

Original scientific paper

PREDICTION OF COLOUR CHARACTERISTICS OF MICROWAVE-DRIED TOMATO SLICES USING ARTIFICIAL NEURAL NETWORK AND ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS



ISSN 2466-4774
<https://www.contagri.info/>

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Submitted: 06.10.2022.
Accepted: 06.07.2023.

SUMMARY

Variation in the colour of dried tomatoes is frequently a problem for both consumers and processors. This study investigated digital imaging and applied soft-computational modelling using the Artificial Neural Network (ANN) and Adaptive Neuro-fuzzy Inference System (ANFIS) to evaluate the surface colour of microwave-dried tomato slices. The tomatoes were pretreated with water blanching, ascorbic acid, and sodium metabisulphite, then cut into slices of 4, 6, and 8 mm thickness. The slices were then dried in a microwave oven at power levels of 90, 180, and 360 W. The colour characteristics of the dried tomato slices (L^* , a^* , b^* , colour change, browning index, hue, and chroma) were determined. The response variables were modelled and optimised using ANN and ANFIS. The efficiency and performance of the model were assessed using the coefficient of determination (R^2), the root means square error (RMSE), and the mean absolute error (MAE). The results revealed the ranges of 36.70 – 48.83, 36.81 – 44.56, 31.03 – 40.34, 8.43 – 21.24, 11.78 – 39.82, 48.15 – 60.11, and 0.82 – 0.87 for the colour characteristics of L^* , a^* , b^* , colour change, browning index, hue, and chroma, respectively. The outcomes showed that ANN and ANFIS models could make more accurate predictions. The predictive models were experimentally validated and agreed with the experimentally obtained values. However, the ANFIS model gave better performance, with higher values for R^2 (1.000) and lower values for RMSE (0.02952) and MAE (0.02209). These findings will be helpful to processors and can be scaled up and adjusted for the bulk colour characteristics of microwave-dried tomatoes.

Key words:

colour, microwave drying, tomatoes, ANN, ANFIS, modelling

INTRODUCTION

One of the fundamental characteristics consumers and processors examine and use as a signal of whether to accept or reject food is colour. It might impact sweetness perceptions, flavour thresholds, and pleasantness (Kulanthaisami et al., 2010). The two primary methods for evaluating the colour of food ingredients are visually (by a person) or

objectively (using tools for measuring colour). Under controlled lighting, the subjective systems compare food samples to coloured references. Colour standards are frequently used as reference materials, and observers must receive additional specialised training. Unfortunately, it denotes a more leisurely examination and varies from observer to observer (Afshari-Jouybari & Farahnaky, 2011). For these reasons, colour measuring tools are preferred as an objective method of determining colour.

The most popular devices for analysing food colour are Dr. Lange colorimeter, Minolta chromameter, and Hunter lab colorimeter. However, these instruments are often ineffective for measuring large food items like fruits and vegetables because they can only measure small samples (Tarafdar et al., 2018). These colorimeter instruments, according to Yam & Papadakis (2004), are primarily designed for quality control and provide average measurement values. Colorimeters allow for fast and precise evaluation of the colour qualities of food products by providing average measurement values. For the purposes of quality control, product consistency, maintaining brand identity, monitoring shelf life, and complying with regulatory requirements, colorimeters are indispensable in the food colouring measurement process. However, they are inappropriate for food engineering research because it would take too long and be laborious to measure colour distribution at numerous points. In order to obtain uniform colour distributions, some of these colorimeters also demand that the food samples be homogenised using a grinder or blender. Due to this time-consuming grinding or blending, the food sample becomes useless for other purposes.

Nowadays, the food processing industries use digital imaging, computer vision, and spatial image acquisition methods for grading and sorting fruits, vegetables, and other prepared goods, as well as for quality assessments, identifications, and defect detection (Afshari-Jouybari & Farahnaky, 2011). However, the majority of these methods rely on expensive, difficult-to-use, and occasionally unavailable sophisticated instruments, control systems, and algorithms (Tarafdar et al., 2018). This has led to the search for a low-cost, simple and robust imaging technique capable of detecting colour values in food samples. Yam & Papadakis (2004), Afshari-Jouybari & Farahnaky (2011), Makino et al. (2016), Tarafdar et al. (2018) conducted studies to assess the visual qualities of food samples using a digital camera, image analysis software like Adobe Photoshop, and computer vision. Notwithstanding the widely used methods in image analysis, applying them to optimise complex food processes like microwave drying to produce good products with acceptable colour characteristics remains unexplored.

A different technique to speed up drying, enhance the quality of dried goods, and use less energy is microwave drying (Hussein et al., 2019). The materials could be heated to the desired temperature simultaneously due to the volumetric heating brought on by microwave penetration, which speeds up the process of drying (Celen & Kahveci, 2013). Because of this, microwave drying of tomatoes is a challenging thermal operation that is time- and energy-intensive due to inconsistent heat and moisture migration. Thus, to predict the drying characteristics of tomatoes, either empirically-based or semi-empirically-based models were employed to simulate the drying. However, for a proper simulation of drying as well as a better comprehension of the colour changes in microwave-dried tomatoes, more realistic models are required. Because of this, the effects are frequently complex and call for a few suppositions that are unsupported by drying systems. Therefore, anticipating colour changes is essential and will improve the quality of the drying process and the finished product.

An artificial neural network (ANN) is a generalised computational model of human perception and an effective tool for solving complex, nonlinear problems (Oke et al., 2017). The complex nonlinear relationships that emerge during drying have been modelled using ANN due to its high learning capacity and capacity to distinguish between a system's input and output. Additionally, ANN facilitates adequate and accurate drying process control in industrial applications. Many researchers have developed drying kinetics models using the multi-layer interconnected design based on biological neural networks. They have also used it to forecast results with high precision for fruits and vegetables (Kumar et al., 2016; Bai et al., 2018; Dash et al., 2020). The adaptive Neuro-Fuzzy Inference System (ANFIS), a soft computation model, combines fuzzy systems and neural networks (Sharabiani et al., 2022). In an effort to forecast the microwave drying of a variety of agricultural products using ANFIS, Bousselma et al. (2021) and Zadhosseine et al. (2021) made their attempt and they all indicated the predictive accuracy of ANFIS model. Hussein et al. (2023) investigated the feasibility of estimating tomato drying characteristics using the ANN and ANFIS techniques. The ANN and ANFIS error values demonstrated the suitability of these methods for anticipating microwave drying.

ANNs and ANFIS models have received much attention in earlier studies as valuable tools for modelling complex phenomena like drying. As a result, the goal of this study was to forecast the colour change of microwave-dried tomatoes using ANN and ANFIS models.

MATERIAL AND METHODS

Sample preparation

The tomatoes (UTC variety) were scrubbed thoroughly under running water and prepared as described by Hussein et al. (2016). According to Hussein et al. (2019), twelve (12) kilogrammes of tomatoes were pretreated in three different ways: for one minute with hot water (WB), for five minutes with 5% w/v ascorbic acid (AA), and five minutes with 5% w/v Na_2SO_3 (SM). The ratio of tomatoes to dipping liquid used was 1:10 (w/v). The Roma tomato slicer (NEMCO 56610-13/16") was adopted to slice the tomatoes to thickness of 4, 6, and 8 mm.

