ESTIMATING VISCOSITY OF LOW SUGAR APPLE MARMALADE USING BACKPROPAGATION NEURAL NETWORK

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Abstract

In this paper, a backpropagation neural network (BPNN) model was developed for the prediction of viscosity values of apple marmalade using experimental data collected from several measurements. Stevioside or Sucralose sweetener was used instead of sugar (sucrose) in some of the formulations. In the BPNN architecture, the shear stress, and shear strain with mass concentrations of the Stevioside, Sucrolase, and Sucrose were utilized as input, whereas the viscosity value of apple marmalade was used as an output to be estimated. The Stochastic gradient descent algorithm (SGD) was used to minimize the loss of the BPNN based on the experimental data set. The Mean squared error (MSE), and the coefficient (R^2) were employed to assess the performance of the BPNN. The number of hidden neurons was found to be 20 using the adaptive hidden neuron algorithm. With 20 hidden neurons, the least MSE and the highest R^2 value were attained. Furthermore, the predicted viscosity values were found to be within 1% of the experimental viscosity values. The developed BPNN model can, therefore, be effectively utilized to predict the viscosity of any fruit marmalade using the same input and output parameters in the data range where the new data is normalized with the experimental data used in this paper.

Keywords: *Backpropagation neural network, stochastic gradient descent algorithm, viscosity, apple marmalade, stevioside, sucrolase*

1. INTRODUCTION

Belonging to the rose (Rosaceae) family of plants, apples are a significant fruit crop. The scientific name for domesticated apple cultivars is Malus domestica Borkh, as noted by [1-2]. The major commercial groups of cultivars, including Golden Delicious, Granny Smith, Fuji, and Gala, are responsible for most of the world's apple production, comprising over 60% of its output [2]. From 2006 to 2016, the world's average annual apple production was 89.329.179 tonnes [3]. Asia is the largest producer of apples, followed by Europe. China is the top apple-producing country, accounting for approximately 40% of global production. Meanwhile, Turkey is the fifth-largest producer in the world, with a fruit yield of 2.638.207 tonnes.

Turkey's diverse ecological variation and favorable climate make it an abundant source of apple crops. Apples have been traditionally cultivated across the country. In 2017, the Red Delicious (Starking) variety dominated Turkey's commercial production, accounting for about 1.5 million tons of the crop. Meanwhile, Gala apples contributed approximately 0.6 million tons to the overall production.

When it comes to the quality of fresh apple fruits, their visual appearance is an essential factor. Among the different varieties, Gala apples are known for their attractive appearance, sweet flavor, crisp texture, and refreshing aroma [4-5]. The red color of the apples is attributed to the anthocyanin content, which is the main color pigment [6-7]. Because of their higher water content compared to other varieties, Gala apples are ideal for certain processes such as jam, jelly, marmalade, desserts, and drying [8]. Apple trees can adapt to different climatic condition, so apple fruit is available in all-season and attract customers. But they may exhibit slightly different tastes, shapes, color, and sizes according to the season that they have harvested. Thus, most of the researchers mainly investigated the hardness, scent, stiffness, taste, color, shape, and size of apples [9].

The external and internal characteristics of apples, such as their morphology, and biochemical and physical structures, are important indicators of fruit quality. The internal quality of apples, including firmness, sugar content, and flavor, are important factors in determining their ripeness and quality of [10-11]. While taste analysis by consumers is a common way to assess fruit quality, it is not the only way to evaluate the value of the fruit. The nutritional value of fruits is also crucial due to their nutritive ingredients. Apples are mostly made up of water (about 85%) and contain sugars (mainly fructose, followed by glucose and sucrose), organic acids (primarily malic acid), vitamins (with Vitamin C having the highest content at 4.6 mg), minerals (ash content of 0.20) [12], and dietary fibers (about 2-3%, with pectin accounting for less than 50% of apple fibers) [13].

