A New Image Classification Approach to Recognizing Maize Diseases

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Abstract: The spot, streak and rust are the most common diseases in maize, which require an effective way to recognize and handle. This paper presents a new image classification approach to the recognition of these maize diseases with high accuracy. Firstly, the K-Means clustering algorithm is deployed in LAB color space to reduce the influence of image noise and irrelevant background so that the area of maize diseases could be effectively extracted. Then the statistic pattern recognition method and Gray Level Co-occurrence Matrix (GLCM) method are used to segment maize disease leaf images in order to obtain their texture, shape and color features accurately. Finally, Support Vector Machine (SVM) classification method is used to identify three diseases. The experiment results are given to show the feasibility and effectiveness of the proposed method.

Keywords: Maize Diseases, Image Processing, Color Segmentation, Feature Extraction, Support Vector Machine.

1 Introduction

In China, crops are affected by pests and diseases all the time in the growth process (Li et al. 2017). Traditionally, agricultural workers have to use their eyes to identify and diagnose crops diseases and make subjective judgments, which are time-consuming, tedious, and inaccurate. As a result, the misuse of pesticides or excessive use of pesticides could bring ecological pollution to the environment, and the pesticide remaining on corps may endanger the health of human beings (Ali et al. 2017).

In recent years, computer technology and machine vision have gradually deployed into the field of agriculture to assist farmers to deal with the recognition of corp diseases (Wang et al. 2012, Wei and Zhang 2016). Especially, image recognition and classification technology can quickly and accurately diagnosis the crops' diseases and achieve the "right remedy" to reduce the pollution caused by pesticides on the ecological environment (Anshuka et al. 2014). Therefore, recognition and classification of crop diseases and insect pests have become one of hot issue in the field of image research.

Marcelo et al. (2017) focused on nutritional deficiencies identification in coffee tree leaves by using GLCM image processing technique and KNN computational intelligence tools, which could obtain modest results. Pulido et al. (2017) presented a classification system for weeds and vegetables from images by using SVM and Principal Component Analysis (PCA) method and achieved a high performance of 90%. Wu et al. (2015) researched a new invariant matrix parameters combining with ant colony optimization support vector machine method to identify two kinds of crop disease images based on color feature analysis. These features were extracted from the original images and the recognition rate reached to 83%.

Some other automatic segmentation methods were proposed to identify crop disease based on the edge feature detection and support vector machine (Wu et al. 2014, Zhai et al. 2015, Zhang et al. 2015, Camargo and Smith 2009). These methods used color, shape or texture as distinguishing evidences to recognize plant diseases. However, the extraction of a single color feature or shape feature or texture feature can not accurately identify the disease. In order to improve the identification accuracy for different maize diseases, we propose to use both the color and texture features for maize diseases classification in this paper. The GLCM texture features extraction and SHV color features extraction methods are utilized to obtain the suitable 2D feature space, and SVM is used to training the classifier.

The rest of the paper is organized as follows. Section II introduces a new the identification approach for maize diseases, which has three phases, namely image preprocessing, feature extraction and recognition. More specifically, the K-means clustering method is used in LAB color space in the image preprocessing phase. GLCM texture and SHV color features are utilized in the feature extraction phase. Then, SVM classification method is used to identify spot, streak and rust diseases in the recognition phase. Section III presents the experiment results and analysis to verify the feasibility and performance of our approach. Finally, a brief conclusion and the future directions of our research work are given in Section IV.

2 Research Methods

The feature extraction can be used to identify different types of maize diseases via their inherent characteristics in the original images. In this study, two kinds of feature were selected for image processing and image recognition in order to improve the accuracy: one is SHV color features (such as first moment, second moment and third moment in SHV color space), and another is GLCM texture features (such as energy, entropy, contrast and inertia). We proposes a new image classification approach to recognizing corps diseases, which contains three phases: (1) image preprocessing; (2) image feature extraction; (3) image recognition, as shown in Figure 1.

