325(48) Bird Species - Classification

Kaggle Computer Vision Dataset
CP494 Directed Research Project
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In this research peoject, I will classify the 48 species of birds (I only used 48 instead 325, because macbook can't handle such huge amounts of data, it took 3h for each epochs and will breakdown my mac)
I will comapare the model from scratch and the pre_trained model to see the performance differecne of them, and trying to figure out how transfer learning can improve efficiency in computer vision area
Finally we will using our model to test some sample

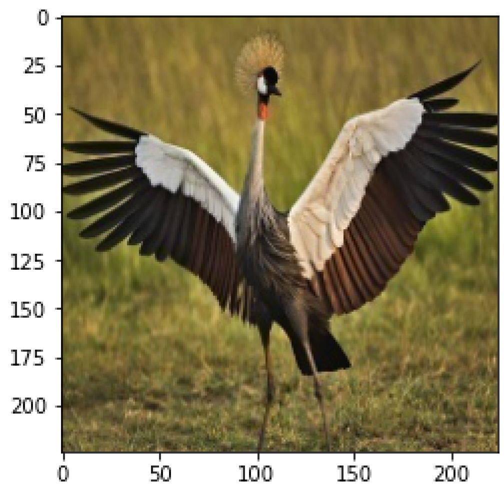
In [2]:
```
import numpy as np
import pandas as pd
from tensorflow.keras.optimizers import SGD, Adam
from tensorflow.keras.preprocessing import text, sequence
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation
from tensorflow.keras.layers import Conv2D, MaxPool2D, Flatten
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator, load_img, img_to_array
pd.options.mode.chained_assignment = None
```

Prepare Data for Training
Analysis Data and Generating Data

In [3]:
```
#We set datasets directory first
train_dir = './train' #training dataset
valid_dir = './valid' #validation dataset
test_dir = './test'   #testing dataset

#We checking the image shape to help us define the target size for generating
Bird = load_img("./train/AFRICAN CROWNED CRANE/002.jpg")
plt.imshow(Bird)
plt.show
shape = img_to_array(Bird).shape
print('Picture shape is: ', shape)
```

```
Picture shape is:  (224, 224, 3)
```



In [4]:
```
#Create image generator for train, validation and test data
Generator = ImageDataGenerator(rescale = 1./255)

#using build-in fuciton flow_from_directory to read the image
train = Generator.flow_from_directory(
    './train',
    target_size = (224, 224),
    batch_size = 32,
    class_mode = 'categorical')

valid = Generator.flow_from_directory(
    './valid',
    target_size = (224, 224),
    batch_size = 32,
    class_mode = 'categorical')

test = Generator.flow_from_directory(
    './test',
    target_size = (224, 224),
    batch_size = 32,
    class_mode = 'categorical')
print("The length of train: {}\nvalid: {}\ntest: {}".format(len(train),len(valid),len(test)))
```

```
Found 6924 images belonging to 48 classes.
```

```
Found 240 images belonging to 48 classes.
Found 240 images belonging to 48 classes.
The length of train: 217
valid: 8
test: 8
```

We can see there is huge amounts of data,
we may need to control the training steps for each opochs to reduce training time

In [42]:

```
#Lets show some example of data
import random
images = []
labels = []
for i in range(0,9):
    n = random.randint(0, len(train.filenames))
    images.append(train_dir+'/'+train.filenames[n])
    labels.append(train.filenames[n].split('/')[0])

plt.figure(figsize=(10,10))
for i in range(9):
    Bird = load_img(images[i])
    plt.subplot(3,3,+1+i)
    plt.title(labels[i], fontsize = 12)
    plt.axis(False)
    plt.imshow(Bird)
plt.show()
```

Build the CNN Model

I will build two models, one using pre_trained VGG16 as base model
and other has similar architecture to VGG16 but we will build it from scratch.