Taguchi experiments procedure and drying methodology

Taguchi experimental design with three factors at three levels with an array of L_9 (3×3) parameters was used for this study. Nine experimental runs were used to examine the interactions between the input parameter on the colour properties. Microwave oven (Model number: HMT84G451) was used for drying the sliced tomatoes using the approach reported in Hussein et al. (2019). Following the experimental runs in Table 1, the pretreated samples were dried at three levels of microwave powers of 90, 180, and 360 W with thicknesses of 4, 6, and 8 mm. To get rid of the surface fluid, paper towels were used to blot the pretreated samples. A 200 g sample was evenly distributed in a glass dish with a diameter of 30 cm and a depth of about 1 cm, and it was positioned in the centre of the microwave. To ensure even microwave energy absorption and lower levels of reflected microwaves onto the magnetron, the glass dish was rotatable inside the microwave chamber while it was operating. For the first hour of drying, the microwave oven was used for a cycle of 5 minutes ON and 25 minutes OFF, and for the subsequent drying times, the cycle was 1 minute ON and 5 minutes OFF. A digital control facility on the microwave oven was used to adjust the microwave output power and processing time. At 5-minute intervals, the glass dish containing the sample was removed and weighed using a digital electronic balance (OEM, Freebang-SKU323367) accurate to within 0.001 g. In addition, at 15-minute intervals, the samples were turned over. When weight loss after drying reached less than 0.001 g, drying was complete. According to each power level, the final drying time and moisture content were noted. The data provided is the average of three replications of each experiment that were carried out in accordance with the predetermined drying process schedule.

Table 1. Outline of Taguchi experimental design L_9 (3×3) for microwave oven drying

Experimental runs	Independent variables in coded form			Experimental variables in their natural units		
	A	B	C	Pretreatments	Thickness (mm)	Microwave power (W)
1	1	1	1	WB	4	90
2	1	2	2	WB	6	180
3	1	3	3	WB	8	360
4	2	1	2	AA	4	180
5	2	2	3	AA	6	360
6	2	3	1	AA	8	90
7	3	1	3	SM	4	360
8	3	2	1	SM	6	90
9	3	3	2	SM	8	180

Determination of colour

The fundamental method used was digital imaging discussed by Yam & Papadakis (2004) and Al-Sulaiman (2011). A high-resolution digital camera was used to take pictures of the dried tomato samples (Canon XUS105, 12.0 MegaPixel, 4 digital zooms). The photos were taken in a primarily controlled environment. The camera was positioned perpendicular to the stage, 60 cm away. On both sides of the viewing axis, the dried samples were simultaneously illuminated at 45 degrees above and 45 degrees to the right or left. They were both represented using cast shadows. The colour was then quantitatively assessed using Photoshop (Adobe-Systems, 2015). The histogram window displays the statistics (mean, standard deviation, median, percentage, etc.) for the colour value and lightness (L) of a selected area in the image of dried tomato samples. The statistics for the other two colour values (a and b) were also displayed in the histogram window by selecting a and b from the channel drop-down menu (Fig. 1). The L , a , and b values displayed in the histogram window are not the usual colour values. Therefore, they are converted to the standard colour values (L^* , a^* , and b^*) using formulas 1, 2, and 3. Lightness, redness, and yellowness are denoted by the letters L^* , a^* , and b^* , respectively.

$$L^* = \frac{\text{lightness}}{255} \times 100 \quad (1)$$

$$a^* = \frac{240 \times a}{255} - 120 \quad (2)$$

$$b^* = \frac{240 \times b}{255} - 120 \quad (3)$$

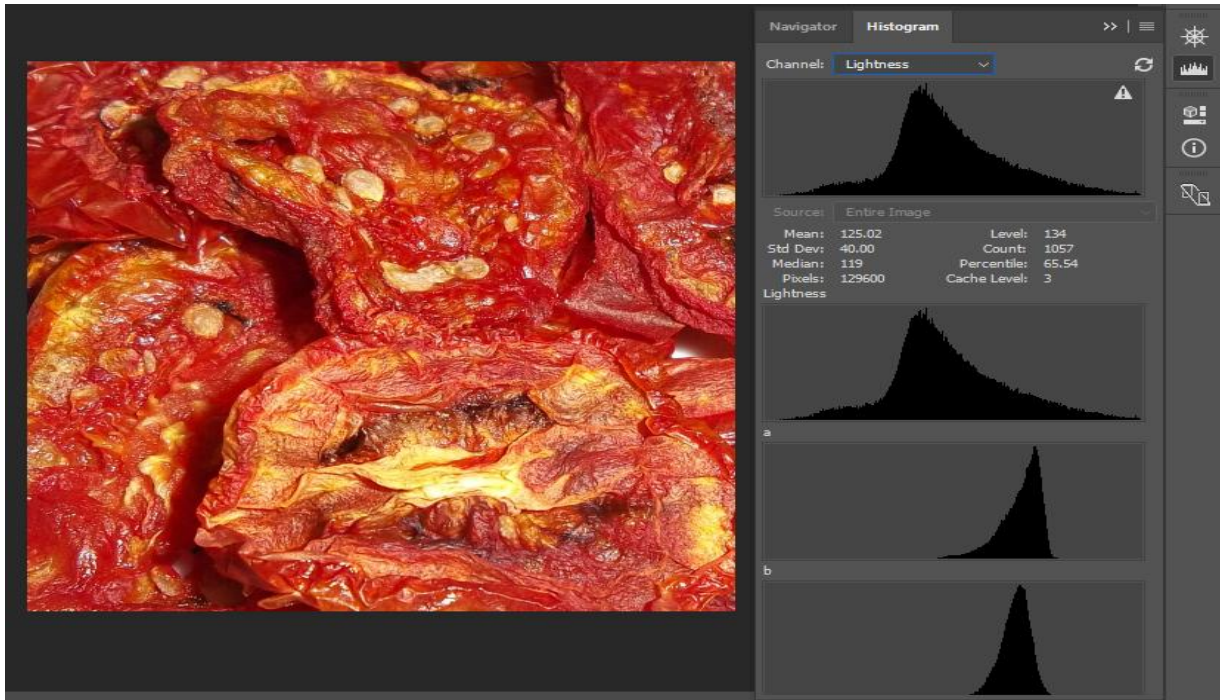


Figure 1. The histogram window displays for the statistics of the microwave-dried tomatoes

Determination of a^*/b^* , chroma (C), and hue angle (α)

The ratio of a^* and b^* , which is an indicator of tomato ripeness, was determined as described by Al-Sulaiman (2011). The chroma and hue angle were also estimated and used to describe the colour changes of the tomatoes after drying (Dadali et al., 2007).

$$\text{Ratio of } a^* \text{ and } b^* = \frac{a^*}{b^*} \quad (4)$$

$$C = \sqrt{(a^*)^2 + (b^*)^2} \quad (5)$$

$$\alpha = \tan^{-1}\left(\frac{a^*}{b^*}\right) \quad (6)$$

Determination of the total colour change (ΔE)

Fresh tomatoes were used as the ideal sample, and Dadali et al. (2007) method of how to estimate the total colour change (ΔE) was followed.

$$\Delta E = [(L^* - L^{**})^2 + (a^* - a^{**})^2 + (b^* - b^{**})^2]^{0.5} \quad (7)$$

where:

ΔE - the total colour change of the dried tomato slices

L^* and L^{**} - lightness of fresh and dried tomato samples

a^* and a^{**} - redness of fresh and dried tomato samples

b^* and b^{**} - yellowness of fresh and dried tomato samples.

