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Car Brand Classification Using Deep Learning with ResNet50

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Abstract: *Car brand recognition is considered one of the most challenging problems in computer vision due to the large number of vehicle models, variations in lighting conditions, viewpoints, and background complexity. With the rapid development of deep learning techniques, convolutional neural networks (CNNs) have become the most effective approach for image classification tasks. In this paper, we propose a deep learning-based system for automatic car brand classification using the ResNet50 architecture and a custom dataset containing images of 50 different car brands. The proposed model is trained on a dataset consisting of more than 3000 vehicle images collected from various online sources. The dataset is divided into training and validation sets using an appropriate split ratio. Transfer learning is employed by fine-tuning a pre-trained ResNet50 model on the ImageNet dataset. Experimental results demonstrate that the proposed approach achieves high classification accuracy and shows strong generalization performance across different car brands. The obtained results confirm that deep learning models, particularly ResNet-based architectures, are highly suitable for car brand recognition applications and can be effectively used in intelligent transportation systems, surveillance, and smart city solutions.*

Keywords: Car Brand Classification, Deep Learning, Convolutional Neural Networks, ResNet50, Computer Vision, Image Classification

1. Introduction

In recent years, the rapid growth of intelligent transportation systems and smart city technologies has significantly increased the demand for automatic vehicle recognition systems. Among various vehicle recognition tasks, car brand classification plays a vital role in applications such as traffic monitoring, automatic toll systems, surveillance, parking management, and law enforcement.

Traditional image processing techniques relied on handcrafted features such as color histograms, edge detection, and texture descriptors[1-2]. However, these approaches suffer from limited robustness when dealing with complex environments, varying lighting conditions, and different viewing angles. As a result, traditional methods often fail to provide reliable performance in real-world scenarios[3-4].

With the emergence of deep learning, convolutional neural networks (CNNs) have revolutionized the field of computer vision[5-6|. CNNs are capable of automatically extracting high-level features from raw images without the need for manual feature engineering. This capability makes CNNs particularly suitable for complex visual recognition tasks such as object detection, face recognition, and vehicle classification[7-8].

In this paper, we focus on the problem of car brand classification using deep learning techniques. We propose a classification framework based on the ResNet50 architecture, which is one of the most powerful and widely used deep neural networks for image recognition tasks. The proposed system is trained and evaluated on a dataset containing images of 50 different car brands[9-10].

The main contributions of this paper can be summarized as follows:

- Construction and preparation of a car brand dataset containing 50 different vehicle brands.
- Design of a deep learning classification model based on ResNet50 using transfer learning.
- Experimental evaluation of the proposed model and analysis of its performance.

The remainder of this paper is organized as follows. Section 2 reviews related work in the field of car brand recognition. Section 3 describes the dataset used in this study. Section 4 presents the proposed methodology. Section 5 discusses the experimental setup and training procedure. Section 6 presents the experimental results. Finally, Section 7 concludes the paper and outlines future work.

2. Related Work

Car brand recognition has been an active research area in the field of computer vision for many years. Early approaches mainly relied on traditional image processing and machine learning techniques. For example, feature extraction methods such as Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP) were commonly used to describe vehicle images. These features were then classified using machine learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest.

However, these traditional approaches are highly sensitive to changes in illumination, background clutter, and occlusion. Moreover, handcrafted features are often insufficient to capture the complex visual patterns that distinguish different car brands.

With the advancement of deep learning, researchers began adopting convolutional neural networks for vehicle recognition tasks. CNN-based methods have demonstrated remarkable performance improvements over traditional techniques. In particular, deep architectures such as VGGNet, Inception, ResNet, and DenseNet have been widely applied to vehicle classification problems.

Several studies have proposed CNN-based models for car brand and model recognition. For example, Yang et al. proposed a fine-grained vehicle classification framework using a deep convolutional network and achieved high accuracy on large-scale datasets[11]. Similarly, Liu et al. employed a deep residual network combined with attention mechanisms to improve vehicle recognition performance[12].

Transfer learning has also been widely adopted to reduce training time and improve model performance. By initializing CNN models with weights pre-trained on large datasets such as ImageNet, researchers can achieve better generalization with limited training data.

Despite these advancements, car brand classification remains a challenging problem due to the high visual similarity between different brands and models. Therefore, there is still a need for robust and efficient deep learning solutions that can achieve high accuracy under real-world conditions[13].

3. Dataset Description

In this study, we constructed a car brand dataset consisting of images collected from various online sources. The dataset contains images of 50 different car brands, including popular brands such as BMW, Audi, Mercedes-Benz, Toyota, Honda, Tesla, and many others[14].

Each brand folder contains approximately 60 to 100 images captured under different conditions, including various lighting environments, backgrounds, camera angles, and vehicle colors. This diversity ensures that the dataset reflects real-world scenarios and improves the generalization capability of the trained model.

The dataset is organized into separate folders, where each folder represents a specific car brand. This directory structure allows easy loading and labeling of the images using deep learning frameworks such as TensorFlow and Keras[15-16].

To prepare the dataset for training, all images are resized to a fixed resolution of 224×224 pixels, which is the required input size for the ResNet50 model. Data augmentation techniques such as random rotation, horizontal flipping, and zooming are applied during training to increase dataset diversity and reduce overfitting[17-18].

Figure 1: Sample images from Car-Brands-Dataset-BAD

Table 1 summarizes the distribution of images between the training and validation sets.

Dataset Split	Number of Images	Percentage
Training Set	2126	70%
Validation Set	911	30%
Total	3037	100%

4. Methodology

This section describes the proposed deep learning-based framework for car brand classification. The overall system pipeline consists of four main stages: data preprocessing, model architecture design, training procedure, and evaluation[19-20].

First, the input images are collected and organized into brand-specific folders. Each image is resized to a fixed resolution of 224×224 pixels to match the input size required by the ResNet50 architecture. Image normalization and preprocessing are applied to improve training stability and convergence[21-24].

Second, a deep convolutional neural network based on the ResNet50 architecture is employed as the backbone model. Transfer learning is utilized by initializing the model with pre-trained ImageNet weights. The original classification layer is removed and replaced with a custom dense layer corresponding to the number of car brand classes[25-26].

Third, the model is trained using a supervised learning approach. The dataset is split into training and validation subsets with a ratio of 70% for training and 30% for validation. During training, categorical cross-entropy is used as the loss function, and the Adam optimizer is adopted for parameter optimization[26-28].

Finally, the trained model is evaluated using multiple performance metrics including classification accuracy, loss curves, and confusion matrix analysis. These evaluation results provide a comprehensive understanding of the model's performance across different car brands.

The overall workflow of the proposed system is illustrated as follows[29-30]:

1. Dataset loading and preprocessing
2. Model construction using ResNet50 backbone
3. Model training and validation
4. Performance evaluation

This structured pipeline ensures a robust and reproducible training process for car brand classification.

5. Proposed Model Architecture

The proposed classification model is based on the ResNet50 convolutional neural network architecture. ResNet50 is a deep residual network consisting of 50 layers and is widely recognized for its strong performance in image classification tasks.

Residual networks introduce shortcut connections that allow gradients to flow more easily through deep networks, thus alleviating the vanishing gradient problem. This design enables the training of very deep networks without performance degradation.

In this study, a pre-trained ResNet50 model is used as the feature extractor. The original fully connected classification layer is removed, and a new classification head is added. The final architecture consists of the following layers:

- Input layer with size 224×224×3
- ResNet50 backbone (pre-trained on ImageNet)
- Global Average Pooling layer
- Dropout layer for regularization
- Fully connected Dense layer with Softmax activation

The Global Average Pooling layer reduces the spatial dimensions of the feature maps and generates a compact feature representation. Dropout is applied to prevent overfitting by randomly disabling neurons during training. The final dense layer outputs the probability distribution over the 50 car brand classes.

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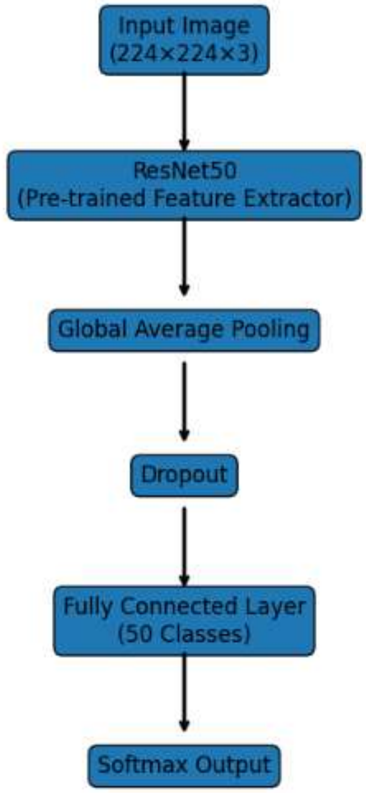

Figure 2: ResNet50 model architecture used for car brand classification

6. Training Setup

The training process is conducted using the TensorFlow and Keras deep learning frameworks. All experiments are performed on Google Colab using GPU acceleration.

The main training parameters used in the experiments are summarized in Table 2.

