Devices and circuits for Artificial Intelligence

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Final exam project

In this notebook I introduce the project for the final exam of the course *Devices and circuits for artificial intelligence* from the Data Analysis degree of the University of Messina. The project consists in building a machine learning model for image classification.

The dataset to be used is hosted at kaggle, and is called BIRDS 525 SPECIES- IMAGE CLASSIFICATION. The dataset currently contains images from 525 bird species to be classified by the model. I downloaded the dataset on April, 17th, 2023, and that version contains 515 bird species.

It is useful to note that images in the dataset should have all the exact same shape (224, 224, 3), while I found that all images of the 'PLUSH CRESTED JAY' species and one image from the 'DON'T REMEMBER THE SPECIES, FILL INFO WITH FUTURE COMMIT' species have variable shapes. Hence, in my code, I check for images' shapes and remove images that don't match the common shape. This is important because imported images have the shape of 3D Numpy (np, when imported) arrays and I need to transform the list of images into a 4D Numpy array. The function np.array() can do it automatically when fed a list of 3D Numpy arrays, but images must have all the same shape.

The following cell is for importing necessary modules in the file used for describing the data, the model and the results. I previously uploaded data for bird species classification on Colab, in the *content/kaggle_data* folder.

In [ ]:
```
##########################################
### allow importing from Google Drive   ###
###  after uploading the needed files   ###
##########################################
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
import sys
sys.path.insert(0,'/content/drive/MyDrive/Colab Notebooks/da_dcAI_project

##########################################
### unzip reshaped dataset from Google ###
###  Drive to colab's content folder   ###
##########################################
!unzip '/content/drive/MyDrive/Colab Notebooks/da_dcAI_project/reshaped_d

##########################################
### import necessary or useful modules ###
##########################################
import os
import numpy as np
#import tensorflow as tf
from    matplotlib                  import pyplot as plt
from    tensorflow.keras.utils      import to_categorical
from    keras.preprocessing.image   import ImageDataGenerator
from    sklearn.metrics             import classification_report, confusion
from    a_selectRandomFolders       import selectRandomFolders
from    b_viewClasses               import viewRandomClasses, viewRandomCla
from    c_selectData                import selectData, classesToInt, countL
from    d_tl_model_DenseNet         import seqModel
from    e_plotConfusionMatrix       import plotCM
```

Retrieve data folders

The following code cell is used for retrieving the system folders where the data are located.

In [2]:
```
### 1) set path to the directory of the dataset (this is the targetFolder
###    and show how many bird classes there are in the path and their nam
trainPathWin = 'C:/Users/mzlarosa/OneDrive - unime.it/Learning/CdL Inform
testPathWin = 'C:/Users/mzlarosa/OneDrive - unime.it/Learning/CdL Informa
validPathWin = 'C:/Users/mzlarosa/OneDrive - unime.it/Learning/CdL Inform
trainPathMac = '/Users/mau/OneDrive - unime.it/Learning/CdL Informatica/A
testPathMac = '/Users/mau/OneDrive - unime.it/Learning/CdL Informatica/An
validPathMac = '/Users/mau/OneDrive - unime.it/Learning/CdL Informatica/A
trainPath = '/content/reshaped/train'
testPath = '/content/reshaped/test'
validPath = '/content/reshaped/valid'
classes = os.listdir(trainPath)
if '.DS_Store' in classes:
    classes.remove('.DS_Store')
nOfClasses = len(classes)
print('\nThere are', nOfClasses, 'classes in the dataset.\n' +
      '\nHere is a list of the first 50 classes:')
print(classes[0 : 50], end = '')
print('[...]')
```

```
There are 515 classes in the dataset.

Here is a list of the first 50 classes:
['BLACK-CAPPED CHICKADEE', 'BLONDE CRESTED WOODPECKER', 'WHITE BROWED CR
AKE', 'AMERICAN GOLDFINCH', 'LIMPKIN', 'APAPANE', 'BLACKBURNIAM WARBLE
R', 'NORTHERN FLICKER', 'PAINTED BUNTING', 'AUSTRALASIAN FIGBIRD', 'ANDE
AN SISKIN', 'EMPEROR PENGUIN', 'TRICOLORED BLACKBIRD', 'RUBY THROATED HU
MMINGBIRD', 'PHILIPPINE EAGLE', 'MALACHITE KINGFISHER', 'GYRFALCON', 'MI
LITARY MACAW', 'GOLD WING WARBLER', 'VARIED THRUSH', 'GROVED BILLED AN
I', 'EASTERN BLUEBONNET', 'MALLARD DUCK', 'NORTHERN MOCKINGBIRD', 'HOUSE
SPARROW', 'OYSTER CATCHER', 'CAPPED HERON', 'ASIAN CRESTED IBIS', 'COMMO
N POORWILL', 'OCELLATED TURKEY', 'IVORY BILLED ARACARI', 'NORTHERN RED B
ISHOP', 'QUETZAL', 'TROPICAL KINGBIRD', 'CRIMSON SUNBIRD', 'AFRICAN CROW
NED CRANE', 'GREAT TINAMOU', 'GREAT KISKADEE', 'FRILL BACK PIGEON', 'GIL
A WOODPECKER', 'HYACINTH MACAW', 'HARLEQUIN DUCK', 'GREY PLOVER', 'LILAC
ROLLER', 'FASCIATED WREN', 'BROWN CREPPER', 'SATYR TRAGOPAN', 'ABBOTTS B
ABBLER', 'CEDAR WAXWING', 'BEARDED BELLBIRD'][...]
```

