

Experimental Evaluation and Modeling of Strawberry Slices Drying Kinetics Based on Machine Learning

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Abstract: The research explores the drying kinetics of strawberry slices (5 mm thick with initial moisture content of 88.04% wb) through the application of both traditional mathematical models and advanced machine learning method. The study aims to optimize the drying process by examining the effects of variables such as temperature, air velocity, and drying duration. Traditional models, derived from Fick's Second Law and Newton's Law of Cooling, were compared with artificial neural networks (ANN) and recurrent neural networks (RNN) to predict moisture content during the drying process. Ten network models were formed, and each model had three "hidden" layers with 20, 30, and 40 nodes in each layer. Findings revealed that RNN models, particularly RNN04, surpassed traditional models in accuracy, with a maximum deviation of up to 2% from experimental data. RNN models showed lower deviations in the range of 0.65% to 2%, while the ANN models had deviations in the interval of 2.6% to 5.6%. The ANN and RNN models included parameters like temperature, air flow speed, and drying time, with RNN models exhibiting superior adaptability and precision. These results indicate that machine learning approaches, especially RNNs, can greatly improve the understanding and management of the drying process, providing more precise and efficient methods for the drying industry.

Keywords: artificial neural networks; drying kinetics; machine learning; mathematical modelling; recurrent neural networks; strawberry slices

1 INTRODUCTION

Drying is one of the oldest techniques for preserving food, and even today, convective drying remains one of the most commonly used methods in industry due to its simplicity. However, the relatively high temperatures to which the wet material is exposed, and the long drying times can lead to undesirable effects such as nutrient degradation, and changes in colour and shape [1, 2]. Pre-treatment applications can shorten the process time [3]. The choice of the shape of the drying material can also strongly influence the drying process and the quality of the end product. In this context, dried fruit and vegetable slices have become increasingly popular in recent years and have also found their place on the market as healthy snacks.

To understand the complex phenomena of mass and energy transfer that occur during convective drying between a hot air flow (acting as a working fluid) and a moist material, methods to determine the kinetics of drying by establishing functional relationships between drying time and moisture ratio are commonly used [4, 5]. Mathematical models and simulations of drying curves are very important tools for controlling the process itself and for determining the quality of the final product, attracting the interest of researchers for years and even in recent research on fruit drying [6, 7]. Theoretical models involve sets of differential equations that account for internal moisture movement mechanisms, external conditions, and material properties, making them challenging to solve. Simpler, semi-empirical models are derived either from Fick's Second Law of Diffusion or Newton's Law of Cooling.

Well-known mathematical formulations have so far been applied to many studied samples, representing the entire drying process through the dependence of moisture content on drying time, considering the shape and type of wet material and drying mode. The application of artificial intelligence and machine learning methods offers the possibility of investigating the kinetics of drying using a larger number of parameters, thus obtaining more universal

models [8-10]. In addition to numerical simulations, machine learning can also include image recognition tests that allow for a broader range of analyses of the drying process.

The aim of the research is to select machine learning methods that are best suited for drying processes, such as artificial neural networks and recurrent neural networks [11-13]. The optimization of these techniques, based on their hyperparameters, aims to select the most suitable machine learning technique that can generalize the process of drying fruit slices [14].

Strawberries are highly valued by consumers in any form, whether fresh or processed, especially for their nutritional properties. The strawberry is a perennial herbaceous plant from the rose family (Rosaceae). Research in this area mainly focuses on nutritional and functional properties or quality attributes of fruit slices during drying [15, 16]. According to earlier studies, strawberry slices with a thickness of 5 mm were convectively dried in a temperature range of 50-80 °C and an air flow velocity of 0.5-1.5 ms⁻¹, with or without pre-treatment, over a time interval of 300 min to over 1000 min [17-19]. The aim of this study is to optimize the input parameters of the air flow to shorten the drying time and thus avoid undesirable microbiological processes that can occur in wet material.

2 MATERIALS AND METHODS

2.1 Materials

The Aprica strawberry variety, characterized by larger fruits, an intense red colour, and a drier texture, was used in the experiment. Fresh strawberries, cooled to an ambient temperature of 20 °C, were cut into 5 mm thick slices. The initial mass of the samples used in all experiments was 150 g of fresh strawberries. The initial moisture content was determined gravimetrically according to the standard method of drying at 105 °C at 24-hour intervals.

