ARTIFICIAL NEURAL NETWORK FOR OPTIMIZING THE CONVECTIVE DRYING PROCESS OF PEAR SLICES / *REŢEA NEURALĂ ARTIFICIALĂ PENTRU OPTIMIZAREA PROCESUL DE USCARE CONVECTIVĂ A FELIILOR DE PERE*

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ABSTRACT

This study develops an artificial neural network (ANN) model to optimize the convective drying process of pear slices. Experimental data from drying at 50°C, 60°C, and 70°C were used to train an ANN with three hidden layers. The model predicted drying rate with high accuracy (98.823% validation fidelity), capturing the nonlinear relationship between moisture content, time, and drying rate. Results demonstrated that higher temperatures accelerated drying but required careful control to maintain quality. The ANN effectively identified optimal drying parameters, balancing energy efficiency and product quality preservation, providing a valuable tool for industrial drying process optimization.

REZUMAT

Acest studiu dezvoltă un model de rețea neurală artificială (ANN) pentru optimizarea uscării convective a feliilor de pere. Date experimentale de la uscarea la 50°C, 60°C și 70°C au fost folosite pentru antrenarea unei ANN cu trei straturi ascunse. Modelul a prezis viteza de uscare cu precizie ridicată (98,823% fidelitate de validare), capturând relația neliniară dintre umiditate, timp și viteză. Rezultatele au arătat că temperaturile mai mari accelerează uscarea, dar necesită control atent. ANN-ul a identificat parametrii optimi, echilibrând eficiența energetică și calitatea produsului, oferind un instrument valoros pentru optimizarea procesului industrial de uscare.

INTRODUCTION

Convective drying remains one of the most extensively utilized preservation techniques in the global food industry, particularly for perishable commodities like fruits and vegetables, which are subject to significant seasonal and geographical production constraints *(Sagar and Kumar, 2010)*. The core objective of this process is the controlled removal of moisture to a level that ensures microbial stability, thereby extending the product's shelf life. However, the challenge extends far beyond simple dehydration; it is equally critical to preserve the nutritional composition, color, texture, and overall sensory quality of the final product *(Sablani, 2006, Calín-Sánchez et al., 2022).* Traditional approaches to optimizing the drying process have historically relied on empirical models and first-principles physics-based formulations. While these methods provide a foundational understanding, they often fall short in capturing the highly complex, non-linear, and dynamic relationships that exist between key process parameters such as air temperature, velocity, and humidity and the evolving physical and chemical properties of the biological material *(Erbay and Icier, 2010).*

The inherent heterogeneity of biological matrices like pear slices, combined with the intricate interplay of heat and mass transfer phenomena during drying, creates a formidable barrier to developing universally applicable mathematical models *(Khan et al., 2022, Farid, 2019).* These classical models, often based on Fick's law of diffusion or other simplified assumptions, struggle to accurately predict drying behavior across diverse fruit and vegetable types and under varying operational conditions *(Kalantari et al., 2022).* This limitation has driven the search for more robust and flexible modeling tools capable of learning directly from experimental data without being constrained by a priori assumptions about the underlying physical mechanisms (*Lenart, 1996*).

In this context, Artificial Neural Networks (ANNs) have emerged as a powerful and versatile computational paradigm for modeling complex systems in food engineering *(Francik et al., 2024).* ANNs are data-driven, non-linear mapping functions inspired by the human brain's structure, which can learn intricate patterns and relationships from a set of input-output data pairs *(El-Mesery et al., 2025).* By leveraging experimental drying data, ANNs can effectively model the non-linear dynamics of the drying process, making them exceptionally well-suited for food drying applications where multiple interacting factors influence the final product quality *(Selvi et al., 2022).* The application of ANNs in convective drying offers significant potential for improving process efficiency, reducing energy consumption, and enhancing product quality through more precise prediction and control capabilities *(Đaković et al., 2023).*

One of the most immediate and valuable applications of ANNs in fruit drying is the accurate prediction of moisture content as a function of time, temperature, and other process variables. A well-trained ANN model would allow processors to anticipate the exact moisture content at any point during the drying cycle in real-time, without the need for disruptive and time-consuming offline measurements *(Tepe, 2024).* This capability is crucial for targeting specific, critical moisture levels required for optimal product stability, as different fruits have varying thresholds for microbial safety and quality preservation. Furthermore, ANNs can be used to model the instantaneous drying rate as a function of the current moisture content and process temperature, providing insights into the transition points between the constant-rate and falling-rate drying phases *(Kalsi et al., 2023).* This knowledge enables the development of more sophisticated, adaptive control strategies that can dynamically adjust process parameters to match the changing drying kinetics throughout the process, thereby preventing quality degradation from excessive heat exposure in the later stages.

