Front. Agr. Sci. Eng. 2025, 12(4): 779–792 https://doi.org/10.15302/J-FASE-2025620

REVIEW

Application of artificial neural networks in agricultural product drying

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KEYWORDS

Agricultural products, artificial intelligence, deep learning, drying, neural network

HIGHLIGHTS

- Several artificial neural network models used in the drying of agricultural products are presented.
- Artificial neural networks have been applied to moisture content detection, drying process optimization, and drying equipment control system improvement.
- In the field of agricultural product drying, traditional artificial neural networks are being transformed to deep neural networks.

Received October 14, 2024;
Accepted March 26, 2025.

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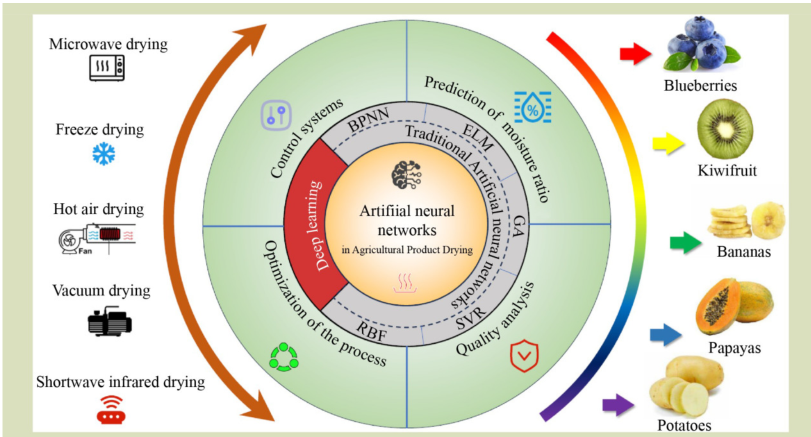
GRAPHICAL ABSTRACT



ABSTRACT

Drying is a critical process in postharvest handling of agricultural products, significantly impacting their preservation, quality and market value. This review explores the application of artificial neural networks (ANNs) in the drying of agricultural products, focusing on four key areas: moisture ratio prediction, quality detection, process optimization, and control systems. ANNs have remarkable potential for accurately modeling the highly nonlinear drying processes, optimizing energy consumption and improving product quality. Despite their advantages, challenges, such as data dependency, computational complexity and model interpretability, remain. This review highlights recent advancements in ANN-based drying models, discusses their limitations, and envisions future directions, including the integration of ANNs with other artificial intelligence (AI) technologies and the development of hybrid models. Through literature research in recent years, it has been found that ANN have achieved development from standard ANN to machine learning and even deep learning. Deep learning is gradually becoming the mainstream direction in agricultural product drying. The findings underscore the transformative potential of AI in revolutionizing the agricultural drying industry, paving the way for more efficient, sustainable and intelligent drying systems.

1 Introduction

1.1 The significance of drying agricultural products

Agricultural products refer to the primary products derived from planting, forestry, animal husbandry and fishery, that is, plants, animals, microorganisms and their products obtained in agricultural activities, mainly including food crops, fruits and vegetables[1]. Drying is a basic and important processing method in the production and processing of agricultural products. Through appropriate drying treatment, the preservation performance and market value of agricultural products can be significantly improved, and it helps ensure food security, value-added and income generation[2]. Fresh agricultural products are prone to decay and deterioration. In China, about 21 Mt of grain is spoiled every year due to excessive mycotoxins caused by improper drying[3]. Drying can effectively reduce the moisture ratio (MR) and inhibit the growth of microorganisms[4]. Therefore, dried agricultural products can be stored for a longer time at room temperature and are not easy to deteriorate. It is particularly important for the long-distance transportation of agricultural products. The drying technology of agricultural products can solve problems in the process of storage and transportation of agricultural products, as well as improve the quality and economic benefits of agricultural products. It is important for ensuring food safety and promoting the sustainable development of agriculture.

1.2 Challenges faced by agricultural products drying industry

Currently, the drying industry is challenged by high energy consumption and the demand for high quality product[5]. Inadequate drying can lead to product deterioration whereas over-drying can lead to quality degradation, affecting the flavor of the product or even producing harmful ingredients[6,7] and increased energy use, carbon footprint and product weight loss, which directly affects profitability[8]. Therefore, it is important to apply appropriate drying methods in order to maximize the retention of nutrients, such as vitamins and minerals, in the agricultural products. Some of these challenges can be solved by accurate modeling, control and optimization of the drying process[9].

Existing mathematical models of drying are categorized into first, second, third and fourth generation models as shown in Fig. 1. The first generation models are an empirical models, which mainly depends on the process conditions and worker experience, and therefore their application is limited[10]. The second generation models are a semi-physical based models with better predictive ability compared to the empirical model[11]. For decades, researchers have worked on developing fully physics-based models, also known as third generation models. Third-generation physical field-dependent model packages have significant challenges in accurately solving partial differential equations due to mesh distortions, complex boundary conditions, and noisy and incomplete data sets, and their applicability is limited by high computational costs, especially when modeling microstructural changes during drying[12], and model predictive control is often encountered with overshoots or oscillations[13]. Fourth generation of models are considered to be artificial neural network-based approaches for food drying modeling to reduce processing time and

