Gandalf vs Dumbledore

Introduction

In this challenge we will train a neural network to distinguish between two different types of images using convolutional nerual networks.

In particular, we will train a model that can distinguish between images of Gandalf (from *Lord of the Rings*) and Dumbledore (from *Harry Potter*).

This is a challenging visual task for a few reasons:

- Both are grey-bearded old white men
- Both wear wizard robes and hats
- Two different actors played Dumbledore (yes, we will ignore the Jude Law incarnation), Richard Harris and Michael Gambon, and they did not look very much alike. In fact, you could argue that Michael Gambon looks much more like Ian McKellen than like Richark Harris.
- Gandalf has two incarnations that look significantly different: Gandalf the Grey and Gandalf the White

With a very limited training set of images, this task would be close to impossible if we were training a neural network from scratch.

Thankfully, but we will not start from scratch. We will use Transfer Learning to benefit from the representations learned by other networks previously trained on huge datasets with many image classes, and apply those representations to our much more specific problem, with much more limited data.

Suggested resources

- Easy way to manipulate an image dataset with Keras: https://keras.io/api/preprocessing/image/
- You will probably find this Transfer Learning example in Keras very useful: https://keras.io/examples/vision/image_classification_efficientnet_fine_tuning/
- Data augmentation layers in Keras: https://www.tensorflow.org/api_docs/python/tf/keras/layers/experimental/preprocessing
- There are many pre-trained state-of-art models available directly through the Keras API, such as EfficientNet: https://keras.io/api/applications/efficientnet/

Setup

First, we will install and load all of the libraries we will be using.

Please update it as you need, importing whatever libraries you use in your code.

1. Data Analysis

Include any imports you need in the cell below.

I have included some imports to give you hints on what you might want to make use of.

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from PIL import Image
from google_drive_downloader import GoogleDriveDownloader as gdd
from sklearn.model_selection import train_test_split
import shutil
from tensorflow import keras
from tensorflow.keras import layers
import pandas as pd
from sklearn import preprocessing
from keras.utils import np_utils
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.layers import Activation
from keras.callbacks import EarlyStopping
SEED = 1534  # Set this to whichever value you want and use this parameters in any seeded pseudor
```

Dataset

You can download the training data by running the cell below. You will get the following folder structure:

```
train_data
 |_ dumbledore
    |_ dumbledore_0000.jpg
    |_ dumbledore_0001.jpg
    |_ dumbledore_0002.jpg
    |_ ...
 |_ gandalf
    |_ gandalf_0000.jpg
    |_ gandalf_0001.jpg
    |_ gandalf_0002.jpg
```

Load the data: Dumbledore and Gandalf dataset

[ ] ↳ *1 celda oculta*

Filter out corrupted images

```
import os

num_skipped = 0
for folder_name in ("dumbledore", "gandalf"):
    folder_path = os.path.join("/content/drive/MyDrive/datasets/DL2_GvD/train_data", folder_name)
    for fname in os.listdir(folder_path):
        fpath = os.path.join(folder_path, fname)
        try:
            fobj = open(fpath, "rb")
```

```
            is_jfif = tf.compat.as_bytes("JFIF") in fobj.peek(10)
        finally:
            fobj.close()

        if not is_jfif:
            num_skipped += 1
            # Delete corrupted image
            os.remove(fpath)

print("Deleted %d images" % num_skipped)
```

```
Deleted 0 images
```

Generate a Dataset

```
image_size = (180, 180)
batch_size = 32 # El bach no puede ser mucho mayor debido al tamaño del dataset
validation_split = 0.2  # 20%del dataset para validacion

# Se crea el conjunto de datos
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "train_data",
    validation_split=0.2,
    subset="training",
    seed=1337,
    image_size=image_size,
    batch_size=batch_size,
)

# Se crea el conjunto de validacion
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "train_data",
    validation_split=0.2,
    subset="validation",
    seed=1337,
    image_size=image_size,
    batch_size=batch_size,
)
train_ds
```

