Innovating the diagnosis of possible brain cancer.

José Luis Higuera Caraveo

May 28 2022

1 Problem Statemen

The evolution of artificial intelligence is great, and it is increasingly impacting the way of working in different areas. Such is the case of the health area, where it is revolutionizing care in areas such as:

- Diagnosis of diseases with medical images.
- Surgical robots.
- Maximizing hospital efficiency.

The Artificial Intelligence healthcare market is expected to reach $45.2 billion by 2026.

The current valuation is $4.9 billion.

The application of Artificial Intelligence, mainly deep learning, has been shown to be superior in detecting diseases from X-rays, MRIs and CT scans, which could significantly improve the speed and accuracy of diagnosis.

For a better approach: https://research.aimultiple.com/looking-for-better-medical-imaging-for-early-diagnostic-and-monitoring-contact-the-leading-vendors-here/

In this case study we will assume that we are working as an AI/ML consultant and have been hired by a medical diagnostic company in New York.

It has been assigned the task of improving the speed and accuracy of brain tumor detection and localization based on magnetic resonance imaging.

The goal is to reduce cost and aid in early diagnosis of tumors, which would essentially increase the likelihood of successful treatment.

The team was given the task of collecting magnetic resonance images of the brain, a total of 3,929 brain images with which they have to develop the algorithm.

Original data source: https://www.kaggle.com/datasets/mateuszbuda/lgg-mri-segmentation

Deep learning pipeline to perform classification and localization

Two stages will be carried out to detect and locate the brain tumor (if there is one).

1. Use of a ResNet to classify images into:
   - 0: There is no tumor.
   - 1: There is a tumor.
2. Once this process is finished, the next stage is different depending on the result obtained in the first stage:

- If the result is 1: The image will serve as input for a segmentation model supported by a ResUNet to help us locate the tumor.
- If the result is 0: It is considered as a healthy patient, so it is not necessary to submit the image to the second stage.

A review of, what is image segmentation

The goal of image segmentation is to understand and extract information from images at the pixel level. It can be used for object recognition and location, offering great value in applications related to medical imaging and self-driving cars.

The objective of image segmentation is to train a neural network to produce a pixel mask of the image, highlighting the part where the object to be detected and located is located.

2 Import libraries and datasets

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import cv2
from skimage import io

import tensorflow as tf
from tensorflow.keras.layers import Dense, Input, AveragePooling2D, Flatten,␣
↪Dropout, Conv2D, MaxPooling2D, BatchNormalization, ReLU, Input, Activation,␣
↪Add, UpSampling2D, Concatenate
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,␣
↪LearningRateScheduler

import os
import random
%matplotlib inline
```

[ ]:
```
# Data containing the path to Brain MRI and its corresponding mask
brain_df = pd.read_csv('./data/data_mask.csv')
brain_df.head()
```

[ ]:
```
               patient_id                                          image_path  \
0  TCGA_CS_5395_19981004  TCGA_CS_5395_19981004/TCGA_CS_5395_19981004_1.tif
1  TCGA_CS_5395_19981004  TCGA_CS_4944_20010208/TCGA_CS_4944_20010208_1.tif
2  TCGA_CS_5395_19981004  TCGA_CS_4941_19960909/TCGA_CS_4941_19960909_1.tif
3  TCGA_CS_5395_19981004  TCGA_CS_4943_20000902/TCGA_CS_4943_20000902_1.tif
4  TCGA_CS_5395_19981004  TCGA_CS_5396_20010302/TCGA_CS_5396_20010302_1.tif

                                           mask_path  mask
```

```
0  TCGA_CS_5395_19981004/TCGA_CS_5395_19981004_1_…     0
1  TCGA_CS_4944_20010208/TCGA_CS_4944_20010208_1_…     0
2  TCGA_CS_4941_19960909/TCGA_CS_4941_19960909_1_…     0
3  TCGA_CS_4943_20000902/TCGA_CS_4943_20000902_1_…     0
4  TCGA_CS_5396_20010302/TCGA_CS_5396_20010302_1_…     0
```

Let's understand the data set.

- **patient_id**: Refers to the Id of the patient from whom the magnetic resonance was taken.
- **image_path**: Provides us with the path where the image has been saved.
- **mask_path**: Gives us the path where the mask has been saved
- **mask**: Binary value where 0 means absence of tumors, 1 presence of tumors.

[ ]:
```
brain_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3929 entries, 0 to 3928
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   patient_id  3929 non-null   object
 1   image_path  3929 non-null   object
 2   mask_path   3929 non-null   object
 3   mask        3929 non-null   int64
dtypes: int64(1), object(3)
memory usage: 122.9+ KB
```

With the above information we can verify that there is no null data within the dataset.

Taking into account the data, let us verify how many of these are classified as healthy patients (mask = 0) and how many had some type of tumor detected (mask = 1).

[ ]:
```
brain_df['mask'].value_counts()
```

[ ]:
```
0    2556
1    1373
Name: mask, dtype: int64
```

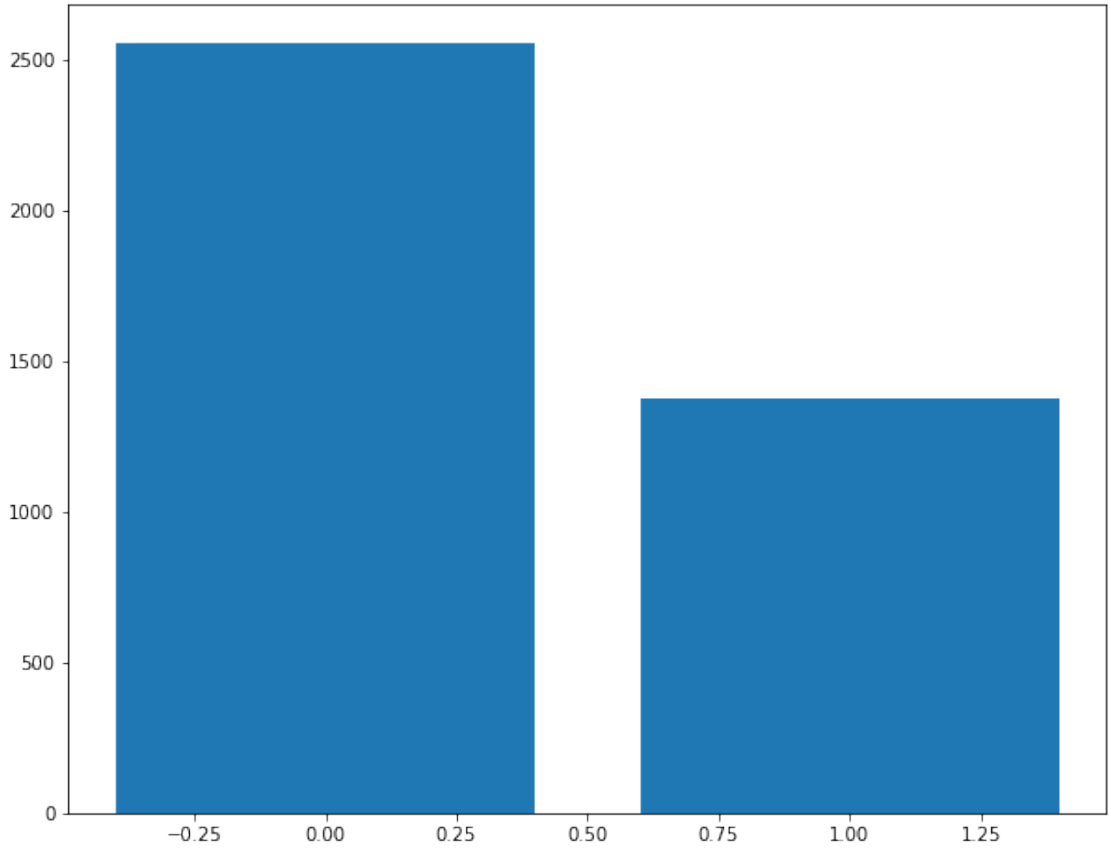
We have a dataset with 2,556 healthy patients and 1,373 with some type of tumor.

This is an unbalanced data set, that is, the number of examples per category are very different, which can lead to poor training of our classifier model. It is necessary that before starting the training the dataset must be similar for both categories.

2.1 Data visualization

Let us visualize in a bar graph the distribution of healthy patients and patients with some type of tumor.

[ ]:
```
plt.figure(figsize=(10,8))
plt.bar(brain_df['mask'].value_counts().index, brain_df['mask'].value_counts())
plt.show()
```



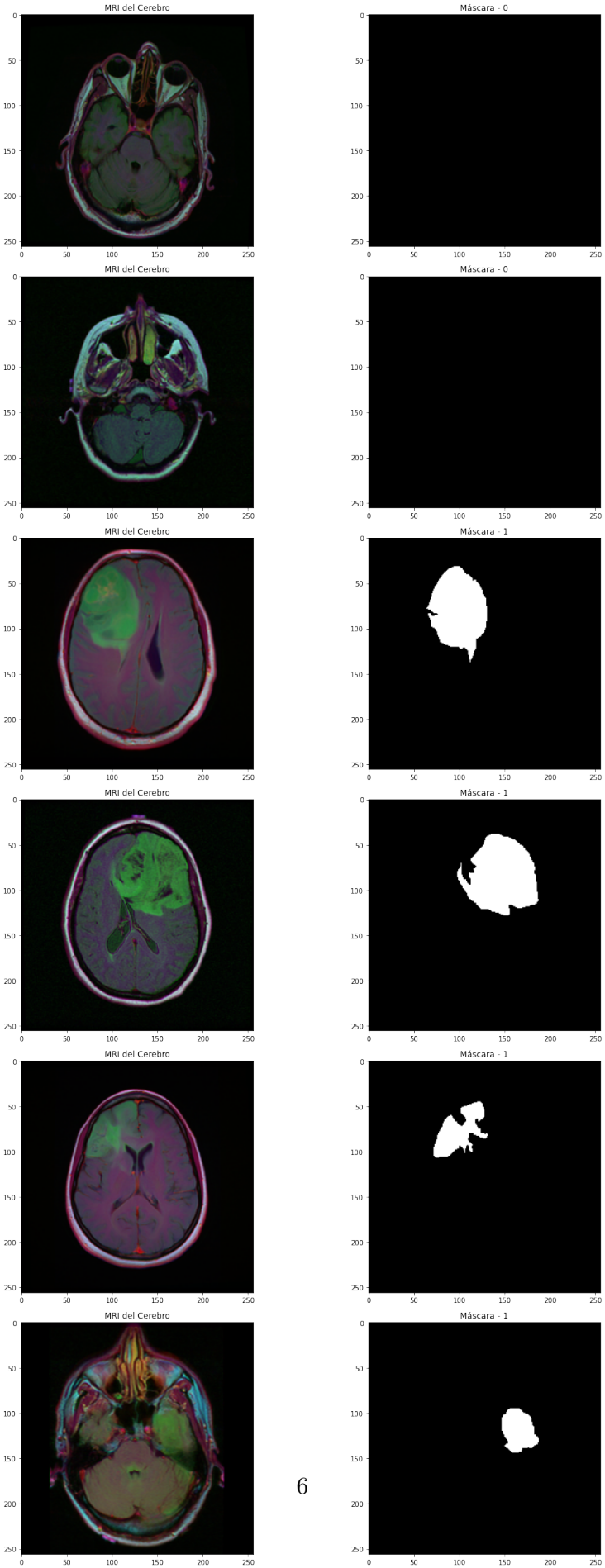
In the graph we can see how the dataset is unbalanced, where the number of healthy patients is greater than the number of patients with some type of tumor, at the time of training our model may acquire a little bias, it will translate that there is a greater probability that a patient is healthy. This is not correct, we have to supply the data knowing that the chances of being healthy or having some type of tumor is the same.

Let's see some pictures

Let us remember that our dataset is made up of the paths where the images are stored, we can access these and thus visualize the tomography with its respective mask.

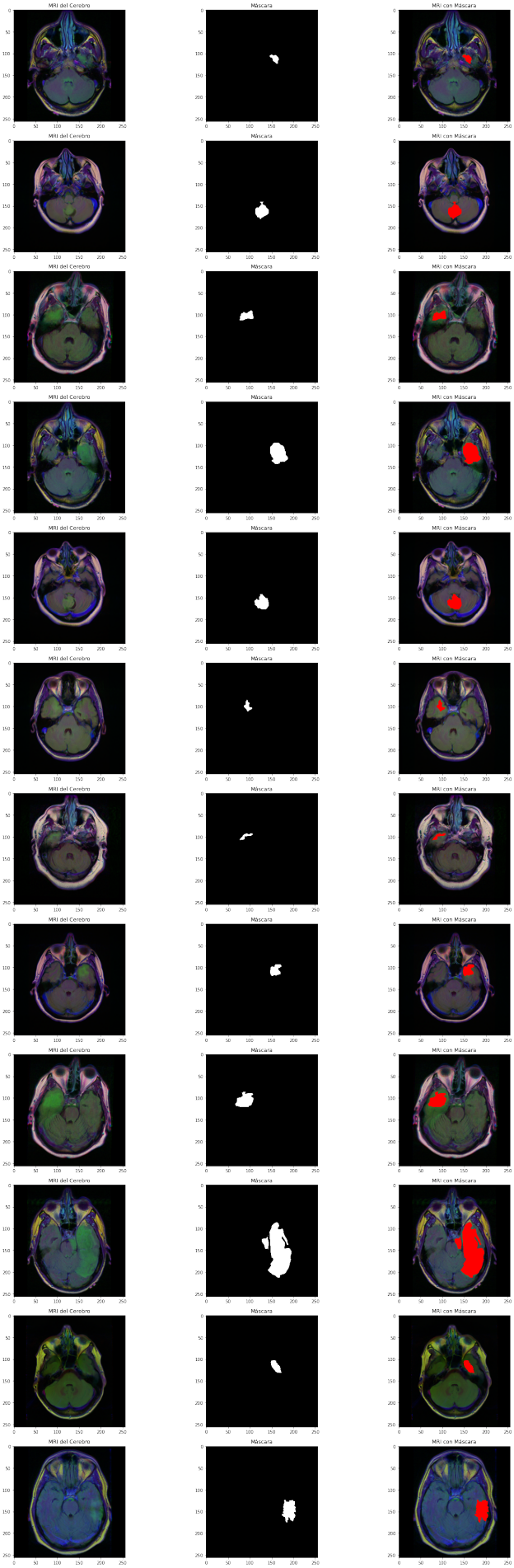
[ ]:
```
import random
fig, axs = plt.subplots(6,2, figsize=(16,32))
count = 0
for x in range(6):
    # We select a random index
    i = random.randint(0, len(brain_df))
```

