Projeto Inteligência Artifical (Afonso Fernandes - 2221437, Luís Oliveira - 2221441)

- **Conjunto de validação train4**

Modelos:

S

- **Modelo de raíz**

- **Otimizador:**

- **Com e sem Data Augmentation**

Dados Base:

In [1]:

```
from keras.utils import image_dataset_from_directory
import tensorflow as tf
train_dir_1 = 'trainning/train1'
train_dir_2 = 'trainning/train2'
train_dir_3 = 'trainning/train3'
validation_dir = 'train4' # Validation
train_dir_5 = 'trainning/train5'
test_dir = 'test'

trainning = [train_dir_1, train_dir_2,train_dir_3,train_dir_5]

train_dir = train_dir_2
IMG_SIZE = 32 # 32x32

# image_dataset_from_directory with labels="inferred" for
# getting the images in the subdirectories and translating the subdirectory as a class
# of type categorical
#train_dataset = image_dataset_from_directory(train_dir,image_size=(IMG_SIZE, IMG_SIZE),b
atch_size=32, labels="inferred", label_mode="categorical")
test_dataset = image_dataset_from_directory(test_dir,image_size=(IMG_SIZE, IMG_SIZE), lab
els="inferred",label_mode="categorical")
validation_dataset = image_dataset_from_directory(validation_dir,image_size=(IMG_SIZE, IM
G_SIZE), labels="inferred",label_mode="categorical")

train_dataset = tf.data.Dataset

for i in trainning:
    if i == trainning[0]:
        train_dataset = image_dataset_from_directory(i, image_size=(IMG_SIZE, IMG_SIZE),
labels="inferred", label_mode="categorical")
        continue
    train_dataset = train_dataset.concatenate( image_dataset_from_directory(i, image_size
=(IMG_SIZE, IMG_SIZE), labels="inferred", label_mode="categorical"))
```

```
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.
```

Found 10000 files belonging to 10 classes.
Found 10000 files belonging to 10 classes.

Gráfico da validation accuracy vs test accuracy

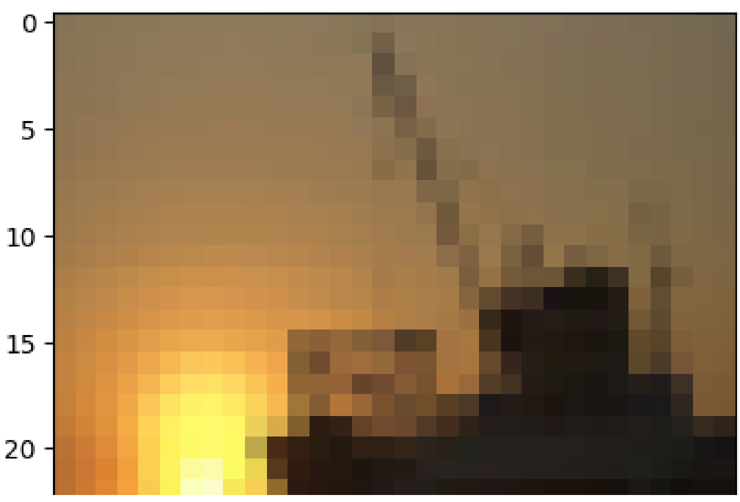
In [2]:

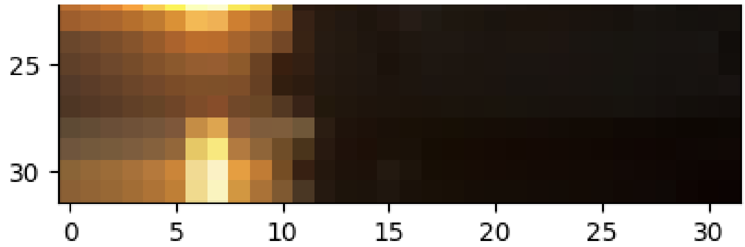
```
import matplotlib.pyplot as plt

def graph(history):
    # Use the correct key names from the history object
    acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']
    loss = history.history['loss']
    val_loss = history.history['val_loss']

    epochs = range(1, len(acc) + 1)

    plt.figure(figsize=(14, 5))

    # Plot training and validation accuracy
    plt.subplot(1, 2, 1)
    plt.plot(epochs, acc, 'bo-', label='Training accuracy')
    plt.plot(epochs, val_acc, 'b-', label='Validation accuracy')
    plt.title('Training and validation accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Plot training and validation loss
    plt.subplot(1, 2, 2)
    plt.plot(epochs, loss, 'bo-', label='Training loss')
    plt.plot(epochs, val_loss, 'b-', label='Validation loss')
    plt.title('Training and validation loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.show()
```

