12MBID_Proyecto_Programacion_Entrega2

May 22, 2022

0.1 Proyecto de programación ”Deep Vision in classification tasks Pre-entrenado”

[ ]:
```
%%capture
!pip freeze
```

Hola voy a ejecutar el comando `!pip freeze` para cotillear a Google Colab

[ ]:
```
#Importemos TensorFlow 2.X y Numpy
import numpy as np
import tensorflow as tf
tf.__version__
```

[ ]:
```
'2.8.0'
```

0.2 - Cargando el conjunto de datos

1 Escritura de datos tomando como referencia un BASE_FOLDER

[ ]:
```
# Conectamos con nuestro Google Drive
from google.colab import drive
drive.mount('/content/drive')
```

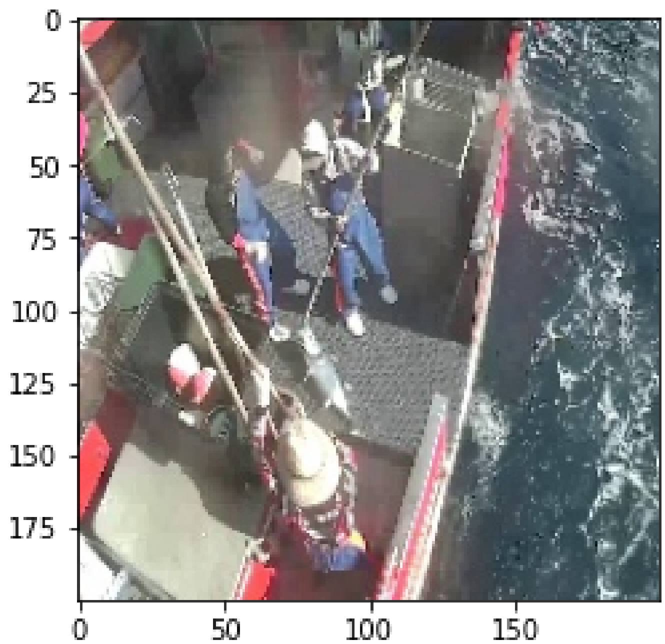
```
Mounted at /content/drive
```

[ ]:
```
# Establezco una ruta absoluta a un directorio existente de mi Google Drive

BASE_FOLDER = "/content/drive/MyDrive/12MBID_Proyecto_Programacion_Colab/
↪my_dataset/"
```

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import cv2

# Escogiendo y mostrando una imagen al azar del conjunto de test
```

```python
indx = 12
img = cv2.imread(BASE_FOLDER + 'Train/ALB/img_00012.jpg', cv2.COLOR_BGR2RGB)
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
plt.imshow(img)
```

[ ]: <matplotlib.image.AxesImage at 0x7f2cf6240110>



[ ]:
```python
import os
categorias = []
categorias = os.listdir(BASE_FOLDER + 'Train/')
print(categorias)
```

```
['YFT', 'SHARK', 'OTHER', 'NoF', 'LAG', 'DOL', 'BET', 'ALB']
```

[ ]:
```python
# Generando datos con etiquetas a partir de imagenes  por cada categoria para␣
↪el test
x_train =[]
y_train =[]

# Generando subcarpetas con imagenes  por cada categoria
idx = 0
for cat in categorias:
    parent_dir = BASE_FOLDER + "Train/"
    path = os.path.join(parent_dir, cat)
```

```
    # creamos las imagenes para el entranamiento redimensionandolos
    for imagen in os.listdir(path):
      img = cv2.imread(os.path.join(path, imagen))
      img = cv2.resize(img, (200,200))
      img = np.asarray(img)
      x_train.append(img)
      y_train.append(idx)
    idx += 1
x_train = np.asarray(x_train)
y_train = np.asarray(y_train)
print(x_train.shape)
print(y_train.shape)
```

```
(3404, 200, 200, 3)
(3404,)
```

[ ]:
```
# Generando datos de entrenamiento extrayendo del directory Test/
x_test = []
y_test = []

