African Wildlife Object Classification

The purpose if this project is to build a model from a pretrained model to identify wild life in africa. In essence, This is an object classification for the classification of 4 classes of animal in africa, buffalos, elephants, rhinoes and zebras.

We explain with a lot of details the different section of our pipeline and display metrics, results and the testing evaluation of model.

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```
# This section is done to upload kaggle configuration files
from google.colab import files
files.upload()
```

```
# We install the library that we are going to use for this project
# We need to clarify that a lot of the library use for displaying
# and plotting data is already pre install in google colab
!pip install kaggle
!pip install opencv-python
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages (1.
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: certifi>=2023.7.22 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages (fr
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.10/dist
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10
```

```
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: opencv-python in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/dist-packa
```

```
#We move our kaggle configuration file to a different directory and
#give them permission so the os can access the file
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

Download African Wildlife Dataset from Kaggel

This dataset is contains around 376 images for each animal, the list of animals are elephants, buffalo, zebras and rhinos.

```
!kaggle datasets download -d biancaferreira/african-wildlife
```

```
Dataset URL: https://www.kaggle.com/datasets/biancaferreira/african-wildlife
License(s): unknown
Downloading african-wildlife.zip to /content
100% 447M/448M [00:23<00:00, 18.4MB/s]
100% 448M/448M [00:23<00:00, 19.8MB/s]
```

```
# Unzip file and move the data into images directory
!unzip -qq african-wildlife.zip -d ./images
```

Exploring the dataset images

In this section, we take a look at a sample of images from our dataset.

```
import os
import matplotlib.pyplot as plt
import cv2

# From our images directory
images_path = "./images"
# We get a sample from each of the directories that would serve as our classes
elephant_image = os.path.join(images_path, 'elephant', os.listdir(os.path.join(images_pa
zebra_image = os.path.join(images_path, 'zebra', os.listdir(os.path.join(images_path, 'ze
buffalo_image = os.path.join(images_path, 'buffalo', os.listdir(os.path.join(images_path
rhino_image = os.path.join(images_path, 'rhino', os.listdir(os.path.join(images_path, 'rh

sample_images = [elephant_image, zebra_image, buffalo_image, rhino_image]

plt.figure(figsize=(10,10))
```

```
for i in range(len(sample_images)):
  img = cv2.imread(sample_images[i])
  img = cv2.resize(img, [600,400])
  ax = plt.subplot(2, 2, i + 1)
  plt.imshow(img)
  plt.axis("off")

plt.show()
```

Preparing the data and Applying some data

preprocessing

```
# We need to preparer the data to adjust it for our Model.
# We decide to split the data into 70% for training, 20% for validation and 10% for test:

#Preparing the directories for the data split
base_dir = "dataset_split"
#Training data directories
os.makedirs(os.path.join(base_dir, 'train/buffalo'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'train/elephant'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'train/rhino'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'train/zebra'), exist_ok=True)
#Validation
os.makedirs(os.path.join(base_dir, 'validation/buffalo'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'validation/elephant'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'validation/rhino'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'validation/zebra'), exist_ok=True)
#Testing
os.makedirs(os.path.join(base_dir, 'test/buffalo'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'test/elephant'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'test/rhino'), exist_ok=True)
os.makedirs(os.path.join(base_dir, 'test/zebra'), exist_ok=True)
```

```
from PIL import Image
import shutil
from sklearn.model_selection import train_test_split

#Using Pillow (PIL) to only copy the images
def is_valid_image_pillow(filename):
    try:
        with Image.open(filename) as img:
            img.verify()
            return True
    except (IOError, SyntaxError):
        return False

#We create a method to split the dataset into their directories
def split_data(SOURCE, TRAINING, VALIDATION, TESTING, split_size_train, split_size_val):
  files = []
  for filename in os.listdir(SOURCE):
    if is_valid_image_pillow(f'{SOURCE}/{filename}'):
      file = os.path.join(SOURCE, filename)
      if os.path.isfile(file):
        files.append(file)

  #After getting the images, we split them into the percentages previously mentioned
  train_files, temp_files = train_test_split(files, test_size=(1 - split_size_train))
  val_files, test_files = train_test_split(temp_files, test_size=(1 - split_size_val / (
```

```
  val_files, test_files = train_test_split(temp_files, test_size=(1 - split_size_val / (

# Copying the files into their directories
  for file in train_files:
    shutil.copy(file, TRAINING)

  for file in val_files:
    shutil.copy(file, VALIDATION)

  for file in test_files:
    shutil.copy(file, TESTING)

base_dir = './dataset_split'
classes = ['buffalo', 'elephant', 'rhino', 'zebra']

for cls in classes:
  split_data(
      SOURCE=f'images/{cls}',
      TRAINING=f'{base_dir}/train/{cls}',
      VALIDATION=f'{base_dir}/validation/{cls}',
      TESTING=f'{base_dir}/test/{cls}',
      split_size_train=0.7,
      split_size_val=0.2
  )
```

