```
In [1]:
```

#### In [2]:

```
#General imports
from __future__ import print_function
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import progressbar
from sklearn.model selection import train test split
from sklearn.preprocessing import normalize
from sklearn.decomposition import PCA
# Keras imports
import keras
from tensorflow.keras import layers
from keras.preprocessing.image import load img
from keras.models import Sequential, Model
from tensorflow.keras.optimizers import *
from keras.utils.np utils import to categorical
import keras.backend as K
# application (model) imports
from tensorflow.keras import applications
#from keras.applications.inception v3 import preprocess input
from keras.layers import Dense
import tensorflow as tf
import tensorflow datasets as tfds
import tensorflow addons as tfa
```

## In [3]:

```
# load the data from Tensorflow
tfds.disable_progress_bar()
(train, validation, test), info = tfds.load(
    "oxford_flowers102",
    split=["train", "validation", "test"],
    as_supervised=True, # Include labels
    with_info = True,
    try_gcs = True,
)

print("Number of training samples: %d" % tf.data.experimental.cardinality(train))
print("Number of validation samples: %d" % tf.data.experimental.cardinality(validation))
print("Number of test samples: %d" % tf.data.experimental.cardinality(test))
```

Downloading and preparing dataset oxford\_flowers102/2.1.1 (download: 328.90 MiB, generate d: 331.34 MiB, total: 660.25 MiB) to /root/tensorflow\_datasets/oxford\_flowers102/2.1.1...

```
Shuffling and writing examples to /root/tensorflow_datasets/oxford_flowers102/2.1.1.incom
\verb|pleteMECMLO|/oxford_flowers102-train.tfrecord|
Shuffling and writing examples to /root/tensorflow\_datasets/oxford flowers102/2.1.1.incom
pleteMECMLO/oxford flowers102-test.tfrecord
Shuffling and writing examples to /root/tensorflow datasets/oxford flowers102/2.1.1.incom
pleteMECMLO/oxford flowers102-validation.tfrecord
Dataset oxford flowers102 downloaded and prepared to /root/tensorflow datasets/oxford flo
wers102/2.1.1. Subsequent calls will reuse this data.
Number of training samples: 1020
Number of validation samples: 1020
Number of test samples: 6149
In [4]:
print(info)
tfds.core.DatasetInfo(
    name='oxford flowers102',
    version=2.1.1,
    description='The Oxford Flowers 102 dataset is a consistent of 102 flower categories
commonly occurring
in the United Kingdom. Each class consists of between 40 and 258 images. The images have
large scale, pose and light variations. In addition, there are categories that have large
variations within the category and several very similar categories.
The dataset is divided into a training set, a validation set and a test set.
The training set and validation set each consist of 10 images per class (totalling 1020 i
mages each).
The test set consists of the remaining 6149 images (minimum 20 per class).',
    homepage='https://www.robots.ox.ac.uk/~vgg/data/flowers/102/',
    features=FeaturesDict({
        'file name': Text(shape=(), dtype=tf.string),
        'image': Image(shape=(None, None, 3), dtype=tf.uint8),
        'label': ClassLabel(shape=(), dtype=tf.int64, num classes=102),
    }),
    total num examples=8189,
    splits={
        'test': 6149,
        'train': 1020,
        'validation': 1020,
    supervised keys=('image', 'label'),
    citation="""@InProceedings{Nilsback08,
       author = "Nilsback, M-E. and Zisserman, A.",
       title = "Automated Flower Classification over a Large Number of Classes",
       booktitle = "Proceedings of the Indian Conference on Computer Vision, Graphics and
Image Processing",
       year = "2008",
       month = "Dec"
    redistribution info=,
)
In [5]:
#combine training and validation data as training data
train = train.concatenate(validation)
In [6]:
plt.figure(figsize=(10, 10))
for i, (image, label) in enumerate(train.take(9)):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(image)
    plt.title(int(label))
    plt.axis("off")
```



### In [7]:

```
#resize the augmented images to 224 * 224

size = (224, 224)

train = train.map(lambda x, y: (tf.image.resize(x, size), y))
test = test.map(lambda x, y: (tf.image.resize(x, size), y))
#we don't need to resize the test image
```

