## 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 [111...
#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"
```

# Fazer o Tensorflow carregar as imagens para a RNA

```
In [112...
          import tensorflow as tf
          print(tf.config.list_physical_devices('GPU'))
          print(tf.__version__)
         2.6.1
In [113...
          from tensorflow.keras.utils import image dataset from directory
          #image dataset from directory monta uma estrutura de dados com imagens 180x1&
          # de 32 em 32 imagens
          train dataset = image dataset from directory(train folder,
                                                         image_size=(180, 180),
                                                        batch size=32)
          #validation_dataset = image_dataset_from_directory(val_folder,
                                                              #image_size=(180, 180),
                                                              #batch size=32)
          test dataset = image dataset from directory(test folder,
                                                        image size=(180, 180),
                                                       batch size=32)
         Found 34931 files belonging to 2 classes.
         Found 484 files belonging to 2 classes.
In [114...
```

for data\_batch, labels\_batch in train\_dataset:

print(data batch[0].shape)

break

print("data batch shape:", data\_batch.shape)
print("labels batch shape:", labels batch.shape)

```
data batch shape: (32, 180, 180, 3) labels batch shape: (32,) (180, 180, 3)
```

#### Treinando o modelo

```
In [115...
                  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', input_shape=(180,
                  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=['adam', metrics=[
In [116...
                  from tensorflow.keras.callbacks import ModelCheckpoint
                  callbacks = [
                         ModelCheckpoint(
                                 filepath="classificacao11.keras",
                                 save best only=True,
                                 monitor="loss"
                          )
                  ]
                  history = model.fit(
                         train dataset,
                          epochs=100.
                          #validation data=validation dataset,
                          callbacks=callbacks)
                 Epoch 1/100
                 accuracy: 0.7446
                 Epoch 2/100
                 accuracy: 0.7617
                 Epoch 3/100
                                                              1092/1092 [=======
                 accuracy: 0.7689
                 Epoch 4/100
                 accuracy: 0.7700
                 Epoch 5/100
                 accuracy: 0.7951
                 Epoch 6/100
                 accuracy: 0.8446
                 Epoch 7/100
                 accuracy: 0.8857
                 Epoch 8/100
```

```
accuracy: 0.9034
Epoch 9/100
accuracy: 0.9307
Epoch 10/100
accuracy: 0.9503
Epoch 11/100
accuracy: 0.9570
Epoch 12/100
accuracy: 0.9643
Epoch 13/100
accuracy: 0.9683
Epoch 14/100
accuracy: 0.9725
Epoch 15/100
accuracy: 0.9750
Epoch 16/100
accuracy: 0.9751
Epoch 17/100
accuracy: 0.9810
Epoch 18/100
accuracy: 0.9862
Epoch 19/100
accuracy: 0.9859
Epoch 20/100
accuracy: 0.9823
Epoch 21/100
accuracy: 0.9869
Epoch 22/100
accuracy: 0.9904
Epoch 23/100
accuracy: 0.9876
Epoch 24/100
accuracy: 0.9895
Epoch 25/100
accuracy: 0.9922
Epoch 26/100
accuracy: 0.9924
Epoch 27/100
accuracy: 0.9910
Epoch 28/100
accuracy: 0.9942
Epoch 29/100
```

```
accuracy: 0.9925
Epoch 30/100
accuracy: 0.9930
Epoch 31/100
accuracy: 0.9941
Epoch 32/100
accuracy: 0.9937
Epoch 33/100
accuracy: 0.9939
Epoch 34/100
accuracy: 0.9946
Epoch 35/100
accuracy: 0.9950
Epoch 36/100
accuracy: 0.9952
Epoch 37/100
accuracy: 0.9948
Epoch 38/100
accuracy: 0.9954
Epoch 39/100
accuracy: 0.9960
Epoch 40/100
accuracy: 0.9956
Epoch 41/100
accuracy: 0.9947
Epoch 42/100
accuracy: 0.9951
Epoch 43/100
accuracy: 0.9963
Epoch 44/100
accuracy: 0.9952
Epoch 45/100
accuracy: 0.9960
Epoch 46/100
accuracy: 0.9948
Epoch 47/100
accuracy: 0.9960
Epoch 48/100
accuracy: 0.9953
Epoch 49/100
accuracy: 0.9967
Epoch 50/100
accuracy: 0.9962
```

