# TFM LauraRivera objectivo1 marca

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Identificación de huellas de calzado a partir de imágenes con redes neuronales convolucionales

MU Ingeniería Computacional y Matemática / Área de Inteligencia Artificial

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# 1 Identificación de huellas de calzado a partir de imágenes con redes neuronales convolucionales

El objetivo de este apartado es, a parte de la creación y entrenamiento de un red neuronal capaz de determinar la marca de calzado de una huella a partir de los datos disponibles. Se realizan diferentes experimentos con diferentes parámetros y procesos para analizar los resultados y poder concluir si éstas pueden dar un resultado satisfactorio.

Con este proyecto se quiere dar respuesta a las siguientes preguntas o hipótesis mediante los experimentos: 1. ¿Qué preprocesado de imágenes funciona mejor? 2. ¿Utilizar más epochs, resulta siempre en mejor resultado? 3. ¿Un mayor tamaño de las imágenes utilizadas, resulta en un mejor resultado? (En otro cuaderno) 4. ¿Cuál es el mínimo de muestras por marcas aceptable para el modelo?

```
import pandas as pd
import numpy as np
from zipfile import ZipFile
import matplotlib.pyplot as plt
from PIL import Image
import os
import random
import skimage
import cv2 as cv
import pickle
from datetime import datetime
```

```
[3]: #En caso de utilizar google colab: #from google.colab import drive
```

```
#drive.mount('/content/gdrive')
```

## 2 Lectura y análisis de los conjuntos de datos

## 2.1 Base de datos 2d FootWear con información de marca

```
[4]: def unzipImages(folder='images'):
    with ZipFile('data/2dFootwear/Part1.zip', 'r') as zipObj:
        zipObj.extractall(folder)

with ZipFile('data/2dFootwear/Part2.zip', 'r') as zipObj:
        zipObj.extractall(folder)

with ZipFile('data/2dFootwear/Part3.zip', 'r') as zipObj:
        zipObj.extractall(folder)

with ZipFile('data/2dFootwear/Part4.zip', 'r') as zipObj:
        zipObj.extractall(folder)

with ZipFile('data/2dFootwear/Part5.zip', 'r') as zipObj:
        zipObj.extractall(folder)
```

```
[5]: if not os.path.isdir("images"):
    unzipImages("images")
```

#### 2.1.1 Análisis de los datos 2d Footwear

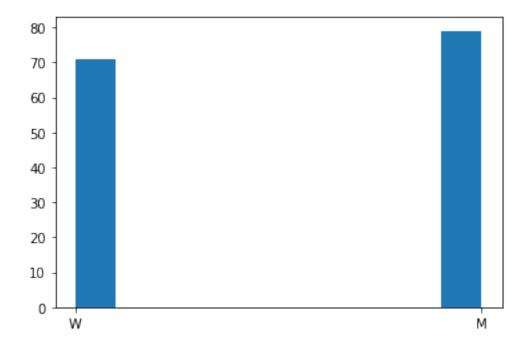
Consiste en 1500 imágenes de la huella de 150 pares de zapatos de 28 individuos diferentes. Además, se dispone de 62 marcas de calzado diferentes, y las que más aparecen son Nike, Asics y Adidas. Por último, existen 70 registros de calzado de mujer y 80 de hombre.

```
Tag example: 001_01
Nº lines: 150
Nº different people: 28
Nº of different brands: 60
['Adidas' 'Airspeed' 'Airwalk' 'Aldo' 'American Eagle' 'Arizona' 'Asics'
'BAGO' 'BASS' 'Birkenstock' 'Brooks' 'CalvinKlain' 'Champion' 'Clarks'
'Columbus' 'Converse' 'Cooeli' 'Court classic' 'Dansko' 'Deer Stags'
'Dockers' 'Ecco' 'Elcanto' 'Fadedglory' 'Feiyue' 'Fila' 'G.H.Bass&Co'
'Guho' 'HeyBear' 'K-swiss' 'Keen' 'Landya' 'Namuhana' 'Newbalance' 'Nike'
'Ninewest' 'None' 'OP' 'Ofem' 'Prospecs' 'Puma' 'Robin' 'Saucony'
'Shoedy' 'Shoopen' 'Simply vera' 'Skechers' 'Soma' 'Sonoma' 'Sorel'
'Sperry' 'Stone' 'Sugar' 'T2R' 'Teva' 'Truesoft' 'Under Amour' 'Vans'
'Vibram' 'Yonex']
```

A continuación, el histograma con el número de muestras según género, en este caso hay 70 muestras de mujeres y 80 de hombres.

```
[7]: plt.hist(df['Gender'])
```

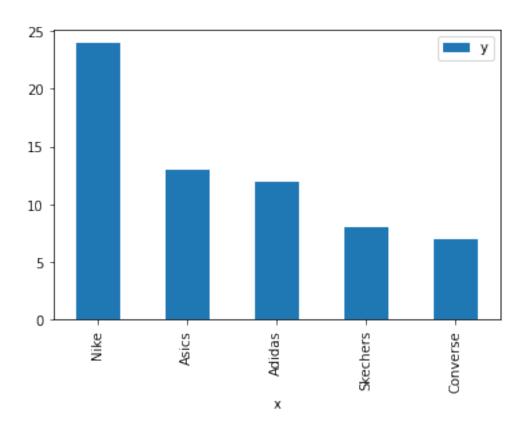
```
[7]: (array([71., 0., 0., 0., 0., 0., 0., 0., 0., 79.]),
array([0., 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]),
<BarContainer object of 10 artists>)
```



Por último, se muestran las cinco marcas que más aparecen en el conjunto de datos.

Además se seleccionan esas marcas que aparecen minimo X veces en la muestra (X=5 por defecto), para crear un subconjunto de datos que elimine las marcas con una única muestra y comprobar en los siguientes casos si influye en el resultado.

```
[8]: def filterMinSamples(data, minSamples, deleteNone=True):
         if deleteNone == True:
             data=data[data['x']!="None"] #eliminar marca = "None"
         dataone=data[data['y'] <minSamples] #marcas con pocas muestras
         if deleteNone == True:
             data=data[data['v']>=minSamples] #marcas con minimo "minSamples"
      \rightarrow muestras
         else:
             data.loc[data['y']<minSamples, 'x'] ="None"</pre>
             values_brand, counts_brand = np.unique(data['x'], return_counts=True)
             data = pd.DataFrame({'x':values_brand, 'y':counts_brand})
             \#data = data.qroupby('x').aqq(y=('y', 'sum'))
         print(data)
         num_classes=len(data)
         print('Brands with at least '+str(minSamples)+' samples: %d' %num_classes)
         print('Brands with only 1 register: %d' %len(dataone))
         return data, dataone
     dfbrandall = pd.DataFrame({'x':values_brand, 'y':counts_brand})
     dfbrand, dfbrandone = filterMinSamples(dfbrandall, 5)
     num_classes=len(dfbrand)
     dfbrand = dfbrand.sort_values('y', ascending = False) #ordenar descendientemente
     # mostrar las 5 marcas que más aparecen en el conjunto de datos
     dfbrand.head(5).plot('x', 'y', kind='bar') #mostrar gráfica
               Х
    0
          Adidas 12
    6
           Asics 13
    15 Converse
            Nike 24
    34
    42
         Saucony
    46 Skechers
    50
          Sperry
    Brands with at least 5 samples: 7
    Brands with only 1 register: 52
[8]: <AxesSubplot: xlabel='x'>
```



```
[11]: def crop_jpeg(crop_size, imgPath):
          dir_list = os.listdir("./"+imgPath)
          for f in dir_list:
              im = Image.open("./"+imgPath+"/"+f)
              h,w,c = im.shape
              im3 = im2.crop((crop_size,crop_size,h-(crop_size*2),w-(crop_size*2)))__
       \hookrightarrow #Quitar marco medidor
      def get_images_full_to_jpeg(imgPath):
        dir_list = os.listdir("./"+imgPath)
        result = []
        for f in dir_list:
          im = Image.open("./"+imgPath+"/"+f)
          im.save("./"+imgPath+"/"+f[0:-4]+'jpeg')
          result.append(f[0:-4]+'jpeg')
          os.remove("./"+imgPath+"/"+f)
        print('Nº files:',len(result))
```

```
return result
def get_images_to_jpeg(imgPath):
  dir_list = os.listdir("./"+imgPath)
  result = []
 for f in dir_list:
    im = Image.open("./"+imgPath+"/"+f)
    im2=im.resize((400,912))
    im3 = im2.crop((40,40,320,872)) #Quitar marco medidor
    im3.save("./"+imgPath+"/"+f[0:-4]+'jpeg')
    result.append(f[0:-4]+'jpeg')
    os.remove("./"+imgPath+"/"+f)
 print('Nº files:',len(result))
  return result
def get_images(imgPath):
  dir_list = os.listdir("./"+imgPath)
  result = []
  for f in dir_list:
    if "jpeg" in f:
        result.append(f)
 print('Nº files:',len(result))
 return result
```

```
[12]: # Get the list of all files in /images and convert to jpeg
#shoeFiles = get_images_to_jpeg("images") #la primera vez para convertir las_
→imágenes
shoeFiles = get_images("images")
```

Nº files: 1500

### 2.1.2 Visualización de imágenes

Se ha creado la función *plot\_image* que permite la visualización de las imágenes de cualquiera de las dos bases de datos.

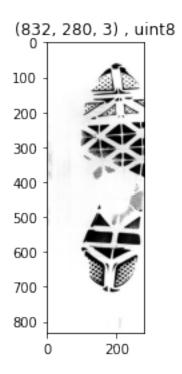
#### Parámetros:

imgPath: carpeta donde estan las imágenesfileNames: array con los nombres de los ficheros a mostrar

```
[13]: import skimage
      def plot_image(imgPath, fileNames):
        for i in range(len(fileNames)):
          filename = fileNames[i]
          img = skimage.io.imread(imgPath+filename)
          plt.figure()
          plt.title(str(img.shape)+" , "+str(img.dtype))
          plt.imshow(img)
        print(fileNames)
        plt.show()
      def plot_image2(img):
          plt.figure()
          plt.title(str(img.shape)+" , "+str(img.dtype))
          plt.imshow(img)
         plt.show()
      def plot_image_grey(img):
          plt.figure()
          plt.title(str(img.shape)+" , "+str(img.dtype))
          plt.imshow(img, cmap='gray')
          plt.show()
```

A continuación, se muestra una imagen aleatória de cada uno de los 3 datasets del proyecto:

```
[14]: plot_image("images/",random.choices(shoeFiles,k=1))
['025_02_R_03.jpeg']
```



#### 2.2 División de los datos

Para la división de los datos se ha utilizado la función train\_test\_split dos veces, primero para dividir entre el 80% de train y el 20% de test y después para extraer el equivalente al 10% para la validación.

De esta manera se dispone de 70% train, 20% test y 10% validación.

Antes de dividir los datos de la base de datos 2d Footwear, se ha formateado la tabla ya que actualmente solo muestra la información de marca según el calzado del usuario, pero no contiene el nombre de la imagen, se ha creado la siguiente función para que el conjunto de datos contenga dos columnas (X:fichero, y:marca)

```
[15]: def filesWithBrand(shoeFiles):
    files = []
    brands = []
    for image in shoeFiles:
        files.append(image) #filename
        person = df[df['ID'].str[:6]==image[:6]] #persona+contador de calzado
        brands.append(person['Brand'].iloc[0])

    return pd.DataFrame({'X':files, 'y':brands})

def filterBrands(data, one, deleteNone=True):
    #dfbrandone creado antes con las marcas que no cumplen.
```

```
if not one.empty:
              df_shoe_brand=data[~data['y'].isin(one['x'].to_numpy())]
          else: #Nothing to remove
              df_shoe_brand = data
          if deleteNone == True:
              df_shoe_brand=df_shoe_brand[df_shoe_brand['y']!="None"]
          df_shoe_brand['factor_brand'] = pd.Categorical(pd.
       →factorize(df_shoe_brand['y'])[0].astype(np.float32))
          return df_shoe_brand
      df_shoe_brand_all = filesWithBrand(shoeFiles) #contiene todas las muestras
      #eliminar aquellas marcas que no aparecen mínimo en "minSample" muestras
      df_shoe_brand = filterBrands(df_shoe_brand_all,dfbrandone)
      print(df_shoe_brand)
      #número de marcas con 5 o más muestras:
      print('Nº of brands: %d' %num_classes)
                          Х
                                    y factor_brand
     3
           009_08_R_05.jpeg
                                               0.0
                                Asics
     8
           010_01_L_01.jpeg Skechers
                                               1.0
     13
           025_05_R_01.jpeg
                                Asics
                                               0.0
                                               2.0
     15
           020_03_R_03.jpeg
                               Sperry
     17
           011_03_L_04.jpeg
                              Adidas
                                               3.0
     1490 020_02_L_01.jpeg Skechers
                                               1.0
     1493 011_01_R_04.jpeg
                              Adidas
                                               3.0
     1494 026_07_L_03.jpeg
                                               6.0
                             Saucony
     1496 018_04_R_02.jpeg
                               Sperry
                                               2.0
     1499 025_03_L_04.jpeg
                                 Nike
                                               4.0
     [770 rows x 3 columns]
     N^{\circ} of brands: 7
[16]: def checkBalancedSample(train, test, val):
          checkTest = False
          checkVal = False
          #Comprobar si existen en train
          test_in = test.y.isin(train.y).astype(int)
          val_in=val.y.isin(train.y).astype(int)
          #Comprobar que existen todos (todo 1)
          if all(x==1 for x in test_in):
```

```
checkTest = True
if all(x==1 for x in val_in):
    checkVal = True
#Devuelve True si en test y val aparecen marcas que existen en train:
if checkTest and checkVal:
    return True
return False
```

## 3 Clasificadores

En este apartado, primero se utilizan diferentes clasificadores para comparar, posteriormente, su resultado con el de la red neuronal convolucional propuesta.

#### 3.1 Extracción de características

La extracción de características es el proceso de recuperar los datos más importantes de los datos sin procesar. La extracción de características es encontrar el conjunto de parámetros que definen la forma de una imagen de manera precisa y única.

Para la extracción de características se utiliza la técnica Bag of Features, que extrae N características de las imágenes utilizando los descriptores SIFT (Scale Invariant Feature Transform).

Existen diferentes algoritmos de extracción de caraterísticas y para este proyecto se escoge utilizar SIFT ya que KAZE y ORB tienen cuenta las rotaciones y en este caso no sería necesario, ya que todas las muestras se toman con la misma metodologia.

Se hace uso de la librería OpenCV, de uso libre y con funcionalidades de visión por computador.

```
[87]: | pip install opency-contrib-python==4.4.0.44
```

```
Requirement already satisfied: opency-contrib-python==4.4.0.44 in
     /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages
     (4.4.0.44)
     Requirement already satisfied: numpy>=1.17.3 in
     /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages
     (from opency-contrib-python==4.4.0.44) (1.23.4)
     [notice] A new release of pip is
     available: 23.0.1 -> 23.1.2
     [notice] To update, run:
     pip install --upgrade pip
[92]: #extrae y calcula los descriptores SIFT para el conjunto de imágenes enviado
      def extractSIFT(input_files):
          all_features_dict = {}
          feature_extractor = cv.SIFT.create()
          for i, fname in enumerate(input_files):
              rgb = cv.cvtColor(cv.imread("images/"+fname), cv2.COLOR_BGR2RGB)
              gray = cv.cvtColor(rgb, cv.COLOR_RGB2GRAY)
              kp, desc = feature_extractor.detectAndCompute(gray, None)
              all_features_dict[fname] = desc
          return all_features_dict
[93]: #Esta función extrae las características de cada categoria (marca)
      #input: listado de categorias (marcas), listado de ficheros, marca de cadau
      \rightarrow fichero
      #output: lista ficheros, lista categorias, lista de características
      def getFiles(cat_list, X_files, y_values):
        all_files = []
        all_files_labels = {}
        all_features = {}
        cat_indexes= []
        cat files = []
        cat_features = []
        #values_train contiene el listado de categorias sin repeticiones
        for cat, label in zip(cat_list, range(len(cat_list))):
            #primero buscar los indices en el listado de cada categoria (dentro bucle)
            cat_indexes = [i for i,x in enumerate(y_values) if x == cat]
            #como se saben las posiciones, se cogen esas imagenes de esa categoria:
            cat_files = [X_files.iloc[i] for i in cat_indexes]
            cat_features = extractSIFT(cat_files)
            all_files = all_files + cat_files
            all_features.update(cat_features)
            for i in cat_files:
```

```
all_files_labels[i] = label
return all_files, all_files_labels, all_features
```

```
[94]: def getFilesBySubset(subset, tipo):
          #values_brand= np.unique(subset['y']) #listado marcas únicas que aparecen_
       →en subconjunto TRAIN
          if os.path.exists("saved/all_files_nonone2_"+tipo+".pkl"):
              with open('saved/all_files_nonone_'+tipo+'.pkl', 'rb') as fp:
                  all_files = pickle.load(fp)
              with open('saved/all_files_nonone_labels_'+tipo+'.pkl', 'rb') as fp:
                  all_files_labels = pickle.load(fp)
              with open('saved/all_features_nonone_'+tipo+'.pkl', 'rb') as fp:
                  all_features = pickle.load(fp)
              #all_files_train = np.loadtxt('saved/all_files_train.txt')
              #all_files_labels_train = np.loadtxt('saved/all_files_labels_train.txt')
              #all features train = np.loadtxt('saved/all features train.txt')
              all_files, all_files_labels,_
       →all_features=getFiles(values_brand, subset['X'], subset['y'])
          return all_files, all_files_labels, all_features
```

```
[95]: values_brand= np.unique(df_shoe_brand['y']) #listado marcas únicas que aparecenu → en subconjunto TRAIN

all_files_train, all_files_labels_train, u
 →all_features_train=getFilesBySubset(shoes_train, "train")

#Este proceso tarda 40 minutos aproximadamente, por eso se guarda en un ficherou → para agilizar las pruebas
```

```
[83]: if not os.path.exists("saved/all_files_nonone_train.pkl"):
    with open('saved/all_files_nonone_train.pkl', 'wb') as fp:
        pickle.dump(all_files_train, fp)
    with open('saved/all_files_labels_nonone_train.pkl', 'wb') as fp:
        pickle.dump(all_files_labels_train, fp)
    with open('saved/all_features_nonone_train.pkl', 'wb') as fp:
        pickle.dump(all_features_train, fp)
```

A continuación un ejemplo de la matriz de características y la impresión de la imagen con los puntos puntos de interés detectados.

```
[96]: #guarda la primera imagen con los puntos de interés
img = cv.imread("images/"+all_files_train[0])
gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
```

```
features = cv2.SIFT_create()
      keypoints = features.detect(gray, None)
      img2=cv.drawKeypoints(gray,keypoints,0,(0,0,255), flags=cv2.
      →DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
      cv.imwrite('results/'+all files train[0], img2)
[96]: True
[97]: #Se crea el Bag of Features con un diccionario de tamaño 75:
      dictionarySize =75
      if not os.path.exists("saved/bow_dict_nonone.pkl"):
          BOW = cv.BOWKMeansTrainer(dictionarySize)
          for feat in all_features_train:
              BOW.add(all_features_train[feat])
          dictionary = BOW.cluster()
      else:
          with open('saved/bow_dict_nonone.pkl', 'rb') as fp:
              dictionary = pickle.load(fp)
      print(dictionary.shape)
      print(all_features_train[all_files_train[0]].shape) #subdivisión de train:
       \hookrightarrow shoes_train
     (75, 128)
     (1024, 128)
[98]: import pickle
      if not os.path.exists("saved/bow_dict_nonone.pkl"):
          with open('saved/bow_dict_nonone.pkl', 'wb') as fp:
              pickle.dump(dictionary, fp)
              print('BOW dictionary saved successfully to file')
      #Como se trata de un proceso que toma bastante tiempo, también se ha decidido_{\sf L}
       → quardar el resultado en un fichero para futuras ejecuciones
[99]: def getFeatures(all_files, all_features, all_files_labels):
        X = np.empty((len(all_files),dictionarySize))
        y = np.empty((len(all_files),))
        all_features_BOW = {}
        count = 0
        for filename in all_files:
            desc_query = all_features[filename]
            matches = matcher.match(desc_query,dictionary)
            train_idxs = []
```

for j in range(len(matches)):

```
train_idxs.append(matches[j].trainIdx)
hist, bin_edges = histogram(train_idxs, bins=range(dictionarySize+1))
all_features_BOW[filename] = hist
X[count,:] = hist
y[count] = all_files_labels[filename]
count = count + 1
return X,y
```

```
[100]: from numpy import histogram import numpy as np

#Comentario: A continuación se normaliza el numero de caracteristicas para que

todas tengan la misma cantidad,

#ya que con el proceso anterior (BOW) es muy probable que las imagenes tengan

numero de caracteristicas diferentes.

matcher = cv.BFMatcher(normType=cv.NORM_L2)

X, y = getFeatures(all_files_train, all_features_train, all_files_labels_train)
```

#### 3.1.1 Support Vector Machines (SVM)

Tiene como objetivo encontrar el hiperplano que clasifica claramente los puntos. Este hiperplano se calcula maximizando el margen de las instancias de entrenamiento en el espacio de destino.

```
[101]: from sklearn.model_selection import train_test_split
       from sklearn import svm
       from sklearn.model_selection import GridSearchCV
       X_train, X_test_t, y_train, y_test_t = train_test_split(X, y, test_size=0.3,_
       →random_state=0)
       # Set the parameters by cross-validation
       kernels = ["rbf", "linear", "poly", "sigmoid"]
       Cs=[1, 2,3,4, 5, 10, 20]
       #Se utiliza GridSearchCV para identificar la mejor configuración de entre losu
       \rightarrow differentes kernel con differentes
       #valores de C.
       clf = GridSearchCV(estimator=svm.SVC(), param_grid=dict(C=Cs,__
       →kernel=kernels),n_jobs=-1)
       clf.fit(X_train, y_train)
       print('Mejor configuración kernel=%s, c= %s con un score de %s' %(clf.
        →best_estimator_.kernel, clf.best_estimator_.C, clf.best_score_))
```

Mejor configuración kernel=rbf, c= 20 con un score de 0.9783783783783784

```
[102]: #Ejecuto la configuración con mejor resultado kernel=rbf, c=20:

clf_train = svm.SVC(kernel='rbf', C=20).fit(X_train, y_train)

clf_train.score(X_test_t, y_test_t)
```

[102]: 0.9811320754716981

### 3.1.2 KNeighborsClassifier

Determina la clase de la información mirando los puntos cercanos. De manera que selecciona la clase (o grupo) que tiene más puntos de la instancia.

```
[105]: from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors=num_classes)
model.fit(X_train, y_train)
model.score(X_test_t, y_test_t)
```

/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages/sklearn/neighbors/\_classification.py:189: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.

mode, \_ = stats.mode(\_y[neigh\_ind, k], axis=1)

[105]: 0.8679245283018868

#### 3.1.3 DecisionTreeClassifier

Las normas de clasificación se extraen construyendo un árbol de decisiones con los datos de entrenamiento. En cada nodo del árbol, se utiliza el atributo con mayor diferencia en entropía para dividir los datos.

```
[107]: from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
model.score(X_test_t, y_test_t)
```

[107]: 0.7547169811320755

# 4 Objetivo 1: Predicción de la marca de calzado utilizando redes neuronales convolucionales

### 4.1 Red neuronal convolucional propuesta

En este caso los datos ya estan etiquetados, por lo que se puede crear un modelo para que entrene según esa etiqueta.

Es necesario transformar las etiquetas de marcas a numérico para el correcto funcionamiento del modelo. Paso realizado en los primeros pasos

```
[34]: #Se ha creado un generador para añadir la aumentación de las imágenes
      import torchvision.io
      import torch
      from tensorflow.keras.utils import Sequence
      import torchvision.transforms as T
      from torchvision.transforms import Resize
      from skimage.io import imread
      from skimage.util import img as float, random noise
      from skimage.transform import rotate
      from skimage.color import rgb2gray
      import numpy as np
      import random
      import os
      from skimage import io
      from skimage import transform, util
      #función que elimina las filas y columnas en blanco:
      def crop_image(gray, pixel_value=220):
          #gray = cv2.imread(filename, cv2.IMREAD_GRAYSCALE)
          crop rows = gray[~np.all(gray > pixel value, axis=1), :]
          cropped_image = crop_rows[:, ~np.all(crop_rows > pixel_value, axis=0)]
          return cropped_image
      def create_variation(theImage,doFlip,doNoise,doRotate):
        image = img_as_float(theImage)
        if doFlip==True:
          image = np.fliplr(image)
        if doNoise==True:
          image = util.random_noise(image)
        if doRotate==True:
          image = transform.rotate(image, random.randint(-45, 45),mode='symmetric')
        return image
      class DataGenerator2dFootwear(Sequence):
          # Constructor. Input parameters are:
          # * fileNames : List of sample file names
          \#* doRandomize : If True, the provided file names are shuffled after each
       \hookrightarrow training epoch
                            and each image can be left unchanged, flipped, corrupted
          #
       \rightarrow with
```

```
noise or rotated. 8 possible combinations is chosen
→ randomly with equal probability.
                     If False, file names are not shuffled and each image is
\rightarrowprovided unchanged.
   # * imgPath : Path to the images
   # * batchSize : Number of sample images and ground truth items in each \square
\rightarrow batch
   def __init__(self,data, df_shoe_brand,doRandomize=False,imgPath='images',__
→doGray=True,doBin=True, doCrop = True,batchSize=10):
       # Store parameters
       self.imgPath=imgPath
       self.fileNames=data.copy()
       self.batchSize=batchSize
       self.doRandomize=doRandomize
       self.df_shoe_brand=df_shoe_brand
       self.doGray=doGray
       self.doBin=doBin
       self.doCrop=doCrop
       # Get number of files (to avoid computing them later)
       self.numImages=len(data)
       # Shuffle them if required
       self.on epoch end()
   # Shuffle data if required
   def on_epoch_end(self):
       if self.doRandomize:
           random.shuffle(self.fileNames)
   # Returns the number of total batches
   def __len__(self):
       return int(np.ceil(float(self.numImages)/float(self.batchSize)))
   # Input : theIndex - Index of the image to load within self.fileNames.
   # Output : the Image - Loaded (and possibly transformed) image. Must be
                         of float type with values within [0,1]
              theClass - Shoe brand
   def _load_image_(self,theIndex):
       file = self.fileNames[theIndex]
       img = io.imread(self.imgPath+file)
       h,w,c = img.shape #guardar el shape por si se hace crop poder hacer el_{\sqcup}
\rightarrow resize
```

```
if self.doGray: #escala de grises
           img = rgb2gray(img)
           #plot_image_grey(img)
       if self.doBin: #blanco y negro
           test_binary_high,img = cv.threshold(img,0, 255, cv2.THRESH_BINARY)
       if self.doCrop: #quitar columnas/filas blancas
           img = crop_image(img)
           img = cv2.resize(img, (h,w), interpolation = cv2.INTER_AREA)
       theImage = img_as_float(img)
       theImage=theImage /255.0 #normalizar (quito rescaling del modelo)
       #añadir aumentación a las imágenes:
       if self.doRandomize:
         the Image = create variation (img, random.choice([True, False]), random.
#else:
        # theImage=create variation(img,False, False, False)
       #Buscar la imagen en el csv para extraer la Marca:
      person = self.df_shoe_brand[self.df_shoe_brand['X'].str[:6]==file[:6]] _
→#persona+contador de calzado
       theClass = person['factor_brand'].iloc[0]#self.classes[theIndex] #¿debeu
⇒ser numérico o podría ser la etiqueta?
      return the Image, the Class
   # Provides the images, class batch
  # Batch format:
   \# - X: The data. Numpy array of shape (bs, nr, nc, 3)
   # - y : The ground truth. Numpy array of shape (bs,1)
   # Where nb=batch size, nr=num rows, nc=num cols
  def __getitem__(self,theIndex):
      X = \Gamma 
      y=[]
      bStart=max(theIndex*self.batchSize,0)
      bEnd=min((theIndex+1)*self.batchSize,self.numImages)
       for i in range(bStart,bEnd):
           [curImage,curGT]=self._load_image_(i)
           X.append(curImage)
           y.append(curGT)
      return np.array(X),np.array(y)
```

```
[35]: #Modelo con dropout: from tensorflow.keras import models
```

```
from tensorflow.keras import optimizers
from tensorflow.keras.layers import Conv2D, MaxPooling2D, UpSampling2D, Dense,
→Flatten, Softmax, Rescaling, Dropout
import tensorflow as tf
def createModelTest(color, n=num classes):
    if color == True:
        shape = (280,832,3)
    else:
        shape = (280,832,1)
    model_test = models.Sequential([
      Conv2D(16, 3, padding='same', activation='relu', input_shape=shape),
      MaxPooling2D(),
      Conv2D(32, 3, padding='same', activation='relu'),
      MaxPooling2D(),
      Conv2D(64, 3, padding='same', activation='relu'),
      MaxPooling2D(),
      Flatten(),
      Dense(128, activation='relu'),
      Dropout(0.5),
      Dense(n, activation='softmax'),
      Flatten()
    ])
    return model_test
```

```
[36]: def createModelTestCustomShape(color,w,h):
          if color == True:
              shape = (w,h,3)
          else:
              shape = (w,h,1)
          model_test = models.Sequential([
            \#Rescaling(1./255, input shape=(280,832,3)),
            Conv2D(16, 3, padding='same', activation='relu', input_shape=shape),
            MaxPooling2D(),
            Conv2D(32, 3, padding='same', activation='relu'),
            MaxPooling2D(),
            Conv2D(64, 3, padding='same', activation='relu'),
            MaxPooling2D(),
            Flatten(),
            Dense(128, activation='relu'),
            Dropout(0.5),
            Dense(num_classes, activation='softmax'),
            Flatten()
            #Dense(num_classes, activation='softmax')
            # ,Flatten()
          ])
          return model test
```

```
[37]: def plot_history(history):
      # summarize history for accuracy
          plt.plot(history.history['accuracy'])
          plt.plot(history.history['val_accuracy'])
          plt.title('model accuracy')
          plt.ylabel('accuracy')
          plt.xlabel('epoch')
          plt.legend(['train', 'test'], loc='upper left')
          plt.show()
          # summarize history for loss
          plt.plot(history.history['loss'])
          plt.plot(history.history['val_loss'])
          plt.title('model loss')
          plt.ylabel('loss')
          plt.xlabel('epoch')
          plt.legend(['train', 'test'], loc='upper left')
          plt.show()
      def plot_history_2(history):
          plt.plot(history.history['accuracy'])
          plt.title('model accuracy')
          plt.ylabel('accuracy')
          plt.xlabel('epoch')
          plt.legend(['train', 'test'], loc='upper left')
          plt.show()
          # summarize history for loss
          plt.plot(history.history['loss'])
          plt.title('model loss')
          plt.ylabel('loss')
          plt.xlabel('epoch')
          plt.legend(['train', 'test'], loc='upper left')
          plt.show()
[38]: def showResult(predicted, test, array):
          filename = test['X']
          img = skimage.io.imread("images/"+filename)
          plt.figure()
          plt.title(test['y']+" "+str(test['factor_brand']))
          plt.imshow(img)
          if array == True:
              print(predicted)
              sort_index = np.argsort(-predicted)
              print(sort_index)
          else:
              print(predicted)
```

```
[39]: #Calular porcentaje que aparecen en las 3 primera posiciones
      def getXfirstOk(predicted, test, x):
          sort_index = np.argsort(-predicted)
          if test['factor brand'] in sort index[:x]:
              return True
          return False
[40]: def checkAccuracyFirstPositions(predicted_y, shoes_test, x):
          total = len(predicted_y)
          ok = 0
          for i in range(total):
              if getXfirstOk(predicted_y[i],shoes_test.iloc[i],x):
                  ok = ok+1
          print(ok)
          print(ok/total)
[41]: | #Devuelve el % de veces que la marca se predijo con un porcentage >= minPercent
      #Porcentaje de aceptación.
      def checkBrandPercent(predicted_y, shoes_test, minPercent):
          total = len(predicted_y)
          ok = 0
          for i in range(total):
              #print(shoes_test['factor_brand'].iloc[i])
              #print(predicted_y[int(shoes_test['factor_brand'].iloc[i])])
              if predicted_y[0][int(shoes_test['factor_brand'].iloc[i])] >=__
       →minPercent:
                  ok = ok+1
          print(ok/total)
[42]: from sklearn.metrics import confusion_matrix,
       →plot_confusion_matrix,ConfusionMatrixDisplay
      def printConfMatrix(predicted, test, n ):
          sort_index = np.argsort(-predicted)
          cm = confusion_matrix(test['factor_brand'],[item[0] for item in sort_index])
          cm_display = ConfusionMatrixDisplay(confusion_matrix = cm, display_labels = __
       \rightarrowrange(n))
          cm_display.plot()
          plt.show()
```

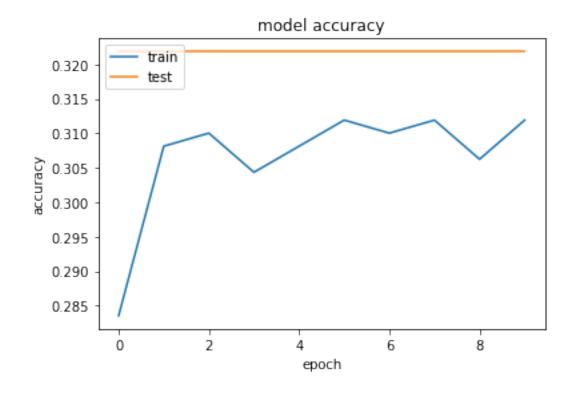
```
[43]: def checkModel(modelTest, testGenerator, shoes_test, num_classes):
         predicted_y = modelTest.predict(testGenerator)
         print("Test evaluation:")
         print(modelTest.evaluate(testGenerator))
         print("% of correct brand in the first 3 positions:")
          checkAccuracyFirstPositions(predicted_y, shoes_test,3)
         print("% of brand predicted with percentage >= 0.25") #independent from
      \rightarrowposition
          checkBrandPercent(predicted_y, shoes_test,0.25)
         print("% of brand predicted with percentage >= 0.5")
          checkBrandPercent(predicted_y, shoes_test,0.5)
         print("% of brand predicted with percentage >= 0.75")
          checkBrandPercent(predicted_y, shoes_test,0.75)
         print("Matriz de confusión:")
         printConfMatrix(predicted_y,shoes_test, num_classes)
[44]: def executeModel(aumentation, gray, binary, crop, epoch):
         modelTest = createModelTest(not gray)
         modelTest.compile(optimizer='adam',
                   loss=tf.keras.losses.
       →SparseCategoricalCrossentropy(from_logits=False),
                   metrics=['accuracy'])
          \#Configurar el preprocesado que se hará en las imágenes desntro del_{\sqcup}
       \hookrightarrow Generator.
          trainGenerator=DataGenerator2dFootwear(shoes_train['X'].
       →tolist(),df_shoe_brand,aumentation, "images/", gray, binary, crop)
          testGenerator=DataGenerator2dFootwear(shoes_test['X'].
      →tolist(),df_shoe_brand,False, "images/", gray, binary, crop)
         valGenerator=DataGenerator2dFootwear(shoes val['X'].
       →tolist(),df_shoe_brand,False, "images/", gray, binary, crop)
         print(" ")
         print('Training model with aumentation:'+str(aumentation)+', gray:
       →'+str(epoch))
         trainHistory = modelTest.fit(trainGenerator, validation_data=valGenerator, u
       →epochs=epoch)
         plot_history(trainHistory)
          checkModel(modelTest, testGenerator, shoes test, num classes)
         return modelTest #Devuelve el modelo por si se necesita hacer más pruebas
       \rightarrowsin volver a entrenar.
```