```
    axs[count][0].title.set_text("MRI del Cerebro")
    axs[count][0].imshow(cv2.imread('./data/{}'.format(brain_df.image_path[i])))
    axs[count][1].title.set_text("Máscara - " + str(brain_df['mask'][i]))
    axs[count][1].imshow(cv2.imread('./data/{}'.format(brain_df.mask_path[i])))

    count += 1

fig.tight_layout()
```


MRI del Cerebro
Máscara - 0
MRI del Cerebro
Máscara - 0
MRI del Cerebro
Máscara - 1
MRI del Cerebro
Máscara - 1
MRI del Cerebro
Máscara - 1
MRI del Cerebro
Máscara - 1

In order to better understand what a mask represents, we chose to superimpose it on the MRI image to visualize in which part of the brain the tumor is located, if it exists.

[ ]:
```
count = 0
fig, axs = plt.subplots(12, 3, figsize = (20, 50))
for i in range(len(brain_df)):
    if brain_df['mask'][i] == 1 and count < 12:
        img = io.imread('./data/{}'.format(brain_df.image_path[i]))
        axs[count][0].title.set_text('MRI del Cerebro')
        axs[count][0].imshow(img)

        mask = io.imread('./data/{}'.format(brain_df.mask_path[i]))
        axs[count][1].title.set_text('Máscara')
        axs[count][1].imshow(mask, cmap='gray')

        # We change the mask to RGB and highlight the red color
        img[mask == 255] = (255, 0, 0)
        axs[count][2].title.set_text('MRI con Máscara')
        axs[count][2].imshow(img)
        count+=1

fig.tight_layout()
```


MRI del Cerebro
Máscara
MRI con Máscara

2.2 Data cleaning

The patient id column is not necessary, we proceed to eliminate it.

[ ]:
```
brain_df_train = brain_df.drop(columns = ['patient_id'])
brain_df_train.shape
```

[ ]:
```
(3929, 3)
```

Tensorflow, in its flow_from_dataframe function, requires that the variable to be predicted be in string format, currently it is in numeric format.

[ ]:
```
brain_df_train['mask'] = brain_df_train['mask'].apply(lambda x: str(x))
```

[ ]:
```
brain_df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3929 entries, 0 to 3928
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   image_path  3929 non-null   object
 1   mask_path   3929 non-null   object
 2   mask        3929 non-null   object
dtypes: object(3)
memory usage: 92.2+ KB
```

2.3 Balancing the data set

In order to have a balanced data set, the technique that will be used will be to reduce the data size of healthy patients to 1400, a number close to patients with some type of tumor.

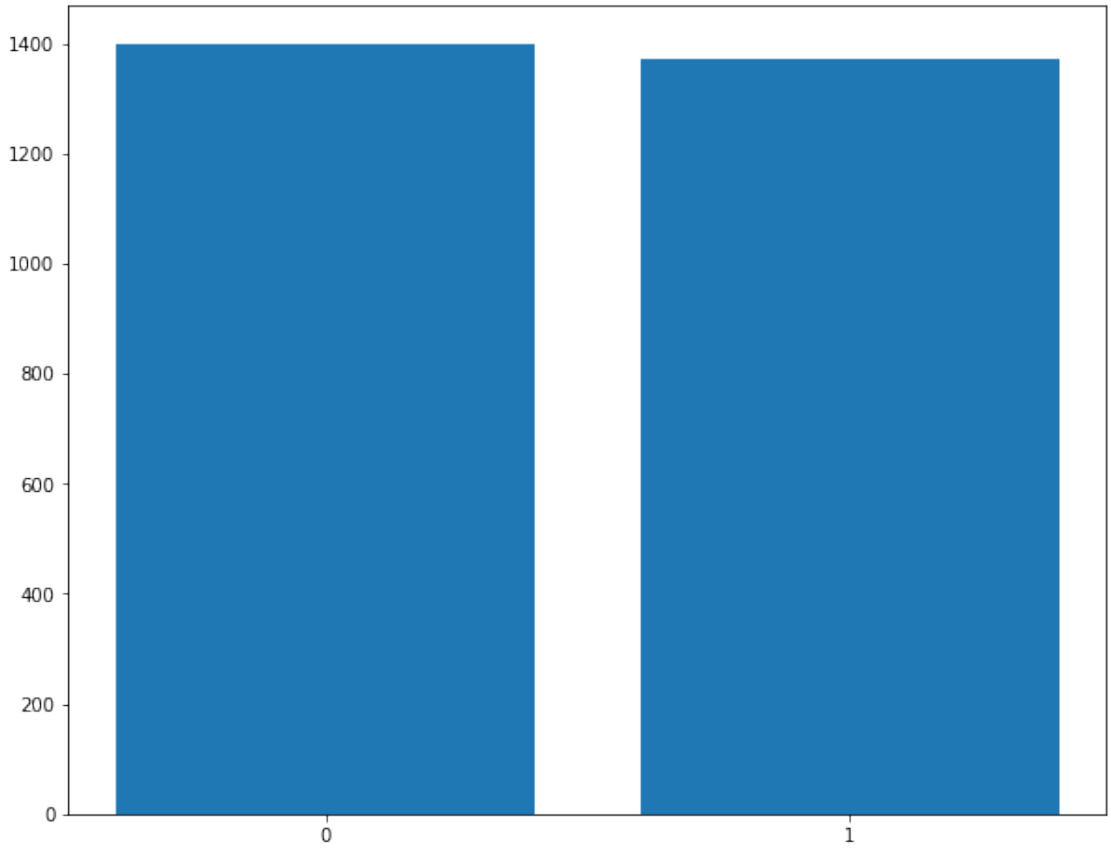
[ ]:
```
# Obtaining only healthy patients
healthy_patient = brain_df_train[brain_df_train['mask'] == '0'].reset_index()

# Randomly select 1400 patients
range_list = np.arange(0, len(healthy_patient))
to_select = np.random.choice(range_list, 1400, replace=False)

# We keep the randomly selected patients
healthy_patient_to_train = healthy_patient.iloc[to_select, :]
```

[ ]:
```
# Obtaining only patients with tumor
unhealthy_patient = brain_df_train[brain_df_train['mask'] == '1'].reset_index()

# Concatenate both dataframes
```

```
brain_df_balanced = pd.concat([healthy_patient_to_train, unhealthy_patient]).
 ↪reset_index()
```

Let's verify with a graph if the dataframe was balanced

[ ]:
```
plt.figure(figsize=(10,8))
plt.bar(brain_df_balanced['mask'].value_counts().index,␣
 ↪brain_df_balanced['mask'].value_counts())
plt.show()
```



3 Train a classifier model

The objective of this model will be to detect if there is a tumor present in the magnetic resonance or not.

3.1 Build the training and test set.

[ ]:
```
from sklearn.model_selection import train_test_split

train, test = train_test_split(brain_df_balanced, test_size = 0.15,␣
↪shuffle=True)
```

3.1.1 Data pre-processing

Before starting with the training it is necessary to normalize the data, we will help ourselves with the Image Dta Generator of Keras, in addition we will create the sets for training, validation and testing.

[ ]:
```
from keras_preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(rescale=1./255.,
                             validation_split = 0.15)

test_datagen=ImageDataGenerator(rescale=1./255.)
```

[ ]:
```
# Training set
train_generator = datagen.flow_from_dataframe(
    dataframe=train,
    directory='./data/',
    x_col='image_path',
    y_col='mask',
    subset='training',
    batch_size=16,
    shuffle=True,
    class_mode='binary',
    target_size=(256,256)
)

# Validation set
valid_generator = datagen.flow_from_dataframe(
    dataframe=train,
    directory='./data/',
    x_col='image_path',
    y_col='mask',
    subset='validation',
    batch_size=16,
    shuffle=True,
    class_mode='binary',
    target_size=(256,256)
)

# Test set
test_generator = test_datagen.flow_from_dataframe(
```

```
    dataframe=test,
    directory='./data/',
    x_col='image_path',
    y_col='mask',
    batch_size=16,
    class_mode='binary',
    target_size=(256,256)
)
```

```
Found 2004 validated image filenames belonging to 2 classes.
Found 353 validated image filenames belonging to 2 classes.
Found 416 validated image filenames belonging to 2 classes.
```

3.2 Training model

For the training of the model we will use the ResNet architecture, for more information you can consult the papaer or the following this article.

Model architecture:

- **First layer:**
  - Convolution layer with 32 filters of size 3, stride of 1 and padding valid.
  - Batch Normalization Layer
  - MaxPooling layer, poolsize of 2
  - ReLu Layer
- **Second layer:**
  - Convolution layer with 64 filters of size 3, stride of 1 and padding valid.
  - Batch Normalization Layer
  - MaxPooling layer, poolsize of 2
  - ReLu Layer

The first two layers help us, in addition to reducing the size of the image, to find the first linear patterns such as horizontal and vertical patterns, among others.

- Three ResNet blocks with 64, 128, 256 filters respectively, these layers will help us find more specific patterns to identify the tumor.
- **Third layer:**
  - Convolution layer with 256 filters of size 3, stride of 1 and padding valid.
  - Batch Normalization Layer
  - MaxPooling layer, poolsize of 2
  - ReLu Layer
- AveragePooling Layer
- Flatten Layer
- Fully Connected Layers
  - Dense first layer with 128 neurons and ReLu activation.
  - Batch Normalization to aid in training.
  - Droput of 20% to avoid overfitting.

  - Dense second layer with 128 neurons and ReLu activation.
  - Batch Normalization to aid in training.
  - Droput of 20% to avoid overfitting.
  - Dense third layer with 128 neurons and ReLu activation.
  - Batch Normalization to aid in training.

- Prediction layer with 1 neuron and sigmoid activation.

[ ]:
```
def resblock(X, f):
    '''
    Function to create a resblock where:
    - X_shortcut is equal to the inputs X
    - For X:
      - Conv2D(f, kernel_size=1, stride=1, kernel_initializer='he_normal')
      - BatchNormalization() and ReLu activation
      - Conv2D(f, kernel_size=1, stride=1, padding='same',␣
↪kernel_initializer='he_normal')
      - BatchNormalization()
    - For X_shortcut:
      - Conv2D(f, kernel_size=1, stride=1, padding='same',␣
↪kernel_initializer='he_normal')
      - BatchNormalization()
    - X = Add()([X, X_shortcut]).
    - ReLu activation
    **Args:**
    - X: output for the previous layer
    - f: filters number to apply on the resblock
    **Returns:**
    - resblock X
    '''
    # We make the copy of the entry
    X_shortcut = X

    # Main pathl
    X = Conv2D(f, kernel_size=(1,1)␣
↪,strides=(1,1),kernel_initializer='he_normal')(X)
    X = BatchNormalization()(X)
    X = Activation('relu')(X)

    X = Conv2D(f, kernel_size=(3,3), strides=(1,1), padding='same',␣
↪kernel_initializer='he_normal')(X)
    X = BatchNormalization()(X)

    # Short path
    X_shortcut = Conv2D(f, kernel_size=(1,1), strides=(1,1),␣
↪kernel_initializer='he_normal')(X_shortcut)
    X_shortcut = BatchNormalization()(X_shortcut)
```

```
    # Add the output of the main route and the short route together
    X = Add()([X,X_shortcut])
    X = Activation('relu')(X)

    return X
```

[ ]:
```
INPUT_SHAPE = (256,256,3)
inputs = Input(shape=INPUT_SHAPE, name='input_layer')

# Layer 1
x = Conv2D(filters=32, kernel_size=3, strides=(1,1), padding='valid',␣
 ↪name='cov_layer_1')(inputs)
x = BatchNormalization(name='batchNorm_layer_1')(x)
x = MaxPooling2D(pool_size=(2,2), name='MaxPooling_layer_1')(x)
x = ReLU(name='ReLu_layer_1')(x)

# Layer 2
x = Conv2D(filters=64, kernel_size=3, strides=(1,1), padding='valid',␣
 ↪name='cov_layer_2')(x)
x = BatchNormalization(name='batchNorm_layer_2')(x)
x = MaxPooling2D(pool_size=(2,2), name='MaxPooling_layer_2')(x)
x = ReLU(name='ReLu_layer_2')(x)

