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Flower Classification using Combined *a* b** Color and Fractal-based Texture Feature

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Abstract

*Flower classification is a useful way for grouping a flower in certain class using specific features. This research propose a new method of flower classification system using combination of color and texture features. The first phase is getting the crown of the flower, which is localized from a flower image by using pillbox filtering and OTSU's thresholding. In the next phase, color and texture features are extracted from the crown. The color features are extracted by removing L channel in L*a*b* color space, and taking only a* and b* channel, because of ignoring different lighting condition in flower image. The texture features are extracted by Segmentation-based Fractal Texture Analysis (SFTA). The combination features which are consisted of 10 color features and 48 texture features are used as input in k-Nearest Neighbor (kNN) classifier method with cosine distance. The flower classification achieves the best result with accuracy 73.63%.*

Keywords: *flower classification, L*a*b*, fractal texture analysis, kNN*

1. Introduction

Flower classification research has been growing nowadays and it is mainly used to recognize the flower by extracting its features. Most of researchers in agriculture, such as botanists and taxonomist still difficult to define various flower images without flower guide books [1]. Classification method is needed to help the researcher in finding the relevant name of the flower easily. Nilsback and Zisserman [2], successfully carried out a research in flower classification using three kinds of vocabularies for extracting feature, there are shape, color and texture. Nilsback and Zisserman used flower dataset provided by Oxford University and used only several classes, there are 10 species, and 40 images in each species. The performance of color features is computed using k-means clustering and achieves 49% efficiency. Hue, Saturation, Value (HSV) color spaces are applied in this research to obtain the effect of illumination variations. For extraction of shape vocabulary, SIFT descriptor is used and the performance achieves 75.3% efficiency with 800 clusters. The texture vocabulary used in that research is MR8 filter that was introduced by Varma and Zisserman [3]. The result shows that using color vocabulary achieves the best extraction, and when using texture extraction, the performance of classification is very poor. In 2008, Nilsback and Zisserman used graph cut segmentation to get the boundary of a flower [4]. There were 103 classes of flower, using four features, which are local shape/texture, the shape of the boundary, the overall spatial distribution of petals, and the color. Support Vector Machine (SVM) classifier was used and getting performance of 72.8% efficiency.

Other researches [5], use kNN classification of flower images based on texture extraction

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using gray-level occurrence matrix (GLCM) and Gabor texture. Guru, Sharath, and Manjunath explained that a specific variety of flower might have several colors, therefore the color feature is not critical feature for determining the species of the flower. Flower dataset consists of 25 flower species was obtained by world wide web. The experiment was conducted using 20 training samples and 30 testing samples. Combined GLCM and Gabor texture shows the best result and outperforms as individual features. Alceu, Gabriel, and Agma proposed SFTA for extracting texture feature in image classification, and also used Content Based Image Retrieval (CBIR), then comparing the performance of SFTA to other feature extraction methods such as Gabor filter [6]. Those compared methods are Fast Fractal Satck (FFS), Haralick, Gabor, Histogram, Basic Texture, and combination of Haralich, Histogram, Basic Texture, and Zernike moments, SFTA show the best result with 8 thresholds as input.

Determining the best feature is the appropriate path used in the dataset, which provided by Oxford University. Nilsback and Zisserman used shape feature extraction in their research because of the dataset contains extreme rotation, viewpoint parts, scale differences, and may have a differences shapes within a class. Based on those variations, shape feature is hard to reveal, then in other opinions, Guru, Sharath, and Manjunath, argue that color feature isn't needed, so they just use texture as specific feature. Guru, Sharath, and Manjunath, tried to observe flower classification with dataset that contains similar flowers, but has different colors. The total classes are 17, and 4 classes contain similar flower in different colors. In these dataset also may has the same color in different classes and in each class may have different lighting conditions. Nilsback and Zisserman use HSV color space, where *V* channel represents the brightness of flower image. However, HSV has a problem with calculation of intensity or luminance that gives equal weighting to the RGB component. This problem causes of inappropriate brightness the color image in human eye perception. The range of maximum component saturation depends on hue component. Therefore, $L*a*b*$ color space is needed for getting uniform characteristics in human eye perception [7]. Li and Pong experimental results show that $L*a*b*$ color space always gives the best result in color transformation [8].

