

```
In [29]: 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
```

```
In [30]: tf.__version__
```

```
Out[30]: '2.19.0'
```

```
In [31]: 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 [32]: 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 [33]: train_dataset = image_dataset_from_directory(
    train_dir,
    image_size=(IMG_SIZE, IMG_SIZE),
    batch_size=BATCH_SIZE,
    label_mode='categorical'
)
```

Found 4276 files belonging to 7 classes.

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

```
In [34]: 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 [35]: 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.

## Métricas para avaliar os modelos

```
In [36]: # Utiliza uma função (do scikit-Learn) para avaliar o desempenho do modelo, indicando:
# 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))
```

## MODELO 2 (VGG16)

### Feature Extraction

### Data Augmentation

```
In [37]: from tensorflow import keras
from keras import layers
from keras.applications import VGG16 # Importa a arquitetura VGG16 pré-treinada

# Data augmentation
data_augmentation_vgg16 = keras.Sequential([
    layers.RandomFlip("vertical"), # Aplica inversão vertical nas imagens.
    layers.RandomFlip("horizontal"), # Aplica inversão horizontal nas imagens
    layers.RandomTranslation(0.1, 0.2),
    layers.RandomRotation(0.4), # Aplica rotação de 20%
    #layers.RandomZoom(0.1)
]) # Aplica zoom de 20%

# Carregar a base VGG16 pré-treinada
conv_base = VGG16(weights='imagenet', include_top=False, input_shape=(150, 150, 3))
conv_base.trainable = False # Congela todas as camadas da VGG16, impedindo que o modelo seja treinado

# Usar data augmentation
inputs = layers.Input(shape=(150, 150, 3)) # Define a camada de entrada do novo modelo
x = data_augmentation_vgg16(inputs) # Aplica as transformações de aumento de dados
x = keras.applications.vgg16.preprocess_input(x) # Aplica o pré-processamento das imagens
x = conv_base(x) # Passa as imagens (pré-processadas e aumentadas) através da base VGG16
x = layers.Flatten()(x) # Achata as características extraídas para um vetor 1D.
x = layers.Dense(256, activation='relu')(x) # Adiciona uma camada densa com 256 neurônios
```

```
x = layers.Dropout(0.5)(x) # Aplica Dropout (50%) para regularização e prevenção
outputs = layers.Dense(7, activation='softmax')(x) # Adiciona a camada de saída

model_t = models.Model(inputs, outputs) # Cria o model_t

# Compilar e treinar (feature extraction)
model_t.compile( # Compila o modelo para configurar o processo de treino.
    loss='categorical_crossentropy', # Define a função de loss categorical cross
    optimizer=keras.optimizers.Adam(learning_rate=1e-3), # Configura o otimizador
    metrics=['accuracy'] # Define 'accuracy' (precisão) como a métrica a ser monitorada
)

history_t = model_t.fit( # Treina o modelo.
    train_dataset, # Usa o conjunto de dados de treino.
    validation_data=validation_dataset, # Usa o conjunto de dados de validação
    epochs=15 # Treina o modelo por 10 épocas.
)
```