```
Found 80 files belonging to 2 classes.
Using 64 files for training.
Found 80 files belonging to 2 classes.
Using 16 files for validation.
<BatchDataset element_spec=(TensorSpec(shape=(None, 180, 180, 3), dtype=tf.float32, name=None)
```

Visualize the data

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
```

```
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(int(labels[i]))
        plt.axis("off")
```

2. Data Pocessing

Using image data augmentation

When you don't have a large image dataset, it's a good practice to artificially introduce sample diversity by applying random yet realistic transformations to the training images, such as random horizontal flipping or small random rotations. This helps expose the model to different aspects of the training data while slowing down overfitting.

```
image_augmentation = keras.Sequential(
    [
        layers.RandomFlip(),
        layers.RandomRotation(factor=0.1),
        layers.RandomContrast(0.01),
        #layers.RandomTranslation(height_factor=0.1, width_factor=0.1, seed=SEED),
        #layers.RandomZoom(0.2, fill_mode='nearest', seed=SEED),
    ],
```

```
    name = "image_augmentation"
)
```

Let's visualize what the augmented samples look like, by applying `data_augmentation` repeatedly to the first image in the dataset:

```
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
    for i in range(9):
        augmented_images = image_augmentation(images)
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(augmented_images[0].numpy().astype("uint8"))
        plt.axis("off")
```

3. Build a model

Model

I haven chosen to use the ResNet152 architecture, replacing the top layers to adjust it to our binary classification problem. We have the choise to import either a blank model or a pretrained one, depending on the train parameter. We will shortly see the difference of performance between both options

```
# ResNet152
from keras.applications.resnet import ResNet152 as Architecture

def build_model(input_shape, num_classes, trained):# Depending on the train parameter, it returns
  base_model = Architecture (include_top=False, input_shape=input_shape, weights='imagenet'if tra
  base_model.trainable = not trained

  inputs = keras.Input(shape=input_shape, name='input')
  x = image_augmentation(inputs)
  x = base_model(x)
  x = layers.GlobalAveragePooling2D(name='avg_pool')(x)
  x = layers.BatchNormalization()(x)
  x = layers.Dropout(0.2,name='top_dropout')(x)

  if num_classes == 2:
    activation = 'sigmoid'
    units = 1
  else:
    activation = 'softmax'
    units = num_classes

  outputs = layers.Dense(units,activation=activation, name='pred')(x)
  return keras.Model(inputs, outputs, name=Architecture.__name__)
```

```
# function to plot the accuracy
def plot_model_hist(model_history):
    sns.set()
    ig, axs = plt.subplots(1,2, figsize=(15,5))
    # Summarize history for accuracy
    axs[0].plot(range(1,len(model_history.history['accuracy'])+1), model_history.history['accurac
    axs[0].plot(range(1,len(model_history.history['val_accuracy'])+1), model_history.history['val
    axs[0].set_title('Model Accuracy')
    axs[0].set_ylabel('Accuracy')
    axs[0].set_xlabel('Epoch')
    axs[0].legend(['train','val'],loc='best')

    # Summarize history for loss
    axs[1].plot(range(1,len(model_history.history['loss'])+1), model_history.history['loss'])
    axs[1].plot(range(1,len(model_history.history['val_loss'])+1), model_history.history['val_los
    axs[1].set_title('Model Loss')
    axs[1].set_ylabel('Loss')
    axs[1].set_xlabel('Epoch')
    axs[1].legend(['train','val'],loc='best')

    plt.show()
```

Blanck Model

In this model, the ResNet 152 presents random weights, that is, it does not have pre-trained parameters.