Applying normalization and Loading the splited dataset

In this part we apply normalization while generating the datasets for each group.

```
import tensorflow as tf

base_dir = './dataset_split'

def load_dataset(data_dir, img_size, batch_size):
    dataset = tf.keras.preprocessing.image_dataset_from_directory(
        data_dir,
        labels='inferred',
        label_mode='int',
        image_size=(img_size, img_size),
        batch_size=batch_size,
        shuffle=True
    )
    return dataset

img_size = 224
batch_size = 32

train_dataset = load_dataset('dataset_split/train', img_size, batch_size)
```

```
val_dataset = load_dataset('dataset_split/validation', img_size, batch_size)
test_dataset = load_dataset('dataset_split/test', img_size, batch_size)
```

```
Found 1276 files belonging to 4 classes.
Found 646 files belonging to 4 classes.
Found 393 files belonging to 4 classes.
```

```
# Access class names and their indices to confirm that the images are in the correct data
# This way we have an idea of what are our classes and their IDs
class_names = train_dataset.class_names
class_indices = {class_name: idx for idx, class_name in enumerate(class_names)}

print("Class Names:", class_names)
print("Class Indices:", class_indices)
```

```
Class Names: ['buffalo', 'elephant', 'rhino', 'zebra']
Class Indices: {'buffalo': 0, 'elephant': 1, 'rhino': 2, 'zebra': 3}
```

Data augmentation

We don't have a lot of pictures for our training operation, so we use data augmentation to reduce the posibility the overfitting and increase the amount of samples.

```
from tensorflow import keras
from keras import layers
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.2),
        layers.RandomZoom(0.2)
    ]
)
```

Get the pretrained model, VGG16.

VGG16 is a deep convolutional neural used for image classification. Checking the model and making sure there are not trainable parameters.

```
# We get the model from keras and use the weights from imagenet
# It's possible to use another models weight, but we are not going to explore that posib
conv_base = keras.applications.vgg16.VGG16(
    weights = "imagenet",
    include_top= False
)
# We set the parameter trainable as False
```

```
# We prefer to leave the weights of the model as it is, and only train the last layers tl
conv_base.trainable = False
conv_base.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/v
80134624/80134624 [==============================] - 1s 0us/step
Model: "vgg19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_7 (InputLayer)        [(None, None, None, 3)]   0

 block1_conv1 (Conv2D)       (None, None, None, 64)    1792

 block1_conv2 (Conv2D)       (None, None, None, 64)    36928

 block1_pool (MaxPooling2D)  (None, None, None, 64)    0

 block2_conv1 (Conv2D)       (None, None, None, 128)   73856

 block2_conv2 (Conv2D)       (None, None, None, 128)   147584

 block2_pool (MaxPooling2D)  (None, None, None, 128)   0

 block3_conv1 (Conv2D)       (None, None, None, 256)   295168

 block3_conv2 (Conv2D)       (None, None, None, 256)   590080

 block3_conv3 (Conv2D)       (None, None, None, 256)   590080

 block3_conv4 (Conv2D)       (None, None, None, 256)   590080

 block3_pool (MaxPooling2D)  (None, None, None, 256)   0

 block4_conv1 (Conv2D)       (None, None, None, 512)   1180160

 block4_conv2 (Conv2D)       (None, None, None, 512)   2359808

 block4_conv3 (Conv2D)       (None, None, None, 512)   2359808

 block4_conv4 (Conv2D)       (None, None, None, 512)   2359808

 block4_pool (MaxPooling2D)  (None, None, None, 512)   0

 block5_conv1 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv2 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv3 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv4 (Conv2D)       (None, None, None, 512)   2359808

 block5_pool (MaxPooling2D)  (None, None, None, 512)   0

=================================================================
Total params: 20024384 (76.39 MB)
```

```
Trainable params: 0 (0.00 Byte)
Non-trainable params: 20024384 (76.39 MB)
_________________________________________________________________
```