The predictive power of ANNs extends to critical operational planning tasks. For instance, these models can reliably estimate the total drying time required to achieve a target moisture content at a specified set of drying conditions, which is essential for production scheduling and resource allocation in commercial operations *(Nguyen et al., 2025).* Conversely, they can also be used in an inverse manner to determine the optimal drying temperature and air velocity needed to reach a desired final moisture content within a predefined time frame, a common industry challenge that requires balancing throughput demands with stringent quality requirements *(Demir et al., 2023).* A particularly sophisticated application involves using ANNs to predict the critical moisture content, the point at which the drying rate begins its significant decline which is not a fixed value but varies with temperature and the specific physical structure of the fruit or vegetable being processed *(Das et al., 2018).*

Beyond basic process parameters, the true potential of ANNs lies in their ability to integrate moisture removal kinetics with final product quality outcomes. Advanced ANN models can be developed to predict key quality indicators-such as vitamin C retention, color change (ΔE), or textural hardness, based on the entire drying history *(Khan et al., 2022).* While such comprehensive models require a rich dataset that includes both drying kinetics and post-process quality analyses, they represent a paradigm shift from traditional time or energy – oriented optimization toward a holistic, quality driven process design optimization *(Asrate et al., 2025).* This approach is especially important for high-value fruits like pears, where even minor quality degradation during drying can significantly impact market value and consumer acceptance.

The ability of ANNs to interpolate accurately between tested experimental conditions and to modestly extrapolate to untested but approximate parameter ranges offers substantial practical and economic benefits for food processors *(Ming et al., 2021).* Rather than conducting extensive and costly new experiments for every new product variant or slight change in processing conditions, manufacturers can leverage validated ANN models to predict drying behavior for similar fruits and vegetables, drastically reducing product development time and resource expenditure *(Hossan et al., 2023).* This capability is increasingly valuable in a global food industry facing intense pressure to innovate, develop new dried products with optimized nutritional and sensory profiles, and simultaneously minimize energy consumption and environmental impact *(Spagnuolo et al., 2023).*

Ultimately, the integration of robust ANN based models into modern drying process control systems represents a clear pathway toward more intelligent, adaptive, and efficient food processing operations *(El-Mesery et al., 2025).* By enabling real-time prediction and dynamic adjustment of process parameters based on the current state of the product – which is also the aim of our study, these AI-driven models can help achieve the dual, and often competing, objectives of energy efficiency and superior product quality preservation that are central to the future of sustainable food manufacturing *(Yao et al., 2023).*

MATERIALS AND METHODS

To generate a robust experimental dataset for training the artificial neural network (ANN), a systematic series of convective drying experiments was conducted using the GUNT CE130 drying apparatus (GUNT Hamburg, Germany) as part of a structured research internship. The experimental protocol involved drying 1000 g batches of fresh pear slices (Pyrus communis L.), pre-cut to a uniform thickness of 3.0 mm using a precision slicer, as illustrated in Fig. 1. This standardization of slice thickness and initial mass ensured consistent starting conditions, a critical prerequisite for capturing reproducible drying kinetics and minimizing variability in the dataset. The CE130 convective drying system was configured with advanced process control and monitoring capabilities to ensure precise experimental conditions. Key components included a proportional-integral-derivative (PID) controller for maintaining channel temperature within ±0.5°C of the setpoint, an adjustable axial fan system for airflow regulation, and integrated sensors for real-time monitoring of channel temperature (accuracy: ±0.5°C) and relative humidity (accuracy: ±3% RH). A high-precision digital scale (KERN 440, Germany; resolution: 0.1 g) was located above the drying channel to continuously record mass loss of the pear samples, enabling detailed quantification of moisture ratio dynamics. All experimental parameters were controlled and logged via the manufacturer's proprietary software (CE130 v.16.1.3.4), which facilitated automated data acquisition at 5-minute intervals, thereby capturing high-resolution temporal profiles of the drying process.

Fig. 1 - Experimental setup of the GUNT CE130 convective dryer, including sample preparation, instrumentation, and data acquisition system

The experimental design incorporated three drying temperatures (50, 60, and 70 °C) at a constant hot air velocity of 2.0 m/s, selected to represent a range of industrially relevant conditions while elucidating the nonlinear thermal behavior of pear tissue. Each temperature condition was replicated several times to assess data reproducibility and statistical reliability. Prior to each trial, the drying channel was preheated to the target temperature, and ambient conditions (initial temperature: 22 ± 1 °C; relative humidity: 45 ± 5%) were recorded to account for environmental variability. The drying process was terminated when the pear slices reached a moisture content slightly below 15% (dry basis), a threshold determined through preliminary trials to balance product quality retention and energy efficiency.