Determination of the browning index (BI)

Browning index (BI) gave the brown colour purity and was estimated as described by Dadali et al. (2007).

$$BI = \frac{[100(x - 0.31)]}{0.17} \quad (8)$$

where:

$$x = \frac{(a^{**} + 1.75L^{**})}{(5.645L^{**} + a^* - 3.012b^{**})}$$

Modelling with artificial neural networks (ANNs)

Neural Network Toolbox 8.0 by MATLAB was used for the modelling. The design of the ANN goes through three crucial phases. The basic model that will be built was organised in the first stage. According to Turan et al. (2011) and Hussein et al. (2023), the most popular ANN learning technique, backpropagation, was used to reduce errors at each iteration. In the final phase, the prediction accuracy of the improved ANN model was assessed. This was accomplished by contrasting the actual results of the numerical simulation with the expected results. Figure 2 illustrates the relationship between the input variables and the total colour change and browning index.

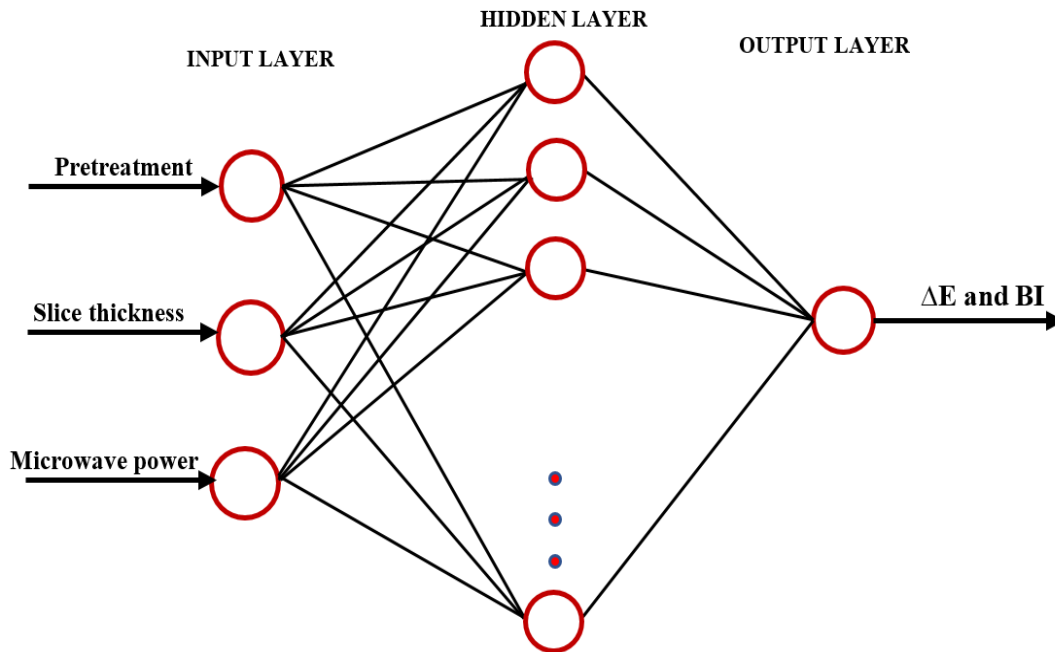


Figure 2. ANN schematic diagram

Three groups of the experimental data – training (70%), validation (15%), and testing (15%) – were randomly selected from the data. Equation 9 was used to carry out the normalisation, which was discussed by Abdalla et al. (2014).

$$Y_n = \frac{Y_a - Y_{min}}{Y_{max} - Y_{min}} \quad (9)$$

where: Y_n , Y_a , Y_{min} , and Y_{max} are normalised, real, lowest, and highest values, respectively. Equation 10 was then used to convert the (0–1) range of the network predicted values into actual values.

$$Y_a = Y_n(Y_{max} - Y_{min}) + Y_{min} \quad (10)$$

Modelling with adaptive neuro-fuzzy inference system (ANFIS)

The model for the variations in the colour of dried tomatoes was created using the ANFIS programme in MATLAB (The MathWorks Inc., USA). Before choosing the most important inputs that affect the colour of dried tomatoes, an exhaustive search was conducted as described by Hussein et al. (2023). Backpropagation and the least squares method were used to create the ANFIS model. The parameters of the input membership function were estimated using least-squares estimation, and the parameters of the output membership function were estimated using backpropagation. To determine the optimum functions and their amounts, the created model was optimised using a range of membership functions. The quantity, nature, and variety of training epochs for membership functions determine the precision of ANFIS models. Figure 3 showed the ANFIS schematic diagram. Before launching, the input and output data points for the ANFIS modelling were established. First, the data were arranged in three groups, which are 70%, 15%, and 15% for training, validation, and testing of data, respectively. According to Tao et al. (2016), the optimised model was identified using the triangular, trapezoidal, and Gaussian membership functions, two membership functions, and the model's bivariate input. The best epoch for the ANFIS configuration was first identified through preliminary simulation analysis. The best epoch value, which was determined to be between 500 and 1000, was then used in the following simulation.

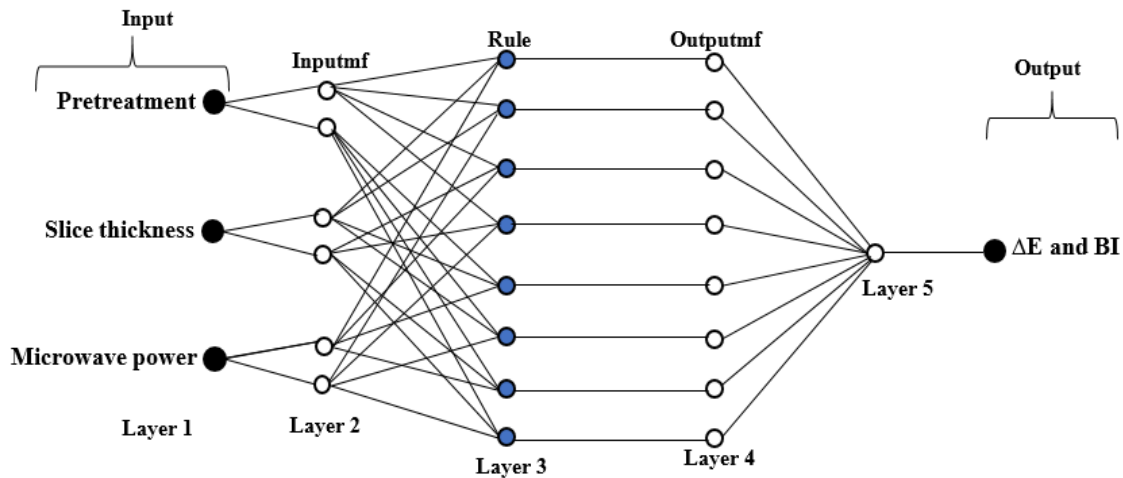


Figure 3. ANFIS schematic diagram

Execution of the models

The following metrics as used by Hussein et al. (2022) were employed to assess the performance and efficacy of the model: coefficient of correlation (R), coefficient of determination (R^2), mean square error (MSE), mean absolute error (MAE) and root mean square error ($RMSE$). These metrics are described by equations 11, 12, 13, 14, and 15.

