ISPEC Tarım Bilimleri Dergisi, 9(1):74-88, 2025
ISPEC Journal of Agricultural Sciences, 9(1):74-88, 2025
DOI: https://doi.org/10.5281/zenodo.14564833

Prediction of Moisture Content in Kiwi (*Actinidia deliciosa*) Dried Using Machine Learning Approaches

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Abstract
Predicting product drying kinetics is crucial for achieving optimal drying processes without compromising product quality. This prediction technique necessitates the development of numerical drying models. The aim of this research is to compare prediction models developed using two popular machine learning approaches in recent years: Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Artificial Neural Networks (ANN). In this study, kiwi slices of three different thicknesses were dried using 90 W microwave power. Prediction models were developed using experimental data. The input for the training algorithm included kiwi slice thickness and drying time, while the output was the moisture content of the product. The performance of the models was evaluated by comparing the obtained outputs with experimental data from test sets. These models were assessed using mean absolute percentage error, correlation coefficient, root mean square error and mean bias error metrics. The ANN-based prediction model demonstrated better performance compared to the ANFIS model. The results of these tests indicate that both methods can be used for predicting the moisture content of kiwi slices.

Research Article

Article History
Received :27.08.2024
Accepted :28.09.2024

Keywords
Anfis
kiwi
machine learning
microwave drying

1. Introduction

Food products become unsuitable for consumption in a relatively short time due to activities caused by water. To obtain a long-term product without significant quality deterioration, the water within food products needs to be removed. Drying is one of the most commonly used processes for this purpose (Akal et al., 2014). In natural drying applications, prolonged drying times, exposure to environmental effects, and a decrease in nutritional value can lead to a loss in both quality and economic value of the products. Therefore, performing the drying process with specially designed artificial dryers not only shortens the drying time but also results in cleaner, higher-quality products with longer shelf life (Darıcı and Şen, 2012; Çelen et al., 2018). Kiwi fruit (*Actinidia deliciosa*) is highly nutritious due to its strong antioxidant capacity, which is attributed to its high levels of vitamin C, carotenoids, lutein, phenolics, flavonoids, and chlorophyll. The drying process has become a suitable food preservation method to extend the shelf life of food products. Various methods are needed to preserve many fruits to prolong their shelf life (Kaya et al., 2008; Acar et al., 2023).

One of the most commonly used methods is convective hot air drying. The aim is to change the moisture content on the outer surface of the food by applying hot air to the product. The change in moisture on the outer surface creates a difference in moisture concentration between the inner surfaces and the other. Microwave energy drives molecular activity that causes water to evaporate. It achieves this by increasing the kinetic energy of the molecules and thus increasing the friction forces. This process creates a pressure difference by increasing the internal pressure, which allows moisture to be transferred from the inner surface to the outside. The method of removing water vapor with the help of pressure differences significantly increases the drying rate (Akal et al., 2014).

Drying is a complex process characterized by the simultaneous occurrence of heat, mass, and momentum transfer phenomena. Effective models are required to design, optimize, and regulate the drying process (Khazaei et al., 2013). This study focuses on developing a model to predict the drying process. Mathematical modeling, which typically consists of equations that describe the behavior of a process or system, offers a certain level of convenience and is widely used in agriculture and many other fields (Şevik et al., 2014).

Today, the use of machinery is widespread in various processes such as soil cultivation, harvesting, product processing, transportation, fertilization, and plant protection (Taşova et al., 2020). Artificial intelligence techniques like ANN and ANFIS are effective for predicting optimal conditions as they do not require any assumptions or simplifications. These methods aim to mimic the human brain's ability to learn patterns. Both techniques aim to derive a relationship between a previously obtained set of model inputs and their corresponding outputs (Mousavifard et al., 2015; Bulus, 2024).

ANFIS is known as the logical artificial neural network model. With existing data, training and classification of the system and prediction of error and unknown values can be achieved. It is used effectively in the continuation and modeling of inaccurate problems (Turan et al., 2015). The structure of ANFIS includes a network architecture representing the neural learning capabilities of Sugeno-type fuzzy systems. ANFIS integrates both artificial neural networks and fuzzy logic within its framework.

Artificial Neural Networks (ANNs) mathematically replicate the human brain's abilities to learn, generate, and discover new knowledge, learning through experiences and using this information in decision-making. ANNs are computational systems inspired by the biological neural networks of the brain. In recent years, artificial neural networks (ANNs) have gained widespread popularity and utility across various disciplines, particularly for tasks such as classification, clustering, pattern recognition, and prediction. As a type of machine learning model, ANNs have proven to be relatively competitive with traditional regression and statistical models in terms of performance and applicability (Levent, 2023). ANNs consist of interconnected layers, with neurons in each layer connected to those in the subsequent layer. Typically, artificial neural networks are organized into three primary layers: the input layer, hidden layer(s), and output layer (Tektaş and Karataş, 2004).

Experimentally obtained kiwi fruits drying data were used as a training set to estimate the drying parameters of the fruit. The aim of this study is to develop mathematical models to achieve this goal. By creating models, time and energy spent in laboratory studies will be reduced and suitable conditions for the drying process can be determined. It is aimed to realize the mathematical model with two leading methods in the field of artificial intelligence. These two methods are designated as ANN and ANFIS. The results obtained with these methods were compared with experimental data and their performance was evaluated. To create the model, a comparison of the effects of different slice thicknesses of the kiwi product and the effects of time variables was also made.

