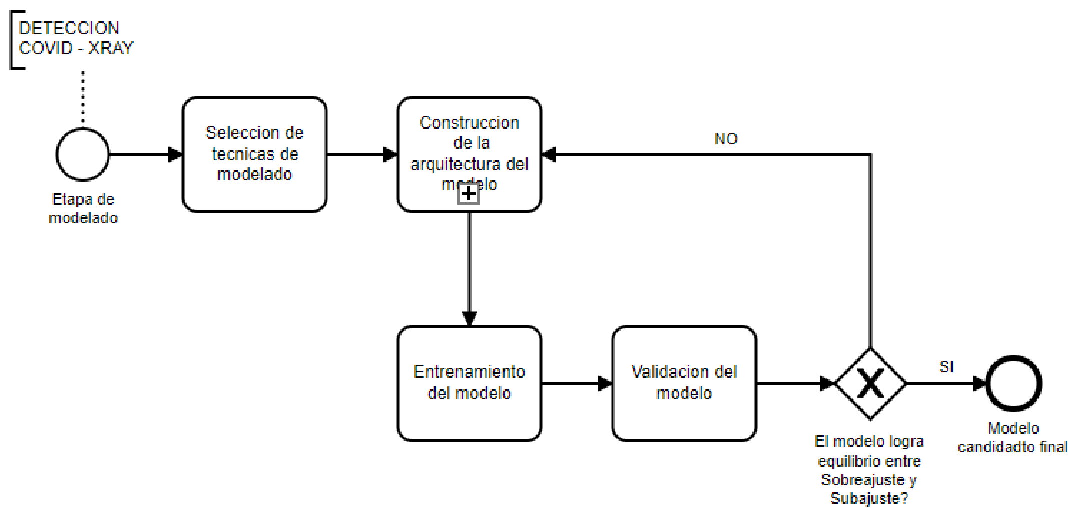
Modelado

August 29, 2021

Esta fase de la metdologia consiste en extraer el valor de los datos desarrollando un modelo que aprenda de los patrones en los datos.

- El diagrama en cuestion de esta fase esta a continuacion:



0.0.1 Selección de tecnicas de Modelado

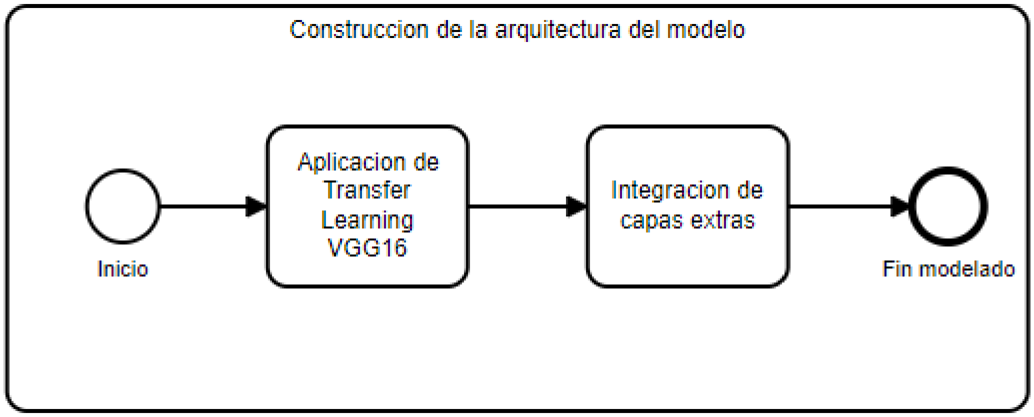
Al tratarse de un problema de clasificacion de imagenes entre los posibles candidatos tenemos:

- MultiLayer Pereptron: Red neuronal de capas densamente conectadas
- Convolutional Neuronal Network: Red neuronal convolucional.
- Modelos de machine learning clasico (Maquinas de soporte vectorial, arboles de decision e impulso, etc.)

Escogi la red neuronal convolucional porque **aprende de patrones locales** como rasgos pequeños y en bloques de informacion, mientras que el **MLP** aprende de patrones especficos, e decir de todo el espacio de entrada en general.

0.0.2 Construcción de la arquitectura del modelo

- Para la construccion de la arquitectura aplicaremos Transfer Learning de la arquitectura **MobileNETV2** y la acomplaremos anuestras capas personalizadas para el problema.



[2]:
```
import tensorflow as tf
from tensorflow.keras.utils import plot_model
```

- Implementamos la arquitectura de MobileNet V2, por ser liviana y consumir menos recursos.

[3]:
```
INPUT_SHAPE=(256,256,3) #256x256  pixeles, y 3 canales de colores(R,G,B)

model_mobilenetv2=tf.keras.applications.MobileNetV2(
                                            input_shape=INPUT_SHAPE,
                                            weights="imagenet", #obtener los␣
 ↪pesos del entrenamiento con las imagenes ImageNetV3
                                            include_top=False, #no obtener el␣
 ↪clasificador final (LO PERSONALIZAMOS),
                                )
```

```
WARNING:tensorflow:`input_shape` is undefined or non-square, or `rows` is not in
[96, 128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as
the default.
```

0.0.3 Arquitectura del modelo adaptado

- Capa de entrada **Input** para las imagenes.
- Capa de Modelo **MobileNetv2** para hacer **Transfer Learning**.
- Capa MaxAveragePooling.
- Capa Densa personalizada que responda a las clases a predecir.