2.2 Drying Equipment

For the purposes of the experiments, the experimental dryer shown in Fig. 1 was used. The experimental dryer is divided into 15 sections. Air is pushed through the installation by a centrifugal fan (section 1) and heated in section 4. The temperature of the hot air is regulated by a PID thermo-regulator. The experimental dryer includes an air recirculation system located in section 14. However, during all measurements, the installation operated with 100% fresh air, without recirculation. The experiments were carried out in chamber 5 [20].

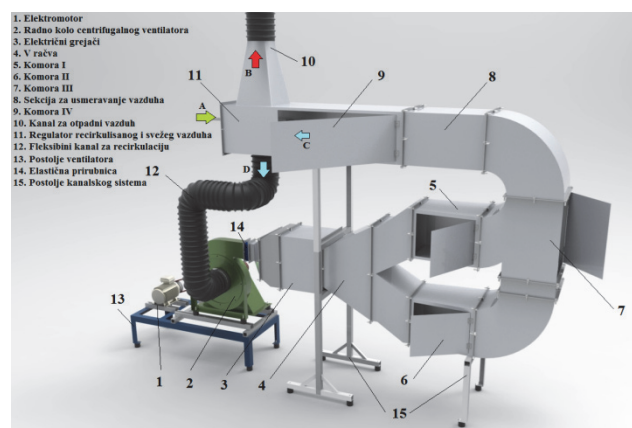


Figure 1 Experimental dryer by sections [20]

The mass change of the material was recorded at 5-minute intervals using a balance placed beneath the drying chamber. The balance used was a *KERN & Sohn, KB 3600-2N* with an accuracy of ± 0.01 g. The hot air temperature was measured and regulated by a PID thermo-regulator (REX C-100) with an accuracy of ± 0.1 °C, and the thermocouple also had an accuracy of ± 0.1 °C. The air velocity was adjusted using a frequency regulator attached to a fan, and it was set to 1.5 ms^{-1} and 3.5 ms^{-1} for all temperature regimes. The air velocity was verified by the hot wire anemometer *AirflowTM TA35* with an accuracy of $\pm 0.05 \text{ ms}^{-1}$. The temperatures of the hot air during the drying process ranged between 50 and 70 °C. The experiments are numbered as presented in Tab. 1, detailing the drying time and drying parameters.

Table 1 Performed drying experiments

Experiment	Temperature / °C	Air velocity / m/s	Drying time / min
E5015	50	1.5	335
E5035	50	3.5	235
E6015	60	1.5	275
E6035	60	3.5	215
E7015	70	1.5	255
E7035	70	3.5	175

2.3 Mathematical Modelling of Drying Curves

Mathematical models, commonly used for fruit and vegetable drying, were applied to describe the drying kinetics of strawberry slices. The dimensionless moisture ratio (MR) was plotted against experiment time to obtain the experimental curve. Then, drying curves were fitted to semi-empirical models as presented in Tab. 2. The correlating parameters in these models consider external conditions, such as hot air velocity, temperature, and

relative humidity, as well as internal mechanisms of moisture transport through the material.

Table 2 Drying models

Model	Equation	Ref.
Page	$MR = \exp(-k \cdot t^n)$	[21]
Wang and Sing	$MR = a \cdot t^2 + b \cdot t + c$	[22]
Modified Page Equation	$MR = \exp(-(k \cdot t)^n)$	[23]
Logarithmic	$MR = a \cdot \exp(-k \cdot t) + c$	[24]
Henderson and Pabis	$MR = a \cdot \exp(-k \cdot t)$	[25]

In the thin layer drying model, the rate of change of the material moisture content during the phase of decreasing drying rate is proportional to the actual difference between the moisture content of the material and the expected equilibrium moisture content. Assuming that the layer of wet material is thin enough or the air velocity is high, the conditions of the hot air flow (humidity and temperature) are kept constant over the entire surface of the material during the flow. The values for the moisture ratio can be determined from Eq. (1) [26]:

$$MR = \frac{(M_t - M_e)}{(M_o - M_e)} \quad (1)$$

where are: M_t is the moisture content at any given time (kg water/ kg solids), M_e is equilibrium moisture content (kg water/kg solids), M_o is the initial moisture content.

