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Prediction of water content, sucrose and invert sugar of sugarcane using bioelectrical properties and artificial neural network

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Abstract

The study aimed to predict moisture content, sucrose and invert sugar of sugarcane (*Saccharum officinarum* L.) using artificial neural network (ANN) prediction model. The ANN model was developed based on the bioelectrical properties of the sugarcane. Bioelectrical properties were measured using LCR meter within 0.1 to 10 kHz range of frequency. The researchers then correlated the result of measurement with chemical content of sugarcane to develop an ANN prediction model. The best ANN topology (3-20-40-3) consisted of 3 nodes of input layer (inductance, capacitance and resistance), 20 nodes in hidden layer 1, 40 nodes in hidden layer 2 and 3 nodes of output layer (water content, sucrose and invert sugar) with training algorithm (trainlm), activation function of hidden layer (logsig), activation function of output layer (purelin), learning rate 0.1 and momentum 0.5. Based on the best topology, the researchers figured out that the validation of mean square error (MSE) was obtained at 0.0122. These results indicated that an ANN model based on the bioelectrical properties can be used to predict the chemical content of sugarcane.

Introduction

Specifically, sugar recovery of sugarcane is determined by water content, sucrose and invert sugar. Generally, the measurement of water content in foodstuffs using the gravimetric method is destructive and time consuming (Gradinarsky *et al*., 2006). Spectroscopy method can be used to measure the water contain without destroy the product (Edwards *et al*., 2001). In the other hand, sucrose content and invert sugar is measured using refractometer which is quick but destructive and low sensitivity. Furthermore, Pan *et al.* (2015) stated that high performance liquid chromatography (HPLC) method produces high accuracy and sensitivity, but it is laborious. Nawi e*t al.* (2013) applied a fast and high accuracy method using visible near infrared (Vis/ NIR) to estimate the sucrose content of sugarcane, yet it is costly. Therefore, it is necessary to develop a method that is quick, simple, non-destructive, accurate and relatively inexpensive. There is one method that can be used as non-destructive technique. Such method is able to measure the change of bioelectricity produced as a prior parameter to determine another material compound. This method has been applied to determine the quality of food, such as sugar content and honey (Guo *et al.*, 2010) and sugar concentration in sugarcane (Naderi-Boldaji *et al*., 2015). Moreover, the bioelectricity properties of foodstuffs depend on the water content, frequency and material composition (Nelson and Trabelsi, 2012). Sucrose concentration is determined by invert sugar content in sugarcane. Therefore, prediction on the chemical content of sugarcane is thought to have a strong relationship with its natural bioelectricity.

The development of analysis techniques on sugarcane chemical content can be conducted by designing the prediction model. This research applied back propagation algorithm of ANN method. This method has been used to estimate the quality of foodstuffs, including estimation of the sugar content of honey (Ozbalci *et al*., 2013), the water content of

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tea leaves (Mizukami *et al*., 2006). ANN topology is vital to the performance of the model (Hendrawan and Murase, 2010), which is affected by the input, hidden layers and nodes per hidden layer. Improved hidden layer makes the network becomes more complex and longer in training (Soltani and Omid, 2015). The acceleration of training can be performed by modifying the learning rate, momentum and the training function. However, the use of parameters is different for each problem. This research was conducted to analyze the sensitivity of learning rate, momentum, nodes per hidden layer, hidden layer, activation function and training function to get the best network with the lowest MSE validation. Last but not least, the researchers expected that this research is able to produce a prediction models for estimating the sugar recovery of sugarcane with chemical and bioelectrical approach.

Materials and Methods

Materials preparation

This research used 3 sugarcane varieties, they were Bululawang (BL), Pasuruan series 4 (PS 864), and Pasuruan series 2 (PS 862) obtained from Indonesian Sugar Research Institute in Pasuruan, East Java, Indonesia. The cultivars were selected according to their variation in °Brix, in which BL showed the lowest and PS864 the highest one. The samples were also cut in different segment (top, middle, and bottom segment) to capture a wide range of variation in °Brix. The invert sugar has been analyzed using Fehling titration, while sucrose contains determined with brix sucromat automatic saccharimeter in Indonesian Sugar Research Institute.