Para esta implementacion usaremos la **API Functional**.

[5]:
```
N_CLASSES=4 #Clases a predecir ->COV
BASE_LEARNING_RATE=0.0001
def build_model_base():
    model_mobilenetv2.trainable=False #las capas del modelo no actualizan su␣
 ↪peso.
    inputs=tf.keras.layers.Input(shape=INPUT_SHAPE)
    x=model_mobilenetv2(inputs)
```

```
    x=tf.keras.layers.GlobalAveragePooling2D()(x)
    outputs=tf.keras.layers.Dense(units=N_CLASSES,activation="softmax")(x)

    model=tf.keras.Model(inputs,outputs)

    #compilamos el modelo
    model.compile(loss="categorical_crossentropy",
                  optimizer=tf.keras.optimizers.Adam(lr=BASE_LEARNING_RATE),
                  metrics=["accuracy",tf.keras.metrics.Recall()]
                  )
    return model
```

[6]:
```
model_base=build_model_base()
model_base.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
mobilenetv2_1.00_224 (Functi (None, 8, 8, 1280)        2257984
_________________________________________________________________
global_average_pooling2d (Gl (None, 1280)              0
_________________________________________________________________
dense (Dense)                (None, 4)                 5124
=================================================================
Total params: 2,263,108
Trainable params: 5,124
Non-trainable params: 2,257,984
_________________________________________________________________
```

- Carga y aumento de datos

[7]:
```
from tensorflow.keras.preprocessing.image import ImageDataGenerator #generator␣
↪de imagenes
```

- Configuracion del generador de datasets de entrenamiento, validacion y prueba

[8]:
```
train_datagen=ImageDataGenerator(
            rescale=1.0/127.5, #escalamos los datos en rangos de [-1,1] El␣
↪modelo espera esta configuracion
            zoom_range=0.2, #agregamos rotacion a las imagenes
            rotation_range=5,
            horizontal_flip=True
        )
#sobre los datos de validacion y test no se hace ningun aumento de datos.
```

```
validation_datagen=ImageDataGenerator(rescale=1.0/127.5) #escalamiento de␣
↪validacion a un rango de [-1,1]
test_datagen=ImageDataGenerator(rescale=1.0/127.5)       #escalamiento de test␣
↪a un rango de [-1,1]
```

- Obtencion de los datos para generar

[9]:
```
#definimos las rutas para el acceso a los datos
train_path="../Datasets/train/"
validation_path="../Datasets/val/"
test_path="../Datasets/test/"

#creamos los generadores de datos a partir de los flujos de informacion
BATCH_SIZE=32 #tamaño del lote que se ira pasando poco a poco
IMAGE_SIZE=(256,256)

train_generator=train_datagen.flow_from_directory(
    train_path,
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode="categorical"
)

validation_generator=train_datagen.flow_from_directory(
    validation_path,
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode="categorical"
)

test_generator=train_datagen.flow_from_directory(
    test_path,
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode="categorical"
)
```

```
Found 15238 images belonging to 4 classes.
Found 1694 images belonging to 4 classes.
Found 4233 images belonging to 4 classes.
```

- Generando **Callbacks** para detener el entrenamiento cuando no se tienen buenos resultados

[12]:
```
early_stopping=tf.keras.callbacks.EarlyStopping(monitor="val_loss",patience=3)␣
↪#cuando la funcion de perdida ya no mejora
n_epochs=10
```

0.0.4 Entrenamiento el modelo BASE

[10]:
```
model_base=build_model_base()
model_history=model_base.fit_generator(
                    train_generator,
                    epochs=n_epochs,
                    validation_data=validation_generator,
                    validation_steps=validation_generator.samples//BATCH_SIZE,
                    callbacks=[early_stopping]
            )
```

```
C:\Users\avira\anaconda3\envs\mlearning\lib\site-
packages\tensorflow\python\keras\engine\training.py:1844: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  warnings.warn('`Model.fit_generator` is deprecated and '
```

```
Epoch 1/10
477/477 [==============================] - 839s 2s/step - loss: 1.0436 -
accuracy: 0.5648 - recall_1: 0.3902 - val_loss: 0.6909 - val_accuracy: 0.7302 -
val_recall_1: 0.6382
Epoch 2/10
477/477 [==============================] - 748s 2s/step - loss: 0.6853 -
accuracy: 0.7348 - recall_1: 0.6481 - val_loss: 0.6096 - val_accuracy: 0.7668 -
val_recall_1: 0.7067
Epoch 3/10
477/477 [==============================] - 738s 2s/step - loss: 0.6108 -
accuracy: 0.7637 - recall_1: 0.6996 - val_loss: 0.5683 - val_accuracy: 0.7794 -
val_recall_1: 0.7260
Epoch 4/10
477/477 [==============================] - 719s 2s/step - loss: 0.5620 -
accuracy: 0.7862 - recall_1: 0.7325 - val_loss: 0.5445 - val_accuracy: 0.7951 -
val_recall_1: 0.7404
Epoch 5/10
477/477 [==============================] - 734s 2s/step - loss: 0.5310 -
accuracy: 0.7994 - recall_1: 0.7484 - val_loss: 0.5321 - val_accuracy: 0.7993 -
val_recall_1: 0.7452
Epoch 6/10
477/477 [==============================] - 721s 2s/step - loss: 0.5199 -
accuracy: 0.8011 - recall_1: 0.7550 - val_loss: 0.5063 - val_accuracy: 0.8035 -
val_recall_1: 0.7578
Epoch 7/10
477/477 [==============================] - 727s 2s/step - loss: 0.4895 -
accuracy: 0.8181 - recall_1: 0.7757 - val_loss: 0.4886 - val_accuracy: 0.8173 -
val_recall_1: 0.7728
Epoch 8/10
477/477 [==============================] - 678s 1s/step - loss: 0.4913 -
accuracy: 0.8138 - recall_1: 0.7725 - val_loss: 0.4737 - val_accuracy: 0.8281 -
val_recall_1: 0.7873
```

```
Epoch 9/10
477/477 [==============================] - 687s 1s/step - loss: 0.4707 -
accuracy: 0.8206 - recall_1: 0.7840 - val_loss: 0.4557 - val_accuracy: 0.8395 -
val_recall_1: 0.7945
Epoch 10/10
477/477 [==============================] - 679s 1s/step - loss: 0.4716 -
accuracy: 0.8201 - recall_1: 0.7834 - val_loss: 0.4703 - val_accuracy: 0.8269 -
val_recall_1: 0.7861
```

