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Detection of Cucumber Fruits with Excessive Consumption of Nitrogen using Hyperspectral imaging (With Emphasis on Sustainable Agriculture)

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Abstract

Uncontrolled consumption of nitrogen in cucumber fruit causes nitrate accumulation in the fruit that is harmful for humans and ecosystem. One of precise way to diagnose nutritional disorders is plant analysis, which is a destructive, costly, and time-consuming method. Hence, present study aims to evaluate cucumbers non-destructively using hyperspectral imaging. Cucumber seeds were planted in 16 pots and after the growth of plants and the appearance of fruits, the pots were divided into 4 categories. One was considered as a control sample (with normal nitrogen) and rest were treated with excess nitrogen by 30%, 60% and 90%, respectively. Hyperspectral images were obtained during two stages namely before treatment and 10 days after treatment. Three proposed methods namely hybrid neural network-cultural algorithm (ANN-CA), multilayer perceptron neural network (MLP) and support vector machine (SVM) were used to analyse and classify fruits. The findings represented the correct classification rates of 92%, 89.51% and 78.97% for ANN-CA, MLP and SVM, respectively. Thus, the ANN-CA algorithm had a good ability to identify excess nitrogen fruits.

Keywords

Cucumber; Nitrogen; Hyperspectral Imaging; Artificial Neural Network

Introduction

Among the essential nutrients, nitrogen is the most important element for plant growth, flowering and fruiting [1]. One of the results of nitrogen deficiency is lack of chlorophyll formation in leaves, while its high consumption, in addition to increasing nitrate accumulation, reduces the amount of vitamin C. Managing the use of nitrogen fertilizers should be considered by researchers and farmers. The average uptake of this fertilizer is estimated at only 33% and 67% of it is extracted from the soil and pollutes surface and groundwater [2-3]. Swamps and ecosystems are very sensitive to the indiscriminate use of nitrate fertilizers. And this causes severe and sudden changes in them. Excessive consumption of nitrogen causes a decline in yield and exacerbates many diseases and pests of the plant.Recently, hyperspectral imaging has been introduced as a useful technique for detection of internal and external features of products [4-7]. Hyperspectral imaging is a combination of vision imaging and spectroscopy techniques to obtain spectral and spatial information of an object. The spatial information is important to achieve the goal of the detection system, the spectral imaging method has more advantages than near-visible-infrared spectroscopy which just relies on single-point measurement. In order to use spectral information to analyze the physical or chemical properties of products, the entire surface must be evaluated to achieve a complete diagnosis. The hyperspectral imaging method meets these needs and has been applied for detection of contaminants, diseases, and defects in various biological products.Lu et al. [8] considered individual wavelength as an independent classifier and used receiver operating curve (ROC) analysis to select the best classifiers based on their performance. Dhaka et al. [9] used the convolutional neural network (CNN) to identify nitrogen deficiency in maize in three growth stages. 384 hyperspectral images were generated. The results showed that the plant growth stage was an influential factor. Ghosal et al. [10] used a relatively simple CNN for classification of soybean leaf into classes including food deficiency (potassium and iron), herbicide-damaged, and healthy leaves; CNN classification had an accuracy of 94%. Yu et al. [11] investigated on detection of heavy metal stress of mercury in tobacco using hyperspectral and machine learning methods. The appearance and texture of the tobacco plant were examined. Partial least squares discrimination analysis and support vector machine were used to estimate the status of mercury-stressed tobacco plants. The performance of these models was evaluated using confusion matrices and ROC. The results revealed that hyperspectral imaging combined with machine learning methods has a powerful potential to differentiate tobacco under pressure by the heavy metal mercury. Jarolmasjed et al [12] recognized bitter pit of apples using spectroscopic imaging. Their method was able to classify apples with accuracy of 85%. Imer et al. [13] studied on detection hollow heart in potatoes using hyperspectral imaging.

Reliable diagnosis of the nutritional status of agricultural products is an essential part of farm management [14], since both excess and deficiencies of nutrient can cause severe damage and reduced yields. Here, attempts were made to identify nitrogen-rich cucumbers using three different multi- layer perceptron neural network (MLP) and hybrid neural network-cultural (ANN-CA) algorithms and support vector machine.

2. Materials and Methods

The different steps for identifying cucumber based on nitrogen content are presented in Fig 1. As can be seen, the proposed algorithm includes six main steps: data collection, hyperspectral imaging, extraction the spectral data, classification and comparison the used methods.

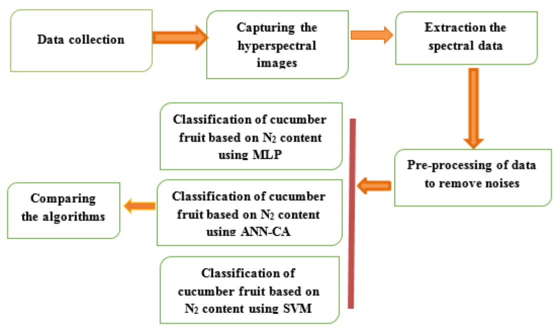


Figure 1. Flowchart of different stages of training the algorithm for classification of cucumber based on nitrogen

2.1. Sample preparation for hyperspectral imaging

To prepare samples of cucumber fruits with excess and standard nitrogen, cucumber seeds, Super Arshiya'F1 cultivar, were planted in 16 pots. All pots received the same inputs and fertilizers as needed until the plants grew and the fruit emerged. Excess nitrogen by 30%, 60% and 90% was then added to 12 pots (each class includes 4 pots). Hyperspectral images of each class were taken in two stages i.e. the day before the application of excess fertilizer and 10 days after it (Fig 2).

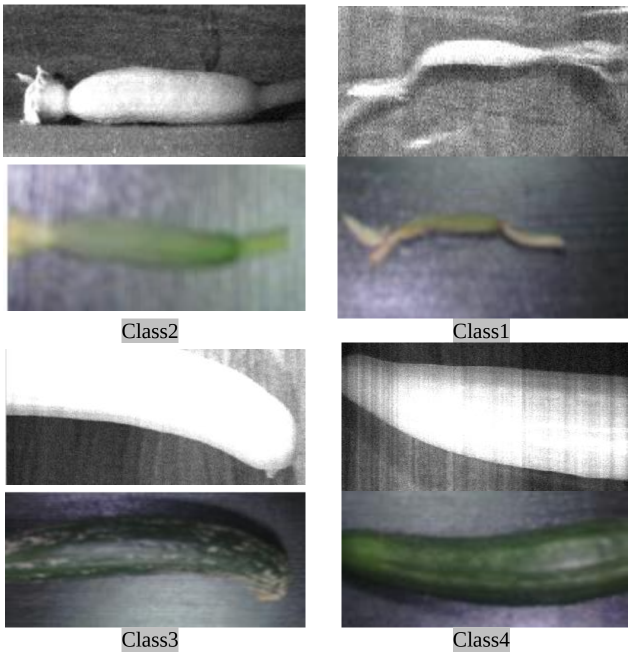


Figure 2. Examples of color and hyperspectral images of cucumbers related to each class

Hardware system used to extract spectral-spatial characteristics in each individual wavelength, included LabTop (Intel Corei5, 2430M at 2.40GHz, 4GB of RAM, Windows 10), hyperspectral camera (Imantajhiz Co., Iran; www.hyperspectralimaging.ir) in the range of 400 to 1100 nm, two tungsten halogen lamps (SLI-CAL (StellarNet, USA)) and a lighting chamber to omit ambient light.

2.2. Classification algorithms of Cucumber fruit based on nitrogen content

2.2.1. Classifier hybrid artificial neural network -cultural algorithm (ANN-CA)

The cultural algorithm is based on the rules of cultural evolution that contains the knowledge, traditions, beliefs and ethics of member of society. The work space of algorithm includes 2 sections namely population and cultural space. Population space searches candidature solutions while cultural space is the knowledge-based space that obtained data is stored and accessible to the current generation. A linkage is used to link two spaces for interaction and exchange the information. In fact, the method is that parameters are selected in the form of a vector by the cultural algorithm and fed to the artificial neural network [15]. The squared mean error is used to examine the performance of network after each proposed structure. The input and output of artificial neural network are spectral data and cucumber classes. At the end, the structure with least mean square error is introduced as the selected structure by the cultural algorithm. The involved parameters are number of layers and neurons, transfer function, back-propagation network training and back propagation weight / bias learning function.

After selection of optimal structure, 200 replications were done to evaluate the validity of the artificial neural network. For each replication, 60% of the data were randomly selected for training, 10% for validation and 30% for artificial neural network testing.

2.2.2. Multilayer perceptron neural network classifier

Multilayer Perceptron (MLP) is a type of neural network that has a supervised learning technique using the back-propagation method. Figure 2 shows that MLP benefits from a three-layer structure, including the input layer, hidden layer/s, and output layer/s, in which each neuron is connected to all the neurons in the next layer. It is frequently reported that MLP has a great function in non-linear problems [16]. There are various adjustable parameters in the artificial neural network that ensure their high performance by optimally adjusting them. In this study, using trial and error, the structure of multilayer perceptron neural network was selected according to Table 1.