```
Epoch 1/15
134/134 18s 122ms/step - accuracy: 0.3233 - loss: 5.1769 - val_accuracy: 0.4718 - val_loss: 1.4558
Epoch 2/15
134/134 16s 121ms/step - accuracy: 0.4248 - loss: 1.5484 - val_accuracy: 0.5134 - val_loss: 1.2832
Epoch 3/15
134/134 16s 121ms/step - accuracy: 0.4333 - loss: 1.4760 - val_accuracy: 0.5303 - val_loss: 1.2436
Epoch 4/15
134/134 16s 121ms/step - accuracy: 0.4524 - loss: 1.4186 - val_accuracy: 0.5824 - val_loss: 1.1935
Epoch 5/15
134/134 16s 121ms/step - accuracy: 0.4836 - loss: 1.3557 - val_accuracy: 0.5577 - val_loss: 1.2682
Epoch 6/15
134/134 16s 122ms/step - accuracy: 0.4890 - loss: 1.3777 - val_accuracy: 0.5880 - val_loss: 1.1366
Epoch 7/15
134/134 16s 122ms/step - accuracy: 0.5043 - loss: 1.2932 - val_accuracy: 0.5866 - val_loss: 1.1227
Epoch 8/15
134/134 16s 122ms/step - accuracy: 0.5086 - loss: 1.2801 - val_accuracy: 0.6190 - val_loss: 1.0998
Epoch 9/15
134/134 16s 122ms/step - accuracy: 0.5255 - loss: 1.2515 - val_accuracy: 0.6289 - val_loss: 1.0766
Epoch 10/15
134/134 16s 122ms/step - accuracy: 0.5218 - loss: 1.2273 - val_accuracy: 0.6014 - val_loss: 1.1036
Epoch 11/15
134/134 16s 122ms/step - accuracy: 0.5098 - loss: 1.2513 - val_accuracy: 0.5986 - val_loss: 1.1445
Epoch 12/15
134/134 16s 122ms/step - accuracy: 0.5276 - loss: 1.1916 - val_accuracy: 0.6120 - val_loss: 1.1432
Epoch 13/15
134/134 16s 123ms/step - accuracy: 0.5396 - loss: 1.2117 - val_accuracy: 0.6148 - val_loss: 1.1390
Epoch 14/15
134/134 16s 123ms/step - accuracy: 0.5551 - loss: 1.2063 - val_accuracy: 0.6239 - val_loss: 1.0785
Epoch 15/15
134/134 16s 123ms/step - accuracy: 0.5538 - loss: 1.1864 - val_accuracy: 0.6239 - val_loss: 1.1262
```

