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Questions –

1. Find out the make and model that is most represented and the one that is least represented class? Is there a class imbalance problem, how would you handle class imbalance if it were to exist (2 marks)
2. Apply the image processing techniques and explain the benefits of those technique (2 marks)
3. Train a lightweight model, show train and validation loss curves, show steps taken to tune hyper params (1 marks)
4. Determine metric to evaluate performance of the model. Report how the model is performing on the metric (2 Marks)
5. Deploy (3 marks) a. As a rest api endpoint b. Mobil app model

```
# Car Images classification using CNN
```

```
# Import Modules
```

In [8]:

```
# import the libraries as shown below
import os
import shutil
import random
import numpy as np
import numpy as np
from glob import glob
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow.keras.layers import Input, Lambda, Dense, Flatten,Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator,load_img
from tensorflow.keras.callbacks import LearningRateScheduler, EarlyStopping
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img, img_
```

In [4]:

```
import tensorflow as tf
print("TensorFlow version:", tf.__version__)
```

```
TensorFlow version: 2.4.1
```

In [18]:

```
#Set all the Constants
BATCH_SIZE = 32
IMAGE_SIZE = 224
CHANNELS=3
EPOCHS=50
```

In [6]:

```
#defining the path
train_path = 'train'
valid_path = 'test'

```

1) Find out the make and model that is most represented and the one that is least represented class?

In [8]:

```
data_dir = train_path
class_counts = {}

for class_name in os.listdir(data_dir):
    class_dir = os.path.join(data_dir, class_name)
    if os.path.isdir(class_dir):
        class_count = len(os.listdir(class_dir))
        class_counts[class_name] = class_count

# Find the most and least represented classes
most_represented_class = max(class_counts, key=class_counts.get)
least_represented_class = min(class_counts, key=class_counts.get)

print(f"Most Represented Class: {most_represented_class}, Count: {class_counts[most_
print(f"Least Represented Class: {least_represented_class}, Count: {class_counts[le
```

```
Most Represented Class: Audi, Count: 814
Least Represented Class: Hyundai Creta, Count: 271
```

Is there a class imbalance problem, how would you handle class imbalance if it were to exist Apply the image processing techniques and explain the benefits of those technique

In [9]:

```
train_folder = train_path
# Initialize an empty dictionary to store class counts
class_counts = {}

# Iterate through the subfolders (each representing a class)
for class_folder in os.listdir(train_folder):
    if os.path.isdir(os.path.join(train_folder, class_folder)):
        # Count the number of files (images) in each class folder
        class_count = len(os.listdir(os.path.join(train_folder, class_folder)))
        # Store the class count in the dictionary with the class name as the key
        class_counts[class_folder] = class_count

# Print the class distribution for the training set
for car_class, count in class_counts.items():
    print(f"Class: {car_class}, Count: {count}")

```

```
Class: Hyundai Creta, Count: 271
Class: Mahindra Scorpio, Count: 316
Class: Swift, Count: 424
Class: Rolls Royce, Count: 311
Class: Tata Safari, Count: 441
Class: Toyota Innova, Count: 775
Class: Audi, Count: 814
```

In [13]:

```
#balance dataset
# Define the path to your train data directory
train_data_dir = 'train'  # Update with your actual path

# Create a directory for balanced training data
balanced_train_dir = 'balanced_train_dir'
os.makedirs(balanced_train_dir, exist_ok=True)
 Create an instance of the ImageDataGenerator with desired transformations
datagen = ImageDataGenerator(
    rescale=1./255,              # Normalize pixel values to the range [0, 1]
    rotation_range=20,           # Randomly rotate images by up to 20 degrees
    width_shift_range=0.2,       # Randomly shift the width of images by up to 20%
    height_shift_range=0.2,      # Randomly shift the height of images by up to 20
    shear_range=0.2,             # Randomly apply shear transformations
    zoom_range=0.2,              # Randomly zoom in on images by up to 20%
    horizontal_flip=True,        # Randomly flip images horizontally
    fill_mode='nearest'          # Fill in empty areas created by transformations
)

# Define the desired count for 'Audi'
desired_count = 814

# List all class directories and their counts
class_directories = os.listdir(train_data_dir)
class_counts = {}

# Iterate through each class directory
for class_name in class_directories:
    class_dir = os.path.join(train_data_dir, class_name)
    class_files = os.listdir(class_dir)

    # Create a directory for the class in the balanced dataset
    balanced_class_dir = os.path.join(balanced_train_dir, class_name)
    os.makedirs(balanced_class_dir, exist_ok=True)

    # Calculate the number of samples needed for this class to match the desired co
    num_original_samples = len(class_files)
    num_samples_to_copy = min(desired_count, num_original_samples)

    # Calculate the number of samples needed to augment
    num_samples_to_augment = desired_count - num_samples_to_copy

    # Copy the original samples to the balanced dataset
    files_to_copy = random.sample(class_files, num_samples_to_copy)
    for file_name in files_to_copy:
        src_path = os.path.join(class_dir, file_name)
        dst_path = os.path.join(balanced_class_dir, file_name)
        shutil.copy(src_path, dst_path)

    # Update the class counts
    class_counts[class_name] = num_samples_to_copy

    # Apply data augmentation if needed
    if num_samples_to_augment > 0:
        # Iterate through the original samples and apply augmentation
        for i in range(num_samples_to_augment):
            # Randomly select an image from the original samples
            original_image_name = random.choice(class_files)
            original_image_path = os.path.join(class_dir, original_image_name)
```

```

            # Load the image using PIL (Pillow)
            img = load_img(original_image_path)

            # Convert the image to a NumPy array
            img_array = img_to_array(img)

            # Reshape the image to (1, height, width, channels)
            img_array = np.expand_dims(img_array, axis=0)

            # Generate augmented images using the data generator
            augmented_images = datagen.flow(img_array, batch_size=1)

            # Get the first augmented image from the generator
            augmented_image_array = next(augmented_images)[0].astype(np.uint8)
            augmented_image = array_to_img(augmented_image_array)

            # Save the augmented image with a new name
            augmented_image_name = f"augmented_{i}_{original_image_name}"
            augmented_image_path = os.path.join(balanced_class_dir, augmented_image_
            augmented_image.save(augmented_image_path)
```

