# Evaluacion del modelo

## August 29, 2021

```
[54]: import tensorflow as tf
from sklearn.metrics import classification_report
import seaborn as sns;sns.set()
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import confusion_matrix
import numpy as np
import tensorflow.keras as K
from skimage.transform import resize
from tensorflow.keras.models import Model
import cv2
```

#### 0.0.1 Cargamos los mejores modelos serializados

Los mejores modelos de todos los candidatos fueron 2:

- Modelo usando transfer learning DenseNet169 con balanceo de Penalizacion de clases
- Modelo usando tranfer learning sobre DenseNet169 con balanceo de perdida focal
- Primero cargamos la funcion personalizada usada para la perdida focal, esta es importante para realizar la evaluacion del modelo

```
[2]: def focal_loss(gamma=2., alpha=4.):

gamma = float(gamma)
alpha = float(alpha)

def focal_loss_fixed(y_true, y_pred):
    """Focal loss for multi-classification
    FL(p_t)=-alpha(1-p_t) ~{gamma}ln(p_t)
    Notice: y_pred is probability after softmax
    gradient is d(Fl)/d(p_t) not d(Fl)/d(x) as described in paper
    d(Fl)/d(p_t) * [p_t(1-p_t)] = d(Fl)/d(x)
    Focal Loss for Dense Object Detection
    https://arxiv.org/abs/1708.02002
    Arguments:
        y_true {tensor} -- ground truth labels, shape of [batch_size, u]
    →num_cls]

y_pred {tensor} -- model's output, shape of [batch_size, num_cls]
```

```
Keyword Arguments:
              gamma \{float\} -- (default: \{2.0\})
              alpha {float} -- (default: {4.0})
              [tensor] -- loss.
           epsilon = 1.e-9
           y_true = tf.convert_to_tensor(y_true, tf.float32)
           y_pred = tf.convert_to_tensor(y_pred, tf.float32)
           model_out = tf.add(y_pred, epsilon)
           ce = tf.multiply(y_true, -tf.math.log(model_out))
           weight = tf.multiply(y_true, tf.pow(tf.subtract(1., model_out), gamma))
           fl = tf.multiply(alpha, tf.multiply(weight, ce))
           reduced_fl = tf.reduce_max(fl, axis=1)
           return tf.reduce_mean(reduced_fl)
       return focal_loss_fixed
[3]: path_model_weighted="../input/modelosfinales/
     →tranferlearning densenet169 with balanced focal loss 3 class equalized wgt.
    path_model_focal="../input/modelosfinales/

-- tranferlearning_densenet169_with_balanced_focal_loss_3_class_equalized.h5"

    #modelo con penalizacion de clases para el balanceo
    model_transfer_class_weight=tf.keras.models.load_model(path_model_weighted)
    #modelo con balanceo usando perdida focal
    model_transfer_focal_loss=tf.keras.models.load_model(path_model_focal,_
     [4]: model transfer class weight.summary()
   Model: "model 1"
   Layer (type)
                           Output Shape
                                                 Param #
   ______
   input_4 (InputLayer) [(None, 256, 256, 3)]
   densenet169 (Functional) (None, 8, 8, 1664) 12642880
   flatten_1 (Flatten) (None, 106496)
   batch_normalization_2 (Batch (None, 106496)
                                                 425984
   _____
                   (None, 256)
   dense_3 (Dense)
                                                  27263232
   dropout_2 (Dropout) (None, 256)
```

1024

batch\_normalization\_3 (Batch (None, 256)

dense_4 (Dense)	(None, 128)	32896
dropout_3 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 3)	387

Total params: 40,366,403 Trainable params: 33,423,619 Non-trainable params: 6,942,784

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### [5]: model\_transfer\_focal\_loss.summary()

Model: "model\_1"

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 256, 256, 3)]	0
densenet169 (Functional)	(None, 8, 8, 1664)	12642880
flatten_1 (Flatten)	(None, 106496)	0
batch_normalization_2 (Batch	(None, 106496)	425984
dense_3 (Dense)	(None, 256)	27263232
dropout_2 (Dropout)	(None, 256)	0
batch_normalization_3 (Batch	(None, 256)	1024
dense_4 (Dense)	(None, 128)	32896
dropout_3 (Dropout)	(None, 128)	0
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### 0.0.2 Cargamos el flujo de datos de TEST

• A traves de la libreria

```
[6]: path_test="../input/datasettestcovid19/test"
     IMAGE_SIZE=(256,256)
     test_datagen=ImageDataGenerator(rescale=1.0/255)
     test_generator=test_datagen.flow_from_directory(
                 path_test,
                 target_size=IMAGE_SIZE,
                 batch_size=32,
                 shuffle=False,
                 class_mode="categorical"
     )
    Found 4233 images belonging to 3 classes.
[7]: test_generator.class_indices
```

```
[7]: {'COVID': 0, 'Enfermedades Pulmonares No COVID19': 1, 'Normal': 2}
[8]: test_generator.reset()
[9]: model_transfer_class_weight.evaluate(test_generator)
   accuracy: 0.9213 - recall: 0.9178
[9]: [0.22444237768650055, 0.9213323593139648, 0.9177888035774231]
[10]: test_generator.reset()
[11]: model_transfer_focal_loss.evaluate(test_generator)
```

```
accuracy: 0.9242 - recall: 0.9187
```