Introduce the data

The number of available pictures varies with the class.
I select a random sample of 15 bird species from the train data and show how many images are available for each sampled species.

In [ ]:
```
### 2) select a random sample of n (15) subfolders from the targetFolder
###    and show their content (subfolders represent bird classes)
###    modules: os, random, selectRandomFolders
targetClasses = selectRandomFolders(trainPath, 15)
```

```
There are 0 folders and 139 image files in /content/reshaped/train/NORTH
ERN FLICKER
There are 0 folders and 160 image files in /content/reshaped/train/BORNE
AN LEAFBIRD
There are 0 folders and 173 image files in /content/reshaped/train/HORNE
D LARK
There are 0 folders and 139 image files in /content/reshaped/train/TRICO
LORED BLACKBIRD
There are 0 folders and 165 image files in /content/reshaped/train/TOWNS
ENDS WARBLER
There are 0 folders and 175 image files in /content/reshaped/train/HARPY
EAGLE
There are 0 folders and 168 image files in /content/reshaped/train/BLACK
-THROATED SPARROW
There are 0 folders and 175 image files in /content/reshaped/train/KILLD
EAR
There are 0 folders and 136 image files in /content/reshaped/train/BARRE
D PUFFBIRD
There are 0 folders and 187 image files in /content/reshaped/train/AUCKL
AND SHAQ
There are 0 folders and 193 image files in /content/reshaped/train/VARIE
D THRUSH
There are 0 folders and 135 image files in /content/reshaped/train/GOLDE
N CHLOROPHONIA
There are 0 folders and 156 image files in /content/reshaped/train/GREEN
JAY
There are 0 folders and 134 image files in /content/reshaped/train/ANDEA
N GOOSE
There are 0 folders and 159 image files in /content/reshaped/train/FRIGA
TE
```