Flower dataset may have similar color and texture in different classes, and different color within a class, therefore color and texture are better to combined because of the complexity problems between color and texture. Those combined feature can be represented as dependent features that are extracted in collaboration. In this paper we propose a novel method to classify a flower in correct species using those combined features. In addition, in the color extraction phase, flower image is processed without regard to the lighting condition. Consequently, *L* channel of $L\ a*\ b*$color space is removed.

This paper is organized as follows: In Section 2, the research method will explain, and experimental details presented. The result and analysis are discussed in Section 3. Finally Section 4 concluding the paper.

2. Research Method

The method is divided into three main phases, which are preprocessing, feature extraction using color and texture feature, and feature classification using kNN classifier. Rescaling image is needed for light computation during classification process. This experimental model is conducted in MATLAB environment. The proposed model of flower classification is drawn in Figure 1. Training and testing dataset uses as input of the system, then rescaled for both dataset. To get crown region, the process of thresholding and filtering is used.

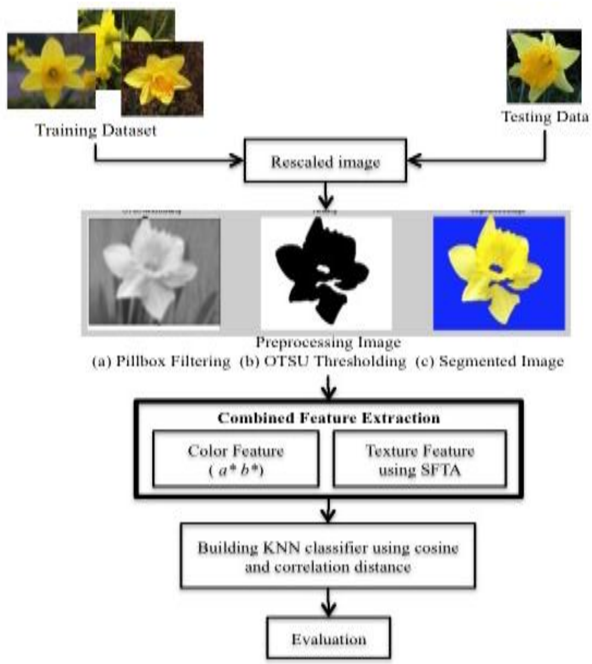

Figure 1. Proposed method of flower classification using combined color and texture

2.1 Preprocessing

Image prepocessing is used for enhancing the image classification performance, therefore, filtering and segmentation are used in this phase. Circular average filter also known as pillbox filtering has a circular mask, which is able to smoothen the image. This filter can be used for removing the detail parts of particular image sizes. The output of filtering phase is a blurred image, which is helpful in the thresholding phase to clear segmented image.

This paper uses Otsu's thresholding for extracting region of flower image. Otsu utilized histogram method for maximizing between class variance and minimizing inter-class variance. The principle of Otsu's method is to compute the difference of intensities from image pixel and separated in certain classes, that are foreground and background [9]. Figure 2 shows the preprocessing step.