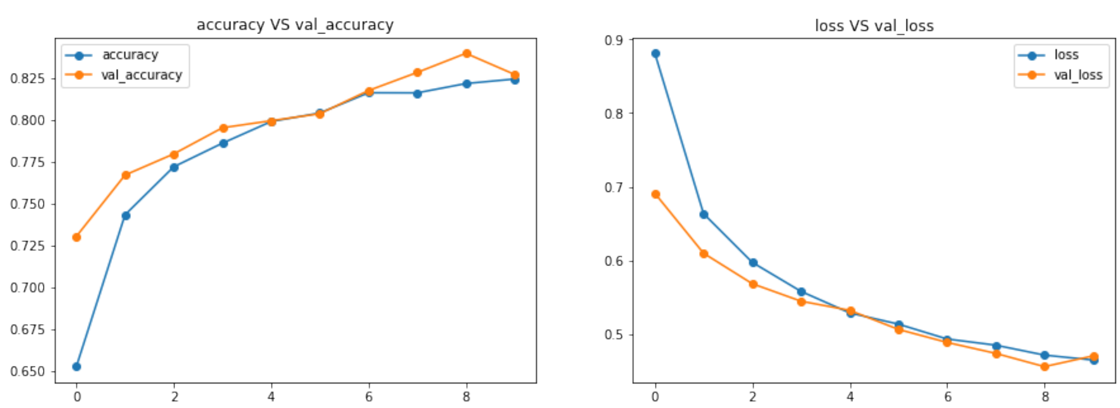
[16]:
```
#deseo guardar el History devuelto del entrenamiento
dfhist=pd.DataFrame(model_history.history)
dfhist.to_csv("model_historyV1.csv",index=False)
```

Mostramos los resultados encontrados

[20]:
```
import pandas as pd
import matplotlib.pyplot as plt
def plot_results(history,columns=[],ax=None):
    if ax is None:
        fig,(ax)=plt.subplots(1,1)
    df=pd.DataFrame(history)[columns]
    df.plot(kind="line",ax=ax,style="o-")
    ax.set_title(" VS ".join(columns))
```

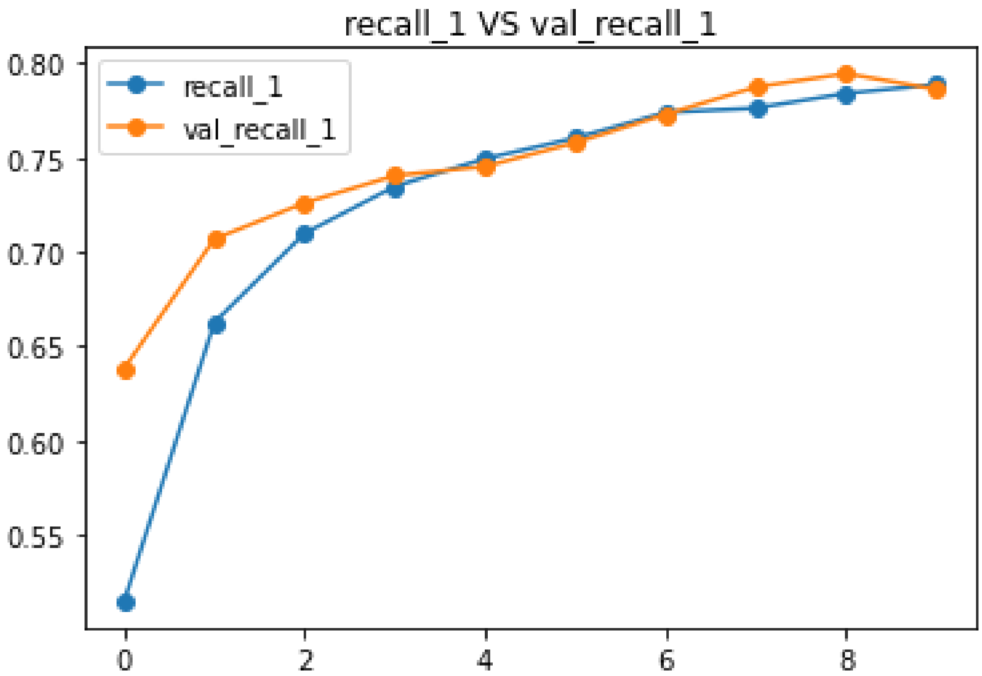
Trazamos la curva de la accuracy y funcion de perdida