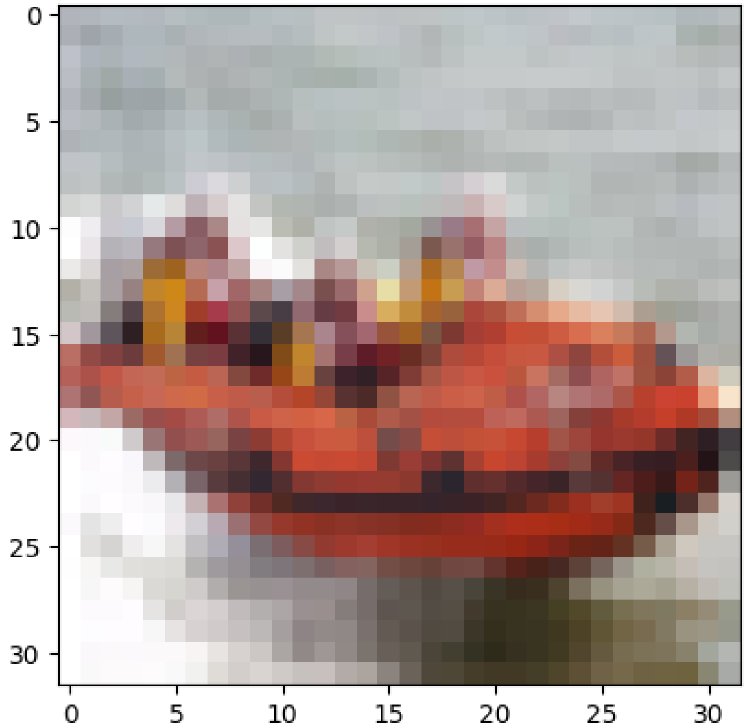
In [3]:

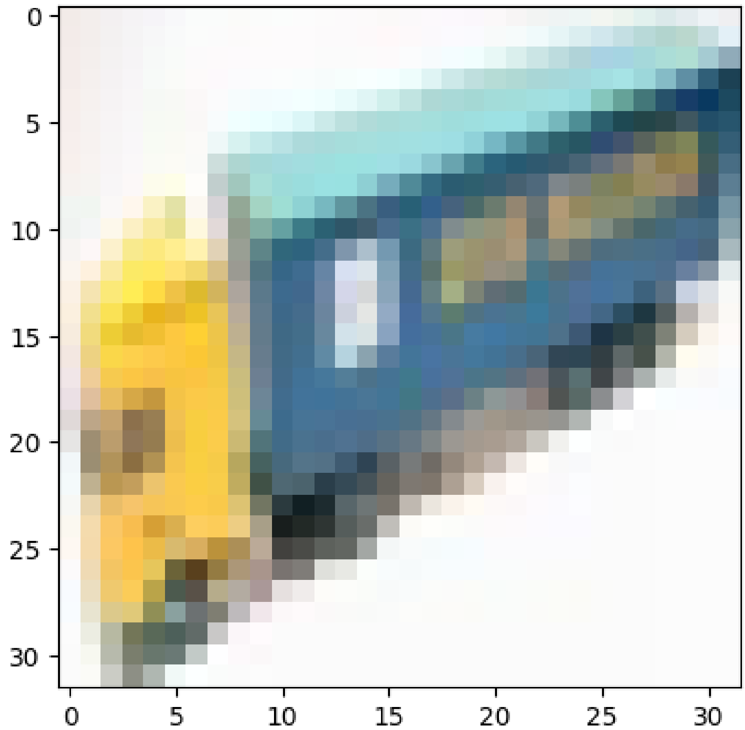
```
import matplotlib.pyplot as plt
for data_batch, labels_batch in train_dataset:
  print('data batch shape:', data_batch.shape)
  print('labels batch shape:', labels_batch.shape)
  break
for data_batch, _ in train_dataset.take(1):
  for i in range(3):
    plt.imshow(data_batch[i].numpy().astype("uint8"))
    plt.show()
```

```
data batch shape: (32, 32, 32, 3)
labels batch shape: (32, 10)
```









Modelo S sem Data augmentation:

In [ ]:

```
import os
import tensorflow as tf
# Para revêr ou treinar mais
model_path = "models_S/S_without_DA.h5"
model =  tf.keras.models.load_model(model_path)
```

In [ ]:

```
model.summary()
```

Optimização da procura de hyperparâmetros através do optuna

In [ ]:

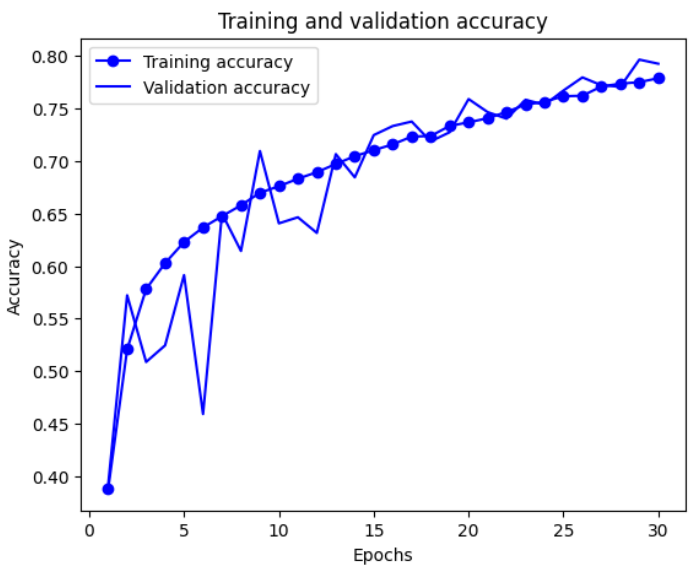
```
import optuna
import keras
from keras import layers



def create_model(trial):
    n_conv_layers = trial.suggest_int('n_conv_layers', 2, 3)
    #making the model
    reg = keras.regularizers.l2(0.005)
    dropConv = 0.2
    dropFinal = 0.5
    inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
    x = layers.Rescaling(1./255)(inputs)
    for i in range(n_conv_layers):
        n_filters = trial.suggest_int('n_filters1_{}'.format(i), 32, 128, step=32)
        n_filters2 = trial.suggest_int('n_filters2_{}'.format(i), 32, 128, step=32)
        n_ksize = trial.suggest_int('n_ksize1_{}'.format(i), 2, 3)
        n_ksize1 = trial.suggest_int('n_ksize2_{}'.format(i), 2, 3)
        x = layers.Conv2D(filters=n_filters, kernel_size=n_ksize,padding="same", activat
ion="relu",kernel_regularizer=reg)(x)
        x = layers.BatchNormalization(axis=-1)(x)
        x = layers.Conv2D(filters=n_filters2, kernel_size=n_ksize1,padding="same", activ
ation="relu",kernel_regularizer=reg)(x)
        x = layers.BatchNormalization(axis=-1)(x)
        x = layers.MaxPooling2D(pool_size=2)(x)
        x = layers.Dropout(dropConv)(x)


    #The flatten and classification process
    x = layers.Flatten()(x)
    x = layers.Dense(512, activation="relu", kernel_regularizer=reg)(x) #trial.suggest_i
nt('dense_units', 512, 1024, step=512)
    x = layers.BatchNormalization()(x)
    x = layers.Dropout(dropFinal)(x)

    outputs = layers.Dense(10, activation="softmax")(x)
    model = keras.Model(inputs=inputs, outputs=outputs)

    lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate=trial.suggest_float('learning_rate_IN', 1e-3, 1e-2, log=True),
    decay_steps=10000,
    decay_rate=0.6)

    # Suggest optimizer
    optimizer_options = ['Adam', 'RMSprop']
    optimizer_selected = trial.suggest_categorical('optimizer', optimizer_options)
    if optimizer_selected == 'Adam':
        optimizer = keras.optimizers.Adam(learning_rate=lr_schedule)
    else:
        optimizer = keras.optimizers.RMSprop(learning_rate=lr_schedule)

    model.compile(optimizer=optimizer,
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

    return model

def objective(trial):
    model = create_model(trial)

    callbacks = [keras.callbacks.ModelCheckpoint(
```

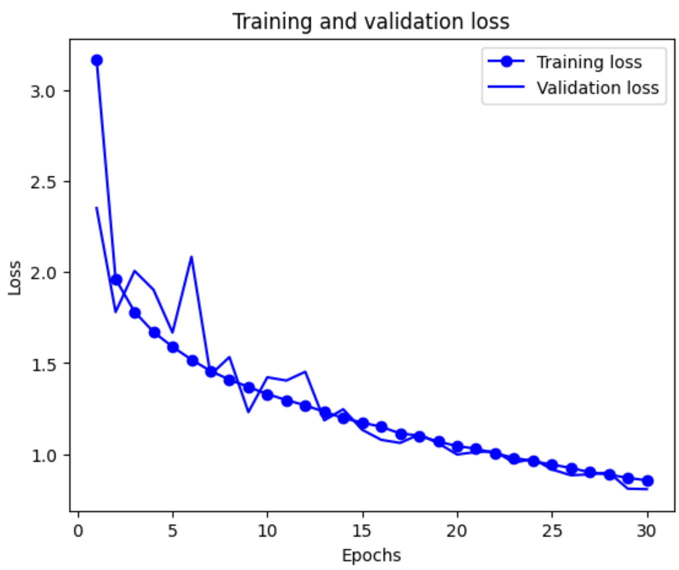
```
        filepath=f'models_S/model_best_{trial.number}.h5',
        save_best_only=True,
        monitor='val_loss',
        mode='min',
        verbose=0
    ),
    keras.callbacks.EarlyStopping(
        monitor='val_loss',
        min_delta=0,
        patience=4,
        verbose=0,
        mode='min',
        restore_best_weights=True,
    )]
    batch_size = trial.suggest_int('batch_size', 32, 128, step=32)


    history = model.fit(train_dataset,
                        batch_size=batch_size,
                        epochs=30,
                        validation_data=validation_dataset,
                        callbacks=callbacks,
                        verbose=0)   # não verboso
    graph(history)
    val_loss = history.history['val_loss'][-1]
    return val_loss
```

Utilização do Optuna:

- **Criação do Modelo com os campos dos hyperparâmetros com sugestões de valores para serem testados**
- **Definição do objetivo de maximizar a accuracy e callback para guardar sempre o melhor modelo definido pela accuracy**

