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Recent developments of artificial intelligence in drying of fresh food: A review

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Abstract

Intellectualization is an important direction of drying development and artificial intelligence (AI) technologies have been widely used to solve problems of nonlinear function approximation, pattern detection, data interpretation, optimization, simulation, diagnosis, control, data sorting, clustering, and noise reduction in different food drying technologies due to the advantages of self-learning ability, adaptive ability, strong fault tolerance and high degree robustness to map the nonlinear structures of arbitrarily complex and dynamic phenomena. This article presents a comprehensive review on intelligent drying technologies and their applications. The paper starts with the introduction of basic theoretical knowledge of ANN, fuzzy logic and expert system. Then, we summarize the AI application of modeling, predicting, and optimization of heat and mass transfer, thermodynamic performance parameters, and quality indicators as well as physiochemical properties of dried products in artificial biomimetic technology (electronic nose, computer vision) and different conventional drying technologies. Furthermore, opportunities and limitations of AI technique in drying are also outlined to provide more ideas for researchers in this area.

Keywords

Artificial intelligence, Artificial neural network, Fuzzy logic, Computer vision, Food drying, Advanced process control

Introduction

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Drying preserves the product by lowering the amount of moisture in the material (Banakar and Karimi Akandi, 2012). As the primary method of fresh food preservation, drying technique has evident advantages in permitting early harvest, reducing shipping weights and costs, minimizing packaging requirements and increasing shelf-life (Zielinska et al., 2013). Many conventional thermal methods include hot air drying, vacuum drying, and freeze drying etc. Different drying methods have their own advantages. The drying equipment of hot air drying is simple, safe, and relatively low in cost. The freeze drying technology can preserve color, odor and nutrition of food, and is especially suitable for heat sensitive material. The vacuum drying technology is adapted to the easily oxidizing material. The drying rate of microwave technology is fast and the quality of the product is uniform. However, due to the complexity of materials and the variety of properties, the single form of drying technology is often difficult to meet the quality requirements of the final product. According to the characteristics of materials, some high-efficiency, energy-saving, and environment friendly combined drying technologies such as heat pump drying, superheated steam drying, freeze drying, vacuum drying, microwave drying as well as multistage combined drying have gradually replaced traditional drying technologies to concurrently shorten drying time and improve product quality (Zielinska et al., 2013; Barzegar et al., 2015). For example, combined hot air and microwave/freeze drying could minimize the shortcomings such as shrinkage and discoloration, case hardening, flavor loss and the problem of incomplete rehydration existed in the hot air drying. Zhang et al. (Zhang et al., 2006) reviewed the development

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of combined drying technologies such as combined hot air and microwave drying, combined hot air and freeze drying, combined hot air and microwave/vacuum drying, combined osmotic and microwave drying. Field assisted methods have been attempted for newer drying techniques including physical field assisted technology (infrared, radio frequency and microwave) electromagnetic heating, multi energy complementary heat pump and fast freeze drying technology as well as combined air hot/vacuum and pulsed physical field drying technology to solve the problem of low drying efficiency and uneven drying of fruits and vegetables. Zhang et al. (Zhang et al., 2010) reviewed the recent developments in microwave-assisted drying of vegetables, fruits, and aquatic products. Jiang et al. (Jiang et al., 2017; Jiang et al., 2016) investigated the effect of dielectric drying methods on the structure and morphological characteristics of potato starch-water model starch system and analyzed the impact of microwave application on the main components of foods and agricultural products from the point of dielectric constant. Computer simulation was used to improve radio frequency heating uniformity of food products (Huang et al., 2016). Lv et al. (Lv et al., 2016) selected different drying processes such as pulse-spouted microwave vacuum drying (MVD), vacuum infrared drying (VID), hot air-drying (AD) and microwave drying (MD) to analyse the drying properties of vacuum-impregnated edamame and found that MVD product was the most suitable sample for impregnation after the anlysis of microstructure, color, texture, and flavor. With regard to the outstanding problem in intelligent drying process, real time monitor and control technology based on the moisture content and drying end point discrimination are becoming more and more concerned. Lv et al. (Lv et al., 2017) designed a microwave vacuum drying

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(MVD)-low field nuclear magnetic resonance (NMR) smart device and investigated the feasibility of NMR method for online measurement of state of moisture during MVD. Su et al. (Su et al., 2014) reviewed the recent developments in the area of smart drying technology for fresh foods. These technologies included biomimetic systems, computer vision technology, microwave dielectric spectroscopy, near infrared reflectance spectroscopy (NIR), magnetic resonance imaging (MRI), ultrasound techniques, electrostatic sensor technology, which can be cost-effective in detecting and monitoring various food quality parameters which vary with time of the drying process, thus controlling the conditions of drying and producing high-quality products.

In drying processes, the most important aspect of drying technology is the drying mathematical modeling which is crucial for optimizing the operating parameters and performance improvements of the drying systems (Hacihafizoglu et al., 2008). To simulate drying, a number of easily applied empirical or semi-empirical models have been developed for the mathematical modeling of drying behavior and determining the drying kinetics of various vegetables and fruits such as kiwifruit, red pepper (Banakar and Karimi Akandi, 2012). But drying of wet materials is a complex, dynamic, unsteady, highly nonlinear, strongly interactive, successively interconnected, and multivariable thermal process whose underlying mechanisms are not yet perfectly understood. The complexity of the drying process becomes an even more problematic issue due to simultaneous transient coupled momentum, heat and mass transfers, phase transformations, time-varying physicochemical and structural changes of the product being dried, intensive chemical and

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biochemical reactions, irregular component migration, and abrupt surface hardening. Moreover, in a typical drying process, some key parameters, including drying conditions and product formulation or treatment, which govern the quality of the finished product, should be analyzed. Due to the factors discussed above, mathematical and regression approaches are considered undesirable to accurately reflect the relationship between moisture content, water activity and drying conditions.

Intelligent process control is another problem existed in the drying of food industry. Classic traditional control, mainly represented by the proportional-integral-derivative (PID) controller, has been successfully used in a broad range of applications, but has difficulty in achieving complex control objectives, especially when the control objectives are affected by many factors, such as dielectric parameters, material properties, the climatic conditions, and the drying process (Kondakci and Zhou, 2016). Thus, it is desirable to develop an intelligent real-time control system that can automatically learn the effective curing process. At the same time, the accuracy of drying end point is still need to be improved.

AI (Mohd Adnan et al., 2013) is a smart machine for science and engineering. It is related to the analogous task of using computers to understand human intelligence, but AI is not limited to methods of biological observation. AI consists of many branches viz., ANN, fuzzy logic, expert system, and various swarm intelligence (Mohd Adnan et al., 2013). AI has produced a number of powerful tools, which are practically used in engineering to solve difficult problems normally requiring human intelligence (Ramakrishna et al.,

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2018; Echeverría and Tabarés, 2016; Villarrubia et al., 2018; Huang and Mujumdar, 1993). Combined with other advanced technologies such as big data and cloud computing, AI is changing the face of the world and the way of the life (Monroy et al., 2006). As mentioned earlier, dry intelligence innovation, energy conservation and intelligent process control are what we must solve to obtain high quality end-products, to reduce operating and energy costs, to increase production rate, and to optimize design and operating parameters of industrial-scale dryers. With the advantages of self-learning ability, adaptive ability, strong fault tolerance and high degree robustness to map the nonlinear structures of arbitrarily complex and dynamic phenomena, AI gives an alternative strategy solution in drying modeling, analysis of physicochemical properties and quality, and online testing and control. This paper mainly focuses on the progress of AI and application in fresh food drying. In Section of overview of Artificial Intelligence, three kinds of AI technologies, viz. ANN, fuzzy logic and expert system are involved in the introduction of basic theoretical knowledge of learning style of ANN, learning rules of ANN, feed forward neural network, feedback neural network, principles of fuzzy logic and expert system. In the section of AI application, we introduce modeling, predicting, and optimization of heat and mass transfer, thermodynamic performance parameters, and quality indicators as well as physiochemical properties of dried products in artificial biomimetic technology (electronic nose, computer vision) and different conventional drying technologies. Furthermore, limitations and suggestions of AI technique are also outlined. The last section is the conclusion of this paper.

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Overview of Artificial Intelligence

Artificial Neural Network

ANN is a theoretical mathematical model of human brain activities and consists of a number of linear or nonlinear processing elements, also called nodes, which are interconnected through weighted connections such as the models showed in Fig. 1. Generally speaking, ANN contains 3 parts of the input layer, the hidden layer and the output layer and is typically specified by architecture, learning algorithm and neuron model, in which architecture represents the interconnection pattern between the different layers of neurons, learning algorithm is for updating the weights in order to correctly model a particular task and neuron model defined by activation function is to transform a neuron's weighted input to its output activation (Samatin Njikam and Zhao, 2016). In general, the ANN model can be divided into feed-forward neural network and feed-back neural network according to the type of neural network architecture and learning with teacher (supervision) style and learning without teacher (no supervision) style according to the learning style (Shi, 2009).