Phenolic compounds are considered "magic" ingredients in apples' content, and apples are a significant source of these compounds [14]. Among various fruits, apples rank second in terms of the concentration of phenolic substances, which are secondary metabolites found in plants [15-16]. Apples also contain two types of vitamin C, ascorbic acid, and dehydroascorbic acid, which have antioxidant properties [17--18]. Recent studies have examined the effects of flavonoids and phenolic acids from apples on tumor cell proliferation and found that antioxidant compounds, such as phenolic acids and flavonoids, were the predominant compounds in apples, showing a potential to prevent a high amount of tumor cell proliferation in vitro [19]. Moreover, phenolics contribute to the flavor, color, and astringency of apples [20].

Fiber is another important component of apples, comprising pectins, lignins, celluloses, and hemicelluloses, which have soluble and insoluble parts that are essential for biological regulation. Soluble fiber is linked to lipid metabolism, which reduces low-density lipoprotein (LDL) cholesterol, commonly known as "bad" cholesterol, whereas water adsorption and intestinal regulation are associated with insoluble fibers [21-22]. Apples have been linked to many beneficial health effects, including decreased risks of certain cancers, cardiovascular diseases, and diabetes, as well as significant weight loss [23]. Additionally, apples are a major source that reduces the risk of Alzheimer's disease and improves brain health [24]. Given their high nutritional content, apples are commonly consumed fresh worldwide. However, consumers also prefer to consume apples in dried form, as well as in marmalade, jam, and jelly forms.

2. MATERIALS AND METHODS

2.1 Preparation of Traditional Marmalade

Sugar plays a crucial role in the traditional production of marmalade, where a high concentration of sucrose is typically used. This impacts the physical, chemical, and sensory characteristics of marmalades, and reduces water activity to approximately 0.8, inhibiting microbial growth by binding water through pectin gelatinization [25]. However, excessive sucrose intake contributes to several health problems. Hence, sweeteners have become a popular alternative in the food industry. To produce low-sugar marmalade, the concentration of pectin and the type of sweetener used, along with sugar reduction, are crucial. The gel's structure and texture depend on the composition of sugar, acid, and pectin, and the mixture is boiled rapidly to reduce water content and concentrate it to achieve the desired gel consistency. Sucrose is preferred for its gelling ability in food gels. Sugar types and concentrations of soluble solids influence the gelling ability of pectin with sugar and acid. Sugar partially dehydrates the pectin molecule, promoting aggregation, while acid addition prevents the separation of negatively charged pectin molecules, allowing the formation of hydrogen bonds. The texture of the product is determined by its firmness and brittleness, which increase with sugar content but may lead to excessive sugar crystallization.

2.1.1 Sample preparation

To prepare low-sugar apple marmalade in a homemade style, the first step was to sort and clean the apples by removing any foreign materials such as branches, leaves, and defective portions. The fruits were washed with tap water and the stalks and cores were removed. Then, the fruits were divided into four equal parts and boiled in water in a saucepan. After the fruits softened, they were filtered through a sieve to obtain apple pulp. Next, a desired amount of sucrose and sweetener was added and the mixture was thoroughly stirred and boiled until it reached marmalade consistency. Just before removing the mixture from the stove, 15 ml of lemon juice was added. The heating was stopped when the total soluble content (TSS) reached 60–65°Bx. The jars were sterilized by steeping them in a pot of boiling water, and the hot marmalades were filled into the hot jars. The jars were turned upside down on a clean towel and completely cooled before storage. The samples were then stored at 4 ± 2 °C.

2.1.2 Experimental Design

Table 1 illustrates the experimental plan for the preparation of apple marmalade with alternative sweeteners, with a basis of 1000 g apple.

Table 1. The design and analyses were performed with the marmalade samples.

Formulation No	Sucrose level (g)	Sucrose Replaced (%)	Amount of Sucrose (g)	Stevioside (mg)	Sucrolase (mg)
1	500	0	500	0	0
2	500	25	375	416.67	0
3	500	50	250	833.33	0
4	500	25	375	0	208
5	500	50	250	0	416
6	600	0	600	0	0
7	600	25	450	500	0
8	600	50	300	1000	0
9	600	25	450	0	250
10	600	50	300	0	500

Initially, the appropriate amount of sucrose to produce 1 kg of apple marmalade was determined through preliminary sensory analysis. Two levels of sucrose, 500 g, and 600 g were used as control samples. In addition, ten different formulations of marmalade were created, two of which were control samples. Approximately 800 g of product was obtained from each marmalade production.

