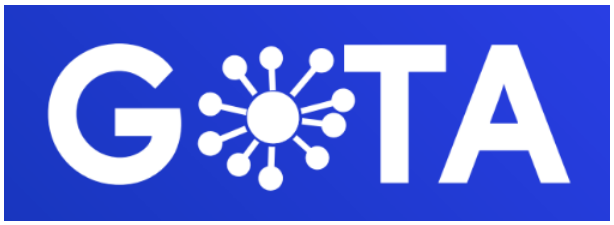


dia**G**nóstico **Ó**ptico-morfoma**T**emático **A**utomático

Prueba de screening de *COVID-19* en una sola gota

Demo técnica

Clasificador *COVID-19*

02/06/2020

Índice

1. Clasificador COVID-19

El problema a resolver es la clasificación de imágenes de muestras vísricas para detectar el virus *COVID-19*.

Esta prueba deberá ser capaz de reconocer si el paciente está infectado por algun virus de la familia *Coronaviridae*, que con mucha probabilidad, será el *COVID-19*.

[1]:
```
import tensorflow as tf
import numpy as np
import os # Funciones del sistema operativo
from PIL import Image # Para obtener el valor de los pixeles de las imágenes
import matplotlib.pyplot as plt
import random as rng
from tensorflow.keras import layers, models
```

1.1. Datos

Se usará el 80 % de los datos para entrenamiento, y el 20 % restante para evaluar el modelo.

Los datos serán imágenes en blanco y negro de distintos tamaños, y estarán etiquetadas como **muestra vacía**, **otro virus** o ***COVID-19***.

[2]:
```
IMG_SIZE = 500
BIG_IMG_SIZE = 750
```

[3]:
```
className = ["blank", "other", "coronaviridae"]
```

Transformar las imágenes a blanco y negro puro, porque parece haber errores en las imágenes, y se detectan como RGB en lugar de escala de grises. También se va a definir un tamaño de **500x500**px.

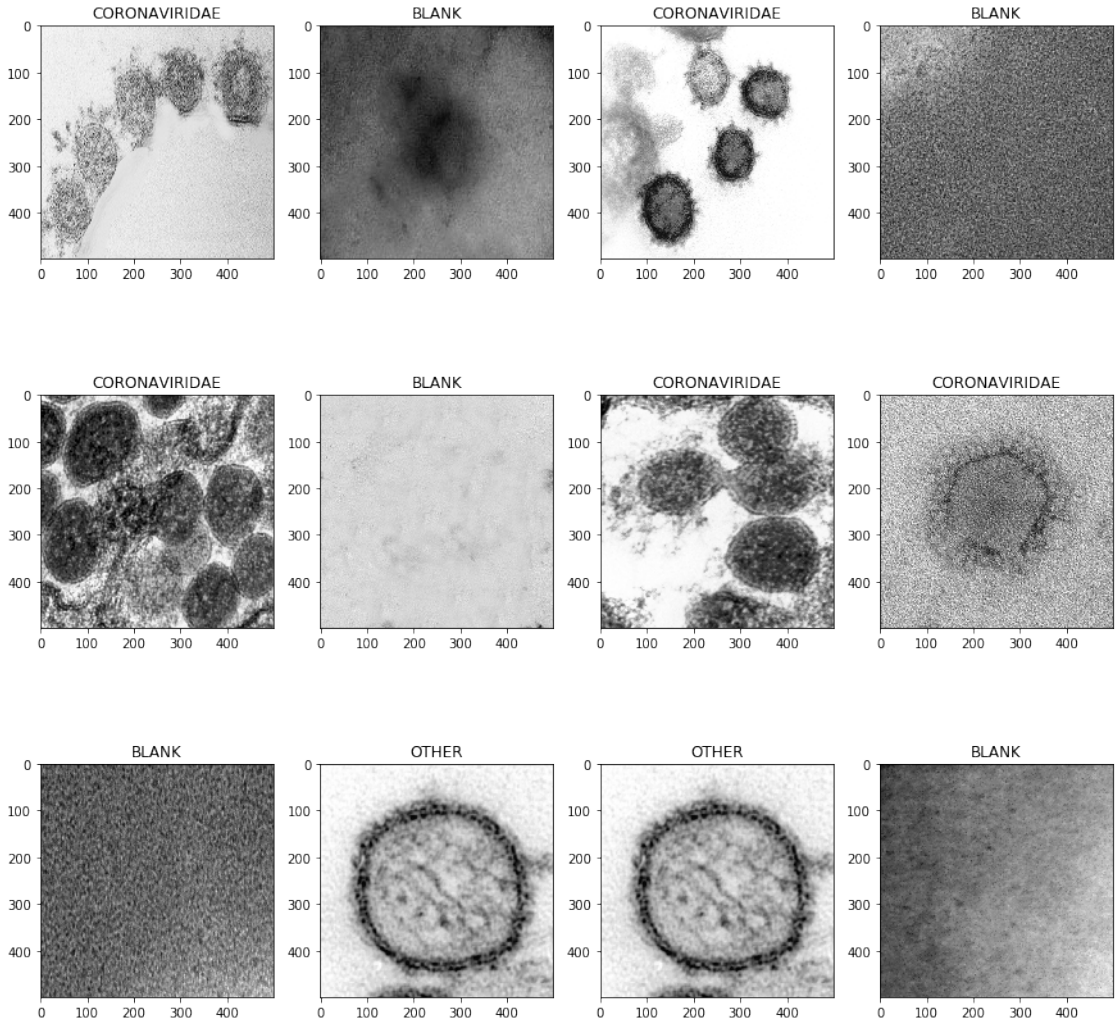
Se dividen los datos en el set de entrenamiento y evaluación.

