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نشریه ماشین‌های کشاورزی
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Comparison of the Laser Backscattering and Digital Imaging Techniques on Detection of α-Solanine in Potatoes

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Abstract

The overall objective of this research is to check the abilities of two non-destructive techniques, the digital imaging (DI) and laser light backscattering imaging (LLBI), on detection of α-solanine toxicant in potatoes. Potato samples were classified in healthy and toxic categories based on the amount of α-solanine. For quantifying α-solanine in potato tubers, high-performance liquid chromatography (HPLC) has been used. The results of classification showed that single layer perceptron neural networks can classify potatoes with the accuracies of 94.28% and 98.66% by DI and LLBI systems (Donald cultivar), respectively. It can be said that LLBI systems might take precedent over DI systems due to their high accuracy, rapidity, and industrial capability.

Keywords: Backscattering imaging, Digital imaging, Glycoalkaloids, Liquid chromatography, Quality inspection

Introduction

Food safety is a key factor in the food and agriculture industries, because consumers prefer to purchase qualitative and reasonable products (Wu and Sun, 2013b). Potato (*Solanum tuberosum* L.), is one of the most important food crops of the world (Ji *et al.*, 2012), which can solve the poverty problem in all the world due to its valuable nutrients. So it can guarantee the food security of today and tomorrow generations (FAO, 2008). Unlike wheat and beans, some vegetables such as onion, garlic, and potato lose their nutritional values when sprouted (Tavakoli and Najafzadeh, 2015) and therefore, toxic compounds would be produced in the sprouts, flowers, and skin of potato tubers. Hence, the recognition of these toxic compounds that appear in green color at the skin of potato samples is necessary due to food safety and quality inspection of potatoes.

Potato tubers may consist of high levels of α-solanine and α-chaconine. These are two glycoalkaloids that can occur with each other and are issued under a unique heading, “solanine”. Light exposure of potato tubers is inevitable at different stages of harvest and post-harvest periods that leads to physiological changes in tubers. These changes are due to chlorophyll synthesis and toxic glycoalkaloids in all the surrounded layers of potato tubers. Accumulations of these toxic compounds lead to economic losses. Since the suggested safety amount of glycoalkaloids is about 200 mg kg^{-1} (fresh weight) of potato (FAO/WHO, 2003), efforts should be made to decrease these toxins in potatoes to minimize possible values, especially for people who use them a lot. It is notable that this issue is more important for children.

Currently, different apparatuses are widely used to detect solanine in potatoes, tomatoes, and eggplants, which however are time-consuming, tedious, costly, and destructive. These methods are gas chromatography, liquid chromatography, spectrophotometry, etc. Therefore, it is critical and necessary to apply accurate, rapid, reliable, efficient, and non-invasive alternatives to evaluate the quantity and quality-related attributes of food products (Espinoza *et al.*, 2014). Recently, optical sensors have been studied as potential tools due to the non-destructive inspection of food safety (Wu and Sun, 2013a). Geng *et al.*

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(2019) reported a technique for separating clods and stones from potatoes using laser backscattering imaging. The recognition results showed that the best wavelength for separation with the high accuracy of 98% was at 850 nm (Geng *et al.*, 2019). Maestresalas *et al.* (2016) study developed a system of hyper-spectral imaging to recognize potatoes that have been affected by black-spot. In Ji *et al.* (2019) study, intact potatoes were separated from defective ones using hyper-spectral imaging and were classified using support vector machine with the accuracy of 90%. Ye *et al.* (2018) detected and classified major bruised potatoes by hyper-spectral imaging.

In this paper, the abilities of two non-invasive techniques, which are the digital imaging (DI) and laser light backscattering imaging (LLBI), have been studied on detection of only α-solanine in potato tubers. For this purpose, algorithms were developed for both techniques and compared with each other.