```
In [38]: print_classification_metrics(model_t, test_dataset, "Modelo 2 : VGG16 (Feature E")
```

1/1 ————— 0s 220ms/step  
 1/1 ————— 0s 109ms/step  
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 1/1 ————— 0s 109ms/step  
 1/1 ————— 0s 177ms/step

Modelo 2 : VGG16 (Feature Extraction com Augmentation)

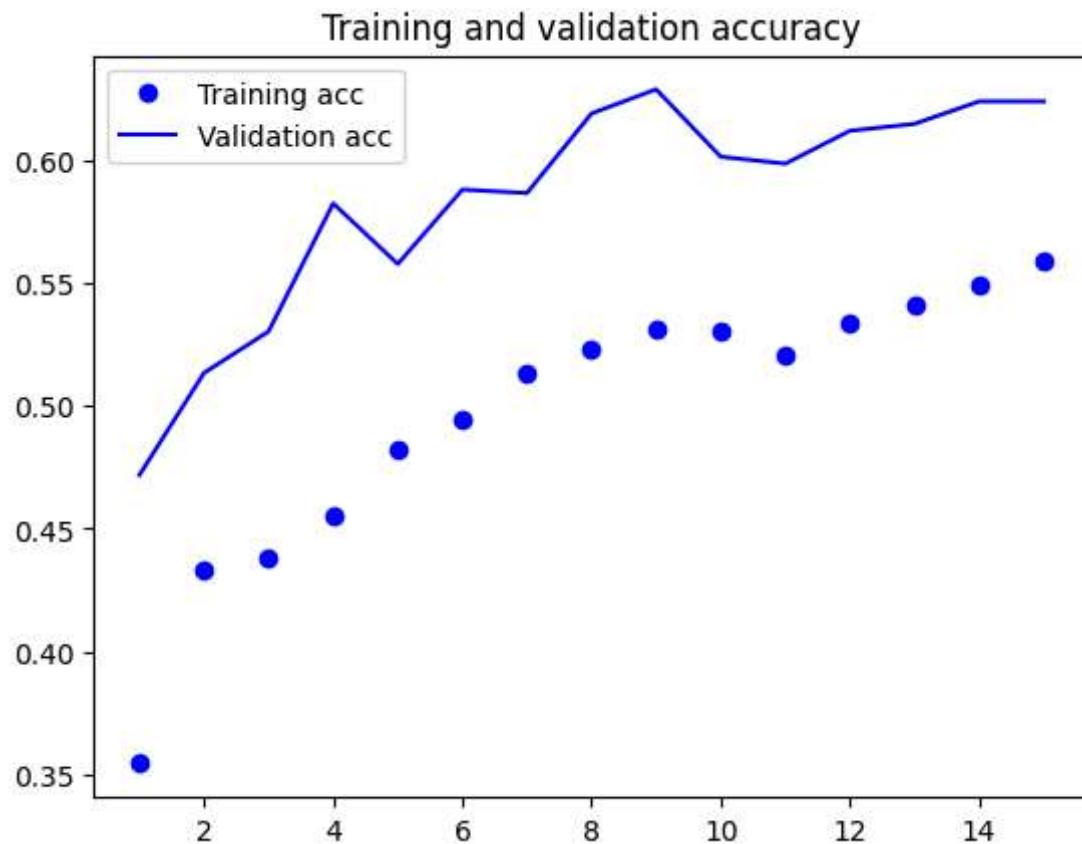
	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.7105	0.4154	0.5243	195
1	0.6807	0.5707	0.6209	198
2	0.4857	0.3881	0.4315	219
3	0.6885	0.6562	0.6720	192
4	0.4049	0.5180	0.4545	222
5	0.5166	0.7800	0.6215	200
6	0.9490	0.9588	0.9538	194

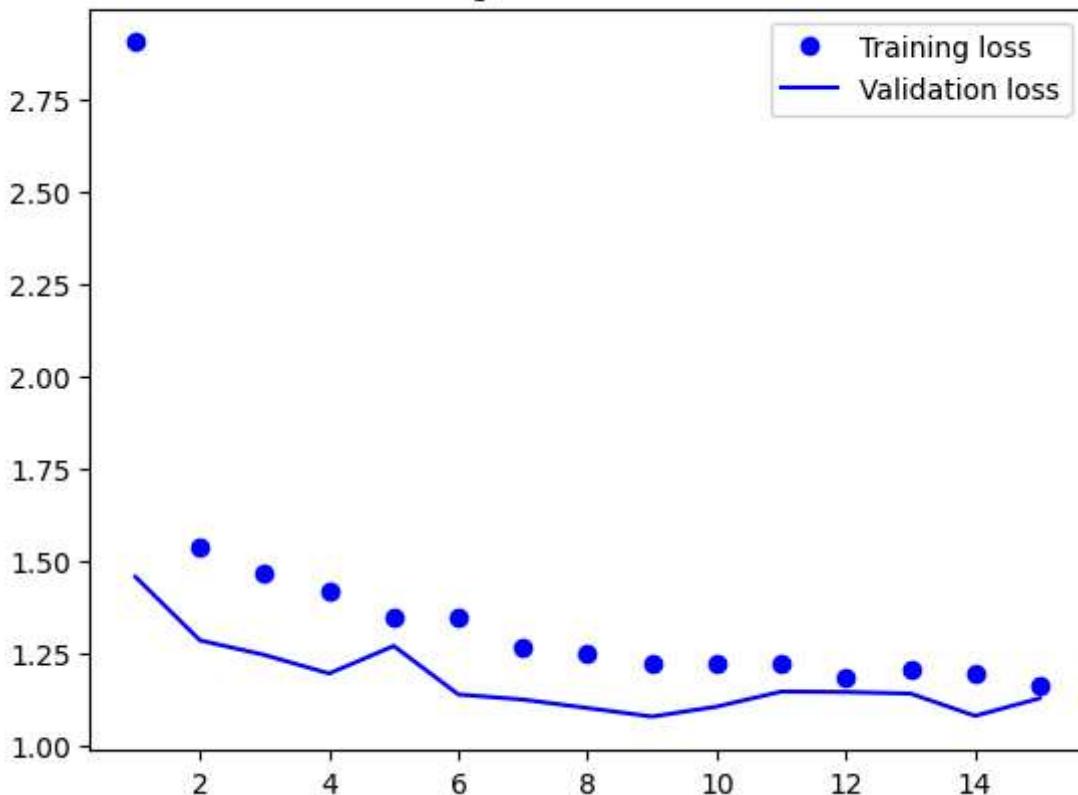
accuracy			0.6070	1420
macro avg	0.6337	0.6125	0.6112	1420

weighted avg	0.6262	0.6070	0.6049	1420
--------------	--------	--------	--------	------