$$R = \frac{\sum (y_0 - y_0^1)(y_e - y_e^1)}{\sqrt{\sum (y_0 - y_0^1)^2 \sum (y_e - y_e^1)^2}} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_0 - y_e)^2}{\sum_{i=1}^N (y_0 - y_0^1)^2} \quad (12)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_0 - y_e)^2 \quad (13)$$

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^N (y_0 - y_e)^2 \right)^{1/2} \quad (14)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_0 - y_e| \quad (15)$$

where: N is the number of experiments, y_o is the predicted value, y_o^1 is the average predicted value, y_e is the experimental value and y_e^1 is the average of actual values.

RESULTS AND DISCUSSION

Effect of drying conditions on the colour characteristics of microwave-dried tomatoes

Table 2 displays the variations in the colour of the pretreated microwave-dried tomato slices; the lightness (L^*) ranges from 36.70 to 48.83, according to the table. When compared to fresh tomatoes, it was found that the dried slices were slightly darker (L^* decreased). With each drying microwave power that was considered, the lightness of the dried tomato slices decreased. This pattern indicated that the luminance of the tomato slices decreased after drying. A similar decline in the lightness of dried tomato slices was noted by Izli & Isik (2015). The redness (a^*) and yellowness (b^*) were slightly less intense compared to fresh tomatoes. This demonstrated that the pigments in microwave-dried tomatoes only slightly to barely degraded. This minimal pigment degradation was consistent with the results of the microwave oven drying of tomatoes reported by Qadri & Srivastava (2014). In addition, pigment degradation in the microwave, convection, and microwave-convection-microwave oven-dried tomatoes was also reported by Izli & Isik (2015). The interactions between reducing sugars and amino acids in the tomatoes during drying may explain why dried tomatoes are less colourful than fresh ones (Abano et al., 2011).

The redness of the finished product is determined by a^*/b^* ratio of the tomatoes. It serves as a colour index and positively correlates with the amount of lycopene (Idris et al., 2013). According to Idris et al. (2013), ratio of a^*/b^* greater than 1 indicates an excellent red colour, while lesser values signify immaturity or colour deterioration. As a result, when compared to the fresh sample, the value of a^*/b^* in both the WB and SM pretreated tomatoes decreased significantly ($p < 0.05$). However, AA pretreated tomato showed an increase in the value of a^*/b^* and was slightly higher than the fresh sample. Kerkhofs et al. (2005) reported that after air-drying tomatoes, the a^*/b^* value decreased. However, an increase in the value of a^*/b^* was reported by Ashebir et al. (2009). To determine the difference in colour between the fresh and dried tomato samples, the overall colour change (ΔE) was computed. ΔE was noticeably higher at higher microwave power and slice thickness compared to lower microwave power and slice thickness. This suggests that a higher microwave power and thicker slice will result in a faster degradation rate because tomatoes absorb much electromagnetic energy. Tomatoes that had been pretreated with AA showed an increase in ΔE value, followed by those that had been pretreated with SM and WB. Compared to SM and WB treated samples, AA treated samples showed more pronounced colour changes. According to Gnanasekharan et al. (1992), changes in the three coordinates may be related to variations in tomato colour. Additionally, Talih et al. (2017) noted that as microwave power increases and sample thickness decreases, the lightness value of a dried black carrot pulp decreases.

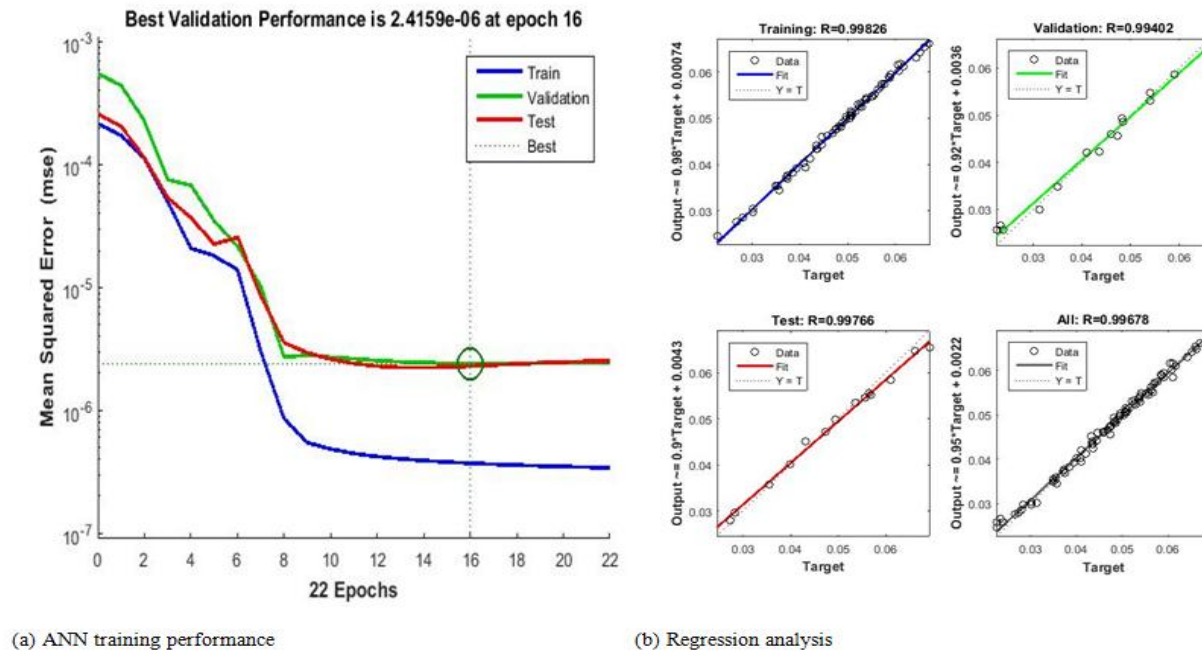
The browning in the dried tomatoes was measured using the browning index (BI). According to Cernisev (2009), the browning reaction significantly degraded the quality of dried tomatoes. The BI ranged from 11.78 to 39.82. These findings unambiguously demonstrate how processing conditions significantly impact tomato browning reactions. The black carrot pulp BI from microwave drying that Talih et al. (2017) reported supports the trend. It was found that the pretreatment significantly decreased the BI, and SM pretreatment significantly reduced the BI more than AA and WB pretreatments.