To produce marmalade with alternative sweeteners, sucrose was partially replaced in the formulation. The substitution of sucrose was done on a weight basis, with Stevioside (a natural sweetener) and Sucralose (an artificial sweetener) at two levels of sucrose substitution, 25% and 50%. The relative sweetness factor of Stevia and Sucralose was considered for calculating the amount needed for supplementation. The relative sweetness of Stevioside and Sucralose was 300 and 600, respectively.

Apple marmalade was prepared using alternative sweeteners, and each quantity of added sweetener was named an alternative sweetener quantity in the experimental design (Table 1). The concentration of sucrose in the marmalades was 62.5% and 75%, requiring 500 g or 600 g of sucrose to produce 800 g of marmalade from 1 kg apple. The reduced sugar marmalades were created by partially replacing the sucrose with the sweeteners. For instance, to replace 25% of sucrose in the recipe that used 500 g of sucrose, 125 g of sugar was removed, and 0.416 g of stevia and 0.208 g of sucralose were used instead, considering their sweetness index.

2.2 Methods

The apple marmalade using experimental data was collected from several measurements by utilizing the formulations given in Table 1. Stevioside or Sucralose sweetener was used instead of sugar (sucrose) in some of the formulations. The shear stress, and shear strain with mass concentrations of the Stevioside, Sucrolase, and Sucrose were utilized as input, whereas the viscosity value of apple marmalade was used as an output to be estimated by the backpropagation neural network.

2.2.1 Backpropagation Neural Network

In this paper, we utilized a Backpropagation Neural Network (BPNN) consisting of two layers: an input layer with 5 neurons and an output layer with one neuron. A hidden layer is sandwiched between them, and information flows in one direction only [26]. Neurons in each layer receive inputs exclusively from the outputs of neurons in previous layers, and their outputs are passed exclusively to neurons in the following layers. The output of each neuron is a function of its inputs, and the activation of the output-layer neuron can be computed in one deterministic pass, given the inputs of shear stress, shear strain, and mass concentrations of Stevioside, Sucrolase, and Sucrose to the BPNN.

To optimize the number of neurons in the hidden layer, we employed an adaptive hidden neural network algorithm, starting with two neurons and increasing the number by one when learning did not improve within 400 epochs. We continued this process until we found the optimized number of hidden neurons, which we determined to be 20 for our project.

The activation function, a non-linear function used to determine the output of a neuron based on its net input, is limited to a range between 0 and 1. In our BPNN, we used the rectified linear unit (ReLU) as the activation function for the hidden layer neurons, with the formula f(x) = x (if x > 0, else 0). For the output-layer neuron, we used the identity function f(x) = x, which means that the output of the neuron is equal to its net input. Figure 1 illustrates the BPNN we used in this study to estimate the viscosity values.