[I 2024-06-19 17:12:17,850] A new study created in memory with name: no-name-c2f53027-0f57-40d9-a0d9-0a731b6b2db8





[I 2024-06-19 18:05:48,769]

Trial 1 finished with value: 0.8066616654396057 and parameters:

{'n_conv_layers': 3,

'n_filters1_0': 128,

'n_filters2_0': 96,

'n_ksize1_0': 3,

'n_ksize2_0': 2,

'n_filters1_1': 32,

'n_filters2_1': 32,

'n_ksize1_1': 3,

'n_ksize2_1': 2,

'n_filters1_2': 96,

'n_filters2_2': 32,

'n_ksize1_2': 2,

'n_ksize2_2': 2,

'learning_rate_IN': 0.0020018655778243685,

'optimizer': 'RMSprop',

'batch_size': 128}.

Best is trial 1 with value: 0.8066616654396057.

In [ ]:

```
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=6)   # Ajustar número de trials para um estudo mais com
pleto

print(f"Best trial: {study.best_trial.params}")
```

- **Com o modelo já carregado do ficheiro, continuar o treino**

In [ ]:

```
import os
import tensorflow as tf

model_path = "models_S/S_without_DA_1.h5"
model =  tf.keras.models.load_model(model_path)
```

In [28]:

```
callbacks = [keras.callbacks.ModelCheckpoint(
        filepath='models_S/S_without_DA.h5',
        save_best_only=True,
        monitor='val_loss',
        mode='min',
        verbose=1
    ),keras.callbacks.EarlyStopping(
    monitor='val_loss',
    min_delta=0,
    patience=5,
    verbose=1,
    mode='auto',
    restore_best_weights=True,
)]


history = model.fit(
    train_dataset,
    epochs=100,
    batch_size=128,
    validation_data=validation_dataset,
    callbacks=callbacks,
    verbose=1
)   # # sim/não verboso
```

```
Epoch 1/100
```

```
1251/1252 [============================>.] - ETA: 0s - loss: 0.8367 - accuracy: 0.7999
Epoch 1: val_loss improved from inf to 0.81660, saving model to models_S\S_without_DA.h5
1252/1252 [==============================] - 103s 80ms/step - loss: 0.8367 - accuracy: 0.
7999 - val_loss: 0.8166 - val_accuracy: 0.8015
Epoch 2/100
1250/1252 [============================>.] - ETA: 0s - loss: 0.8224 - accuracy: 0.8013
Epoch 2: val_loss improved from 0.81660 to 0.81083, saving model to models_S\S_without_DA
.h5
1252/1252 [==============================] - 37s 29ms/step - loss: 0.8224 - accuracy: 0.8
013 - val_loss: 0.8108 - val_accuracy: 0.7999
Epoch 3/100
1252/1252 [==============================] - ETA: 0s - loss: 0.8118 - accuracy: 0.8068
Epoch 3: val_loss did not improve from 0.81083
1252/1252 [==============================] - 31s 24ms/step - loss: 0.8118 - accuracy: 0.8
068 - val_loss: 0.8255 - val_accuracy: 0.7993
Epoch 4/100
1252/1252 [==============================] - ETA: 0s - loss: 0.8060 - accuracy: 0.8067
Epoch 4: val_loss did not improve from 0.81083
1252/1252 [==============================] - 31s 25ms/step - loss: 0.8060 - accuracy: 0.8
067 - val_loss: 0.8220 - val_accuracy: 0.7983
Epoch 5/100
1252/1252 [==============================] - ETA: 0s - loss: 0.7875 - accuracy: 0.8099
Epoch 5: val_loss did not improve from 0.81083
1252/1252 [==============================] - 31s 25ms/step - loss: 0.7875 - accuracy: 0.8
099 - val_loss: 0.8480 - val_accuracy: 0.7889
Epoch 6/100
1252/1252 [==============================] - ETA: 0s - loss: 0.7840 - accuracy: 0.8093
Epoch 6: val_loss did not improve from 0.81083
1252/1252 [==============================] - 31s 25ms/step - loss: 0.7840 - accuracy: 0.8
093 - val_loss: 0.8455 - val_accuracy: 0.7877
Epoch 7/100
1250/1252 [============================>.] - ETA: 0s - loss: 0.7806 - accuracy: 0.8115
Epoch 7: val_loss improved from 0.81083 to 0.79669, saving model to models_S\S_without_DA
.h5
1252/1252 [==============================] - 32s 25ms/step - loss: 0.7804 - accuracy: 0.8
116 - val_loss: 0.7967 - val_accuracy: 0.8021
Epoch 8/100
1249/1252 [============================>.] - ETA: 0s - loss: 0.7730 - accuracy: 0.8152
Epoch 8: val_loss improved from 0.79669 to 0.77490, saving model to models_S\S_without_DA