Chroma (C) values decreased and followed the same reduction pattern as b^* values. The C value relates the colour intensity to the colour saturation level. When comparing the samples pretreated with WB to fresh tomato samples, slight differences in C values were found. Nevertheless, there was a significant difference between them ($p < 0.05$). This demonstrated that the red colour of the dried, pretreated tomato was stable. In comparison to the fresh samples, the dried tomatoes had a relatively lower hue angle (α). This suggests that the dried samples underwent browning. According to Hawlader et al. (2006), a decline in the value denotes the formation of more brown pigment and a move away from yellowness. The previous study corroborates the result by Arslan & Ozcan (2010) for microwave-dried onions.

Table 2. Effect of drying conditions on the colour characteristics of microwave-dried tomatoes

Experimental Runs	L*	a*	b*	a*/b*	ΔE	BI	C	hue (α)
Fresh	56.73 $\pm$ 3.08 ^a	44.51 $\pm$ 3.14 ^a	38.38 $\pm$ 2.00 ^{ab}	1.16 $\pm$ 0.02 ^{ab}	-	-	58.77 $\pm$ 3.68 ^a	0.86 $\pm$ 0.01 ^{ab}
WB; 4 mm; 90 W	48.83 $\pm$ 1.66 ^b	44.56 $\pm$ 0.94 ^a	40.34 $\pm$ 1.06 ^a	1.11 $\pm$ 0.01 ^{bc}	8.43 $\pm$ 1.52 ^d	32.01 $\pm$ 3.76 ^{ab}	60.11 $\pm$ 1.40 ^a	0.84 $\pm$ 0.01 ^{bc}
WB; 6 mm; 180 W	48.65 $\pm$ 0.34 ^b	41.23 $\pm$ 0.47 ^{ab}	38.67 $\pm$ 0.23 ^{ab}	1.07 $\pm$ 0.01 ^c	8.74 $\pm$ 0.47 ^d	39.82 $\pm$ 0.81 ^a	56.51 $\pm$ 0.48 ^{ab}	0.82 $\pm$ 0.01 ^c
WB; 8 mm; 360 W	47.77 $\pm$ 1.62 ^{bc}	42.02 $\pm$ 0.37 ^{ab}	38.43 $\pm$ 0.82 ^{ab}	1.09 $\pm$ 0.01 ^{bc}	9.38 $\pm$ 1.66 ^{cd}	36.26 $\pm$ 2.87 ^a	56.94 $\pm$ 0.82 ^{ab}	0.83 $\pm$ 0.01 ^{bc}
AA; 4 mm; 180 W	41.62 $\pm$ 0.38 ^{bcd}	40.47 $\pm$ 0.27 ^{abc}	37.86 $\pm$ 0.42 ^{ab}	1.07 $\pm$ 0.02 ^c	15.67 $\pm$ 0.31 ^{bcd}	21.50 $\pm$ 1.40 ^{bcd}	55.42 $\pm$ 0.26 ^{ab}	0.82 $\pm$ 0.01 ^c
AA; 6 mm; 360 W	38.91 $\pm$ 1.45 ^d	36.81 $\pm$ 0.48 ^c	31.03 $\pm$ 0.98 ^c	1.19 $\pm$ 0.02 ^a	20.77 $\pm$ 1.76 ^a	31.56 $\pm$ 2.57 ^{ab}	48.15 $\pm$ 1.01 ^c	0.87 $\pm$ 0.01 ^a
AA; 8 mm; 90 W	41.53 $\pm$ 2.30 ^{bcd}	42.14 $\pm$ 1.07 ^{ab}	35.38 $\pm$ 1.34 ^b	1.19 $\pm$ 0.02 ^a	15.76 $\pm$ 2.61 ^{bcd}	22.36 $\pm$ 3.70 ^{bc}	55.02 $\pm$ 1.68 ^{ab}	0.87 $\pm$ 0.01 ^a
SM; 4 mm; 360 W	42.08 $\pm$ 2.25 ^{bcd}	41.60 $\pm$ 0.88 ^{ab}	38.69 $\pm$ 1.82 ^{ab}	1.08 $\pm$ 0.03 ^c	15.24 $\pm$ 2.15 ^{bcd}	19.50 $\pm$ 2.5 ^c	56.82 $\pm$ 1.89 ^{ab}	0.82 $\pm$ 0.01 ^c
SM; 6 mm; 90 W	40.97 $\pm$ 3.72 ^{bc}	39.79 $\pm$ 0.80 ^{bc}	37.56 $\pm$ 2.06 ^{ab}	1.06 $\pm$ 0.04 ^c	16.75 $\pm$ 3.76 ^{bc}	20.30 $\pm$ 7.16 ^{bc}	54.74 $\pm$ 1.99 ^{ab}	0.82 $\pm$ 0.02 ^c
SM; 8 mm; 180 W	36.70 $\pm$ 3.42 ^d	38.56 $\pm$ 1.52 ^{bc}	35.46 $\pm$ 1.98 ^b	1.09 $\pm$ 0.02 ^c	21.24 $\pm$ 3.85 ^{ab}	11.78 $\pm$ 5.56 ^c	52.39 $\pm$ 2.45 ^{bc}	0.83 $\pm$ 0.01 ^c

Legend: Mean values in the same columns bearing the same superscript are not significantly different ($p > 0.05$); WB = Water blanched; AA = Ascorbic acid; SM = Sodium metabisulphite; L* = Lightness; a* = redness; b* = yellowness; a*/b* = ratio of redness to yellowness; ΔE = total colour change; BI = browning index; C = Chroma value

Figure 4. The total colour change (ΔE) using ANN

ANN modelling of overall colour changes (ΔE) and browning index (BI) of microwave-dried tomatoes

The ANN architecture with the 3-9-1 and 3-7-1 topologies was found to have the best topology and transfer function for predicting ΔE and BI after extensive testing with various topologies. The best performance model was influenced by the logarithmic sigmoid function at the hidden layer, a tangent sigmoid function at the output layer for ΔE , and a tangent sigmoid function at both the hidden and output layer for BI. An ANN model was developed to simulate how the input data might affect output data. The most effective optimal architecture had cutoffs at high R and low MSE. Figures 4 and 5 show the ANN training performance and regression analysis for the ΔE and BI training and validation datasets. After 22 epochs for ΔE (Fig. 4a) and 43 epochs for BI, the training was terminated (Fig. 5a). Following the completion of training, the optimal ANN network was found at 16 epochs for ΔE and 37 epochs for BI. The regression analysis between the ANN outputs and the experimental data successfully predicted the ANN model with R values of 0.99826, 0.99402, 0.99766, and 0.99678 for ΔE and 0.99934, 0.99746, 0.99810, and 0.99879 for BI, for training, validation, testing, and all data, respectively. Figure 4b shows the values for ΔE of 2.4159E-06 at 16 epochs and 0.000001 at 37 epochs (Fig. 5b) as the MSE values for the ideal architect.