Training Model

In this point, we are going to use the model VGG16 with the weight of imagenet

```
from tensorflow import keras
from keras import layers
from tensorflow.keras.regularizers import l2

inputs = keras.Input(shape=(img_size, img_size, 3))
x = data_augmentation(inputs)
x = keras.applications.vgg16.preprocess_input(x)
x = conv_base(x)
# GlobalAveragePooling2D help us reduce the dimension and It also help us reduce the amou
# Reducing the amount of parameters is crucial at reducing potentia for overfitting and s
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dense(512, activation = 'relu', kernel_regularizer=l2(0.001))(x)
x = layers.Dropout(0.5)(x) #It would seen too harsh to dropout half of the neuron,
# but in other experiment for classification problems this approach has proveed to yield
outputs = layers.Dense(4, activation="softmax")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

from tensorflow.keras.optimizers import Adam
# Compile the model
model.compile(
    optimizer=Adam(learning_rate=1e-4),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
    )

#Final overview at the model before training
model.summary()
```

```
Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_6 (InputLayer)        [(None, 224, 224, 3)]     0

 sequential_1 (Sequential)   (None, 224, 224, 3)       0

 tf.__operators__.getitem_2  (None, 224, 224, 3)       0
  (SlicingOpLambda)

 tf.nn.bias_add_2 (TFOpLamb  (None, 224, 224, 3)       0
 da)
```

```
 vgg16 (Functional)          (None, None, None, 512)   14714688

 global_average_pooling2d_2  (None, 512)               0
  (GlobalAveragePooling2D)

 dense_4 (Dense)             (None, 512)               262656

 dropout_2 (Dropout)         (None, 512)               0

 dense_5 (Dense)             (None, 4)                 2052

=================================================================
Total params: 14979396 (57.14 MB)
Trainable params: 264708 (1.01 MB)
Non-trainable params: 14714688 (56.13 MB)
_________________________________________________________________
```

```
# Defining some callbacks Checkpoint and early stopping
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath ="./vgg16_african_wildlife_classifier5.h5",
        save_best_only=True,
        monitor="val_loss"
    ),
    keras.callbacks.EarlyStopping(monitor="loss", patience=3)
]
# Checkpoint to save the best model during training
# Early stopping to get the best possible model if the loss experince no changes or mino
# Early stopping also helps us avoid overfitting by finalizing the training under the co

# Training the model
history = model.fit(
    train_dataset,
    validation_data=val_dataset,
    callbacks = callbacks,
    epochs=50
)
# We started with 10 epoch, we notice that the model was learning and It didn't appear t
# So we increase the number of epoch to 50, along with the early stoping assure us to ge
```

```
Epoch 1/50
33/33 [==============================] - 15s 379ms/step - loss: 3.5743 - accuracy: 0
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarni
  saving_api.save_model(
Epoch 2/50
33/33 [==============================] - 13s 354ms/step - loss: 2.1773 - accuracy: 0
Epoch 3/50
33/33 [==============================] - 15s 371ms/step - loss: 1.7562 - accuracy: 0
Epoch 4/50
33/33 [==============================] - 13s 331ms/step - loss: 1.5176 - accuracy: 0
Epoch 5/50
```

```
Epoch 5/50
33/33 [==============================] - 13s 331ms/step - loss: 1.3361 - accuracy: 0
Epoch 6/50
33/33 [==============================] - 13s 342ms/step - loss: 1.1361 - accuracy: 0
Epoch 7/50
33/33 [==============================] - 13s 346ms/step - loss: 1.1807 - accuracy: 0
Epoch 8/50
33/33 [==============================] - 14s 365ms/step - loss: 1.0506 - accuracy: 0
Epoch 9/50
33/33 [==============================] - 13s 340ms/step - loss: 1.1035 - accuracy: 0
Epoch 10/50
33/33 [==============================] - 13s 339ms/step - loss: 1.0378 - accuracy: 0
Epoch 11/50
33/33 [==============================] - 13s 341ms/step - loss: 1.0154 - accuracy: 0
Epoch 12/50
33/33 [==============================] - 14s 375ms/step - loss: 0.9427 - accuracy: 0
Epoch 13/50
33/33 [==============================] - 14s 357ms/step - loss: 0.9721 - accuracy: 0
Epoch 14/50
33/33 [==============================] - 13s 350ms/step - loss: 0.9456 - accuracy: 0
Epoch 15/50
33/33 [==============================] - 13s 349ms/step - loss: 0.9191 - accuracy: 0
Epoch 16/50
33/33 [==============================] - 13s 343ms/step - loss: 0.8179 - accuracy: 0
Epoch 17/50
33/33 [==============================] - 13s 350ms/step - loss: 0.8430 - accuracy: 0
Epoch 18/50
33/33 [==============================] - 13s 347ms/step - loss: 0.8467 - accuracy: 0
Epoch 19/50
33/33 [==============================] - 13s 341ms/step - loss: 0.8545 - accuracy: 0
```