[11]: [0.26700618863105774, 0.924167275428772, 0.9187337756156921]

• Y efectivamente el modelo que logro una mayor precision fue el Transferencia de informacion con un accuracy de 92.42% de aciertos en datos NUNCA ANTES VISTOS.

Elaboremos su matriz de clasificación.

```
[15]: test_generator.reset()
[16]: y_true=test_generator.classes
      predictions=model_transfer_focal_loss.predict(test_generator)
      y_pred=np.argmax(predictions,axis=1)
[20]: test_generator.class_indices
[20]: {'COVID': 0, 'Enfermedades Pulmonares No COVID19': 1, 'Normal': 2}
```

Matriz de confusion En esta tendremos una version mas realista de cada clase mal predecida.

```
[23]: target_names={"COVID-19":0,"Enfermedades":1,"Normal":2}#test_generator.

→ class_indices

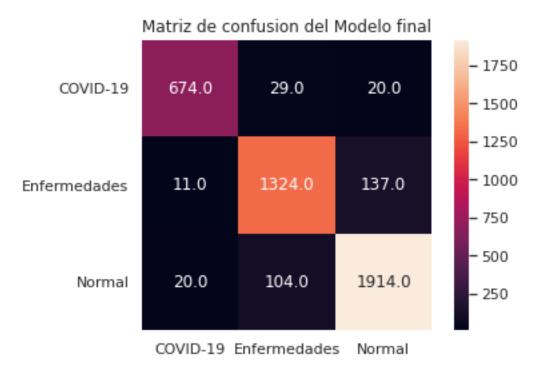
mat=confusion_matrix(y_true,y_pred)

sns.heatmap(mat,annot=True,fmt="0.

→1f",square=True,xticklabels=target_names,yticklabels=target_names)

plt.title("Matriz de confusion del Modelo final")

plt.show()
```



• Reporte de clasificacion: Aqui tendremos un reporte sobre la precision en las predicciones de cada clase.

```
[24]: report=classification_report(y_true,y_pred,target_names=target_names) print(report)
```

	precision	recall	f1-score	support
COVID-19	0.96	0.93	0.94	723
Enfermedades	0.91	0.90	0.90	1472
Normal	0.92	0.94	0.93	2038
accuracv			0.92	4233

macro	avg	0.93	0.92	0.93	4233
weighted	avg	0.92	0.92	0.92	4233

#### 0.1 INTERPRETABILIDAD DEL MODELO

• A veces la pregunta suele ser porque modelo predice lo que predice, para ello usaremos el metodo de activacion en capas llamado CamGrad que nos muestra un mapa de calor sobre las partes donde el modelo ha tenido mayor actividad sobre la imagen a clasificar, esto nos puede ayudar a determinar que lugares de una radiografia son determinantes para predecir si una radiografia de rayos-X es de COVID-19

El codigo usado en el siguiente espacio pertenece a la libreria Keras

[31]:

## [34]: model\_transfer\_focal\_loss.summary()

Model: "model\_1"

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 256, 256, 3)]	0
densenet169 (Functional)	(None, 8, 8, 1664)	12642880
flatten_1 (Flatten)	(None, 106496)	0
batch_normalization_2 (Batch	(None, 106496)	425984
dense_3 (Dense)	(None, 256)	27263232
dropout_2 (Dropout)	(None, 256)	0
batch_normalization_3 (Batch	(None, 256)	1024
dense_4 (Dense)	(None, 128)	32896
dropout_3 (Dropout)	(None, 128)	0
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Total params: 40,366,403 Trainable params: 33,423,619

```
Non-trainable params: 6,942,784
```

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• Una vez obtenido el modelo de transfer learning. Necesitamos la imagen preprocesada

```
[24]: tf.keras.Model
```

[24]: tensorflow.python.keras.engine.training.Model

```
import random
import os

def get_random_path(origin):
    return random.sample([ arch.path for arch in os.scandir(origin)],1)[0]

def preprocess_image(img_path,target_size=None):
    img = tf.keras.preprocessing.image.load_img(img_path,__
    -target_size=target_size)
    array = tf.keras.preprocessing.image.img_to_array(img)
    #array=np.expand_dims(array,axis=0)
    array=array*1.0/255
    return array

img_path=get_random_path("../Datasets/test/COVID")
img_array=preprocess_image(img_path,target_size=(256,256))
```

```
[90]: print("La imagen fue extraida de:",img_path)
```