```
In [39]: import matplotlib.pyplot as plt
accuracy = history_t.history['accuracy']
val_acc = history_t.history['val_accuracy']
loss = history_t.history['loss']
val_loss = history_t.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()
```



### Training and validation loss



Durante a feature extraction, observa-se uma subida constante na acurácia de treino (0.35 para 0.56) e validação (0.47 para 0.62), com curvas próximas e paralelas. Esse padrão indica que o modelo está a aprender de forma gradual e equilibrada, com boa capacidade de generalização.

As perdas de treino e validação diminuem progressivamente, com valores bastante próximos (1.0–1.5), o que sugere que o modelo está a convergir bem e sem sinais de overfitting nesta etapa inicial.

## Fine Tuning

```
In [40]: # Descongelar parte da VGG16 (últimas camadas)
conv_base.trainable = True
for layer in conv_base.layers[:-4]: # Descongelar as ultimas -8
    layer.trainable = False # manter as primeiras camadas congeladas

# Recompilar o modelo com Learning rate menor
model_t.compile(
    loss='categorical_crossentropy',
    optimizer=keras.optimizers.Adam(learning_rate=1e-5),
    metrics=['accuracy']
)

# Treinar novamente
history_t = model_t.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=15
)
```

```
Epoch 1/15
134/134 21s 141ms/step - accuracy: 0.5550 - loss: 1.1736 - val_accuracy: 0.6535 - val_loss: 1.0091
Epoch 2/15
134/134 19s 139ms/step - accuracy: 0.5877 - loss: 1.0485 - val_accuracy: 0.6613 - val_loss: 1.0168
Epoch 3/15
134/134 19s 140ms/step - accuracy: 0.6067 - loss: 1.0131 - val_accuracy: 0.6493 - val_loss: 1.0757
Epoch 4/15
134/134 19s 140ms/step - accuracy: 0.6187 - loss: 0.9626 - val_accuracy: 0.6634 - val_loss: 1.0168
Epoch 5/15
134/134 19s 140ms/step - accuracy: 0.6246 - loss: 0.9596 - val_accuracy: 0.6634 - val_loss: 1.0332
Epoch 6/15
134/134 19s 140ms/step - accuracy: 0.6427 - loss: 0.9297 - val_accuracy: 0.6690 - val_loss: 0.9782
Epoch 7/15
134/134 19s 140ms/step - accuracy: 0.6357 - loss: 0.9442 - val_accuracy: 0.6908 - val_loss: 0.9736
Epoch 8/15
134/134 19s 140ms/step - accuracy: 0.6476 - loss: 0.8951 - val_accuracy: 0.6930 - val_loss: 0.9054
Epoch 9/15
134/134 19s 140ms/step - accuracy: 0.6414 - loss: 0.9262 - val_accuracy: 0.6634 - val_loss: 1.0338
Epoch 10/15
134/134 19s 140ms/step - accuracy: 0.6565 - loss: 0.8900 - val_accuracy: 0.6824 - val_loss: 0.9270
Epoch 11/15
134/134 19s 140ms/step - accuracy: 0.6637 - loss: 0.8588 - val_accuracy: 0.6739 - val_loss: 0.9859
Epoch 12/15
134/134 19s 140ms/step - accuracy: 0.6578 - loss: 0.8427 - val_accuracy: 0.6873 - val_loss: 0.9574
Epoch 13/15
134/134 19s 140ms/step - accuracy: 0.6667 - loss: 0.8453 - val_accuracy: 0.6796 - val_loss: 1.0026
Epoch 14/15
134/134 19s 140ms/step - accuracy: 0.6788 - loss: 0.8244 - val_accuracy: 0.6930 - val_loss: 0.9527
Epoch 15/15
134/134 19s 140ms/step - accuracy: 0.6898 - loss: 0.7990 - val_accuracy: 0.6965 - val_loss: 0.9479
```