idx = 0
for cat in categorias:
    parent_dir = BASE_FOLDER + "Test/"
    path = os.path.join(parent_dir, cat)
    # creamos las imagenes para el entranamiento redimensionandolos
    for imagen in os.listdir(path):
      img = cv2.imread(os.path.join(path, imagen))
      img = cv2.resize(img, (200,200))
      img = np.asarray(img)
      x_test.append(img)
      y_test.append(idx)
    idx += 1
x_test = np.asarray(x_test)
y_test = np.asarray(y_test)
print(x_test.shape)
print(y_test.shape)
```

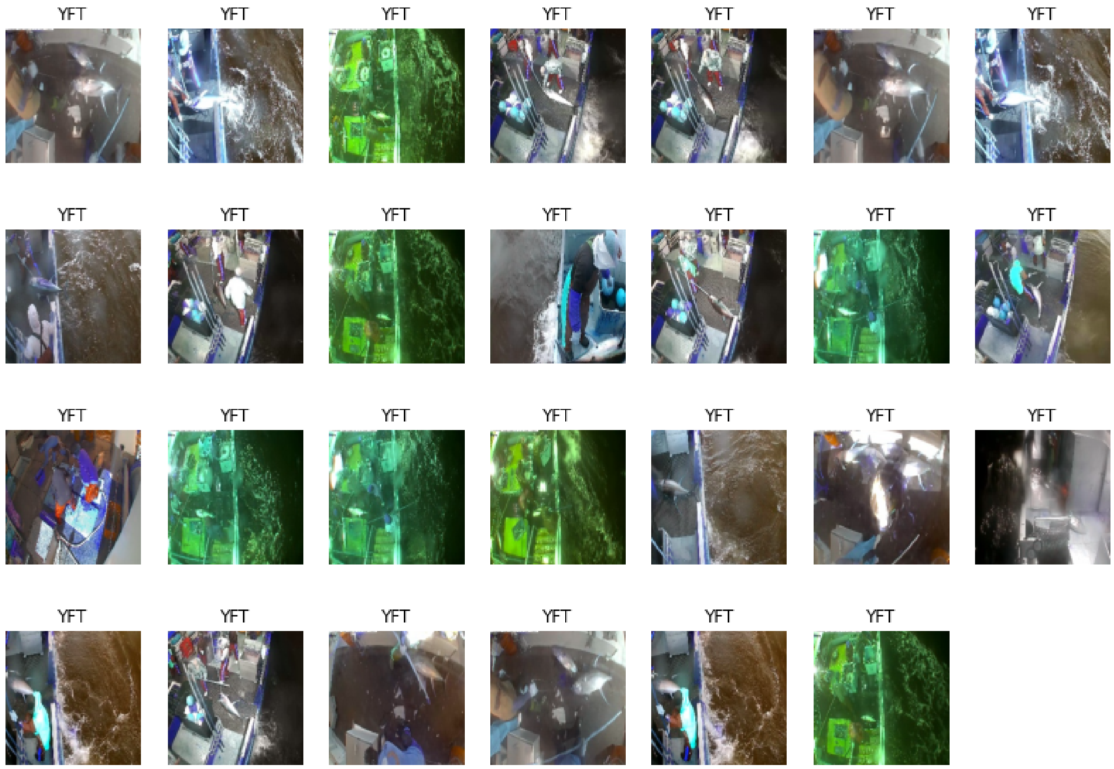
```
(373, 200, 200, 3)
(373,)
```

[ ]:
```
import pandas as pd
data_df = pd.DataFrame(y_test)
y_test = np.asarray(y_test)
print(y_test.shape)
```

```
(373,)
```

2 Verificando las imagenes

[ ]:
```
fig = plt.figure(figsize=(14,10))
for i in range(1, 28):
  fig.add_subplot(4,7,i)
  plt.xticks([])
  plt.yticks([])
  plt.grid(False)
  plt.imshow(x_train[i])
  plt.title(categorias[y_train[i]])
  plt.axis('off')
```



3 TRABAJANDO CON REDES PRE-ENTRENADAS

3.1 Acondicionamiento del conjunto de datos como en la VGG

[ ]:
```
from tensorflow.keras.applications import imagenet_utils
from sklearn.preprocessing import LabelBinarizer
from tensorflow.keras.backend import expand_dims
```

```
#One-hot encoding
lb = LabelBinarizer()
trainY = lb.fit_transform(y_train)
testY = lb.transform(y_test)

# IMPORTANTE: Se normalizan los datos como se normalizaron en el entrenamiento␣
↪con ImageNet!!
trainX = imagenet_utils.preprocess_input(x_train)
testX = imagenet_utils.preprocess_input(x_test)

labelNames = categorias

print(trainX.shape)
print(trainY.shape)
print(testX.shape)
print(testY.shape)
```

