# Training a CNN

In this lab we are going to be working with a "17 Category Flower Dataset" (https://www.robots.ox.ac.uk/~vgg/data/flowers/17/index.html) 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/17/1
7flowers.tgz"
split_description_url = "https://www.robots.ox.ac.uk/~vgg/data/fl
owers/17/datasplits.mat"
#segmentation_ground_truth_url = "https://www.robots.ox.ac.uk/~vg
g/data/flowers/17/trimaps.tgz"
readme_url = "https://www.robots.ox.ac.uk/~vgg/data/flowers/17/RE
ADME.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 t
imes
def get_file(file_url, target_folder=""):
    filename = os.path.basename(file_url)
    # express explicitly the filepath where data will be download
ed
    target_filepath = os.path.join(target_folder, filename)
    filepath, response = urllib.request.urlretrieve(file_url, tar
get_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 cat
egories.
The images were acquired by searching the web and taking picture
s. 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.{p
df,ps.gz}.

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

There are 3 separate splits. The results in the paper are average
d over the 3 splits.
Each split has a training file (trn1,trn2,trn3), a validation fil
e (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 diff
erent
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.(pd
f,ps.gz).

The ground truth file also contains the file imlist.mat, which in
dicated
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 d
etailed in:
    Nilsback, M-E. and Zisserman, A.  A Visual Vocabulary for Flo
wer Classification.
    Proceedings of the IEEE Conference on Computer Vision and Pat
tern Recognition(2006)
    http://www.robots.ox.ac.uk/~vgg/publications/papers/nilsback0
6.{pdf,ps.gz}.

2. distancematrices17itfeat08.mat
```

```
- Distance matrices using the same features as described in:
    Nilsback, M-E. and Zisserman, A. Automated flower classificat
ion over a large number of classes.
    Proceedings of the Indian Conference on Computer Vision, Grap
hics and Image Processing (2008)
    http://www.robots.ox.ac.uk/~vgg/publications/papers/nilsback0
8.{pdf,ps.gz}.
  and the iterative segmenation scheme detailed in
    Nilsback, M-E. and Zisserman, A. Delving into the whorl of fl
ower segmentation.
    Proceedings of the British Machine Vision Conference (2007)
    http:www.robots.ox.ac.uk/~vgg/publications/papers/nilsback0
6.(pdf,ps.gz).
```

Now, let's download the data

In [8]:
```
# 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]:
```
import tarfile
```

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

What have we extracted?

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

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

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

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

Out[12]:
```
['.ipynb_checkpoints',
 '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']
```

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_f
older)
```

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

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

Out[15]:
```
dict_keys(['__header__', '__version__', '__globals__', 'trn1', 't
rn2', 'trn3', 'tst1', 'tst2', 'tst3', '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.shap
e[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.
- Display some of the images.
- Are those color images?
- What are their shape?
- Are they all of the same shape?

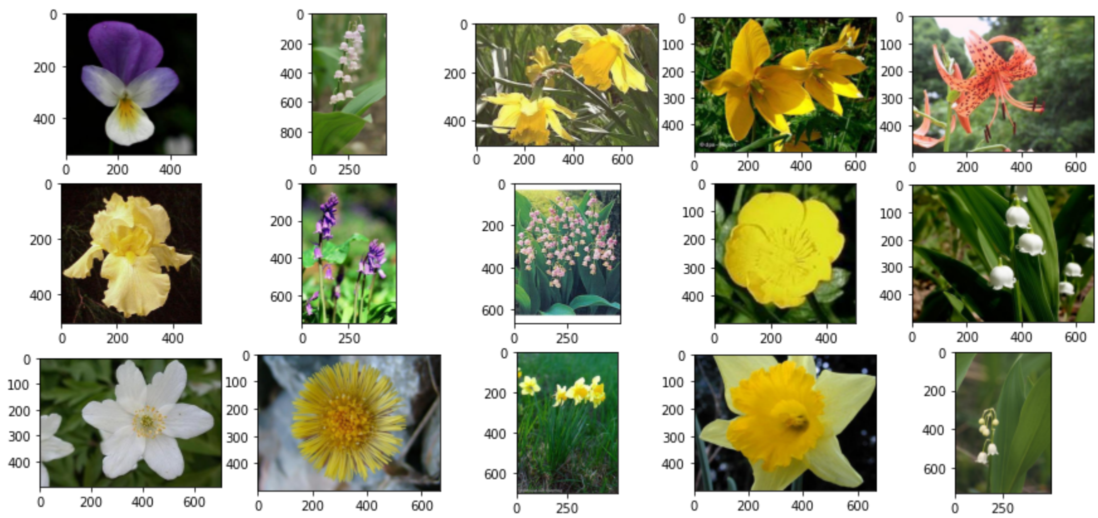
In [17]:
```
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
import random
random.seed(42)
```