Plot pictures from sample species

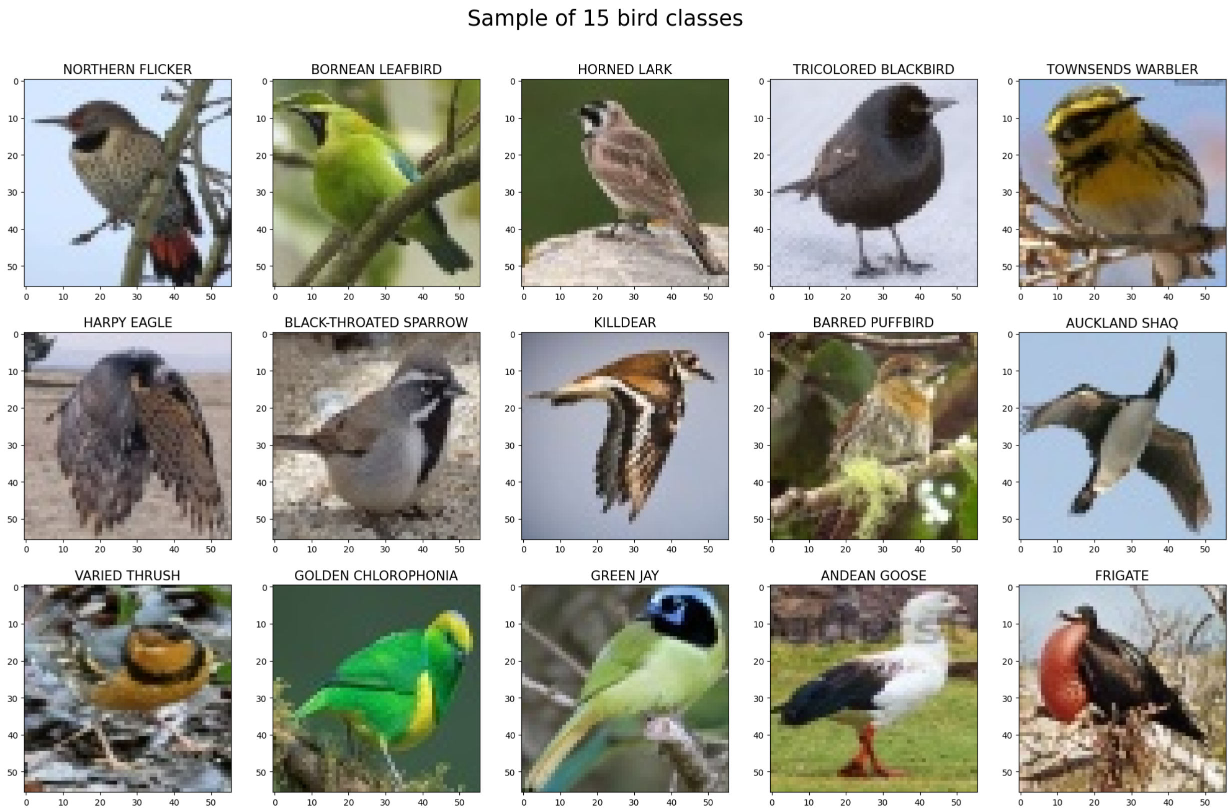
Plot one picture from 15 randomly selected species

Then I draw a random picture from each class and show their shape and size. A picture's shape shows tipically three dimensions. The first two dimensions build a 2D matrix of n rows by m columns. The number of rows represents the image height in pixels, while the number of columns represents the image width in pixels. So each matrix coordinate point represents the intensity value of a single pixel. The third dimension refers to the number of color planes (or channels). There is one plane (2D matrix) for each RGB color, so the value of the third dimension is 3. A picture's size shows its total number of pixels, which results by multiplying the dimensions of the 2D matrices by themselves and by the number of color planes.

In [ ]:
```
### 3) plot one random image from each bird class
###    modules: b_viewClasses
randomClasses = viewRandomClasses(trainPath, targetClasses[0])
plt.show()
```

```
Class: NORTHERN FLICKER
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: BORNEAN LEAFBIRD
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: HORNED LARK
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: TRICOLORED BLACKBIRD
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: TOWNSENDS WARBLER
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: HARPY EAGLE
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: BLACK-THROATED SPARROW
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: KILLDEAR
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: BARRED PUFFBIRD
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: AUCKLAND SHAQ
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: VARIED THRUSH
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: GOLDEN CHLOROPHONIA
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: GREEN JAY
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: ANDEAN GOOSE
```

```
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408

Class: FRIGATE
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
```



Plot 15 pictures from one of the previously selected random species

Finally, we print 15 random images from one of the previously chosen species and show their shape and size as before defined.

In [ ]:
```
### 4) plot 15 random images from one of the classes
###     modules: b_viewClasses
randomClass = viewRandomClass(trainPath, targetClasses[0])
plt.show()
print('\nI conclude that, although there is a varying number of images',
      'for each bird class,')
print('in our sample of 15 classes there is a minimum',
      'of', min(targetClasses[2]), 'images, and a maximum of',
      max(targetClasses[2]), 'images.\n')
```

```
VARIED THRUSH
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
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Image shape (rows, columns, channels): (56, 56, 3)
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Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
Image shape (rows, columns, channels): (56, 56, 3)
Image size (number of pixels): 9408
```

VARIED THRUSH

```
I conclude that, although there is a varying number of images for each b
ird class,
in our sample of 15 classes there is a minimum of 134 images, and a maxi
mum of 193 images.
```

Data preparation

The following code allows me to load each image of the train and test sets into Python lists. The lists containing the images are then turned into numerical arrays, with 4 dimensions: the first one represents the number of images, while the other three represent the images' shape, which has been rendered homogeneous (56, 56, 3) by removing those not matching the common shape within the execution of the custom *selectData* function.