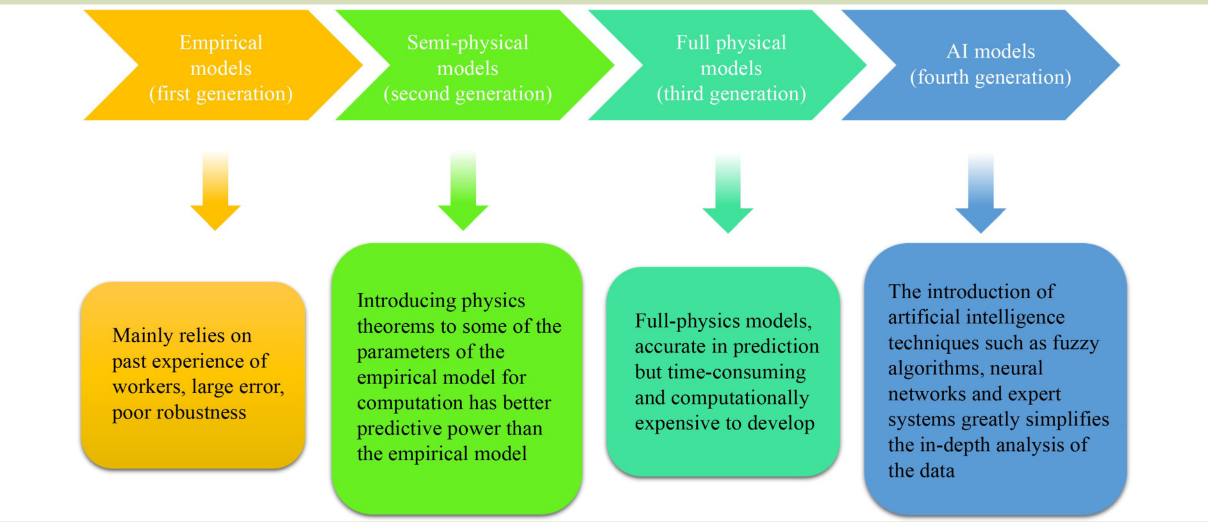


Fig. 1 Development of the drying model.

computational cost, thereby enhancing the understanding of food drying[14]. For example, artificial neural network-based models can be developed to rapidly calculate drying rates[15] as well as to predict temperature and moisture content in real time during the drying process[16]. Considering these benefits, many researchers have recently attempted to develop food drying models using machine learning algorithms[17].

1.3 Application of artificial neural networks in agricultural products drying

Real-time monitoring and intelligent control have opened up new opportunities for the revolution of drying technology[18]. By analyzing data from sensors, AI can dynamically adjust drying conditions to optimize energy consumption while maximizing product quality. Research on the use of AI in the drying industry dates back to the early 1990s when fuzzy logic (FL) was applied to process control[19], and since then research on the use of AI in the drying industry has been growing.

With the progress of science and technology, new drying technologies are emerging. Artificial neural networks (ANNs), as a part of AI technology, is a computational model that imitates the working principle of the human brain. A simple neural network mapping structure is shown in Fig. 2. It consists of a large number of nodes. These nodes are organized into input layer, hidden layer and output layer in a hierarchical way[20]. Each node is connected to other nodes by weight and each node has an activation function to determine whether the node is activated[21]. Deep learning refers to a neural network model with multiple hidden layers[22]. Deep learning technology adopts a deep neural network structure, which can nonlinearly map shallow data features layer by layer and automatically construct deep features[23,24]. Deep learning is thus a neural network that models the deep network structure. Common deep learning network structures include convolutional neural networks (CNN) and recurrent neural networks.

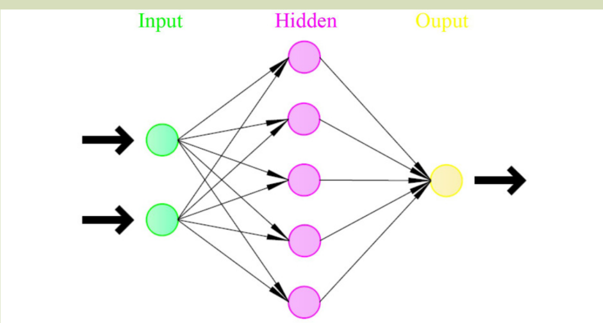


Fig. 2 A simple artificial neural network.

1.4 Common drying techniques

Common drying techniques include hot air drying (HAD), freeze drying (FD), and vacuum drying (VD), each having its own advantages and disadvantages[25]. For example, prolonged and high-temperature hot air drying greatly reduces the content of vitamin C and chlorophyll in dried samples, and can lead to excessive shrinkage and cracking[26]. FD preserves the original flavor of fresh foods but consumes a lot of energy[27]. VD is an effective method for the preservation of temperature-sensitive ingredients but is not economical[28]. Fruits and vegetables contain a large amount of water and the common drying techniques are prone to uneven drying and tend to over-dry resulting in structural damage to the fruits and vegetables. This greatly affects the flavor of the dried product and causes loss of nutrients, making it difficult to meet the requirements for use or consumption of the product. If the drying process can be fully analyzed and controlled, dried products with high edibility and nutritional value can be obtained[29].

2 Research on artificial neural networks for the drying of agricultural products

As shown in Fig. 3, this section describes the current state of development of ANN in the field of agricultural product drying from four aspects.

