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Research Article

CLASSIFICATION OF HEALTHY AND DISEASED VINE LEAVES USING THE FULL SPECTRA OF OBJECT AREA IN IMAGE

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ABSTRACT

Grape plant diseases cause critical harm and financial loses in crops. In this manner, early identification of diseases is important on the contemporary stage of development of science and technologies. Optical methods have been widely used to solve the task of detecting diseases in vineyards. The determination of diseases on vines by outer indications of the leaves is made by video cameras, the estimations of the colour components of various colour models are used. The disadvantage of direct using of colour components is that there are high classification errors because of complexity of colours on the surface of vine leaves. The use of full spectra of image object areas with healthy and diseased part of leaves is proposed. Lower values of classification errors are comparable with those, obtained by neural network classifier.

Keywords: grape leaves; full spectra of image; spectral range; discriminant function analysis

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1. INTRODUCTION

A software based identification of vine leaves diseases is a basic research theme as it might demonstrate benefits in observing huge fields of harvests, and distinguish the side effects of sicknesses when they show up on plant. In this manner the searching for quick, more affordable and exact techniques to identify plant infection cases is of incredible importance. Late and wrong distinguishing proof of the harm made by infections on vines can cause noteworthy harvest misfortune or even the loss of the whole yield. Over the top utilization of pesticides for vines diseases treatment builds expenses and raises the threat of lethal buildup levels on rural items This requires the infection to be recognized precisely and furthermore the phase in which it occurs [3].

On the modern stage of development of technics, optical methods are used to obtain information on infection of vine leaves [1,10,11]. These methods are:

- Video camera;
- Spectrophotometer;
- Hyperspectral camera;
- Thermal camera.

The primary trends at contemporary stage are the utilization of video cameras for identification of outer indications of diseases in vineyards and the utilization of hyper-spectral visual images in diagnosing of inward imperfections.

The examination of the known publications [3,4,15] regarding the matter – determination of infections on vine leaves by investigation of colour digital images demonstrates that there is a need to complete a more top to bottom examination of the known techniques and the methodologies utilized up until this point, which will prompt change and help of the characterization procedure for incorporation into automated systems.

In the accessible literature sources [1,3,7,12] for the determination of diseases on vines by outer indications of the leaves by video camera, the estimations of the colour components of various colour models are used.

The representation of digital images of vine leaves in a RGB color model has various restrictions, making it hard to recognize image regions and assess their characteristics.

The literature states that on account of complex images of natural items, for example, the vine leaves concerned, it is helpful to utilize the full spectra of the image.

Utilizing the full spectral range of the image requires changing over RGB esteems into spectral characteristics of visible range [2,14,15].

The aim of the article is to make a comparative analysis between the application of colour components and the use of the full spectrum of the image in the detection of diseases on vine leaves.

2. MATERIAL AND METHODS

Examined material are 200 vine leaves collected from vineyards in the village of Boyanovo, district Yambol, Bulgaria. Randomly chosen leaves without respect to the place of manor and variety of grape plants. The leaves, chosen by expert are infected by downy mildew (figure 1). The pictures of the vine leaves are captured by industrial video camera The Imaging Source DFK41AU02.

The method used in the study is conversion of RGB values of object areas of healthy and diseased vine leaves to spectral characteristics in the visible (VIS) region. These conversion techniques are described in detail in [2,14].

Selection of spectral regions for classification is made by second derivative.

Two methods for reducing the amount of data in the spectral characteristics are used – principal components (PC) and latent variables (LV) [8].

Fig.1. Examples of vine leaves infected with mildew

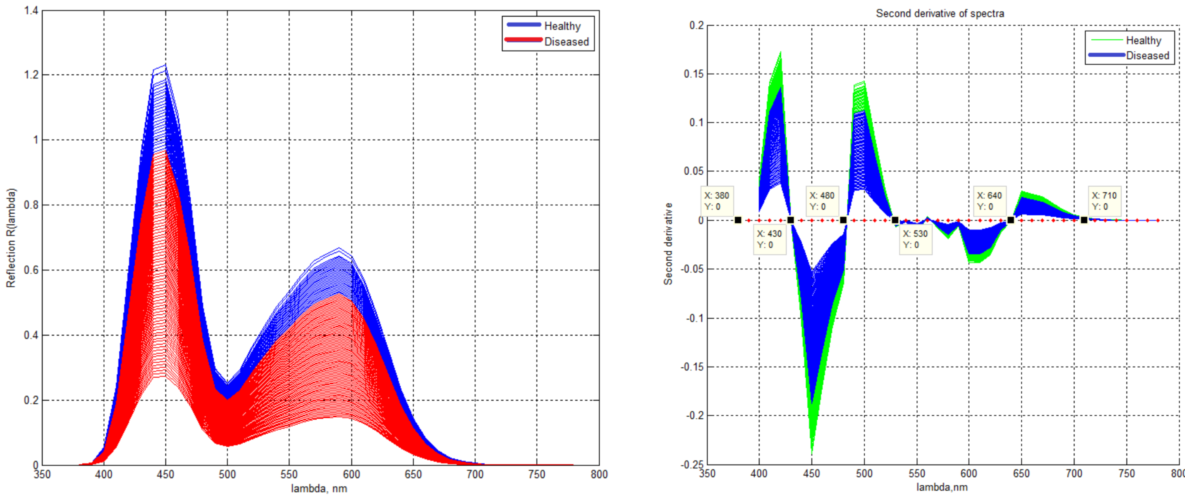
3. RESULTS AND DISCUSSION

The data consisted of 200 images of infected vine leaves. 1000 pixels are used represented in

RGB color model on randomly chosen of healthy object areas on vine leaves (class 1) and 1000 pixels on mildew (class 2). 30% of these pixels are taken for validation. From the remaining 700 pixels 30% are used for training and 70% for testing of the classifier.

All of the pixels are converted to full spectra. Figure 2 presents the resulting spectral characteristics of the object areas of healthy and diseased part of vine leaves. There is a little overlap between the spectral characteristics of the object areas.

For practical purposes the spectral characteristics are not used in their raw form. The methods used to reduce the amount of their data are principal components and latent variables. Another practical importance is to find which ranges of these spectral characteristics in visible spectrum are suitable to separate the object areas [8]. These ranges are defined by second derivative of the spectral characteristics. They are used for implementation of filters that will increase the separation of object areas with healthy and diseased part of leaves. Another implementation of these ranges is for multispectral cameras where this device use only part of the full spectrum in visible range [15].

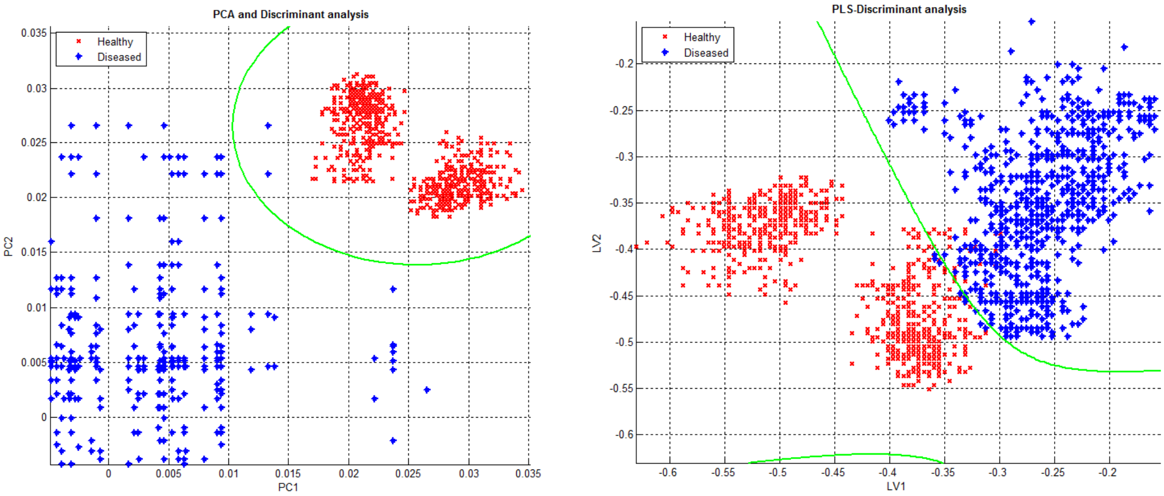


a) spectral characteristics b) second derivative of spectral data

Fig.2. Spectral characteristics of healthy and diseased vine leaves and their second derivative

The results of classification by PCs and LV of spectral characteristics in selected ranges are presented on figures.