.h5
1252/1252 [==============================] - 33s 26ms/step - loss: 0.7732 - accuracy: 0.8
152 - val_loss: 0.7749 - val_accuracy: 0.8112
Epoch 9/100
1252/1252 [==============================] - ETA: 0s - loss: 0.7582 - accuracy: 0.8167
Epoch 9: val_loss did not improve from 0.77490
1252/1252 [==============================] - 32s 25ms/step - loss: 0.7582 - accuracy: 0.8
167 - val_loss: 0.7931 - val_accuracy: 0.8020
Epoch 10/100
1251/1252 [============================>.] - ETA: 0s - loss: 0.7551 - accuracy: 0.8202
Epoch 10: val_loss did not improve from 0.77490
1252/1252 [==============================] - 33s 26ms/step - loss: 0.7553 - accuracy: 0.8
202 - val_loss: 0.7902 - val_accuracy: 0.8058
Epoch 11/100
1250/1252 [============================>.] - ETA: 0s - loss: 0.7477 - accuracy: 0.8180
Epoch 11: val_loss did not improve from 0.77490
1252/1252 [==============================] - 34s 27ms/step - loss: 0.7475 - accuracy: 0.8
181 - val_loss: 0.7826 - val_accuracy: 0.8047
Epoch 12/100
1250/1252 [============================>.] - ETA: 0s - loss: 0.7449 - accuracy: 0.8186
Epoch 12: val_loss improved from 0.77490 to 0.76458, saving model to models_S\S_without_D
A.h5
1252/1252 [==============================] - 33s 27ms/step - loss: 0.7452 - accuracy: 0.8
185 - val_loss: 0.7646 - val_accuracy: 0.8123
Epoch 13/100
1251/1252 [============================>.] - ETA: 0s - loss: 0.7378 - accuracy: 0.8227
Epoch 13: val_loss improved from 0.76458 to 0.76322, saving model to models_S\S_without_D
A.h5
1252/1252 [==============================] - 31s 25ms/step - loss: 0.7377 - accuracy: 0.8
227 - val_loss: 0.7632 - val_accuracy: 0.8123
Epoch 14/100
1250/1252 [============================>.] - ETA: 0s - loss: 0.7346 - accuracy: 0.8201
Epoch 14: val_loss did not improve from 0.76322
```

```
1252/1252 [==============================] - 31s 25ms/step - loss: 0.7350 - accuracy: 0.8
201 - val_loss: 0.7646 - val_accuracy: 0.8113
Epoch 15/100
1251/1252 [============================>.] - ETA: 0s - loss: 0.7301 - accuracy: 0.8241
Epoch 15: val_loss did not improve from 0.76322
1252/1252 [==============================] - 32s 25ms/step - loss: 0.7300 - accuracy: 0.8
241 - val_loss: 0.7703 - val_accuracy: 0.8101
Epoch 16/100
1251/1252 [============================>.] - ETA: 0s - loss: 0.7195 - accuracy: 0.8279
Epoch 16: val_loss did not improve from 0.76322
1252/1252 [==============================] - 31s 25ms/step - loss: 0.7195 - accuracy: 0.8
280 - val_loss: 0.7716 - val_accuracy: 0.8060
Epoch 17/100
1252/1252 [==============================] - ETA: 0s - loss: 0.7162 - accuracy: 0.8266
Epoch 17: val_loss did not improve from 0.76322
1252/1252 [==============================] - 31s 25ms/step - loss: 0.7162 - accuracy: 0.8
266 - val_loss: 0.7682 - val_accuracy: 0.8084
Epoch 18/100
1251/1252 [============================>.] - ETA: 0s - loss: 0.7142 - accuracy: 0.8261
Epoch 18: val_loss did not improve from 0.76322
Restoring model weights from the end of the best epoch: 13.
1252/1252 [==============================] - 31s 24ms/step - loss: 0.7141 - accuracy: 0.8
261 - val_loss: 0.7705 - val_accuracy: 0.8102
Epoch 18: early stopping
```

- **Avaliar Modelo:**

In [29]:

```
val_loss, val_acc = model.evaluate(test_dataset)
print('val_acc:', val_acc,'\nval_loss:', val_loss)
```

```
313/313 [==============================] - 4s 13ms/step - loss: 0.7557 - accuracy: 0.8209
val_acc: 0.820900022983551
val_loss: 0.7556588649749756
```

- **Guardar o modelo depois de ter sido treinado:**

In [ ]:

```
# Guardar por alguma razão extra
keras.models.save_model(model,"models_S\S_without_DA.h5")
```

Modelo S com Data augmentation:

- **Parecido com o feito anteriormente mas com Data augmentation:**

Optimização da procura de hyperparâmetros através do optuna com Data Augmentation