[4]:
```
trainingSet = []
evaluationSet = []

bigSizeTraining = []

for folder in os.listdir('./images'):
    for i, img in enumerate(os.listdir('./images/' + folder)):
        imgClass = folder
        path = os.path.join('./images/' + folder, img)
        imgData = Image.open(path)
        imgData = imgData.convert("L")

        bigImg = imgData.resize((BIG_IMG_SIZE, BIG_IMG_SIZE), Image.ANTIALIAS)
        bigImg = np.array(bigImg)

        imgData = imgData.resize((IMG_SIZE, IMG_SIZE), Image.ANTIALIAS)
        imgData = np.array(imgData)
        if i % 10 < 8:
            bigSizeTraining.append((bigImg, imgClass))
            trainingSet.append((imgData, imgClass))
        else:
            evaluationSet.append((imgData, imgClass))
```

[5]:
```
print("Tamaño del set de entrenamiento: ", len(trainingSet))
print("Tamaño del set de evaluación: ", len(evaluationSet))
```

```
Tamaño del set de entrenamiento:  102
Tamaño del set de evaluación:  24
```

[6]:
```
w=10
h=10
fig=plt.figure(figsize=(15, 15))
columns = 4
rows = 3
for i in range(1, columns*rows +1):
    data = trainingSet[np.random.randint(len(trainingSet))]
    img = data[0]
    fig.add_subplot(rows, columns, i)
    plt.imshow(img, cmap = 'gist_gray')
    plt.title(data[1].upper())
plt.show()
```



Dado que el número de datos que se tienen es muy reducido, se va a optar por usar técnicas para aumentar el número de datos. Esto se hace para evitar el *overfitting*, dado que con un número pequeño de datos, es más fácil que se produzca.

El aumento de datos se realizará en todas las imágenes de entrenamiento, para aumentar el máximo posible el número de datos. En un principio no se va a realizar un aumento de datos al set evaluación.

Las técnicas de aumento de datos que se van a utilzar son: **rotación**, **volteo**, **traslación** y **zoom**. También se hacee una combinación entre zoom, y rotación y volteo.

Otras técnicas que serían también útiles son: alejar la imagen, rotaciones no solo de 90º, mezclar varias técnicas de distinta forma, añadir ruido, invertir los colores de la imagen, etc.

Se van a realizar 3 volteos, 3 rotaciones, 4 traslaciones, 1 zoom y 3 zoom con rotación y 3 zoom con volteo. De forma que por cada imagen se crean 17 nuevas.