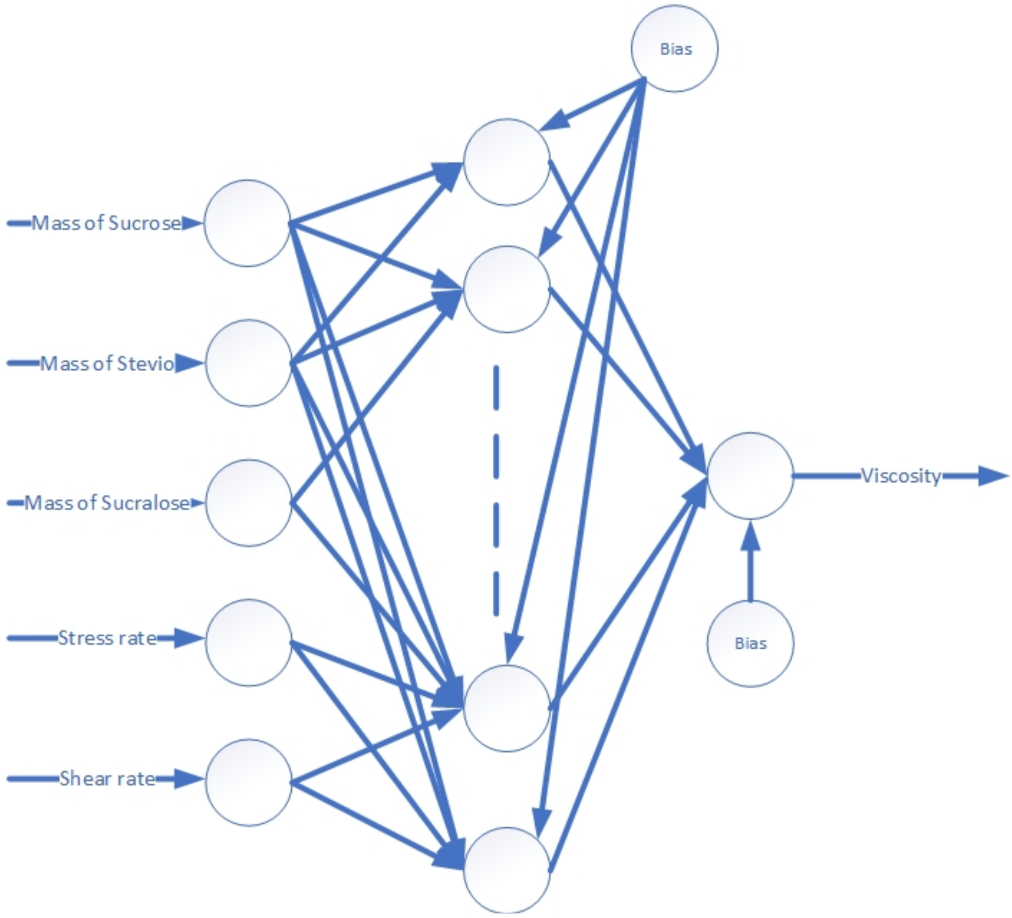

Figure 1. The architecture of the Backpropagation neural network

The initial step of the training process involves setting all weights to small non-zero values, generated randomly. In total, 2920 datasets were prepared, of which 80% were used as a subset presented to the neural network illustrated in Figure 1. The BPNN generates an error measure, and the weights are updated to reduce this error, following the stochastic gradient descent algorithm. This process is repeated until the desired level of accuracy is achieved and is referred to as an epoch, which involves presenting the training set, measuring errors, and updating weights. Python 3.6 was used for coding the neural network, and a code snippet is provided in Figure 2.

```
from tensorflow import keras
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import SGD

model = Sequential()
model.add(Dense(20,input_dim=5,activation='relu',kernel_initializer='he_uniform'))
model.add(Dense(1, activation='linear'))
model.compile(loss='mean_squared_error', optimizer=SGD(lr=0.01, momentum=0.9))
```

Figure 2. Code snippet for the BPNN

The Mean squared error (MSE), and the coefficient (R^2) were employed to assess the performance of the BPNN. The results are given in the next section.

3. RESULTS AND DISCUSSION

Statistical analysis of the training dataset and the testing dataset were done. The results are presented in Table 2 for the training data and Table 3 for the testing data. From these tables, the prediction values are very close to the desired values. The lower the coefficient variation (CV) shows that the more precise the prediction is. Low Kurtosis values depict that the outliers do not exist inside the datasets. Furthermore, datasets have low skewness values indicating that they are close to symmetric.

Table 2. Statistical values for the training data

Statistical values	Desired values	Predicted values
Median	44.67	42.87
Mean	1027.64	1030.44
Standard error	208.35	208.06
Standard deviation	2375.50	2372.20
Coefficient Variation	2.31	2.30
Skewness	1.24	1.25
Kurtosis	9.84	9.77

Table 3. Statistical values for the testing data

Statistical values	Desired Values	Predicted Values
Median	45.90	43.32
Mean	1001.51	1006.00
Standard error	216.20	216.10
Standard deviation	2465.05	2463.96
Coefficient Variation	2.46	2.45
Skewness	1.16	1.17
Kurtosis	13.50	13.35

The BPNN was trained with 2336 datasets in 1000 epochs. Figure 3 shows the graph of Loss / Mean Squared Error (MSE). The MSE for training was 0.00004, and the testing MSE was 0.0000218.