In [ ]:

```
import optuna
import keras
from keras import layers


def create_model(trial):
    n_conv_layers = trial.suggest_int('n_conv_layers', 2, 3)
    # Definição da augmentação da informação
    reg = keras.regularizers.l2(0.005)
    dropConv = 0.2
    dropFinal = 0.5
    data_augmentation = keras.Sequential(
```

```
        [layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),])
    #
    # Criação do dito Modelo
    inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
    # Data augmentation
    x = data_augmentation(inputs)
    #
    x = layers.Rescaling(1./255)(inputs)
    for i in range(n_conv_layers):
        n_filters = trial.suggest_int('n_filters1_{}'.format(i), 32, 128, step=32)
        #n_filters2 = trial.suggest_int('n_filters2_{}'.format(i), 32, 128, step=32)
        n_filters2 = n_filters
        n_ksize = trial.suggest_int('n_ksize1_{}'.format(i), 2, 3)
        #n_ksize1 = trial.suggest_int('n_ksize2_{}'.format(i), 2, 3)
        n_ksize1 = n_ksize
        x = layers.Conv2D(filters=n_filters, kernel_size=n_ksize,padding="same", activat
ion="relu",kernel_regularizer=reg)(x)
        x = layers.BatchNormalization(axis=-1)(x)
        x = layers.Conv2D(filters=n_filters2, kernel_size=n_ksize1,padding="same", activ
ation="relu",kernel_regularizer=reg)(x)
        x = layers.BatchNormalization(axis=-1)(x)
        x = layers.MaxPooling2D(pool_size=2)(x)
        x = layers.Dropout(dropConv)(x)


    #The flatten and classification process
    x = layers.Flatten()(x)
    x = layers.Dense(trial.suggest_int('dense_units', 256, 512, step=256), activation="r
elu", kernel_regularizer=reg)(x)
    x = layers.BatchNormalization()(x)
    x = layers.Dropout(dropFinal)(x)

    outputs = layers.Dense(10, activation="softmax")(x)
    model = keras.Model(inputs=inputs, outputs=outputs)

    lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate=trial.suggest_float('learning_rate_IN', 1e-3, 1e-2, log=True),
    decay_steps=10000,
    decay_rate=0.6)

    # Suggest optimizer
    optimizer_options = ['Adam', 'RMSprop']
    optimizer_selected = trial.suggest_categorical('optimizer', optimizer_options)
    if optimizer_selected == 'Adam':
        optimizer = keras.optimizers.Adam(learning_rate=lr_schedule)
    else:
        optimizer = keras.optimizers.RMSprop(learning_rate=lr_schedule)

    model.compile(optimizer=optimizer,
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

    return model

def objective(trial):
    model = create_model(trial)

    callbacks = [keras.callbacks.ModelCheckpoint(
        filepath=f'models_S/model_best_DA_{trial.number}.h5',
        save_best_only=True,
        monitor='val_loss',
        mode='min',
        verbose=0
    ),
    keras.callbacks.EarlyStopping(
        monitor='val_loss',
        min_delta=0,
        patience=4,
        verbose=1,
        mode='min',
```

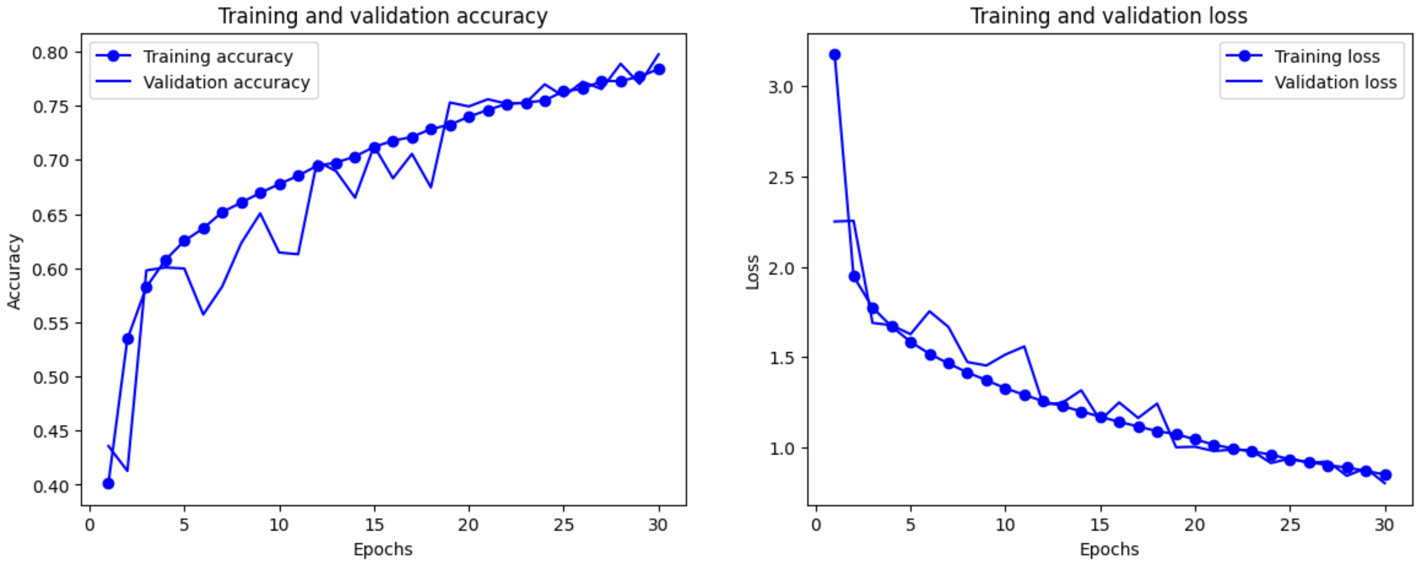
```
        restore_best_weights=True,
    )]
    batch_size = trial.suggest_int('batch_size', 32, 128, step=32)


    history = model.fit(train_dataset,
                        batch_size=batch_size,
                        epochs=50,
                        validation_data=validation_dataset,
                        callbacks=callbacks,
                        verbose=0)   # não verboso
    graph(history)
    val_loss = history.history['val_loss'][-1]
    return val_loss
```

