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Momento de Retroalimentación: Módulo 2 Implementación de un modelo de deep learning. (Portafolio Implementación)

Introducción

En el campo de la medicina, la detección temprana y precisa de tumores cerebrales es un desafío crítico. Exsite una gran dificultad en la clasificación precisa de tumores cerebrales, esto ha llevado al desarrollo de sistemas y técnicas más avanzadas y precisas. Con esto en mente, las redes neuronales se presentan como una herramienta con gran potencial para la identificación y clasificación de estos tumores.

La relevancia del proyecto nace de la capacidad de mejorar la precisión de diagnóstico de tumores cerebrales, lo que puede conducir a tratamientos más tempranos y, en consecuencia, más eficaces. La tardanza en la detección de tumores en general generalmente resulta en un tratamiento inadecuado y un pronóstico menos favorable para el paciente. Por tanto, el desarrollo de un modelo capaz de distinguir entre cerebros sanos y cerebros con tumores es importante en el área medica y puede marcar una diferencia en la vida de los pacientes.

Descarga del dataset y preparación de los conjuntos

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import zipfile
import random
import matplotlib.image as mpimg
```

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import binary_crossentropy, categorical_crossentropy
from tensorflow.keras.metrics import F1Score
from sklearn.metrics import f1_score
from tensorflow.keras.layers import Dropout
from tensorflow.keras.callbacks import EarlyStopping

```

```
#Configuración del acceso a kaggle para descargar el dataset
!mkdir -p /root/.kaggle
!cp "/content/drive/MyDrive/7 Semestre/Parte 2/Blumenkron/kaggle.json" /root/.kaggle/
```

```
#Descarga y descompresión del dataset
!kaggle datasets download -d preetviradiya/brian-tumor-dataset
path = "/content/brian-tumor-dataset.zip"
with zipfile.ZipFile(path, 'r') as zip_ref:
    zip_ref.extractall("/content/" )
```

```
brian-tumor-dataset.zip: Skipping, found more recently modified local copy (use --force to force download)
```

```
#Imprimir imagenes aleatorias de cada directorio/categoría
image = random.choice(os.listdir('/content/Brain Tumor Data Set/Brain Tumor Data Set/Brain Tumor'))
image=os.path.join('/content/Brain Tumor Data Set/Brain Tumor Data Set/Brain Tumor', image)
img = mpimg.imread(image)
plt.imshow(img)
plt.axis('off')
plt.title('Imagen aleatoria del subconjunto con tumor')
plt.show()

```

```
image = random.choice(os.listdir('/content/Brain Tumor Data Set/Brain Tumor Data Set/Healthy'))
image=os.path.join('/content/Brain Tumor Data Set/Brain Tumor Data Set/Healthy', image)
img = mpimg.imread(image)
plt.imshow(img)
plt.title('Imagen aleatoria del subconjunto sano')
plt.axis('off')
plt.show()
```


```
#Se usa la liberia de split-folders para hacer la división de conjuntos en
#entrenamiento, validación y prueba
!pip install split-folders
!split-folders '/content/Brain Tumor Data Set/Brain Tumor Data Set' --output train_data --ratio 0.7 0.3 --seed
!split-folders '/content/train_data/val' --output test_val_data --ratio 0.5 0.5 --seed 6


```

```
Requirement already satisfied: split-folders in /usr/local/lib/python3.10/dist-packages (0.5.1)
Copying files: 4600 files [00:00, 5038.13 files/s]
Copying files: 1381 files [00:00, 4107.46 files/s]
```

```
#Uso de herramientas de keras para crear los dataset de entrenamiento, validación y prueba desde los directori
train_dir = '/content/train_data/train'
val_dir = '/content/test_val_data/val'
test_dir = '/content/test_val_data/train'
batch_size = 32  # Tamaño del lote
image_size = (256, 256)  # Tamaño de las imágenes
# Carga de datos de entrenamiento desde el directorio
train = tf.keras.utils.image_dataset_from_directory(
    train_dir,
```

```
    image_size=image_size,
    batch_size=batch_size,
    shuffle=True,
    seed=6,label_mode='binary', labels='inferred'
)
val = tf.keras.utils.image_dataset_from_directory(
    val_dir,
    image_size=image_size,
    batch_size=batch_size,
    shuffle=True,
    seed=6, label_mode='binary', labels='inferred'
)

test = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=image_size,
    batch_size=batch_size,
    shuffle=True,
    seed=6, label_mode='binary', labels='inferred'
)

# Visualización de las clases para confirmar que se crearon correctamente los datasets
class_names, val_classes, test_classes = train.class_names, val.class_names, test.class_names
print("Clases:", class_names, val_classes, test_classes)
```

```
Found 3161 files belonging to 2 classes.
Found 676 files belonging to 2 classes.
Found 677 files belonging to 2 classes.
Clases: ['Brain Tumor', 'Healthy'] ['Brain Tumor', 'Healthy'] ['Brain Tumor', 'Healthy']
```

Primer modelo (Arquitectura de CNN básica)

Para la red neuronal, dada la problematica basada en la clasificación de imagenes se decidio usar una red neuronal convoluciones, ya que este tipo de arquitecturas son especialmente útiles para reconocer patrones en imágenes. Primero se decidió crear un modelo con una arquitectura sencilla, con hiperparametros base para tener una base sobre la cual trabajar y poder mejorar la red posteriormente utilizando técnicas de regularización, modificación de la estructura o usando hiperparametros.

Se creó un modelo secuencial, la primera capa es una capa de convolución a la que se le indica el tamaño de entrada de la imagen, por comodidad se usaran potencias de 2 en el número de neuronas en las capa de convolución y densa. Después de las capas de convolución se utilizan capas de pooling para reducir la dimensionalidad y controlar el número de parámetros a entrenar

```
#Primera versión del modelo con una arquitectura básica
model = Sequential(name='BrainTumorDetector')
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

```
model.summary()
```

```
Model: "BrainTumorDetector"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 254, 254, 32)      896

 max_pooling2d_2 (MaxPoolin  (None, 127, 127, 32)      0
 g2D)

 conv2d_3 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_3 (MaxPoolin  (None, 62, 62, 64)        0
 g2D)

 flatten_1 (Flatten)         (None, 246016)            0
```

```
 dense_2 (Dense)             (None, 128)               31490176

 dense_3 (Dense)             (None, 1)                 129

=================================================================
Total params: 31509697 (120.20 MB)
Trainable params: 31509697 (120.20 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Además, usaremos el optimizador Adam con parametros default, como función de pérdida usaremos binary_crossentropy y para evaluar la red usaremos la métrica F1, que es muy comunmente usada en este tipo de problemas ya que es sumamanete importante clasificar correctamente, tanto positivos como negativos.

Usaremos 30 epocas para entrenar la red y evaluaremos su desemepeño al final del entrenamiento

```
optimizer = Adam()
loss = binary_crossentropy
metric = F1Score(threshold=0.5)
#metrics = CategoricalAccuracy()
model.compile(optimizer=optimizer, loss=loss, metrics=metric)
```

```
history = model.fit(train, epochs=30,validation_data=val)
```

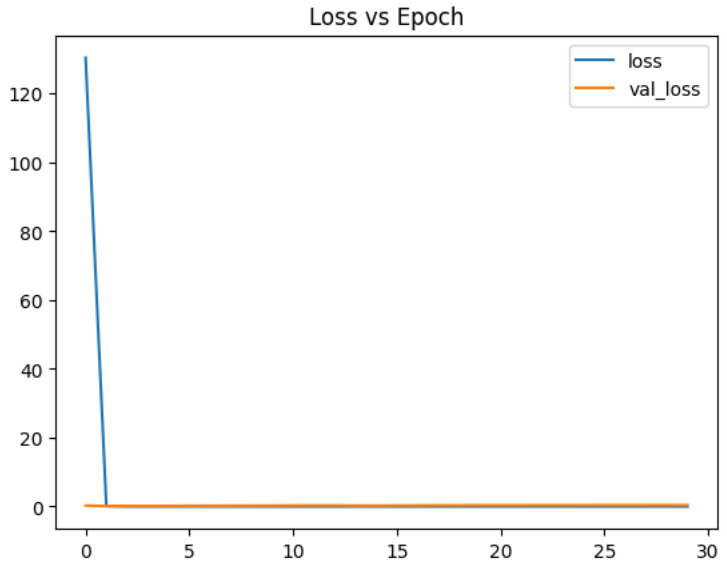
```
Epoch 2/30
99/99 [==============================] - 15s 143ms/step - loss: 0.1088 - f1_score: 0.9639 - val_loss: 0.1510 - val_f1_score:
Epoch 3/30
99/99 [==============================] - 8s 73ms/step - loss: 0.0256 - f1_score: 0.9945 - val_loss: 0.1609 - val_f1_score: 0
Epoch 4/30
99/99 [==============================] - 10s 93ms/step - loss: 0.0080 - f1_score: 0.9983 - val_loss: 0.1686 - val_f1_score:
Epoch 5/30
99/99 [==============================] - 9s 89ms/step - loss: 0.0025 - f1_score: 1.0000 - val_loss: 0.1774 - val_f1_score: 0
Epoch 6/30
99/99 [==============================] - 9s 85ms/step - loss: 7.0181e-04 - f1_score: 1.0000 - val_loss: 0.2019 - val_f1_scor
Epoch 7/30
99/99 [==============================] - 9s 91ms/step - loss: 3.0936e-04 - f1_score: 1.0000 - val_loss: 0.2201 - val_f1_scor
Epoch 8/30
99/99 [==============================] - 8s 72ms/step - loss: 1.7276e-04 - f1_score: 1.0000 - val_loss: 0.2400 - val_f1_scor
Epoch 9/30
99/99 [==============================] - 11s 108ms/step - loss: 1.1315e-04 - f1_score: 1.0000 - val_loss: 0.2498 - val_f1_sc
Epoch 10/30
99/99 [==============================] - 8s 74ms/step - loss: 7.4219e-05 - f1_score: 1.0000 - val_loss: 0.2653 - val_f1_scor
Epoch 11/30
99/99 [==============================] - 10s 95ms/step - loss: 4.9376e-05 - f1_score: 1.0000 - val_loss: 0.2965 - val_f1_sco
Epoch 12/30
99/99 [==============================] - 7s 72ms/step - loss: 3.2916e-05 - f1_score: 1.0000 - val_loss: 0.3148 - val_f1_scor
Epoch 13/30
99/99 [==============================] - 10s 95ms/step - loss: 2.1885e-05 - f1_score: 1.0000 - val_loss: 0.3103 - val_f1_sco
Epoch 14/30
99/99 [==============================] - 8s 74ms/step - loss: 3.5123e-05 - f1_score: 1.0000 - val_loss: 0.2652 - val_f1_scor
Epoch 15/30
99/99 [==============================] - 10s 95ms/step - loss: 3.9670e-05 - f1_score: 1.0000 - val_loss: 0.2549 - val_f1_sco
Epoch 16/30
99/99 [==============================] - 8s 75ms/step - loss: 1.6905e-05 - f1_score: 1.0000 - val_loss: 0.2946 - val_f1_scor
Epoch 17/30
99/99 [==============================] - 10s 98ms/step - loss: 1.0118e-05 - f1_score: 1.0000 - val_loss: 0.3149 - val_f1_sco
Epoch 18/30
99/99 [==============================] - 8s 74ms/step - loss: 6.6129e-06 - f1_score: 1.0000 - val_loss: 0.3377 - val_f1_scor
Epoch 19/30
99/99 [==============================] - 10s 97ms/step - loss: 4.7390e-06 - f1_score: 1.0000 - val_loss: 0.3498 - val_f1_sco
Epoch 20/30
99/99 [==============================] - 8s 74ms/step - loss: 3.5231e-06 - f1_score: 1.0000 - val_loss: 0.3619 - val_f1_scor
Epoch 21/30
99/99 [==============================] - 10s 96ms/step - loss: 2.6370e-06 - f1_score: 1.0000 - val_loss: 0.3702 - val_f1_sco
Epoch 22/30
99/99 [==============================] - 8s 76ms/step - loss: 2.1184e-06 - f1_score: 1.0000 - val_loss: 0.3714 - val_f1_scor
Epoch 23/30
99/99 [==============================] - 10s 93ms/step - loss: 1.7168e-06 - f1_score: 1.0000 - val_loss: 0.3779 - val_f1_sco
Epoch 24/30
99/99 [==============================] - 9s 90ms/step - loss: 1.4264e-06 - f1_score: 1.0000 - val_loss: 0.3832 - val_f1_scor
Epoch 25/30
99/99 [==============================] - 9s 81ms/step - loss: 1.1843e-06 - f1_score: 1.0000 - val_loss: 0.3878 - val_f1_scor
Epoch 26/30
99/99 [==============================] - 10s 97ms/step - loss: 9.9980e-07 - f1_score: 1.0000 - val_loss: 0.3930 - val_f1_sco
Epoch 27/30
99/99 [==============================] - 8s 74ms/step - loss: 8.6130e-07 - f1_score: 1.0000 - val_loss: 0.3946 - val_f1_scor
```

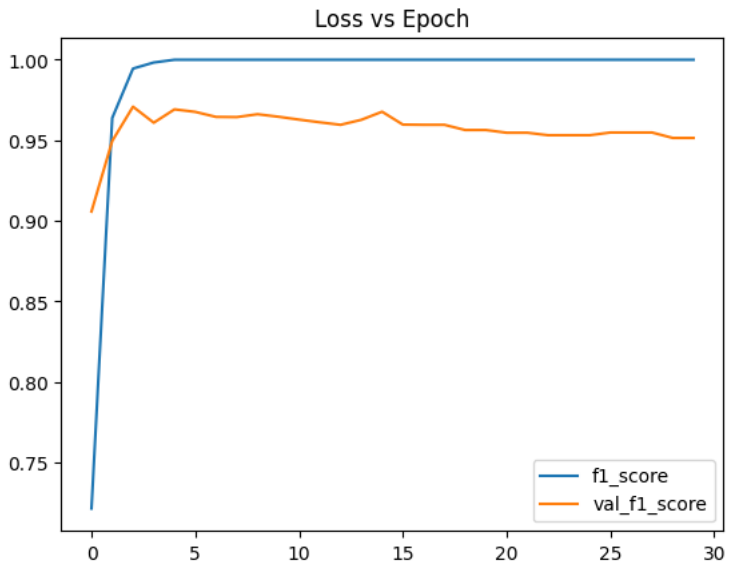
```
Epoch 29/30
99/99 [==============================] - 9s 90ms/step - loss: 6.4847e-07 - f1_score: 1.0000 - val_loss: 0.4004 - val_f1_scor
Epoch 30/30
99/99 [==============================] - 9s 83ms/step - loss: 5.7088e-07 - f1_score: 1.0000 - val_loss: 0.4053 - val_f1_scor
```

Gráficando el historial de entrenamiento de la red podemos observar que tiene un aprendizaje rápido y solo existe perdida significativa del modelo en la primera epoca, sin embargo la perdida significativa solo existe en el conjunto de entrenamiento. En cuanto a la métrica de evaluación F1 Score observamos que se observa una mejoríaen el desempeño del modelo de manera rápida y el modelo converge poco después de 5 épocas. Sin embargo, observamos que el modelo llega al 100% en el F1 Score, algo bastante inusual en este tipo de problemas. A continuación usaremos el conjunto de prueba para poder llegar a conclusiones finales sobre el modelo

```
df = pd.DataFrame(history.history)
df['f1_score'] = df['f1_score'].apply(lambda x: x[0])
df['val_f1_score'] = df['val_f1_score'].apply(lambda x: x[0])
df.plot(y=["loss", "val_loss"], title="Loss vs Epoch")
df.plot(y=["f1_score", "val_f1_score"], title="Loss vs Epoch")
```

```
<Axes: title={'center': 'Loss vs Epoch'}>
```





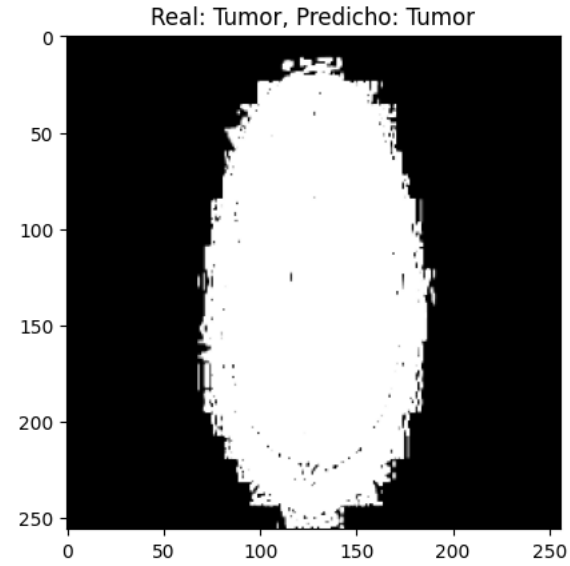
Resultados en el conjunto de prueba

```
images = []
true_labels = []
predicted_labels = []
for x, y in test:
    predictions = model.predict(x)
    images.extend(x)
```

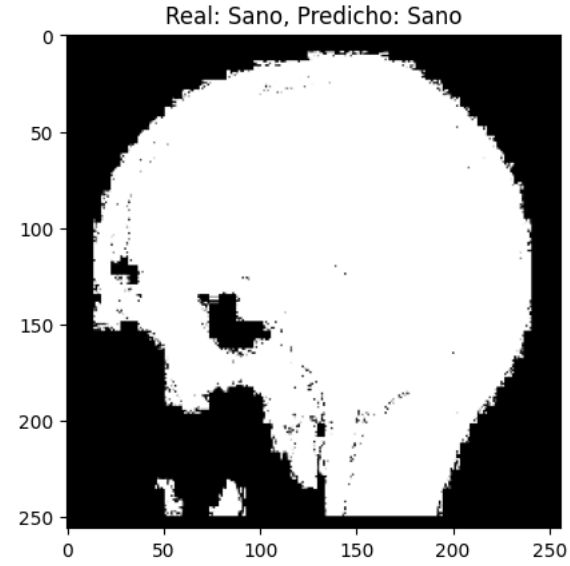
```
    true_labels.extend(y)
    predicted_labels.extend(predictions)

true_binary_labels = [1 if label[0] == 1 else 0 for label in true_labels]
predicted_binary_labels = [1 if label[0] >= 0.5 else 0 for label in predicted_labels]
f1 = f1_score(true_binary_labels, predicted_binary_labels)
print(f'F1-score en el conjunto de prueba: {f1:.2f}')
for i in range(5):
    image = images[i]
    true_label = true_labels[i]
    predicted_label = predicted_labels[i]
    true_class = 'Tumor' if true_label[0] == 1 else 'Sano'
    predicted_class = 'Tumor' if predicted_label[0] >= 0.5 else 'Sano'
    plt.imshow(image)
    plt.title(f'Real: {true_class}, Predicho: {predicted_class}')
    plt.show()
```

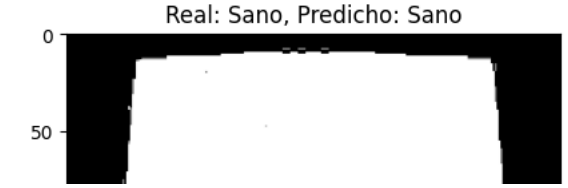
```
1/1 [==============================] - 0s 98ms/step
1/1 [==============================] - 0s 63ms/step
1/1 [==============================] - 0s 43ms/step
1/1 [==============================] - 0s 43ms/step
1/1 [==============================] - 0s 54ms/step
1/1 [==============================] - 0s 51ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 42ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 35ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 57ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 45ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 93ms/step
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for
F1-score en el conjunto de prueba: 0.98
```




```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for
```




```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for
```



Depués de realizar predicciones y evaluar el conjunto de prueba llegamos a la conclusión de que, efectivamente el modelo tiene un buen desempeño con puntajes de 100%, 96% y 95% en los conjuntos de entrenamiento, validación y prueba respectivamente. Podemos considerar que tiene un comportamiento inusual por el puntaje perfecto en el conjunto de entrenamiento ya que por la naturaleza del problema esto no debería ser posible, podemos considerar un mínimo overfitting en el modelo,por esto para mejorar el modelo vamos a agregar herramientas contra el overfitting, modificaciones en el learning rate y evitaremos que se sobreentrene si se alcanza convergencia.

Modelo mejorado

Después de iterar por varios modelos, agregando capas de batch normalziation, dropout, cambios en el optimizador e incluso cambios completos de la arquitectura de la red se llegó a este modelo como una mejor propuesta. Este modelo agrega una capa de dropout como herramienta para combatir el overfitting e incluye early stopping monitoreando la perdida en el conjunto de validación.

```
tf.keras.backend.clear_session()

model = Sequential(name='BrainTumorDetectorUpdated')
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))
```

```
model.summary()
```

```
Model: "BrainTumorDetectorUpdated"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 254, 254, 32)      896

 max_pooling2d (MaxPooling2  (None, 127, 127, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 62, 62, 64)        0
 g2D)

 flatten (Flatten)           (None, 246016)            0

 dense (Dense)               (None, 128)               31490176

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 31509697 (120.20 MB)
Trainable params: 31509697 (120.20 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
optimizer = Adam(learning_rate=0.001)
loss = binary_crossentropy
metric = F1Score(threshold=0.5)
model.compile(optimizer=optimizer, loss=loss, metrics=metric)
early_stopping = EarlyStopping(monitor='val_loss',
                               patience=5,
                               restore_best_weights=True)
```

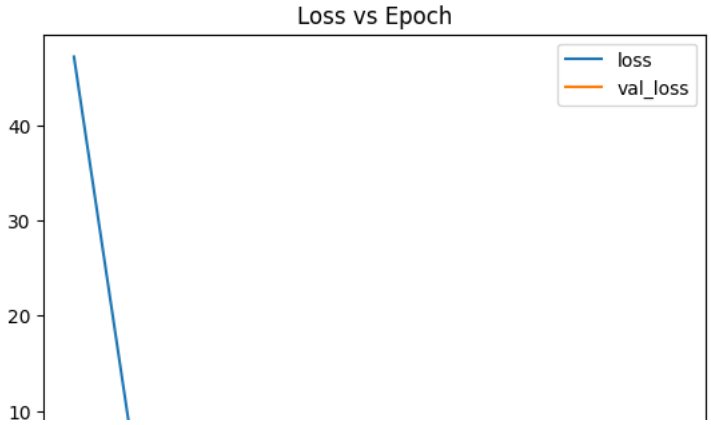
```
history = model.fit(train, epochs=30,validation_data=val,callbacks=early_stopping)
```

```
Epoch 1/30
99/99 [==============================] - 12s 100ms/step - loss: 90.0445 - f1_score: 0.6548 - val_loss: 0.3872 - val_f1_score
Epoch 2/30
99/99 [==============================] - 9s 82ms/step - loss: 0.3312 - f1_score: 0.8538 - val_loss: 0.2739 - val_f1_score: 0
Epoch 3/30
99/99 [==============================] - 10s 100ms/step - loss: 0.2144 - f1_score: 0.9187 - val_loss: 0.2303 - val_f1_score:
Epoch 4/30
99/99 [==============================] - 8s 76ms/step - loss: 0.1367 - f1_score: 0.9468 - val_loss: 0.1662 - val_f1_score: 0
Epoch 5/30
99/99 [==============================] - 10s 95ms/step - loss: 0.1180 - f1_score: 0.9573 - val_loss: 0.1718 - val_f1_score:
Epoch 6/30
99/99 [==============================] - 8s 73ms/step - loss: 0.0777 - f1_score: 0.9738 - val_loss: 0.1575 - val_f1_score: 0
Epoch 7/30
99/99 [==============================] - 10s 97ms/step - loss: 0.0765 - f1_score: 0.9684 - val_loss: 0.1553 - val_f1_score:
Epoch 8/30
99/99 [==============================] - 8s 74ms/step - loss: 0.0640 - f1_score: 0.9805 - val_loss: 0.1412 - val_f1_score: 0
Epoch 9/30
99/99 [==============================] - 10s 97ms/step - loss: 0.0486 - f1_score: 0.9802 - val_loss: 0.1605 - val_f1_score:
Epoch 10/30
99/99 [==============================] - 8s 73ms/step - loss: 0.0415 - f1_score: 0.9812 - val_loss: 0.2393 - val_f1_score: 0
Epoch 11/30
99/99 [==============================] - 10s 97ms/step - loss: 0.0572 - f1_score: 0.9806 - val_loss: 0.1270 - val_f1_score:
Epoch 12/30
99/99 [==============================] - 8s 74ms/step - loss: 0.0344 - f1_score: 0.9853 - val_loss: 0.2185 - val_f1_score: 0
Epoch 13/30
99/99 [==============================] - 10s 92ms/step - loss: 0.0391 - f1_score: 0.9850 - val_loss: 0.2005 - val_f1_score:
Epoch 14/30
99/99 [==============================] - 9s 88ms/step - loss: 0.0436 - f1_score: 0.9846 - val_loss: 0.1477 - val_f1_score: 0
Epoch 15/30
99/99 [==============================] - 8s 75ms/step - loss: 0.0336 - f1_score: 0.9867 - val_loss: 0.1443 - val_f1_score: 0
Epoch 16/30
99/99 [==============================] - 9s 93ms/step - loss: 0.0355 - f1_score: 0.9873 - val_loss: 0.2134 - val_f1_score: 0
```