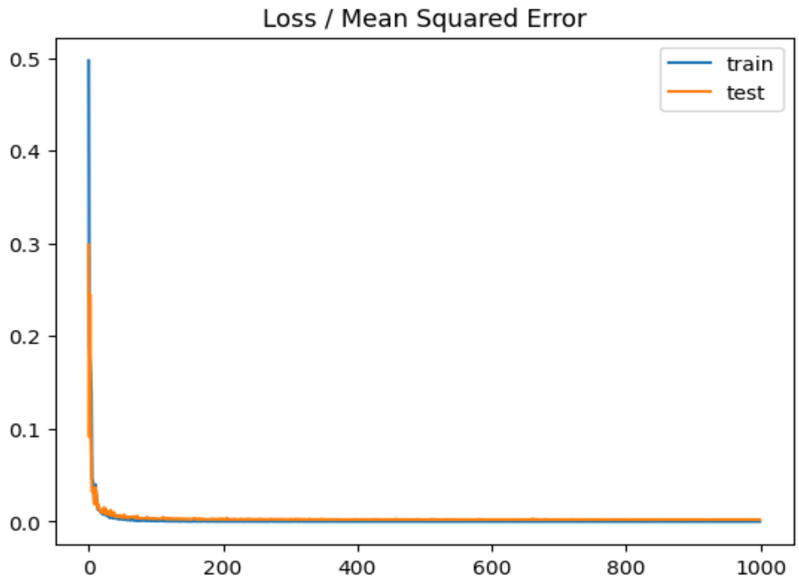

Figure 3. Loss \ mean squared error for the BPNN.

The average distance between the measured and the estimated viscosity values are very small. The R^2 value was calculated as 0.9999 by utilizing the training measured and estimated viscosity values. It is depicted in Figure 4. Same R^2 value was calculated as 0.9998 by using the testing measures and predicted viscosity values. It is depicted in Figure 5.