2. Materials and Methods

Before being used in experimental studies, kiwi samples were stored at 4 °C and then brought to room temperature. The initial mass of the kiwi slices (2, 4, and 6 mm) used in the experiments was 3.65 ± 0.5 g. The weight of the kiwi slices was measured using a digital scale with a precision of ± 0.001 g (Presica XB 620 M; Precisa Instruments AG, Dietikon, Switzerland). The initial moisture content of the kiwi, on a wet basis, was determined to be 82 %. To measure the moisture content, the kiwis were first dried in an oven (Beko brand, 2450 MHz frequency, 800 W power, 19-L capacity, turntable microwave oven) at 90 W, 105 °C for 24 hours, after which their dry mass was recorded. The drying process was continued until the moisture content, on a wet basis, decreased to approximately 24 %. The drying experiments were conducted using a microwave oven (Beko brand, operating at a frequency of 2450 MHz, with a maximum power of 800 W, and equipped with a rotary table).

2.1. Moisture content

Moisture content according to wet basis (Eq-1) was calculated with the following equation (Tınmaz Köse et al., 2019):

$$m\% = [M_w/(M_w + M_d)]x100 \qquad (1)$$

where;
m: Moisture content of Kiwi at a specific time (g water g^{-1} wet matter),
M_w: Wet weight of Kiwi (g),
M_d: Dry weight of Kiwi (g).

(Habashy and Lebda, 2022; Levent et al., 2023).

2.2. Modeling with ANFIS

ANFIS is a neural network based on Takagi-Sugeno inference logic, developed by Jang in 1993. In this study, the implementation of ANFIS, as in ANN, was carried out on the MATLAB (R2016b) platform. MATLAB provides a robust platform for simulation and testing, enabling easy modification of the model's variables and parameters. As a result, it provides a comprehensive graphical representation of parameters and performance

ANFIS is a neural network that works on the basis of an artificial neural network and contains fuzzy logic principles. ANFIS is a structure that combines the predictive power of fuzzy logic with the advantage of the learning capabilities of neural networks. It effectively transmits the input parameters required to produce output to the output. The working logic includes developing a learning rule that creates the behavior of the system through the created fuzzy rules (Putra and Mohamad, 2023).

An adaptive network is a multilayered feedforward system consisting of nodes interconnected to create a single output and perform a specific function. These nodes are parametric and each produces an output. These node parameters are adjustable. Using a given set of parameters and input/output data, the ANFIS method optimizes the membership function parameters through a backpropagation algorithm or least squares method by modeling a fuzzy inference system (FIS) (Walia et al., 2015).

In this inference system, there is a linear combination of a constant term added to the outputs of the rules generated. The weight average of all rules produces the final output. Figure 1 schematizes the ANFIS structure used in this study. In this scheme, there are two inputs (time and slice thickness) and one output (m) (Sonmez et al., 2018; Ali et al., 2019).

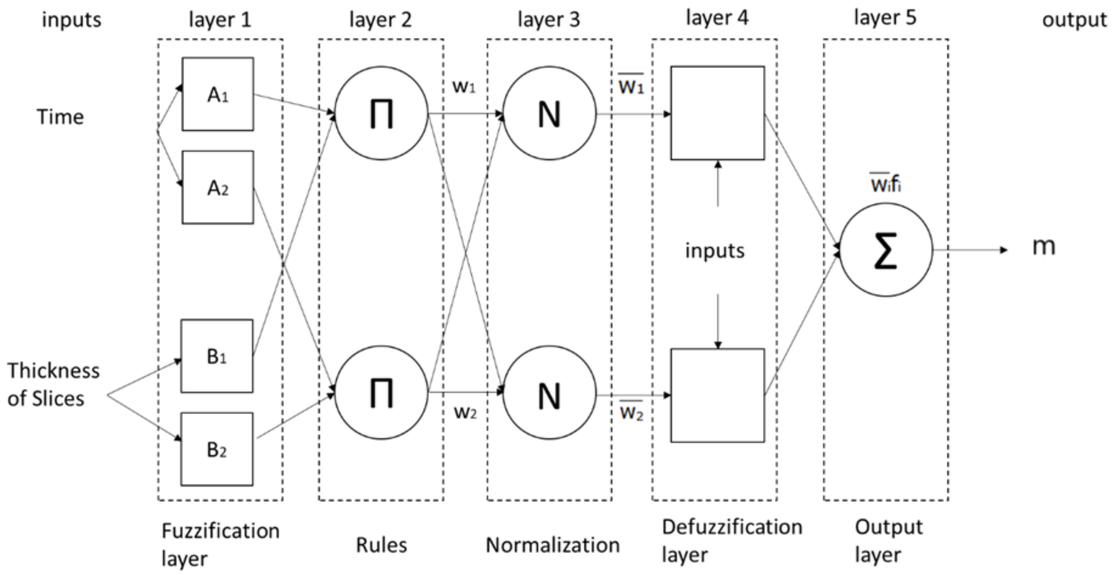

Figure 1. ANFIS model structure

Layer 1 (Fuzzification Layer): Fuzzification is performed in the first layer. Input membership functions are used for this process. Although a formula is not presented for selecting membership functions, methods based on experience or involving trial and error methods are generally used (Şencan and Şencan Şahin, 2022).