Measurement of bioelectrical properties

The bioelectrical properties of sugarcane were determined using parallel plate capacitor. A parallel plate capacitor is a device consisting two plates oppositely and separated by a small space. The spacing between two plates was calibrated with air capacitance which was resulted in 2 cm distance. This space can be filled with internode of the sample. The standardization of parallel plate has been obtained from previous research (Sucipto *et al.,* 2016,2018).

Sugar concentration usually decreases along the stalk height (Nawi *et al*., 2013). Therefore, the whole stalk of sugarcane were first topped and cut into three sections to capture a range of variation as wide as possible. Each section was cut into individual 2 cm internode. Each sample was placed in the thermometric cooler (WAECO) to maintain the temperature. The space between the plates was filled with internode sample and connected to the LCR Meter. As for measurement of the samples, the frequency was swept between 100 Hz to 10 kHz. The bioelectrical properties were recorded in LCR Meter and automatically saved in the computer worksheet.

Topological design of ANN

In the prediction case, selecting features is a critical point to improve the accuracy and speed of prediction system (Hendrawan and Murase, 2009). Several techniques have been developed for selection of important variables. One of the simplest methods is pre-processing data such as smoothing and normalization data. The pre-processing data was conducted using Min-Max normalization.

The normalized data was used to develop an ANN model which can be constructed using 3 layers namely; input layer, hidden layer(s), and output layer (Soltani and Omid, 2015). Each layer was constructed with a bias and several nodes whit each node have one weight that can be obtained after calculation with activation function. The development of ANN model was conducted using several training functions namely, traincgb, traincgf, traincgp, traingd, traingda, traingdm, traingdx, trainlm, trainoss, trainrp, trainscg to obtain the optimum weight in each node.

Sensitivity analysis was then performed to optimize ANN model which can be obtained from optimum weight in each node. Five models of hidden nodes were developed, namely 2, 5, 10, 15, 20, 30 and 40 hidden nodes, with two hidden layers. Learning rate and momentum were chosen at 0.1, 0.5 and 0.9, respectively based on the preliminary result. The best topological design of ANN determined from the lowest Mean Square Error (MSE) and highest correlation coefficient validation from 40 combination treatments. The MSE (computed by Equation 1) is used as performance criteria (Hendrawan and Murase, 2010):

$$MSE = \left[\frac{1}{N}\sum_{i=1}^{N}(Y_{model,i} - Y_{meas,i})^2\right] \quad (1)$$

Explanation:
$Y_{model,i}$ = prediction value
$Y_{meas,i}$ = actual value
N = number of data set

Results and Discussion

Characteristics of sugarcane chemical properties

The sugar recovery of sugarcane was influenced by its chemical compound, including water content, sucrose and invert sugar which had an influence on the sugar recovery of sugarcane as presented

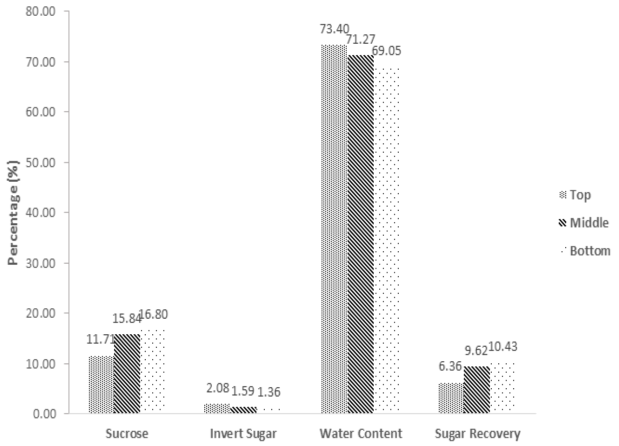


Figure 1. Sugarcane Chemical compound in each segment: top, middle, and bottom.

in Figure 1. It showed that the higher the levels of sucrose, the higher the values of the yield and vice versa. It was caused by a reaction called inversion. According to Wang (2004) inversion reaction is defined as irreversible hydrolysis reaction in which one molecule of sucrose and 1 molecule of water produce one molecule of glucose and one molecule of fructose. Glucose and fructose produced from sucrose hydrolysis then become an invert sugar. In addition, the increasing level of water in sugarcane encouraged the water hydrolysis to be more quickly, increased the invert sugar and decreased the sucrose.