2.2. Feature Extraction

Feature extraction is acquired in the first phase by getting the crown of the flower. The feature extraction consists of color and texture, that are combined by collecting the digital information around the crown area. Color feature is one of important things to assess the diversity of colors at the same class, as shown in Figure 3. Each default image has same color space, *i.e.*, RGB. RGB is non-uniform color, that cannot be represented by human eye perception, so $L*a*b$ is used. Beside that, $L\ a*\ b*$ color space can describe color which contains illumination, so it is clearly known the intensities of the color. L represents lightness, $a*$ encodes the red-green sensation with $a*$ positive represents to red color and $a*$ negative represents green color. The rest, $b*$ color channel encodes the yellow-blue sensation, which is $b*$ positive represents to yellow, and $b*$ negative represents blue. To get $L\ a*\ b*$ from RGB color space requires transformation from RGB to XYZ first, then from XYZ to L $a*b*$. Equation 1 and 2 shows that conversion, respectively [10, 11].

$$\begin{bmatrix} R \\ B \\ B \end{bmatrix} = \begin{bmatrix} 0.41847 & -0.15866 & -0.082835 \\ -0.001160 & 0.25243 & 0.015708 \\ 0.00002000 & -0.0025498 & 0.17860 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \qquad (1)$$

$$L* = \begin{cases} 116(Y/Y_n) - 16, Y/Y_n > 0.008856 \\ 903.3(Y/Y_n), Y/Y_n \end{cases} \qquad (2)$$

$$a* = 500\left[f(X/X_n) - f(Y/Y_n)\right]$$

$$b* = 500\left[f(Y/Y_n) - f(Z/Z_n)\right]$$

where the function *f(s)* defines as follow

$$f(s) = \begin{cases} s^{1/3}, s > 0.008856 \\ 7.787(s) + (16/116), s \leq 0.008856 \end{cases} \qquad (3)$$

The function, X_n, Y_n,, and Z_n, represent the tristimulus coordinate of white point. L channel of L $a*$ $b*$, represents lightness or illuminant. Based on the difference lighting condition in flower image, so L channel is removed, and give two color channels left, that are $a*$ and $b*$. Figure 4 shows that in a flower class have same color, and each image may have several of lighting conditions.

The $L*$ channel will be removed in order to get the only color component of red to green, and yellow to blue. Obtaining all features in each $a*$ and $b*$ color channels, are acquired by statistical computation, that are mean, mode, minimum, maximum, and standard deviation, so in color feature extraction, in each image have 10 features,

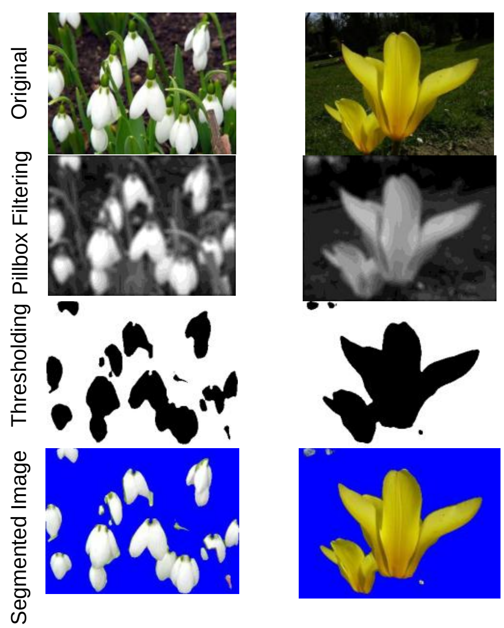

Figure 2. Prepocessing step that using original image as an input represented in the first row, the second one are filtered image using pillbox filtering, the third one are result of thresholding and segmented image obtained as output

In this paper, the color is dependent feature, so the texture feature is involved and cannot be stand-alone. Figure 5 shows that the different class may have same color, so that combined feature can be used to extract information in details among features. Texture feature extraction may give time consuming process, since extract the characteristic of the image. Therefore, in this research, we implement SFTA to deal time-consuming problems [5].

Figure 3. Example of the dataset which has different color in same class.

Figure 4. Example of the dataset (Dandellion), which has different lighting condition in the same class.