$$O_{1i} = \mu_{Ai}(x),\ i = 1, 2 \qquad (2)$$

$$O_{1i} = \mu_{Bi-2}(x),\ i = 3, 4 \qquad (3)$$

Here μA_i and μB_{i-2} are the degrees of membership functions for the fuzzy sets A_i and B_i.**Layer 2 (Rule Layer):** There are rules in this layer. To obtain the output of these rules, the multiplication of the membership degrees from the first layer must be obtained (Demirci 2020).

$$O_{2i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y) \qquad (4)$$

Layer 3 (Normalization Layer): Fixed nodes denoted by N are located in this layer. Every fixed node i. It is the ratio of the trigger weight of the rule to the sum of the trigger weights of all rules. Outputs called normalized trigger weights are obtained (Kaynar et al., 2010).

$$O_{3i} = w_i = \frac{\mathbf{wi}}{\sum_i \mathbf{wi}} \quad (5)$$

Layer 4 (Defuzzification Layer): In this layer, sharp data is obtained from fuzzified data. The values produced by each node of this layer contribute to the output node in the output layer. (Turan et al., 2022).

$$O_{4i} = w_i f_i = w_i(p_i x + q_i y + r_i) \quad (6)$$

Layer 5 (Output Layer): It is a single node layer. The output values of the previous layer nodes are collected and the output value of the system is found (Demirci, 2020).

$$O_{5i} = \sum_i \mathrm{wi}\, fi = \frac{\sum_i \mathrm{wi} fi}{\sum_i \mathrm{wi}} \quad (7)$$

Depending on the behavior of the input values, various one-dimensional membership functions, such as triangular, trapezoidal, Gaussian, sigmoid, and bell-shaped functions, can be utilized. Triangular and trapezoidal membership functions are linear in form, making them simple to design and represent. In contrast, the design of more complex membership functions, such as Gaussian and sigmoid, requires a higher level of complexity (Oğuz Erenler, 2023).

2.2.1. Triangular membership function (Trimf)

As seen in Figure 2, just as a triangle has three coordinates, the triangle membership function also has three parameters (Oğuz Erenler, 2023).

These parameters;
a = starting point,
c = end point,
b = peak point.

At points "a" and "c" the degree of membership is μA(X) = 0, and at point "b" it is μB(X) = 1
(Beşirik, 2016).

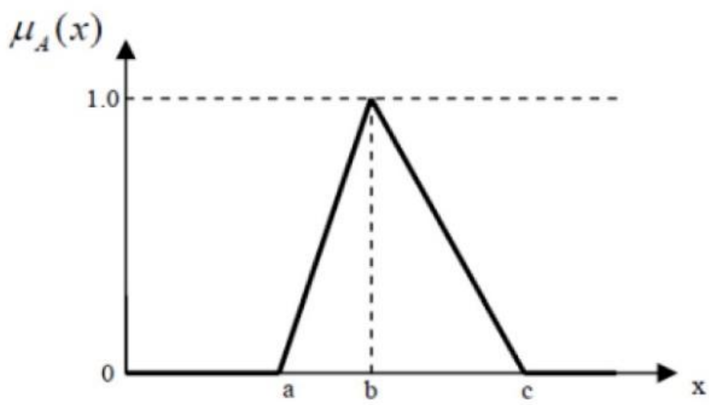

Figure 2. Triangular membership function (Beşirik, 2016)

$$\mu_A(x) = \mu_A(x; a, b, c, d) = \begin{cases} \frac{x-a}{b-a}, if\ a \le x \le b \\ \frac{c-x}{c-b}, if\ b \le x \le c \\ 0, if\ x > c\ or\ x < a \end{cases} \tag{8}$$

2.2.2. Trapezoidal membership function (Trapmf)

In this membership function, it starts from 0 %, reaches 100 % and then decreases to 0 % again. In this function, there are four parameters (a, b, c, d) instead of three parameters as in the triangular membership function as seen in Figure 3 (Oğuz Erenler, 2023).

These parameters;
a = starting point,
b = start of peak,
c = end of vertex,
d = end point.
At points "a" and "d", the degree of membership is $\mu_{A(X)} = 0$, and at points "b" and "c", $\mu_{B(X)} = 1$ (Beşirik, 2016).

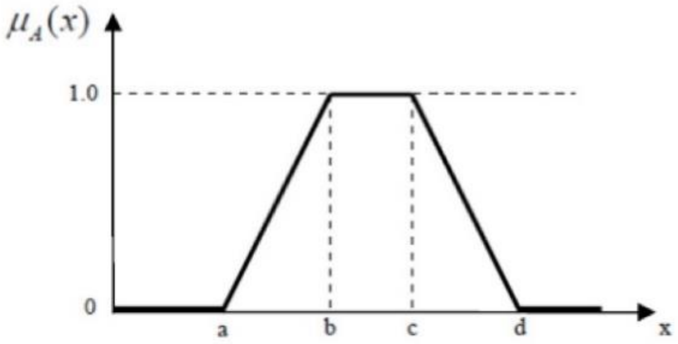

Figure 3. Trapezoidal membership function (Beşirik, 2016)

$$\mu_A(x) = \mu_A(x; a, b, c, d) = \begin{cases} \frac{x-a}{b-a}, if\ a \le x \le b \\ 1, if\ b \le x \le c \\ \frac{d-x}{d-c}, if\ c < x \le d \\ 0, if\ x > d\ or\ x < a \end{cases} \tag{9}$$

2.2.3. Gaussian membership function (Gaussmf)

The Gaussian membership function uses two parameters expressing the distance from the origin and the curve width. As seen in Figure 4, these parameters;
c = center,
σ = width (Karabulut, 2024).