This was apparently in accordance with the Equation 1, where the result of correlation analysis applied multiple linear regressions. This equation was applied to all varieties of sugarcane (BL, PS 862 and PS 864), age (6 and 8 months) in upper, middle and lower segment positions with the standard error value estimated to 0.14102.

$$Y = 0.78X1 - 0.184X2 - 0.003X3 - 2.606 \quad (2)$$

Where:

Y = Sugar recovery of sugarcane
X1 = Levels of sucrose
X2 = Levels of invert sugar
X3 = Water content

The coefficient correlation *(R^2)* of 0.998 showed a strong association of water content, sucrose and invert sugar towards the sugar recovery of sugarcane. Sucrose had the most dominant influence upon the sugar recovery of sugarcane.

Characteristics of sugarcane bioelectricity

Inductance is the cause of voltage in the electrical circuit to be proportional with the change of current in the circuit. Figure 2a showed that the inductances at the top, middle and bottom segment of the sugarcane

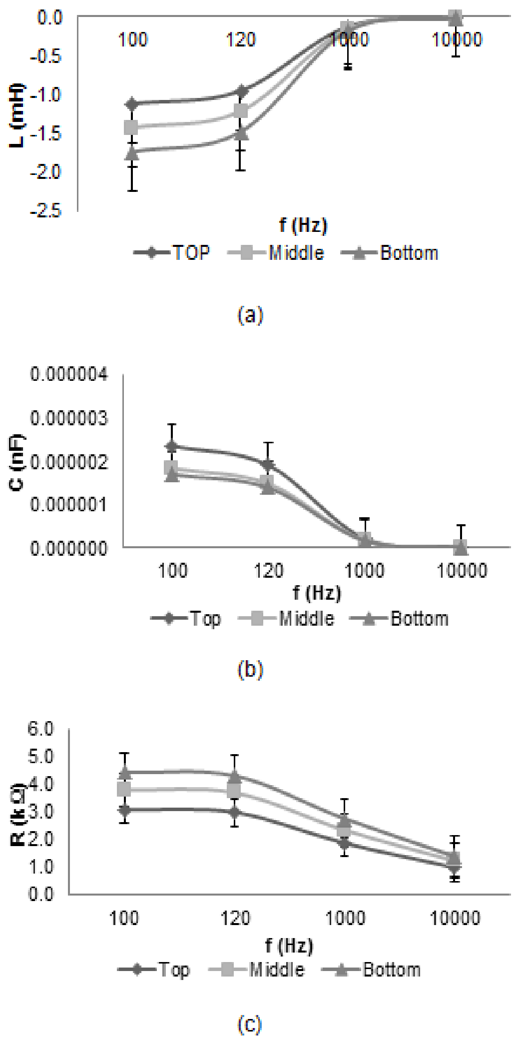


Figure 2. Bioelectrical Properties of Sugarcane at various frequencies: (a) Inductance (L), Capacitance (C) and Resistance (C)

were increased along with the frequency as well. Dixit and Uday (2008) reported that an increase in frequency influences an increase in inductive reactance (X_L) and a decrease in the capacitive reactance (X_c). The highest inductance was possessed by the upper segment of sugarcane with the highest level of water content and invert sugar, yet with lowest level of sucrose.