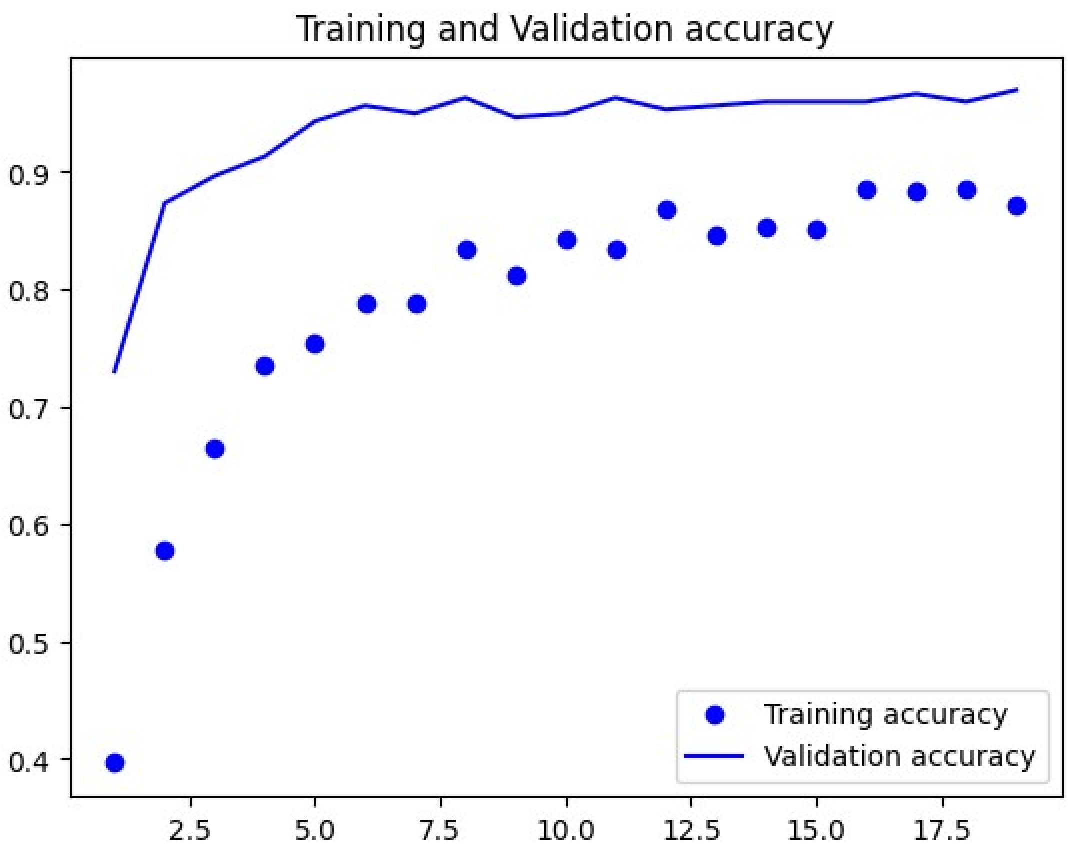
During Training we manage to get an Accuracy of 87%, but at the same time our accuracy for our validation was much much higher. This is due to the harsher regulation that we applied previously, Dropout of 50% and l2 kernerl regularization. At this point the callback for early stopping decided to stop the training. In the evaluation of with the testing data we'll see if our model posees an acceptable accuracy, or if the data shows sight of overfitting.