Model 1: Pre_trained VGG16

In [6]:

```
from tensorflow.keras.applications import VGG16
from keras.applications.vgg16 import preprocess_input
base_vgg16 = VGG16(weights = 'imagenet', include_top = False, input_shape = (224,224,3))
base_vgg16.trainable = False

model_trained = Sequential()
model_trained.add(base_vgg16)
model_trained.add(Flatten())
model_trained.add(Dense(units=2048,activation="relu"))
model_trained.add(Dropout(0.35))
model_trained.add(Dense(units=2048,activation="relu"))
model_trained.add(Dropout(0.35))
model_trained.add(Dense(units=48, #we set units to 48 as birds classes is 48
                activation="softmax"))

model_trained.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
vgg16 (Functional)           (None, 7, 7, 512)         14714688  
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0         
_________________________________________________________________
dense (Dense)                (None, 2048)              51382272  
_________________________________________________________________
dropout (Dropout)            (None, 2048)              0         
_________________________________________________________________
dense_1 (Dense)              (None, 2048)              4196352   
_________________________________________________________________
dropout_1 (Dropout)          (None, 2048)              0         
_________________________________________________________________
dense_2 (Dense)              (None, 48)                98352     
=================================================================
Total params: 70,391,664
Trainable params: 55,676,976
Non-trainable params: 14,714,688
_________________________________________________________________
```

Model 2: Self_build Model

In [7]:

```
model = Sequential()
model.add(Conv2D(input_shape=(224,224,3),filters=64,kernel_size=(3,3),padding="same", activation="relu"))
model.add(Conv2D(filters=32,
                 kernel_size=(3,3),
                 padding="same",
                 activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(filters=64,
                 kernel_size=(3,3),
                 padding="same",
                 activation="relu"))
model.add(Conv2D(filters=64, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(filters=128,
                 kernel_size=(3,3),
                 padding="same",
                 activation="relu"))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(filters=256,
                 kernel_size=(3,3),
                 padding="same",
                 activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(filters=256,
                 kernel_size=(3,3),
                 padding="same",
                 activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
model.add(Flatten())
model.add(Dense(units=2048,activation="relu"))
model.add(Dropout(0.35))
model.add(Dense(units=2048,activation="relu"))
model.add(Dropout(0.35))
model.add(Dense(units=48, #we set units to 48 as birds classes is 48
                activation="softmax"))
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 224, 224, 64)      1792      
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 224, 224, 32)      18464     
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 112, 112, 32)      0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 112, 112, 64)      18496     
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 112, 112, 64)      36928     
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 56, 56, 64)        0         
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 56, 56, 128)       73856     
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 56, 56, 128)       147584    
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 56, 56, 128)       147584    
_________________________________________________________________
```

```
max_pooling2d_2 (MaxPooling2 (None, 28, 28, 128)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 28, 28, 256)        295168
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 28, 28, 256)        590080
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 28, 28, 256)        590080
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 14, 14, 256)        0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 14, 14, 256)        590080
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 14, 14, 256)        590080
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 14, 14, 256)        590080
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 7, 7, 256)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 12544)              0
_________________________________________________________________
dense_3 (Dense)              (None, 2048)               25692160
_________________________________________________________________
dropout_2 (Dropout)          (None, 2048)               0
_________________________________________________________________
dense_4 (Dense)              (None, 2048)               4196352
_________________________________________________________________
dropout_3 (Dropout)          (None, 2048)               0
_________________________________________________________________
dense_5 (Dense)              (None, 48)                 98352
=================================================================
Total params: 33,677,136
Trainable params: 33,677,136
Non-trainable params: 0
_________________________________________________________________
```

In [8]:

```python
model_trained.compile(optimizer = 'adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.compile(optimizer = 'adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

Train the Model

Training our own model first

In [46]:

```python
model_log = model.fit(train,
                      #steps_per_epoch = 50,
                      epochs = 10,
                      validation_data = valid,
                      #validation_steps = 5,
                      verbose = 1)
```