Capacitance is a material's ability to store electrical charges. Figure 2b showed that the capacitance in top, middle and bottom segment of sugarcane decreased as frequency did similarly. According to Rajib *et al.* (2015) the polarizing ability of dielectric material would adjust, in line with the frequency resulting in capacitance value variation. Besides the frequency, sugarcane segment has an influence on the capacitance. The top segment had the highest water content. Nelson and Trabelsi (2012) stated that capacitance of each ingredient varies depending on the frequency and water content. Juansah *et al.* (2014) stated that increasing level of water content in sugar results in a decrease in the dielectric constant, in which it is directly proportional to the capacitance value.

Water content and invert sugar has an inverse correlation with the sucrose level. When the water content and the invert sugar are high, the sucrose level is low. The bottom segment of sugarcane had the highest levels of sucrose and capacitance due to have a lowest water content. According Kesler (2013), the material polarity depends on the composition of the material. Sucrose is a polar compound which causes an increase in capacitance, while nonpolar compounds decrease the capacitance.

Resistance is a property that causes the resistance of a material to the electrical circuit. Figure 2c showed the resistance of sugar sugarcane in the top, middle and bottom segment decreased as the frequency did. Mizukami *et al.* (2006) stated that the resistance of cytoplasmic membrane and cell wall is low at high frequencies.

The top segment of sugarcane had the highest water content. The addition of water content resulted smaller resistance, but the conductivity was increased and vice versa.

The design of ANN model

Preprocessing data

Planning ANN model applied the sample of input and output data, which consisted of training data and validation data. Training data was employed to find the best model suitable to target, while validation data was applied to confirm the best model accuracy before it was implemented in the system or used by the end user. Results of trial and error indicating the proportion of 83.33:16.67 training data and validation data produced higher regression *(R^2)* than 66.67: 33.33 with 0.99977 and 0.99906 respectively. According to Li *et al*. (2015), R^2 represents significant adjustment between output and target. Regression analysis was used as optimal training indicators. R^2 with more than 0.9 showed the ability of network to adjust the output to the valid target.

Selection and training of activation function

This phase was to test the accuracy of the activation and training function used in the hidden layer and output layer with the lowest of MSE validation criteria. Selection of the activation function greatly affected the performance of an ANN. Variations of the activation function used were tansig, logsig for hidden layers and tansig, logsig, purelin for output layer. Logsig activation function in the hidden layer, purelin in the output layer, along with the trainlm training function, were set as the mode default in further neural network design stage because it had the smallest MSE validation. The elected training function with the lowest MSE validation was trainlm.

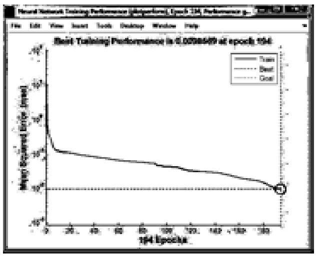
Table 1. ANN Sensitivity Analysis

Learning Rate	Momentum	Topology	MSE Validation
0.1	0.1	3-20-3	0.0673
0.1	0.5	3-30-3	0.0468
0.1	0.9	3-20-3	0.0759
0.5	0.1	3-40-3	0.1679
0.5	0.5	3-30-3	0.0497
0.5	0.9	3-15-3	0.0889
0.9	0.1	3-30-3	0.0626
0.9	0.5	3-40-3	0.5577
0.9	**0.9**	**3-40-3**	**0.0356**
0.1	0.1	3-10-40-3	0.0135
0.1	**0.5**	**3-20-40-3**	**0.0122**
0.1	0.9	3-40-20-3	0.0134
0.5	0.1	3-30-20-3	0.0153
0.5	0.5	3-30-30-3	0.0167
0.5	0.9	3-40-30-3	0.0134
0.9	0.1	3-30-40-3	0.0192
0.9	0.5	3-40-30-3	0.0134
0.9	0.9	3-15-40-3	0.014

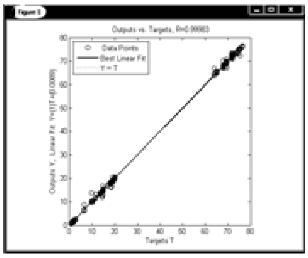
Topology optimization of neural networks