Three different criteria were used for evaluation of the fit: correlation coefficient (R^2), Mean Square Error (MAE), and Root Mean Square Error (RMSE) [27]:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (3)$$

$$RMSE = \sqrt{\sum_{i=1}^n \left[\frac{(\hat{y}_i - y_i)^2}{n} \right]} \quad (4)$$

where are: $\hat{y}$ is the predicted value, y is the measured value, $\bar{y}$ is the mean of measured variables, n is the number of data points.

2.4 Artificial Intelligence (AI) Models

Machine learning (ML) is a subset of artificial intelligence (AI) based on the development of computer algorithms that can automatically improve through experience with large data sets. In simple terms, ML models enable computers to learn from existing data and make predictions or classify data based on that information [28-32].

In traditional programming, a computer follows written instructions to solve a specific problem. In ML,

however, the computer is given data sets from which it must deduce how to make connections between the data and solve the problem. For example, if we want the computer to recognize an image, it does not need explicit instructions on what is in the image. Instead, the computer must create an algorithm based on a large number of images of the same concept to guess what is in the image, even if it has not seen it before [33].

Artificial Neural Networks (ANN) are ML algorithms designed to solve models of complex patterns and make decisions in a way similar to the functioning of the human brain. The human brain processes received data through neurons, which enable us to recognize our environment. Unlike natural neurons, ANNs are designed from connected processing elements-nodes that simulate biological neurons and primarily function to learn patterns from large amounts of data during the training process. The type of training configures a specific ANN for tasks such as image recognition, speech recognition, data classification, or establishing different types of regression. The main advantage of ANN is its application in highly non-linear systems with complex relationships between variables. ANN includes adaptive learning, where the algorithm learns from a set of training data and creates a representation of information based on it [34]. Specifically, in the case of standard mathematical models describing drying kinetics, the ANN model can include more information such as temperatures, drying speed, shape and thickness of the wet material, and type of material, among others [35].

ANNs are composed of collections of nodes, which are arranged in at least three layers: input layer, "hidden" layer, and output layer. ANNs can have more than one "hidden" layer in relation to the input and output layers. The output layer can also have more than one parameter. The learning process is based on the fact that each node in the ANN network has its own linear regression model, composed of input data, weights, bias, and output data. Once the input layer is determined, weights are associated with each node. Weights help in determining the importance of any given variable in terms of how significantly they contribute to the output data compared to other variables. All inputs are then multiplied by their respective weights and summed. After that, the output is passed through an activation function, which determines the output. If that output exceeds a given threshold, it activates a node, passing the data to the next layer in the network. In this way, the output of one node becomes the input of the next node. This process of transferring data from one layer to the next layer defines this neural network as a feed-forward network.

The aim of this study is to compare ANN and RNN algorithm models with the same node structure and the same number of epochs to improve adaptability to drying kinetics modeling. Ten network models were formed (Tab. 3), with the structure shown in Fig. 2. Each model has three "hidden" layers, with 20, 30, and 40 nodes in each layer, respectively. The number of iterations was set to 150, 200, and 250, respectively. The input layer was set with three nodes: current drying time (τ), temperature (t), and air flow speed (v). The output layer has one node - MR. The available data set, obtained from previous measurements, was first preprocessed with standard scaling and then divided into training and test data sets in an 80:20 ratio.

Models were trained with the training data, and model validation was performed with the test data. The learning rate for the ANN model is set to a value of 0.0002 in all models. The performance measure is determined in the same way as in the case of standard mathematical models by Eqs. (2) to (4).

