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Early Detection of Fire Blight Disease of Pome Fruit Trees Using Visible-NIR Spectrometry and Dimensionality Reduction Methods

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Abstract

Fire Blight (FB) is the most destructive bacterial disease of pome fruit trees around the world. In recent years, spectrometry has been shown to be an accurate and real-time sensing technology for plant disease detection. So, the main objective of this research is early detecting FB of pear trees by using Visible-Near-infrared spectrometry. To get this goal, the reflectance spectra of healthy leaves (ND), non-symptomatic (NS), and symptomatic diseased leaves (SY) were captured in the visible–NIR spectral regions. In order to keep the important information of spectra and reduce the dimension of data, three linear and non-linear manifold-based learning techniques were applied such as, Principal Component Analysis (PCA), Sammon mapping and Multilayer auto-encoder (MAE). The output of manifold-based learning techniques was used as an input of the SIMCA (Soft independent modeling by class analogy) classification model to discriminate NS and ND leaves. Based on the results, the best classification accuracy obtained by using PCA on the 1st derivative spectra, with accuracy of 95.8%, 89.3%, and 91.6% for ND, NS, and SY samples, respectively. These results support the capability of manifold-based learning techniques for early detection of FB via spectrometry method.

Keywords: Early detection, Fire blight, Precision agriculture, Remote sensing, Vis/NIR Spectrometry

Introduction

At least 10% of global food production is lost due to plant disease (Zhang *et al.*, 2012). Fire blight (FB) is the most destructive bacterial disease of apple (*Malus domestica*), pear (*Pyrus communis*) and more generally of Maloideae, a subfamily of the Rosaceae. The causal agent is the necrogenic Gram-negative bacterium Erwinia amylovora (Ea). This pathogen enters the plant through natural openings such as the apoplast of parenchyma cells and colonize nectarthodes or through wounds on succulent aerial parts. Once inside the susceptible host plant, the bacteria multiply mainly in actively growing shoots inducing the progressive necrosis of the infected plant tissues. In resistant host plants or in non-host plants, bacteria cause a local cell death (hypersensitive-like reaction) and are unable to further colonize the plant tissue (Gaucher *et al.*, 2013). To decrease product losses, fast and timely identification of FB disease is very important (Bagheri *et al.*, 2018). Scouting is normally used as a method for FB detection, which is time consuming and laborious. Thus, an accurate and real-time sensing technology for improvement of plant disease detection is necessary (Futch *et al.*, 2009). Nowadays, spectrometry in the Visible and Near-Infrared (NIR) spectral ranges shows good potential for detection of plant disease and stress (Sankaran *et al.*, 2010; Bagheri *et al.*, 2018). So, various researchers (Delalieux *et al.*, 2007; Purcell *et al.*, 2009; Spinelli *et al.*, 2006; Yang *et al.*, 2007) have used spectral reflectance-based techniques for plant disease detection (Purcell *et al.*, 2009). Bravo *et al.* (2003) and Moshou *et al.* (2004) developed a ground-based spectral data collecting system for disease detection in winter wheat fields, which achieved a classification accuracy of over 90% (Bravo *et al.*, 2003; Moshou *et al.*, 2004). Naidu *et al.* (2009) applied visible infrared spectrometry (350-2500 nm) for detecting

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grapevine leafroll disease. It was reported that the classification accuracy based on stepwise discriminant analysis ranged from %73 to %81 depending on the features (vegetative indices) used for detecting infected (symptomatic and non-symptomatic) and healthy leaves (Naidu *et al.*, 2009). Lui *et al.* (2010) applied neural network and PCA (Principle Component Analysis) techniques to discriminate different fungal infection levels in rice panicles with a portable spectroradiometer in the laboratory (350 to 2500 nm). Results indicated that it is possible to discriminate different fungal infection levels of rice panicles under laboratory conditions using spectrometry data (Lui *et al.*, 2010). Zhang *et al.* (2012) detected powdery mildew of wheat via a spectroradiometer in a laboratory. Based on the results, the PLSR (Partial Least Square Regression) model with a coefficient of determination (R^2) of 0.80 was good for estimating disease severity and FLDA (Fisher Linear Discriminant Analysis) with accuracy over 90% was produced for the heavily-damaged leaves. Mahlein *et al.* (2013) developed specific spectral disease indices for detection of three leaf diseases, Cercospora leaf spot, sugar beet rust and powdery mildew in sugar beet plants. The classification results for discrimination of healthy leaves from infected with Cercospora leaf spot, sugar beet rust and powdery mildew leaves were obtained as 92%, 87%, and 85%, respectively (Mahlein *et al.*, 2013). Yuan *et al.* (2013) analyzed spectral data of winter wheat leaves for detection of yellow rust disease. The spectral differences showed a stronger response in 380-650 nm for both healthy and diseased leaves at the leaf scale. Phadikar *et al* (2013) classified different types of rice diseases by extracting features from the infected regions of the rice plant images. To reduce complexity of the classifier, important features were selected using rough set theory (RST) to minimize the loss of information. Finally, using selected features, a rule base classifier was built that covered all the diseased rice plant images and provided superior result compare to traditional classifiers. Finally, ten-fold cross validation was performed to measure the efficiency of the proposed method, which showed superiority over other methods (Phadikar *et al.*, 2013). Barbedo *et al.* (2015) presented an algorithm for automatic detection of *Fusarium* head blight in wheat kernels using hyperspectral imaging. With classification accuracy above 91%, the developed algorithm was robust to factors such as shape, orientation, shadowing and clustering of kernels. Huang *et al* (2015) proposed a new method for grading panicle blast based on hyperspectral imaging. The method was based on the concept of the ‘‘bag of textons”, which defines a ‘‘bag of spectra words” (BoSW) model for hyperspectral image data representation. The results indicated that the proposed method could effectively grade panicle blast with classification accuracies of up to 81.4% for six-class grading and 96.4% for two-class grading in the validation datasets (Huang *et al.*, 2015).

Based on literature review, no research has carried out yet for early detection of FB by spectral data. Because of the necessity of developing a system for early detection of FB disease, in the present research, Visible-NIR spectrometry method was used as a non-destructive method for detection of FB in pear trees during growing. For dimensionality reduction, several spectral preprocessing techniques and three manifold-based learning methods were applied on the spectra for more accurate detection of NS infected leaves. In order to extract an identification algorithm, the performance of preprocessed reflectance spectra and the dimensionality reduction methods were evaluated in affected trees at early stages.

Materials and Methods

Pear leave samples

Pear leaves of healthy and infected trees were collected from a 5 ha pear tree orchard at Damavand city of Tehran Province in Iran on May 2016. Collecting leaves was carried out under clear sky conditions between 10:00 am to 14:00 pm. 34 healthy trees (ND), 50 symptomatic infected trees (SY) and 22 non-

symptomatic infected trees (NS) were selected (Fig.1).

After collecting leaves, samples were packed with different plastic bags and transported immediately to a nearby indoor laboratory for spectral measurements. All leaves were tested in the laboratory by Selective Culture Method to confirm presence of *Erwinia amylovora* bacteria in samples. In this laboratory test, all samples were washed in tap water.

ND

NS

SY

Fig.1. Images of ND, NS, and SY trees

Infected tissues were surface sterilized by immersion in 10% household bleach for 3 min and rinsed twice in sterile distilled water (SDW) for a few minutes. Leaf samples were each macerated in a few drops of SDW in a sterile glass Petri dish using a sterile scalpel and forceps. Thirty minutes after maceration, 30 μ L of macerated tissue were streaked onto King's medium agar B (KB). The plates were then incubated at 27°C for 2-3 days and observed daily for bacterial growth. Suspected colonies of *Erwinia amylovora* (white,

circular, mucoid, and curved) were selected and further purified on KB agar at 27°C (King *et al.*, 1954).

Spectral data acquisition

A portable high-resolution fiber-optic spectrometer (Avaspec 3648, Netherland) in the range of 200 to 1100 nm with a resolution of 0.05-20 nm was used to collect the spectral reflectance data of pear leaves under laboratory conditions. The dark spectrum was obtained by turning off the light source (Dep UV, 78W / 0.75A, Dimension: 315 x 165 x 140 mm/weight: 5 kg AVAntes. Netherland) and covering the tip of the fiber-optics reflectance probe (7 fibers 200 mm or 400 mm core, 6 light-fibers, 1 read fiber, N.A.= 0.22. Standard 2 m length, splitting point in the middle. AVAntes. Netherland) completely. The reference spectrum ($R_{reference}$) was measured by turning the light source on and placing the probe in the front of a reference tile. Then the sample spectrum (R_{sample}) was measured to calculate the relative spectrum by following equation:

$$R_{relatuve} = \frac{R_{sample} - R_{dark}}{R_{reference} - R_{dark}} \times 100 \qquad (1)$$

Due to the high level of noise in the 200-400 nm and 1000-1100 nm, further analysis was performed only on the spectral data in the range of 400-1000 nm. The spectral measurements were taken 5 times for each sample. Data of ND, SY, and NS leaf samples was collected and recorded. The absorbance at a certain wavelength (λ) was calculated as [log (1/Reflectance)] at this wavelength (λ) based on Beer Lambert law.

Chemo metric analysis

All data analysis and feature extraction were performed in MATLAB (version 2011b, Math work, Inc. USA). Preprocessing methods and plot visualizations of features were carried out in Unscrambler Software (Version X10; CAMO Software, Oslo, Norway). For each sample, three measurements with two replications were carried out and mean value was obtained for each concentration. Two of the most commonly used scatter-correction techniques in spectroscopy, Multiplicative Scatter Correction (MSC) (Geladi *et al.*, 1985) and Standard Normal Variate (SNV) (Barnes *et al.*, 1989) were used. MSC aims to reduce the scattering effects by fitting each spectrum to a reference spectrum, which usually corresponds to the mean spectrum of the data set. Each spectrum is fitted by linear least square regression. The first derivative filtering based on Savitzky-Golay was used to remove offsets (Savitzky and Golay, 1964). SIMCA classification accuracy of these preprocessing methods is shown in Table 1. To detect ND, NS and SY, samples, spectral variables extracted from the pre-processed spectra were used directly as inputs of classification algorithms. Mentioned manifold-based learning techniques were applied to reduce the magnitude of the high-dimensional spectral variables space in order to improve the performance of the classifier (Tian, 2010).

Most of the time, measured data have high-dimensional vectors while terse and precise manifold data is required (Ghodsi, 2006). Therefore, it is necessary to protect the least vital parameters that describe all data information and manifold learning methods and also remove additional data. Hereon, three more common unsupervised dimensionality reduction methods were used: Principal Component Analysis (PCA) (Jolliffe, 2002), Sammon mapping (Sammon, 1969), and Multilayer auto-encoders (MAE) (Demers and Cottrell, 1993). The number of features were applied for these dimensionality reduction methods was between four to seven. In order to establish the same condition, four features were selected.

Multilayer auto-encoders are feed-forward neural networks with an odd number of hidden layers (Demers and Cottrell, 1993) which share weights between the top and bottom layers (although asymmetric network structures may be employed as well). In PCA, the data transformation is linear, while Sammon mapping and MAE are non-linear methods. PCA is one of the classical methods in dimensional reduction. PCA is also known as the Karhunen Loève transform, or singular value decomposition (SVD). The key idea of PCA is to find the low-dimensional linear subspace which captures the maximum

proportion of the variation within the data. According to Lorente *et al*. (2015) and Lee and Verleysen (2007) research, PCA and Sammon mapping were suitable for the small data sets used in this work, since the simplest models of manifold learning methods are more acceptable for small data sets with high-dimensionality (Lee and Verleysen, 2007; Lorente *et al.*, 2015). Furthermore, MAE as a nonlinear method was applied to support the results of two other manifold leaning techniques. The application of MAE in plant disease detection has not been reported yet, while neural networks are more common (Laurindo *et al.*, 2017; Liu *et al.*, 2010). The goal of SIMCA as a classification method is to get an organization rule for a set of *m* known groups, thus it is used to distinguish *m* classes where the similarity within a class is emphasized (Vanden Braden and Hubert, 2005). In SIMCA algorithm, the format of training samples was described by dimensionality reduction techniques (PCA, Sammon mapping and MAE) for each class. The original SIMCA and modifications by Hawkins (Mahalanobis distance) and Gnanadesikan methods were compared with respect to classification accuracy and their robustness towards the number of PCs selected to describe the different classes. SIMCA modified with the Mahalanobis distance method was found to be a good alternative to the original SIMCA which seems to be more robust for finding outliers when the exact number of PCs for building the model is not known (De Maesschalck *et al.*, 1999).

Leave one out cross-validation (LOOCV) was performed to evaluate and compare the performance of the classification models. 80 percent of data was used for calibration and 20 percent of data was used for validation. Five iterations were applied and 20% of data left out each time. A mean confusion matrix was created as an average of all iterations. For evaluating the classification performance, overall accuracy was computed for each classification model from its associated mean confusion matrix (Fleiss, 1981).

Results and Discussion

Development of classification models

According to the algorithm of SIMCA, all acquired data were classified into healthy and diseased classes. The combination of spectral ranges (visible-short NIR), the pre-processing methods (no pre-processing, SG, MSC and SNV), and the dimensionality reduction techniques (PCA, Sammon mapping and MAE) were evaluated with regards to their classification performance in detecting NS leaves. The results of the SIMCA classifier on the visible–NIR spectra with applying the different preprocessing techniques and three dimensionality reduction methods show in Table 1. The accuracy of SIMCA and other linear classification methods has confirmed early bruises detection of apples in different regions of spectra (Baranowski *et al.*, 2012) and pistachios classification (Vitale *et al.*, 2013). The most accurate SIMCA model was the PCA manifold, with 95.8% accuracy on the derivative spectra. As a whole, the 1st derivative spectra showed the most accurate classification results in comparison with MSC and SNV methods. According to Lorente *et al*. (2015) research, the best classification results belonged to the raw spectra without preprocessing with small differences to SNV and MSC methods (Lorente *et al.*, 2015). This is because the scatter-correction methods only remove the structural and physical variations of spectra, while they save the absorption properties related to the chemical components in the spectra. It should be noted that the 1st derivative preprocessing method was not evaluated with them. In consequence, MSC and SNV probably removed some important information for FB detection from the spectral measurements, as both try to fit spectra to the mean of spectrum. The total accuracy of dimensional reduction methods was almost higher than each class. Since the maximum number of samples belong to SY, then this group had the most weight in the total result. In order to display the classification of NS group, the cooman's plot was also drawn in every dual group. The vertical and horizontal axis of cooman's plot showed two classes and the SIMCA critical distance (0.95) from each

class. In this study, ND, SY and NS data placed in class1, class2 and class3, respectively. Cooman's plot has four parts. The data which is belong to two classes was placed in the lower left square. It means there is just a small distance from both models, while out of ranges' data dispersed in the upper right square. Fig 2 shows the cooman's plot of different sample groups with SIMCA model. For example in Fig. 2a, samples in the horizontal rectangle belong to class2 and the vertical rectangle on the left shows samples of class1. According to Fig. 2, NS samples had more confliction with SY in three studied data reduction methods (c, f and h) whereas ND and SY separated obviously. However, interference was rarely seen between NS and ND (Fig. 2b, e and g). According to Table 1, the 1st derivative preprocessed spectra had the better results in comparison with other methods. Therefore cooman's plot was drawn based on SG. The performance of cooman's plot was also approved by full differentiation of aroma components of wild strawberries (Negri *et al.*, 2015).

Table 1- SIMCA classification accuracy of non-preprocessing and some preprocessing methods for dimensionality reduction techniques in Visible-NIR region (%)

Dimensionality reduction techniques	Classes	Classification accuracy (%)			
		Raw data	1st derivative	SNV	MSC
PCA	ND	90.3	95.8	92.7	93.1
	NS	86.9	89.3	85.7	88.4
	SY	93.1	91.6	94.0	91.6
	Total	96.4	98.0	97.4	96.94
Sammon mapping	ND	85.9	92.0	88.2	91.3
	NS	81.4	83.9	81.5	83.3
	SY	90.5	90.6	91.7	89.1
	Total	92.4	95.0	93.8	93.94
MAE	ND	88.5	94.7	90.9	92.2
	NS	83.9	89.3	83.8	86.5
	SY	92.6	90.4	92.0	89.7
	Total	94.8	97.0	95.3	95.2

Partial Least Square (PLS)

PLS as a full spectrum method was employed for the analysis of FB in pear leaves. The calibration model was developed in order to evaluate test data. Then the first polynomial equation was predicted. PLS regression model using calibration and validation data of raw, SG, SNV and MSC spectra is shown in Fig. 3. The same accuracy was recorded between actual and predicted data for detection of palm oil adulteration in lard (Basri *et al.*, 2017), and between predicted and reference values of tocopherol content in olive oil (Cayuela and Garcia, 2017). Based on the coefficient determination of PLS regression (Fig. 3), the calibration and validation of a PCA classifier on SNV and MSC spectra, was fitted in comparison with nonlinear techniques. According to the results of Table 1, 1st derivative and MSC are more accurate preprocessing methods. Three dimensionality reduction techniques and two preprocessing methods, including 1st derivative and MSC was combined in order to distinguish NS leaves (Table. 2). The results are almost close in studying manifold learning based methods, whereas PCA prediction was more accurate. Lorente *et al* (2015) showed similar results on citrus (Lorente *et al.*, 2015). Based on the result, combination of MSC and PCA showed a better predictive model in comparison with Sammon mapping and MAE. In the most cases, the models for three types of dimensionality reduction techniques are completely strength and accurate because they were able to distinguish the NS leaves as members of SY class.

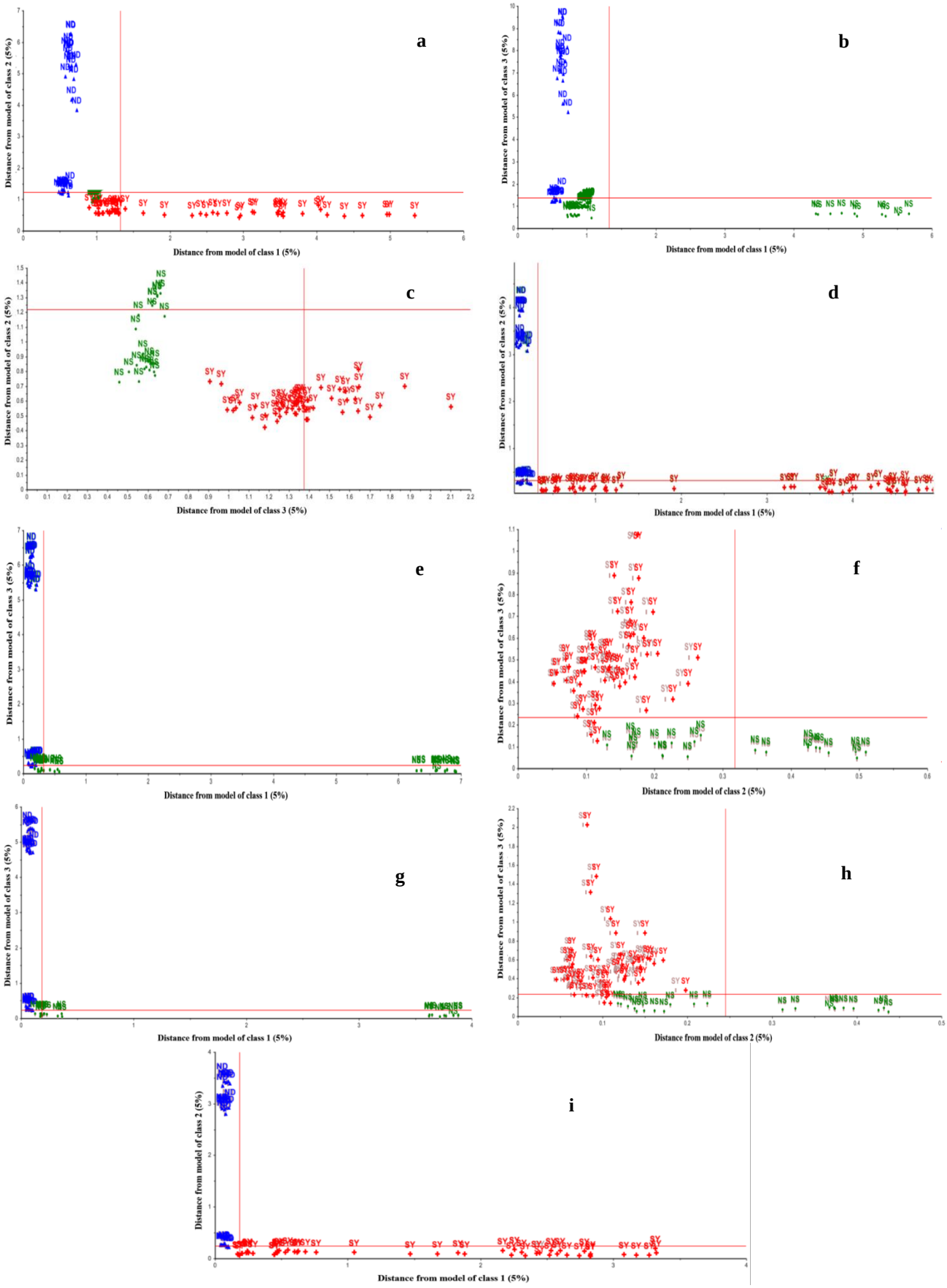

Fig.2. Coomans plot of SIMCA model which a, b and c related to PCA, d, e and f showed the Sammon Mapping results and g, h and i depicted MAE analysis

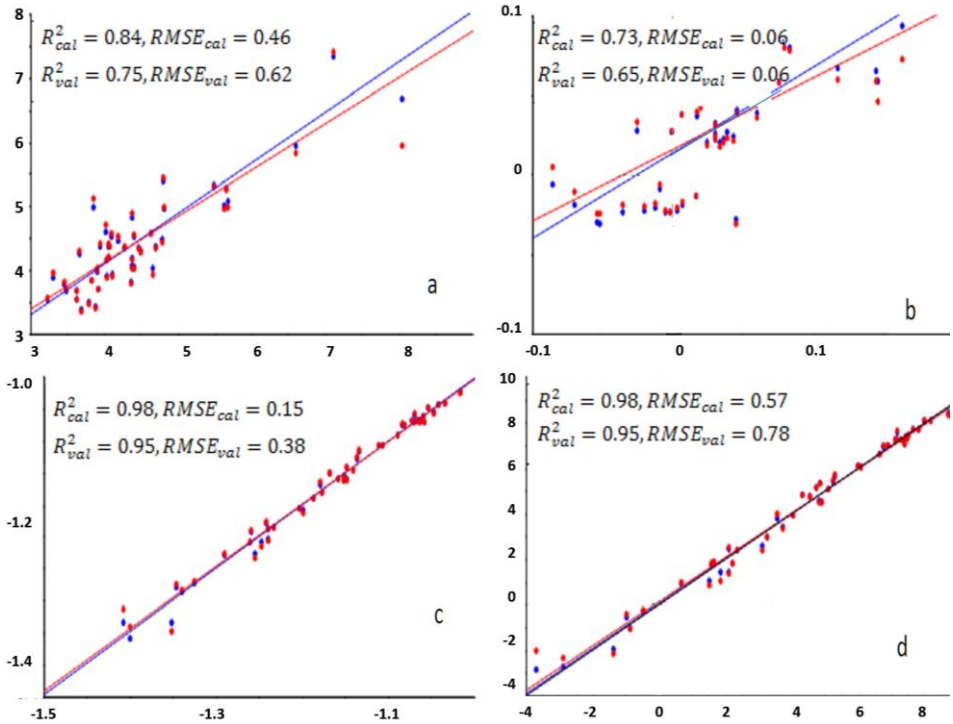

Fig.3. PLS regression model using calibration and validation data of a. raw, b. SG, c. SNV and d. MSC spectra

Table 2- Prediction percent of NS as Diseased or Healthy leaves

		PCA		Sammon mapping		MAE	
		Diseased	**NS**	**Diseased**	**NS**	**Diseased**	**NS**
1st derivative	**Diseased**	96.0	76.5	89.0	55.5	95.0	61.2
	NS	2.7	22.3	11.0	42.1	3.1	36.8
MSC	**diseased**	98.0	75.9	94.0	62.2	97.0	71.4
	NS	2.0	24:0	5.0	32.9	1.6	29.0

Conclusions

In the present research, the ability of spectrometry method for detection of FB disease of pear trees was assessed. For this purpose, the visible and NIR spectra of pear trees' leaves were obtained with a spectrometer (200-1100 nm). In order to eliminate any inappropriate information, several spectral pre-processing techniques (1st derivative SG, MSC and SNV) were then adjusted on the spectra. In order to detect non-symptomatic FB affected leaves in early stage, some manifold-based learning methods (PCA, Sammon mapping and MAE) were applied to transform the high-dimensional spectral data into significant representations of low-dimensional spectral data.

According to the results, the maximum NS classification accuracy (89.3%) was obtained by employing PCA and MAE on the derivative spectra. In the case of visible-NIR spectra, the second NS classification accuracy (88.4%) was acquired by employing PCA on the MSC correction spectra. From these results, it can be concluded that, the linear manifold learning technique for dimensionality reduction (PCA) is more accurate than the non-linear technique (Sammon mapping and MAE). Furthermore, it should be noticed that the 1st derivative SG showed the most accurate classification results than the MSC and then SNV preprocessed spectra and also ND was discriminant from NS and SY in significant level of 5%. As reported by these results, the present research plans the

structure of an automatic commercial system based on dimensionality reduction and classifier methods for early detection of FB in near future.

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تشخیص زودهنگام بیماری آتشک درختان میوه دانه‌دار با استفاده از طیف‌سنجی مرئی- مادون قرمز و نزدیک و روش‌های کاهش ابعاد

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چکیده

بیماری آتشک یکی از مخرّب‌ترین بیماری باکتریایی درختان میوه دانه‌داردر سراسر جهان است. در سال‌های اخیر، طیف‌سنجی به‌عنوان یک روش دقیق و زمان واقعی برای تشخیص بیماری‌های گیاهی شناخته شده است. بنابراین، هدف اصلی این پژوهش تشخیص بیماری آتشک درختان گلابی در مراحل اولیه آلودگی با استفاده از طیف‌سنجی مرئی و مادون قرمز نزدیک است. برای دستیابی به این هدف، طیف بازتابی برگ‌های سالم، برگ‌های شبه‌بیمار و برگ‌های بیمار در محدوده طیفی نور مرئی و مادون قرمز نزدیک اندازه‌گیری شد. به منظور حفظ اطلاعات مهم طیفی و همچنین کاهش ابعاد داده‌ها، روش‌های مختلف خطی و غیرخطی مانند تجزیه و تحلیل PCA، نقشه‌برداری سامون و روش اتوکودر چندلایه (MAE) مورد استفاده قرار گرفت. خروجی روش‌های مذکور به‌عنوان ورودی برای روش طبقه‌بندی SIMCA با هدف تفکیک برگ سالم، بیمار و شبه‌بیمار به‌کار رفت. بر اساس نتایج، بهترین طبقه‌بندی با استفاده از روش PCA در طیف مشتقی، با دقت ۹۵/۸، ۸۹/۳ و ۹۱/۶ درصد به‌ترتیب برای نمونه‌های سالم، شبه‌بیمار و بیمار به‌دست آمد. این نتایج توانایی روش‌های یادگیری چندمنظوره را برای تشخیص زودهنگام بیماری آتشک با استفاده از طیف‌سنجی تأیید می‌کند.

واژه‌های کلیدی: بیماری آتشک، تشخیص زودهنگام، سنجش از دور، طیف‌سنجی مرئی/مادون‌قرمزنزدیک، کشاورزی دقیق

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