[32]:
```
#la curva de precision
history=model_history.history
fig,(ax1,ax2)=plt.subplots(1,2)
fig.set_size_inches(15,5)
plot_results(history,["accuracy","val_accuracy"],ax=ax1)
plot_results(history,["loss","val_loss"],ax=ax2)
#plt.title("Accuracy & Loss function evolution")
plt.show()
```



- Para **recall**

[34]:
```
plot_results(history,["recall_1","val_recall_1"])
```



[38]:
```
#guardamos el modelo base con 10 epochs
tf.saved_model.save(model_base,"baseline")
model_base.save("baseline.h5")
```

```
INFO:tensorflow:Assets written to: baseline\assets
```

2da fase del entrenamiento (2/3)

[10]:
```
#sesion de entramiento restaurada
#El primer entramiento tuvo solo 10 epocas, por temas de tiempo
#El 2do entrenamiento retoma los datos y establece 10 epocas mas, dando lugar␣
↪asi a 20 epocas en total.
model_base=tf.keras.models.load_model("baseline.h5")
```

[14]:
```
n_epochs=20
model_base.fit_generator(
        train_generator,
        epochs=n_epochs,
        initial_epoch=10,
        validation_data=validation_generator,
        validation_steps=validation_generator.samples//BATCH_SIZE,
        callbacks=[early_stopping]
```

```
)
```

```
C:\Users\avira\anaconda3\envs\mlearning\lib\site-
packages\tensorflow\python\keras\engine\training.py:1844: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  warnings.warn('`Model.fit_generator` is deprecated and '
```

```
Epoch 11/20
477/477 [==============================] - 733s 2s/step - loss: 0.4540 -
accuracy: 0.8288 - recall_1: 0.7958 - val_loss: 0.4646 - val_accuracy: 0.8317 -
val_recall_1: 0.7903
Epoch 12/20
477/477 [==============================] - 793s 2s/step - loss: 0.4459 -
accuracy: 0.8324 - recall_1: 0.8012 - val_loss: 0.4575 - val_accuracy: 0.8167 -
val_recall_1: 0.7885
Epoch 13/20
477/477 [==============================] - 823s 2s/step - loss: 0.4431 -
accuracy: 0.8353 - recall_1: 0.8025 - val_loss: 0.4471 - val_accuracy: 0.8431 -
val_recall_1: 0.8077
Epoch 14/20
477/477 [==============================] - 873s 2s/step - loss: 0.4371 -
accuracy: 0.8350 - recall_1: 0.8033 - val_loss: 0.4470 - val_accuracy: 0.8389 -
val_recall_1: 0.8035
Epoch 15/20
477/477 [==============================] - 874s 2s/step - loss: 0.4299 -
accuracy: 0.8394 - recall_1: 0.8098 - val_loss: 0.4514 - val_accuracy: 0.8269 -
val_recall_1: 0.7981
Epoch 16/20
477/477 [==============================] - 850s 2s/step - loss: 0.4267 -
accuracy: 0.8443 - recall_1: 0.8120 - val_loss: 0.4428 - val_accuracy: 0.8389 -
val_recall_1: 0.8029
Epoch 17/20
477/477 [==============================] - 845s 2s/step - loss: 0.4210 -
accuracy: 0.8450 - recall_1: 0.8155 - val_loss: 0.4238 - val_accuracy: 0.8419 -
val_recall_1: 0.8071
Epoch 18/20
477/477 [==============================] - 831s 2s/step - loss: 0.4187 -
accuracy: 0.8431 - recall_1: 0.8134 - val_loss: 0.4220 - val_accuracy: 0.8413 -
val_recall_1: 0.8203
Epoch 19/20
477/477 [==============================] - 811s 2s/step - loss: 0.4149 -
accuracy: 0.8468 - recall_1: 0.8179 - val_loss: 0.4351 - val_accuracy: 0.8444 -
val_recall_1: 0.8137
Epoch 20/20
477/477 [==============================] - 768s 2s/step - loss: 0.4078 -
accuracy: 0.8462 - recall_1: 0.8211 - val_loss: 0.4220 - val_accuracy: 0.8389 -
val_recall_1: 0.8155
```

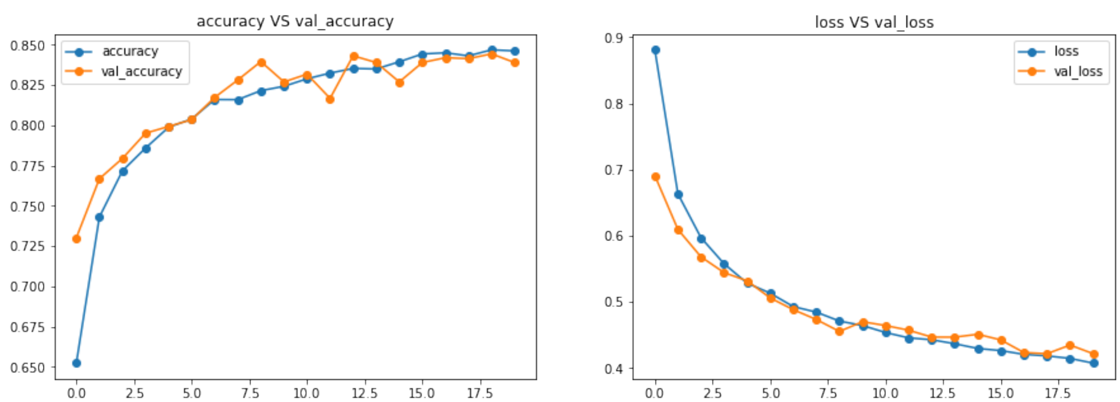
[14]: <tensorflow.python.keras.callbacks.History at 0x1a329708520>