Total parameters: 58,381,185

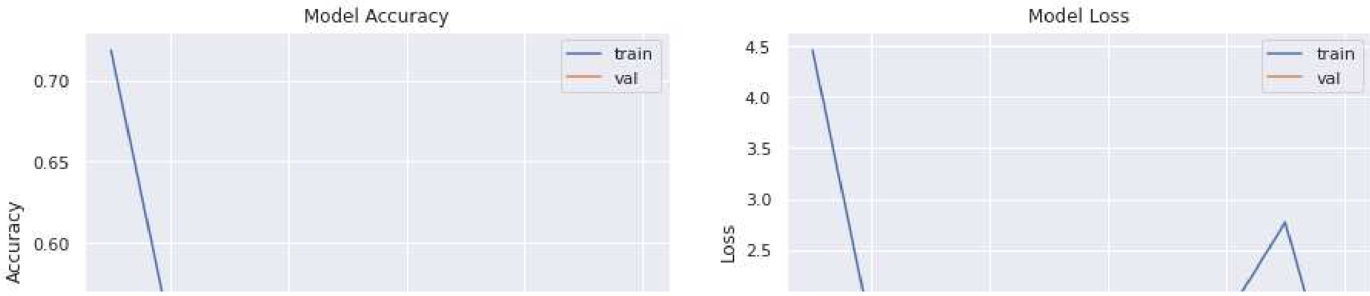
Trainable parameters: 58,225,665

```
model = build_model(image_size+(3,), 2, trained=False)
model.summary()
```

```
Model: "ResNet152"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input (InputLayer)          [(None, 180, 180, 3)]     0

 image_augmentation (Sequent  (None, 180, 180, 3)      0
 ial)

 resnet152 (Functional)      (None, 6, 6, 2048)        58370944

 avg_pool (GlobalAveragePool  (None, 2048)             0
 ing2D)

 batch_normalization_2 (Batc  (None, 2048)             8192
 hNormalization)

 top_dropout (Dropout)       (None, 2048)              0

 pred (Dense)                (None, 1)                 2049

=================================================================
Total params: 58,381,185
Trainable params: 58,225,665
Non-trainable params: 155,520
_________________________________________________________________
```

```
epochs = 50

callbacks = [
    keras.callbacks.EarlyStopping(patience=10, restore_best_weights=True),
    keras.callbacks.ModelCheckpoint(save_best_only=True, mode='min', filepath='model.hdf5')
]

model.compile(
    optimizer=keras.optimizers.Adam(1e-2),
    loss='binary_crossentropy',
    metrics=['accuracy']
)
history=model.fit(train_ds, epochs=epochs, callbacks=callbacks, validation_data=val_ds)
plot_model_hist(history)
```

```
Epoch 1/50
2/2 [==============================] - 127s 54s/step - loss: 4.4609 - accuracy: 0.7188 - v
Epoch 2/50
2/2 [==============================] - 94s 49s/step - loss: 1.6827 - accuracy: 0.5469 - va
Epoch 3/50
2/2 [==============================] - 94s 49s/step - loss: 0.8310 - accuracy: 0.5625 - va
Epoch 4/50
2/2 [==============================] - 93s 49s/step - loss: 0.7864 - accuracy: 0.5156 - va
Epoch 5/50
2/2 [==============================] - 92s 48s/step - loss: 0.9432 - accuracy: 0.5000 - va
Epoch 6/50
2/2 [==============================] - 98s 54s/step - loss: 1.6198 - accuracy: 0.4844 - va
Epoch 7/50
2/2 [==============================] - 95s 49s/step - loss: 1.4286 - accuracy: 0.5312 - va
Epoch 8/50
2/2 [==============================] - 93s 49s/step - loss: 1.8326 - accuracy: 0.5000 - va
Epoch 9/50
2/2 [==============================] - 93s 49s/step - loss: 2.7686 - accuracy: 0.4844 - va
Epoch 10/50
2/2 [==============================] - 93s 49s/step - loss: 0.7260 - accuracy: 0.5312 - va
```



As we can see, we do not seem to have enough images to train a model a from scracth, resulting in a random model with 50% accuracy on the validation set. Lets see how a pretrained model performs instead

