

Enhancing Vehicle Identification in Challenging Conditions Through Fine-Grained Classification

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Summary

1. Introduction
2. Data preparation
3. Experiments and Results
4. Conclusion

Scope: vehicle identification.

Approach: integrating Automatic License Plate Recognition (ALPR) with Fine-Grained Vehicle Classification (FGVC).

Work in progress: enhance vehicle make classification through *class reduction* and *selective prediction*.

Data preparation

Original data: RodoSol-ALPR dataset.

Data preparation: preprocessing; image selection; annotations.

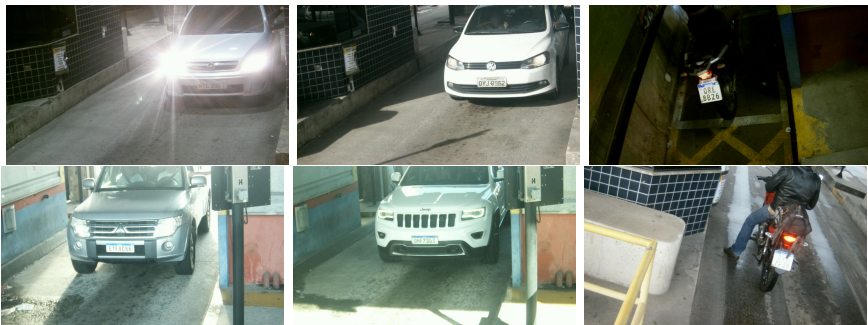


Figure: Sample images from the RodoSol-ALPR dataset.

Data preparation

VehicleMake: 9,553 images categorized into 29 classes.

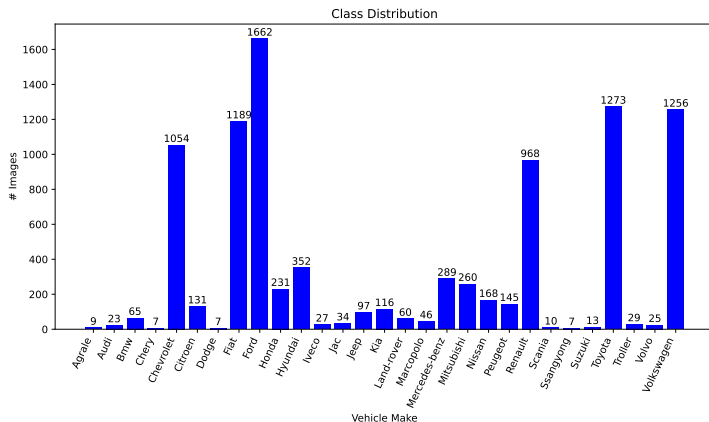


Figure: Distribution of classes in the *VehicleMake* dataset.

Data preparation

VehicleMake: 9,553 images categorized into 29 classes.



Figure: Examples of images from the VehicleMake dataset.

Baseline experiment: evaluate four deep learning models for vehicle make classification.

Methodology:

- *Models;*
- *Split;*
- *Data augmentation;*
- *Training protocols;*
- *Evaluation metrics.*

Additional experiments: class reduction; selective prediction.

Experiments and Results

Baseline experiment

Table: Global metrics on vehicle make task (averaged over five runs). Protocol (*p2*) incorporates oversampling of minority classes, whereas (*p1*) does not.

Protocol	Model	Top-1	Top-2	Precision	Recall	F1
<i>(p1)</i>	ViT b16	55.3%	62.6%	63.9%	55.3%	57.4%
	ResNet-34	38.7%	47.8%	49.3%	38.7%	41.1%
	EfficientNetV2	39.3%	49.1%	45.8%	39.3%	39.5%
	MobileNetV3	40.9%	50.9%	52.2%	40.9%	43.5%
<i>(p2)</i>	ViT b16	65.4%	73.8%	53.0%	65.4%	56.8%
	ResNet-34	49.4%	61.8%	33.9%	49.4%	36.9%
	EfficientNetV2	49.4%	60.2%	31.7%	49.4%	33.8%
	MobileNetV3	50.7%	61.8%	37.7%	50.7%	41.2%

Experiments and Results

Class reduction (static and online)

Table: Class distribution considered for the class reduction experiments.

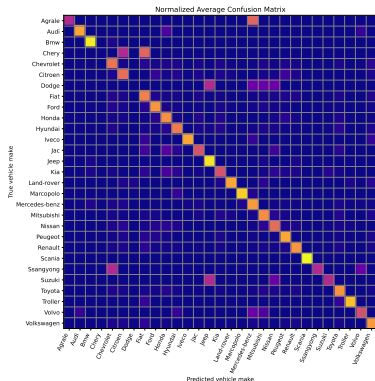
Class	Images
Chevrolet	1,054
Fiat	1,189
Ford	1,662
Honda	231
Hyundai	352
Jeep	97
Nissan	168
Renault	968
Toyota	1,273
Volkswagen	1,256
Others	1,303

Table: Global accuracies using superclass and online superclass (averaged over five runs).

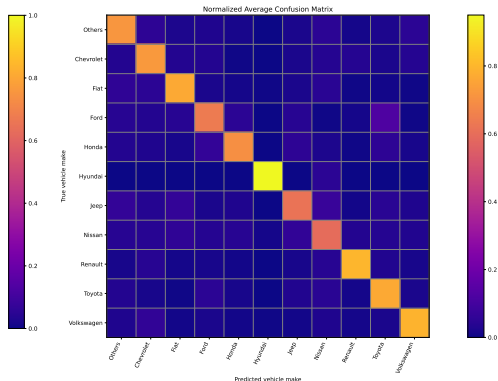
Method	Top-1	Top-2
Baseline	65.4%	73.8%
Static class reduction	73.4%	85.0%
Online class reduction	71.1%	81.5%

Experiments and Results

Class reduction (static and online)



(a) baseline experiment.



(b) static class reduction.

Figure: Average confusion matrices for the baseline experiment (a) and the static class reduction experiment (b)

Experiments and Results

Selective prediction

Table: Global accuracies and rejection rates using only softmax response rejection, and combining it with online class reduction (averaged over five runs).

Method	Minimum confidence	Rejected images	Correct predictions incorrectly rejected	Top-1	Top-2
Baseline	–	–	–	65.4%	73.9%
Selective Prediction	0.1	0 / 0.0%	0 / 0.0%	65.4%	73.9%
	0.2	37 / 3.1%	8 / 23.0%	66.7%	75.0%
	0.3	207 / 17.3%	62 / 30.1%	71.9%	79.5%
	0.4	382 / 32.0%	145 / 38.0%	77.0%	82.5%
	0.5	534 / 44.7%	239 / 44.8%	75.4%	79.7%
	0.6	655 / 54.9%	328 / 50.1%	75.8%	78.5%
	0.7	770 / 64.5%	426 / 55.3%	75.8%	77.0%
	0.8	876 / 73.4%	523 / 59.7%	75.3%	75.8%
	0.9	1013 / 84.8%	656 / 64.8%	71.3%	71.5%
Selective Prediction + Online Class Reducing	0.1	0 / 0.0%	0 / 0.0%	71.1%	81.6%
	0.2	37 / 3.1%	10 / 0.9%	72.6%	83.0%
	0.3	207 / 17.3%	71 / 5.9%	78.6%	87.6%
	0.4	382 / 32.0%	159 / 13.4%	84.7%	91.8%
	0.5	534 / 44.7%	255 / 21.3%	90.2%	94.6%
	0.6	655 / 54.9%	345 / 28.9%	93.4%	95.7%
	0.7	770 / 64.5%	445 / 37.3%	95.8%	97.4%
	0.8	876 / 73.4%	543 / 45.5%	94.3%	94.7%
	0.9	1013 / 84.8%	677 / 56.7%	88.5%	88.8%

Remarks: both selective prediction and class reduction methods can improve overall vehicle make classification accuracy.

Future directions: refine the studied methods; develop a combined ALPR and FGVC system.

Acknowledgments



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