Original Article
Food Science and Technology

ISSN 0101-2061 (Print)
ISSN 1678-457X (Online)

DOI: https://doi.org/10.1590/fst.118821

Application of neural networks in predicting the qualitative characteristics of fruits

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Abstract

In this research, the quality properties of persimmon were predicted using artificial intellect techniques. The persimmon samples were transferred to a computer vision lab, room temperature of 24 °C and 22% RH. The samples were divided into three groups for temperature treatment. They were kept at three temperature levels of 5 °C, 15 °C, and 24°C (control group) for 72 hours. The sample was then placed at room temperature and was imaged every second day for a 14 day period. After imaging, each sample underwent destructive tests to determine their quality attributes, including sugar content, firmness, and pH. The results indicate that the neural network's predicted values of acidity, firmness, and sugar of persimmon were not statistically significant differences from their actual values. In predicting the acidity of persimmon, the sugar RMSE is more than the two factors of firmness and acidity. For this reason, the accuracy of firmness and acidity is higher than sugar. MAPE is 10.11, 20.81, and 6.03 for acidity, firmness, and sugar, respectively. The model for sugar indicates a high difference between the actual values and the predicted values.

Keywords: artificial neural networks; firmness; persimmon; acidity; sugar.

Practical Application: The neural network's predicted values of acidity, firmness, and sugar of persimmon were not statistically significant differences from their actual values. In predicting the acidity of persimmon, the sugar RMSE is more than the two factors of firmness and acidity.

1 Introduction

Recently, consumer demand for high-quality fruits and vegetables has been increasing. Food quality and health is important factor in the modern food industry. Due to this, increasing the accuracy and reliability of the post-harvest operations, including quality assessment, should be done for fruits. Conventional food evaluation methods are now destructive and inefficient. Therefore, it is important to develop a non-destructive evaluation tool.

One of the most important techniques in medicine for diagnosing diseases is Magnetic Resonance Imaging (MRI), which can be used to take clear scans of various tissues of the body without X-rays. MRI is suitable for non-destructive imaging of water-containing materials and is widely used in various fields, especially food science and industry (Rogerio et al., 2014). NMR stands for Nuclear Magnetic Resonance. The researchers were able to show the absorption of electromagnetic radiation as a result of the transfer of the energy level of the nucleus in a strong magnetic field (Silva et al., 2019). Like H +, which have magnetic properties, they act like small magnets. These particles when placed in a magnetic field. They are located in the direction of the field. Also, these particles change direction under the influence of radio waves, and when the current radio source is cut off, these waves begin to move to their original place (Luiz & Vanin, 2021). The speed of movement depends on the connection of this valley to other elements instead of the original. If this valley has a strong connection with other elements, the speed of return to the original state will be fast, and if it does not have a strong connection with other elements, the speed of return to the original state will be slow (Hamdan et al., 2021). In fact, in this system, the physicochemical properties of the material can be understood from the initial velocity of the valley.

One of the most important applications of image processing is as a non-destructive method to examine the texture of fruits during storage and storage. Due to the studies done with this technique, the inside of the fruits can also be examined (Ali, 2017). For example, in pomegranate fruit, the damaged and damaged parts of the fruit can be determined by preparing this concentrate before preparing the concentrate and using the cutting steps. Separate those parts from pomegranate. Other applications of this method in modern agriculture are the study of the ripening stage of fruits, the study of the invasion of pathogens, tissue characteristics, transmission and diffusion, and the release of oxygen in agricultural products (Nayak et al.,

Received 13 Oct., 2021
Accepted 27 Dec., 2021
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2020). This non-destructive technique can study the distribution and motility of protons in water molecules and other metabolites concentrated in biological tissue. This method makes it possible to determine the change in the concentration of oil and water in food and agricultural products, which is usually associated with fruit blight, damage, and rot. By determining this factor, it is easy to understand the maturity or spoilage of the fruit. Some researchers have shown rapid transfer of water in grains during their studies on corn using image processing (Oliveira et al., 2021).