Pretrained Model

```
model = build_model(image_size+(3,), 2,trained=True)
model.summary()
```

```
Model: "ResNet152"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input (InputLayer)          [(None, 180, 180, 3)]     0

 image_augmentation (Sequent  (None, 180, 180, 3)      0
 ial)

 resnet152 (Functional)      (None, 6, 6, 2048)        58370944

 avg_pool (GlobalAveragePool  (None, 2048)             0
 ing2D)

 batch_normalization_3 (Batc  (None, 2048)             8192
 hNormalization)

 top_dropout (Dropout)       (None, 2048)              0

 pred (Dense)                (None, 1)                 2049

=================================================================
```

```
Total params: 58,381,185
Trainable params: 6,145
Non-trainable params: 58,375,040
_________________________________________________________________
```

```
epochs = 50

callbacks = [
    keras.callbacks.EarlyStopping(patience=20, restore_best_weights=True),
    keras.callbacks.ModelCheckpoint(save_best_only=True, mode='min', filepath='petrained_model.hd
]

model.compile(
    optimizer=keras.optimizers.Adam(2e-3),
    loss='binary_crossentropy',
    metrics=['accuracy']
)
history=model.fit(train_ds, epochs=epochs, callbacks=callbacks, validation_data=val_ds)
plot_model_hist(history)
```

```
Epoch 1/50
2/2 [==============================] - 42s 20s/step - loss: 1.0535 - accuracy: 0.4375 - va
Epoch 2/50
2/2 [==============================] - 27s 16s/step - loss: 0.8007 - accuracy: 0.5469 - va
Epoch 3/50
2/2 [==============================] - 27s 16s/step - loss: 0.5551 - accuracy: 0.7500 - va
Epoch 4/50
2/2 [==============================] - 26s 16s/step - loss: 0.3965 - accuracy: 0.8594 - va
Epoch 5/50
2/2 [==============================] - 27s 16s/step - loss: 0.2998 - accuracy: 0.8438 - va
Epoch 6/50
2/2 [==============================] - 27s 16s/step - loss: 0.3973 - accuracy: 0.8438 - va
Epoch 7/50
2/2 [==============================] - 27s 17s/step - loss: 0.2735 - accuracy: 0.8750 - va
Epoch 8/50
2/2 [==============================] - 28s 17s/step - loss: 0.3505 - accuracy: 0.8281 - va
Epoch 9/50
2/2 [==============================] - 25s 15s/step - loss: 0.2062 - accuracy: 0.8906 - va
Epoch 10/50
2/2 [==============================] - 27s 16s/step - loss: 0.2336 - accuracy: 0.9219 - va
Epoch 11/50
2/2 [==============================] - 27s 17s/step - loss: 0.1981 - accuracy: 0.9062 - va
Epoch 12/50
2/2 [==============================] - 27s 16s/step - loss: 0.1679 - accuracy: 0.9375 - va
Epoch 13/50
2/2 [==============================] - 27s 16s/step - loss: 0.1447 - accuracy: 0.9531 - va
Epoch 14/50
2/2 [==============================] - 26s 16s/step - loss: 0.1432 - accuracy: 0.9531 - va
Epoch 15/50
