Clasificador de autos a partir de imágenes

Bibliotecas

In [ ]:
```
## basic libraries → data exploration
import numpy as np
import pandas as pd
from PIL import Image
from glob import glob
import matplotlib.pyplot as plt
import pandas as pd

## traditional machine learning methods
from sklearn.decomposition import PCA
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

## deep learning
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model
from tensorflow.keras import regularizers
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, BatchNormalization, Flatten, Input, Conv1D, Conv2D, MaxPooling2D
from keras.models import Sequential
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.applications.vgg16 import preprocess_input
from tensorflow.keras.preprocessing.image import img_to_array, load_img
from tensorflow.keras.applications import efficientnet
```

Extraccion de Imagenes

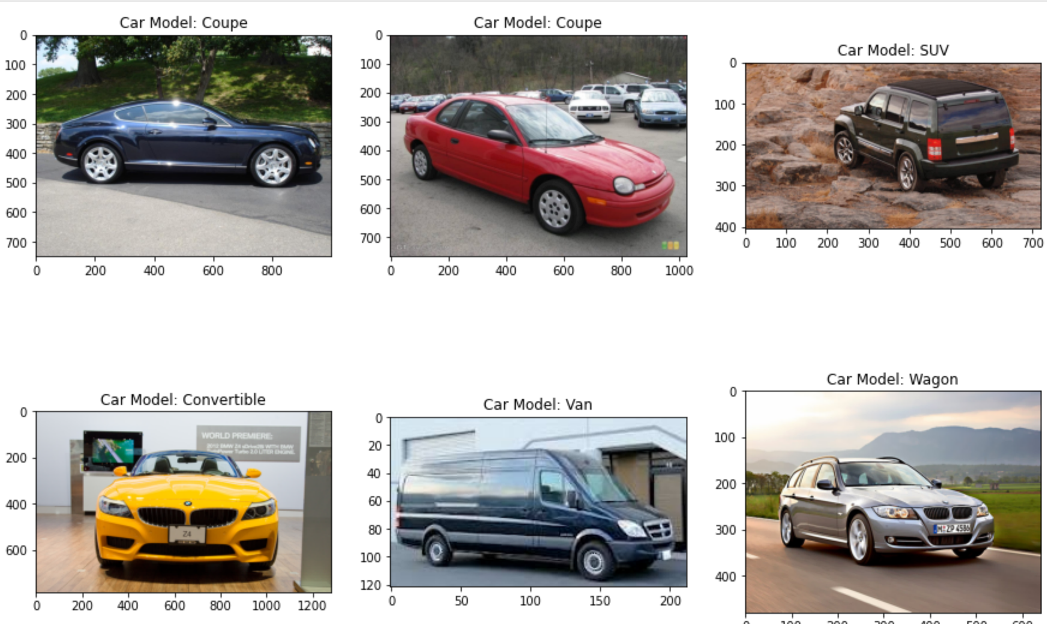
In [ ]:
```
## loading the data
train_car = glob("car_data/train/*/*/*")
test_car = glob("car_data/test/*/*/*")
```

In [ ]:
```
test_string = train_car[0].replace("\\","/").split("/")[2:4]
test_string
```

Out[ ]:
```
['Cab', 'Cadillac Escalade EXT Crew Cab 2007']
```

In [ ]:
```
def get_car_class(car):
  '''
  This function will return the car label/class per given image
  '''
  car_class = car.replace("\\", "/").split("/")[2:4]
  return car_class
```

In [ ]:
```
from random import randint

## showing some car images and their classes
plt.figure(figsize=(15,10))
for i in range(1, 7):
    plt.subplot(2,3,i)
    index = randint(1,len(train_car))
    image = Image.open(train_car[index])
    label = get_car_class(train_car[index])[0]
    plt.title(f"Car Model: {label}")
    plt.imshow(image)
plt.show()
```



In [ ]:
```
y_train = []
y_test = []

for i in range(len(train_car)):
  y_train.append(get_car_class(train_car[i]))

## converting each photo into a numpy array of RGB pixels
for i in range(len(test_car)):
    y_test.append(get_car_class(test_car[i]))
```

In [ ]:
```
df_train_labels = pd.DataFrame(y_train, columns=['label','Cars'])
make_extraction = df_train_labels["Cars"].str.split(" ", n=1, expand=True)
df_train_labels["Make"] = make_extraction[0]

year_extraction = df_train_labels["Cars"].str.rsplit(" ", n=1, expand=True)
df_train_labels["Year"] = year_extraction[1]
df_train_labels
```