[7]:
```
newTrainingSet = []

for data in trainingSet:

    #Imágenes con volteo

    newImgFlipUD = np.flipud(data[0]) #Volteo de arriba a abajo
    newImgFlipLR = np.fliplr(data[0]) #Volteo de izquierda a derecha
    newImgFlipUDLR = np.flip(data[0], (0, 1)) #Volteo izquierda-derecha y arriba-abajo

    #Imágenes con rotación

    newImgRot1 = np.rot90(data[0]) #Una rotación de 90º
    newImgRot2 = np.rot90(data[0], 2) #Dos rotaciones de 90º
    newImgRot3 = np.rot90(data[0], 3) #Tres rotaciones de 90º

    #Imágenes con traslación

    newImgDown = np.zeros(data[0].shape)
    newImgUp = np.zeros(data[0].shape)
    newImgLeft = np.zeros(data[0].shape)
    newImgRight = np.zeros(data[0].shape)


    for i in range(IMG_SIZE):
        for j in range(IMG_SIZE):
            newImgDown[i][j] = data[0][(i-200)%IMG_SIZE][j] #Traslación hacia abajo
            newImgUp[i][j] = data[0][(i+200)%IMG_SIZE][j] #Traslación hacia arriba
            newImgLeft[i][j] = data[0][i][(j+200)%IMG_SIZE] #Traslación hacia izquierda
            newImgRight[i][j] = data[0][i][(j-200)%IMG_SIZE] #Traslación hacia derecha


    newTrainingSet.append((newImgFlipUD, data[1]))
    newTrainingSet.append((newImgFlipLR, data[1]))
    newTrainingSet.append((newImgFlipUDLR, data[1]))

    newTrainingSet.append((newImgRot1, data[1]))
    newTrainingSet.append((newImgRot2, data[1]))
    newTrainingSet.append((newImgRot3, data[1]))
```

```
    newTrainingSet.append((newImgDown, data[1]))
    newTrainingSet.append((newImgUp, data[1]))
    newTrainingSet.append((newImgLeft, data[1]))
    newTrainingSet.append((newImgRight, data[1]))


trainingSet += newTrainingSet
```

[8]:
```
newTrainingSet = []

for data in bigSizeTraining:

    newImgZoom = data[0].copy()

    newImgZoom = newImgZoom[250:]
    newImgZoom = np.rot90(newImgZoom)
    newImgZoom = newImgZoom[250:]

    newTrainingSet.append((newImgZoom, data[1]))
    newTrainingSet.append((np.rot90(newImgZoom), data[1]))
    newTrainingSet.append((np.rot90(newImgZoom, 2), data[1]))
    newTrainingSet.append((np.rot90(newImgZoom, 3), data[1]))

    newTrainingSet.append((np.flipud(newImgZoom), data[1]))
    newTrainingSet.append((np.fliplr(newImgZoom), data[1]))
    newTrainingSet.append((np.flip(newImgZoom, (0, 1)), data[1]))

    newImgZoom2 = data[0].copy()

    newImgZoom2 = newImgZoom2[:500]
    newImgZoom2 = np.rot90(newImgZoom2)
    newImgZoom2 = newImgZoom2[:500]

    newTrainingSet.append((newImgZoom2, data[1]))
    newTrainingSet.append((np.rot90(newImgZoom2), data[1]))
    newTrainingSet.append((np.rot90(newImgZoom2, 2), data[1]))
    newTrainingSet.append((np.rot90(newImgZoom2, 3), data[1]))

    newTrainingSet.append((np.flipud(newImgZoom2), data[1]))
    newTrainingSet.append((np.fliplr(newImgZoom2), data[1]))
    newTrainingSet.append((np.flip(newImgZoom2, (0, 1)), data[1]))


trainingSet += newTrainingSet
```

Dado que el número de imágenes de evaluación es también muy reducido, se realiza un aumento de datos, usando las técnicas de volteo y rotación.

[9]:
```
newEvaluationSet = []

for data in evaluationSet:

    newEvaluationSet.append((np.flipud(data[0]), data[1])) #Volteo de arriba a abajo
```

```
    newEvaluationSet.append((np.fliplr(data[0]), data[1])) #Volteo de izquierda a␣
 ↪derecha
    newEvaluationSet.append((np.flip(data[0], (0, 1)), data[1])) #Volteo␣
 ↪izquierda-derecha y arriba-abajo

    newEvaluationSet.append((np.rot90(data[0]), data[1])) #Una rotación de 90º
    newEvaluationSet.append((np.rot90(data[0], 2), data[1])) #Dos rotaciones de 90º
    newEvaluationSet.append((np.rot90(data[0], 3), data[1])) #Tres rotaciones de 90º

evaluationSet += newEvaluationSet
```

[10]:
```
rng.shuffle(trainingSet)
```

[11]:
```
print("Tamaño del set de entrenamiento ampliado: ", len(trainingSet))
print("Tamaño del set de evaluación ampliado: ", len(evaluationSet))
```

```
Tamaño del set de entrenamiento ampliado:  2550
Tamaño del set de evaluación ampliado:  168
```

1.2. Modelo

Se va a utilizar una **red neuronal convolucional** (CNN) porque es un problema de clasificación de imágenes.