Artificial neural network development training and validation. An artificial neural network (ANN) was developed and trained within Simcenter Amesim V2310 (Siemens Digital Industries Software) to model and optimize the convective drying kinetics of pear slices. The experimental dataset, acquired from the GUNT CE130 drying apparatus, was systematically partitioned into six subsets: three training datasets (TD_cd50C, TD_cd60C, TD_cd70C) and three validation datasets (VD_cd50C, VD_cd60C, VD_cd70C), corresponding to the three drying temperatures (50, 60, and 70 °C). Each dataset comprised time-resolved measurements of drying time [min], moisture content (u) [%], and drying rate (du/dt) [%/min], with the latter derived from numerical differentiation of moisture loss profiles. These variables were selected as critical inputs and outputs to capture the transient behavior of the drying process, where du/dt [%/min] serves as a direct indicator of process efficiency.

Data preprocessing and model ANN configuration. The training and validation subsets were imported into Simcenter Amesim via a structured file directory, ensuring traceability and reproducibility of data handling (Fig. 2). The ANN architecture was configured with three hidden layers (30, 20, and 10 neurons), each employing hyperbolic tangent (tanh) activation functions to model the nonlinear relationships between input variables and drying rate. This configuration was selected through iterative hyperparameter tuning to balance model complexity and generalization capability, minimizing overfitting while retaining sufficient capacity to capture the intricate dynamics of moisture diffusion and heat transfer in pear tissue.

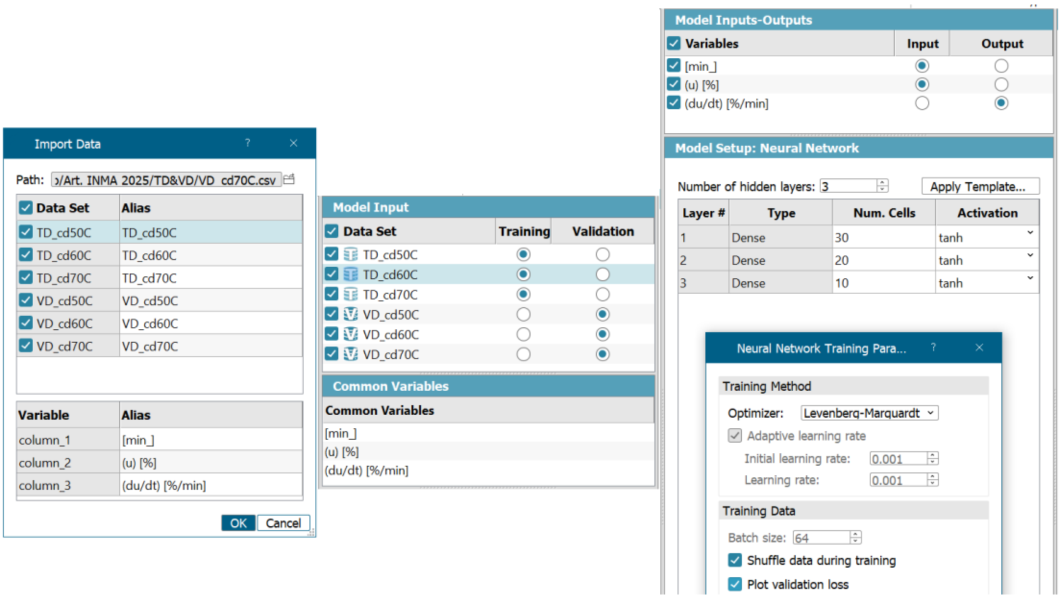


Fig. 2 - Software interface for ANN configuration, data partitioning, and training parameters in convective drying process optimization

Left: Data import and variable mapping for training (TD) and validation (VD) datasets (center) across 50°C, 60°C, and 70°C drying conditions. Right: ANN architecture (3 hidden layers with 30, 20, and 10 neurons) and input-output configuration (drying time and moisture content as inputs; drying rate as output). Right: Training parameters, including Levenberg-Marquardt optimization, adaptive learning rate, and batch size settings.

Training methodology and validation. The network was trained using the Levenberg-Marquardt (LM) optimizer, a robust algorithm well-suited for small-to-medium-sized datasets due to its rapid convergence and low computational overhead. Key training parameters included: adaptive learning rate (initial value: 0.001), dynamically adjusted during training to stabilize convergence; batch size: 64 samples, selected to balance gradient accuracy and training speed; data shuffling prior to each epoch to eliminate sequence bias; validation loss monitoring to prevent overfitting (Fig. 2, right panel).

ANN model design. The choice of du/dt as the primary output variable reflects its critical role in process optimization, as it directly quantifies the rate of moisture removal, a key metric for energy efficiency and product quality preservation. By focusing on this parameter, the ANN enables real-time prediction of drying dynamics, facilitating the identification of optimal operating parameters (e.g., temperature, airflow) that minimize energy consumption while avoiding thermal degradation of the fruit. The inclusion of drying time and moisture content as inputs ensures the model accounts for both temporal and state-dependent effects, providing a comprehensive representation of the drying process.