[17]:
```
import pandas as pd
#deseo guardar el History devuelto del entrenamiento
model_history=_
dfhist=pd.DataFrame(model_history.history)
dfhist.to_csv("model_historyV2.csv",index=False)
```

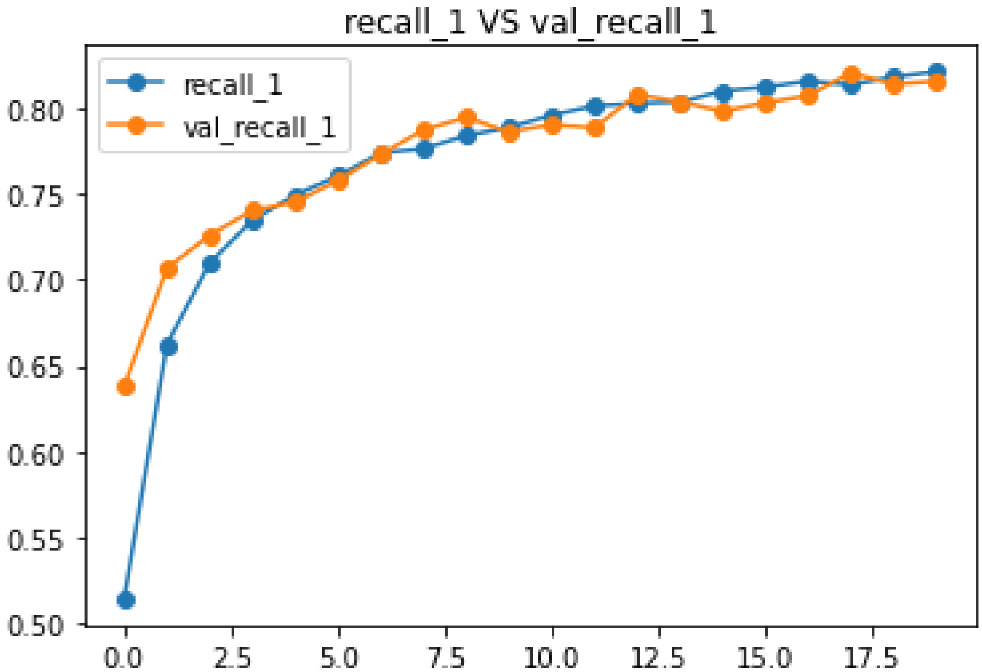
- Graficar las dos sesiones de entrenamiento

[18]:
```
df1=pd.read_csv("model_historyV1.csv",sep=",")
df2=pd.read_csv("model_historyV2.csv",sep=",")
df_history=pd.concat([df1,df2],axis=0)
```

[21]:
```
#la curva de precision
history=df_history.to_dict("list")
fig,(ax1,ax2)=plt.subplots(1,2)
fig.set_size_inches(15,5)
plot_results(history,["accuracy","val_accuracy"],ax=ax1)
plot_results(history,["loss","val_loss"],ax=ax2)
#plt.title("Accuracy & Loss function evolution")
plt.show()
```



[22]:
```
plot_results(history,["recall_1","val_recall_1"])
```



- Guardamos el modelo base final. sesion (2/3)

[23]:
```
model_base.save("baselinev2.h5")
```

- Evaluamos el puntaje en el **conjunto de entrenamiento**.

[24]:
```
model_base.evaluate(train_generator)
```

```
477/477 [==============================] - 650s 1s/step - loss: 0.4047 -
accuracy: 0.8498 - recall_1: 0.8218
```

[24]:
```
[0.40467602014541626, 0.8498490452766418, 0.8217613697052002]
```

- Evaluamos el puntaje en el **conjunto de validacion**.

[25]:
```
model_base.evaluate(validation_generator)
```

```
53/53 [==============================] - 77s 1s/step - loss: 0.4248 - accuracy:
0.8430 - recall_1: 0.8117
```

[25]:
```
[0.42475569248199463, 0.8429751992225647, 0.8116883039474487]
```

- **RESULTADOS PARCIALES**:

El accuracy para el conjunto de entrenamiento es de **ACC=84.98%** y **Recall=82.18%**.

El accuracy para el conjunto de validación es de **ACC=84.29%** y **Recall=81.16%**.

