

Car Model Prediction Using Deep Learning

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Abstract: In today's globe, there are numerous car models to choose from. We are utilising deep learning algorithms to anticipate the various car models. Deep learning has been demonstrated to be a successful method for increasing the precision of model prediction in a certain set of data. For the prediction of a picture, we use a deep learning technique with various parameters including image size and the quantity of images in data sets. The goal of this research is to create a reliable and effective method for predicting car models. For each new task at hand, we create a model in classical (machine) learning and train it on fresh data. Transfer learning is being used in this project, which is different from that transferring information from one work to another is the approach. With the aid of transfer learning, we can complete a task utilising all or a portion of a model that has already been trained for a separate job. ResNet is a deep learning model that is employed in computer vision applications. It is a convolutional neural network (CNN), which is mostly used for image processing, pattern recognition, and other related tasks. This study seeks to resolve this problem by enhancing the projected model's accuracy through the use of deep learning techniques. The project uses oversampling, undersampling, and hybrid sampling approaches, among other strategies, to deal with unbalanced datasets. The project's findings demonstrate that the deep learning-based method that has been suggested is quite good at predicting car models.

I.INTRODUCTION

The classification of car models is a crucial activity in the automobile industry with numerous uses, including surveillance, traffic control, and car design. Hand-crafted features and rule-based classification algorithms, which can be time-

consuming and may not be capable of identifying complicated aspects, are used in traditional ways of classifying car models. By automatically extracting characteristics from the raw input data, deep learning-based algorithms have demonstrated promising results in the classification of car model types. Things in the image are simple to recognise and analyse by people. Humans have a quick, accurate visual system that is capable of complex tasks like object recognition and obstacle recognition. However, one of the biggest challenges in computer vision is object recognition because we shouldn't just concentrate on categorising various images also correctly identify the car model in each image. Recent years have seen the development of sophisticated deep learning models like CNN. In comparison to conventional classification approaches, CNN demonstrate significant differences. Without the need for manual design, effective representations of car models are possible thanks to expressiveness and reliable training techniques. However, it might be challenging to identify models due of the wide variations in types, poses, occlusions, and lighting. In this project, we demonstrate how algorithmic change that generates a deep network performance map results in a complex and successful solution.

LITERATURE REVIEW

The goal of this literature review is to present an overview of the methods and research that have been done so far in order to anticipate automobile models. The difficult task of predicting car models from their outside look has received a lot of attention lately. The primary strategies, datasets, evaluation criteria, and difficulties encountered in this field are outlined in this survey. The results of this literature review will be used as a starting point for the creation of a precise and trustworthy system for automobile model prediction.

Introduction

Overview of automotive model prediction and its uses
The significance and difficulties of predicting car models

Goals of the Literature Review

Techniques for Predicting Car Models

Deep Learning Methodologies

- Transfer Learning, Convolutional Neural Networks (CNNs), and Pretrained Models
GANs, or generative adversarial networks
Recurrent neural networks and autoencoders.

2.2 Conventional Approaches to Computer Vision

- Shape-based Methods and Feature Extraction and Matching

Template matching and Bag-of-Words models (BoW)

Datasets for Predicting Car Models

Overview of datasets that are freely accessible

Dataset CARPK

Stanford Vehicle Database

Dataset for CompCars

Dataset for Vehicle Recognition in the Wild (VIRAT)

II. PROBLEM STATEMENT

To create a model that can correctly recognise a car's make and model from an input photograph. The classification of cars from various angles and perspectives should be correct regardless of changes in background, illumination, and angle.

-The objective is to create a model that may be applied in practical settings, such as security applications or autonomous car identification systems.

-The model's accuracy should be sufficient to guarantee consistent performance in these applications and its efficiency sufficient to support real-time processing.

III. METHODOLOGY

The identification of automobile models is the

main focus of this investigation. To identify car models, the segmentation, attribute extraction, and classification procedures are employed. A digital camera or similar device is used to capture pictures of automobiles from various angles, and the images are then utilised to classify the afflicted region in the cars. In the suggested design, a Convolutional neural network is used to determine the automobile model. In order to accurately identify car models, this study suggests an architecture that makes use of open-source, inexpensive software.

Convolutional Neural Network, version 1.1

A type of neural network known as a convolutional neural network specialises in processing data with a grid-like architecture. A binary representation of visual data is a digital image. It includes a sequence of pixels arranged in a grid-like pattern, with pixel values indicating the brightness and colour of each pixel. A Deep Learning classification system called a convolutional neural network takes an image as input, extracts the features, and ranks the significance of the various objects in the image.