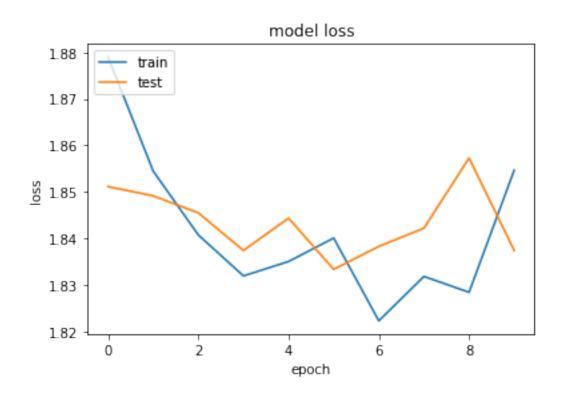
```
[46]: import cv2
             def executeModelData(aumentation, gray, binary, crop, epoch, train, test, val, u
                \rightarrowdf, n):
                      modelTest = createModelTest(not gray, n)
                      modelTest.compile(optimizer='adam',
                                              loss=tf.keras.losses.
                →SparseCategoricalCrossentropy(from_logits=False),
                                             metrics=['accuracy'])
                       #Configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en las imágenes desntro del la configurar el preprocesado que se hará en la configurar el preprocesado que se desntro del la configurar el preprocesado que se del configurar el preprocesado del conf
                \rightarrow Generator.
                       trainGenerator=DataGenerator2dFootwear(train['X'].tolist(),df,aumentation,__
                →"images/", gray, binary, crop)
                      testGenerator=DataGenerator2dFootwear(test['X'].tolist(),df,False, "images/
                →", gray, binary, crop)
                      valGenerator=DataGenerator2dFootwear(val['X'].tolist(),df,False, "images/",u
                ⇒gray, binary, crop)
                      print(" ")
                      print('Training model with aumentation:'+str(aumentation)+', gray:
                →'+str(gray)+', binary:'+str(binary)+', crop:'+str(crop)+' and epochs = u
                →'+str(epoch))
                      trainHistory = modelTest.fit(trainGenerator, validation_data=valGenerator, u
                →epochs=epoch)
                      plot_history(trainHistory)
                      predicted_y = modelTest.predict(testGenerator)
                      print("Test evaluation:")
                      print(modelTest.evaluate(testGenerator)) #first position
                      print("% of correct brand in the first 3 positions:")
                       checkAccuracyFirstPositions(predicted_y, test,3)
                      print("% of brand predicted with percentage >= 0.25") #independent from
                \rightarrow position
                       checkBrandPercent(predicted_y, test,0.25)
                       print("% of brand predicted with percentage >= 0.5")
                       checkBrandPercent(predicted_y, test,0.5)
                      print("% of brand predicted with percentage >= 0.75")
                      checkBrandPercent(predicted_y, test, 0.75)
                       if n \le 20:
                                print("Matriz de confusión:")
                                printConfMatrix(predicted_y,test,n)
```

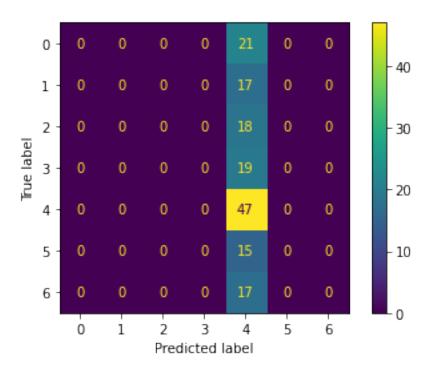
# 4.1.1 Experimentos con diferentes valores de epoch y diferentes preprocesos en las imágenes

```
[177]: model_test01=executeModel(False, False, False, False, 10)
```

```
Training model with aumentation: False, gray: False, binary: False, crop: False and
epochs = 10
Epoch 1/10
0.2836 - val_loss: 1.8511 - val_accuracy: 0.3218
53/53 [============== ] - 70s 1s/step - loss: 1.8544 - accuracy:
0.3081 - val_loss: 1.8491 - val_accuracy: 0.3218
Epoch 3/10
0.3100 - val_loss: 1.8455 - val_accuracy: 0.3218
Epoch 4/10
0.3043 - val_loss: 1.8374 - val_accuracy: 0.3218
Epoch 5/10
53/53 [============== ] - 84s 2s/step - loss: 1.8350 - accuracy:
0.3081 - val_loss: 1.8443 - val_accuracy: 0.3218
Epoch 6/10
0.3119 - val_loss: 1.8333 - val_accuracy: 0.3218
Epoch 7/10
0.3100 - val_loss: 1.8382 - val_accuracy: 0.3218
Epoch 8/10
0.3119 - val loss: 1.8422 - val accuracy: 0.3218
Epoch 9/10
0.3062 - val_loss: 1.8572 - val_accuracy: 0.3218
Epoch 10/10
53/53 [============== ] - 84s 2s/step - loss: 1.8546 - accuracy:
0.3119 - val_loss: 1.8374 - val_accuracy: 0.3218
```

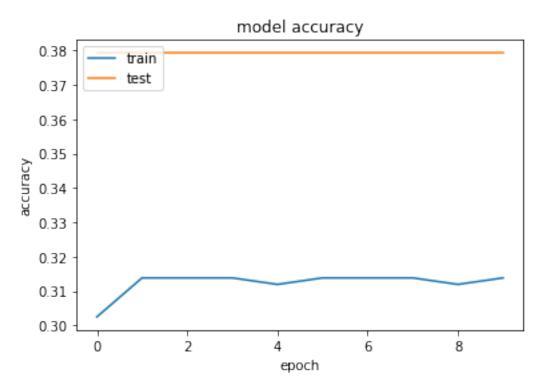


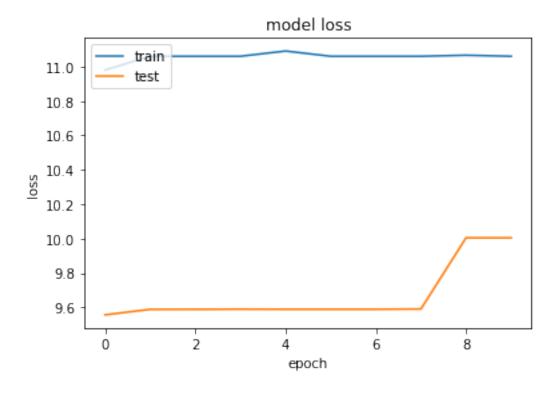




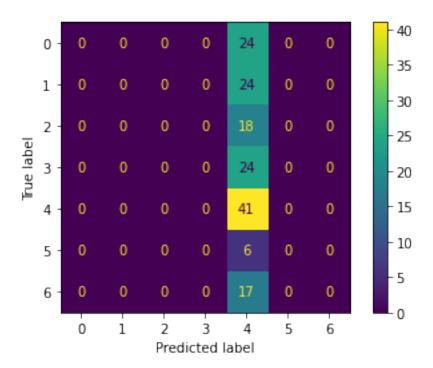
```
[47]: model_test02=executeModel(True, False, False, False, 10)
```

```
0.3138 - val_loss: 9.5880 - val_accuracy: 0.3793
Epoch 3/10
0.3138 - val_loss: 9.5882 - val_accuracy: 0.3793
Epoch 4/10
0.3138 - val_loss: 9.5891 - val_accuracy: 0.3793
Epoch 5/10
0.3119 - val_loss: 9.5885 - val_accuracy: 0.3793
Epoch 6/10
0.3138 - val_loss: 9.5885 - val_accuracy: 0.3793
Epoch 7/10
0.3138 - val_loss: 9.5885 - val_accuracy: 0.3793
53/53 [============= ] - 60s 1s/step - loss: 11.0602 - accuracy:
0.3138 - val_loss: 9.5901 - val_accuracy: 0.3793
0.3119 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 10/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
```



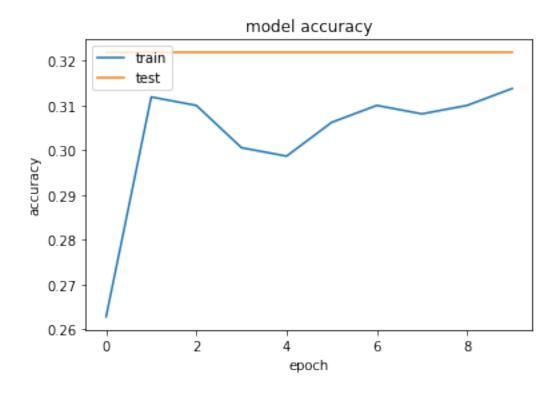


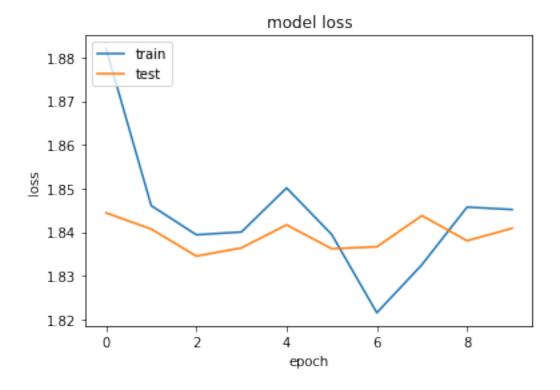
```
16/16 [=======] - 4s 222ms/step
Test evaluation:
16/16 [=====
                               ====] - 4s 223ms/step - loss: 11.8269 -
accuracy: 0.2662
[11.826915740966797, 0.26623377203941345]
% of correct brand in the first 3 positions:
89
0.577922077922078
% of brand predicted with percentage >= 0.25
0.2662337662337662
\% of brand predicted with percentage >= 0.5
0.2662337662337662
% of brand predicted with percentage >= 0.75
0.2662337662337662
Matriz de confusión:
```



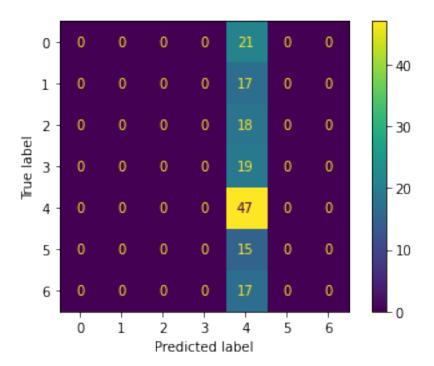
#### [179]: model\_test03=executeModel(False, True, False, False, 10)

```
Training model with aumentation: False, gray: True, binary: False, crop: False and
epochs = 10
Epoch 1/10
53/53 [============== ] - 76s 1s/step - loss: 1.8820 - accuracy:
0.2628 - val_loss: 1.8444 - val_accuracy: 0.3218
Epoch 2/10
0.3119 - val_loss: 1.8407 - val_accuracy: 0.3218
Epoch 3/10
0.3100 - val_loss: 1.8345 - val_accuracy: 0.3218
Epoch 4/10
0.3006 - val_loss: 1.8364 - val_accuracy: 0.3218
Epoch 5/10
53/53 [============== ] - 75s 1s/step - loss: 1.8501 - accuracy:
0.2987 - val_loss: 1.8417 - val_accuracy: 0.3218
Epoch 6/10
53/53 [============== ] - 75s 1s/step - loss: 1.8395 - accuracy:
0.3062 - val_loss: 1.8362 - val_accuracy: 0.3218
Epoch 7/10
```



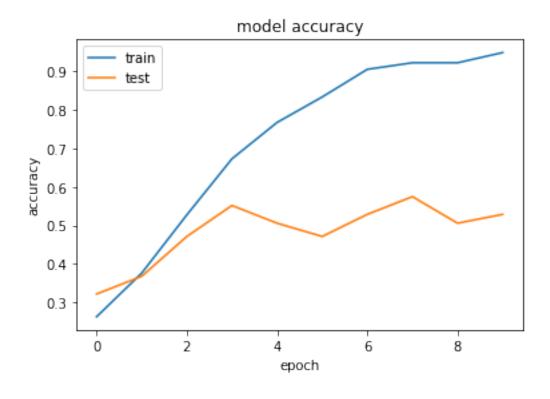


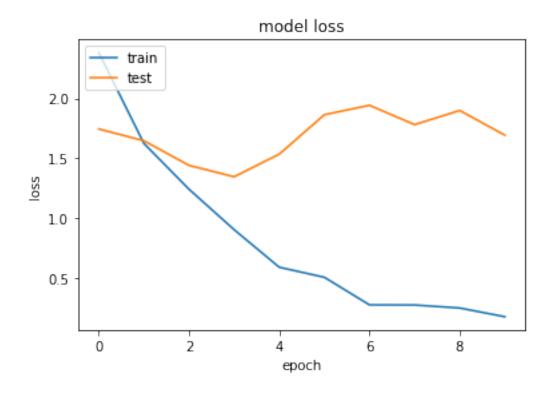
```
16/16 [========
                   =========] - 5s 309ms/step
Test evaluation:
accuracy: 0.3052
[1.8761883974075317, 0.30519479513168335]
% of correct brand in the first 3 positions:
87
0.564935064935065
\% of brand predicted with percentage >= 0.25
0.3051948051948052
\% of brand predicted with percentage >= 0.5
0.0
\% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```



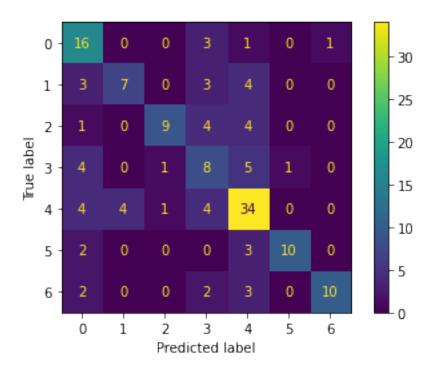
#### [187]: model\_test04=executeModel(False, True, True, False, 10)

```
Training model with aumentation: False, gray: True, binary: True, crop: False and
epochs = 10
Epoch 1/10
53/53 [============== ] - 62s 1s/step - loss: 2.3828 - accuracy:
0.2628 - val_loss: 1.7450 - val_accuracy: 0.3218
Epoch 2/10
0.3762 - val_loss: 1.6468 - val_accuracy: 0.3678
Epoch 3/10
0.5274 - val_loss: 1.4411 - val_accuracy: 0.4713
Epoch 4/10
0.6730 - val_loss: 1.3460 - val_accuracy: 0.5517
Epoch 5/10
53/53 [============== ] - 85s 2s/step - loss: 0.5910 - accuracy:
0.7675 - val_loss: 1.5350 - val_accuracy: 0.5057
Epoch 6/10
53/53 [============== ] - 77s 1s/step - loss: 0.5069 - accuracy:
0.8336 - val_loss: 1.8639 - val_accuracy: 0.4713
Epoch 7/10
```



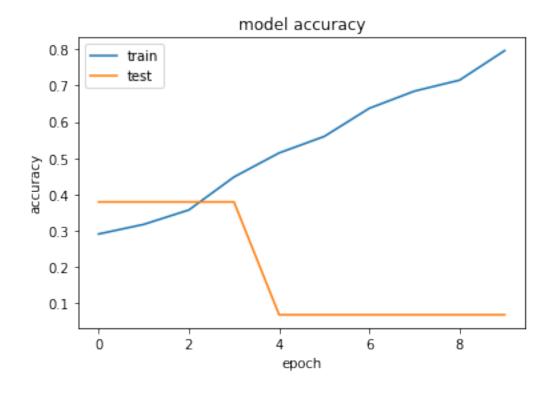


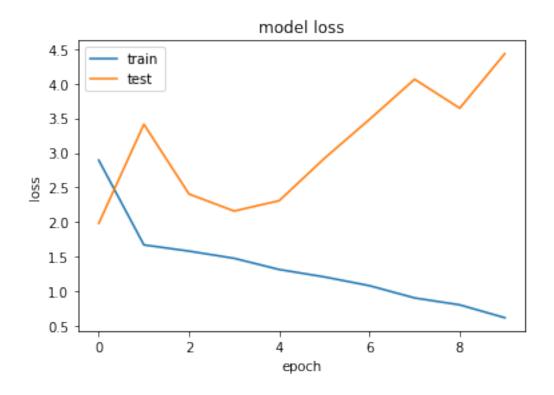
```
16/16 [=======
                       ======== ] - 5s 301ms/step
Test evaluation:
16/16 [============= ] - 5s 303ms/step - loss: 1.4311 -
accuracy: 0.6104
[1.4310550689697266, 0.6103895902633667]
% of correct brand in the first 3 positions:
130
0.8441558441558441
\% of brand predicted with percentage >= 0.25
0.12337662337662338
\% of brand predicted with percentage >= 0.5
0.12337662337662338
% of brand predicted with percentage >= 0.75
0.12337662337662338
Matriz de confusión:
```



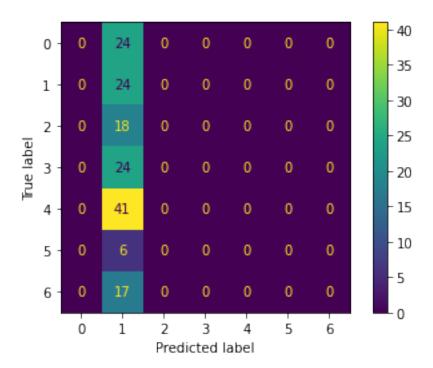
#### [48]: model\_test05=executeModel(True, True, False, False, 10)

```
Training model with aumentation: True, gray: True, binary: False, crop: False and
epochs = 10
Epoch 1/10
53/53 [============== ] - 57s 1s/step - loss: 2.8948 - accuracy:
0.2911 - val_loss: 1.9839 - val_accuracy: 0.3793
Epoch 2/10
0.3176 - val_loss: 3.4131 - val_accuracy: 0.3793
Epoch 3/10
0.3573 - val_loss: 2.4062 - val_accuracy: 0.3793
Epoch 4/10
0.4480 - val_loss: 2.1607 - val_accuracy: 0.3793
Epoch 5/10
53/53 [============== ] - 54s 1s/step - loss: 1.3163 - accuracy:
0.5142 - val_loss: 2.3105 - val_accuracy: 0.0690
Epoch 6/10
53/53 [============== ] - 55s 1s/step - loss: 1.2099 - accuracy:
0.5595 - val_loss: 2.9211 - val_accuracy: 0.0690
Epoch 7/10
```



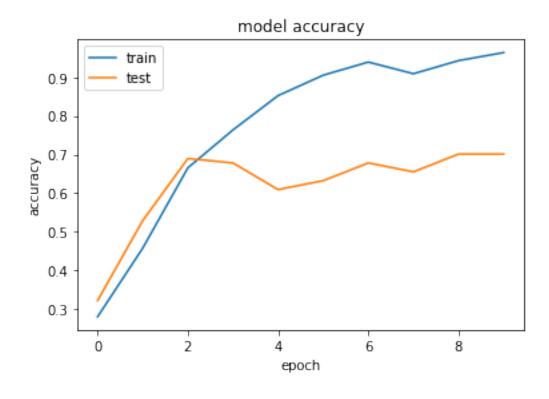


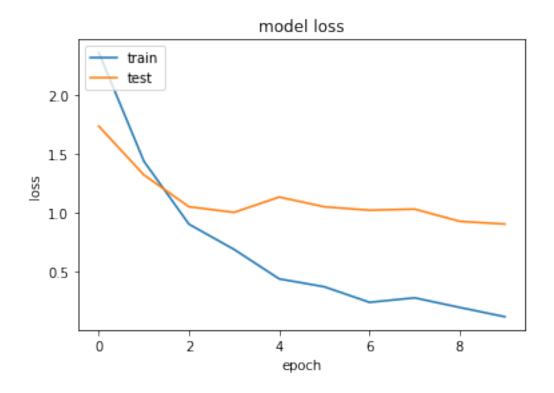
```
16/16 [=======
                       ========] - 3s 191ms/step
Test evaluation:
16/16 [============= ] - 3s 185ms/step - loss: 4.1703 -
accuracy: 0.1558
[4.170345783233643, 0.15584415197372437]
% of correct brand in the first 3 positions:
72
0.4675324675324675
\% of brand predicted with percentage >= 0.25
0.3116883116883117
\% of brand predicted with percentage >= 0.5
0.15584415584415584
% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```



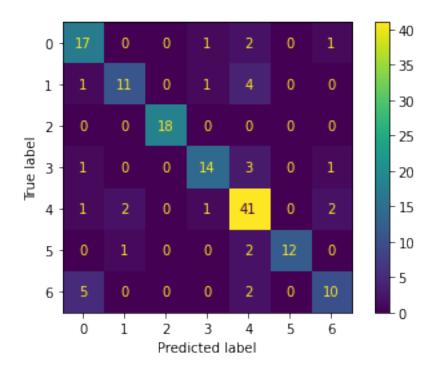
## [188]: model\_test06=executeModel(False, True, True, True, 10)

```
Training model with aumentation: False, gray: True, binary: True, crop: True and
epochs = 10
Epoch 1/10
53/53 [============== ] - 83s 2s/step - loss: 2.3565 - accuracy:
0.2798 - val_loss: 1.7333 - val_accuracy: 0.3218
Epoch 2/10
0.4575 - val_loss: 1.3203 - val_accuracy: 0.5287
Epoch 3/10
0.6654 - val_loss: 1.0504 - val_accuracy: 0.6897
Epoch 4/10
0.7637 - val_loss: 1.0032 - val_accuracy: 0.6782
Epoch 5/10
53/53 [============== ] - 79s 1s/step - loss: 0.4395 - accuracy:
0.8526 - val_loss: 1.1328 - val_accuracy: 0.6092
Epoch 6/10
0.9055 - val_loss: 1.0501 - val_accuracy: 0.6322
Epoch 7/10
```



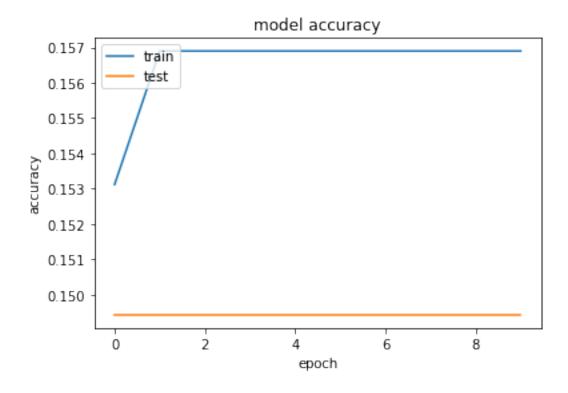


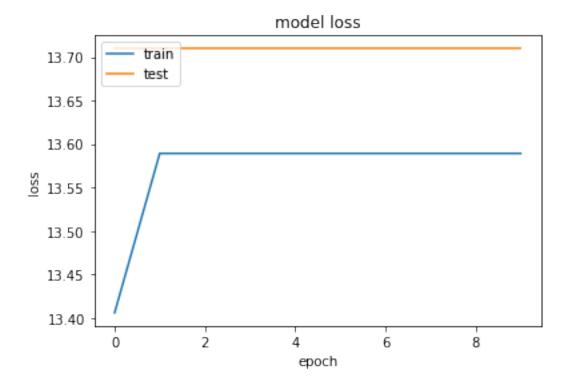
```
16/16 [=======
                       ========] - 6s 349ms/step
Test evaluation:
16/16 [============= ] - 6s 375ms/step - loss: 0.7334 -
accuracy: 0.7987
[0.7333762645721436, 0.798701286315918]
% of correct brand in the first 3 positions:
145
0.9415584415584416
\% of brand predicted with percentage >= 0.25
0.11688311688311688
\% of brand predicted with percentage >= 0.5
0.11688311688311688
% of brand predicted with percentage >= 0.75
0.11688311688311688
Matriz de confusión:
```



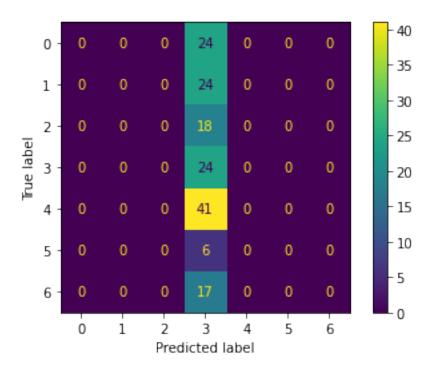
```
[49]: model_test07=executeModel(True, True, True, True, 10)
  Training model with aumentation: True, gray: True, binary: True, crop: True and
  epochs = 10
  Epoch 1/10
  0.1531 - val_loss: 13.7096 - val_accuracy: 0.1494
  Epoch 2/10
  0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
  Epoch 3/10
  0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
  Epoch 4/10
  0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
  Epoch 5/10
  0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
  Epoch 6/10
  0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
```

[]: modeltest06.summary()





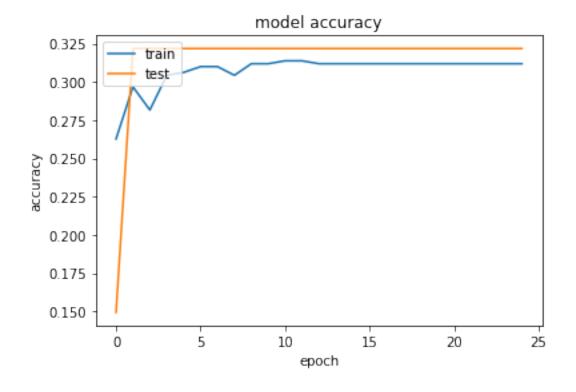
```
16/16 [======
                    ========] - 4s 207ms/step
Test evaluation:
accuracy: 0.1558
[13.606184959411621, 0.15584415197372437]
% of correct brand in the first 3 positions:
72
0.4675324675324675
\% of brand predicted with percentage >= 0.25
0.15584415584415584
\% of brand predicted with percentage >= 0.5
0.15584415584415584
\% of brand predicted with percentage >= 0.75
0.15584415584415584
Matriz de confusión:
```

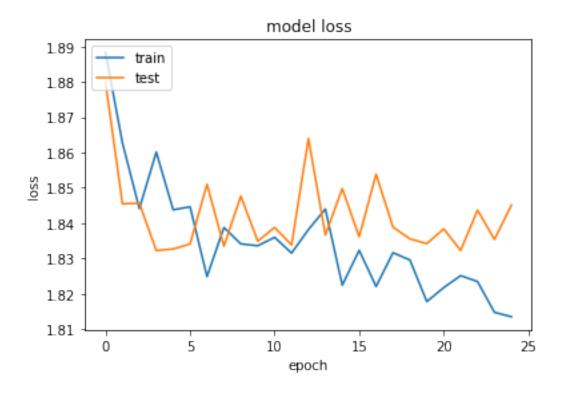


## [191]: model\_test08=executeModel(False, False, False, False, 25)

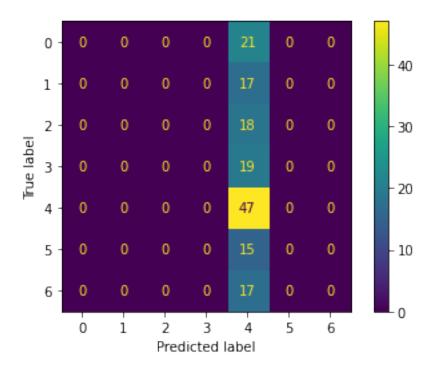
```
Training model with aumentation: False, gray: False, binary: False, crop: False and
epochs = 25
Epoch 1/25
53/53 [============== ] - 66s 1s/step - loss: 1.8883 - accuracy:
0.2628 - val_loss: 1.8797 - val_accuracy: 0.1494
Epoch 2/25
0.2968 - val_loss: 1.8455 - val_accuracy: 0.3218
Epoch 3/25
0.2817 - val_loss: 1.8457 - val_accuracy: 0.3218
Epoch 4/25
0.3043 - val_loss: 1.8323 - val_accuracy: 0.3218
Epoch 5/25
0.3062 - val_loss: 1.8327 - val_accuracy: 0.3218
Epoch 6/25
0.3100 - val_loss: 1.8341 - val_accuracy: 0.3218
Epoch 7/25
```

```
0.3100 - val_loss: 1.8510 - val_accuracy: 0.3218
Epoch 8/25
0.3043 - val_loss: 1.8335 - val_accuracy: 0.3218
Epoch 9/25
0.3119 - val_loss: 1.8477 - val_accuracy: 0.3218
Epoch 10/25
0.3119 - val_loss: 1.8349 - val_accuracy: 0.3218
Epoch 11/25
0.3138 - val_loss: 1.8388 - val_accuracy: 0.3218
Epoch 12/25
0.3138 - val_loss: 1.8338 - val_accuracy: 0.3218
Epoch 13/25
0.3119 - val_loss: 1.8639 - val_accuracy: 0.3218
Epoch 14/25
0.3119 - val_loss: 1.8367 - val_accuracy: 0.3218
Epoch 15/25
0.3119 - val_loss: 1.8498 - val_accuracy: 0.3218
Epoch 16/25
0.3119 - val_loss: 1.8362 - val_accuracy: 0.3218
Epoch 17/25
0.3119 - val_loss: 1.8539 - val_accuracy: 0.3218
Epoch 18/25
0.3119 - val_loss: 1.8389 - val_accuracy: 0.3218
Epoch 19/25
0.3119 - val loss: 1.8356 - val accuracy: 0.3218
Epoch 20/25
53/53 [============== ] - 84s 2s/step - loss: 1.8178 - accuracy:
0.3119 - val_loss: 1.8342 - val_accuracy: 0.3218
Epoch 21/25
0.3119 - val_loss: 1.8384 - val_accuracy: 0.3218
Epoch 22/25
0.3119 - val_loss: 1.8323 - val_accuracy: 0.3218
Epoch 23/25
```





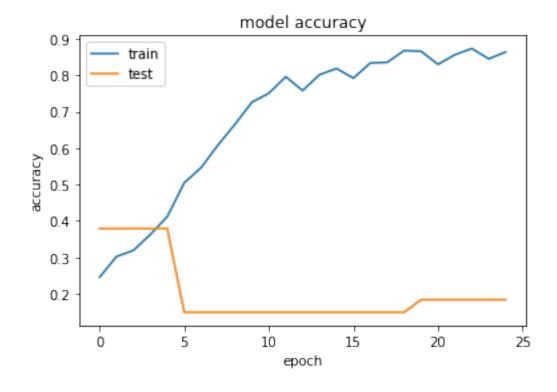
```
16/16 [=======
                     ========] - 7s 388ms/step
Test evaluation:
accuracy: 0.3052
[1.9063286781311035, 0.30519479513168335]
% of correct brand in the first 3 positions:
87
0.564935064935065
\% of brand predicted with percentage >= 0.25
0.3051948051948052
\% of brand predicted with percentage >= 0.5
0.0
\% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```

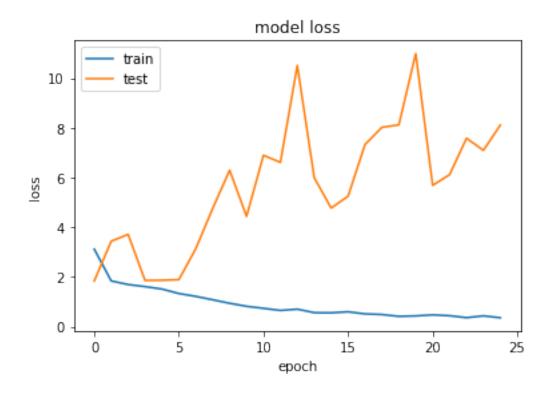


### [50]: model\_test09=executeModel(True, False, False, False, 25)

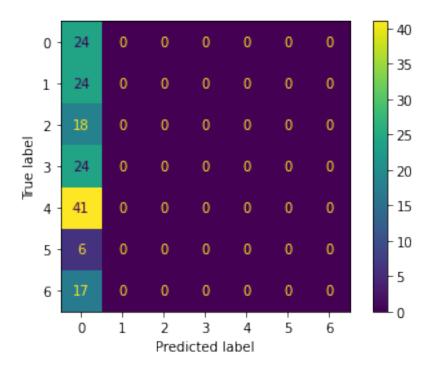
```
Training model with aumentation: True, gray: False, binary: False, crop: False and
epochs = 25
Epoch 1/25
53/53 [============== ] - 60s 1s/step - loss: 3.1171 - accuracy:
0.2457 - val_loss: 1.8418 - val_accuracy: 0.3793
Epoch 2/25
0.3025 - val_loss: 3.4349 - val_accuracy: 0.3793
Epoch 3/25
0.3195 - val_loss: 3.7137 - val_accuracy: 0.3793
Epoch 4/25
0.3629 - val_loss: 1.8591 - val_accuracy: 0.3793
Epoch 5/25
53/53 [============== ] - 58s 1s/step - loss: 1.5133 - accuracy:
0.4121 - val_loss: 1.8674 - val_accuracy: 0.3793
Epoch 6/25
53/53 [============== ] - 59s 1s/step - loss: 1.3334 - accuracy:
0.5047 - val_loss: 1.8905 - val_accuracy: 0.1494
Epoch 7/25
```

```
0.5463 - val_loss: 3.1388 - val_accuracy: 0.1494
Epoch 8/25
0.6087 - val_loss: 4.7569 - val_accuracy: 0.1494
Epoch 9/25
0.6654 - val_loss: 6.2931 - val_accuracy: 0.1494
Epoch 10/25
0.7259 - val_loss: 4.4359 - val_accuracy: 0.1494
Epoch 11/25
0.7505 - val_loss: 6.8937 - val_accuracy: 0.1494
Epoch 12/25
0.7958 - val_loss: 6.6072 - val_accuracy: 0.1494
Epoch 13/25
0.7580 - val_loss: 10.5051 - val_accuracy: 0.1494
Epoch 14/25
0.8015 - val_loss: 5.9937 - val_accuracy: 0.1494
Epoch 15/25
0.8185 - val_loss: 4.7698 - val_accuracy: 0.1494
Epoch 16/25
0.7921 - val_loss: 5.2450 - val_accuracy: 0.1494
Epoch 17/25
0.8336 - val_loss: 7.3252 - val_accuracy: 0.1494
Epoch 18/25
0.8355 - val_loss: 8.0166 - val_accuracy: 0.1494
Epoch 19/25
53/53 [================== ] - 59s 1s/step - loss: 0.4161 - accuracy:
0.8677 - val_loss: 8.1152 - val_accuracy: 0.1494
Epoch 20/25
53/53 [============== ] - 59s 1s/step - loss: 0.4333 - accuracy:
0.8658 - val_loss: 10.9824 - val_accuracy: 0.1839
Epoch 21/25
0.8299 - val_loss: 5.6836 - val_accuracy: 0.1839
Epoch 22/25
0.8563 - val_loss: 6.1126 - val_accuracy: 0.1839
Epoch 23/25
53/53 [============== ] - 59s 1s/step - loss: 0.3633 - accuracy:
```





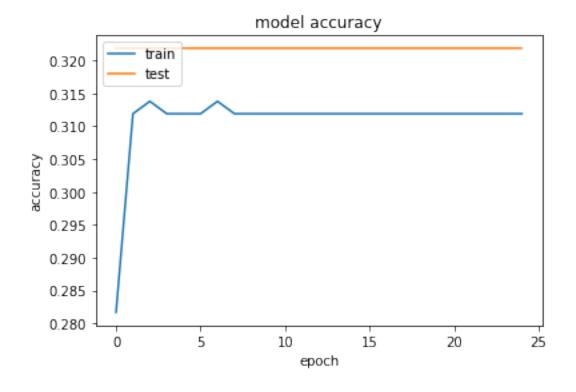
```
16/16 [=======
                      =======] - 4s 218ms/step
Test evaluation:
accuracy: 0.1558
[9.587703704833984, 0.15584415197372437]
% of correct brand in the first 3 positions:
89
0.577922077922078
\% of brand predicted with percentage >= 0.25
0.15584415584415584
\% of brand predicted with percentage >= 0.5
0.15584415584415584
% of brand predicted with percentage >= 0.75
0.15584415584415584
Matriz de confusión:
```

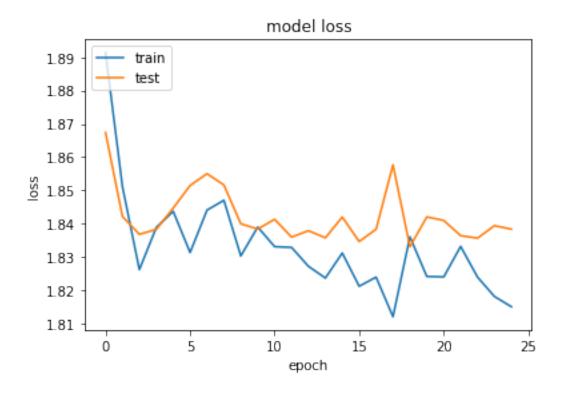


#### [193]: model\_test10=executeModel(False, True, False, False, 25)

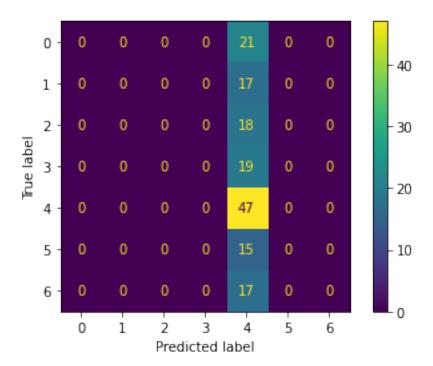
```
Training model with aumentation: False, gray: True, binary: False, crop: False and
epochs = 25
Epoch 1/25
53/53 [============== ] - 85s 2s/step - loss: 1.8914 - accuracy:
0.2817 - val_loss: 1.8674 - val_accuracy: 0.3218
Epoch 2/25
0.3119 - val_loss: 1.8421 - val_accuracy: 0.3218
Epoch 3/25
0.3138 - val_loss: 1.8368 - val_accuracy: 0.3218
Epoch 4/25
0.3119 - val_loss: 1.8383 - val_accuracy: 0.3218
Epoch 5/25
53/53 [============== ] - 87s 2s/step - loss: 1.8437 - accuracy:
0.3119 - val_loss: 1.8447 - val_accuracy: 0.3218
Epoch 6/25
0.3119 - val_loss: 1.8515 - val_accuracy: 0.3218
Epoch 7/25
```

