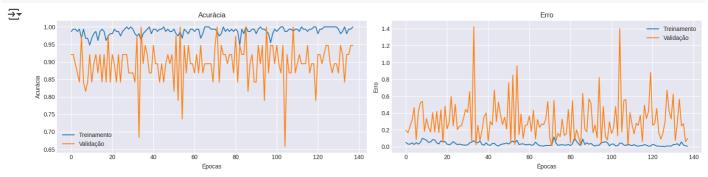
```
from google.colab import drive
drive.mount('/content/drive')
path = '/content/drive/MyDrive/trabalhofinalES2/dataset.zip'
Expression Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
import zipfile
zip_path = '/content/drive/MyDrive/trabalhofinalES2/dataset.zip'
extract_path = '/content/drive/MyDrive/trabalhofinalES2/
# Descompactar
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(extract_path)
print("Extração realizada!")
→ Extração realizada!
import os
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, Input
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.utils.class_weight import compute_class_weight
import seaborn as sns
#teste de grãos quebrados e inteiros
x_teste = '/content/drive/MyDrive/trabalhofinalES2/dataset/testes_graos_arroz'
#treino de grãos inteiros e quebrados
x_treino = '/content/drive/MyDrive/trabalhofinalES2/dataset/treino_graos_arroz'
#fazer alterções na imagem para ser melhor resultado
train_datagen = ImageDataGenerator(
   rescale=1./255, #estou normalizando com o data aumentation
   rotation_range=25,
   width_shift_range=0.1,
   height_shift_range=0.1,
   zoom range=0.2,
   horizontal_flip=True
)
# Gerador para o conjunto de dados de treinamento
train_generator = train_datagen.flow_from_directory(
   x treino,
   target_size=(64, 64), #redimensionando todas as imagens para 64x64
   batch_size=16,
   class_mode='binary',
    shuffle=True #embaraljando a cada ciclo(epochs)
)
test_datagen = ImageDataGenerator(rescale=1./255)
test_generator = test_datagen.flow_from_directory(
   x_teste,
   target_size=(64, 64),
   batch_size=16,
   class_mode='binary',
   shuffle=False
\rightarrow Found 154 images belonging to 2 classes.
     Found 38 images belonging to 2 classes.
# Cálculo dos pesos para lidar com desequilíbrio entre as classes
classes = np.array([0, 1]) # 0: grao_quebrado, 1: graos_inteiros
```

```
weights = compute_class_weight(
   class weight='balanced',
    classes=classes,
   y=train_generator.classes
class_weights = dict(zip(classes, weights))
print("Class weights:", class_weights)
Class weights: {np.int64(0): np.float64(0.802083333333334), np.int64(1): np.float64(1.3275862068965518)}
model = Sequential([
   Input(shape=(64, 64, 3)),
    Conv2D(32, (3, 3), activation='relu'),
    MaxPooling2D(2, 2),
    Dropout(0.2), # mais leve na primeira camada
   Conv2D(64, (3, 3), activation='relu'), #o relu vai melhorar o aprendizado
    MaxPooling2D(2, 2),
   Dropout(0.3),
    Flatten(),
   Dense(128, activation='relu', kernel_initializer='he_normal'),
    Dropout(0.5), # aumenta para regular melhor a camada densa
   Dense(1, activation='sigmoid') # saída binária
])
model.compile(
    optimizer=Adam(learning_rate=0.0005),
    loss='binary_crossentropy',
   metrics=['accuracy']
)
history = model.fit(
   train generator,
   epochs=138,
   validation_data=test_generator,
   class_weight=class_weights
)
# Avaliação
loss, acc = model.evaluate(test_generator)
→ Epoch 1/138
                              - 1s 130ms/step - accuracy: 0.9849 - loss: 0.0511 - val_accuracy: 0.9211 - val_loss: 0.1969
     10/10
     Epoch 2/138
     10/10
                              - 2s 120ms/step - accuracy: 0.9943 - loss: 0.0284 - val_accuracy: 0.9211 - val_loss: 0.1654
     Epoch 3/138
                              - 1s 91ms/step - accuracy: 0.9955 - loss: 0.0301 - val accuracy: 0.8947 - val loss: 0.2441
     10/10
     Epoch 4/138
     10/10
                              - 1s 91ms/step - accuracy: 0.9970 - loss: 0.0302 - val_accuracy: 0.8684 - val_loss: 0.3184
     Epoch 5/138
     10/10
                              - 1s 95ms/step - accuracy: 0.9877 - loss: 0.0304 - val_accuracy: 0.8421 - val_loss: 0.4638
     Epoch 6/138
     10/10
                             — 1s 97ms/step - accuracy: 0.9719 - loss: 0.0401 - val_accuracy: 0.9737 - val_loss: 0.0856
     Epoch 7/138
     10/10
                              - 1s 94ms/step - accuracy: 0.9910 - loss: 0.0327 - val_accuracy: 0.8421 - val_loss: 0.4060
     Epoch 8/138
                              - 1s 90ms/step - accuracy: 0.9759 - loss: 0.0431 - val accuracy: 0.8158 - val loss: 0.5220
     10/10
     Epoch 9/138
                              - 1s 92ms/step - accuracy: 0.9659 - loss: 0.0767 - val_accuracy: 0.8421 - val_loss: 0.5375
     10/10
     Epoch 10/138