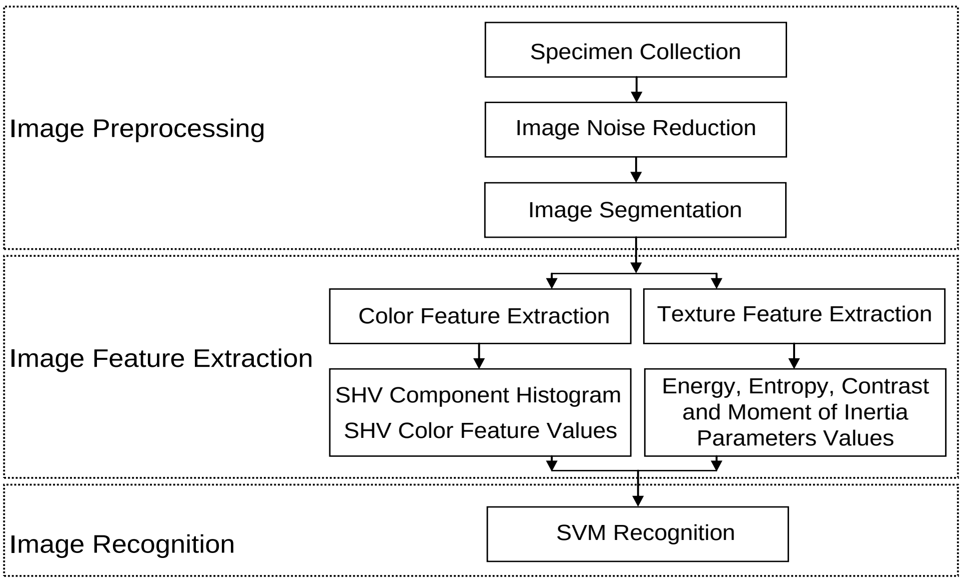


Figure 1 The flowchart of the proposed approach to recognizing maize diseases

To recognize maize diseases, the first image preprocessing phase aims to reduce the influence of light, image noise and irrelevant background, and to make the maize spot area easy to extract. The second phase is the image feature extraction, in which the HSV component histogram and its eigenvalues are used in combination with the texture parameters by GLCM method. The main purpose of this phase is to extract different types of maize diseases accurately. In the third phase, the SVM method is deployed to train the classifier in order to accurately recognize different types of maize diseases.

2.1 Image preprocessing

In general, the image noise can be reduced and the image quality can be improved effectively by using the data smoothing method. For instance, the median filter is a popular way to remove 'salt-and-pepper' noise from an image and at the same time preserve edges and keep useful information (Astola et al. 1990, Li et al.2015). In this paper, the median filter is adopted to preprocess and smooth the corn image by taking the average of all vectors in a corn image. The used formula is as follows (He et al. 2013):

$$F'\left(x_0, y_0\right) = \left[\underset{(x,y)\in S}{sort} F\left(x, y\right)\right]_{\frac{N+1}{2}}, N \geq 0 \qquad (1)$$

where $F'\left(x_0, y_0\right)$ is the median of the gray value of the image. s is the Neighborhood collection of pixel. (x, y) is the element of s. $F\left(x, y\right)$ is the gray value of (x, y). N expressed as the number of the elements in the set of *S*. *sort* is expressed as sequencing. $[g(\square)]_{N+1/2}$ is the median of the function $g(\square)$.

By using median filtering algorithm, the original images are denoised and their quality is enhanced. In order to extract the texture details accurately, K Means clustering method is used to segment the lesion area of images. The images are firstly converted from RGB color space to XYZ color space, and then further converted to $L*a*b$ color space. By using the following conversion equations:

$$\begin{cases} R = gamma\left(r/255\right) \\ G = gamma\left(g/255\right) \\ B = gamma\left(b/255\right) \end{cases} \qquad (2)$$

$$gamma\left(x\right) = \begin{cases} \left(\dfrac{x+0.055}{1.055}\right)^{2.4}, x \in \left(0.04045, +\infty\right) \\ \dfrac{x}{12.92}, \qquad other \end{cases} \qquad (3)$$

where R, G, B is the red, green and blue three colors respectively. $gamma(\cdot)$ is the transform function, which is mainly used for processing nonlinear color image to improve the contrast of pixels in the color space.

Substituting equation (3) into equation (2), we obtain the following conversion relationship between RGB color space and XYZ color space (Yuan et al. 2016):

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

where X , Y , Z is the three color values of XYZ color space respectively.