RESULTS

The experimental results of the convective drying process kinetics of pear slices across three temperature regimes (50°C, 60°C, and 70°C), establishing the empirical foundation for the artificial neural network model development. These systematic measurements capture the time-dependent moisture removal behavior and drying rate dynamics essential for understanding the physical mechanisms governing the drying process. The data reveals clear temperature-dependent patterns that demonstrate the trade-off between processing speed and potential quality implications, providing critical insights for subsequent optimization of the drying parameters. This characterization serves as the basis for training the ANN model that will ultimately identify the optimal drying conditions while preserving product quality.

Fig. 3 illustrate the temperature-dependent moisture content evolution during convective drying, with 70°C achieving 14.5% moisture content at 180 minutes compared to 260 minutes at 50°C. The sigmoidal drying curves (with 3 slopes) reveal the characteristic heating period followed by active drying and approach to equilibrium moisture content, with higher temperatures accelerating the entire process.

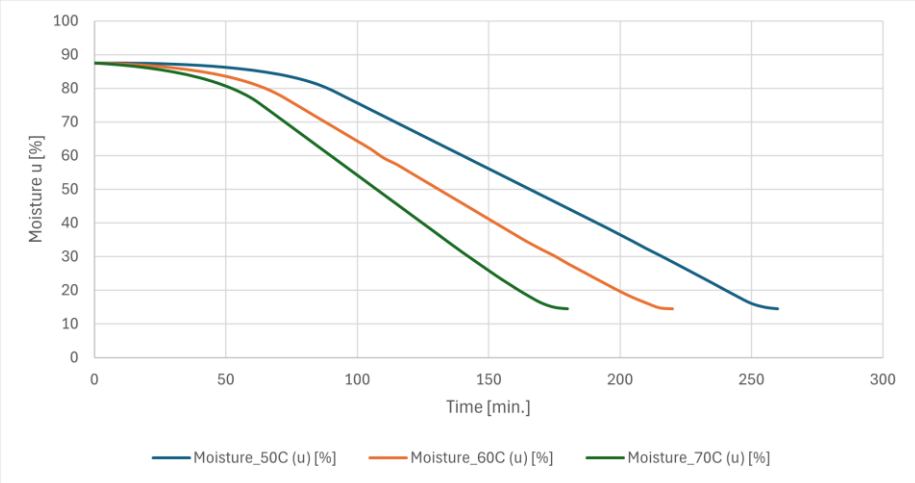


Fig. 3 - Moisture content evolution during convection drying of pear slices at 50°C, 60°C, and 70°C.

Fig. 4 presents the drying rate profiles showing temperature-dependent maximum rates of 0.57 %/min (70°C), 0.46 %/min (60°C), and 0.40 %/min (50°C), with first peak drying rate occurring progressively later as temperature decreases (70 minutes at 70°C, 75 minutes at 60°C and 95 minutes at 50°C). The curves exhibit the expected pattern of initial rate increase followed by a sharp decline, with higher temperatures reaching their maximum drying rates earlier and showing more pronounced falling rate periods. This information is essential for identifying the transition points between drying phases and optimizing energy input timing during the process.

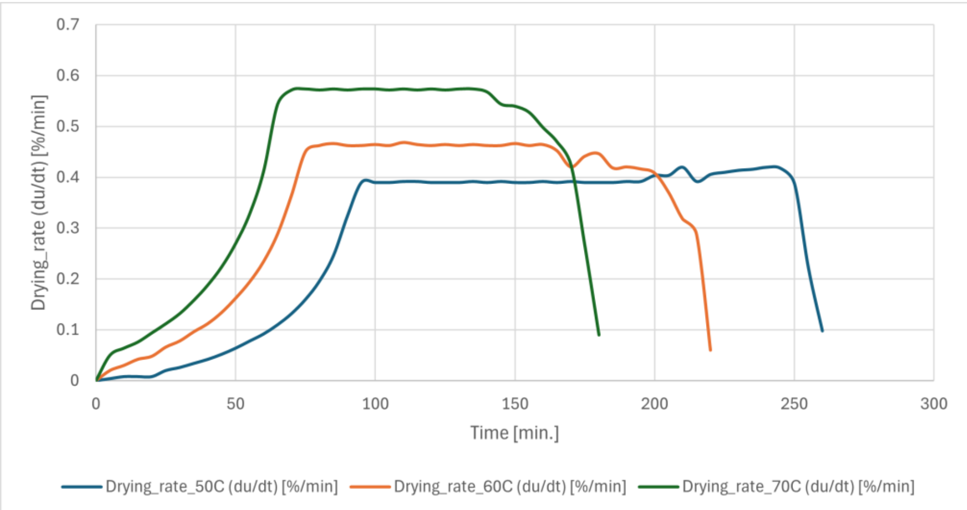


Fig. 4 - Drying rate profiles during convection drying of pear slices at 50°C, 60°C, and 70°C

Fig. 5 reveals the relationship between moisture content and drying rate, showing that maximum drying rates occur at different moisture contents: 74% (70°C), 76% (60°C), and 77% (50°C), with higher temperatures consistently demonstrating greater drying rates at equivalent moisture levels. The approximately linear decline during the falling rate period confirms diffusion-controlled drying behavior, with the steeper slopes at higher temperatures indicating enhanced moisture diffusivity. This relationship provides the critical basis for modeling drying kinetics and determining optimal operating parameters that balance process efficiency with product quality requirements.

