Vehicle Color Recognition Based on Smooth Modulation Neural Network with Multi-Scale Feature Fusion

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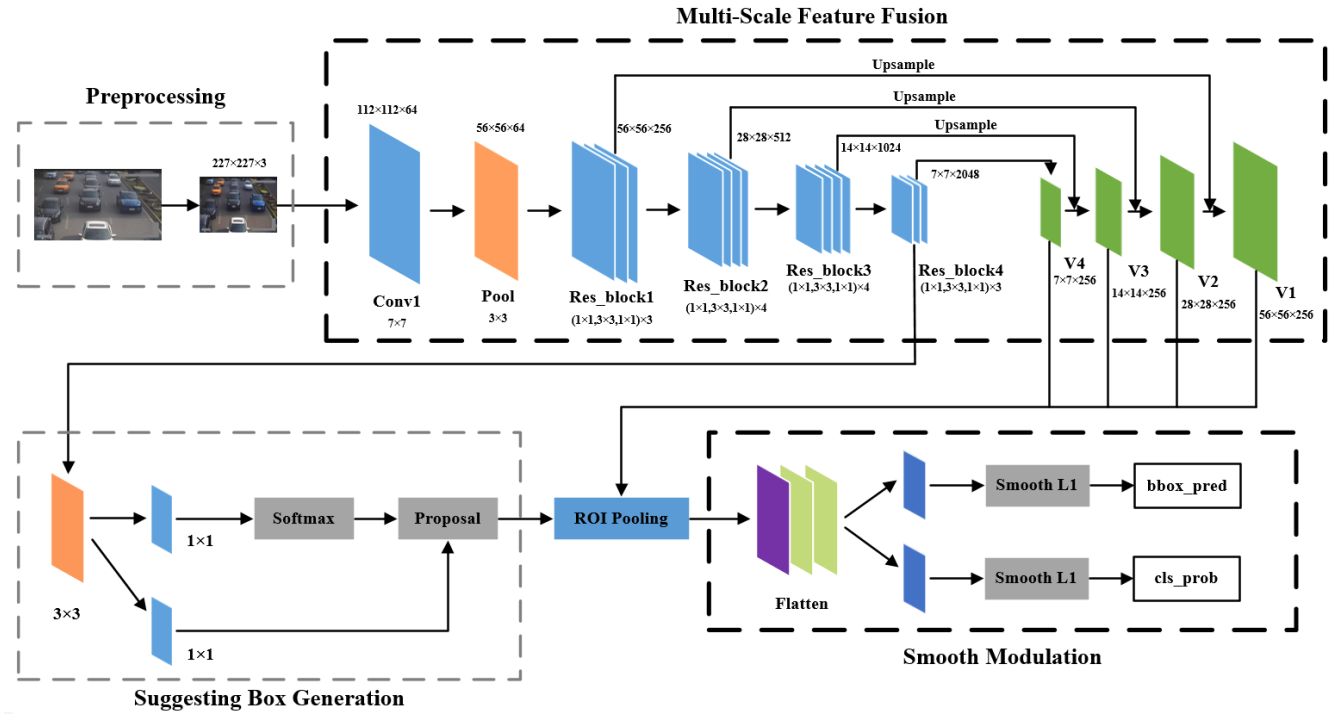
Problems & Ideas

- Problems of conventional vehicle color recognition:
  - The existing vehicle color datasets only cover 13 classes, which can not meet the current actual demand;
  - Although lots of efforts are devoted to vehicle color recognition, they suffer from the problem of class imbalance in datasets.
- Ideas: We propose a method based on Smooth Modulation Neural Network with Multi-Scale Feature Fusion (SMNN-MSFF).



The Multi-Scale Feature Fusion aims to extract feature information from local to global, and the Smooth Modulation Neural Network could increase the loss of the images of tail class instances for training with class-imbalance.

Main Contributions

- Contributions:
  - We build a new dataset with 24 vehicle color types, called Vehicle Color-24;
  - We propose a novel vehicle color recognition method based on SMNN-MSFF;
  - Complicative experiments confirmed that performance of SMNN-MSFF has achieved significant improvement in classifying vehicle color.

Table 6 Comparison of recognition accuracy of 24 colors in different network classifications

	Faster-RCNN [12]	SSD [13]	YOLO-v3 [14]	YOLO-v4 [15]	Efficient-Det [16]	Center-Net [17]	Retina-Net [18]	SMNN-MSFF
white	0.84	0.96	0.97	0.98	0.95	0.97	0.98	**0.98**
black	0.82	0.95	0.96	0.96	0.93	0.94	0.97	**0.97**
orange	0.81	0.96	0.97	0.98	0.96	0.97	0.98	**0.98**
silver-gray	0.77	0.91	0.92	0.92	0.87	0.88	**0.97**	0.96
grass-green	0.70	0.96	0.97	0.98	0.95	0.97	0.98	**0.98**
dark-gray	0.66	0.84	0.82	0.93	0.73	0.73	0.94	**0.94**
dark-red	0.78	0.93	0.94	0.94	0.91	0.92	0.97	**0.98**
gray	0.18	0.54	0.50	0.40	0.28	0.28	0.82	**0.89**
red	0.60	0.88	0.88	0.81	0.79	0.77	0.96	**0.96**
cyan	0.75	0.92	0.93	0.92	0.82	0.89	**0.98**	0.97
champagne	0.63	0.81	0.83	0.77	0.66	0.76	**0.94**	0.91
dark-blue	0.66	0.86	0.85	0.87	0.76	0.77	**0.97**	0.96
blue	0.73	0.87	0.85	0.87	0.75	0.82	0.97	**0.97**
dark-brown	0.45	0.71	0.68	0.60	0.49	0.64	0.88	**0.97**
brown	0.30	0.58	0.52	0.25	0.36	0.25	0.80	**0.88**
yellow	0.51	0.79	0.72	0.56	0.47	0.42	0.95	**0.97**
lemon-yellow	0.87	0.93	0.84	0.77	0.66	0.64	0.99	**0.99**
dark-orange	0.65	0.78	0.66	0.60	0.66	0.53	0.94	**0.96**
dark-green	0.38	0.58	0.63	0.00	0.23	0.66	0.91	**0.94**
red-orange	0.24	0.61	0.61	0.05	0.33	0.13	0.94	**0.99**
earthy-yellow	0.62	0.74	0.69	0.43	0.43	0.29	0.92	**0.97**
green	0.61	0.74	0.77	0.54	0.33	0.40	0.89	**0.93**
pink	0.50	0.71	0.75	0.03	0.18	0.01	0.90	**0.94**
purple	0.00	0.19	0.08	0.00	0.10	0.00	0.48	**0.80**
mAP	**58.59%**	**78.13%**	**76.38%**	**62.77%**	**60.86%**	**61.07%**	**91.79%**	**94.96%**

The experimental results show that the mAP of our method in our paper is 94.96\% in recognizing 24 types of colors and the mAP of recognizing 8 types of colors is 97.25\%.