```
Epoch 1/10
217/217 [==============================] - 996s 5s/step - loss: 3.8676 - accuracy: 0.0279 - val_loss: 3.8749 - val_accur
acy: 0.0208
Epoch 2/10
217/217 [==============================] - 1008s 5s/step - loss: 3.8669 - accuracy: 0.0280 - val_loss: 3.8749 - val_accu
racy: 0.0208
Epoch 3/10
217/217 [==============================] - 1010s 5s/step - loss: 3.8668 - accuracy: 0.0266 - val_loss: 3.8763 - val_accu
racy: 0.0208
Epoch 4/10
217/217 [==============================] - 2070s 10s/step - loss: 3.8667 - accuracy: 0.0280 - val_loss: 3.8757 - val_acc
uracy: 0.0208
Epoch 5/10
217/217 [==============================] - 10861s 50s/step - loss: 3.8665 - accuracy: 0.0280 - val_loss: 3.8761 - val_ac
curacy: 0.0208
Epoch 6/10
217/217 [==============================] - 13010s 60s/step - loss: 3.8661 - accuracy: 0.0280 - val_loss: 3.8764 - val_ac
curacy: 0.0208
Epoch 7/10
217/217 [==============================] - 9345s 43s/step - loss: 3.8660 - accuracy: 0.0280 - val_loss: 3.8764 - val_acc
uracy: 0.0208
Epoch 8/10
217/217 [==============================] - 1161s 5s/step - loss: 3.8662 - accuracy: 0.0279 - val_loss: 3.8764 - val_accu
racy: 0.0208
Epoch 9/10
217/217 [==============================] - 975s 4s/step - loss: 3.8658 - accuracy: 0.0280 - val_loss: 3.8769 - val_accur
acy: 0.0208
Epoch 10/10
217/217 [==============================] - 992s 5s/step - loss: 3.8659 - accuracy: 0.0280 - val_loss: 3.8773 - val_accur
acy: 0.0208
```

Training pre_trained model

In [9]:

```python
model_trained_log = model_trained.fit(train,
                                      epochs = 10,
                                      validation_data = valid,
                                      verbose = 1)
```