Rescaling (Normalization):

Benefit: Normalizing pixel values to the range [0, 1] helps in convergence during training by ensuring that the model deals with small and consistent input values. Rotation, Width Shift, Height Shift, Shear, and Zoom:

Benefit: These transformations increase the diversity of your training data. They help the model become robust to variations in input images, such as changes in orientation, position, and scale. Horizontal Flip:

Benefit: Flipping images horizontally introduces mirror-image versions of existing data, further enhancing dataset diversity and training stability. Fill Mode (Nearest):

Benefit: This mode fills in areas of the image that may become empty due to transformations like rotation or shearing. It ensures that no information is lost during augmentation.

In [14]:

```
#after blanching dataset
```

In [10]:

```
train_folder =  'balanced_train_dir'
# Initialize an empty dictionary to store class counts
class_counts = {}

# Iterate through the subfolders (each representing a class)
for class_folder in os.listdir(train_folder):
    if os.path.isdir(os.path.join(train_folder, class_folder)):
        # Count the number of files (images) in each class folder
        class_count = len(os.listdir(os.path.join(train_folder, class_folder)))
        # Store the class count in the dictionary with the class name as the key
        class_counts[class_folder] = class_count

# Print the class distribution for the training set
for car_class, count in class_counts.items():
    print(f"Class: {car_class}, Count: {count}")
```

```
Class: Hyundai Creta, Count: 814
Class: Mahindra Scorpio, Count: 814
Class: Swift, Count: 814
Class: Rolls Royce, Count: 814
Class: Tata Safari, Count: 814
Class: Toyota Innova, Count: 814
Class: Audi, Count: 814
```

Train a lightweight model, show train and validation loss curves, show steps taken to tune hyper params

In [19]:

```
dataset = tf.keras.preprocessing.image_dataset_from_directory(
    "balanced_train_dir",
    seed=123,
    shuffle=True,
    image_size=(IMAGE_SIZE,IMAGE_SIZE),
    batch_size=BATCH_SIZE
)
```

```
Found 5698 files belonging to 7 classes.
```

In [20]:

```
class_names = dataset.class_names
print(class_names)
len(class_names)
```

```
['Audi', 'Hyundai Creta', 'Mahindra Scorpio', 'Rolls Royce', 'Swift', 'Ta
ta Safari', 'Toyota Innova']
```

Out[20]:

```
7
```

In [17]:

```
len(dataset)
```

Out[17]:

```
179
```

In [79]:

```
class_labels = training_set.class_indices
print(class_labels)
```

```
{'Audi': 0, 'Hyundai Creta': 1, 'Mahindra Scorpio': 2, 'Rolls Royce': 3,
'Swift': 4, 'Tata Safari': 5, 'Toyota Innova': 6}
```

In [18]:

```
class_labels = np.array(dataset.class_names)
print(class_labels)
```

```
['Audi' 'Hyundai Creta' 'Mahindra Scorpio' 'Rolls Royce' 'Swift'
 'Tata Safari' 'Toyota Innova']
```

In [80]:

```
class_labels_list = list(class_labels.keys())
print(class_labels_list)

```

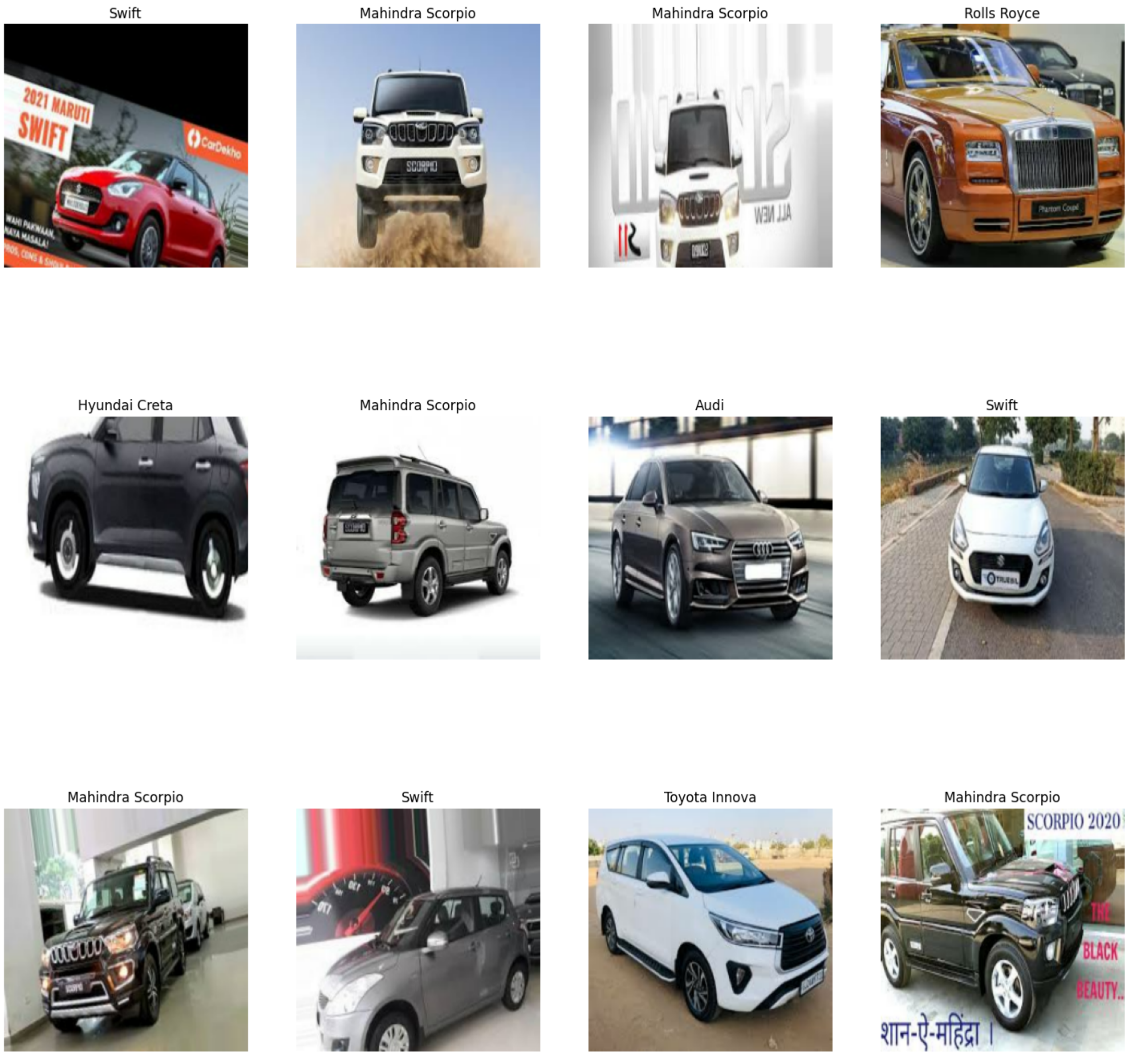
```
['Audi', 'Hyundai Creta', 'Mahindra Scorpio', 'Rolls Royce', 'Swift', 'Ta
ta Safari', 'Toyota Innova']
```