In [9]:
```
### 5) load the train, test and validation data and labels into memory
#trainData, trainClasses, testData, testClasses, validData, validClasses,
trainData, trainClasses = selectData(trainPath)
testData, testClasses = selectData(testPath)
validData, validClasses = selectData(validPath)
#train, test and validation data lists into numpy arrays
npTrainData = np.array(trainData)
npTestData = np.array(testData)
npValidData = np.array(validData)

print('Our train data array has', npTrainData.ndim, 'dimensions, and a sh
      npTrainData.shape, 'for a total number of elements of', npTrainData
print('Our test data array has', npTestData.ndim, 'dimensions, and a shap
      npTestData.shape, 'for a total number of elements of', npTestData.s
print('Our validation data array is equivalent in number to the test data
      npValidData.ndim, 'dimensions, and a shape of', npValidData.shape,
      'for a total number of elements of', npValidData.size, '.')
```

```
Our train data array has 4 dimensions, and a shape of (82724, 56, 56, 3)
for a total number of elements of 778267392 .
Our test data array has 4 dimensions, and a shape of (2575, 56, 56, 3) f
or a total number of elements of 24225600 .
Our validation data array is equivalent in number to the test data arra
y. It has 4 dimensions, and a shape of (2575, 56, 56, 3) for a total num
ber of elements of 24225600 .
```

The data labels represent the bird species to which the images belong. They are first converted into 2D arrays and finally turned into categorical data: bird classes are substituted by numerical categories.
Bird species should be homogeneous across train and test data, so I check if it's actually the case.

In [4]:
```
### 6) turn the train, test and validation labels into categorical arrays
# train labels
trainClasses = classesToInt(trainClasses)
npTrainClasses = np.array(trainClasses)
npTrainClasses = np.expand_dims(npTrainClasses, axis = 1) # add dimension
npTrainLabels = to_categorical(npTrainClasses)
# test labels
testClasses = classesToInt(testClasses)
npTestClasses = np.array(testClasses)
npTestClasses = np.expand_dims(npTestClasses, axis = 1) # add dimension t
npTestLabels = to_categorical(npTestClasses)
# validation labels
validClasses = classesToInt(validClasses)
npValidClasses = np.array(validClasses)
npValidClasses = np.expand_dims(npValidClasses, axis = 1) # add dimension
npValidLabels = to_categorical(npValidClasses)

trainCount = countLabels(npTrainClasses) # count train labels
testCount = countLabels(npTestClasses)   # count test labels
validCount = countLabels(npValidClasses) # count validation labels
if trainCount == testCount and trainCount == validCount:
    print('There are', npTrainClasses.size, 'categories (it means that ea
          'belongs to a category) for a set of', trainCount, 'categories.
else:
    print('ERROR: train labels count, test labels count and validation la

# free up memory
del trainData, testData, validData, trainClasses, testClasses, validClass
```

```
There are 82724 categories (it means that each image belongs to a catego
ry) for a set of 515 categories.
```

Data normalization

At this point I normalize the data by dividing them for the maximum value they can assume. In this way the data range from 0 to 1 and allow for better speed and prediction results.

In [5]:
```
### 7) normalize the data
npTrainData = np.array(npTrainData / npTrainData.max(), dtype = np.float1
npTestData = np.array(npTestData / npTestData.max(), dtype = np.float16)
npValidData = np.array(npValidData / npValidData.max(), dtype = np.float1
```