```
0.3138 - val_loss: 1.8550 - val_accuracy: 0.3218
Epoch 8/25
0.3119 - val_loss: 1.8516 - val_accuracy: 0.3218
Epoch 9/25
0.3119 - val_loss: 1.8400 - val_accuracy: 0.3218
Epoch 10/25
53/53 [============== ] - 79s 1s/step - loss: 1.8390 - accuracy:
0.3119 - val_loss: 1.8384 - val_accuracy: 0.3218
Epoch 11/25
0.3119 - val_loss: 1.8413 - val_accuracy: 0.3218
Epoch 12/25
0.3119 - val_loss: 1.8360 - val_accuracy: 0.3218
Epoch 13/25
0.3119 - val_loss: 1.8379 - val_accuracy: 0.3218
Epoch 14/25
0.3119 - val_loss: 1.8357 - val_accuracy: 0.3218
Epoch 15/25
0.3119 - val_loss: 1.8420 - val_accuracy: 0.3218
Epoch 16/25
0.3119 - val_loss: 1.8346 - val_accuracy: 0.3218
Epoch 17/25
0.3119 - val_loss: 1.8383 - val_accuracy: 0.3218
Epoch 18/25
0.3119 - val_loss: 1.8577 - val_accuracy: 0.3218
Epoch 19/25
0.3119 - val_loss: 1.8331 - val_accuracy: 0.3218
Epoch 20/25
53/53 [============== ] - 80s 2s/step - loss: 1.8241 - accuracy:
0.3119 - val_loss: 1.8420 - val_accuracy: 0.3218
Epoch 21/25
0.3119 - val_loss: 1.8410 - val_accuracy: 0.3218
Epoch 22/25
0.3119 - val_loss: 1.8364 - val_accuracy: 0.3218
Epoch 23/25
53/53 [============== ] - 77s 1s/step - loss: 1.8239 - accuracy:
```





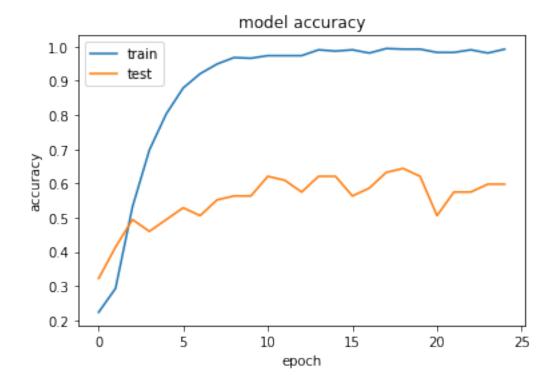
```
16/16 [=======
                        ========] - 8s 474ms/step
Test evaluation:
16/16 [============ ] - 8s 495ms/step - loss: 1.8908 -
accuracy: 0.3052
[1.890782356262207, 0.30519479513168335]
% of correct brand in the first 3 positions:
87
0.564935064935065
\% of brand predicted with percentage >= 0.25
0.3051948051948052
\% of brand predicted with percentage >= 0.5
0.0
\% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```

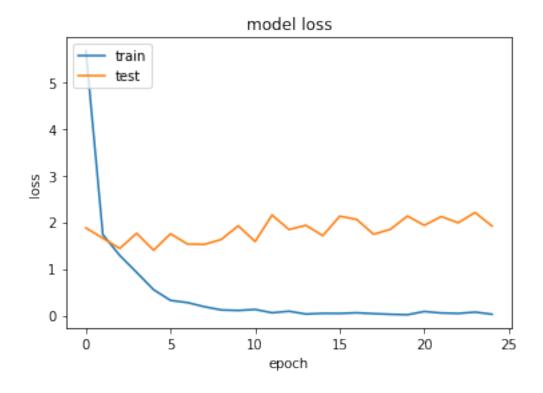


## [194]: model\_test11=executeModel(False, True, True, False, 25)

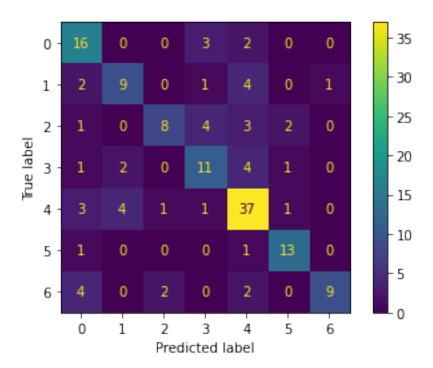
```
Training model with aumentation: False, gray: True, binary: True, crop: False and
epochs = 25
Epoch 1/25
0.2231 - val_loss: 1.8762 - val_accuracy: 0.3218
Epoch 2/25
0.2930 - val_loss: 1.6575 - val_accuracy: 0.4138
Epoch 3/25
0.5312 - val_loss: 1.4377 - val_accuracy: 0.4943
Epoch 4/25
0.6975 - val_loss: 1.7630 - val_accuracy: 0.4598
Epoch 5/25
0.8034 - val_loss: 1.3991 - val_accuracy: 0.4943
Epoch 6/25
0.8790 - val_loss: 1.7523 - val_accuracy: 0.5287
Epoch 7/25
```

```
0.9206 - val_loss: 1.5324 - val_accuracy: 0.5057
Epoch 8/25
0.9490 - val_loss: 1.5246 - val_accuracy: 0.5517
Epoch 9/25
53/53 [============== ] - 82s 2s/step - loss: 0.1217 - accuracy:
0.9679 - val_loss: 1.6299 - val_accuracy: 0.5632
Epoch 10/25
0.9660 - val_loss: 1.9227 - val_accuracy: 0.5632
Epoch 11/25
0.9735 - val_loss: 1.5855 - val_accuracy: 0.6207
Epoch 12/25
0.9735 - val_loss: 2.1528 - val_accuracy: 0.6092
Epoch 13/25
0.9735 - val_loss: 1.8416 - val_accuracy: 0.5747
Epoch 14/25
0.9905 - val_loss: 1.9335 - val_accuracy: 0.6207
Epoch 15/25
0.9868 - val_loss: 1.7111 - val_accuracy: 0.6207
Epoch 16/25
0.9905 - val_loss: 2.1288 - val_accuracy: 0.5632
Epoch 17/25
53/53 [============= ] - 77s 1s/step - loss: 0.0602 - accuracy:
0.9811 - val_loss: 2.0594 - val_accuracy: 0.5862
Epoch 18/25
0.9943 - val_loss: 1.7410 - val_accuracy: 0.6322
Epoch 19/25
0.9924 - val_loss: 1.8482 - val_accuracy: 0.6437
Epoch 20/25
53/53 [============== ] - 80s 2s/step - loss: 0.0189 - accuracy:
0.9924 - val_loss: 2.1314 - val_accuracy: 0.6207
Epoch 21/25
0.9830 - val_loss: 1.9325 - val_accuracy: 0.5057
Epoch 22/25
0.9830 - val_loss: 2.1212 - val_accuracy: 0.5747
Epoch 23/25
53/53 [============== ] - 80s 2s/step - loss: 0.0468 - accuracy:
```





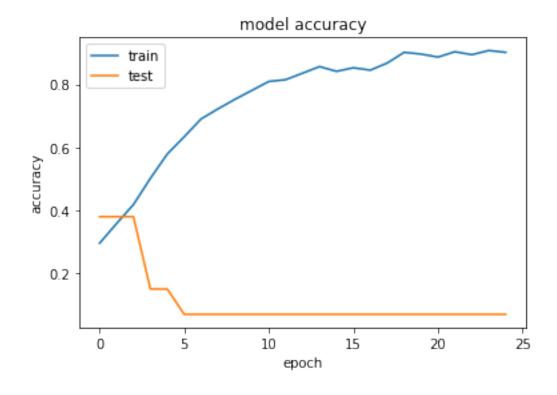
```
16/16 [=======
                         ========] - 5s 306ms/step
Test evaluation:
16/16 [============= ] - 5s 311ms/step - loss: 1.7246 -
accuracy: 0.6688
[1.7245663404464722, 0.6688311696052551]
% of correct brand in the first 3 positions:
139
0.9025974025974026
\% of brand predicted with percentage >= 0.25
0.12337662337662338
\% of brand predicted with percentage >= 0.5
0.12337662337662338
% of brand predicted with percentage >= 0.75
0.12337662337662338
Matriz de confusión:
```

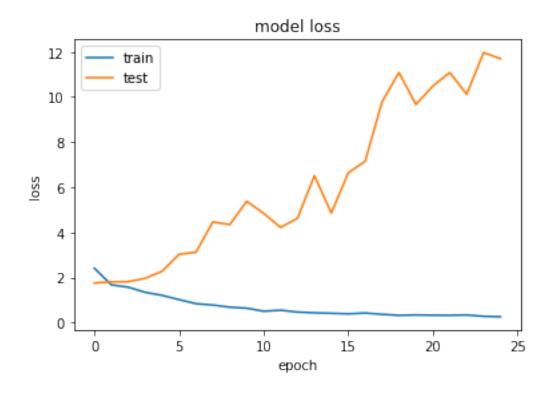


### [51]: model\_test12=executeModel(True, True, False, False, 25)

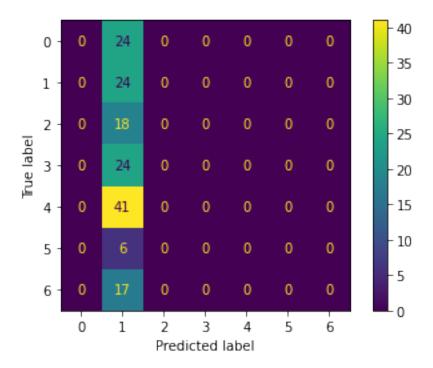
```
Training model with aumentation: True, gray: True, binary: False, crop: False and
epochs = 25
Epoch 1/25
53/53 [============== ] - 56s 1s/step - loss: 2.4070 - accuracy:
0.2949 - val_loss: 1.7542 - val_accuracy: 0.3793
Epoch 2/25
0.3573 - val_loss: 1.8065 - val_accuracy: 0.3793
Epoch 3/25
0.4178 - val_loss: 1.8127 - val_accuracy: 0.3793
Epoch 4/25
0.5009 - val_loss: 1.9631 - val_accuracy: 0.1494
Epoch 5/25
0.5784 - val_loss: 2.2761 - val_accuracy: 0.1494
Epoch 6/25
53/53 [============== ] - 55s 1s/step - loss: 1.0199 - accuracy:
0.6333 - val_loss: 3.0260 - val_accuracy: 0.0690
Epoch 7/25
```

```
0.6900 - val_loss: 3.1203 - val_accuracy: 0.0690
Epoch 8/25
0.7221 - val_loss: 4.4622 - val_accuracy: 0.0690
Epoch 9/25
0.7524 - val_loss: 4.3450 - val_accuracy: 0.0690
Epoch 10/25
0.7807 - val_loss: 5.3769 - val_accuracy: 0.0690
Epoch 11/25
0.8091 - val_loss: 4.8443 - val_accuracy: 0.0690
Epoch 12/25
0.8147 - val_loss: 4.2201 - val_accuracy: 0.0690
Epoch 13/25
0.8355 - val_loss: 4.6212 - val_accuracy: 0.0690
Epoch 14/25
0.8563 - val_loss: 6.5107 - val_accuracy: 0.0690
Epoch 15/25
0.8412 - val_loss: 4.8553 - val_accuracy: 0.0690
Epoch 16/25
0.8526 - val_loss: 6.6382 - val_accuracy: 0.0690
Epoch 17/25
0.8450 - val_loss: 7.1472 - val_accuracy: 0.0690
Epoch 18/25
0.8677 - val_loss: 9.7880 - val_accuracy: 0.0690
Epoch 19/25
0.9017 - val_loss: 11.0824 - val_accuracy: 0.0690
Epoch 20/25
53/53 [============== ] - 54s 1s/step - loss: 0.3373 - accuracy:
0.8960 - val_loss: 9.6671 - val_accuracy: 0.0690
Epoch 21/25
0.8866 - val_loss: 10.4817 - val_accuracy: 0.0690
Epoch 22/25
0.9036 - val_loss: 11.0810 - val_accuracy: 0.0690
Epoch 23/25
53/53 [============== ] - 54s 1s/step - loss: 0.3365 - accuracy:
```





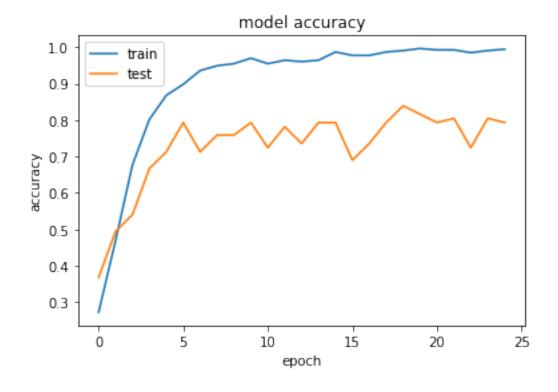
```
16/16 [========
                       ========] - 3s 185ms/step
Test evaluation:
16/16 [============ ] - 3s 183ms/step - loss: 11.0019 -
accuracy: 0.1558
[11.001900672912598, 0.15584415197372437]
% of correct brand in the first 3 positions:
89
0.577922077922078
\% of brand predicted with percentage >= 0.25
0.15584415584415584
\% of brand predicted with percentage >= 0.5
0.15584415584415584
\% of brand predicted with percentage >= 0.75
0.15584415584415584
Matriz de confusión:
```

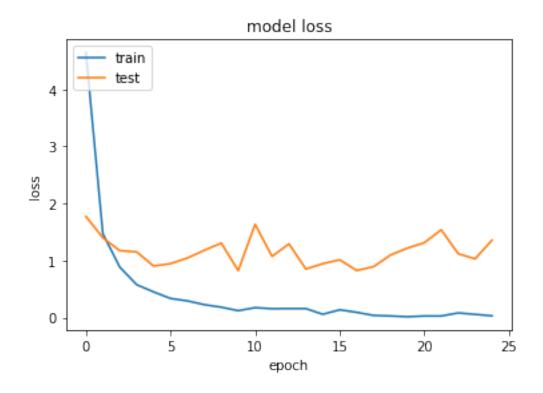


### [196]: model\_test13=executeModel(False, True, True, True, 25)

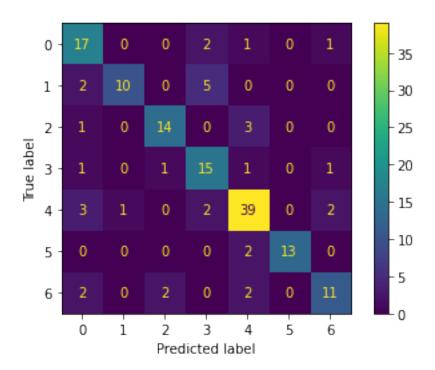
```
Training model with aumentation: False, gray: True, binary: True, crop: True and
epochs = 25
Epoch 1/25
0.2722 - val_loss: 1.7720 - val_accuracy: 0.3678
Epoch 2/25
0.4688 - val_loss: 1.3985 - val_accuracy: 0.4943
Epoch 3/25
0.6767 - val_loss: 1.1727 - val_accuracy: 0.5402
Epoch 4/25
0.8015 - val_loss: 1.1511 - val_accuracy: 0.6667
Epoch 5/25
53/53 [============== ] - 57s 1s/step - loss: 0.4494 - accuracy:
0.8677 - val_loss: 0.9026 - val_accuracy: 0.7126
Epoch 6/25
53/53 [============== ] - 58s 1s/step - loss: 0.3347 - accuracy:
0.8979 - val_loss: 0.9449 - val_accuracy: 0.7931
Epoch 7/25
```

```
0.9357 - val_loss: 1.0437 - val_accuracy: 0.7126
Epoch 8/25
0.9490 - val_loss: 1.1797 - val_accuracy: 0.7586
Epoch 9/25
0.9546 - val_loss: 1.3051 - val_accuracy: 0.7586
Epoch 10/25
0.9698 - val_loss: 0.8232 - val_accuracy: 0.7931
Epoch 11/25
0.9546 - val_loss: 1.6337 - val_accuracy: 0.7241
Epoch 12/25
0.9641 - val_loss: 1.0714 - val_accuracy: 0.7816
Epoch 13/25
0.9603 - val_loss: 1.2920 - val_accuracy: 0.7356
Epoch 14/25
0.9641 - val_loss: 0.8498 - val_accuracy: 0.7931
Epoch 15/25
0.9868 - val_loss: 0.9446 - val_accuracy: 0.7931
Epoch 16/25
0.9773 - val_loss: 1.0123 - val_accuracy: 0.6897
Epoch 17/25
0.9773 - val_loss: 0.8254 - val_accuracy: 0.7356
Epoch 18/25
0.9868 - val_loss: 0.8915 - val_accuracy: 0.7931
Epoch 19/25
0.9905 - val_loss: 1.0961 - val_accuracy: 0.8391
Epoch 20/25
53/53 [============== ] - 58s 1s/step - loss: 0.0141 - accuracy:
0.9962 - val_loss: 1.2172 - val_accuracy: 0.8161
Epoch 21/25
0.9924 - val_loss: 1.3118 - val_accuracy: 0.7931
Epoch 22/25
0.9924 - val_loss: 1.5378 - val_accuracy: 0.8046
Epoch 23/25
53/53 [============== ] - 57s 1s/step - loss: 0.0814 - accuracy:
```





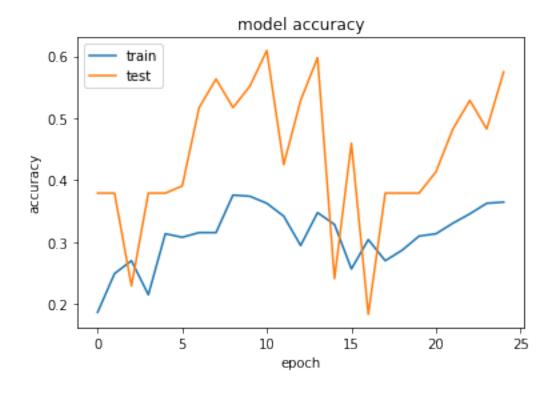
```
16/16 [========
                    ========] - 4s 265ms/step
Test evaluation:
accuracy: 0.7727
[1.1136705875396729, 0.7727272510528564]
% of correct brand in the first 3 positions:
148
0.961038961038961
\% of brand predicted with percentage >= 0.25
0.11688311688311688
\% of brand predicted with percentage >= 0.5
0.11688311688311688
\% of brand predicted with percentage >= 0.75
0.11688311688311688
Matriz de confusión:
```

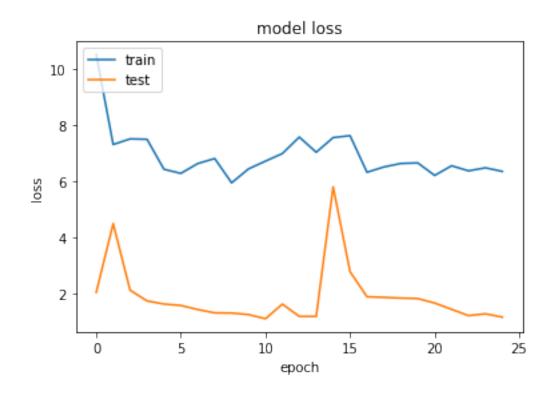


### [52]: model\_test14=executeModel(True, True, True, True, 25)

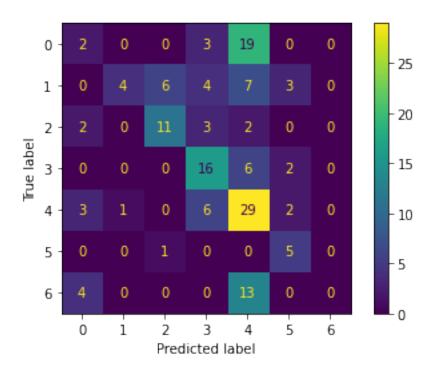
```
Training model with aumentation: True, gray: True, binary: True, crop: True and
epochs = 25
Epoch 1/25
0.1871 - val_loss: 2.0613 - val_accuracy: 0.3793
Epoch 2/25
0.2495 - val_loss: 4.5063 - val_accuracy: 0.3793
Epoch 3/25
0.2703 - val_loss: 2.1345 - val_accuracy: 0.2299
Epoch 4/25
0.2155 - val_loss: 1.7536 - val_accuracy: 0.3793
Epoch 5/25
0.3138 - val_loss: 1.6408 - val_accuracy: 0.3793
Epoch 6/25
53/53 [============== ] - 57s 1s/step - loss: 6.2977 - accuracy:
0.3081 - val_loss: 1.5909 - val_accuracy: 0.3908
Epoch 7/25
```

```
0.3157 - val_loss: 1.4453 - val_accuracy: 0.5172
Epoch 8/25
0.3157 - val_loss: 1.3261 - val_accuracy: 0.5632
Epoch 9/25
0.3762 - val_loss: 1.3197 - val_accuracy: 0.5172
Epoch 10/25
0.3743 - val_loss: 1.2661 - val_accuracy: 0.5517
Epoch 11/25
0.3629 - val_loss: 1.1176 - val_accuracy: 0.6092
Epoch 12/25
0.3422 - val_loss: 1.6382 - val_accuracy: 0.4253
Epoch 13/25
0.2949 - val_loss: 1.2011 - val_accuracy: 0.5287
Epoch 14/25
0.3478 - val_loss: 1.2019 - val_accuracy: 0.5977
Epoch 15/25
0.3289 - val_loss: 5.8167 - val_accuracy: 0.2414
Epoch 16/25
0.2571 - val_loss: 2.7942 - val_accuracy: 0.4598
Epoch 17/25
0.3043 - val_loss: 1.9006 - val_accuracy: 0.1839
Epoch 18/25
0.2703 - val_loss: 1.8794 - val_accuracy: 0.3793
Epoch 19/25
0.2873 - val_loss: 1.8530 - val_accuracy: 0.3793
Epoch 20/25
0.3100 - val_loss: 1.8365 - val_accuracy: 0.3793
Epoch 21/25
0.3138 - val_loss: 1.6761 - val_accuracy: 0.4138
Epoch 22/25
0.3308 - val_loss: 1.4526 - val_accuracy: 0.4828
Epoch 23/25
53/53 [============== ] - 58s 1s/step - loss: 6.3877 - accuracy:
```



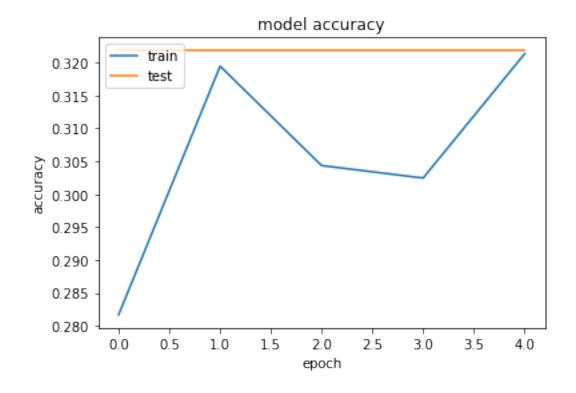


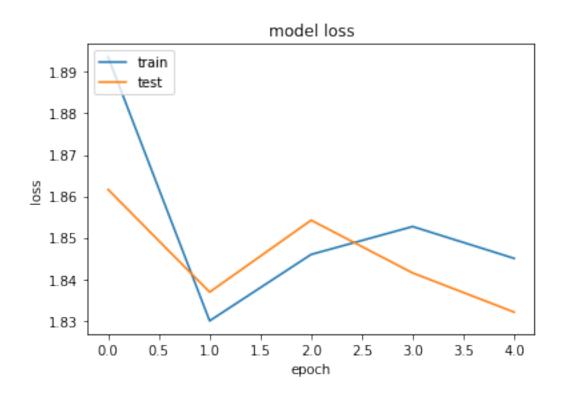
```
16/16 [========
                   =========] - 4s 227ms/step
Test evaluation:
accuracy: 0.4351
[1.4072834253311157, 0.4350649416446686]
% of correct brand in the first 3 positions:
123
0.7987012987012987
\% of brand predicted with percentage >= 0.25
0.42207792207792205
\% of brand predicted with percentage >= 0.5
0.0
\% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```

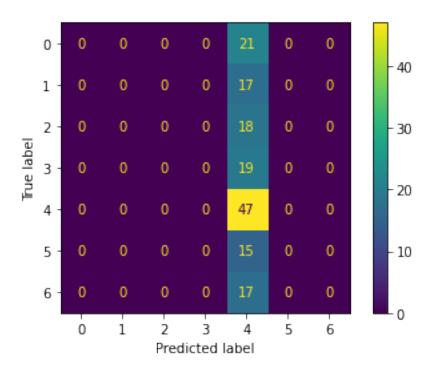


# [198]: model\_test15=executeModel(False, False, False, False, 5)

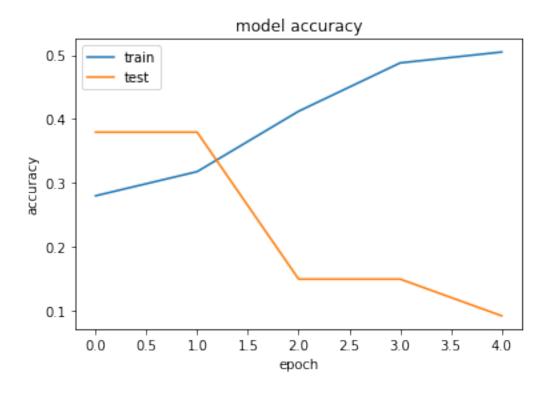
```
Training model with aumentation: False, gray: False, binary: False, crop: False and
epochs = 5
Epoch 1/5
0.2817 - val_loss: 1.8616 - val_accuracy: 0.3218
Epoch 2/5
0.3195 - val_loss: 1.8369 - val_accuracy: 0.3218
Epoch 3/5
0.3043 - val_loss: 1.8542 - val_accuracy: 0.3218
Epoch 4/5
0.3025 - val_loss: 1.8415 - val_accuracy: 0.3218
Epoch 5/5
53/53 [============== ] - 61s 1s/step - loss: 1.8450 - accuracy:
0.3214 - val_loss: 1.8320 - val_accuracy: 0.3218
```

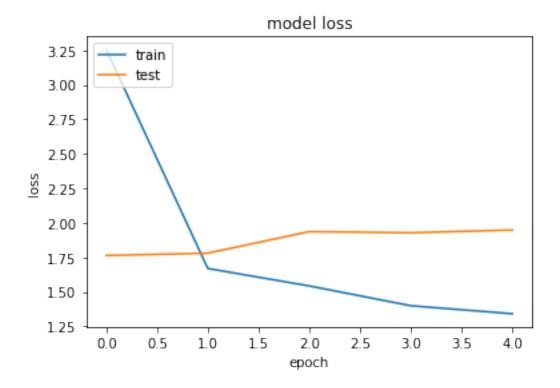


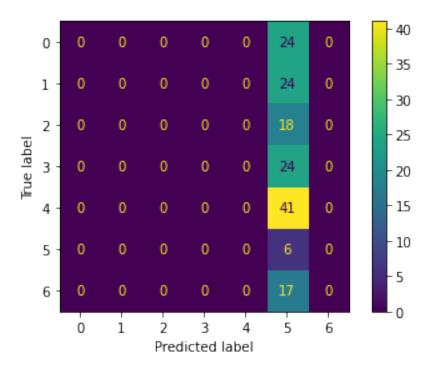




```
[53]: model_test16=executeModel(True, False, False, False, 5)
```

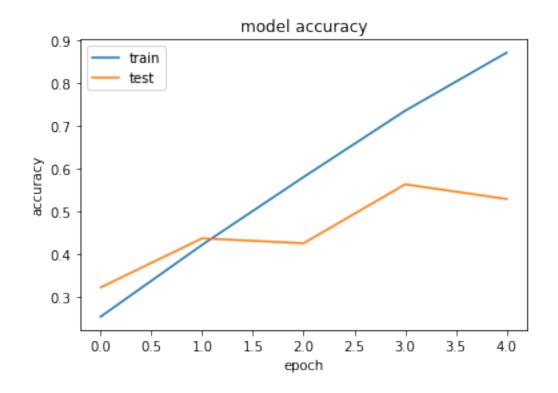


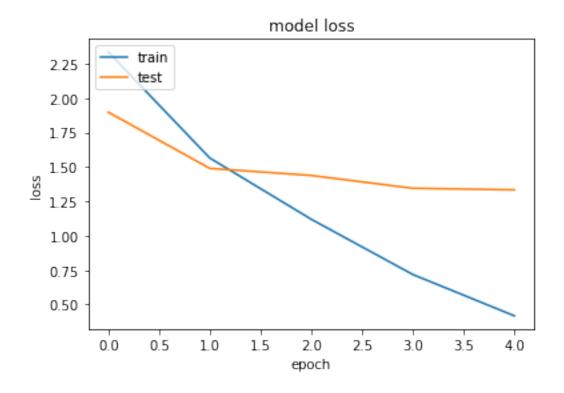


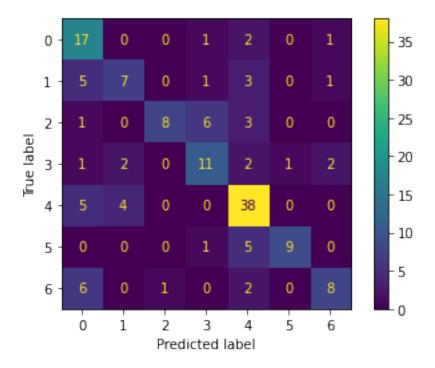


## [201]: model\_test17=executeModel(False, True, True, False, 5)

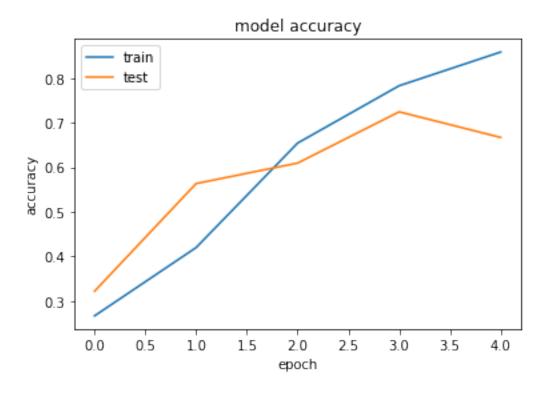
```
Training model with aumentation: False, gray: True, binary: True, crop: False and
epochs = 5
Epoch 1/5
53/53 [============== ] - 64s 1s/step - loss: 2.3362 - accuracy:
0.2533 - val_loss: 1.8988 - val_accuracy: 0.3218
Epoch 2/5
0.4216 - val_loss: 1.4903 - val_accuracy: 0.4368
Epoch 3/5
0.5803 - val_loss: 1.4387 - val_accuracy: 0.4253
Epoch 4/5
0.7353 - val_loss: 1.3458 - val_accuracy: 0.5632
Epoch 5/5
0.8715 - val_loss: 1.3342 - val_accuracy: 0.5287
```

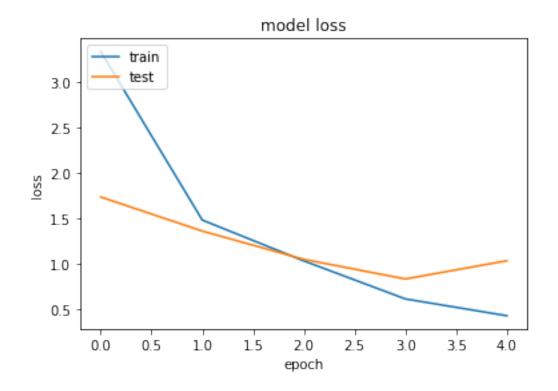




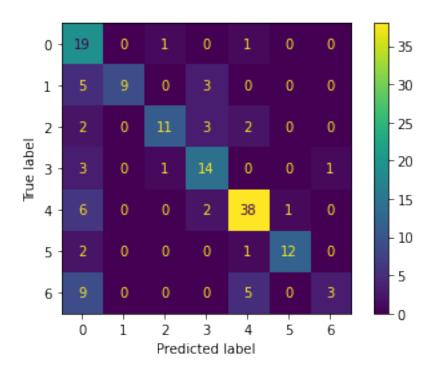


```
[204]: model_test18=executeModel(False, True, True, 5)
```



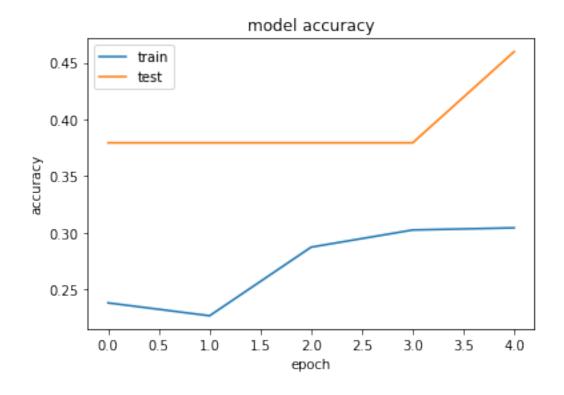


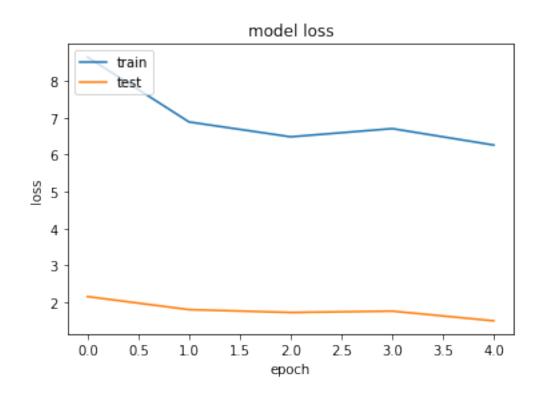
```
16/16 [=======
                    ======== ] - 4s 239ms/step
Test evaluation:
accuracy: 0.6883
[1.069715976715088, 0.6883116960525513]
% of correct brand in the first 3 positions:
141
0.9155844155844156
\% of brand predicted with percentage >= 0.25
0.11688311688311688
\% of brand predicted with percentage >= 0.5
0.11688311688311688
% of brand predicted with percentage >= 0.75
0.11688311688311688
Matriz de confusión:
```



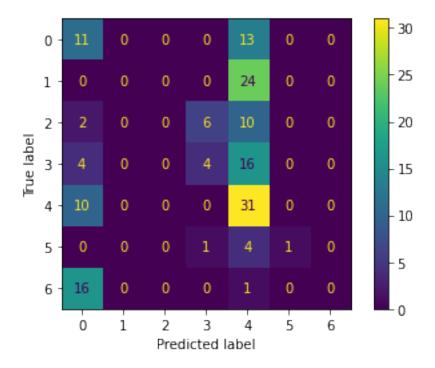
## [54]: model\_test19=executeModel(True, True, True, 5)

```
Training model with aumentation: True, gray: True, binary: True, crop: True and
epochs = 5
Epoch 1/5
0.2382 - val_loss: 2.1593 - val_accuracy: 0.3793
Epoch 2/5
0.2268 - val_loss: 1.8063 - val_accuracy: 0.3793
Epoch 3/5
0.2873 - val_loss: 1.7292 - val_accuracy: 0.3793
Epoch 4/5
0.3025 - val_loss: 1.7658 - val_accuracy: 0.3793
Epoch 5/5
0.3043 - val_loss: 1.5028 - val_accuracy: 0.4598
```