```
(3404, 200, 200, 3)
(3404, 8)
(373, 200, 200, 3)
(373, 8)
```

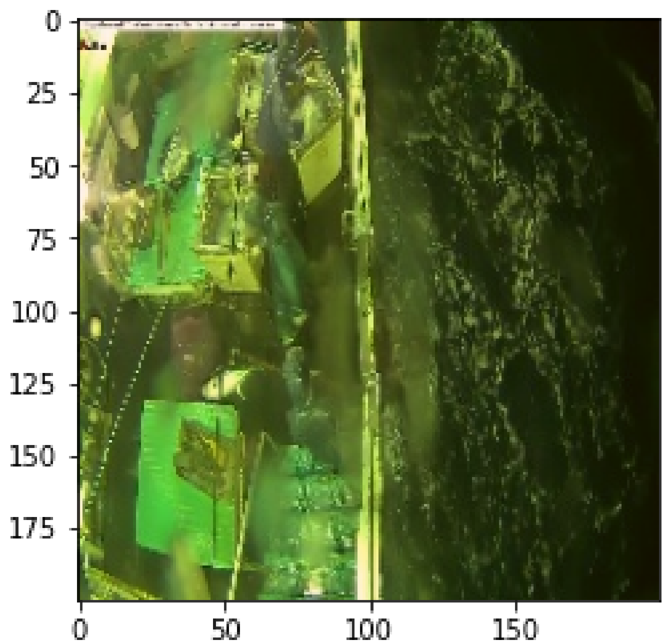
3.2 Creando un contenedor DataGenerator para el aumento automatico de muestras

[ ]:
```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=15, # grados de rotacion aleatoria
    width_shift_range=0.2, # fraccion del total (1) para mover la imagen
    height_shift_range=0.2, # fraccion del total (1) para mover la imagen
    horizontal_flip=True, # girar las imagenes horizontalmente (eje vertical)
    # shear_range=0, # deslizamiento
    zoom_range=0.2, # rango de zoom
    # fill_mode='nearest', # como rellenar posibles nuevos pixeles
    # channel_shift_range=0.2 # cambios aleatorios en los canales de la imagen
)
```

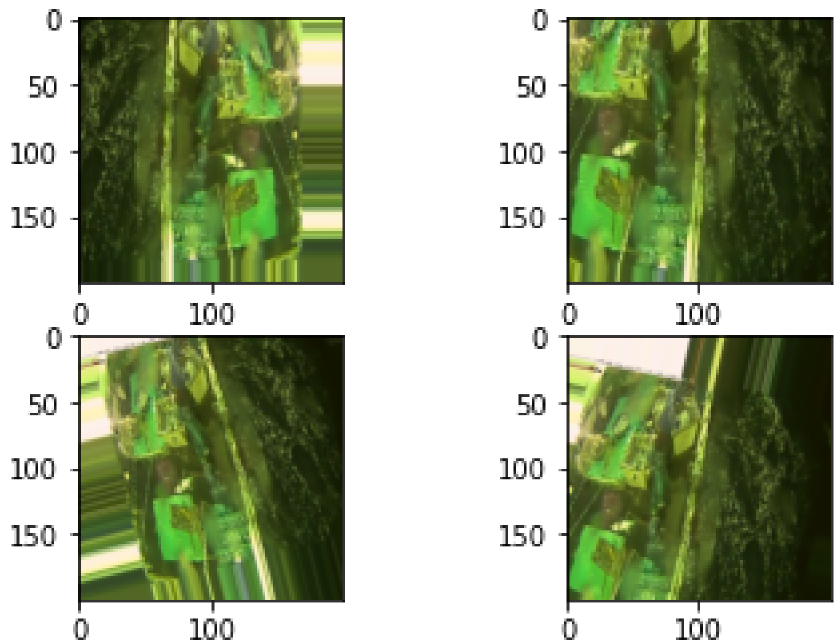
3.3 Inspeccionando las muestras generadas sinteticamente

[ ]:
```
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
%matplotlib inline

sample = 45
```

```
plt.imshow(image.array_to_img(trainX[sample]))
plt.show()
print('Label = {}'.format(labelNames[trainY[sample].argmax(axis=0)]))

fig, axes = plt.subplots(2,2)
i = 0
for batch in datagen.flow(trainX[sample].reshape((1,200,200,3)),batch_size=1):
    #plt.figure(i)
    axes[i//2,i%2].imshow(image.array_to_img(batch[0]))
    i += 1
    if i == 4:
        break
plt.show()
```




```
Label = YFT
```



4 Cargando la topologia de CNN (base model)

```
[ ]: #keras incluye varias arquitecturas
     # VGG16, VGG19, ResNet50, Xception, InceptionV3, InceptionResNetV2,␣
      ↪MobileNetV2, DenseNet, RasNet
     # documentacion https://keras.io/applications/
     # Visual Geometry Group 16 / 19 (numero de layers)
     # 1 y 2 en la competicion ImageNet 2014
     # Kernels pequeños de 3x3

     from tensorflow.keras.applications import VGG16

     base_model = VGG16(weights='imagenet',
                        include_top=False, # No incluir el top model, i.e. la parte␣
      ↪densa destinada a la clasificación (fully connected layers)
                        input_shape=(200,200,3))
     base_model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58892288/58889256 [==============================] - 0s 0us/step
58900480/58889256 [==============================] - 0s 0us/step
Model: "vgg16"
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 200, 200, 3)]     0

 block1_conv1 (Conv2D)       (None, 200, 200, 64)      1792

 block1_conv2 (Conv2D)       (None, 200, 200, 64)      36928

 block1_pool (MaxPooling2D)  (None, 100, 100, 64)      0

 block2_conv1 (Conv2D)       (None, 100, 100, 128)     73856

 block2_conv2 (Conv2D)       (None, 100, 100, 128)     147584

 block2_pool (MaxPooling2D)  (None, 50, 50, 128)       0

 block3_conv1 (Conv2D)       (None, 50, 50, 256)       295168

 block3_conv2 (Conv2D)       (None, 50, 50, 256)       590080

 block3_conv3 (Conv2D)       (None, 50, 50, 256)       590080

 block3_pool (MaxPooling2D)  (None, 25, 25, 256)       0

 block4_conv1 (Conv2D)       (None, 25, 25, 512)       1180160

 block4_conv2 (Conv2D)       (None, 25, 25, 512)       2359808

 block4_conv3 (Conv2D)       (None, 25, 25, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 12, 12, 512)       0

 block5_conv1 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_conv2 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_conv3 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 6, 6, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