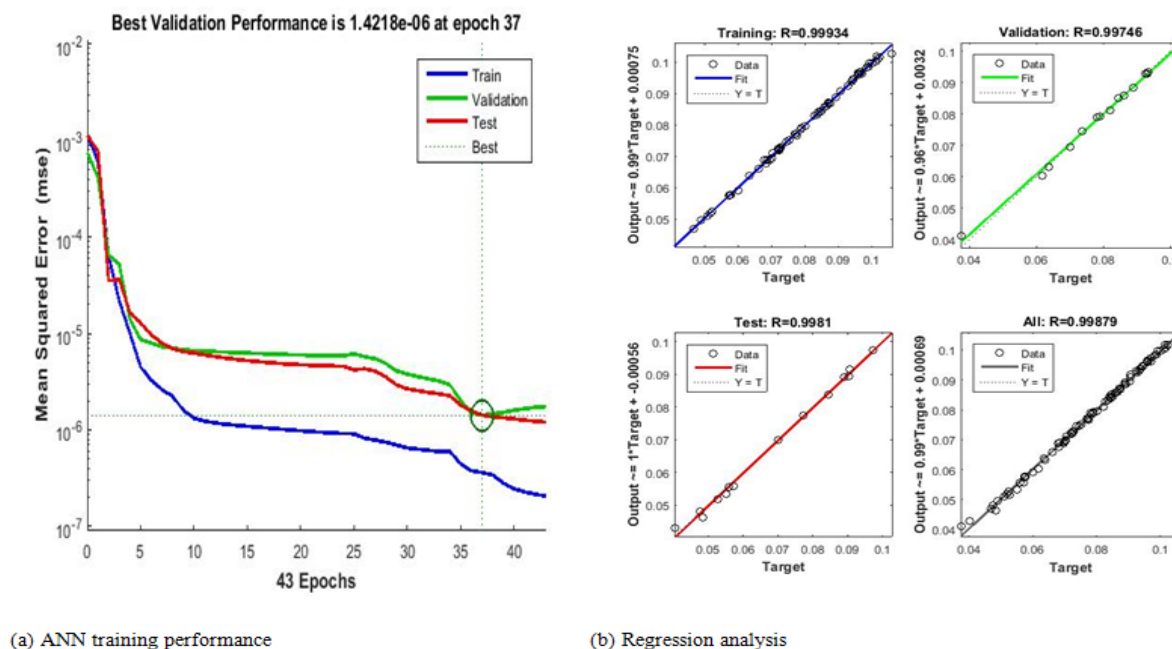


Figure 5. The BI one and two input variables for ANFIS exhaustive search

The experimental versus predicted values for the simulated ΔE and BI are displayed in Figure 6. The simulated regression plot's R^2 values for ΔE and BI were 0.9936 and 0.9976, respectively. For ΔE and BI, the RMSE and MAE were 0.2968 and 0.1946 and 0.3544 and 0.2424, respectively. The R^2 , RMSE, and MAE values for the E and BI in the calculated prediction model demonstrated that the model accurately predicted the experiments. The ANN model showed excellent generalisation in predicting the E and BI of the dried tomato slices. Results from microwave dehydration of a variety of fruits, such as tomatoes (Al-Sulaiman, 2011), rehydrated apple cubes (Winiczenko et al., 2018), and *Ginkgo biloba* seeds (Bai et al., 2018), are used to support this conclusion.

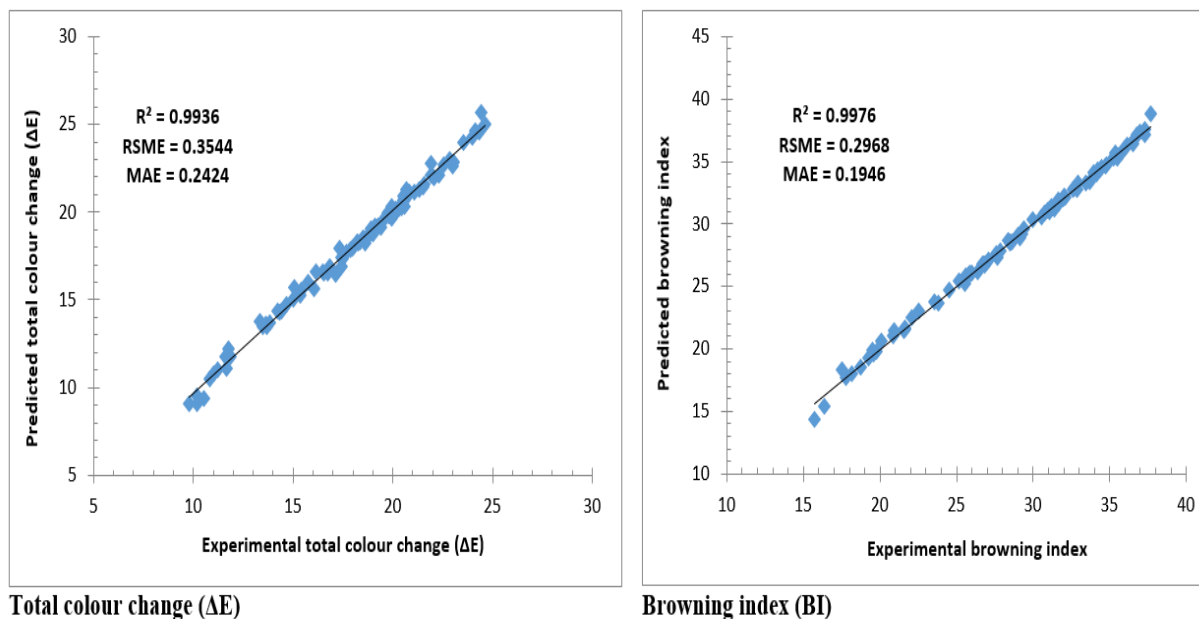
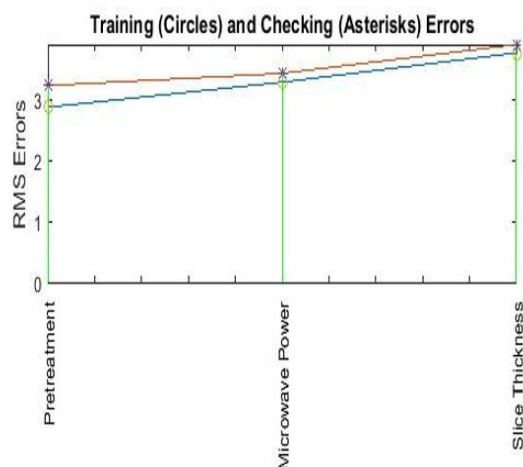


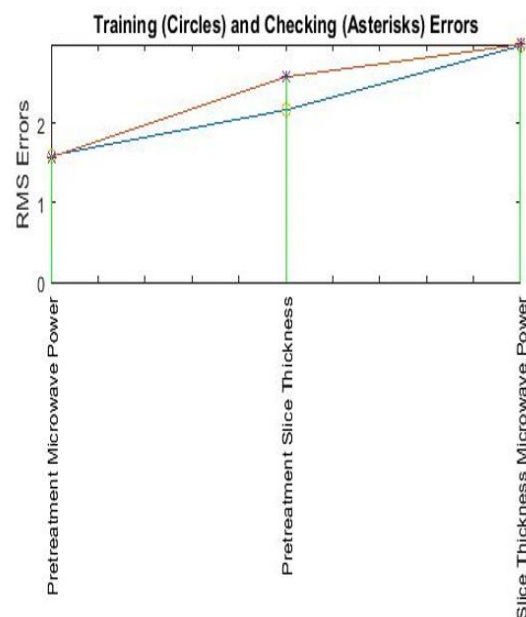
Figure 6. ANN model comparison of experimental and predicted values for ΔE and BI