```
16/16 [==============] - 5s 266ms/step
Test evaluation:
16/16 [=============] - 5s 277ms/step - loss: 1.7120 -
accuracy: 0.3052
[1.7119717597961426, 0.30519479513168335]
% of correct brand in the first 3 positions:
117
0.7597402597402597
% of brand predicted with percentage >= 0.25
0.2662337662337662
% of brand predicted with percentage >= 0.5
0.2662337662337662
% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```

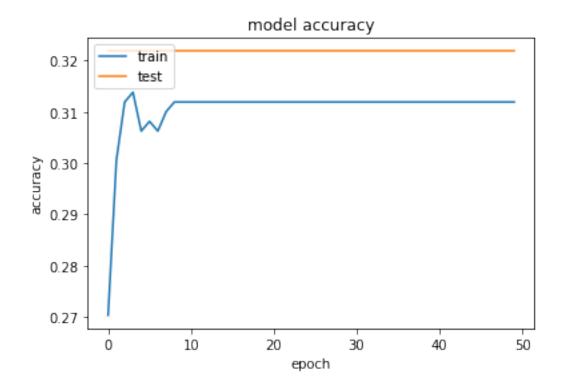


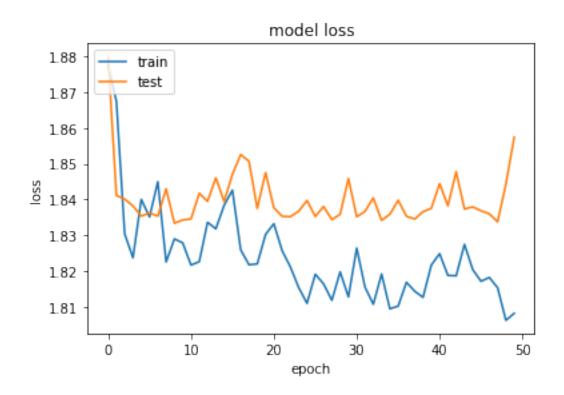
```
[206]: model_test20=executeModel(False, False, False, False, 50)
```

```
0.3006 - val_loss: 1.8411 - val_accuracy: 0.3218
Epoch 3/50
0.3119 - val_loss: 1.8402 - val_accuracy: 0.3218
Epoch 4/50
0.3138 - val_loss: 1.8383 - val_accuracy: 0.3218
Epoch 5/50
0.3062 - val_loss: 1.8354 - val_accuracy: 0.3218
Epoch 6/50
0.3081 - val_loss: 1.8363 - val_accuracy: 0.3218
Epoch 7/50
0.3062 - val_loss: 1.8354 - val_accuracy: 0.3218
Epoch 8/50
0.3100 - val_loss: 1.8430 - val_accuracy: 0.3218
0.3119 - val_loss: 1.8334 - val_accuracy: 0.3218
Epoch 10/50
53/53 [============== ] - 61s 1s/step - loss: 1.8280 - accuracy:
0.3119 - val_loss: 1.8343 - val_accuracy: 0.3218
Epoch 11/50
0.3119 - val_loss: 1.8346 - val_accuracy: 0.3218
Epoch 12/50
0.3119 - val_loss: 1.8418 - val_accuracy: 0.3218
Epoch 13/50
0.3119 - val_loss: 1.8395 - val_accuracy: 0.3218
Epoch 14/50
0.3119 - val_loss: 1.8461 - val_accuracy: 0.3218
Epoch 15/50
53/53 [============== ] - 61s 1s/step - loss: 1.8384 - accuracy:
0.3119 - val_loss: 1.8395 - val_accuracy: 0.3218
Epoch 16/50
0.3119 - val_loss: 1.8471 - val_accuracy: 0.3218
Epoch 17/50
53/53 [=============== ] - 60s 1s/step - loss: 1.8260 - accuracy:
0.3119 - val_loss: 1.8526 - val_accuracy: 0.3218
Epoch 18/50
```

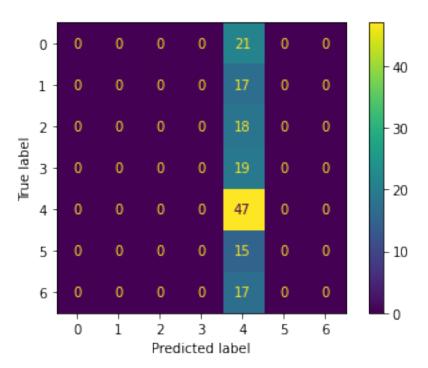
```
0.3119 - val_loss: 1.8507 - val_accuracy: 0.3218
Epoch 19/50
0.3119 - val_loss: 1.8376 - val_accuracy: 0.3218
Epoch 20/50
0.3119 - val_loss: 1.8475 - val_accuracy: 0.3218
Epoch 21/50
0.3119 - val_loss: 1.8377 - val_accuracy: 0.3218
Epoch 22/50
0.3119 - val_loss: 1.8354 - val_accuracy: 0.3218
Epoch 23/50
53/53 [============== ] - 60s 1s/step - loss: 1.8212 - accuracy:
0.3119 - val_loss: 1.8352 - val_accuracy: 0.3218
Epoch 24/50
0.3119 - val_loss: 1.8368 - val_accuracy: 0.3218
Epoch 25/50
0.3119 - val_loss: 1.8398 - val_accuracy: 0.3218
Epoch 26/50
53/53 [============== ] - 63s 1s/step - loss: 1.8192 - accuracy:
0.3119 - val_loss: 1.8353 - val_accuracy: 0.3218
Epoch 27/50
0.3119 - val_loss: 1.8381 - val_accuracy: 0.3218
Epoch 28/50
0.3119 - val_loss: 1.8344 - val_accuracy: 0.3218
Epoch 29/50
0.3119 - val_loss: 1.8359 - val_accuracy: 0.3218
Epoch 30/50
0.3119 - val_loss: 1.8459 - val_accuracy: 0.3218
Epoch 31/50
0.3119 - val_loss: 1.8352 - val_accuracy: 0.3218
Epoch 32/50
0.3119 - val_loss: 1.8367 - val_accuracy: 0.3218
Epoch 33/50
53/53 [================ ] - 54s 1s/step - loss: 1.8108 - accuracy:
0.3119 - val_loss: 1.8405 - val_accuracy: 0.3218
Epoch 34/50
```

```
53/53 [================== ] - 54s 1s/step - loss: 1.8193 - accuracy:
0.3119 - val_loss: 1.8342 - val_accuracy: 0.3218
Epoch 35/50
0.3119 - val_loss: 1.8359 - val_accuracy: 0.3218
Epoch 36/50
0.3119 - val_loss: 1.8398 - val_accuracy: 0.3218
Epoch 37/50
0.3119 - val_loss: 1.8354 - val_accuracy: 0.3218
Epoch 38/50
0.3119 - val_loss: 1.8346 - val_accuracy: 0.3218
0.3119 - val_loss: 1.8366 - val_accuracy: 0.3218
Epoch 40/50
0.3119 - val_loss: 1.8376 - val_accuracy: 0.3218
Epoch 41/50
0.3119 - val_loss: 1.8445 - val_accuracy: 0.3218
Epoch 42/50
0.3119 - val_loss: 1.8383 - val_accuracy: 0.3218
Epoch 43/50
0.3119 - val_loss: 1.8478 - val_accuracy: 0.3218
Epoch 44/50
0.3119 - val_loss: 1.8374 - val_accuracy: 0.3218
Epoch 45/50
0.3119 - val loss: 1.8380 - val accuracy: 0.3218
Epoch 46/50
0.3119 - val_loss: 1.8369 - val_accuracy: 0.3218
Epoch 47/50
53/53 [============== ] - 65s 1s/step - loss: 1.8183 - accuracy:
0.3119 - val_loss: 1.8361 - val_accuracy: 0.3218
Epoch 48/50
0.3119 - val_loss: 1.8338 - val_accuracy: 0.3218
Epoch 49/50
0.3119 - val_loss: 1.8443 - val_accuracy: 0.3218
Epoch 50/50
```





```
16/16 [========= ] - 5s 272ms/step
Test evaluation:
16/16 [======
                                =====] - 5s 330ms/step - loss: 1.9241 -
accuracy: 0.3052
[1.9240790605545044, 0.30519479513168335]
\mbox{\ensuremath{\mbox{\%}}} of correct brand in the first 3 positions:
87
0.564935064935065
% of brand predicted with percentage >= 0.25
0.3051948051948052
% of brand predicted with percentage >= 0.5
0.0
% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```

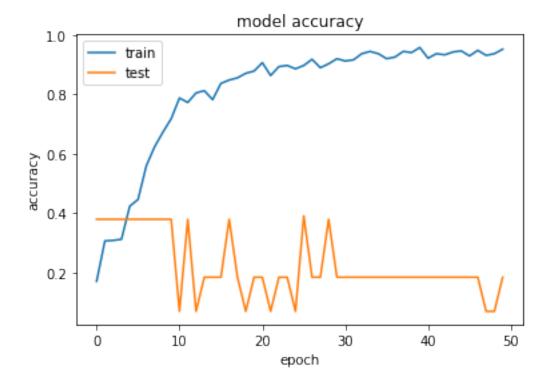


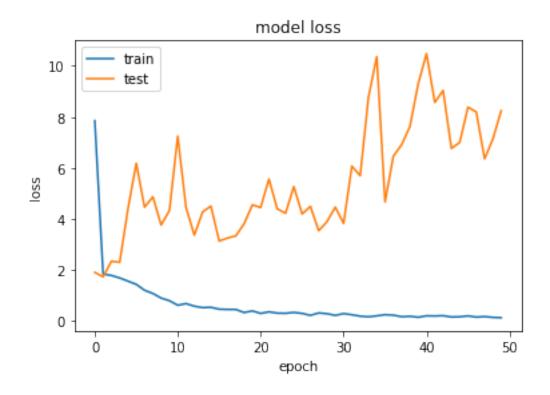


```
0.1701 - val_loss: 1.9095 - val_accuracy: 0.3793
Epoch 2/50
0.3062 - val_loss: 1.7369 - val_accuracy: 0.3793
Epoch 3/50
53/53 [=============== ] - 74s 1s/step - loss: 1.7899 - accuracy:
0.3081 - val_loss: 2.3456 - val_accuracy: 0.3793
Epoch 4/50
0.3119 - val_loss: 2.3048 - val_accuracy: 0.3793
Epoch 5/50
0.4234 - val_loss: 4.4014 - val_accuracy: 0.3793
Epoch 6/50
0.4461 - val_loss: 6.1858 - val_accuracy: 0.3793
Epoch 7/50
0.5595 - val_loss: 4.4645 - val_accuracy: 0.3793
Epoch 8/50
0.6238 - val_loss: 4.8713 - val_accuracy: 0.3793
Epoch 9/50
0.6730 - val_loss: 3.7680 - val_accuracy: 0.3793
Epoch 10/50
53/53 [============== ] - 72s 1s/step - loss: 0.8001 - accuracy:
0.7183 - val_loss: 4.3358 - val_accuracy: 0.3793
Epoch 11/50
0.7883 - val_loss: 7.2474 - val_accuracy: 0.0690
Epoch 12/50
0.7732 - val_loss: 4.4505 - val_accuracy: 0.3793
Epoch 13/50
0.8053 - val_loss: 3.3696 - val_accuracy: 0.0690
Epoch 14/50
53/53 [============== ] - 83s 2s/step - loss: 0.5295 - accuracy:
0.8129 - val_loss: 4.2799 - val_accuracy: 0.1839
Epoch 15/50
0.7826 - val_loss: 4.5071 - val_accuracy: 0.1839
Epoch 16/50
0.8374 - val_loss: 3.1381 - val_accuracy: 0.1839
Epoch 17/50
53/53 [============== ] - 75s 1s/step - loss: 0.4591 - accuracy:
```

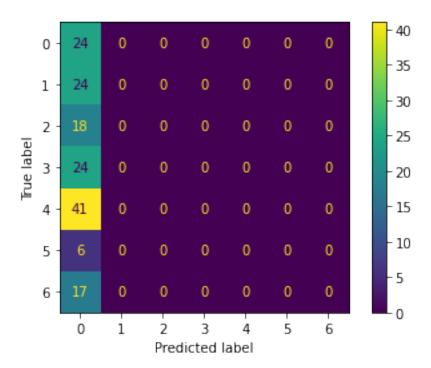
```
0.8488 - val_loss: 3.2556 - val_accuracy: 0.3793
Epoch 18/50
0.8563 - val_loss: 3.3396 - val_accuracy: 0.1839
Epoch 19/50
53/53 [============== ] - 80s 1s/step - loss: 0.3364 - accuracy:
0.8715 - val_loss: 3.8138 - val_accuracy: 0.0690
Epoch 20/50
0.8790 - val_loss: 4.5565 - val_accuracy: 0.1839
Epoch 21/50
0.9074 - val_loss: 4.4507 - val_accuracy: 0.1839
Epoch 22/50
0.8639 - val_loss: 5.5678 - val_accuracy: 0.0690
Epoch 23/50
0.8941 - val_loss: 4.4007 - val_accuracy: 0.1839
Epoch 24/50
0.8979 - val_loss: 4.2266 - val_accuracy: 0.1839
Epoch 25/50
0.8866 - val_loss: 5.2736 - val_accuracy: 0.0690
Epoch 26/50
0.8979 - val_loss: 4.1967 - val_accuracy: 0.3908
Epoch 27/50
0.9187 - val_loss: 4.4966 - val_accuracy: 0.1839
Epoch 28/50
0.8904 - val_loss: 3.5402 - val_accuracy: 0.1839
Epoch 29/50
0.9036 - val_loss: 3.9001 - val_accuracy: 0.3793
Epoch 30/50
53/53 [============== ] - 73s 1s/step - loss: 0.2259 - accuracy:
0.9206 - val_loss: 4.4679 - val_accuracy: 0.1839
Epoch 31/50
0.9130 - val_loss: 3.8258 - val_accuracy: 0.1839
Epoch 32/50
0.9168 - val_loss: 6.0730 - val_accuracy: 0.1839
Epoch 33/50
```

```
0.9376 - val_loss: 5.6985 - val_accuracy: 0.1839
Epoch 34/50
0.9452 - val_loss: 8.7765 - val_accuracy: 0.1839
Epoch 35/50
0.9376 - val_loss: 10.3619 - val_accuracy: 0.1839
Epoch 36/50
0.9206 - val_loss: 4.6730 - val_accuracy: 0.1839
Epoch 37/50
0.9263 - val_loss: 6.4638 - val_accuracy: 0.1839
Epoch 38/50
0.9452 - val_loss: 6.9136 - val_accuracy: 0.1839
Epoch 39/50
0.9414 - val_loss: 7.6281 - val_accuracy: 0.1839
Epoch 40/50
0.9584 - val_loss: 9.3018 - val_accuracy: 0.1839
Epoch 41/50
0.9225 - val_loss: 10.4842 - val_accuracy: 0.1839
Epoch 42/50
0.9376 - val_loss: 8.5669 - val_accuracy: 0.1839
53/53 [=============== ] - 72s 1s/step - loss: 0.2124 - accuracy:
0.9338 - val_loss: 9.0402 - val_accuracy: 0.1839
Epoch 44/50
0.9433 - val_loss: 6.7677 - val_accuracy: 0.1839
Epoch 45/50
0.9471 - val_loss: 7.0008 - val_accuracy: 0.1839
Epoch 46/50
53/53 [============== ] - 73s 1s/step - loss: 0.2045 - accuracy:
0.9301 - val_loss: 8.3842 - val_accuracy: 0.1839
Epoch 47/50
0.9490 - val_loss: 8.1974 - val_accuracy: 0.1839
Epoch 48/50
0.9319 - val_loss: 6.3606 - val_accuracy: 0.0690
Epoch 49/50
53/53 [============== ] - 75s 1s/step - loss: 0.1484 - accuracy:
```





```
16/16 [=======
                         =======] - 5s 277ms/step
Test evaluation:
16/16 [============= ] - 5s 303ms/step - loss: 8.2145 -
accuracy: 0.1558
[8.21447467803955, 0.15584415197372437]
% of correct brand in the first 3 positions:
89
0.577922077922078
\% of brand predicted with percentage >= 0.25
0.3116883116883117
\% of brand predicted with percentage >= 0.5
0.15584415584415584
\% of brand predicted with percentage >= 0.75
0.0
Matriz de confusión:
```



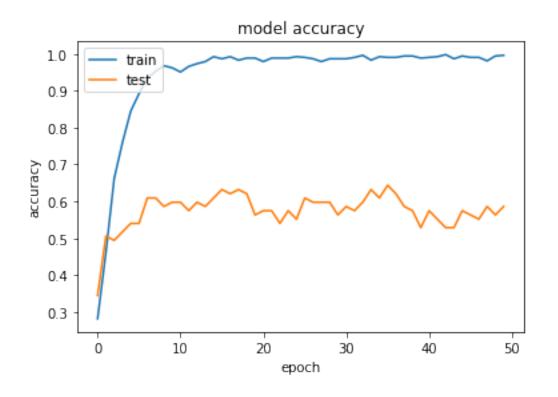
## [208]: model\_test22=executeModel(False, True, True, False, 50)

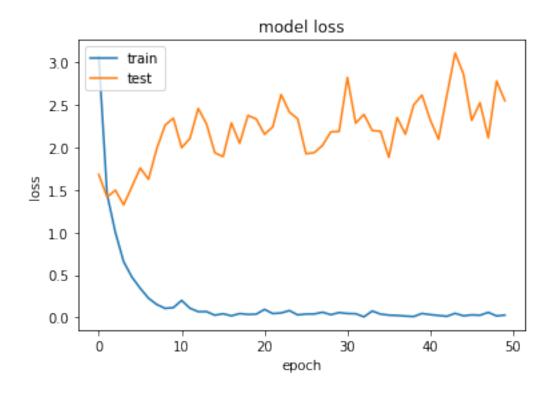
```
Training model with aumentation: False, gray: True, binary: True, crop: False and
epochs = 50
Epoch 1/50
53/53 [============== ] - 57s 1s/step - loss: 3.0693 - accuracy:
0.2817 - val_loss: 1.6831 - val_accuracy: 0.3448
Epoch 2/50
0.4612 - val_loss: 1.4167 - val_accuracy: 0.5057
Epoch 3/50
0.6616 - val_loss: 1.4982 - val_accuracy: 0.4943
Epoch 4/50
0.7599 - val_loss: 1.3249 - val_accuracy: 0.5172
Epoch 5/50
53/53 [============== ] - 55s 1s/step - loss: 0.4764 - accuracy:
0.8450 - val_loss: 1.5395 - val_accuracy: 0.5402
Epoch 6/50
53/53 [============== ] - 56s 1s/step - loss: 0.3444 - accuracy:
0.8922 - val_loss: 1.7589 - val_accuracy: 0.5402
Epoch 7/50
```

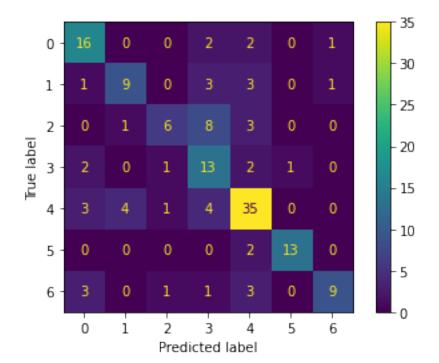
```
0.9338 - val_loss: 1.6263 - val_accuracy: 0.6092
Epoch 8/50
0.9527 - val_loss: 1.9877 - val_accuracy: 0.6092
Epoch 9/50
53/53 [============== ] - 55s 1s/step - loss: 0.1085 - accuracy:
0.9679 - val_loss: 2.2621 - val_accuracy: 0.5862
Epoch 10/50
0.9622 - val_loss: 2.3443 - val_accuracy: 0.5977
Epoch 11/50
0.9509 - val_loss: 1.9974 - val_accuracy: 0.5977
Epoch 12/50
0.9660 - val_loss: 2.1064 - val_accuracy: 0.5747
Epoch 13/50
0.9735 - val_loss: 2.4593 - val_accuracy: 0.5977
Epoch 14/50
0.9792 - val_loss: 2.2762 - val_accuracy: 0.5862
Epoch 15/50
0.9924 - val_loss: 1.9387 - val_accuracy: 0.6092
Epoch 16/50
0.9868 - val_loss: 1.8922 - val_accuracy: 0.6322
Epoch 17/50
0.9924 - val_loss: 2.2886 - val_accuracy: 0.6207
Epoch 18/50
0.9830 - val_loss: 2.0489 - val_accuracy: 0.6322
Epoch 19/50
0.9887 - val_loss: 2.3771 - val_accuracy: 0.6207
Epoch 20/50
53/53 [============== ] - 56s 1s/step - loss: 0.0404 - accuracy:
0.9887 - val_loss: 2.3347 - val_accuracy: 0.5632
Epoch 21/50
0.9792 - val_loss: 2.1551 - val_accuracy: 0.5747
Epoch 22/50
0.9887 - val_loss: 2.2426 - val_accuracy: 0.5747
Epoch 23/50
53/53 [============== ] - 58s 1s/step - loss: 0.0544 - accuracy:
```

```
0.9887 - val_loss: 2.6224 - val_accuracy: 0.5402
Epoch 24/50
0.9887 - val_loss: 2.4164 - val_accuracy: 0.5747
Epoch 25/50
53/53 [============== ] - 56s 1s/step - loss: 0.0315 - accuracy:
0.9924 - val_loss: 2.3374 - val_accuracy: 0.5517
Epoch 26/50
0.9905 - val_loss: 1.9262 - val_accuracy: 0.6092
Epoch 27/50
0.9868 - val_loss: 1.9392 - val_accuracy: 0.5977
Epoch 28/50
0.9792 - val_loss: 2.0253 - val_accuracy: 0.5977
Epoch 29/50
0.9868 - val_loss: 2.1833 - val_accuracy: 0.5977
Epoch 30/50
0.9868 - val_loss: 2.1886 - val_accuracy: 0.5632
Epoch 31/50
0.9868 - val_loss: 2.8232 - val_accuracy: 0.5862
Epoch 32/50
0.9905 - val_loss: 2.2854 - val_accuracy: 0.5747
accuracy: 0.9962 - val_loss: 2.3889 - val_accuracy: 0.5977
Epoch 34/50
53/53 [============ ] - 53s 995ms/step - loss: 0.0775 -
accuracy: 0.9830 - val_loss: 2.1985 - val_accuracy: 0.6322
Epoch 35/50
accuracy: 0.9924 - val loss: 2.1911 - val accuracy: 0.6092
Epoch 36/50
accuracy: 0.9905 - val_loss: 1.8839 - val_accuracy: 0.6437
Epoch 37/50
53/53 [============ ] - 52s 973ms/step - loss: 0.0251 -
accuracy: 0.9905 - val_loss: 2.3510 - val_accuracy: 0.6207
Epoch 38/50
53/53 [============ ] - 52s 983ms/step - loss: 0.0179 -
accuracy: 0.9943 - val_loss: 2.1563 - val_accuracy: 0.5862
Epoch 39/50
```

```
accuracy: 0.9943 - val_loss: 2.5008 - val_accuracy: 0.5747
Epoch 40/50
accuracy: 0.9887 - val_loss: 2.6159 - val_accuracy: 0.5287
Epoch 41/50
accuracy: 0.9905 - val_loss: 2.3225 - val_accuracy: 0.5747
Epoch 42/50
53/53 [============ ] - 51s 967ms/step - loss: 0.0246 -
accuracy: 0.9924 - val_loss: 2.0971 - val_accuracy: 0.5517
Epoch 43/50
53/53 [============= ] - 51s 961ms/step - loss: 0.0150 -
accuracy: 0.9981 - val_loss: 2.6130 - val_accuracy: 0.5287
Epoch 44/50
accuracy: 0.9868 - val_loss: 3.1106 - val_accuracy: 0.5287
Epoch 45/50
accuracy: 0.9943 - val_loss: 2.8654 - val_accuracy: 0.5747
Epoch 46/50
accuracy: 0.9905 - val_loss: 2.3186 - val_accuracy: 0.5632
Epoch 47/50
accuracy: 0.9905 - val_loss: 2.5256 - val_accuracy: 0.5517
Epoch 48/50
53/53 [============ ] - 51s 962ms/step - loss: 0.0613 -
accuracy: 0.9811 - val_loss: 2.1120 - val_accuracy: 0.5862
accuracy: 0.9943 - val_loss: 2.7811 - val_accuracy: 0.5632
Epoch 50/50
accuracy: 0.9962 - val_loss: 2.5502 - val_accuracy: 0.5862
```





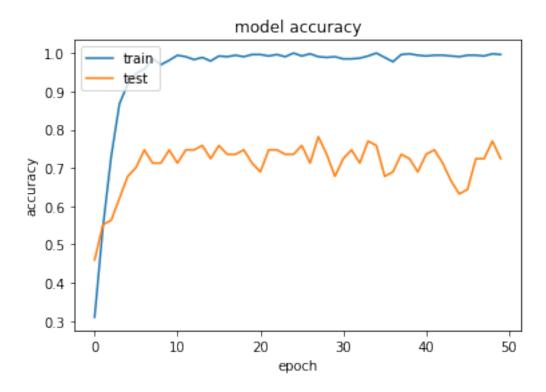


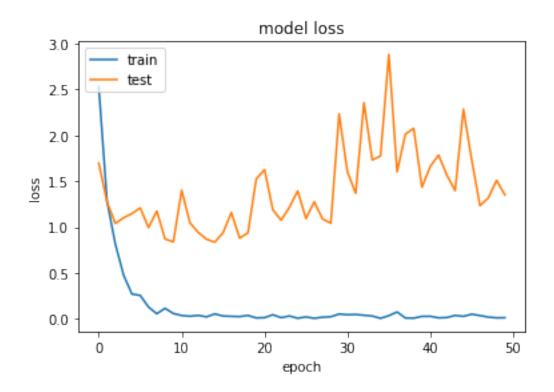
```
[214]: model_test23=executeModel(False, True, True, True, 50)
```

```
0.5444 - val_loss: 1.2705 - val_accuracy: 0.5517
Epoch 3/50
0.7297 - val_loss: 1.0391 - val_accuracy: 0.5632
Epoch 4/50
0.8677 - val_loss: 1.1015 - val_accuracy: 0.6207
Epoch 5/50
0.9187 - val_loss: 1.1465 - val_accuracy: 0.6782
Epoch 6/50
accuracy: 0.9471 - val_loss: 1.2081 - val_accuracy: 0.7011
accuracy: 0.9584 - val_loss: 0.9935 - val_accuracy: 0.7471
53/53 [============== ] - 53s 1s/step - loss: 0.0556 - accuracy:
0.9849 - val_loss: 1.1731 - val_accuracy: 0.7126
0.9698 - val_loss: 0.8700 - val_accuracy: 0.7126
Epoch 10/50
53/53 [============== ] - 59s 1s/step - loss: 0.0586 - accuracy:
0.9811 - val_loss: 0.8385 - val_accuracy: 0.7471
Epoch 11/50
0.9943 - val_loss: 1.4020 - val_accuracy: 0.7126
Epoch 12/50
53/53 [=============== ] - 57s 1s/step - loss: 0.0283 - accuracy:
0.9905 - val_loss: 1.0457 - val_accuracy: 0.7471
Epoch 13/50
0.9830 - val_loss: 0.9414 - val_accuracy: 0.7471
Epoch 14/50
0.9887 - val_loss: 0.8678 - val_accuracy: 0.7586
Epoch 15/50
0.9792 - val_loss: 0.8355 - val_accuracy: 0.7241
Epoch 16/50
0.9924 - val_loss: 0.9396 - val_accuracy: 0.7586
Epoch 17/50
53/53 [=============== ] - 70s 1s/step - loss: 0.0269 - accuracy:
0.9905 - val_loss: 1.1571 - val_accuracy: 0.7356
Epoch 18/50
```

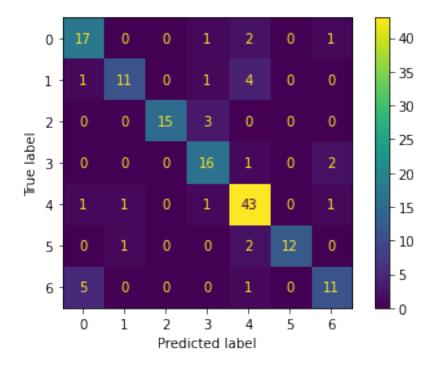
```
0.9943 - val_loss: 0.8790 - val_accuracy: 0.7356
Epoch 19/50
0.9905 - val_loss: 0.9362 - val_accuracy: 0.7471
Epoch 20/50
0.9962 - val_loss: 1.5219 - val_accuracy: 0.7126
Epoch 21/50
53/53 [============== ] - 68s 1s/step - loss: 0.0128 - accuracy:
0.9962 - val_loss: 1.6257 - val_accuracy: 0.6897
Epoch 22/50
0.9924 - val_loss: 1.1889 - val_accuracy: 0.7471
Epoch 23/50
0.9962 - val_loss: 1.0741 - val_accuracy: 0.7471
Epoch 24/50
53/53 [============== ] - 79s 1s/step - loss: 0.0311 - accuracy:
0.9905 - val_loss: 1.2146 - val_accuracy: 0.7356
Epoch 25/50
1.0000 - val_loss: 1.3926 - val_accuracy: 0.7356
Epoch 26/50
53/53 [============== ] - 62s 1s/step - loss: 0.0212 - accuracy:
0.9924 - val_loss: 1.0925 - val_accuracy: 0.7586
Epoch 27/50
0.9981 - val_loss: 1.2747 - val_accuracy: 0.7126
Epoch 28/50
0.9905 - val_loss: 1.0882 - val_accuracy: 0.7816
Epoch 29/50
0.9887 - val_loss: 1.0415 - val_accuracy: 0.7356
Epoch 30/50
0.9905 - val_loss: 2.2324 - val_accuracy: 0.6782
Epoch 31/50
0.9849 - val_loss: 1.6018 - val_accuracy: 0.7241
Epoch 32/50
0.9849 - val_loss: 1.3672 - val_accuracy: 0.7471
Epoch 33/50
0.9868 - val_loss: 2.3536 - val_accuracy: 0.7126
Epoch 34/50
```

```
0.9924 - val_loss: 1.7309 - val_accuracy: 0.7701
Epoch 35/50
1.0000 - val_loss: 1.7737 - val_accuracy: 0.7586
Epoch 36/50
0.9887 - val_loss: 2.8788 - val_accuracy: 0.6782
Epoch 37/50
53/53 [============== ] - 63s 1s/step - loss: 0.0750 - accuracy:
0.9773 - val_loss: 1.6011 - val_accuracy: 0.6897
Epoch 38/50
0.9962 - val_loss: 2.0122 - val_accuracy: 0.7356
Epoch 39/50
0.9981 - val_loss: 2.0745 - val_accuracy: 0.7241
Epoch 40/50
53/53 [============== ] - 63s 1s/step - loss: 0.0269 - accuracy:
0.9943 - val_loss: 1.4339 - val_accuracy: 0.6897
Epoch 41/50
0.9924 - val_loss: 1.6600 - val_accuracy: 0.7356
Epoch 42/50
53/53 [============== ] - 63s 1s/step - loss: 0.0107 - accuracy:
0.9943 - val_loss: 1.7833 - val_accuracy: 0.7471
Epoch 43/50
0.9943 - val_loss: 1.5656 - val_accuracy: 0.7126
Epoch 44/50
53/53 [================ ] - 63s 1s/step - loss: 0.0373 - accuracy:
0.9924 - val_loss: 1.3966 - val_accuracy: 0.6667
Epoch 45/50
0.9905 - val_loss: 2.2837 - val_accuracy: 0.6322
Epoch 46/50
0.9943 - val_loss: 1.7312 - val_accuracy: 0.6437
Epoch 47/50
0.9943 - val_loss: 1.2324 - val_accuracy: 0.7241
Epoch 48/50
0.9924 - val_loss: 1.3165 - val_accuracy: 0.7241
Epoch 49/50
0.9981 - val_loss: 1.5085 - val_accuracy: 0.7701
Epoch 50/50
```





```
16/16 [======== ] - 5s 267ms/step
Test evaluation:
16/16 [======
                                   ===] - 5s 290ms/step - loss: 1.0314 -
accuracy: 0.8117
[1.0313525199890137, 0.8116883039474487]
\mbox{\ensuremath{\mbox{\%}}} of correct brand in the first 3 positions:
150
0.974025974025974
% of brand predicted with percentage >= 0.25
0.11688311688311688
% of brand predicted with percentage >= 0.5
0.11688311688311688
% of brand predicted with percentage >= 0.75
0.11688311688311688
Matriz de confusión:
```



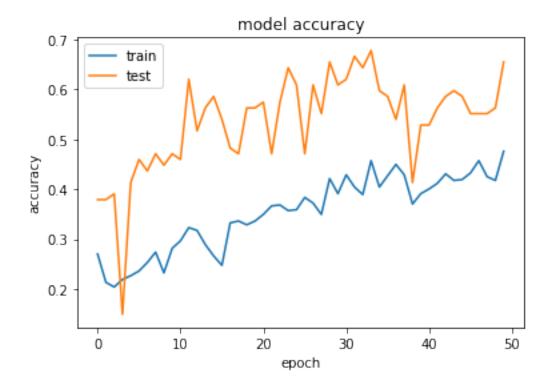
```
[56]: model_test24=executeModel(True, True, True, 50)
```

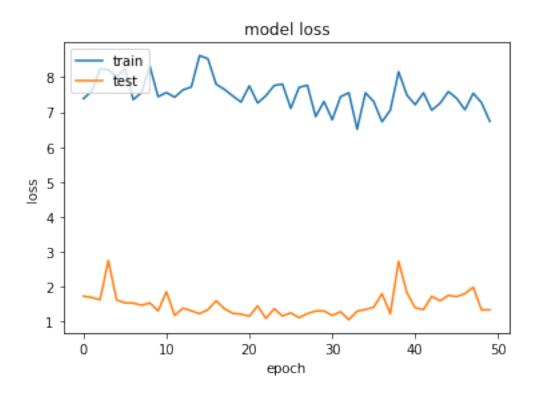
```
0.2703 - val_loss: 1.7350 - val_accuracy: 0.3793
Epoch 2/50
53/53 [============== ] - 70s 1s/step - loss: 7.5945 - accuracy:
0.2136 - val_loss: 1.6944 - val_accuracy: 0.3793
Epoch 3/50
0.2042 - val_loss: 1.6338 - val_accuracy: 0.3908
Epoch 4/50
0.2193 - val_loss: 2.7541 - val_accuracy: 0.1494
Epoch 5/50
0.2268 - val_loss: 1.6242 - val_accuracy: 0.4138
Epoch 6/50
0.2363 - val_loss: 1.5424 - val_accuracy: 0.4598
Epoch 7/50
0.2533 - val_loss: 1.5389 - val_accuracy: 0.4368
Epoch 8/50
0.2741 - val_loss: 1.4743 - val_accuracy: 0.4713
Epoch 9/50
0.2325 - val_loss: 1.5413 - val_accuracy: 0.4483
Epoch 10/50
0.2817 - val_loss: 1.3126 - val_accuracy: 0.4713
Epoch 11/50
0.2968 - val_loss: 1.8611 - val_accuracy: 0.4598
Epoch 12/50
0.3233 - val_loss: 1.1826 - val_accuracy: 0.6207
Epoch 13/50
0.3176 - val_loss: 1.3928 - val_accuracy: 0.5172
Epoch 14/50
53/53 [============== ] - 60s 1s/step - loss: 7.7170 - accuracy:
0.2892 - val_loss: 1.3155 - val_accuracy: 0.5632
Epoch 15/50
0.2665 - val_loss: 1.2336 - val_accuracy: 0.5862
Epoch 16/50
0.2476 - val_loss: 1.3484 - val_accuracy: 0.5402
Epoch 17/50
53/53 [============== ] - 63s 1s/step - loss: 7.7969 - accuracy:
```