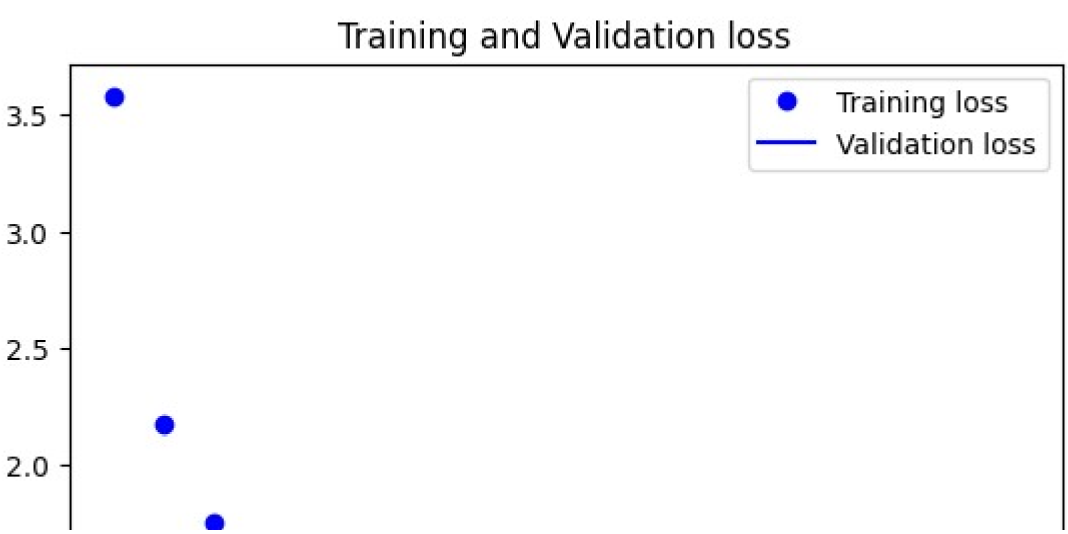
Evaluating of the training.

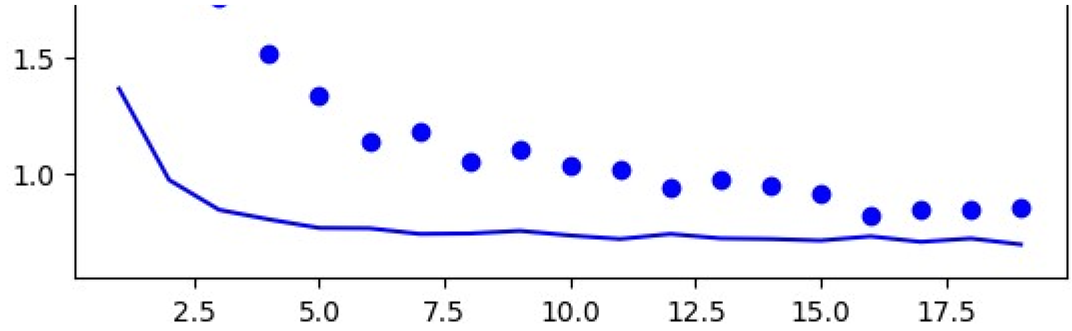
In this section, We evaluate the results of the training of the model. As well as we do try to test the model with an image that It has probably look into.

```
import matplotlib.pyplot as plt


# We look into the epoch and how the training was performing with the data.
accuracy = history.history["accuracy"]
val_accuracy = history.history["val_accuracy"]
```

```
val_accuracy = history.history["val_accuracy"]
loss = history.history["loss"]
val_loss = history.history["val_loss"]
epochs = range(1, len(accuracy) + 1)
plt.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and Validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and Validation loss")
plt.legend()
plt.show()
```







Our graph also reflect this behavior, The training accuracy and loss are lower than the validation but the way of the graph tell us that our model was indeed learning instead of memorizing the dataset.