AI can optimize and control the drying process and improve the quality of dried products, which has advantages that standard drying does not have[30]. ANN as one of the branches in the field of AI technology, has been widely used in the agricultural products drying industry. It is an excellent modeling and prediction platform that can perfectly deal with problems involving a large number of combinatorial spaces or nonlinear processes that are not easy to be solved by standard methods[31]. ANN has the unique intelligence to characterize the physical or chemical properties of various agricultural products such as fruits, vegetables and grains based on some specific input parameters or training. Due to its non-destructive nature, simplicity and real-time monitoring, and is increasingly being considered by engineers and scientists as an advanced tool for modeling complex, dynamic, highly nonlinear and ill-defined scientific and engineering problems

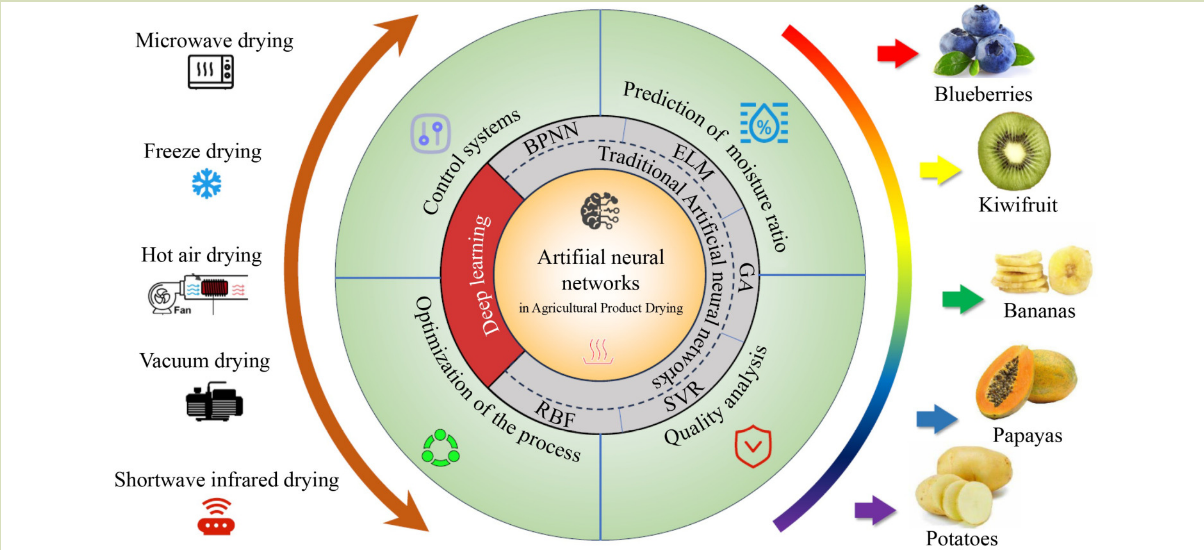


Fig. 3 Artificial neural networks in the field of agricultural product drying from four aspects.

in the drying of agricultural products[32,33]. Specific applications of ANN in drying and processing are described below in terms of MR prediction, quality analysis, process optimization and control systems. Table 1 details the advantages and disadvantages of some common ANN models.

2.1 Prediction of moisture ratio

MR not only has a great impact on the flavor, color, freshness and quality of the product, but also is crucial for the storage and marketing of agricultural products. The MR requirements for different applications are also different. For example, the MR of seeds should be less than 13% to facilitate storage[34], and ultra-dry seeds for long-term storage should be less than 5%[35], and the MR of dried fruit should be less than 20% to ensure the quality of the fruit, and some easy to deteriorate dried fruit need to be less than 15%[36], but the MR is too low may lead to cracking, crushing and other situations. This shows that it is critical to ensure accurate MR during the drying process. The change of MR during the drying process is dynamic and highly nonlinear[37]. ANNs can take advantage of nonlinear fitting in MR prediction to accurately predict MR. Kaveh et al.[38] predicted MR in the drying of mint by RW (heat pump) using different mathematical models and ANN along with various activation functions. The comparison of the results of the models obtained from two earlier modeling methods and the ANN model showed that the ANN has more power than the classical (mathematical) models in predicting the value of the moisture ratio.

Rashvand et al.[39] used two mathematical models (Page and Weibull) and two machine learning techniques (ANN and support vector regression) to predict the moisture ratio of the dried samples. The Page and Weibull models predicted the

Table 1 Characteristics of common neural network models

Neural network type	Main feature
BPNN	Multilayer feedforward neural network trained according to the error back propagation algorithm. Given its negative feedback, the error is small
GA	Method to simulate the natural evolution process to find the optimal solution. It can quickly provide better optimization results and is suitable for solving complex combinatorial optimization problems
MLP	MLP models are more parameterized and can learn more complex feature representations and thus are capable of nonlinear modeling, but require large data sets and computational resources, and are prone to overfitting on the training set
ELM	Connection weights between the hidden layer and the output layer do not need to be adjusted iteratively, but are determined at one time by solving equations
RBF	Fast training speed and high real-time performance

moisture ratios with R^2 = 0.958 and 0.970, respectively. The optimal topology of machine learning to predict the moisture ratio was derived based on the influential parameters within the ANN (training algorithm, transfer function and hidden layer neurons) and support vector regression (kernel function). The performance of the ANN (R^2 = 0.998, RMSE = 0.038 and MAE = 0.024) surpassed that of support vector regression (R^2 = 0.994, RMSE = 0.012 and MAE = 0.009). Overall, the machine learning approach outperformed the mathematical models in terms of performance. Hence, machine learning can be used effectively for both predicting the moisture ratio and facilitating online monitoring and control of the drying processes.