In [18]:
```
files=[]
for name in os.listdir(os.path.join(data_folder, 'jpg')):
    if name.endswith(".jpg"):
            files.append(name)
```

In [19]:
```
print(len(files), 'images are downloaded.')
```

```
1360 images are downloaded.
```

In [20]:
```
plt.figure(figsize = (15, 7))

for i, filename in enumerate(random.sample(files, 15)):
    plt.subplot(3, 5, i+1)

    img = mpimg.imread(os.path.join(data_folder, f'jpg/{filenam
e}'))
    plt.imshow(img)
```



It can be seen from the images I displayed, that those pictures are colorful and have different shapes.

## 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', filena
me)
        copy(source_filepath, target_folder)
    else:
        print(filename)
        print("Not a jpg file, skipping")
```

```
.ipynb_checkpoints
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 (https://papers.nips.cc/paper/5347-how-transferable-are-features-in-deep-neural-networks.pdf)](https://papers.nips.cc/paper/5347-how-transferable-are-features-in-deep-neural-networks.pdf) we have briefly discussed last time. We'll load one of the pretrained models from Keras library with [ImageNet weights (http://www.image-net.org/)](http://www.image-net.org/).

***Model preparation***

In [25]:
```
import keras
from keras.preprocessing.image import ImageDataGenerator
from keras import backend as K
import tensorflow as tf
tf.set_random_seed(42)

import os
```

```
Using TensorFlow backend.
/home/daryna/.local/lib/python3.7/site-packages/tensorflow/python
/framework/dtypes.py:516: FutureWarning: Passing (type, 1) or '1t
ype' 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)])
/home/daryna/.local/lib/python3.7/site-packages/tensorflow/python
/framework/dtypes.py:517: FutureWarning: Passing (type, 1) or '1t
ype' 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)])
/home/daryna/.local/lib/python3.7/site-packages/tensorflow/python
/framework/dtypes.py:518: FutureWarning: Passing (type, 1) or '1t
ype' 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)])
/home/daryna/.local/lib/python3.7/site-packages/tensorflow/python
/framework/dtypes.py:519: FutureWarning: Passing (type, 1) or '1t
ype' 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)])
/home/daryna/.local/lib/python3.7/site-packages/tensorflow/python
/framework/dtypes.py:520: FutureWarning: Passing (type, 1) or '1t
ype' 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)])
/home/daryna/.local/lib/python3.7/site-packages/tensorflow/python
/framework/dtypes.py:525: FutureWarning: Passing (type, 1) or '1t
ype' 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)])
/home/daryna/.local/lib/python3.7/site-packages/tensorboard/compa
t/tensorflow_stub/dtypes.py:541: FutureWarning: Passing (type, 1)
or '1type' as a synonym of type is deprecated; in a future versio
n of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/home/daryna/.local/lib/python3.7/site-packages/tensorboard/compa
t/tensorflow_stub/dtypes.py:542: FutureWarning: Passing (type, 1)
or '1type' as a synonym of type is deprecated; in a future versio
n of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/home/daryna/.local/lib/python3.7/site-packages/tensorboard/compa
t/tensorflow_stub/dtypes.py:543: FutureWarning: Passing (type, 1)
or '1type' as a synonym of type is deprecated; in a future versio
n of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/home/daryna/.local/lib/python3.7/site-packages/tensorboard/compa
t/tensorflow_stub/dtypes.py:544: FutureWarning: Passing (type, 1)
or '1type' as a synonym of type is deprecated; in a future versio
n of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/home/daryna/.local/lib/python3.7/site-packages/tensorboard/compa
t/tensorflow_stub/dtypes.py:545: FutureWarning: Passing (type, 1)
or '1type' as a synonym of type is deprecated; in a future versio
n of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/home/daryna/.local/lib/python3.7/site-packages/tensorboard/compa
t/tensorflow_stub/dtypes.py:550: FutureWarning: Passing (type, 1)
or '1type' as a synonym of type is deprecated; in a future versio
```

```
n of numpy, it will be understood as (type, (1,)) / '(1,)type'.
```

In [26]:
```
# 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', 0.95))
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 [27]:
```
from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input as preprocess_input_vgg

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

In [28]:
```
base_model = VGG16(include_top=False, weights='imagenet', input_s
hape = (224,224,3))
base_model.summary()
```

```
WARNING:tensorflow:From /home/daryna/anaconda3/envs/ml_ukma/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:4070:
The name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2
d instead.

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 [29]:
```
## freezing the layers

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

In [30]:
```
nb_classes = 17
```

In [31]:
```
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='predi
ctions')(dropout_2)
```

