In [1]:
```
import tensorflow as tf
from tensorflow.keras import regularizers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow import keras
from keras import layers
from keras import models
from tensorflow.keras import optimizers
from sklearn.metrics import classification_report
import numpy as np
```

```
2025-06-12 02:14:34.953150: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
E0000 00:00:1749690874.966510   91027 cuda_dnn.cc:8579] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered
E0000 00:00:1749690874.970667   91027 cuda_blas.cc:1407] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered
W0000 00:00:1749690874.980640   91027 computation_placer.cc:177] computation placer already registered. Please check linkage and avoid linking the same target more than once.
W0000 00:00:1749690874.980654   91027 computation_placer.cc:177] computation placer already registered. Please check linkage and avoid linking the same target more than once.
W0000 00:00:1749690874.980656   91027 computation_placer.cc:177] computation placer already registered. Please check linkage and avoid linking the same target more than once.
W0000 00:00:1749690874.980657   91027 computation_placer.cc:177] computation placer already registered. Please check linkage and avoid linking the same target more than once.
2025-06-12 02:14:34.984114: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
tf.__version__
```

Out[2]:
```
'2.19.0'
```

MODELO S

1 - Data Preprocessing

Caminhos dos sets

In [3]:
```
train_dir = 'dataset_balanceado_final/train'
validation_dir = 'dataset_balanceado_final/validation'
test_dir = 'dataset_balanceado_final/test'
```

Definir batch_size e image_size

In [4]:
```
from tensorflow.keras.utils import image_dataset_from_directory

IMG_SIZE = 150
BATCH_SIZE = 32
```

Training set - É o conjunto de dados usado para treinar a rede

In [5]:
```
train_dataset = image_dataset_from_directory(
    train_dir,
    image_size=(IMG_SIZE, IMG_SIZE),
    batch_size=BATCH_SIZE,
    label_mode='categorical' # categorical porque temos várias classes, senão se
)
```

```
Found 4276 files belonging to 7 classes.
I0000 00:00:1749690877.404282   91027 gpu_device.cc:2019] Created device /job:loc
alhost/replica:0/task:0/device:GPU:0 with 4804 MB memory:  -> device: 0, name: NV
IDIA GeForce GTX 1660 SUPER, pci bus id: 0000:03:00.0, compute capability: 7.5
I0000 00:00:1749690877.407857   91027 gpu_device.cc:2019] Created device /job:loc
alhost/replica:0/task:0/device:GPU:1 with 4804 MB memory:  -> device: 1, name: NV
IDIA GeForce GTX 1660 SUPER, pci bus id: 0000:05:00.0, compute capability: 7.5
```

Validation set - Usado para 'testar' o modelo durante o processo de procura da melhor combinação de hiperparâmetros.

In [6]:
```
validation_dataset = image_dataset_from_directory(
    validation_dir,
    image_size=(IMG_SIZE, IMG_SIZE),
    batch_size=BATCH_SIZE,
    label_mode='categorical'
)
```

```
Found 1420 files belonging to 7 classes.
```

Test set - Usado para testar o modelo depois do processo de treino

In [7]:
```
test_dataset = image_dataset_from_directory(
    test_dir,
    image_size=(IMG_SIZE, IMG_SIZE),
    batch_size=BATCH_SIZE,
    label_mode='categorical'
)
```

```
Found 1420 files belonging to 7 classes.
```

Data Augmentation

Gerar mais dados de treino a partir de amostras de treino existentes, aumentando as amostras através de uma série de transformações aleatórias que produzem imagens com aspeto credível.

