Toward Enhancing Vehicle Color Recognition in Adverse Conditions: A Dataset and Benchmark

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Summary

Introduction

Scope: Vehicle Color Recognition (VCR).
Problem: Lack of adverse conditions in datasets.
Approach: UFPR Vehicle Color Recognition (UFPR-VCR) dataset.

(a) Chen et al. [1] dataset.

(b) UFPR-VCR dataset.

Figure: Images in the proposed dataset (b) depict significantly more challenging scenes than those in (a).

The UFPR-VCR dataset

Data: 10,039 images; 9,502 unique vehicles; 11 colors.

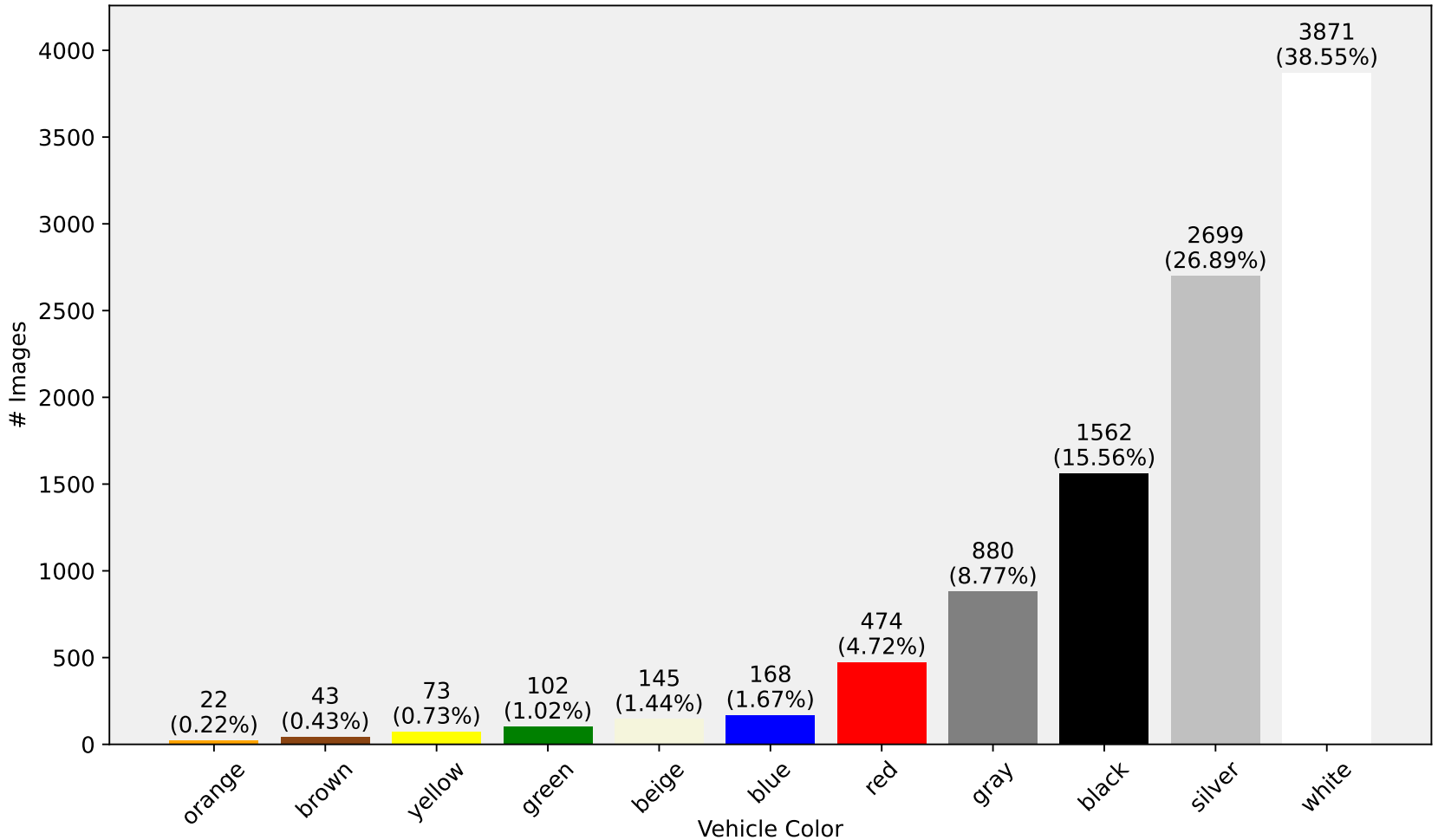


Figure: Distribution of vehicle colors in the UFPR-VCR dataset.

The UFPR-VCR dataset

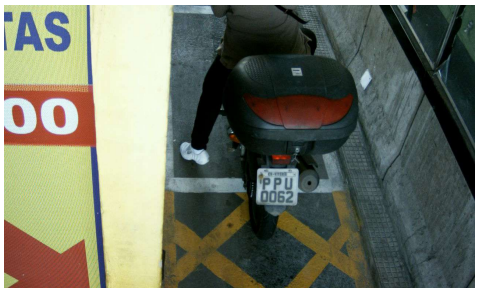
Table: ALPR datasets used to create UFPR-VCR dataset.

Dataset	Year	Images	Resolution	Viewpoint
UFOP	2011	377	800×600	Frontal/Rear
SSIG-SigPlate	2016	2,000	1920×1080	Frontal
OpenALPR-BR	2016	115	Various	Frontal/Rear
UFPR-ALPR	2018	4,500	1920×1080	Frontal/Rear
Vehicle-Rear*	2021	445*	1280×720	Rear
RodoSol-ALPR	2022	20,000	1280×720	Frontal/Rear

*We used only the portion of Vehicle-Rear that includes labels for the license plates.

The UFPR-VCR dataset

Development: I) preprocessing; II) image selection; and III) annotations.



(a) Red

(b) Red

(c) Blue

(d) Multicolored

(e) White

(f) White

Figure: Examples of discarded images due to inability to recognize the vehicle color. The accurate color annotation is displayed bellow each image.

Experiments

Description: evaluate four deep learning models on the proposed dataset and on Chen et al. dataset.

Methodology:

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

Experiments

Table: Global metrics (%) on Chen et al. dataset (averaged over five runs).

Model	Top-1	Top-2	Precision	Recall	F1
EfficientNet-V2 [5]	84.6	93.4	84.5	84.6	84.4
MobileNet-V3 [4]	90.6	96.7	91.7	90.6	91.0
ResNet-34 [3]	89.0	95.6	91.1	89.0	89.9
ViT b16 [2]	**92.8**	**98.0**	**95.3**	**92.8**	**93.9**

Experiments

Table: Global metrics (%) on UFPR-VCR dataset (averaged over five runs).

Protocol	Model	Top-1	Top-2	Precision	Recall	F1
(i)	EfficientNet-V2 [5]	51.2	65.3	65.2	51.2	53.5
	MobileNet-V3 [4]	50.5	65.4	65.8	50.5	53.1
	ResNet-34 [3]	49.1	60.3	64.3	49.1	52.4
	ViT b16 [2]	**59.2**	**71.3**	**76.0**	**59.2**	**62.8**
(ii)	EfficientNet-V2 [5]	55.4	69.5	43.5	55.4	44.6
	MobileNet-V3 [4]	59.3	73.3	42.6	59.4	45.2
	ResNet-34 [3]	59.3	72.9	47.8	59.3	49.9
	ViT b16 [2]	**66.2**	**79.7**	**55.7**	**66.2**	**57.8**

Experiments

Colors consistently identified: yellow, white and red.
Colors that posed challenges: brown, blue, green and gray.

Nighttime images: 32.4% top-1 errors.

GT: White
Pred: Silver

GT: Red
Pred: White

GT: Black
Pred: Gray

Figure: Examples of nighttime images that were misclassified.

Conclusions

Observed: shortcomings in existing Vehicle Color Recognition (VCR) datasets.

Main contribution: UFPR-VCR proposal and benchmark.

Future work: I) improve nighttime scene performance; and II) enrich the dataset for fine-grained vehicle classification.

Acknowledgments

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