```
In [41]: print_classification_metrics(model_t, test_dataset, "Modelo 2 : Fine-tuning")
```

1/1 ————— 0s 219ms/step  
 1/1 ————— 0s 109ms/step  
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 1/1 ————— 0s 110ms/step  
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 1/1 ————— 0s 109ms/step  
 1/1 ————— 0s 109ms/step  
 1/1 ————— 0s 109ms/step  
 1/1 ————— 0s 181ms/step

Modelo 2 : Fine-tuning				
	precision	recall	f1-score	support
0	0.7883	0.5538	0.6506	195
1	0.8298	0.5909	0.6903	198
2	0.5090	0.6484	0.5703	219
3	0.8557	0.8958	0.8753	192
4	0.5402	0.6351	0.5839	222
5	0.7163	0.7450	0.7304	200
6	0.9793	0.9742	0.9767	194
accuracy			0.7169	1420
macro avg	0.7455	0.7205	0.7254	1420

weighted avg	0.7373	0.7169	0.7195	1420
--------------	--------	--------	--------	------

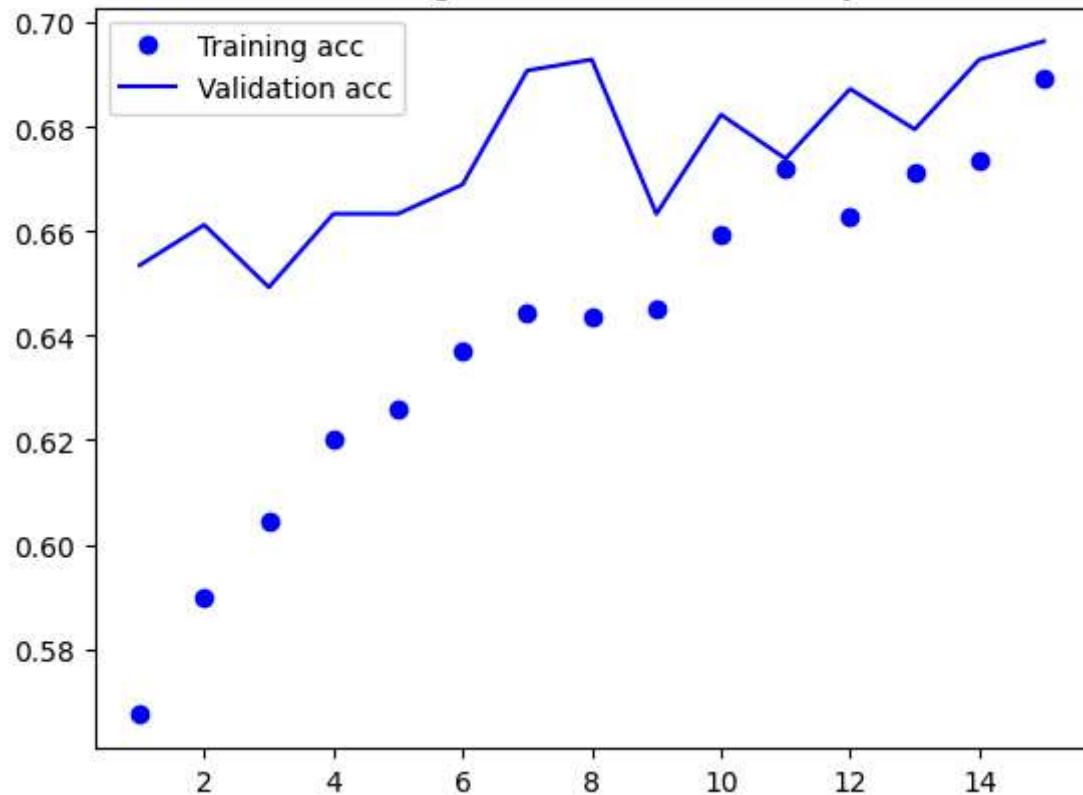
2025-06-12 01:51:08.115895: I tensorflow/core/framework/local\_rendezvous.cc:407] Local rendezvous is aborting with status: OUT\_OF\_RANGE: End of sequence

## Curvas de Loss e de Accuracy

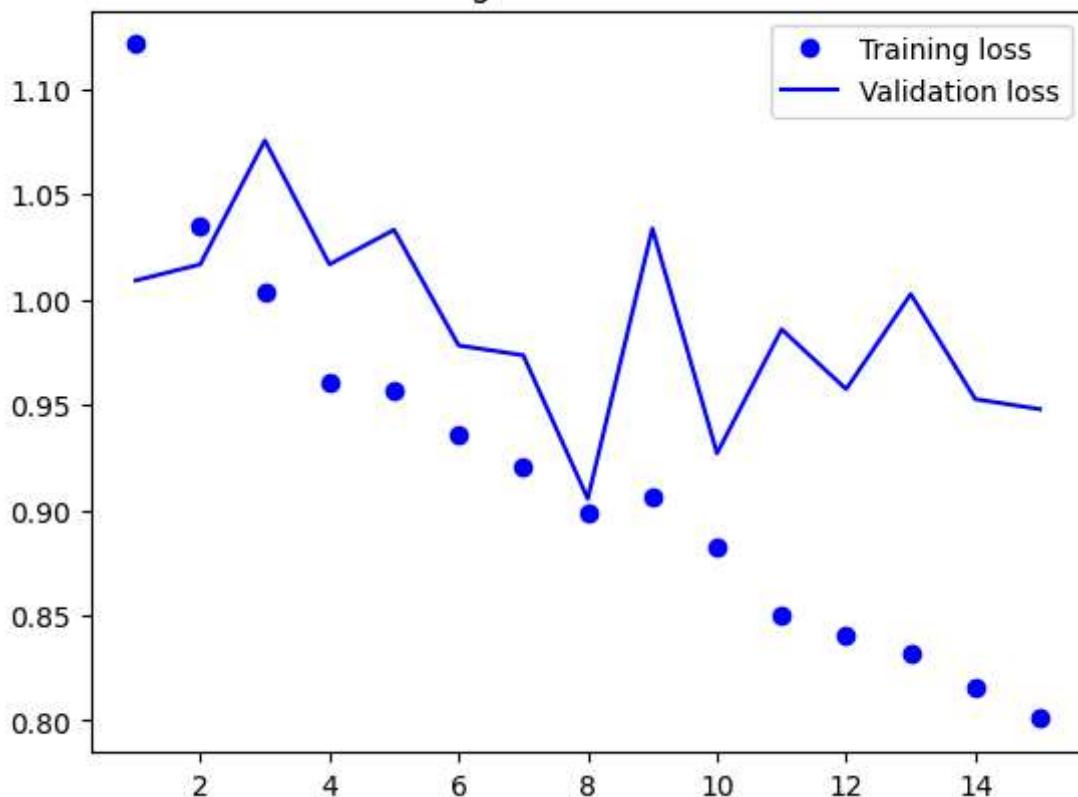
In [42]:

```
import matplotlib.pyplot as plt
accuracy = history_t.history['accuracy']
val_acc = history_t.history['val_accuracy']
loss = history_t.history['loss']
val_loss = history_t.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()
```

Training and validation accuracy



### Training and validation loss



No fine-tuning, as acurárias de treino e validação aumentam de forma consistente, alcançando cerca de 0.69. As curvas estão próximas, o que indica que o modelo está a melhorar seu desempenho sem sinais evidentes de overfitting, o que reflete um ajuste mais equilibrado.

As perdas de treino e validação diminuem ao longo das épocas. Apesar de alguma oscilação na loss de validação, ambas as curvas seguem uma tendência de queda e permanecem próximas, sugerindo convergência estável e boa generalização durante o tuning.

## Matriz de Confusão

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

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

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

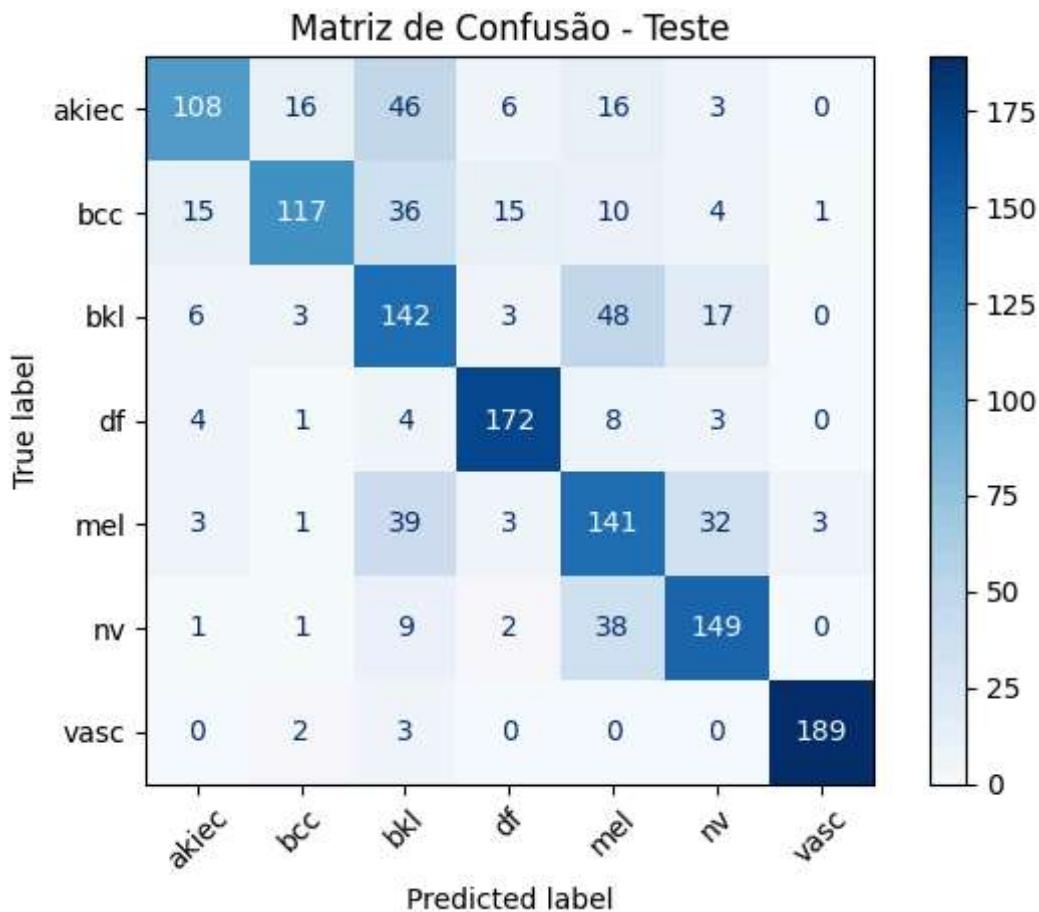
class_names = test_dataset.class_names

# 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()
```

```
1/1 ━━━━━━ 0s 153ms/step
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1/1 ━━━━━━ 0s 111ms/step
1/1 ━━━━━━ 0s 63ms/step
```

<Figure size 1000x800 with 0 Axes>



The Kernel crashed while executing code in the current cell or a previous cell.  
Please review the code in the cell(s) to identify a possible cause of the failure.  
Click [here](https://aka.ms/vscodeJupyterKernelCrash) for more info.  
View Jupyter [log](command:jupyter.viewOutput) for further details.

O modelo apresenta bom desempenho geral, com alta taxa de acerto nas classes 'df', 'nv' e 'vasc', que foram corretamente classificadas na maioria dos casos. No entanto, há confusão significativa entre as classes 'akiec', 'bcc' e 'bkl', o que sugere que o modelo ainda tem dificuldade em distinguir essas lesões, possivelmente devido à semelhança visual entre elas.

## Salvar o Modelo

```
In [44]: model_t.save("modeloT_3A_com_data_aug_adam_cat_cross_best_acc.keras")
```

## Definir a Função para obter Computed Features

```
In [45]: import numpy as np
from tensorflow.keras.applications.vgg16 import preprocess_input

def extract_computed_features(conv_base, dataset, augment_layer=None):
    all_features = []
    all_labels = []
```

```
for images, labels in dataset:  
    # Aplica data augmentation se fornecido  
    if augment_layer:  
        images = augment_layer(images)  
  
    # Pre-processamento obrigatório para VGG16  
    preprocessed = preprocess_input(images)  
  
    # Extrair as computed features  
    features = conv_base.predict(preprocessed)  
  
    all_features.append(features)  
    all_labels.append(labels)  
  
# Junta tudo num único array  
features_array = np.concatenate(all_features)  
labels_array = np.concatenate(all_labels)  
  
return features_array, labels_array
```

Usar a função "extract\_computed\_features"

```
In [46]: train_features, train_labels = extract_computed_features(conv_base, train_dataset)  
val_features, val_labels = extract_computed_features(conv_base, validation_dataset)  
test_features, test_labels = extract_computed_features(conv_base, test_dataset,
```

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```

Salvar as Computed Features

```
In [47]: from numpy import save

save("modelt_3A_train_features.npy", train_features)
save("modelt_3A_train_labels.npy", train_labels)

save("modelt_3A_val_features.npy", val_features)
save("modelt_3A_val_labels.npy", val_labels)

save("modelt_3A_test_features.npy", test_features)
save("modelt_3A_test_labels.npy", test_labels)
```