In [32]:
```
model = Model(input=base_model.input, output=predictions)
```

```
/home/daryna/anaconda3/envs/ml_ukma/lib/python3.7/site-packages/i
pykernel_launcher.py:1: UserWarning: Update your `Model` call to
the Keras 2 API: `Model(inputs=Tensor("in..., outputs=Tensor("p
r...)`
  """Entry point for launching an IPython kernel.
```

In [33]:
```
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
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_1 (Flatten)          (None, 25088)             0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 25088)             0         
_________________________________________________________________
dense_1 (Dense)              (None, 1000)              25089000  
_________________________________________________________________
dropout_2 (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 [34]:
```
from keras import optimizers
```

In [35]:
```
loss = 'categorical_crossentropy'
learning_rate = 0.001
optimizer = optimizers.SGD ## optimizers.SGD ## optimizers.RMSpro
p ## optimizers.Adagrad ## optimizers.Adadelta
metrics = ['accuracy']
```

In [36]:
```
model.compile(loss=loss,
              optimizer=optimizer(learning_rate),
              metrics=metrics)
```

#### *Data preparation*

In [37]:
```
from keras.preprocessing.image import ImageDataGenerator
```

In [38]:
```
train_dir = os.path.join(data_folder, training_folder_name, "trai
n")
val_dir = os.path.join(data_folder, training_folder_name, "val")
test_dir = os.path.join(data_folder, training_folder_name, "tes
t")
```

In [39]:
```
# we'll resize images in correspondance to network input size
image_size = (224,224)
```

In [40]:
```
# 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=preproc
ess_input_vgg
                                  )

validation_datagen = ImageDataGenerator(preprocessing_function=pr
eprocess_input_vgg) # for validation we don't need to augment

train_batchsize = 30
val_batchsize = 30

# this function takes images from folders and feeds to Imagedatag
enerator
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 [41]:
```
epochs = 50
```

In [42]:
```
nb_train_steps = train_generator.samples // train_generator.batch
_size
nb_val_steps = validation_generator.samples // validation_generat
or.batch_size
```