In [8]:
```
data_augmentation = keras.Sequential([layers.RandomFlip("horizontal"), # Efeito
                                      layers.RandomFlip("vertical"),# Aplica inv
                                      layers.RandomTranslation(0.1, 0.2),
                                      layers.RandomRotation(0.4),])
```

Métricas para avaliar os modelos

In [9]:
```
# Utiliza uma função(do sckicit-learn) para avaliar o desempenho do modelo, indi
    # f1-score do modelo
    # accuracy do modelo
    # accuracy por classe

from sklearn.metrics import classification_report
import numpy as np

def print_classification_metrics(model, dataset, phase_name):
    y_true = []
    y_pred = []

    for images, labels in dataset:
        preds = model.predict(images)
        y_true.extend(np.argmax(labels.numpy(), axis=1))
        y_pred.extend(np.argmax(preds, axis=1))

    print(f"\n {phase_name}")
    print(classification_report(y_true, y_pred, digits=4))
```

2 - Construir a CNN (convolucional Neural Network)

In [10]:
```
# Define a camada de entrada do modelo com o formato das imagens (altura, largur
inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
```

In [11]:
```
#Aplica as transformações aleatórias às imagens (definidas no inicio do notebook
x = data_augmentation(inputs)
```

In [12]:
```
# Normaliza os valores dos pixels das imagens de entrada para o intervalo [0, 1]
x = layers.Rescaling(1./255)(x)
```

Passo 1 : Camada Convolucional

In [13]:
```
# Primeira camada convolucional com 64 filtros 3x3 e ativação ReLU
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu", padding="same")(
# adicionado o padding="same" para garantir que o output da camada convolucional
```

Passo 2 : Camada de Pooling

In [14]:
```
# Primeira camada de pooling máximo (2x2) para reduzir a dimensionalidade.
x = layers.MaxPooling2D(pool_size=2)(x)
```

Passo 3 : Adicionar mais camadas

In [15]:
```
# Segunda camada convolucional com 128 filtros 3x3 e ativação ReLU.
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu", padding="same")
# Segunda camada de pooling máximo (2x2).
x = layers.MaxPooling2D(pool_size=2)(x)
```

In [16]:
```
# Terceira camada convolucional com 128 filtros 3x3 e ativação ReLU.
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu", padding="same")
# Terceira camada de pooling máximo (2x2).
x = layers.MaxPooling2D(pool_size=2)(x)
```

Passo 4 : Flattening

In [17]:
```
# Achata o output das camadas convolucionais para um vetor 1D.
x = layers.Flatten()(x)
```

BATCH NORMALIZATION (Facultativo)

In [18]:
```
# tirar comentario desta linha abaixo se queremos usar batch normalization
# porem foi testado varias vezes e em diferentes camadas da rede, mas não melhor
#x = layers.BatchNormalization( axis=-1, momentum=0.99, epsilon=0.001, center=Tr
```

Dropout (facultativo) - funçao de regularização

In [19]:
```
# Aplica Dropout (50%) para desativar aleatoriamente neurónios, prevenindo o ove
# Neste caso, para este modelo em especifico, atingiu a pior acc sem dropout
#x = layers.Dropout(0.5)(x)
```

Passo 5 : Full Connection

In [20]:
```
# Definir funçao de Regularização L2 (opcional)
reg = regularizers.l2(0.01)  # Executar para ativar

# Camada densa (totalmente conectada) com 128 neurónios, ativação ReLU e funçao
x = layers.Dense(128, activation="relu", kernel_regularizer=reg)(x)
```

Passo 6 : Output Layer

In [21]:
```
# Camada de saída densa com 7 neurónios e ativação Softmax (para classificação c
outputs = layers.Dense(7, activation="softmax")(x)
```

In [22]:
```
# Cria o modelo Keras usando as camadas de entrada e saída definidas.
model = keras.Model(inputs=inputs, outputs=outputs)
```

3 - Treinar a rede CNN

Funções de otimização disponíveis: Adam, RMSprop e SGD

Funções de loss disponíveis: categorical_crossentropy , KLDivergence e MSE

In [23]:
```
# Configura o otimizador: SGD
# Define a função de loss: MSE
# Indica que a 'accuracy' (precisão) será a métrica durante o treino.
model.compile(
    optimizer=tf.keras.optimizers.SGD(),
    loss='mse',
    metrics=['accuracy'])
```

In [24]:
```
#model.compile(
    #optimizer='SGD',
    #loss='mse',
    #metrics=['accuracy'])
```