Utilização do Optuna:

- **Criação do Modelo com os campos dos hyperparâmetros com sugestões de valores para serem testados**
- **Definição do objetivo de maximizar a accuracy e callback para guardar sempre o melhor modelo definido pela accuracy**

In [ ]:

```
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=2)   # Ajustar número de trials para um estudo mais co
mpleto

print(f"Best trial: {study.best_trial.params}")
```



Utilização dos parâmetros encontrados no Modelo S sem Data Augmentation

In [33]:

```
import keras
# Load do novo melhor modelo
best_model = keras.models.load_model("models_S\model_best_DA_0.h5")
```

In [34]:

```
model.summary()
```

```
Model: "model_48"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_49 (InputLayer)       [(None, 32, 32, 3)]       0

 rescaling_48 (Rescaling)    (None, 32, 32, 3)         0
```

```
 conv2d_150 (Conv2D)         (None, 32, 32, 128)       3584      
                                                                 
 batch_normalization_216 (Ba  (None, 32, 32, 128)      512       
 tchNormalization)                                               
                                                                 
 conv2d_151 (Conv2D)         (None, 32, 32, 96)        49248     
                                                                 
 batch_normalization_217 (Ba  (None, 32, 32, 96)       384       
 tchNormalization)                                               
                                                                 
 max_pooling2d_117 (MaxPooli  (None, 16, 16, 96)       0         
 ng2D)                                                           
                                                                 
 dropout_183 (Dropout)       (None, 16, 16, 96)        0         
                                                                 
 conv2d_152 (Conv2D)         (None, 16, 16, 32)        27680     
                                                                 
 batch_normalization_218 (Ba  (None, 16, 16, 32)       128       
 tchNormalization)                                               
                                                                 
 conv2d_153 (Conv2D)         (None, 16, 16, 32)        4128      
                                                                 
 batch_normalization_219 (Ba  (None, 16, 16, 32)       128       
 tchNormalization)                                               
                                                                 
 max_pooling2d_118 (MaxPooli  (None, 8, 8, 32)         0         
 ng2D)                                                           
                                                                 
 dropout_184 (Dropout)       (None, 8, 8, 32)          0         
                                                                 
 conv2d_154 (Conv2D)         (None, 8, 8, 96)          12384     
                                                                 
 batch_normalization_220 (Ba  (None, 8, 8, 96)         384       
 tchNormalization)                                               
                                                                 
 conv2d_155 (Conv2D)         (None, 8, 8, 32)          12320     
                                                                 
 batch_normalization_221 (Ba  (None, 8, 8, 32)         128       
 tchNormalization)                                               
                                                                 
 max_pooling2d_119 (MaxPooli  (None, 4, 4, 32)         0         
 ng2D)                                                           
                                                                 
 dropout_185 (Dropout)       (None, 4, 4, 32)          0         
                                                                 
 flatten_48 (Flatten)        (None, 512)               0         
                                                                 
 dense_114 (Dense)           (None, 512)               262656    
                                                                 
 batch_normalization_222 (Ba  (None, 512)              2048      
 tchNormalization)                                               
                                                                 
 dropout_186 (Dropout)       (None, 512)               0         
                                                                 
 dense_115 (Dense)           (None, 10)                5130      
                                                                 
=================================================================
Total params: 380,842
Trainable params: 378,986
Non-trainable params: 1,856
_________________________________________________________________
```