2/2 [==============================] - 27s 17s/step - loss: 0.0910 - accuracy: 0.9844 - va
Epoch 16/50
2/2 [==============================] - 32s 16s/step - loss: 0.1264 - accuracy: 0.9531 - va
Epoch 17/50
2/2 [==============================] - 27s 16s/step - loss: 0.0766 - accuracy: 0.9844 - va
Epoch 18/50
2/2 [==============================] - 26s 16s/step - loss: 0.0503 - accuracy: 1.0000 - va
Epoch 19/50
2/2 [==============================] - 26s 16s/step - loss: 0.0880 - accuracy: 0.9844 - va
Epoch 20/50
2/2 [==============================] - 27s 16s/step - loss: 0.0999 - accuracy: 0.9844 - va
Epoch 21/50
2/2 [==============================] - 27s 17s/step - loss: 0.0690 - accuracy: 0.9844 - va
Epoch 22/50
2/2 [==============================] - 27s 16s/step - loss: 0.0934 - accuracy: 0.9688 - va
Epoch 23/50
2/2 [==============================] - 26s 16s/step - loss: 0.0589 - accuracy: 1.0000 - va
Epoch 24/50
2/2 [==============================] - 25s 15s/step - loss: 0.0355 - accuracy: 1.0000 - va
Epoch 25/50
2/2 [==============================] - 25s 15s/step - loss: 0.0666 - accuracy: 0.9688 - va
Epoch 26/50
2/2 [==============================] - 25s 15s/step - loss: 0.0294 - accuracy: 1.0000 - va
Epoch 27/50
2/2 [==============================] - 25s 15s/step - loss: 0.0514 - accuracy: 1.0000 - va
Epoch 28/50
2/2 [==============================] - 25s 15s/step - loss: 0.0409 - accuracy: 1.0000 - va
Epoch 29/50
2/2 [==============================] - 25s 15s/step - loss: 0.0732 - accuracy: 0.9844 - va
Epoch 30/50
2/2 [==============================] - 25s 15s/step - loss: 0.0735 - accuracy: 0.9844 - va
Epoch 31/50
2/2 [==============================] - 25s 15s/step - loss: 0.0582 - accuracy: 0.9844 - va
Epoch 32/50
2/2 [==============================] - 25s 15s/step - loss: 0.0515 - accuracy: 0.9844 - va
```

```
Epoch 33/50
2/2 [==============================] - 25s 15s/step - loss: 0.0343 - accuracy: 0.9844 - va
Epoch 34/50
2/2 [==============================] - 25s 15s/step - loss: 0.0387 - accuracy: 1.0000 - va
Epoch 35/50
2/2 [==============================] - 25s 15s/step - loss: 0.0324 - accuracy: 1.0000 - va
Epoch 36/50
2/2 [==============================] - 25s 15s/step - loss: 0.0668 - accuracy: 0.9688 - va
Epoch 37/50
2/2 [==============================] - 25s 15s/step - loss: 0.0285 - accuracy: 1.0000 - va
Epoch 38/50
2/2 [==============================] - 25s 15s/step - loss: 0.0248 - accuracy: 1.0000 - va
Epoch 39/50
2/2 [==============================] - 25s 15s/step - loss: 0.0466 - accuracy: 1.0000 - va
Epoch 40/50
2/2 [==============================] - 27s 17s/step - loss: 0.0388 - accuracy: 1.0000 - va
Epoch 41/50
2/2 [==============================] - 27s 16s/step - loss: 0.0321 - accuracy: 1.0000 - va
Epoch 42/50
```