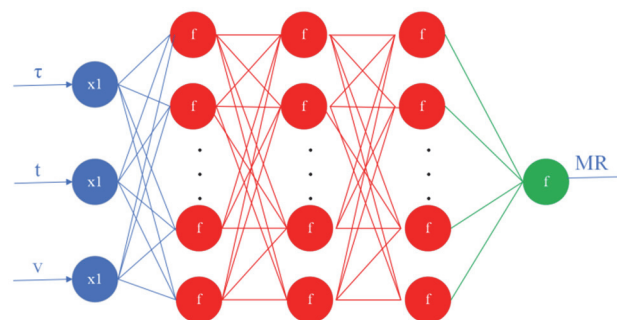


Figure 2 Neural network structure

3 RESULTS AND DISCUSSION

The ANN and RNN models from Tab. 3 employed a multi-layer perceptron network with three hidden layers. Considering the RNN layers have a "tanh" activation function, for a more precise analysis, the ANN models in their hidden layers also have a "tanh" activation function. The output layer is composed of one node, and a linear activation function is applied to it. The model's complexity and effectiveness in predicting moisture ratio versus drying time were assessed by varying the number of nodes in the hidden layer and the number of epochs, as detailed in Tab. 4.

Table 3 Performed ANN | RNN models

Model	Nodes	Trainable parameters	Epochs
RNN01	3×20	2101	150
RNN02	3×30	4651	150
RNN03	3×40	8201	150
RNN04	3×40	8201	200
RNN05	3×40	8201	250
ANN01	3×20	2201	150
ANN02	3×30	4801	150
ANN03	3×40	8401	150
ANN04	3×40	8401	200
ANN05	3×40	8401	250

Table 4 Evaluation metrics for performed ANN | RNN models

Model	R^2	MAE	RMSE
RNN01	0.9753	0.0023	0.0480
RNN02	0.9809	0.0018	0.0422
RNN03	0.9887	0.0010	0.0324
RNN04	0.9952	0.0004	0.0212
RNN05	0.9902	0.0019	0.0305
ANN01	0.9521	0.045	0.0668
ANN02	0.9390	0.0057	0.0753
ANN03	0.9462	0.0050	0.0708
ANN04	0.9592	0.0038	0.0616
ANN05	0.9690	0.0029	0.0537

From Tab. 3, it can be seen that RNN models with the same number of nodes in hidden layers have a smaller number of trainable parameters, which significantly affects the time required for training within each epoch. Although the data processing time itself is not an influential parameter, the efficiency of the model ultimately has an impact. Based on the evaluation metrics shown for all

models in Tab. 4, the advantage of the RNN model over the ANN model can be seen. For each model that has the same number of nodes in the hidden layer, the RNN model shows better performance than the ANN model, with improvements ranging from 2.2% to 4.3%. The RNN04 model proved to be the best model according to the evaluation criteria and was selected for further analysis of the drying kinetics.

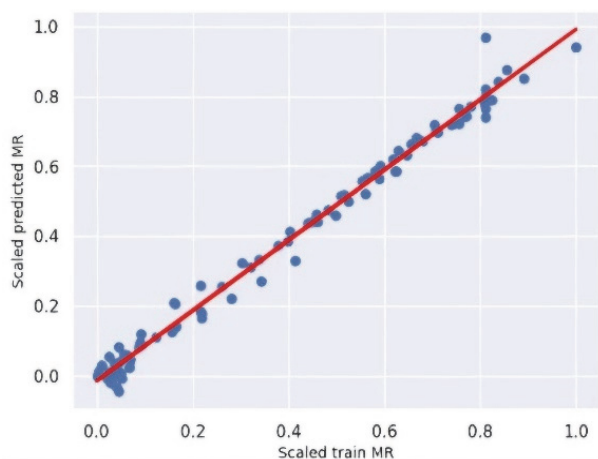


Figure 3 The relationship between training and predicted data

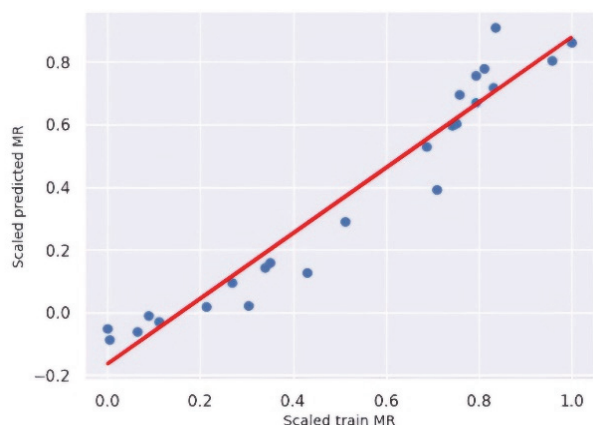
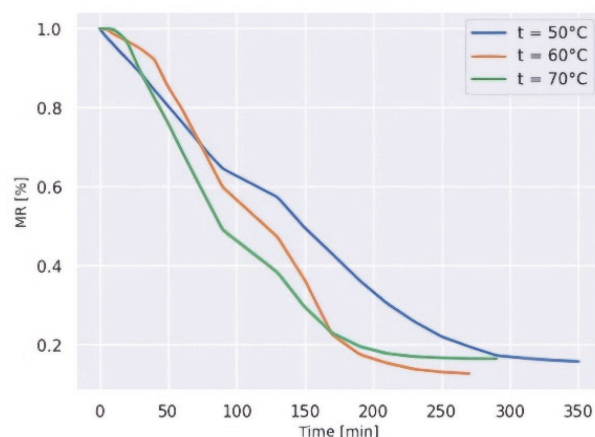