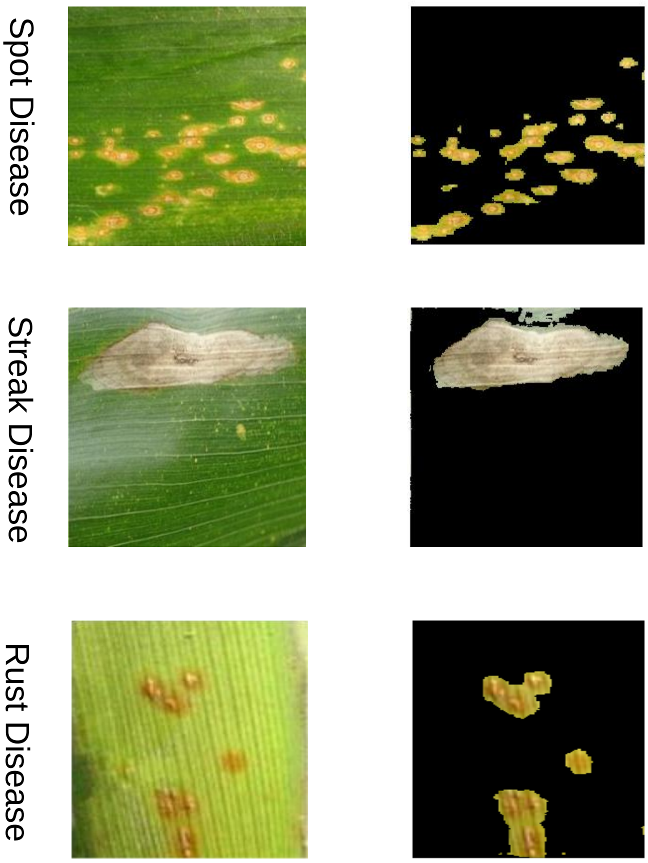
So we have the following $L*a*b$ color space conversion model.

$$\begin{cases} L = 116 f\left(Y/Y_n\right) - 16 \\ a = 500\left[f\left(X/X_n\right) - f\left(Y/Y_n\right)\right] \\ b = 200\left[f\left(Y/Y_n\right) - f\left(Z/Z_n\right)\right] \end{cases} \tag{5}$$

$$f(\mu) = \begin{cases} 7.787\mu + 0.138, \mu \le 0.008856 \\ \mu^{1/3}, \mu > 0.008856 \end{cases} \tag{6}$$

where $f(\mu)$ is a correction function similar to the $gamma(\cdot)$ function. X_n , Y_n , Z_n are usually chosen as a constant, that is $X_n = 96.4, Y_n = 100.0$ and $Z_n = 82.5$ (Zhai et al. 2014, Diao et al. 2013).

According to Equation (2) - Equation (6), each pixel on the image can be described as one data points of L 、 a and b by using the Matlab library functions - makecform and applycform. Then by using *K*-Means method to amend the image of maize disease, the region of different diseases can be extracted, as shown in Figure 2.



a) Source image b) Image Segmentation

Figure 2 The image preprocessing results

2.2 Image feature extraction

1) Color feature extraction

The spot, streak and rust diseases belong to different types of maize diseases, and the color characteristics of their disease symptom are represented by color histogram and color moment. By using HSV color model, three components of sample image H (color), S (saturation) and V (brightness) are extracted to identify the main kinds of maize diseases. H can usually be quantified into 16 levels as follows:

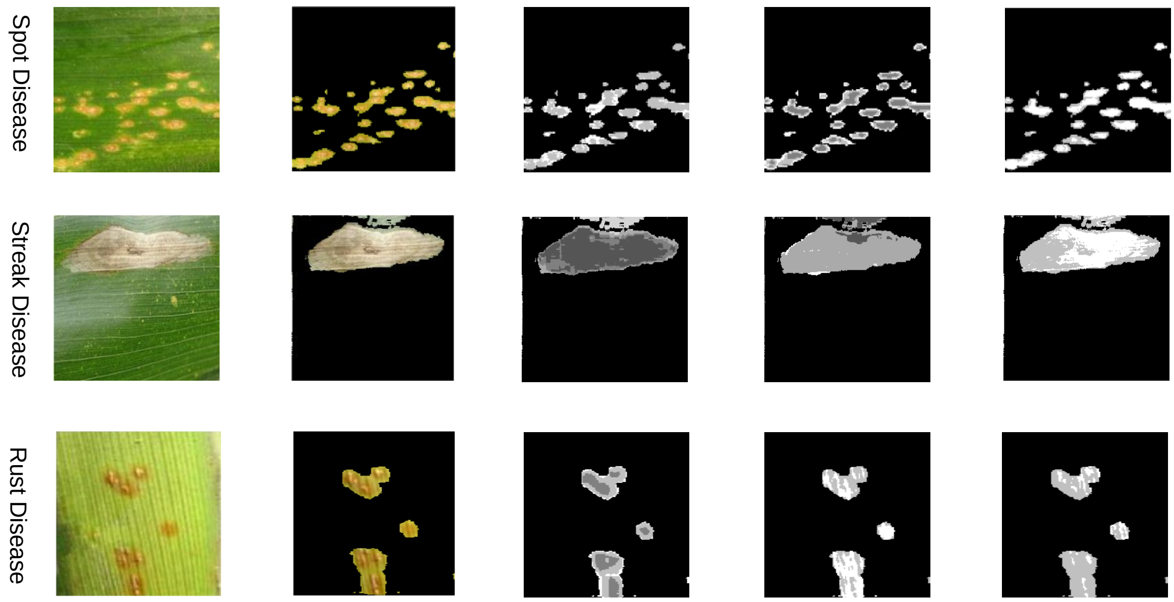
Table 1 H quantification level and scope

H	level	0	1	2	3	4	5	6	7
	range	$(-\infty,15]$ $(345,\infty]$	(15,25]	(25,`45]	(45,55]	(55,80]	(80,108]	(108,140]	(140,165]
H	level	8	9	10	11	12	13	14	15
	range	(165,190]	(190,220]	(220,255]	(255,275]	(275,290]	(290,316]	(316,330]	(330,345]

H, S, V are quantified into four levels below:

$$S=\begin{cases}1 & S\in(0,0.15]\\ 2 & S\in(0.15,0.4]\\ 3 & S\in(0.4,0.75]\\ 4 & S\in(0.75,1]\end{cases},\qquad V=\begin{cases}1 & V\in(0,0.15]\\ 2 & V\in(0.15,0.4]\\ 3 & V\in(0.4,0.75]\\ 4 & V\in(0.75,1]\end{cases}$$

In this way, the HSV components of spot, streak and rust diseases can be obtained to describe the proportion of different colors in the original image. The histogram of different disease is shown in Figure 3.



a) Source image b) Image Segmentation c) H component Image d) S component Image e) V component Image

Figure 3 Souce image and HSV component image of three diseases

The three images in the column of Figure 3a) represent the original images of spot, streak and rust diseases respectively. Similarly, the three images in the column of Figure 3b) represent the segmentation images of spot, streak and rust diseases respectively after color clustering. The images in the columns of Figure 3c) to Figure 3e) are the HSV component diagram of three different maize diseases. In order to facilitate the extraction of maize diseases, the color space of HSV histograms of three different diseases can be used for discrimination. Figure 4 shows the different colors of HSV histograms of three diseases, which are used for discrimination.

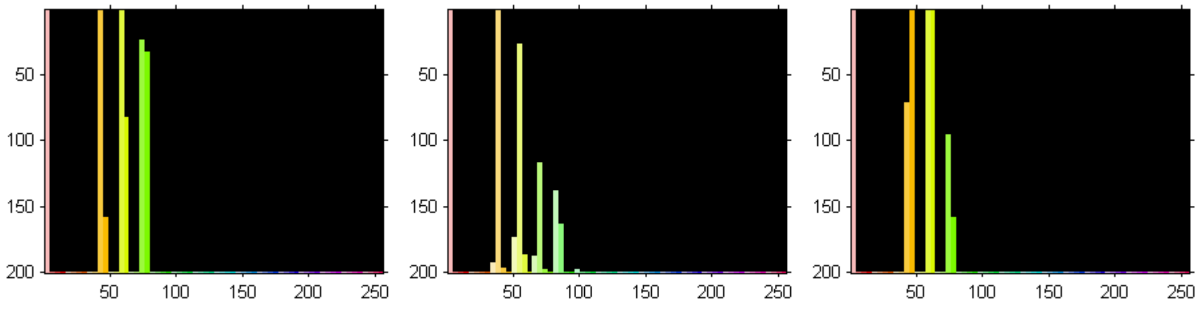


Figure 4 HSV histograms of three diseases

As can be seen from Figure 3, the corn spot disease, leaf spot disease and rust disease in the HSV histogram occupy different proportions. In order to accurately reflect the color distribution information in the image, the 1st moment e_i, 2nd moment σ_i and 3rd moment s_i can be further used to reflect the spatial distribution of *H, S, V* components of the image, which can be expressed as follows (Zeng et al. 2010):

$$e_i = \frac{1}{N}\sum_{j=1}^{N} p_{ij} \tag{7}$$

$$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(p_{ij}-e_i\right)^2\right)^{1/2} \tag{8}$$

$$s_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(p_{ij}-e_i\right)^3\right)^{1/3} \tag{9}$$

where e_i , σ_i , s_i express the first moment, second moment and third moment of color components i, which is the mean, variance and offset of color component i respectively. p_{ij} is the j pixel for the ith color channel, and N is the value of total pixel.

Then nine eigenvectors can obtain by a vector as follows:

$$\tilde{Q} = [e_H, \sigma_H, s_H, e_S, \sigma_S, s_S, e_V, \sigma_V, s_V] \tag{10}$$

where e_H, σ_H, s_H, e_S, σ_S, s_S, e_V, σ_V, s_V are the mean, variance and offset of color components H, S and V respectively.

According to the above analysis, the nine mean values of the color components are expressed in Table 2 which reflects the color eigenvectors corresponding to the three different maize diseases. In this table, $\tilde{Q}_{i1}$, $\tilde{Q}_{i2}$, $\tilde{Q}_{i3}$ is representing the nine eigenvectors of spots, streak and rust respectively. i is H, S or V.

Table 2 Color features of different maize diseases

		e_i	σ_i	s_i
Spot disease	$\tilde{Q}_{H1}$	10.8136	22.3684	62.5884
	$\tilde{Q}_{S1}$	10.9397	30.2192	51.1256
	$\tilde{Q}_{V1}$	28.7972	12.7840	53.4579
Streak disease	$\tilde{Q}_{H2}$	10.0502	23.2030	67.2196
	$\tilde{Q}_{S2}$	13.9207	24.1887	88.3959
	$\tilde{Q}_{V2}$	43.1763	35.1022	130.4662
Rust disease	$\tilde{Q}_{H3}$	5.4906	25.9601	55.5378
	$\tilde{Q}_{S3}$	7.7240	26.7306	65.3916
	$\tilde{Q}_{V3}$	21.5553	32.8085	92.4514

2) Texture feature extraction

In texture feature analysis, the GLCM method is a common technique in statistical image analysis to extract the 2nd order statistical properties. It can preserve the spatial information and obtain first and second order texture measures and has been used in a number of applications (Yuan et al. 2016, Mohanaiah et al. 2013). There are many features of the GLCM. In this paper, the following four important features are selected according to different lesion characteristics of maize:

1) Energy:

$$A_1 = \sum_{i}^{L-1} \sum_{j}^{L-1} G^2(i, j) \tag{11}$$

where A_1 is energy and reflects the degree of image texture thickness. A_1 is small if the texture is fine, and otherwise, A_1 is big if the texture is thicker. $G(i, j)$ is a normalized gray-level co-occurrence matrix, in which i with j represent gray value of pixel. L indicates the grey level of image.

2) Entropy:

$$A_2 = -\sum_{i}^{L-1} \sum_{j}^{L-1} G(i, j) \cdot \lg G(i, j) \tag{12}$$

where A_2 is the image entropy and measures the amount of information inherent in the image. Its value varies with the change of texture. A_2 is large if the lesion texture arrangement is more sparse; conversely, the arrangement of the lesion texture is more compact.

3) Contrast:

$$A_3 = \sum_{i}^{L-1} \sum_{j}^{L-1} G(i, j) \cdot G(i - j)^2 \tag{13}$$

where A_3 is the contrast and used to describe the depth of the image texture groove depth. Its contrast increases when the groove of image texture is deeper. On the contrary, its contrast value is getting smaller when the groove of image texture is shallower.

4) Moment of inertia:

$$A_4 = \sum_{i}^{L-1} \sum_{j}^{L-1} \frac{1}{(i - j)^2 + 1} G(i, j) \tag{14}$$

where A_4 is the moment of inertia and used to describe the degree of roughness of the image texture. Its value is larger when the texture of the corn leaf spot area is thicker. Otherwise, its value is small when the grain of the corn leaf spot area is finer.

According to the above analysis, the texture features of three maize diseases, namely energy, entropy, contrast and moment of inertia, are shown in Figure 5, Figure 6, Figure 7 and Figure 8 respectively.