                              - 1s 95ms/step - accuracy: 0.9505 - loss: 0.0707 - val_accuracy: 0.9211 - val_loss: 0.1813
     10/10
     Epoch 11/138
     10/10
                              - 1s 95ms/step - accuracy: 0.9637 - loss: 0.0866 - val_accuracy: 0.8421 - val_loss: 0.3343
     Epoch 12/138
     10/10
                              - 1s 91ms/step - accuracy: 0.9899 - loss: 0.0377 - val_accuracy: 0.8947 - val_loss: 0.2274
     Epoch 13/138
     10/10
                              - 1s 116ms/step - accuracy: 0.9931 - loss: 0.0439 - val_accuracy: 0.9211 - val_loss: 0.1752
     Epoch 14/138
     10/10
                              - 1s 115ms/step - accuracy: 0.9704 - loss: 0.0591 - val_accuracy: 0.8684 - val_loss: 0.4050
     Epoch 15/138
                              - 1s 135ms/step - accuracy: 0.9937 - loss: 0.0420 - val_accuracy: 0.9211 - val_loss: 0.1754
     10/10
     Epoch 16/138
     10/10
                              - 2s 95ms/step - accuracy: 0.9883 - loss: 0.0626 - val_accuracy: 0.8421 - val_loss: 0.4196
     Epoch 17/138
     10/10
                              - 1s 104ms/step - accuracy: 0.9796 - loss: 0.0405 - val_accuracy: 0.9211 - val_loss: 0.1687
     Epoch 18/138
     10/10
                              - 1s 102ms/step - accuracy: 0.9611 - loss: 0.0796 - val_accuracy: 0.8421 - val_loss: 0.4380
     Epoch 19/138
```

```
10/10
                          - 1s 94ms/step - accuracy: 0.9679 - loss: 0.0665 - val_accuracy: 0.9737 - val_loss: 0.0501
Epoch 20/138
10/10
                         - 1s 97ms/step - accuracy: 0.9698 - loss: 0.0774 - val_accuracy: 0.8421 - val_loss: 0.4809
Epoch 21/138
                           1s 93ms/step - accuracy: 0.9853 - loss: 0.0336 - val_accuracy: 0.9211 - val_loss: 0.2130
10/10
Epoch 22/138
10/10
                          - 1s 92ms/step - accuracy: 0.9966 - loss: 0.0168 - val accuracy: 0.8947 - val loss: 0.2900
Epoch 23/138
10/10
                          - 1s 94ms/step - accuracy: 0.9956 - loss: 0.0195 - val_accuracy: 0.8421 - val_loss: 0.5960
Epoch 24/138
10/10
                          - 1s 117ms/step - accuracy: 0.9909 - loss: 0.0482 - val_accuracy: 0.9211 - val_loss: 0.2490
Epoch 25/138
10/10
                          - 1s 121ms/step - accuracy: 0.9660 - loss: 0.0432 - val_accuracy: 0.8421 - val_loss: 0.5043
Epoch 26/138
                           1s 115ms/step - accuracy: 0.9759 - loss: 0.0320 - val_accuracy: 0.9211 - val_loss: 0.2028
10/10
Epoch 27/138
10/10
                           1s 108ms/step - accuracy: 0.9982 - loss: 0.0291 - val accuracy: 0.9211 - val loss: 0.2423
Epoch 28/138
10/10
                           1s 99ms/step - accuracy: 1.0000 - loss: 0.0271 - val accuracy: 0.9211 - val loss: 0.2507
Epoch 29/138
                                                            1000. 0 0017 .... 20000000... 0 0004
```

```
import matplotlib.pyplot as plt
fig, axs = plt.subplots(1, 2, figsize=(16, 4))
# Gráfico de Acurácia
axs[0].plot(history.history['accuracy'], label='Treinamento')
axs[0].plot(history.history['val_accuracy'], label='Validação')
axs[0].set_title('Acurácia')
axs[0].set_xlabel('Épocas')
axs[0].set vlabel('Acurácia')
axs[0].legend()
axs[0].grid(True)
# Gráfico de Perda
axs[1].plot(history.history['loss'], label='Treinamento')
axs[1].plot(history.history['val_loss'], label='Validação')
axs[1].set_title('Erro')
axs[1].set_xlabel('Épocas')
axs[1].set_ylabel('Erro')
axs[1].legend()
axs[1].grid(True)
plt.tight layout()
plt.savefig('_/content/drive/MyDrive/trabalhofinalES2/graficos.png')
plt.show()
```



```
y_pred_prob = model.predict(test_generator)
y_pred = (y_pred_prob > 0.5).astype("int32")

# Matriz de Confusão
cm = confusion_matrix(test_generator.classes, y_pred)
print("\nMatriz de Confusão:")
print(cm)

target_names = ['grao_quebrado', 'graos_inteiros']
print("\nRelatório de Classificação:")
print(classification_report(test_generator.classes, y_pred, target_names=target_names))

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=target_names, yticklabels=target_names)
plt.title('Matriz de Confusão')
plt.xlabel('Previsto')
```

plt.ylabel('Real') plt.show()



- 0s 42ms/step

Matriz de Confusão: [[20 2] [0 16]]

Relatório de Classificação:

NCIACOI IO GC CI	precision	recall	f1-score	support
grao_quebrado	1.00	0.91	0.95	22
<pre>graos_inteiros</pre>	0.89	1.00	0.94	16
accuracy			0.95	38
macro avg	0.94	0.95	0.95	38
weighted avg	0.95	0.95	0.95	38