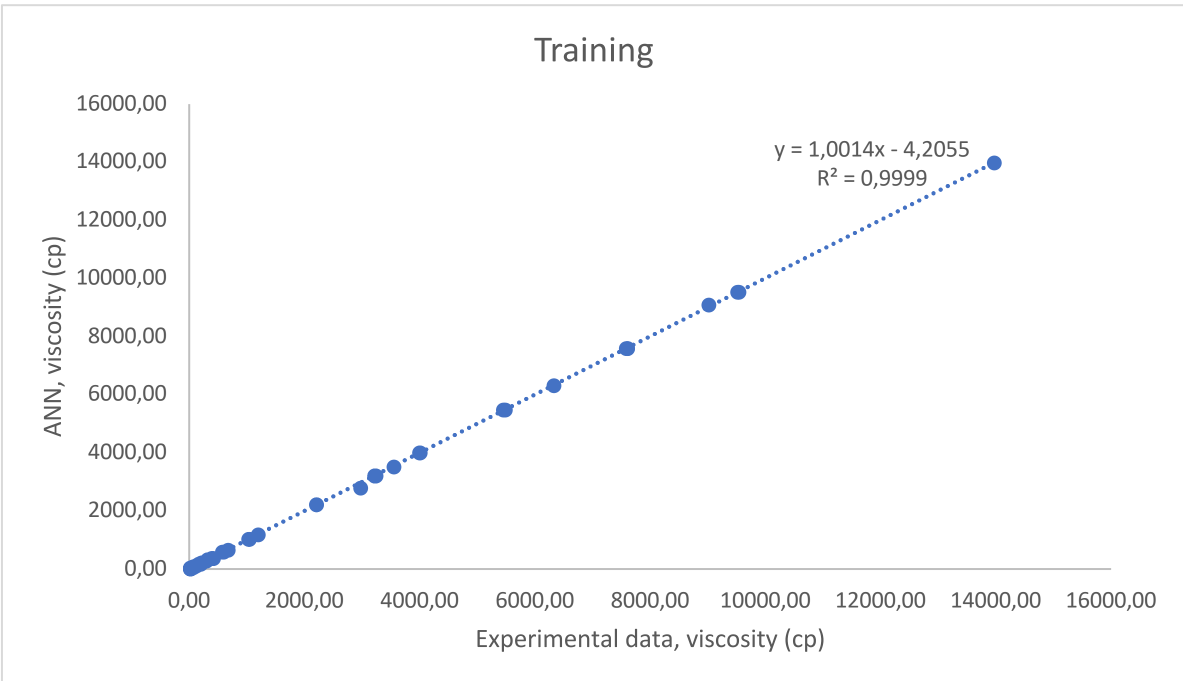

Figure 4. R^2 value for BPNN prediction for training data

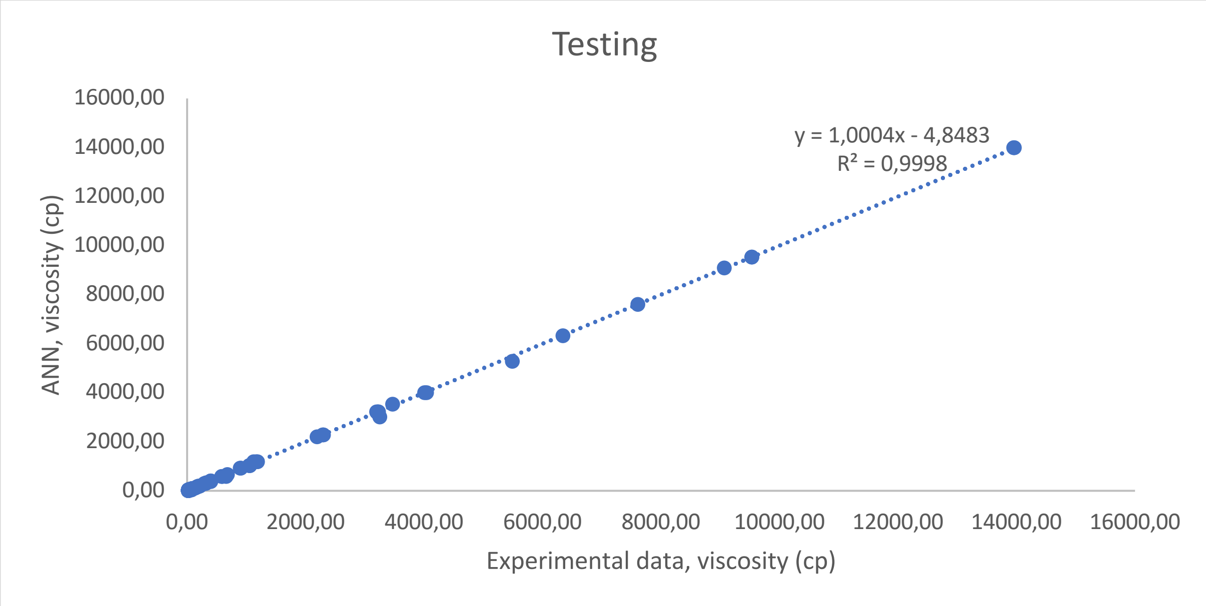

Figure 5. R^2 value for BPNN prediction for testing data

Moreover, the success in the R-squared of the model shows the estimated viscosity values represent the experimental viscosity values perfectly. Because of the BPNN model, the R-squared value attained was very close to unity. The BPNN model is successful in estimating the viscosity values. The more experimental datasets are used, the better the estimation will be attained.

4. CONCLUSIONS

Using two different sweeteners (stevioside and sucralose) at varying concentrations, this study aimed to produce low-sugar apple marmalade formulations that would closely match the physicochemical, textural, rheological, and sensory properties of control samples. The addition of the sweeteners had a significant impact on the properties of the marmalade samples, with most changes attributed to alterations in the gel structure resulting from interactions between sucrose, acid, and pectin. Higher levels of sucrose were found to increase the hardness of the gel, whereas the addition of sweeteners provided a softer and more moist structure to the marmalade formulations, making them a healthier alternative.

2920 datasets were produced using the formulations depicted in Table 1. The BPNN was employed to estimate the viscosity values of the low-sugar apple marmalade utilizing the datasets. The R-squared value was calculated very close to unity. The testing MSE value was very low which shows that the developed BPNN can be effectively used in the estimation of viscosity values.

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