Visualize Dataset

In [19]:

```python
#plotting somesamples
plt.figure(figsize=(18, 18))
for image_batch, labels_batch in dataset.take(1):
    for i in range(12):
        ax = plt.subplot(3, 4, i + 1)
        plt.imshow(image_batch[i].numpy().astype("uint8"))
        plt.title(class_names[labels_batch[i]])
        plt.axis("off")
```

```
2023-09-10 02:01:51.512802: I tensorflow/compiler/mlir/mlir_graph_optimiz
ation_pass.cc:116] None of the MLIR optimization passes are enabled (regi
stered 2)
2023-09-10 02:01:51.529881: I tensorflow/core/platform/profile_utils/cpu_
utils.cc:112] CPU Frequency: 2599990000 Hz
```



Create Model

In [20]:

```
#importing model
# Here we will be using imagenet weights
IMAGE_SIZE = [224, 224]

resnet = ResNet50(input_shape=IMAGE_SIZE  + [3], weights='imagenet', include_top=Fa

```

In [21]:

```
# don't train existing weights
for layer in resnet.layers:
    layer.trainable = False
```

In [22]:

```
  # useful for getting number of output classes
folders = glob("balanced_train_dir/*")
```

In [23]:

```
# our layers
x = Flatten()(resnet.output)
```

In [24]:

```
prediction = Dense(len(folders), activation='softmax')(x)

# create a model object
model = Model(inputs=resnet.input, outputs=prediction)
```

In [25]:

```python

# view the structure of the model
model.summary()

```

```
Model: "model"

__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to                     
==================================================================================================
 input_1 (InputLayer)           [(None, 224, 224, 3) 0                                            
__________________________________________________________________________________________________
 conv1_pad (ZeroPadding2D)      (None, 230, 230, 3)  0           input_1[0][0]                    
__________________________________________________________________________________________________
 conv1_conv (Conv2D)            (None, 112, 112, 64) 9472        conv1_pad[0][0]                  
__________________________________________________________________________________________________
 conv1_bn (BatchNormalization)  (None, 112, 112, 64) 256         conv1
```

In [26]:

```python
# Compiling the model
model.compile(
  loss='categorical_crossentropy',
  optimizer='adam',
  metrics=['accuracy']
)

```

In [10]:

```python
# Use the Image Data Generator to import the images from the dataset
from tensorflow.keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(rescale = 1./255,)

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

In [11]:

```python
# Make sure you provide the same target size as initialied for the image size
training_set = train_datagen.flow_from_directory('balanced_train_dir',
                                                 target_size = (224, 224),
                                                 batch_size = 32,
                                                 class_mode = 'categorical')
```

```
Found 5698 images belonging to 7 classes.
```

In [12]:

```
test_set = test_datagen.flow_from_directory('test',
                                            target_size = (224, 224),
                                            batch_size = 32,
                                            class_mode = 'categorical')
```

```
Found 813 images belonging to 7 classes.
```

In [40]:

```

# Define a learning rate schedule
def lr_schedule(epoch):
    if epoch < 10:
        return 0.001
    elif epoch < 20:
        return 0.0001
    else:
        return 0.00001

# Define early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights
```

In [42]:

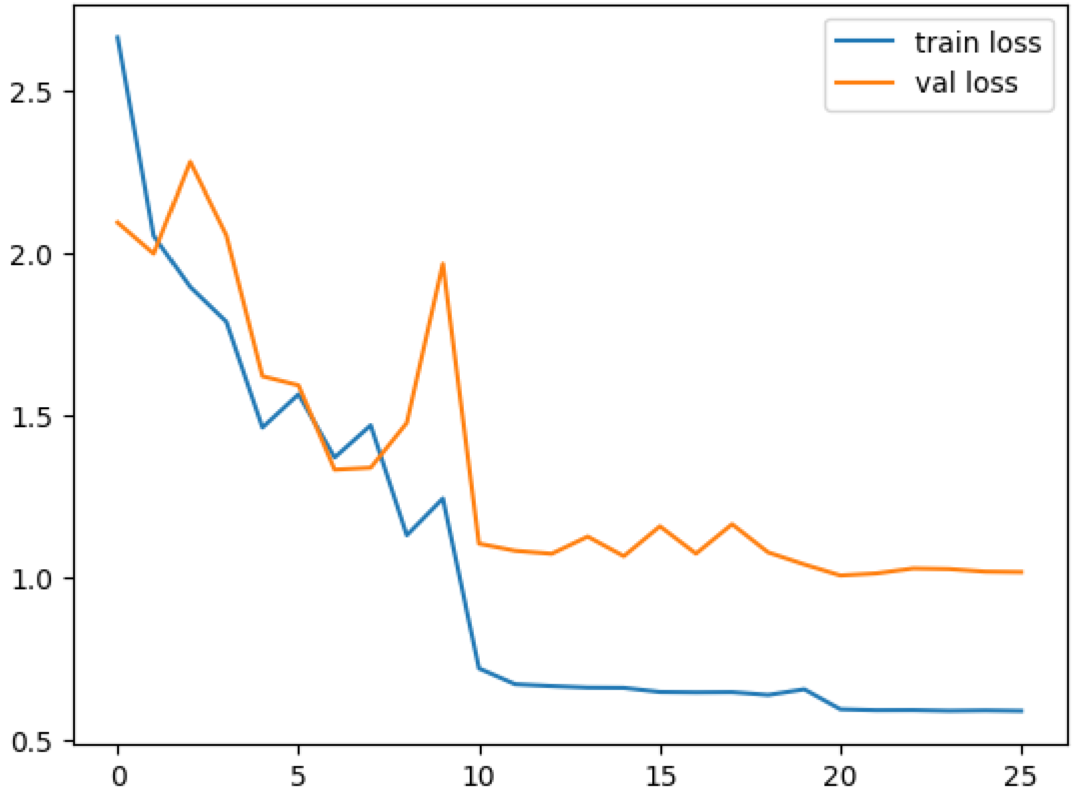
```
# fit the model
# Run the cell. It will take some time to execute
# Train the model with hyperparameter tuning
r = model.fit_generator(
  training_set,
  validation_data=test_set,
  epochs=50,
  steps_per_epoch=len(training_set),
  validation_steps=len(test_set),
    callbacks=[LearningRateScheduler(lr_schedule), early_stopping]
)
```

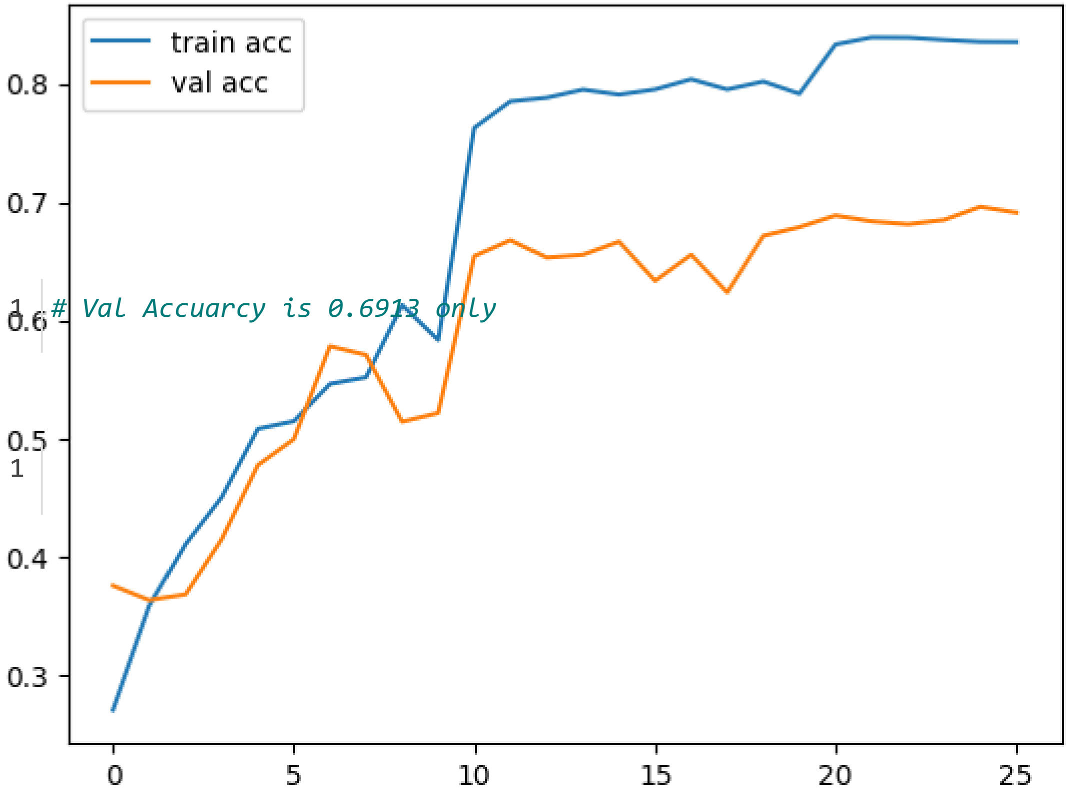
```
Epoch 1/50
179/179 [==============================] - 210s 1s/step - loss: 2.6638 -
accuracy: 0.2701 - val_loss: 2.0943 - val_accuracy: 0.3752
Epoch 2/50
179/179 [==============================] - 226s 1s/step - loss: 2.0530 -
accuracy: 0.3582 - val_loss: 1.9982 - val_accuracy: 0.3629
Epoch 3/50
179/179 [==============================] - 205s 1s/step - loss: 1.8957 -
accuracy: 0.4103 - val_loss: 2.2804 - val_accuracy: 0.3678
Epoch 4/50
179/179 [==============================] - 203s 1s/step - loss: 1.7882 -
accuracy: 0.4502 - val_loss: 2.0547 - val_accuracy: 0.4145
Epoch 5/50
179/179 [==============================] - 207s 1s/step - loss: 1.4617 -
accuracy: 0.5081 - val_loss: 1.6201 - val_accuracy: 0.4772
Epoch 6/50
179/179 [==============================] - 207s 1s/step - loss: 1.5643 -
accuracy: 0.5146 - val_loss: 1.5920 - val_accuracy: 0.4994
Epoch 7/50
179/179 [==============================] - 203s 1s/step - loss: 1.3692 -
accuracy: 0.5462 - val_loss: 1.3316 - val_accuracy: 0.5781
Epoch 8/50
179/179 [==============================] - 209s 1s/step - loss: 1.4686 -
accuracy: 0.5518 - val_loss: 1.3376 - val_accuracy: 0.5707
Epoch 9/50
179/179 [==============================] - 227s 1s/step - loss: 1.1293 -
accuracy: 0.6130 - val_loss: 1.4761 - val_accuracy: 0.5141
Epoch 10/50
179/179 [==============================] - 221s 1s/step - loss: 1.2427 -
accuracy: 0.5834 - val_loss: 1.9673 - val_accuracy: 0.5215
Epoch 11/50
179/179 [==============================] - 220s 1s/step - loss: 0.7200 -
accuracy: 0.7624 - val_loss: 1.1035 - val_accuracy: 0.6544
Epoch 12/50
179/179 [==============================] - 219s 1s/step - loss: 0.6712 -
accuracy: 0.7848 - val_loss: 1.0814 - val_accuracy: 0.6679
Epoch 13/50
179/179 [==============================] - 218s 1s/step - loss: 0.6654 -
accuracy: 0.7880 - val_loss: 1.0721 - val_accuracy: 0.6531
Epoch 14/50
179/179 [==============================] - 217s 1s/step - loss: 0.6607 -
accuracy: 0.7948 - val_loss: 1.1252 - val_accuracy: 0.6556
Epoch 15/50
179/179 [==============================] - 217s 1s/step - loss: 0.6600 -
accuracy: 0.7906 - val_loss: 1.0647 - val_accuracy: 0.6667
Epoch 16/50
179/179 [==============================] - 216s 1s/step - loss: 0.6472 -
accuracy: 0.7950 - val_loss: 1.1569 - val_accuracy: 0.6335
Epoch 17/50
179/179 [==============================] - 216s 1s/step - loss: 0.6460 -
accuracy: 0.8036 - val_loss: 1.0726 - val_accuracy: 0.6556
Epoch 18/50
179/179 [==============================] - 211s 1s/step - loss: 0.6467 -
accuracy: 0.7950 - val_loss: 1.1633 - val_accuracy: 0.6236
Epoch 19/50
179/179 [==============================] - 223s 1s/step - loss: 0.6380 -
accuracy: 0.8017 - val_loss: 1.0764 - val_accuracy: 0.6716
Epoch 20/50
179/179 [==============================] - 224s 1s/step - loss: 0.6555 -
accuracy: 0.7913 - val_loss: 1.0393 - val_accuracy: 0.6790
Epoch 21/50
```

```
179/179 [==============================] - 220s 1s/step - loss: 0.5938 -
accuracy: 0.8331 - val_loss: 1.0051 - val_accuracy: 0.6888
Epoch 22/50
179/179 [==============================] - 234s 1s/step - loss: 0.5909 -
accuracy: 0.8391 - val_loss: 1.0115 - val_accuracy: 0.6839
Epoch 23/50
179/179 [==============================] - 222s 1s/step - loss: 0.5912 -
accuracy: 0.8389 - val_loss: 1.0268 - val_accuracy: 0.6814
Epoch 24/50
179/179 [==============================] - 224s 1s/step - loss: 0.5891 -
accuracy: 0.8370 - val_loss: 1.0250 - val_accuracy: 0.6851
Epoch 25/50
179/179 [==============================] - 215s 1s/step - loss: 0.5903 -
accuracy: 0.8354 - val_loss: 1.0170 - val_accuracy: 0.6962
Epoch 26/50
179/179 [==============================] - 220s 1s/step - loss: 0.5888 -
accuracy: 0.8352 - val_loss: 1.0156 - val_accuracy: 0.6913
```

In [43]:

```
# plot the loss
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')

# plot the accuracy
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('AccVal_acc')
```






```
<Figure size 640x480 with 0 Axes>
```

```
1 # Val Accuarcy is 0.6913 only
```

```
1
```

In [45]:

```
# Define the image size, batch size, and other hyperparameters
IMAGE_SIZE = (224, 224)
BATCH_SIZE = 32
EPOCHS = 50

# Define early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weight

# Create a data generator with aggressive data augmentation for training
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=30,       # Increased rotation range
    width_shift_range=0.3,   # Increased width shift range
    height_shift_range=0.3,  # Increased height shift range
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

# Create a data generator for validation (no augmentation)
validation_datagen = ImageDataGenerator(rescale=1./255)

# Load and prepare the training data
train_generator = train_datagen.flow_from_directory(
    'balanced_train_dir',
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)

# Load and prepare the validation data
validation_generator = validation_datagen.flow_from_directory(
    'test',
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)

```

```
Found 5698 images belonging to 7 classes.
Found 813 images belonging to 7 classes.
```

In [50]:

```

# Load the pre-trained ResNet50 model
resnet = ResNet50(input_shape=IMAGE_SIZE + (3,), weights='imagenet', include_top=Fa

# Fine-tune some of the later layers of the ResNet50 base
for layer in resnet.layers[:-10]:  # Fine-tuning last 10 layers
    layer.trainable = True

# Add custom classification layers with dropout
x = Flatten()(resnet.output)
x = Dropout(0.5)(x)  # Added dropout layer
predictions = Dense(len(train_generator.class_indices), activation='softmax')(x)

# Create the model
model = Model(inputs=resnet.input, outputs=predictions)

# Compile the model with a lower learning rate
model.compile(
    loss='categorical_crossentropy',
    optimizer=Adam(lr=0.0001),  # Adjusted learning rate
    metrics=['accuracy']
)

```

In [51]:

```
# Train the model with increased batch size
history = model.fit(
    train_generator,
    epochs=EPOCHS,
    steps_per_epoch=len(train_generator),
    validation_data=validation_generator,
    validation_steps=len(validation_generator),
    callbacks=[LearningRateScheduler(lr_schedule), early_stopping]
)
```

```
Epoch 1/50
179/179 [==============================] - 942s 5s/step - loss: 5.3101
- accuracy: 0.1837 - val_loss: 206.5125 - val_accuracy: 0.0923
Epoch 2/50
179/179 [==============================] - 934s 5s/step - loss: 2.2589
- accuracy: 0.1859 - val_loss: 3.1113 - val_accuracy: 0.0923
Epoch 3/50
179/179 [==============================] - 914s 5s/step - loss: 1.8233
- accuracy: 0.2676 - val_loss: 2.1553 - val_accuracy: 0.0923
Epoch 4/50
179/179 [==============================] - 918s 5s/step - loss: 1.7083
- accuracy: 0.3314 - val_loss: 3.2394 - val_accuracy: 0.0923
Epoch 5/50
179/179 [==============================] - 939s 5s/step - loss: 1.5959
- accuracy: 0.4053 - val_loss: 3.3886 - val_accuracy: 0.0824
Epoch 6/50
179/179 [==============================] - 966s 5s/step - loss: 1.4248
- accuracy: 0.4771 - val_loss: 1.6765 - val_accuracy: 0.3444
Epoch 7/50
```

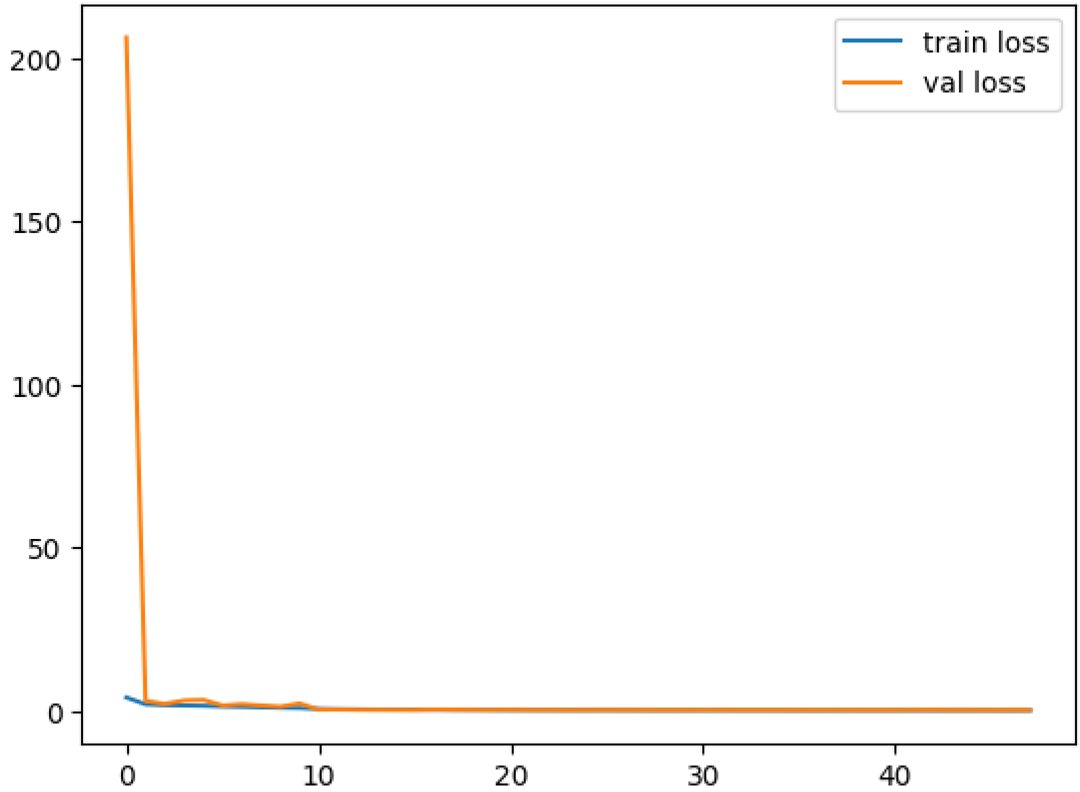
In [52]:

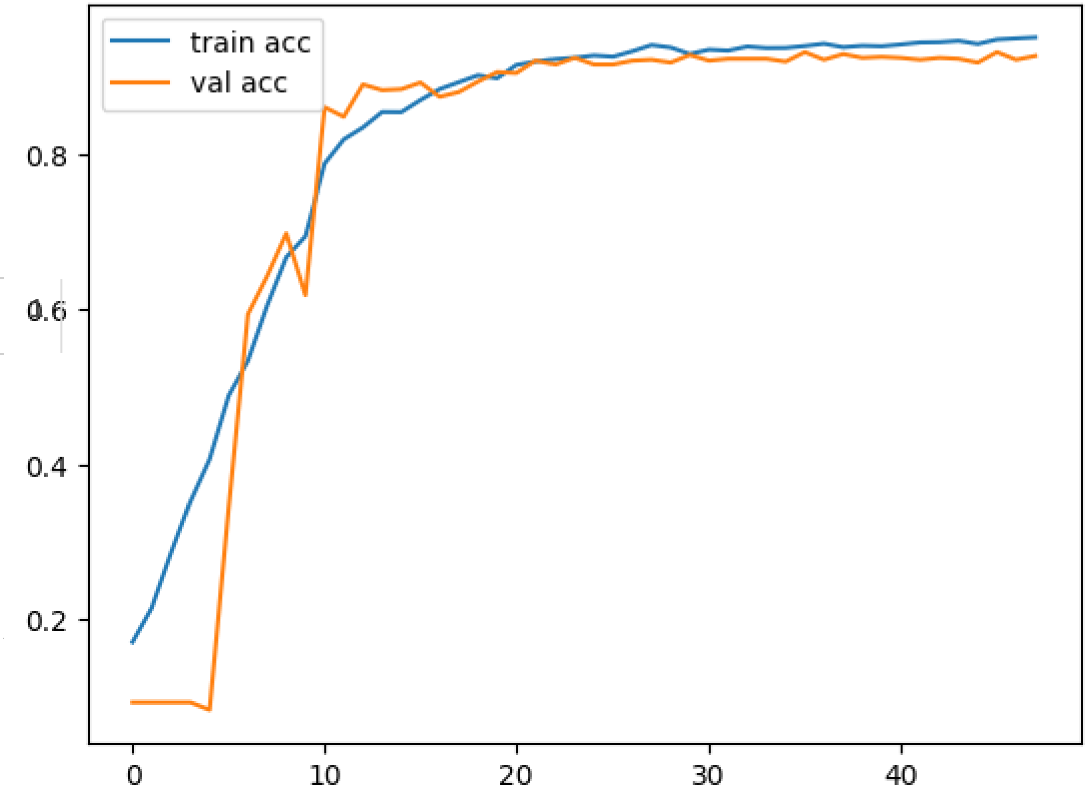
```
# save it as a h5 file