La imagen fue extraida de: ../Datasets/test/COVID\COVID-103.png Implementacion de algoritmo de GradCAM

```
[53]: #aqui obtenemos el modelo original del transfer learning
  def get_transfer_model(model):
        model_transfer=None
        for layer in model.layers:
            if isinstance(layer,tf.keras.Model):
                model_transfer=layer
               break
        return model_transfer

def get_last_conv_layer(model):
        for layer in model.layers[::-1]:
            if isinstance(layer,K.layers.Conv2D):
                return layer
        return None
```

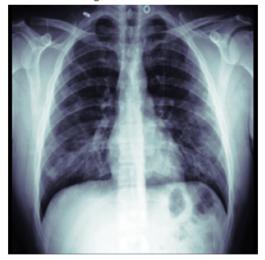
```
[97]: def VizGradCAM(model, image, interpolant=0.6, return_gradcam=True):

# Sanity Check
```

```
#if interpolant < 0 or interpolant >1:
       print("Heatmap Interpolation Must Be Between 0 - 1")
      return None
  transfer_model=get_transfer_model(model)
  last_conv_layer = get_last_conv_layer(transfer_model)
  target layer = transfer model.get layer(last conv layer.name)
  original_img = image
  img = np.expand_dims(original_img, axis=0)
  prediction = model.predict(img)
   # Obtain Prediction Index
  prediction_idx = np.argmax(prediction)
   # Compute Gradient of Top Predicted Class
  with tf.GradientTape() as tape:
       gradient_model = Model([transfer_model.inputs], [target_layer.output,_
→transfer_model.output])
      conv2d_out, prediction = gradient_model(img)
       # Obtain the Prediction Loss
      loss = prediction[:, prediction_idx]
  # Gradient() computes the gradient using operations recorded
   # in context of this tape
  gradients = tape.gradient(loss, conv2d_out)
   # Obtain the Output from Shape [1 x H x W x CHANNEL] -> [H x W x CHANNEL]
  output = conv2d_out[0]
  # Obtain Depthwise Mean
  weights = tf.reduce_mean(gradients[0], axis=(0, 1))
  # Create a 7x7 Map for Aggregation
  activation_map = np.zeros(output.shape[0:2], dtype=np.float32)
  # Multiply Weights with Every Layer
  for idx, weight in enumerate(weights):
       activation_map += weight * output[:, :, idx]
  # Resize to Size of Image
  activation_map = cv2.resize(
      activation map.numpy(), (original_img.shape[1], original_img.shape[0])
  )
```

```
# Ensure No Negative Numbers
           activation_map = np.maximum(activation_map, 0)
           # Convert Class Activation Map to 0 - 255
           activation_map = (activation_map - activation_map.min()) / (
               activation_map.max() - activation_map.min()
           )
           activation_map = np.uint8(255 * activation_map)
           # Convert to Heatmap
           heatmap = cv2.applyColorMap(activation_map, cv2.COLORMAP_JET)
           # Superimpose Heatmap on Image Data
           original_img = np.uint8(
               (original_img - original_img.min())
               / (original_img.max() - original_img.min())
               * 255
           )
           cvt_heatmap = cv2.cvtColor(heatmap, cv2.COLOR_BGR2RGB)
           # Enlarge Plot
           plt.rcParams["figure.dpi"] = 100
           if return_gradcam == True:
               return np.uint8(original_img * interpolant + cvt_heatmap * (1 -__
        →interpolant))
               #plt.savefig("./grad_cam_image.png")
           else:
               return cvt_heatmap
[117]: def compare_gradcam(model,path_image):
           fig, (ax1,ax2)=plt.subplots(1,2)
           fig.set_size_inches(10,10)
           array_image=preprocess_image(path_image,target_size=(256,256))
           im=plt.imread(path_image)
           ax1.imshow(im,cmap="bone")
           ax1.set_title("Radiografia con COVID-19")
           ax1.axis(False)
           array_gradcam=VizGradCAM(model, img_array, return_gradcam=True,_
        →interpolant=0.35)
           ax2.imshow(array gradcam)
           ax2.set_title("Mayor actividad del Modelo")
           ax2.axis(False)
[118]: compare_gradcam(model_transfer_focal_loss,img_path)
```

Radiografia con COVID-19





• Observamos que el modelo tiene mayor actividad sobre zonas centrales en los pulmones, esto indica cierto factor determinante para escoger COVID-19

#### 0.2 CONCLUSIONES:

Este modelo posee una precision del 92% sobre datos nunca antes vistos, a su vez podemos afirmar que clasifica correctamente como:

- $\bullet~$  COVID-19 el 96% de los casos
- $\bullet\,$  Enfermedades pulmonares el 91% de los casos
- Radiografias normales el 92% de los casos

El siguiente paso en la metodologia CRISP-DM es el despliegue del modelo a produccion.