In [43]:
```
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
)
```

```
WARNING:tensorflow:From /home/daryna/anaconda3/envs/ml_ukma/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:422: T
he name tf.global_variables is deprecated. Please use tf.compat.v
1.global_variables instead.

Epoch 1/50
22/22 [==============================] - 15s 663ms/step - loss: 
5.3156 - accuracy: 0.0338 - val_loss: 2.8815 - val_accuracy: 0.05
45
Epoch 2/50
22/22 [==============================] - 9s 405ms/step - loss: 2.
8358 - accuracy: 0.0538 - val_loss: 2.8299 - val_accuracy: 0.0097
Epoch 3/50
22/22 [==============================] - 8s 385ms/step - loss: 2.
8308 - accuracy: 0.0492 - val_loss: 2.8369 - val_accuracy: 0.0387
Epoch 4/50
22/22 [==============================] - 9s 387ms/step - loss: 2.
8225 - accuracy: 0.0600 - val_loss: 2.8372 - val_accuracy: 0.0645
Epoch 5/50
22/22 [==============================] - 9s 392ms/step - loss: 2.
8125 - accuracy: 0.0636 - val_loss: 2.7177 - val_accuracy: 0.0581
Epoch 6/50
22/22 [==============================] - 9s 388ms/step - loss: 2.
8030 - accuracy: 0.0844 - val_loss: 2.8239 - val_accuracy: 0.0387
Epoch 7/50
22/22 [==============================] - 9s 398ms/step - loss: 2.
8058 - accuracy: 0.0818 - val_loss: 2.7842 - val_accuracy: 0.0645
Epoch 8/50
22/22 [==============================] - 8s 386ms/step - loss: 2.
8022 - accuracy: 0.0719 - val_loss: 2.8692 - val_accuracy: 0.0484
Epoch 9/50
22/22 [==============================] - 9s 395ms/step - loss: 2.
7904 - accuracy: 0.0742 - val_loss: 2.8398 - val_accuracy: 0.0903
Epoch 10/50
22/22 [==============================] - 9s 387ms/step - loss: 2.
7751 - accuracy: 0.0984 - val_loss: 2.8354 - val_accuracy: 0.0516
Epoch 11/50
22/22 [==============================] - 9s 401ms/step - loss: 2.
8037 - accuracy: 0.0879 - val_loss: 2.8175 - val_accuracy: 0.1097
Epoch 12/50
22/22 [==============================] - 8s 384ms/step - loss: 2.
7693 - accuracy: 0.0906 - val_loss: 3.6355 - val_accuracy: 0.1097
Epoch 13/50
22/22 [==============================] - 9s 391ms/step - loss: 2.
7881 - accuracy: 0.0862 - val_loss: 2.7573 - val_accuracy: 0.0939
Epoch 14/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
7546 - accuracy: 0.1045 - val_loss: 2.5787 - val_accuracy: 0.0548
Epoch 15/50
22/22 [==============================] - 9s 393ms/step - loss: 2.
7716 - accuracy: 0.0875 - val_loss: 2.7258 - val_accuracy: 0.0516
Epoch 16/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
7364 - accuracy: 0.1000 - val_loss: 2.7895 - val_accuracy: 0.1129
Epoch 17/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
7788 - accuracy: 0.0969 - val_loss: 2.4569 - val_accuracy: 0.1032
Epoch 18/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
```

```
7285 - accuracy: 0.1242 - val_loss: 2.9941 - val_accuracy: 0.0290
Epoch 19/50
22/22 [==============================] - 9s 392ms/step - loss: 2.
7210 - accuracy: 0.1215 - val_loss: 2.6563 - val_accuracy: 0.1613
Epoch 20/50
22/22 [==============================] - 9s 392ms/step - loss: 2.
7851 - accuracy: 0.0906 - val_loss: 2.7768 - val_accuracy: 0.1419
Epoch 21/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
7107 - accuracy: 0.1215 - val_loss: 2.7350 - val_accuracy: 0.1065
Epoch 22/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
7233 - accuracy: 0.1167 - val_loss: 2.8136 - val_accuracy: 0.1032
Epoch 23/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
7319 - accuracy: 0.1123 - val_loss: 2.8323 - val_accuracy: 0.1226
Epoch 24/50
22/22 [==============================] - 9s 394ms/step - loss: 2.
6484 - accuracy: 0.1631 - val_loss: 3.3182 - val_accuracy: 0.1452
Epoch 25/50
22/22 [==============================] - 9s 397ms/step - loss: 2.
6274 - accuracy: 0.1338 - val_loss: 2.6404 - val_accuracy: 0.1485
Epoch 26/50
22/22 [==============================] - 9s 407ms/step - loss: 2.
5678 - accuracy: 0.1815 - val_loss: 2.6195 - val_accuracy: 0.2032
Epoch 27/50
22/22 [==============================] - 9s 405ms/step - loss: 2.
6062 - accuracy: 0.1708 - val_loss: 2.8934 - val_accuracy: 0.1774
Epoch 28/50
22/22 [==============================] - 9s 401ms/step - loss: 2.
5742 - accuracy: 0.1631 - val_loss: 2.2188 - val_accuracy: 0.2000
Epoch 29/50
22/22 [==============================] - 9s 396ms/step - loss: 2.
4760 - accuracy: 0.1923 - val_loss: 0.9369 - val_accuracy: 0.2194
Epoch 30/50
22/22 [==============================] - 9s 401ms/step - loss: 2.
5027 - accuracy: 0.1985 - val_loss: 2.8543 - val_accuracy: 0.2000
Epoch 31/50
22/22 [==============================] - 9s 401ms/step - loss: 2.
4569 - accuracy: 0.2108 - val_loss: 2.6838 - val_accuracy: 0.2613
Epoch 32/50
22/22 [==============================] - 9s 400ms/step - loss: 2.
4984 - accuracy: 0.1969 - val_loss: 2.3388 - val_accuracy: 0.3097
Epoch 33/50
22/22 [==============================] - 9s 405ms/step - loss: 2.
3781 - accuracy: 0.2318 - val_loss: 2.5576 - val_accuracy: 0.2806
Epoch 34/50
22/22 [==============================] - 9s 401ms/step - loss: 2.
3018 - accuracy: 0.2562 - val_loss: 2.7176 - val_accuracy: 0.3129
Epoch 35/50
22/22 [==============================] - 9s 409ms/step - loss: 2.
2859 - accuracy: 0.2500 - val_loss: 2.8134 - val_accuracy: 0.3613
Epoch 36/50
22/22 [==============================] - 9s 399ms/step - loss: 2.
1451 - accuracy: 0.3215 - val_loss: 3.3031 - val_accuracy: 0.3903
Epoch 37/50
22/22 [==============================] - 9s 407ms/step - loss: 2.
2689 - accuracy: 0.2677 - val_loss: 1.7559 - val_accuracy: 0.2879
Epoch 38/50
22/22 [==============================] - 9s 407ms/step - loss: 2.
```

```
1326 - accuracy: 0.3046 - val_loss: 1.5104 - val_accuracy: 0.3290
Epoch 39/50
22/22 [==============================] - 9s 404ms/step - loss: 1.
9735 - accuracy: 0.3406 - val_loss: 2.0352 - val_accuracy: 0.3645
Epoch 40/50
22/22 [==============================] - 9s 410ms/step - loss: 1.
9475 - accuracy: 0.3394 - val_loss: 1.0960 - val_accuracy: 0.4548
Epoch 41/50
22/22 [==============================] - 9s 405ms/step - loss: 1.
9477 - accuracy: 0.3538 - val_loss: 1.3002 - val_accuracy: 0.3710
Epoch 42/50
22/22 [==============================] - 9s 406ms/step - loss: 1.
7029 - accuracy: 0.4354 - val_loss: 1.1354 - val_accuracy: 0.3290
Epoch 43/50
22/22 [==============================] - 9s 405ms/step - loss: 1.
7417 - accuracy: 0.4031 - val_loss: 2.1094 - val_accuracy: 0.4258
Epoch 44/50
22/22 [==============================] - 9s 405ms/step - loss: 1.
5758 - accuracy: 0.4431 - val_loss: 1.5066 - val_accuracy: 0.5065
Epoch 45/50
22/22 [==============================] - 9s 405ms/step - loss: 1.
7179 - accuracy: 0.4231 - val_loss: 1.8550 - val_accuracy: 0.5032
Epoch 46/50
22/22 [==============================] - 9s 405ms/step - loss: 1.
6164 - accuracy: 0.4938 - val_loss: 1.6743 - val_accuracy: 0.5387
Epoch 47/50
22/22 [==============================] - 9s 410ms/step - loss: 1.
5296 - accuracy: 0.4877 - val_loss: 2.0965 - val_accuracy: 0.5000
Epoch 48/50
22/22 [==============================] - 9s 404ms/step - loss: 1.
3912 - accuracy: 0.5692 - val_loss: 2.3185 - val_accuracy: 0.5871
Epoch 49/50
22/22 [==============================] - 9s 409ms/step - loss: 1.
3233 - accuracy: 0.5631 - val_loss: 0.7601 - val_accuracy: 0.5727
Epoch 50/50
22/22 [==============================] - 9s 411ms/step - loss: 1.
```

