Application of Mobile Device as a Tool for Early Diagnosis of Diseases on Vine Leaves

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Abstract

The search for new methods and technical tools for early diagnosis of diseases in vineyards, in order to adequately apply plant protection products, requires new knowledge and supplementation of existing solutions in this area. In the present work the possibility for early diagnosis of diseases on vineyards by using a built-in video sensor on mobile devices is tested. Spectral characteristics from the adaxial and abaxial sides of the leaves were used. From the comparative analyzes it was found that suitable for early diagnosis of diseases of vine plants are spectral characteristics obtained from the abaxial part of the leaves, reduced with latent variables and classified by nonlinear separating functions of the used classifiers.

Keywords: Disease management, Disease detection, Biophysical parameters, Spectral characteristics, Classification

1 Introduction

Collecting and processing the necessary information for decision-making for plant protection activities of vineyards is a complex and time-consuming process. To remain competitive, the modern farmer often seeks the help of agricultural specialists and consultants in order to provide information for decision-making (Nedeva et al., 2012; Zlatev, 2016; Albetis et al., 2018). Unfortunately, the agricultural help of the specialist is not always available to the farmer. These circumstances lead to the need to introduce and apply information technology in the field of plant protection.

The forecasting of diseases on agricultural crops is fundamental for the successful implementation of plant protection. In general, for the time being, the prognosis of the diseases is carried out sparingly by relevant specialists by visiting the agricultural lands. However, this is not enough to reliably detect diseases in their early stages. The late detection of diseases is often associated with the impossibility of their eradication.

The analyzes of the development of diseases on the vineyards are context-based, which means that additional research is needed to refine the developed advisory systems and applications for mobile devices in specific geographical regions. (Pichon et al., 2020).

In recent years, a number of mobile applications have been developed to determine the condition of vineyards (https://play.google.com).

From the review of the scientific literature and the developed mobile applications, it was found that there are few publications related to the early diagnosis of diseases in vineyards, using mobile phones (Pongnumkul et al., 2015).

The aim of the present work is to test the possibility for early diagnosis of diseases in vineyards by using a built-in video sensor on mobile devices.

2 Material and methods

An analysis of diseases of vineyards grown in the region of the village of Hadjidimitrovo, Tundzha municipality, Yambol district, the southeastern part of Bulgaria was made.

2.1 Technological measurements

Planar chromatography. The method presented in Priyadarshini et al. (2016), with some modifications.

Measuring instruments used: Active acidity pH, pH meter PH-108 (Hangzhou Lohand Biological Co., Ltd); Electrical conductivity EC, μS/cm, Conductivity Meter AP-2 (HM Digital, Inc); Total amount of solutes TDS, ppm, TDS-3 measuring instrument (HM Digital, Inc.); Oxidation-reduction potential ORP, mV, Measuring Instrument Model ORP-2069 (Shanghai Longway Optical Instruments Co., Ltd).

2.2 Measurements with non-contact technical tools

In the present work, a video sensor of a Samsung Galaxy J7 SM-J727P (SAMSUNG Inc.) mobile phone is used. The video sensor of the rear camera used is HERO_12M_2PD (Sony Corp., Japan). 12MP resolution (OIS driver). Dimensions of the module 12.07 x 12 x 5.5 mm (WxLxH). Pixel size 1,4 μm x 1,4 μm. It has a built-in autofocus mechanism.

The homogeneous lighting of the captured scene was obtained with a light source, which consists of a domed part, the inner part of which is covered with glossy paint, with pure white color RAL 9010, and the outer part is covered with black acrylic paint RAL 9005.

White LEDs with a maximum intensity of emitted light at 450nm are mounted in the domed part. The lighting of the captured stage is provided by diode lighting SMD3528-120/1, 6500K white IP65 (V-TAC Innovative LED Lighting), mounted in a domed part in two rows, with a distance between them of 10 cm.

The lighting system is supplied with a switching source of constant voltage, with nominal output voltage and current U = 12V, I = 2,5A.

The full spectrum of the images was used. The transformation is made according to the mathematical dependencies presented in (Glassner, 1989). Conversion functions for observer 2^o (Stiles and Burch 2^o, RGB (1955)) and D65 illumination (average daylight with UV component (6500K)) are applied, according to mathematical dependences, in which the conversion is possible in both directions of equality (Wyman et al., 2013).

Reduction of spectral characteristics data. The methods used (Mladenov et al., 2015; Zlatev et al., 2019):

- ✓ Latent variables (LV) obtained by the method of partial regression of least squares;
- ✓ Linear variant of principal components (PC) obtained by the principal components analysis method.

The following classification methods were used (Vasilev, 2016):

- ✓ Discriminant analysis (DA) with five separating functions: linear (L), diagonal linear (DL), quadratic (Q), diagonal quadratic (DQ) and Mahalanobis (M);
- ✓ Support vector machines method (SVM), with four separating functions: linear (L), quadratic (Q), polynomial (P) and radial basis element (RBF).

The assessment of the separability of object areas by vine leaves, with these classifiers is made by a general classification error which is conditionally marked with e_m,%.

Matlab 2013 software product (The Mathworks Inc.) was used to process the experimental data.

The measurements were made at a room temperature of 20±2 ^oC and a relative humidity of 45% RH. All data were processed at a level of significance $\alpha = 0,05$.

3 Results and discussion

Physico-chemical characteristics of healthy and infected with powdery mildew and vine scab vine leaves were obtained.Tables 1 and 2 show the results of these measurements. It can be seen that the obtained data have similar values and they partially overlap.

Compared to healthy, infected leaves have lower values of active acidity, higher values of electrical conductivity, TDS and ORP.

According to planar chromatography, it is difficult to distinguish healthy from infected leaves by the content of chlorophyll, xanthophyll and carotene. Powdery mildew leaves have elevated values of these characteristics, while those with vine scab have characteristics close to healthy leaves.

Table 1. Parameters of studied vine leaves (mean±SD)

Parameter / Disease	pH	EC, µS	TDS, ppm	ORP, mV
Healthy	6,67±0,36	345±1	151±0,6	211±13,1
Mildew	6,52±0,35	361±2	155±1	216±12,3
Scab	6,02±0,41	394±2	166±1	215±9

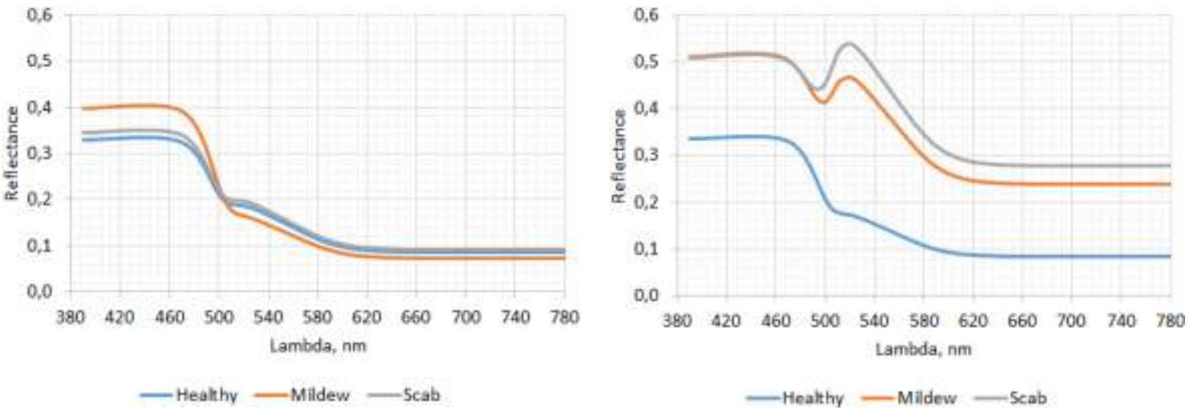
Table 2. Results from planar chromatography (mean±SD)

Disease / Content	Healthy	Mildew	Scab
Carotene	0,84±0,08	0,97±0,22	0,87±0,35
Xantophyll	0,71±0,04	0,81±0,18	0,73±0,31
Cholophyll a	0,55±0,08	0,59±0,15	0,49±0,13
Chlorophyll b	0,32±0,06	0,38±0,09	0,31±0,05
Anthocyanin	0,07±0,05	0,06±0,01	0,08±0,03

Figure 1 shows the obtained spectral characteristics of healthy and infected vine leaves in the early stages of disease development. It can be seen that at the adaxial side of the leaves there is a strong overlap of spectral characteristics. Like their physicochemical parameters, the spectra of healthy leaves are very close to those with vine scab. In the initial range of the spectrum (380-480nm) a resolution of these characteristics is observed. In the spectral characteristics obtained from the abaxial part of the leaves, a separation is observed between healthy and infected leaves. Separation between the two types of analyzed diseases is seen in a narrow spectral range (500-580nm).

The results of processing the obtained experimental data with discriminant analysis, reduced by latent variables and principal components, are shown in Table 3. It can be seen that when using latent variables, regardless of the type of separation function, low values of the total error of classification. These results are obtained regardless of whether the spectral characteristics of the adaxial or abaxial part of the vine leaves are used.

When using principal components, significantly higher values of the total classification error are observed. When using this method to reduce the amount of data, lower error values are obtained by using spectral characteristics from the abaxial part of the leaf. The type of the separating function is also important in this case. The total classification error is significantly lower (2-5%) when using nonlinear separation functions than linear ones.



a) Adaxial part b) Abaxial part

Figure 1. Spectral characteristics of vine leaves in early stage of disease development

Table 3. Total classification error (e_m,%) using Discriminant analysis

DRM	Class	H-M		H-S		M-S	
	Part / DF	Adaxial	Abaxial	Adaxial	Abaxial	Adaxial	Abaxial
LV	L	1%	1%	1%	1%	1%	1%
	DL	1%	1%	1%	1%	1%	1%
	Q	1%	1%	1%	1%	1%	1%
	DQ	1%	1%	1%	1%	1%	1%
	M	1%	1%	1%	1%	1%	1%
	e_m, %	**1%**	**1%**	**1%**	**1%**	**1%**	**1%**
PC	L	15%	13%	15%	15%	14%	13%
	DL	15%	13%	15%	15%	14%	13%
	Q	2%	2%	5%	3%	3%	1%
	DQ	2%	2%	5%	3%	2%	1%
	M	31%	29%	37%	25%	27%	16%
	e_m, %	**13%**	**12%**	**15%**	**12%**	**12%**	**9%**

DRM-data reduction method; DF-discriminant function; LV-latent variables; PC-principal components; L-linear; DL-diagonal-linear; Q-quadratic; DQ-diagonal-guadratic; M-Mahalanobis; H-healthy; M-powldery mildew; S-vine scab

Table 4 shows the results of processing the experimental data by the Support vector machines method. When using latent variables, low values of the total classification error (up to 1%) are obtained. The use of principal components leads to an increase in the total classification error. When using linear separation functions, high error values are obtained compared to non-linear ones. Whether adaxial or abaxial leaf data is used, the errors are similar.

Table 4. Total classification error (e_m,%) when using the Support Vector Machines method

DRM	Class	H-M		H-S		M-S	
	Part / DF	Adaxial	Abaxial	Adaxial	Abaxial	Adaxial	Abaxial

LV	**L**	1%	1%	1%	1%	1%	1%
	Q	1%	1%	1%	1%	1%	1%
	P	1%	1%	1%	1%	1%	1%
	RBF	1%	1%	1%	1%	1%	1%
	e_m, %	**1%**	**1%**	**1%**	**1%**	**1%**	**1%**
PC	**L**	13%	12%	14%	11%	13%	7%
	Q	10%	9%	9%	5%	9%	4%
	P	1%	2%	1%	3%	2%	2%
	RBF	1%	2%	1%	2%	2%	2%
	e_m, %	**6%**	**6%**	**6%**	**5%**	**6%**	**4%**
DRM-data reduction method; DF-discriminant function; LV-latent variables; PC-principal components; L-linear; Q-quadratic; RBF-radial basis function; H-healthy; M-powldery mildew; S-vine scab							

Analyzes show that the separation of healthy and infected vine leaves is possible using spectral characteristics reduced by latent variables. The use of a linear variant of the principal components is inexpedient because it leads to high values of the total classification error (over 15%). Regardless of the classifier used, the application of linear separation functions results in high values of the total classification error.

The obtained results complement those of the available literature. AL-Saddik et al. (2017) used only the SVM classifier and achieved low values of the total classification error (up to 1%) after reducing the experimental data by spectral indices. The data used by the authors are for already visibly developed signs of the studied diseases, according to data from the adaxial part of the vine leaves. In the present work, in the analysis of the early stage of the development of diseases on the vine leaves, such an error is achieved by reducing the amount of data with latent variables and using nonlinear separating functions of a classifier.

Albetis et al. (2018) receive a low classification error (again up to 1%), but with already clearly distinguishable signs of vine leaf disease.

Bendel et al., (2020), in the early diagnosis of diseases on vine leaves reach a total classification error of 5-30%, using spectral characteristics in the visible region obtained from the upper part of the leaves. This is confirmed by the results obtained in this paper.

4 Conclusion

Spectral analysis, which is one of the main tools of artificial intelligence, can be used to make an assessment of early diagnosis of the degree of infestation of the plant object with diseases.

The system for obtaining, processing and analysis of spectral characteristics is offered as a tool of obtaining initial data for the tested sample and thus allows on the basis of the measured information by using a database and knowledge base of the computer system to automatically determine the disease of a plant which symptom is a change in its spectral characteristics.

It has been found that the use of linear separation functions to distinguish healthy from infected vine leaves, as well as the early detection of various diseases, is inappropriate because high values of classification errors are obtained, regardless of the classifier used. Similarly, an unsuitable tool for reducing the amount of data is the linear version of the principal components.

The comparative analysis shows that a higher degree of recognition of diseases in vineyards is achieved by using spectral data from the abaxial part of the leaves. This necessitates the search for new methods and technical tools for early diagnosis of diseases in vineyards, in order to adequately apply plant protection products.

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