Moisture is usually removed from the crop during drying, which is a very important amount of moisture left in agricultural products, so that if a little moisture is removed from the crop due to drying, it may cause mold during storage or if too much moisture is removed. Cause wrinkles and tissue damage. In rice, the drying stage is also very important, so that if the rice dries properly, it will find the best quality during cooking. Image processing is a good way to check the drying process of agricultural products. For example, in a study on drying rice, the results showed that drying the amount of water up to 60 °C increases rapidly, but then a slight decrease in the amount of water can be seen (Parewai et al., 2020).

Freezing is one of the most important methods of storing vegetables, especially for a long time. To re-use frozen vegetables, the defrosting process is necessary. This freezing process causes more damage to the plant tissue (Sun et al., 2019). Using the MRI technique, the best temperature and the best time for the freezing and thawing process can be determined using imaging of vegetables and fruits (Zhu et al., 2021). For example, in a study of okra, asparagus, soybeans, and broad beans, the results showed that during the thawing process, the curves from the MRI signals in okra and asparagus were linear, but for soybeans and broad beans, they were convex and convex (Djuris et al., 2020).

Numerous studies have been performed on the process of freezing and thawing meat using the MRI technique. This technique can be used to study the process of cooking meat to obtain the best quality of meat in terms of sensory evaluation. This method can be used to determine the interaction of sharp broth. With this method, the effect of different freezing methods on salmon muscles can be seen (Bhagya-Raj & Dash, 2020).

There are several definitions for artificial intelligence, all of which can be placed in the two main approaches of weak artificial intelligence and strong artificial intelligence. A strong approach to the problem of artificial intelligence is building a machine with all the capabilities associated with intelligence in humans (Xu et al., 2021). Nowadays, due to the expansion and more complex decision-making, information systems, especially industrial intelligence systems, have become more important in supporting decision-making (Khadir, 2021). Artificial intelligence, then, refers to systems that can behave similarly to intelligent human behaviors (such as understanding complex situations, simulating human thought processes and reasoning methods, and learning and the ability to know and reason to solve problems) (Das et al., 2021).

Expert systems are grounded in applications in artificial intelligence and engineering, which due to the growing need of societies to adopt solutions and quick decisions in cases where complex and multiple human knowledge is needed, their importance is increased. Expert systems solve problems that typically require expertise and expertise (Chen & Yu, 2021). Machine iodine is known as expert system iodine only if it has a series of special capabilities, such as knowing its existence, which means that the machine is aware of its existence (Alamir, 2021).

In a communication network, communication signals are in the form of electrical waves. It is the main component of neurons, which consists of a cellular structure and a set of grooves and lines, and the grooves are where the information enters the neurons and the lines where the information leaves the neurons (Gonçalves et al., 2021). The connection of the neuron to the other neuron is calledsenations, which acts as a gateway or key. If the reactions that millions of different neurons give to different dulcimers coincide with each other, important observations may occur in the brain (Jawa et al., 2020). Of all the AI disciplines, the most useful are computerized and mechanized visual systems. The range of applications of the growing technology is very wide and ranges from common applications such as production line quality control and video surveillance to new technologies such as driverless cars. The range of applications of technology varies based on the techniques used in them (Ali & Dildar, 2021).

Some of our visual object systems, capable of shooting in the visible range, are also able to market objects in the invisible range. The information received from objects in the range of colored light can be useful in determining the maturity of plants, disease, and body and determining varieties, mating, the composition of functional properties, and contamination and disease of plants, seeds, fruits, vegetables, and fruits (Nosratabadi et al., 2021).

2 Material and methods

The persimmon samples were transferred to a computer vision lab, room temperature of 24 °C and 22% RH. The samples were divided into three groups for temperature treatment. They were kept at three temperature levels of 5 °C, 15 °C, and 24 °C (control group) for 72 hours. The sample was then placed at room temperature and was imaged every second day for a 14 day period. After imaging, each sample underwent destructive tests to determine their quality attributes, including sugar content, firmness, and acidity.