3era fase de entrenamiento (3/3)

- Retomamos el entrenamiento pasado y continuamos el entrenamiento

[28]:
```
epochs=30
early_stopping=tf.keras.callbacks.EarlyStopping(monitor="val_loss",patience=3)␣
↪#cuando la funcion de perdida ya no mejora
BATCH_SIZE=32
model_history=model_base.fit_generator(
                        train_generator,
                        epochs=epochs,
                        initial_epoch=20,
                        validation_data=validation_generator,
                        validation_steps=validation_generator.samples//
↪BATCH_SIZE,
                        callbacks=[early_stopping]
                )
```

```
C:\Users\avira\anaconda3\envs\mlearning\lib\site-
packages\tensorflow\python\keras\engine\training.py:1844: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  warnings.warn('`Model.fit_generator` is deprecated and '
```

```
Epoch 21/30
477/477 [==============================] - 839s 2s/step - loss: 0.4072 -
accuracy: 0.8470 - recall_1: 0.8196 - val_loss: 0.4243 - val_accuracy: 0.8431 -
val_recall_1: 0.8083
Epoch 22/30
477/477 [==============================] - 866s 2s/step - loss: 0.4028 -
accuracy: 0.8521 - recall_1: 0.8267 - val_loss: 0.4133 - val_accuracy: 0.8450 -
val_recall_1: 0.8203
Epoch 23/30
477/477 [==============================] - 849s 2s/step - loss: 0.4043 -
accuracy: 0.8512 - recall_1: 0.8255 - val_loss: 0.4106 - val_accuracy: 0.8438 -
val_recall_1: 0.8191
Epoch 24/30
477/477 [==============================] - 826s 2s/step - loss: 0.4070 -
accuracy: 0.8495 - recall_1: 0.8236 - val_loss: 0.4160 - val_accuracy: 0.8534 -
val_recall_1: 0.8233
Epoch 25/30
477/477 [==============================] - 817s 2s/step - loss: 0.3970 -
accuracy: 0.8502 - recall_1: 0.8248 - val_loss: 0.4008 - val_accuracy: 0.8468 -
val_recall_1: 0.8263
Epoch 26/30
477/477 [==============================] - 904s 2s/step - loss: 0.3924 -
accuracy: 0.8508 - recall_1: 0.8271 - val_loss: 0.4045 - val_accuracy: 0.8564 -
val_recall_1: 0.8299
Epoch 27/30
```

```
477/477 [==============================] - 854s 2s/step - loss: 0.3935 -
accuracy: 0.8548 - recall_1: 0.8299 - val_loss: 0.4068 - val_accuracy: 0.8462 -
val_recall_1: 0.8239
Epoch 28/30
477/477 [==============================] - 847s 2s/step - loss: 0.3913 -
accuracy: 0.8569 - recall_1: 0.8325 - val_loss: 0.4144 - val_accuracy: 0.8486 -
val_recall_1: 0.8251
```

[29]:
```
dtf=pd.DataFrame(model_history.history)
dtf.to_csv("model_historyV3.csv",index=False)
```

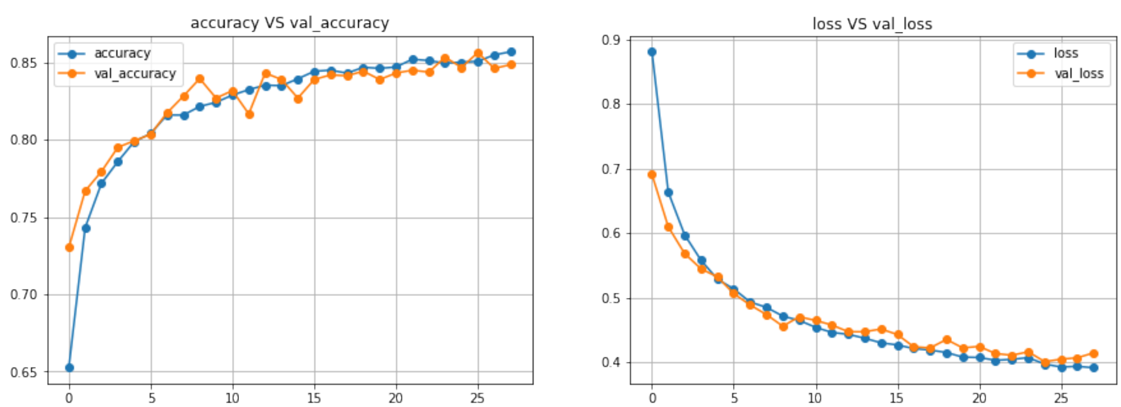
- Volvemos a ejecutar la secuencia de pasos de verificacion de resultados

[30]:
```
df1=pd.read_csv("model_historyV1.csv",sep=",")
df2=pd.read_csv("model_historyV2.csv",sep=",")
df3=pd.read_csv("model_historyV3.csv",sep=",")
df_history=pd.concat([df1,df2,df3],axis=0)
```