Graficando el historial de la red podemos ver que la perdida en el conjunto de entrenamienot se estabiliza rapidamente, además de que el F1 Score en ambos conjuntos es muy similar, demostrando que generaliza bien en los datos, además que este score se estabiliza rapidamente, obtenemos resultados ligeramente peores en los puntajes que en la red anterior, sin embargo la diferencia es mínima y saliendo antes del entrenamiento estamos evitando la posibilidad de que el modelo este memorizando los datos. Para evaluar este aspecto primero revisaremos el desempeño del modelo en el conjunto de prueba

```
df = pd.DataFrame(history.history)
df['f1_score'] = df['f1_score'].apply(lambda x: x[0])
df['val_f1_score'] = df['val_f1_score'].apply(lambda x: x[0])
df.plot(y=["loss", "val_loss"], title="Loss vs Epoch")
df.plot(y=["f1_score", "val_f1_score"], title="Loss vs Epoch",ylim=(0,1))
```

```
<Axes: title={'center': 'Loss vs Epoch'}>
```



Resultados con el conjunto de prueba

```
images = []
true_labels = []
predicted_labels = []
for x, y in test:
    predictions = model.predict(x)
    images.extend(x)
    true_labels.extend(y)
    predicted_labels.extend(predictions)

true_binary_labels = [1 if label[0] == 1 else 0 for label in true_labels]
predicted_binary_labels = [1 if label[0] >= 0.5 else 0 for label in predicted_labels]

f1 = f1_score(true_binary_labels, predicted_binary_labels)
print(f'F1-score en el conjunto de prueba: {f1:.2f}')

for i in range(10):
    image = images[i]
    true_label = true_labels[i]
    predicted_label = predicted_labels[i]
    true_class = 'Tumor' if true_label[0] == 1 else 'Sano'
    predicted_class = 'Tumor' if predicted_label[0] >= 0.5 else 'Sano'
    plt.imshow(image)
    plt.title(f'Real: {true_class}, Predicho: {predicted_class}')
    plt.show()

```