ANN performance is influenced by the input, hidden layers and node per hidden layer. Hidden layer is applied to solve a complex non-linear function on the network (Vani *et al.*, 2015). Number of hidden layer can be varied and determined to get the R^2 optimum value on the model (Ghaffari *et al.,* 2006). Accuracy level is determined by calculating the error output during training (Erkaymaz and Ozer, 2016). The minimum value of error in the validation phase was used as the criteria for selecting the optimal neural network topology. The results of network sensitivity analysis (Table 1) showed that network of MSE validation with 2 hidden layers was smaller than that with 1 hidden layer. The result of sensitivity analysis was the best network with MSE validation of 0.0122. Ozbalci *et al.* (2013) stated that the network with the lowest of MSE validation is the optimal network.

The best topology was produced from two hidden layer with 20 nodes and 40 nodes, learning rate 0.1 and momentum 0.5. This topology required training time of 2 minutes 12 seconds and stopped at the 194 iteration, when minimum error value was reached. This is conducted to reduce over fitting in ANN (Maulidiani *et al*., 2013). Over fitting occurs because there are too many neurons in the hidden layer, while if the number of neuron is smaller than the complexity of the data, under fitting might occur, since there are too few neurons in the hidden layer to reliably detect signals in the complex dataset. This encourages the error minimization to be very long or even unachieved.



(a) Performance of ANN



(b) Training Data Regression

Figure 3. Performance of ANN and Training Data Regression

Error was minimized through several cycles of training called epoch or iteration until it reaches the expected accuracy (Sharma and Venugopalan, 2014). Error at the beginning of the training process decreased as the increase of iteration number, which was stopped when reaching its lowest MSE of 0.0098569, as demonstrated in Figure 3a. According to Torrecilla *et al*. (2007) the more the number of iterations, the network's ability to recognize patterns will improve, marked by decreasing the MSE.

According Benković *et al.* (2015) correlation coefficient is used to compare the expected output data and targets. The simulation results of training data in Figure 3b showed uniformity in data distribution on the regression line, in which it showed that the value of its error was getting smaller and predictions then became more accurate. Correlation coefficient of 0.99983 indicated a strong relationship between the output data and the target due to equivalence in ANN model pattern. This too occurred in the data correlation which presented a very strong data validation, equal to 0.9998.

Artificial neural network equation model

ANN equation model was generated from the best ANN topology with final weight and bias when reaching the lowest MSE validation. The best ANN topology (3-20-40-3) in Figure 4, consisted of 3 nodes input layer (inductance, capacitance and resistance), 20 nodes in hidden layer 1, 40 nodes in hidden layer 2 and 3 nodes output layer (water content, sucrose and invert sugar) while the learning rate of 0.1 and momentum 0.5. The best ANN topology showed the lowest MSE validation (0.0122). The model

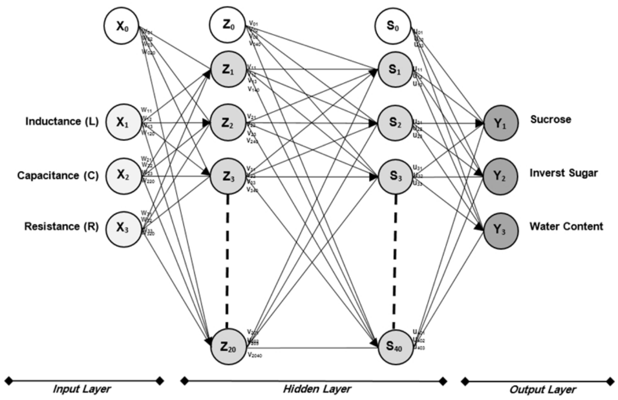


Figure 4. Selected ANN topology

equations was enclosed in the Equation 1.