In [44]:

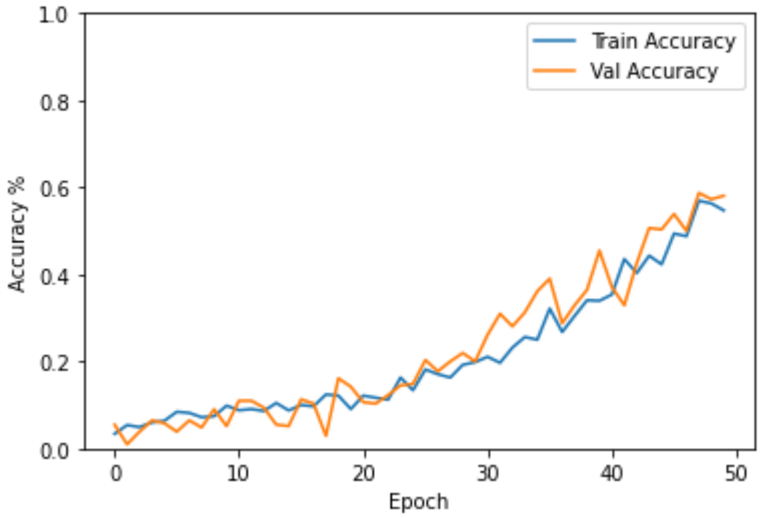
```
print('training acc.:',history.history['accuracy'][-1])
print('val acc.:', (history.history['val_accuracy'])[-1])
```

```
training acc.: 0.5469697
val acc.: 0.5806451439857483
```

In [45]:

```
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['accuracy
']),
    label='Train Accuracy')
    plt.plot(history.epoch, np.array(history.history['val_accurac
y']),
    label = 'Val Accuracy')
    plt.legend()
    plt.ylim([0, 1])
```

In [46]:
```
plot_history(history)
```




***Save model***

In [47]:
```
weights_folder = "weights"
os.makedirs(weights_folder, exist_ok=True)
```

In [48]:
```
model_name = 'vgg16_transfer_weights.h5'
```

In [49]:
```
model_path = os.path.join(weights_folder, model_name)
```

In [50]:
```
# uncomment to save model
model.save(model_path)
```

***Do the test on images***

In [51]:
```
from keras.preprocessing import image
from keras.models import load_model
```

In [52]:
```
model = load_model(model_path, compile=False)
```

***Single image prediction***

In [53]:
```
#test_dir = "data/training_folder/test"
#image_size = (224,224)
```

In [54]:
```
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 [55]:
```
image_path
```

Out[55]:
```
'data/training_folder/test/08/image_0564.jpg'
```

In [56]:
```
# 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)
```