In [25]:
```
#model.compile(
    #optimizer=tf.keras.optimizers.RMSprop(),
    #loss=tf.keras.losses.KLDivergence(),
    #metrics=['accuracy'])
```

Treinar o modelo

In [26]:
```
history = model.fit(
    train_dataset, #Inicia o treino do modelo usando o conjunto de dados de trei
    epochs=25,     # O modelo será treinado por 25 épocas (passagens completas p
    validation_data=validation_dataset) # Usa o conjunto de dados de validação p
```

```
Epoch 1/25
I0000 00:00:1749690880.720096   98298 cuda_dnn.cc:529] Loaded cuDNN version 90300
```

```
134/134 ━━━━━━━━━━━━━━━━━━━━ 13s 80ms/step - accuracy: 0.1599 - loss: 2.6415 - va
l_accuracy: 0.1535 - val_loss: 2.5420
Epoch 2/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.1738 - loss: 2.5099 - va
l_accuracy: 0.1514 - val_loss: 2.4157
Epoch 3/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.1718 - loss: 2.3853 - va
l_accuracy: 0.1444 - val_loss: 2.2959
Epoch 4/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.1667 - loss: 2.2672 - va
l_accuracy: 0.1577 - val_loss: 2.1824
Epoch 5/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.1798 - loss: 2.1552 - va
l_accuracy: 0.1662 - val_loss: 2.0749
Epoch 6/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.1946 - loss: 2.0490 - va
l_accuracy: 0.1768 - val_loss: 1.9729
Epoch 7/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.1957 - loss: 1.9484 - va
l_accuracy: 0.1993 - val_loss: 1.8763
Epoch 8/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2141 - loss: 1.8531 - va
l_accuracy: 0.2162 - val_loss: 1.7847
Epoch 9/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2201 - loss: 1.7627 - va
l_accuracy: 0.2261 - val_loss: 1.6979
Epoch 10/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2303 - loss: 1.6770 - va
l_accuracy: 0.2507 - val_loss: 1.6156
Epoch 11/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2292 - loss: 1.5958 - va
l_accuracy: 0.2465 - val_loss: 1.5376
Epoch 12/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2309 - loss: 1.5189 - va
l_accuracy: 0.2465 - val_loss: 1.4637
Epoch 13/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2427 - loss: 1.4460 - va
l_accuracy: 0.2451 - val_loss: 1.3936
Epoch 14/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2397 - loss: 1.3768 - va
l_accuracy: 0.2648 - val_loss: 1.3272
Epoch 15/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2407 - loss: 1.3113 - va
l_accuracy: 0.2732 - val_loss: 1.2643
Epoch 16/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2563 - loss: 1.2491 - va
l_accuracy: 0.2810 - val_loss: 1.2046
Epoch 17/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2584 - loss: 1.1902 - va
l_accuracy: 0.2789 - val_loss: 1.1480
Epoch 18/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2663 - loss: 1.1344 - va
l_accuracy: 0.2845 - val_loss: 1.0944
Epoch 19/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2671 - loss: 1.0815 - va
l_accuracy: 0.2908 - val_loss: 1.0436
Epoch 20/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2781 - loss: 1.0313 - va
l_accuracy: 0.2908 - val_loss: 0.9954
Epoch 21/25
```

```
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2796 - loss: 0.9838 - va
l_accuracy: 0.2866 - val_loss: 0.9497
Epoch 22/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2691 - loss: 0.9387 - va
l_accuracy: 0.2859 - val_loss: 0.9064
Epoch 23/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2804 - loss: 0.8960 - va
l_accuracy: 0.2901 - val_loss: 0.8654
Epoch 24/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2656 - loss: 0.8555 - va
l_accuracy: 0.2873 - val_loss: 0.8265
Epoch 25/25
134/134 ━━━━━━━━━━━━━━━━━━━━ 10s 72ms/step - accuracy: 0.2782 - loss: 0.8170 - va
l_accuracy: 0.2859 - val_loss: 0.7896
```