2.1 Imaging

A 32-megapixel camera captured images in the visible spectrum. In order to fully position the samples in the field of view of the camera, according to the focal length of the lens in the camera, the distance between the camera and the samples was considered to be 20 cm. Imaging is done in such a way that the samples are placed under the camera, and the image is taken from a specified view of the sample. Proper lighting during shooting makes it easy to analyze images. Lighting is such as to prevent the formation of shadows and light focal points in the image. A blue background was also used for imaging. A refractometer was used to measure fruit sugar.

2.2 Artificial neural networks

In a communication network, communication signals are in the form of electrical waves. It is the main component of neurons which consists of a cellular structure and a set of grooves and lines. In this paper, a multilayer network of perceptron with a hidden layer has been used. The optimum number of neurons in the hidden layer was found to be 25. The maximum iterations were set as 1000, and the learning rate was set as 0.001. Input variables include temperature treatment at three levels (control, 15 and 5 °C), color channels (L, a, b), and the standard deviation of color channels (stdl, stda, stdb). Output variables include sugar, acidity, and firmness. The next step after preparing the data is to normalize it so that the training and test data sets have a statistically almost uniform distribution. This conversion must also be done in the range of appropriate changes to converge the network to the optimal point. Therefore, the best data conversion domain is 0.1 to 0.9 for the Tansig network (Rohani et al., 2011). For this purpose, linear normalization has been used to convert the data (Equation 1) (Nourani et al., 2019; Molajou et al., 2021):

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \times \left(r_{max} - r_{\min}\right) + r_{\min} \quad (1)$$

Where x is primary data, x_n is normalized data, x_{max} and x_{min} are maximum and minimum of primary data, respectively, and r_{max} and r_{min} are maximum and minimum of conversion data, respectively. 70% of the data were used as training data, 15% of the data were used for the model validation phase, and the remaining 15% in the test phase.

3 Results and discussion

Figure 1 shows the neural network performance diagram for the three modes of training, validation, and testing for all three modes of acidity, stiffness, and sugar. Figure 1 includes three blue, green, and red lines for training, validation, and testing data, respectively. In this figure, the horizontal axis indicates the number of repetitions of the network training in which the network repetition is trained as can be seen for the factor of acidity the number of repetitions of the network respectively equal to 6 (mean square error value is 0.055). Meanwhile, the number of repetitions of the network for firmness is 7 (mean square error value is 0.018) and for sugar is 8 (mean square error value is 0.007). After this stage, the error of the training, validation, and testing steps has been constant. Functional diagrams start from a point with a specific error, and by repeating the network training, the error value is reduced and fixed after the convergence point. As can be seen, to predict the acidity of persimmon, the squares error is greater than the two factors of firmness and sugar.

Table 1 shows the evaluation factors of the neural network model for the three variables of acidity, firmness, and sugar, respectively. The RMSE (Root Mean Square Error) values are 0.69, 0.72, and 0.77 for acidity, firmness, and sugar. Furthermore, MAPE indicates the average neural network prediction error. MAPE is 10.11, 20.81, and 6.03 for acidity, firmness, and sugar, respectively. According to the results, the network Efficiency Factor (EF) for firmness is greater than acidity and sugar.