Taheri-Garavand et al.[40] found that an ANN performs well in predicting drying parameters (MR, dry basis, energy efficiency and effective energy efficiency) during HAD of banana slices. Nihan et al.[41] analyzed a drying kinetics model of peppermint using an ANN, and found that the ANN could describe well the variation of diffusion coefficient and MR during drying process. Omari et al.[42] used an ANN to study the drying kinetic model of microwave drying on MR in mushrooms, their results showed that the use of 3-6-7-1 neural network topology was better than other topologies. Also, the predicted value and the experimental value of drying prediction control system was R^2 of 0.991, and the RMSE was 0.218. The model fitting results can be very good prediction and control of microwave drying system. Saeedeh et al.[43] used an ANN to predict the temperature and MR of lentil seeds. A hidden layer and 10 hidden neurons, a logistic sigmoid transfer function in the hidden layer and a linear function in the output layer were identified as the optimal structure for the ANN. The weights and biases were found by training the network with Bayesian regularization, and the optimal MSE of the test set was 0.999. Their results showed that ANNs can be used for accurate prediction of the MR and temperature of lentil seeds in the drying process of microwave fluidized bed.

Extreme learning machine (ELM) is an ANN learning algorithm proposed by Huang et al.[44]. It belongs to a kind of feedforward neural networks (FNN) and is especially known for its fast learning speed and relatively simple implementation process[45]. He et al.[46] established a 3-8-1 ELM model to explore the microwave drying characteristics of hawthorn and realize the prediction of MR. Their results showed that: the drying temperature of 60 °C and relative humidity of 30% were the optimal drying conditions, the color change of hawthorn was the smallest and the total flavonoid content was the highest, and the coefficient of determination between its predicted value and the experimental value was R^2 of 0. 996, and RMSE was 0.00952. This ELM model was able to predict the MR of hawthorn in the process of microwave drying efficiently.

Back propagation neural network (BPNN) is a multilayer FNN trained in accordance with the error back propagation algorithm, comparing the output with the desired output and back propagating the error generated by the comparison using the network, and continuously adjusting the weights between the nodes on the network through multiple iterations. It is essentially a negative feedback process and has a high accuracy. Sun et al.[47] established an MR prediction model of BPNN in ultrasound-enhanced hot air drying pear slices test. The result is that the coefficient of determination R^2 of the test is 0.996, which indicates that the predicted value of BPNN model fits well with the measured value, and it can over estimate the performance prediction of the drying process. Xi et al.[48] constructed ELM and BPNN models to predict the effects of different ultrasonic power, far-infrared radiation temperature, and drying time on the MR of potatoes, in which the predicted value of the BPNN using the optimization algorithm is the closest to the real value, and it can quickly and accurately predict the MR of the potato in the process of ultrasound-enhanced far-infrared radiation drying.

Genetic algorithm (GA) is a method that mimics the natural evolutionary process to find the optimal solution, which provides better optimization results quickly and is suitable for solving complex combinatorial optimization problems[49,50]. Amin et al.[51] investigated hybrid genetic neural networks for thin-layer drying process to predict and model the potential application of MR in savory leaves. A genetic neural network was created by modeling the drying process of savory leaves. The neural network optimized by genetic algorithm has two hidden layers, the first and second hidden layers have 9 and 17 neurons, respectively. The MSE value (0.0000946) and the correlation coefficient (0.999) of the experiments showed that the MR could be accurately predicted based on the input variables: air temperature, airflow velocity, relative humidity and drying time.

Dong et al.[52] designed remote monitoring and online moisture detection for edible mushroom drying system based on matrix decomposition discrete Hopfield neural network and edible mushroom dielectric constant. The final test results: real-time moisture prediction accuracy was verified for six kinds of edible mushrooms, including shiitake, flat and enoki mushrooms, and the results showed that the Hopfield neural network moisture prediction model was close to the measured data.

Onwude et al.[53] combined ANN with computer vision (CV) and laser backscattering imaging techniques for monitoring shrinkage and MR changes in sweet potatoes during drying. They found that the optimal ANN topology had three input layers, two hidden layers containing 18 neurons and five output layers.

Xu et al.[54] collected 720 images of sea buckthorn fruits with different MRs and investigated the performance of eight network models based on fine-tuned deep learning. 180 images were randomly selected from various MR ranges for testing, and it was concluded that the MobileNet-v2 network model outperformed the other network models in terms of training speed and training accuracy, with excellent feature extraction for subtle feature changes and an accuracy rate of 98.6% in the validation set. This model also performs well during testing, with an accuracy of 99.4% on the test data and an average detection time of about 0.5 s when using the trained network model.

Most of the MR prediction models use standard ANNs, of which the most well-known algorithms are ELM, BP and GA. With the popularity of deep learning in the last few years, it also gradually produces research using deep learning in the field of drying. Of these, the BPNN is more effective, which belongs to the derivation and algorithmic improvement of multilayer perceptron neural network. The learning process has two processes, forward transfer and error reverse iteration, with excellent nonlinear mapping ability, generalization ability and fault tolerance. Since the drying process is difficult to describe mathematically, and lacks expert experience and high nonlinearity, this gives BPNNs a wide range of potential applications in MR prediction.

2.2 Quality analysis

Usually the effectiveness of drying determines the quality of the dehydrated product, including color, taste, composition, saturation, morphology and other characteristics. Inappropriate drying can cause oxidation, browning, loss of nutrients, uneven drying and shrinking, and other problems. These changes will reduce the desirability of the product to traders and consumers and will not conducive to development of the industry. Therefore, high quality dried products are important growth of an agricultural industry.