Figure 4 The relationship between test and predicted data

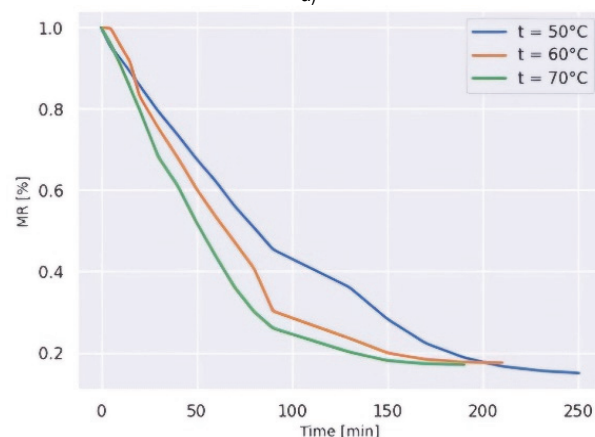
The RNN04 model showed the best evaluation metrics between training and predicted data (Fig. 3). A slightly weaker fit between test and predicted data (Fig. 4) is the result of a smaller number of test data. However, the trend of dependency between the data is still easily recognizable in Fig. 4. Compared to the selected RNN04, the other RNN models showed lower deviations in the range of 0.65% to 2%, while the ANN models had deviations in the interval of 2.6% to 5.6%. These results also demonstrate the advantage of using RNN networks in drying models compared to standard ANN models.

The initial moisture content (M_0) was 1.14 ± 0.01 kg water per kg of dry matter (88.04% wb). The equilibrium moisture content (M_e) depended on the drying regime and was 13.9% per kg wet basis. Fig. 5 shows all experimental MR - time curves for air flow speeds of 1.5 ms^{-1} (a) and 3.5 ms^{-1} (b). The experiments with higher air flow speed showed a greater response to changes in drying regimes, resulting in more stable drying. Higher drying temperatures indicate shorter drying times. However, from Fig. 4, it can be clearly seen that drying takes place in the falling rate period.

The lower instability observed in the curves for the lower air flow rate can be explained by the slower drying rate.



a)



b)

Figure 5 MR - time drying curves depending on air flow speed



a)



b)

Figure 6 Strawberries before and after drying

Fig. 6 shows the fresh (a) and dried (b) strawberries. It can be concluded that the samples exhibit less shrinkage during the drying process, despite the small thickness of the sample. Shrinkage causes rupture of the tissue, allowing more bound moisture to be exposed to the hot air. The colour of the samples became more intense after drying, suggesting that the material has retained much of its sensory properties.

Fig. 7a, b, c shows the fitting of experimental curves to the mathematical models given in Tab. 2 for an air flow speed of 3.5 ms^{-1} .