4.1 Creando el top model y congelando TODAS las capas convolucionales (TRANSFER LEARNING)

[ ]:
```
# conectarlo a nueva parte densa
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers

base_model.trainable = False # Evitar que los pesos se modifiquen en la parte␣
↪convolucional -> TRANSFER LEARNING
pre_trained_model = Sequential()
pre_trained_model.add(base_model)
pre_trained_model.add(layers.Flatten())
pre_trained_model.add(layers.Dense(256, activation='relu'))
pre_trained_model.add(layers.Dense(8, activation='softmax'))

pre_trained_model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 6, 6, 512)         14714688

 flatten (Flatten)           (None, 18432)             0

 dense (Dense)               (None, 256)               4718848

 dense_1 (Dense)             (None, 8)                 2056

=================================================================
Total params: 19,435,592
Trainable params: 4,720,904
Non-trainable params: 14,714,688
_________________________________________________________________
```

4.2 Entrenando la Solucion

[ ]:
```
# Import the necessary packages
import numpy as np
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Input, Conv2D, Activation, Flatten, Dense,␣
↪Dropout, BatchNormalization, MaxPooling2D
from tensorflow.keras.models import Model
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import SGD, Adam
from sklearn.metrics import classification_report
```

```python
import matplotlib.pyplot as plt
from google.colab import drive

# Compilar el modelo
print("[INFO]: Compilando el modelo...")
pre_trained_model.compile(loss="categorical_crossentropy", optimizer=Adam(lr=0.
↪0005,decay=0, beta_1=0.9, beta_2=0.999, epsilon=1e-08), metrics=["accuracy"])

# Entrenamiento de la red
print("[INFO]: Entrenando la red...")
H_pre = pre_trained_model.fit(trainX, trainY, batch_size=128, epochs=20,␣
↪validation_split=0.2)
# Almaceno el modelo en Drive
# Montamos la unidad de Drive
# drive.mount('/content/drive')
# Almacenamos el modelo empleando la función mdoel.save de Keras
pre_trained_model.save(BASE_FOLDER+"deepCNN_FISH_pretrained.h5") #(X)

# Evaluación del modelo
print("[INFO]: Evaluando el modelo...")
# Efectuamos la predicción (empleamos el mismo valor de batch_size que en␣
↪training)
predictions = pre_trained_model.predict(testX, batch_size=128)
# Sacamos el report para test
print(classification_report(testY.argmax(axis=1), predictions.argmax(axis=1),␣
↪target_names=labelNames))

# Gráficas
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, 20), H_pre.history["loss"], label="train_loss")
plt.plot(np.arange(0, 20), H_pre.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, 20), H_pre.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, 20), H_pre.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.show()
```