Call the sequential model

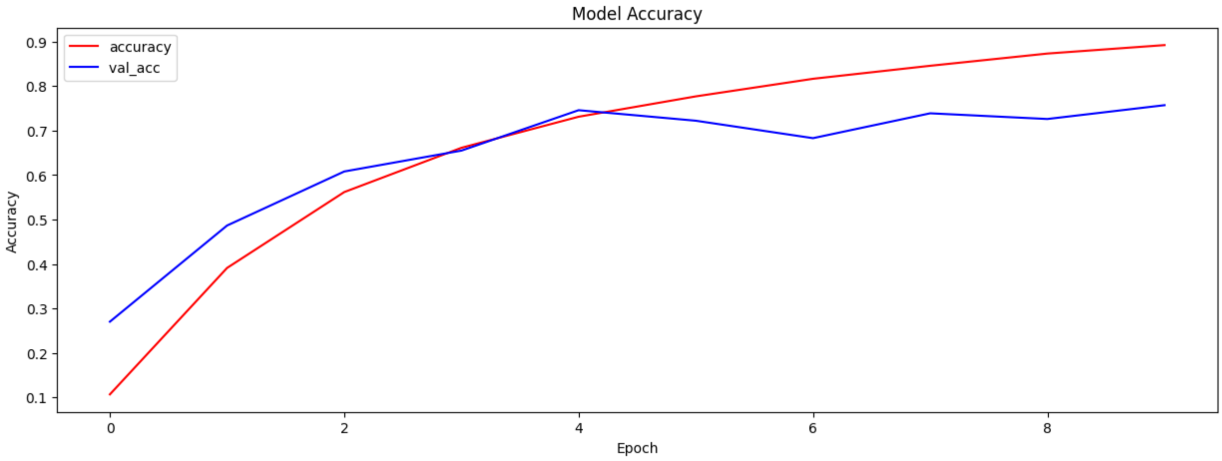
I call the function executing the sequential model from the file d_sequentialModel. The function returns the model history, which is used to train the model and plot the loss function and the model accuracy.

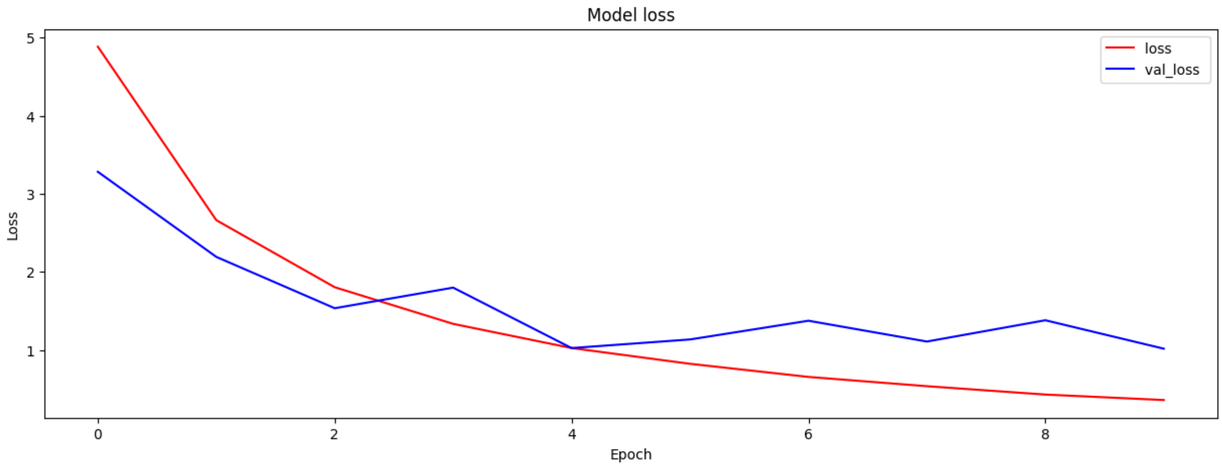
In [6]:
```
### 8) call the sequential model
myModel, Y_pred = seqModel(npTrainData, npTrainLabels, npTestData, npTest
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-ap
plications/densenet/densenet121_weights_tf_dim_ordering_tf_kernels_noto
p.h5
29084464/29084464 [==============================] - 0s 0us/step
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 densenet121 (Functional)    (None, 1024)              7037504

 FC (Dense)                  (None, 515)               527875

 Softmax (Activation)        (None, 515)               0

=================================================================
Total params: 7565379 (28.86 MB)
Trainable params: 7481731 (28.54 MB)
Non-trainable params: 83648 (326.75 KB)
_________________________________________________________________
Epoch 1/10
1293/1293 [==============================] - 202s 100ms/step - loss: 4.8
840 - accuracy: 0.1068 - val_loss: 3.2819 - val_accuracy: 0.2703
Epoch 2/10
1293/1293 [==============================] - 124s 96ms/step - loss: 2.66
25 - accuracy: 0.3912 - val_loss: 2.1923 - val_accuracy: 0.4866
Epoch 3/10
1293/1293 [==============================] - 122s 95ms/step - loss: 1.80
37 - accuracy: 0.5618 - val_loss: 1.5347 - val_accuracy: 0.6082
Epoch 4/10
1293/1293 [==============================] - 122s 94ms/step - loss: 1.33
48 - accuracy: 0.6614 - val_loss: 1.7983 - val_accuracy: 0.6551
Epoch 5/10
1293/1293 [==============================] - 121s 94ms/step - loss: 1.02
50 - accuracy: 0.7313 - val_loss: 1.0247 - val_accuracy: 0.7460
Epoch 6/10
1293/1293 [==============================] - 119s 92ms/step - loss: 0.82
31 - accuracy: 0.7771 - val_loss: 1.1351 - val_accuracy: 0.7223
Epoch 7/10
1293/1293 [==============================] - 121s 93ms/step - loss: 0.65
51 - accuracy: 0.8166 - val_loss: 1.3748 - val_accuracy: 0.6831
Epoch 8/10
1293/1293 [==============================] - 119s 92ms/step - loss: 0.53
63 - accuracy: 0.8459 - val_loss: 1.1084 - val_accuracy: 0.7390
Epoch 9/10
1293/1293 [==============================] - 121s 94ms/step - loss: 0.42
92 - accuracy: 0.8733 - val_loss: 1.3809 - val_accuracy: 0.7262
Epoch 10/10
1293/1293 [==============================] - 120s 93ms/step - loss: 0.35
91 - accuracy: 0.8924 - val_loss: 1.0168 - val_accuracy: 0.7573

Test loss: 0.8293160200119019
Test accuracy: 0.7957281470298767
81/81 [==============================] - 3s 15ms/step
```

