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A Novel Image Segmentation Combined Color Recognition Algorithm through Boundary Detection and Deep Neural Network

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Abstract

With the fast development of industry and computer science technology, the image color recognition has been a hot topic. The prior research focus more on sensor and hardware based approaches which are not intelligent or convenient. In this paper, we present a novel image segmentation combined color recognition algorithm through boundary detection and deep neural network. The deep learning algorithm can largely increase the accuracy of classification whereas cut down the processing time consumed, we adopt the deep neural network and support vector machine to extract image features both in RGB and YUV color spaces. Boundary detection in sudden change, by contrast, is more global in nature, such as texture, so need to integrate the whole information of the image. Under the guidance, we modify the current segmentation methods with boundary detection technique to serve as the pre-processing step before classifying colors. Experimental results on synthetic and real images show that the new algorithm is effective and efficient, and is relatively independent of this type of noise. Further analysis is also conducted in the final section.

***Keywords**: Color Recognition, Image Segmentation, Deep Neural Network (DNN), Boundary Detection Algorithm, Information Retrieve and Classification*

1. Introduction

In recent years, with the bursting developments in information and communication processing technologies, researchers have discovered the huge potential diverse application areas related to multimedia science and data analysis such as remote sensing based geographic information system [1], medical image processing and operating [2], data guided and instructed human entertainment [3], and online web service based information sharing and servicing centers [4]. Traditional database management system designed to alphanumeric data organized into a collection of inter-connected, such information storage and retrieval can be convenient and efficient. However, this method is not suitable for organization, management, and effective use of multimedia information. The literature review and prior research basis have indicated that in a plenty of practical real-world applications, accurate and low time-consuming color recognition algorithm for large-scale image database is urgently needed. There are several search engines which can undertake the search and retrieval task for information text and graphics. Universal tool, however, are able to search and retrieval of data is not suitable for special applications. For this reason, specific methods and system characteristics based on image search and retrieval of data specific applications are being studied recently. In [5], zimmer designed an amorphous silicon-based unipolar detector for color recognition which is based on hardware device. Spectral response curve and linear response of the linear independence since the photocurrent of the incident light intensity is the prerequisite for the generation of red, green and blue signals, the influence of light intensity in the color separation spectral response measurement in different monochromatic prejudice lighting. In [6],

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Bartlett proposed a novel visual recognition methodology based on image color recognition and pattern classification. The core algorithm is based on the assumption that serious construction and time limits in the primate visual system support object recognition in the early stages of speculation in the brain is based on the hierarchical structure of the feedforward feature extraction. Moreover, in [7], Rege's group proposed a novel 2D geometric shape and color recognition method using basic digital image processing techniques (DIPT). Their algorithm involved the method of two-dimensional three-dimensional RGB image black and white image conversion, color pixels classification object-background separation, based on the size of the filter, and the use of the bounding box and its property index calculation object. Object index and target value, it is the shape of a particular object. Identify the shape of the object is by rotation invariant. In addition, the color of the object is recognized based on the analysis of all pixels of RGB information within each object.

In this paper, due to the index methods using traditional manual note image is slow, labor intensive and expensive. In addition, the text annotations cannot effectively all the available information in a given image coding. In addition, based on the characteristics of a large number of pixels of the image data, the concept of complex application specific pattern, domain-specific concept may not be suitable for simple and effective text description. Therefore, we propose a novel image segmentation combined color recognition algorithm through boundary detection and deep neural network. The paper is organized as the follows. Section 2 provides a basic theoretical review on segmentation based-color space models, and novel segmentation methodology is also introduced. In section 3, we primarily discuss the core features of deep neural network and boundary detection techniques to serve as the modification for the prior segmentation and the future color recognition task. Section 4 presents our segmentation and deep learning combined color recognition algorithm, experimental analysis and discussion is shown in the section 5. As the conclusion and prospect, we conclude the research and finalize our future research area in the last section.