# In [8]:

```
size = (224, 224,3)

train = train.map(lambda x, y: (tf.image.random_flip_left_right(x), y))
train = train.map(lambda x, y: (tf.image.random_crop(x, size), y))
#train = train.map(lambda x, y: (tf.image.random_saturation(x, size), y))
```

# In [9]:

```
#batch the data and use caching & prefetching to optimize loading speed
batch_size = 64

train = train.batch(batch_size).prefetch(buffer_size=10)
test = test.batch(batch_size).prefetch(buffer_size=10)
```

### In [10]:

```
#set up base model
input_shape = (224,224,3)
num_classes=102

base_model = applications.resnet_v2.ResNet101V2(input_shape=input_shape, include_top=Fal
se, weights='imagenet', pooling='avg')

x = base_model.output #We use Keras Functional API here
predictions = Dense(num_classes, activation='softmax')(x)
```

```
model = Model(inputs = base model.input, outputs=predictions)
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet
/resnet101v2 weights tf dim ordering tf kernels notop.h5
In [11]:
# compile the model
# Optimizer: Nesterov's Accelerated Gradient
alpha = 0.0001 #weight decay
momentum = 0.9
model.compile(optimizer=tfa.optimizers.SGDW(momentum = momentum, weight decay = alpha, n
esterov=True, learning rate=0.01),
        loss=['sparse categorical crossentropy'], metrics=['sparse categorical acc
uracy'])
In [12]:
#train the model
history = model.fit(train, epochs=15, validation_data= test, batch_size=256)
Epoch 1/15
accuracy: 0.4294 - val loss: 7.3995 - val sparse categorical accuracy: 0.1226
al accuracy: 0.9005 - val loss: 3.0069 - val sparse categorical accuracy: 0.4558
Epoch 3/15
al accuracy: 0.9897 - val loss: 1.7892 - val sparse categorical accuracy: 0.6221
Epoch 4/15
al accuracy: 0.9971 - val loss: 0.9182 - val_sparse_categorical_accuracy: 0.7845
Epoch 5/15
al_accuracy: 0.9995 - val_loss: 0.6394 - val_sparse_categorical_accuracy: 0.8379
Epoch 6/15
al accuracy: 0.9995 - val loss: 0.6844 - val sparse categorical accuracy: 0.8235
Epoch 7/15
accuracy: 0.9995 - val loss: 0.5130 - val sparse categorical accuracy: 0.8644
Epoch 8/15
al accuracy: 0.9995 - val loss: 0.4754 - val sparse categorical accuracy: 0.8720
al accuracy: 1.0000 - val loss: 0.4576 - val sparse categorical accuracy: 0.8754
Epoch 10/15
al accuracy: 1.0000 - val loss: 0.4507 - val sparse categorical accuracy: 0.877\overline{4}
Epoch 11/15
al accuracy: 1.0000 - val loss: 0.4489 - val sparse categorical accuracy: 0.8787
Epoch 12/15
al accuracy: 1.0000 - val_loss: 0.4500 - val_sparse_categorical_accuracy: 0.8784
Epoch 13/15
al accuracy: 1.0000 - val loss: 0.4501 - val sparse categorical accuracy: 0.8785
Epoch 14/15
al accuracy: 1.0000 - val loss: 0.4496 - val sparse categorical accuracy: 0.8798
Epoch 15/15
```

al accuracy: 1.0000 - val loss: 0.4503 - val sparse categorical accuracy: 0.8797

#### In [13]:

```
def plot_loss_accuracy(history):
    historydf = pd.DataFrame(history.history, index=history.epoch)
    plt.figure(figsize=(8, 6))
    historydf.plot(ylim=(0, max(1, historydf.values.max())))
    loss = history.history['loss'][-1]
    acc = history.history['sparse_categorical_accuracy'][-1]
    val_acc = history.history['val_sparse_categorical_accuracy'][-1]
    val_error = (1 - val_acc)
    plt.title('Loss: %.3f, sparse_categorical_accuracy: %.3f' % (loss, acc))
    print('Validation Error: %.3f' % (val_error))
```

## In [14]:

```
plot_loss_accuracy(history)
```

Validation Error: 0.120

<Figure size 576x432 with 0 Axes>

