```
#Used to mount google drive to colab so that files can be accessed
from google drive
from google.colab import drive
drive.mount('/content/drive')
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force remount=True).
#Importing necessary libraries for the project
import tensorflow as tf
from keras.utils import image dataset from directory
from keras.applications.vgg16 import VGG16
from tensorflow import keras
from keras import layers
# Directories
#specifying the directories where the datasets of train, validation
and test are stored
train dirs = [
    '/content/drive/MyDrive/ProjetoIA/dataset/train1',
    '/content/drive/MyDrive/ProjetoIA/dataset/train2',
    '/content/drive/MyDrive/ProjetoIA/dataset/train4',
    '/content/drive/MyDrive/ProjetoIA/dataset/train5'
1
validation dir = '/content/drive/MyDrive/ProjetoIA/dataset/train3'
test dir = '/content/drive/MyDrive/ProjetoIA/dataset/test'
# Parameters
IMG SIZE = 150
BATCH SIZE = 32
# Function to load datasets from multiple directories and concatenate
def load and concatenate datasets(directories, img size, batch size):
    datasets = [] #list to store the datasets
    for directory in directories:
        # Load dataset from directory
        dataset = image dataset from directory(
            directory,
            image size=(img size, img size),
            batch size=batch size
        datasets.append(dataset) #append the dataset to the list
    return datasets
# Load train datasets and concatenate
train datasets = load and concatenate datasets(train dirs, IMG SIZE,
BATCH SIZE)
#combine the train datasets in a unique dataset
train dataset = tf.data.Dataset.sample from datasets(train datasets)
```

```
# Load validation and test datasets
validation dataset = image dataset from directory(
   validation_dir,
   image size=(IMG SIZE, IMG_SIZE),
   batch size=BATCH SIZE
test dataset = image dataset from directory(
   test dir,
   image_size=(IMG SIZE, IMG SIZE),
   batch size=BATCH SIZE
)
# Extract class names from one of the datasets
example dataset = image dataset from directory(
   train dirs[0],
   image size=(IMG SIZE, IMG_SIZE),
   batch size=BATCH SIZE
class names = example dataset.class names
print(class names)
Found 10400 files belonging to 10 classes.
Found 9600 files belonging to 10 classes.
Found 10000 files belonging to 1 classes.
Found 10400 files belonging to 10 classes.
['000_airplane', '001_automobile', '002_bird', '003_cat', '004_deer',
'005 dog', '006 frog', '007 horse', '008 ship', '009 truck']
# Build the model
# Create the base model from the pre-trained model VGG16 with weights
from ImageNet
# excluding the top layers
# Fine-tuning the model
conv base = VGG16(weights="imagenet", include top=False)
conv base.trainable = True #defining that the convolutional base is
trainable
for layer in conv base.layers[:-2]: #excluding the last two layers
   layer.trainable = False #defining that the layers are not
trainable
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16 weights tf dim ordering tf kernels notop.h5
```

```
# Data augmentation
#Flip horizontal ramdomly, rotate randomly 10%, and zoom randomly 20%
data augmentation = keras.Sequential(
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)