```
[[1.7272340e-01 9.9440487e-03 3.2333194e-03 1.6651471e-03 7.57508
27e-04
  3.1511445e-04 1.0703150e-02 1.0364726e-01 2.7331822e-03 9.66377
48e-02
  2.1522368e-04 3.6130797e-02 1.6528781e-01 5.4327287e-02 3.27790
35e-01
  9.5128659e-03 4.3757381e-03]]
```

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

Out[57]:
```
(1, 224, 224, 3)
```

In [58]:
```
img_array.shape
```

Out[58]:
```
(224, 224, 3)
```

In [59]:
```
classes = ["{:02d}".format(i) for i in range(1, 18)]
pred_class_idx = np.argmax(pred, axis=1)
classes[pred_class_idx[0]]
```

Out[59]:
```
'15'
```

In [60]:
```
pred[0][pred_class_idx]
```

Out[60]:
```
array([0.32779035], dtype=float32)
```

***Multiple image predictions***

In [61]:
```
from sklearn.metrics import classification_report, confusion_matr
ix
import seaborn as sns; sns.set()
```

In [62]:
```
test_datagen = ImageDataGenerator(preprocessing_function=preproce
ss_input_vgg)
```

In [63]:
```
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_sample
s)
```

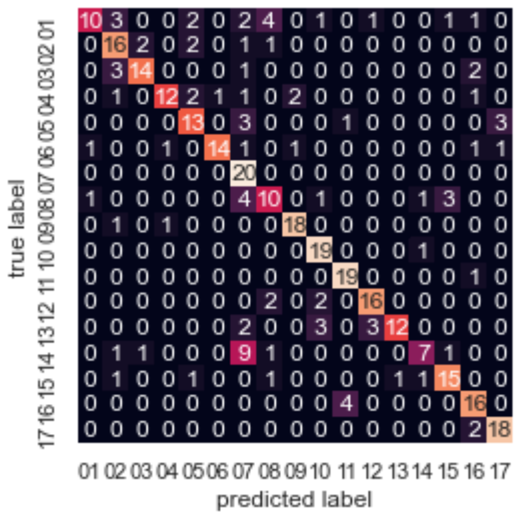
```
Found 347 images belonging to 17 classes.
```

In [64]:
```
predict.shape
```

Out[64]:
```
(347, 17)
```

In [65]:
```
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
```



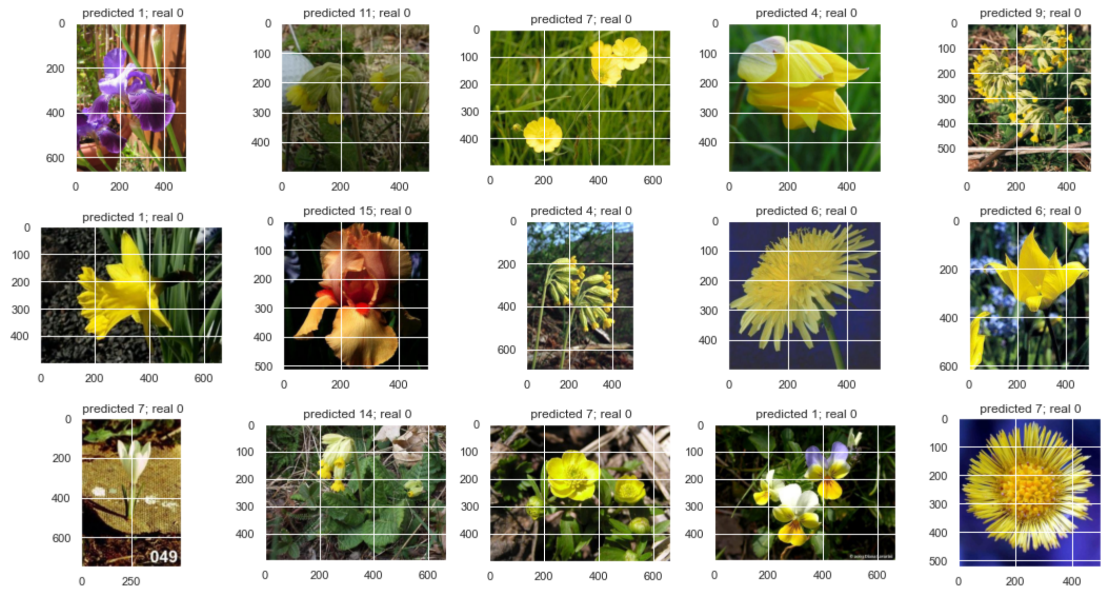
In [66]:
```
print(classification_report(test_generator.classes + 1, y_pred +
1))  ## adding 1 to preserve the class naming
```

