### **Paper 1: Two decades of vehicle make and model recognition – Survey, challenges and future directions**

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#### **Main Purpose**

The main purpose of this survey is to review the progress of Vehicle Make and Model Recognition (VMMR) technologies over the past twenty years, highlighting the advancements, challenges, and future directions in the field. It aims to provide a comprehensive overview of existing methodologies and their application in real-world scenarios, such as traffic management and intelligent transportation systems.

#### **Dataset**

The article analyzes various datasets commonly used in VMMR research, emphasizing the need for larger and more diverse datasets. It highlights the Stanford Cars dataset and other publicly available datasets that support evaluating the accuracy and robustness of VMMR models.

#### **Methodology**

1. **Review and Analysis**:
   * Comprehensive analysis of machine learning and deep learning models applied to VMMR, including methods like CNNs and RNNs.
   * Comparison of model performances under varying conditions like lighting, weather, and camera angles.
   * Discussion of techniques for pre-training models using ImageNet and then fine-tuning them with vehicle-specific datasets.
2. **Survey of Approaches**:
   * Examination of existing VMMR models, including popular architectures like ResNet, VGG, and more.
   * Focus on the challenges these models face in practical applications, such as handling low-light images and partial occlusions.
   * Insight into the development of real-time recognition systems and their integration into transportation infrastructure.

#### **Conclusion**

* The survey concludes that while significant progress has been made in the field, VMMR models still face challenges related to data diversity and real-time deployment.
* It stresses the importance of creating larger, more varied datasets to improve model robustness.
* Future research should focus on enhancing model scalability, exploring edge-computing capabilities, and developing systems that perform effectively in diverse real-world environments.

**Paper 2:** An Empirical Analysis of Deep Learning Architectures for Vehicle Make and Model Recognition

**https://ieeexplore.ieee.org/document/9460843**

* **Main Objective**

The study will compare and improve the recognition of vehicle make and model using state-of-the-art deep learning techniques. This is aimed at classifying every different kind of vehicle based on its make, model, and year through the use of recent deep neural network architectures and performance optimization by various means.

* **Dataset**

Used within this study are two sources:

**Stanford Cars Dataset:** It consists of images of cars from 196 classes. For training, the dataset contains approximately 8,144 images, and for testing, it has about 8,041 images.

**VMMRdb-51 Dataset:** This is a subset of the VMMRdb dataset, which contains 51 classes common to the Stanford Cars dataset. It was used for exclusively testing the generalization performance of the models.

* **Methodology**

1. **Data Augmentation:** Several augmentation techniques were applied to the training dataset in order to increase the number of images and provide robustness for the model. It includes random erasing, horizontal flipping, random cropping, resizing, rotation, and sharpening.
2. **Transfer Learning:** Pre-trained models of ImageNet were used to reduce the time taken for training by enhancing its performance. Additional dropout layers were added so that issues regarding the fitting of data could be avoided, which would also improve generalization.
3. **Mix-up and cyclical learning rate:** policies were further employed for optimization in model training in order to avoid overfitting. The cyclical policy, on the other hand, provided a more suitable range of the learning rate for convergence with much higher efficiency.
4. **Some deep learning models here included:**
5. MobileNetV2
6. ResNet152
7. DenseNet121
8. Xception
9. Inception ResNetV2
10. DenseNet201

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1. **Ensemble Learning:** An ensemble of five homogeneous models was developed using k-fold cross-validation. In this approach, different models are combined in their predictions to increase general accuracy and robustness.

* **Conclusion**

This work also demonstrated that ensemble learning combined with state-of-the-art deep learning architectures and techniques for optimization of training has a significant positive impact on vehicle make and model recognition. The final results obtained using ensemble learning with DenseNet201 showed significant improvement over previous approaches; this evidences that the proposed approach effectively realizes high accuracy in vehicle classification tasks.

**Paper 3: Framework for Vehicle Make and Model Recognition—A New Large-Scale Dataset and an Efficient Two-Branch–Two-Stage Deep Learning Architecture**

https://www.mdpi.com/1424-8220/22/21/8439

**Main Purpose**  
The main aim of this project is to develop a novel deep learning framework for Vehicle Make and Model Recognition (VMMR). The proposed system is designed to improve classification accuracy and reduce confusion between vehicle makes and models, especially in applications like Intelligent Transportation Systems (ITS), intelligent surveillance, and autonomous driving.

**Dataset**  
The new DVMM (Diverse large-scale VMMR) dataset is introduced, containing 228,463 images of 23 vehicle makes and 326 models. The dataset focuses on capturing diverse samples from various viewpoints, lighting conditions, and backgrounds to ensure robust training.

**Methodology**

1. **Two-Branch–Two-Stage (2B–2S) Framework**:
   * **Architecture**: The model includes two separate branches—one for vehicle make recognition and another for model recognition. The make recognizer helps refine model predictions and reduce ambiguity.
   * **Training**: The framework employs a two-stage training process where each branch is trained separately, and then a decision module refines the final prediction.
   * **Evaluation Metric**: A novel metric called the Gain (G) score is proposed to assess the framework's ability to reduce classification confusion compared to single-branch models.
2. **Model Comparisons**:
   * Tested with different backbones like AlexNet, ResNet50, and DenseNet201.
   * The 2B–2S framework with the **DenseNet201 backbone** achieved the highest accuracy of **93.95% on the DVMM dataset** and **95.85% on traditional datasets** (such as VMMRDB-495), outperforming single-branch approaches by better handling inter-make and intra-make ambiguities.

**Conclusion**

* The proposed 2B–2S framework with the DenseNet201 backbone demonstrates superior performance, achieving 93.95% accuracy on the DVMM dataset and 95.85% on traditional VMMR datasets, significantly reducing vehicle model confusion.
* The framework's dual-branch design ensures robustness, making it suitable for real-world ITS applications.
* Future research directions include exploring lightweight model architectures for a balance between complexity and performance, as well as early feature fusion strategies for further improvement.