Feed forward neural network is organized in three or more layers, an input layer, an output layer, and one or more hidden layers. From the input layer to the output layer, the network is one-way connection. Only the two neurons in adjacent layers connect each other. There is no connection between the neurons at the same level and connections between the neurons do not form a directed cycle. So the received signals from the upper layer are only sent to the next layer of neurons and there is no feedback between the neurons (Fuangkhon, 2017).

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Typical feed forward networks mainly include Multi-layer Perceptron (MLP), error back propagation network (BP), radial basis function neural network (RBF) and learning vector quantization neural network (LVQ) (Shi, 2009). Most feed forward networks are learning networks, which are more suitable for pattern recognition, prediction, classification and evaluation. For example, two separate one-hidden-layer BP-trained MLP ANN models for data smoothing and quality modeling and two dynamic RBF ANN models for moisture content and temperature modeling were proposed to estimate the drying kinetics and quality index in the fluidized bed drying process of fresh green peas, diced potatoes, and silica gel saturated with ascorbic acid (Kamiński et al., 1998). Mainly studying the mapping relationship between output and input and without feedback relationship between input layer and output layer, the feed forward neural network analysis and design is relatively simple. Compared with feed forward neural network, the output neurons of feedback neural network have at least one feedback loop, and the signal can flow forward or reverse. The typical feedback networks include Hopfield neural network, Boltzmann neural network and the Kohonen neural network(Shi, 2009).

In terms of learning style (Shi, 2009), learning with teacher and without teacher are introduced (Shi and Zheng, 2006). Learning with teacher is also called supervised learning, and its structure is shown in Figure. 2. The design training process is guided by teacher and gets the data selected from the application environment (a series of expected input and output data as training samples). The network connection intensity is constantly adjusted by the error between the desired output and the actual output until the satisfactory input-output relationship is reached. Under the guidance of teacher, learning

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neural network can adapt to the changes in the environment, but it is easy to forget the knowledge they have learned while learning new knowledge. There are teachers' learning algorithms including back propagation (BP) algorithm and learning vector quantization (LVQ) algorithm etc. Compared the data of expectation and target output in the process of learning with teacher, there is no expectation data in the process of learning without teacher which can be divided into unsupervised learning and enhanced learning. Without teacher's guidance (expected input information) and evaluation mechanism, the neural network of unsupervised learning automatically adjusts the weight of the connection according to the input data and classifies the data with similar features according to the statistics rule in the training process. By adopting competitive learning rules, the commonly used unsupervised learning algorithms include adaptive resonance theory (ART) and Kohonen algorithm etc. Reinforcement learning (Niv and Langdon, 2016; Gershman, 2016) defines a small set of normative targets (accurately predicting the sum of future rewards, choosing actions that maximize reward attained etc.) and formalizes the process through which stimulus-reward predictions are acquired and used to guide choice behavior. Reinforcement learning algorithms mainly include Q learning algorithms, genetic algorithms, immune algorithms and DNA soft computing. With the advantages of online and adaptive learning capability, reinforcement learning has been a powerful strategy tool to solve optimization problems (Kara and Dogan, 2018) in many fields (Miljkovi et al., 2013).

The learning rules (Shi, 2009) involve the optimization theory, calculation method and signal processing etc. In addition to the basic algorithm, learning

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rules can make some improvements combined with other algorithms such as genetic algorithm, simulated annealing algorithm, perturbation algorithm and particle swarm algorithm. Generally speaking, learning rules include Hebb rule, Delata rule and competitive rule. As the basic learning rule of ANN, error correction learning (also known Delta δ learning), is a sort of supervised learning method. The input and output are used to denote the two neurons on the two sides of one synapse, and link weight is used to denote the link strength of the synapse. The objective of the system optimization is to find the optimal weights between output and expected value by the iterative method. Hebb learning rule is a sort of unsupervised learning method and it determines the link weight of neural network according to the current input and output of system. The objective of the system optimization is to find the optimal weights between inputs and outputs by the iterative method. As the activity law of neuron, viz., if the two neurons on the two sides of one synapse are activated at the same time, the strength of the synapse will be increased, When the input and output take positive numbers, they are regarded to be activated and the link weight will be increased. The competition of neural networks means that when input mode is provided, the processing elements in a neural network will compete for the "resources", such as the output. For every input pattern, all the processing elements will generate an output. Only the "most desirable" output is adopted, and only the winning processing element is renovated. So competitive learning rule is a sort of unsupervised learning method and it can modify the link weights to adapt to the changes of the external environment by the simulation of human experience based on past experience. Compared the characteristic of Hebb

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learning rule, viz., many neurons could be activated at the same time, only the output layer neuron which wins the competition in processing of competitive learning is activated, and the strength of the synapse will be increased. When the input and output take positive numbers, they are regarded to be activated and the link weight will be increased, which makes competitive learning very suitable for finding statistical features of input patterns and classifying input patterns automatically. The competitive neural network generally consists of the input layer and the competition layer such as the self-organizing feature map (SOM) and counter propagation network (CPN) which are also structurally feed forward neural networks.

Fuzzy Logic

Fuzzy logic (a way of AI) (Shi, 2009) is mainly designed by simulating human brain's reasoning ability and decision making ability and composed of fuzzy rule base, fuzzification, fuzzy inference and defuzzification (Mohd Adnan et al., 2013). According to the working principle of fuzzy logic as shown in Fig. 3, the operator's technical knowledge or expert experience is translated into forms of fuzzy rules and compose a fuzzy rule base. The precise input signal becomes fuzzy input signal after fuzzy processing. Then fuzzy input signal is dealt through fuzzy inference in fuzzy rule base to get fuzzy conclusions. After defuzzification of fuzzy conclusions, the system gives precise and specific output data.

One method that creates the most useful fuzzy rules is the “IF-THEN” rule statement (Mohd Adnan et al., 2013) which has been used in PID drying Controller (Dai et al., 2017), intelligent monitoring (Tavakolipour et al., 2014), and parameter

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optimization (Nadian et al., 2017) etc. The fuzzification process should be concerned with two aspects, viz, fuzzy set whose general way is Zadeh representation and sequence pair representation and membership function which commonly include triangle function, trapezoidal function, sigmoid function, Gauss function etc. The fuzzy inference is a method to get fuzzy conclusions by calculating the membership degree of the input to the related fuzzy sets according fuzzy rules and generally used the maximum and minimum synthesis regulation. The commonly used methods for defuzzification process are center of gravity (COG), central mean (CA), the maximum criterion method and the mean value method of maximum value.

Expert System

Expert system (Shi, 2009; Wagner, 2017) is a kind of computer intelligent system with professional knowledge and experience and has the ability as well as experts to solve complex problems by the experts thinking model using knowledge representation and knowledge reasoning in AI. According to knowledge representation technology, it can be divided into logical album system, rule-based expert system, expert system based on semantic network and frame based expert system. According to objective and task characteristics of the solved problem, it can be divided into interpretation expert system, prediction expert system, diagnosis expert system, debugging expert system, maintenance expert system, planning expert system, design expert system, detection expert system, controlling expert system and educational expert system. The function and structure of different types of expert system are different, and the general form of expert system is given in Fig. 4. As shown,

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expert system generally consists of 6 parts: human-machine interface, knowledge acquisition, knowledge base, inference engine, dynamic database and interpreter.

The human-machine interface is the place where system and user communicate and user inputs basic information, answers the questions raised by the system, and gets the reasoning results and related explanations. Knowledge acquisition is the key to the superiority of expert system knowledge base, as well as the bottleneck problem of expert system design. Through knowledge acquisition, knowledge base can be expanded and modified and the system realizes automatic learning function. A knowledge base is used to store the knowledge provided by an expert. The problem solving process of expert system is to simulate the way of thinking of experts through knowledge in knowledge base used to store the knowledge provided by experts. So knowledge base is an important part of expert system, the quality and quantity of which determine the level of expert system. Generally speaking, knowledge base in expert system is independent from other expert system programs so that users can change and modify the content of knowledge base to improve the performance of expert system. In view of the current condition or known information, inference engine repeatedly matches the rules in the knowledge base in order to get new conclusions and results of problem solving. Dynamic database as a temporary storage area is usually used to store the original data, intermediate results and final conclusions needed in the process of reasoning. Interpreter can make a description of the conclusion and the solution process

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according to the user's questions, which makes expert system more humanized and friendly.

The form of knowledge representation in AI is production system, framing, semantic network etc, while knowledge in expert system is generally production system whose form is “IF... THEN...”. Such an acronym for beginner's all-purpose symbolic instruction code and other programming languages, IF is followed by conditional (preceding part), and THEN is followed by the conclusion (the last part), which conditions and conclusions can be combined by logical operation AND, OR and NOT. Production system is simply described as if the precondition is satisfied, and the corresponding action or conclusion is produced.