```
              precision    recall  f1-score   support

           1       0.83      0.40      0.54        25
           2       0.62      0.73      0.67        22
           3       0.82      0.70      0.76        20
           4       0.86      0.60      0.71        20
           5       0.65      0.65      0.65        20
           6       0.93      0.70      0.80        20
           7       0.45      1.00      0.62        20
           8       0.53      0.50      0.51        20
           9       0.86      0.90      0.88        20
          10       0.73      0.95      0.83        20
          11       0.79      0.95      0.86        20
          12       0.80      0.80      0.80        20
          13       0.92      0.60      0.73        20
          14       0.70      0.35      0.47        20
          15       0.75      0.75      0.75        20
          16       0.67      0.80      0.73        20
          17       0.82      0.90      0.86        20

    accuracy                           0.72       347
   macro avg       0.75      0.72      0.71       347
weighted avg       0.75      0.72      0.71       347
```

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

In [67]:
```
incorect_images = np.array(test_generator.filenames)[test_generator.classes!= y_pred]
incorect_real = test_generator.classes[test_generator.classes!= y_pred]
incorect_pred = y_pred[test_generator.classes!= y_pred]

plt.figure(figsize = (15, 8))
for i, name in enumerate(random.sample(list(incorect_images), 15)):
    plt.subplot(3,5, i+1)
    img = mpimg.imread(os.path.join(data_folder, f'training_folder/test/{name}'))
    plt.title(f' predicted {incorect_pred[i]}; real {incorect_real[i]}')
    plt.imshow(img)
plt.tight_layout()
```




In [68]:
```
from keras.applications.resnet import ResNet50
from keras.applications.resnet import preprocess_input as preprocess_input_resnet
from keras.callbacks import EarlyStopping
```

In [79]:
```
base_model = ResNet50(include_top=False, weights='imagenet', input_shape = (112,112,3))
# base_model.summary()
```

In [80]:
```
flatten = Flatten()(base_model.output)
dropout_1 = Dropout(0.25)(flatten)
fc_1 = Dense(100)(dropout_1)
dropout_2 = Dropout(0.5)(fc_1)
predictions = Dense(nb_classes, activation="softmax", name='predictions')(dropout_2)
model = Model(inputs=base_model.input, outputs=predictions)
```

In [81]:
```
optimizer = optimizers.Adam
learning_rate = 0.0001
```

In [82]:
```
model.compile(loss=loss,
              optimizer=optimizer(learning_rate),
              metrics=metrics)
```

In [83]:
```
image_size = (112,112)
```

In [84]:
```
# 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=preproc
ess_input_resnet
                                  )

validation_datagen = ImageDataGenerator(preprocessing_function=pr
eprocess_input_resnet) # for validation we don't need to augment