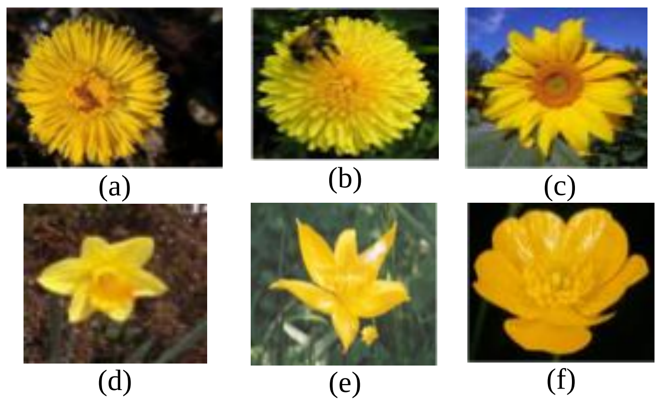

Figure 5. Example of the dataset which has same color in the different classes. (a) Colts' Foot, (b) Dandellion, (c) Sunflower, (d) Daffodil, (e) Tulip, (f) Buttercup

SFTA applied multi level Otsu thresholding to decompose segmented image in several parts. Two-Thresholding Binary Decomposition (TTBD) is computed for generating image in a couple. If the default number of thresholds input is 8, there were obtained 16 images in each input image, in which each image has 3 vector features that represent boundaries of fractal dimension. The measurement of the fractal applied to describe the complexities of boundary and structures of segmented image, so the SFTA feature vector corresponds to the number of binary images obtained in TTBD phase. Three vector features extracted in each binary image are fractal dimension, mean gray level, and size of area image. SFTA algorithm can be explained in Figure 6 [5]. I is grayscale image, I_b is binary image, Δ is border image, is gray level range, T set of threshold values, n_t is number of thresholds, t_l is lower threshold, t_u is upper threshold, fractal dimension, is box counting algorithm, and V_{SFTA} is SFTA feature vector. Figure 7 shows the decomposition image with number of treshold is 8. The total texture feature are 48 features, which is in each 16 images binary image have 3 vector features. So, the number of all features extraction in a flower image are 58 features.

Require: Grayscale image I and number of thresholds n_t.
Ensure: Feature vector V_{SFTA}.
1: $T \leftarrow$ **MultiLevelOtsu**(I, n_t)

$TA \leftarrow \{\{t_i, t_{i+1}\} : t_i, t_{i+1} \in T, i \in [1..|T|-1]\}$
$TB \leftarrow \{\{t_i, n_l\} : t_i \in T, i \in [1..||]\}$
$i \leftarrow 0$
for $\{\{t_l, t_u\} : \{t_l, t_u\} \in TA \cup TB\}$ do
    $I_b \leftarrow$ **TwoThresholdSegmentation**(I, t_l, t_u)
    $\Delta(x, y) \leftarrow$ **FindBorders**(I_b)
    $V_{SFTA}[i] \leftarrow$ **BoxCounting**(Δ)
    $V_{SFTA}[i + 1] \leftarrow$ **MeanGrayLevel**(I, I_b)
    $V_{SFTA}[i + 2] \leftarrow$ PixelCount(I_b)
    $i \leftarrow i+3$
end for
return V_{SFTA}

Figure 6. SFTA extraction algorithm

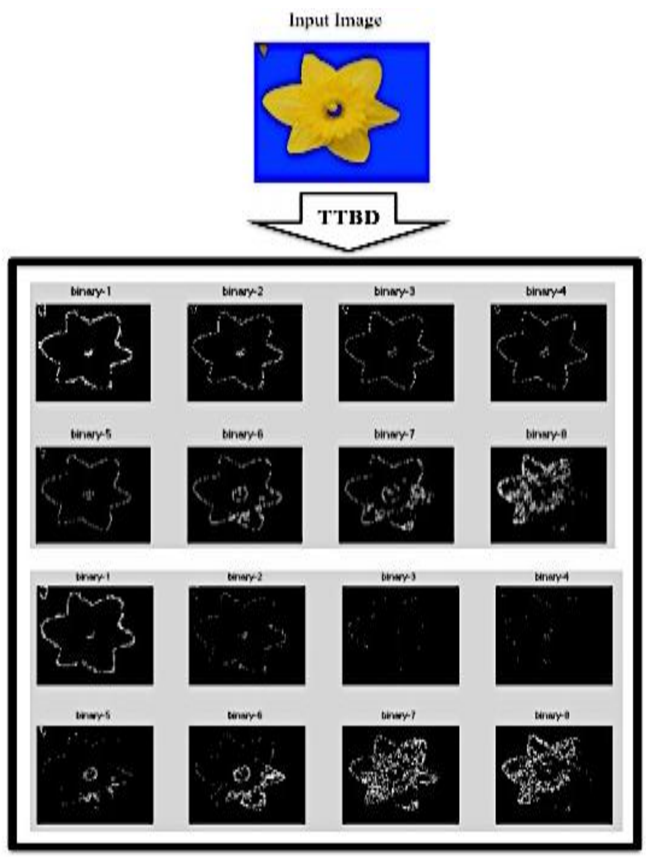

Figure 7. The results of decomposition binary image that generate from Two-Thresholding Binary Image. There are 16 images output of a single input image

2.3. Flower Classification

Classification is one of techniques to recognize the flower species. In this paper we use kNN as the simplest algorithm that is widely used in machine learning problems. The features are classified by distance from its neighbor in the image's feature, which are assigned to the class that most common among in its *k*- distance nearest neighbor. Distance is the important thing to get the information among features in multidimensional spaces. Beside the distance, choosing of k value in kNN method is quite critical. The best of choosing appropriate k can enhance a good performance of classification. In this paper, there are 58 features in each training and testing dataset, under $k = 7$, $k = 9$, and $k = 11$. Testing dataset are also classified with cosine and correlation distance.

3. Results and Analysis

The dataset is taken from Robotics Research Group at University of Oxford which consists of 17 classes. Not all the dataset was used, therefore, cleaning data in preprocessing phase was needed in order to get dataset which has better segmentation. Bad segmentation was happened if the result of segmented image cannot distinguish between foreground and background clearly. So that, the bad segmentation was removed, then gives 13 classes left after cleaning data. There are 416 images were obtained, that are 25 images as training set and 7 images as testing set, in each class, respectively.

3.1. Perfomance Measure

The performance of the proposed method is measured by accuracy. Accuracy is simplest form for predicting how much a classifier can classify into the correct class, by using the ratio of the corrected classify number to the total number of testing dataset. The experiment of performance measure, was applied in both combined color and texture feature, in which color feature using $L*$ and without $L*$ color channel.

The accuracy of KNN classification was undertaken in $k = 7$, $k = 9$, and $k = 11$ as input, then the input of k will be evaluated using cosine and correlation distance measure. Table 1 shows evaluation of flower image classification using combined $L*a*b*$ color and SFTA. Table 2 shows accuracy of flower image classification using $a*b*$ color channel combined with texture feature. Both evaluation measures give the information about the accuracy when the color feature stands alone, the texture feature stand alone, and combined of both.

3.2. Results

The results show that the accuracy will be poor if the color feature extraction independently used for classifying flower. Comparing the color feature extraction, the accuracy of texture feature is better to stand alone, and help the performance to achieve the accuracy when all features combined. Table 1 and Table 2 shows that using cosine measure gives better result in each evaluation, than using correlation measure and choosing of k value in KNN is the best for $k = 9$ in both evaluation.

The best result of classification using KNN is shown when using cosine measure under $k = 9$, that is 73.63%, with combined $a*b*$ color and texture feature. Removing L, give the bad result for color feature performance when the feature classify in stand-alone. However, using cosine measure distance with combined of $a*b*$ color and texture is better than combined $L*a*b*$ color. The texture feature is sufficient robust to classify flower image in stand-alone feature.

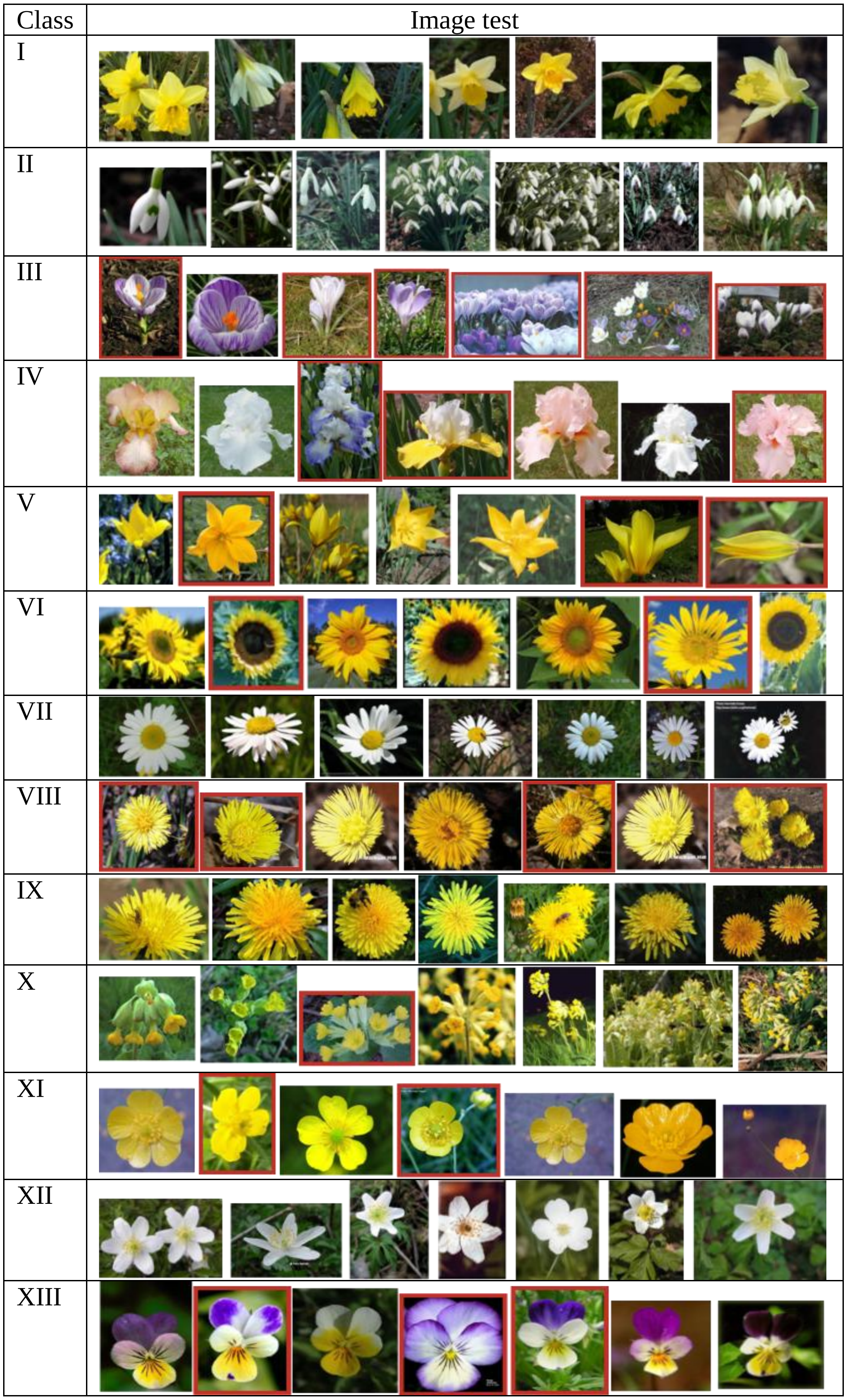

Figure 8.The example result of the flower images classification using combined *a*b*b*color and texture feature with cosine under *k*=9. The red border

in images shows the incorrect classification in each class. No border represent the correct classification. There are 13 classess and each class contains 7 images as testing dataset. The classess are Daffodil (I), Snowdrop (II), Crocus (III), Iris (IV), Tulip (VI), Sunflower (VII), Daisy (VIII), Colts' Foot (VIII), Dandellion (IX), Cowslip (X), Buttercup (XI), Windflower (XII), and Pansy (XIII).