Bai et al.[55] applied the short- and medium-wave infrared drying technology to the drying of white fruits, studied the color changes of white fruits at different temperatures, and established a color prediction model by using a multilayer forward-type ANN. The coefficient of determination of the total color difference of white fruits was 0.925 and the RMSE was 3.06. The model was shown to be able to predict the variation of color parameters during drying process well. Khawas et al.[56] evaluated the effects of drying temperature, slice thickness and pretreatment on the color of edible bananas by using ANN and response surface methodology (RSM), respectively. The effects of drying temperature, thickness of slices and pretreatment on the attributes of rehydration rate, scavenging activity, color (in terms of non-enzymatic browning) and texture (in terms of hardness) of banana were evaluated using ANN and RSM, respectively, they found that the prediction of the ANN model was more accurate when it was properly trained.

Vasighi-Shojae et al.[57] developed an ANN model based on back propagation algorithm for predicting the relationship between hardness and texture of apples. Scala et al.[58] investigated the effect of hot air drying conditions on dried apple color, water retention, and total phenolic content by using ANN as an intelligent modeling system. Sun et al.[59] also used a BPNN to assist in monitoring the flavor changes during garlic drying. Zhang et al.[60] used the BPNN algorithm to construct a model for evaluating the drying suitability of apple raw materials. The model was based on 34 apple cultivars and analyzes 22 indicators of raw materials to predict the quality of processed products. The results show that the first and the last are cvs Liaoning Huahong and Shaanxi Qinguan, respectively, and the average value of the coefficient of determination of the prediction results is 0.968, and the predicted value fits the actual value to a high degree, which proves that the neural network model is able to accurately and stably evaluate the suitability of raw apple materials for crispy flakes processing. Chen et al.[61] analyzed the relationship between drying temperature, initial tannin content, drying time and MR and soluble tannins, and established an ANN model to build a 4-4-1 topology. The results showed that the correlation coefficient between the predicted and experimental values of the soluble tannin BPNN model reached 0.93, and the model could be used to predict the tolerable tannin content in the drying process of persimmon cake. Wang et al.[62] conducted a prediction study on the quality parameters of kiwifruit slices after vacuum freeze-drying by means of BPNN, and established the neural network with the input variables of drying chamber pressure, slicing thickness and temperature of the heating plate, and the output variable of the shrinkage rate of kiwifruit slices, which showed that the predicted value of the BPNN was close to that of actual data, and the average relative error was only 2.65%, which indicated that the prediction of kiwifruit quality by means of neural network in practice was not possible without the help of the BPNN. The results showed that the BPNN prediction was close to the actual data with an average relative error of only 2.65%, indicating that it is feasible to predict kiwifruit quality in practice using a BPNN.

The Broyden-Fletcher-Goldfarb-Shanno algorithm is an optimization method that has recently been used to increase computational efficiency, improve convergence and solve unconstrained nonlinear optimization problems during ANN modeling of drying processes. Voca et al.[63] used this optimizer to develop a ANN model for predicting maize quality during drying process properties. The model reliably estimated various attributes including 1000 kernel weight, hectoliter weight and starch pasting rate, as well as levels of reducing sugars, glucose and ethanol, resulting in an R^2 value of 0.832.

There are a large number of studies among the design of ANN models to optimize the process and improve the quality with the goal of drying quality. Physical morphological changes and chemical composition changes caused by different drying conditions on agricultural products vary greatly. The establishment of appropriate evaluation indexes can reduce drying shrinkage, reduce surface hardening, improve rehydration and reduce nutrient loss. An ANN can be used for color prediction, fruit and vegetable slice quality prediction, and nutrient content prediction are very suitable to fit the ANN model. More models will be used for fruit and vegetable drying quality analysis as research progresses.

2.3 Optimization of the process

To improve the quality and reduce the cost, the optimization of drying process is also an important for improving the pretreatment technology, combining a variety of complementary drying methods and changing the drying parameters to improve the quality. An ANN can be trained to predict more accurate process parameters for optimal drying.

Liu et al.[64] used an ANN to study the optimal drying conditions of kiwifruit during pulsation vacuum drying. Ju et al.[65] used drying time, drying temperature, atmospheric pressure time and vacuum time as input neurons, MR as output neurons, and seven hidden layers to establish a drying model with topology 4-7-1, which was used to investigate the optimal process conditions of light-skinned papaya under vacuum pulsation drying. Their results showed that the optimal drying temperature, vacuum time, atmospheric pressure time were 60 °C, and 10 and 4 min, respectively, with a total drying time is 12.1 h, the rehydration ratio was 6.28 ± 0.05, and the coefficient of determination between measured and predicted values R^2 was 0.999, which indicates that the BPNN can suitably optimize the drying process of the bare skin papaya. Gorjian et al.[66] discussed the influence of topological structure and transfer function on the accuracy of the model based on a BPNN. They used a bayberry drying experiment and pointed out that when the transfer function was logsig, the optimal model structures were 4-20-1 and 4-25-5-1, and the MSE were 0.00318 and 0.001, respectively. The optimal models using tansig as the transfer function were 4-20-1 and 4-15-15-1, and the MSE were 0.0093 and 0.00130, respectively.