from tensorflow.keras.models import load_model

model.save('model_resnet50.h5')
```

Plotting the accuracy and loss curves

In [81]:

```
# plot the loss
plt.plot(history.history['loss'], label='train loss')
plt.plot(history.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')

# plot the accuracy
plt.plot(history.history['accuracy'], label='train acc')
plt.plot(history.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('AccVal_acc')
```





hat measures the
used for multi-

It measures the
ercentage of

```
<Figure size 640x480 with 0 Axes>
```

These accuracy values are an indication of how well the model is performing on the classification task. The higher the accuracy, the better the model is at correctly classifying car images. It's important to look at both training and validation accuracy to assess whether the model is overfitting (i.e., performing well on the training data but poorly on unseen data).

the validation accuracy is close to the training accuracy, suggesting that the model is generalizing well to unseen data.

To summarize, the model is performing well on the classification task, achieving an accuracy of around 92-94% on both the training and validation datasets.

In [ ]:

```
#Predications test data
```

In [54]:

```

y_pred = model.predict(test_set)

```

In [55]:

```
y_pred
```

Out[55]:

```
array([[4.9484480e-04, 1.6264601e-05, 4.9876604e-08, ..., 4.3519353e-07,
        1.8654418e-08, 9.9948823e-01],
       [9.9923325e-01, 3.1886596e-08, 1.6346821e-05, ..., 1.4597697e-07,
        1.2856311e-06, 1.6910975e-06],
       [9.0483147e-05, 1.0181155e-04, 9.9973267e-01, ..., 5.3417116e-06,
        1.3362401e-05, 4.4991310e-05],
       ...,
       [1.8275303e-09, 2.7658618e-09, 1.4352742e-13, ..., 1.0000000e+00,
        1.0588677e-10, 5.7752483e-09],
       [8.6054235e-05, 4.1282263e-05, 9.6249998e-08, ..., 9.3085415e-05,
        9.9977869e-01, 1.6830202e-07],
       [3.0426646e-03, 1.5796209e-09, 2.5382731e-06, ..., 5.1020194e-08,
        7.3144967e-08, 1.0517252e-08]], dtype=float32)
```

In [56]:

```
import numpy as np
y_pred = np.argmax(y_pred, axis=1)
```

In [57]:

```
y_pred
```

Out[57]:

```
array([6, 0, 2, 5, 0, 1, 6, 3, 1, 0, 5, 0, 0, 1, 4, 5, 0, 6, 0, 0, 0, 6,
       0, 5, 3, 0, 0, 5, 6, 4, 3, 2, 1, 0, 0, 4, 3, 1, 0, 4, 4, 3, 1, 0,
       6, 0, 6, 1, 2, 0, 6, 1, 0, 6, 2, 0, 4, 0, 4, 6, 5, 2, 5, 6, 5, 0,
       0, 0, 6, 4, 3, 0, 2, 5, 2, 6, 0, 0, 2, 2, 6, 5, 2, 5, 4, 5, 6, 6,
       0, 3, 6, 5, 3, 0, 4, 0, 5, 1, 2, 5, 0, 6, 5, 4, 4, 0, 6, 0, 0, 4,
       0, 2, 6, 4, 0, 3, 4, 6, 5, 6, 0, 5, 1, 6, 0, 6, 0, 5, 0, 5, 3, 4,
       3, 3, 2, 6, 6, 0, 4, 3, 6, 0, 0, 0, 4, 1, 6, 5, 6, 0, 4, 4, 3, 4,
       3, 5, 6, 3, 5, 2, 5, 5, 5, 6, 0, 6, 0, 2, 4, 6, 5, 2, 6, 3, 0, 5,
       3, 6, 0, 5, 0, 3, 6, 6, 6, 6, 0, 6, 5, 0, 4, 6, 4, 6, 3, 2, 0, 5,
       0, 6, 6, 6, 5, 4, 4, 6, 6, 6, 0, 6, 4, 0, 4, 6, 5, 5, 6, 0, 0, 4,
       0, 3, 0, 0, 3, 5, 5, 3, 5, 6, 6, 0, 6, 2, 1, 4, 0, 4, 6, 6, 6, 3,
       2, 6, 0, 6, 6, 5, 2, 0, 0, 6, 0, 6, 6, 3, 3, 0, 0, 2, 3, 0, 6, 5,
       2, 4, 3, 0, 6, 1, 0, 6, 5, 6, 0, 0, 4, 6, 2, 3, 5, 0, 6, 4, 0, 2,
       5, 4, 0, 3, 1, 0, 6, 0, 1, 0, 3, 2, 2, 1, 4, 5, 6, 5, 6, 0, 3, 6,
       5, 6, 4, 2, 5, 0, 0, 2, 4, 0, 6, 3, 3, 0, 3, 2, 4, 1, 0, 5, 0, 4,
       4, 6, 6, 3, 6, 0, 6, 1, 6, 0, 4, 0, 3, 0, 4, 6, 0, 6, 3, 6, 3, 0,
       2, 0, 6, 0, 5, 0, 6, 2, 0, 6, 0, 6, 0, 1, 2, 3, 5, 3, 1, 0, 6, 6,
       6, 2, 4, 4, 6, 5, 0, 6, 4, 2, 0, 0, 0, 1, 6, 5, 6, 5, 0, 6, 0, 6,
       2, 5, 0, 4, 5, 5, 0, 6, 6, 3, 5, 5, 6, 0, 0, 5, 3, 5, 0, 2, 2, 4,
       6, 4, 0, 0, 5, 4, 4, 6, 2, 0, 6, 5, 5, 0, 4, 2, 2, 4, 3, 6, 4, 2,
       1, 4, 0, 2, 0, 0, 6, 0, 6, 4, 0, 4, 0, 2, 0, 6, 6, 2, 4, 6, 6, 1,
       5, 1, 0, 0, 5, 1, 2, 3, 5, 6, 5, 1, 3, 4, 6, 6, 4, 5, 0, 0, 6, 2,
       0, 3, 0, 0, 1, 0, 6, 6, 0, 6, 2, 0, 3, 6, 5, 5, 3, 3, 6, 5, 5, 6,
       5, 6, 0, 0, 0, 4, 2, 6, 0, 0, 4, 4, 1, 2, 5, 4, 0, 3, 1, 0, 3, 0,
       3, 5, 1, 0, 5, 3, 5, 3, 6, 3, 1, 0, 6, 5, 0, 1, 6, 6, 6, 6, 4, 6,
       2, 5, 0, 1, 6, 0, 0, 1, 3, 0, 0, 0, 0, 1, 6, 2, 6, 6, 5, 0, 5, 4,
       0, 4, 2, 5, 5, 1, 3, 0, 6, 5, 2, 6, 6, 6, 6, 0, 6, 0, 5, 0, 6, 5,
       2, 0, 5, 6, 6, 6, 6, 1, 0, 6, 0, 6, 0, 0, 3, 4, 0, 6, 5, 6, 6, 2,
       0, 3, 6, 1, 6, 4, 5, 0, 5, 2, 0, 6, 4, 6, 0, 4, 3, 1, 0, 1, 5, 0,
       6, 2, 0, 6, 5, 4, 2, 0, 3, 1, 1, 0, 6, 5, 6, 0, 6, 5, 0, 4, 1, 2,
       0, 6, 0, 0, 5, 0, 6, 4, 4, 6, 0, 0, 4, 0, 4, 6, 0, 0, 4, 0, 0, 6,
       0, 6, 1, 3, 5, 0, 0, 6, 4, 1, 5, 6, 0, 2, 6, 0, 0, 2, 0, 4, 6, 3,
       4, 5, 0, 6, 4, 1, 6, 6, 4, 6, 3, 6, 4, 6, 2, 0, 3, 0, 1, 6, 2, 5,
       6, 1, 5, 3, 0, 0, 1, 0, 6, 1, 5, 5, 6, 4, 0, 0, 3, 6, 6, 6, 6, 6,
       0, 6, 4, 0, 5, 0, 1, 5, 0, 6, 1, 2, 4, 6, 6, 3, 2, 3, 0, 0, 6, 0,
       4, 4, 3, 4, 6, 4, 0, 0, 0, 3, 1, 3, 5, 0, 3, 4, 1, 5, 5, 0, 6, 6,
       4, 3, 4, 3, 6, 0, 0, 4, 4, 6, 0, 5, 0, 5, 5, 4, 2, 3, 4, 5, 3])
```

In [ ]:

```
#testing the model
```

In [4]:

```
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
```

In [5]:

```
model=load_model('model_resnet50.h5')
```

In [6]:

```
model
```

Out[6]:

```
<keras.engine.functional.Functional at 0x1f47750bc40>
```

In [51]:

```
img=image.load_img('test/Audi/23.jpg',target_size=(224,224))


```

In [55]:

```
x=image.img_to_array(img)

```

In [56]:

```
x.shape
```

Out[56]:

```
(224, 224, 3)
```

In [57]:

```
x=x/255
```

In [47]:

```
x=np.expand_dims(x,axis=0)
#img_data=preprocess_input(x)
img_data.shape
```

Out[47]:

```
(1, 224, 224, 3)
```

In [60]:

```
preds =model.predict(img_data)
```

```
1/1 [==============================] - 0s 166ms/step
```

In [61]:

```
a=np.argmax(model.predict(img_data), axis=1)
```

```
1/1 [==============================] - 0s 222ms/step
```

In [62]:

```
preds=np.argmax(preds, axis=1)
```

In [65]:

```
preds
```

Out[65]:

```
array([2], dtype=int64)
```

In [77]:

```
#COnverting the model to tensorflow lite for mobile app
```

In [ ]:

```
#b. Mobil app model
```

In [73]:

```
import tensorflow as tf
from tensorflow.keras.models import load_model

# load the best saved model from our last training
myModel = load_model('model_resnet50.h5')
```

In [74]:

```
# create a TFLiteConverter object from a TensorFlow Keras model
converter = tf.lite.TFLiteConverter.from_keras_model(myModel)

# converts a Keras model based on instance variable
myModel_tflite = converter.convert()
```

```
WARNING:absl:Found untraced functions such as _jit_compiled_convolution_o
p, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compi
led_convolution_op, _jit_compiled_convolution_op while saving (showing 5
of 53). These functions will not be directly callable after loading.
```

```
INFO:tensorflow:Assets written to: C:\Users\hbolla\AppData\Local\Temp\tmp
4bq81o_w\assets
```



```
INFO:tensorflow:Assets written to: C:\Users\hbolla\AppData\Local\Temp\tmp
4bq81o_w\assets
```

In [75]:

```
from pathlib import Path

# Save the model
tflite_model_file = Path('car_model_classifier.tflite')
tflite_model_file.write_bytes(myModel_tflite)

# with tf.io.gfile.GFile('clothing_classifier.tflite', mode='wb') as file:
#     file.write(myModel_tflite)
```

Out[75]:

96780488

By Harsha Teja

In [ ]:

```

```