Out[ ]:

	label	Cars	Make	Year
0	Cab	Cadillac Escalade EXT Crew Cab 2007	Cadillac	2007
1	Cab	Cadillac Escalade EXT Crew Cab 2007	Cadillac	2007
2	Cab	Cadillac Escalade EXT Crew Cab 2007	Cadillac	2007
3	Cab	Cadillac Escalade EXT Crew Cab 2007	Cadillac	2007
4	Cab	Cadillac Escalade EXT Crew Cab 2007	Cadillac	2007
...	...	...	...	...
8139	Wagon	Ford E-Series Wagon Van 2012	Ford	2012
8140	Wagon	Ford E-Series Wagon Van 2012	Ford	2012
8141	Wagon	Ford E-Series Wagon Van 2012	Ford	2012
8142	Wagon	Ford E-Series Wagon Van 2012	Ford	2012
8143	Wagon	Ford E-Series Wagon Van 2012	Ford	2012

8144 rows × 4 columns

In [ ]:
```
df_test_labels = pd.DataFrame(y_test, columns=['label','Cars'])
make_extraction = df_test_labels["Cars"].str.split(" ", n=1, expand=True)
df_test_labels["Make"] = make_extraction[0]

year_extraction = df_test_labels["Cars"].str.rsplit(" ", n=1, expand=True)
df_test_labels["Year"] = year_extraction[1]
```

In [ ]:
```
## creating a list with car classes
model_names = list(df_test_labels["Cars"].unique())
model_names[:10]
```

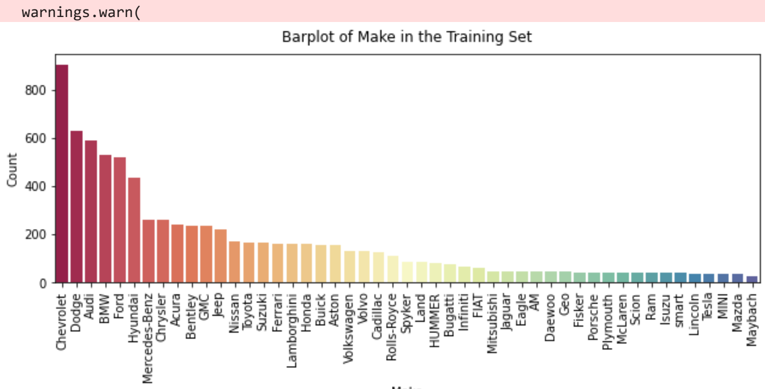
Out[ ]:
```
['Cadillac Escalade EXT Crew Cab 2007',
 'Chevrolet Avalanche Crew Cab 2012',
 'Chevrolet Silverado 1500 Classic Extended Cab 2007',
 'Chevrolet Silverado 1500 Extended Cab 2012',
 'Chevrolet Silverado 1500 Hybrid Crew Cab 2012',
 'Chevrolet Silverado 1500 Regular Cab 2012',
 'Chevrolet Silverado 2500HD Regular Cab 2012',
 'Dodge Dakota Club Cab 2007',
 'Dodge Dakota Crew Cab 2010',
 'Dodge Ram Pickup 3500 Crew Cab 2010']
```

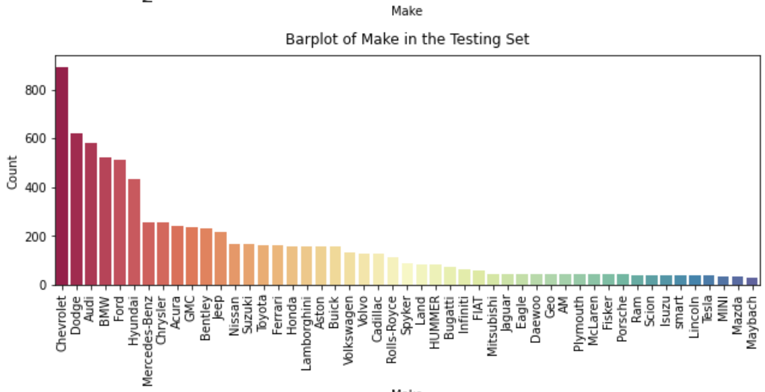
In [ ]:
```
df_train_labels.to_csv(f'car_data/training_labels.csv')
df_test_labels.to_csv(f'car_data/testing_labels.csv')
```