```
0.3327 - val_loss: 1.6010 - val_accuracy: 0.4828
Epoch 18/50
0.3365 - val_loss: 1.3740 - val_accuracy: 0.4713
Epoch 19/50
0.3289 - val_loss: 1.2434 - val_accuracy: 0.5632
Epoch 20/50
0.3365 - val_loss: 1.2204 - val_accuracy: 0.5632
Epoch 21/50
0.3497 - val_loss: 1.1602 - val_accuracy: 0.5747
Epoch 22/50
0.3667 - val_loss: 1.4549 - val_accuracy: 0.4713
Epoch 23/50
0.3686 - val_loss: 1.0996 - val_accuracy: 0.5747
Epoch 24/50
0.3573 - val_loss: 1.3773 - val_accuracy: 0.6437
Epoch 25/50
0.3592 - val_loss: 1.1678 - val_accuracy: 0.6092
Epoch 26/50
0.3837 - val_loss: 1.2575 - val_accuracy: 0.4713
Epoch 27/50
0.3724 - val_loss: 1.1180 - val_accuracy: 0.6092
Epoch 28/50
0.3497 - val_loss: 1.2362 - val_accuracy: 0.5517
Epoch 29/50
0.4216 - val_loss: 1.3097 - val_accuracy: 0.6552
Epoch 30/50
53/53 [============== ] - 59s 1s/step - loss: 7.3034 - accuracy:
0.3913 - val_loss: 1.3118 - val_accuracy: 0.6092
Epoch 31/50
0.4291 - val_loss: 1.1816 - val_accuracy: 0.6207
Epoch 32/50
0.4045 - val_loss: 1.2907 - val_accuracy: 0.6667
Epoch 33/50
53/53 [============== ] - 59s 1s/step - loss: 7.5538 - accuracy:
```

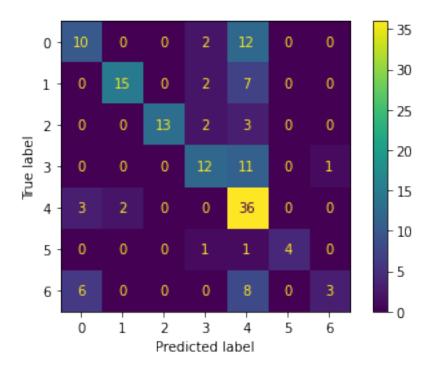
```
0.3894 - val_loss: 1.0600 - val_accuracy: 0.6437
Epoch 34/50
0.4575 - val_loss: 1.3035 - val_accuracy: 0.6782
Epoch 35/50
0.4045 - val_loss: 1.3514 - val_accuracy: 0.5977
Epoch 36/50
0.4272 - val_loss: 1.4175 - val_accuracy: 0.5862
Epoch 37/50
0.4499 - val_loss: 1.8053 - val_accuracy: 0.5402
Epoch 38/50
0.4291 - val_loss: 1.2295 - val_accuracy: 0.6092
Epoch 39/50
0.3705 - val_loss: 2.7324 - val_accuracy: 0.4138
Epoch 40/50
0.3913 - val_loss: 1.8344 - val_accuracy: 0.5287
Epoch 41/50
0.4008 - val_loss: 1.4004 - val_accuracy: 0.5287
Epoch 42/50
0.4121 - val_loss: 1.3501 - val_accuracy: 0.5632
53/53 [=============== ] - 59s 1s/step - loss: 7.0536 - accuracy:
0.4310 - val_loss: 1.7284 - val_accuracy: 0.5862
Epoch 44/50
0.4178 - val_loss: 1.6022 - val_accuracy: 0.5977
Epoch 45/50
0.4197 - val_loss: 1.7571 - val_accuracy: 0.5862
Epoch 46/50
53/53 [============== ] - 59s 1s/step - loss: 7.3932 - accuracy:
0.4329 - val_loss: 1.7208 - val_accuracy: 0.5517
Epoch 47/50
0.4575 - val_loss: 1.8047 - val_accuracy: 0.5517
Epoch 48/50
0.4253 - val_loss: 1.9903 - val_accuracy: 0.5517
Epoch 49/50
53/53 [============== ] - 59s 1s/step - loss: 7.2685 - accuracy:
```

0.4764 - val\_loss: 1.3451 - val\_accuracy: 0.6552





```
16/16 [=======
                        ========] - 4s 233ms/step
Test evaluation:
16/16 [============ ] - 4s 243ms/step - loss: 1.6034 -
accuracy: 0.6039
[1.6033967733383179, 0.6038960814476013]
% of correct brand in the first 3 positions:
144
0.935064935064935
\% of brand predicted with percentage >= 0.25
0.2662337662337662
\% of brand predicted with percentage >= 0.5
0.2662337662337662
% of brand predicted with percentage >= 0.75
0.2662337662337662
Matriz de confusión:
```



## 4.1.2 Experimentos con diferentes valores de muestras mínimas por marca

```
[57]: def returnDataByMinSample ( minSample, deleteNone=True):
    dfbrandMin, dfbrandoneMin = filterMinSamples(dfbrandall, minSample, u)
    deleteNone)
    num_classesMin=len(dfbrandMin)
    df_shoe_brandMin = filterBrands(df_shoe_brand_all,dfbrandoneMin, deleteNone)
    print(df_shoe_brandMin.shape)
    shoes_trainMin, shoes_testMin, shoes_valMin = u
    split_datafiles(df_shoe_brandMin)

    while checkBalancedSample(shoes_trainMin, shoes_testMin, shoes_valMin) == u
    split_datafiles(df_shoe_brandMin)

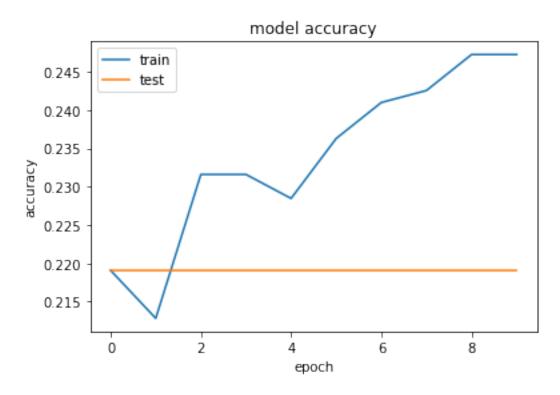
    return num_classesMin, df_shoe_brandMin, shoes_trainMin, shoes_testMin, u
    shoes_valMin
[58]: num_classes3, df_shoe_brand3,shoes_train3, shoes_test3, shoes_val3 = u
```

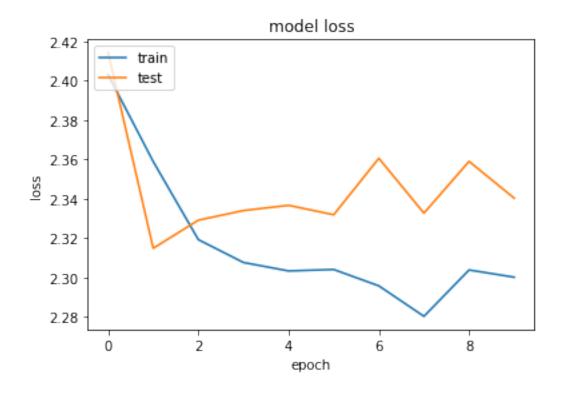
 $\begin{array}{ccc} & & x & y \\ 0 & & \texttt{Adidas} & 12 \end{array}$ 

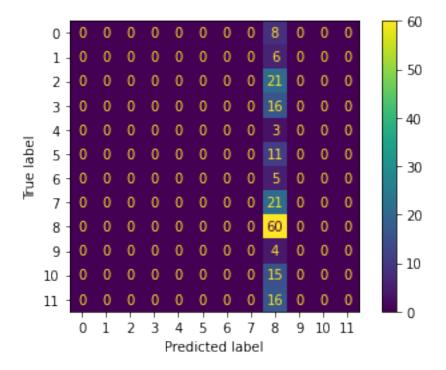
→returnDataByMinSample(3)

```
6
        Asics 13
   12
      Champion
            3
   15
      Converse
            7
   30
         Keen
   33 Newbalance
         Nike 24
   34
   42
       Saucony
   44
       Shoopen
   46
      Skechers 8
   50
       Sperry
            7
   54
         Teva
            3
   Brands with at least 3 samples: 12
   Brands with only 1 register: 47
   (930, 3)
[225]: model_test25=executeModelData(False, False, False, False, 10, shoes_train3,__
    →shoes_test3, shoes_val3, df_shoe_brand3,num_classes3)
   Training model with aumentation: False, gray: False, binary: False, crop: False and
   epochs = 10
   Epoch 1/10
   0.2191 - val_loss: 2.4143 - val_accuracy: 0.2190
   Epoch 2/10
   0.2128 - val_loss: 2.3148 - val_accuracy: 0.2190
   0.2316 - val_loss: 2.3290 - val_accuracy: 0.2190
   0.2316 - val_loss: 2.3340 - val_accuracy: 0.2190
   Epoch 5/10
   0.2285 - val_loss: 2.3366 - val_accuracy: 0.2190
   Epoch 6/10
   0.2363 - val_loss: 2.3318 - val_accuracy: 0.2190
   Epoch 7/10
   0.2410 - val_loss: 2.3605 - val_accuracy: 0.2190
   Epoch 8/10
   0.2426 - val_loss: 2.3326 - val_accuracy: 0.2190
   Epoch 9/10
```

0.2473 - val\_loss: 2.3590 - val\_accuracy: 0.2190





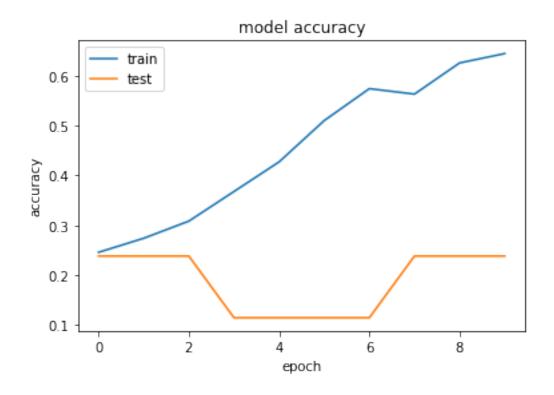


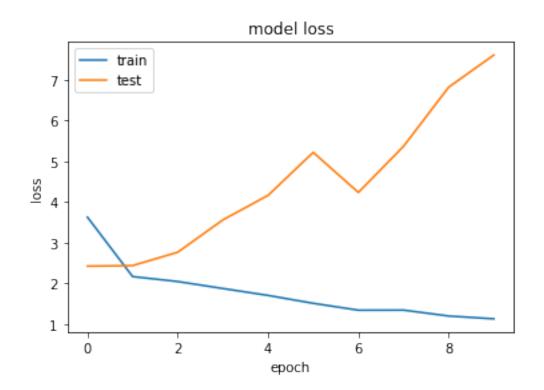
```
[59]: model_test26=executeModelData(True, False, False, False, 10, shoes_train3, ⊔

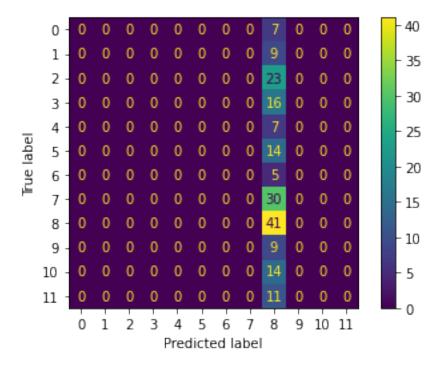
⇒shoes_test3, shoes_val3, df_shoe_brand3,num_classes3)
```

Training model with aumentation:True, gray:False, binary:False, crop:False and epochs = 10 Epoch 1/10

```
0.2457 - val_loss: 2.4276 - val_accuracy: 0.2381
Epoch 2/10
0.2739 - val_loss: 2.4399 - val_accuracy: 0.2381
Epoch 3/10
0.3083 - val_loss: 2.7687 - val_accuracy: 0.2381
Epoch 4/10
0.3678 - val_loss: 3.5619 - val_accuracy: 0.1143
Epoch 5/10
0.4272 - val_loss: 4.1632 - val_accuracy: 0.1143
0.5102 - val_loss: 5.2166 - val_accuracy: 0.1143
Epoch 7/10
0.5743 - val_loss: 4.2342 - val_accuracy: 0.1143
Epoch 8/10
0.5634 - val_loss: 5.3661 - val_accuracy: 0.2381
Epoch 9/10
0.6260 - val_loss: 6.8163 - val_accuracy: 0.2381
Epoch 10/10
0.6448 - val_loss: 7.6047 - val_accuracy: 0.2381
```



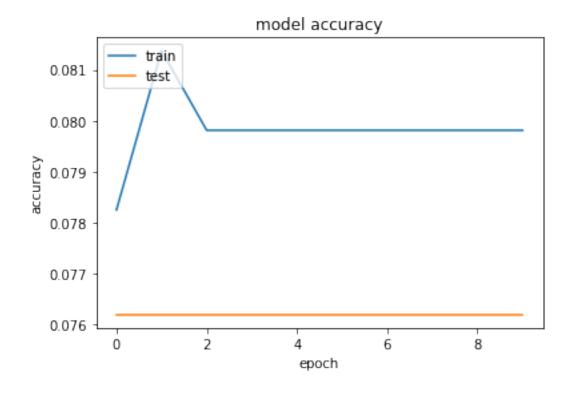


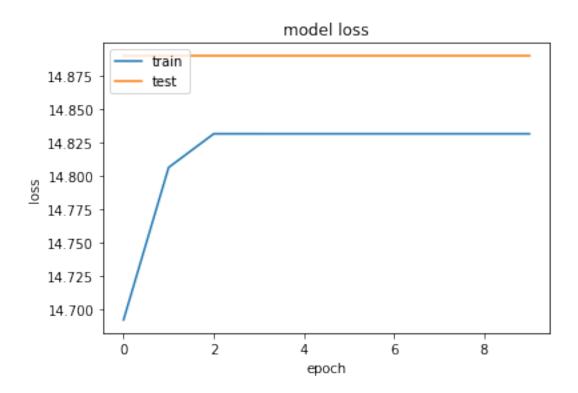


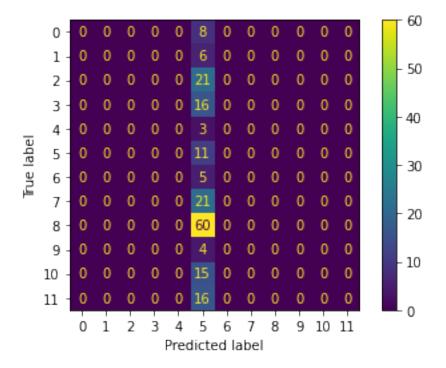
```
[227]: model_test27=executeModelData(False, True, True, True, 10, shoes_train3, 

→shoes_test3, shoes_val3, df_shoe_brand3,num_classes3)
```

```
Epoch 2/10
accuracy: 0.0814 - val_loss: 14.8901 - val_accuracy: 0.0762
accuracy: 0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
accuracy: 0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
Epoch 5/10
0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
Epoch 6/10
0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
Epoch 7/10
64/64 [============ ] - 72s 1s/step - loss: 14.8317 - accuracy:
0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
Epoch 8/10
0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
Epoch 9/10
0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
Epoch 10/10
0.0798 - val_loss: 14.8901 - val_accuracy: 0.0762
```



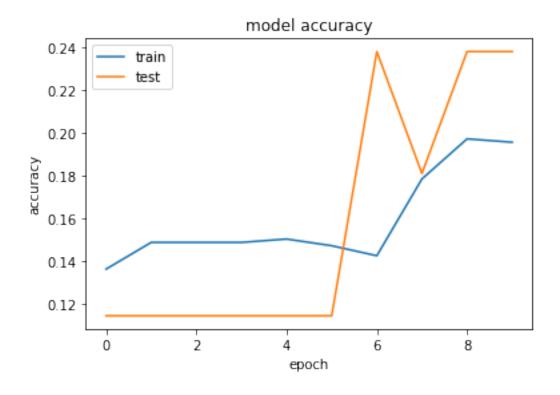


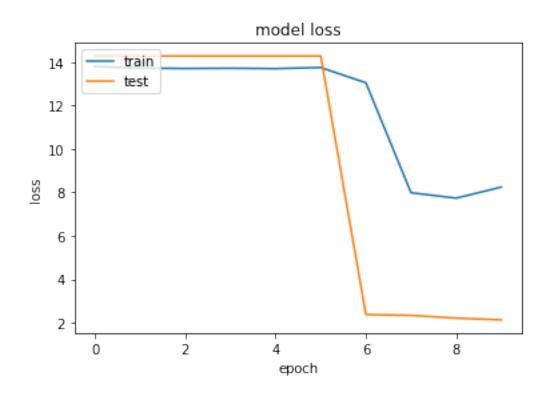


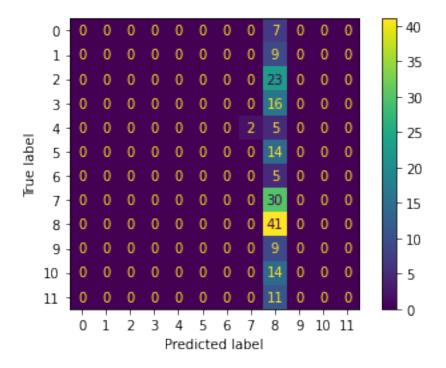
```
[60]: model_test28=executeModelData(True, True, True, True, 10, shoes_train3, 

→shoes_test3, shoes_val3, df_shoe_brand3,num_classes3)
```

```
Epoch 2/10
0.1487 - val_loss: 14.2760 - val_accuracy: 0.1143
Epoch 3/10
0.1487 - val_loss: 14.2760 - val_accuracy: 0.1143
Epoch 4/10
0.1487 - val_loss: 14.2760 - val_accuracy: 0.1143
Epoch 5/10
0.1502 - val_loss: 14.2760 - val_accuracy: 0.1143
Epoch 6/10
0.1471 - val_loss: 14.2760 - val_accuracy: 0.1143
Epoch 7/10
0.1424 - val_loss: 2.3781 - val_accuracy: 0.2381
Epoch 8/10
0.1784 - val_loss: 2.3399 - val_accuracy: 0.1810
Epoch 9/10
0.1972 - val_loss: 2.2106 - val_accuracy: 0.2381
Epoch 10/10
0.1956 - val_loss: 2.1331 - val_accuracy: 0.2381
```





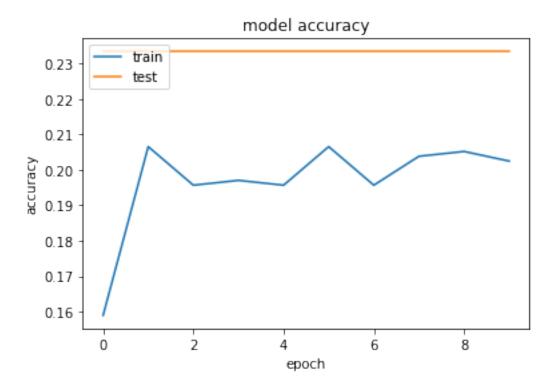


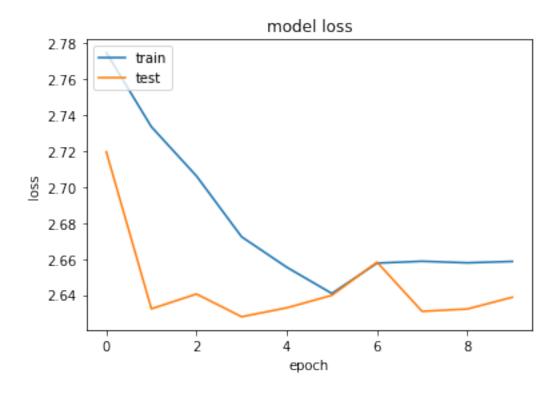
[61]: num\_classes2, df\_shoe\_brand2,shoes\_train2, shoes\_test2, shoes\_val2 = □ → returnDataByMinSample(2)

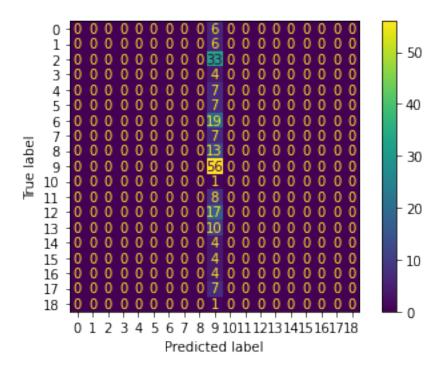
x y
0 Adidas 12
6 Asics 13
10 Brooks 2
12 Champion 3
15 Converse 7

```
21
          Ecco
              2
   30
          Keen
              3
       Namuhana
   32
              2
   33 Newbalance
   34
          Nike 24
       Prospecs
   39
   42
        Saucony
   44
        Shoopen
       Skechers
   46
             8
   49
         Sorel
              2
        Sperry 7
   50
          T2R
             2
   53
   54
          Teva
              3
          Vans
              2
   57
   Brands with at least 2 samples: 19
   Brands with only 1 register: 40
   (1070, 3)
[230]: model_test29=executeModelData(False, False, False, False, 10, shoes_train2,__
    ⇒shoes_test2, shoes_val2, df_shoe_brand2,num_classes2)
   Training model with aumentation: False, gray: False, binary: False, crop: False and
   epochs = 10
   Epoch 1/10
   0.1590 - val_loss: 2.7197 - val_accuracy: 0.2333
   0.2065 - val_loss: 2.6323 - val_accuracy: 0.2333
   Epoch 3/10
   0.1957 - val_loss: 2.6405 - val_accuracy: 0.2333
   Epoch 4/10
   0.1970 - val_loss: 2.6279 - val_accuracy: 0.2333
   Epoch 5/10
   0.1957 - val_loss: 2.6329 - val_accuracy: 0.2333
   Epoch 6/10
   0.2065 - val_loss: 2.6398 - val_accuracy: 0.2333
   Epoch 7/10
   0.1957 - val_loss: 2.6583 - val_accuracy: 0.2333
   Epoch 8/10
```

0.2038 - val\_loss: 2.6309 - val\_accuracy: 0.2333



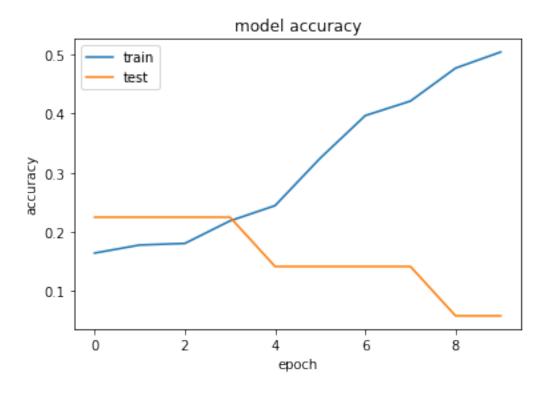


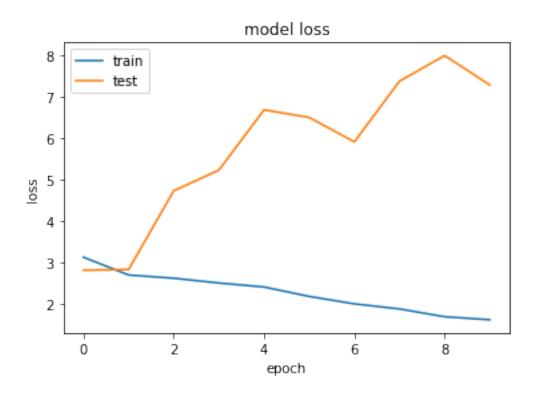


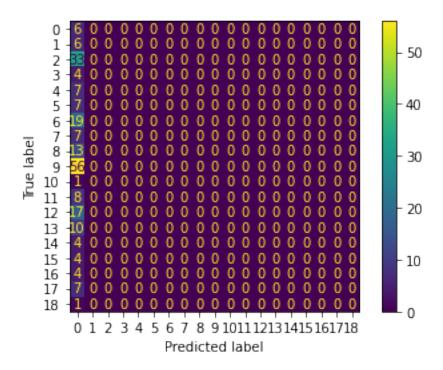
```
[62]: model_test30=executeModelData(True, False, False, False, 10, shoes_train2, 

→shoes_test2, shoes_val2, df_shoe_brand2,num_classes2)
```

```
Training model with aumentation: True, gray: False, binary: False, crop: False and
epochs = 10
Epoch 1/10
0.1644 - val_loss: 2.8141 - val_accuracy: 0.2250
Epoch 2/10
0.1780 - val_loss: 2.8321 - val_accuracy: 0.2250
Epoch 3/10
0.1807 - val_loss: 4.7316 - val_accuracy: 0.2250
Epoch 4/10
0.2188 - val_loss: 5.2323 - val_accuracy: 0.2250
0.2446 - val_loss: 6.6873 - val_accuracy: 0.1417
Epoch 6/10
0.3247 - val_loss: 6.5034 - val_accuracy: 0.1417
Epoch 7/10
```

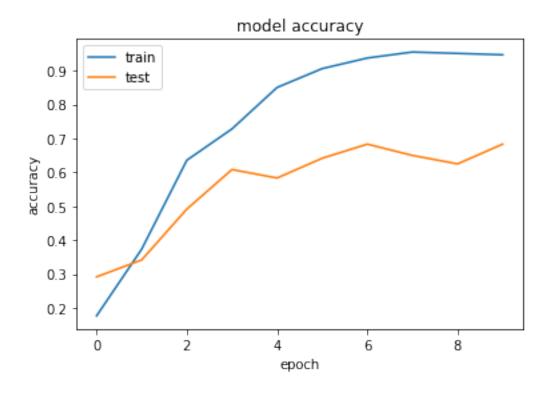


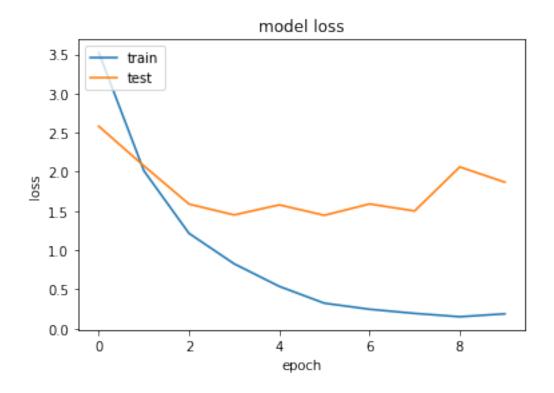




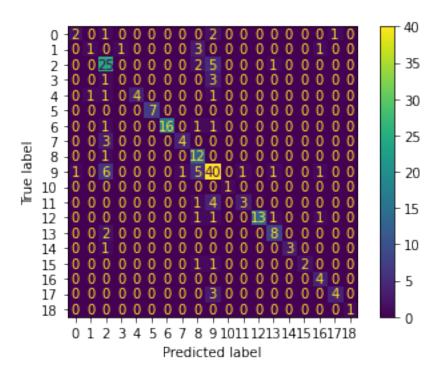
```
[232]: model_test31=executeModelData(False, True, True, True, 10, shoes_train2,______shoes_test2, shoes_val2, df_shoe_brand2,num_classes2)
```

```
Training model with aumentation: False, gray: True, binary: True, crop: True and
epochs = 10
Epoch 1/10
0.1766 - val_loss: 2.5816 - val_accuracy: 0.2917
Epoch 2/10
0.3736 - val_loss: 2.0762 - val_accuracy: 0.3417
Epoch 3/10
0.6359 - val_loss: 1.5886 - val_accuracy: 0.4917
Epoch 4/10
0.7283 - val_loss: 1.4501 - val_accuracy: 0.6083
0.8505 - val_loss: 1.5785 - val_accuracy: 0.5833
Epoch 6/10
0.9062 - val_loss: 1.4453 - val_accuracy: 0.6417
Epoch 7/10
```





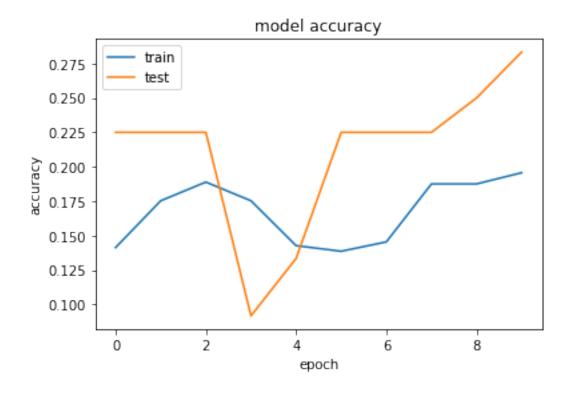
```
22/22 [======
                         =======] - 5s 232ms/step
Test evaluation:
22/22 [========== ] - 6s 276ms/step - loss: 1.3484 -
accuracy: 0.7009
[1.3483635187149048, 0.7009345889091492]
% of correct brand in the first 3 positions:
196
0.9158878504672897
\% of brand predicted with percentage >= 0.25
0.1542056074766355
\% of brand predicted with percentage >= 0.5
0.1542056074766355
% of brand predicted with percentage >= 0.75
0.1542056074766355
Matriz de confusión:
```

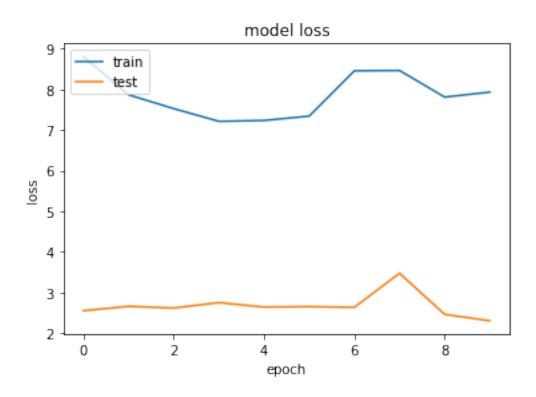


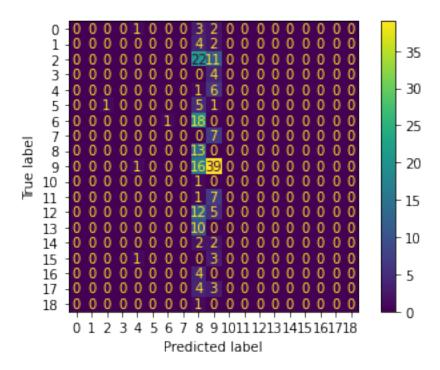
```
[63]: model_test32=executeModelData(True, True, True, True, 10, shoes_train2, 

→shoes_test2, shoes_val2, df_shoe_brand2,num_classes2)
```

```
Training model with aumentation: True, gray: True, binary: True, crop: True and
epochs = 10
Epoch 1/10
0.1413 - val_loss: 2.5498 - val_accuracy: 0.2250
Epoch 2/10
0.1753 - val_loss: 2.6580 - val_accuracy: 0.2250
Epoch 3/10
0.1889 - val_loss: 2.6154 - val_accuracy: 0.2250
Epoch 4/10
0.1753 - val_loss: 2.7495 - val_accuracy: 0.0917
Epoch 5/10
0.1427 - val_loss: 2.6391 - val_accuracy: 0.1333
Epoch 6/10
0.1386 - val_loss: 2.6498 - val_accuracy: 0.2250
Epoch 7/10
```







[64]: num\_classes1, df\_shoe\_brand1,shoes\_train1, shoes\_test1, shoes\_val1 = u
→returnDataByMinSample(1)

```
х
                        У
0
              Adidas
                       12
1
           Airspeed
                        1
2
            Airwalk
                        1
3
                Aldo
                        1
4
    American Eagle
                        1
5
            Arizona
                        1
6
                       13
               Asics
7
                BAGO
                        1
8
                BASS
                        1
9
        Birkenstock
                        1
10
              Brooks
                        2
11
        {\tt CalvinKlain}
                        1
12
                        3
           Champion
13
              Clarks
                        1
14
           Columbus
                        1
15
           Converse
                        7
16
              Cooeli
                        1
17
     Court classic
                        1
18
              Dansko
                        1
19
         Deer Stags
                        1
20
            Dockers
```

```
21
                       2
               Ecco
22
            Elcanto
                       1
23
        Fadedglory
                       1
24
             Feiyue
                       1
               Fila
25
                       1
26
        G.H.Bass&Co
                       1
27
               Guho
            HeyBear
28
                       1
29
            K-swiss
                       1
30
               Keen
                       3
31
                       1
             Landya
32
           Namuhana
                       2
33
        Newbalance
                       4
34
               Nike
                      24
35
                       1
           Ninewest
                 0P
37
                       1
38
               Ofem
                       1
39
                       2
           Prospecs
40
               Puma
                       1
41
              Robin
                       1
42
            Saucony
                       6
43
             Shoedy
                       1
44
            Shoopen
                       3
45
        Simply vera
                       1
46
           Skechers
                       8
47
               Soma
                       1
48
             Sonoma
                       1
                       2
49
              Sorel
                       7
50
             Sperry
51
              Stone
                       1
52
              Sugar
                       1
                       2
53
                T2R
54
               Teva
                       3
55
           Truesoft
                       1
56
       Under Amour
                       1
                       2
57
               Vans
                       1
58
             Vibram
              Yonex
Brands with at least 1 samples: 59
Brands with only 1 register: 0
(1470, 3)
<ipython-input-15-6f4ddfca829a>:22: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

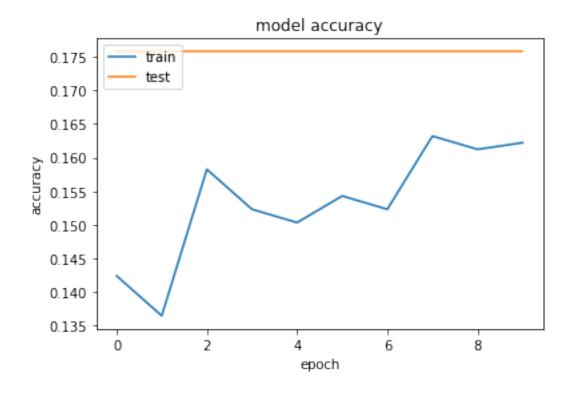
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy

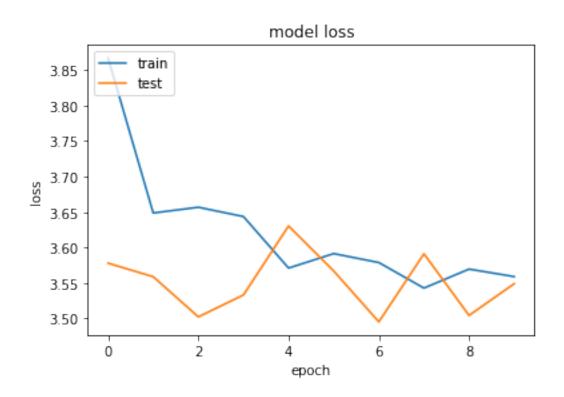
Try using .loc[row\_indexer,col\_indexer] = value instead

```
df_shoe_brand['factor_brand'] =
pd.Categorical(pd.factorize(df_shoe_brand['y'])[0].astype(np.float32))
```

[239]: model\_test33=executeModelData(False, False, False, False, 10, shoes\_train1, shoes\_test1, shoes\_val1, df\_shoe\_brand1,num\_classes1)

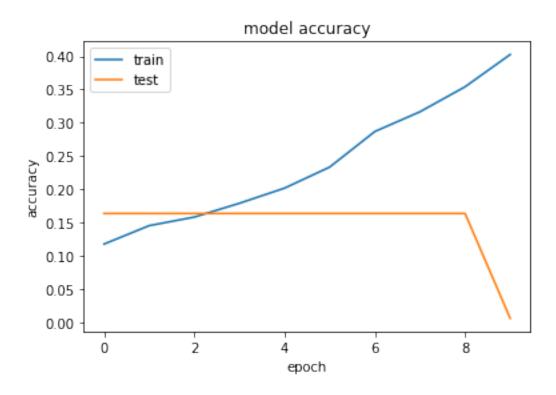
```
Training model with aumentation: False, gray: False, binary: False, crop: False and
epochs = 10
Epoch 1/10
accuracy: 0.1424 - val_loss: 3.5780 - val_accuracy: 0.1758
Epoch 2/10
accuracy: 0.1365 - val_loss: 3.5589 - val_accuracy: 0.1758
Epoch 3/10
102/102 [============ ] - 217s 2s/step - loss: 3.6568 -
accuracy: 0.1583 - val_loss: 3.5024 - val_accuracy: 0.1758
Epoch 4/10
accuracy: 0.1523 - val_loss: 3.5332 - val_accuracy: 0.1758
Epoch 5/10
accuracy: 0.1503 - val_loss: 3.6305 - val_accuracy: 0.1758
Epoch 6/10
accuracy: 0.1543 - val_loss: 3.5670 - val_accuracy: 0.1758
accuracy: 0.1523 - val_loss: 3.4954 - val_accuracy: 0.1758
accuracy: 0.1632 - val_loss: 3.5912 - val_accuracy: 0.1758
Epoch 9/10
accuracy: 0.1612 - val_loss: 3.5044 - val_accuracy: 0.1758
Epoch 10/10
accuracy: 0.1622 - val_loss: 3.5491 - val_accuracy: 0.1758
```