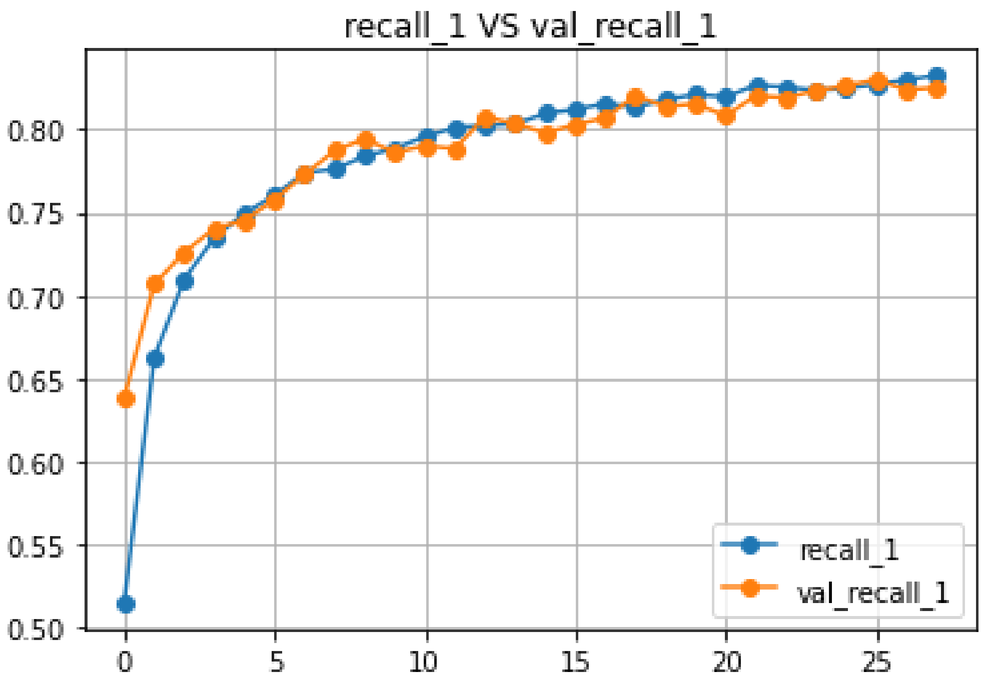
- Creamos una funcion para reutilizar la funcion que genera el grafico, para los modelos que se porbaran mas adelante.

[46]:
```
def plot_metrics(history,metrics=[]): #retorna una lista de tuplas
    fig,axes=plt.subplots(1,len(metrics))
    fig.set_size_inches(15,5)
    graph=pd.DataFrame(history)
    for i,ax in enumerate(axes.flat):
        graph[list(metrics[i])].plot(kind="line",style="o-",ax=ax)
        ax.set_title(" VS ".join(list(metrics[i])))
        ax.grid(True)
    plt.show()
```

[47]:
```
model_history=df_history.to_dict("list")
metrics=[("accuracy","val_accuracy"),("loss","val_loss")]
plot_metrics(model_history,metrics=metrics)
```



[43]:
```
plot_results(model_history,["recall_1","val_recall_1"])
plt.grid(True)
```



- Guardamos el modelo final (3/3) para validarlo.

[48]:
```
model_base.save("baselinev3.h5")
```

- El entrenamiento del modelo se detuvo en 28 epochs lo que nos dice que la funcion de perdida en la data de validacion no mejoro por 3 epochs consecutivos, probablemente, ya no mejore para futuras epocas.

Ahora veamos el rendiemiento del modelo base en los datos de entrenamiento y validacion

[52]:
```
model_base.evaluate(train_generator)
```

```
477/477 [==============================] - 704s 1s/step - loss: 0.3878 -
accuracy: 0.8566 - recall_1: 0.8322
```

[52]:
```
[0.3877873122692108, 0.8566084504127502, 0.8321958184242249]
```

[53]:
```
model_base.evaluate(validation_generator)
```

```
53/53 [==============================] - 81s 2s/step - loss: 0.4038 - accuracy:
0.8512 - recall_1: 0.8253
```