Application In Food Drying

Artificial Biomimetic Technology

Artificial biomimetic technology is a kind of intelligence method based on the change of smell, taste, and appearance and contains odor-sensing system (electronic nose), taste-sensing system (electronic tongue) and visual image analysis system (computer vision). With the advantages of non-destructiveness, real-time, efficiency, generalization, simplicity etc, the technology is increasingly under consideration by food engineers and scientists for application as a superior tool to model complex, dynamic, highly nonlinear, and ill-defined scientific and engineering problems in food processing operations such as drying, freezing sorting, storage and quality assessment of food

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products (Su et al., 2014; Xu et al., 2017; Di Rosa et al., 2017; Kiani et al., 2016).

Electronic Nose

Electronic nose (E-nose), sometimes called the artificial nose, is an electronic system which tries to emulate the structure of the biological nose and is developed to detect and discriminate complex odors using an array of sensors and pattern recognition techniques (Xu et al., 2017), which generally contains three main components of the vapor delivery system, the sensor array, and pattern recognition algorithm. The sensor array consists of non-specific sensors treated with a variety of chemical materials, and each element measures the different properties of the sensed chemical. As soon as the sensor array is exposed to the volatile molecules, smell prints are generated from the sensors. Patterns from known scents are used to construct databases and train pattern recognition systems to allow unknown odors to be classified and identified (Kiani et al., 2016).

Coupled with chemometric techniques, E-nose could be applied as a reliable instrument for aroma monitoring in the drying process. The changes in volatile composition of button mushroom slices were investigated and compared by using headspace GC-MS and E-nose during freeze drying (FD) or combined with microwave vacuum drying with the result that E-nose could clearly discriminate button mushroom samples subject to different drying periods and the result obtained by e-nose showed good identity compared with GC-MS (Pei et al., 2016). E-nose was used to determine if there were differences in the aroma-active volatile components from the different edamame samples

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during different drying methods such as MD, MVD, VID, and AD (Lv et al., 2016). Olfactory characteristics of the different apples dried in freeze-drying and convective-air drying and packaged in natural polysaccharides films were investigated by electronic nose. Compared olfactory characteristics with tissue texture properties, it was shown that apples better retaining olfactory properties had shown the most intact cell walls (Laurienzo et al., 2013). Using E-nose to detect volatile compounds of dried carrot samples, Wang et al.(Wang et al., 2018) studied the effect of low frequency ultrasound (LFU) pretreatment prior to intermediate-wave infrared radiation (IW-IR) drying on volatile compounds. What is more, the electronic nose was found to be able to distinguish the difference among dried carrot slices. To improve the application range and precision of E-nose, Bari et al. (Barié et al., 2006) designed a novel E-nose based on miniaturized surface acoustic wave sensor arrays coupled with solid phase micro extraction process enhanced headspace-analysis and successfully conducted different tests such as differentiation between apple varieties, ripe and unripe pineapple etc.

Unfortunately, the researches of application of E-nose combined with computer vision, fuzzy logic and expert system are relatively few, mainly focusing on monitoring and optimization of drying process and automatic control. In a study by Raghavan et al. (Raghavan et al., 2010), a real-time aroma monitoring system to control a microwave drying process was designed using electronic nose based on the fuzzy logic algorithm for dynamically determining drying temperatures and automatic phase controller for adjusting the microwave power level to meet the temperature requirement. The tests of carrot and apple drying showed that their newly developed control strategies could improve the quality of the dried products undergoing microwave drying in

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terms of aroma retention. What is more, Li et al. (Li et al., 2009) also designed a real-time, volatile-detection-assisted control system for microwave drying. In the system, detected volatile signals were integrated to a fuzzy logic algorithm to determine the drying temperature. A phase controller was used to realize automatic and continuous adjustment of microwave power and a data acquisition unit with developed program was employed to integrate the entire control. The carrot drying test showed that the designed system could successfully achieve the desired power, temperature, volatility control and ensure the quality of the product.

Computer Vision

Computer vision is one of the earliest techniques employed in the food drying process for real-time determination of physical properties of the products, including size, and shape, as well as the quality parameters (Aghbashlo et al., 2014; Su et al., 2014) and has rapidly increased in the fields of quality inspection, classification and evaluation in processing a large number of food products (Sun, 2004). As a kind of intelligence technology based on the artificial eye, advantages of computer vision such as fast, reliability, and non-destructiveness for continuous monitoring, quality assurance and controlling in drying process were discussed in excellent reviews of Du (Du and Sun, 2004), Zheng et al. (Zheng et al., 2006) and Martynenko (Martynenko, 2017). Generally, the basic components of computer vision systems include digital camera(s), source of illumination, computer hardware and software and the process usually includes five steps as follows: image acquisition, segmentation, image feature extraction (external and internal image features),

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recognition, classification and interpretation (Fernández et al., 2005). Schematic diagram of a computer-vision system is shown in Fig. 5 (Su et al., 2014). The progress of computer vision technology in food processing and particularly in drying went through three distinctive stages: (1) offline imaging for food quality evaluation, (2) online imaging to relate image features with food quality degradation, and (3) online imaging of critical control points for control and optimization of drying (Martynenko, 2017).

During drying process, the color, shrinkage and structure of dried food are the main physical parameters affecting the quality and subsequent marketability of final product (Achata et al., 2015; Hosseinpour et al., 2013). Computer vision has been extensively employed to analyze the effect of drying condition such as temperature (Chen and Martynenko, 2013), power intensity (Barzegar et al., 2015; Nahimana and Zhang, 2011), air flow velocity (Shahabi et al., 2014), pretreatment (Nadian et al., 2016a), browning components (Gao et al., 2017a) on the shape, size and color changes to improve the drying process and ensure high-quality dried products. (Hosseinpour et al., 2011; Yadollahinia and Jahangiri, 2009; Martynenko, 2006; Chen and Martynenko, 2013). The color observability of ginseng drying process was provided due to online image analysis and correlation of image attributes (area, color, texture) with physical parameters of drying (moisture, quality) (Martynenko, 2006). Hosseinpour et al.(Hosseinpour et al., 2011; Hosseinpour et al., 2013) investigated the effects of drying temperature and drying medium velocity on color change kinetics of shrimp viz. lightness redness, yellowness, total color difference, chroma, hue angle (abbreviated L*, a*, b*, ΔE, CH, H), during superheated steam drying

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(SSD) and hot air drying (HAD). The results showed that temperature significantly influenced color parameters, compared with the increase of other color, samples lightness decreased. In the intermittent microwave convective drying experiment of apple slices (Aghilinategh et al., 2016), a real-time computer vision technique was employed to detect the effect of drying parameters on color properties of samples and results indicated that lightness and color change were mainly influenced by microwave power and pulse ratios. Gao et al. (Gao et al., 2017b; Gao et al., 2017a) gave the evaluation of browning ratio in an image analysis of apple slices at different stages of instant controlled pressure drop-assisted hot-air drying and studied the influences of reducing sugar, amino acids, ascorbic acids, and phenolic compounds on the nonenzymatic browning reactions. CVS was also used to evaluate the drying uniformity of pulse-spouted microwave-freeze drying (Jiang et al., 2015) and measure diameter and thickness to estimate bulk volume of cylindrically shaped apple slices (Wang et al., 2016). Some researches pay attention to the point of improving the precision of CVS. Using computer vision methods in combination with optical scattering analysis of light at 650 nm, Udomkun et al. (Udomkun et al., 2016) assessed the feasibility of a multi-sensor approach for predicting shrinkage of papaya during convective hot-air drying. Using CVS combined approach with backscattering analysis using laser diodes, Udomkun et al. (Udomkun et al., 2017) predicted color changes of papaya during hot-air drying and accurately described the behavior of L*, a*, b*, and ΔE by the color image of papaya values (R^2 is 0.9474, 0.9237, 0.9732, 0.9814, 0.9804, respectively). CVS combined with Magnetic resonance imaging (MRI)

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technique was used to analyze the sensory attributes of dry-cured loins in a non-destructive way (Giovagnoli-Vicuña et al., 2017). To improve quality of kiwifruit drying, Nadiana et al. (Nadian et al., 2016b) monitored shrinkage and color changes of kiwifruit slices in real time with CVS and proposed a hybrid approach with hot air drying (HAD) at the first stage and hybrid hot air-infrared drying (HID) at the second stage of drying as a reasonable compromise between drying time and product quality.