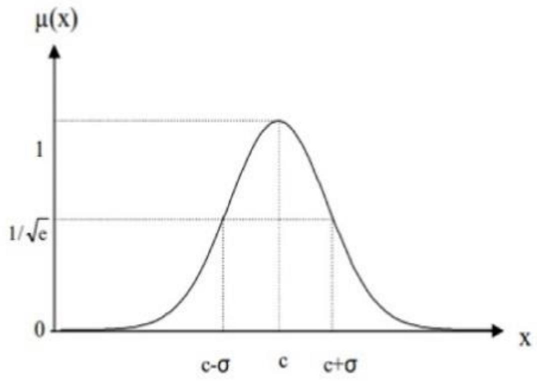

Figure 4. Gaussian membership function (Beşirik, 2016)

$$\mu(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (10)$$

2.3. Modeling with ANN

The transfer function chosen for the ANN model used in this study was determined as tangent sigmoid (tansig). Implementation of the created network model was carried out on the MATLAB platform. Figure 5 schematizes the architecture of the produced model.

As shown in the model structure, a basic ANN consists of three layers, each performing distinct functions: the input layer, the hidden layer, and the output layer. The neurons within each layer are responsible for processing information, with the layers interacting to achieve the network's overall function. The hidden layer receives and processes data from the input layer, and the processed data are subjected to activation functions, generating results in the output layer (Kaplan, 2019).

In order to determine an efficient ANN model to be used in this study, different network models were used in preliminary experiments by changing parameters such as different number of neurons and different transfer functions. As a result of these experiments, the model containing 25 neurons and using tangent sigmoid as the transfer function was determined to be an efficient model.

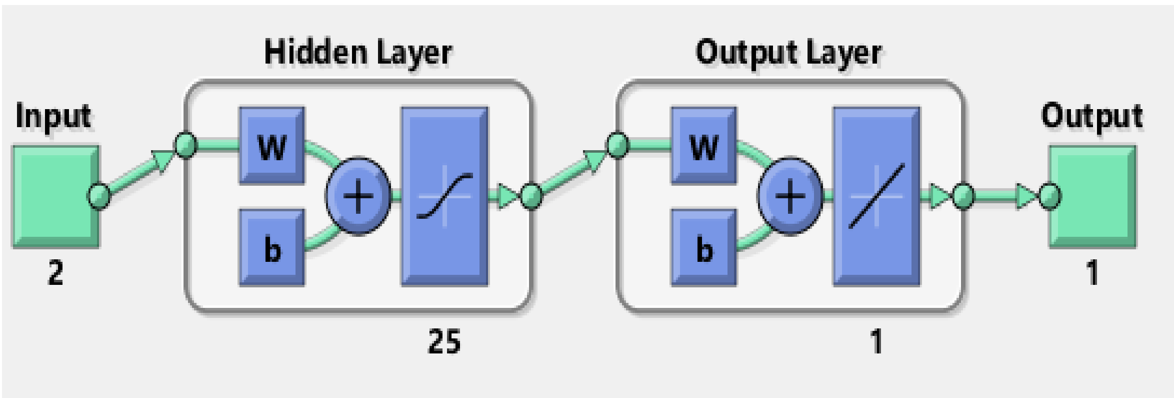

Figure 5. Illustration of the ANN model

In artificial neural networks (ANNs), weights and bias constitute the mathematical function that determines the output of a neuron. This structure is typically used in conjunction with an activation function. The fundamental function describing the operation of a neuron is as follows:

$$z = \sum_{i=1}^{n} w_i x_i + b \quad (11)$$

where;
x_i**:** Inputs (the data fed into the neuron or outputs from the previous layer).
w_i**:** Weights (coefficients that determine the importance of each input).
b**:** Bias (a constant term that adjusts the weighted sum).
z**:** Weighted sum (the value before applying the activation function).

2.4. Statistical analysis

Once ANN is trained using a training algorithm to extract knowledge from the provided data, it can be employed to either predict unknown input variables or rank the input variables based on their influence on the output. To enhance the model's performance, various key parameters were tested through a trial-and-error method. The accuracy of the model was ultimately evaluated by selecting the output with the smallest estimation error, measured using the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Bias Error (MBE) (Eqs. 12-15) (Bakar et al., 2022; Buluş et al., 2023).

ANN creates a model that must be tested to confirm it meets the desired criteria. This validation process assesses how effectively ANN has modeled the system by comparing outputs from the training data with those from a separate, non-training data set. The discrepancy between these outputs is quantified by the RMSE, which indicates the model's performance. A lower RMSE value reflects a more accurate model (Solichin et al., 2021).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(o_i - t_i)^2}{n}} \quad (12)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{t_i - o_i}{t_i} \right| \quad (13)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (o_i - t_i)^2}{\sum_{i}^{N} (t_i)^2} \right) \quad (14)$$

$$MBE = \frac{1}{n} \sum_{i=1}^{N} (t_i - o_i) \quad (15)$$

In order to demonstrate the accuracy of the produced ANN model, experimental data and prediction data were analyzed using equations 12-15. In these equations, n symbolizes the number of data, t_i symbolizes the experimental data and o_i symbolizes the predicted values.