Potentiality of implementation of bioelectrical properties measurement to predict water content, sucrose, invert sugar and sugar recovery of sugarcane

A strong relationship among water content, sucrose and invert sugar towards the sugar recovery can be applied as the basis of sugar recovery measurement using a chemical approach. Comercially, the measurement of sugarcane yield was conducted using physics approach. This research presented that sucrose had the most dominant influence on the sugar recovery of sugarcane (Equation 2).

Since the foodstuff bioelectricity is dependent to its composition, thus the bioelectric measurement accelerates the prediction of chemical content and sugar recovery of sugarcane. The presence of bioelectric gauges integrated with ANN models enables to ease bioelectric data acquisition to create such an accurate and sensitive instrument for predicting the chemical content and the sugar recovery of sugarcane.

Conclusion

Bioelectrical properties were assessed using a parallel-plate capacitor within 0.1 to 10kHz range of frequency for a non-destructive measurement chemical content of sugarcane. It is found that the water content and invert sugar are in linear comparison to the inductance, while the sucrose concentration is inversely proportional to the inductance. On the other hand, the inductance is inversely proportional to the capacitance and resistance, while sucrose concentration is linear comparison to the sugar recovery and water content, but invert sugar is inversely proportional with sugar recovery of sugarcane. ANN model is developed to predict the chemical content of sugarcane as a function of bioelectrical properties. This model shows a highly accurate prediction result (MSE 0.0122 and R^2 0.9997). For most experiment, ANN topology consists of two hidden layer with 20 and 40 nodes. Sensitivity analysis in the training functions (trainlm), activation functions (logsig) and (purelin) generate the lowest MSE validation (0.0347). These results provide potential use of bioelectric properties as the basis of ANN model to predict the chemical content and sugar recovery of sugarcane.

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References

Benković, M., Tušek, A. J., Belščak-Cvitanović, A., Lenart, A., Domian, E., Komes, D. and Bauman, I. 2015. Artificial neural network modelling of changes in physical and chemical properties of cocoa powder mixtures during agglomeration. LWT - Food Science and Technology 64: 140-48.

Dixit and Uday. 2008. Modeling of metal forming and machining processes. In Engineering Materials and Processes. London: Springer.

Edwards, C. S., Barwood, G. P., Bell, S. A., Gill, P. and Stevens, M. 2001. A tunable diode laser absorption spectrometer for moisture measurements in the low parts in 10 9 range. Measurement Science and Technology 12: 1214-18.

Erkaymaz, O. and Ozer, M. 2016. Impact of small-world network topology on the conventional artificial neural network for the diagnosis of diabetes. Chaos, Solitons & Fractals 83: 178-85.

Ghaffari, A., Abdollahi, H., Khoshayand, M. R., Bozchalooi, I. S., Dadgar, A. and Rafiee-Tehrani, M. 2006. Performance comparison of neural network training algorithms in modeling of bimodal drug delivery. International Journal of Pharmaceutics 327: 126-38.

Gradinarsky, L., Brage, H., Lagerholm, B., Björn, I. N. and Folestad, S. 2006. *In situ* monitoring and control of moisture content in pharmaceutical powder processes using an open-ended coaxial probe. Measurement Science and Technology 17: 1847-53.

Guo, W., Zhu, X., Liu, Y. and Zhuang, H. 2010. Sugar and water contents of honey with dielectric property sensing. Journal of Food Engineering 97: 275-81.

Hendrawan, Y. and Murase, H. 2009. Precision irrigation for sunagoke moss production using intelligent image analysis. Environment Control in Biology 47: 21-36.

Hendrawan, Y. and Murase, H. 2010. Neural-genetic algorithm as feature selection technique for determining sunagoke moss water content. Engineering in Agriculture, Environment and Food 3: 25-31.

Juansah, J., Budiastra, I. W., Dahlan, K. and Seminar, K. B. 2014. Electrical properties of garut citrus fruits at low alternating current signal and its correlation with physicochemical properties during maturation. International Journal of Food Properties 17: 1498-517.