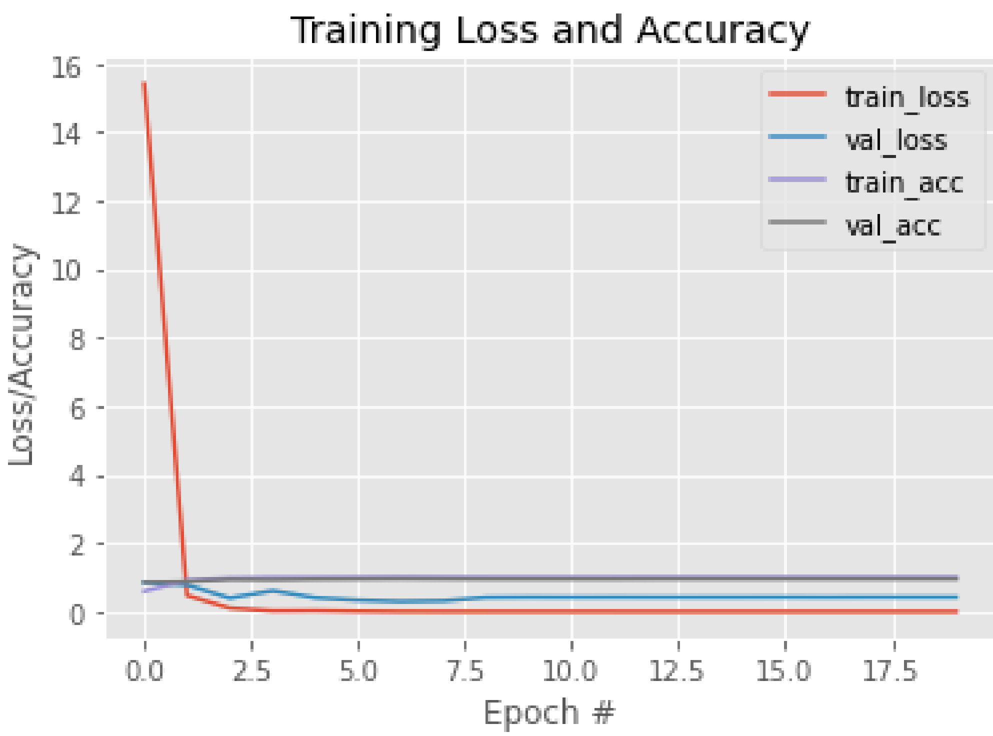
```
[INFO]: Compilando el modelo…
[INFO]: Entrenando la red…
```

```
/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/adam.py:105:
UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super(Adam, self).__init__(name, **kwargs)
```

```
Epoch 1/20
```

```
22/22 [==============================] - 38s 930ms/step - loss: 15.4111 -
accuracy: 0.5986 - val_loss: 0.8578 - val_accuracy: 0.8605
Epoch 2/20
22/22 [==============================] - 14s 636ms/step - loss: 0.4734 -
accuracy: 0.9141 - val_loss: 0.7814 - val_accuracy: 0.8811
Epoch 3/20
22/22 [==============================] - 14s 650ms/step - loss: 0.1049 -
accuracy: 0.9791 - val_loss: 0.3969 - val_accuracy: 0.9413
Epoch 4/20
22/22 [==============================] - 15s 667ms/step - loss: 0.0249 -
accuracy: 0.9952 - val_loss: 0.6112 - val_accuracy: 0.9325
Epoch 5/20
22/22 [==============================] - 15s 676ms/step - loss: 0.0298 -
accuracy: 0.9967 - val_loss: 0.4064 - val_accuracy: 0.9501
Epoch 6/20
22/22 [==============================] - 15s 698ms/step - loss: 0.0128 -
accuracy: 0.9985 - val_loss: 0.3362 - val_accuracy: 0.9559
Epoch 7/20
22/22 [==============================] - 16s 721ms/step - loss: 0.0023 -
accuracy: 0.9996 - val_loss: 0.3007 - val_accuracy: 0.9648
Epoch 8/20
22/22 [==============================] - 16s 729ms/step - loss: 0.0014 -
accuracy: 1.0000 - val_loss: 0.3172 - val_accuracy: 0.9589
Epoch 9/20
22/22 [==============================] - 15s 709ms/step - loss: 8.9068e-04 -
accuracy: 1.0000 - val_loss: 0.4165 - val_accuracy: 0.9559
Epoch 10/20
22/22 [==============================] - 15s 698ms/step - loss: 7.5947e-04 -
accuracy: 1.0000 - val_loss: 0.4231 - val_accuracy: 0.9559
Epoch 11/20
22/22 [==============================] - 15s 699ms/step - loss: 6.4752e-04 -
accuracy: 1.0000 - val_loss: 0.4208 - val_accuracy: 0.9559
Epoch 12/20
22/22 [==============================] - 15s 711ms/step - loss: 5.6603e-04 -
accuracy: 1.0000 - val_loss: 0.4227 - val_accuracy: 0.9559
Epoch 13/20
22/22 [==============================] - 16s 717ms/step - loss: 5.0197e-04 -
accuracy: 1.0000 - val_loss: 0.4216 - val_accuracy: 0.9589
Epoch 14/20
22/22 [==============================] - 16s 715ms/step - loss: 4.5130e-04 -
accuracy: 1.0000 - val_loss: 0.4219 - val_accuracy: 0.9589
Epoch 15/20
22/22 [==============================] - 16s 712ms/step - loss: 4.1108e-04 -
accuracy: 1.0000 - val_loss: 0.4221 - val_accuracy: 0.9589
Epoch 16/20
22/22 [==============================] - 15s 711ms/step - loss: 3.7272e-04 -
accuracy: 1.0000 - val_loss: 0.4235 - val_accuracy: 0.9589
Epoch 17/20
```

```
22/22 [==============================] - 15s 710ms/step - loss: 3.4572e-04 -
accuracy: 1.0000 - val_loss: 0.4214 - val_accuracy: 0.9589
Epoch 18/20
22/22 [==============================] - 16s 712ms/step - loss: 3.1707e-04 -
accuracy: 1.0000 - val_loss: 0.4240 - val_accuracy: 0.9589
Epoch 19/20
22/22 [==============================] - 16s 711ms/step - loss: 2.9062e-04 -
accuracy: 1.0000 - val_loss: 0.4235 - val_accuracy: 0.9589
Epoch 20/20
22/22 [==============================] - 15s 711ms/step - loss: 2.6918e-04 -
accuracy: 1.0000 - val_loss: 0.4229 - val_accuracy: 0.9589
[INFO]: Evaluando el modelo…
              precision    recall  f1-score   support

         YFT       0.82      0.85      0.83        73
       SHARK       1.00      0.88      0.94        17
       OTHER       0.76      0.55      0.64        29
         NoF       0.86      0.91      0.88        46
         LAG       1.00      0.33      0.50         6
         DOL       1.00      0.64      0.78        11
         BET       0.85      0.85      0.85        20
         ALB       0.87      0.94      0.90       171

    accuracy                           0.86       373
   macro avg       0.89      0.74      0.79       373
weighted avg       0.86      0.86      0.86       373
```



[ ]:
```
inputs = Input(shape=(trainX.shape[1], trainX.shape[2], trainX.shape[3]))
print(inputs.shape)
```

```
(None, 200, 200, 3)
```