3. Results and Discussion

The development, training, and testing of the ANFIS and the ANN model were conducted using the MATLAB software package. MATLAB offers a robust simulation and testing platform for this purpose, enabling easy manipulation of the model's variables and parameters. As a result, it provides a comprehensive graphical representation of parameters and performance (Habashy and Lebda, 2022).

ANFIS training involves the use of both the gradient descent method and the least squares method. The training algorithms provided in the MATLAB fuzzy inference toolbox streamline data processing by offering training and forecasting functions. The main computational process of ANFIS consists of five stages. The first stage is data input, while the second stage involves assigning fuzzy sets (Sonmez et al., 2018). In this study, the established ANFIS model is set to use 4 membership functions to create rules.

While developing the ANN model, a model with a single hidden layer and 25 neurons in the hidden layer was considered. In addition, the Levenberg - Marquardt training function, which is frequently mentioned in the literature, was used to train the network.

Figure 6 displays the training and test data used in the ANFIS model for m. In these graphs, the data represented by circles correspond to the training data, while the data indicated by dots represent the test data.

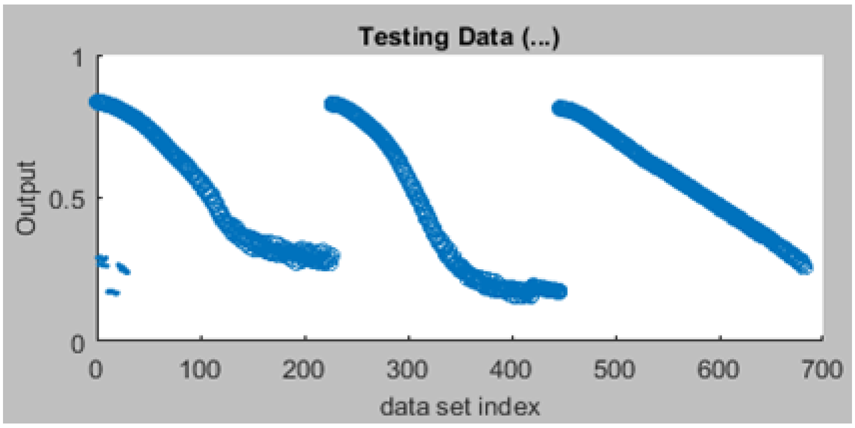

Figure 6. Training and test dataset for m

An ANFIS model with 2 inputs and 1 output was trained over 5000 iterations. Figure 6 displays the training and testing data, while Figure 7 illustrates the training error. The circles in Figure 6 symbolize the training data, and the dots symbolize the test data. This allows for an assessment of the proximity between the experimental and predicted values.

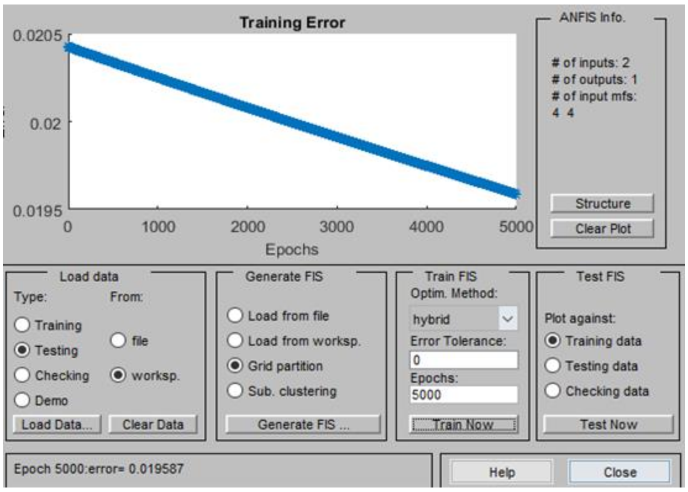

Figure 7. M prediction error rate for ANFIS in 5000 epochs

The number of rules to be created in an ANFIS system is found by the Eq. 16. Here NR: the number of rules, NI: the number of inputs and NMF: the number of membership functions used in the input laye

$$NR = NMF^{NI} \quad (16)$$

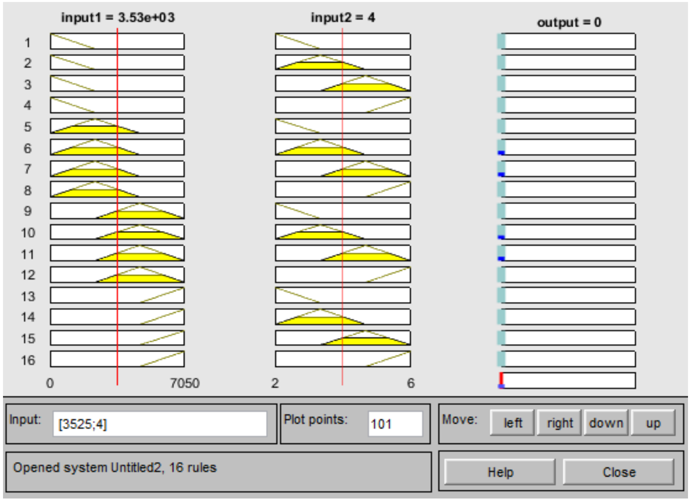

Figure 8. Rules created for model of m

Figure 8 shows part of the set of rules calculated according to equation 16. 16 rules of the developed models, intended for use in predictions, are displayed. In the model, the triangular membership function was used as the input membership function. The model was trained with 16. As seen in Figure 8, the error value produced by the network was fixed at 0.019587.