2. The Color Image Segmentation

2.1. The Color Space Model

The most widely used color space is the RGB color space. In this popular adopted model, a point of color pixel is divided and de-composited into three individual components denoted as the red, green, blue, respectively. Because there are a large number of color spaces, however, it is a useful approach to undertake the classification work into the category of the less of their definitions and property. We could therefore classify the color spaces into the following sorts. (1) The main space is based on the theory assumes that we can match any color mixing appropriate amount of primary colors. The primary spaces are the real RGB, the subtractive CMY, and the imaginary XYZ primary spaces. The following formula 1 and 2 show the conversion process between RGB and XYZ. (2) The luminance-chrominance spaces. It is a kind of color component which represents the brightness and chromaticity color said two components. The YUV is a sample color space, the conversion formula between YUV and RGB is shown is the equation 3. (3) Humans attempt to quantify the perceptual space of subjective color perception through the three measures, intensity, the hue and saturation. HSV represents the discussed model in which the H denotes the hue, S represents the saturation and V is the visual intensity. The formula 4 illustrates the transformation process.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.41245 & 0.35758 & 0.18042 \\ 0.21267 & 0.71516 & 0.07217 \\ 0.01933 & 0.11919 & 0.95023 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

(1)

$$\begin{aligned} C' &= 1 - R & C &= \min\left(1, \max\left(0, \mathrm{C}' - K'\right)\right) \\ \mathrm{M}' &= 1 - G & M &= \min\left(1, \max\left(0, \mathrm{M}' - K'\right)\right) \\ \mathrm{Y}' &= 1 - B & Y &= \min\left(1, \max\left(0, \mathrm{Y}' - K'\right)\right) \end{aligned}$$

(2)

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.115 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

(3)

$$H = \begin{cases} 0, & if \quad Max = Min \\ \left(60^\circ \times \dfrac{G-B}{Max-Min} + 360^\circ\right) \times \mathrm{mod}, & if \quad Max = R \\ \left(60^\circ \times \dfrac{B-R}{Max-Min} + 120^\circ\right) & if \quad Max = G \\ \left(60^\circ \times \dfrac{R-G}{Max-Min} + 240^\circ\right) & if \quad Max = B \end{cases}$$

$$S = \begin{cases} 0, & if \quad \max = 0 \\ \dfrac{Max-Min}{Max} & others \end{cases} \qquad V = Max$$

(4)

2.2. The Color Model Based Image Segmentation

In this section we first define and analyze some prerequisite. Suppose we are given a large-scale data set denoted as: $A = \left[a_1, a_2, ..., a_n\right]^T \in R^{n \times p}$, as the following step, we adopt the normalized Laplacian matrix (NLM) to derivate the time for commuting. The formula 5 shows this step.

$$c_{ij} = vol\left(e_i - e_j\right)^T L^+ \left(e_i - e_j\right) = vol\left(e_i - e_j\right)^T D^{-1/2}\left(e_i - e_j\right)$$

(5)

The eigen-decomposition of A can be formulated as the following:

$$A = U \sum V^T$$

(6)

The essential parameters equation can be defined as: $UU^T = I \in R^{n \times n}, VV^T = E \in R^{p \times p}$, $\sum = diag\left(\sigma_1, \sigma_2, ..., \sigma_p\right)$ in which $\sigma_1 \geq \sigma_2 \geq ... \geq \sigma_p = 0, p \ll n$.

Gaussian kernel is popularly adopted such as [8-11] to denote the similarity measurement notation. However, it lacks efficiency and accuracy. Therefore, we will use cosine function [12-15] which is formulated in the formula 7 and the following steps are also discussed as the formula 8 and 9.

$$U = A\left(\sum V^T\right)^{RP} = A\left(\sum V^T\right)^T \left[\sum V^T \left(\sum V^T\right)^T\right]^{-1} = AV\sum{}^{+}$$

(7)

$$L_n^+ = \left(D^{-1/2} L D^{-1/2}\right)^+ = \left(\overline{U} E U^T - \overline{U} \Lambda^2 \overline{U}^T\right)^+ = \overline{U}\left(E - \Lambda^2\right)^+ \overline{U}^T$$

(8)

$$Z = \sqrt{vol}\left[\left(E - \Lambda^2\right)^+\right]^{1/2} \overline{U}^T D^{-1/2}$$

(9)

Finally, we will use RGB color space to describe the feature vector of any pixel in an image. The Figure 1 shows the main steps.

Input	Initialization image $A \in R^{n \times p}$ and classes k
Step1	Design the similarity matrix W
Step2	Compute the degree matrix of W and value of vol
Step3	Compute the $U\sum V^T$
Step4	Compute the $\left(\overline{U} E U^T - \overline{U} \Lambda^2 \overline{U}^T\right)^+$
Step5	Calculating the $\sqrt{vol}\left[\left(E - \Lambda^2\right)^+\right]^{1/2}$ in formula 9
Step6	Solving the edge detection issues and segment the image
Output	Segmented color images

Figure 1. The Flowchart of Our Segmentation Algorithm

3. Deep Neural Network Based Boundary Detection

3.1. Unsupervised Feature Learning for Detection

Our network architecture can be conceptually divided into two parts, the first to feature extraction, and the second using the boundary prediction. We rely on the rest of the characteristics of unsupervised learning skills. Detect this change is a challenging problem, is very different from the simple edge detection, edge detection, is a technical inspection of the low-level image features such as sudden changes in brightness or color. Boundary detection in sudden change, by contrast, is more global in nature, such as texture, so need to integrate the whole information of the image. For example, may cause many serious deformation on the edge of the area, but there should be no defined border area. Although the task is difficult, accurate boundary detection is very important because it helps many visual tasks include segmentation, recognition and understanding. The mcRBM-model [16-21] is a generative model for images. We consider the allocation of an energy variation of joint configuration is visible unit v h and hidden units are as follows:

$$E = -\sum_j h_j^c \left(d_j - \sum_f \frac{\pi fj}{2}\left[K_f{}^T AV\right]^2\right) + \sum_i \frac{\left(v_i - a\right)^2}{2\sigma^2} - \sum_l h_l^m \left(b_l + \frac{1}{\sigma^2} M_l{}^T V\right)$$

(10)

In our experiments we use diagonally-tiled parameter sharing, with 8*8 receptive fields, stride of two units per site. In the Figure 2, we provide a simplified illustration of such a diagonally-tiled convolutional McRBM model instance. Function study our deep architecture development McRBM belief network, extend it there is an additional binary hidden layer unit. In the Figure 3, we present the traditional deep learning framework according to the literature review [22-31]. We use the same diagonally-tiled convolutional function sharing structure the pace of the additional layer of a second floor unit.

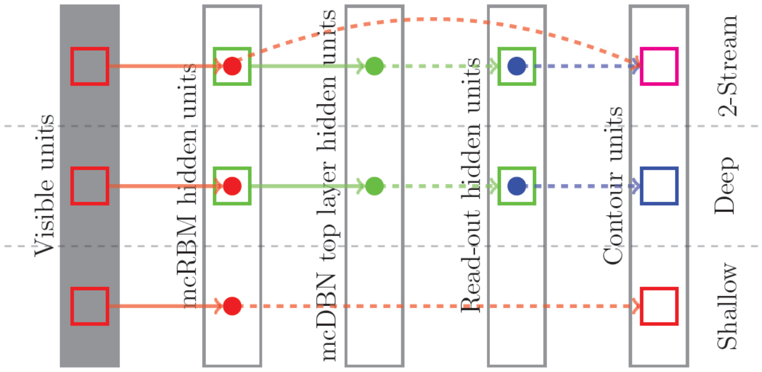

Figure 2. The Streams of the Considered Networks

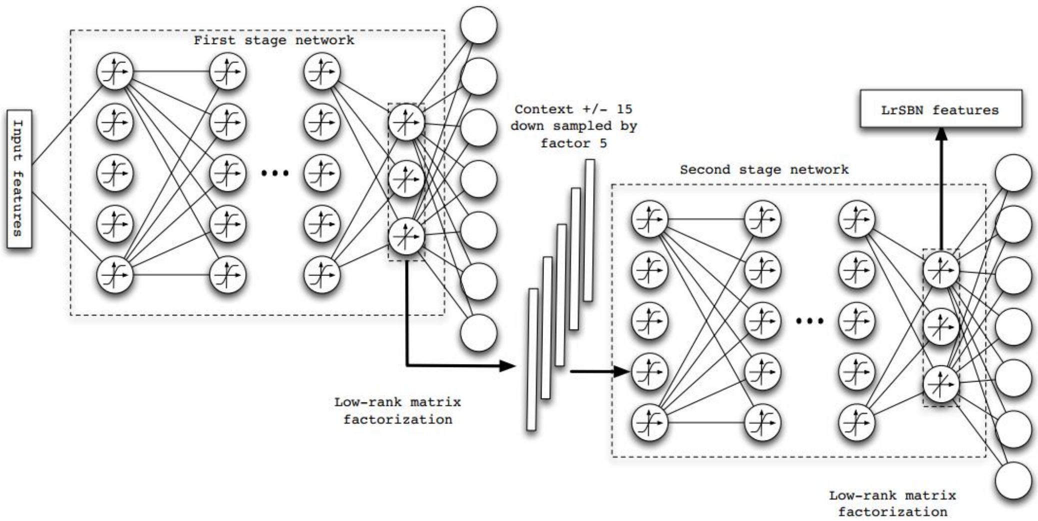

Figure 3. The General Structure of Deep Neural Network (DNN)

3.2. The Supervised Prediction

We consider feedforward sigmoidal neural networks for boundary prediction. Characteristics of aircraft in our network are always the first hidden layer to form the activation probability of mean and covariance TmcRBM hidden units. The corresponding serve as the hidden layers is based on this design pattern. In the feature plane denoted as k given the input X^k, activation for the individual unit z_i^k could be computed as the following:

$$z_i^k = sig\left(g^k + \sum_j W_{ij}^k x_j^k \right) \tag{11}$$

In which, W^k denotes the weight matrix (WM), g^k represents the scalar bias, and sig the logistic sigmoid function $sig(z) = \frac{1}{(1+e^{-z})}$.

The output layer has the same dimensionality as the input image and each pixel has a corresponding contour unit expressed as: $u_i = z_i^{out}$ .Its activation interpreted as probability prediction, pixel is part of an outline. According to the architecture, the output layer receives input from one or more network in the hidden layer. Importantly we can think of each stream having two parts: image feature extraction, and hypothesis propagation/read out. In our network, we use a mirror to connect the two parts of the structure. Add an extra layer coding and adds another read hidden layer. The one reason is to reduce the hidden deeper network unit grid position. In these deep flow, the quantity characteristics of aircraft is also applied to antisymmetric fashion, so the first and the last hidden layer flow has the same number of aircraft. Multiple streams are motivated by the need to capture the image multi-scale information and semantic level. Such a network is expected to only detect very local image discontinuities such as edges. At a deeper level of network input from the larger area may need to distinguish between discontinuous. Our result is in line with this view. Due to the sparse space application of filters in the entire network, only much coarser scales is expected at a deeper level-scale about the data information, and contour website with local is discontinuity cannot be detected effectively. Compare with related proposed deep neural network, we draw the Figure 4 to show the computational complex for reference.

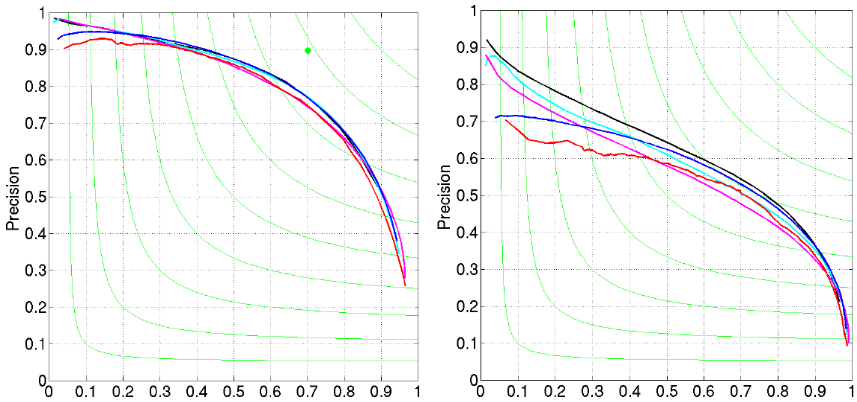

Figure 4. The Demonstration for Computational Efficiency

4. Color Recognition with Segmentation and Boundary Detection Prior

4.1. The Feature Extraction Algorithm

Feature extraction was based on the automatically segmented regions. For each region representing a lesion, in addition to the basic RGB color components, six images were generated. Color histogram extraction is based on the HSV (hue, saturation and value) color space, by HSV color component is more related to human perception. Traditional color in HSV color space quantization separate bins of grey Numbers and the other based on component, and a divided. The Figure 5 shows the example. To overcome this problem, the cylindrical HSV space needs to be transformed into a cone. Suppose a cylindrical HSV point. Usually after segmentation image segmentation to several objects. The characteristic of each object is composed of three parts. First is the color histogram, color histogram weighted average of all areas belong to the area of the object. The second part is the texture feature, this is by wavelet energy. As a result, each texture feature vector wavelet energy is a 9 elements. The area of the object of texture feature vector weighted average wavelet energy from all the corresponding area.

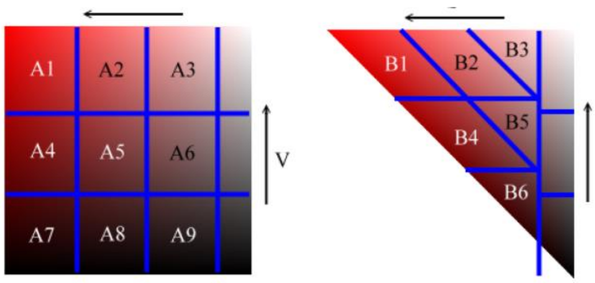

Figure 5. The Color Image Feature Extraction

4.2. The Combined Color Recognition and Classification Algorithm

SVM is based on the theory of statistical learning methods. The ideas of the SVM is for the classification of the 2 types of problems for multi-class problem, need to re-construct the SVM classifier. There are 4 patterns in the research and we employed the use of cluster analysis in the distance between the class and the binary tree structure of multi-class classification method. We used the complete binary tree structure. The structure is the inner nodes can be multiple classes with multiple classes of split. The classification principle of binary tree: Should make the most easy to split the class the first partition. Namely on the upper deck of the binary tree node split, in this way can make the upper of the SVM classification has higher generalization performance, reduce the fault points rate. When use starting from the root node decision function, according to the value of the positive and negative decision the next node, it goes on, until you reach a leaf node, this leaf node represents a class is to test samples Category. The Euclidean distance between class and class can be formulated as the formula 12.

$$\bar{x}_t = \frac{1}{n_t} \sum_{x_i \in s_t} x_i \tag{12}$$

This article think the left hand movement, imagine the right hand movement, masseter click, masseter double-click the four movements of sample set respectively marked as A1, A2, A3, A4.Firstly, training (A1,A2)and (A3,A4) to obtain SVM1 by clustering in the SVM training process. After completing the SVM training, we can get the svm multi-classification surface of dimension reduction space. Can confirm the boundary surface is effective by texting. In the course of the test sample belongs to which class should start from SVM1, drill down until the sign function is positive so far, to get classes. Finally, deep learning algorithm introduced in the previous section will verify the accuracy of the classification result.

5. Experimental Analysis

5.1. The Simulation Set-up and Environment

In order to verify the effectiveness of the proposed method above, we took some experiments and simulation. The simulation environment is as the follows. Six physical machines equipped with 4 TB hard disk and 16 GB of RAM, and the simulation software is installed on Windows Win7 platform and Intel core 4 quad core 3.6 GHz and 6 GB of RAM. The testing images are gathered through google image search engine and Flickr.

5.2. The Experiment for the Segmentation Part

In this section, to better simulate and test the effectiveness of our method, we describe the experimental results on one synthetic image and one natural image with different types of noises. We compare our method with some other state-of-the-art algorithms. The Figure 6 and 7 show the result. In addition, to demonstrate the efficiency of our method, we draw the time-consuming curve in the Figure 8.