Material and Methods

Sample preparation

Potato tubers of 'Donald' and 'Ceasar' cultivars were bought in late June and November 2016 from a market in Urmia, Iran (70 and 100 homogenous samples of 'Donald' and 'Ceasar' cultivars, respectively). Then, potato samples were kept in the dark and cool (4±2 ºC) room until doing the experiments, because light exposure and high temperature can induce the potato tubers and increase the formation of these glycoalkaloids in them. Finally, potato tubers have been washed with water and dried.

Two dimensional (2-D) imaging systems

The imaging was done in two different environments for RGB digital imaging and laser light backscattering imaging methods, one under white LED bubble into the imaging chamber and the other under laser light in absolutely dark room.

Imaging set-ups

Digital imaging chamber

Image preparation of potato tubers was performed in an imaging chamber with the dimensions of 55×40×25 cm. It has consisted of the white LED bubbles per each side and a cavity for locating the camera lenses at the top. A digital camera equipped with a CCD sensor (Sony Cyber-Shot, Model DSC-W200, Japan) was used for this purpose.

Optical set-up

A laser imaging system has been used to this study. It included the following tools; a CMOS camera (Sony Cyber-Shot, Model DSC-HX9V, Japan), a semiconductor laser at 635 nm (3 mW power, the diameter of 2 mm for beam spot), two polarized filters, a cubic beam splitter, and a potato holder. The camera was assembled perpendicular toward the laser light, and the backscattering light was recorded by a camera (Fig.1).

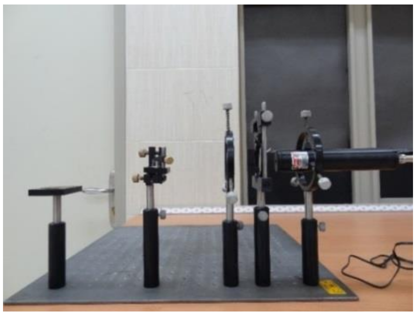


Fig.1. The laser light backscattering imaging optical set-up

Acquiring digital images

The images were captured by the CCD digital camera from both sides of potato with 3264×2448 pixels resolution in RGB color space. 140 and 200 images were taken from potato tubers of cv. 'Donald' and 'Ceasar', respectively. Additionally, different regions of potatoes were in the exposure of the laser light. Therefore, images have been acquired by the CMOS camera with the resolution of

4608×3456 pixels in RGB space. In LLBI method, 210 and 300 images were captured from the surface of potato tubers of cv. ‘Donald’ and ‘Ceasar’, respectively.

Digital image processing

RGB Digital imaging processes

After transferring the images to a personal computer (PC), processing operations were done by MATLAB software as following:

- Distinguishing potato tubers from the backgrounds (*DPB*) by equations 1 and 2:

$$DPB = 1.7G - R - B \quad \text{(cv. Donald)} \qquad (1)$$

$$DPB = B - G + 0.5R \quad \text{(cv. Ceasar)} \qquad (2)$$

- Calculating the total area of potato on binary image (showed as *A*)
- Extracting the green parts of potato by *XOR* function
- Acquiring the area of the extracted region (showed as *C*)
- Calculating the percentage of green parts in total parts of potato by equation 3:

$$S = \frac{C}{A} \times 100 \qquad (3)$$

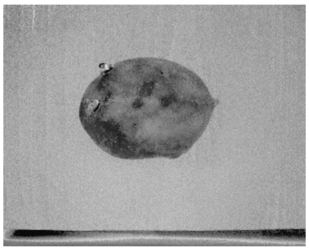
- Multiplying the binary image of extracted green regions by *R*, *G*, and *B* components
- Averaging the values of *R*, *G*, and *B* components for green regions.

Some morphological features such as the percentage of green parts of potato in total parts of potato and mean values of R, G, and B components for green parts were extracted. Fig.2 shows the processing levels of the images. Since some features such as the conditions of environment and the instrument can influence the RGB measurements of a digital camera, the calibration of the device is necessary. For this reason, Minolta colorimeter (Konica Minolta Chroma Meter, Model CR-400, Japan) has been used in $L^*a^*b^*$ color space.