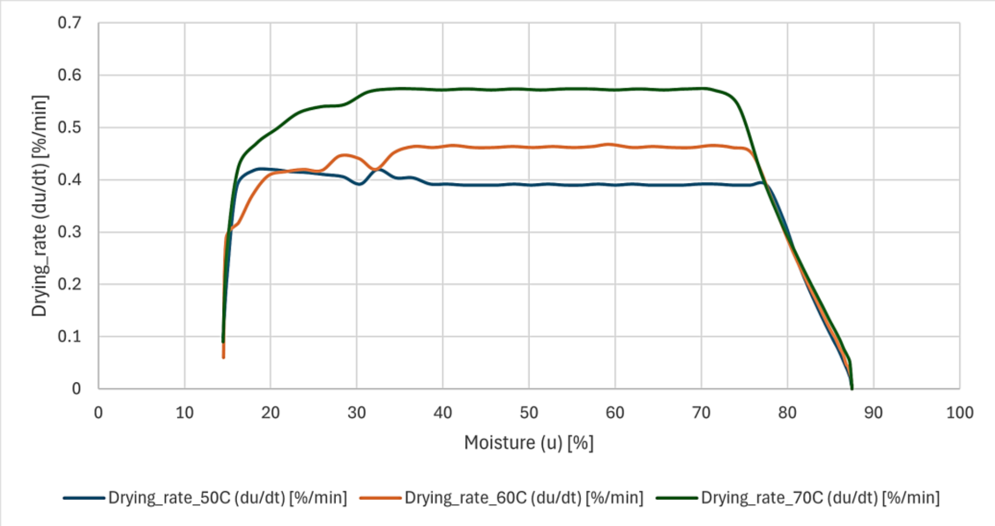


Fig. 5 - Relationship between moisture content and drying rate during convection drying of pear slices

The three trays presented in Fig. 6 display the final product appearance after completing the convective drying process at different temperature conditions, with the left tray representing the 50°C treatment, the middle tray the 60°C treatment, and the right tray the 70°C treatment. Visual examination reveals distinct but subtle differences in color, texture, and structural integrity among the samples, demonstrating the critical relationship between drying temperature and product quality. The 70°C treatment shows the most pronounced browning and edge curling, with some slices exhibiting significant shrinkage and deformation due to rapid moisture removal. The 50°C treatment maintains the most uniform light color and structural integrity, preserving the original shape of the pear slices with minimal deformation and shrinkage. The 60°C treatment demonstrates an intermediate quality profile, showing moderate color change while maintaining reasonable structural integrity. These visual differences align with the drying kinetics data presented in Figures 3-5, where higher temperatures accelerated moisture removal but potentially at the cost of quality degradation. The observed variations underscore the importance of temperature optimization for balancing process efficiency with product quality attributes such as color retention, texture, and visual appearance - factors that directly impact consumer acceptance and market value.

Fig. 6 - Final product quality of dried pear slices following convective drying at 50°C, 60°C, and 70°C

Fig. 7 presents the comprehensive performance evaluation of the trained ANN, demonstrating its capability to accurately predict drying behavior and establish a foundation for process optimization. Fig. 7 presents a comprehensive assessment of the ANN's predictive capability for drying rate (du/dt) in pear slice convective drying at 60°C. The top-left plot demonstrates successful training convergence, with training and validation losses both stabilizing below or around 0.01 after approximately 1,000 epochs, indicating effective learning without significant overfitting. The top-right plot reveals exceptional correlation between predicted and reference drying rate values ($R^2 > 0.99$), confirming the model's high prediction accuracy for this critical process parameter.