Figure 8 shows the result of the classification when using combined *a*b** color and texture feature with cosine distance and k = 9, that result shows the image flower which correctly classified and misclassified. The third class, Crocus flower in Figure 6, give worst accuracy of classification, because just one image that correctly classified, however the classification of Daffodil, Snowdrop, Daisy, Dandellion and Windflower are correctly classified. By that result, the system can be used for detecting image flower, which has different illumination and different rotations.

Table 1. The evaluation of flower image classification using *La*b color feature, texture feature and combined**

Distance	***k***	**L*a* b Color**	**Texture**	**Color and Texture**
Cosine	7	0.4286	0.6044	0.6044
	9	**0.4615**	**0.7143**	**0.7253**
	11	0.4286	0.6044	0.6154
Correlation	7	0.4286	0.5934	0.6044
	9	0.4396	0.6703	0.7143
	11	0.4945	0.6154	0.6154

Table 2. The evaluation of flower image classification using *a*bcolor feature, texture feature, and combined**

Distance	***k***	**a* b Color**	**Texture**	**Color and Texture**
Cosine	7	0.4176	0.6044	0.6154
	9	**0.5165**	**0.7143**	**0.7363**
	11	0.4615	0.6044	0.6154
Correlation	7	0.4066	0.5934	0.6044
	9	0.42725	0.6703	0.6923
	11	0.4396	0.6154	0.6154

Beside that, the system also detects a flower, which has similar shape in same color, as shown in classification result of Colts' Foot and Dandelion. The result classification of Colts' Foot has 3 images misclassified. Those misclassified images are recognized as Dandellion as shown in Figure 9. The system also shows that in one class may have different number of flower, as shown in figure 10.

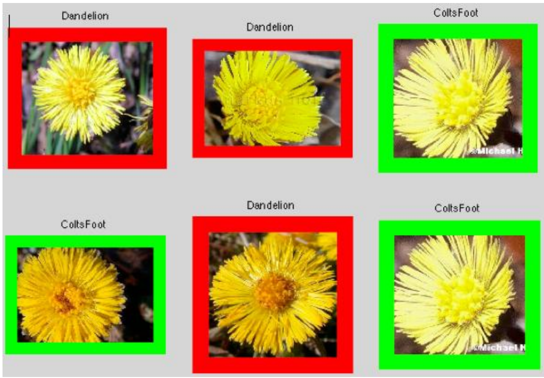

Figure 9. Testing dataset which has Colts' Foot as target. The green border represents corrected classify and the red one represents misclassified.

Figure 10. The system correctly classified into the different number of flower in each class

4. Conclusion and Future Work

The proposed model is sufficient to overcome the image flower classification in different lighting condition and color in the same class. KNN classifier is used to assess similarity among image flowers. Cosine measure outperforms to all distance measures under k = 9. Combined feature extraction, between color and texture are needed in these conditions of datasets. The combined $a*b*$ features and texture gives the better performance when using cosine measure, than using $L*$ color channel when combined with texture feature.

The results are depends on the feature information in database. Bad segmentation will affect the performance of the classification, so removing the bad segmentation is needed. The data training is chosen based on the best segmentation, which can be separated clearly between background and object. The extracted featured can be obtained from the crown of the flower by means of the best segmentation result.

Further research is very important to recognize leaves and soil around flower, because mostly flower image has leaves' and soil background. Leaves and soil detection then removing them can achieves good performance of flower classification, especially for segmentation phase, because only the crown of the flower that need to be extracted in order to get the main feature.

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