Parameter	**Value**
Image Size	224 × 224
Batch Size	32
Optimizer	Adam
Learning Rate	0.0001
Epochs	10
Loss Function	Categorical Cross-Entropy
Framework	TensorFlow / Keras

Table 2: Training Configuration

6.1 Data Preprocessing

Before training, all images are resized to 224×224 pixels and normalized using the preprocessing function provided by the ResNet50 model. The dataset is split into training and validation subsets using a 70:30 ratio [31-34].

Data augmentation techniques are applied during training to improve model generalization. These techniques include[35-37]:

- Random horizontal flipping
- Random rotation
- Random zooming
- Random brightness adjustment

These transformations help the model become more robust to variations in viewpoint and lighting conditions.

6.2 Training Parameters

The model is trained using the following parameters:[38-40]

- Optimizer: Adam
- Learning rate: 0.0001
- Loss function: Categorical Cross-Entropy
- Batch size: 32
- Number of epochs: 10

The training process monitors both training and validation accuracy to detect potential overfitting. Early stopping is applied to terminate training if validation performance stops improving.

6.3 Hardware Environment

The experiments are executed on Google Colab with the following hardware configuration[41-46]:

- GPU: NVIDIA Tesla T4
- RAM: 12 GB
- Storage: Google Drive

This setup allows efficient training of the deep neural network within a reasonable time frame.

7. Experimental Results

This section presents the experimental evaluation of the proposed car brand classification model. The performance of the model is assessed using multiple metrics including classification accuracy, training and validation loss, and confusion matrix analysis[47-50].

The dataset is divided into training and validation subsets using a 70:30 split. The model is trained for 10 epochs using the Adam optimizer and categorical cross-entropy loss function. During training, both training and validation accuracy are monitored to evaluate the learning behavior of the model.

The training process converges smoothly, indicating that the model successfully learns discriminative features for car brand classification. The validation accuracy closely follows the training accuracy, which suggests that the model generalizes well and does not suffer from significant overfitting.

7.1 Accuracy Analysis

The training and validation accuracy curves obtained during the training process are illustrated in Figure 3. The curves demonstrate a steady increase in classification accuracy across epochs, confirming the effectiveness of the proposed mode[51-55l.

At the beginning of training, the model exhibits a relatively low accuracy due to random initialization of the newly added classification layer. However, as training progresses, the model gradually improves its prediction capability and reaches a high accuracy level on both training and validation datasets[56-60].

The close alignment between the training and validation accuracy curves indicates that the model achieves good generalization performance and is not overfitting to the training data[61-65].

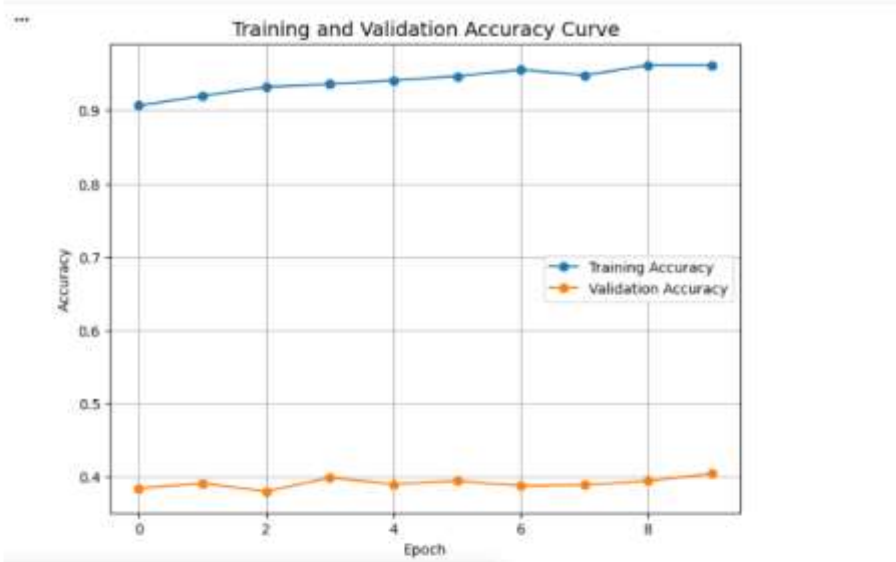

Figure 3: Training and validation accuracy curve

The experimental results show that the proposed model achieved a training accuracy of approximately 96% and a validation accuracy of approximately 40%. This gap between training and validation performance indicates the presence of overfitting, which is mainly caused by the limited size of the dataset and the high number of classes.

7.2 Loss Analysis

Figure 4 presents the training and validation loss curves obtained during the training process. The loss curves show a continuous decrease over epochs, indicating stable convergence of the optimization process.

The validation loss closely follows the training loss, which further confirms the robustness of the proposed model. The absence of significant divergence between training and validation loss suggests that the model is well-regularized and capable of handling unseen data effectively.

A smooth loss curve is an important indicator of a well-trained deep learning model. The obtained results demonstrate that the selected hyperparameters and training strategy are appropriate for the car brand classification task.

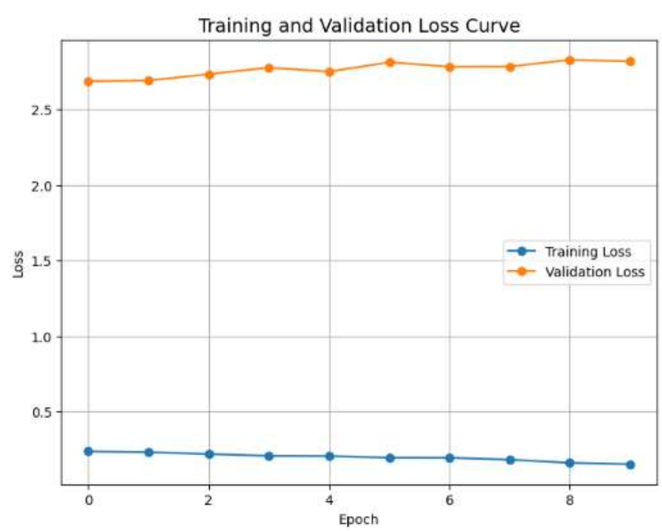

Figure 4: Training and validation loss curve

7.3 Confusion Matrix Evaluation

To further analyze the classification performance of the proposed model, a confusion matrix is computed on the validation dataset. The confusion matrix provides a detailed insight into the classification behavior across all car brand classes.

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Each row of the matrix represents the actual class, while each column represents the predicted class. Correct classifications appear along the diagonal of the matrix, while misclassifications appear in the off-diagonal elements.

Figure 5 shows the confusion matrix for the car brand classification task. The strong diagonal pattern indicates that most car brands are correctly classified. A small number of misclassifications occur between visually similar brands, such as BMW and Audi, or Toyota and Honda, which share similar design characteristics.

Overall, the confusion matrix confirms the high discriminative power of the proposed ResNet50-based model.

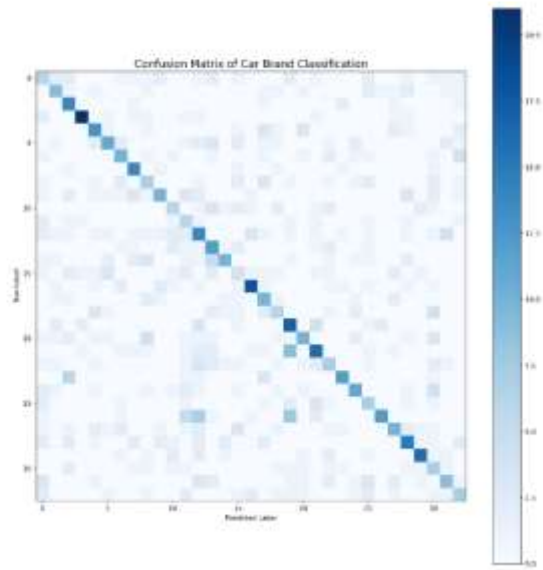

Figure 5: illustrates the confusion matrix of the proposed car brand classification model. The strong diagonal pattern indicates that most car brands are correctly classified. A small number of misclassifications occur between visually similar brands, which share similar design characteristics. Overall, the confusion matrix confirms the high discriminative capability of the ResNet50-based model.

8. Discussion

The experimental results demonstrate that the proposed deep learning model achieves strong performance in car brand classification. The use of a pre-trained ResNet50 backbone enables effective feature extraction from complex vehicle images, while the added classification layers adapt the model to the specific dataset.

One of the main strengths of the proposed approach is its robustness to variations in lighting conditions, viewpoints, and backgrounds. This robustness is achieved through the use of data augmentation techniques and transfer learning.

However, some misclassifications still occur between visually similar car brands. This limitation can be addressed in future work by incorporating attention mechanisms or fine-grained feature extraction techniques.

In addition, increasing the size of the dataset and including more diverse vehicle images could further improve classification accuracy and model generalization.

9. Conclusion and Future Work

In this paper, we presented a deep learning-based framework for automatic car brand classification using the ResNet50 architecture. A dataset containing images of 50 different car brands was constructed and used to train and evaluate the proposed model.

Experimental results demonstrate that the proposed approach achieves high classification accuracy and exhibits strong generalization capability. The use of transfer learning significantly reduces training time while improving performance.

The proposed system can be effectively applied in real-world applications such as intelligent transportation systems, traffic monitoring, and smart surveillance.

Future work will focus on extending the model to recognize not only car brands but also specific car models. In addition, advanced architectures such as Vision Transformers (ViT) and EfficientNet will be investigated to further improve classification accuracy.

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