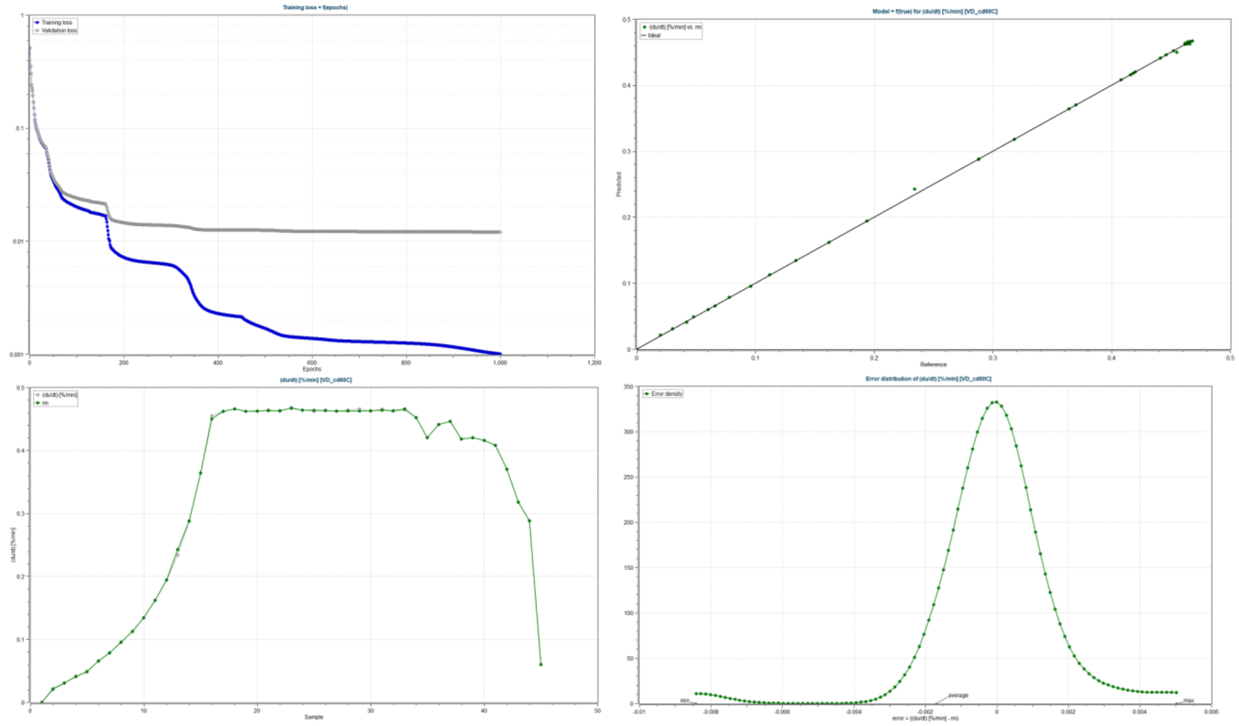
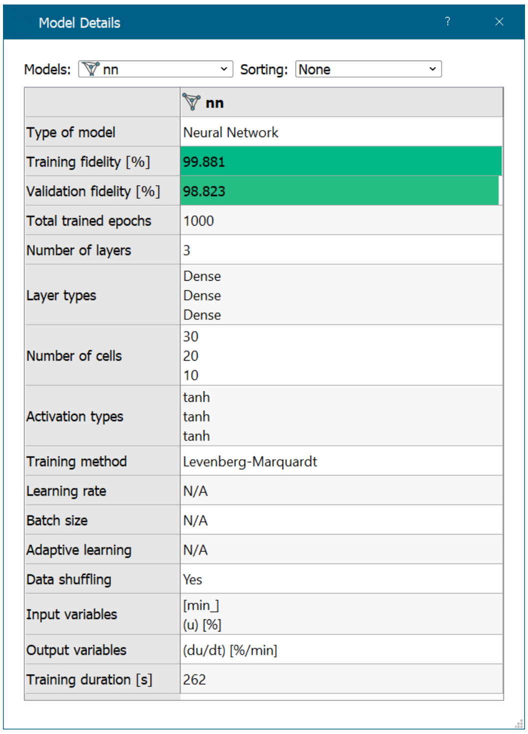


Fig. 7 - Performance evaluation of the artificial neural network model for predicting moisture loss rate during convective drying of pear slices

The bottom-left plot (from Fig. 7) illustrates how the ANN successfully captures the characteristic drying rate pattern, including the initial increase to maximum rate (reaching approximately 0.46-0.47 %/min) followed by the gradual decline during the falling rate period. The bottom-right error distribution follows a near-normal curve centered at zero with minimal deviation (average error < 0.002 %/min), demonstrating the model's reliability and absence of systematic bias. This high-precision drying rate prediction capability directly supports the ANN's application in dynamically adjusting drying parameters based on current process conditions, potentially optimizing energy consumption while maintaining product quality. As noted in the experimental results, understanding these drying rate patterns is crucial for identifying the critical moisture content where the drying rate begins to decline significantly, which is essential for determining when internal moisture diffusion becomes the rate-limiting step in the process.

Fig. 8. presents the detailed configuration and performance metrics of the artificial neural network developed for predicting drying rate (du/dt) in the convective drying of pear slices. The model demonstrates exceptional performance with a training fidelity of 99.881% and validation fidelity of 98.823%, confirming its robustness and generalization capability across the three temperature conditions. The high validation fidelity (98.823%) indicates the model's reliability in predicting the critical drying rate parameter, which is essential for understanding the transition from constant rate period to falling rate period at different temperatures. This predictive capability directly supports the optimization framework by enabling precise determination of when internal moisture diffusion becomes the rate-limiting step, allowing processors to dynamically adjust drying parameters for optimal energy efficiency while maintaining product quality.



Model Details

Models: nn Sorting: None

	nn
Type of model	Neural Network
Training fidelity [%]	99.881
Validation fidelity [%]	98.823
Total trained epochs	1000
Number of layers	3
Layer types	Dense Dense Dense
Number of cells	30 20 10
Activation types	tanh tanh tanh
Training method	Levenberg-Marquardt
Learning rate	N/A
Batch size	N/A
Adaptive learning	N/A
Data shuffling	Yes
Input variables	[min_] (u) [%]
Output variables	(du/dt) [%/min]
Training duration [s]	262

Fig. 8 - Neural network architecture and performance metrics for drying rate prediction model

CONCLUSIONS

The present study successfully developed and validated an artificial neural network (ANN) model for optimizing the convective drying process of pear slices, demonstrating exceptional predictive capability for drying rate dynamics with 98.823% validation fidelity. The model accurately captured the complex nonlinear relationships between moisture content, drying time, and drying rate across three temperature regimes (50°C, 60°C, and 70°C), providing valuable insights into the drying kinetics of pear slices. Experimental results revealed that higher temperatures significantly accelerated the drying process, with 70°C achieving target moisture content (14.5 %) in 180 minutes compared to 260 minutes at 50°C, while also producing higher maximum drying rates (0.57 %/min at 70°C versus 0.40 %/min at 50°C).

The ANN model successfully identified the critical moisture content thresholds (74% at 70°C, 76% at 60°C, and 77% at 50°C) where the drying rate begins to decline significantly, enabling precise determination of when internal moisture diffusion becomes the rate-limiting step. This capability is essential for implementing adaptive control strategies that dynamically adjust drying parameters to balance energy efficiency with product quality preservation.

This research demonstrates that artificial neural networks represent a powerful tool for optimizing convective drying processes in the food industry, offering substantial advantages over traditional empirical models. The developed ANN model provides processors with the ability to predict drying behavior accurately, identify optimal operating conditions, and minimize energy consumption while maintaining critical quality parameters.

Future work should focus on expanding the model to incorporate additional quality indicators (such as color change, texture, and nutrient retention) and testing its applicability across different fruit varieties and drying configurations. The integration of such models into industrial control systems presents a promising pathway toward more intelligent, adaptive, and sustainable food processing operations that simultaneously optimize energy efficiency and product quality.

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REFERENCES

[1] Asrate D.A., Ali A.N., (2025), Review on the recent trends of food dryer technologies and optimization of drying parameters, *Applied Food Research,* vol.5, no.1, 100927, Amsterdam/Netherlands. DOI: https://doi.org/10.1016/j.afres.2025.100927

[2] Calín-Sánchez Á., Lipan L., Cano-Lamadrid M., Kharaghani A., Masztalerz K., Carbonell-Barrachina Á.A., Figiel A., (2020), Comparison of Traditional and Novel Drying Techniques for Fruits, Vegetables, and Aromatic Herbs, Vegetables and Aromatic Herbs, *Foods,* vol.9, no.9, 1261, Basel/Switzerland. DOI: https://doi.org/10.3390/foods9091261

[3] Das M., Akpinar E.K., (2018), Investigation of Pear Drying Performance by Different Solar Dryers, *Applied Sciences,* vol.8, no.2, 215, Basel/Switzerland. DOI: https://doi.org/10.3390/app8020215

[4] Demir H., Demir H., Lončar B., Pezo L., Brandić I., Voća N., Yilmaz F., (2023), Optimization of Caper Drying Using Response Surface Methodology and Artificial Neural Network, *Energies,* vol.16, no.4, 1687, Basel/Switzerland. DOI: https://doi.org/10.3390/en16041687

[5] Đaković D., Kljajić M., Milivojević N., Doder Đ., Anđelković A.S., (2023), Review of Energy-Related Machine Learning Applications in Food Drying, *Energies,* vol.17, no.1, 224, Basel/Switzerland. DOI: https://doi.org/10.3390/en17010224

[6] El-Mesery H.S., Qenawy M., ElMesiry A.H., Ali M., Adelusi O.A., Hu Z., Salem A., (2025), Application of experimental, numerical, and machine learning techniques to improve drying performance and decrease energy consumption infrared continuous dryer, *Case Studies in Thermal Engineering,* vol.69, 106025, Amsterdam/Netherlands. DOI: https://doi.org/10.1016/j.csite.2025.106025

[7] Erbay Z., Icier F., (2010), A Review of Thin Layer Drying of Foods: Theory, Modeling, and Experimental Results, *Critical Reviews in Food Science and Nutrition,* vol.50, no.5, pp.441-464, London/UK. DOI: https://doi.org/10.1080/10408390802437063

[8] Farid M., (2019), Chapter 17 - Heat and Mass Transfer in Food Processing, in *Handbook of Farm, Dairy and Food Machinery Engineering*, 3rd ed., Academic Press, ISBN 978-0-12-814803-7, New York/USA. DOI: https://doi.org/10.1016/B978-0-12-814803-7.00017-8

[9] Francik S., Łapczyńska-Kordon B., Hajos M., Basista G., Zawiślak A., Francik R., (2024), Modeling the Drying Process of Onion Slices Using Artificial Neural Networks, *Energies,* vol.17, no.13, 3199, Basel/Switzerland. DOI: https://doi.org/10.3390/en17133199

[10] Hossan S., Wasim S., Yiasmin M.N., Saqib M.N., Easdani M., Liu S., (2023), Advanced Research Progress of Food Drying Technology, *North American Academic Research,* vol.6, no.9, pp.18-47, Genève/Switzerland. DOI: https://doi.org/10.5281/zenodo.8415214

[11] Kalantari D., Naji-Tabasi S., Kaveh M., Azadbakht M., Majnooni M., Khorshidi Y., Asghari A., Khalife E., (2022), Drying kinetics and shrinkage rate of thin-sliced pears in different drying stages, *Journal of Food Process Engineering*, vol.46 no.3, e14264, Hoboken/USA. DOI: https://doi.org/10.1111/jfpe.14264

[12] Kalsi B.S., Singh S., Alam M.S., Sidhu G.K., (2023), Comparison of ANN and ANFIS modeling for predicting drying kinetics of Stevia rebaudiana leaves in a hot-air dryer and characterization of dried powder, *International Journal of Food Properties*, vol.26, no.2, pp.3356-3375, London/UK. DOI: https://doi.org/10.1080/10942912.2023.2283380

[13] Khan Md.I.H., Sablani S.S., Joardder M.U.H., Karim M.A., (2022), Application of machine learning-based approach in food drying: opportunities and challenges, *Drying Technology*, vol.40, no.6, 1051-1067, London/UK. DOI: https://doi.org/10.1080/07373937.2020.1853152

[14] Lenart A., (1996), Osmo-convective drying of fruits and vegetables: technology and application, *Drying Technology*, vol.14, no.6, pp.391-413, London/UK. DOI: https://doi.org/10.1080/07373939608917104

[15] Ming J.L.K., Anuar M.S., How M.S., Noor S.B.M., Abdullah Z., Taip F.S., (2021), Development of an Artificial Neural Network Utilizing Particle Swarm Optimization for Modeling the Spray Drying of Coconut Milk, *Foods,* vol.10, no.11, 2708, Basel/Switzerland. DOI: https://doi.org/10.3390/foods10112708

[16] Nguyen T.D., Thai T.Q., Bui H.M., (2025), Application of Machine Learning Models for Hot Air Dryer Design in Food Drying Process, *Journal of Food Processing and Preservation*, vol.2025, 5594122, Hoboken/USA. DOI: https://doi.org/10.1155/jfpp/5594122

[17] Sablani S.S., (2006), Drying of Fruits and Vegetables: Retention of Nutritional/Functional Quality, *Drying Technology*, vol.24, no.2, pp.123–135, London/UK. DOI: https://doi.org/10.1080/07373930600558904

[18] Sagar V.R., Kumar P.S., (2010), Recent advances in drying and dehydration of fruits and vegetables: a review, *Journal of Food Science and Technology*, vol.47, pp.15-26, Berlin/Germany. DOI: https://doi.org/10.1007/s13197-010-0010-8

[19] Selvi K.Ç., Alkhaled A.Y., Yıldız T., (2022), Application of Artificial Neural Network for Predicting the Drying Kinetics and Chemical Attributes of Linden (Tilia platyphyllos Scop.) during the Infrared Drying Process, *Processes,* vol.10, no.10, 2069, Basel/Switzerland. DOI: https://doi.org/10.3390/pr10102069

[20] Spagnuolo A., Vetromile C., Masiello A., De Santo G., Suriano M., Mercuri G., Pellegrino M., Piccolo G., Lubritto C., Di Cicco M.R., (2023), Industrial Drying of Fruit and Vegetable Products: Customized Smart Monitoring and Analytical Characterization of Process Variables in the OTTORTO Project, *Processes*, vol.11, no.6, 1635, Basel/Switzerland. DOI: https://doi.org/10.3390/pr11061635

[21] Tepe T.K., (2024), Improvement of pear slices drying by pretreatments and microwave-assisted convective drying method: drying characteristics, modeling of artificial neural network, principal component analysis of quality parameters, *Journal of Thermal Analysis and Calorimetry*, vol.149, pp.7313–7328, Berlin/Germany. DOI: https://doi.org/10.1007/s10973-024-13280-8

[22] Yao J., Chen W., Fan K., (2023), Novel Efficient Physical Technologies for Enhancing Freeze Drying of Fruits and Vegetables: A Review, *Foods,* vol.12, no.23, 4321, Basel/Switzerland. DOI: https://doi.org/10.3390/foods12234321