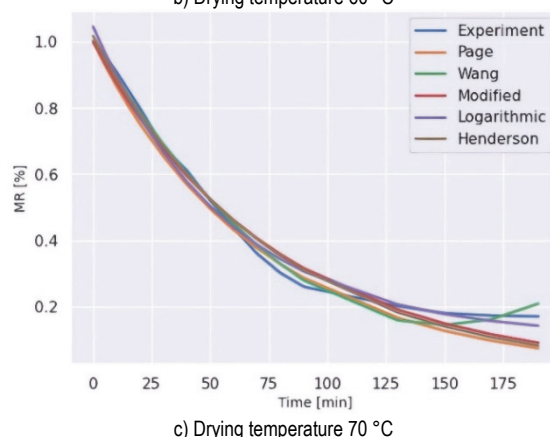
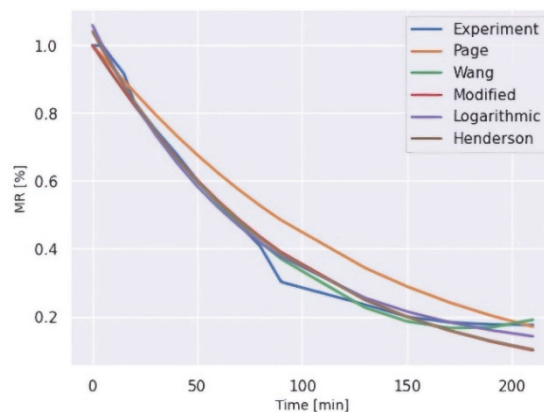
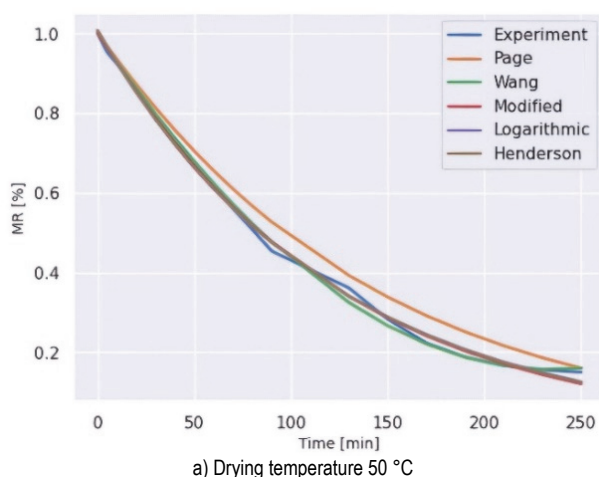


Figure 7 Drying kinetics of strawberry slices for air flow speed 3.5 ms^{-1}

Table 5 Evaluation metric for drying experiments and RNN04 model

Experiment	Model	R^2	MAE	RMSE
E5015	Page	0.9090	0.0642	0.2534
	Wang and Sing	0.9969	0.0030	0.0169
	Modified Page	0.9964	0.0003	0.0183
	Logarithmic	0.9952	0.0004	0.0210
	Henderson and Pabis	0.9919	0.0007	0.0274
	RNN04	0.8987	0.0133	0.1151
E5035	Page	0.9812	0.0016	0.0404
	Wang and Sing	0.9982	0.0002	0.0123
	Modified Page	0.9981	0.0002	0.0130
	Logarithmic	0.9979	0.0002	0.0134
	Henderson and Pabis	0.9979	0.0002	0.0084
	RNN04	0.9398	0.0133	0.1151
E6015	Page	0.8174	0.2703	0.5200
	Wang and Sing	0.9188	0.0121	0.1099
	Modified Page	0.9557	0.0066	0.0812
	Logarithmic	0.9766	0.0035	0.0590
	Henderson and Pabis	0.9684	0.0047	0.0685
	RNN04	0.9121	0.0112	0.1061
E6035	Page	0.9343	0.0061	0.0778
	Wang and Sing	0.9918	0.0007	0.0274
	Modified Page	0.9846	0.0014	0.0378
	Logarithmic	0.9910	0.0008	0.0289
	Henderson and Pabis	0.9874	0.0012	0.0341
	RNN04	0.9200	0.0108	0.1041
E7015	Page	0.9054	0.1005	0.3171
	Wang and Sing	0.9807	0.0022	0.0466
	Modified Page	0.9829	0.0019	0.0438
	Logarithmic	0.9887	0.0013	0.0356
	Henderson and Pabis	0.9884	0.0013	0.0081
	RNN04	0.9250	0.0108	0.1040
E7035	Page	0.9773	0.0019	0.0442
	Wang and Sing	0.9944	0.0005	0.0222
	Modified Page	0.9831	0.0019	0.0385
	Logarithmic	0.9923	0.0007	0.0261
	Henderson and Pabis	0.9836	0.0014	0.0380
	RNN04	0.9243	0.0097	0.0982

Evaluation metrics for mathematical models of strawberry slices drying kinetics, along with the results of the selected RNN04 model, are shown in Tab. 5. The Page model exhibited slightly lower deviations in the range of 6.9% to 16.13% compared to the other selected models for temperature regimes of 50 °C and 60 °C, even at higher air flow speeds. This leads to the conclusion that drying temperature also has a significant effect, especially for thin samples such as fruit or vegetable slices. For a temperature of 70 °C, all selected models showed almost identical agreement.