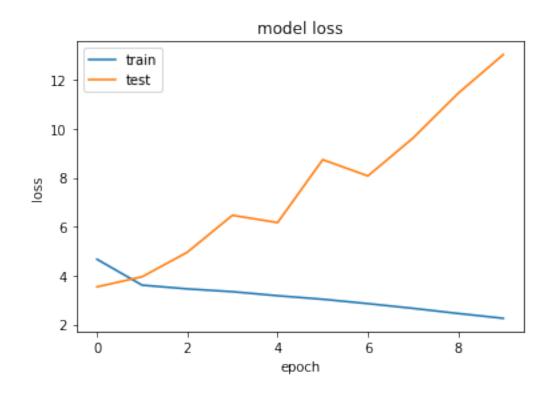




```
30/30 [=========== ] - 15s 489ms/step
    Test evaluation:
    accuracy: 0.1565
    [3.601834774017334, 0.15646257996559143]
    % of correct brand in the first 3 positions:
    98
    0.3333333333333333
    % of brand predicted with percentage >= 0.25
    % of brand predicted with percentage >= 0.5
    0.0
    % of brand predicted with percentage >= 0.75
    0.0
[65]: model_test34=executeModelData(True, False, False, False, 10, shoes_train1,__
     →shoes_test1, shoes_val1, df_shoe_brand1,num_classes1)
    Training model with aumentation: True, gray: False, binary: False, crop: False and
    epochs = 10
    Epoch 1/10
    102/102 [============ ] - 126s 1s/step - loss: 4.6684 -
    accuracy: 0.1177 - val_loss: 3.5402 - val_accuracy: 0.1636
    Epoch 2/10
    102/102 [============= ] - 122s 1s/step - loss: 3.6103 -
    accuracy: 0.1454 - val_loss: 3.9533 - val_accuracy: 0.1636
    102/102 [============== ] - 121s 1s/step - loss: 3.4582 -
    accuracy: 0.1583 - val_loss: 4.9559 - val_accuracy: 0.1636
    102/102 [============= ] - 122s 1s/step - loss: 3.3429 -
    accuracy: 0.1790 - val_loss: 6.4668 - val_accuracy: 0.1636
    102/102 [============== ] - 122s 1s/step - loss: 3.1782 -
    accuracy: 0.2018 - val_loss: 6.1674 - val_accuracy: 0.1636
    Epoch 6/10
    accuracy: 0.2334 - val_loss: 8.7387 - val_accuracy: 0.1636
    Epoch 7/10
    102/102 [============= ] - 121s 1s/step - loss: 2.8561 -
    accuracy: 0.2868 - val_loss: 8.0752 - val_accuracy: 0.1636
    Epoch 8/10
    102/102 [=========== ] - 121s 1s/step - loss: 2.6624 -
    accuracy: 0.3165 - val_loss: 9.6229 - val_accuracy: 0.1636
    Epoch 9/10
```

accuracy: 0.3541 - val\_loss: 11.4523 - val\_accuracy: 0.1636





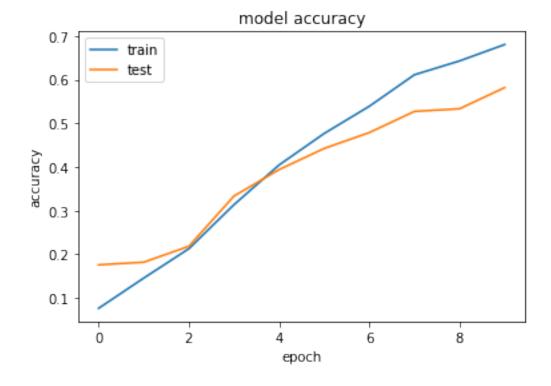
```
Test evaluation:
     accuracy: 0.0102
     [13.38359546661377, 0.010204081423580647]
     % of correct brand in the first 3 positions:
     53
     0.18027210884353742
     % of brand predicted with percentage >= 0.25
     0.01020408163265306
     % of brand predicted with percentage >= 0.5
     0.01020408163265306
     % of brand predicted with percentage >= 0.75
     0.01020408163265306
[241]: model_test35=executeModelData(False, True, True, True, 10, shoes_train1,
      ⇒shoes_test1, shoes_val1, df_shoe_brand1,num_classes1)
     Training model with aumentation: False, gray: True, binary: True, crop: True and
     epochs = 10
     Epoch 1/10
     accuracy: 0.0762 - val_loss: 3.7318 - val_accuracy: 0.1758
     Epoch 2/10
     accuracy: 0.1454 - val_loss: 3.2858 - val_accuracy: 0.1818
     Epoch 3/10
     102/102 [============ ] - 151s 1s/step - loss: 3.2100 -
     accuracy: 0.2127 - val_loss: 3.0592 - val_accuracy: 0.2182
     Epoch 4/10
     102/102 [============ ] - 152s 1s/step - loss: 2.6628 -
     accuracy: 0.3136 - val_loss: 2.7814 - val_accuracy: 0.3333
     Epoch 5/10
     102/102 [============ ] - 152s 1s/step - loss: 2.1699 -
     accuracy: 0.4045 - val_loss: 2.2784 - val_accuracy: 0.3939
     Epoch 6/10
     102/102 [============ ] - 152s 1s/step - loss: 1.7935 -
     accuracy: 0.4768 - val_loss: 2.0763 - val_accuracy: 0.4424
     Epoch 7/10
     102/102 [============= ] - 136s 1s/step - loss: 1.5352 -
     accuracy: 0.5391 - val_loss: 1.9642 - val_accuracy: 0.4788
     Epoch 8/10
     accuracy: 0.6113 - val_loss: 1.9943 - val_accuracy: 0.5273
```

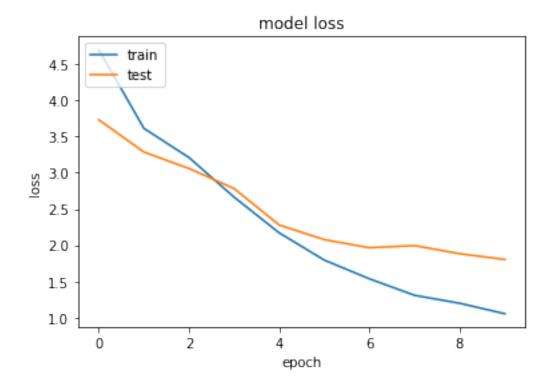
30/30 [========= ] - 8s 269ms/step

Epoch 9/10

```
102/102 [==========] - 148s 1s/step - loss: 1.1976 - accuracy: 0.6429 - val_loss: 1.8819 - val_accuracy: 0.5333

Epoch 10/10
102/102 [============] - 160s 2s/step - loss: 1.0534 - accuracy: 0.6805 - val_loss: 1.8024 - val_accuracy: 0.5818
```





=======] - 14s 442ms/step

```
accuracy: 0.5374
[1.8061199188232422, 0.5374149680137634]
% of correct brand in the first 3 positions:
223
0.7585034013605442
% of brand predicted with percentage >= 0.25
0.1564625850340136
% of brand predicted with percentage >= 0.5
0.1564625850340136
% of brand predicted with percentage >= 0.75
0.1564625850340136
% of brand predicted with percentage >= 0.75
0.1564625850340136
[66]: model_test36=executeModelData(True, True, True, True, 10, shoes_train1,u_shoes_test1, shoes_val1, df_shoe_brand1,num_classes1)

Training model with aumentation:True, gray:True, binary:True, crop:True and
```

30/30 [======

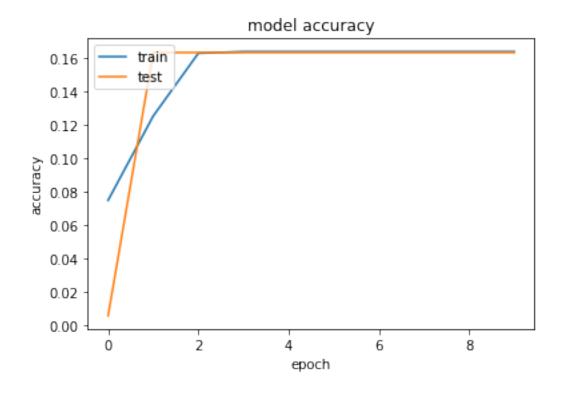
Test evaluation:

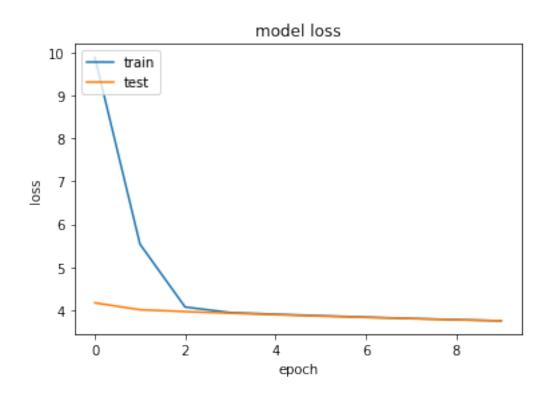
epochs = 10Epoch 1/10

102/102 [=========== ] - 114s 1s/step - loss: 9.8988 -

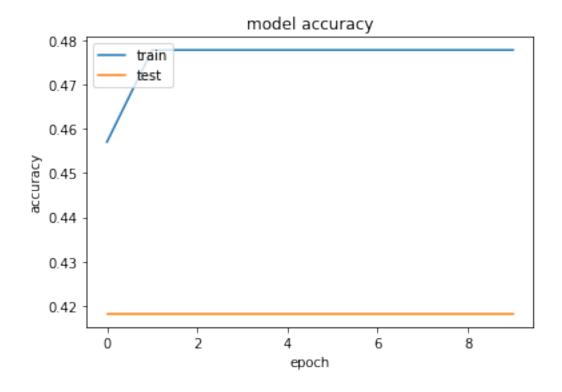
accuracy: 0.0752 - val\_loss: 4.1699 - val\_accuracy: 0.0061

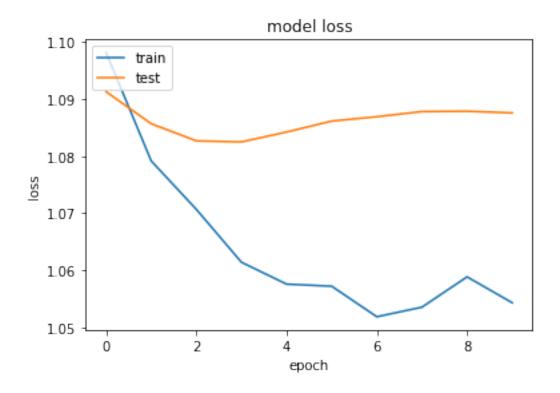
```
Epoch 2/10
102/102 [============= ] - 112s 1s/step - loss: 5.5382 -
accuracy: 0.1256 - val_loss: 4.0087 - val_accuracy: 0.1636
102/102 [============= ] - 111s 1s/step - loss: 4.0720 -
accuracy: 0.1632 - val_loss: 3.9656 - val_accuracy: 0.1636
accuracy: 0.1642 - val_loss: 3.9279 - val_accuracy: 0.1636
Epoch 5/10
102/102 [============ ] - 113s 1s/step - loss: 3.9043 -
accuracy: 0.1642 - val_loss: 3.8921 - val_accuracy: 0.1636
Epoch 6/10
102/102 [=========== ] - 112s 1s/step - loss: 3.8691 -
accuracy: 0.1642 - val_loss: 3.8602 - val_accuracy: 0.1636
Epoch 7/10
102/102 [=========== ] - 111s 1s/step - loss: 3.8361 -
accuracy: 0.1642 - val_loss: 3.8297 - val_accuracy: 0.1636
Epoch 8/10
102/102 [============ ] - 111s 1s/step - loss: 3.8059 -
accuracy: 0.1642 - val_loss: 3.8012 - val_accuracy: 0.1636
Epoch 9/10
102/102 [============ ] - 113s 1s/step - loss: 3.7768 -
accuracy: 0.1642 - val_loss: 3.7754 - val_accuracy: 0.1636
Epoch 10/10
accuracy: 0.1642 - val_loss: 3.7502 - val_accuracy: 0.1636
```

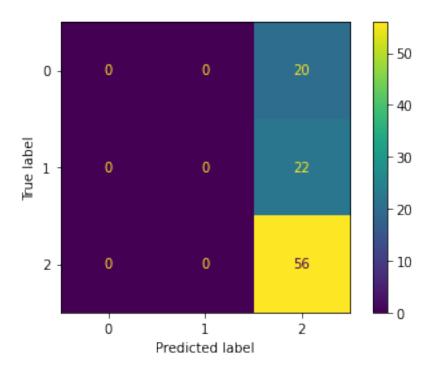




```
30/30 [========== ] - 8s 272ms/step
    Test evaluation:
    accuracy: 0.1599
    [3.7886502742767334, 0.15986394882202148]
    % of correct brand in the first 3 positions:
    0.30952380952380953
    % of brand predicted with percentage >= 0.25
    % of brand predicted with percentage >= 0.5
    0.0
    % of brand predicted with percentage >= 0.75
    0.0
[67]: num_classes10, df_shoe_brand10,shoes_train10, shoes_test10, shoes_val10 = __
    →returnDataByMinSample(10)
            У
    0
      Adidas 12
       Asics 13
    6
       Nike 24
    Brands with at least 10 samples: 3
    Brands with only 1 register: 56
    (490, 3)
[244]: model test37=executeModelData(False, False, False, False, 10, shoes train10,
     ⇒shoes_test10, shoes_val10, df_shoe_brand10,num_classes10)
    Training model with aumentation: False, gray: False, binary: False, crop: False and
    epochs = 10
    Epoch 1/10
    0.4570 - val_loss: 1.0913 - val_accuracy: 0.4182
    Epoch 2/10
    0.4777 - val_loss: 1.0857 - val_accuracy: 0.4182
    Epoch 3/10
    0.4777 - val_loss: 1.0827 - val_accuracy: 0.4182
    Epoch 4/10
    0.4777 - val_loss: 1.0825 - val_accuracy: 0.4182
    Epoch 5/10
    0.4777 - val_loss: 1.0842 - val_accuracy: 0.4182
    Epoch 6/10
```

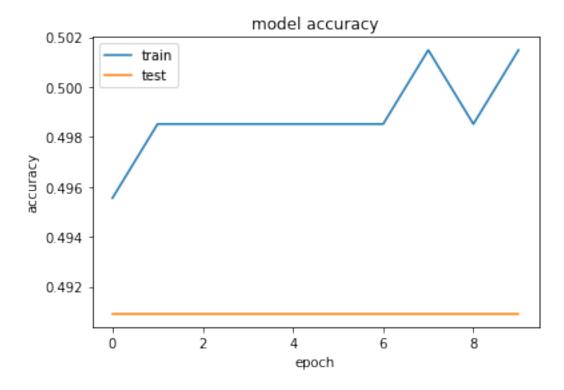


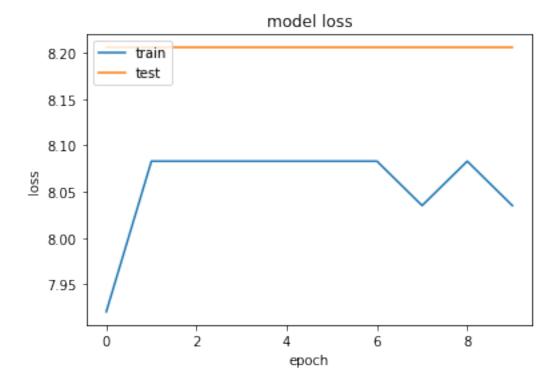




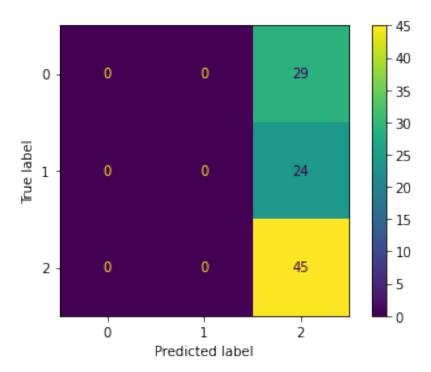
[68]: model\_test38=executeModelData(True, False, False, False, 10, shoes\_train10, ⊔ ⇒shoes\_test10, shoes\_val10, df\_shoe\_brand10,num\_classes10)

```
Training model with aumentation: True, gray: False, binary: False, crop: False and
epochs = 10
Epoch 1/10
0.4955 - val_loss: 8.2056 - val_accuracy: 0.4909
Epoch 2/10
0.4985 - val_loss: 8.2056 - val_accuracy: 0.4909
Epoch 3/10
0.4985 - val_loss: 8.2056 - val_accuracy: 0.4909
Epoch 4/10
0.4985 - val_loss: 8.2056 - val_accuracy: 0.4909
Epoch 5/10
0.4985 - val_loss: 8.2056 - val_accuracy: 0.4909
Epoch 6/10
0.4985 - val_loss: 8.2056 - val_accuracy: 0.4909
Epoch 7/10
```



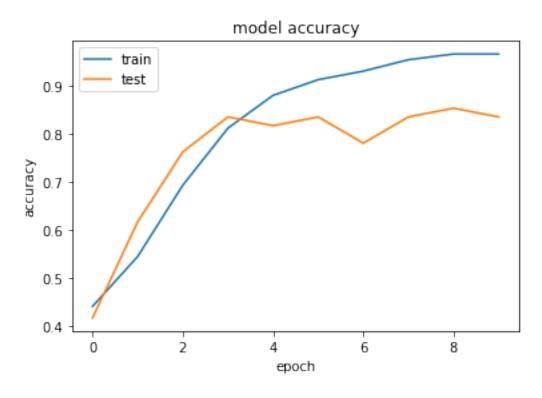


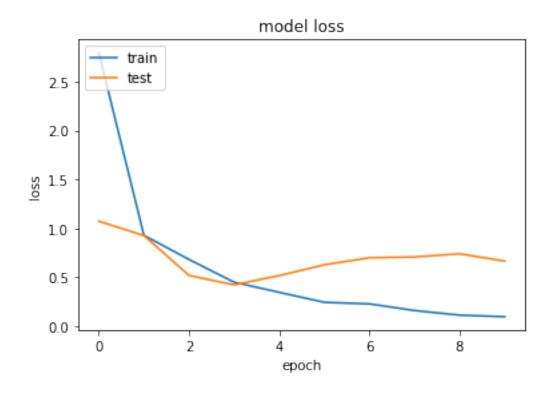
```
10/10 [======
                   ========= ] - 3s 247ms/step
Test evaluation:
accuracy: 0.4592
[8.71692943572998, 0.4591836631298065]
% of correct brand in the first 3 positions:
98
1.0
\% of brand predicted with percentage >= 0.25
0.45918367346938777
\% of brand predicted with percentage >= 0.5
0.45918367346938777
% of brand predicted with percentage >= 0.75
0.45918367346938777
Matriz de confusión:
```



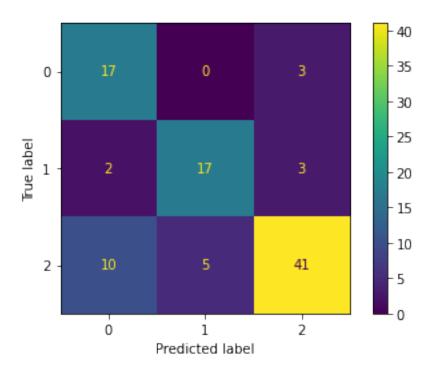
[246]: model\_test39=executeModelData(False, True, True, True, 10, shoes\_train10, shoes\_test10, shoes\_val10, df\_shoe\_brand10,num\_classes10)

```
Training model with aumentation: False, gray: True, binary: True, crop: True and
epochs = 10
Epoch 1/10
0.4421 - val_loss: 1.0735 - val_accuracy: 0.4182
Epoch 2/10
0.5460 - val_loss: 0.9274 - val_accuracy: 0.6182
Epoch 3/10
0.6944 - val_loss: 0.5198 - val_accuracy: 0.7636
Epoch 4/10
0.8131 - val_loss: 0.4233 - val_accuracy: 0.8364
Epoch 5/10
0.8813 - val_loss: 0.5179 - val_accuracy: 0.8182
Epoch 6/10
0.9139 - val_loss: 0.6282 - val_accuracy: 0.8364
Epoch 7/10
```



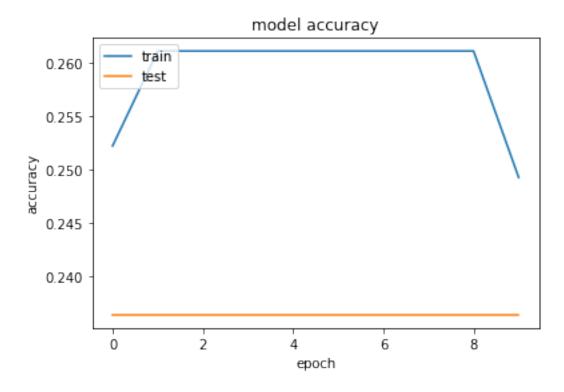


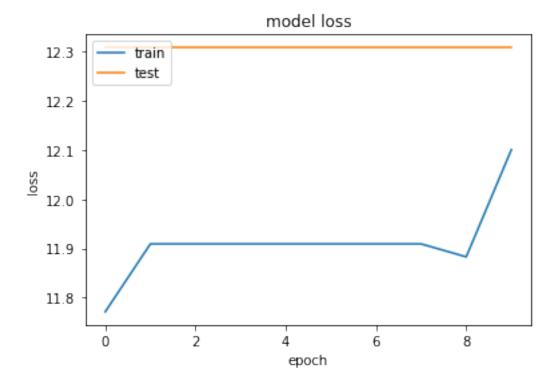
```
10/10 [======
                       ========] - 3s 257ms/step
Test evaluation:
10/10 [============ ] - 3s 281ms/step - loss: 0.9397 -
accuracy: 0.7653
[0.9397358298301697, 0.7653061151504517]
% of correct brand in the first 3 positions:
98
1.0
\% of brand predicted with percentage >= 0.25
0.5714285714285714
\% of brand predicted with percentage >= 0.5
0.5714285714285714
% of brand predicted with percentage >= 0.75
0.5714285714285714
Matriz de confusión:
```



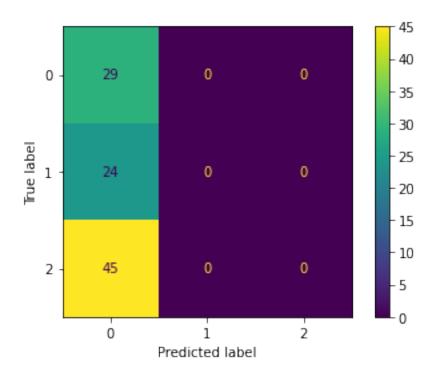
[69]: model\_test40=executeModelData(True, True, True, True, 10, shoes\_train10, →shoes\_test10, shoes\_val10, df\_shoe\_brand10,num\_classes10)

```
Training model with aumentation: True, gray: True, binary: True, crop: True and
epochs = 10
Epoch 1/10
0.2522 - val_loss: 12.3084 - val_accuracy: 0.2364
Epoch 2/10
0.2611 - val_loss: 12.3084 - val_accuracy: 0.2364
Epoch 3/10
0.2611 - val_loss: 12.3084 - val_accuracy: 0.2364
Epoch 4/10
0.2611 - val_loss: 12.3084 - val_accuracy: 0.2364
Epoch 5/10
0.2611 - val_loss: 12.3084 - val_accuracy: 0.2364
Epoch 6/10
0.2611 - val_loss: 12.3084 - val_accuracy: 0.2364
Epoch 7/10
```





```
10/10 [======
                         =======] - 3s 234ms/step
Test evaluation:
10/10 [========
                      ========] - 3s 244ms/step - loss: 11.3485 -
accuracy: 0.2959
[11.348454475402832, 0.29591837525367737]
% of correct brand in the first 3 positions:
98
1.0
\% of brand predicted with percentage >= 0.25
0.29591836734693877
\% of brand predicted with percentage >= 0.5
0.29591836734693877
% of brand predicted with percentage >= 0.75
0.29591836734693877
Matriz de confusión:
```



## 4.2 Variaciones en las capas

En este apartado se analizan los resultados al utilizar más o menos capas en el modelo para comprender la utilizadad de cada una de ellas.

Para estos experimentos se usan las imágenes con tamaño 280x832, epoch = 10, preprocesado a blanco y negro sin espacios en blanco y con o sin aumentación. En total, dos experimentos por variación. Las variaciones se van a realizar eliminando una o varias capas del modelo presentado como solución para ver si influye en el resultado.

Ls capas utilizadas son las siguientes:

- Conv2D
- MaxPooling2D
- Flatten
- Dense relu
- Dense softmax
- Dropout

```
[70]: from tensorflow.keras import models from tensorflow.keras import optimizers from tensorflow.keras.layers import Conv2D, MaxPooling2D, UpSampling2D, Dense, ⊔ →Flatten, Softmax, Rescaling, Dropout
```

```
import cv2
      def createCustomModel(n, withActivation='relu', withMax = True, extraLayers = u
       →True, withFlatten=True, withDense=True,
                            withDropout = True , dropout value = 0.5, withSoftmax
      →=True):
          print("Activation: "+withActivation+", maxPooling2D: "+str(withMax)+
               ", extraLayers: "+str(extraLayers)+", withFlatten: "+ str(withFlatten)+
               ", withDense: "+str(withDense)+", withDropout: "+str(withDropout)+
               ", Dropout value: "+str(dropout_value)+", withSoftmax:
       →"+str(withSoftmax))
          modelC = models.Sequential()
          modelC.add(Conv2D(16, 3, padding='same', activation=withActivation, ___
       \rightarrowinput_shape=(280,832,1)))
          #if withMax == True:
          modelC.add(MaxPooling2D())
          if extraLayers == True:
              modelC.add(Conv2D(32, 3, padding='same', activation=withActivation))
              if withMax == True:
                  modelC.add(MaxPooling2D())
              modelC.add(Conv2D(64, 3, padding='same', activation=withActivation))
              if withMax == True:
                  modelC.add(MaxPooling2D())
          if withFlatten == True:
              modelC.add(Flatten())
          if withDense==True:
              modelC.add(Dense(128, activation = "relu"))
          if withDropout == True:
              modelC.add(Dropout(dropout value))
          if withSoftmax == True:
              modelC.add(Dense(n, activation='softmax'))
          if withFlatten==True:
              modelC.add(Flatten())
          return modelC
[71]: def testCustomModel(n, withActivation='relu', withMax = True, extraLayers = ___
       →True, withFlatten=True, withDense=True,
                            withDropout = True , dropout_value = 0.5, withSoftmax_
       →=True, aumentation = False):
          print("Aumentation: "+str(aumentation))
          start = datetime.now()
```

import tensorflow as tf

```
model = createCustomModel(num_classes,withActivation, withMax, extraLayers,_
⇒withFlatten, withDense,
                             withDropout, dropout_value, withSoftmax)
   model.compile(optimizer='adam',
             loss=tf.keras.losses.
→SparseCategoricalCrossentropy(from_logits=False),
             metrics=['accuracy'])
   trainGenerator=DataGenerator2dFootwear(shoes_train['X'].
-tolist(),df_shoe_brand, aumentation, "images/", True, True, True)
   testGenerator=DataGenerator2dFootwear(shoes test['X'].
→tolist(),df_shoe_brand, False, "images/", True, True, True)
   valGenerator=DataGenerator2dFootwear(shoes_val['X'].tolist(),df_shoe_brand,_
→False, "images/", True, True, True)
   model.summary()
   history = model.fit(trainGenerator, validation_data=valGenerator, epochs=10)
   end= datetime.now()
   print("Time used: "+str(end-start))
   plot_history(history)
   checkModel(model, testGenerator, shoes_test, num_classes)
   return history, model
```

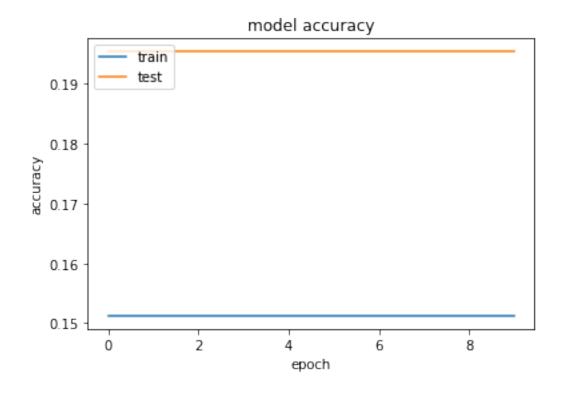
## 4.2.1 Sin Dropout

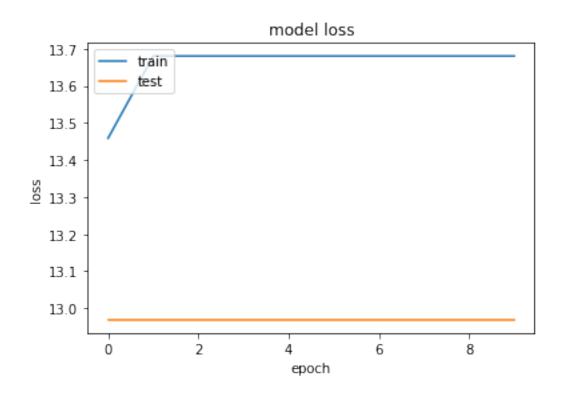
```
[76]: model_1 = testCustomModel(num_classes, 'relu', True, True, True, True, False)
```

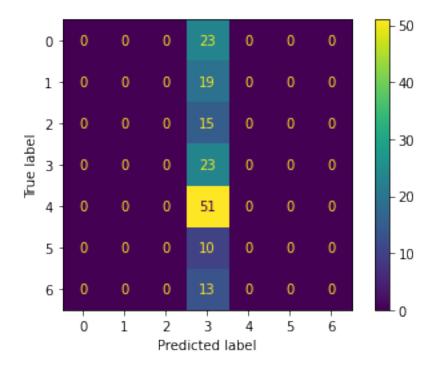
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: False, Dropout value: 0.5, withSoftmax: True Model: "sequential\_17"

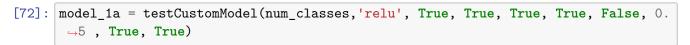
Layer (type)	Output Shape	 Param #
conv2d_51 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_41 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_52 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_42 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_53 (Conv2D)	(None, 70, 208, 64)	18496

```
max_pooling2d_43 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_26 (Flatten)
               (None, 232960)
                             0
dense 31 (Dense)
               (None, 128)
                             29819008
dense 32 (Dense)
               (None, 7)
                             903
flatten_27 (Flatten)
               (None, 7)
______
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
-----
Epoch 1/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 3/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 4/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 5/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 6/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 7/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 8/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 9/10
53/53 [============ ] - 70s 1s/step - loss: 13.6806 - accuracy:
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Epoch 10/10
0.1512 - val_loss: 12.9686 - val_accuracy: 0.1954
Time used: 0:10:53.507221
```









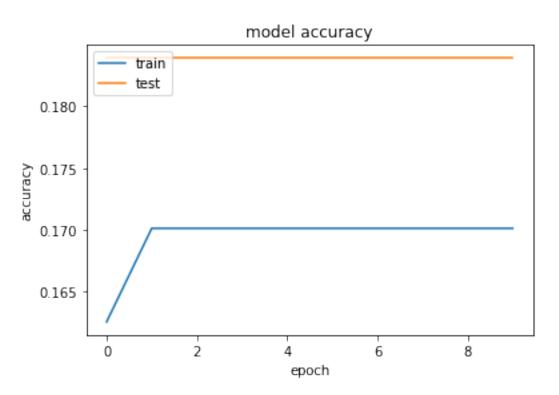
Aumentation: True

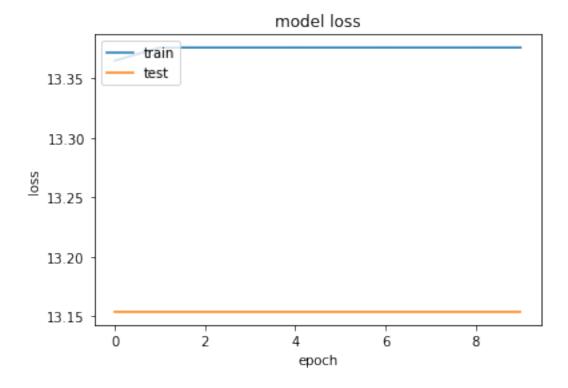
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: False, Dropout value: 0.5, withSoftmax: True

Model: "sequential\_21"

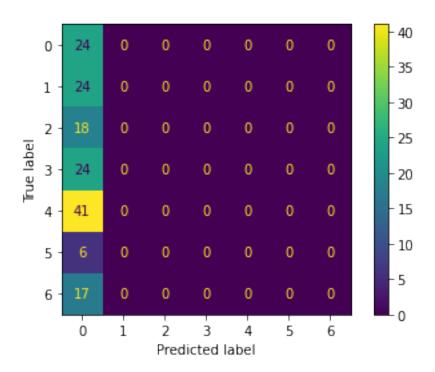
Layer (type) Output Shape Param #

```
conv2d_63 (Conv2D)
                   (None, 280, 832, 16)
                                     160
max_pooling2d_63 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 64 (Conv2D)
                   (None, 140, 416, 32)
                                     4640
max_pooling2d_64 (MaxPoolin (None, 70, 208, 32)
g2D)
                   (None, 70, 208, 64)
conv2d_65 (Conv2D)
                                    18496
max_pooling2d_65 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_42 (Flatten)
                   (None, 232960)
dense_42 (Dense)
                   (None, 128)
                                     29819008
dense_43 (Dense)
                   (None, 7)
                                     903
flatten_43 (Flatten)
                   (None, 7)
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
        -----
Epoch 1/10
0.1626 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 2/10
0.1701 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 3/10
0.1701 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 4/10
0.1701 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 5/10
53/53 [============ ] - 59s 1s/step - loss: 13.3759 - accuracy:
0.1701 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 6/10
0.1701 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 7/10
```





```
16/16 [======
                     ========] - 4s 239ms/step
Test evaluation:
accuracy: 0.1558
[13.606184959411621, 0.15584415197372437]
% of correct brand in the first 3 positions:
66
0.42857142857142855
\% of brand predicted with percentage >= 0.25
0.15584415584415584
\% of brand predicted with percentage >= 0.5
0.15584415584415584
\% of brand predicted with percentage >= 0.75
0.15584415584415584
Matriz de confusión:
```



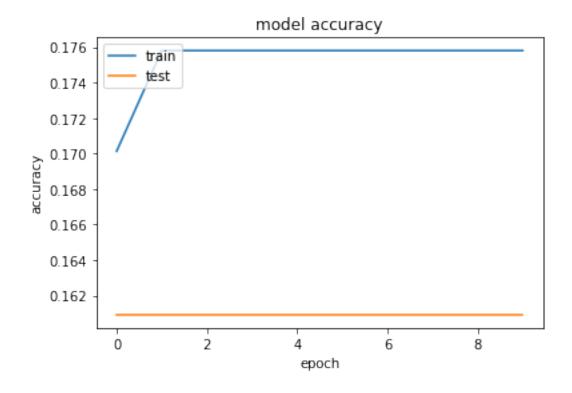
## **4.2.2** Dropout del **0.1**

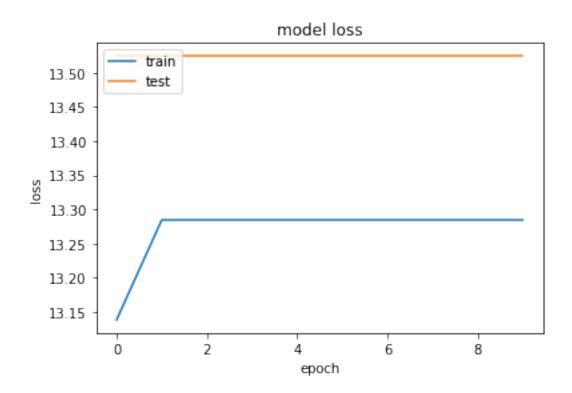
[78]: model\_2 = testCustomModel(num\_classes, 'relu', True, True, True, True, True, 0.1)

