313ms/step - loss: 0.1297 - acc: 0.9585 - val_loss: 0.5
742 - val_acc: 0.8818

Epoch 00023: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 23/50
22/22 [==============================] - 7s 303ms/step - loss: 0.1512 - acc: 0.9554 - val_loss: 0.4
994 - val_acc: 0.8939

Epoch 00024: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 24/50
22/22 [==============================] - 7s 298ms/step - loss: 0.2205 - acc: 0.9400 - val_loss: 0.5
376 - val_acc: 0.8909

Epoch 00025: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 25/50
22/22 [==============================] - 7s 297ms/step - loss: 0.1690 - acc: 0.9554 - val_loss: 0.5
475 - val_acc: 0.8939

Epoch 00026: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 26/50
22/22 [==============================] - 7s 300ms/step - loss: 0.1406 - acc: 0.9530 - val_loss: 0.5
203 - val_acc: 0.9030

Epoch 00027: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 27/50
22/22 [==============================] - 7s 298ms/step - loss: 0.1282 - acc: 0.9625 - val_loss: 0.5
081 - val_acc: 0.9121

Epoch 00028: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 28/50
22/22 [==============================] - 7s 298ms/step - loss: 0.1756 - acc: 0.9538 - val_loss: 0.5
260 - val_acc: 0.8939

Epoch 00029: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
Epoch 29/50
22/22 [==============================] - 7s 298ms/step - loss: 0.1757 - acc: 0.9538 - val_loss: 0.5
174 - val_acc: 0.8939

Epoch 00030: LearningRateScheduler reducing learning rate to 0.0008100000559352338.
```

```
Epoch 30/50
22/22 [==============================] - 7s 298ms/step - loss: 0.1500 - acc: 0.9569 - val_loss: 0.5
045 - val_acc: 0.8939

Epoch 00031: LearningRateScheduler reducing learning rate to 0.0007290000503417104.
Epoch 31/50
22/22 [==============================] - 7s 304ms/step - loss: 0.0891 - acc: 0.9712 - val_loss: 0.4
930 - val_acc: 0.9000

Epoch 00032: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 32/50
22/22 [==============================] - 7s 301ms/step - loss: 0.1509 - acc: 0.9600 - val_loss: 0.5
186 - val_acc: 0.9000

Epoch 00033: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 33/50
22/22 [==============================] - 7s 302ms/step - loss: 0.1219 - acc: 0.9688 - val_loss: 0.4
956 - val_acc: 0.9030

Epoch 00034: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 34/50
22/22 [==============================] - 7s 310ms/step - loss: 0.0617 - acc: 0.9803 - val_loss: 0.4
989 - val_acc: 0.9030

Epoch 00035: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 35/50
22/22 [==============================] - 7s 309ms/step - loss: 0.1295 - acc: 0.9615 - val_loss: 0.5
475 - val_acc: 0.8939

Epoch 00036: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 36/50
22/22 [==============================] - 7s 312ms/step - loss: 0.1150 - acc: 0.9662 - val_loss: 0.5
194 - val_acc: 0.9000

Epoch 00037: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 37/50
22/22 [==============================] - 7s 304ms/step - loss: 0.1354 - acc: 0.9631 - val_loss: 0.5
153 - val_acc: 0.9000

Epoch 00038: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 38/50
22/22 [==============================] - 7s 304ms/step - loss: 0.0663 - acc: 0.9800 - val_loss: 0.5
020 - val_acc: 0.8939

Epoch 00039: LearningRateScheduler reducing learning rate to 0.0007290000794455409.
Epoch 39/50
22/22 [==============================] - 8s 341ms/step - loss: 0.0911 - acc: 0.9692 - val_loss: 0.4
815 - val_acc: 0.8970
```

In [76]:

```
print('training acc.:',history.history['acc'][-1])
print('val acc.:', (history.history['val_acc'])[-1])
```

```
training acc.: 0.9692308
val acc.: 0.8969697
```

In [77]:

```
import matplotlib.pyplot as plt
%matplotlib inline
def plot_history(history):
    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy %')
    plt.plot(history.epoch, np.array(history.history['acc']),
    label='Train Accuracy')
    plt.plot(history.epoch, np.array(history.history['val_acc']),
    label = 'Val Accuracy')
    plt.legend()
    plt.ylim([0, 1])
```

In [78]:

```
plot_history(history)
```


### 3.2.1 Data augmentation

Better data augmentation can easily give a boost to a model. Some of the useful tools include

- imgaug
- mixup

In [76]:
```
!pip install imgaug
```

```
Collecting imgaug
  Downloading imgaug-0.4.0-py2.py3-none-any.whl (948 kB)
Collecting opencv-python
  Downloading opencv_python-4.4.0.46-cp37-cp37m-win_amd64.whl (33.5 MB)
Requirement already satisfied: numpy>=1.15 in c:\users\eddie\appdata\local\programs\python\python37
\lib\site-packages (from imgaug) (1.19.4)
Requirement already satisfied: matplotlib in c:\users\eddie\appdata\local\programs\python\python37
\lib\site-packages (from imgaug) (3.3.3)
Collecting scikit-image>=0.14.2
  Downloading scikit_image-0.17.2-cp37-cp37m-win_amd64.whl (11.5 MB)
Requirement already satisfied: Pillow in c:\users\eddie\appdata\local\programs\python\python37\lib
\site-packages (from imgaug) (8.0.1)
Collecting imageio
  Downloading imageio-2.9.0-py3-none-any.whl (3.3 MB)
Requirement already satisfied: six in c:\users\eddie\appdata\local\programs\python\python37\lib\sit
e-packages (from imgaug) (1.15.0)
Requirement already satisfied: scipy in c:\users\eddie\appdata\local\programs\python\python37\lib\s
ite-packages (from imgaug) (1.5.4)
Collecting Shapely
  Downloading Shapely-1.7.1-cp37-cp37m-win_amd64.whl (1.0 MB)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in c:\users\eddie\appdata\l
ocal\programs\python\python37\lib\site-packages (from matplotlib->imgaug) (2.4.7)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\eddie\appdata\local\programs\python
\python37\lib\site-packages (from matplotlib->imgaug) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\eddie\appdata\local\programs\python\py
thon37\lib\site-packages (from matplotlib->imgaug) (1.3.1)
Requirement already satisfied: cycler>=0.10 in c:\users\eddie\appdata\local\programs\python\python3
7\lib\site-packages (from matplotlib->imgaug) (0.10.0)
Collecting tifffile>=2019.7.26
  Downloading tifffile-2020.10.1-py3-none-any.whl (152 kB)
Collecting PyWavelets>=1.1.1
  Downloading PyWavelets-1.1.1-cp37-cp37m-win_amd64.whl (4.2 MB)
Collecting networkx>=2.0
  Downloading networkx-2.5-py3-none-any.whl (1.6 MB)
Requirement already satisfied: decorator>=4.3.0 in c:\users\eddie\appdata\local\programs\python\pyt
hon37\lib\site-packages (from networkx>=2.0->scikit-image>=0.14.2->imgaug) (4.4.2)
Installing collected packages: opencv-python, tifffile, imageio, PyWavelets, networkx, scikit-imag
e, Shapely, imgaug
Successfully installed PyWavelets-1.1.1 Shapely-1.7.1 imageio-2.9.0 imgaug-0.4.0 networkx-2.5 openc
v-python-4.4.0.46 scikit-image-0.17.2 tifffile-2020.10.1
```

In [ ]:
```
from imgaug import augmenters as iaa
```

```
seq = iaa.Sequential([
    iaa.Crop(px=(0,32)),
    iaa.Friplr(0.5),
    iaa.GaussianBlur(sigma=(0,4.4))
])
base_model = ResNet50(include_top=False, weights='imagenet', input_shape = (112,112,3))
model = Model(base_model.input, predictions)
```

### 3.2.2 Learning rate scheduling and early stopping criteria

In Keras learning rate scheduling and early stopping criteria can be implemented using Callbacks. In particular, the following are quite useful: LearningRateScheduler, ReduceLROnPlateau, EarlyStopping, CSVLogger, ModelCheckpoint.

In [ ]:

In [ ]:

In [ ]: