Classificaço de Patologias usando Imagens Médicas

Carregar imagens do diretório

```
import os
   current_dir = os.path.abspath(os.getcwd())
```

Converter base de dados para treino, validação e teste

```
In [2]: #cria nova pasta para cachorros e gatos atendendo a estrutura do Keras/Tensor
folder = "/novo"
    train_folder = current_dir + folder + "/train"
    val_folder = current_dir + folder + "/val"
    test_folder = current_dir + folder + "/test"

model_filepath = "keras/classificacao_02_03.keras"
    conversao_path = "conversao/conversao_02_03"
```

Fazer o Tensorflow carregar as imagens para a RNA

```
In [3]:
         import tensorflow as tf
         print(tf.config.list_physical_devices('GPU'))
         print(tf. version )
        2022-06-28 22:00:50.274870: W tensorflow/stream executor/platform/default/dso
        loader.cc:64] Could not load dynamic library 'libcudart.so.11.0'; dlerror: l
        ibcudart.so.11.0: cannot open shared object file: No such file or directory
        2022-06-28 22:00:50.274885: I tensorflow/stream executor/cuda/cudart stub.cc:
        29] Ignore above cudart dlerror if you do not have a GPU set up on your machi
        ne.
        []
        2.6.1
        2022-06-28 22:00:50.976439: W tensorflow/stream_executor/platform/default/dso
        loader.cc:64] Could not load dynamic library 'libcuda.so.1'; dlerror: libcud
        a.so.1: cannot open shared object file: No such file or directory
        2022-06-28 22:00:50.976459: W tensorflow/stream executor/cuda/cuda driver.cc:
        269] failed call to cuInit: UNKNOWN ERROR (303)
        2022-06-28 22:00:50.976476: I tensorflow/stream_executor/cuda/cuda_diagnostic
        s.cc:156] kernel driver does not appear to be running on this host (pc): /pro
        c/driver/nvidia/version does not exist
```

```
from tensorflow.keras.utils import image_dataset_from_directory
#image_dataset_from_directory monta uma estrutura de dados com imagens 180x18
# de 32 em 32 imagens
train_dataset = image_dataset_from_directory(train_folder, image_size=(180, 1)
validation_dataset = image_dataset_from_directory(val_folder,image_size=(180, 1))
```

```
test_dataset = image_dataset_from_directory(test_folder, image_size=(180, 186))
```

```
Found 34931 files belonging to 2 classes.
Found 16 files belonging to 2 classes.
Found 484 files belonging to 2 classes.
```

2022-06-28 22:00:51.507237: I tensorflow/core/platform/cpu_feature_guard.cc:1 42] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations: AVX2 FMA

To enable them in other operations, rebuild TensorFlow with the appropriate c ompiler flags.

```
for data_batch, labels_batch in train_dataset:
    print("data batch shape:", data_batch.shape)
    print("labels batch shape:", labels_batch.shape)
    print(data_batch[0].shape)
    break
```

```
2022-06-28 22:00:51.562763: I tensorflow/compiler/mlir_graph_optimizatio n_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered 2) data batch shape: (32, 180, 180, 3) labels batch shape: (32,) (180, 180, 3)
```

Treinando o modelo

```
from tensorflow import keras
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.layers.experimental.preprocessing import Rescaling

#cria uma arquitetura de uma rede neural profunda vazia
model = keras.Sequential()
model.add(Rescaling(scale=1.0/255))
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(Flatten())
model.add(Dense(1, activation="sigmoid"))
model.compile(loss="binary_crossentropy",optimizer="adam",metrics=["accuracy'
#model.add(Dense(4, activation='softmax'))
#model.compile(loss='categorical_crossentropy',optimizer='adam', metrics=['accuracy'
#model.compile(loss='categorical_crossentropy',optimizer='adam', metrics=['accuracy']
```

validation_data=validation_dataset,
callbacks=callbacks)

```
Epoch 1/100
accuracy: 0.7815 - val loss: 0.2444 - val accuracy: 0.8750
Epoch 2/100
accuracy: 0.8782 - val loss: 0.1097 - val accuracy: 1.0000
Epoch 3/100
accuracy: 0.9076 - val loss: 0.2194 - val accuracy: 0.8125
Epoch 4/100
accuracy: 0.9287 - val loss: 0.1275 - val accuracy: 0.9375
Epoch 5/100
accuracy: 0.9502 - val loss: 0.0861 - val accuracy: 0.9375
Epoch 6/100
accuracy: 0.9688 - val loss: 0.1164 - val accuracy: 0.9375
Epoch 7/100
accuracy: 0.9816 - val_loss: 0.0182 - val_accuracy: 1.0000
Epoch 8/100
accuracy: 0.9903 - val loss: 0.0216 - val accuracy: 1.0000
Epoch 9/100
accuracy: 0.9921 - val loss: 0.0194 - val accuracy: 1.0000
Epoch 10/100
accuracy: 0.9938 - val loss: 8.6307e-04 - val accuracy: 1.0000
Epoch 11/100
accuracy: 0.9950 - val loss: 3.6635e-04 - val accuracy: 1.0000
Epoch 12/100
accuracy: 0.9950 - val loss: 5.0544e-04 - val accuracy: 1.0000
Epoch 13/100
accuracy: 0.9952 - val_loss: 5.5288e-04 - val_accuracy: 1.0000
Epoch 14/100
accuracy: 0.9970 - val_loss: 1.3414e-04 - val_accuracy: 1.0000
Epoch 15/100
accuracy: 0.9965 - val loss: 0.0018 - val accuracy: 1.0000
Epoch 16/100
accuracy: 0.9960 - val_loss: 2.4300e-05 - val_accuracy: 1.0000
Epoch 17/100
accuracy: 0.9970 - val_loss: 1.4156e-04 - val_accuracy: 1.0000
Epoch 18/100
accuracy: 0.9979 - val loss: 4.5876e-06 - val accuracy: 1.0000
Epoch 19/100
accuracy: 0.9979 - val loss: 1.9808e-05 - val accuracy: 1.0000
Epoch 20/100
accuracy: 0.9974 - val_loss: 1.3595e-04 - val_accuracy: 1.0000
Epoch 21/100
```

```
accuracy: 0.9976 - val loss: 8.7040e-06 - val accuracy: 1.0000
Epoch 22/100
accuracy: 0.9977 - val loss: 1.0753e-04 - val accuracy: 1.0000
Epoch 23/100
accuracy: 0.9985 - val loss: 3.7298e-05 - val accuracy: 1.0000
Epoch 24/100
accuracy: 0.9979 - val loss: 1.6303e-05 - val accuracy: 1.0000
Epoch 25/100
accuracy: 0.9987 - val loss: 0.0012 - val accuracy: 1.0000
Epoch 26/100
accuracy: 0.9977 - val loss: 5.4656e-05 - val accuracy: 1.0000
Epoch 27/100
accuracy: 0.9983 - val loss: 4.9920e-07 - val accuracy: 1.0000
Epoch 28/100
accuracy: 0.9987 - val loss: 9.2779e-06 - val accuracy: 1.0000
Epoch 29/100
accuracy: 0.9976 - val loss: 3.4694e-04 - val accuracy: 1.0000
Epoch 30/100
accuracy: 0.9993 - val loss: 0.0015 - val accuracy: 1.0000
Epoch 31/100
accuracy: 0.9983 - val loss: 8.2806e-04 - val accuracy: 1.0000
Epoch 32/100
accuracy: 0.9989 - val loss: 1.4387e-04 - val_accuracy: 1.0000
Epoch 33/100
accuracy: 0.9985 - val loss: 7.4121e-04 - val accuracy: 1.0000
Epoch 34/100
accuracy: 0.9988 - val loss: 1.5277e-04 - val accuracy: 1.0000
Epoch 35/100
accuracy: 0.9986 - val_loss: 4.8540e-04 - val_accuracy: 1.0000
Epoch 36/100
accuracy: 0.9992 - val_loss: 8.7021e-05 - val_accuracy: 1.0000
Epoch 37/100
accuracy: 0.9989 - val loss: 3.7087e-04 - val accuracy: 1.0000
Epoch 38/100
accuracy: 0.9990 - val_loss: 4.6718e-06 - val_accuracy: 1.0000
Epoch 39/100
accuracy: 0.9991 - val_loss: 2.4948e-04 - val_accuracy: 1.0000
Epoch 40/100
accuracy: 0.9991 - val loss: 4.1633e-08 - val accuracy: 1.0000
Epoch 41/100
accuracy: 0.9987 - val loss: 1.8814e-04 - val accuracy: 1.0000
Epoch 42/100
```

```
accuracy: 0.9989 - val_loss: 1.5844e-06 - val_accuracy: 1.0000
Epoch 43/100
accuracy: 0.9989 - val_loss: 5.4654e-05 - val_accuracy: 1.0000
Epoch 44/100
accuracy: 0.9989 - val loss: 4.2107e-06 - val accuracy: 1.0000
Epoch 45/100
accuracy: 0.9993 - val loss: 1.4065e-04 - val accuracy: 1.0000
Epoch 46/100
accuracy: 0.9987 - val loss: 0.0064 - val accuracy: 1.0000
Epoch 47/100
accuracy: 0.9991 - val loss: 4.0472e-04 - val accuracy: 1.0000
Epoch 48/100
accuracy: 0.9995 - val loss: 1.4891e-06 - val accuracy: 1.0000
Epoch 49/100
accuracy: 0.9989 - val loss: 9.2724e-04 - val accuracy: 1.0000
Epoch 50/100
accuracy: 0.9992 - val loss: 1.8490e-06 - val accuracy: 1.0000
Epoch 51/100
accuracy: 0.9993 - val loss: 3.4134e-06 - val accuracy: 1.0000
Epoch 52/100
accuracy: 0.9992 - val loss: 2.5919e-05 - val accuracy: 1.0000
Epoch 53/100
accuracy: 0.9991 - val loss: 7.7228e-05 - val accuracy: 1.0000
Epoch 54/100
accuracy: 0.9990 - val loss: 3.3098e-04 - val accuracy: 1.0000
Epoch 55/100
accuracy: 0.9996 - val loss: 1.5359e-05 - val accuracy: 1.0000
Epoch 56/100
accuracy: 0.9992 - val_loss: 3.0660e-06 - val_accuracy: 1.0000
Epoch 57/100
accuracy: 0.9993 - val loss: 2.4181e-06 - val accuracy: 1.0000
Epoch 58/100
accuracy: 0.9993 - val loss: 0.0072 - val accuracy: 1.0000
Epoch 59/100
accuracy: 0.9992 - val_loss: 6.9940e-05 - val_accuracy: 1.0000
Epoch 60/100
accuracy: 0.9991 - val loss: 1.7703e-07 - val accuracy: 1.0000
Epoch 61/100
accuracy: 0.9992 - val_loss: 1.0900e-04 - val_accuracy: 1.0000
Epoch 62/100
accuracy: 0.9995 - val_loss: 2.3213e-06 - val_accuracy: 1.0000
Epoch 63/100
accuracy: 0.9993 - val_loss: 9.0748e-04 - val_accuracy: 1.0000
```

```
Epoch 64/100
accuracy: 0.9992 - val_loss: 5.5922e-04 - val_accuracy: 1.0000
Epoch 65/100
accuracy: 0.9992 - val loss: 3.1599e-07 - val accuracy: 1.0000
Epoch 66/100
accuracy: 0.9991 - val loss: 9.5662e-06 - val accuracy: 1.0000
Epoch 67/100
accuracy: 0.9993 - val loss: 6.2262e-04 - val accuracy: 1.0000
Epoch 68/100
accuracy: 0.9992 - val loss: 2.4832e-04 - val accuracy: 1.0000
Epoch 69/100
accuracy: 0.9997 - val loss: 3.3305e-05 - val accuracy: 1.0000
Epoch 70/100
accuracy: 0.9996 - val loss: 1.1397e-04 - val accuracy: 1.0000
Epoch 71/100
accuracy: 0.9992 - val loss: 3.9482e-07 - val accuracy: 1.0000
Epoch 72/100
accuracy: 0.9990 - val loss: 6.1107e-05 - val accuracy: 1.0000
Epoch 73/100
accuracy: 0.9997 - val_loss: 7.8678e-05 - val_accuracy: 1.0000
Epoch 74/100
accuracy: 0.9995 - val loss: 2.0989e-06 - val accuracy: 1.0000
Epoch 75/100
accuracy: 0.9996 - val loss: 2.1671e-04 - val accuracy: 1.0000
Epoch 76/100
accuracy: 0.9994 - val loss: 0.0012 - val accuracy: 1.0000
Epoch 77/100
accuracy: 0.9993 - val loss: 1.8847e-06 - val accuracy: 1.0000
Epoch 78/100
accuracy: 0.9998 - val_loss: 6.6884e-06 - val_accuracy: 1.0000
Epoch 79/100
accuracy: 0.9992 - val loss: 8.4854e-06 - val accuracy: 1.0000
Epoch 80/100
accuracy: 0.9997 - val loss: 1.0245e-06 - val accuracy: 1.0000
Epoch 81/100
           1092/1092 [========
accuracy: 0.9993 - val_loss: 1.8646e-07 - val_accuracy: 1.0000
Epoch 82/100
accuracy: 0.9994 - val loss: 5.0891e-06 - val accuracy: 1.0000
Epoch 83/100
accuracy: 0.9996 - val loss: 2.9979e-08 - val accuracy: 1.0000
Epoch 84/100
accuracy: 0.9993 - val_loss: 1.0366e-06 - val_accuracy: 1.0000
Epoch 85/100
```

```
accuracy: 0.9995 - val loss: 1.8609e-07 - val accuracy: 1.0000
Epoch 86/100
accuracy: 0.9994 - val loss: 6.1276e-07 - val accuracy: 1.0000
Epoch 87/100
accuracy: 0.9997 - val loss: 1.8801e-06 - val accuracy: 1.0000
Epoch 88/100
accuracy: 0.9996 - val loss: 3.1015e-09 - val accuracy: 1.0000
Epoch 89/100
accuracy: 0.9993 - val loss: 3.1217e-06 - val accuracy: 1.0000
Epoch 90/100
accuracy: 0.9995 - val loss: 1.7480e-08 - val accuracy: 1.0000
Epoch 91/100
accuracy: 0.9997 - val loss: 1.2252e-05 - val accuracy: 1.0000
Epoch 92/100
accuracy: 0.9994 - val loss: 1.2314e-06 - val accuracy: 1.0000
Epoch 93/100
accuracy: 0.9996 - val loss: 1.5645e-05 - val accuracy: 1.0000
Epoch 94/100
accuracy: 0.9996 - val loss: 4.6160e-04 - val accuracy: 1.0000
Epoch 95/100
accuracy: 0.9996 - val loss: 0.0052 - val accuracy: 1.0000
Epoch 96/100
accuracy: 0.9994 - val loss: 2.7932e-08 - val_accuracy: 1.0000
Epoch 97/100
accuracy: 0.9996 - val loss: 1.0433e-06 - val accuracy: 1.0000
Epoch 98/100
accuracy: 0.9997 - val loss: 5.6527e-08 - val accuracy: 1.0000
Epoch 99/100
accuracy: 0.9996 - val loss: 5.1649e-05 - val accuracy: 1.0000
Epoch 100/100
accuracy: 0.9996 - val_loss: 4.9131e-06 - val_accuracy: 1.0000
```