LLBI processing

After taking the backscattering images, processing operations were done using MATLAB software. Acquired Laser parameters for each image were backscattered area (A_{635}), the amplitude (a_1), and half-width (c_1) coefficients of Gaussian curves. Fig.3 shows the intensity diagrams of scattering light in red channels of the images for both groups of potatoes.

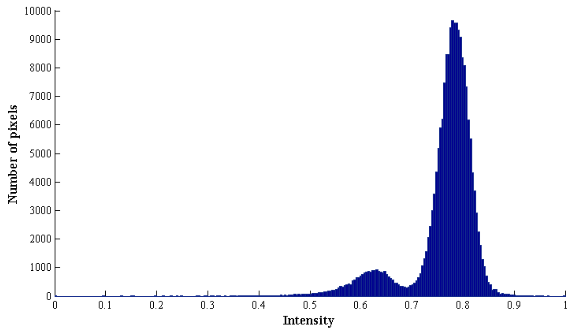
(a)



(b)

(c)

(d)



(e)

Fig.2. The processing stages of images (cv. ‘Ceasar’); (a) the original image, (b) gray- level image, (c) binary image, (d) extracted green region, (e) histogram for separating potato tubers from background

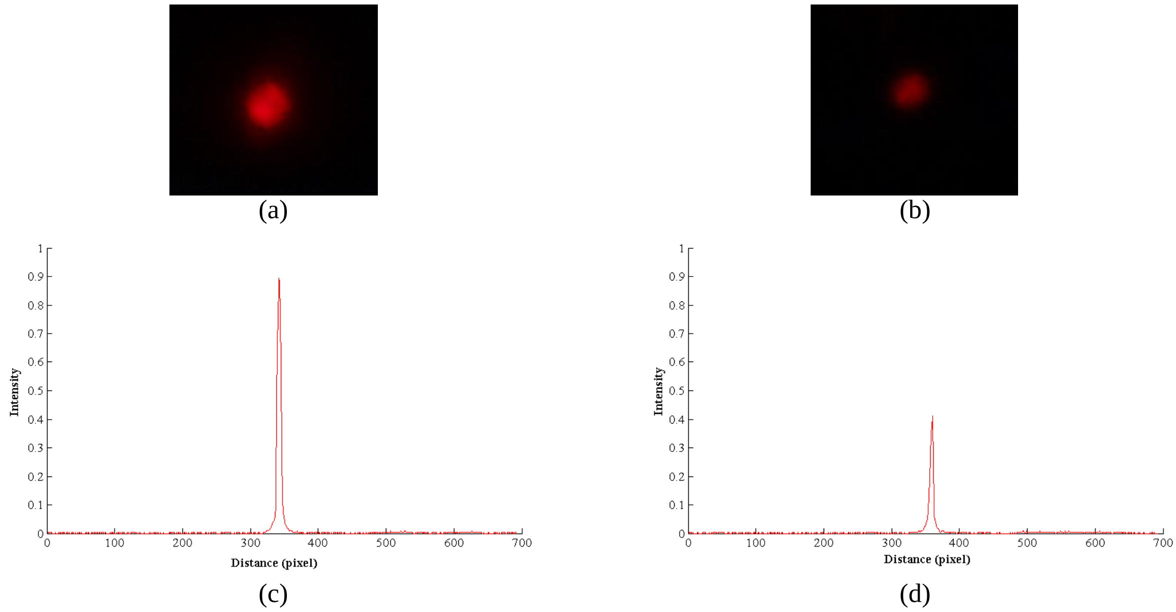


Fig.3. (a & b) The backscattered images for healthy and toxic potatoes, respectively, (c & d) the intensity diagrams of scattering light in red channels for healthy and toxic potatoes, respectively (cv. 'Donald')

Destructive test for measuring solanine

A chemical and destructive analysis is needed to quantify glycoalkaloids in potato samples, including high-performance liquid chromatography (HPLC) system. Based on Rytel (2012) study, the ratio between α-chaconine and α-solanine has been concluded about 65 to 35, so the acceptable level of α-solanine in tubers is 70 mg kg^{-1} fresh weight of potato. Therefore, potatoes would be categorized based on this quantity. For this purpose, HPLC instrument (Smartline series, Knauer Co., Germany) was used and α-solanine was separated during the elution with the mobile phase at the flowing rate of 1.5 mL/min. Then, α-solanine was determined by a UV detector at 207 nm, and the amount of α-solanine in samples was measured by comparing it with the peak area of standard chromatogram at the retention time of 2.6 min.

Table ***1*** shows the chromatography analysis of potato samples in some tubers.

Table 1- HPLC analysis of potato tubers (cv. 'Donald & Ceasar')

	cv. 'Donald'	**cv. 'Ceasar'**
Potato classification	**α- solanine (mg kg^{-1} of fresh potato)**	**α- solanine (mg kg^{-1} of fresh potato)**
Healthy	44.5	39.81
	61.93	50.45
	64.55	68.98
Toxic	83.60	70.15
	93.43	88.76
	113.98	107.69

Classification of potatoes by artificial neural networks (ANNs)

The artificial neural networks classified potatoes into healthy and toxic categories based on the extracted features. The

Levenberg-Marquardt network was trained with 70 percent of the data. This network depends on improving the descent gradient and mean square error (MSE) (Kaveh *et al.*, 2019). For applying error back-propagation network, differentiating of transfer function is important. Therefore, the hyperbolic tangent sigmoid function was applied as a transfer function in a single layer perceptron neural network (SLPN).

Results and Discussion

Digital camera calibration

The results demonstrated that relationships between the digital camera and colorimeter data were linear and correlation coefficients for L^*, a^*, and b^* values were 0.917, 0.948, and 0.903, respectively (Fig.4).

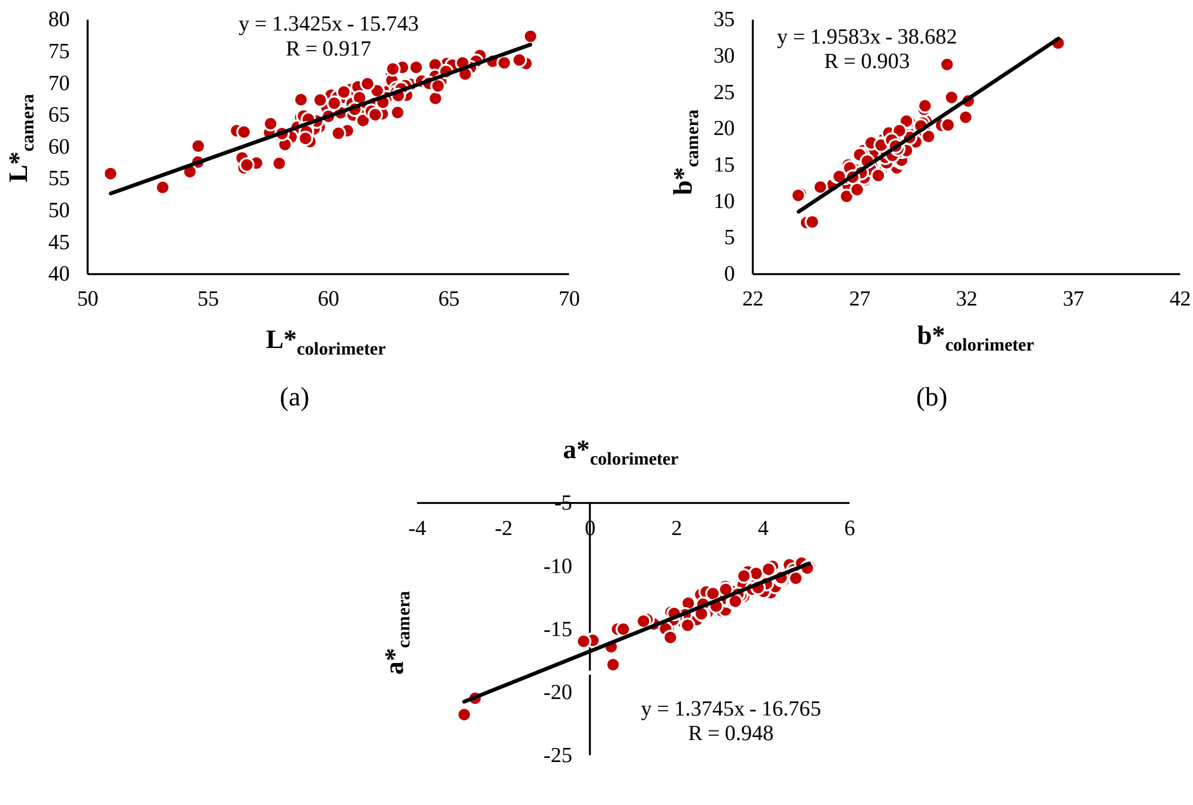
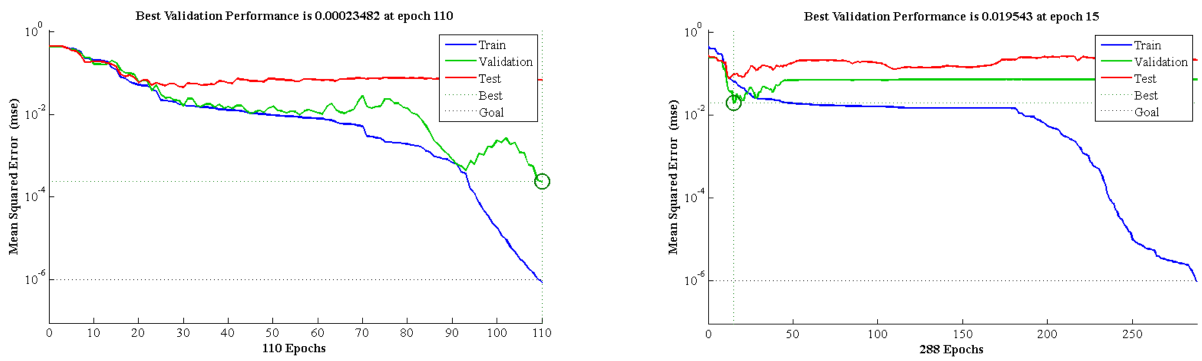


Fig.4. Correlation diagrams between Minolta colorimeter and digital camera in $L^*a^*b^*$ space

Classification of potatoes using digital images

The potato tubers were classified into two categories, healthy and toxic, based on four extracted characteristics using ANNs. These features such as the percentage of green parts of potato in total parts of potato and mean values of R, G, and B components of green parts were the inputs in topography of the designed ANNs. The best performance in ANNs was achieved when the numbers of neurons were six based on MSE of 0.019543 for cv. 'Donald' and five with the MSE of 0.00023482 for cv. 'Ceasar' (Fig.5). The accuracies for these topographies were reported to be 94.28% and 98.88% for cv. 'Donald' and 'Ceasar', respectively. The main reason for achieving the high accuracies is determining the different relations for each cultivar to separate the potato tubers from the background. Extracting the threshold relations was based on trial and error that this method is quite difficult for all cultivars of potatoes in on-line applications. Fig.6 demonstrates a sample of confusion matrixes of LED-excitation imaging system for cv. 'Ceasar'.



(a) (b)

Fig.5. The performance diagram in DI system; a) ‘Ceasar’, and b) ‘Donald’ cultivars

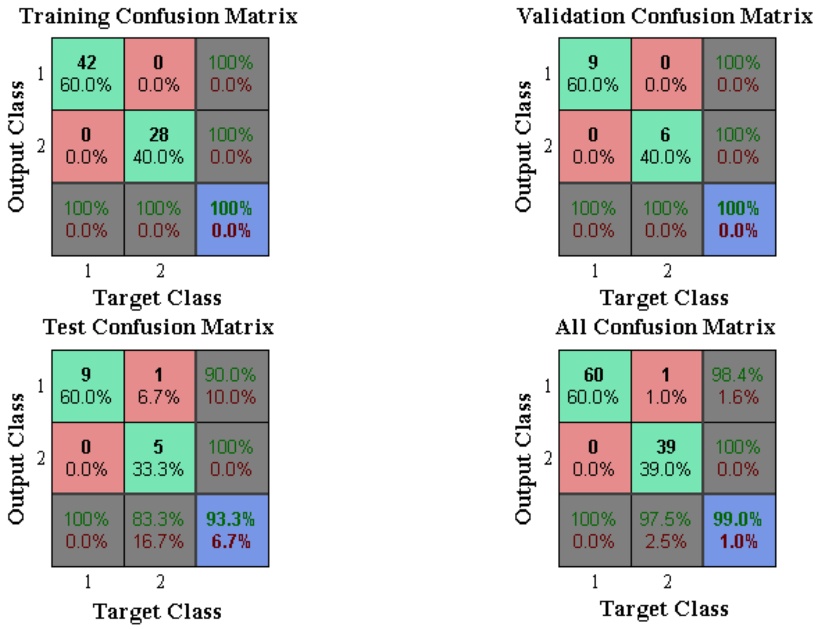


Fig.6. A sample of confusion matrixes for the digital imaging system (cv. ‘Ceasar’)

Classification of potatoes by LLBI images