inputs = keras.Input(shape=(150, 150, 3)) # defining the input shape,
considering the image redimensioned to 150x150 with 3 channels(RGB)
x = data augmentation(inputs) #applying the transformations of the
data augmentation
x = keras.applications.vgg16.preprocess input(x) # Apply input value
scalina
x = conv base(x)
x = layers.Flatten()(x)
x = layers.Dense(256, activation='relu')(x)
x = lavers.Dropout(0.5)(x)
outputs = layers.Dense(10, activation="softmax")(x)
model = keras.Model(inputs, outputs)
# Compile the model
model.compile(
    loss="sparse categorical crossentropy",
    optimizer=keras.optimizers.RMSprop(learning rate=1e-5),
    metrics=["accuracy"]
)
# Adding ModelCheckpoint callback
# its for saving the best model based on the validation loss
# and has a patience of 5 epochs to avoid overfitting
checkpoint cb = tf.keras.callbacks.ModelCheckpoint(
'/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA bes
t.h5',
    save best only=True,
    monitor='val loss',
    mode='min',
    verbose=1
early stop = tf.keras.callbacks.EarlyStopping(monitor='val loss',
                           patience=5,
                           verbose=1)
# Train the model with fine-tuning and checkpointing
history = model.fit(
    train dataset,
    epochs=30,
```

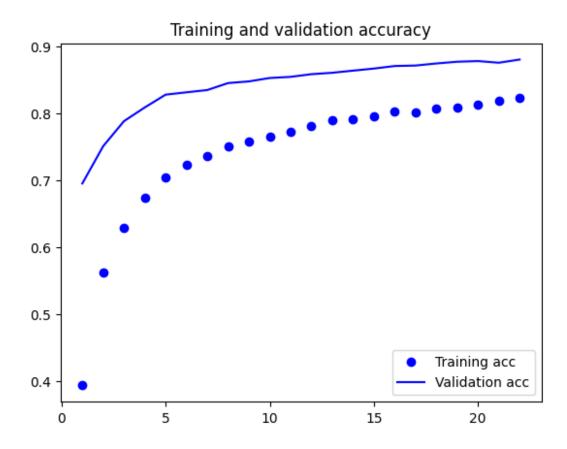
```
validation data=validation dataset,
   callbacks=[checkpoint cb, early stop]
)
# Save the final model
model.save('/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT
with DA.h5')
Epoch 1/30
  1251/Unknown - 432s 343ms/step - loss: 4.7180 - accuracy: 0.3935
Epoch 1: val loss improved from inf to 1.10213, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
. h5
/usr/local/lib/python3.10/dist-packages/keras/src/engine/
training.py:3103: UserWarning: You are saving your model as an HDF5
file via `model.save()`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my model.keras')`.
 saving api.save model(
4.7180 - accuracy: 0.3935 - val loss: 1.1021 - val accuracy: 0.6955
Epoch 2/30
accuracy: 0.5622
Epoch 2: val loss improved from 1.10213 to 0.78613, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
.h5
1.5968 - accuracy: 0.5622 - val loss: 0.7861 - val accuracy: 0.7512
Epoch 3/30
accuracy: 0.6291
Epoch 3: val loss improved from 0.78613 to 0.67552, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
. h5
1.2200 - accuracy: 0.6291 - val loss: 0.6755 - val accuracy: 0.7887
Epoch 4/30
accuracy: 0.6738
Epoch 4: val loss improved from 0.67552 to 0.62552, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
.h5
1.0614 - accuracy: 0.6738 - val loss: 0.6255 - val accuracy: 0.8092
Epoch 5/30
accuracy: 0.7042
```

```
Epoch 5: val loss improved from 0.62552 to 0.59257, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
.h5
0.9670 - accuracy: 0.7042 - val loss: 0.5926 - val accuracy: 0.8283
Epoch 6/30
accuracy: 0.7232
Epoch 6: val loss improved from 0.59257 to 0.58089, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
0.9084 - accuracy: 0.7232 - val loss: 0.5809 - val accuracy: 0.8318
Epoch 7/30
accuracy: 0.7358
Epoch 7: val_loss improved from 0.58089 to 0.55890, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN_modeloT_TL_FT_with_DA_best
0.8698 - accuracy: 0.7358 - val loss: 0.5589 - val accuracy: 0.8352
Epoch 8/30