Testing and evaluation of the model

Now we are going to evaluate our model based on the testing of the test_dataset. This is the final evaluation for our model and what is going to tell us if It was correctly trained.

Evaluating the model over the test dataset gave us an accuracy of over 95%. In this case It was 96%, but depending of the data it could increase as high as 98%.

```
from tensorflow import keras
#Let's try to see how the model perform with the test dataset.
test_model = keras.models.load_model("/content/vgg16_african_wildlife_classifier5.h5")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc: .3f}")
```

```
13/13 [==============================] - 5s 184ms/step - loss: 0.6527 - accuracy: 0.
Test accuracy:  0.962
```

Accuracy is one part, but to have a better idea, we go futher. We are going to create the confusion matrix and ROC graph to see how the performance in other metrics.

```
import numpy as np

# Get true labels and predicted labels
true_labels = []
predicted_labels = []
predicted_probabilities = []

for images, labels in test_dataset:
    predictions = test_model.predict(images)
    predicted_labels.extend(np.argmax(predictions, axis=1))
```

```
    predicted_probabilities.extend(predictions)
    true_labels.extend(labels.numpy())

true_labels = np.array(true_labels)
predicted_labels = np.array(predicted_labels)
predicted_probabilities = np.array(predicted_probabilities)
```

```
WARNING:tensorflow:5 out of the last 11 calls to <function Model.make_predict_functi
1/1 [==============================] - 0s 229ms/step
1/1 [==============================] - 0s 55ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 32ms/step
1/1 [==============================] - 0s 150ms/step
```

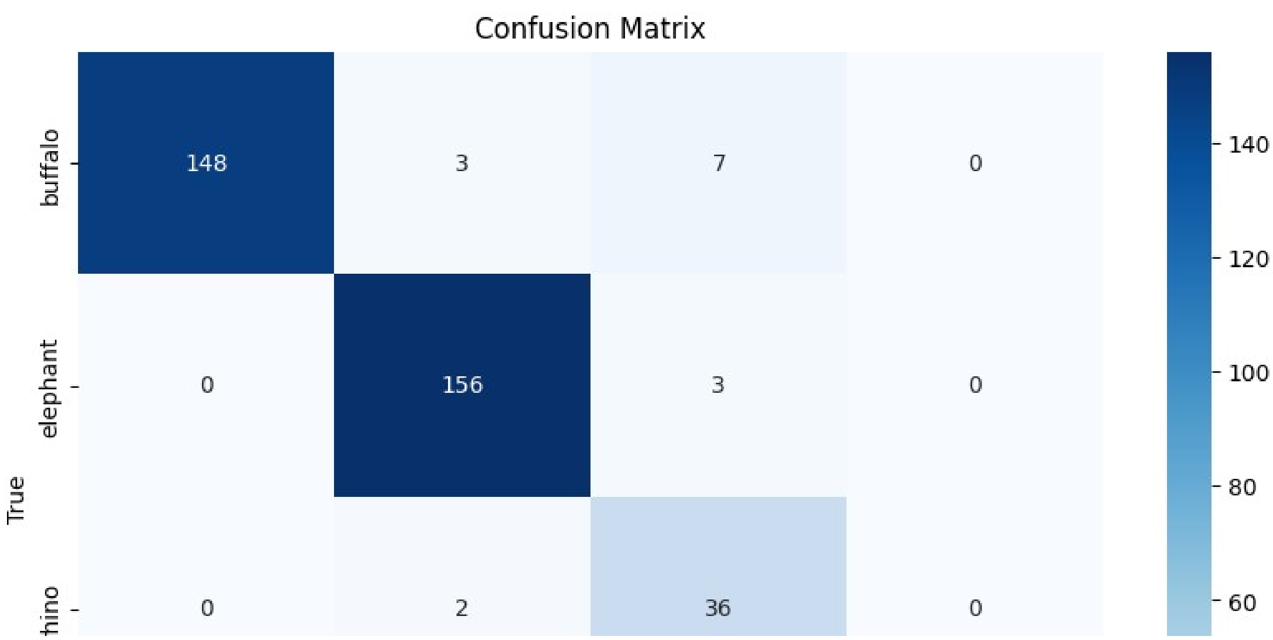
Here we create our Classification report to evaluate the true positive, true negative, false positive and false negative.