The training data comprised 95.8 % of the dataset (682 data), while 4.2 % (30 data) was allocated for testing in the ANFIS model. The relationships between input and output variables, defined by 16 rules, are illustrated in Figure 8. The ANFIS model demonstrated a high correlation coefficient, for training and testing. The performance of these models was evaluated for both training and testing phases. Table 1 presents metrics including the RMSE, MAPE, MBE and R^2.

Table 1. Correlation values of training and test dataset in ANFIS model

ANFIS		
Training	RMSE	0.019587
	MAPE	3.693615
	R^2	0.998692
	MBE	0.000000
Test	**RMSE**	0.022469
	MAPE	9.522044
	R^2	0.991238
	MBE	-0.019312
All	RMSE	0.019717
	MAPE	3.939195
	R^2	0.998629
	MBE	-0.000813704

Multiple adjustments were made with different parameters to optimize the ANFIS model for predicting mositure content (m). The R^2, MAPE, MBE and RMSE values have been calculated for these four outputs. The goal is to achieve an R^2 value as close to 1 as possible, along with RMSE and MAPE values approaching zero. For R^2, the values ranging from 0.991238 to 0.998692 for the ANFIS model indicates a very high degree of correlation. A MAPE value of less than 0.10 denotes highly accurate predictions, between 0.10 and 0.20 reflects good predictions, between 0.20 and 0.50 suggests reasonable predictions, and a MAPE value greater than 0.50 indicates low accuracy (Kacar and Korkmaz, 2022; Buluş, 2024). As shown in Table 1, the MAPE values reflect both good and reasonable levels of prediction. Additionally, the RMSE values, which range between 0.019587 and 0.022469, being close to zero, further validate the accuracy of the models. Additionally, in an ideal situation, MBE should be close to zero. This indicates that there is no systematic bias in the model's predictions, and that the predictions are generally linear. If the MBE value is positive, the model is overestimating; if it is negative, the model is underpredicting.

Another method that models the drying parameters of kiwi product was chosen as ANN in the study. The architecture of the ANN model is set to have 2 inputs, one output, 1 hidden layer and 25 neurons in the hidden layer. In this model, Levenberg-Marquardt was chosen as the training function used to perform the training process with experimentally obtained data.

Of the 712 experimentally obtained data – the same data sets as the ANFIS model – 95.8 % was reserved for training and the remaining 4.2 % was reserved for testing the trained network. The 95.8 % portion was used in the training phase, with 70 % for training, 15 % for validation and 15 % for testing.

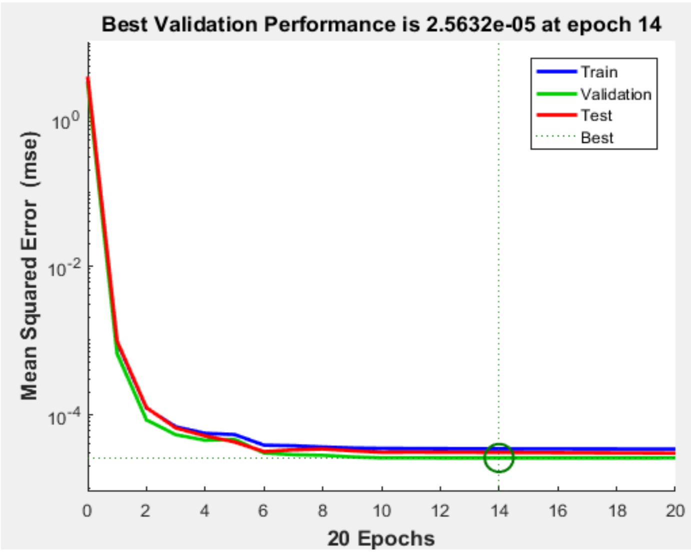

Figure 9. Validation performance of ANN

Although ANN training was set to 1000 epochs, the specified error threshold value was reached in the 20th epoch. When the validation performance is examined in Figure 9, it is seen that the best performance value is obtained in the 14th epoch as 2.5632×10^{-5}.