Qenawy et al.[67] used an ANN control model to optimize energy consumption, offering a new approach to improving the efficiency of the drying process. During the experiment, the airflow velocity was varied from 0.7 to 1.5 $m \cdot s^{-1}$, the airflow temperature was varied from 40 to 60 °C, and the radiation intensity was varied from 1500 to 3000 $W \cdot m^{-2}$. Their results showed that the transient behavior exhibited four data groups with consistent MR and DR through the mean and statistical analysis. Increasing radiation intensity and air temperature decreased the drying time, while higher airflow increased the drying time. The energy indices were enhanced by increasing radiation intensity and temperature while reducing airflow velocity. The measured MR of all groups had similar kinetics behavior and the associated DR had similar clustering through the self-organizing map. Those findings were further controlled using an ANN model with 99% predicting accuracy. With airborne heating at 60 °C and airflow at 0.7 $m \cdot s^{-1}$, the radiation intensity was transiently controlled, delivering a 6.5% drying time reduction and a 36% energy saving. Thus, controlling the radiation intensity and its impact on the slice properties is highly desirable in future work. This work could help designers improve the processing efficiency and energy conservation of garlic slices drying.

El-Mesery et al.[68] used a continuous IR hot air dryer to dry garlic slices. The experiments were conducted at different levels of IR power, air velocities (V) and temperature (T). The relationships between the input process parameters (IR, V and T) and response parameters, including effective moisture diffusivity (Deff), drying time, and physicochemical properties of the dried slices (rehydration ratio [RR], total color change, flavor strength and allicin content in the garlic), were modeled using an ANN. These indicated that optimal drying conditions (IR of 3000 $W \cdot m^{-2}$, air velocity of 0.7 $m \cdot s^{-1}$, and 60 °C temperature) yielded a maximum Deff of 6.8×10^{-10} $m^2 \cdot s^{-1}$ and minimized processing time to 225 min. Color variation and RR values exhibited positive correlations with IR and higher air temperature, but demonstrated inverse relationships with increased airflow rates. Also, the flavor strength of garlic and its allicin content levels decreased as the IR and air temperature increased. The results demonstrated a significant influence of the independent parameters on the response parameters (p < 0.01). Interestingly, the ANN demonstrated strong predictive accuracy against experimental validation data, establishing a robust framework for process optimization and mechanistic understanding of dehydration dynamics in garlic processing.

Lin et al.[69] used hot air-microwave combined drying purple cabbage to explore the optimal drying process parameters. In the experiment, ANN was used to simulate the effects of different parameters on the protein and total sugar content of seaweed in the process of hot air-microwave combined drying of seaweed, and the data were combined with a genetic algorithm to optimize the drying process. It was found that the shortest time required for hot air drying was 1 h followed by 400 W microwave drying of about 62.5 min. Yang et al.[70] used a genetic algorithm to optimize the initial weights and thresholds of the ANN in order to simulate the process of air impingement drying of walnuts. The researchers observed a significant improvement in the GA-ANN model with R^2 values exceeding 0.99 for various parameters including shell breakage rate, drying time and specific energy consumption (SEC). In addition, the GA-ANN model reduced the RMSE of the corresponding parameters by 50.5%, 32.8%, and 23.14%, respectively, compared to the standard ANN model.

The above study shows that there was no significant difference in the performance of ANN with different transfer functions when using optimal topology. Exploring the optimal drying process is to find the optimal solution between the influencing factors, ANN is mainly used to predict the possible results, ANN from the known data to launch the unknown results, so as to achieve the effect of finding the optimal. The seaweed example above is incorporating a genetic algorithm, which is an excellent algorithm for finding an optimal solution and is closely linked to ANN.

2.4 Control systems

Control problems have been an important area of ANN applications. ANN have obvious superiority compared to common control methods. Such methods often lead to uneven product quality because of unsatisfactory accuracy, while ANN can effectively solve the problem of uncoordinated control of temperature, humidity and wind speed in the drying process. The combination of ANN with fuzzy control and PID (proportional-integral-derivative) control can be an effective solution to temperature and humidity instability brought about by the drying process, and can also improve the drying efficiency. The basic principle of a typical control system is shown in Fig. 4. The wind blown by the fan is heated by the electric heating wire and blown into the drying room, and there is a camera above the material being dried to collect images and transmit the data to the computer, and the computer has a built-in ANN program, and the program performs the operations of feature extraction, scaling, filtering and data segmentation of these images, then it predicts the suitable drying parameters by ANN. The drying parameters are passed to the PID controller, which is used to control the rotational

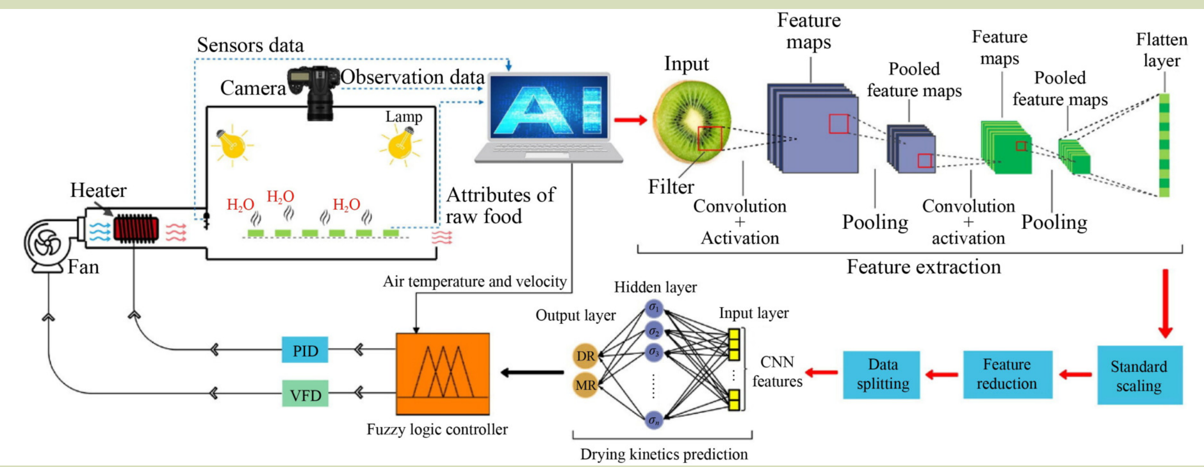


Fig. 4 Drying control system based on artificial neural network.

speed of the fan and the power of the heating filament. With standard control systems, the drying parameters are set manually, and generally will not be changed after setting. The introduction of ANN can be optimized according to the state of the material to be dried in real-time drying parameters.