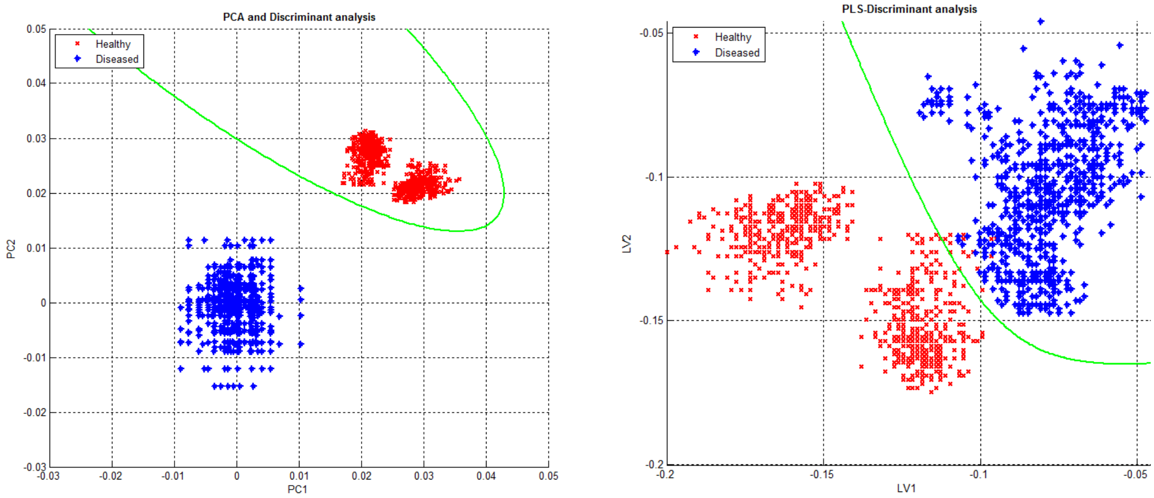
Figure 3 presents results of classification with discriminant analysis in spectral range 430-480nm by PCs and LVs. The error of classification by principal components is 1% and 3% for latent variables. The reason is that there is small overlap of the object areas represented by these methods.



a) by PCs, e=1%   b) by LVs, e=3%

Fig.3. Classification with discriminant analysis in spectral range 430-480nm by PCs and LVs

Figure 4 presents examples of classification with discriminant analysis in spectral range 480-530nm by PCs and LVs. Using principal components the classification error is 0% there is distance between classes and no overlap of them. In the case of latent variables there is small overlap of the two classes and the classification error is 1%.



a) by PCs, e=0%   b) by LVs, e=1%

Fig.4. Classification with discriminant analysis in spectral range 480-530nm by PCs and LVs

The results of classification with discriminant analysis with different separation functions are presented in Table 1. The spectral characteristics in different spectral ranges are converted to PCs and LVs. The classification errors for these ranges are reported. Lower values of this error are obtained in spectral range 480-530nm whether used PCs or LVs. The error varies depending on the spectral range and used data reducing function between 0% and 5%.

The analysis of the results with those reported from other authors shows that:

- Li et al [6] use Support vector machines (SVM) classifier with different kernel functions and report error of classification error 7% for downy mildew on grape leaves.
- Sannakki et al. [13] report classification error of 0% using neural network classifier.
- Georgieva et al. [1] used colour features from six colour model for classification with Support vector machines (SVM) and k-nearest neighbors (kNN) classifiers for downy mildew and report classification error for SVM 4% and 3% for kNN.
- Narvekar et al. [9] proposed novel algorithm that detects three types of desieses on vine leaves. This algorithm uses cluster analysis and HSV colour features as input data. The error of classification is 60% for downy mildew.
- Kharde et al. [5] proposed a novel technique for grape leaves disease detection. Using the colour component from HSI colour model as input data they reported the error of recognition 10% for downy mildew on leaves.

The comparison of the results obtained with the above shows that using full spectra of image the error of classification is smaller than this obtained by direct use ot colour features of object areas with healthy part of leaves and the diseased one. The resulting error rates are comparable to those obtained with a neural network.

Table 1. Classification error of discriminant analysis in different spectral ranges

	PC e,%				LV e,%			
λ, nm	Linear	Quadratic	Diagquadratic	Mahalanobis	Linear	Quadratic	Diagquadratic	Mahalanobis
380-780	0%	0%	0%	0%	3%	2%	3%	2%
380-430	0%	0%	0%	0%	3%	2%	3%	2%
430-480	5%	1%	1%	5%	3%	2%	3%	2%
480-530	0%	0%	0%	0%	1%	1%	1%	1%
530-640	0%	0%	0%	0%	3%	2%	3%	2%
640-710	0%	0%	0%	0%	3%	2%	3%	2%
710-780	0%	0%	0%	0%	3%	2%	3%	2%
min	0%	0%	0%	0%	1%	1%	1%	1%
max	5%	1%	1%	5%	3%	2%	3%	2%

PC – principal components; LV – latent variables; e – classification error

4. CONCLUSION

The essential research at contemporary stage of development of science and technologies are the use of video cameras and image processing systems for conspicuous confirmation of outside indications of diseases in vineyards, due to their advantages over other optical techniques as phantom and hyperspectral examination.

The paper presents evaluation of classification error of utilizing otherworldly attributes and strategies for diminishing the measure of information for order of healthy and diseased vine leaves by Discriminant function Analysis.

It is found that the classification error is in the range from 0% to 5% as indicated by the chosen spectral range and discriminant function. The lower classification error is accomplished in spectral range 480-530nm. The outcomes are similar with those acquired by using colour components and neural network classifier, where the error is 0% in separation of healthy and diseased part of vine leaves.

Future work of this research can the utility of these classification errors in separation of healthy part of leaves and various diseases of grapes as powdery mildew and black rot. Instead of discriminant function analysis, other classification systems can be utilized to improve the accuracy and reduce errors.

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