Este modelo recibe como entrada un vector tridimensional de dimensiones **500x500x1** y tiene como salida **3** posibles clases.

La arquitectura usada para ello es: 6 capas convolucionales, una capa densa y una capa de salida.

[12]:
```
model = models.Sequential()
```

1.2.1. Capas convolucionales

Cada capa convolucional está seguida por una capa de *pooling* y de *batch normalization*.

[13]:
```
#Capa de entrada
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(IMG_SIZE,␣
 ↪IMG_SIZE, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())

model.add(layers.Conv2D(32, (2, 2), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.2))

model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.2))

model.add(layers.Conv2D(96, (2, 2), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.2))
```

```
model.add(layers.Conv2D(96, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.2))

model.add(layers.Conv2D(32, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.2))
```

[14]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 498, 498, 32)      320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 249, 249, 32)      0
_________________________________________________________________
batch_normalization (BatchNo (None, 249, 249, 32)      128
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 248, 248, 32)      4128
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 124, 124, 32)      0
_________________________________________________________________
batch_normalization_1 (Batch (None, 124, 124, 32)      128
_________________________________________________________________
dropout (Dropout)            (None, 124, 124, 32)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 122, 122, 64)      18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 61, 61, 64)        0
_________________________________________________________________
batch_normalization_2 (Batch (None, 61, 61, 64)        256
_________________________________________________________________
dropout_1 (Dropout)          (None, 61, 61, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 60, 60, 96)        24672
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 30, 30, 96)        0
_________________________________________________________________
batch_normalization_3 (Batch (None, 30, 30, 96)        384
_________________________________________________________________
dropout_2 (Dropout)          (None, 30, 30, 96)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 28, 28, 96)        83040
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 14, 14, 96)        0
_________________________________________________________________
batch_normalization_4 (Batch (None, 14, 14, 96)        384
_________________________________________________________________
dropout_3 (Dropout)          (None, 14, 14, 96)        0
```

```
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 12, 12, 32)        27680
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 6, 6, 32)          0
_________________________________________________________________
batch_normalization_5 (Batch (None, 6, 6, 32)          128
_________________________________________________________________
dropout_4 (Dropout)          (None, 6, 6, 32)          0
=================================================================
Total params: 159,744
Trainable params: 159,040
Non-trainable params: 704
_________________________________________________________________
```

1.2.2. Capa densa

Para poder recibir la entrada en la capa densa es necesario que el vector sea unidimensional. Por tanto, usamos una capa de *flatten*.

[15]:
```
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.3))

model.add(layers.Dense(3))
```

[16]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 498, 498, 32)      320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 249, 249, 32)      0
_________________________________________________________________
batch_normalization (BatchNo (None, 249, 249, 32)      128
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 248, 248, 32)      4128
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 124, 124, 32)      0
_________________________________________________________________
batch_normalization_1 (Batch (None, 124, 124, 32)      128
_________________________________________________________________
dropout (Dropout)            (None, 124, 124, 32)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 122, 122, 64)      18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 61, 61, 64)        0
_________________________________________________________________
batch_normalization_2 (Batch (None, 61, 61, 64)        256
```

```
_________________________________________________________________
dropout_1 (Dropout)          (None, 61, 61, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 60, 60, 96)        24672
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 30, 30, 96)        0
_________________________________________________________________
batch_normalization_3 (Batch (None, 30, 30, 96)        384
_________________________________________________________________
dropout_2 (Dropout)          (None, 30, 30, 96)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 28, 28, 96)        83040
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 14, 14, 96)        0
_________________________________________________________________
batch_normalization_4 (Batch (None, 14, 14, 96)        384
_________________________________________________________________
dropout_3 (Dropout)          (None, 14, 14, 96)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 12, 12, 32)        27680
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 6, 6, 32)          0
_________________________________________________________________
batch_normalization_5 (Batch (None, 6, 6, 32)          128
_________________________________________________________________
dropout_4 (Dropout)          (None, 6, 6, 32)          0
_________________________________________________________________
flatten (Flatten)            (None, 1152)              0
_________________________________________________________________
dense (Dense)                (None, 256)               295168
_________________________________________________________________
dropout_5 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               65792
_________________________________________________________________
dropout_6 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 387
=================================================================
Total params: 553,987
Trainable params: 553,283
Non-trainable params: 704
_________________________________________________________________
```

1.2.3. Compilación del modelo

La función de optimización que se usa en el modelo es *adam*, que experimentalemte ofrece mejores resultados que *descenso del gradiente*. La función de coste va a ser *SparseCategoricalCrossentropy*, que calcula la entropia como la probabiolidad entre dos distribuciones. Se utiliza generalmente en problemas con más de dos clases, como es el caso.