Kaveh et al.[71] used machine learning to estimate apricot drying characteristics in various advanced and conventional dryers. In this study, five machine learning approaches [multilayer perceptron (MLP), Gaussian processes, support vector regression, k-nearest neighbors, and random forest (RF)] were used to estimate moisture content and moisture ratio of apricot in five various dryers [convective (CV), microwave (MW), infrared (IR), microwave-convective (MW-CV), and infrared-convective]. Also, the values of SEC and Deff were calculated in these dryers. Accordingly, the best result of the Deff (3.14×10^{-10} $m^2 \cdot s^{-1}$) and the minimum value of the drying time (130 min) and SEC (18.7 $MJ \cdot kg^{-1}$) were obtained using MW-CV hybrid dryer. While the lowest values of Deff (2.09×10^{-11} $m^2 \cdot s^{-1}$) and highest drying time (18.5 h) and SEC (209 $MJ \cdot kg^{-1}$) were detected in CV dryer at 50 °C. The best correlation coefficients for the estimation of moisture content were gained using RF technique for k-fold cross validation and train-test split with the values of 0.991 and 0.991, respectively. Also, moisture ratio results showed that the MLP achieved the highest R value over 0.999 for both validation methodologies. In the discrimination of the drying methods, the MLP had the greatest accuracy as 82.0% and 86.0% for *k*-fold cross validation and train-test split, respectively. These results show that the RF and ML models could potentially be used for estimation and discrimination for drying applications.

Çetin et al.[72] used a digital single-lens reflex camera to image banana slices. The acquired images were processed to extract texture parameters. The classification models were developed based on image texture parameters selected from a big data set of 2172 textures of images in different color channels using artificial neural networks. Wide neural network, bilayered neural network, medium neural network and three classifiers from the group of function, such as RBF network and multilayer perceptron, were applied. Banana slices belonging to 15 classes with different combinations of pretreatment and microwave drying were distinguished with an average accuracy of up to 97.2% for a model built using multilayer perceptron. For most models, banana samples microwave-dried at 200 W without pretreatment were classified with the highest correctness. This study revealed that the objective, non-destructive, correct and robust quality assessment of pretreated and microwave-dried banana slices may be performed using image processing and artificial intelligence.

Yang et al.[73] developed an improved neural network PID controller (INN-PID) that uses a GA to regulate the temperature of an air impingement dryer. Their simulation results showed a significant improvement in the dynamic performance of the control system. Specifically, the regulation time and maximum overshoot of the INN-PID controller were reduced by 73.4% and 87.7%, respectively, compared to a similar NN-PID controller, and by 89.9% and 91.6%, respectively, compared to a standard PID controller. Zhu et al.[74] designed a fuzzy neural network controller for drying process based on improved GA, and used the adaptive regulation and fuzzy control of neural network to realize the precise control of temperature and humidity in the drying process. This study showed that compared with the classical fuzzy controller and conventional PID controller, after the introduction of neural network, the convergence efficiency is high, the dynamic response is suitable, and the accuracy and stability have been improved to realize the intelligent control of drying process.

CV for process observation and FL for decision making developed by Nadian et al.[75] Through the use of ANN, the system is able to accurately predict MR, color change and shrinkage by analyzing image data. These predicted parameters were then used within the framework of a genetic algorithm to optimize the fuzzy controller and fine-tune the exogenous input variables of the dryer. The implementation of this fuzzy control system resulted in a significant reduction of drying time by 40% compared to hot air drying alone, while improving product quality by reducing color change from 7.9 to 2.1. Martynenko & Kudra[76] developed a non-isothermal drying intelligent system based on CV, fusion sensors and ANN for drying ginseng root and blueberries by controlling drying temperature to improve drying speed and ensure their quality. The drying time of ginseng was reduced to a quarter of the original time, and the drying efficiency of blueberries was also improved, with the drying time being reduced from 110 to 30 h.

Wu & Yang[77] proposed a tobacco leaf baking method based on CNN called TobaccoNet. It can set the target dry bulb temperature (TD) and target wet bulb temperature (TW) of the bulk curing barn according to the tobacco leaf image. The performance of TobaccoNet is compared with the standard manual image feature extraction method and the deep learning method based on stacked sparse autoencoder. The test results show that TobaccoNet is superior to the comparison method in predicting TD and TW. Specifically, the correlation coefficients were 0.997 and 0.968, the average relative errors were 1.62% and 1.77%, and the root mean square errors were 1.06 and 0.858 °C, respectively. The results show that TobaccoNet is effective and reliable for the modeling of intelligent bulk tobacco baking process.

In summary, it can be seen that PID control in fruits and vegetables, grain and other drying control is widely used, PID control is flexible and convenient, combined with neural network algorithms, the main advantage of the main advantages in the ease of compilation and modification of the control parameters, applicability of a wide range of uses, robustness. Design for PID drying control is nonlinear, time-varying and coupled with many other uncertainties.