Table 1. Specification of selected structure of neural network for classification of cucumber based on nitrogen content in 200 replications

Number of Layers	3
Number of Neurons	1st layer:15; 2nd layer: 17; 3rd layer:23
Transfer Function	1st layer:netinv; 2nd layer: radbas; 3rd layer:tribas
Back- propagation Network Training Function	traincgb
Back propagation Weight / Bias Learning Function	learnh

2.2.3. Support vector machine classifier

Support vector machines (SVMs) are a kind of supervised learning methods based on the linear classification of data. In the linear division of data, an attempt is made to select a line that has a more reliable margin. Finding the optimal line for data is done by QP methods, which are known methods for solving constrained problems. Before linear division, the data is taken to a much larger space by the phi function. In order to solve the problem of very high dimensions using these methods, the Lagrange double theorem is used.

2.3. Evaluation of the performance of classifiers

Table 2 gives the equations used to evaluate the performance of classifiers (Pourdarbani et al, 2020).

Table2. Equations used to evaluate the performance of classifiers

Equations	Eq.
$Recall = \frac{TP}{TP+FN} \times 100$	(1)
$Precision = \frac{TP}{TP+FP} \times 100$	(2)
$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100$	(3)
$Specificity = \frac{TN}{TN+FP} \times 100$	(4)
$F\_measure = \frac{2 \times Recall \times Precision}{Recall+Precision}$	(5)
$FP\ Rate = \frac{FP}{TN+FP} \times 100$	(6)
TP: True Positive	
TN: True Negative	
FP: False Positive	
FN: False Negative	

3. Results & Discussion

3.1. Comparison of the results obtained with different classifiers

Table 3 gives the performance of the various classifiers studied in this study using a confusion matrix, the correct classification rate, and incorrect classification rate for test data at 200 replications.According to the table, it can be seen that the hybrid neural network-cultural (ANN-CA) algorithm has been more successful than the MLP and SVM methods.

Table 3 Performance of different classifiers for classification of cucumber based on nitrogen

	Classes	Class1	Class2	Class3	Class4	Total Data	Misclassified (%)	CCR
ANN-CA	Class1	45785	59	0	0	45844	0.12	92.00
	Class2	247	37703	5014	340	43304	14.85	
	Class3	1	6701	38699	501	45902	18.61	
	Class4	0	141	627	34582	35350	2.22	
MLP	Class1	45602	242	0	0	45844	0.53	89.51
	Class2	244	35522	7020	518	43304	21.90	
	Class3	0	7736	37224	942	45902	23.31	
	Class4	0	311	852	34187	35350	3.40	

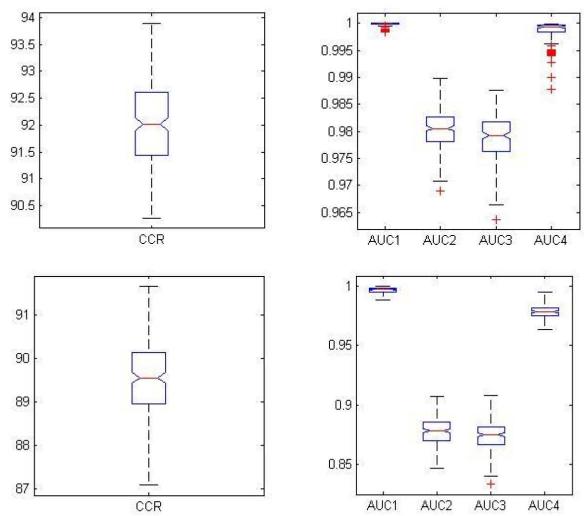
SVM	Class1	45841	0	0	3	45844	0.006	78.97
	Class2	236	26996	3722	12350	43304	60.40	
	Class3	1	6352	27510	12039	45902	66.85	
	Class4	0	217	913	34220	35350	3.30	

The different criteria for performance evaluation of classifiers are presented in Table 4. According to the table, the accuracy of the class1 (normal fertilizer) and class4 (excess nitrogen by 90%) is highest in ANN-CA and MLP methods, which indicates that the results of both classes are closer to the actual value of that class. The precision value of the first and fourth class is also the highest, which means that the standard deviation was less. The high value related to recall criteria of class 1 and class 4 indicates that the classifier was more capable of correctly distinguishing cucumbers with normal and excess nitrogen by 60%. On the other hand, the specificity of class 1 and class 4 are more than others, which indicates the ability of the classifier to correctly identify the sample. Better results in class1 and class4 is an expected and logical result because it is easier to identify these two classes than class2 and class3. Overall, according to the table, it can be concluded that ANN-CA and MLP methods were able to classify cucumbers in terms of nitrogen content, but SVM results are not acceptable.

Table 4. Different criteria for evaluating performance of classifiers

	Classes	Recall (%)	Accuracy (%)	Specificity (%)	Precision (%)	F (%)
ANN-CA	Class1	99.46	99.80	99.94	99.87	99.66
	Class2	84.52	92.61	95.50	87.06	85.77
	Class3	87.27	92.42	94.25	84.30	85.76
	Class4	97.62	98.98	99.37	97.82	97.72
	Class1	99.46	99.68	99.77	99.47	99.46
	Class2	81.08	90.46	93.76	82.02	81.55
MLP	Class3	82.54	90.21	93.00	81.09	81.81
	Class4	95.90	98.30	99.02	96.71	96.30
	Class1	99.48	99.82	99.99	99.99	99.73
SVM	Class2	80.42	85.46	86.83	62.34	70.23
	Class3	85.58	85.38	85.33	59.93	70.49
	Class4	58.38	84.05	98.88	96.80	72.83

Figure 4 evaluates the performance of the classifiers at 200 replications for the test data using box plots of correct classification rate (CCR), and the areas under the ROC curve (AUCs). If the box plots are more compact, they indicate higher performance (Pourdarbani et al. 2020). In general, in all classes, box plots relater to class1 and class4 are more compact, indicating the higher ability of algorithm to identify cucumbers related to these classes.



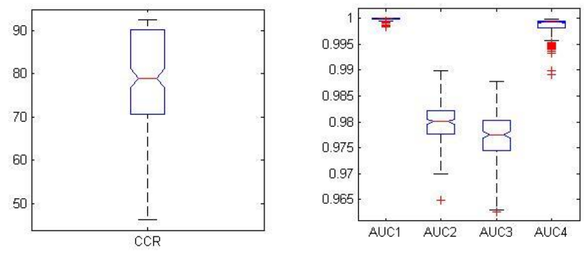
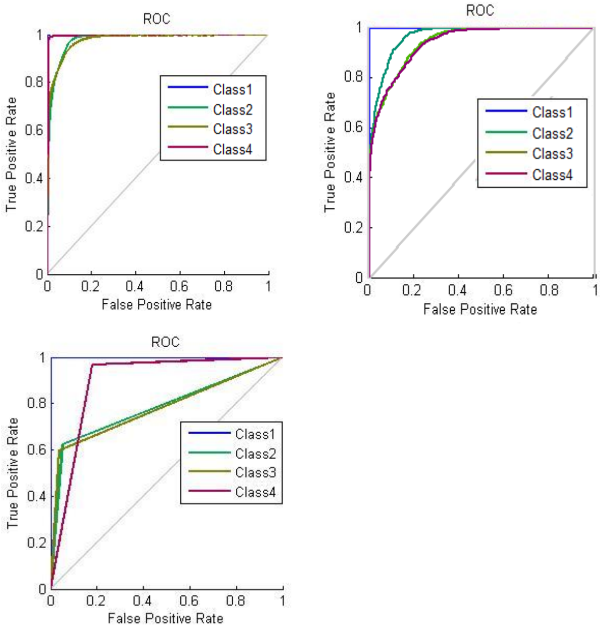


Figure 4. Box plots of the CCR and AUCs of the classifiers: 1st row: ANN-CA; 2nd row: MLP; 3rd row: SVM

Figure 5 represents the receiver operating curve of classifiers in 200 replications. If the curve is farther from the bisector line and closer to the vertical, it indicates the high performance of the classifier in that class. Except for the SVM classifier, the rest have high performance.

(a) (b)



(c)

Figure 5. Receiver operating curve (ROC) of classifiers in 200 replications to identify the cucumber in terms of nitrogen content; a) Method of ANN-CA, b) MLP and c) SVM

3.2. Comparison of the results obtained in this study with previous results from other researchers

Table 5 shows results of the different methods used in the form of the correct classification rate (CCR) criterion.

Table 5. Comparison of the results obtained in this study with the results of other researchers

Researchers	Product	CCR (%)
Xie et al [17]	Tomato	94.44
Zhang et al. [18]	Tomato	90
Yuan et al. [19]	Tea	94

4. Conclusions

Increasing population and demand requires increasing production per unit area. Competition for increasing yields has led to overuse of nitrate. Inappropriate application of chemical fertilizers in addition to imposing a high cost on the farmer, has harmful effects. It causes nitrate accumulation in the fruit and results in food poisoning and variety of diseases including cancer in the human body. Therefore, it is necessary to identify nitrogen-rich cucumber. Hyperspectral imaging is recognized as a non-destructive and rapid analytical tool for product quality assessment and disease diagnosis. In this study, the excess nitrogen was added to the treated pots and categorized by different classifier include hybrid neural network-cultural algorithm (ANN-CA), support vector machine (SVM) and multilayer perceptron neural network (MLP).The results showed that the correct classification rates of ANN-CA, MLP and SVM were 92%, 89.51% and 78.97%, respectively. In this way, hybrid ANN-CA algorithm had a good ability to identify nitrogen-rich cucumber.

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