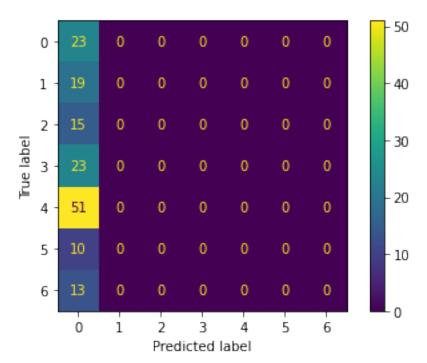
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.1, withSoftmax: True Model: "sequential\_19"

Layer (type)	Output Shape	Param #
conv2d_57 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_47 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_58 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_48 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_59 (Conv2D)	(None, 70, 208, 64)	18496
<pre>max_pooling2d_49 (MaxPooling2D)</pre>	(None, 35, 104, 64)	0

```
flatten_30 (Flatten)
             (None, 232960)
                                0
dense_35 (Dense)
                 (None, 128)
                                29819008
dropout 12 (Dropout)
                 (None, 128)
dense 36 (Dense)
                 (None, 7)
                                903
flatten_31 (Flatten)
                 (None, 7)
_____
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
     _____
Epoch 1/10
53/53 [============ ] - 75s 1s/step - loss: 13.1383 - accuracy:
0.1701 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 2/10
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 3/10
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 4/10
53/53 [============ ] - 73s 1s/step - loss: 13.2845 - accuracy:
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 5/10
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 6/10
53/53 [============ ] - 68s 1s/step - loss: 13.2845 - accuracy:
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 7/10
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 8/10
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 9/10
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Time used: 0:11:29.758197
```









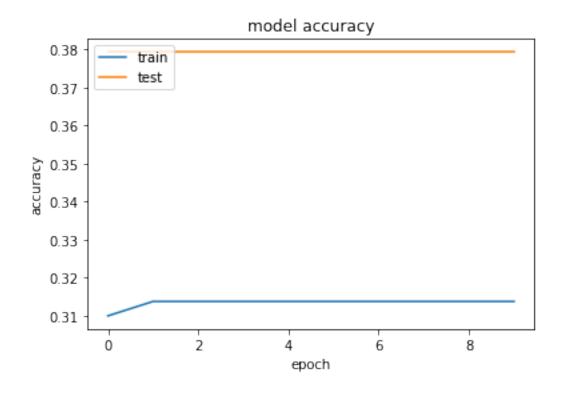
Aumentation: True

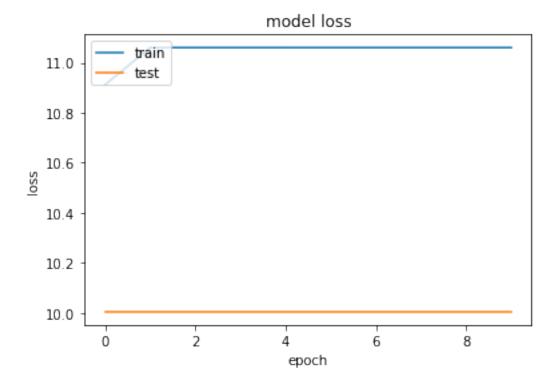
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.1, withSoftmax: True

Model: "sequential\_22"

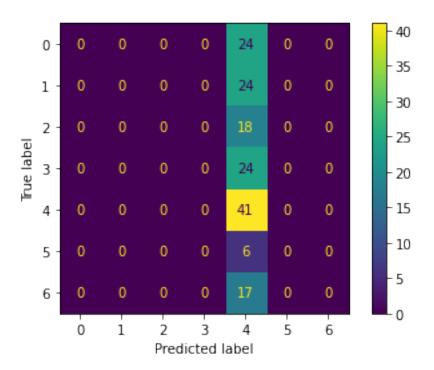
Layer (type) Output Shape Param #

```
conv2d_66 (Conv2D)
                 (None, 280, 832, 16)
                                  160
max_pooling2d_66 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 67 (Conv2D)
             (None, 140, 416, 32)
                                  4640
max_pooling2d_67 (MaxPoolin (None, 70, 208, 32)
g2D)
conv2d_68 (Conv2D)
                  (None, 70, 208, 64)
                                  18496
max_pooling2d_68 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_44 (Flatten)
                 (None, 232960)
dense_44 (Dense)
                  (None, 128)
                                  29819008
dropout_21 (Dropout)
              (None, 128)
dense_45 (Dense)
                 (None, 7)
                                  903
flatten_45 (Flatten) (None, 7)
_____
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
           -----
Epoch 1/10
0.3100 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 2/10
53/53 [============= ] - 59s 1s/step - loss: 11.0602 - accuracy:
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 3/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 4/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 5/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 6/10
```





```
16/16 [=======
                         =======] - 4s 241ms/step
Test evaluation:
16/16 [============= - 4s 246ms/step - loss: 11.8269 -
accuracy: 0.2662
[11.826915740966797, 0.26623377203941345]
% of correct brand in the first 3 positions:
89
0.577922077922078
% of brand predicted with percentage >= 0.25
0.2662337662337662
\% of brand predicted with percentage >= 0.5
0.2662337662337662
% of brand predicted with percentage >= 0.75
0.2662337662337662
Matriz de confusión:
```



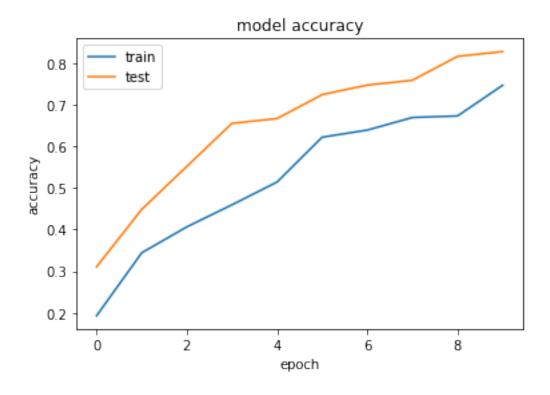
## 4.2.3 Dropout del 0.8

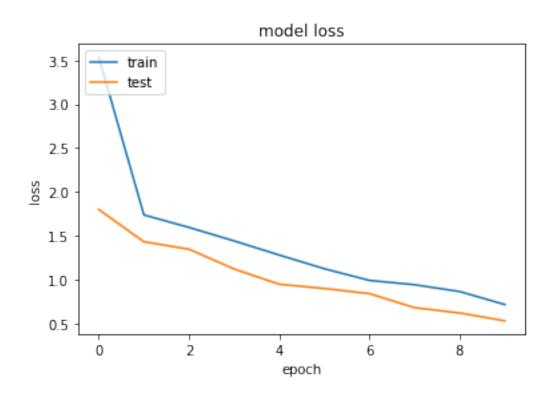
[80]: model\_3 = testCustomModel(num\_classes,'relu', True, True, True, True, True, 0.8)

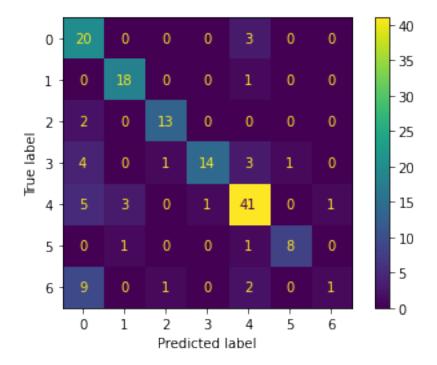
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.8, withSoftmax: True Model: "sequential\_21"

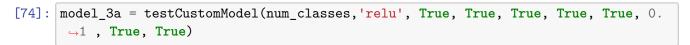
Layer (type)	Output Shape	Param #
conv2d_63 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_53 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_64 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_54 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_65 (Conv2D)	(None, 70, 208, 64)	18496
<pre>max_pooling2d_55 (MaxPoolin g2D)</pre>	(None, 35, 104, 64)	0

```
flatten_34 (Flatten)
           (None, 232960)
                          0
dense_39 (Dense)
              (None, 128)
                           29819008
dropout 14 (Dropout)
              (None, 128)
dense 40 (Dense)
              (None, 7)
                           903
flatten_35 (Flatten)
              (None, 7)
______
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
-----
Epoch 1/10
0.1928 - val_loss: 1.7982 - val_accuracy: 0.3103
Epoch 2/10
0.3440 - val_loss: 1.4303 - val_accuracy: 0.4483
Epoch 3/10
0.4064 - val_loss: 1.3458 - val_accuracy: 0.5517
Epoch 4/10
0.4594 - val_loss: 1.1199 - val_accuracy: 0.6552
Epoch 5/10
0.5142 - val_loss: 0.9462 - val_accuracy: 0.6667
Epoch 6/10
0.6219 - val_loss: 0.8975 - val_accuracy: 0.7241
Epoch 7/10
0.6389 - val_loss: 0.8390 - val_accuracy: 0.7471
Epoch 8/10
0.6692 - val_loss: 0.6791 - val_accuracy: 0.7586
Epoch 9/10
0.6730 - val_loss: 0.6177 - val_accuracy: 0.8161
0.7467 - val_loss: 0.5288 - val_accuracy: 0.8276
Time used: 0:09:53.758722
```









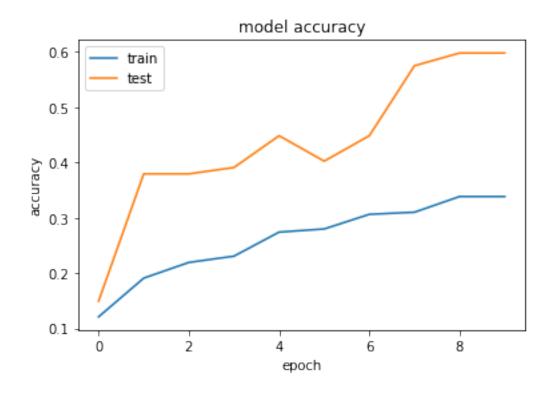
Aumentation: True

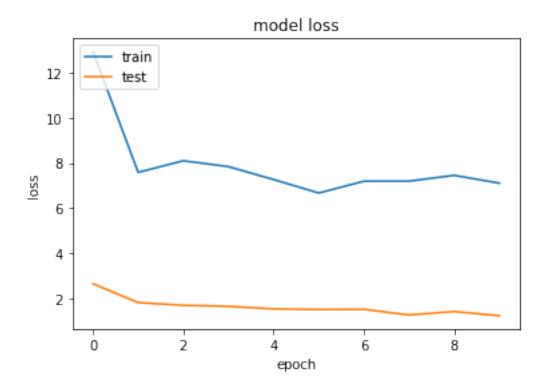
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.1, withSoftmax: True

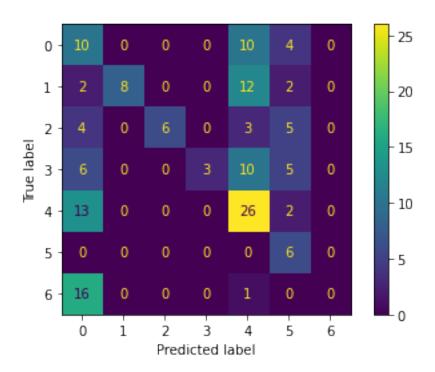
Model: "sequential\_23"

Layer (type) Output Shape Param #

```
(None, 280, 832, 16)
conv2d_69 (Conv2D)
                                  160
max_pooling2d_69 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 70 (Conv2D)
             (None, 140, 416, 32)
                                  4640
max_pooling2d_70 (MaxPoolin (None, 70, 208, 32)
g2D)
conv2d_71 (Conv2D)
                  (None, 70, 208, 64)
                                  18496
max_pooling2d_71 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_46 (Flatten)
                 (None, 232960)
dense_46 (Dense)
                  (None, 128)
                                  29819008
dropout_22 (Dropout)
              (None, 128)
dense_47 (Dense)
                 (None, 7)
                                  903
flatten_47 (Flatten) (None, 7)
_____
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
           -----
Epoch 1/10
0.1210 - val_loss: 2.6626 - val_accuracy: 0.1494
Epoch 2/10
0.1909 - val_loss: 1.8305 - val_accuracy: 0.3793
Epoch 3/10
0.2193 - val_loss: 1.7104 - val_accuracy: 0.3793
Epoch 4/10
53/53 [============== ] - 58s 1s/step - loss: 7.8395 - accuracy:
0.2306 - val_loss: 1.6639 - val_accuracy: 0.3908
Epoch 5/10
0.2741 - val_loss: 1.5506 - val_accuracy: 0.4483
Epoch 6/10
```







#### 4.2.4 Sin Softmax

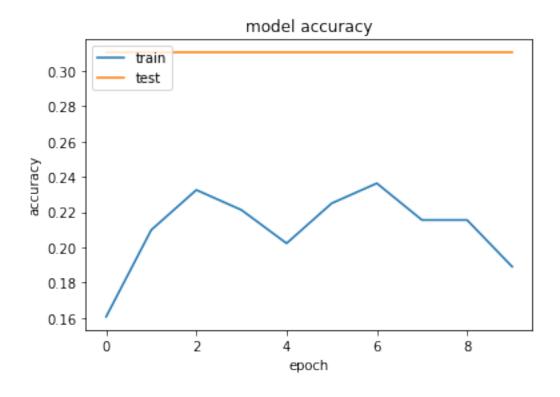
[86]: model\_4 = testCustomModel(num\_classes, 'relu', True, True, True, True, True, 0.

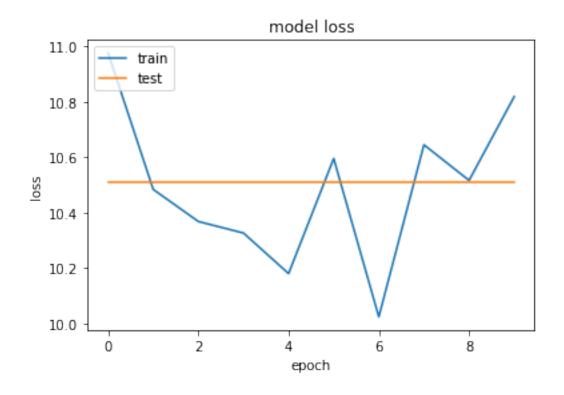
→5, False)

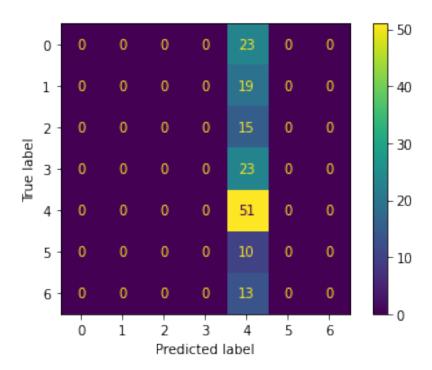
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.5, withSoftmax: False Model: "sequential\_26"

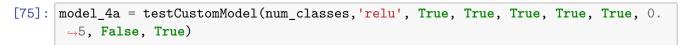
Layer (type)	Output Shape	Param #
conv2d_74 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_64 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_75 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_65 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_76 (Conv2D)	(None, 70, 208, 64)	18496
<pre>max_pooling2d_66 (MaxPoolin g2D)</pre>	(None, 35, 104, 64)	0

```
flatten_44 (Flatten)
                 (None, 232960)
dense_48 (Dense)
                  (None, 128)
                                   29819008
dropout_19 (Dropout)
                  (None, 128)
flatten_45 (Flatten)
              (None, 128)
Total params: 29,842,304
Trainable params: 29,842,304
Non-trainable params: 0
-----
Epoch 1/10
0.1607 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 2/10
accuracy: 0.2098 - val_loss: 10.5122 - val_accuracy: 0.3103
53/53 [============= ] - 54s 1s/step - loss: 10.3681 - accuracy:
0.2325 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 4/10
0.2212 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 5/10
0.2023 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 6/10
0.2250 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 7/10
53/53 [============= ] - 56s 1s/step - loss: 10.0244 - accuracy:
0.2363 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 8/10
53/53 [============= ] - 55s 1s/step - loss: 10.6446 - accuracy:
0.2155 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 9/10
0.2155 - val_loss: 10.5122 - val_accuracy: 0.3103
Epoch 10/10
53/53 [============ ] - 55s 1s/step - loss: 10.8179 - accuracy:
0.1890 - val_loss: 10.5122 - val_accuracy: 0.3103
Time used: 0:09:06.140455
```







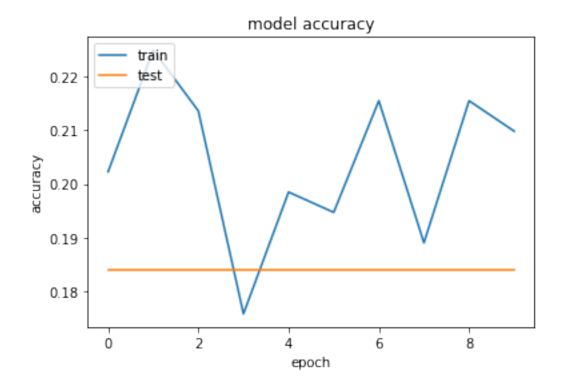


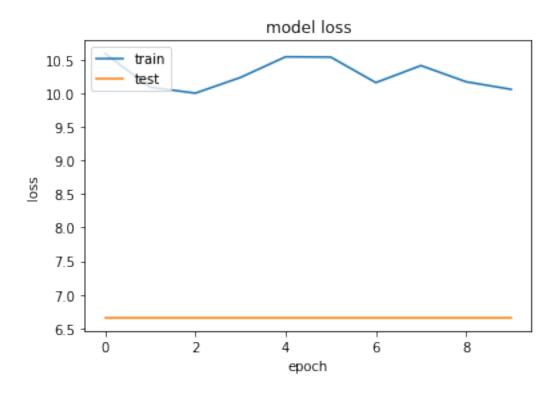
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.5, withSoftmax: False

Model: "sequential\_24"

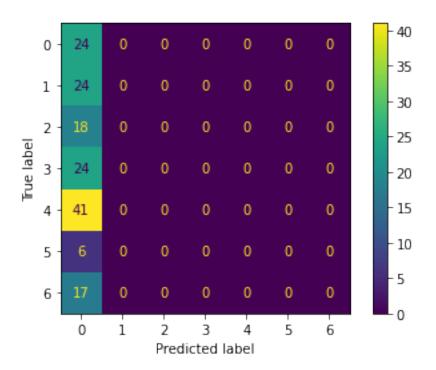
Layer (type) Output Shape Param #

```
conv2d_72 (Conv2D)
                   (None, 280, 832, 16)
                                    160
max_pooling2d_72 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 73 (Conv2D)
                   (None, 140, 416, 32)
                                    4640
max_pooling2d_73 (MaxPoolin (None, 70, 208, 32)
g2D)
conv2d_74 (Conv2D)
                   (None, 70, 208, 64)
                                    18496
max_pooling2d_74 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_48 (Flatten)
                   (None, 232960)
dense_48 (Dense)
                                    29819008
                   (None, 128)
dropout_23 (Dropout)
                   (None, 128)
flatten_49 (Flatten)
                  (None, 128)
Total params: 29,842,304
Trainable params: 29,842,304
Non-trainable params: 0
      _____
Epoch 1/10
0.2023 - val_loss: 6.6566 - val_accuracy: 0.1839
Epoch 2/10
0.2250 - val loss: 6.6566 - val accuracy: 0.1839
Epoch 3/10
0.2136 - val_loss: 6.6566 - val_accuracy: 0.1839
Epoch 4/10
0.1758 - val_loss: 6.6566 - val_accuracy: 0.1839
Epoch 5/10
53/53 [============ ] - 54s 1s/step - loss: 10.5447 - accuracy:
0.1985 - val_loss: 6.6566 - val_accuracy: 0.1839
Epoch 6/10
0.1947 - val_loss: 6.6566 - val_accuracy: 0.1839
Epoch 7/10
```





```
16/16 [======
                      =======] - 4s 207ms/step
Test evaluation:
accuracy: 0.1558
[9.785683631896973, 0.15584415197372437]
% of correct brand in the first 3 positions:
71
0.461038961038961
\% of brand predicted with percentage >= 0.25
0.461038961038961
\% of brand predicted with percentage >= 0.5
0.461038961038961
% of brand predicted with percentage >= 0.75
0.461038961038961
Matriz de confusión:
```



## 4.2.5 Sin extra Layers

[83]: model\_5 = testCustomModel(num\_classes, 'relu', True, False)

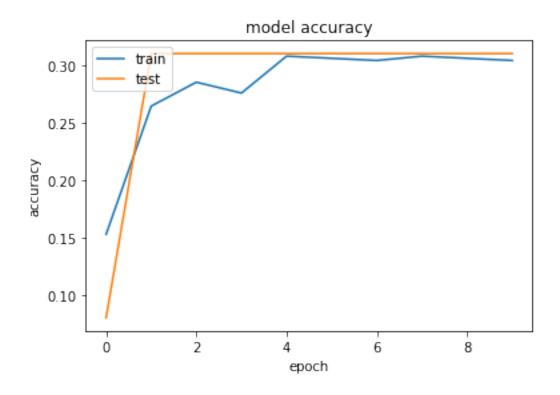
Activation: relu, maxPooling2D: True, extraLayers: False, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.5, withSoftmax: True Model: "sequential\_24"

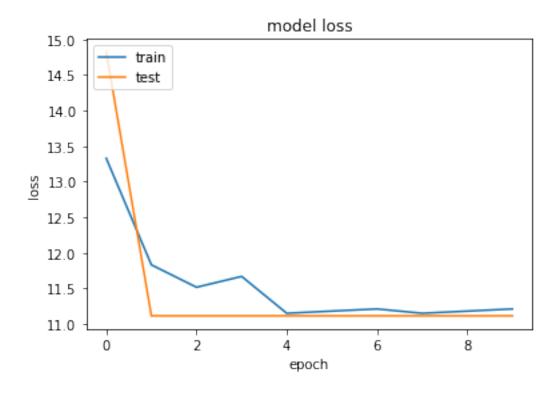
Layer (type)	Output Shape	Param #
conv2d_72 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_62 (MaxPooli g2D)</pre>	n (None, 140, 416, 16)	0
flatten_40 (Flatten)	(None, 931840)	0
dense_44 (Dense)	(None, 128)	119275648
dropout_17 (Dropout)	(None, 128)	0
dense_45 (Dense)	(None, 7)	903
flatten_41 (Flatten)	(None, 7)	0

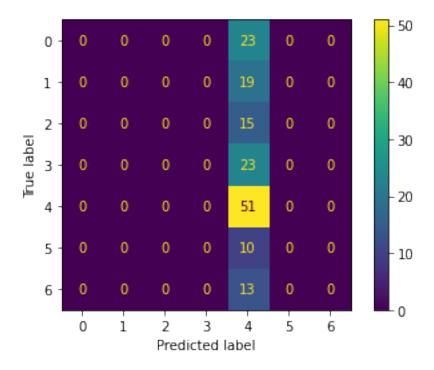
Total params: 119,276,711 Trainable params: 119,276,711 Non-trainable params: 0 \_\_\_\_\_ Epoch 1/10 53/53 [============ ] - 77s 1s/step - loss: 13.3273 - accuracy: 0.1531 - val\_loss: 14.8212 - val\_accuracy: 0.0805 Epoch 2/10 0.2647 - val\_loss: 11.1159 - val\_accuracy: 0.3103 53/53 [============ ] - 71s 1s/step - loss: 11.5173 - accuracy: 0.2854 - val\_loss: 11.1159 - val\_accuracy: 0.3103 0.2760 - val\_loss: 11.1159 - val\_accuracy: 0.3103 Epoch 5/10 0.3081 - val\_loss: 11.1159 - val\_accuracy: 0.3103 53/53 [============= ] - 72s 1s/step - loss: 11.1826 - accuracy: 0.3062 - val\_loss: 11.1159 - val\_accuracy: 0.3103 Epoch 7/10 0.3043 - val\_loss: 11.1159 - val\_accuracy: 0.3103 Epoch 8/10 0.3081 - val\_loss: 11.1159 - val\_accuracy: 0.3103 Epoch 9/10 0.3062 - val\_loss: 11.1159 - val\_accuracy: 0.3103 Epoch 10/10

0.3043 - val\_loss: 11.1159 - val\_accuracy: 0.3103

Time used: 0:12:01.413035







[76]: #sinextra con aumentación
model\_5a=testCustomModel(num\_classes, 'relu',True, False,True, True, True, 0.

→5,True, True)

Activation: relu, maxPooling2D: True, extraLayers: False, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.5, withSoftmax: True

Model: "sequential\_25"

\_\_\_\_\_\_

```
Layer (type)
              Output Shape
______
conv2d_75 (Conv2D)
              (None, 280, 832, 16)
                           160
max pooling2d 75 (MaxPoolin (None, 140, 416, 16)
                           0
g2D)
flatten_50 (Flatten)
           (None, 931840)
dense_49 (Dense)
              (None, 128)
                          119275648
dropout_24 (Dropout)
           (None, 128)
dense_50 (Dense)
              (None, 7)
                           903
flatten_51 (Flatten)
              (None, 7)
______
Total params: 119,276,711
Trainable params: 119,276,711
Non-trainable params: 0
    ._____
Epoch 1/10
0.1153 - val_loss: 15.3770 - val_accuracy: 0.0460
Epoch 2/10
0.1002 - val_loss: 15.3770 - val_accuracy: 0.0460
0.1134 - val_loss: 15.3770 - val_accuracy: 0.0460
0.1021 - val_loss: 14.6360 - val_accuracy: 0.0920
Epoch 5/10
0.0983 - val loss: 13.1538 - val accuracy: 0.1839
Epoch 6/10
0.1304 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 7/10
0.1267 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 8/10
0.1059 - val_loss: 13.1538 - val_accuracy: 0.1839
Epoch 9/10
```

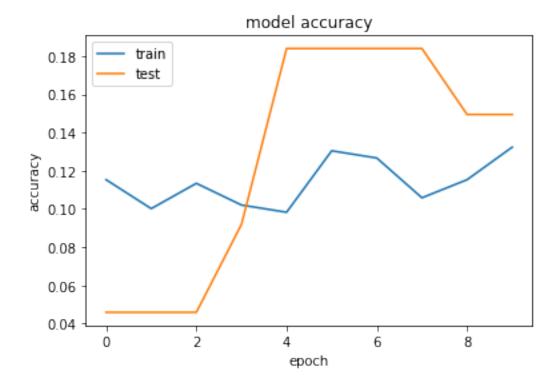
Param #

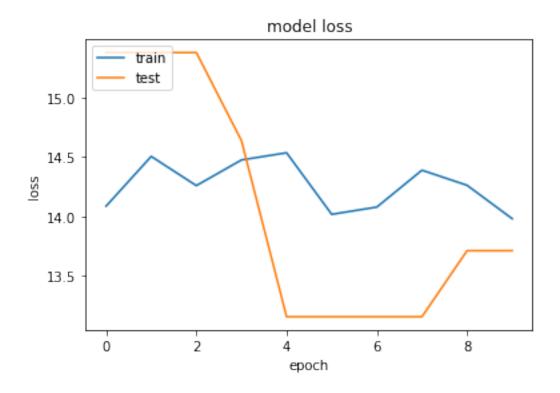
```
0.1153 - val_loss: 13.7096 - val_accuracy: 0.1494
```

Epoch 10/10

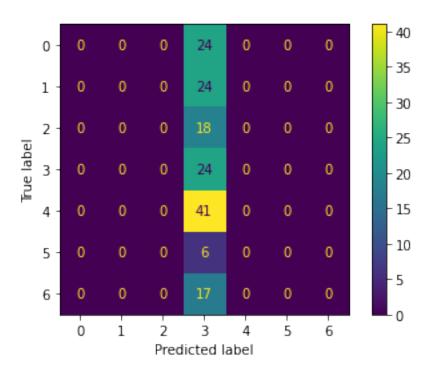
0.1323 - val\_loss: 13.7096 - val\_accuracy: 0.1494

Time used: 0:11:14.643553





```
16/16 [======
                          =======] - 3s 178ms/step
Test evaluation:
16/16 [========
                          =======] - 3s 181ms/step - loss: 13.6062 -
accuracy: 0.1558
[13.606184959411621, 0.15584415197372437]
% of correct brand in the first 3 positions:
72
0.4675324675324675
\% of brand predicted with percentage >= 0.25
0.15584415584415584
\% of brand predicted with percentage >= 0.5
0.15584415584415584
\% of brand predicted with percentage >= 0.75
0.15584415584415584
Matriz de confusión:
```



### **4.2.6** Sin Dense

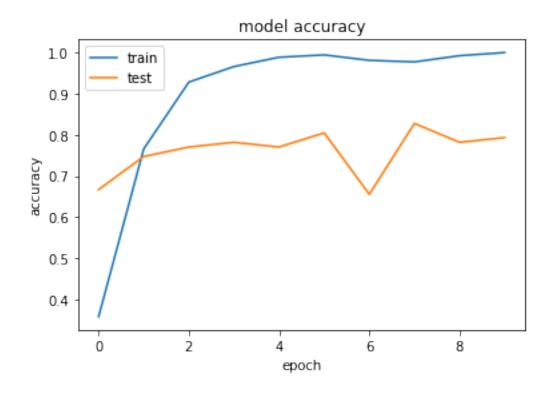
[82]: model\_6 = testCustomModel(num\_classes, 'relu', True, True, True, False)

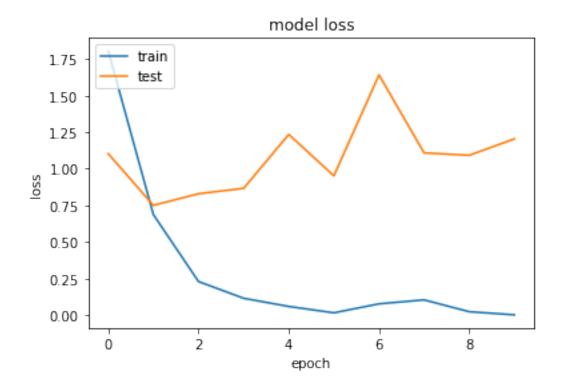
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: False, withDropout: True, Dropout value: 0.5, withSoftmax: True

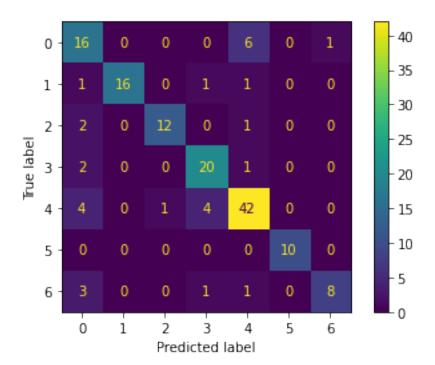
Model: "sequential\_23"

Layer (type)	Output Shape	Param #
conv2d_69 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_59 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_70 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_60 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_71 (Conv2D)	(None, 70, 208, 64)	18496
<pre>max_pooling2d_61 (MaxPoolin g2D)</pre>	(None, 35, 104, 64)	0

```
flatten_38 (Flatten)
           (None, 232960)
dropout_16 (Dropout)
              (None, 232960)
dense 43 (Dense)
              (None, 7)
                            1630727
              (None, 7)
flatten 39 (Flatten)
______
Total params: 1,654,023
Trainable params: 1,654,023
Non-trainable params: 0
______
Epoch 1/10
accuracy: 0.3573 - val_loss: 1.1032 - val_accuracy: 0.6667
Epoch 2/10
accuracy: 0.7656 - val_loss: 0.7500 - val_accuracy: 0.7471
Epoch 3/10
accuracy: 0.9282 - val_loss: 0.8295 - val_accuracy: 0.7701
Epoch 4/10
accuracy: 0.9660 - val_loss: 0.8663 - val_accuracy: 0.7816
Epoch 5/10
accuracy: 0.9887 - val_loss: 1.2350 - val_accuracy: 0.7701
accuracy: 0.9943 - val_loss: 0.9520 - val_accuracy: 0.8046
Epoch 7/10
0.9811 - val_loss: 1.6417 - val_accuracy: 0.6552
Epoch 8/10
0.9773 - val loss: 1.1088 - val accuracy: 0.8276
Epoch 9/10
accuracy: 0.9924 - val_loss: 1.0922 - val_accuracy: 0.7816
Epoch 10/10
accuracy: 1.0000 - val_loss: 1.2042 - val_accuracy: 0.7931
Time used: 0:08:37.719498
```









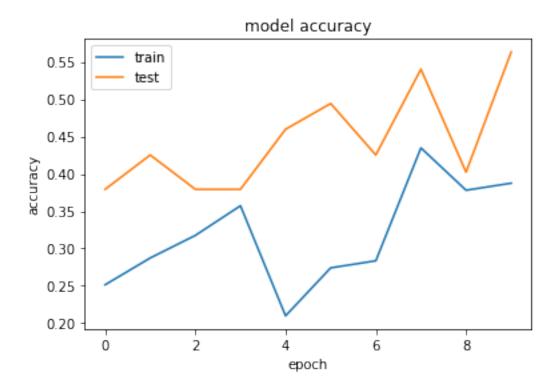
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: False, withDropout: True, Dropout value: 0.5, withSoftmax: True

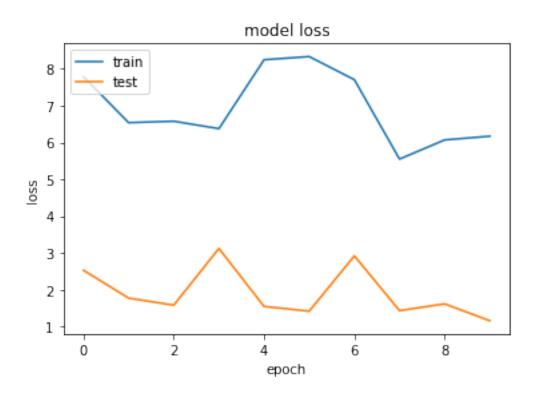
Model: "sequential\_26"

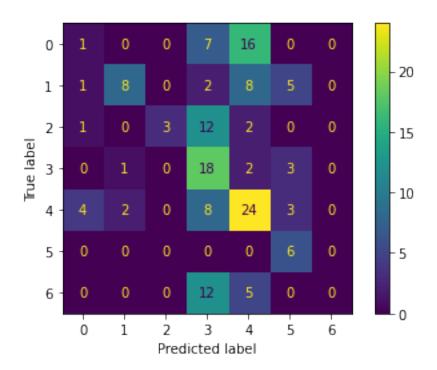
Layer (type) Output Shape Param #

```
conv2d_76 (Conv2D)
                     (None, 280, 832, 16)
                                        160
max_pooling2d_76 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 77 (Conv2D)
                     (None, 140, 416, 32)
                                        4640
max_pooling2d_77 (MaxPoolin (None, 70, 208, 32)
g2D)
                     (None, 70, 208, 64)
conv2d_78 (Conv2D)
                                        18496
max_pooling2d_78 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_52 (Flatten)
                     (None, 232960)
dropout_25 (Dropout)
                (None, 232960)
                     (None, 7)
dense_51 (Dense)
                                        1630727
flatten_53 (Flatten)
                     (None, 7)
Total params: 1,654,023
Trainable params: 1,654,023
Non-trainable params: 0
      -----
Epoch 1/10
accuracy: 0.2514 - val_loss: 2.5278 - val_accuracy: 0.3793
Epoch 2/10
53/53 [============ ] - 44s 824ms/step - loss: 6.5391 -
accuracy: 0.2873 - val_loss: 1.7712 - val_accuracy: 0.4253
Epoch 3/10
53/53 [============= ] - 43s 816ms/step - loss: 6.5784 -
accuracy: 0.3176 - val_loss: 1.5795 - val_accuracy: 0.3793
Epoch 4/10
accuracy: 0.3573 - val_loss: 3.1212 - val_accuracy: 0.3793
Epoch 5/10
accuracy: 0.2098 - val_loss: 1.5440 - val_accuracy: 0.4598
Epoch 6/10
accuracy: 0.2741 - val_loss: 1.4170 - val_accuracy: 0.4943
Epoch 7/10
```

```
53/53 [============ ] - 43s 805ms/step - loss: 7.7073 -
accuracy: 0.2836 - val_loss: 2.9178 - val_accuracy: 0.4253
Epoch 8/10
53/53 [============ ] - 43s 816ms/step - loss: 5.5496 -
accuracy: 0.4348 - val_loss: 1.4313 - val_accuracy: 0.5402
Epoch 9/10
53/53 [============ ] - 43s 807ms/step - loss: 6.0704 -
accuracy: 0.3781 - val_loss: 1.6139 - val_accuracy: 0.4023
Epoch 10/10
                  53/53 [======
accuracy: 0.3875 - val_loss: 1.1560 - val_accuracy: 0.5632
Time used: 0:07:14.104045
```







#### 4.2.7 Sin segunda capa Flatten

```
[]: model_7 = testCustomModel(num_classes,'relu', True, True, False) #error

[]: #model_7a = testCustomModel(num_classes, 'relu',True, True, False, True, True, Use, True, Tr
```

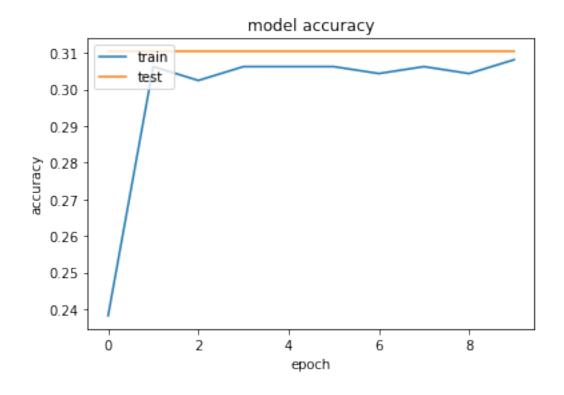
## 4.2.8 Sin MaxPooling

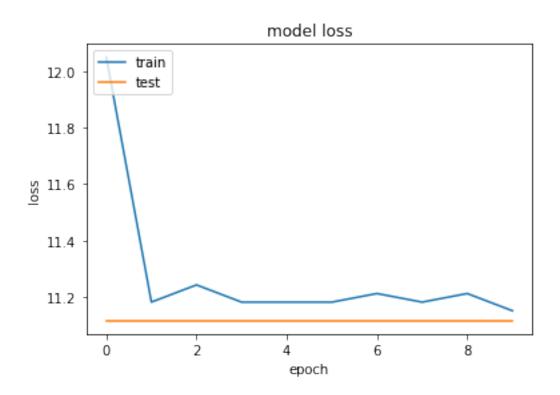
[69]: model\_8 = testCustomModel(num\_classes, 'relu', False)

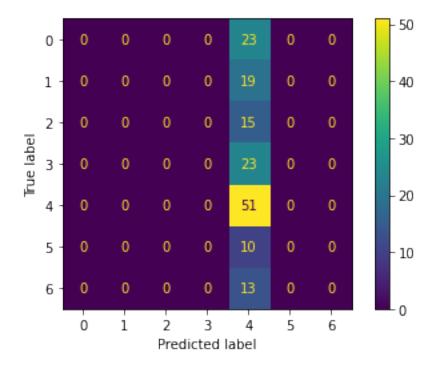
Activation: relu, maxPooling2D: False, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.5, withSoftmax: True Model: "sequential\_10"

Layer (type)	Output Shape	Param #
conv2d_30 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_24 (MaxPooling2D)</pre>	(None, 140, 416, 16)	0
conv2d_31 (Conv2D)	(None, 140, 416, 32)	4640
conv2d_32 (Conv2D)	(None, 140, 416, 64)	18496

```
flatten_14 (Flatten)
                (None, 3727360)
dense_18 (Dense)
                (None, 128)
                               477102208
dropout_7 (Dropout)
                (None, 128)
dense_19 (Dense)
                (None, 7)
                               903
flatten_15 (Flatten)
                (None, 7)
_____
Total params: 477,126,407
Trainable params: 477,126,407
Non-trainable params: 0
     _____
Epoch 1/10
accuracy: 0.2382 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 2/10
53/53 [============== ] - 511s 10s/step - loss: 11.1823 -
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 3/10
accuracy: 0.3025 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 4/10
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
accuracy: 0.3043 - val loss: 11.1159 - val accuracy: 0.3103
Epoch 8/10
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 9/10
accuracy: 0.3043 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 10/10
accuracy: 0.3081 - val_loss: 11.1159 - val_accuracy: 0.3103
Time used: 1:39:30.677803
```









Activation: relu, maxPooling2D: False, extraLayers: True, withFlatten: True, withDense: True, withDropout: 0.5, Dropout value: True, withSoftmax: True

Model: "sequential\_30"

Layer (type) Output Shape Param #

```
conv2d_88 (Conv2D)
                  (None, 280, 832, 16)
                                  160
max_pooling2d_88 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 89 (Conv2D)
                  (None, 140, 416, 32)
                                  4640
                  (None, 140, 416, 64)
conv2d 90 (Conv2D)
                                  18496
flatten_60 (Flatten)
                  (None, 3727360)
dense_58 (Dense)
                  (None, 128)
                                  477102208
dense_59 (Dense)
                  (None, 7)
                                  903
flatten_61 (Flatten)
                  (None, 7)
______
Total params: 477,126,407
Trainable params: 477,126,407
Non-trainable params: 0
     _____
Epoch 1/10
accuracy: 0.0756 - val_loss: 14.8212 - val_accuracy: 0.0805
Epoch 2/10
accuracy: 0.0851 - val_loss: 14.8212 - val_accuracy: 0.0805
Epoch 3/10
accuracy: 0.0851 - val_loss: 14.8212 - val_accuracy: 0.0805
Epoch 4/10
accuracy: 0.0851 - val loss: 14.8212 - val accuracy: 0.0805
Epoch 5/10
53/53 [============= ] - 410s 8s/step - loss: 14.7470 -
accuracy: 0.0851 - val_loss: 14.8212 - val_accuracy: 0.0805
Epoch 6/10
accuracy: 0.0851 - val_loss: 14.8212 - val_accuracy: 0.0805
Epoch 7/10
accuracy: 0.0851 - val_loss: 14.8212 - val_accuracy: 0.0805
Epoch 8/10
accuracy: 0.0851 - val_loss: 14.8212 - val_accuracy: 0.0805
Epoch 9/10
```

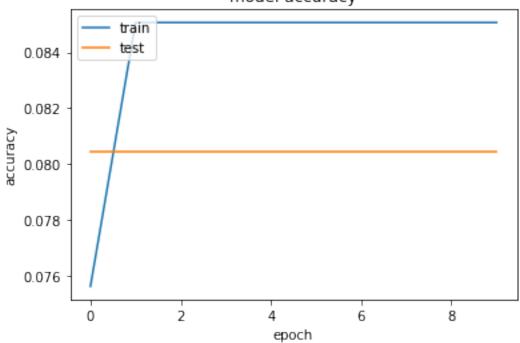
accuracy: 0.0851 - val\_loss: 14.8212 - val\_accuracy: 0.0805

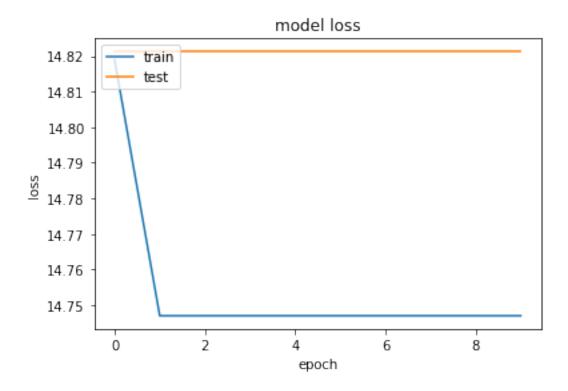
Epoch 10/10

accuracy: 0.0851 - val\_loss: 14.8212 - val\_accuracy: 0.0805

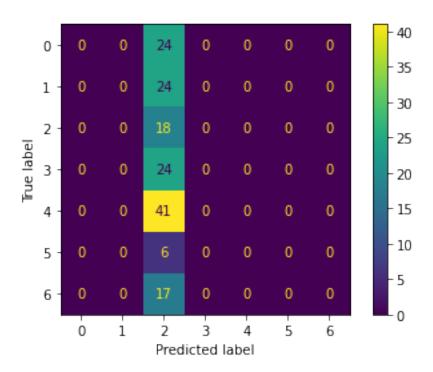
Time used: 1:07:58.339346

# model accuracy





```
16/16 [======
                      =======] - 7s 366ms/step
Test evaluation:
accuracy: 0.1169
[14.234162330627441, 0.11688311398029327]
% of correct brand in the first 3 positions:
66
0.42857142857142855
\% of brand predicted with percentage >= 0.25
0.11688311688311688
\% of brand predicted with percentage >= 0.5
0.11688311688311688
% of brand predicted with percentage >= 0.75
0.11688311688311688
Matriz de confusión:
```



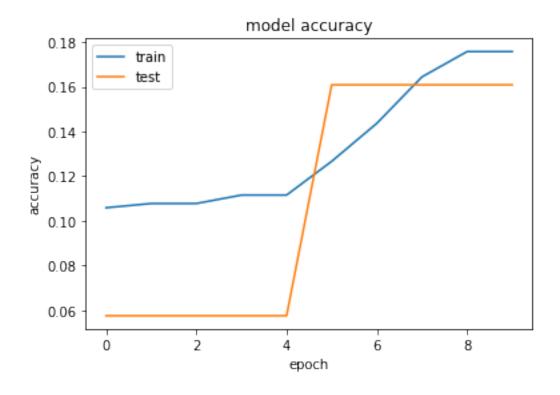
## 4.2.9 Modelo propuesto con diferentes valores de activación:

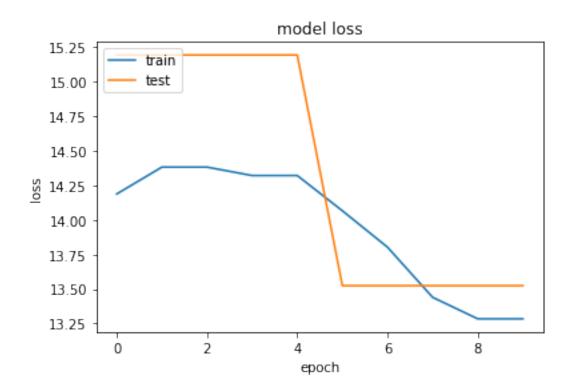
[70]: model\_sigmoid = testCustomModel(num\_classes, 'sigmoid')

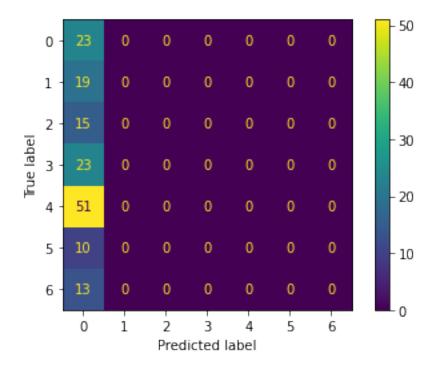
Activation: sigmoid, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.5, withSoftmax: True Model: "sequential\_11"

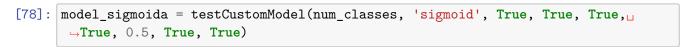
Layer (type)	Output Shape	Param #
conv2d_33 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_25 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_34 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_26 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_35 (Conv2D)	(None, 70, 208, 64)	18496
<pre>max_pooling2d_27 (MaxPoolin g2D)</pre>	(None, 35, 104, 64)	0

```
flatten_16 (Flatten)
               (None, 232960)
                              0
dense_20 (Dense)
                (None, 128)
                              29819008
dropout 8 (Dropout)
                (None, 128)
dense 21 (Dense)
                (None, 7)
                              903
flatten 17 (Flatten)
                (None, 7)
______
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
-----
Epoch 1/10
53/53 [============ ] - 57s 1s/step - loss: 14.1873 - accuracy:
0.1059 - val_loss: 15.1918 - val_accuracy: 0.0575
Epoch 2/10
0.1078 - val_loss: 15.1918 - val_accuracy: 0.0575
Epoch 3/10
0.1078 - val_loss: 15.1918 - val_accuracy: 0.0575
Epoch 4/10
53/53 [============ ] - 55s 1s/step - loss: 14.3204 - accuracy:
0.1115 - val_loss: 15.1918 - val_accuracy: 0.0575
Epoch 5/10
0.1115 - val_loss: 15.1918 - val_accuracy: 0.0575
Epoch 6/10
0.1267 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 7/10
0.1437 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 8/10
0.1645 - val_loss: 13.5244 - val_accuracy: 0.1609
Epoch 9/10
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
0.1758 - val_loss: 13.5244 - val_accuracy: 0.1609
Time used: 0:09:06.040666
```









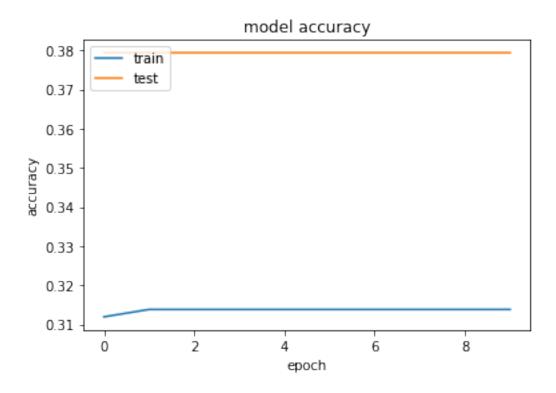
Aumentation: False

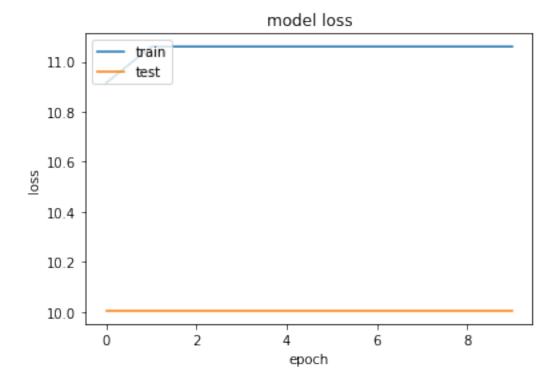
Activation: sigmoid, maxPooling2D: True, extraLayers: True, withFlatten: True,

withDense: True, withDropout: 0.5, Dropout value: True, withSoftmax: True

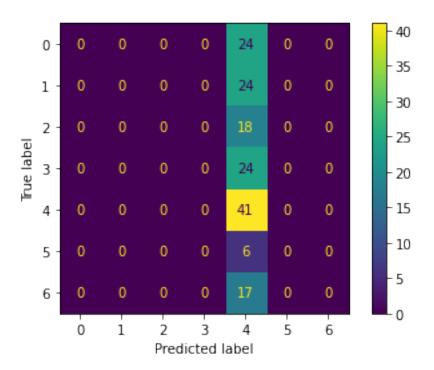
Model: "sequential\_27"

```
conv2d_79 (Conv2D)
                   (None, 280, 832, 16)
                                    160
max_pooling2d_79 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 80 (Conv2D)
                   (None, 140, 416, 32)
                                    4640
max_pooling2d_80 (MaxPoolin (None, 70, 208, 32)
g2D)
conv2d_81 (Conv2D)
                   (None, 70, 208, 64)
                                    18496
max_pooling2d_81 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_54 (Flatten)
                   (None, 232960)
dense_52 (Dense)
                   (None, 128)
                                    29819008
dense_53 (Dense)
                   (None, 7)
                                    903
flatten_55 (Flatten)
                   (None, 7)
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
      _____
Epoch 1/10
0.3119 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 2/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 3/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 4/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 5/10
53/53 [============ ] - 55s 1s/step - loss: 11.0602 - accuracy:
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 6/10
0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 7/10
```





```
16/16 [======
                         =======] - 4s 216ms/step
Test evaluation:
16/16 [============ - 4s 218ms/step - loss: 11.8269 -
accuracy: 0.2662
[11.826915740966797, 0.26623377203941345]
% of correct brand in the first 3 positions:
89
0.577922077922078
% of brand predicted with percentage >= 0.25
0.2662337662337662
\% of brand predicted with percentage >= 0.5
0.2662337662337662
% of brand predicted with percentage >= 0.75
0.2662337662337662
Matriz de confusión:
```



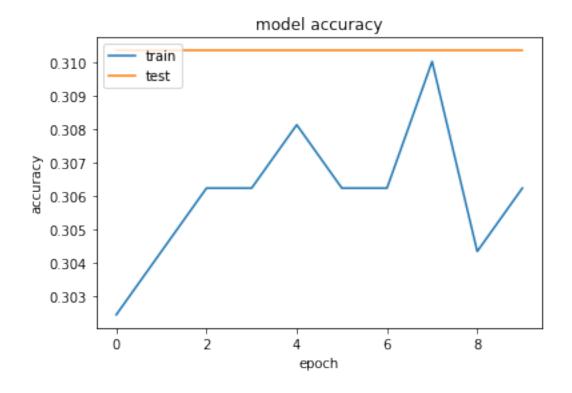
[71]: model\_tanh=testCustomModel(num\_classes, 'tanh')

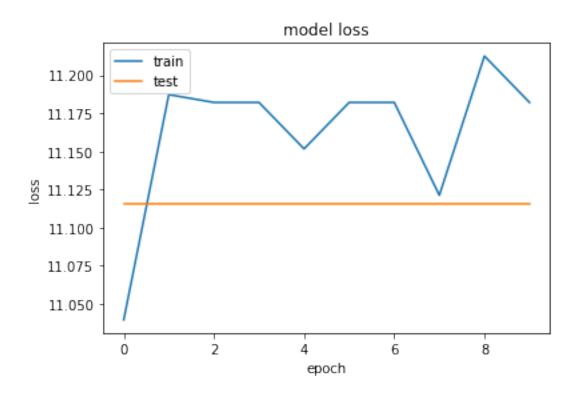
Activation: tanh, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: True, Dropout value: 0.5, withSoftmax: True

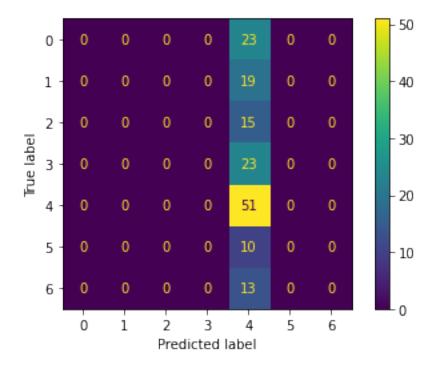
Model: "sequential\_12"

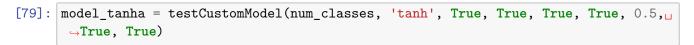
Layer (type)	Output Shape	Param #
conv2d_36 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_28 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_37 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_29 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_38 (Conv2D)	(None, 70, 208, 64)	18496
<pre>max_pooling2d_30 (MaxPoolin g2D)</pre>	(None, 35, 104, 64)	0
flatten_18 (Flatten)	(None, 232960)	0

```
dense_22 (Dense)
               (None, 128)
                             29819008
dropout_9 (Dropout)
               (None, 128)
dense 23 (Dense)
               (None, 7)
                             903
flatten 19 (Flatten)
               (None, 7)
______
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
_____
Epoch 1/10
0.3025 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 2/10
accuracy: 0.3043 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 3/10
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 4/10
0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 5/10
accuracy: 0.3081 - val_loss: 11.1159 - val_accuracy: 0.3103
53/53 [============ ] - 54s 1s/step - loss: 11.1821 - accuracy:
0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 7/10
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
accuracy: 0.3100 - val loss: 11.1159 - val accuracy: 0.3103
Epoch 9/10
accuracy: 0.3043 - val_loss: 11.1159 - val_accuracy: 0.3103
Epoch 10/10
accuracy: 0.3062 - val_loss: 11.1159 - val_accuracy: 0.3103
Time used: 0:08:50.479358
```









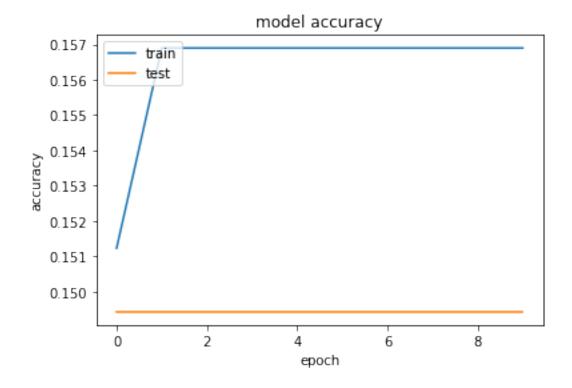
Aumentation: False

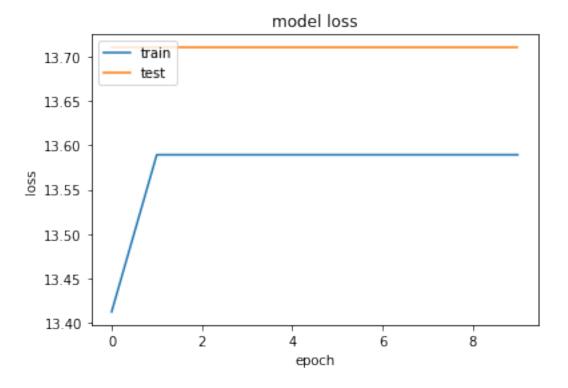
Activation: tanh, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: 0.5, Dropout value: True, withSoftmax: True

Model: "sequential\_28"

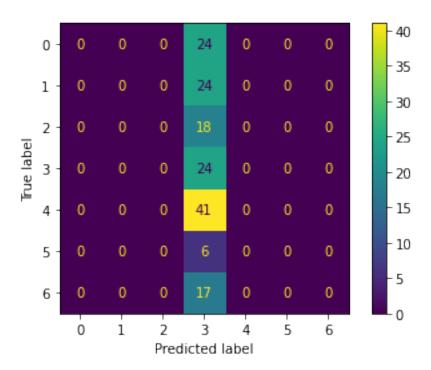
Layer (type) Output Shape Param #

```
conv2d_82 (Conv2D)
                   (None, 280, 832, 16)
                                    160
max_pooling2d_82 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 83 (Conv2D)
                   (None, 140, 416, 32)
                                    4640
max_pooling2d_83 (MaxPoolin (None, 70, 208, 32)
g2D)
conv2d_84 (Conv2D)
                   (None, 70, 208, 64)
                                    18496
max_pooling2d_84 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_56 (Flatten)
                   (None, 232960)
dense_54 (Dense)
                   (None, 128)
                                    29819008
dense_55 (Dense)
                   (None, 7)
                                    903
flatten_57 (Flatten)
                   (None, 7)
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
        _____
Epoch 1/10
0.1512 - val_loss: 13.7096 - val_accuracy: 0.1494
Epoch 2/10
0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
Epoch 3/10
0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
Epoch 4/10
0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
Epoch 5/10
53/53 [============ ] - 54s 1s/step - loss: 13.5892 - accuracy:
0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
Epoch 6/10
0.1569 - val_loss: 13.7096 - val_accuracy: 0.1494
Epoch 7/10
```





```
16/16 [======
                         =======] - 4s 213ms/step
Test evaluation:
                       =======] - 4s 218ms/step - loss: 13.6062 -
16/16 [=========
accuracy: 0.1558
[13.606184959411621, 0.15584415197372437]
% of correct brand in the first 3 positions:
72
0.4675324675324675
\% of brand predicted with percentage >= 0.25
0.15584415584415584
\% of brand predicted with percentage >= 0.5
0.15584415584415584
\% of brand predicted with percentage >= 0.75
0.15584415584415584
Matriz de confusión:
```

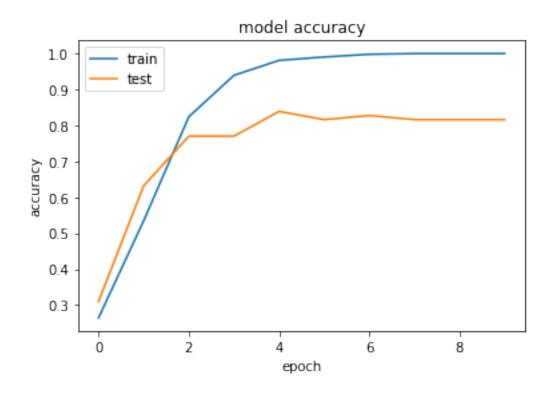


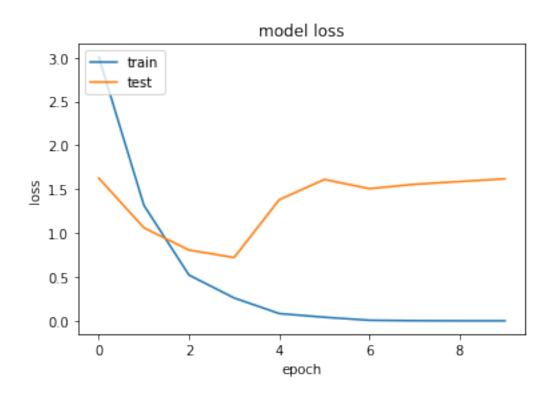
[93]: #sin eliminar nada:
model\_complete = testCustomModel(num\_classes, 'relu', True, True, True, True, True, 0.
→5, True)

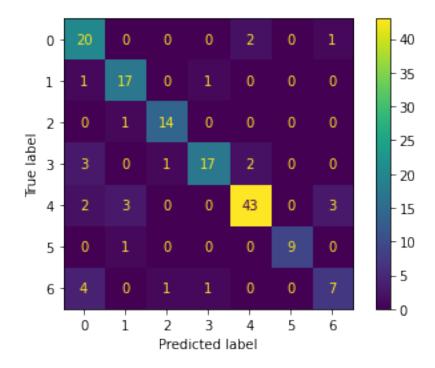
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: 0.5, Dropout value: True, withSoftmax: True Model: "sequential\_33"

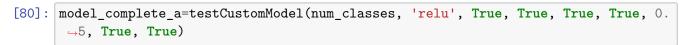
Layer (type)	Output Shape	Param #
conv2d_95 (Conv2D)	(None, 280, 832, 16)	160
<pre>max_pooling2d_83 (MaxPoolin g2D)</pre>	(None, 140, 416, 16)	0
conv2d_96 (Conv2D)	(None, 140, 416, 32)	4640
<pre>max_pooling2d_84 (MaxPoolin g2D)</pre>	(None, 70, 208, 32)	0
conv2d_97 (Conv2D)	(None, 70, 208, 64)	18496
<pre>max_pooling2d_85 (MaxPoolin g2D)</pre>	(None, 35, 104, 64)	0

```
flatten_58 (Flatten) (None, 232960)
dense_60 (Dense)
               (None, 128)
                              29819008
dense 61 (Dense)
               (None, 7)
                              903
flatten 59 (Flatten)
               (None, 7)
______
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
______
Epoch 1/10
accuracy: 0.2647 - val_loss: 1.6264 - val_accuracy: 0.3103
Epoch 2/10
accuracy: 0.5350 - val_loss: 1.0612 - val_accuracy: 0.6322
Epoch 3/10
accuracy: 0.8242 - val_loss: 0.8069 - val_accuracy: 0.7701
Epoch 4/10
accuracy: 0.9395 - val_loss: 0.7218 - val_accuracy: 0.7701
Epoch 5/10
53/53 [============ ] - 52s 972ms/step - loss: 0.0832 -
accuracy: 0.9811 - val_loss: 1.3811 - val_accuracy: 0.8391
accuracy: 0.9905 - val_loss: 1.6120 - val_accuracy: 0.8161
Epoch 7/10
0.9981 - val_loss: 1.5071 - val_accuracy: 0.8276
Epoch 8/10
1.0000 - val loss: 1.5565 - val accuracy: 0.8161
Epoch 9/10
accuracy: 1.0000 - val_loss: 1.5882 - val_accuracy: 0.8161
Epoch 10/10
accuracy: 1.0000 - val_loss: 1.6187 - val_accuracy: 0.8161
Time used: 0:09:07.531068
```









Aumentation: False

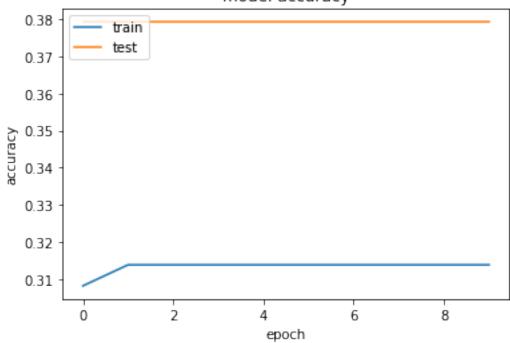
Activation: relu, maxPooling2D: True, extraLayers: True, withFlatten: True, withDense: True, withDropout: 0.5, Dropout value: True, withSoftmax: True

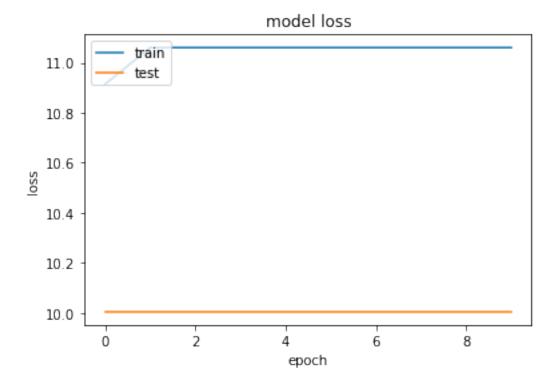
Model: "sequential\_29"

Layer (type) Output Shape Param #

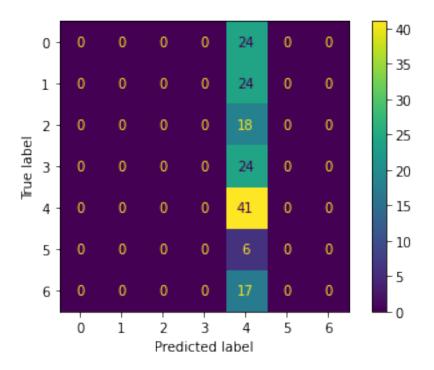
```
conv2d_85 (Conv2D)
                     (None, 280, 832, 16)
                                         160
max_pooling2d_85 (MaxPoolin (None, 140, 416, 16)
g2D)
conv2d 86 (Conv2D)
                     (None, 140, 416, 32)
                                         4640
max_pooling2d_86 (MaxPoolin (None, 70, 208, 32)
g2D)
                     (None, 70, 208, 64)
conv2d_87 (Conv2D)
                                         18496
max_pooling2d_87 (MaxPoolin (None, 35, 104, 64)
g2D)
flatten_58 (Flatten)
                     (None, 232960)
dense_56 (Dense)
                     (None, 128)
                                         29819008
                     (None, 7)
dense_57 (Dense)
                                         903
flatten_59 (Flatten)
                     (None, 7)
Total params: 29,843,207
Trainable params: 29,843,207
Non-trainable params: 0
             -----
Epoch 1/10
accuracy: 0.3081 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 2/10
accuracy: 0.3138 - val loss: 10.0043 - val accuracy: 0.3793
Epoch 3/10
53/53 [============== ] - 52s 986ms/step - loss: 11.0602 -
accuracy: 0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 4/10
53/53 [============ ] - 52s 987ms/step - loss: 11.0602 -
accuracy: 0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 5/10
accuracy: 0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 6/10
accuracy: 0.3138 - val_loss: 10.0043 - val_accuracy: 0.3793
Epoch 7/10
```

## model accuracy





```
=======] - 4s 212ms/step
16/16 [======
Test evaluation:
accuracy: 0.2662
[11.826915740966797, 0.26623377203941345]
% of correct brand in the first 3 positions:
89
0.577922077922078
\% of brand predicted with percentage >= 0.25
0.2662337662337662
\% of brand predicted with percentage >= 0.5
0.2662337662337662
\% of brand predicted with percentage >= 0.75
0.2662337662337662
Matriz de confusión:
```



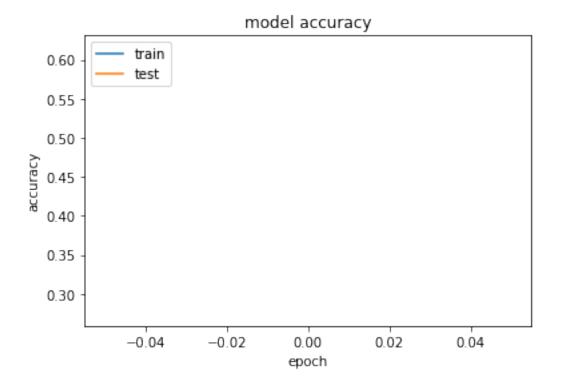
## 4.2.10 RestNet50

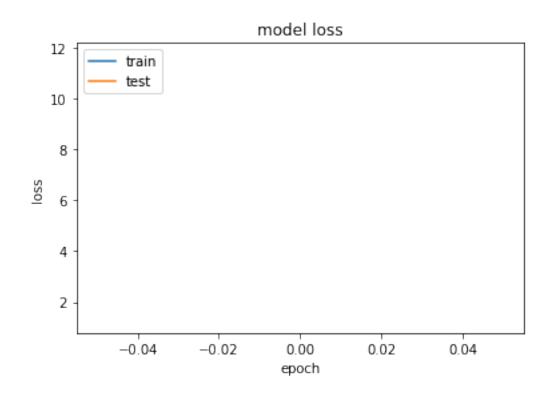
ResNet50 + capas

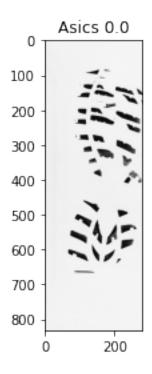
Model: "sequential\_10"

\_\_\_\_\_

```
Layer (type)
                               Output Shape
                                                       Param #
     ______
      resnet50 (Functional)
                                (None, 26, 9, 2048)
                                                       23587712
      flatten_11 (Flatten)
                               (None, 479232)
      dense 21 (Dense)
                                (None, 512)
                                                       245367296
      batch_normalization_10 (Bat (None, 512)
                                                       2048
      chNormalization)
      dropout_12 (Dropout)
                               (None, 512)
      dense_22 (Dense)
                                (None, 7)
                                                       3591
      flatten_12 (Flatten)
                                (None, 7)
     Total params: 268,960,647
     Trainable params: 268,906,503
     Non-trainable params: 54,144
[140]: modelPre3.compile(optimizer='adam',
                   loss=tf.keras.losses.
       →SparseCategoricalCrossentropy(from_logits=False),
                   metrics=['accuracy'])
[141]: trainGeneratorPre3=DataGenerator2dFootwear(shoes_train['X'].
       →tolist(),df_shoe_brand,False, "images/", False, False, False)
      testGeneratorPre3=DataGenerator2dFootwear(shoes test['X'].
       →tolist(),df_shoe_brand,False, "images/", False, False, False)
      valGeneratorPre3=DataGenerator2dFootwear(shoes_val['X'].
       →tolist(),df_shoe_brand,False, "images/",False, False, False)
[143]: preHistory3 = modelPre3.
       →fit(trainGeneratorPre3, validation_data=valGeneratorPre3, epochs=10)
     accuracy: 0.6144 - val_loss: 11.6717 - val_accuracy: 0.2759
[144]: plot_history(preHistory3)
```







```
[152]: checkAccuracyFirstPositions(pre_predicted_y3, shoes_test,3)
91
0.59090909090909
[]: modelPre4 = models.Sequential()
modelPre4.add(ResNet50(include_top=False, input_shape=(832, 280, 3),
```

```
weights="imagenet", classes = num_classes, __
      ⇔classifier_activation="softmax"))
     modelPre4.add(Flatten())
     modelPre4.summary()
     modelPre4.compile(optimizer='adam',
                   loss=tf.keras.losses.
     →SparseCategoricalCrossentropy(from_logits=False),
                   metrics=['accuracy'])
     trainGeneratorPre4=DataGenerator2dFootwear(shoes_train['X'].
     →tolist(),df_shoe_brand,False, "images/", False, False, False)
     testGeneratorPre4=DataGenerator2dFootwear(shoes_test['X'].
     →tolist(),df_shoe_brand,False, "images/", False, False, False)
     valGeneratorPre4=DataGenerator2dFootwear(shoes_val['X'].
      →tolist(),df_shoe_brand,False, "images/",False, False, False)
[]: preHistory4 = modelPre4.
      →fit(trainGeneratorPre4, validation_data=valGeneratorPre4, epochs=10)
[]: print(modelPre4.evaluate(testGeneratorPre4))
[]: test = np.empty([280,832], dtype=int)
     test = np.array([io.imread("images/"+p) for p in shoes_test.X.values])
     pre_predicted_y4 = modelPre4.predict(test)
[]: checkAccuracyFirstPositions(pre_predicted_y4, shoes_test,1)
[]: checkAccuracyFirstPositions(pre_predicted_y4, shoes_test,3)
```

## 4.3 Análisis de resultados

https://pypi.org/project/tabulate/