Modelling the total colour changes (ΔE) and browning index (BI) of dried tomatoes using ANFIS

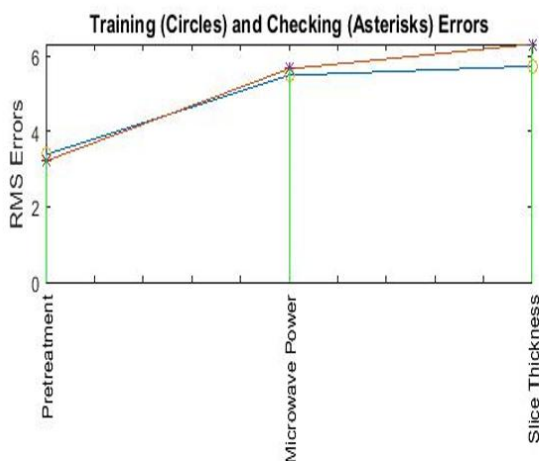
The ANFIS results for ΔE and BI are shown in Figures 7 and 8, respectively. For a single input variable, pretreatment had the lowest training error for ΔE of 2.8762, the lowest checking error of 3.2314, and the lowest training error for BI of 3.3879 and a checking error of 3.2196. As a result, it was clear that pretreatment was the most important input variable for the measurements of ΔE and BI of pretreated tomato slices. For two input variables, it was found that the pretreatment and microwave power combination had the lowest training error of 1.5918 and checking error of 1.5731 for E and the lowest training error of 1.8318 and checking error of 2.0628 for BI. Consequently, these are the most crucial input variables that impact the performance of the output. The figure shows that because the training and checking errors were similar, there was less overfitting during the thorough search. The smaller difference between training and checking errors, according to Aremu et al. (2014) and Oke et al. (2018), indicated less overfitting during the exhaustive search. These three input parameters – pretreatment, slice thickness, and microwave power – were used by the ANFIS prediction technique to forecast the E and BI. It was discovered that the ANFIS design, which combines linear OMF with gauss IMF and tri, gbell, and type 2 MFs, has the highest level of colour quality prediction accuracy. A similar ANFIS modelling structure was reported by Oke et al. (2018) for *Grewia mollis* stem bark gum extraction and Kaveh et al. (2018) for dried cantaloupe, garlic, and potato.



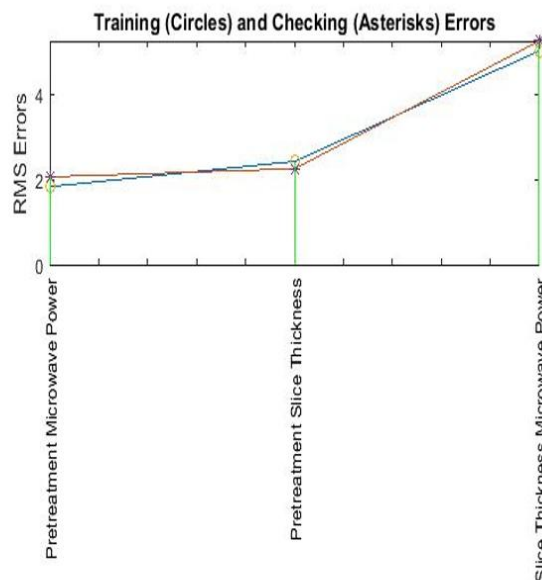
a. One input variable



b. Two input variables combination

Figure 7. The ΔE one and two input variables for ANFIS exhaustive search

a. One input variable



b. Two input variables combination

Figure 8. ANFIS exhaustive search for the one and two input variables for the BI

A correlation coefficient of 0.99997 for ΔE and 0.99999 for BI was predicted by the regression analysis of the ANFIS outputs and experimental data (Fig. 9). The suitability of the model for forecasting the test data was demonstrated by the fact that the data were constrained to the regression plot's optimal trend line. The exceptionally low root-mean-square error (RMSE) of the ANFIS model for both the training (≤ 0.03309) and testing (≤ 0.03467) phases shows the ability of the model to capture the key components underlying the dynamics governing the interactions between the input and output variables. The constructed ANFIS model's simulation accuracy was assessed to confirm the network's dependability. The R^2 of the simulated regression plot for ΔE and BI was 0.9999 and 0.9999, respectively. The RMSE and MAE for ΔE were 0.0331 and 0.0239, while for BI, they were 0.0295 and 0.0221. The empirical model would match the experimental data better the closer the R^2 value was to unity,

according to Hussein et al. (2022). As evidenced by the high R^2 and comparatively low values of RMSE and MAE, the developed ANFIS models faithfully reproduce the ΔE and BI of microwave-treated dried tomato slices.

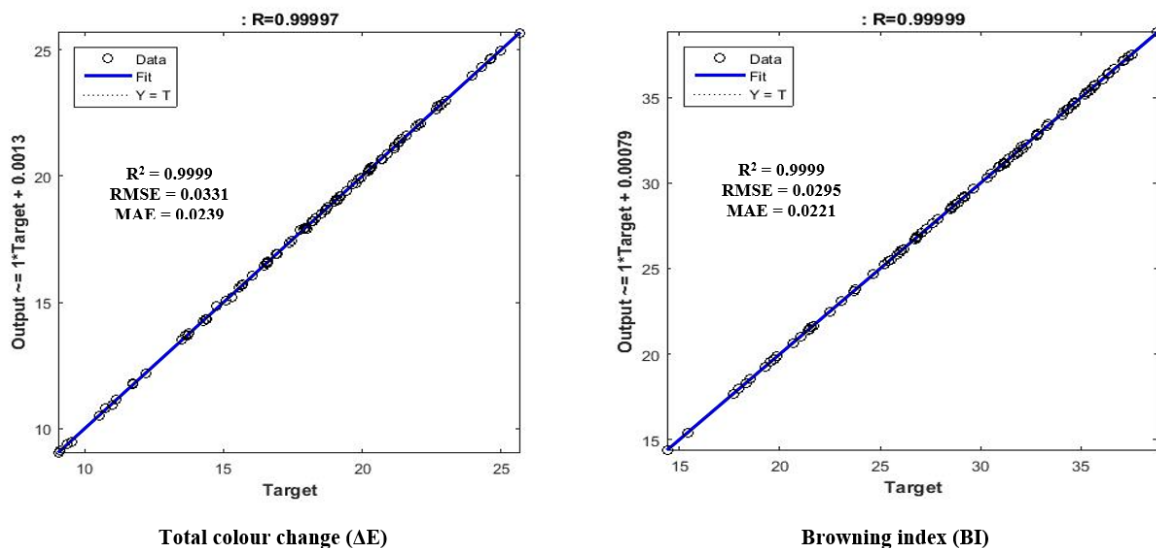


Figure 9. Predicted and experimented values for ΔE and BI using ANFIS model

Figure 10 displays the plot of the ANFIS decision for the relationship between the value of ΔE and processing parameters. The plot shows that as microwave power increases, the ΔE likewise rises. The ΔE decreases when the slice thickness increases at a lower microwave power as well. This suggests that because tomatoes absorb a lot of electromagnetic energy, the rate of colour degradation increases as microwave strength and slice thickness increase. Compared to SM and AA treated tomato samples, more significant ΔE was seen in the colour of WB treated tomato samples. This suggests that WB treated tomato samples showed lower pigment degradation than SM and AA treated tomato samples. This observation is supported by the finding made by Gnanasekharan et al. (1992), who suggested that the browning reactions or pigment degradation could be linked to pigment degradation and relates to colour loss.