accuracy: 0.7515
Epoch 8: val loss improved from 0.55890 to 0.54758, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN_modeloT_TL_FT_with_DA_best
0.8222 - accuracy: 0.7515 - val loss: 0.5476 - val accuracy: 0.8456
Epoch 9/30
accuracy: 0.7589
Epoch 9: val loss improved from 0.54758 to 0.53366, saving model to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
0.7934 - accuracy: 0.7589 - val loss: 0.5337 - val accuracy: 0.8481
Epoch 10/30
accuracy: 0.7658
Epoch 10: val loss did not improve from 0.53366
0.7689 - accuracy: 0.7658 - val loss: 0.5367 - val accuracy: 0.8532
Epoch 11/30
accuracy: 0.7729
Epoch 11: val loss improved from 0.53366 to 0.51702, saving model
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
```

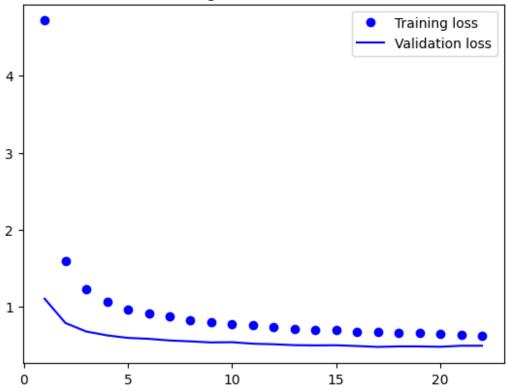
```
. h5
0.7599 - accuracy: 0.7729 - val loss: 0.5170 - val accuracy: 0.8549
Epoch 12/30
accuracy: 0.7819
Epoch 12: val loss improved from 0.51702 to 0.50995, saving model
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
.h5
0.7336 - accuracy: 0.7819 - val loss: 0.5099 - val accuracy: 0.8589
Epoch 13/30
accuracy: 0.7894
Epoch 13: val loss improved from 0.50995 to 0.49804, saving model
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
0.7138 - accuracy: 0.7894 - val_loss: 0.4980 - val_accuracy: 0.8610
Epoch 14/30
accuracy: 0.7911
Epoch 14: val loss improved from 0.49804 to 0.49517, saving model
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
.h5
0.6994 - accuracy: 0.7911 - val loss: 0.4952 - val accuracy: 0.8642
Epoch 15/30
accuracy: 0.7961
Epoch 15: val loss did not improve from 0.49517
0.6965 - accuracy: 0.7961 - val loss: 0.4969 - val accuracy: 0.8673
Epoch 16/30
accuracy: 0.8030
Epoch 16: val loss improved from 0.49517 to 0.48713, saving model
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
0.6730 - accuracy: 0.8030 - val loss: 0.4871 - val accuracy: 0.8711
Epoch 17/30
accuracy: 0.8023
Epoch 17: val loss improved from 0.48713 to 0.47518, saving model
```

```
to
/content/drive/MyDrive/ProjetoIA/models/CNN modeloT TL FT with DA best
. h5
0.6666 - accuracy: 0.8023 - val loss: 0.4752 - val accuracy: 0.8718
Epoch 18/30
accuracy: 0.8078
Epoch 18: val loss did not improve from 0.47518
0.6631 - accuracy: 0.8078 - val loss: 0.4823 - val accuracy: 0.8749
Epoch 19/30
accuracy: 0.8094
Epoch 19: val loss did not improve from 0.47518
0.6527 - accuracy: 0.8094 - val loss: 0.4818 - val accuracy: 0.8775
Epoch 20/30
accuracy: 0.8131
Epoch 20: val loss did not improve from 0.47518
0.6440 - accuracy: 0.8131 - val loss: 0.4770 - val accuracy: 0.8785
Epoch 21/30
accuracy: 0.8186
Epoch 21: val loss did not improve from 0.47518
0.6271 - accuracy: 0.8186 - val loss: 0.4908 - val accuracy: 0.8760
Epoch 22/30
accuracy: 0.8234
Epoch 22: val loss did not improve from 0.47518
0.6234 - accuracy: 0.8234 - val loss: 0.4909 - val accuracy: 0.8808
Epoch 22: early stopping
#Displaying curves of loss and accuracy
import matplotlib.pyplot as plt
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.plot(epochs, acc, '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



Foram avaliados 313 batches no conjunto de validação Perda calculada no conjunto de validação 0.4909 Previsão do conjunto de validação com 88.08% das previsões foram corretas.