To establish the quality of the RNN model in predicting drying kinetics, each of the drying experiments was run through the selected RNN04 model. The results of the dependence of the experimental data on the data predicted by the RNN network are shown in Fig. 8 (a-f).

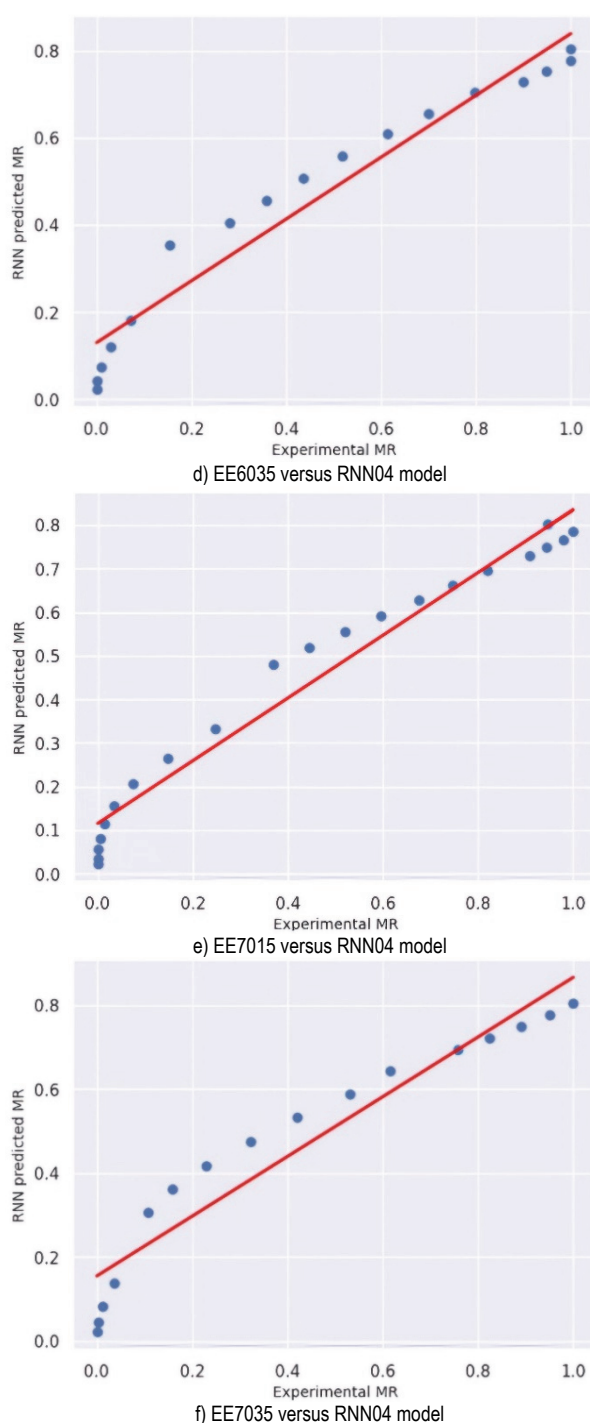
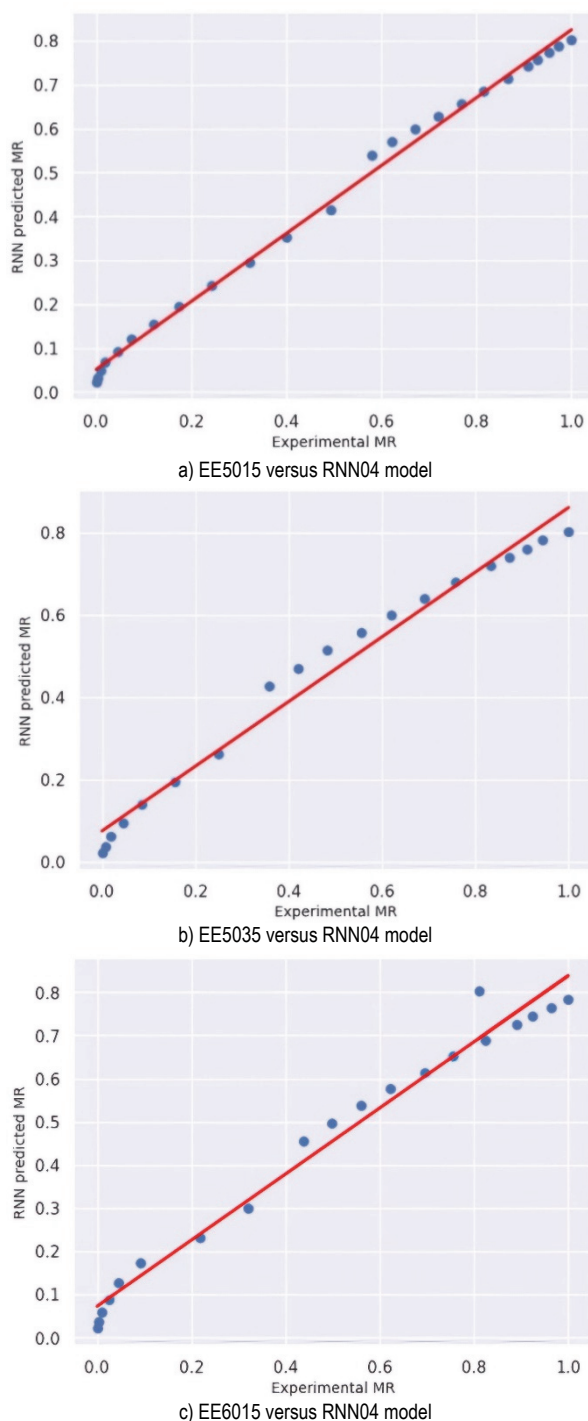