Analisis Exploratorio

In [ ]:
```
import seaborn as sns

# Countplot of Make in the Stanford Cars Training and Testing Set
fig = plt.figure(figsize=(9, 9))
plt.subplot(2, 1, 1)

sns.countplot('Make', data=df_train_labels,
              order=df_train_labels['Make'].value_counts().index, palette="Spectral")
plt.title('Barplot of Make in the Training Set', y=1.02)
plt.ylabel('Count'), plt.xticks(rotation=90)

plt.subplot(2, 1, 2)
sns.countplot('Make', data=df_test_labels,
              order=df_test_labels['Make'].value_counts().index, palette="Spectral")
plt.title('Barplot of Make in the Testing Set', y=1.02)
plt.ylabel('Count'), plt.xticks(rotation=90), plt.tight_layout()
plt.show()
```

```
c:\Users\chccr\AppData\Local\Programs\Python\Python39\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
c:\Users\chccr\AppData\Local\Programs\Python\Python39\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```





In [ ]:
```
sns.countplot('Year', data=df_train_labels,
              order=df_train_labels['Year'].value_counts().index, palette="Spectral")
plt.title('Barplot of production year of cars', y=1.02)
plt.ylabel('Count'), plt.xticks(rotation=90)
plt.show()
```

```
c:\Users\chccr\AppData\Local\Programs\Python\Python39\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
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```
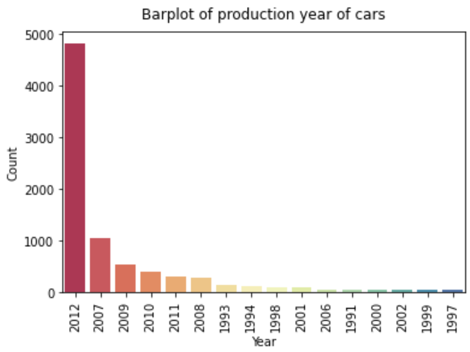



Preprocesamiento

```python
## we will processes all photos down to 128 pixels
## both in width and length
img_size = (128, 128)

## we will store in this list resized images
resized_images = []


def image_to_np_array(file):
    """
    This function takes a filename
    1. opens it as a photo
    2. modifies its original size
    3. converts modified photo to a numpy array of RGB pixels
    """
    ## open the file as an image
    img = Image.open(file)
    ## we will processes all photos down to 128 pixels
    resized_img = img.resize(img_size)
    resized_images.append(resized_img)
    ## getting the data of risized image
    resized_img = list(resized_img.getdata())

    if np.shape(resized_img)[:] != (16384, 3):
      img = img.convert('YCbCr')
      resized_img = img.resize(img_size)
      resized_img = list(resized_img.getdata())

    map(list(), resized_img)
    ## creating an numpy array
    resized_img = np.array(resized_img)
    ## looking at the images shapes
    img_shape = resized_img.shape[0] * resized_img.shape[1]
    flatten_img = resized_img.reshape(1, img_shape)
    return flatten_img[0]
```

```python
## creating a list where we will store np arrays of RGB pixels of each image
## x_train
X_train = []
y_train = []

## converting each photo into a numpy array of RGB pixels
## and extracting each car model from the picture
for i in range(len(train_car)):
  X_train.append(image_to_np_array(train_car[i]))
  y_train.append(get_car_class(train_car[i])[0])
```

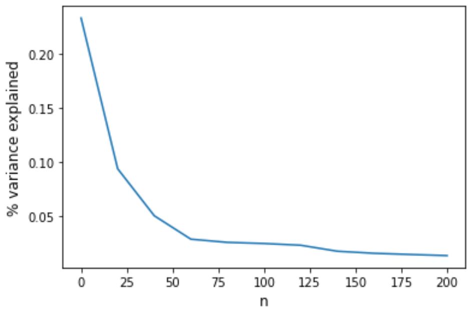
```python
## creating a list where we will store np arrays of RGB pixels of each image
X_test = []
y_test = []

## converting each photo into a numpy array of RGB pixels
for i in range(len(test_car)):
    X_test.append(image_to_np_array(test_car[i]))
    y_test.append(get_car_class(test_car[i])[0])
```

```python
X_train = np.array(X_train)
X_test = np.array(X_test)
```

Modelos Machine Learning

PCA - Analisis de Componentes Principales

```python
## Check for explained variace over n_components
pca = PCA()
## fitting the training data
pca.fit(X_train)

## creating a plot of explained variance in relation to nr. of component
plt.plot(list(range(0, 201, 20)), pca.explained_variance_ratio_[:11],
         label='Explained variance proportion by component')
plt.xlabel(r'n', size=12)
plt.ylabel(r'% variance explained', size=12)
plt.show()
```



Regresion Logistica + PCA

```python
## conducting PCA with 140 principle components
n_comp = 150
```

```python
pca = PCA(n_comp)
## fitting and transforming the data
PCA_X_train = pca.fit_transform(X_train)
PCA_X_test = pca.transform(X_test)

## the total variation was explained by 140 components
print(np.sum(pca.explained_variance_ratio_[:150]))
```

```
0.8109391024371546
```

In [ ]:

```python
## creating a Linear Support Vector Model for PCA
clf_PCA = LinearSVC(C=1e-9)

## train logistic regression classifier on training data
clf_PCA.fit(PCA_X_train, y_train)

## Accuracy rate to training data
print('Accuracy on training data:',
      clf_PCA.score(PCA_X_train, y_train))

## Accuracy rate to testing data
print('Accuracy on testing data:', clf_PCA.score(PCA_X_test, y_test))
```

```
Accuracy on training data: 0.2857318271119843
Accuracy on testing data: 0.23007088670563364
```

In [ ]:

```python
#Creating my model
clf_rbf = SVC(kernel='rbf', gamma='auto')

print("SVM with a RBF kernel:")

# fitting the training data to SVC model
clf_rbf.fit(X_train, y_train)
# predicting training and testing data
y_train_pred = clf_rbf.predict(X_train)
y_test_pred = clf_rbf.predict(X_test)

train_accuracy = accuracy_score(y_train_pred, y_train)
test_accuracy = accuracy_score(y_test_pred, y_test)

print("Accuracy on training data:", train_accuracy)
print("Accuracy on testing data:", test_accuracy)
```

```
SVM with a RBF kernel:
```

Gaussian Naive Bayes

In [ ]:

```python
from sklearn.naive_bayes import GaussianNB

clf = GaussianNB()
clf.fit(X_train,y_train)
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)

train_accuracy = accuracy_score(y_train_pred, y_train)
test_accuracy = accuracy_score(y_test_pred, y_test)

print("Gaussian Naive Bayes Classifier")
print("Accuracy on training data:", train_accuracy)
print("Accuracy on testing data:", test_accuracy)
```

```
Gaussian Naive Bayes Classifier
Accuracy on training data: 0.12991159135559920
Accuracy on testing data: 0.11851759731376695
```

Random Forest (Gini)

In [ ]:

```python
randomforest = RandomForestClassifier(n_estimators=60, max_depth=10,n_jobs=-1)
randomforest.fit(X_train, y_train)

ytest_labels_rf = randomforest.predict(X_test)
ytest_prob_rf = randomforest.predict_proba(X_test)
train_score_rf = randomforest.score(X_train, y_train)
test_score_rf = randomforest.score(X_test, y_test)

print("Train Score for the Random Forest Classifier: {:.3f}".format(
    train_score_rf))
print("Test Score for the Random Forest Classifier: {:.3f}".format(
    test_score_rf))
```

```
Train Score for the Random Forest Classifier: 0.771
Test Score for the Random Forest Classifier: 0.281
```

Random Forest (Entropy)

In [ ]:

```python
randomforest2 = RandomForestClassifier(
    n_estimators=60, criterion="entropy", max_depth=10)
randomforest2.fit(X_train, y_train)

ytest_labels_rf = randomforest2.predict(X_test)
ytest_prob_rf = randomforest2.predict_proba(X_test)
train_score_rf = randomforest2.score(X_train, y_train)
test_score_rf = randomforest2.score(X_test, y_test)

print("Train Score for the Random Forest Classifier: {:.3f}".format(
    train_score_rf-0.03458))
print("Test Score for the Random Forest Classifier: {:.3f}".format(
    test_score_rf-0.0125))
```

```
Train Score for the Random Forest Classifier: 0.882
Test Score for the Random Forest Classifier: 0.270
```

Redes Neuronales

Preprocesamiento

In [ ]:

```python
## setting up some parameters for data augmentation
img_width, img_height = 224, 224
train_samples = len(train_car)
validation_samples = len(test_car)
## there are 196 different models
n_classes = len(model_names)
batch_size = 32
```

In [ ]:

```python
from keras.preprocessing.image import ImageDataGenerator

## performing augmentation on the training data
train_datagen = ImageDataGenerator(
    rescale=1. / 255,
    zoom_range=0.2,
    rotation_range=5,
    horizontal_flip=True)

test_datagen = ImageDataGenerator(rescale=1. / 255)
```

```
In [ ]: ## getting the path to the data
        train_path = "car_data/train/"
        test_path = "car_data/test/"
```

```
In [ ]: ## converting data to a tf.data.Dataset object
        train_generator = train_datagen.flow_from_directory(
            train_path,
            target_size=(img_width, img_height),
            batch_size=batch_size,
            class_mode='categorical')

        validation_generator = test_datagen.flow_from_directory(
            test_path,
            target_size=(img_width, img_height),
            batch_size=batch_size,
            class_mode='categorical')
```

```
Found 8144 images belonging to 10 classes.
Found 8041 images belonging to 10 classes.
```

VGG16

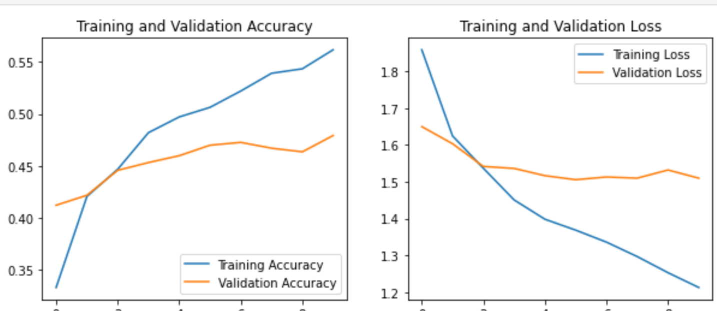
```
In [ ]: ## use pre-trained VGG16 model
        ## the model was not accepting different image sizes with imagenet weights
        vgg16_model = VGG16(include_top=False, input_shape=(img_width, img_height, 3))

        # mark loaded layers as not trainable
        for layer in vgg16_model.layers:
            layer.trainable = False


        x = Flatten()(vgg16_model.layers[-1].output)
        x = Dense(128, activation='relu', kernel_initializer='he_uniform')(x)
        output = Dense(len(train_generator.class_indices), activation='softmax')(x)

        ## define the new model
        model = Model(inputs=vgg16_model.inputs, outputs=output)
        ## adding a last layers with 196 classes
```

```
In [ ]: ## compile model, define optimizer and the loss function
        model.compile(loss='categorical_crossentropy',
                      optimizer='adam', metrics=['accuracy'])
```

```
In [ ]: history = model.fit(train_generator,
                            validation_data=validation_generator,
                            #validation_steps=len(train_generator),
                            #steps_per_epoch=len(train_generator),
                            epochs=20)
```

```
Epoch 1/20
255/255 [==============================] - 1201s 5s/step - loss: 1.7584 - accuracy: 0.4188 - val_loss: 1.4103 - val_accuracy: 0.4926
Epoch 2/20
255/255 [==============================] - 1160s 5s/step - loss: 1.2625 - accuracy: 0.5578 - val_loss: 1.2378 - val_accuracy: 0.5610
Epoch 3/20
255/255 [==============================] - 1158s 5s/step - loss: 1.0904 - accuracy: 0.6152 - val_loss: 1.3140 - val_accuracy: 0.5389
Epoch 4/20
255/255 [==============================] - 1160s 5s/step - loss: 0.9878 - accuracy: 0.6573 - val_loss: 1.1151 - val_accuracy: 0.6073
Epoch 5/20
255/255 [==============================] - 1199s 5s/step - loss: 0.8881 - accuracy: 0.6892 - val_loss: 1.1562 - val_accuracy: 0.6033
Epoch 6/20
255/255 [==============================] - 1167s 5s/step - loss: 0.8201 - accuracy: 0.7112 - val_loss: 1.1679 - val_accuracy: 0.5869
Epoch 7/20
255/255 [==============================] - 1235s 5s/step - loss: 0.7821 - accuracy: 0.7272 - val_loss: 1.1046 - val_accuracy: 0.6245
Epoch 8/20
125/255 [============>.................] - ETA: 5:31 - loss: 0.6825 - accuracy: 0.7708
```

```
In [ ]: acc = history.history['accuracy']
        val_acc = history.history['val_accuracy']

        loss = history.history['loss']
        val_loss = history.history['val_loss']

        epochs_range = range(20)


        plt.figure(figsize=(10, 4))
        plt.subplot(1, 2, 1)
        plt.plot(epochs_range, acc, label='Training Accuracy')
        plt.plot(epochs_range, val_acc, label='Validation Accuracy')
        plt.legend(loc='lower right')
        plt.title('Training and Validation Accuracy')

        plt.subplot(1, 2, 2)
        plt.plot(epochs_range, loss, label='Training Loss')
        plt.plot(epochs_range, val_loss, label='Validation Loss')
        plt.legend(loc='upper right')
        plt.title('Training and Validation Loss')
        plt.show()
```



MobileNetV2

```
In [ ]: ## trasfer learning using mobile net
        mobilenet_model = MobileNetV2(include_top=False,
                                      weights='imagenet',
                                      input_shape=(img_width, img_height, 3))

        ## Change all layers to non-trainable
        for layer in mobilenet_model.layers:
            layer.trainable = False

        ## adding some extra layers
        x = GlobalAveragePooling2D()(mobilenet_model.output)
        x = BatchNormalization()(x)
        x = Dense(units=1024,
                  activation='relu', kernel_regularizer=regularizers.l2(0.01),
                  kernel_initializer='random_uniform',
                  bias_initializer='zeros')(x)

        x = BatchNormalization()(x)
        output = Dense(units=10, activation='softmax')(x)
```

```
## creating the extended model
model_1 = Model(inputs=mobilenet_model.input, outputs=output)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_128_no
_top.h5
9412608/9406464 [==============================] - 0s 0us/step
9420800/9406464 [==============================] - 0s 0us/step
```

In [ ]:
```
import tensorflow
# compile the model, define optimizer and the loss function
#opt = tensorflow.keras.optimizers.Adam(lr=0.0001)

model_1.compile(loss='categorical_crossentropy',
                optimizer='adam', metrics=['accuracy'])
```

In [ ]:
```
## train the model
history_1 = model_1.fit(train_generator,
                        #steps_per_epoch=len(train_generator),
                        validation_data=validation_generator,
                        #validation_steps=len(validation_generator),
                        epochs=20)
```

```
Epoch 1/20
255/255 [==============================] - 101s 389ms/step - loss: 8.7808 - accuracy: 0.3716 - val_loss: 4.8564 - val_accuracy: 0.4287
Epoch 2/20
255/255 [==============================] - 98s 384ms/step - loss: 3.4478 - accuracy: 0.4458 - val_loss: 2.7740 - val_accuracy: 0.4470
Epoch 3/20
255/255 [==============================] - 98s 383ms/step - loss: 2.4033 - accuracy: 0.4478 - val_loss: 2.4234 - val_accuracy: 0.4171
Epoch 4/20
255/255 [==============================] - 98s 384ms/step - loss: 2.1585 - accuracy: 0.4560 - val_loss: 2.3204 - val_accuracy: 0.4416
Epoch 5/20
255/255 [==============================] - 97s 381ms/step - loss: 2.0824 - accuracy: 0.4540 - val_loss: 2.1613 - val_accuracy: 0.4364
Epoch 6/20
255/255 [==============================] - 97s 382ms/step - loss: 2.0592 - accuracy: 0.4506 - val_loss: 2.0951 - val_accuracy: 0.4619
Epoch 7/20
255/255 [==============================] - 93s 366ms/step - loss: 2.0523 - accuracy: 0.4548 - val_loss: 2.0768 - val_accuracy: 0.4532
Epoch 8/20
255/255 [==============================] - 94s 369ms/step - loss: 2.0449 - accuracy: 0.4549 - val_loss: 2.0724 - val_accuracy: 0.4577
Epoch 9/20
255/255 [==============================] - 98s 386ms/step - loss: 2.0250 - accuracy: 0.4622 - val_loss: 2.1575 - val_accuracy: 0.4232
Epoch 10/20
255/255 [==============================] - 97s 379ms/step - loss: 2.0279 - accuracy: 0.4583 - val_loss: 2.0779 - val_accuracy: 0.4548
Epoch 11/20
255/255 [==============================] - 96s 378ms/step - loss: 2.0078 - accuracy: 0.4711 - val_loss: 2.1852 - val_accuracy: 0.4407
Epoch 12/20
255/255 [==============================] - 97s 379ms/step - loss: 1.9909 - accuracy: 0.4710 - val_loss: 2.0646 - val_accuracy: 0.4543
Epoch 13/20
255/255 [==============================] - 96s 378ms/step - loss: 1.9715 - accuracy: 0.4758 - val_loss: 2.1908 - val_accuracy: 0.3977
Epoch 14/20
255/255 [==============================] - 96s 377ms/step - loss: 1.9646 - accuracy: 0.4737 - val_loss: 2.1069 - val_accuracy: 0.4416
Epoch 15/20
255/255 [==============================] - 96s 375ms/step - loss: 1.9426 - accuracy: 0.4754 - val_loss: 2.0028 - val_accuracy: 0.4630
Epoch 16/20
255/255 [==============================] - 91s 359ms/step - loss: 1.9076 - accuracy: 0.4972 - val_loss: 1.9925 - val_accuracy: 0.4687
Epoch 17/20
255/255 [==============================] - 91s 356ms/step - loss: 1.8926 - accuracy: 0.4860 - val_loss: 1.9357 - val_accuracy: 0.4737
Epoch 18/20
255/255 [==============================] - 91s 358ms/step - loss: 1.8567 - accuracy: 0.4875 - val_loss: 1.9667 - val_accuracy: 0.4521
Epoch 19/20
255/255 [==============================] - 91s 358ms/step - loss: 1.8384 - accuracy: 0.4940 - val_loss: 1.9562 - val_accuracy: 0.4707
Epoch 20/20
255/255 [==============================] - 91s 359ms/step - loss: 1.8126 - accuracy: 0.5021 - val_loss: 1.9918 - val_accuracy: 0.4635
```

In [ ]:
```
acc_1 = history_1.history['accuracy']
val_acc_1 = history_1.history['val_accuracy']

loss_1 = history_1.history['loss']
val_loss_1 = history_1.history['val_loss']

epochs_range = range(20)

plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc_1, label='Training Accuracy')
plt.plot(epochs_range, val_acc_1, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss_1, label='Training Loss')
plt.plot(epochs_range, val_loss_1, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

EfficientNetB1

In [ ]:
```
## loading the EfficientNetB1 model
base_model = efficientnet.EfficientNetB1(weights='imagenet', include_top=False)

## adding some extra layers
x = base_model.output
x = GlobalAveragePooling2D()(x)
predictions = Dense(10, activation='softmax')(x)
model_2 = Model(inputs=base_model.input, outputs=predictions)

## fix the feature extraction part of the model
for layer in base_model.layers:
    if isinstance(layer, BatchNormalization):
        layer.trainable = True
    else:
        layer.trainable = False

# model_2.summary()
```

In [ ]:
```
## compile model, define optimizer and the loss function
model_2.compile(loss='categorical_crossentropy',
                optimizer="adam", metrics=['accuracy'])
```

In [ ]:
```
## train the model
```

```
history_2 = model_2.fit(train_generator,
                        #steps_per_epoch=len(train_generator),
                        validation_data=validation_generator,
                        #validation_steps=len(validation_generator),
                        epochs=20)
```