# Block 1
x = resblock(x, 64)

# Block 2
x = resblock(x, 128)

# Block 3
x = resblock(x, 256)

# Layer 3
x = Conv2D(filters=256, kernel_size=3, strides=(1,1), padding='valid',␣
 ↪name='cov_layer_3')(x)
x = BatchNormalization(name='batchNorm_layer_3')(x)
x = MaxPooling2D(pool_size=(2,2), name='MaxPooling_layer_3')(x)
x = ReLU(name='ReLu_layer_3')(x)

# Average Pooling
x = AveragePooling2D(pool_size=(2,2), name='Final_AveragePooling')(x)

# Flatten Layer
x = Flatten(name='Flatten_layer')(x)

# FC Layer
x = Dense(128, activation='relu', name='FC_layer_1')(x)
```

```
x = BatchNormalization(name='batchNorm_FC_layer_1')(x)
x = Dropout(0.2, name='Dropout_FC_layer_1')(x)
x = Dense(128, activation='relu', name='FC_layer_2')(x)
x = BatchNormalization(name='batchNorm_FC_layer_2')(x)
x = Dropout(0.2, name='Dropout_FC_layer_2')(x)
x = Dense(64, activation='relu', name='FC_layer_3')(x)
x = BatchNormalization(name='batchNorm_FC_layer_3')(x)

outputs = Dense(1, activation='sigmoid', name='Outputs')(x)

model_res = Model(inputs=inputs, outputs=outputs)

model_res.summary()
```

```
Model: "model_9"
_________________________________________________________________________________
__________________
 Layer (type)                   Output Shape         Param #     Connected to
=================================================================================
==================
 input_layer (InputLayer)       [(None, 256, 256, 3  0           []
                                )]

 cov_layer_1 (Conv2D)           (None, 254, 254, 32  896
['input_layer[0][0]']
                                )

 batchNorm_layer_1 (BatchNormal  (None, 254, 254, 32  128
['cov_layer_1[0][0]']
 ization)                       )

 MaxPooling_layer_1 (MaxPooling  (None, 127, 127, 32  0
['batchNorm_layer_1[0][0]']
 2D)                            )

 ReLu_layer_1 (ReLU)            (None, 127, 127, 32  0
['MaxPooling_layer_1[0][0]']
                                )

 cov_layer_2 (Conv2D)           (None, 125, 125, 64  18496
['ReLu_layer_1[0][0]']
                                )

 batchNorm_layer_2 (BatchNormal  (None, 125, 125, 64  256
['cov_layer_2[0][0]']
 ization)                       )
```

```
 MaxPooling_layer_2 (MaxPooling  (None, 62, 62, 64)  0
['batchNorm_layer_2[0][0]']
 2D)

 ReLu_layer_2 (ReLU)            (None, 62, 62, 64)   0
['MaxPooling_layer_2[0][0]']

 conv2d_141 (Conv2D)            (None, 62, 62, 64)   4160
['ReLu_layer_2[0][0]']

 batch_normalization_141 (Batch  (None, 62, 62, 64)  256
['conv2d_141[0][0]']
 Normalization)

 activation_94 (Activation)     (None, 62, 62, 64)   0
['batch_normalization_141[0][0]']

 conv2d_142 (Conv2D)            (None, 62, 62, 64)   36928
['activation_94[0][0]']

 conv2d_143 (Conv2D)            (None, 62, 62, 64)   4160
['ReLu_layer_2[0][0]']

 batch_normalization_142 (Batch  (None, 62, 62, 64)  256
['conv2d_142[0][0]']
 Normalization)

 batch_normalization_143 (Batch  (None, 62, 62, 64)  256
['conv2d_143[0][0]']
 Normalization)

 add_47 (Add)                   (None, 62, 62, 64)   0
['batch_normalization_142[0][0]',
'batch_normalization_143[0][0]']

 activation_95 (Activation)     (None, 62, 62, 64)   0
['add_47[0][0]']

 conv2d_144 (Conv2D)            (None, 62, 62, 128)  8320
['activation_95[0][0]']

 batch_normalization_144 (Batch  (None, 62, 62, 128)  512
['conv2d_144[0][0]']
 Normalization)

 activation_96 (Activation)     (None, 62, 62, 128)  0
['batch_normalization_144[0][0]']
```

```
 conv2d_145 (Conv2D)            (None, 62, 62, 128)  147584
['activation_96[0][0]']

 conv2d_146 (Conv2D)            (None, 62, 62, 128)  8320
['activation_95[0][0]']

 batch_normalization_145 (Batch  (None, 62, 62, 128)  512
['conv2d_145[0][0]']
 Normalization)

 batch_normalization_146 (Batch  (None, 62, 62, 128)  512
['conv2d_146[0][0]']
 Normalization)

 add_48 (Add)                   (None, 62, 62, 128)  0
['batch_normalization_145[0][0]',
'batch_normalization_146[0][0]']

 activation_97 (Activation)     (None, 62, 62, 128)  0
['add_48[0][0]']

 conv2d_147 (Conv2D)            (None, 62, 62, 256)  33024
['activation_97[0][0]']

 batch_normalization_147 (Batch  (None, 62, 62, 256)  1024
['conv2d_147[0][0]']
 Normalization)

 activation_98 (Activation)     (None, 62, 62, 256)  0
['batch_normalization_147[0][0]']

 conv2d_148 (Conv2D)            (None, 62, 62, 256)  590080
['activation_98[0][0]']

 conv2d_149 (Conv2D)            (None, 62, 62, 256)  33024
['activation_97[0][0]']

 batch_normalization_148 (Batch  (None, 62, 62, 256)  1024
['conv2d_148[0][0]']
 Normalization)

 batch_normalization_149 (Batch  (None, 62, 62, 256)  1024
['conv2d_149[0][0]']
 Normalization)

 add_49 (Add)                   (None, 62, 62, 256)  0
['batch_normalization_148[0][0]',
'batch_normalization_149[0][0]']
```

```
 activation_99 (Activation)     (None, 62, 62, 256)  0
['add_49[0][0]']

 cov_layer_3 (Conv2D)           (None, 60, 60, 256)  590080
['activation_99[0][0]']

 batchNorm_layer_3 (BatchNormal  (None, 60, 60, 256)  1024
['cov_layer_3[0][0]']
 ization)

 MaxPooling_layer_3 (MaxPooling  (None, 30, 30, 256)  0
['batchNorm_layer_3[0][0]']
 2D)

 ReLu_layer_3 (ReLU)            (None, 30, 30, 256)  0
['MaxPooling_layer_3[0][0]']

 Final_AveragePooling (AverageP  (None, 15, 15, 256)  0
['ReLu_layer_3[0][0]']
 ooling2D)

 Flatten_layer (Flatten)        (None, 57600)        0
['Final_AveragePooling[0][0]']

 FC_layer_1 (Dense)             (None, 128)          7372928
['Flatten_layer[0][0]']

 Dropout_FC_layer_1 (Dropout)   (None, 128)          0
['FC_layer_1[0][0]']

 batchNorm_FC_layer_1 (BatchNor  (None, 128)         512
['Dropout_FC_layer_1[0][0]']
 malization)

 FC_layer_2 (Dense)             (None, 128)          16512
['batchNorm_FC_layer_1[0][0]']

 batchNorm_FC_layer_2 (BatchNor  (None, 128)         512
['FC_layer_2[0][0]']
 malization)

 Dropout_FC_layer_2 (Dropout)   (None, 128)          0
['batchNorm_FC_layer_2[0][0]']

 FC_layer_3 (Dense)             (None, 64)           8256
['Dropout_FC_layer_2[0][0]']
```

```
 batchNorm_FC_layer_3 (BatchNor  (None, 64)          256
['FC_layer_3[0][0]']
 malization)

 Outputs (Dense)                (None, 1)            65
['batchNorm_FC_layer_3[0][0]']

==================================================================================
==================
Total params: 8,880,897
Trainable params: 8,876,865
Non-trainable params: 4,032
----------------------------------------------------------------------------------
------------------
```

[ ]:
```
# Learning rate scheduler for better training
def scheduler(epoch, lr):
    '''
    Function to make a learning rate sheduler
    **Args:**
    - epoch: Training epoch number
    - lr: Current learning rate of the optimizer algorithm
    **Return:**
    - Current learning rate if the epoch number is less than 20
    - Fine tuning learning rate if the epoch es equal or grader than 20
    '''
    if epoch < 20:
        return lr
    else:
        return lr * tf.math.exp(-0.1)
```

[ ]:
```
# Model compilation
model_res.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=["accuracy"])

# We save the best model with the least validation loss
checkpointer = ModelCheckpoint(filepath="classifier-weights_res.hdf5",␣
 ↪verbose=1, save_best_only=True)
# Lr scheduler callback
lr_scheduler = tf.keras.callbacks.LearningRateScheduler(scheduler)

# Model training
history_res = model_res.fit(train_generator, steps_per_epoch= train_generator.n␣
 ↪// 16, epochs=40,
                    validation_data=valid_generator, validation_steps=␣
 ↪valid_generator.n // 16,
                    callbacks=[checkpointer, lr_scheduler])
```

```
Epoch 1/40
125/125 [==============================] - ETA: 0s - loss: 0.6730 - accuracy:
0.6665
Epoch 1: val_loss improved from inf to 1.42052, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 24s 167ms/step - loss: 0.6730 -
accuracy: 0.6665 - val_loss: 1.4205 - val_accuracy: 0.5085 - lr: 0.0010
Epoch 2/40
125/125 [==============================] - ETA: 0s - loss: 0.5735 - accuracy:
0.7289
Epoch 2: val_loss improved from 1.42052 to 0.87298, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 159ms/step - loss: 0.5735 -
accuracy: 0.7289 - val_loss: 0.8730 - val_accuracy: 0.5057 - lr: 0.0010
Epoch 3/40
125/125 [==============================] - ETA: 0s - loss: 0.5208 - accuracy:
0.7525
Epoch 3: val_loss did not improve from 0.87298
125/125 [==============================] - 19s 148ms/step - loss: 0.5208 -
accuracy: 0.7525 - val_loss: 1.0115 - val_accuracy: 0.4943 - lr: 0.0010
Epoch 4/40
125/125 [==============================] - ETA: 0s - loss: 0.4761 - accuracy:
0.7777
Epoch 4: val_loss improved from 0.87298 to 0.82164, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 157ms/step - loss: 0.4761 -
accuracy: 0.7777 - val_loss: 0.8216 - val_accuracy: 0.5966 - lr: 0.0010
Epoch 5/40
125/125 [==============================] - ETA: 0s - loss: 0.4487 - accuracy:
0.7762
Epoch 5: val_loss improved from 0.82164 to 0.45602, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 161ms/step - loss: 0.4487 -
accuracy: 0.7762 - val_loss: 0.4560 - val_accuracy: 0.7898 - lr: 0.0010
Epoch 6/40
125/125 [==============================] - ETA: 0s - loss: 0.4419 - accuracy:
0.7887
Epoch 6: val_loss improved from 0.45602 to 0.39251, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 21s 167ms/step - loss: 0.4419 -
accuracy: 0.7887 - val_loss: 0.3925 - val_accuracy: 0.8267 - lr: 0.0010
Epoch 7/40
125/125 [==============================] - ETA: 0s - loss: 0.3893 - accuracy:
0.8255
Epoch 7: val_loss did not improve from 0.39251
125/125 [==============================] - 18s 143ms/step - loss: 0.3893 -
accuracy: 0.8255 - val_loss: 2.6417 - val_accuracy: 0.6108 - lr: 0.0010
Epoch 8/40
```

```
125/125 [==============================] - ETA: 0s - loss: 0.4160 - accuracy:
0.7973
Epoch 8: val_loss did not improve from 0.39251
125/125 [==============================] - 19s 149ms/step - loss: 0.4160 -
accuracy: 0.7973 - val_loss: 0.4415 - val_accuracy: 0.7784 - lr: 0.0010
Epoch 9/40
125/125 [==============================] - ETA: 0s - loss: 0.4197 - accuracy:
0.8018
Epoch 9: val_loss improved from 0.39251 to 0.38901, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 163ms/step - loss: 0.4197 -
accuracy: 0.8018 - val_loss: 0.3890 - val_accuracy: 0.8267 - lr: 0.0010
Epoch 10/40
125/125 [==============================] - ETA: 0s - loss: 0.3518 - accuracy:
0.8370
Epoch 10: val_loss did not improve from 0.38901
125/125 [==============================] - 18s 143ms/step - loss: 0.3518 -
accuracy: 0.8370 - val_loss: 0.4072 - val_accuracy: 0.7869 - lr: 0.0010
Epoch 11/40
125/125 [==============================] - ETA: 0s - loss: 0.3429 - accuracy:
0.8481
Epoch 11: val_loss did not improve from 0.38901
125/125 [==============================] - 18s 145ms/step - loss: 0.3429 -
accuracy: 0.8481 - val_loss: 0.5799 - val_accuracy: 0.7330 - lr: 0.0010
Epoch 12/40
124/125 [============================>.] - ETA: 0s - loss: 0.3369 - accuracy:
0.8427
Epoch 12: val_loss improved from 0.38901 to 0.33099, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 156ms/step - loss: 0.3393 -
accuracy: 0.8421 - val_loss: 0.3310 - val_accuracy: 0.8494 - lr: 0.0010
Epoch 13/40
125/125 [==============================] - ETA: 0s - loss: 0.3215 - accuracy:
0.8566
Epoch 13: val_loss did not improve from 0.33099
125/125 [==============================] - 18s 147ms/step - loss: 0.3215 -
accuracy: 0.8566 - val_loss: 0.3763 - val_accuracy: 0.8438 - lr: 0.0010
Epoch 14/40
125/125 [==============================] - ETA: 0s - loss: 0.3069 - accuracy:
0.8637
Epoch 14: val_loss did not improve from 0.33099
125/125 [==============================] - 18s 146ms/step - loss: 0.3069 -
accuracy: 0.8637 - val_loss: 0.4058 - val_accuracy: 0.8466 - lr: 0.0010
Epoch 15/40
125/125 [==============================] - ETA: 0s - loss: 0.3426 - accuracy:
0.8456
Epoch 15: val_loss did not improve from 0.33099
125/125 [==============================] - 18s 147ms/step - loss: 0.3426 -
```

```
accuracy: 0.8456 - val_loss: 0.3783 - val_accuracy: 0.8239 - lr: 0.0010
Epoch 16/40
125/125 [==============================] - ETA: 0s - loss: 0.3052 - accuracy:
0.8682
Epoch 16: val_loss improved from 0.33099 to 0.30836, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 19s 155ms/step - loss: 0.3052 -
accuracy: 0.8682 - val_loss: 0.3084 - val_accuracy: 0.8750 - lr: 0.0010
Epoch 17/40
125/125 [==============================] - ETA: 0s - loss: 0.4135 - accuracy:
0.8164
Epoch 17: val_loss did not improve from 0.30836
125/125 [==============================] - 18s 147ms/step - loss: 0.4135 -
accuracy: 0.8164 - val_loss: 0.3913 - val_accuracy: 0.8125 - lr: 0.0010
Epoch 18/40
125/125 [==============================] - ETA: 0s - loss: 0.3563 - accuracy:
0.8380
Epoch 18: val_loss did not improve from 0.30836
125/125 [==============================] - 18s 147ms/step - loss: 0.3563 -
accuracy: 0.8380 - val_loss: 0.4595 - val_accuracy: 0.7841 - lr: 0.0010
Epoch 19/40
125/125 [==============================] - ETA: 0s - loss: 0.3669 - accuracy:
0.8224
Epoch 19: val_loss did not improve from 0.30836
125/125 [==============================] - 18s 146ms/step - loss: 0.3669 -
accuracy: 0.8224 - val_loss: 0.4128 - val_accuracy: 0.8210 - lr: 0.0010
Epoch 20/40
125/125 [==============================] - ETA: 0s - loss: 0.3712 - accuracy:
0.8290
Epoch 20: val_loss did not improve from 0.30836
125/125 [==============================] - 18s 145ms/step - loss: 0.3712 -
accuracy: 0.8290 - val_loss: 0.3178 - val_accuracy: 0.8494 - lr: 0.0010
Epoch 21/40
125/125 [==============================] - ETA: 0s - loss: 0.3198 - accuracy:
0.8627
Epoch 21: val_loss improved from 0.30836 to 0.30761, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 19s 154ms/step - loss: 0.3198 -
accuracy: 0.8627 - val_loss: 0.3076 - val_accuracy: 0.8636 - lr: 9.0484e-04
Epoch 22/40
125/125 [==============================] - ETA: 0s - loss: 0.3053 - accuracy:
0.8662
Epoch 22: val_loss did not improve from 0.30761
125/125 [==============================] - 18s 145ms/step - loss: 0.3053 -
accuracy: 0.8662 - val_loss: 0.3291 - val_accuracy: 0.8551 - lr: 8.1873e-04
Epoch 23/40
125/125 [==============================] - ETA: 0s - loss: 0.2622 - accuracy:
0.8929
```

```
Epoch 23: val_loss improved from 0.30761 to 0.28840, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 156ms/step - loss: 0.2622 -
accuracy: 0.8929 - val_loss: 0.2884 - val_accuracy: 0.8693 - lr: 7.4082e-04
Epoch 24/40
125/125 [==============================] - ETA: 0s - loss: 0.3081 - accuracy:
0.8667
Epoch 24: val_loss improved from 0.28840 to 0.27981, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 157ms/step - loss: 0.3081 -
accuracy: 0.8667 - val_loss: 0.2798 - val_accuracy: 0.8807 - lr: 6.7032e-04
Epoch 25/40
125/125 [==============================] - ETA: 0s - loss: 0.2559 - accuracy:
0.8858
Epoch 25: val_loss did not improve from 0.27981
125/125 [==============================] - 18s 145ms/step - loss: 0.2559 -
accuracy: 0.8858 - val_loss: 0.2983 - val_accuracy: 0.8750 - lr: 6.0653e-04
Epoch 26/40
125/125 [==============================] - ETA: 0s - loss: 0.2197 - accuracy:
0.9039
Epoch 26: val_loss improved from 0.27981 to 0.22313, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 20s 156ms/step - loss: 0.2197 -
accuracy: 0.9039 - val_loss: 0.2231 - val_accuracy: 0.9034 - lr: 5.4881e-04
Epoch 27/40
125/125 [==============================] - ETA: 0s - loss: 0.2111 - accuracy:
0.9120
Epoch 27: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 147ms/step - loss: 0.2111 -
accuracy: 0.9120 - val_loss: 0.2671 - val_accuracy: 0.8750 - lr: 4.9659e-04
Epoch 28/40
125/125 [==============================] - ETA: 0s - loss: 0.2005 - accuracy:
0.9155
Epoch 28: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 147ms/step - loss: 0.2005 -
accuracy: 0.9155 - val_loss: 0.2373 - val_accuracy: 0.8949 - lr: 4.4933e-04
Epoch 29/40
125/125 [==============================] - ETA: 0s - loss: 0.1786 - accuracy:
0.9351
Epoch 29: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 145ms/step - loss: 0.1786 -
accuracy: 0.9351 - val_loss: 0.2618 - val_accuracy: 0.8977 - lr: 4.0657e-04
Epoch 30/40
125/125 [==============================] - ETA: 0s - loss: 0.1917 - accuracy:
0.9256
Epoch 30: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 147ms/step - loss: 0.1917 -
accuracy: 0.9256 - val_loss: 0.2361 - val_accuracy: 0.9034 - lr: 3.6788e-04
```

```
Epoch 31/40
125/125 [==============================] - ETA: 0s - loss: 0.1722 - accuracy:
0.9331
Epoch 31: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 145ms/step - loss: 0.1722 -
accuracy: 0.9331 - val_loss: 0.2258 - val_accuracy: 0.9148 - lr: 3.3287e-04
Epoch 32/40
125/125 [==============================] - ETA: 0s - loss: 0.1666 - accuracy:
0.9351
Epoch 32: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 145ms/step - loss: 0.1666 -
accuracy: 0.9351 - val_loss: 0.2458 - val_accuracy: 0.8977 - lr: 3.0119e-04
Epoch 33/40
125/125 [==============================] - ETA: 0s - loss: 0.1528 - accuracy:
0.9406
Epoch 33: val_loss did not improve from 0.22313
125/125 [==============================] - 19s 152ms/step - loss: 0.1528 -
accuracy: 0.9406 - val_loss: 0.2734 - val_accuracy: 0.8977 - lr: 2.7253e-04
Epoch 34/40
125/125 [==============================] - ETA: 0s - loss: 0.1541 - accuracy:
0.9401
Epoch 34: val_loss did not improve from 0.22313
125/125 [==============================] - 19s 149ms/step - loss: 0.1541 -
accuracy: 0.9401 - val_loss: 0.2467 - val_accuracy: 0.9034 - lr: 2.4660e-04
Epoch 35/40
125/125 [==============================] - ETA: 0s - loss: 0.1571 - accuracy:
0.9411
Epoch 35: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 145ms/step - loss: 0.1571 -
accuracy: 0.9411 - val_loss: 0.2512 - val_accuracy: 0.9034 - lr: 2.2313e-04
Epoch 36/40
125/125 [==============================] - ETA: 0s - loss: 0.1443 - accuracy:
0.9416
Epoch 36: val_loss did not improve from 0.22313
125/125 [==============================] - 18s 145ms/step - loss: 0.1443 -
accuracy: 0.9416 - val_loss: 0.2280 - val_accuracy: 0.9062 - lr: 2.0190e-04
Epoch 37/40
125/125 [==============================] - ETA: 0s - loss: 0.1474 - accuracy:
0.9432
Epoch 37: val_loss improved from 0.22313 to 0.21263, saving model to classifier-
weights_res.hdf5
125/125 [==============================] - 19s 155ms/step - loss: 0.1474 -
accuracy: 0.9432 - val_loss: 0.2126 - val_accuracy: 0.9148 - lr: 1.8268e-04
Epoch 38/40
125/125 [==============================] - ETA: 0s - loss: 0.1531 - accuracy:
0.9452
Epoch 38: val_loss did not improve from 0.21263
125/125 [==============================] - 18s 145ms/step - loss: 0.1531 -
```

```
accuracy: 0.9452 - val_loss: 0.2727 - val_accuracy: 0.8835 - lr: 1.6530e-04
Epoch 39/40
125/125 [==============================] - ETA: 0s - loss: 0.1559 - accuracy:
0.9416
Epoch 39: val_loss did not improve from 0.21263
125/125 [==============================] - 18s 145ms/step - loss: 0.1559 -
accuracy: 0.9416 - val_loss: 0.2314 - val_accuracy: 0.9148 - lr: 1.4957e-04
Epoch 40/40
125/125 [==============================] - ETA: 0s - loss: 0.1307 - accuracy:
0.9467
Epoch 40: val_loss did not improve from 0.21263
125/125 [==============================] - 18s 146ms/step - loss: 0.1307 -
accuracy: 0.9467 - val_loss: 0.2171 - val_accuracy: 0.9062 - lr: 1.3534e-04
```

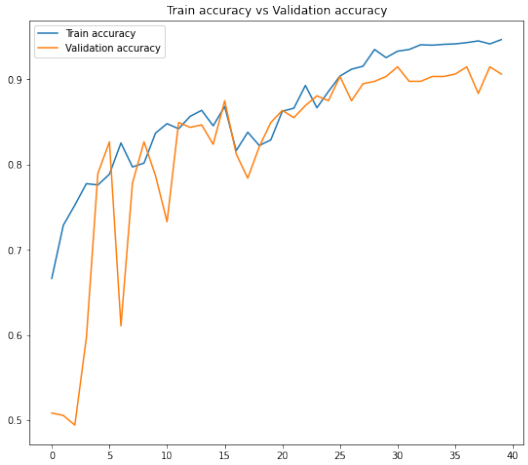
We have managed to obtain a balanced model, achieving good results both in the training set and in the validation set.

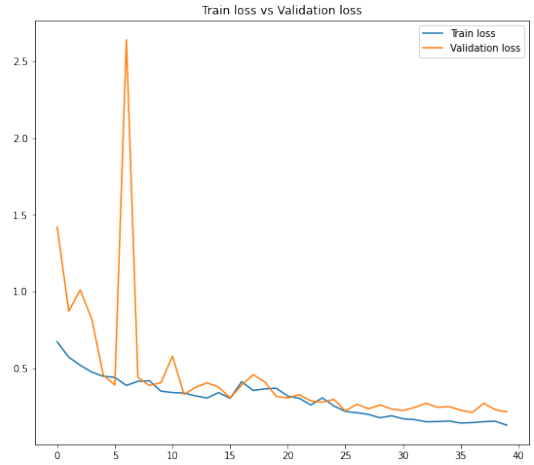
To corroborate this, let's check the behavior graphs of the metrics.

[ ]:
```python
def plot_metrics(history):
    '''
    Function to plot the metrics arround the epoch

    **Args:**:
    * history: The model history list with accuray, loss, val_accuracy and␣
 ↪val_loss values
    '''
    metrics = []
    for metric in history.keys():
        metrics.append(metric)

    loss = history[metrics[0]]
    accuracy = history[metrics[1]]
    val_loss = history[metrics[2]]
    val_accuracy = history[metrics[3]]

    plt.figure(figsize=(20,8))
    plt.subplot(1,2,1)
    plt.plot(accuracy, label='Train accuracy')
    plt.plot(val_accuracy, label='Validation accuracy')
    plt.title('Train accuracy vs Validation accuracy')
    plt.legend(loc='best')
    plt.subplot(1,2,2)
    plt.plot(loss, label='Train loss')
    plt.plot(val_loss, label='Validation loss')
    plt.title('Train loss vs Validation loss')
    plt.legend(loc='best')
```

```
    plt.show()
```

[ ]:
```
plot_metrics(history_res.history)
```





We can draw the following conclusions based on the graphs above:

- The accuracy for the training set improves from epoch to epoch. In the validation set we observe the same trend, achieving a good metric in both sets.
- The loss in the training set kept decreasing each epoch, we observed the same trend in the validation set.

Thanks to the checkpointer we managed to save the weights where the least loss was obtained in the validation set.

[ ]:
```
model_res.evaluate(test_generator)
```

```
26/26 [==============================] - 103s 4s/step - loss: 0.2373 - accuracy:
0.8942
```

[ ]:
```
[0.2372908741235733, 0.8942307829856873]
```

[ ]:
```
# We save the architecture of the model in a json file for future use
model_json = model_res.to_json()
with open("classifier_model_res.json","w") as json_file:
    json_file.write(model_json)
```

3.3 Model Evaluation

[ ]:
```
import json
# We load the pretrained model
with open('classifier_model_res.json', 'r') as json_file:
    json_savedModel = json_file.read()
```

```
model_res = tf.keras.models.model_from_json(json_savedModel)
model_res.load_weights('classifier-weights_res.hdf5')
model_res.compile(loss = 'binary_crossentropy', optimizer='adam', metrics=␣
↪["accuracy"])
```

Evaluation metrics

It is time to make some predictions, for this we will use the test dataset, we will pass image by image to the model to make the prediction of it, at the end we will verify with a confusion matrix to evaluate the precision, recall and f1-score.

[ ]:
```
def make_predictions(model, image_paths, threshold=0.5):
    '''
    Funtion to make predictions according one model already trained.
    **Args**:
    * model: Model already trained
    * image_paths: The path where the images are saved,
    * threshold: For binary classification models, threshold to be take in care␣
↪to decide if
    a prediction is 1 or 0.
    **Returs**:
    It returns a list of prediction, 0 or 1 in string format due flow from␣
↪dataset test_generator
    '''
    predictions = []
    for path in image_paths:
        # We read the image and normalize its values
        img = io.imread('./data/{}'.format(path))
        img = img / 255.
        # We transform the image to a tensor of the form [m, h, w, c]
        img = tf.reshape(img, shape=[1, img.shape[0], img.shape[1], img.
↪shape[2]])
        # We apply the prediction
        pred = model.predict(img)
        # We keep 0 or 1 according to probability.
        if pred[0][0] >= threshold:
            predictions.append(str(1))
        else:
            predictions.append(str(0))

    return predictions
```

[ ]:
```
df = test[['image_path', 'mask']].reset_index()
df.head()
```

[ ]:

	index	image_path	mask
0	231	TCGA_DU_7008_19830723/TCGA_DU_7008_19830723_44…	0
1	1137	TCGA_HT_A61B_19991127/TCGA_HT_A61B_19991127_2.tif	0
2	1303	TCGA_DU_7304_19930325/TCGA_DU_7304_19930325_10…	0
3	29	TCGA_HT_7602_19951103/TCGA_HT_7602_19951103_18…	0
4	450	TCGA_DU_6407_19860514/TCGA_DU_6407_19860514_56…	0

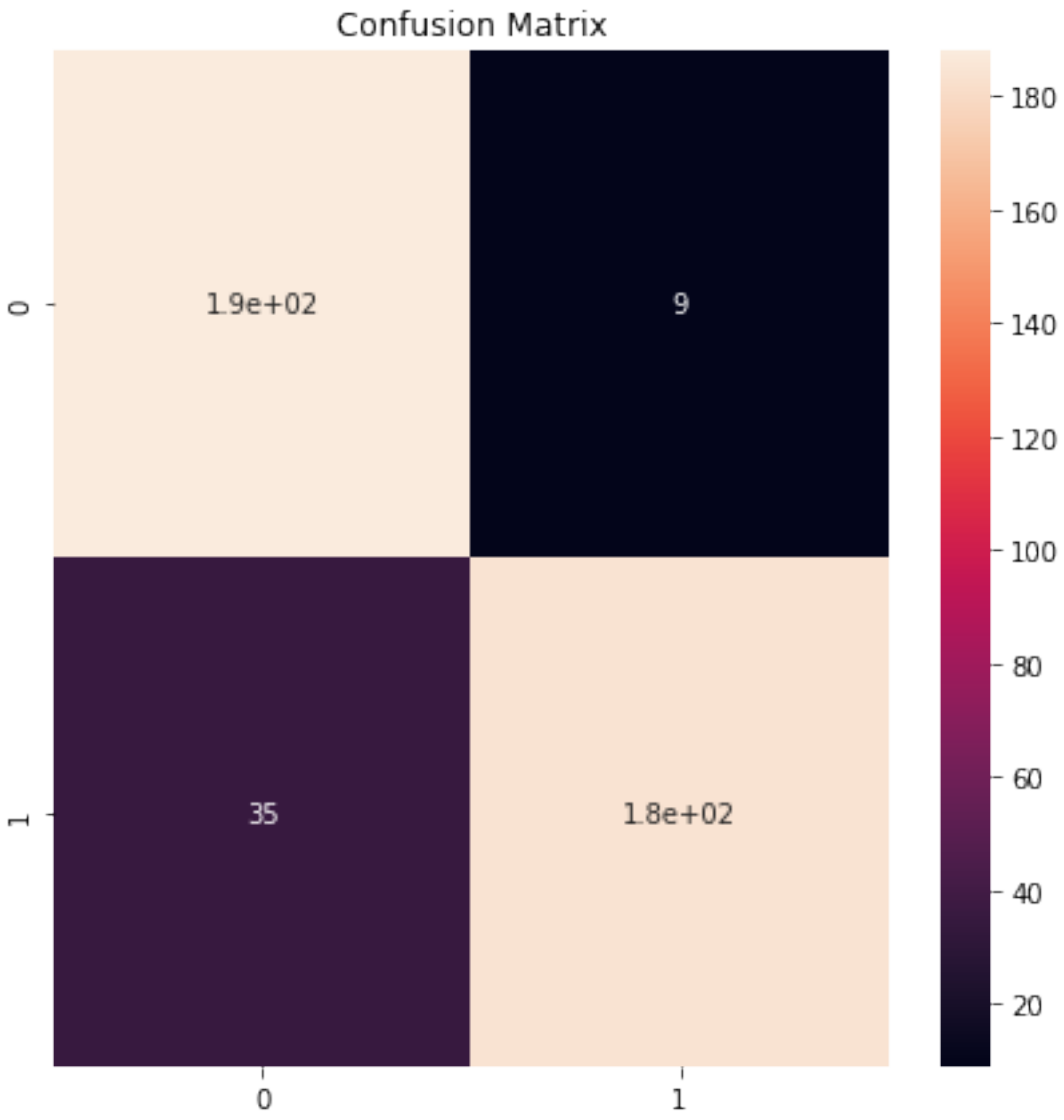
[ ]:
```
# We get the path of the images
image_paths = df['image_path'].to_list()
```

[ ]:
```
# We predict if the image shows a tumor or not
predictions = make_predictions(model=model_res, image_paths=image_paths)
```

[ ]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

def cm_and_report(y_true, y_pred):
    '''
    Function to make reports for a clasification model
    **Args:**
    - y_true: Actual clasification label
    - y_pred: Prediction for the actual input
    '''
    accuracy = accuracy_score(y_true, y_pred)
    print(f'The accuracy of the model is {accuracy}\n')

    cm = confusion_matrix(test['mask'], predictions)
    plt.figure(figsize = (7,7))
    sns.heatmap(cm, annot=True)
    plt.title('Confusion Matrix')
    plt.show()

    report = classification_report(test['mask'], predictions)
    print('\nPrecision-Recall trade-off report')
    print(f'\n{report}')
```

[ ]:
```
# Reports
cm_and_report(test['mask'], predictions)
```

```
The accuracy of the model is 0.8942307692307693
```



Precision-Recall trade-off report

	precision	recall	f1-score	support
0	0.84	0.95	0.90	197
1	0.95	0.84	0.89	219
accuracy			0.89	416
macro avg	0.90	0.90	0.89	416
weighted avg	0.90	0.89	0.89	416

Conclusions:

We have a model that captures negatives with good precision, but classifies some positives as no tumor present. We can see this in the recall, where, for a prediction of 0, we have it raised, up to 0.95, whereas, for a prediction of 1, this metric drops to 0.84.

Due to the nature of the study, lowering the false negative metric has to be the objective, to achieve this we can apply one of the following techniques:

- **New architecture:** We can continue testing with a different architecture of the model that helps to find those false negatives, add layers, find a way to find new inputs, etc.
- **Change the prediction Threshold:** The output of the neural network is a probability where, according to a threshold, we can determine if a patient has a tumor or not, we can lower that threshold and determine that, for example, if the algorithm shows that there is a 5% chance of having a tumor and having it as suspicious and classifying it as positive, this helps to capture the greatest number of true positives.

Let us remember that thanks to the precision-recall trade-off, if we want to increase one of these metrics, the other decreases, in our case, increasing the recall for positives, without much concern for the precision of the model.

Lowering false positives would not be the most relevant task since, if the patient is diagnosed as positive, but really is not, a second clinical analysis would rule out the diagnosis. We would give the patient a hard time, but that is preferable to diagnosing someone with a tumor as a false negative.

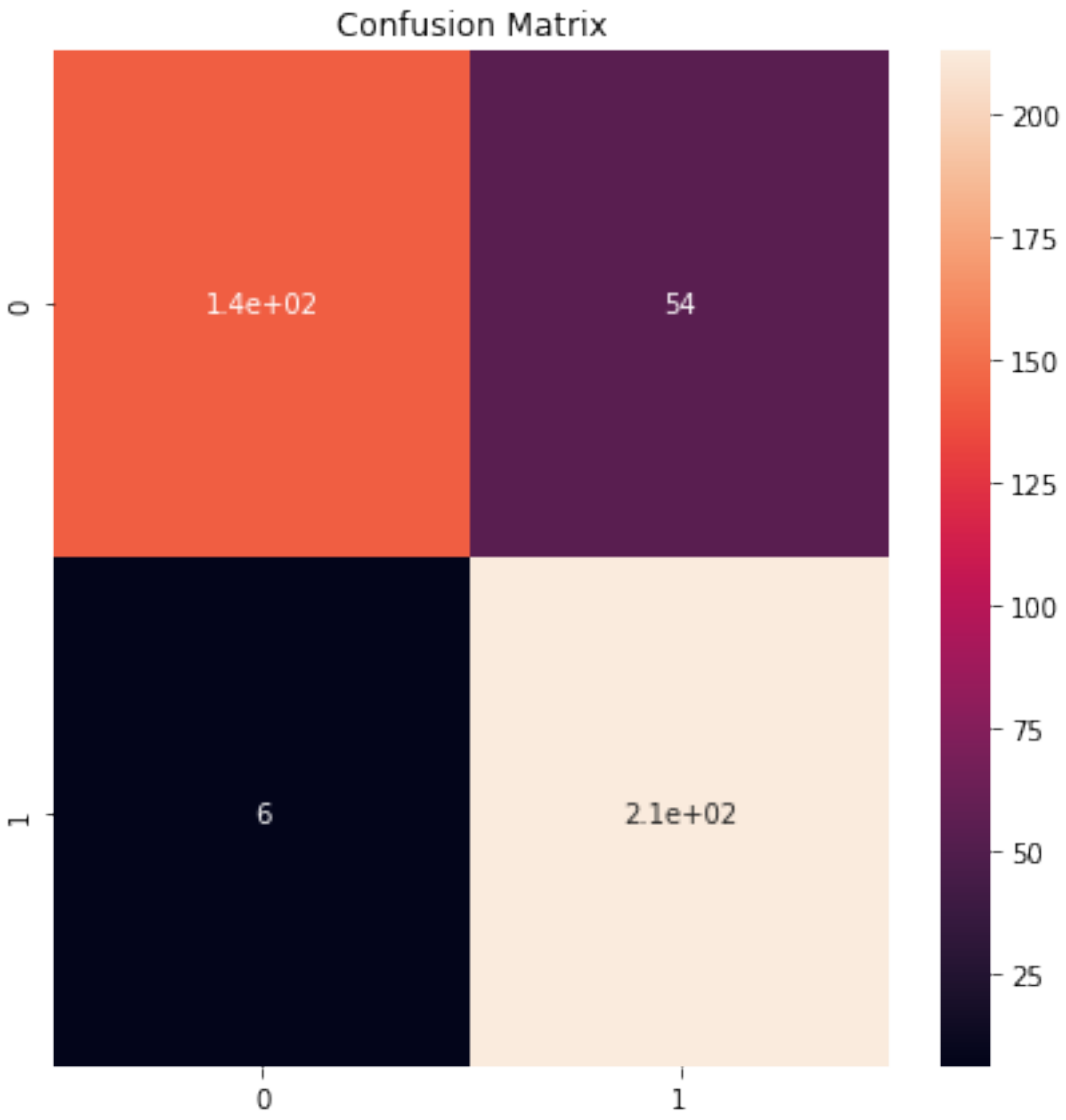
Checking for a low threshold.

We will use a threshold of 0.5 to help us reduce false negatives.

[ ]:
```
predictions = make_predictions(model=model, image_paths=image_paths,␣
↪threshold=0.05)
```

[ ]:
```
cm_and_report(test['mask'], predictions)
```

```
The accuracy of the model is 0.8557692307692307
```



Precision-Recall trade-off report

	precision	recall	f1-score	support
0	0.96	0.73	0.83	197
1	0.80	0.97	0.88	219
accuracy			0.86	416
macro avg	0.88	0.85	0.85	416
weighted avg	0.87	0.86	0.85	416

Thanks to the fact that we can change the threshold, we now have a lower precision, but this, due to the nature of the problem, does not mean a worse result, let's analyze the reports.

- False negatives have been reduced to 6, while false positives increased to 54. This helps us to give a more accurate diagnosis for when we really are in the presence of a tumor, sacrificing those who test positive, but really are not.
- This change translates into the recall of the model for a prediction of 1, where it rises to 97%, a good result.

Let us remember that machine learning models are not 100% accurate, although they can be better than humans, we cannot rule out their experience, which is why a prediction cannot be taken for granted. This talking about problems where health is involved.

4 Training a segmentation model

[ ]:
```
# We obtain the dataframe that contains the magnetic resonances that have␣
↪associated masks.
brain_df_mask = brain_df[brain_df['mask'] == 1]
brain_df_mask.shape
```

[ ]:
```
(1373, 4)
```

[ ]:
```
# Split the data into test and training data
from sklearn.model_selection import train_test_split

X_train, X_val = train_test_split(brain_df_mask, test_size=0.15)
X_test, X_val = train_test_split(X_val, test_size=0.5)
```

[ ]:
```
# Crear una lista separada para imageId, classId y pasarlos al generador
train_ids = list(X_train.image_path)
train_mask = list(X_train.mask_path)

val_ids = list(X_val.image_path)
val_mask= list(X_val.mask_path)
```

[ ]:
```
# Add data/ to the beginning of paths
train_ids = [f'data/{id}' for id in train_ids]
train_mask = [f'data/{id}' for id in train_mask]

val_ids = [f'data/{id}' for id in val_ids]
val_mask = [f'data/{id}' for id in val_mask]
```

The utilities file contains the code for the custom loss function and the custom data generator

[ ]:
```
from utilities import DataGenerator

# We create the image generators
training_generator = DataGenerator(train_ids, train_mask)
```

```
validation_generator = DataGenerator(val_ids, val_mask)
```

[ ]:
```
# Función para escalar y concatenar los valores pasados
def upsample_concat(x, skip):
    '''
    Function to concatenate two layers.
    - This function is used on U-Net architecture
    **Args:**
    - x: Current layer
    - skip: layer to concatenate to the current layer
    **Returns:**
    - merge: The two layers already concatenated
    '''
    x = UpSampling2D((2,2))(x)
    merge = Concatenate()([x, skip])

    return merge
```

Model architecture:

The segmentation model will have an architecture that resembles ResUNet networks, for more information you can consult the corresponding paper

First phase: - A convolution layer with 16 filters, kernel of 3 and padding same, to keep the original size we will use a he-normal kernel initiator. - Batch normalization layer - A second convolution layer with 16 filters, kernel of 3 and padding same, to keep the original size we will use a he-normal kernel initiator. - Batch normalization layer - MaxPooling layer

Second, third, fourth and fifth phase: (Reduction phase) - We will use ResNet blocks for these three phases, with this we seek to reduce the size little by little to deepen with 32, 64, 128 and 256 filters respectively.

Sixth, seventh, eighth and ninth layer: (Rescaling phase) - In these layers we do the opposite of the previous ones, we increase the size of the image until we obtain the original size. We apply 128, 64, 32 and 16 filters respectively. We use the upsample_concat function to join the resblock applied in this stage with its respective reduction stage.

[ ]:
```
input_shape = (256,256,3)

# Input Tensor Shape
X_input = Input(input_shape)

# Phase 1
conv1_in = Conv2D(16,3,activation='relu', padding='same',␣
 ↪kernel_initializer='he_normal')(X_input)
conv1_in = BatchNormalization()(conv1_in)
conv1_in = Conv2D(16,3,activation='relu', padding='same',␣
 ↪kernel_initializer='he_normal')(conv1_in)
conv1_in = BatchNormalization()(conv1_in)
```

```
pool_1 = MaxPooling2D(pool_size=(2,2))(conv1_in)

# Phase 2
conv2_in = resblock(pool_1, 32)
pool_2 = MaxPooling2D(pool_size=(2,2))(conv2_in)

# Phase 3
conv3_in = resblock(pool_2, 64)
pool_3 = MaxPooling2D(pool_size=(2,2))(conv3_in)

# Phase 4
conv4_in = resblock(pool_3, 128)
pool_4 = MaxPooling2D(pool_size=(2,2))(conv4_in)

# Phase 5 (Bottleneck)
conv5_in = resblock(pool_4, 256)

# Escalation Phase 1
up_1 = upsample_concat(conv5_in, conv4_in)
up_1 = resblock(up_1, 128)

# Escalation Phase 2
up_2 = upsample_concat(up_1, conv3_in)
up_2 = resblock(up_2, 64)

# Escalation Phase 3
up_3 = upsample_concat(up_2, conv2_in)
up_3 = resblock(up_3, 32)

# Escalation Phase 4
up_4 = upsample_concat(up_3, conv1_in)
up_4 = resblock(up_4, 16)

# Final Output
output = Conv2D(1, (1,1), padding="same", activation="sigmoid")(up_4)

model_seg = Model(inputs=X_input, outputs=output)

model_seg.summary()
```

```
Model: "model_10"
__________________________________________________________________________________
__________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================
==================
 input_1 (InputLayer)           [(None, 256, 256, 3  0           []
```

```
                                )]

 conv2d_150 (Conv2D)            (None, 256, 256, 16  448
['input_1[0][0]']
                                )

 batch_normalization_150 (Batch  (None, 256, 256, 16  64
['conv2d_150[0][0]']
 Normalization)                 )

 conv2d_151 (Conv2D)            (None, 256, 256, 16  2320
['batch_normalization_150[0][0]']
                                )

 batch_normalization_151 (Batch  (None, 256, 256, 16  64
['conv2d_151[0][0]']
 Normalization)                 )

 max_pooling2d (MaxPooling2D)   (None, 128, 128, 16  0
['batch_normalization_151[0][0]']
                                )

 conv2d_152 (Conv2D)            (None, 128, 128, 32  544
['max_pooling2d[0][0]']
                                )

 batch_normalization_152 (Batch  (None, 128, 128, 32  128
['conv2d_152[0][0]']
 Normalization)                 )

 activation_100 (Activation)    (None, 128, 128, 32  0
['batch_normalization_152[0][0]']
                                )

 conv2d_153 (Conv2D)            (None, 128, 128, 32  9248
['activation_100[0][0]']
                                )

 conv2d_154 (Conv2D)            (None, 128, 128, 32  544
['max_pooling2d[0][0]']
                                )

 batch_normalization_153 (Batch  (None, 128, 128, 32  128
['conv2d_153[0][0]']
 Normalization)                 )

 batch_normalization_154 (Batch  (None, 128, 128, 32  128
['conv2d_154[0][0]']
```

```
 Normalization)                 )

 add_50 (Add)                   (None, 128, 128, 32  0
['batch_normalization_153[0][0]',
                                )
'batch_normalization_154[0][0]']

 activation_101 (Activation)    (None, 128, 128, 32  0
['add_50[0][0]']
                                )

 max_pooling2d_1 (MaxPooling2D)  (None, 64, 64, 32)  0
['activation_101[0][0]']

 conv2d_155 (Conv2D)            (None, 64, 64, 64)   2112
['max_pooling2d_1[0][0]']

 batch_normalization_155 (Batch  (None, 64, 64, 64)  256
['conv2d_155[0][0]']
 Normalization)

 activation_102 (Activation)    (None, 64, 64, 64)   0
['batch_normalization_155[0][0]']

 conv2d_156 (Conv2D)            (None, 64, 64, 64)   36928
['activation_102[0][0]']

 conv2d_157 (Conv2D)            (None, 64, 64, 64)   2112
['max_pooling2d_1[0][0]']

 batch_normalization_156 (Batch  (None, 64, 64, 64)  256
['conv2d_156[0][0]']
 Normalization)

 batch_normalization_157 (Batch  (None, 64, 64, 64)  256
['conv2d_157[0][0]']
 Normalization)

 add_51 (Add)                   (None, 64, 64, 64)   0
['batch_normalization_156[0][0]',
'batch_normalization_157[0][0]']

 activation_103 (Activation)    (None, 64, 64, 64)   0
['add_51[0][0]']

 max_pooling2d_2 (MaxPooling2D)  (None, 32, 32, 64)  0
['activation_103[0][0]']
```

```
 conv2d_158 (Conv2D)            (None, 32, 32, 128)  8320
['max_pooling2d_2[0][0]']

 batch_normalization_158 (Batch  (None, 32, 32, 128)  512
['conv2d_158[0][0]']
 Normalization)

 activation_104 (Activation)    (None, 32, 32, 128)  0
['batch_normalization_158[0][0]']

 conv2d_159 (Conv2D)            (None, 32, 32, 128)  147584
['activation_104[0][0]']

 conv2d_160 (Conv2D)            (None, 32, 32, 128)  8320
['max_pooling2d_2[0][0]']

 batch_normalization_159 (Batch  (None, 32, 32, 128)  512
['conv2d_159[0][0]']
 Normalization)

 batch_normalization_160 (Batch  (None, 32, 32, 128)  512
['conv2d_160[0][0]']
 Normalization)

 add_52 (Add)                   (None, 32, 32, 128)  0
['batch_normalization_159[0][0]',
'batch_normalization_160[0][0]']

 activation_105 (Activation)    (None, 32, 32, 128)  0
['add_52[0][0]']

 max_pooling2d_3 (MaxPooling2D)  (None, 16, 16, 128)  0
['activation_105[0][0]']

 conv2d_161 (Conv2D)            (None, 16, 16, 256)  33024
['max_pooling2d_3[0][0]']

 batch_normalization_161 (Batch  (None, 16, 16, 256)  1024
['conv2d_161[0][0]']
 Normalization)

 activation_106 (Activation)    (None, 16, 16, 256)  0
['batch_normalization_161[0][0]']

 conv2d_162 (Conv2D)            (None, 16, 16, 256)  590080
['activation_106[0][0]']

 conv2d_163 (Conv2D)            (None, 16, 16, 256)  33024
```

```
['max_pooling2d_3[0][0]']

 batch_normalization_162 (Batch  (None, 16, 16, 256)  1024
['conv2d_162[0][0]']
 Normalization)

 batch_normalization_163 (Batch  (None, 16, 16, 256)  1024
['conv2d_163[0][0]']
 Normalization)

 add_53 (Add)                   (None, 16, 16, 256)  0
['batch_normalization_162[0][0]',
'batch_normalization_163[0][0]']

 activation_107 (Activation)    (None, 16, 16, 256)  0
['add_53[0][0]']

 up_sampling2d (UpSampling2D)   (None, 32, 32, 256)  0
['activation_107[0][0]']

 concatenate (Concatenate)      (None, 32, 32, 384)  0
['up_sampling2d[0][0]',
'activation_105[0][0]']

 conv2d_164 (Conv2D)            (None, 32, 32, 128)  49280
['concatenate[0][0]']

 batch_normalization_164 (Batch  (None, 32, 32, 128)  512
['conv2d_164[0][0]']
 Normalization)

 activation_108 (Activation)    (None, 32, 32, 128)  0
['batch_normalization_164[0][0]']

 conv2d_165 (Conv2D)            (None, 32, 32, 128)  147584
['activation_108[0][0]']

 conv2d_166 (Conv2D)            (None, 32, 32, 128)  49280
['concatenate[0][0]']

 batch_normalization_165 (Batch  (None, 32, 32, 128)  512
['conv2d_165[0][0]']
 Normalization)

 batch_normalization_166 (Batch  (None, 32, 32, 128)  512
['conv2d_166[0][0]']
 Normalization)
```

```
 add_54 (Add)                   (None, 32, 32, 128)  0
['batch_normalization_165[0][0]',
'batch_normalization_166[0][0]']

 activation_109 (Activation)    (None, 32, 32, 128)  0
['add_54[0][0]']

 up_sampling2d_1 (UpSampling2D)  (None, 64, 64, 128)  0
['activation_109[0][0]']

 concatenate_1 (Concatenate)    (None, 64, 64, 192)  0
['up_sampling2d_1[0][0]',
'activation_103[0][0]']

 conv2d_167 (Conv2D)            (None, 64, 64, 64)   12352
['concatenate_1[0][0]']

 batch_normalization_167 (Batch  (None, 64, 64, 64)  256
['conv2d_167[0][0]']
 Normalization)

 activation_110 (Activation)    (None, 64, 64, 64)   0
['batch_normalization_167[0][0]']

 conv2d_168 (Conv2D)            (None, 64, 64, 64)   36928
['activation_110[0][0]']

 conv2d_169 (Conv2D)            (None, 64, 64, 64)   12352
['concatenate_1[0][0]']

 batch_normalization_168 (Batch  (None, 64, 64, 64)  256
['conv2d_168[0][0]']
 Normalization)

 batch_normalization_169 (Batch  (None, 64, 64, 64)  256
['conv2d_169[0][0]']
 Normalization)

 add_55 (Add)                   (None, 64, 64, 64)   0
['batch_normalization_168[0][0]',
'batch_normalization_169[0][0]']

 activation_111 (Activation)    (None, 64, 64, 64)   0
['add_55[0][0]']

 up_sampling2d_2 (UpSampling2D)  (None, 128, 128, 64  0
['activation_111[0][0]']
                                )
```

```
 concatenate_2 (Concatenate)    (None, 128, 128, 96  0
['up_sampling2d_2[0][0]',
                                )
'activation_101[0][0]']

 conv2d_170 (Conv2D)            (None, 128, 128, 32  3104
['concatenate_2[0][0]']
                                )

 batch_normalization_170 (Batch  (None, 128, 128, 32  128
['conv2d_170[0][0]']
 Normalization)                 )

 activation_112 (Activation)    (None, 128, 128, 32  0
['batch_normalization_170[0][0]']
                                )

 conv2d_171 (Conv2D)            (None, 128, 128, 32  9248
['activation_112[0][0]']
                                )

 conv2d_172 (Conv2D)            (None, 128, 128, 32  3104
['concatenate_2[0][0]']
                                )

 batch_normalization_171 (Batch  (None, 128, 128, 32  128
['conv2d_171[0][0]']
 Normalization)                 )

 batch_normalization_172 (Batch  (None, 128, 128, 32  128
['conv2d_172[0][0]']
 Normalization)                 )

 add_56 (Add)                   (None, 128, 128, 32  0
['batch_normalization_171[0][0]',
                                )
'batch_normalization_172[0][0]']

 activation_113 (Activation)    (None, 128, 128, 32  0
['add_56[0][0]']
                                )

 up_sampling2d_3 (UpSampling2D)  (None, 256, 256, 32  0
['activation_113[0][0]']
                                )

 concatenate_3 (Concatenate)    (None, 256, 256, 48  0
```

```
['up_sampling2d_3[0][0]',
                                )
'batch_normalization_151[0][0]']

 conv2d_173 (Conv2D)            (None, 256, 256, 16  784
['concatenate_3[0][0]']
                                )

 batch_normalization_173 (Batch  (None, 256, 256, 16  64
['conv2d_173[0][0]']
 Normalization)                 )

 activation_114 (Activation)    (None, 256, 256, 16  0
['batch_normalization_173[0][0]']
                                )

 conv2d_174 (Conv2D)            (None, 256, 256, 16  2320
['activation_114[0][0]']
                                )

 conv2d_175 (Conv2D)            (None, 256, 256, 16  784
['concatenate_3[0][0]']
                                )

 batch_normalization_174 (Batch  (None, 256, 256, 16  64
['conv2d_174[0][0]']
 Normalization)                 )

 batch_normalization_175 (Batch  (None, 256, 256, 16  64
['conv2d_175[0][0]']
 Normalization)                 )

 add_57 (Add)                   (None, 256, 256, 16  0
['batch_normalization_174[0][0]',
                                )
'batch_normalization_175[0][0]']

 activation_115 (Activation)    (None, 256, 256, 16  0
['add_57[0][0]']
                                )

 conv2d_176 (Conv2D)            (None, 256, 256, 1)  17
['activation_115[0][0]']

==================================================================================
==================
Total params: 1,210,513
Trainable params: 1,206,129
```

```
Non-trainable params: 4,384
__________________________________________________________________________________
__________________
```

4.1 Segmentation model training

In a segmentation problem, to evaluate how well the algorithm is learning and to determine the loss, it is necessary to use metrics that help when a dataset is unbalanced, that is, when one category dominates over the others. In our case, the masks are a set of pixels where most of them are 0, and few are 1, or pixels of a different color.

If we use the common metrics, we can fall into the fact that the algorithm does not properly handle false positives and false negatives, giving rise to bad predictions, this is because the algorithm would understand that the probability that a pixel is black (0) is greater. to be of another color (1).

We will use a metric that is based on the Tversky indices, what this metric does is penalize, according to the dataset, the false positives or negatives to maintain a balance of them. For more information, you can consult the paper at this link. https://arxiv.org/pdf/1706.05721v1.pdf

the metrics are implemented in the utilities file that is imported below. All credit for the metrics implemented in Python to Nabs Abraham.

https://github.com/nabsabraham/focal-tversky-unet/blob/master/losses.py

[ ]:
```
from utilities import focal_tversky, tversky_loss, tversky
```

[ ]:
```
# We compile the model
adam = tf.keras.optimizers.Adam(learning_rate=0.01, epsilon=0.1)
model_seg.compile(optimizer=adam, loss=focal_tversky, metrics=[tversky])

# We save the best model with less validation loss
checkpointer_unet = ModelCheckpoint(filepath="ResUNet-weights.hdf5", verbose=1,␣
 ↪save_best_only=True)

history = model_seg.fit(training_generator, epochs=30,␣
 ↪validation_data=validation_generator,
                        callbacks=[checkpointer_unet, lr_scheduler])
```

```
Epoch 1/30
72/72 [==============================] - ETA: 0s - loss: 0.9007 - tversky:
0.1300
Epoch 1: val_loss improved from inf to 0.88962, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 325s 4s/step - loss: 0.9007 - tversky:
0.1300 - val_loss: 0.8896 - val_tversky: 0.1443 - lr: 0.0100
Epoch 2/30
72/72 [==============================] - ETA: 0s - loss: 0.8656 - tversky:
0.1749
Epoch 2: val_loss improved from 0.88962 to 0.85676, saving model to ResUNet-
weights.hdf5
```

```
72/72 [==============================] - 19s 258ms/step - loss: 0.8656 -
tversky: 0.1749 - val_loss: 0.8568 - val_tversky: 0.1861 - lr: 0.0100
Epoch 3/30
72/72 [==============================] - ETA: 0s - loss: 0.8130 - tversky:
0.2409
Epoch 3: val_loss improved from 0.85676 to 0.80934, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 201ms/step - loss: 0.8130 -
tversky: 0.2409 - val_loss: 0.8093 - val_tversky: 0.2457 - lr: 0.0100
Epoch 4/30
72/72 [==============================] - ETA: 0s - loss: 0.6582 - tversky:
0.4256
Epoch 4: val_loss improved from 0.80934 to 0.61161, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 200ms/step - loss: 0.6582 -
tversky: 0.4256 - val_loss: 0.6116 - val_tversky: 0.4793 - lr: 0.0100
Epoch 5/30
72/72 [==============================] - ETA: 0s - loss: 0.4758 - tversky:
0.6262
Epoch 5: val_loss improved from 0.61161 to 0.44084, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 202ms/step - loss: 0.4758 -
tversky: 0.6262 - val_loss: 0.4408 - val_tversky: 0.6632 - lr: 0.0100
Epoch 6/30
72/72 [==============================] - ETA: 0s - loss: 0.4003 - tversky:
0.7033
Epoch 6: val_loss improved from 0.44084 to 0.37734, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 200ms/step - loss: 0.4003 -
tversky: 0.7033 - val_loss: 0.3773 - val_tversky: 0.7242 - lr: 0.0100
Epoch 7/30
72/72 [==============================] - ETA: 0s - loss: 0.3502 - tversky:
0.7516
Epoch 7: val_loss improved from 0.37734 to 0.32640, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 14s 199ms/step - loss: 0.3502 -
tversky: 0.7516 - val_loss: 0.3264 - val_tversky: 0.7741 - lr: 0.0100
Epoch 8/30
72/72 [==============================] - ETA: 0s - loss: 0.3278 - tversky:
0.7724
Epoch 8: val_loss improved from 0.32640 to 0.32231, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 14s 200ms/step - loss: 0.3278 -
tversky: 0.7724 - val_loss: 0.3223 - val_tversky: 0.7777 - lr: 0.0100
Epoch 9/30
72/72 [==============================] - ETA: 0s - loss: 0.3036 - tversky:
0.7944
Epoch 9: val_loss improved from 0.32231 to 0.31322, saving model to ResUNet-
```

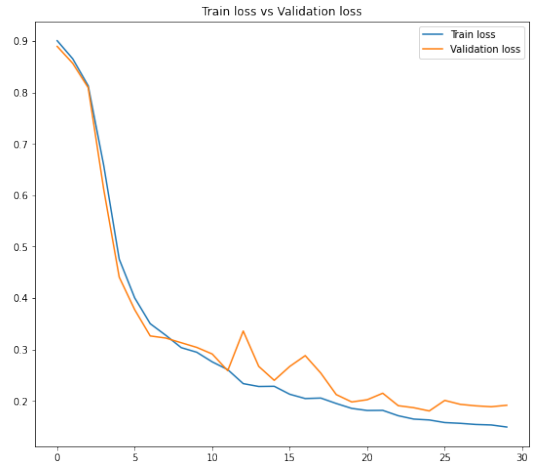
```
weights.hdf5
72/72 [==============================] - 15s 201ms/step - loss: 0.3036 -
tversky: 0.7944 - val_loss: 0.3132 - val_tversky: 0.7858 - lr: 0.0100
Epoch 10/30
72/72 [==============================] - ETA: 0s - loss: 0.2947 - tversky:
0.8024
Epoch 10: val_loss improved from 0.31322 to 0.30413, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 207ms/step - loss: 0.2947 -
tversky: 0.8024 - val_loss: 0.3041 - val_tversky: 0.7933 - lr: 0.0100
Epoch 11/30
72/72 [==============================] - ETA: 0s - loss: 0.2759 - tversky:
0.8188
Epoch 11: val_loss improved from 0.30413 to 0.29125, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 200ms/step - loss: 0.2759 -
tversky: 0.8188 - val_loss: 0.2912 - val_tversky: 0.8043 - lr: 0.0100
Epoch 12/30
72/72 [==============================] - ETA: 0s - loss: 0.2609 - tversky:
0.8321
Epoch 12: val_loss improved from 0.29125 to 0.25883, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 14s 199ms/step - loss: 0.2609 -
tversky: 0.8321 - val_loss: 0.2588 - val_tversky: 0.8341 - lr: 0.0100
Epoch 13/30
72/72 [==============================] - ETA: 0s - loss: 0.2336 - tversky:
0.8555
Epoch 13: val_loss did not improve from 0.25883
72/72 [==============================] - 14s 190ms/step - loss: 0.2336 -
tversky: 0.8555 - val_loss: 0.3359 - val_tversky: 0.7626 - lr: 0.0100
Epoch 14/30
72/72 [==============================] - ETA: 0s - loss: 0.2281 - tversky:
0.8599
Epoch 14: val_loss did not improve from 0.25883
72/72 [==============================] - 14s 190ms/step - loss: 0.2281 -
tversky: 0.8599 - val_loss: 0.2672 - val_tversky: 0.8262 - lr: 0.0100
Epoch 15/30
72/72 [==============================] - ETA: 0s - loss: 0.2284 - tversky:
0.8591
Epoch 15: val_loss improved from 0.25883 to 0.24000, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 202ms/step - loss: 0.2284 -
tversky: 0.8591 - val_loss: 0.2400 - val_tversky: 0.8486 - lr: 0.0100
Epoch 16/30
72/72 [==============================] - ETA: 0s - loss: 0.2130 - tversky:
0.8720
Epoch 16: val_loss did not improve from 0.24000
72/72 [==============================] - 14s 190ms/step - loss: 0.2130 -
```

```
tversky: 0.8720 - val_loss: 0.2671 - val_tversky: 0.8274 - lr: 0.0100
Epoch 17/30
72/72 [==============================] - ETA: 0s - loss: 0.2046 - tversky:
0.8785
Epoch 17: val_loss did not improve from 0.24000
72/72 [==============================] - 14s 190ms/step - loss: 0.2046 -
tversky: 0.8785 - val_loss: 0.2881 - val_tversky: 0.8095 - lr: 0.0100
Epoch 18/30
72/72 [==============================] - ETA: 0s - loss: 0.2056 - tversky:
0.8778
Epoch 18: val_loss did not improve from 0.24000
72/72 [==============================] - 14s 190ms/step - loss: 0.2056 -
tversky: 0.8778 - val_loss: 0.2542 - val_tversky: 0.8375 - lr: 0.0100
Epoch 19/30
72/72 [==============================] - ETA: 0s - loss: 0.1950 - tversky:
0.8863
Epoch 19: val_loss improved from 0.24000 to 0.21230, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 202ms/step - loss: 0.1950 -
tversky: 0.8863 - val_loss: 0.2123 - val_tversky: 0.8732 - lr: 0.0100
Epoch 20/30
72/72 [==============================] - ETA: 0s - loss: 0.1854 - tversky:
0.8936
Epoch 20: val_loss improved from 0.21230 to 0.19797, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 200ms/step - loss: 0.1854 -
tversky: 0.8936 - val_loss: 0.1980 - val_tversky: 0.8844 - lr: 0.0100
Epoch 21/30
72/72 [==============================] - ETA: 0s - loss: 0.1814 - tversky:
0.8967
Epoch 21: val_loss did not improve from 0.19797
72/72 [==============================] - 14s 190ms/step - loss: 0.1814 -
tversky: 0.8967 - val_loss: 0.2023 - val_tversky: 0.8804 - lr: 0.0090
Epoch 22/30
72/72 [==============================] - ETA: 0s - loss: 0.1816 - tversky:
0.8964
Epoch 22: val_loss did not improve from 0.19797
72/72 [==============================] - 14s 190ms/step - loss: 0.1816 -
tversky: 0.8964 - val_loss: 0.2150 - val_tversky: 0.8704 - lr: 0.0082
Epoch 23/30
72/72 [==============================] - ETA: 0s - loss: 0.1712 - tversky:
0.9044
Epoch 23: val_loss improved from 0.19797 to 0.19072, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 202ms/step - loss: 0.1712 -
tversky: 0.9044 - val_loss: 0.1907 - val_tversky: 0.8897 - lr: 0.0074
Epoch 24/30
72/72 [==============================] - ETA: 0s - loss: 0.1646 - tversky:
```

```
0.9092
Epoch 24: val_loss improved from 0.19072 to 0.18679, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 201ms/step - loss: 0.1646 -
tversky: 0.9092 - val_loss: 0.1868 - val_tversky: 0.8922 - lr: 0.0067
Epoch 25/30
72/72 [==============================] - ETA: 0s - loss: 0.1629 - tversky:
0.9105
Epoch 25: val_loss improved from 0.18679 to 0.18047, saving model to ResUNet-
weights.hdf5
72/72 [==============================] - 15s 200ms/step - loss: 0.1629 -
tversky: 0.9105 - val_loss: 0.1805 - val_tversky: 0.8976 - lr: 0.0061
Epoch 26/30
72/72 [==============================] - ETA: 0s - loss: 0.1579 - tversky:
0.9142
Epoch 26: val_loss did not improve from 0.18047
72/72 [==============================] - 14s 190ms/step - loss: 0.1579 -
tversky: 0.9142 - val_loss: 0.2010 - val_tversky: 0.8820 - lr: 0.0055
Epoch 27/30
72/72 [==============================] - ETA: 0s - loss: 0.1564 - tversky:
0.9152
Epoch 27: val_loss did not improve from 0.18047
72/72 [==============================] - 14s 190ms/step - loss: 0.1564 -
tversky: 0.9152 - val_loss: 0.1934 - val_tversky: 0.8875 - lr: 0.0050
Epoch 28/30
72/72 [==============================] - ETA: 0s - loss: 0.1542 - tversky:
0.9167
Epoch 28: val_loss did not improve from 0.18047
72/72 [==============================] - 14s 190ms/step - loss: 0.1542 -
tversky: 0.9167 - val_loss: 0.1904 - val_tversky: 0.8894 - lr: 0.0045
Epoch 29/30
72/72 [==============================] - ETA: 0s - loss: 0.1532 - tversky:
0.9174
Epoch 29: val_loss did not improve from 0.18047
72/72 [==============================] - 14s 191ms/step - loss: 0.1532 -
tversky: 0.9174 - val_loss: 0.1887 - val_tversky: 0.8909 - lr: 0.0041
Epoch 30/30
72/72 [==============================] - ETA: 0s - loss: 0.1492 - tversky:
0.9205
Epoch 30: val_loss did not improve from 0.18047
72/72 [==============================] - 14s 192ms/step - loss: 0.1492 -
tversky: 0.9205 - val_loss: 0.1916 - val_tversky: 0.8887 - lr: 0.0037
```

A visual aid to be able to really observe what is happening with our model, how it learns and its behavior.

[ ]:
```
plot_metrics(history.history)
```



Conclusions:

- We can see how our model learns until it reaches 90% accuracy, we see this trend in the validation set.
- In the graph on the right we see how the loss decreases from season to season in both data sets.

[ ]:
```
# We save the architecture of the model in a json file for future use
model_json = model_seg.to_json()
with open("ResUNet-model.json","w") as json_file:
    json_file.write(model_json)
```

4.2 Evaluación del modelo

[ ]:
```
from utilities import focal_tversky, tversky_loss, tversky

with open('ResUNet-model.json', 'r') as json_file:
    json_savedModel= json_file.read()

model_seg = tf.keras.models.model_from_json(json_savedModel)
model_seg.load_weights('ResUNet-weights.hdf5')
adam = tf.keras.optimizers.Adam(learning_rate=0.01, epsilon=0.1)
model_seg.compile(optimizer=adam, loss =focal_tversky, metrics=[tversky])
```

[ ]:
```
# We add /data to the path
test_df = test.copy()
test_df['image_path'] = test_df['image_path'].apply(lambda x: f'data/{x}')
test_df['mask_path'] = test_df['mask_path'].apply(lambda x: f'data/{x}')
test_df.head()
```

[ ]:
```
      level_0  index                                          image_path  \
231      2242   3534  data/TCGA_DU_7008_19830723/TCGA_DU_7008_198307…
1137      206    206  data/TCGA_HT_A61B_19991127/TCGA_HT_A61B_199911…
1303     1014   1095  data/TCGA_DU_7304_19930325/TCGA_DU_7304_199303…
29       1464   1939  data/TCGA_HT_7602_19951103/TCGA_HT_7602_199511…
450      2409   3776  data/TCGA_DU_6407_19860514/TCGA_DU_6407_198605…

                                              mask_path mask
231   data/TCGA_DU_7008_19830723/TCGA_DU_7008_198307…    0
1137  data/TCGA_HT_A61B_19991127/TCGA_HT_A61B_199911…    0
1303  data/TCGA_DU_7304_19930325/TCGA_DU_7304_199303…    0
29    data/TCGA_HT_7602_19951103/TCGA_HT_7602_199511…    0
450   data/TCGA_DU_6407_19860514/TCGA_DU_6407_198605…    0
```

[ ]:
```
def predictions_2_models(model, seg_model, image_paths, threshold=0.5):
    '''
    Funtion to make predictions according the classification model already␣
↪trained.
    **Args**:
    * model: Clasification model already trained
    * seg_model: Segmentation model already trained
    * image_paths: The path where the images are saved,
    * threshold: For binary classification models, threshold to be take in care␣
↪to decide if
    a prediction is 1 or 0.
    **Returs**:
    It returns a list of prediction, 0 or 1 in string format due flow from␣
↪dataset test_generator
    '''
    mask = []
    has_mask = []
    image_id = []
    count = 0
    for path in image_paths:
        # We read the image and normalize its values
        img = io.imread('./data/{}'.format(path))
        img = img / 255.
        # We transform the image to a tensor of the form [m, h, w, c]
        img = tf.reshape(img, shape=[1, img.shape[0], img.shape[1], img.
↪shape[2]])
        # Prediction
        pred = model.predict(img)
        # We keep 0 or 1 according to probability.
    if pred[0][0] <= threshold:
        image_id.append(count)
        has_mask.append(0)
        mask.append('No mask')
```

```
        count += 1
        continue

        # Read the image
        img = io.imread('./data/{}'.format(path))

        # Creating a empty array of shape 1,256,256,1
        X = np.empty((1, 256, 256, 3))

        # Resizing the image and coverting them to array of type float64
        img = cv2.resize(img,(256,256))
        img = np.array(img, dtype = np.float64)

        # Standardising the image
        img -= img.mean()
        img /= img.std()

        # Converting the shape of image from 256,256,3 to 1,256,256,3
        X[0,] = img

        #make prediction
        predict = model_seg.predict(X)

        # If the sum of predicted values is equal to 0 then there is no tumour
        if predict.round().astype(int).sum() == 0:
            image_id.append(count)
            has_mask.append(0)
            mask.append('No mask')
        else:
        # If the sum of pixel values are more than 0, then there is tumour
            image_id.append(count)
            has_mask.append(1)
            mask.append(predict)

        count += 1

    return image_id, mask, has_mask
```

[ ]:
```
df_test = test[['image_path', 'mask_path', 'mask']].reset_index()
image_paths = df['image_path'].to_list()
```

We have already trained both models, now we can evaluate with the test set how our model works.

1. We will pass the images through the classification model, this will help us determine whether or not there is a tumor.
2. If there is a tumor, that image is passed to the segmentation model, which is in charge of predicting the mask trying to find the location of the tumor.

```
[ ]: image_id, mask, has_mask = predictions_2_models(model_res, model_seg,␣
     ↪image_paths, threshold=0.5)
```

```
[ ]: # We create the dataframe for the result
     df_pred = pd.DataFrame({'image_path': image_paths,
                             'mask_path' : df_test['mask_path'].to_list(),
                             'predicted_mask': mask,
                             'has_mask': has_mask})
     df_pred.head()
```

```
[ ]:                                           image_path  \
     0  TCGA_DU_7008_19830723/TCGA_DU_7008_19830723_44…
     1  TCGA_HT_A61B_19991127/TCGA_HT_A61B_19991127_2.tif
     2  TCGA_DU_7304_19930325/TCGA_DU_7304_19930325_10…
     3  TCGA_HT_7602_19951103/TCGA_HT_7602_19951103_18…
     4  TCGA_DU_6407_19860514/TCGA_DU_6407_19860514_56…

                                            mask_path  \
     0  TCGA_DU_7008_19830723/TCGA_DU_7008_19830723_44…
     1  TCGA_HT_A61B_19991127/TCGA_HT_A61B_19991127_2_…
     2  TCGA_DU_7304_19930325/TCGA_DU_7304_19930325_10…
     3  TCGA_HT_7602_19951103/TCGA_HT_7602_19951103_18…
     4  TCGA_DU_6407_19860514/TCGA_DU_6407_19860514_56…

                                       predicted_mask  has_mask
     0                                        No mask         0
     1                                        No mask         0
     2                                        No mask         0
     3  [[[[7.03549e-05], [9.556252e-05], [0.00014688]…         1
     4                                        No mask         0
```

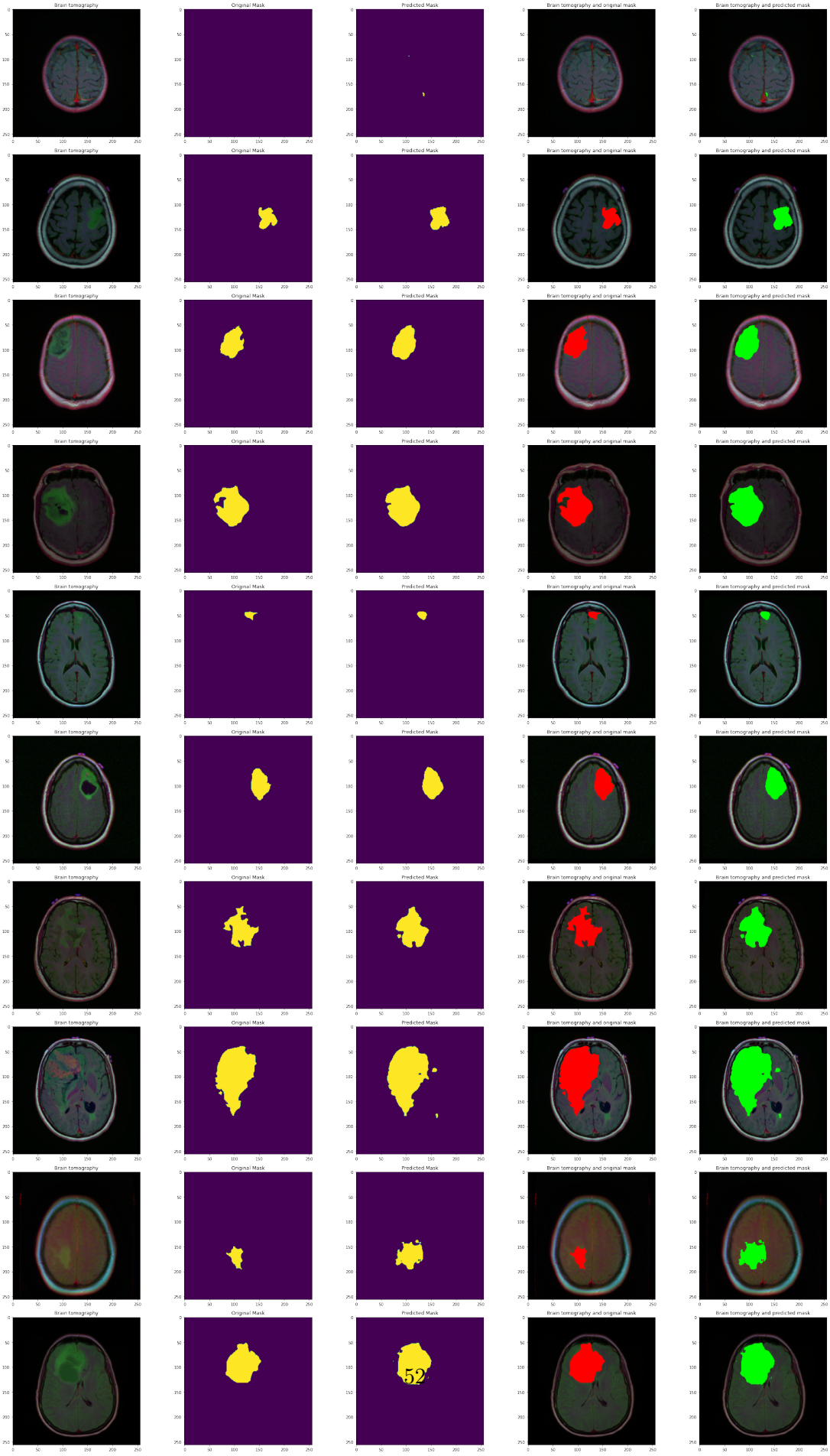
For better understanding we will draw some images where:

- We will visualize the original image of the magnetic resonance.
- We will display the mask for that image and overlay it on the resonance.
- We will do the same, but with the mask that our model predicted.

Visually we will be able to corroborate how well our model can locate brain tumors.

```
[ ]: count = 0
     fig, axs = plt.subplots(10, 5, figsize=(30, 50))
     for i in range(len(df_pred)):
         if df_pred['has_mask'][i] == 1 and count < 10:
         # Read the images and convert them to RGB format
         img = io.imread(f'./data/{df_pred.image_path[i]}')
         img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
         axs[count][0].title.set_text("Brain resonance")
         axs[count][0].imshow(img)
```

```
    # We get the mask for the image
    mask = io.imread(f'./data/{df_pred.mask_path[i]}')
    axs[count][1].title.set_text("Original Mask")
    axs[count][1].imshow(mask)

    # We obtain the prediction mask for said image
    predicted_mask = np.asarray(df_pred.predicted_mask[i])[0].squeeze().round()
    axs[count][2].title.set_text("Predicted Mask")
    axs[count][2].imshow(predicted_mask)

    # We apply the mask to the image 'mask==255'
    img[mask == 255] = (255, 0, 0)
    axs[count][3].title.set_text("Brain resonance and original mask")
    axs[count][3].imshow(img)

    img_ = io.imread(f'./data/{df_pred.image_path[i]}')
    img_ = cv2.cvtColor(img_, cv2.COLOR_BGR2RGB)
    img_[predicted_mask == 1] = (0, 255, 0)
    axs[count][4].title.set_text("Brain resonance and predicted mask")
    axs[count][4].imshow(img_)
    count += 1

fig.tight_layout()
```


Brain tomography
Original Mask
Predicted Mask
Brain tomography and original mask
Brain tomography and predicted mask

Conclusions:

We can now see how both models work together to reach a result.

1. The first model predicts the presence of tumor.
2. The second model predicts, by means of a mask, its location.

Thanks to the progress of this type of algorithm, we can diagnose the presence of abnormalities in the human body early, this will help to apply early treatment.