In addition to the above applications, CVS has also been successfully applied in sorting and grading. Except the comparison of color assessment between CVS and conventional instrumental methods, an extremely high 99.5% of deteriorated figs were classified correctly in Benalia research (Benalia et al., 2016). Apple discs can also be classified into classes as 95% based on external image features at different stages of drying (Fernández et al., 2005). Because of the close correlations between uniformity of intensity and with moisture content, a low cost dual-view computer-vision system to measure volume and color co-occurrence image textural features of apple slices was designed to find the end of drying process by comparing physical texture parameters and moisture content (Sampson et al., 2014). Quality parameters (color, porosity and shrinkage) of persimmon fruit were observed by the CVS to describe the evolution of temperature and moisture content distributions during drying process (Giovagnoli-Vicuña et al., 2017). Performance of the CVS for control of drying processes was tested in industrial conditions on pilot batch dryer. Estimated moisture content was used as a global feedback parameter for the identification of the drying stage and adjustment of the drying conditions

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according to the specified control strategy. Result showed that moisture content at the endpoint could be predicted as an interval estimate from 0.08 to 0.12 with 95% confidence. The control system of moisture content at the endpoint showed the stability and robustness, combined with high accuracy in the estimation of drying time (8-14% of error with 95% confidence).

However, there is limited work on the application of computer vision combined with AI technology, which is mainly focused on parameter optimization of neural network model, prediction of water content during drying process, relation of experimental parameters and intelligent control of drying process. In order to determine the best time for drying turmeric-based machine vision by using ANN and know the best ANN in the turmeric drying process, Zakaria (Zakaria., 2017) studied the effect of different learning rates and momentum rates on the precision and found that best result was showed on the learning process of learning rate 0.3 and momentum rate 0.9 ANN models. In order to quantify the contribution of chemical pre-treatment on the color changes of apple slices during hot air drying, Nadian et al. (Nadian et al., 2016c) built a multilayer perceptron (MLP) network trained by Levenberg-Marquardt error minimization algorithm as 3-4-3 with tangent sigmoid function in hidden layer and linear function in output layer which correlated the outputs viz. drying air temperature, moisture ratio, and type of treatment (with and without pre-treatment). to the inputs viz. total amount of color changes, browning index, chroma. Several configurations of a multilayer perceptron artificial neural network (MLP-ANN) were also used to predict the moisture ratio and the geometrical characteristics of the shrimp batch during hot air drying and

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superheated steam drying using the image texture parameters with correlation coefficients higher than 0.99 (Hosseinpour et al., 2014). A MLP-ANN with input layer containing three cells, two hidden layers (18 neurons), and five cells for output layer, was used to develop a model that can monitor, control and predict the shrinkage parameters and moisture content of sweet potato slices under different drying conditions (Onwude et al., 2017). The developed ANN model combined with computer vision, laser light backscattering imaging satisfactorily predicted the shrinkage and dimensionless moisture content of sweet potato with correlation coefficient greater than 0.95. In the drying experiment of grapes shrinkage based on the CSV technology, ANN with the inputs of air drying temperature, velocity, shrinkage and moisture content at time and output of moisture content at time $t+\Delta_t$ was developed to predictive model of the grape drying in a hot air dryer. The best ANN was obtained by three layers (4 inputs, 5 nodes in hidden layer and 1 output) with 0.00004 the mean squared error (MSE)and 0.99947 R^2 for training and 0.00003 MSE and 0.99952 R^2 for testing data (Behroozi Khazaei et al., 2013). A optimized ANN topology was also found as 5-7-1 with inputs of air temperature, air velocity, and L*, a*, b* values and Logsig transfer function in hidden layer and Tansig in output layer to predict the moisture content of paddy during thin-layer drying process (Golpour, 2015). Energy saving and automatic intelligent control of the drying system are the hot areas of research. Five ANN models with inputs drying air temperatures, radiation intensities and depth of green peas in bed were developed to model the drying process (time and moisture content) and the product quality factors (shrinkage, roundness, and color components) in hot air

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infrared-assisted vibratory bed drying and the result showed that the specific energy consumption and drying time and SEC decreased significantly in the vibratory bed ($p < 0.01$) (Barzegar et al., 2015). In Mohammad's study (Nadian et al., 2017a), combining ANN technology, an intelligent control system of fuzzy machine vision was developed to control the operating variables during a combined hot air-infrared drying process. CVS was used to monitor total discoloration and the shrinkage of thin layer kiwifruit slices in real time. These values of image information (ΔE and Sh) were used in ANN for predicting the moisture ratio of materials and were fed into a genetic algorithm (GA) framework to optimize a fuzzy logic control system.

Conventional Drying Technology

AI technologies, especially the ANN technique, have been widely used to solve problems of nonlinear function approximation, pattern detection, data interpretation, optimization, simulation, diagnosis, monitoring, control, data sorting, clustering, and noise reduction in drying technology such as batch convective thin-layer drying, fluidized bed drying, osmotic dehydration, osmotic-convective drying, infrared, microwave, infrared- and microwave-assisted drying processes, spray drying, freeze drying, rotary drying, renewable drying, deep bed drying, spout bed drying. This article presents a comprehensive review of significant AI applications of fresh food in modeling, predicting, and optimization of heat and mass transfer, thermodynamic performance parameters, and quality indicators as well as physiochemical properties of dried products during the recent 5 years.

As shown in Table 1, the main application areas of AI in drying are drying kinetics modeling, followed by heat and mass transfer, physicochemical properties and quality

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modeling. In Momenzadeh's experiment (Momenzadeh, 2012), the application of ANN with input variables (microwave power, drying air temperature, and green pea moisture content) was investigated to predict the drying time of green pea in a fluidized bed dryer assisted by microwave heating. The influence of transfer functions and training algorithms were also studied and network with the logsig (Log sigmoid) transfer function and trainrp back propagation algorithm made the most accurate predictions for the green pea drying system with R2 of 98%. In case of ANN model, four inputs (product type, sorption state, temperature and equilibrium moisture content), one output (equilibrium relative humidity) and two hidden layers were used to estimated moisture sorption isotherms (Al-Mahasneh et al., 2014). A feed forward ANN (Guine et al., 2015) using the Levenberg-Marquartd method for training was accurately in predicting phenolic contents and antioxidant activity of banana from the input variables banana variety, dryness state and type and order of extract with the result that drying state and extract order were found to have larger impact in the values of antioxidant activity and phenolic compounds. Mahjoorian et al. (Mahjoorian et al., 2017) feasibly predicted dried kiwi slices moisture ratio by the MLP-ANN model with logsig activation function base on 13 neurons in first and second hidden layers. In case of BP-ANN model (Husna and Purqon, 2016), four inputs (mass, temperature, thickness and drying time), and one hidden layers with ten neurons was used to predict the moisture content of durian slices with R2 value 98.47% during microwave oven drying. Özdemir et al. (Özdemir et al., 2017) predicted the performance of a convective-infrared system with heat recovery at different drying temperatures (40℃, 45℃, 50℃ and 55℃) and 0.5 m/s air velocity on energy consumption and drying

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kinetics of sliced kiwifruit using ANNs where the back-propagation learning algorithm with Levenberge-Marquardt and Fermi transfer function were used.

Jena (Jena and Sahoo, 2013) studied the drying characteristics in terms of diffusivity for mushrooms and different vegetables by ANN modeling in a fluidized bed dryer and compared the values of diffusivity obtained through the method with the experimentally measured values indicating the wide applicability of the developed correlations for industrial uses. In another investigation, Nadian et al. (Nadian et al., 2015) applied a MLP-ANN to correlate moisture content and color parameters of apple slices with drying variables and drying time in hot air drying. Mathematical models and ANNs were applied to best describe water loss and solids gain during osmotic dehydration of eggplant in salt concentrations of 5, 10 and 15%, sample to osmotic solutions ratios of 1:10, 1:15 and 1:20 and temperatures of 30, 45 and 60℃, supplemented by oven drying at 70℃ (Bahmani et al., 2016). Predicting percentages of water loss and solids gain by ANNs was maximized in topologies of 4-25-2 and 4-16-2 with R2 coefficients of 0.9825 and 0.9761, respectively. In another study of convective drying (Guiné et al., 2014), the mass transfer properties, drying kinetics and the effect of drying on some chemical and physical properties of apples were evaluated using feed-forward neural networks. The results obtained using ANN and regression analysis were also compared showing that all the studied properties can be correctly modeled using ANN. A feed forward multilayered perceptron trained by back-propagation algorithms for five independent variables (microwave power, air flow rate, temperature, starting time of microwave input, and amount of loaded material) was developed to predict nine outputs (drying time, rehydration capacity, density, porosity, hardness, water activity, phenolic compounds content, anthocyanins content, and the

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antioxidant activity) of black raspberry during microwave-assisted fluidized bed drying. The results indicated that the experimental and ANN-predicted data sets were in good agreement with R2 of 0.92 (Fazaeli et al., 2011). In another research, A multilayer perceptron ANN (Aghbashlo et al., 2013) with tangent sigmoid transfer function, Levenberg-Marquardt error minimization algorithm was developed in the spray drying method to predict the performance indices, namely capsules' residual moisture content, particle size, encapsulation efficiency, bulk density, and peroxide value. The relation amongst inlet-drying air temperature, outlet-drying air temperature, aspirator rate, peristaltic pump rate, and spraying air flow rate with performance indices was bridged by selected 5-10-5 structural ANN with R2 value higher than 0.87. Using a feed forward ANN with Levenberg-Marquartd method for training and MSE method for performance assessment, Barroca et al. (Barroca et al., 2017) evaluated the effect of various pre-drying treatments (type and concentration of soaking solution, pre-treatment times and blanching time) on the quality of dried carrots by assessing the values of moisture, ash, protein, fibre, sugars and color.