5 REDUCIENDO OVERFITTING MEDIANTE DATA AUGMENTATION

5.1 Creando el top model y descongelando bloques convolucionales (FINE TUNING)

[ ]:
```
# Imports que vamos a necesitar
%tensorflow_version 1.x
# from tensorflow.keras.datasets import cifar10
from tensorflow.keras.layers import Input, Conv2D, Activation, Flatten, Dense,␣
↪Dropout, BatchNormalization, MaxPooling2D
from tensorflow.keras.applications import VGG16, imagenet_utils
from tensorflow.keras.utils import to_categorical
from tensorflow.keras import optimizers
from tensorflow.keras.layers import Dropout, Flatten, Dense
from tensorflow.keras import Model
```

```python
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
import numpy as np

#Cargamos el dataset CIFAR10
# (trainX, trainY), (testX, testY) = cifar10.load_data()
inputs = Input(shape=(trainX.shape[1], trainX.shape[2], trainX.shape[3]))
# Normalizamos las entradas de idéntica forma a como lo hicieron para entrenar␣
↪la VGG16 en imageNet
trainX = imagenet_utils.preprocess_input(x_train)
testX = imagenet_utils.preprocess_input(x_test)

# Definimos dimensiones de nuestros datos de entrada y lista con las categorias␣
↪de las clases
input_shape = (200, 200, 3)
# labelNames = ["Avión", "Automóvil", "Pájaro", "Gato", "Ciervo", "Perro",␣
↪"Rana", "Caballo", "Barco", "Camión"]
labelNames = categorias
# En caso de inestabilidades numéricas pasar datos a one-hot encoding
trainY = to_categorical(y_train)
testY = to_categorical(y_test)

# Importamos VGG16 con pesos de imagenet y sin top_model especificando tamaño␣
↪de entrada de datos
base_model = VGG16(weights='imagenet', include_top=False,␣
↪input_shape=input_shape)
# Mostramos la arquitectura
base_model.summary()

# Congelamos las capas de los 4 primeros bloques convolucionales, el quinto se␣
↪re-entrena
# En base_model.layers.name tenemos la información del nombre de la capa
for layer in base_model.layers:
  if layer.name == 'block3_conv1':
    break
  layer.trainable = False
  print('Capa ' + layer.name + ' congelada...')

# Cogemos la última capa del model y le añadimos nuestro clasificador␣
↪(top_model)
last = base_model.layers[-1].output
x = Flatten()(last)
x = Dense(1024, activation='relu', name='fc1')(x)
x = Dropout(0.3)(x)
x = Dense(256, activation='relu', name='fc2')(x)
predictions = Dense(8, activation='softmax', name='predictions')(x)
```

```python
model_aug = Model(base_model.input, outputs=predictions)


# Compilamos el modelo
# model_aug.compile(optimizer='sgd', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
model_aug.compile(loss="categorical_crossentropy", optimizer=Adam(lr=0.
↪001,decay=0, beta_1=0.9, beta_2=0.999, epsilon=1e-08), metrics=["accuracy"])

# Vamos a visualizar el modelo prestando especial atención en el número de␣
↪pesos total y el número de pesos entrenables.
# ¿tiene sentido en comparación al ejemplo de transfer learning?
model_aug.summary()

# Unimos las entradas y el modelo mediante la función Model con parámetros␣
↪inputs y ouputs (Consultar la documentación)
# model_aug = Model(inputs=inputs, outputs=predictions)

# Entrenamos el modelo
# H = model_aug.fit(trainX, trainY, validation_split=0.2, batch_size=256,␣
↪epochs=20, verbose=1)
H = model_aug.fit(datagen.flow(trainX, trainY, batch_size=128),  epochs=20,␣
↪validation_data=(testX, testY))

# Evaluación del modelo
print("[INFO]: Evaluando el modelo...")
predictions = model_aug.predict(testX, batch_size=64)
# Obtener el report de clasificación
print(classification_report(testY.argmax(axis=1), predictions.argmax(axis=1),␣
↪target_names=labelNames))

# Gráficas
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, 20), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, 20), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, 20), H.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, 20), H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.show()
```

```
TensorFlow is already loaded. Please restart the runtime to change versions.
Model: "vgg16"
```