train_batchsize = 5
val_batchsize = 5

# this function takes images from folders and feeds to Imagedatag
enerator
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.
```

In [85]:
```
epochs = 100
nb_train_steps = train_generator.samples // train_generator.batch
_size
nb_val_steps = validation_generator.samples // validation_generat
or.batch_size
```

In [86]:
```
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 = [EarlyStopping(monitor="val_loss", min_delta=1e
-2, patience=10)]
)
```

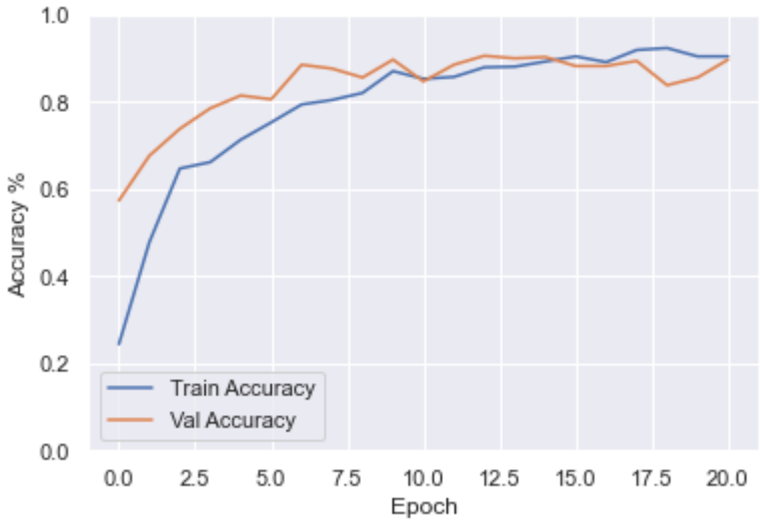
```
Epoch 1/100
136/136 [==============================] - 16s 120ms/step - loss:
5.6936 - accuracy: 0.2441 - val_loss: 4.9913 - val_accuracy: 0.57
35
Epoch 2/100
136/136 [==============================] - 10s 74ms/step - loss:
3.2445 - accuracy: 0.4779 - val_loss: 5.8907 - val_accuracy: 0.67
65
Epoch 3/100
136/136 [==============================] - 10s 74ms/step - loss:
2.0295 - accuracy: 0.6471 - val_loss: 2.9547 - val_accuracy: 0.73
820 - accura - ETA: 0s - loss: 2.1012 - ac - ETA: 0s - loss: 2.06
96 - accuracy:  - ETA: 0s - loss: 2.0349 - accuracy: 0.64
Epoch 4/100
136/136 [==============================] - 10s 75ms/step - loss:
2.0318 - accuracy: 0.6618 - val_loss: 2.1029 - val_accuracy: 0.78
53
Epoch 5/100
136/136 [==============================] - 10s 75ms/step - loss:
1.5227 - accuracy: 0.7132 - val_loss: 4.1367 - val_accuracy: 0.81
47
Epoch 6/100
136/136 [==============================] - 10s 75ms/step - loss:
1.3705 - accuracy: 0.7529 - val_loss: 1.8650 - val_accuracy: 0.80
59
Epoch 7/100
136/136 [==============================] - 10s 75ms/step - loss:
1.0977 - accuracy: 0.7941 - val_loss: 0.0193 - val_accuracy: 0.88
53
Epoch 8/100
136/136 [==============================] - 10s 75ms/step - loss:
0.9504 - accuracy: 0.8044 - val_loss: 2.2415 - val_accuracy: 0.87
65
Epoch 9/100
136/136 [==============================] - 10s 75ms/step - loss:
0.7063 - accuracy: 0.8206 - val_loss: 0.8863 - val_accuracy: 0.85
59
Epoch 10/100
136/136 [==============================] - 10s 76ms/step - loss:
0.6200 - accuracy: 0.8706 - val_loss: 0.0342 - val_accuracy: 0.89
71
Epoch 11/100
136/136 [==============================] - 10s 77ms/step - loss:
0.8151 - accuracy: 0.8529 - val_loss: 0.0011 - val_accuracy: 0.84
71
Epoch 12/100
136/136 [==============================] - 11s 78ms/step - loss:
0.5550 - accuracy: 0.8574 - val_loss: 0.0370 - val_accuracy: 0.88
53
Epoch 13/100
136/136 [==============================] - 11s 78ms/step - loss:
0.5437 - accuracy: 0.8794 - val_loss: 0.0010 - val_accuracy: 0.90
59
Epoch 14/100
136/136 [==============================] - 11s 78ms/step - loss:
0.5077 - accuracy: 0.8809 - val_loss: 1.1992e-05 - val_accuracy:
0.9000
Epoch 15/100
136/136 [==============================] - 11s 78ms/step - loss:
```

```
0.4757 - accuracy: 0.8926 - val_loss: 6.9421e-04 - val_accuracy:
0.9029
Epoch 16/100
136/136 [==============================] - 11s 78ms/step - loss:
0.3674 - accuracy: 0.9044 - val_loss: 0.4457 - val_accuracy: 0.88
24
Epoch 17/100
136/136 [==============================] - 11s 78ms/step - loss:
0.5384 - accuracy: 0.8912 - val_loss: 1.2851 - val_accuracy: 0.88
24
Epoch 18/100
136/136 [==============================] - 11s 78ms/step - loss:
0.4028 - accuracy: 0.9191 - val_loss: 0.0203 - val_accuracy: 0.89
41
Epoch 19/100
136/136 [==============================] - 11s 78ms/step - loss:
0.3431 - accuracy: 0.9235 - val_loss: 1.8122 - val_accuracy: 0.83
82
Epoch 20/100
136/136 [==============================] - 11s 79ms/step - loss:
0.3999 - accuracy: 0.9044 - val_loss: 0.2111 - val_accuracy: 0.85
59
Epoch 21/100
136/136 [==============================] - 10s 76ms/step - loss:
0.3889 - accuracy: 0.9044 - val_loss: 0.0296 - val_accuracy: 0.89
71
```

In [87]:
```
print('training acc.:',history.history['accuracy'][-1])
print('val acc.:', (history.history['val_accuracy'])[-1])
```

```
training acc.: 0.9044118
val acc.: 0.8970588445663452
```

In [88]:
```
plot_history(history)
```




#### 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 (https://arxiv.org/pdf/1812.01187.pdf) or object detection (https://arxiv.org/pdf/1902.04103.pdf) model.

#### *3.2.1 Data augmentation*

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

- imgaug (https://github.com/aleju/imgaug)
- mixup (https://arxiv.org/pdf/1710.09412.pdf)

#### *3.2.2 Learning rate scheduling and early stopping criteria*

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

In [ ]:

In [ ]:

In [ ]:

In [ ]: