Applying Multi Support Vector Machine for Flower Image Classification

Thai Hoang Le[1], Hai Son Tran[2], and Thuy Thanh Nguyen[3]

[1] Computer Science Department, University of Science, Ho Chi Minh City, Vietnam
lhthai@fit.hcmus.edu.vn
[2] Informatics Technology Department, University of Pedagogy, Ho Chi Minh City, Vietnam
member of AICSIT
haits@hcmup.edu.vn
[3] VNU University of Engineering and Technology, Ha Noi City, Vietnam
nguyenthanhthuy@vnu.edu.vn

Abstract. Image classification is the significant problems of concern in image processing and image recognition. There are many methods have been proposed for solving image classification problem such as k nearest neighbor (K-NN), Bayesian Network, Adaptive boost (Adaboost), Artificial Neural Network (NN), and Support Vector Machine (SVM). The aim of this paper is to propose a novel model using multi SVMs concurrently to apply for image classification. Firstly, each image is extracted to many feature vectors. Each of feature vectors is classified into the responsive class by one SVM. Finally, all the classify results of SVM are combined to give the final result. Our proposal classification model uses many SVMs. Let it call multi_SVM. As a case study for validation the proposal model, experiment trials were done of Oxford Flower Dataset divided into three categories (lotus, rose, and daisy) has been reported and compared on RGB and HIS color spaces. Results based on the proposed model are found encouraging in term of flower image classification accuracy.

Keywords: image classification, flower image classification, multi Support Vector Machine.

1 Introduction

Image classification is the significant problem of concern in image processing and image recognition. The aim of image classification is to identify the right categories of images based on image features. The first problem in image classification is image feature extraction and the second problem is to classify image into the suitable classes.

Many transformations such as Fourier, Wavelet [1,2], Hough [3], Principal Component Analysis (PCA) [4], Independent Component Analysis (ICA) [5], curvelet and ridgelet [6]… can be used to extract the image's features. Every transformation has some advantages and dis advantages. The researchers need to choose to the suitable transformation for their interesting problem.

P.C. Vinh et al. (Eds.): ICCASA 2012, LNICST 109, pp. 268–281, 2013.

Classification problem can be solved by various techniques such as k nearest neighbor (K-NN)[7], Bayesian Network [8], Adaptive boost (Adaboost), Artificial Neural Network (NN), and Support Vector Machine (SVM)...

The k-NN classifier identifies the categories of the input image based on the distance between the feature vector of the input image and the feature vector dataset of training images.

Adaboost classifier is a fast classifier based on the set of weak classifiers. It uses an iterative learning algorithm to create one classifier by using a training dataset and a “weak” learning algorithm. The disadvantages of Adaboost classifier is the non- high classification precision. This classifier need to integrate with another technique for improving the precision [9].

Artificial Neural Network (ANN) has been built for many applications. There are many ANN’s structures which have been designed suitable with their problem. The difficulty of using ANN is how to develop good ANN structure for the application. For an example, the number of node of the hidden layer is not easily to identify in the specific context [10].

SVM is one the feasible method applying for pattern classification and can be used for image classification. SVM separates of a training dataset two classes and builds the optimal separating hyperplanes. The feature vector of image in one category lies on one side of the hyperplanes, and the others lie on the opposite side of the hyperplanes [11].

2 Background and Related Work

SVM is one of popular kernel based classification learning algorithm that can apply for pattern classification and image classification. The researchers often use the Gaussian or Polynomial kernel function in developing SVM. The number of hyperplanes of a SVM is dependent on the number of classes. For example, if we use one vs. one strategy for classifying into L different classes, then the number of hyperplanes is L-1. If we use one vs. rest strategy for classifying into L different classes, then the number of hyperplanes is L(L-1)/2.

The aim of Classification via SVM [12] is to find a computationally efficient way of learning good separating hyperplanes in a hyperspace, where ‘good’ hyperplanes mean ones optimizing the generalizing bounds and by ‘computationally efficient’ we mean algorithms able to deal with sample sizes of very high order.

Devis Tuia has suggested an algorithm with margin rescaling applying for remote sensing image classification [13]:

In this research, we suggest a model using multiple SVM to apply for image classification. For example, every image is extracted to m feature vectors and need to classify into L different classes. Our proposed model use m SVM(s) with kernel function Gauss or Polynomial.

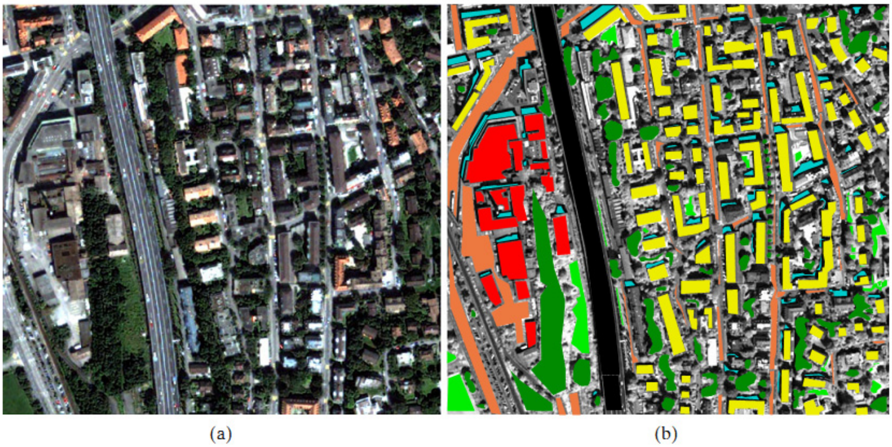

Fig. 1. Multispectral very high resolution Quickbird image acquired over Zurich. A RGB composition of the image and b ground survey of the seven classes of interest identified: 'trees'(Dark green), 'meadows' (light green), 'highway' (black), 'road' (brown), 'residential' (orange), 'commercial' (red) 'and shadow' (blue) [13].

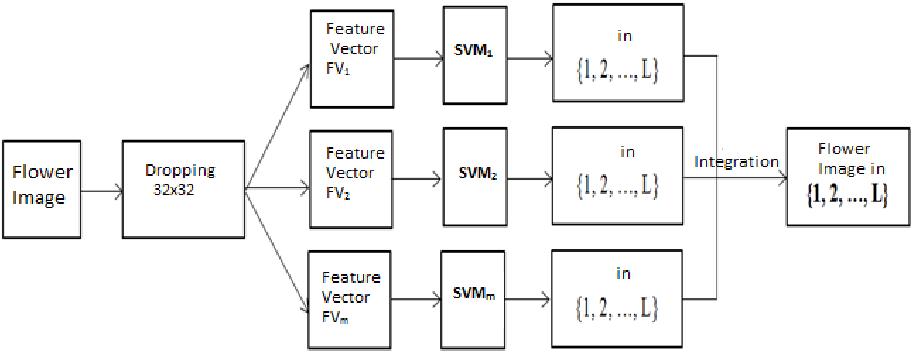

Fig. 2. Multi SVM model (m,L)

Where m = the number of image feature vectors = the number of SVM(s)

L = the number of classes

The number of hyperplanes of one SVM is dependent on L and what kind of hyperplane building strategy (one vs. one, or one vs. rest…) has been used.

3 Multi SVM Apply for Flower Image Classification

Color is the critical feature of images, especially in flower images. It does not require the careful preprocessing. Thus color is one the popular feature using in image classification. There are many color spaces in image processing and image classification. Some color spaces orient to devices such as RGB, CMYK, YIQ… and other color space orient to user such as HSI, HSV, HCV…

In this research, we use two typical color spaces which are RGB and HSI to check the feasibility of multi_SVM model for flower image classification. The input flower image must be classified into L=3 categories (rose, lotus, and daisy).

3.1 Multi SVM Model Apply for Flower Image Classification

3.1.1 Flower Image Classification Based on RGB Color Space

The flower image's size is dropped 32x32 and represent in RGB color space. We set the average threshold to transform the image to the digital matrix based on every component color (R, G, B) like below:

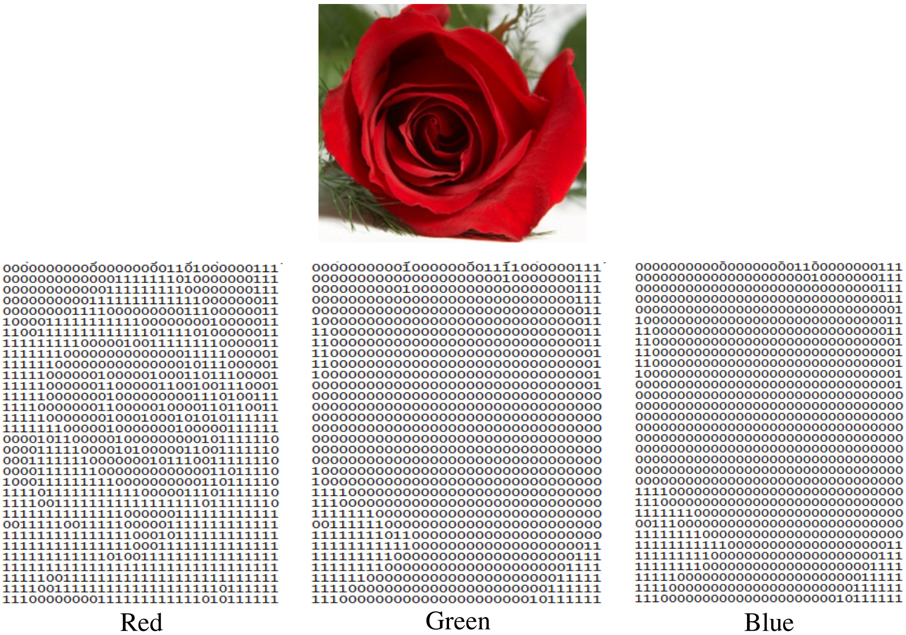

Fig. 3. Flower image color extraction using RGB color space

The red feature of flower image is the digital matrix 32x32 with the value 0 or 1. The value of an element in the matrix set to 0 if its red color value is lower than the average threshold. The SVM_R get the red feature of an image to identify the category of the image. We do the same to SVM_G and SVM_B.

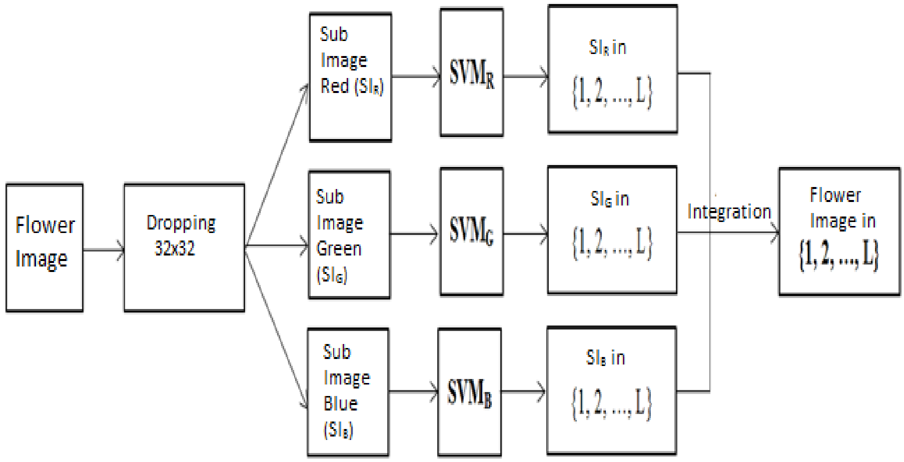

Fig. 4. Flower image classification using RGB color space

The input flower image are extracted to 3 sub-image based on each R, G, B component color. Let them denote SI_R, SI_G, and SI_B. Thus the multi_SVM system must have three SVM components SVM_R, SVM_G, and SVM_B. Each of three SVM components gives the conclusion of the categories of flower images. We need to integrate three results of classification. We can use majority or average to integrate all SVM(s) result to give the final result of the multi_SVM classification system.

3.1.2 Flower Image Classification Based on HSI Color Space

The flower image's size is dropped 32x32 and represent in HSI color space. We set the average threshold to transform the image to the digital matrix based on every component color (H, S, I) like below:

The hue feature of flower image is the digital matrix 32x32 with the value 0 or 1. The value of an element in the matrix set to 0 if its red color value is lower than the average threshold. The SVM_H get the red feature of an image to identify the category of the image. We do the same to SVM_S and SVM_I.

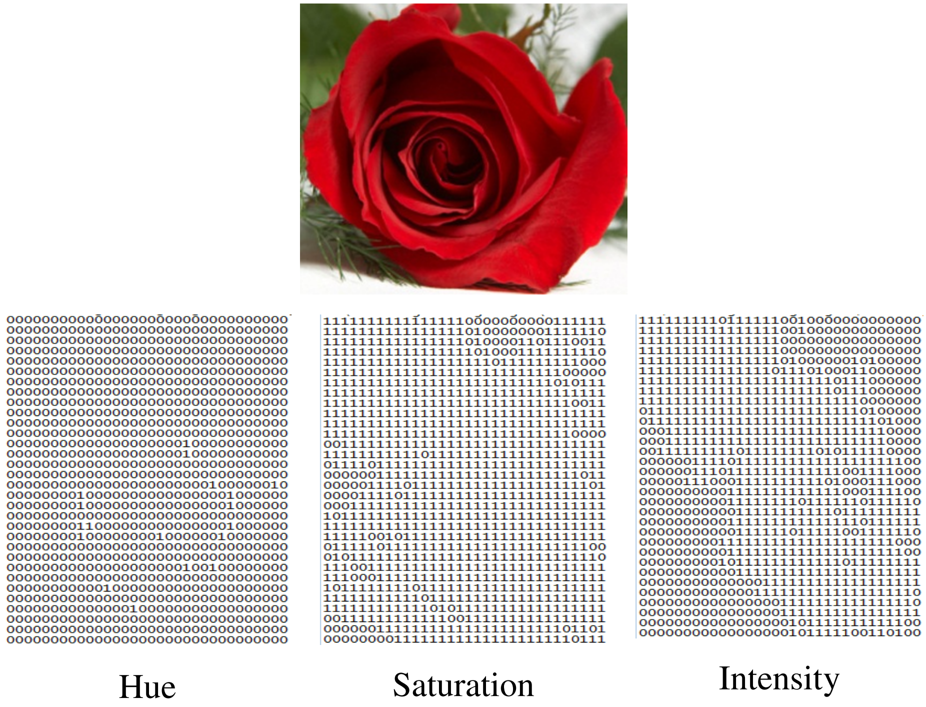

Fig. 5. Flower image color extraction using HSI color space

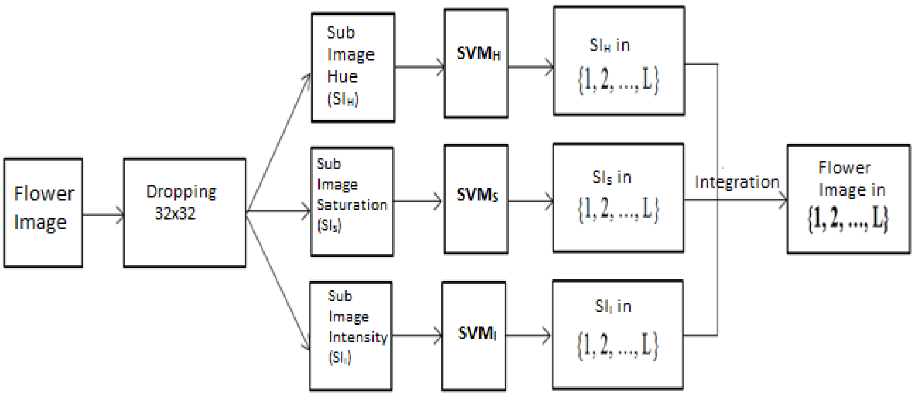

Fig. 6. Flower image classification using HSI color space

The mechanism of flower image classification system using HIS color space is the same to using the above RGB color space. The detail of integration method will explain in the next section.

3.2 Integration of Multi SVM Classification Result

3.2.1 Majority Integration Method

Majority Integration Method is a simple and easy to implementation method. The final result is the highest consensus result. In this problem, we have three results of three SVM components (SVM_R, SVM_G, SVM_B or SVM_H, SVM_S, SVM_I). The final conclusion is the result having the same of two or three classification results. For example in using RGB color, if both of SVM_R and SVM_B show that the flower image is lotus and the SVM_G shows that the flower image is the rose, then the final result is lotus.

In order to test the feasibility of the majority integration method, we have tested in the 80 flower images of three categories consisting 27 rose images, 25 lotus images and 28 daisy images. The kernel functions of SVM (Gaussian, and Polynomial kernel) have been used in the implementing experiments.

Table 1. Majority integration method in RGB color space and SVM using Gaussian kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Majority
Rose	13/27	22/27	20/27	17/27
Lotus	20/25	23/25	25/25	24/25
Daisy	14/28	25/28	27/28	24/28
All	**47/80**	**69/80**	**72/80**	**64/80**
Precision	**59%**	**86%**	**90%**	**80%**

Table 2. Majority integration method in HSI color space and SVM using Gaussian kernel function

Flower Image	SVM_H	SVM_S	SVM_I	Majority
Rose	14/27	16/27	11/27	9/27
Lotus	22/25	24/25	20/25	17/25
Daisy	26/28	22/28	14/28	12/28
All	**62/80**	**62/80**	**45/80**	**38/80**
Precision	**78%**	**78%**	**56%**	**48%**

Table 3. Majority integration method in RGB color space and SVM using Polynomial kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Majority
Rose	14/27	26/27	15/27	14/27
Lotus	19/25	16/25	25/25	16/25
Daisy	15/28	25/28	27/28	23/28
All	**48/80**	**67/80**	**67/80**	**53/80**
Precision	**60%**	**84%**	**84%**	**66%**

Table 4. Majority integration method in RGB color space and SVM using Polynomial kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Majority
Rose	17/27	12/27	13/27	9/27
Lotus	20/25	21/25	19/25	20/25
Daisy	28/28	23/28	17/28	23/28
All	**65/80**	**56/80**	**49/80**	**52/80**
Precision	**81%**	**70%**	**61%**	**65%**

The experimental results show that the precision of the majority integration method is low and does not improve the classification result of each SVM component. Although we use Gaussian or Polynomial kernel function for SVM component, RGB color space are more suitable for improving the precision of flower image classification than HIS color space.

In the special case, there is no majority result. The final result is not identification. For example in using RGB color, SVM_R shows that the flower image is lotus, SVM_G shows that the flower image is the rose and SVM_B shows that the flower image is the daisy. We can choose any majority result. Thus the final result is not identification. This is a disadvantage of majority integration method. To overcome this disadvantage, the majority integration method need to combine average method and will be explained in the section 3.2.3.

3.2.2 Average Integration Method

Average Integration Method is a natural and simple integration method. The final result is the average of result of all components. The distance between the sub images and the hyperplanes of SVM component are used to calculate the average distance.

The final classification result is identified based on this distance. In order to test the feasibility of the average integration method, we have also tested in the 80 flower images of three categories (rose, lotus, and daisy) and two kernel functions (Gaussian, and Polynomial). The experimental results show in the below tables:

Table 5. Average integration method in RGB color space and SVM using Gaussian kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Average Method
Rose	13/27	22/27	20/27	25/27
Lotus	20/25	23/25	25/25	25/25
Daisy	14/28	25/28	27/28	26/28
All	**47/80**	**69/80**	**72/80**	**76/80**
Precision	**59%**	**86%**	**90%**	**95%**

Table 6. Average integration method in HSI color space and SVM using Gaussian kernel function

Flower Image	SVM_H	SVM_S	SVM_I	Average Method
Rose	14/27	16/27	11/27	20/27
Lotus	22/25	24/25	20/25	22/25
Daisy	26/28	22/28	14/28	26/28
All	**62/80**	**62/80**	**45/80**	**68/80**
Precision	**78%**	**78%**	**56%**	**85%**

Table 7. Average integration method in RGB color space and SVM using Polynomial kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Average Method
Rose	14/27	26/27	15/27	24/27
Lotus	19/25	16/25	25/25	22/25
Daisy	15/28	25/28	27/28	27/28
All	**48/80**	**67/80**	**67/80**	**73/80**
Precision	**60%**	**84%**	**84%**	**91%**

Table 8. Average integration method in RGB color space and SVM using Polynomial kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Average Method
Rose	17/27	12/27	13/27	23/27
Lotus	20/25	21/25	19/25	21/25
Daisy	28/28	23/28	17/28	25/28
All	**65/80**	**56/80**	**49/80**	**69/80**
Precision	**81%**	**70%**	**61%**	**86%**

The experimental results show that the precision of the average integration method have improved the precision of the classification result of each SVM component. Although Gaussian or Polynomial kernel function for SVM component has been used, the precision of average integration method is stable and does not change too much.

3.2.3 Fusion of Majority and Average Integration Method

Fusion of Majority and Average Integration Method is an integration method overcoming the disadvantage of the majority integration method in the special case (not identify). The final result is the same to the majority integration method in the normal case. In the not identify case, the final result is the same to the average integration method. In order to test the feasibility of this integration method, we have also tested in the 80 flower images and two kernel functions like above. The experimental results show in the below tables:

Table 9. Fusion of Majority and Average integration method in RGB color space and SVM using Gaussian kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Fusion Method
Rose	13/27	22/27	20/27	25/27
Lotus	20/25	23/25	25/25	25/25
Daisy	14/28	25/28	27/28	26/28
All	**47/80**	**69/80**	**72/80**	**76/80**
Precision	**59%**	**86%**	**90%**	**95%**

Table 10. Fusion of Majority and Average integration method in HSI color space and SVM using Gaussian kernel function

Flower Image	SVM_H	SVM_S	SVM_I	Fusion Method
Rose	14/27	16/27	11/27	19/27
Lotus	22/25	24/25	20/25	23/25
Daisy	26/28	22/28	14/28	26/28
All	**62/80**	**62/80**	**45/80**	**68/80**
Precision	**78%**	**78%**	**56%**	**85%**

Table 11. Fusion of Majority and Average integration method in RGB color space and SVM using Polynomial kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Fusion Method
Rose	14/27	26/27	15/27	24/27
Lotus	19/25	16/25	25/25	22/25
Daisy	15/28	25/28	27/28	27/28
All	**48/80**	**67/80**	**67/80**	**73/80**
Precision	**60%**	**84%**	**84%**	**91%**

Table 12. Fusion of Majority and Average integration method in RGB color space and SVM using Polynomial kernel function

Flower Image	SVM_R	SVM_G	SVM_B	Fusion Method
Rose	17/27	12/27	13/27	21/27
Lotus	20/25	21/25	19/25	22/25
Daisy	28/28	23/28	17/28	26/28
All	**65/80**	**56/80**	**49/80**	**69/80**
Precision	**81%**	**70%**	**61%**	**86%**

The experimental results show that the precision of the fusion of majority and average integration method have improved the precision of the classification result of each SVM component. This method gets precision more than the average integration method. The experimental results show that this integration method is suitable to use Gaussian kernel function than Polynomial kernel function.

4 Analysis of Experiments

The flower images database get from The Oxford Flower Dataset (www.flowers.vg) are used for our experiments.

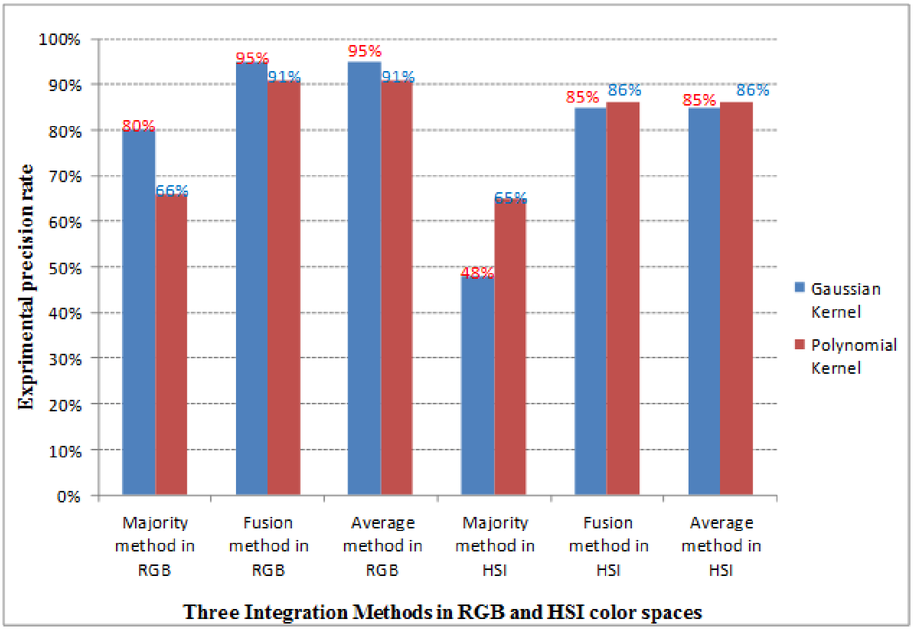

Fig. 7. Overview of experimental results in flower image classification

The majority method is very easy to develop, but the average and fusion methods are better method than majority method in general. The precision of average method are minor higher than fusion method. The Gaussian kernel function of SVM is suitable to RGB color features, while the Polynomial kernel function of SVM is suitable to HIS color features.

All experimental results show that the feature of RGB color are better than HSI color when we use it to apply for flower image classification. The image in the flower dataset often focuses on the flower object and changes the intensity a little. So that HIS color with the Intensity element does not support much the classification processes.

5 Conclusion

In this paper, we propose and implement a multi Support Vector Machines model having two parameters (m and L) to apply for image classification, called multi_SVM. Where, L = the number of categories of images = the number of hyperplanes of one SVM; m = the number of a flower image's feature vectors = the number of SVM(s).

Multi_SVM model is easy to design and deploy for the specific image classification application with high precision. We can apply multi_SVM for the complex image such flower or facial images. When the number of categories of images increases, we just increase the number of hyperplanes of one SVM. It means that the developer only update the SVM component. Multi_SVM model has been applied for three categories of flower image classification in Oxford Flower Dataset and the precision rate can reach 95% in the best case. The experimental results show the feasibility of our proposal model. Multi_SVM model require that the number of image's feature vectors must be a constant.

References

1. Yang, Z., Rongyi, H., Muwei, J.: Comparison of Two Methods for Texture Image Classification. In: Second International Workshop on Computer Science and Engineering, WCSE 2009, vol. 1, pp. 65–68. IEEE Press (2009)
2. Linlin, S., Li, B., Picton, P.: Facial recognition/verification using Gabor wavelets and kernel methods. In: International Conference on Image Processing, ICIP 2004, vol. 3, pp. 1433–1436. IEEE Press (2004)
3. White, K.P., Kundu, B., Mastrangelo, C.M.: Classification of Defect Clusters on Semiconductor Wafers Via the Hough Transformation. IEEE Transactions on Semiconductor Manufacturing 21(2), 272–278 (2008)
4. Zhao, L., Guo, Z.: Face Recognition Method Based on Adaptively Weighted Block-Two Dimensional Principal Component Analysis. In: Third International Conference on Computational Intelligence, Communication Systems and Networks (CICSyN), pp. 22–25. IEEE Press (2011)
5. Xingfu, Z., Xiangmin, R.: Two Dimensional Principal Component Analysis based Independent Component Analysis for face recognition. In: International Conference on Multimedia Technology (ICMT), pp. 934–936. IEEE Press (2011)
6. Wakin, M.B.: Sparse Image and Signal Processing: Wavelets, Curvelets, Morphological Diversity. Signal Processing Magazine 28(5), 144–146 (2011)
7. McSherry, D., Stretch, C.: An Analysis of Order Dependence in *k*-NN. In: Coyle, L., Freyne, J. (eds.) AICS 2009. LNCS, vol. 6206, pp. 207–218. Springer, Heidelberg (2010)
8. Madden, M.G.: A New Bayesian Network Structure for Classification Tasks. In: O'Neill, M., Sutcliffe, R.F.E., Ryan, C., Eaton, M., Griffith, N.J.L. (eds.) AICS 2002. LNCS (LNAI), vol. 2464, p. 203. Springer, Heidelberg (2002)
9. Li, S., Zhu, L., Jiang, T.-Z.: Active Shape Model Segmentation Using Local Edge Structures and AdaBoost. In: Yang, G.Z., Jiang, T.-Z. (eds.) MIAR 2004. LNCS, vol. 3150, pp. 121–128. Springer, Heidelberg (2004)
10. Yong, L., Xin, Y.: Negatively correlated neural networks for classification. Artificial Life and Robotics 3(4), 255–259 (1999)
11. Rud, S., Yang, J.-S.: A Support Vector Machine (SVM) Classification Approach to Heart Murmur Detection. In: Zhang, L., Lu, B.-L., Kwok, J. (eds.) ISNN 2010, Part II. LNCS, vol. 6064, pp. 52–59. Springer, Heidelberg (2010)

12. Agrawal, S., Verma, N.K., Tamrakar, P., Sircar, P.: Content Based Color Image Classification using SVM. In: Eighth International Conference on Information Technology: New Generations (ITNG), pp. 1090–1094. IEEE Press (2011)
13. Devis, T., Jordi, M., Mikhail, K., Gustavo, C.V.: Structured Output SVM for Remote Sensing Image Classification. Journal of Signal Processing Systems 65(3), 301–310 (2011)
14. Demir, B., Erturk, S.: Improving SVM classification accuracy using a hierarchical approach for hyperspectral images. In: 16th IEEE International Conference on Image Processing (ICIP), pp. 2848–2852. IEEE Press (2009)