```
Epoch 51/100
accuracy: 0.9963
Epoch 52/100
accuracy: 0.9969
Epoch 53/100
accuracy: 0.9971
Epoch 54/100
accuracy: 0.9964
Epoch 55/100
accuracy: 0.9963
Epoch 56/100
accuracy: 0.9971
Epoch 57/100
accuracy: 0.9968
Epoch 58/100
accuracy: 0.9960
Epoch 59/100
accuracy: 0.9965
Epoch 60/100
accuracy: 0.9976
Epoch 61/100
accuracy: 0.9970
Epoch 62/100
accuracy: 0.9973
Epoch 63/100
accuracy: 0.9973
Epoch 64/100
accuracy: 0.9966
Epoch 65/100
accuracy: 0.9972
Epoch 66/100
accuracy: 0.9956
Epoch 67/100
accuracy: 0.9968
Epoch 68/100
accuracy: 0.9971
Epoch 69/100
accuracy: 0.9976
Epoch 70/100
accuracy: 0.9976
Epoch 71/100
1092/1092 [======
        =========] - 312s 286ms/step - loss: 0.0512 -
accuracy: 0.9971
Epoch 72/100
```

```
accuracy: 0.9971
Epoch 73/100
accuracy: 0.9976
Epoch 74/100
accuracy: 0.9979
Epoch 75/100
accuracy: 0.9976
Epoch 76/100
accuracy: 0.9974
Epoch 77/100
accuracy: 0.9979
Epoch 78/100
accuracy: 0.9967
Epoch 79/100
accuracy: 0.9978
Epoch 80/100
accuracy: 0.9975
Epoch 81/100
accuracy: 0.9973
Epoch 82/100
accuracy: 0.9978
Epoch 83/100
accuracy: 0.9983
Epoch 84/100
accuracy: 0.9976
Epoch 85/100
accuracy: 0.9975
Epoch 86/100
accuracy: 0.9964
Epoch 87/100
accuracy: 0.9979
Epoch 88/100
accuracy: 0.9972
Epoch 89/100
accuracy: 0.9983
Epoch 90/100
accuracy: 0.9977
Epoch 91/100
accuracy: 0.9982
Epoch 92/100
accuracy: 0.9974
Epoch 93/100
```

```
accuracy: 0.9972
     Epoch 94/100
     accuracy: 0.9975
     Epoch 95/100
     accuracy: 0.9978
     Epoch 96/100
                   ========= ] - 310s 284ms/step - loss: 0.0604 -
     1092/1092 [=====
     accuracy: 0.9973
     Epoch 97/100
     accuracy: 0.9985
     Epoch 98/100
     accuracy: 0.9974
     Epoch 99/100
                  1092/1092 [======
     accuracy: 0.9977
     Epoch 100/100
     accuracy: 0.9980
In [117...
     model.summary()
     Model: "sequential 9"
     Layer (type)
                     Output Shape
                                    Param #
     conv2d 18 (Conv2D)
                     (None, 178, 178, 32)
                                    896
     max pooling2d 9 (MaxPooling2 (None, 89, 89, 32)
     conv2d 19 (Conv2D)
                     (None, 87, 87, 64)
                                    18496
     flatten 9 (Flatten)
                     (None, 484416)
```

Total params: 503,809 Trainable params: 503,809 Non-trainable params: 0

dense 9 (Dense)

\_\_\_\_\_

(None, 1)

```
In [118...
```

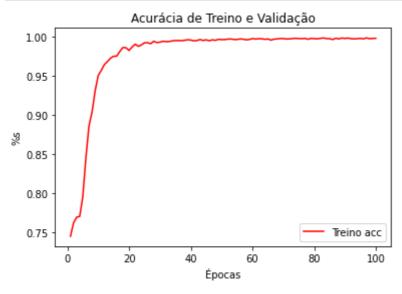
```
#https://www.tensorflow.org/js/tutorials/conversion/import_keras?hl=pt-br#ali
import tensorflowjs as tfjs
tfjs.converters.save_keras_model(model, "conversao_01_11")
```

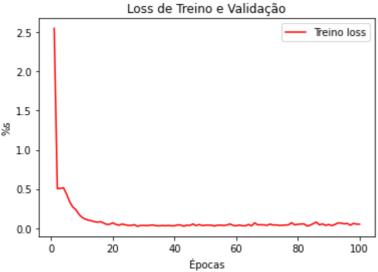
484417

# Visualização de Resultados

```
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

```
In [120... #from tensorflow import keras
    #model = keras.models.load_model("classificacao01.keras")
    # serialize model to JSON
    #model_json = model.to_json()
    #with open("classificacao01.json", "w") as json_file:json_file.write(model_js)
    # serialize weights to HDF5
    #model.save_weights("classificacao01.h5")
    #print("Saved model to disk")
In [121... test_loss, test_acc = model.evaluate(test_dataset)
    print(f"Test accuracy: {test_acc:.3f}")
```

	cy: 0.9835 Test accuracy: 0.983	25	/9ms/step	- LOSS:	0.7895	- accura
In [ ]:						
In [ ]:						
In [ ]:						

## Referências

- https://machinelearningmastery.com/how-to-develop-a-convolutional-neural-network-toclassify-photos-of-dogs-and-cats/
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