[53]:
```
[0.4038473963737488, 0.8512396812438965, 0.825265645980835]
```

- Mostramos la matriz de confusion en los datos de entrenamiento y validacion

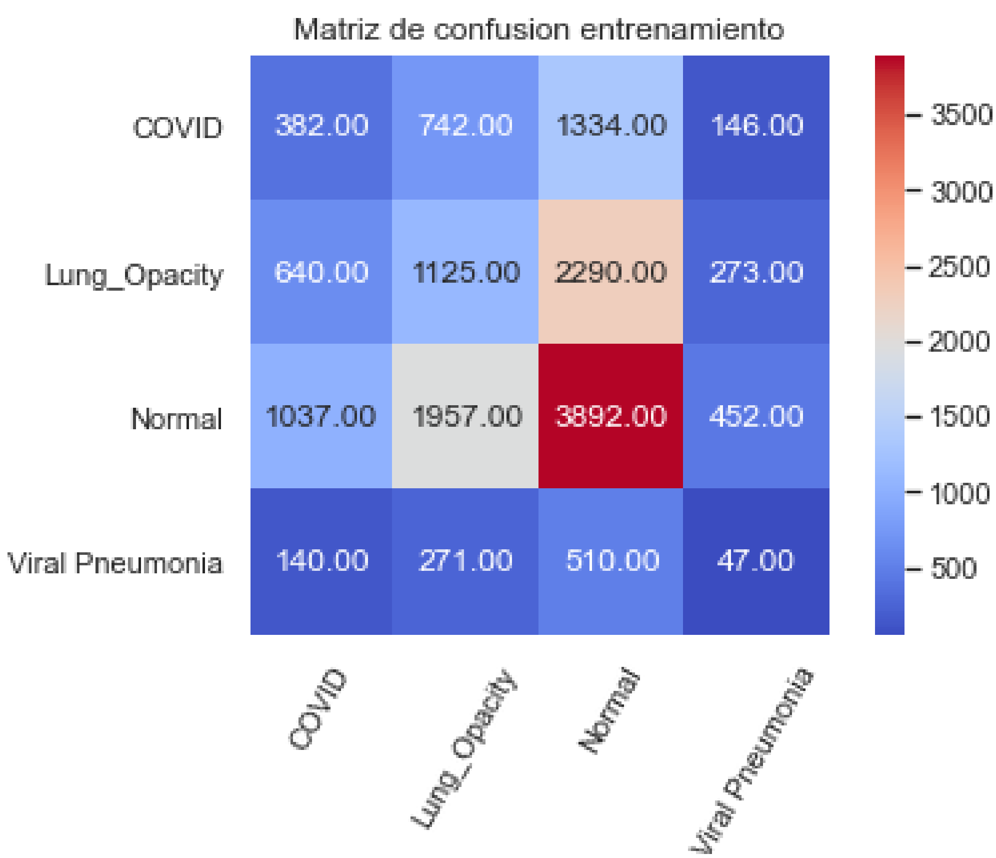
Para el conjunto de entrenamiento

[59]:
```
import numpy as np,seaborn as sns; sns.set()

y_true=train_generator.classes
y_pred=np.argmax(model_base.predict(train_generator),axis=1)
```

[66]:
```
train_generator.class_indices
```

[66]: {'COVID': 0, 'Lung_Opacity': 1, 'Normal': 2, 'Viral Pneumonia': 3}

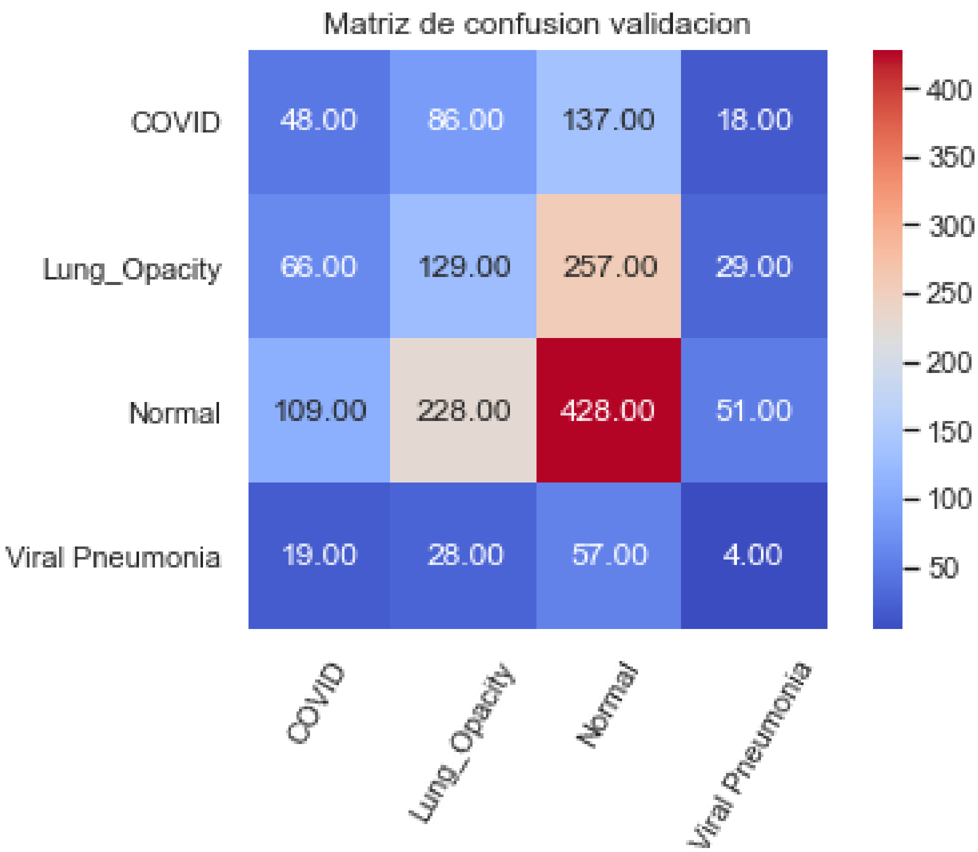
[76]:
```
#obtenemos la matriz de confusion de sklearn
from sklearn.metrics import confusion_matrix

classes=train_generator.class_indices.keys()
mat_train=confusion_matrix(y_true,y_pred)
sns.heatmap(mat_train,square=True,annot=True,fmt="0.
 ↪2f",cmap="coolwarm",xticklabels=classes,yticklabels=classes)
plt.xticks(rotation=60)
plt.title("Matriz de confusion entrenamiento")
plt.show()
```



- Para el conjunto de validacion

[77]:
```
y_true=validation_generator.classes
y_pred=np.argmax(model_base.predict(validation_generator),axis=1)
```

[78]:
```
classes=validation_generator.class_indices.keys()
mat_val=confusion_matrix(y_true,y_pred)
sns.heatmap(mat_val,square=True,annot=True,fmt="0.
 ↪2f",cmap="coolwarm",xticklabels=classes,yticklabels=classes)
plt.xticks(rotation=60)
plt.title("Matriz de confusion validacion")
plt.show()
```



0.0.5 RESULTADOS FINALES: MODELO BASE

- El modelo base ha obtenido un puntaje de accuracy **ACC=85.66%** y recall **RECALL=83.22%** en el **conjunto de entrenamiento**.
- El modelo ha obtendio un puntaje de accuracy **ACC=85.12%** y recall **RECALL=82.52%**

en el **conjunto de validacion**.

IMPORTANTE: El modelo ha alcanzado el equilibrio entre los datos de entrenamiento y validacion, lo que siginifica que es un modelo final con aproximadamente 85% de precision. Este modelo pasará a la **Fase de evaluación del modelo**.

```
[ ]:
```