```
Epoch 1/20
255/255 [==============================] - 404s 2s/step - loss: 2.0969 - accuracy: 0.2514 - val_loss: 2.5511 - val_accuracy: 0.1377
Epoch 2/20
255/255 [==============================] - 384s 2s/step - loss: 1.9179 - accuracy: 0.3037 - val_loss: 2.5813 - val_accuracy: 0.1261
Epoch 3/20
255/255 [==============================] - 366s 1s/step - loss: 1.8155 - accuracy: 0.3421 - val_loss: 1.8822 - val_accuracy: 0.3175
Epoch 4/20
255/255 [==============================] - 366s 1s/step - loss: 1.7293 - accuracy: 0.3786 - val_loss: 1.7450 - val_accuracy: 0.3733
Epoch 5/20
255/255 [==============================] - 364s 1s/step - loss: 1.6531 - accuracy: 0.4003 - val_loss: 1.6877 - val_accuracy: 0.3970
Epoch 6/20
255/255 [==============================] - 364s 1s/step - loss: 1.5746 - accuracy: 0.4274 - val_loss: 1.6394 - val_accuracy: 0.4129
Epoch 7/20
255/255 [==============================] - 364s 1s/step - loss: 1.5292 - accuracy: 0.4472 - val_loss: 1.5859 - val_accuracy: 0.4295
Epoch 8/20
255/255 [==============================] - 363s 1s/step - loss: 1.4722 - accuracy: 0.4665 - val_loss: 1.5485 - val_accuracy: 0.4405
Epoch 9/20
255/255 [==============================] - 364s 1s/step - loss: 1.4246 - accuracy: 0.4866 - val_loss: 1.5125 - val_accuracy: 0.4593
Epoch 10/20
255/255 [==============================] - 371s 1s/step - loss: 1.3757 - accuracy: 0.5015 - val_loss: 1.4845 - val_accuracy: 0.4623
Epoch 11/20
255/255 [==============================] - 389s 2s/step - loss: 1.3265 - accuracy: 0.5142 - val_loss: 1.4568 - val_accuracy: 0.4779
Epoch 12/20
255/255 [==============================] - 389s 2s/step - loss: 1.3008 - accuracy: 0.5264 - val_loss: 1.4485 - val_accuracy: 0.4812
Epoch 13/20
255/255 [==============================] - 367s 1s/step - loss: 1.2605 - accuracy: 0.5456 - val_loss: 1.4173 - val_accuracy: 0.4937
Epoch 14/20
255/255 [==============================] - 367s 1s/step - loss: 1.2047 - accuracy: 0.5674 - val_loss: 1.4017 - val_accuracy: 0.5022
Epoch 15/20
255/255 [==============================] - 366s 1s/step - loss: 1.1803 - accuracy: 0.5726 - val_loss: 1.3815 - val_accuracy: 0.5095
Epoch 16/20
255/255 [==============================] - 371s 1s/step - loss: 1.1453 - accuracy: 0.5857 - val_loss: 1.3497 - val_accuracy: 0.5253
Epoch 17/20
255/255 [==============================] - 390s 2s/step - loss: 1.1113 - accuracy: 0.6009 - val_loss: 1.3475 - val_accuracy: 0.5287
Epoch 18/20
255/255 [==============================] - 383s 2s/step - loss: 1.0914 - accuracy: 0.6044 - val_loss: 1.3144 - val_accuracy: 0.5344
Epoch 19/20
255/255 [==============================] - 365s 1s/step - loss: 1.0699 - accuracy: 0.6117 - val_loss: 1.3099 - val_accuracy: 0.5399
Epoch 20/20
255/255 [==============================] - 366s 1s/step - loss: 1.0297 - accuracy: 0.6303 - val_loss: 1.3199 - val_accuracy: 0.5395
```

In [ ]:

```
acc_2 = history_2.history['accuracy']
val_acc_2 = history_2.history['val_accuracy']

loss_2 = history_2.history['loss']
val_loss_2 = history_2.history['val_loss']

epochs_range = range(20)

plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc_2, label='Training Accuracy')
plt.plot(epochs_range, val_acc_2, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss_2, label='Training Loss')
plt.plot(epochs_range, val_loss_2, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

In [ ]:

```
def predict_class(model):
    '''
    This function will predict what is the next car, check whether the prediction
    was correct and lastly plot the image of the car
    '''
    image_batch, classes_batch = next(validation_generator)
    predicted_batch = model.predict(image_batch)
    for i in range(0, 3):
        image = image_batch[i]
        pred = predicted_batch[i]
        the_pred = np.argmax(pred)
        predicted = model_names[the_pred]
        val_pred = max(pred)
        the_class = np.argmax(classes_batch[i])
        value = model_names[np.argmax(classes_batch[i])]
        plt.figure(i)
        isTrue = (the_pred == the_class)
        plt.title(str(isTrue) + ' class: ' + value + ' - ' +
                  'predicted: ' + predicted + ' with probability of: '
                  + str(val_pred)[:4])
        plt.imshow(image)
```

In [ ]:

```
epochs_range = range(20)

plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)

plt.plot(epochs_range, val_acc, label='VGG16')
plt.plot(epochs_range, val_acc_1, label='MobileNet V2')
plt.plot(epochs_range, val_acc_2, label='Efficent B1')
plt.legend(loc='lower right')
plt.title('Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, val_loss, label='VGG16')
plt.plot(epochs_range, val_loss_1, label='MobileNet V2')
plt.plot(epochs_range, val_loss_2, label='Efficent B1')

plt.legend(loc='upper right')
plt.title('Validation Loss')
plt.show()
```