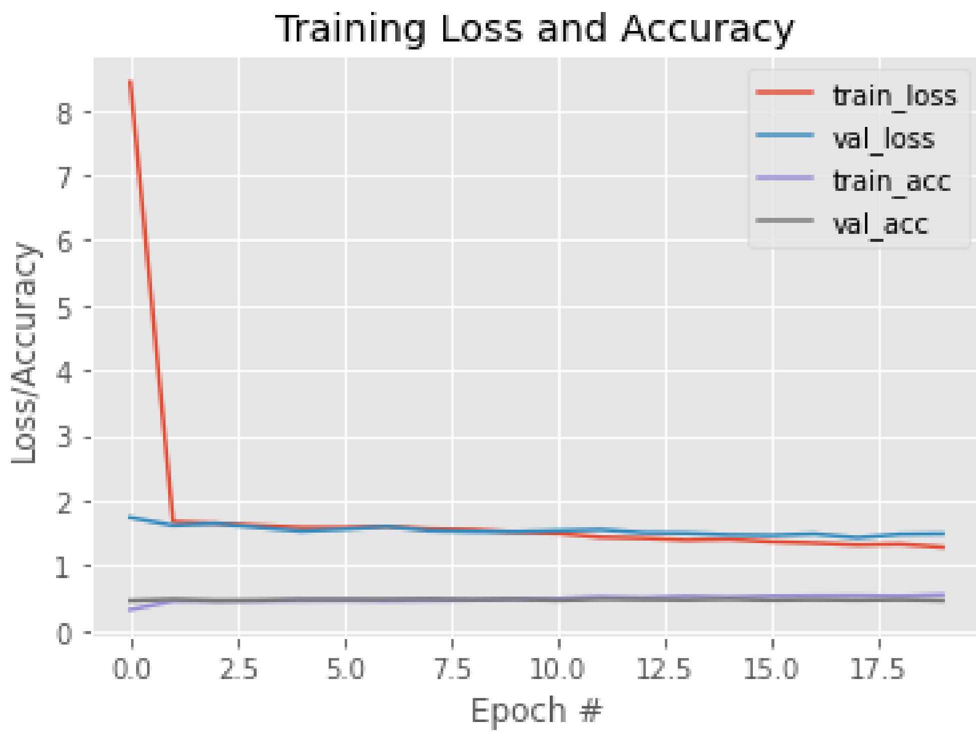
```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_5 (InputLayer)        [(None, 200, 200, 3)]     0

 block1_conv1 (Conv2D)       (None, 200, 200, 64)      1792

 block1_conv2 (Conv2D)       (None, 200, 200, 64)      36928

 block1_pool (MaxPooling2D)  (None, 100, 100, 64)      0

 block2_conv1 (Conv2D)       (None, 100, 100, 128)     73856

 block2_conv2 (Conv2D)       (None, 100, 100, 128)     147584

 block2_pool (MaxPooling2D)  (None, 50, 50, 128)       0

 block3_conv1 (Conv2D)       (None, 50, 50, 256)       295168

 block3_conv2 (Conv2D)       (None, 50, 50, 256)       590080

 block3_conv3 (Conv2D)       (None, 50, 50, 256)       590080

 block3_pool (MaxPooling2D)  (None, 25, 25, 256)       0

 block4_conv1 (Conv2D)       (None, 25, 25, 512)       1180160

 block4_conv2 (Conv2D)       (None, 25, 25, 512)       2359808

 block4_conv3 (Conv2D)       (None, 25, 25, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 12, 12, 512)       0

 block5_conv1 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_conv2 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_conv3 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 6, 6, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
Capa input_5 congelada…
Capa block1_conv1 congelada…
```

```
Capa block1_conv2 congelada…
Capa block1_pool congelada…
Capa block2_conv1 congelada…
Capa block2_conv2 congelada…
Capa block2_pool congelada…
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_5 (InputLayer)        [(None, 200, 200, 3)]     0

 block1_conv1 (Conv2D)       (None, 200, 200, 64)      1792

 block1_conv2 (Conv2D)       (None, 200, 200, 64)      36928

 block1_pool (MaxPooling2D)  (None, 100, 100, 64)      0

 block2_conv1 (Conv2D)       (None, 100, 100, 128)     73856

 block2_conv2 (Conv2D)       (None, 100, 100, 128)     147584

 block2_pool (MaxPooling2D)  (None, 50, 50, 128)       0

 block3_conv1 (Conv2D)       (None, 50, 50, 256)       295168

 block3_conv2 (Conv2D)       (None, 50, 50, 256)       590080

 block3_conv3 (Conv2D)       (None, 50, 50, 256)       590080

 block3_pool (MaxPooling2D)  (None, 25, 25, 256)       0

 block4_conv1 (Conv2D)       (None, 25, 25, 512)       1180160

 block4_conv2 (Conv2D)       (None, 25, 25, 512)       2359808

 block4_conv3 (Conv2D)       (None, 25, 25, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 12, 12, 512)       0

 block5_conv1 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_conv2 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_conv3 (Conv2D)       (None, 12, 12, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 6, 6, 512)         0

 flatten_2 (Flatten)         (None, 18432)             0
```

```
 fc1 (Dense)                 (None, 1024)              18875392

 dropout_1 (Dropout)         (None, 1024)              0

 fc2 (Dense)                 (None, 256)               262400

 predictions (Dense)         (None, 8)                 2056

=================================================================
Total params: 33,854,536
Trainable params: 33,594,376
Non-trainable params: 260,160
_________________________________________________________________
/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/adam.py:105:
UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super(Adam, self).__init__(name, **kwargs)

Epoch 1/20
27/27 [==============================] - 40s 1s/step - loss: 8.4299 - accuracy:
0.3193 - val_loss: 1.7380 - val_accuracy: 0.4584
Epoch 2/20
27/27 [==============================] - 39s 1s/step - loss: 1.6706 - accuracy:
0.4539 - val_loss: 1.6145 - val_accuracy: 0.4799
Epoch 3/20
27/27 [==============================] - 39s 1s/step - loss: 1.6459 - accuracy:
0.4548 - val_loss: 1.6424 - val_accuracy: 0.4584
Epoch 4/20
27/27 [==============================] - 39s 1s/step - loss: 1.6128 - accuracy:
0.4548 - val_loss: 1.5821 - val_accuracy: 0.4638
Epoch 5/20
27/27 [==============================] - 38s 1s/step - loss: 1.5825 - accuracy:
0.4595 - val_loss: 1.5259 - val_accuracy: 0.4799
Epoch 6/20
27/27 [==============================] - 38s 1s/step - loss: 1.5821 - accuracy:
0.4615 - val_loss: 1.5560 - val_accuracy: 0.4799
Epoch 7/20