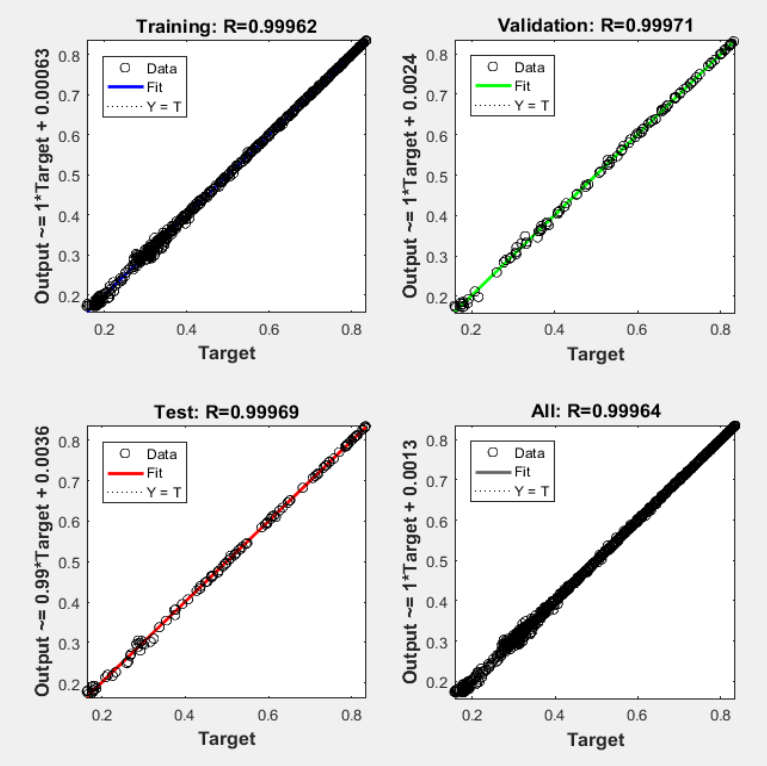

Figure 10. Regression graphs of the network

When the training regression graphs of the network (as seen Figure 10) were examined, it was seen that the results obtained from the graphs covering training, validation and testing were between 0.99962 - 0.99971. The fact that these values are very close to 1 indicates that the training of the network was successful. When the 4.2 % value that was not used in training the network and was allocated for testing was given to the network for predictions, the results in Table 2 were obtained.

Tabel 2. Correlation values of training and test dataset in ANN model

ANN		
Training	RMSE	0.005684
	MAPE	1.147826
	R^2	0.999890
	MBE	-0.000212
Test	**RMSE**	0.009842
	MAPE	3.591697
	R^2	0.998319
	MBE	0.001202
All	RMSE	0.005918
	MAPE	1.250798
	R^2	0.999876
	MBE	-0.00015285

Considering the values in Table 2, it can be seen that the ANN model performs the prediction process successfully.

4. Conclusions

In this study, we predicted moisture content (m) within a 90 W microwave system for kiwi using an ANFIS and an ANN model. The ANFIS model, which consists of 16 rules, provided accurate results using 712 data inputs, with 95.8 % (682 data points) allocated for training and 4.2 % (30 data points) for testing. The statistical results for RMSE, MAPE, R^2, and MBE were 0.022469, 9.522044, 0.991238, and -0.019312, respectively, indicating the accuracy of the test. Similarly, when the ANN model was examined, it was seen that these values were 0.009842, 3.591697, 0.998319 and 0.001202, respectively. When the values of the two models were compared with each other, it was determined that the ANN model gave slightly better results, while the ANFIS model also achieved successful results. The primary goal of these predictive models is to reduce the number of tests required in future drying processes. Additionally, it will facilitate the prediction of various other parameters within the drying system.

In this manuscript, the drying process of kiwi fruit was modeled using two widely used artificial intelligence techniques. The modeling process demonstrated a high degree of accuracy. Based on this information, the drying processes of different products can also be modeled in a similar manner, thereby reducing experimental costs. Furthermore, similar studies can be conducted using different artificial intelligence methods.

Declaration of Author Contributions

The authors declare that they have contributed equally to the article. All authors declare that they have seen/read and approved the final version of the article ready for publication.

Declaration of Conflicts of Interest

All authors declare that there is no conflict of interest related to this article.

References

Acar, B., Dağdeviren A., Özkaymak M., Guinaleh, A.R., 2023. Freeze drying process of kiwi slices with various thicknesses and investigation drying characteristic of process, *Journal of Polytechnic*, 26(1): 415-423.

Akal, D., Çelen, S., Kahveci, K., Akyol, U., 2014. An Experimental study on microwave drying behavior of kiwi, *Materials, Methods and Technologies*, 8: 449-456.

Ali, N.S., Mohd-Yusof, K., Othman, M.F., Latip, R.A., Ismail, M.S.N., 2019. Adaptive neuro fuzzy İnference system (ANFIS) modelling for quality estimation in palm oil refining process, *Journal of Mechanical Engineering*, 8(1): 36-47.

Bakar, M.A.A., Ghani, A.T.A., Abdullah, M.L., Ismail, N., Aziz, A.S., 2022. Adaptive neuro-fuzzy inference system (ANFIS) formulation to predict students' neuroscience mechanistic: a concept of an ıntelligent model to enhance mathematics learning ability, *TEM Journal*, 11(4): 1942-1951.

Beşirik, B.A., 2016. A case study on predicting trading decisions in the cryptocurrency market using fuzzy logic and fuzzy artificial neural networks (ANFIS) techniques, Master Thesis, Dokuz Eylül University, Institute of Natural and Applied Sciences, İzmir.

Bulus, H.N., 2024. Adaptive neuro-fuzzy inference system and artificial neural network models for predicting time-dependent moisture levels in hazelnut shells (*Corylus avellana L.*) and prina (*Oleae europaeae L.*), *Processes*, 12: 1703.

Çelen S., Arda S.O., Karataşer M.A., 2018. Modeling of drying behavior using microwave conveyor dryer assisted solar energy, *El-Cezerî*. 5: 267-271.

Darıcı, S., Şen, S., 2012. Kivi meyvesinin kurutulmasında kurutma havası hızının kurumaya etkisinin incelenmesi, *Tesisat Mühendisliği*, 130, 51-58.

Darvishi, H., Mohammadi, P., Azadbakht, M., Farhudi, Z., 2018. Effect of different drying conditions on the mass transfer characteristics of kiwi slices, *Journal of Agricultural Science and Technology*. 20: 249-264.

Demirci, E., 2020. Anfis and natural gas request estimated; the case of Turkey. *International Journal of Social Sciences Academy*, (3): 495-511.