Quite a few research studies have also reported the comparison of ANN modeling with traditional mathematical or statistical methods for predicting drying process. The applicability of ANNs was tested for prediction of drying kinetics of mushroom in microwave vacuum drier under the condition of various powers (130, 260, 380 and 450 W) and absolute pressures (200, 400, 600 and 800 mbar) (Ghaderi., 2012). For comparison with the existing mathematical models purpose, 6 thin-layer drying models and ANN model were fitted to the experimental data to predict moisture ratio and drying rate (DR). The study revealed that ANN model showed its high ability to predict the moisture ratio and DR quite well with R^2 of 0.9991, 0.9995 and 0.9996 for training,

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validation and testing, respectively and mean square error were 0.00086, 0.00042 and 0.00052, respectively for the predictions. In study of dried potatoes (Yaghoubi et al., 2013), the comparison of the obtained results of ANNs and classical modeling indicated that the neural networks have a higher capability for predicting moisture ratio (R^2 values 0.9972 and 0.996, respectively) compared with classical modeling in hot air drying (AD), microwave drying (MW) and combinative hot air drying-microwave drying (AD-MW). Mathematical models and ANN models were used to determine the effect of microwave power on moisture content, moisture ratio, drying rate, drying time and effective diffusivity in microwave drying process of mango ginger (Krishna Murthy and Manohar, 2012). The result showed that the semi-empirical Midilli model described the drying kinetics very well with $R^2 > 0.999$ and a feed forward ANN using back-propagation algorithm was found adequate to predict the drying kinetics with R^2 of 0.985. In another comparison of application of mathematical models and artificial neural networks used to estimate the effect of air temperature, air velocity and infrared (IR) radiation on the drying kinetics of sour cherry in a laboratory infrared dryer, the trained ANN model was relatively better than the empirical models with R^2 of 0.9944 and 0.9905 for predication of moisture diffusivity and energy consumption, respectively (Chayjan, 2014). Kaven (Kaveh and Amiri Chayjan, 2017) had the same conclusion that the trained ANN model of feed forward back-propagation with 4-10-10-2 structure, training algorithm of Bayesian regulation and threshold functions of tansigpurelin-logsig was better than the empirical models for predicting moisture ratio and drying rate. The dynamic neural network which contains both a huge number of feed forward and feedback synaptic connections provides computational advantages than that of purely feed forward neural structure. Samadi et al. (Samadi et al., 2013)

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compared static and dynamic ANNs and thin-layer drying models for modeling the drying characteristics of apple slices in a combined heat and power dryer at different temperatures (50, 65, 80, and 95℃) and three levels of drying product thickness (3, 5,and 7 mm) with the constant air flow velocity of 1 m/s. It was found that the selected dynamic ANN topology had a better estimation capability than the two other approaches with R^2 of 0.9989 and 0.9985 for moisture ratio and drying ratio, respectively. Silva et al. (Guzzo da Silva et al., 2014) used eight kinds of classical models and four different ANN models to estimate the drying kinetics and the drying rate of Brazilian pepper-tree fruits in thin-layer drying and found that results of Henderson model with the ANN model were satisfactory and very similar. In another study (Murthy and Manohar, 2014), prediction of drying kinetics by mathematical modeling and ANN in hot air drying characteristics of mango ginger showed ANN suitable to describe the drying kinetics with very high correlation coefficient of 0.998. Two intelligent tools (Tavakolipour et al., 2014), fuzzy expert engine and ANN, were also used to predict moisture content of zucchini slices during drying process. Finally, comparison of these results revealed that ANN model with R^2 of 0.998 had greater accuracy than fuzzy expert engine to predict moisture ratio of dried zucchini. What is more, Jafari et al. (Jafari et al., 2016a) studied a comparative performed among nonlinear regression techniques, fuzzy logic and ANNs to estimate the dynamic drying behavior of onion by a custom designed fluidized bed dryer equipped with a heat pump dehumidifier. Results revealed that the selected classical model with R^2 of 0.999 showed the best fit with experimental data and feed forward back propagation neural system with application of Levenberg-Marquardt training algorithm, hyperbolic tangent sigmoid transfer function, and 2-5-1 topology was determined as the best neural

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model in terms of statistical indices. He also applied this method in the green bell pepper drying and found ANN method was much more precise than two other methods in prediction of drying kinetics and control of drying parameters (Jafari et al., 2016b).

Some researchers made attempts to modify the available methods to improve the performance of AI technology in drying by some measures such as development of advanced ANN models, the combination of classical ANN with mathematical models, fuzzy logic system and other algorithms etc. The comparison of layer, pure neural network and hybrid neural model used in modeling the convective drying of potatoes and carrots showed that hybrid neural models, formulated as a combination of both theoretical and neural network models, were capable of offering the most accurate predictions of system behavior (Saraceno et al., 2010). A novel hybrid system of multiple output-dependent data scaling (MODDS) combined with an adaptive neuro-fuzzy inference system (ANFIS) was proposed to model and predict the freeze drying behavior of apples (Polat and Kirmaci, 2011). First, input parameters were scaled by the way of MODDS. And then, the outputs were predicted with the scaled input parameters using ANFIS algorithm. Tangent hyperbolic (tanh) and logarithmic sigmoid (logsig) were utilized to estimate the influence of different activation function of neural networks on the characteristics of whole pistachio in hot air convective drying at a constant airflow velocity of 2 $m.s^{-1}$ and air temperature in the range of 40-70°C (Tavakolipour and Mokhtarian, 2012). Key parameters such as training algorithm, threshold function, number of layers and neurons were tested to optimize the ANN models for predicting the drying moisture diffusivity, energy consumption, shrinkage, drying rate and moisture ratio of terebinth fruit in infrared fluidized bed drying (Kaveh and Chayjan, 2014). Balbay et al. (Balbay et al., 2012) selected extreme learning

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machine (ELM) for predicting the moisture ratio of black cumin seeds in microwave assisted drying system and compared the application with other classical ANN models, in which different types of activation functions including sigmoid, tangent sigmoid, triangular, radial basis, hard limit and sine, the number of hidden layer neurons from 10 to 100, as well as the a comparison with various ANN modeling techniques including Levenberge-Marquardt algorithm and scaled conjugate gradient algorithm (SCG) were investigated. The results revealed that the ELM model by 93 neurons with Sine transfer function in hidden layer were more effective and accurate than the selected ANN models. Azadeh et al. (Azadeh et al., 2011) designed the ANN and ANFIS approaches based on partial least squares (PLS) to identify the optimal process settings regarding to the desired process response. With feed-forward back-propagation ANN trained by genetic algorithm, Khawas et al. (Khawas et al., 2015) successfully evaluated the influence of drying temperature, sample slice thickness, and pretreatment on quality attributes like rehydration ratio, scavenging activity, color, and texture of culinary banana in vacuum drying.

Intelligent Control and Optimization

Drying process control aids the main objectives of the food industry which focus on food safety, food quality control, increasing yield, and minimizing production cost. The most commonly used controller in industrial drying applications is proportional-integral-derivative (PID) controller based on a precise mathematical description of the control object for the control of first- and second-order plants, and even high-order plants with well-defined conditions. However, getting a poor performance is the major disadvantage whenever the plant is subjected to some kind of disturbance ,or the plant has nonlinear structure of high order. Drying of wet materials

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is a complex, dynamic, unsteady, highly nonlinear, strongly interactive, successively interconnected, and multivariable thermal process. So it is difficult for the conventional mathematical model based on control strategies to obtain the exact representative model of the plant due to the uncertainty, multivariable interaction, complexity and constraints of the plant. The development of sophisticated control strategies with the help of the latest mathematical tools such as ANN, fuzzy logic and genetic algorithms has inspired new resources for the possible implementation of better and more efficient control.

Liu et al. (Liu et al., 2011) detailed discussed principles of the neural network algorithm for improving the universality of detection system and adaptive ability within limited memory, processor and external equipment in the embedded intelligent measuring system. A genetically optimized adaptive fuzzy logic controller was efficiently implemented in the real-time determination and control the optimal conditions for fluidized bed paddy drying system that maintains paddy moisture content closed to the desire level with efficient energy consumption (Atthajariyakul and Leephakpreeda, 2006). Arvin et al. (Arvin et al., 2011) designed a microcontroller base controller circuit based on fuzzy logical system with input of temperature and out puts of heater power and speed of fan. Lutfy et al. (Lutfy et al., 2011) proposed an effective intelligent control strategy for a newly designed paddy (rough rice) grain dryer plant in which the input-output data obtained from preliminary experiments were presented to an ANFIS network to develop a control-oriented dryer model and a simplified proportional-integral-derivative (PID)-like ANFIS controller trained by a real-coded genetic algorithm was utilized to control the drying process. The robustness tests and a comparative study with a genetically tuned conventional PID controller showed that the simplified ANFIS controller had remarkable ability in controlling the grain drying process. Zhang et al. (Zhang et al., 2015) developed a decoupling approach based on sugeno type of FIS assisted by ANFIS for the real-time control of temperature and relative humidity in drying room. In this study, a network structure of 1-5-5-5-1 was selected to correspond the input of fuzzy logic system, fuzzification, fuzzy inference, normalization and consequent, and aggregation respectively. Compared with the traditional PID control, the relative humidity fluctuation after the decoupling treatment was reduced from ±2.5% to ±0.6%. As shown in Fig 6, Nadian et al. (Nadian et al., 2017b) designed an intelligent fuzzy-machine vision control system (FMCS) based on fuzzy logic and computer vision technology. Two ANNs (ANN-1 and ANN-2) were employed. The former was in charge of predicting the material characteristics including ΔE, Sh and moisture ratio with four input variables: time, IR lamps mode (ON = 1 and OFF = 0), temperature (T) and air velocity and optimizing the fuzzy controller using genetic algorithm. The ANN-2 network was responsible for predicting sample's moisture ratio from ΔE and Sh as inputs based on image information. The performance of the intelligence controller was evaluated for kiwifruit drying using a laboratory-scale hot air-infrared dryer with the results indicating that the hybrid drying could significantly reduce the drying load/time compared with the hot air drying and the FMCS application showed a good balance between energy consumption (0.158 kW h) and product quality (ΔE = 2.32). Dai et al. (Dai et al., 2017) designed and simulated a genetically optimized fuzzy immune proportional integral derivative controller (GOFIP) for a novel grain dryer. By simulation comparisons of the step response of the outlet grain moisture content with three other controllers (the general PID controller, the fuzzy PID controller, and the fuzzy immune PID controller), it is shown that the

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GOFIP controller had the best control performances to bring the outlet grain moisture content to the target value rapidly, enabling the drying control system to have no overshoot, better accuracy, and stronger anti-disturbance performance.

An improvement in control accuracy for drying is not only to increase the quality of products, but also to reduce energy cost in control systems. However, the reducing energy consumption is the main concern in food industry and particularly in drying. Nazghelichi et al. (Nazghelichi et al., 2011) used recurrent multilayer feed-forward ANNs with the gradient descent with momentum leaning algorithm and tansig transfer function to correlate the outputs (energy$_{(t+\Delta t)}$ and exergy$_{(t+\Delta t)}$ of carrot cubes) to the five inputs (drying time, drying air temperature, carrot cube size, bed depth and energy$_{(t)}$ and exergy$_{(t)}$ of carrot cubes). Comparison of the static and recurrent ANNs showed that all selected recurrent ANN models outperformed the static ANN and the optimal recurrent model could be utilized for determining the appropriate drying conditions of carrot cubes to reach the optimal energy efficiency in fluidized bed drying. BP-ANN and response surface methodology (RSM) desirably modeled energy and exergy criteria regarding input factors with highly acceptable coefficient of determination (R^2) values thin-layer drying of sour pomegranate arils with microwave treatment. (Nikbakht et al., 2014).To accurately predict the energy and exergy parameters, such as energy utilization, energy utilization ratio, exergy loss and exergy efficiency, related to the fluidized bed drying for potato cubes, a two-layer feed forward network with 15 neurons in the hidden layer was constructed from learning algorithms (Levenberg-Marquardt) and transfer functions (hyperbolic tangent sigmoid) (Azadbakht et al., 2017).

Disadvantages of AI and Suggestions for Future Research

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While ANN, fuzzy logic, expert system, evolutionary algorithms or their combinations were recognized as excellent tools for simulation, estimation, optimization, monitoring, control of different drying process, it is fruitful to think of AI technologies not as a perfect substitution, but rather a technique to complement available methodologies due to the objective problems to be solved (Aghbashlo et al., 2015). The development and application of AI still face many challenges as following:

(1) ANN paradigm is able to overcome any inaccuracies of the phenomenological models due to the overlooked existence of uncertainties. However, ANNs are like a ‘‘black-box’’ and it is laborious to interpret the internal relationships between the input and output variables, since this does not provide actual knowledge of weighting parameters of individual components to the user.

(2) Except the research on neural network technology theory, the design, optimization and improvement of ANN model is another problem that is currently facing. There is no theoretical guidance for the structural design of the neural network. The selection of the hidden layer number, the number of hidden layer nodes, the incentive function and the training algorithm are all based on experience design, and can only be obtained by experimental calculation, which causes more redundancy to the network and invisibly adds the amount of research work and programming calculation. Hence, work on the basic theory of neural network is the key direction of scientific research in the future.

(3) The strongest driving and the greatest challenge of the development of neural network theory is the study of nonlinear problems including the research of nonlinear dynamic system, adaptation, self-organizing, chaotic neural network and neural

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network mathematical theory. Moreover, it is also necessary to study the basic characteristics of ANN such as stability, convergence, fault tolerance, robustness. Understanding the principles of the basic theory and its potential will permit these available techniques to be extended further and form an important part of modern drying technology for smart controlling of industrial dryers.

(4) What is more, the innovation and optimization of ANN's learning algorithm, transfer function etc should be studied to make the ANN technology having more rapid convergence speed and generalization ability. The AI technologies of ANN, fuzzy logic, expert system or other evolutionary methods are all very useful for the drying process and some researchers made attempts to use a hybrid models through the combination of classical models and mathematical models for eliminating the disadvantages. But there are not many references in the literature on the applications of combined advanced intelligent drying technology such as hybrid mathematical-ANN, hybrid mathematical-ANFIS, neuro-evolutionary, neuro-fuzzy, and neuro-fuzzy-evolutionary. Undoubtedly, the application of neural network combined technology will be promising with other methods such as fuzzy logic, expert system, genetic algorithm, grey coefficient, data mining technology, wavelet analysis, chaos, rough set theory etc. In the near future, advanced ANN approaches will gradually find their way into a wide range of industrial drying applications due to the enormous advent in computer power and neural network algorithms.

(5) The development of automation system based on AI technology still faces a severe test. Maybe due to the business secret, reported studies on the application of the AI to industrial-scale dryers under varying drying conditions for monitoring and controlling purposes were scarce. At the same time, the majority of studies frequently

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applied the AI technology in offline mode. Modeling systems to drying modeling, monitoring, and control industrial applications of AI in drying technology seem to be very few.

With the development of big data and cloud computing, it is thus envisaged that this review article can stimulate more research for developing intelligent real-time control systems for dryers by employing advanced measurement tools such as real-time CVS, electronic nose and tongue, electronic mucosa, bioelectronics tongue, spectroscopic method, etc. for pattern detection and process optimization, tracking, and control.

Conclusion

This review presents a comprehensive study on the basic theoretical knowledge of artificial intelligence technologies and applications in food drying technology and process control. The basic theoretical knowledge of artificial neural network, fuzzy logic and expert system is briefly introduced. We also summarize the AI applications of modeling, predicting, and optimization of heat and mass transfer, thermodynamic performance parameters, and quality indicators as well as physiochemical properties of dried products in artificial biomimetic technology (electronic nose, computer vision) and different conventional drying technologies. It was found that ANN, fuzzy logic, expert system, evolutionary algorithms or their combinations were excellent tools to solve the problems in drying process. However, AI (Aghbashlo et al., 2015) also has many limitations on the respect of interpretation of model, theoretical guidance and innovation, hybrid AI technologies and automation AI control system. Considering the above problems, we make the following recommendations about AI study in the fresh

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food drying. (1) Online application of AI for monitoring, optimization and control system by the assistance of real-time CVS, electronic nose and tongue, electronic mucosa, bioelectronics tongue, spectroscopic method etc in drying process. (2) Hybrid AI drying technologies combined ANN, fuzzy logic, expert system, or their combinations with classical models, mathematical models or other evolutionary algorithm to improve computational efficiency and robustness. (3) Advanced embedded controller based on AI or hybrid AI technologies in industrial drying application. (4) User-friendly software and hardware of AI for drying process. It is worth mentioning that the emergence of supercomputers, big data and cloud computing will provide a powerful engine for the development of AI. Through the mutual promotion of advanced technologies, AI technique will be applied in almost every field of the drying industry more effectively and precisely in the future.

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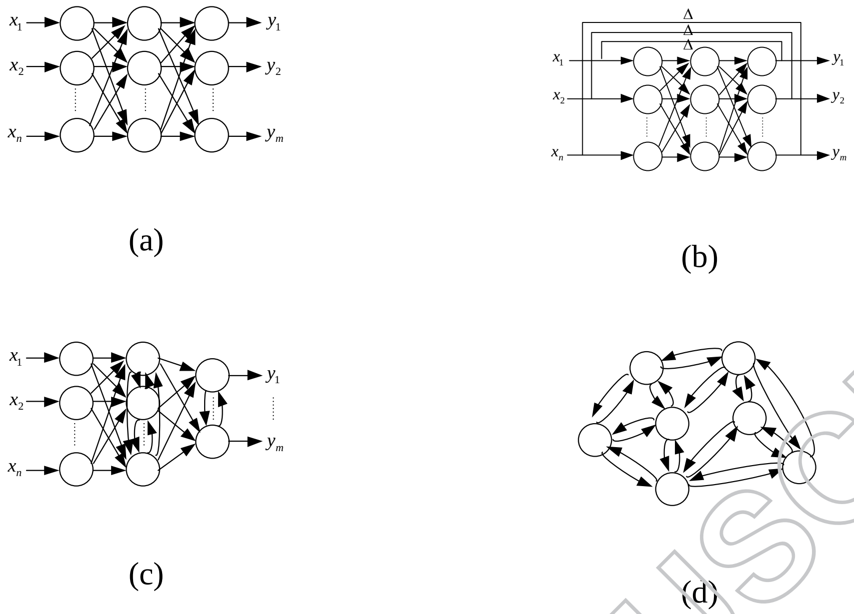

Fig 1 models of ANN: (a) BP Feed-forward Network; (b) Recurrent Network; (c) mixed Network; (d) Interconnected Network

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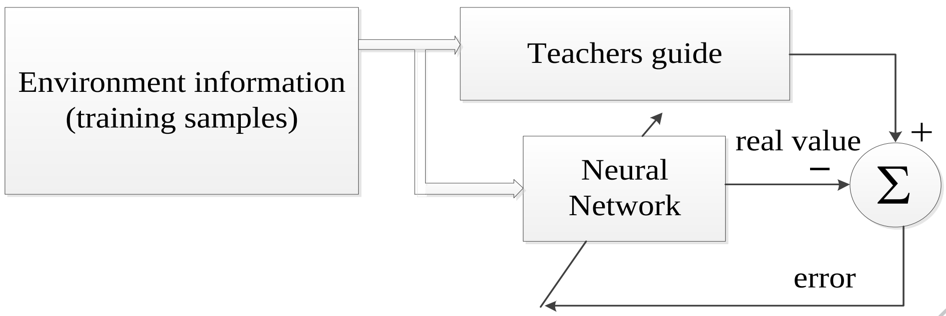

Fig. 2 Schematic diagram of Learning with teacher

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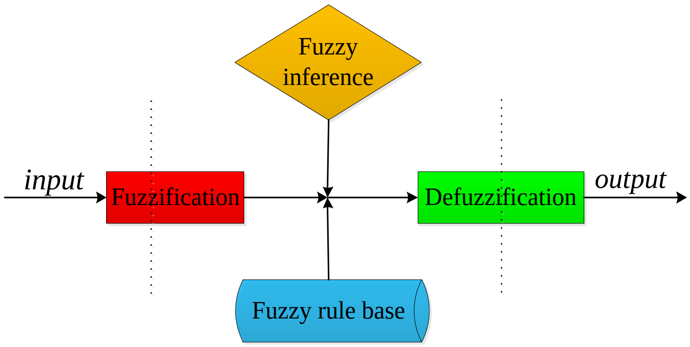

Fig. 3 Schematic diagram of fuzzy logic

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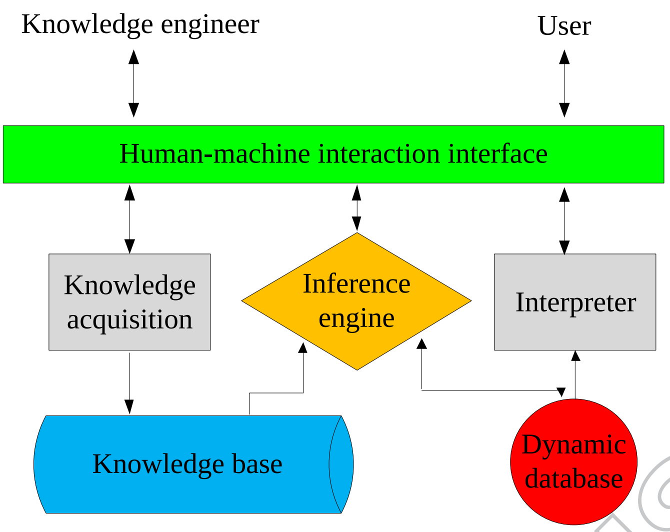

Fig. 4 Schematic diagram of expert system

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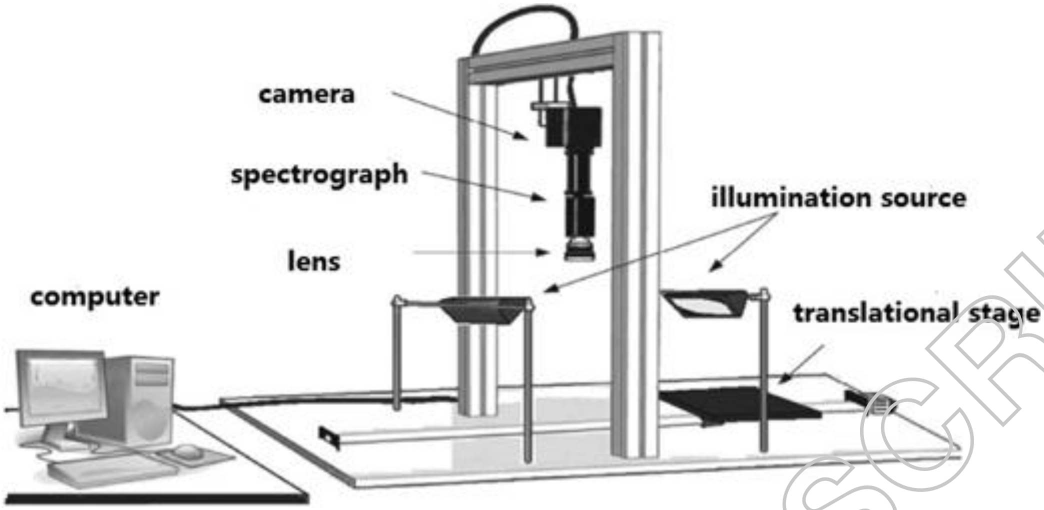

Fig. 5 Schematic diagram of computer-vision system(Su et al., 2014)

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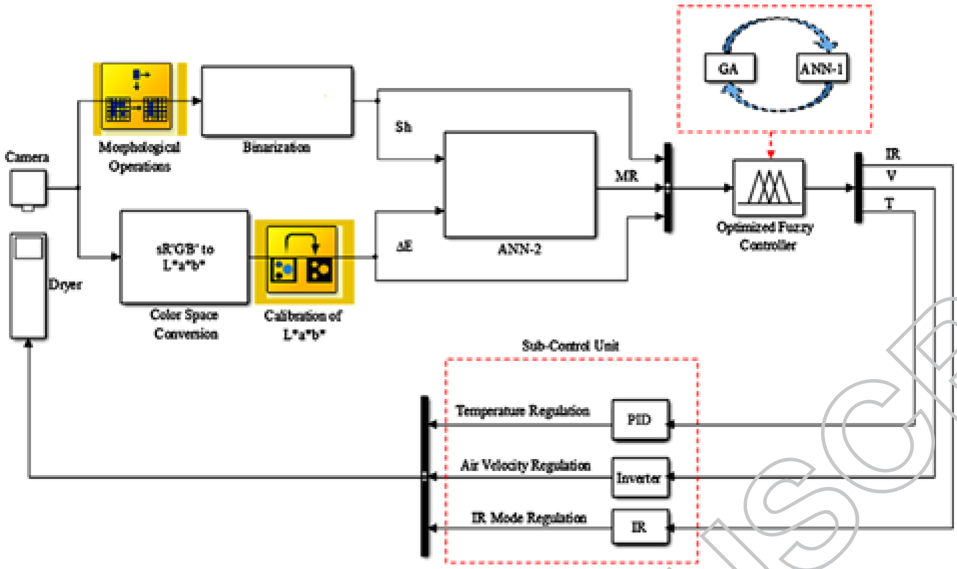

Fig. 6 An intelligent integrated control of hybrid hot air-infrared dryer based on fuzzy logic and computer vision system(Nadian et al., 2017)

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Table 1 AIs' applications in drying processes

Author(s)	Product(s)	Aim(s)	Best model input(s)	Best model output(s)	Best ANN(s) model	Results
Murthy(Krishna Murthy and Manohar, 2012)	Mango ginger	To model the moisture content	Drying time and microwave power	Moisture content	One-hidden-layer BP-trained MLP ANN	Appropriate modeling using the ANN and Midilli et al. model
Chayjan(Chayjan et al., 2014)	Sour cherry	To model the moisture diffusion and energy consumption during infrared-convective drying process	Infrared power and temperature and velocity of the drying air	Effective moisture diffusivity and specific energy consumption	Two separate two-hidden layer BP-trained feed-forward MLP ANN	Precise modeling of both output parameters
Yaghoubi(Yaghoubi et al., 2013)	Potato cub	To predict the drying kinetics	Drying time, drying air temperature, and	Moisture ratio	One-hidden layer	Exact modeling of the drying

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	es	during hot air, microwave, combined hot air-microwave drying processes	drying technique		BP-trained MLP ANN	kinetics
Mahasnehm(Al-Mahasneh et al., 2014)	Grains and legumes	To model the moisture sorption isotherms	Product type, sorption state (adsorption or desorption), temperature and equilibrium moisture content	Equilibrium relative humidity	Two-hidden layer ANN	Precise modeling of equilibrium relative humidity
Aghbashlo(Aghbashlo et al., 2013)	Fish oil emulsion	To estimate the thermodynamic performance parameters	Inlet drying air temperature, drying air flow rate, feed mass flow rate, and spraying airflow rate	Inlet, outlet, lost, and destructed exergies, exergy efficiency, improvement potential rate, and entropy	One-hidden layer BP-trained MLP ANN	Precise performance of the ANN compared to the MLR

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				generation		
Jena(Jena and Sahoo, 2013)	Mushrooms and vegetables	To estimate the moisture diffusivity using the ANN and regression models	Drying time, drying temperature, air velocity, length/ diameter ratio of the sample, and effective diffusivity	Six constants of an empirical model	One-hidden-layer feed-forward BPtrained MLP ANN	Slightly better performance of the regression analysis than the ANN model
Momenzadeh(Momenzadeh et al., 2012)	Green Pea	To predict the drying time	Drying time	Drying air temperature, and green pea moisture content	A BP -ANN with the logsig (Log sigmoid) transfer function	Make the most accurate predictions for the green pea drying system
Guiné(Guine et al., 2015)	Banana	To model of the antioxidant activity and phenolic compounds	Variety, state/dehydration method, extract type and extract order	Antioxidant activity and phenolic compounds contents	A feed forward model ANN with the L-M method	Accurately predict that the antioxidant activity and phenolic compounds

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						contents
Barroca(Barroca et al., 2017)	Carrot	To model of the chemical composition of carrots submitted to different pre-drying treatments	Drying temperature, ascorbic acid concentration and time, Sodium metabisulphite concentration and time, temperature and time of water	Moisture, ash, protein, fibre, total sugars, reducing sugars, non-reducing sugars, total color difference	Not given	Successfully obtain the best process parameters
Nadian (Nadian et al., 2015)	Apple slices	To model the moisture ratio and color parameters obtained using a real-time CVS	Drying air temperature and velocity, sample thickness, and drying time	Lightness, redness, and yellowness, total color difference, and moisture ratio	Two-hidden-layer BP-trained MLP ANN	Accurate prediction of the color features and moisture ratio
Ozdemir(Özdemir et al., 2017)	kiwi	To model drying process	Surface temperature, inlet temperature, velocity, time	Energy consumption, moisture content	Four-hidden layer BP-ANN	Excellent prediction of the desired outputs

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			weight, relative humidity		with L-M algorithms and Fermi transfer function	
Mahjoorian(Mahjoorian et al., 2017)	kiwi	To predict moisture ratio	Time and temperature	Moisture ratio	Two-hidden layer BP -ANN with logsig activation function	Successful prediction of the drying moisture ratio
Husna(Husna and Purqon, 2016)	Durian	To predict moisture content	Sample mass, temperature, diameter, time	Moisture content	A BP-ANN with 10 neurons in hidden layer	Good agreement between the experimental and simulated data
Yousefi(Yousefi et al., 2013)	Raspberry	To model the impact of microwave-fluidized bed drying	Microwave power, temperature, air flow rate, starting time of microwave input, and amount of	Drying time, rehydration capacity, density,	One hidden layer BP-trained MLP ANN	Acceptable prediction of the quality indicators

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		process on the physiochemical properties	material	porosity, hardness, water activity, phenolic compounds content, anthocyanins content, and antioxidant activity		
Guiné(Guiné et al., 2014)	Apple	To predict the dehydration process	Variety and temperature	Moisture, Acidity, Hardness, Springiness, Cohesiveness, Chewiness	A feed-forward model with L-M algorithms	Predict all properties with high accuracy
Bahmani(Bahmani et al., 2016)	Eggplant	To describe the water loss and solids gain using ANN and mathematical	Sample to osmotic solution ratio, temperature, time and concentration of osmotic solution	Percentages of water loss and solids gain	One-hidden-layer BP-trained MLP ANN model	Significant improvement in the prediction power of both outputs using the ANN model compared with

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		models				conventional mathematical models
Polat(Polat and Kirmaci, 2011)	Ap ple slic es	To predict the freeze-drying behavior of the product using an ANFIS model as well as a hybrid approach combining the multiple output–dependent data-scaling method and ANFIS model	Sample thicknesses, drying time, pressure, relative humidity, chamber temperature, and sample temperature	Moisture content, moisture ratio, and drying rate	ANFIS with Sugeno fuzzy model	Suggestion of a robust and promising data preprocessing technique for estimating the drying characteristics
Saraceno(Saraceno et al., 2010)	Cyl ind rica l-	To model the drying kinetics using the	Dry bulb temperature, air velocity and relative humidity of the	Moisture ratio and drying rate constant from	One-hidde n-layer MLP ANN with	Efficient modeling through the application of the

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	and slab-shaped potato and carrot samples	mathematical, classical ANN, and hybrid ANN models	drying air, characteristic sample size, and drying time in the classical ANN	classical and hybrid ANN models, respectively	hybrid scheme	hybrid architecture
Balbay(Balbay et al., 2012)	Peeled bittim nuts	To predict the drying kinetics	Temperature and flow rate of the drying air	Moisture content	One-hidden-layer MLP ANN model with ELMalgorithm	Suitable modeling of the drying process by ELM algorithm over the LM and SCG algorithms
Azadeh(Azadeh et al., 2011)	Ceramic slur	To model the particle size using the ANN,	Viscosity and density of the feed, drying air temperature, air	Particle size	ANFIS with Takagi-Sugeno fuzzy	Acceptable performance of the PLS-ANFIS approach over

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	ry	PLS-ANN, and PLS-ANFIS models	suction pressure, feed slip pressure, and outlet air temperature in terms of its correlated variables		model	two other strategies
Khawas(Khawas et al., 2015)	uli nar y ban ana slic es	To model and optimize the process parameters	Temperature , slice thickness, and pretreatment	Rehydra tion ratio , scavenging activity , nonenzymati c browning , and hardness	BP-tr ained MLP ANN model with sigmoid function.	More accurate in prediction than RSM
Samadi(Samadi et al., 2013)	Ap ple slic es	To model the drying kinetics in a combined heat and power dryer using the static and dynamic	Drying air temperature, sample thickness, drying time, current moisture ratio, and drying rate	One-step-ahe ad moisture ratio and drying rate	Two-hidde n-layer BP-trained dynamic MLP ANN model	Superior prediction via dynamic ANN model compared to the two other techniques

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		ANNs				
Murthy(Murthy and Manohar, 2014)	Mango ginger	To model the drying kinetics	Temperature and velocity of the drying air and drying time	Moisture content	One-hidden-layer BP-trained MLP ANN model	Good estimation using both ANN and Midilli et al. drying models
Tavakolipour(Tavakolipour et al., 2014)	Zucchini slices	To predict the drying process via a fuzzy expert engine and an ANN model	Drying air temperature, sample thickness, and drying time	Moisture ratio	Two-hidden-layer BP-trained MLP ANN model	Better performance of the ANN model over the fuzzy model
Nazghelichi(Nazghelichi et al., 2011)	Carrot cubes	To optimize a MLP ANN structure using integrated RSM and GA techniques	Drying time, drying air temperature, cubes size, and initial bed depth	Energy utilization value and ratio and exergy loss and efficiency	One-hidden-layer BP-trained MLP ANN	Successful prediction of the thermodynamics performance parameters

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