I finally plot the loss function for the model and the model accuracy.

In [7]:
```
### 9) plot model accuracy and loss function
# accuracy
plt.figure(figsize=(15, 5))
plt.plot(myModel.history['accuracy'], 'r', label='accuracy')
plt.plot(myModel.history['val_accuracy'], 'b', label='val_acc ')
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()

# loss
plt.figure(figsize=(15, 5))
plt.plot(myModel.history['loss'], 'r', label='loss ')
plt.plot(myModel.history['val_loss'], 'b', label='val_loss ')
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend()

plt.show()
```





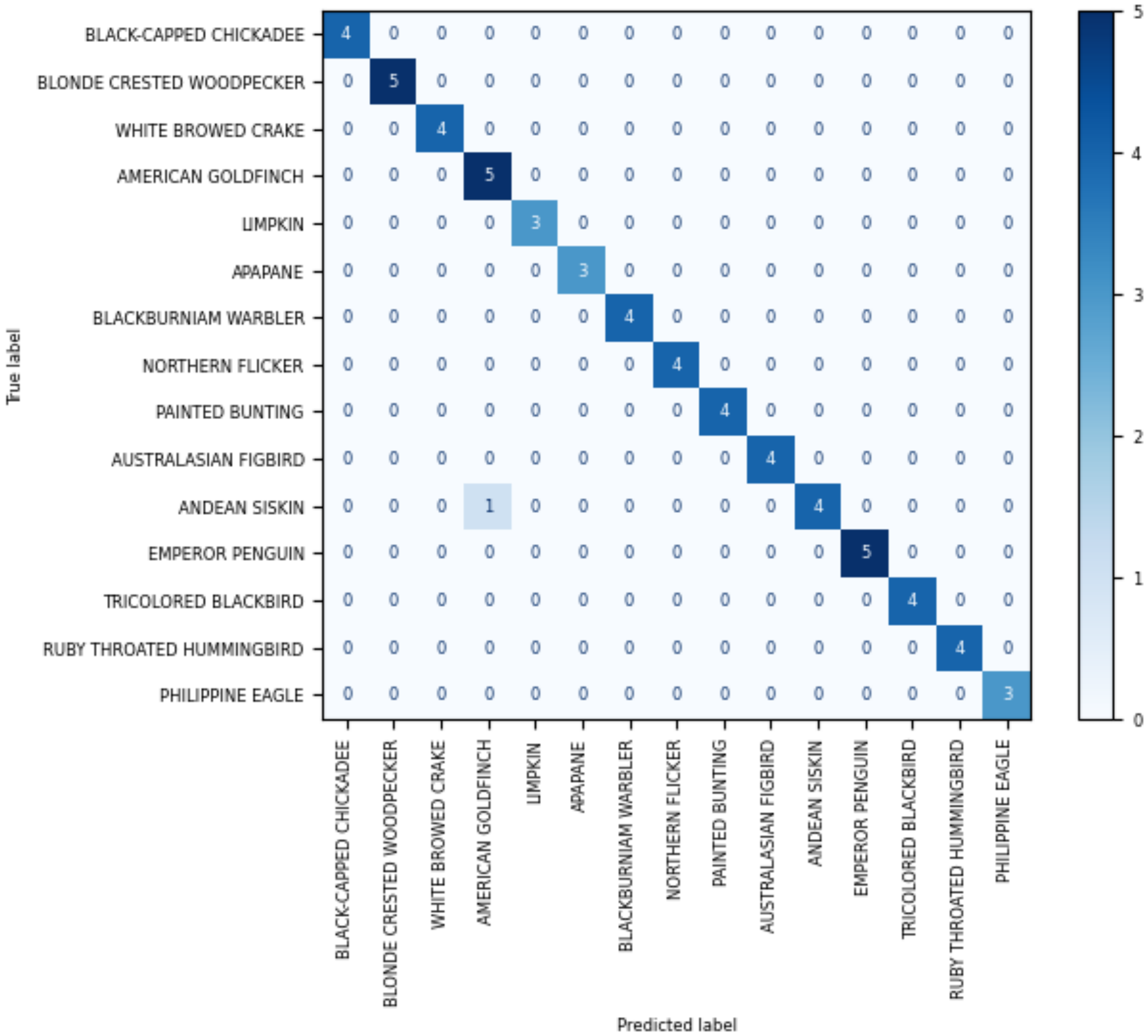
Plot confusion matrix and classification report

I finally plot the confusion matrix and the classification report for a small sample of bird species.

In [8]:
```
### 10) Confution Matrix and Classification Report
y_pred = np.argmax(Y_pred, axis=1)
cm = confusion_matrix(npTestClasses, y_pred)
thresh = cm.max() / 2.
tick_marks = np.arange(len(classes))
target_names = classes
print('\nConfusion Matrix (small sample)\n')
print(cm[0 : 15, 0 : 15])
plotCM(cm[0 : 15, 0 : 15], target_names[0 : 15])
print('\n\nClassification Report (small sample)\n')
class_report = classification_report(npTestClasses, y_pred, target_names
print(class_report[0 : 1142], (' ' * 18) + '[...]\n') # print a few lines
```

```
Confusion Matrix (small sample)

[[4 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 5 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 4 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 5 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 3 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 3 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 4 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 4 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 4 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 4 0 0 0 0 0]