4 - Testar o modelo

In [27]:
```
print_classification_metrics(model, test_dataset, "Modelo 1 : CNN de raiz")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 103ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 84ms/step

 Modelo 1 : CNN de raiz
              precision    recall  f1-score   support

           0     0.2807    0.4923    0.3575       195
           1     0.2057    0.4040    0.2726       198
           2     0.5000    0.0183    0.0352       219
           3     0.0000    0.0000    0.0000       192
           4     0.2807    0.4640    0.3497       222
           5     0.3917    0.6150    0.4786       200
           6     0.0000    0.0000    0.0000       194

    accuracy                         0.2859      1420
   macro avg     0.2370    0.2848    0.2134      1420
```

```
weighted avg     0.2434    0.2859    0.2146      1420
```

```
2025-06-12 02:18:48.451744: I tensorflow/core/framework/local_rendezvous.cc:407]
Local rendezvous is aborting with status: OUT_OF_RANGE: End of sequence
/home/eliana/escola/venv/lib/python3.12/site-packages/sklearn/metrics/_classifica
tion.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/eliana/escola/venv/lib/python3.12/site-packages/sklearn/metrics/_classifica
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0.0 in labels with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```
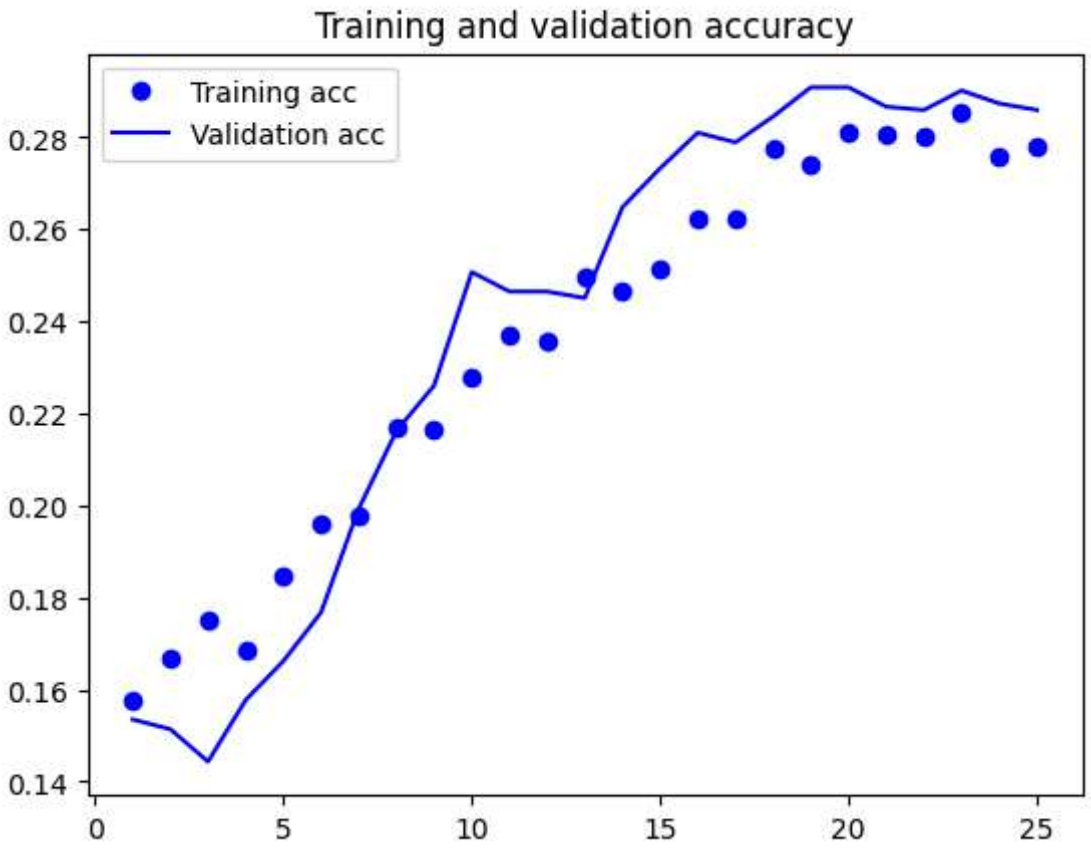
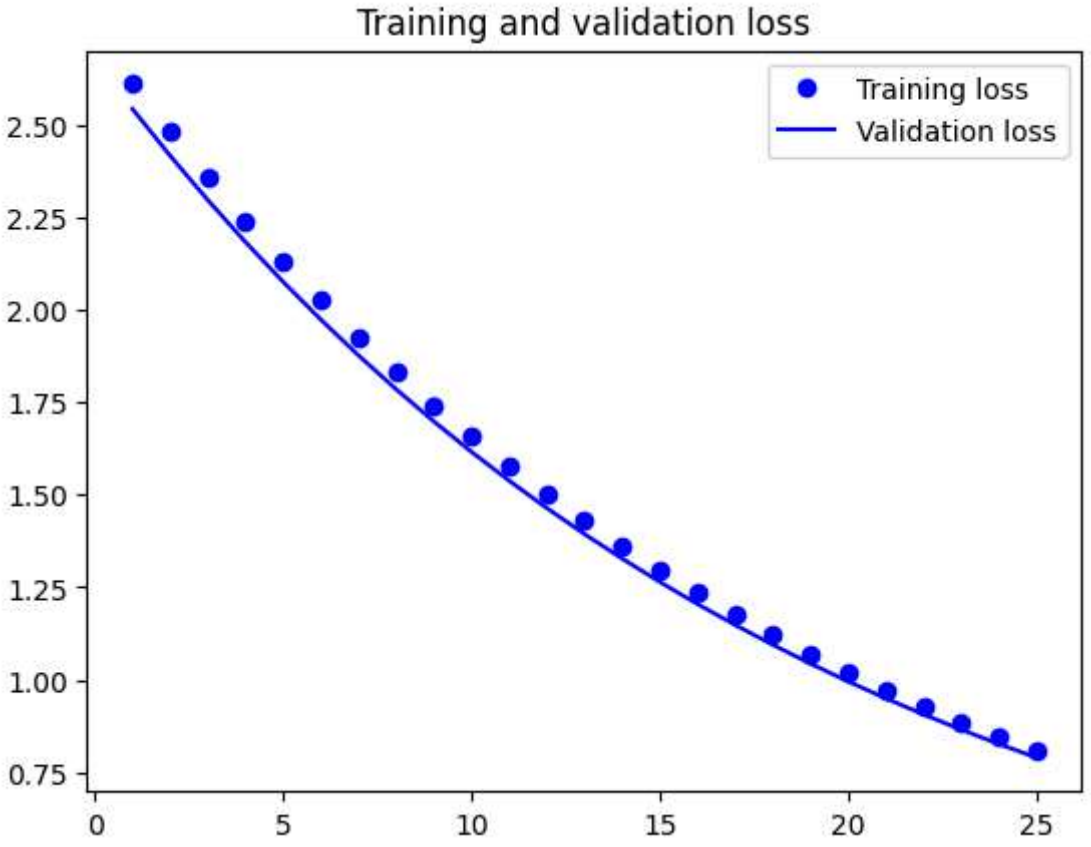

Ver as Curvas de Loss e de Accuracy

In [28]:

```
import matplotlib.pyplot as plt
accuracy = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(accuracy) + 1)
plt.plot(epochs, accuracy, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```





A acurácia de treino e validação aumentam de forma gradual ao longo das 25 épocas, atingindo cerca de 0.29, o que indica que o modelo está a aprender, mas ainda tem desempenho bastante limitado. Isso pode estar relacionado ao uso da MSE como função de perda, que não é ideal para classificação.

As perdas de treino e validação diminuem de forma consistente e estão muito próximas, o que indica que não há overfitting, mas sim que o modelo está a aprender de forma ineficiente para a tarefa proposta. A função de perda MSE pode estar a dificultar a convergência para uma solução que realmente separe bem as classes.

Matriz de Confusão

In [30]:
```
import numpy as np
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

# Obter predições no test_dataset
y_true = []
y_pred = []

for images, labels in test_dataset:
    preds = model.predict(images)
    y_true.extend(np.argmax(labels.numpy(), axis=1))
    y_pred.extend(np.argmax(preds, axis=1))

class_names = test_dataset.class_names

# Criar e mostrar a matriz de confusão
cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)

plt.figure(figsize=(10, 8))
disp.plot(cmap=plt.cm.Blues, xticks_rotation=45, values_format='d')
plt.title("Matriz de Confusão - Teste")
plt.tight_layout()
plt.show()
```

```
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
2025-06-12 02:18:52.545861: I tensorflow/core/framework/local_rendezvous.cc:407]
Local rendezvous is aborting with status: OUT_OF_RANGE: End of sequence
<Figure size 1000x800 with 0 Axes>
```

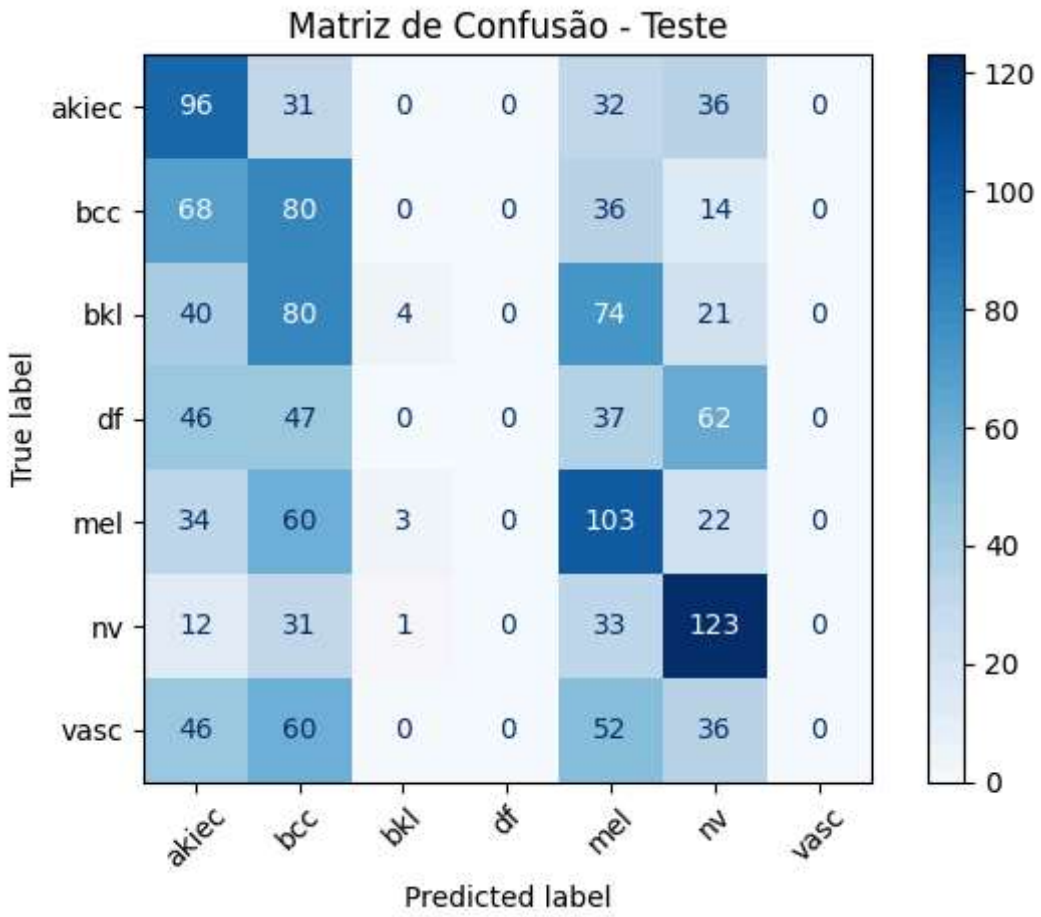

Salvar o modelo

In [29]:
```
model.save("modelS_2B3_com_data_aug_SGD_MSE_worst_acc.keras")
```