[17]:
```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

1.2.4. Entrenando el modelo

El entrenamiento va a ser muy ligero, con tan solo 20 *epoch*, para que actue como demo y se pueda comprobar si es útil o no.

[18]:
```
trainingData = []
trainingLabel = []

testData = []
testLabel = []

for element in trainingSet:
    trainingData.append(np.reshape(element[0], (IMG_SIZE, IMG_SIZE, 1)))
    trainingLabel.append(className.index(element[1]))

for element in evaluationSet:
    testData.append(np.reshape(element[0], (IMG_SIZE, IMG_SIZE, 1)))
    testLabel.append(className.index(element[1]))

trainingData = np.array(trainingData)
trainingLabel = np.array(trainingLabel)

testData = np.array(testData)
testLabel = np.array(testLabel)
```

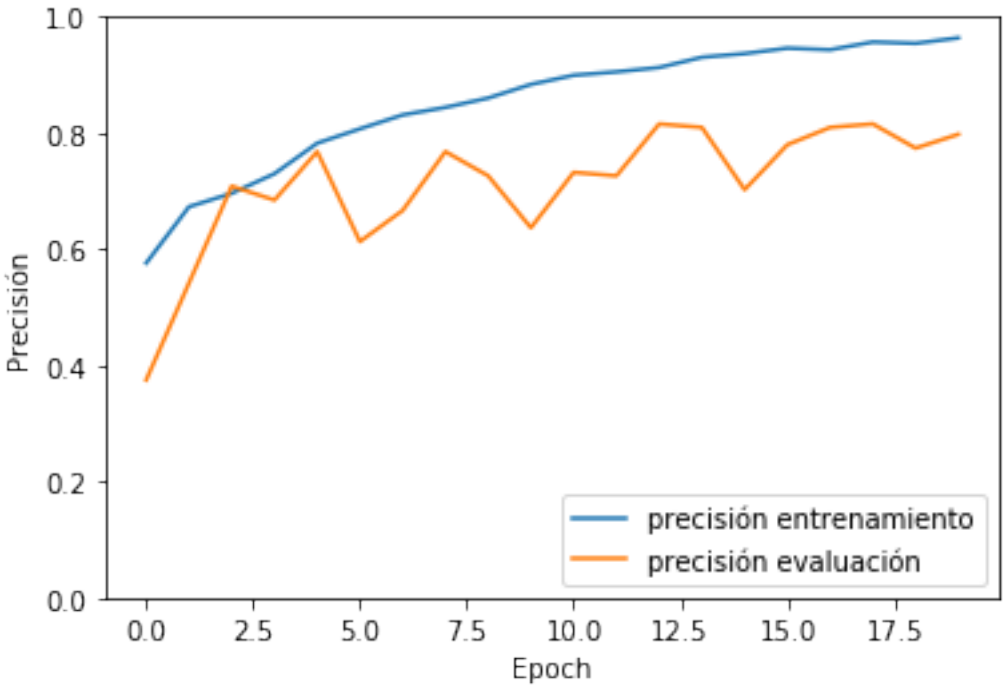
[19]:
```
history = model.fit(trainingData, trainingLabel, batch_size=25, epochs=20,␣
 ↪validation_data=(testData, testLabel))
```

```
Train on 2550 samples, validate on 168 samples
Epoch 1/20
2550/2550 [==============================] - 274s 107ms/sample - loss: 0.8826 -
accuracy: 0.5761 - val_loss: 2.0590 - val_accuracy: 0.3750
Epoch 2/20
2550/2550 [==============================] - 195s 77ms/sample - loss: 0.5780 -
accuracy: 0.6729 - val_loss: 0.9923 - val_accuracy: 0.5417
Epoch 3/20
2550/2550 [==============================] - 192s 75ms/sample - loss: 0.5557 -
accuracy: 0.6961 - val_loss: 0.5198 - val_accuracy: 0.7083
Epoch 4/20
2550/2550 [==============================] - 192s 75ms/sample - loss: 0.4923 -
accuracy: 0.7298 - val_loss: 0.8605 - val_accuracy: 0.6845
Epoch 5/20
2550/2550 [==============================] - 196s 77ms/sample - loss: 0.4286 -
accuracy: 0.7824 - val_loss: 0.7113 - val_accuracy: 0.7679
Epoch 6/20
2550/2550 [==============================] - 193s 76ms/sample - loss: 0.4117 -
accuracy: 0.8071 - val_loss: 0.5487 - val_accuracy: 0.6131
Epoch 7/20
2550/2550 [==============================] - 184s 72ms/sample - loss: 0.3736 -
accuracy: 0.8310 - val_loss: 1.0377 - val_accuracy: 0.6667
```

```
Epoch 8/20
2550/2550 [==============================] - 198s 78ms/sample - loss: 0.3610 -
accuracy: 0.8439 - val_loss: 0.4421 - val_accuracy: 0.7679
Epoch 9/20
2550/2550 [==============================] - 197s 77ms/sample - loss: 0.3202 -
accuracy: 0.8600 - val_loss: 0.6686 - val_accuracy: 0.7262
Epoch 10/20
2550/2550 [==============================] - 194s 76ms/sample - loss: 0.2738 -
accuracy: 0.8835 - val_loss: 1.5392 - val_accuracy: 0.6369
Epoch 11/20
2550/2550 [==============================] - 194s 76ms/sample - loss: 0.2587 -
accuracy: 0.8992 - val_loss: 1.5242 - val_accuracy: 0.7321
Epoch 12/20
2550/2550 [==============================] - 189s 74ms/sample - loss: 0.2582 -
accuracy: 0.9051 - val_loss: 0.6480 - val_accuracy: 0.7262
Epoch 13/20
2550/2550 [==============================] - 198s 78ms/sample - loss: 0.2268 -
accuracy: 0.9125 - val_loss: 0.8323 - val_accuracy: 0.8155
Epoch 14/20
2550/2550 [==============================] - 192s 75ms/sample - loss: 0.1842 -
accuracy: 0.9302 - val_loss: 0.4775 - val_accuracy: 0.8095
Epoch 15/20
2550/2550 [==============================] - 191s 75ms/sample - loss: 0.1736 -
accuracy: 0.9365 - val_loss: 1.5909 - val_accuracy: 0.7024
Epoch 16/20
2550/2550 [==============================] - 200s 78ms/sample - loss: 0.1578 -
accuracy: 0.9459 - val_loss: 1.0236 - val_accuracy: 0.7798
Epoch 17/20
2550/2550 [==============================] - 202s 79ms/sample - loss: 0.1569 -
accuracy: 0.9431 - val_loss: 0.5587 - val_accuracy: 0.8095
Epoch 18/20
2550/2550 [==============================] - 201s 79ms/sample - loss: 0.1324 -
accuracy: 0.9565 - val_loss: 0.5225 - val_accuracy: 0.8155
Epoch 19/20
2550/2550 [==============================] - 200s 79ms/sample - loss: 0.1378 -
accuracy: 0.9541 - val_loss: 0.7266 - val_accuracy: 0.7738
Epoch 20/20
2550/2550 [==============================] - 200s 78ms/sample - loss: 0.1053 -
accuracy: 0.9635 - val_loss: 0.6383 - val_accuracy: 0.7976
```

[20]:
```
plt.plot(history.history['accuracy'], label='precisión entrenamiento')
plt.plot(history.history['val_accuracy'], label = 'precisión evaluación')
plt.xlabel('Epoch')
plt.ylabel('Precisión')
plt.ylim([0, 1])
plt.legend(loc='lower right')

test_loss, test_acc = model.evaluate(testData,  testLabel, verbose=2)
```

```
168/1 - 2s - loss: 0.3225 - accuracy: 0.7976
```



1.2.5. Guardar el modelo

[21]:
```
model.save('./modelo')
```

```
WARNING:tensorflow:From /home/pheithar/anaconda3/lib/python3.7/site-
packages/tensorflow_core/python/ops/resource_variable_ops.py:1781: calling
BaseResourceVariable.__init__ (from tensorflow.python.ops.resource_variable_ops)
with constraint is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
INFO:tensorflow:Assets written to: ./modelo/assets
```