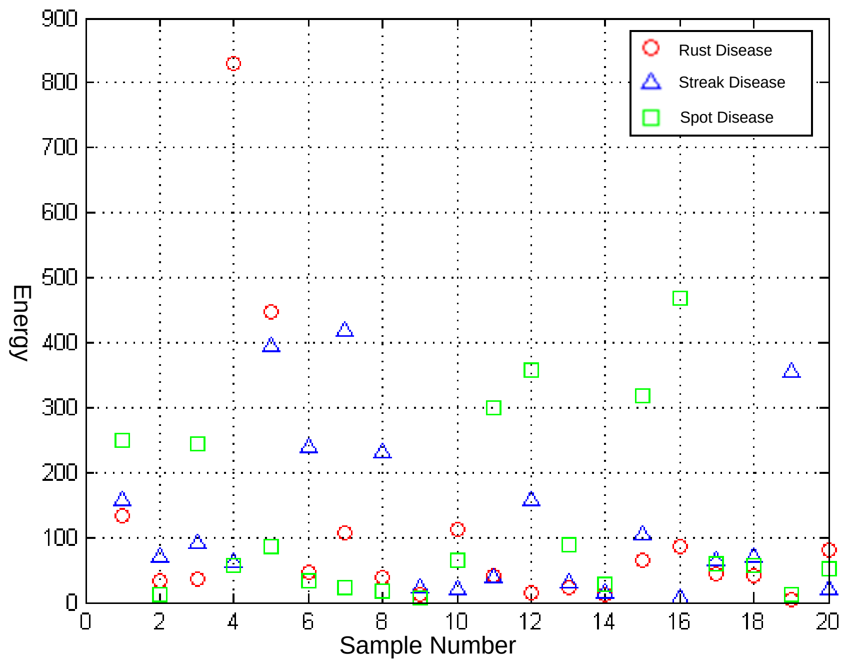


Figure 5 Feature of energy

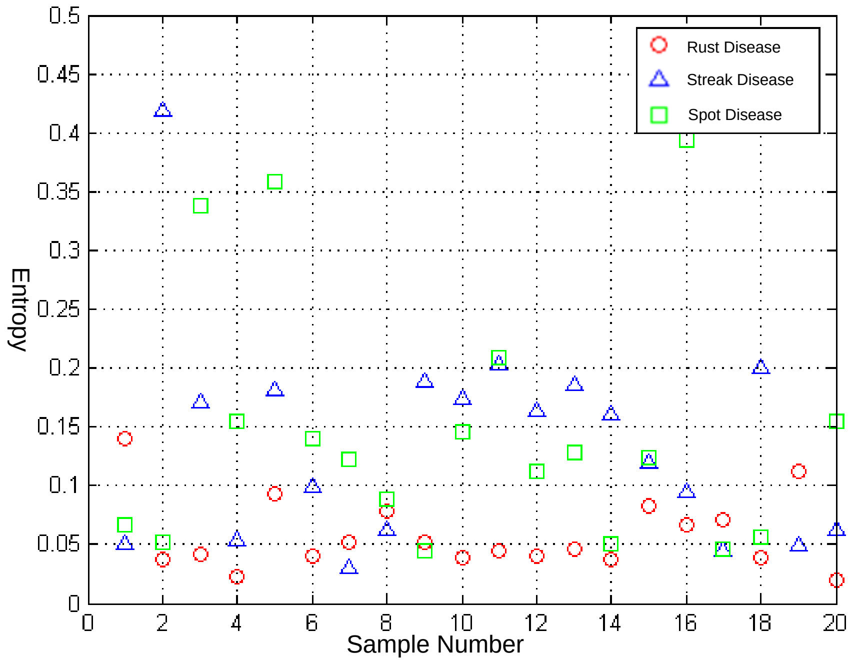


Figure 6 Feature of entropy

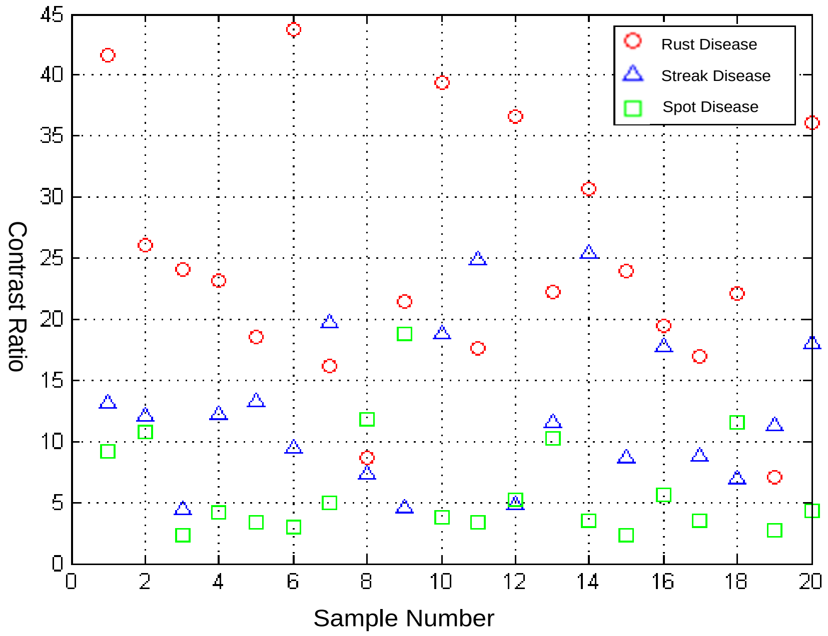


Figure 7 Feature of entropy contrast

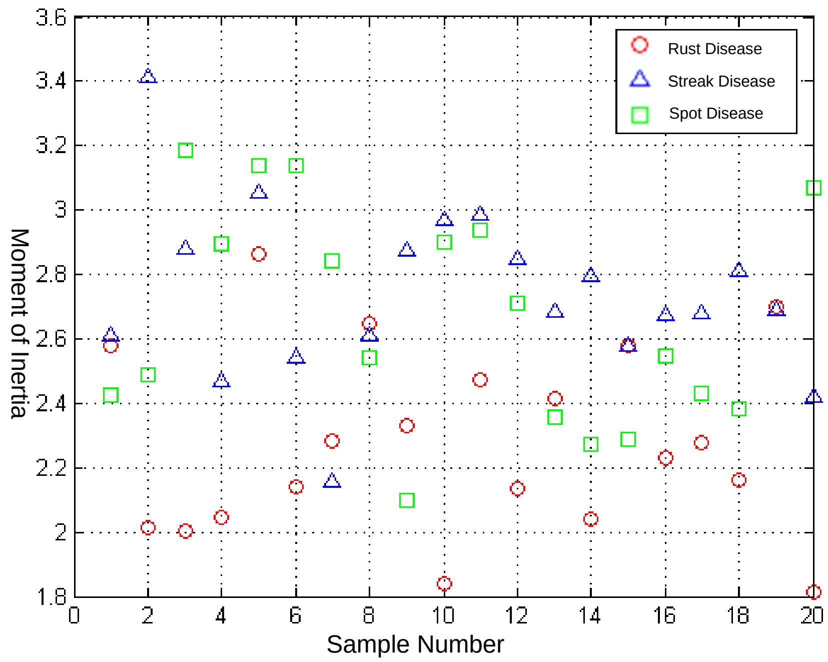


Figure 8 Feature of entropy inertia moment

From the above four figures, it can be seen that there are discrepancies in the discrete spots presented by different lesions, such as entropy values and contrast values, which can effectively reflect the relationships between the leaf rusts. More specifically, the rust of corn in Figure 6 is relatively gentle and has a low entropy value. In Figure 7, the value corresponding to corn spot disease is lower than the value corresponding to leaf spot and rust, and the contrast value of rust is larger than leaf spot and rust according to a definite rule, so it has achieved recognition effect. Tables 3 shows the texture features of different maize disease for the convenience of comparison.

Table 3 Texture features of different maize disease

	Energy		Entropy		Contrast		Moment of inertia	
Spot disease	min	max	min	max	min	max	min	max
	0.043	0.335	2.329	5.202	0.083	0.611	0.801	0.988
Streak disease	min	max	min	max	min	max	min	max
	0.072	0.181	3.110	4.233	0.082	0.422	0.855	0.923
Rust disease	min	max	min	max	min	max	min	max
	0.050	0.221	2.764	4.856	0.121	0.530	0.800	0.949

2.3 Disease identification

SVM is the statistical method based on the statistical learning theory, which is suitable for the classification of small sample numbers. It can obtain the minimized training error and a confidence interval term by analyzing the given training set to predict the test set. In this paper, we use SVM to identify three different maize diseases. Firstly, the sample number and training number are selected from the extracted features (such as color feature and texture feature), and then by using the rational kernel function of support vector machine, the classification model can be established.

On this foundation, we change the different penalty factors to classify the maize diseases. As a result, the optimal recognition effect can be realized when the penalty factor $C = 50$. The optimal classification function and the kernel function are as follows:

$$f(x) = \operatorname{sgn}\left\{\left(\sum_{j=1}^{n} a_j y_j k(x_i, x_j)\right) + b^*\right\} \tag{15}$$

$$k\left(x_i, x_j\right) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right) \tag{16}$$

where a_j is a Lagrange multiplier, b^* is the bias, and $k(x_i, x_j)$ is a kernel function.

3 Results and Discussion

This section presents the experimental results to show the feasibility, accuracc and effectiveness of the proposed approach. Three common maize diseases (spot disease, streak disease and rust disease) are selected as the research objects. The disease images mainly came from some maize disease atlas and maize disease database, partly from the internet gallery. Twenty-one test samples are selected from each disease characteristic data for the experiment, and the classification results are given in Table 4 for comparison.

As can be seen, the average recognition rate for using color feature identification method to recognize three kinds of maize diseases is 57.1%. The average recognition rate for using text feature identification method to recognize three kinds of maize diseases is 63.5%. In contrast, average recognition rate for using a combination of color and texture feature identification method to recognize three kinds of maize diseases is 85.7%. Therefore, it is clear that the average classification accuracy was low by using a single feature to recognize the maize diseases. However, the average classification accuracy by using color and texture features to identify the three kinds of diseases became very high.

Table 4 Recognition result of maize diseases

Category Identification	Spot Disease	Streak Disease	Rust Disease	Average Recognition Rate (%)
Color Feature Identification (Number of Test Samples / Number of Identification)	21/13	21/12	21/11	57.1
Texture Feature Identification (Number of Test Samples / Number of Identification)	21/14	21/14	21/12	63.5
Color Feature + Texture Feature Identification (Number of test Samples / Number of Identification)	21/19	21/17	21/18	85.7

In order to further verify the effectiveness of the proposed method, we conducted some experiments in comparison with the previous work in [11] (Zhang et al. 2015), [23] (Li et al. 2014) and [24] (Christos et al. 2013). Table 5 shows the comparison results of different recognition methods.

Table 5 Comparison results of different recognition methods

Recognition methods	Spot disease			Streak disease			Rust disease		
	Sample value	Recognize value	Recognition rate(%)	Sample value	Recognize value	Recognition rate(%)	Sample value	Recognize value	Recognition rate(%)
Reference [11] (Zhang et al. 2015)	21	15	71.4	21	17	80.9	21	17	80.9
Reference [23] (Li et al. 2014)	21	14	66.7	21	14	66.7	21	13	61.9
Reference [24] (Christos et al. 2013)	21	14	66.7	21	16	76.1	21	18	85.7
The proposed method	21	19	90.4	21	17	80.9	21	18	85.7

As can be seen in Table 5, the recognition rates of the proposed classification approach are 90.4%, 80.9% and 85.7% for the spot disease, streak disease and rust disease respectively, which are higher than the existing approaches, such as the highest recognition rate was 80.9% in [11], the highest recognition rates were 66.7% and 85.7% in [23][24] respectively. It is clear that this study provided a certain basis and solution for rapid and accurate image recognition of maize diseases based on pre-processing and extracting features combined with the color features and texture features.

4. Conclusion

This paper presents a new image classification approach to identify the three kinds of maize diseases. Some theoretical basis and practical technology have been deployed for developing the automatic maize disease diagnosis system. Firstly, a median filter and K Means clustering method are used in color maize images to remove the noise on disease leaf and segment the disease spot effectively. Then the statistic pattern recognition and GLCM method are deployed to extract the color and texture features. Finally, the SVM classification model is used to obtain the acceptable recognition results for maize diseases. Experimental results are given to show the feasibility and good accuracy of the proposed approach. Our future work will focus on the investigation of how to increase sample data and how to improve the performance on large amount of images that contain maize diseases.

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Conflicts of Interest

The authors declare that they have no conflicts of interest.

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