3 Existing issues, limitations and development trends

3.1 Existing issues

At present, many research scholars and organizations have established dry neural network models and conducted a large number of experimental studies, but there are still deficiencies in some aspects, and the application of ANN still must overcome many problems.

A large number of existing studies are designed based on existing experience, the topology of the neural network, function relationships, but neuron design failed to form a theoretical basis for the drying industry, greatly increasing the redundancy of the neural network.

At present, most of the network models are in the shallow neural network, and deep learning is still in the primary phase. There are many excellent models in neural networks that have not been applied to the field of food drying, including pattern recognition, time series prediction and cluster analysis. Most of the neural networks in the existing research are predictive models, which can be attributed to function fitting.

The combination of neural network models with other theories in existing research is somewhat limited. Expert system is very useful in drying process analysis, fuzzy logic is applicable in controlling temperature and humidity, and there is no doubt that the integration of multiple theories will certainly make drying models more accurate.

3.2 Limitations

Despite their significant advantages, the application of ANNs in agricultural product drying faces several limitations that need to be addressed to fully realize their potential.

Data dependency: ANNs require large data sets for training, which can be challenging to obtain, especially for niche or novel agricultural products. Also, the quality and representativeness of the data are crucial; poor-quality data can lead to suboptimal model performance or even misleading results.

Computational complexity: training deep neural networks is computationally intensive, demanding significant time and resources. Additionally, there is a risk of overfitting, where models perform well on training data but fail to generalize effectively to new data.

Model interpretability: one of the major criticisms of ANN is their black-box nature, making it difficult to understand how decisions are made. This lack of transparency can hinder trust and acceptance in industrial applications, where understanding model behavior is essential.

Technical implementation challenges: selecting appropriate network architectures, activation functions, and optimization algorithms requires specialized knowledge and often involves extensive trial and error. Integrating ANN with existing control systems or other AI technologies, such as fuzzy logic and expert systems, can also pose technical and practical difficulties.

Real-world application issues: environmental conditions during drying can vary, and pre-trained models may not adapt well to these changes without regular retraining or updates. Also, ANN can be sensitive to outliers in input data, necessitating robust preprocessing steps to detect and handle such anomalies.

In summary, while ANN offer substantial benefits for optimizing drying processes, their limitations in terms of data dependency, computational complexity, interpretability and real-world applicability must be carefully considered. Addressing these challenges through improved model transparency, more efficient training algorithms and hybrid approaches combining ANN with other technologies will enhance their overall robustness and practical utility in the field of agricultural product drying.

3.3 Development trends

Currently, ANN have been widely used in various fields of agricultural products drying and have achieved gains in constructing models, optimizing processes, predicting MR and controlling programming, which reveals the broad prospects of neural networks in agricultural products drying. However, the application of neural networks is still insufficient, and it is still only shallow neural network modeling, and the model design, optimization and improvement of deep neural networks is an important issue currently facing. This paper provides the following recommendations for the future development of neural networks in the field of fruit and vegetable drying.

The is a need to improve the theoretical basic research to form a neural network modeling systems suitable for drying, and add more help for the development of neural network in the field of drying.

Future work should explore the application of other neural network models to agricultural product drying. For example, RBF network can solve the nonlinear classification problem through nonlinear changes, which can be applied to the drying quality classification problem. Another example is that the error of BP algorithm will gradually dissipate until it disappears with the increase of the level, and it cannot regulate the weights efficiently, and the deep neural network can solve the defects of the training algorithm by using the multi-hidden layer common algorithm.

Other excellent theories, such as fuzzy logic, expert system and neural network, can be jointly applied to realize drying intelligent control in modern industry. The is a need for combined drying model, drying strategy and online detection with big data to realize automation, and to apply virtual technology and neural network technology to develop drying control software and establish drying network database.

4 Conclusions

Although ANNs have been used for drying prediction, optimization and control, they are not intended to replace existing techniques but rather to serve as a complementary option. The drying process is inherently nonlinear with variable moisture migration mechanisms. Neural network algorithms significantly simplify the in-depth analysis required for establishing drying models, leading to rapid advancements in neural networks within drying applications.

The application of ANNs in the drying of agricultural products has significant promise for addressing challenges posed by current drying methods. For example, ANNs provide powerful tools for accurately predicting moisture ratios, optimizing drying processes and enhancing product quality. However, several limitations must be addressed to fully realize their potential, including data dependency, computational complexity and model interpretability. Future research should focus on developing more interpretable and robust ANN models, integrating ANNs with other AI technologies, such as fuzzy logic and expert systems and exploring hybrid models that combine ANNs with physical drying models. Additionally, integrating ANNs with IoT for real-time monitoring and control provides great promise for developing intelligent drying systems. As this field continues to evolve, more sophisticated and diverse drying models can be evaluated. This would not only aim to enhance drying efficiency and product quality but also to promote sustainable agricultural production. Consequently, it is anticipated that ANNs will make an increasingly crucial contribution to advancing the efficiency, sustainability and quality in agricultural product drying.

In summary, while ANNs offer substantial benefits, there are still challenges to overcome. By addressing these issues and exploring new integration possibilities, the future of drying technology looks promising. With ongoing studies into drying principles and neural networks, even richer and more effective drying models could be developed, further advancing the field of agricultural product drying.

Compliance with ethics guidelines

Shaoying LU, Shanyu WANG, and Qing WEI declare that they have no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

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