Figure 8 The relationship between experimental and RNN04 predicted data

4 CONCLUSIONS

This research considered the drying kinetics of strawberry slices in two ways: using well-known mathematical formulations and applying artificial neural networks (ANN) and recurrent neural networks (RNN). The goal was to establish the quality of the application of ANN and RNN networks in drying processes. In addition to the dependence of the moisture ratio on drying time, the drying parameters themselves were included. The experiments showed that the time and intensity of drying are highly dependent on the selected drying temperature and air flow speed.

Mathematical formulations showed very good agreement with experimental data, except for the Page

mathematical model, which exhibited deviations in the range of 6.9% to 16.3%. The reason for this deviation can be explained by the smaller number of sampled data, because the time of data sampling in all experiments was identical.

The advantage of neural networks lies in their ability to include many parameters of different structures in the model description. In addition to numerical data, categorical values and visual data can also be included, in which neural networks have proven to be extremely efficient. The inclusion of drying parameters, and possibly in future analyses, the physico-chemical characteristics of the wet material, its shape, and dimensions, can cover the drying kinetics in a broader way and systematize it for groups of related materials being dried. This research demonstrated the application of ANN and RNN networks in modelling drying kinetics. The selected RNN model showed good agreement with predicted data and experimental data, with a maximum deviation from measured data of up to 2%, indicating that such models can be effectively applied for the analysis of the drying process. Compared to the selected RNN04, the other RNN models showed lower deviations in the range of 0.65% to 2%, while the ANN models had deviations in the interval of 2.6% to 5.6%.

The trend of dependence between the experimental data and that predicted by the model is similar across all experiments. The best fit was shown by EE5015 compared to the ML model, which can be explained by smaller changes in the moisture content of the material at lower drying temperatures and lower air flow speeds. In contrast, moisture transfer is more intense in the other models at higher temperatures and air flow speeds. The deviations that occurred, especially for models EE7015 and EE7035, can be explained by the smaller number of sampled data during the drying process itself, given that the data in all experiments were sampled at the same time intervals.

The ANN and RNN models might be used to evaluate the drying time with great accuracy based on initial drying parameters. Therefore, process parameters, such as energy consumption, could be also evaluated, which could lead to optimization of the drying process and reduction of costs on industrial scale drying.

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