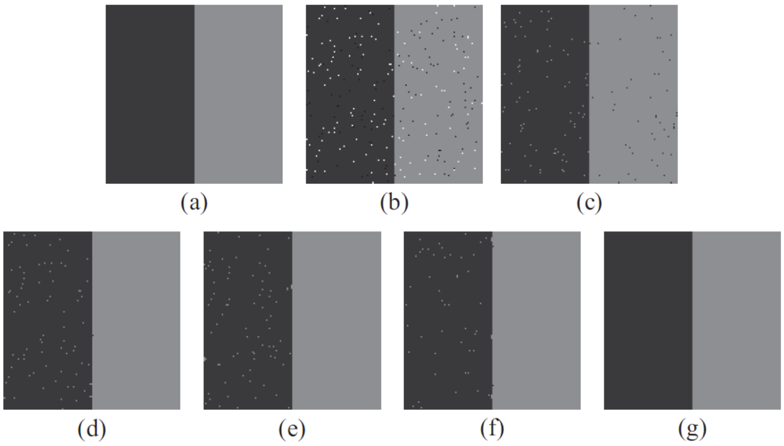

Figure 6. Our Algorithm (g) Compared with Others Under Noise Environment

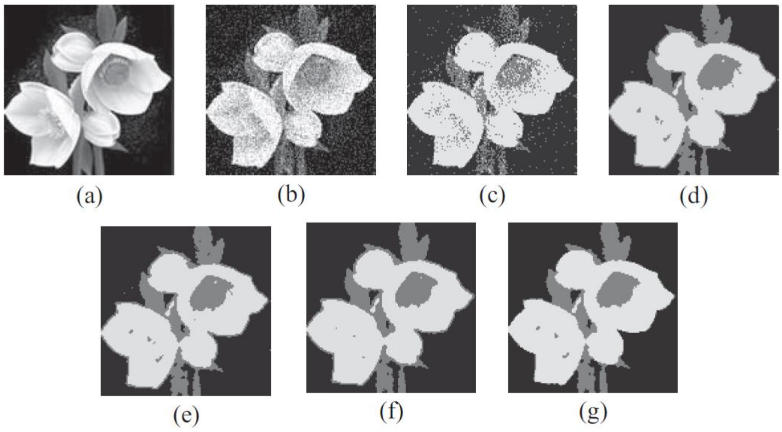

Figure 7. Our Algorithm (g) Compared with Others Under Natural Scene

5.3. The Experiment for the Color Recognition Part

In this section, we verify the combined algorithm for image color classification. The experimental images are downloaded from google image search engine, we take shoe images as the example for the reason that the shape and structure of shoes varies largely, and therefore, we could show the effectiveness and robustness of proposed methodology. The simulation result is shown in the Figure 9. The recognition accuracy data is stored in the table one.

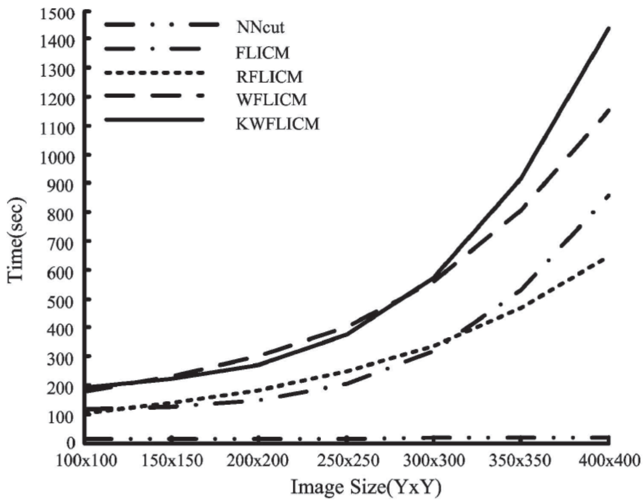

Figure 8. Running Time of the Algorithms

Figure 9. The Experimental Image Dataset

	Algorithms		
	Bayesian	**Graph-Cut**	**Ours**
Test1	75.33%	85.17%	**93.47%**
Test2	65.20%	90.75%	**91.73%**
Test3	83.12%	88.73%	**95.33%**
Test4	69.74%	81.97%	**90.76%**
Test5	66.84%	**92.33%**	91.33%
Test6	80.33%	83.69%	**90.61%**
Test7	81.75%	92.12%	**96.31%**
Test8	78.61%	77.89%	**96.35%**

Table 1. Experiment Result for Color Recognation

6. Conclusion and Summary

Deep learning has become one of the hottest research topics in the machine learning community. In this paper, we propose a novel image segmentation combined color recognition algorithm through boundary detection and deep neural network. The results reported in this paper show that DNN based classification method is an effective approach to constructing a robust image color recognition algorithm. Furthermore, the improved algorithm introduced a re-formulated boundary detection technique, with the application to the original algorithm. Compared with its preexistences, it is able to incorporate the local information more exactly. In addition, SVM is also adopted to verify the result of our proposed methodology. In our experiments, we test the proposed algorithm on natural and noise based image sets. The experiment results show that the proposed algorithm obviously improves the performance of color recognition, as well as the robustness to the type of noises and shapes. In the future, we plan to do more research on deep learning algorithm to boost the efficiency of current algorithm.

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