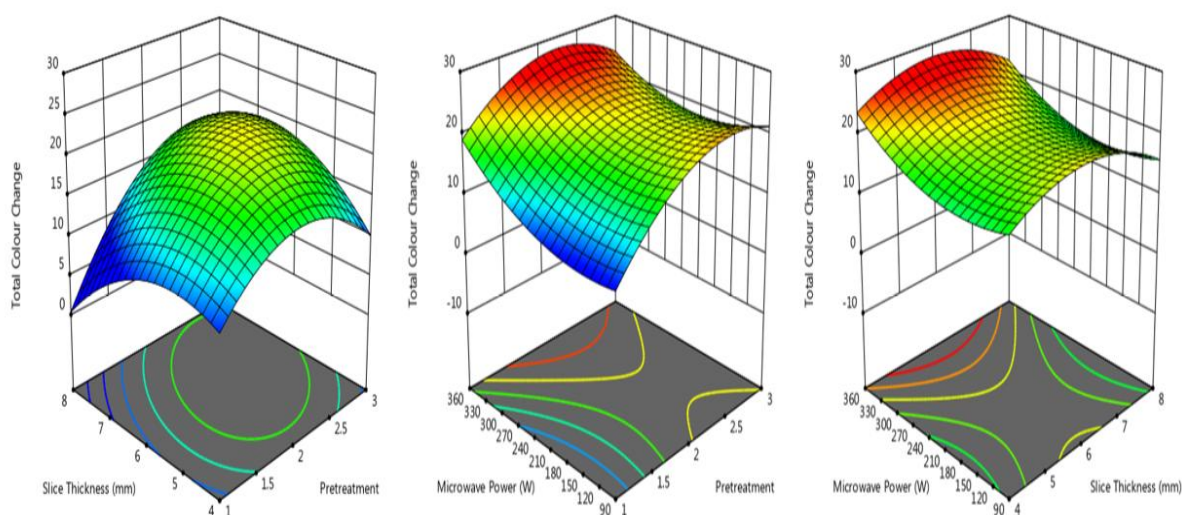


Figure 10. The plot of the ANFIS decision for the relationship between the value of ΔE and processing parameters

Figure 11 displays the plot of the ANFIS decision for the relationship between the value of ΔE and processing parameters. As seen from the plot, BI of the dried tomato increased as microwave power was increased while slice thickness was decreased. However, because the rate of the drying process had slowed down, microwave power and

tomato slice thickness caused the browning index to reduce. This little pigment degradation was consistent with what was reported by Qadri & Srivastava (2014) for microwave oven drying of tomatoes and microwave drying of black carrot pulp by Talih et al. (2017). WB and AA pretreatment increased the rate of browning, while SM pretreatment reduced it. This was observed due to an increase in the intensity of the drying process with WB and AA pretreated samples. The BI of the SM pretreated tomato sample was reduced. Baloch et al. (1997) reported that sulfites reduced the browning of dried tomato powder. The browning index of the dried tomato was thus reduced by SM pretreatment using a thinner slice and lower microwave power.

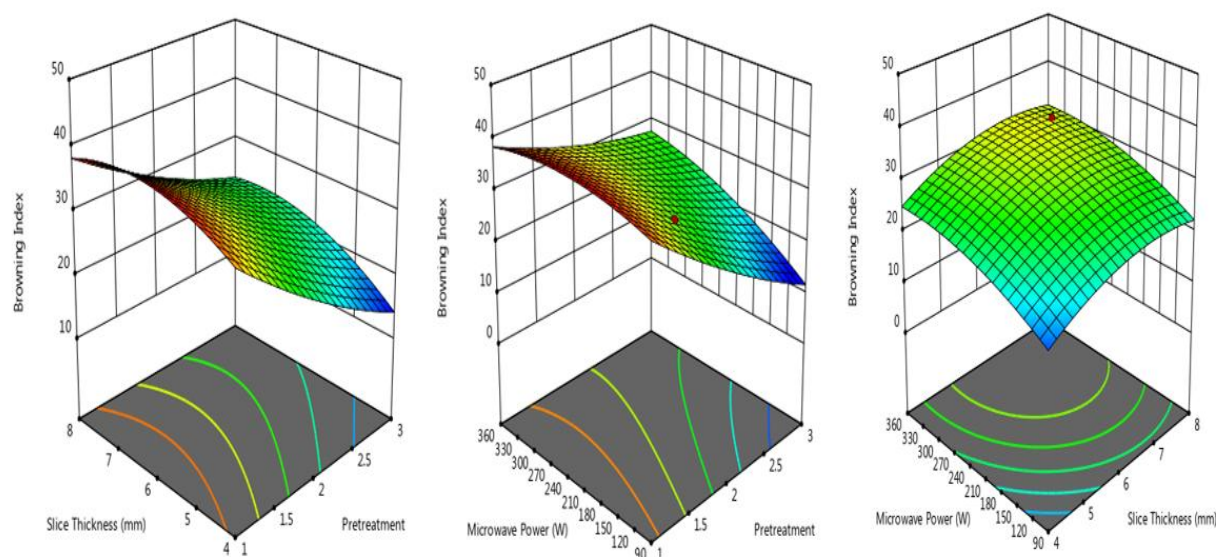


Figure 11. The plot of the ANFIS decision for the relationship between the value of BI and processing parameters

CONCLUSION

Digital imaging was used to assess the surface colour of microwave-dried tomato slices. Fresh tomatoes had L^* , a^* , and b^* values of 56.73, 44.51, and 38.38, respectively. For L^* , a^* , b^* , ΔE , BI, hue, and chroma, the dried sample displayed the ranges of 36.70 – 48.83, 36.81 – 44.56, 31.03 – 40.34, 8.43 – 21.24, 11.78 – 39.82, 48.15 – 60.11, and 0.82 – 0.87, respectively. According to the findings, dual of models of ANFIS and ANN could make more accurate predictions. The ANFIS model, however, provided better performance with higher values for R^2 (0.9999) and lower values for RMSE (0.0295) and MAE (0.0221). After experimental validation, it was found that the predicted values and the experiment outcomes were in agreement. The digital imaging colour measurements of dried tomato slices offer an adequate means of non-destructive colour analysis. Pilot and commercial processors could use the information presented here as an operation guide in drying of tomato fruits using microwave.

Acknowledgements: The authors appreciate the TETFund PhD Study Fellowship Grant offered by Modibbo Adama University, Yola.

Conflict of interest: The authors declare that they have no conflict of interest.

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