In [35]:

```
callbacks = [keras.callbacks.ModelCheckpoint(
        filepath='models_S/S_with_DA.h5',
        save_best_only=True,
        monitor='val_loss',
        mode='min',
        verbose=0
    ), keras.callbacks.EarlyStopping(
```

```python
        monitor='val_loss',
        min_delta=0,
        patience=2,
        verbose=0,
        mode='min',
        restore_best_weights=True,
    )]


history = best_model.fit(
    train_dataset,
    epochs=100, batch_size=128,
    validation_data=validation_dataset,
    callbacks=callbacks,
    verbose=1
)
```

```
Epoch 1/100
1252/1252 [==============================] - 51s 39ms/step - loss: 0.8115 - accuracy: 0.7
906 - val_loss: 0.7876 - val_accuracy: 0.7982
Epoch 2/100
1252/1252 [==============================] - 48s 38ms/step - loss: 0.7882 - accuracy: 0.7
959 - val_loss: 0.7700 - val_accuracy: 0.8023
Epoch 3/100
1252/1252 [==============================] - 49s 39ms/step - loss: 0.7799 - accuracy: 0.7
983 - val_loss: 0.7618 - val_accuracy: 0.8073
Epoch 4/100
1252/1252 [==============================] - 49s 39ms/step - loss: 0.7652 - accuracy: 0.8
001 - val_loss: 0.8270 - val_accuracy: 0.7853
Epoch 5/100
1252/1252 [==============================] - 49s 39ms/step - loss: 0.7522 - accuracy: 0.8
021 - val_loss: 0.7307 - val_accuracy: 0.8153
Epoch 6/100
1252/1252 [==============================] - 51s 40ms/step - loss: 0.7387 - accuracy: 0.8
076 - val_loss: 0.7288 - val_accuracy: 0.8113
Epoch 7/100
1252/1252 [==============================] - 49s 39ms/step - loss: 0.7318 - accuracy: 0.8
084 - val_loss: 0.7160 - val_accuracy: 0.8147
Epoch 8/100
1252/1252 [==============================] - 51s 41ms/step - loss: 0.7170 - accuracy: 0.8
124 - val_loss: 0.7158 - val_accuracy: 0.8143
Epoch 9/100
1252/1252 [==============================] - 53s 42ms/step - loss: 0.7030 - accuracy: 0.8
158 - val_loss: 0.7004 - val_accuracy: 0.8169
Epoch 10/100
1252/1252 [==============================] - 51s 41ms/step - loss: 0.6949 - accuracy: 0.8
174 - val_loss: 0.7054 - val_accuracy: 0.8148
Epoch 11/100
1252/1252 [==============================] - 52s 42ms/step - loss: 0.6812 - accuracy: 0.8
213 - val_loss: 0.6948 - val_accuracy: 0.8184
Epoch 12/100
1252/1252 [==============================] - 52s 41ms/step - loss: 0.6777 - accuracy: 0.8
211 - val_loss: 0.6928 - val_accuracy: 0.8168
Epoch 13/100
1252/1252 [==============================] - 51s 41ms/step - loss: 0.6665 - accuracy: 0.8
234 - val_loss: 0.6810 - val_accuracy: 0.8195
Epoch 14/100
1252/1252 [==============================] - 54s 43ms/step - loss: 0.6520 - accuracy: 0.8
304 - val_loss: 0.6813 - val_accuracy: 0.8196
Epoch 15/100
1252/1252 [==============================] - 52s 42ms/step - loss: 0.6509 - accuracy: 0.8
270 - val_loss: 0.6696 - val_accuracy: 0.8230
Epoch 16/100
1252/1252 [==============================] - 53s 42ms/step - loss: 0.6355 - accuracy: 0.8
300 - val_loss: 0.6646 - val_accuracy: 0.8239
Epoch 17/100
1252/1252 [==============================] - 53s 42ms/step - loss: 0.6254 - accuracy: 0.8
343 - val_loss: 0.6708 - val_accuracy: 0.8199
Epoch 18/100
1252/1252 [==============================] - 51s 41ms/step - loss: 0.6235 - accuracy: 0.8
345 - val_loss: 0.6522 - val_accuracy: 0.8249
Epoch 19/100
```

```
1252/1252 [==============================] - 53s 42ms/step - loss: 0.6173 - accuracy: 0.8
348 - val_loss: 0.6556 - val_accuracy: 0.8256
Epoch 20/100
1252/1252 [==============================] - 53s 42ms/step - loss: 0.6052 - accuracy: 0.8
391 - val_loss: 0.6442 - val_accuracy: 0.8265
Epoch 21/100
1252/1252 [==============================] - 57s 46ms/step - loss: 0.6005 - accuracy: 0.8
403 - val_loss: 0.6489 - val_accuracy: 0.8253
Epoch 22/100
1252/1252 [==============================] - 56s 44ms/step - loss: 0.5926 - accuracy: 0.8
439 - val_loss: 0.6390 - val_accuracy: 0.8279
Epoch 23/100
1252/1252 [==============================] - 71s 56ms/step - loss: 0.5879 - accuracy: 0.8
426 - val_loss: 0.6307 - val_accuracy: 0.8313
Epoch 24/100
1252/1252 [==============================] - 53s 42ms/step - loss: 0.5858 - accuracy: 0.8
417 - val_loss: 0.6329 - val_accuracy: 0.8308
Epoch 25/100
1252/1252 [==============================] - 60s 48ms/step - loss: 0.5767 - accuracy: 0.8
442 - val_loss: 0.6310 - val_accuracy: 0.8277
```

- **Avaliar Modelo:**

In [37]:

```
val_loss, val_acc = best_model.evaluate(validation_dataset)
print('val_acc:', val_acc,'\nval_loss:', val_loss)
```

```
313/313 [==============================] - 5s 15ms/step - loss: 0.6307 - accuracy: 0.8313
val_acc: 0.8313000202178955
val_loss: 0.6306564211845398
```

- **Guardar o modelo depois de ter sido treinado:**

In [38]:

```
keras.models.save_model(best_model,"models_S\S_with_DA.h5")
```