 [0 0 0 1 0 0 0 0 0 0 4 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 5 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 4 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 4 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 3]]


Classification Report (small sample)

                            precision    recall  f1-score   support

      BLACK-CAPPED CHICKADEE       1.00      0.80      0.89         5
   BLONDE CRESTED WOODPECKER       0.71      1.00      0.83         5
          WHITE BROWED CRAKE       1.00      0.80      0.89         5
          AMERICAN GOLDFINCH       0.56      1.00      0.71         5
                     LIMPKIN       0.75      0.60      0.67         5
                     APAPANE       1.00      0.60      0.75         5
        BLACKBURNIAM WARBLER       0.80      0.80      0.80         5
            NORTHERN FLICKER       0.57      0.80      0.67         5
             PAINTED BUNTING       1.00      0.80      0.89         5
        AUSTRALASIAN FIGBIRD       1.00      0.80      0.89         5
               ANDEAN SISKIN       0.57      0.80      0.67         5
             EMPEROR PENGUIN       0.83      1.00      0.91         5
         TRICOLORED BLACKBIRD       1.00      0.80      0.89         5
   RUBY THROATED HUMMINGBIRD       0.80      0.80      0.80         5
             PHILIPPINE EAGLE       1.00      0.60      0.75         5
                        [...]
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.
py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined a
nd being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.
py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined a
nd being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.
py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined a
nd being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
<Figure size 600x600 with 0 Axes>
```



In [ ]: