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Computer vision and artificial neural network techniques for classification of damage in potatoes during the storage process

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Abstract: The research methodology consists of several stages to develop a noninvasive method of identifying the turgor of potato tubers during the storage. During the first stage, a graphic database (set of training data) has been created for selected varieties of potatoes. As a next step, special proprietary software called 'PID system' was used together with a commercial MATLAB package to extract parameters defining the digital image descriptors. This included: hue space models, shape coefficient and image texture. Thirdly, Artificial Neural Network (ANN) training was conducted with the use of Statistica and MATLAB tools. As a result of the analysis, a neural model has been obtained, which had the greatest classification features.

Keywords: artificial neural networks; Haralick's texture analysis; image analysis; storage of potatoes

Maintaining high product quality for as long as possible requires optimal conditions for storage after harvest. In order to do so, the life processes of tubers must be minimized. Such factors like temperature and humidity have the biggest impact on the ensuring appropriate potato storage.

In order to ensure correct classification of products and reduce losses during their storage, efforts were focused on the sensory evaluation of potatoes with the use of modern techniques, such as computer image analysis and neural modelling. Computer image analysis is a method of segmenting objects and extracting the characteristics (numerical data) encoded in a digital image (Boniecki *et al.* 2013; Koszela *et al.* 2013; Przybył *et al.* 2014). Neural image analysis was used for classification of dried carrots into different levels, and a genetic algorithm used in the process of drying carrots was designed based on regression analysis (Koszela *et al.* 2012). Image classification has been used in detection of damage in olives (Riquelme *et al.* 2008). It was noted that this technique has become an object of interest for scientists all over the world. This is confirmed by the verifiability of this method in solving the scientific and technological problems.

The aim of this study was to develop a method to assist the identification of either varieties and the turgor of potato tubers carried out based on the graphical data encoded in the form of digital images, obtained using algorithms interpret the image descriptors, using the modern tools (methods) such as: computer vision and artificial neural network techniques.

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MATERIAL AND METHODS

Potatoe samples. The research covered five basic varieties of potatoes: Denar, Lord, Gala, Nandina and Vineta, which are more popular in Poland than in other countries. This is due to the fact that they possess such valued qualities as shape, colour of skin, pulp, fertility, resistance to viruses and storage durability.

Samples were collected at random from selected batches of each potato variety. The potatoes were placed in pallet boxes measuring 1.5 × 1.5 × 1.5 m. Every sample batch was placed in 6 different locations of the technological storage room. Each sample was taken from three different layers of pallet-boxes (in accordance with the standard PN-R-74452).

The image acquisition process, coupled with the use of measurement and research equipment, allowed for the development of a graphical database. The collection of more than 21 000 images of 5 varieties of potatoes was obtained. The primary image was processed then by cutting the object from the image. The object on the secondary image was then placed under analysis.

Before starting the process of generating the specific numerical data of the object, damage to the tubers was identified organolepticly by experts using manual methods (Figure 1). As a result, potatoes were divided into the following classes:

(1) Denar variety,
(2) Gala variety,
(3) Nandina variety,
(4) Lord variety,
(5) Vineta variety,
(6) damaged potatoes (1, 2, 3, 4, 5, 6).

Image aquisition. The measurement and research station was used for the acquisition of graphical database from the research material. The parameters of the equipment were appropriately calibrated for making digital images (by standard PN-EN 12464-1: 2004). Measurement was performed using a CFM DT-1308 luxmeter. According to the norm, condition of light was checked using luminance distribution factor of 0.71, which means that it fully meets determined requirements concerning rules of even lighting in rooms, among other things, in laboratory site (Przybył *et al.* 2016).

In order to obtain a set of image descriptors used an original IT application 'PID system', together with MATLAB software. Later STATISTICA software was used to analyse the test results. 'PID system' is original software written in environment called Microsoft Visual Studio using programming language C# (Przybył *et al.* 2016). 'PID system' was designed and manufactured in order to process and analyse images. It uses inbuilt open libraries AForge.NET (http://www.aforgenet.com/) as well as Open Source Computer Vision (http://opencv.org/). This software comprises a sequence of components having influence on the change of digital images. It also has a several dozen of functions, for example the one detecting edges from image or building learning databases ANN based on extracted features from image. It is a universal program, which has already found application in analysis – apart from potatoes – of fruit powders, among other things, strawberry powder (Przybył *et al.* 2018) and rhubarb powder.

In classification, representative features of types of potato damage were gained. It was selected 102 specific parameters determining, among other things, colour, shape and texture (Figure 2). All the same, the selected factors were used as input variables for simulator ANN.

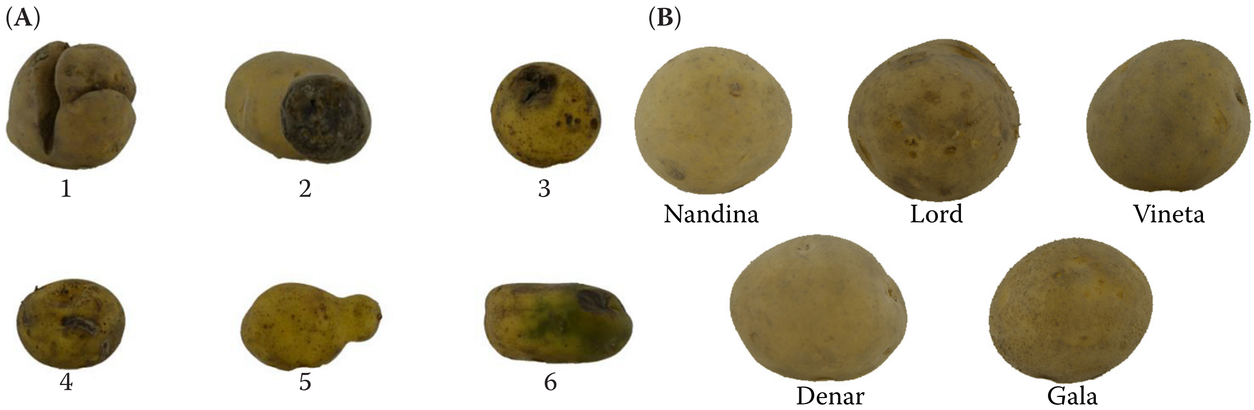

Figure 1. Examples of images of defects (**A**) and various varieties of potatoes (**B**). (**1**) potato irregular, mechanically damaged; (**2**) bulb with a wet of rot; (**3**) bulb from dry of rot; (**4**) potato from mechanical damage and signs of rot; (**5**) developed secondary tubers; (**6**) the potato of rot and greening

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The first group of representative image features determined 4 geometric parameters (height, width, perimeter and area of the object) (variables: 1–4), 1 descriptor defining RGB described form a single number (Nowakowski *et al.* 2011) (variable: 5) and 48 descriptors of the image based on the histogram of colour space models, such as RGB (variables: 6–20), HSB and HSL (Hue–3 variables: min, max, mean), saturation (5 parameters), brightness (5 parameters), lightness (5 parameters) (variables: 21–38), and YCbCr (variables: 39–53) (Brancati *et al.* 2017). Circumference of the object was calculated using the third method of determining contour (Korohoda & Tadeusiewicz 1997). The area was calculated based on the number of pixels of the object.

The second group concerned shape factors, which are commonly used in image analysis. Shape factors allow to distinguish the figures (objects) based on their shape, depicted in the digital image. As part of the research, 13 descriptors defining the shape of the empirical object were used, whose numerical values were obtained using 'PID system', i.e. Feret coef., circularity factor 1 and 2, Malinowska, Blair-Bliss, Danielsson, Haralick, Lp1, Lp2 and Mz coef., dimensionless shape factor, regular shape factor, compactness of shape factor (variables: 54–66) (Korohoda & Tadeusiewicz 1997; Ercisli *et al.* 2012).

The third group is defined by texture parameters, which were obtained using this software and the MATLAB environment with Haralick library. Image texture descriptors are based on the GLCM matrix (Gray-Level Co-occurrence Matrix) (Kumar *et al.* 2010). When specifying the texture features, GLCM calculates how often a pair of pixels of given values occurs over a strip of gray image (Clausi 2002). The measurements and statistics of representative features of texture (the value of the minimum and maximum) are based on the matrix GLCM, making a set of 36 variables such as: angular second moment, contrast, correlation, sum of square variance, inverse difference moment pairs of pixels, sum of average pairs of pixels, sum of variance, entropy, difference variance, difference entropy, and info. Measure of correlation 1 and 2, cluster prominence, cluster shade, dissimilarity, homogeneity, maximum probability and inverse difference normalized (variables: 67–102) (Park *et al.* 2001; Lin *et al.* 2009). The purpose of process of image processing and analysis was to determine the geometric parameters and known factors of shape and texture (Figure 2).

Neural modeling. Artificial Neural Networks (ANN) make it possible to filter signals and eliminate noise (Arlorio *et al.* 2009). In classification problems, occurring during the process of generating models (testing, validation and verification), factors that affect the quality of the network parameters include: learning speed, size of mistake and ability to generalize (Boniecki *et al.* 2013). In order to make an impartial evaluation of classification of food products in the agro-food sector, appropriate mathematical models are designed and developed which make it possible to support the decision-making processes using expert systems to identify fruit and vegetables (Koszela *et al.* 2014).

It is worth noting that classification of fruit and vegetables, including potatoes, by means of neural modeling can effectively assess their quality parameters (Boniecki *et al.* 2012; Koszela *et al.* 2014).

The aim of designing neural models is to obtain in the process of simulation (on the basis of a set of representative features) such a model or models that have the greatest ability to classify damage and identify varieties of potatoes.

RESULTS AND DISCUSSION

Among the thousands of tested neural networks one was selected that was characterized by balancing the best quality of learning with the lowest validation error (Buciński *et al.* 2009). It was the network of Multilayer Perceptron (MLP).

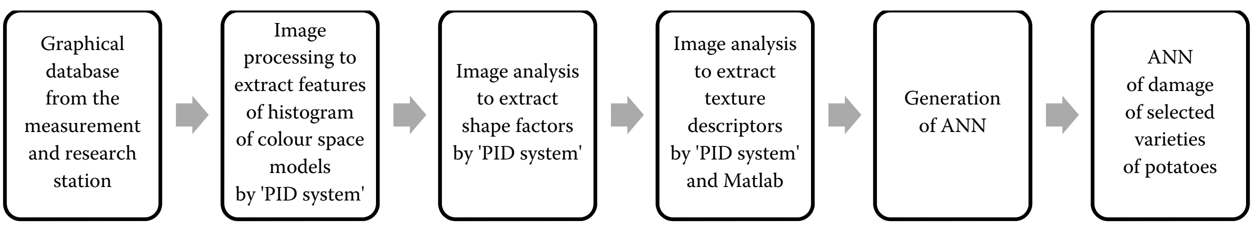

Figure 2. Procedure scheme

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An MLP-type ANN with structure 102: 102-12-6 2, shown in Figure 3, is proved to be an adequate neural network. The model of this network contained 102 input variable informative features of the image, 21356 training cases, 12 neurons in the hidden layer and 6 neurons in the output layer. The first output variable is a binary variable 'good' or 'bad', classifying the turgor of tubers with 1 neuron to 2 sets: potato damaged or not damaged. The other 5 states of the output variable 'type' of potato attributed to one of the 5 neurons respectively for the specific varieties.

RMS error is the summary value of the error committed with regard to the training set, test and validation (1) (Barile *et al.* 2006). Table 1 presented the resulting RMS error for an adequate MLP neural network was respectively.

In order to compare the similar neural networks used in classification problems, an example of a mathematical model for the development of noninvasive methods for assessing the quality of oocytes was carried out, based on the graphic data encoded in the form of monochrome digital images obtained by microscope. Usage also the generated network MLP 22: 22-54-4: 1, which was characterized by a low RMS error, the value of which for a validation set was adequately 0.1030 (Koszela *et al.* 2015). It was performed in the contrast to the MLP type network, in which a PNN-type network was obtained: 13-404-5-1. The issue related to the estimation of intramuscular level of marbling among white headed mutton sheep lambsu, obtained RMS error for a set of validation was at the level of 0.12 (Przybylak *et al.* 2016). Small values of RMS error may indicate that both MLP neural networks possess an appropriate ability to generalize knowledge in classification issues, Equation (1).

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{n}(y_{\mathrm{i}} - z_{\mathrm{i}})^2}{n}} \qquad (1)$$

where: n – number of cases; y_{i} – real values; z_{i} – values determined with ANN

The ANN value determines the number of correct answers obtained by the network in comparison to the total number of responses provided in Table 1. The DLGNV training set is a collection of learning cases, which belong to 5 varieties of potatoes. An MLP-type of neural network 102: 102-12-6: 2 contains algorithms that optimize the ANN weightings. Backward propagation of errors (BP) is a known and proven technique for teaching about neural networks (Rumelhart *et al.* 1986; Chayjan *et al.* 2011). Table 1 depicts an algorithm BP50, i.e. the learning function, which in the first stage of learning obtained the lowest level of error in 50 training sets. The conjugate gradient algorithm (CG) is a learning function using the conjugate gradient, which is usually faster than the BP algorithm (Khadse *et al.* 2016). Table 1 illustrates CG254b method of training, which task was to provide the further training to the network at a later stage and obtaining the slightest error resulting in iteration 254.

Evaluation of neural classifiers was based on an analysis of sensitivity to input variables (Rad *et al.* 2015). The procedure of sensitivity analysis is implemented in Statistica, in order to determine the effect of empirical data (input variables) on the performance of the

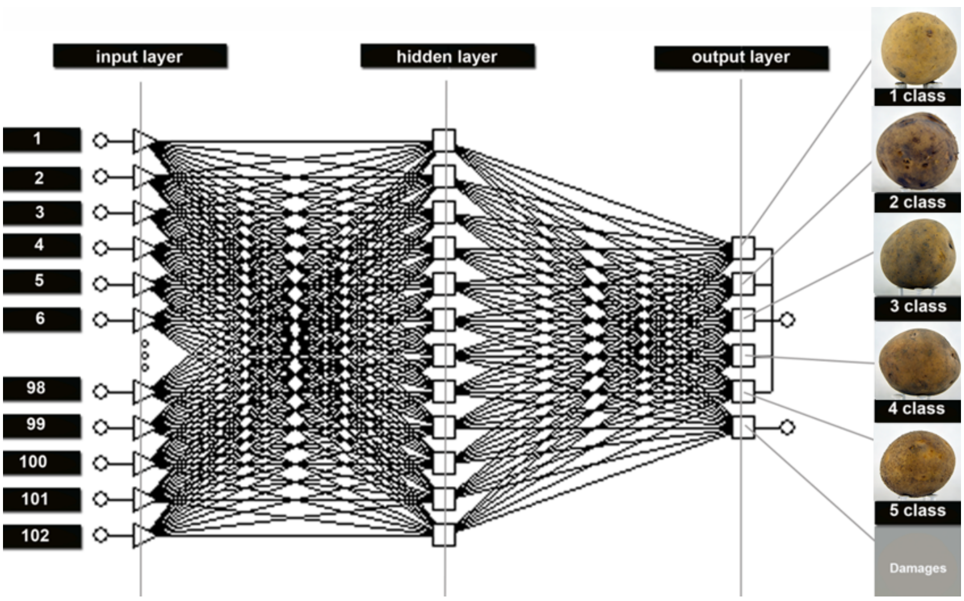

Figure 3. Structure of MLP-type ANN
1 class – Denat; 2 class – Gala; 3 class – Nandina; 4 class – Lord; 5 class – Vineta; 6 class – damages

Table 1. Characteristics of adequate model for neural classification damage potatoes

Training set	ANN	Quality of training	Quality of validation	Quality of testing	Training error	Validation error	Testing error	Method of training
						(RMS)		
DLGNV	MLP 102:102-12-6:2	0.9779	0.97678	0.97227	0.12959	0.13502	0.13713	BP50, CG254b

generated mathematical model (neural classifier). It was noted that in the MLP network 102:102-12-6: 2 and in the DLGNV training set, the 102 variables determining the features of the colour models, texture and shape factors had influence on the precision of network. This is due to the fact that the value of the error quotient in most of these cases is higher than 1. If the value of the error ratio reached a value equal to (or less) than 1, then the selected input variable should be skipped, given that it does not affect the quality of neural model. Among the 102 representative features, input variables defining the colour space model and texture image obtained the greatest importance (rank) for the ANN. The highest value of the error quotient was given to the input concerning the deviation of standard red ('R_STD') with the error quotient amounting to 1.52647. In the case of image texture, it was the variable determining the extent of correlation information for 2 pairs of pixels with the minimum value ('INF21H_MIN'), where the error ratio was 1.16930.

In the basis of an analysis of sensitivity to input variables show the highest correlation between R, G, and B values from encoded information of graphical objects of model RGB using computer image analysis (Figure 4). A strong correlation was found between R and G values from model RGB (r^2 = 0.9297); whereas for R and B values, the correlation coefficient was lower (r^2 = 0.6111).

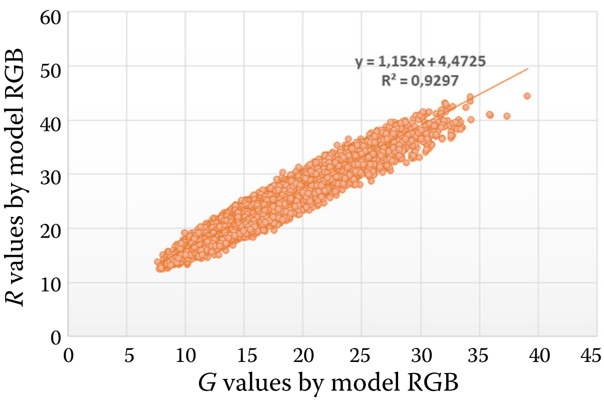

Figure 4. Correlation of parameters in RGB, coefficient of determination R^2 = 0.9297, respectively

CONCLUSIONS

The following conclusions can be presented:

(1) The generated neural model MLP-102: 102-12-6: 2 allows to estimate the damage in selected varieties of potatoes.

(2) The analysis of the precision of neural model MLP-102: 102-12-6: 2 on the input variables showed that the following descriptors are the most important: standard deviation for red ('R_STD') in RGB, the standard deviation of the difference component of the light intensity and the colour red ('CR_STD') in YCbCr, the information about the extent of correlation No. 2 for a pair of the minimum value ('inf21h_Min') in GLCM texture.

The generated neural model of MLP-102: 102-12-6 2 reached RMS error of 0.13.

(3) The mathematical model can provide a basis for the construction of an expert system dedicated to the purpose of identifying failures of potatoes in the agri-food sector.

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