Habashy, D.M., Lebda, H.I., 2022. Comparison between artificial neural network and adaptive neuro-fuzzy ınference system for the baryon-to-meson ratios in proton-proton collisions, arXiv:2209.12709.

Kacar, İ., Korkmaz, C., 2022. Prediction of agricultural drying using multi-layer perceptron network, long short-term memory network and regression methods, *Gümüşhane University Journal of Science and Technology*, 12(4): 1188-1206.

Kaplan, R., 2019. Artificial neural networks method and a research on forecasting economics indicators, Master's Thesis, Dokuz Eylul University, Institute of Natural and Applied Sciences, İzmir.

Karabulut, M., 2024. An application in Red Crescent businesses for predicting breakage risks in supply chains using artificial intelligence methods, PhD Thesis, İnönü University, Institute of Natural and Applied Sciences, Malatya.

Kaya, A., Aydın, O., Dincer, I., 2008. Experimental and numerical investigation of heat and mass transfer during drying of Hayward kiwi fruits (*Actinidia Deliciosa Planch*), *Journal of Food Engineering,* 88: 323–330.

Kaynar, O., Zontul, M., Demirkoparan, F., 2010. Crude oil price forecasting by using ANFIS. *Journal of Anadolu Bil Vocational School of Higher Education*, 17: 3–14.

Khazaei, N.B., Tavakoli T., Ghassemian H., Khoshtaghaza M.H., Banakar A., 2013. Applied machine vision and artificial neural network for modeling and controlling of the grape drying process. *Computers and Electronics in Agriculture*. 98: 205–213.

Mousavifard, S.M., Attar, M.M., Ghanbari, A., Dadgar, M., 2015. Application of artificial neural network and adaptive neuro-fuzzy inference system to investigate corrosion rate of zirconium-based nano-ceramic layer on galvanized steel in 3.5% NaCl solution. *Journal of Alloys and Compounds*, 639: 315-324.

Levent, M., 2023. Modeling of drying processes with fuzzy logic and artifical neural network methods, MSc. Thesis, Institute of Natural and Applied Sciences, Tekirdağ Namik Kemal University, Tekirdağ.

Levent, M., Buluş, H.N., Moralar, A., Çelen, S., 2023. Fındık kabuğu kurutma parametre tahmininde yapay sinir ağı modellerinin karşılaştırılması, Bilgisayar ve Elektronik Bilimlerinde Güncel Gelişmeler 2, Iksad Publishing House, Ankara, 24-46.

Oğuz Erenler, G., 2023. Prediction of wind power with fuzzy logic and artificial neural networks, MSc Thesis, Institute of Natural and Applied Sciences, Tekirdağ Namik Kemal University, Tekirdağ.

Putra, V.G.V., Mohanad, J.N., 2023. Adaptive neuro-fuzzy inference systems (ANFIS) and artificial neural networks (ANNs) for optimizing electrospun PVA/TIO2 fiber diameter, *The Journal of The Textile Institute*, 114(12): 1898-1908.

Solichin, A., Saputri, F.H., 2021.An adaptive neuro-fuzzy inference system (ANFIS) method for recommending employee mutations in a manufacturing company, *Journal of Physics: Conference Series.* 1908 012016.

Şencan, D., Şencan Şahin, A., 2022. Forecasting GDP in Türkiye using Anfis method. *Kafkas University Journal of Economics and Administrative Sciences Faculty*, 13(26): 953–71.

Şevik, S., Aktaş, M., Özdemir, M.B., Doğan, H., 2014. Modeling of drying behaviors of mushroom in a solar assisted heat pump dryer by using artificial neural network. *Journal of Agricultural Sciences.* 20: 187-202.

Sonmez, A.Y., Kale, S., Ozdemir, R.C., Kadak, A.E., 2018. An adaptive neuro-fuzzy inference system (ANFIS) to predict of cadmium (cd) concentrations in the Filyos River, Turkey, *Turkish Journal of Fisheries and Aquatic Sciences,* 18:1333-1343.

Taşova, M., Erdoğan, M., Başakın, E.E., 2020. Determination of drying machine potential by different estimation methods, *Yuzuncu Yil University Journal of the Institute of Natural and Applied Sciences*, 25(2): 49-55.

Tektaş, A., Karataş, A., 2004. Yapay sinir ağları ve finans alanına uygulaması: Hisse senedi fiyat tahminlemesi, *Journal of Economics and Administrative Sciences*, 18(3-4): 337-349.

Tınmaz Köse, E., Çelen, S., Çelik, S.Ö., 2019. Conventional and microwave drying of hydrocarbon cutting sludge, *Environmental Progress & Sustainable Energy*, 38(4): 1-7.

Turan, T., Turan, G., Köse, U., 2022. Prediction of the Covid-19 number of death in Turkey by adaptive neuro-fuzzy ınference system and artifical neural networks. *Journal of Information Technologie*s, 15(2): 97–105.

Walia, N., Singh, H., Sharma, A., 2015. ANFIS: Adaptive neuro-fuzzy inference system- a survey, *International Journal of Computer Applications*, 123(13): 32-38.

To Cite	Bulus, H.N., Celen, S., 2025. Prediction of Moisture Content in Kiwi (*Actinidia deliciosa*) Dried Using Machine Learning Approaches. *ISPEC Journal of Agricultural Sciences*, 9(1): 74-88. DOI: https://doi.org/10.5281/zenodo.14564833.