In [8]:

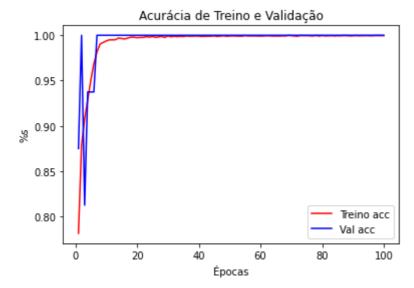
model.summary()

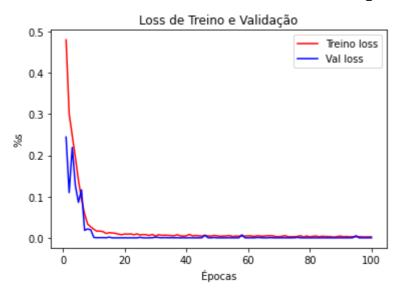
Model: "sequential"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 178, 178, 32)	896
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 89, 89, 32)	0
conv2d_1 (Conv2D)	(None, 87, 87, 64)	18496
flatten (Flatten)	(None, 484416)	0

Visualização de Resultados

```
In [10]:
           import matplotlib.pyplot as plt
           accuracy = history.history["accuracy"]
           val accuracy = history.history["val accuracy"]
           loss = history.history["loss"]
           val loss = history.history["val loss"]
           epochs = range(1, len(accuracy) + 1)
           plt.plot(epochs, accuracy, "r", label="Treino acc")
plt.plot(epochs, val_accuracy, "b", label="Val acc")
           plt.xlabel("Épocas")
           plt.ylabel("%s")
           plt.title("Acurácia de Treino e Validação")
           plt.legend()
           plt.figure()
           plt.plot(epochs, loss, "r", label="Treino loss")
           plt.plot(epochs, val loss, "b", label="Val loss")
           plt.xlabel("Épocas")
           plt.ylabel("%s")
           plt.title("Loss de Treino e Validação")
           plt.legend()
           plt.show()
```





Resultados do Conjunto de Teste

Referências

- https://machinelearningmastery.com/how-to-develop-a-convolutional-neural-network-toclassify-photos-of-dogs-and-cats/
- https://stackoverflow.com/questions/3430372/how-do-i-get-the-full-path-of-the-current-filesdirectory
- https://www.geeksforgeeks.org/python-list-files-in-a-directory/
- https://pynative.com/python-random-sample/
- https://machinelearningmastery.com/how-to-develop-a-convolutional-neural-network-toclassify-photos-of-dogs-and-cats/
- https://www.mygreatlearning.com/blog/keras-tutorial/
- https://www.machinecurve.com/index.php/2020/03/30/how-to-use-conv2d-with-keras/
- https://www.pyimagesearch.com/2021/06/30/how-to-use-the-modelcheckpoint-callbackwith-keras-and-tensorflow/