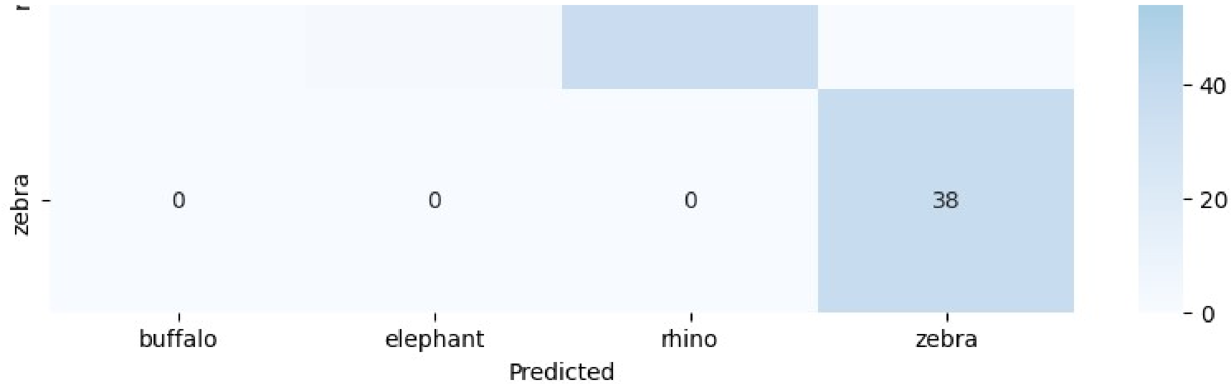
Also the ROC Graph, this graph is typically use for binary classification but, we can also use for multi class classification to se the performance of the different classes.