As we can observe from these results, using a pretrained model allows us to focus on the training the last layer, used for classification while letting to bottom layers frozen. The bottom layers seem to be extracting good features for our top layers to use, but could be do better?

Fine Turing

```
2/2 [==============================] - 27s 16s/step - loss: 0.0349 - accuracy: 1.0000 - va
```

We unfreeze the bottom layers of our model and train them, hopefully improving the predicting power of our model

```
def unfreeze_model(model):
# We unfreeze the top 20 layers while leaving BachtNorm layers frozen
  for layer in model.layers[-20:]:
    if not isinstance(layer, layers.BatchNormalization):
      layer.trainable=True
  return model
```

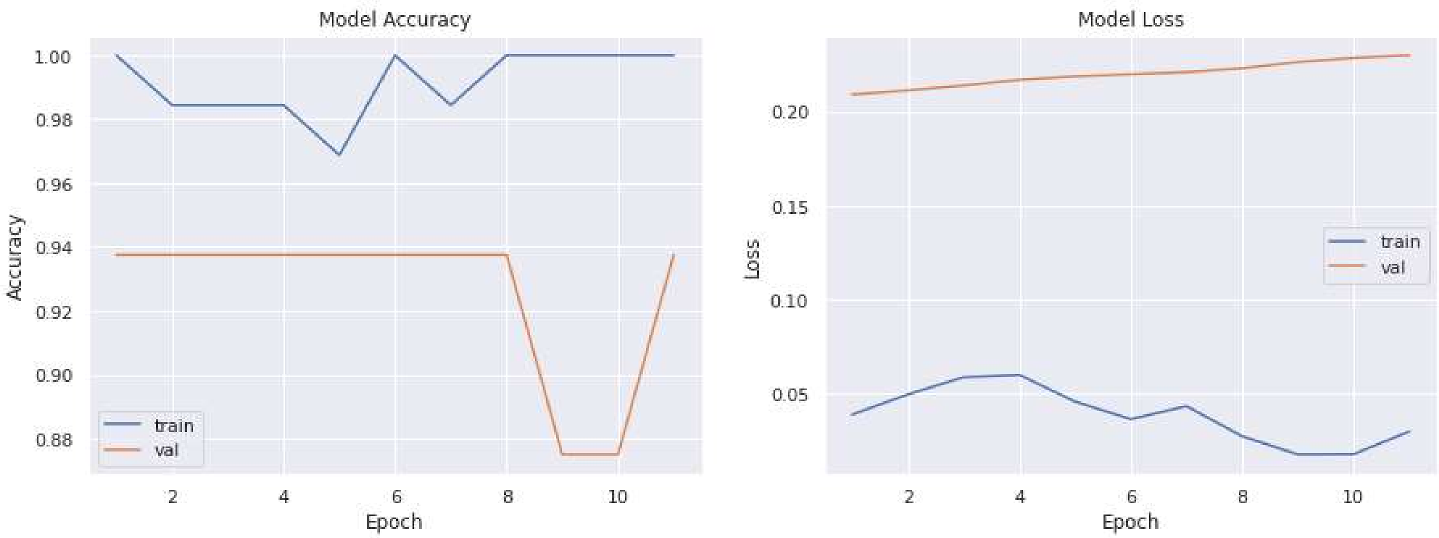
```
model = unfreeze_model(model)
model.summary()
```

```
Model: "ResNet152"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input (InputLayer)          [(None, 180, 180, 3)]     0

 image_augmentation (Sequent  (None, 180, 180, 3)      0
 ial)

 resnet152 (Functional)      (None, 6, 6, 2048)        58370944

 avg_pool (GlobalAveragePool  (None, 2048)             0
 ing2D)

 batch_normalization_3 (Batc  (None, 2048)             8192
 hNormalization)

 top_dropout (Dropout)       (None, 2048)              0
```

```
 pred (Dense)                (None, 1)                 2049

=================================================================
Total params: 58,381,185
Trainable params: 58,225,665
Non-trainable params: 155,520
_________________________________________________________________
```

```
epochs = 50

callbacks = [
    keras.callbacks.EarlyStopping(patience=10, restore_best_weights=True),
    keras.callbacks.ModelCheckpoint(save_best_only=True, mode='min', filepath='finetunedpetrained
]
history=model.fit(train_ds, epochs=epochs, callbacks=callbacks, validation_data=val_ds)
plot_model_hist(history)
```

```
Epoch 1/50
2/2 [==============================] - 28s 18s/step - loss: 0.0387 - accuracy: 1.0000 - val_los
Epoch 2/50
2/2 [==============================] - 25s 15s/step - loss: 0.0494 - accuracy: 0.9844 - val_los
Epoch 3/50
2/2 [==============================] - 25s 15s/step - loss: 0.0586 - accuracy: 0.9844 - val_los
Epoch 4/50
2/2 [==============================] - 25s 15s/step - loss: 0.0599 - accuracy: 0.9844 - val_los
Epoch 5/50
2/2 [==============================] - 25s 15s/step - loss: 0.0456 - accuracy: 0.9688 - val_los
Epoch 6/50
2/2 [==============================] - 25s 15s/step - loss: 0.0363 - accuracy: 1.0000 - val_los
Epoch 7/50
2/2 [==============================] - 25s 15s/step - loss: 0.0432 - accuracy: 0.9844 - val_los
Epoch 8/50
2/2 [==============================] - 25s 15s/step - loss: 0.0272 - accuracy: 1.0000 - val_los
Epoch 9/50
2/2 [==============================] - 25s 15s/step - loss: 0.0175 - accuracy: 1.0000 - val_los
Epoch 10/50
2/2 [==============================] - 25s 15s/step - loss: 0.0177 - accuracy: 1.0000 - val_los
Epoch 11/50
2/2 [==============================] - 26s 15s/step - loss: 0.0298 - accuracy: 1.0000 - val_los
```



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```
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```

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