Keras Layer 1.2

The layer is the cornerstone of Keras models. Each layer receives data from the previous layer, processes it, and then outputs the new information. The input for the subsequent layer will be the output of the previous layer.

1.3 Remove Layer

A flatten layer is used to flatten the input. Flatten deploys the subsequent `defence.keras.layers.data format=None;flatten;`

1.4 Dense Layer

The dense layer, which has numerous connections, is the typical layer of a neural network. It is the most often and widely used layer. Dense layer processes the input and then returns the outcome of the action underneath.

output is equal to activation ($\text{dot}(\text{input}, \text{kernel})$ plus bias).

Dropout Layer 1.5

Dropout is a fundamental concept in machine

learning. To solve the overfitting issue, it is used. The undesired information that is sometimes referred to as noise may be present in the input data. In order to prevent overfitting the model, Dropout will make an effort to omit the noisy data. The following are Dropout's three main countermeasures. keras.layers.Dropout (rate, None for the noise_shape, and No seed)

1.6 Vehicle Dataset

Models of cars are shown in the photographs in this dataset. Depending on the manufacturer, the photos are divided into three classes: Audi, Mercedes, and Lamborghini.

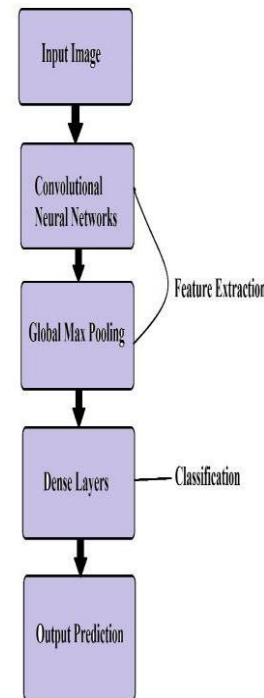
Image Segmentation (1.7)

A collection of various pixels make up a photograph. We use picture segmentation to group several pixels with similar characteristics. The process of filtering or classifying a database of images into instructions, subsets, or regions based on specific functions or attributes is known as image segmentation. Each object in the image receives a pixel-detailed mask thanks to image segmentation. This approach provides us with a far more detailed understanding of the object(s) in the picture.

Sample dataset in Figure 1

Feature Extraction: 1.8

The process of transforming raw data into numerical functions that can be handled while preserving the information in the original data set is known as feature extraction. It produces better results than using equipment to learn the raw data right away.



IV. EXPERIMENTAL RESULTS

1.1 Datasets for training and validation

64 RGB photos of three different automobiles—Audi, Mercedes, and Lamborghini—were examined. It is advised to use validation data while choosing the best hyper-parameters to avoid overfitting the model.

Model Summary 1.2

Building a CNN model with Keras, Flatten, Dense, and Dropout layers, as shown in Figure 2.

```

Epoch 1/50
1/1 [====] - 2s 2s/step - loss: 1.0024 - accuracy: 0.5625
Epoch 2/50
1/1 [====] - 2s 2s/step - loss: 0.9556 - accuracy: 0.5312
Epoch 3/50
1/1 [====] - 2s 2s/step - loss: 0.9353 - accuracy: 0.5938
Epoch 4/50
1/1 [====] - 2s 2s/step - loss: 0.8992 - accuracy: 0.5938
Epoch 5/50
1/1 [====] - 2s 2s/step - loss: 0.8590 - accuracy: 0.6250
Epoch 6/50
1/1 [====] - 2s 2s/step - loss: 1.0388 - accuracy: 0.5625
Epoch 7/50
1/1 [====] - 2s 2s/step - loss: 1.1175 - accuracy: 0.4375
Epoch 8/50
1/1 [====] - 2s 2s/step - loss: 0.9158 - accuracy: 0.4688
Epoch 9/50
1/1 [====] - 2s 2s/step - loss: 0.8983 - accuracy: 0.5938
Epoch 10/50
1/1 [====] - 2s 2s/step - loss: 0.9680 - accuracy: 0.5312
Epoch 11/50
1/1 [====] - 2s 2s/step - loss: 0.8519 - accuracy: 0.5625
Epoch 12/50
1/1 [====] - 2s 2s/step - loss: 0.8564 - accuracy: 0.5625
Epoch 13/50
1/1 [====] - 2s 2s/step - loss: 0.8801 - accuracy: 0.5312
Epoch 14/50
1/1 [====] - 2s 2s/step - loss: 0.8378 - accuracy: 0.5625
Epoch 15/50
1/1 [====] - 2s 2s/step - loss: 0.8176 - accuracy: 0.5625
Epoch 16/50
1/1 [====] - 2s 2s/step - loss: 0.8129 - accuracy: 0.5938
Epoch 17/50
1/1 [====] - 2s 2s/step - loss: 0.8639 - accuracy: 0.5625
Epoch 18/50
1/1 [====] - 2s 2s/step - loss: 0.7993 - accuracy: 0.6250
Epoch 19/50
1/1 [====] - 2s 2s/step - loss: 0.7686 - accuracy: 0.7188
Epoch 20/50
1/1 [====] - 2s 2s/step - loss: 0.7470 - accuracy: 0.6875
Epoch 21/50
1/1 [====] - 2s 2s/step - loss: 0.7925 - accuracy: 0.7812
Epoch 22/50
1/1 [====] - 2s 2s/step - loss: 0.7334 - accuracy: 0.5938
Epoch 23/50
1/1 [====] - 2s 2s/step - loss: 0.6485 - accuracy: 0.7500
Epoch 24/50
1/1 [====] - 2s 2s/step - loss: 0.6936 - accuracy: 0.6250
Epoch 25/50
1/1 [====] - 2s 2s/step - loss: 0.6788 - accuracy: 0.6875
Epoch 26/50
1/1 [====] - 2s 2s/step - loss: 0.6661 - accuracy: 0.7812
Epoch 27/50
1/1 [====] - 2s 2s/step - loss: 0.6273 - accuracy: 0.6250
Epoch 28/50
1/1 [====] - 2s 2s/step - loss: 0.6163 - accuracy: 0.6562
Epoch 29/50
1/1 [====] - 2s 2s/step - loss: 0.5836 - accuracy: 0.8125
Epoch 30/50
1/1 [====] - 2s 2s/step - loss: 0.4388 - accuracy: 0.9862
Epoch 31/50
1/1 [====] - 2s 2s/step - loss: 0.5272 - accuracy: 0.7500
Epoch 32/50
1/1 [====] - 2s 2s/step - loss: 0.6167 - accuracy: 0.7188
Epoch 33/50
1/1 [====] - 2s 2s/step - loss: 0.6759 - accuracy: 0.6562
Epoch 34/50
1/1 [====] - 2s 2s/step - loss: 0.5850 - accuracy: 0.7188
Epoch 35/50
1/1 [====] - 2s 2s/step - loss: 0.7373 - accuracy: 0.6875
Epoch 36/50
1/1 [====] - 2s 2s/step - loss: 0.3538 - accuracy: 0.9862
Epoch 37/50
1/1 [====] - 2s 2s/step - loss: 0.5376 - accuracy: 0.7812
Epoch 38/50
1/1 [====] - 2s 2s/step - loss: 0.5462 - accuracy: 0.7500
Epoch 39/50
1/1 [====] - 2s 2s/step - loss: 0.4490 - accuracy: 0.8125
Epoch 40/50
1/1 [====] - 2s 2s/step - loss: 0.3857 - accuracy: 0.8375
  
```

```
second image to predict
actual label: lamborghini
1/1 [=====] - 0s 500ms/step
predicted label: audi
```



```
first image to predict
actual label: audi
1/1 [=====] - 1s 742ms/step
predicted label: audi
```



Figure -3: Examples of Results

A few instances of incorrectly classified photos discovered by our CNN-based model are shown in Figure 3.

Graphs in Figure -4

1.3 Epochs' impact

The CNN model is trained using the first 50 epochs. Since there have been no additional gains

in training and validation accuracy, epoch 50 is the best optimised one. Figure -4 shows the 93% accuracy as a result of the training and validation accuracies and losses.

V. CONCLUSION

To summarise, the task of classifying cars into several models based on their features and requirements is known as car model classification. We can automate the process of accurately recognising and classifying cars by putting the proposed method for car model classification into practise. Data collection, preprocessing, feature extraction, model training, evaluation, fine-tuning, deployment, and maintenance are just a few of the processes that this system entails.

We can create a machine learning model that learns the patterns and traits of several car models from a large dataset by employing this methodical approach. Using the discovered patterns, the model may then forecast the automobile model from new, unforeseen data. The quality of the dataset, the selection of pertinent features, and the choice of an appropriate algorithm all affect the accuracy and performance of the system. A suitable machine learning algorithm must be used, and the model's hyperparameters must be adjusted.

Implementing a system for categorising automobile models can be useful for a variety of practical reasons, including simplifying online car marketplaces, helping car valuation procedures, assisting with inventory management, and promoting automotive research and development.

However, as the automotive industry develops, it is crucial to consistently update and maintain the system to include new car models and specs. The model will need to be regularly updated and improved, and its performance will be tracked to assure the system's accuracy and dependability over time.

Overall, a well-designed system for categorising car models can offer the automotive sector useful insights and automation, reducing procedures and improving decision-making about car models.

VI. REFERENCES

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