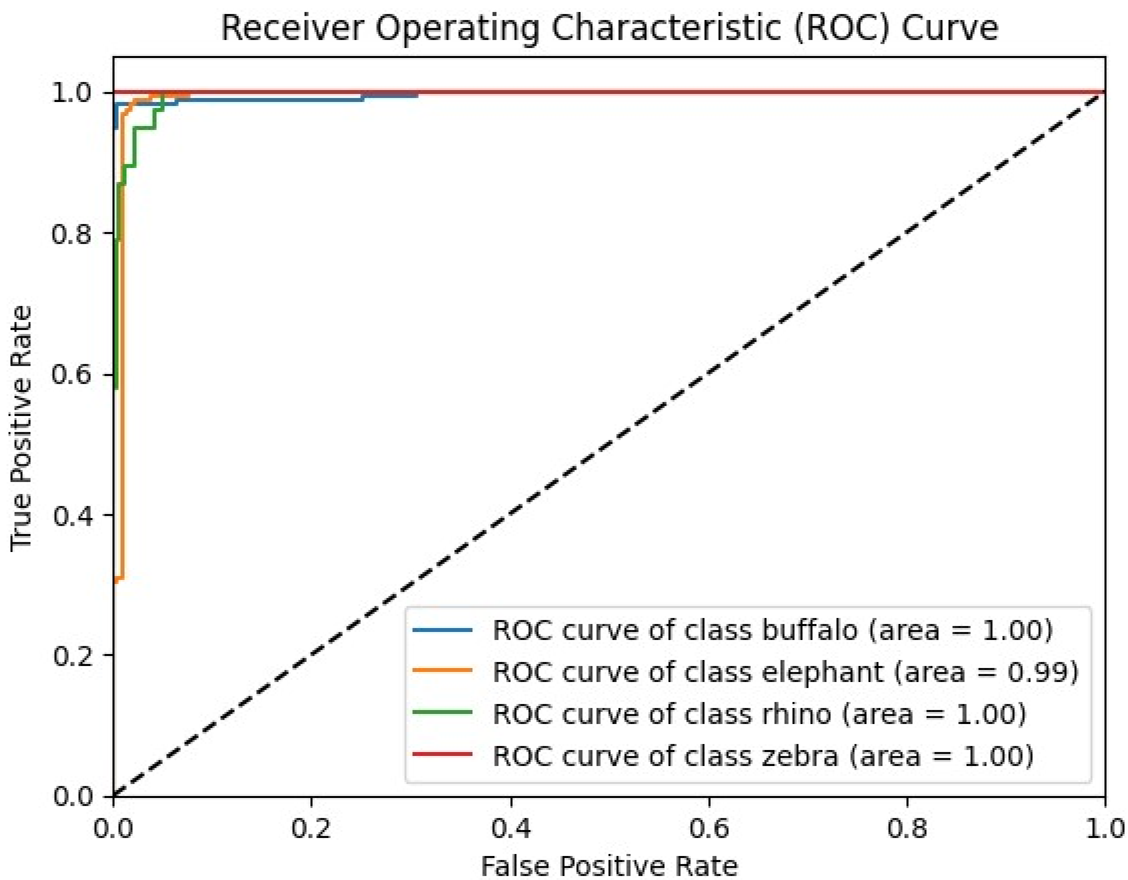
```
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import label_binarize

# Class labels
class_labels = ['buffalo', 'elephant', 'rhino', 'zebra']

# Classification Report
print("Classification Report:")
print(classification_report(true_labels, predicted_labels, target_names=class_labels))

# Confusion Matrix
cm = confusion_matrix(true_labels, predicted_labels)
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_labels, yticklabels=c
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

# ROC Curve and AUC
```

```
true_labels_binarized = label_binarize(true_labels, classes=[0, 1, 2, 3])
fpr = dict()
tpr = dict()
roc_auc = dict()
n_classes = len(class_labels)

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(true_labels_binarized[:, i], predicted_probabilities[:,
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure()
for i in range(n_classes):
    plt.plot(fpr[i], tpr[i], label=f'ROC curve of class {class_labels[i]} (area = {roc_auc

plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
Classification Report:
              precision    recall  f1-score   support

     buffalo       1.00      0.94      0.97       158
    elephant       0.97      0.98      0.97       159
       rhino       0.78      0.95      0.86        38
       zebra       1.00      1.00      1.00        38

    accuracy                           0.96       393
   macro avg       0.94      0.97      0.95       393
weighted avg       0.97      0.96      0.96       393
```







Conclusion

We managed to train a VGG16 model to classify pictures between 4 different classes. From our orginal dataset we split the data, prepare it and use a pretrained model with its weight, where we then create a layer over the one we train it with our dataset. Thanks to this, the training was relative resources friendly and the complexity from our layers was also relative moderate. It wasn't necessary for us to built an architecture from the scrath saving us a lot of time while provinding with reasonable accuracy for the task.

Leason learned

There were a lot of lesson learned during the creating of this project. Most important one where:
-Splitting the dataset: We needed to split the dataset without using the default tools from sklearn or the one provide from Tensorflow or Keras. Manually we needed to move the images and then load the dataset.

-Getting the classes from the dataset: Minor detail, but necessary. Understanding that some of the tools can infer the classes based on the directory was a welcome finding.

-Data augmentation: We tested different configurations with this part of the pipeline. We identify that our dataset didn't have enough images so this was a necesity to avoid overfitting.

-Getting the pretrained model and building the layers: We first started with a flatten and dense layer without regularitation, but not only this prove to be too resource hungry, It took a lot of time to train. Ultimately, we found GlobalAveragePooling2D function to reduce the dimension and the parameters to train.

-The importance of evaluation: Our first iteration was overfitting, without the evaluation of the training, We wouldn't find out about this and do the necessary stepts to reduce it.