27/27 [==============================] - 39s 1s/step - loss: 1.5983 - accuracy:
0.4568 - val_loss: 1.5974 - val_accuracy: 0.4799
Epoch 8/20
27/27 [==============================] - 39s 1s/step - loss: 1.5615 - accuracy:
0.4618 - val_loss: 1.5332 - val_accuracy: 0.4853
Epoch 9/20
27/27 [==============================] - 39s 1s/step - loss: 1.5477 - accuracy:
0.4680 - val_loss: 1.5192 - val_accuracy: 0.4745
Epoch 10/20
27/27 [==============================] - 39s 1s/step - loss: 1.5102 - accuracy:
0.4880 - val_loss: 1.5152 - val_accuracy: 0.4799
```

```
Epoch 11/20
27/27 [==============================] - 39s 1s/step - loss: 1.4925 - accuracy:
0.4888 - val_loss: 1.5334 - val_accuracy: 0.4638
Epoch 12/20
27/27 [==============================] - 39s 1s/step - loss: 1.4325 - accuracy:
0.5182 - val_loss: 1.5499 - val_accuracy: 0.4826
Epoch 13/20
27/27 [==============================] - 39s 1s/step - loss: 1.4182 - accuracy:
0.5032 - val_loss: 1.5009 - val_accuracy: 0.4772
Epoch 14/20
27/27 [==============================] - 39s 1s/step - loss: 1.3894 - accuracy:
0.5273 - val_loss: 1.4938 - val_accuracy: 0.4718
Epoch 15/20
27/27 [==============================] - 39s 1s/step - loss: 1.4023 - accuracy:
0.5138 - val_loss: 1.4696 - val_accuracy: 0.4826
Epoch 16/20
27/27 [==============================] - 39s 1s/step - loss: 1.3642 - accuracy:
0.5300 - val_loss: 1.4614 - val_accuracy: 0.4665
Epoch 17/20
27/27 [==============================] - 39s 1s/step - loss: 1.3425 - accuracy:
0.5335 - val_loss: 1.4847 - val_accuracy: 0.4745
Epoch 18/20
27/27 [==============================] - 38s 1s/step - loss: 1.3146 - accuracy:
0.5376 - val_loss: 1.4247 - val_accuracy: 0.4665
Epoch 19/20
27/27 [==============================] - 39s 1s/step - loss: 1.3268 - accuracy:
0.5288 - val_loss: 1.4787 - val_accuracy: 0.4745
Epoch 20/20
27/27 [==============================] - 39s 1s/step - loss: 1.2797 - accuracy:
0.5494 - val_loss: 1.4865 - val_accuracy: 0.4611
[INFO]: Evaluando el modelo…
              precision    recall  f1-score   support

         YFT       0.08      0.01      0.02        73
       SHARK       0.31      0.24      0.27        17
       OTHER       0.00      0.00      0.00        29
         NoF       0.48      0.22      0.30        46
         LAG       0.00      0.00      0.00         6
         DOL       0.00      0.00      0.00        11
         BET       0.00      0.00      0.00        20
         ALB       0.48      0.92      0.63       171

    accuracy                           0.46       373
   macro avg       0.17      0.17      0.15       373
weighted avg       0.31      0.46      0.34       373

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318:
```

```
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



[4]:
```
name_IPYNB_file = '12MBID_Proyecto_Programacion_Entrega1.ipynb'
get_ipython().system(
        "apt update >> /dev/null && apt install texlive-xetex␣
 ↪texlive-fonts-recommended texlive-generic-recommended >> /dev/null"
    )
get_ipython().system(
            "jupyter nbconvert --output-dir='$BASE_FOLDER'␣
 ↪'$BASE_FOLDER''$name_IPYNB_file' --to pdf"
```

```
        )
```

```
WARNING: apt does not have a stable CLI interface. Use with caution in scripts.


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.

Extracting templates from packages: 100%
[NbConvertApp] Converting notebook /content/drive/MyDrive/12MBID_Proyecto_Progra
macion_Colab/my_dataset/12MBID_Proyecto_Programacion_Entrega1.ipynb to pdf
[NbConvertApp] Support files will be in
12MBID_Proyecto_Programacion_Entrega1_files/
[NbConvertApp] Making directory ./12MBID_Proyecto_Programacion_Entrega1_files
[NbConvertApp] Making directory ./12MBID_Proyecto_Programacion_Entrega1_files
[NbConvertApp] Making directory ./12MBID_Proyecto_Programacion_Entrega1_files
[NbConvertApp] Making directory ./12MBID_Proyecto_Programacion_Entrega1_files
[NbConvertApp] Writing 219562 bytes to ./notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', './notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', './notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 1019498 bytes to /content/drive/MyDrive/12MBID_Proyecto_P
rogramacion_Colab/my_dataset/12MBID_Proyecto_Programacion_Entrega1.pdf
```