In this technique, three features that have been mentioned before were the inputs of designed ANNs. The ANNs accuracy values for cv. ‘Donald’ and ‘Ceasar’ were 98.66% and 99.16%, respectively. The performance diagram for LLBI system is shown in Fig.7. Here is the reason that how changes in the amount of solanine can affect the backscattering area of laser in potato tubers. Solanine appears in green color at the surface of the potato. When the laser beam in the wavelength of red region encounters with the tuber, it can cause a deduction in the backscattered area. Hence, changes in backscattering area lead to variations in amplitude and half-width parameters in the Gaussian curves, thus the amount of solanine can be predicted using of these parameters.

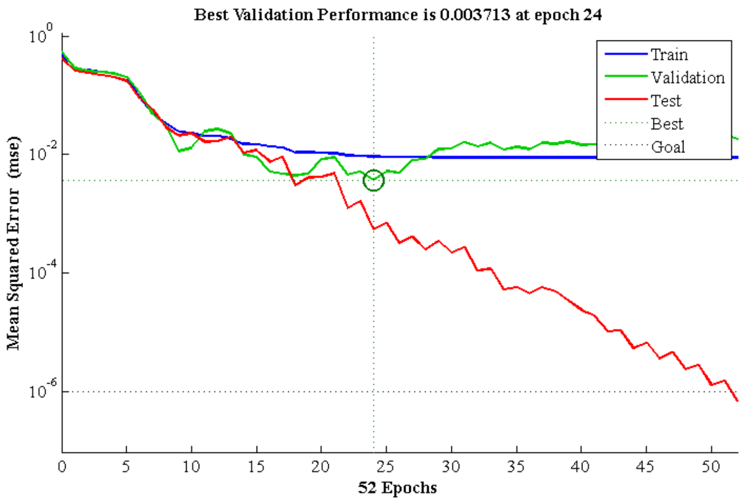


Fig.7. The performance diagram of LLBI system for cv. 'Ceasar'

Comparison of two non-invasive techniques

In this research, two varieties of potato tubers have been studied using two imaging (DI and LLBI) systems. In the DI system, the accuracy of the network in 'Donald' cultivar was fewer than 'Ceasar' tubers. The reason can be described based on this fact that 'Donald' tubers had brighter skin than 'Ceasar' potatoes. Therefore, the algorithm has been mistaken in the calculation of area in some samples. As well as, the classification algorithm in 'Ceasar' cultivar was better than 'Donald' tubers in the LLBI system. The comparison of results in both cultivars shows that the accuracies of networks in 'Ceasar' potato tubers were higher than 'Donald' samples due to the textural properties of potato samples, because 'Donald' variety is a spring cultivar of potato that has an easily-to-cut and soft skin. During the time, there can be occurred enzymatic browning phenomena surround the bruised regions and can cause errors. However, 'Ceasar' samples have a thicker skin in comparison with another variety and they do not have the problem of scabbing.

In general, LLBI system was more accurate than DI system in both cultivars, but there were some advantages and disadvantages of each ones. In DI systems, the reflectance of light in the imaging chamber can influence the results, so finding the best relationship between R, G, and B components for separating the considered region from the background is difficult. Moreover, the algorithm needs more neurons to have a good classification. Therefore, this causes the complexity in the structure and topography of the designed ANN. However, the structure of ANN in LLBI systems was simple, especially in cv. 'Donald' with just three neurons. In this case, the study should be done in an absolutely dark environment that is difficult for human beings to work in these situations, but it is suitable for industrial and optical devices that decreases the errors resulting from the environmental noises. It can be stated that LLBI system has this opportunity to be commercialized.

Recently, these non-invasive methods for detection of glycoalkaloids in potato tubers have been employed. There are few studies about the determination of solanine with the image processing method. Ebrahimi *et al.* (2011) reported that the average error of image processing for estimating the greening areas of potatoes was 5.26% just for 25 images without doing any reference test to be sure about the real quantities of glycoalkaloids. In the current research, there was a widespread data with a less amount of error that shows the reliability of the used technique. In addition, HPLC technique was necessary to confirm the image processing data that other studies did not do it at all. In Tavakoli and Najafzadeh (2015) study, the authors used the image processing method for recognizing just the sprouts without reporting any accuracy for their work. Gao *et al.* (2018) used hyper-spectral imaging for identifying the sprouted potatoes from the others with the accuracy of 95.3%. In the case of LLBI, there is not any study by other researchers to use it for detecting solanine, but this technique has been used in many areas such as measuring the moisture content and shrinkage of agricultural products after drying (Udomkun *et al.*, 2014), soluble solid content, and firmness of products (Mollazade *et al.*, 2013).

Conclusions

In this research, α-solanine could be detected by digital imaging and laser light backscattering imaging techniques in potato tubers. So, both methods can be successfully used in the food industry. In LLBI technique, it can be applicable in cultivars with smooth surfaces. But in the digital imaging system, different relations are needed for different cultivars of potatoes separation from the background. Although, LLBI technique is used in a dark environment, it can be said that LLBI systems might take precedent over LED imaging systems due to their high accuracy, rapidity, and industrial capability. There is little information about laser backscattering imaging and more studies are needed to check the effects of some morphological parameters on LLBI systems.

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مقایسه‌ی روش‌های پس‌پراکنشی لیزر و تصویربرداری دیجیتال روی تشخیص آلفا- سولانین در سیب‌زمینی

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چکیده

هدف اصلی این تحقیق، بررسی توانایی‌های دو روش غیر مخرّب، تصویربرداری دیجیتال (DI) و تصویربرداری پس‌پراکنشی نور لیزر (LLBI)، روی تشخیص سم آلفا- سولانین در سیب‌زمینی است. نمونه‌های سیب‌زمینی در گروه‌های سالم و سمّی براساس مقدار آلفا- سولانین موجود دسته‌بندی شدند. کروماتوگرافی مایع با عملکرد بالا (HPLC) برای تعیین مقدار آلفا- سولانین موجود در غده‌های سیب‌زمینیی استفاده گردید. نتایج طبقه‌بندی نشان داد که شبکه عصبی پرسپترون تک لایه می‌تواند سیب‌زمینی‌ها را با دقّت ۹۴/۲۸٪ و ۹۸/۶۶٪ به ترتیب توسط سیستم‌های تصویربرداری دیجیتال و پس پراکنشی لیزر (رقم دونالد) طبقه‌بندی نماید. می‌توان گفت که سیستم‌های پس‌پراکنشی لیزر ممکن است از سیستم‌های تصویربرداری دیجیتال به دلیل دقّت و سرعت بالای آن و همچنین قابلیت صنعتی شدن آن سبقت گیرد.

واژه‌های کلیدی: بررسی کیفیت، تصویربرداری پس‌پراکنشی، تصویربرداری دیجیتال، کروماتوگرافی مایع، گلیکوآلکالوئیدها

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