```
Epoch 1/10
217/217 [==============================] - 736s 3s/step - loss: 3.4378 - accuracy: 0.1948 - val_loss: 1.7548 - val_accur
```

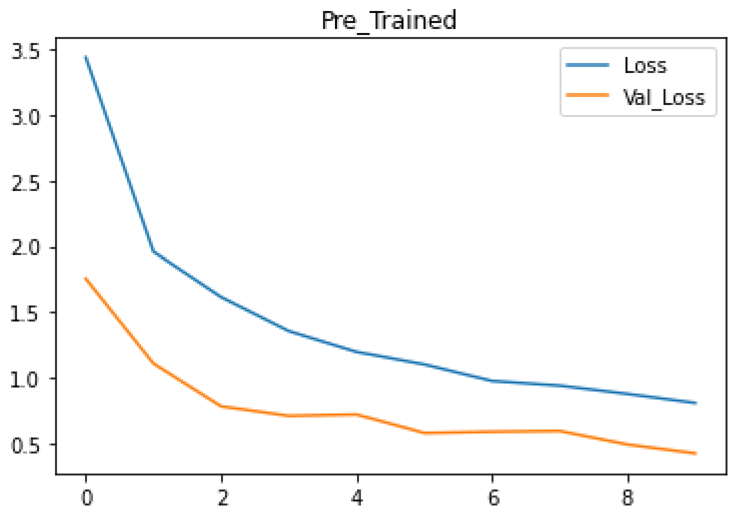
```
acy: 0.5583
Epoch 2/10
217/217 [==============================] - 736s 3s/step - loss: 1.9592 - accuracy: 0.4363 - val_loss: 1.1094 - val_accur
acy: 0.6792
Epoch 3/10
217/217 [==============================] - 738s 3s/step - loss: 1.6153 - accuracy: 0.5253 - val_loss: 0.7828 - val_accur
acy: 0.7917
Epoch 4/10
217/217 [==============================] - 744s 3s/step - loss: 1.3567 - accuracy: 0.5955 - val_loss: 0.7105 - val_accur
acy: 0.8208
Epoch 5/10
217/217 [==============================] - 744s 3s/step - loss: 1.1980 - accuracy: 0.6326 - val_loss: 0.7204 - val_accur
acy: 0.8208
Epoch 6/10
217/217 [==============================] - 752s 3s/step - loss: 1.1018 - accuracy: 0.6641 - val_loss: 0.5795 - val_accur
acy: 0.8625
Epoch 7/10
217/217 [==============================] - 744s 3s/step - loss: 0.9760 - accuracy: 0.6989 - val_loss: 0.5893 - val_accur
acy: 0.8458
Epoch 8/10
217/217 [==============================] - 746s 3s/step - loss: 0.9406 - accuracy: 0.7132 - val_loss: 0.5948 - val_accur
acy: 0.8125
Epoch 9/10
217/217 [==============================] - 743s 3s/step - loss: 0.8775 - accuracy: 0.7292 - val_loss: 0.4921 - val_accur
acy: 0.8750
Epoch 10/10
217/217 [==============================] - 755s 3s/step - loss: 0.8087 - accuracy: 0.7478 - val_loss: 0.4247 - val_accur
acy: 0.8833
```

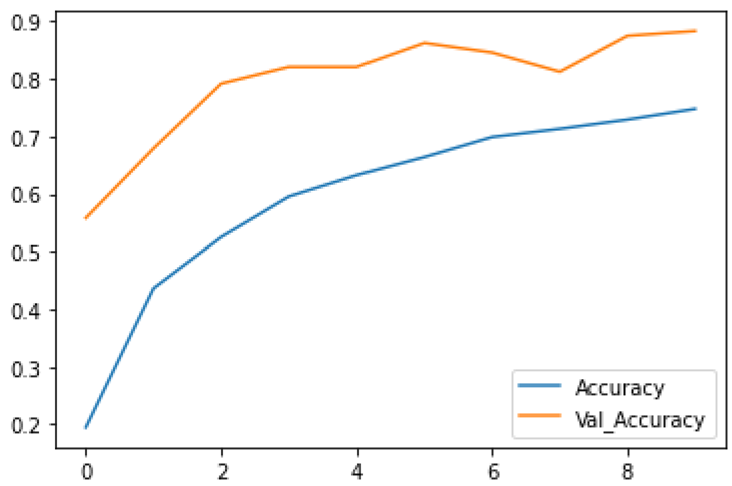
The model build on pre_trained vgg16 give us really good performance and we are estimate get accuracy over 90% after 20 epochs!

Evaluate Model

In [13]:

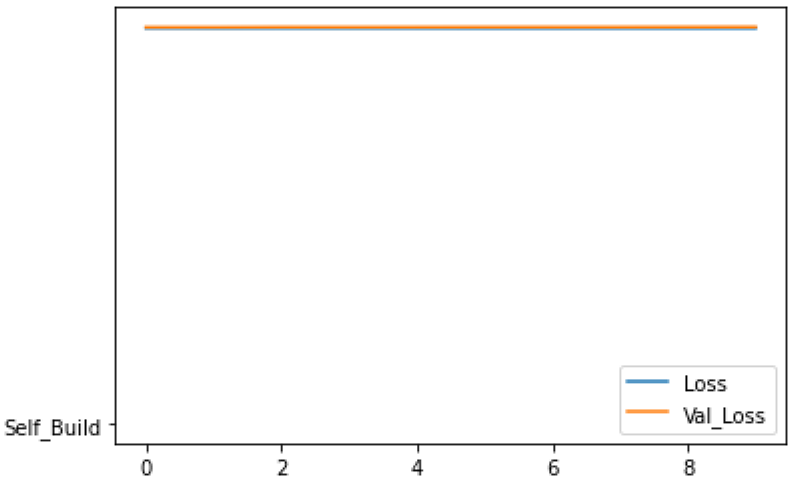
```
#Plot the model_trained_log history
plt.plot(model_trained_log.history['loss'],label='Loss')
plt.plot(model_trained_log.history['val_loss'],label='Val_Loss')
plt.title('Pre_Trained')
plt.legend()
plt.show()
plt.plot(model_trained_log.history['accuracy'],label='Accuracy')
plt.plot(model_trained_log.history['val_accuracy'],label='Val_Accuracy')
plt.legend()
plt.show()
```

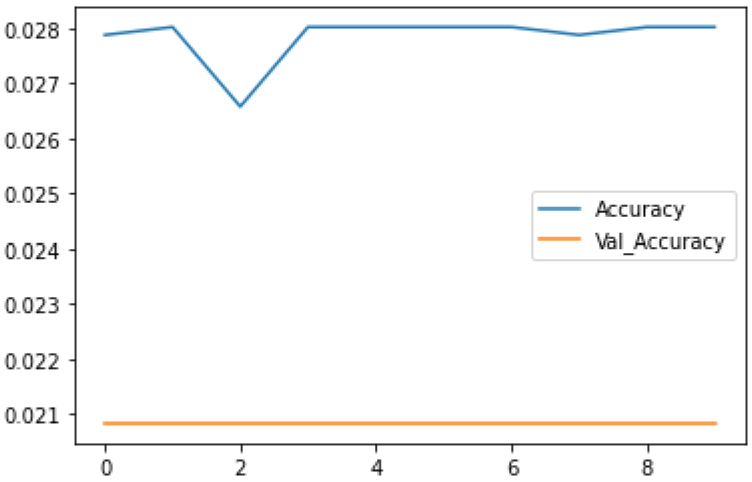




In [47]:

```
plt.plot(model_log.history['loss'],label='Loss')
plt.plot(model_log.history['val_loss'],label='Val_Loss')
plt.plot('Self_Build')
plt.legend()
plt.show()
plt.plot(model_log.history['accuracy'],label='Accuracy')
plt.plot(model_log.history['val_accuracy'],label='Val_Accuracy')
plt.legend()
plt.show()
```





Conlusion:

LOG for self_build model: I first trained the self_model with bigger size of shape, and it's too big for personal labtop, then decrease the number of parameter to limit time as 20min for each epochs, I tried both adam and sgd as optimizer but they can't imprve the accuracy.
After the evaluation, we can see that the self build model has terrible performance on our datasets, we didn't see any improvement during 10 epochs. It's hard to training large scale on a large network with millin parameters from scratch on our own labtop, even this network has similar architecture with VGG16 who is won a champion of competition.
Compare to self model, the pre_trained model has really good performace, it's get almost 80% acuuracy only in 10 epochs, the transfer learning provides a very high level of efficiency to our training process. We have steep gradient on loss and accuracy plot, this shows model is doing well on right direction.
I believe transfer learning can provide convenience for personal machine learning engineers. Without a powerful GPU, even with a large amount of data, it is difficult for us to train an efficient model by ourselves, which will destroy our computers and spend a lot of time.

Testing Model by Predict Sample

Using Pre_Trained model to predict test dataset sample

In [10]:
```
#Helper function for predict
label_dic = train.class_indices
label_dic = {i:j for j,i in label_dic.items()}
def predict(location):
    img = load_img(location, target_size = (224, 224, 3))
    img = img_to_array(img)
    img = img / 255
    img = np.expand_dims(img, [0])
    answer = model_trained.predict(img)
    y_class = answer.argmax(axis = -1)
    y = " ".join(str(x) for x in y_class)
    predict = label_dic[int(y)]
    return predict
```

In [45]:
```
#We randomly choose sample to predict
test_images = []
test_labels = []
for i in range(0,9):
    name = random.randint(0, len(test.filenames))
    test_images.append(test_dir+'/'+test.filenames[name])
    test_labels.append(test.filenames[name].split('/')[0])

#show 9 predict samples
plt.figure(figsize=(12,12))
for i in range(9):
    Bird = load_img(test_images[i])
    pred = int
    plt.subplot(3,3,+1+i)
    plt.title("It's "+ predict(test_images[i]), fontsize = 12)
    plt.axis(False)
    plt.imshow(Bird)
plt.show()
print("Right answer(top_left->down_right): ")
for label in test_labels:
    print(label)
```


```
Right answer(top_left->down_right):
ARARIPE MANAKIN
BLONDE CRESTED WOODPECKER
BLACK VULTURE
BLUE COAU
AMERICAN PIPIT
AFRICAN FIREFINCH
ARARIPE MANAKIN
BARN SWALLOW
BLACK-NECKED GREBE
```

We successfully predicted 9 Birds Species with 100% accuracy!