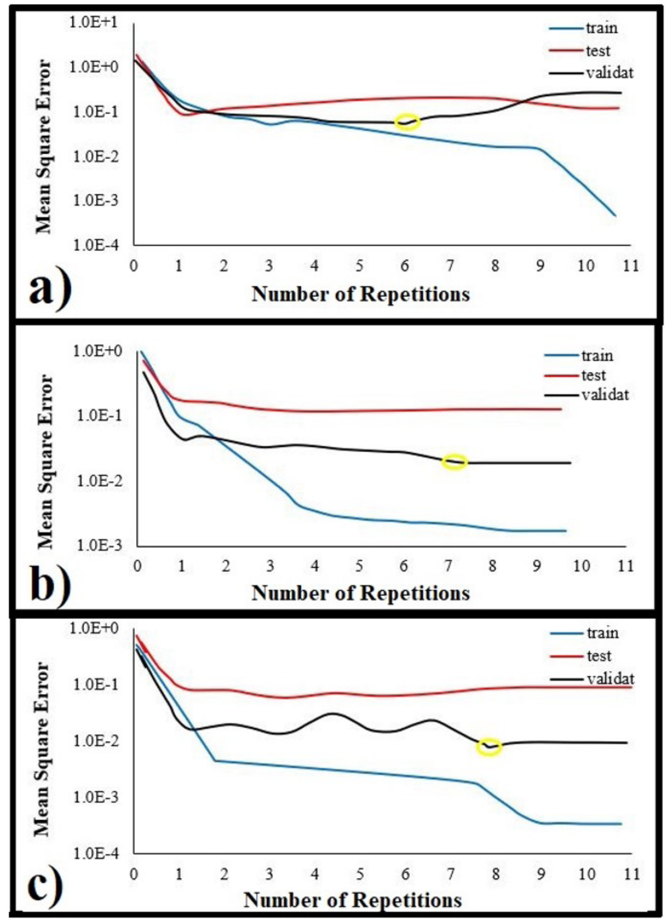

Figure 1. Neural network performance diagram for three acidity variables: a) Acidity, b) Firmness, and c) Sugar.

Table 1. Evaluation factors of neural network model related to output variables.

Output	Evaluation factor	result
Acidity	RMSE	0.69
	MAPE	10.11
	EF	0.80
Firmness	RMSE	0.72
	MAPE	20.81
	EF	0.91
Sugar	RMSE	0.77
	MAPE	6.03
	EF	0.88

Table 2 presents linear regression models in three training, validation, and test phases. According to Table 2, in the training and validation phase, the obtained relationships have a high coefficient of explanation. In the test phase of the obtained models, the value of the model explanation coefficient for prediction of acidity is 0.83, while this coefficient is 0.89 and 0.30 for prediction of firmness and sugar. The results show that the obtained relations are accurate enough to predict the acidity and firmness factors. However, prediction of sugar using this method is possible with non-applied accuracy.

Table 2. Predictive regression models from MLP neural network for three variables of acidity, firmness, and sugar.

Prediction Factor	Training phase	Validation phase	Test phase
Acidity	PV = 0.68 × dv + 0.20	PV = 1.12 × dv + 0.40	PV = 0.98 × dv-0.11
	R^2 = 0.88	R^2 = 0.85	R^2 = 0.83
Firmness	PV = 0.50 × dv-0.23	PV = 0.91 × dv + 0.81	PV = 0.74 × dv-0.13
	R^2 = 0.98	R^2 = 0.91	R^2 = 0.89
Sugar	PV = 0.15 × dv-0.20	PV = 0.22 × dv-0.41	PV = 0.32 × dv + 0.09
	R^2 = 0.74	R^2 = 0.70	R^2 = 0.30

4 Conclusion

In this study, the performance of the MLP artificial neural network was predicted to evaluate the acidity, firmness, and sugar of persimmon. The results indicate that the neural network's predicted values of acidity, firmness, and sugar of persimmon were not statistically significant differences from their actual values. In predicting the acidity of persimmon, the sugar RMSE is more than the two factors of firmness and acidity. For this reason, the accuracy of firmness and acidity is higher than sugar. MAPE is 10.11, 20.81, and 6.03 for acidity, firmness, and sugar, respectively. Comparison of the performance criteria of the neural network model showed that the firmness and acidity models are very close to each other, whereas the neural network model for sugar indicates a high difference between the actual values and the predicted values. Comparison of neural network results in training and testing stages showed that this technique could be used as a reliable method for estimating firmness and acidity factors with sufficient accuracy.

Acknowledgment

This research was funded by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R145), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

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