Kesler, J. 2013. The water molecule and dissolving. National science teacher association web seminar. Retrieved on August 24, 2015 from Website: *https://learningcenter.nsta.org/products/symposia_seminars/ACS/files/TheWaterMoleculeandDissolving_3-18-2013.pdf*

Li, X., Chen, F., Sun, D. and Tao, M. 2015. Predicting menopausal symptoms with artificial neural network. Expert Systems with Applications 42: 8698-706.

Maulidiani, Abas, F., Khatib, A., Shitan, M., Shaari, K. and Lajis, N. H. 2013. Comparison of partial least squares and Artificial Neural Network for the prediction of antioxidant activity in extract of pegaga (centella) varieties from 1 h nuclear magnetic resonance spectroscopy. Food Research International 54: 852-60.

Mizukami, Y., Sawai, Y. and Yamaguchi, Y. 2006. Moisture content measurement of tea leaves by electrical impedance and capacitance. Biosystems Engineering 93: 293-99.

Naderi-Boldaji, M., Fazeliyan-Dehkordi, M., Mireei, S. A. and Ghasemi-Varnamkhasti, M. 2015. Dielectric power spectroscopy as a potential technique for the non-destructive measurement of sugar concentration in sugarcane. Biosystems Engineering 140: 1-10.

Nawi, N. M., Chen, G., Jensen, T. and Mehdizadeh, S. A. 2013. Prediction and classification of sugar content of sugarcane based on skin scanning using visible and shortwave near infrared. Biosystems Engineering 115: 154-61.

Nelson, S. O. and Trabelsi, S. 2012. Factors influencing the dielectric properties of agricultural and food products. Journal of Microwave Power and Electromagnetic Energy 46: 93-107.

Ozbalci, B., Boyaci, I. H., Topcu, A., Kadilar, C. and Tamer, U. 2013. Rapid analysis of sugars in honey by processing Raman spectrum using chemometric methods and artificial neural networks. Food Chemistry 136: 1444-52.

Pan, L., Zhu, Q., Lu, R. and McGrath, J. M. 2015. Determination of sucrose content in sugar beet by portable visible and near-infrared spectroscopy. Food Chemistry 167: 264-71.

Rajib, M., Arif Ishtiaque Shuvo, M., Karim, H., Delfin, D., Afrin, S. and Lin, Y. 2015. Temperature influence on dielectric energy storage of nanocomposites. Ceramics International 41: 1807-13.

Sharma, B. and Venugopalan, K. 2014. Comparison of neural network training functions for hematoma classification in brain ct images. IOSR Journal of

Computer Engineering 16: 31-35.
Soltani, M. and Omid, M. 2015. Detection of poultry egg freshness by dielectric spectroscopy and machine learning techniques. LWT - Food Science and Technology 62: 1034-42.
Sucipto, S., Al Riza, D. F., Hasan, M. L. A., Yuliatun, S., Supriyanto, S. and Somantri, A. S. 2016. Effect of sample size, frequency, and temperature on the bioelectrical properties of sugarcane (*Saccharum officanarum* l.) for rapid prediction of sugarcane yield. Industria: Jurnal Teknologi dan Manajemen Agroindustri 5(3): 140-148.
Sucipto, S., Rhamdani Widyo Utomo, R. W, Al-Riza, D. F., Yuliatun, S., Supriyanto, S., Somantri, A. S. 2018. Modelling sugarcane recovery prediction using bioelectrical properties and artificial neural network. Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK) 5(3): 315-324.
Torrecilla, J. S., Otero, L. and Sanz, P. D. 2007. Optimization of an artificial neural network for thermal/pressure food processing: Evaluation of training algorithms. Computers and Electronics in Agriculture 56: 101-10.
Vani, S., Sukumaran, R. K. and Savithri, S. 2015. Prediction of sugar yields during hydrolysis of lignocellulosic biomass using artificial neural network modeling. Bioresource Technology 188: 128-35.
Wang, N. S. 2004. Enzyme kinetics of invertase via initial rate determination. University of Maryland. Retrieved on August 24, 2015 from website: *www.eng.umd.edu/~nsw/ench485/lab14.htm*