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Review

Applications MLP and Other Methods in Artificial Intelligence of Fruit and Vegetable in Convective and Spray Drying

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Abstract: The seasonal nature of fruits and vegetables has an immense impact on the process of seeking methods that allow extending the shelf life in this category of food. It is observed that through continuous technological changes, it is also possible to notice changes in the methods used to examine and study food and its microbiological aspects. It should be added that a new trend of bioactive ingredient consumption is also on the increase, which translates into numerous attempts that are made to keep the high quality of those products for a longer time. New and modern methods are being sought in this area, where the main aim is to support drying processes and quality control during food processing. This review provides deep insight into the application of artificial intelligence (AI) using a multi-layer perceptron network (MLPN) and other machine learning algorithms to evaluate the effective prediction and classification of the obtained vegetables and fruits during convection as well as spray drying. AI in food drying, especially for entrepreneurs and researchers, can be a huge chance to speed up development, lower production costs, effective quality control and higher production efficiency. Current scientific findings confirm that the selection of appropriate parameters, among others, such as color, shape, texture, sound, initial volume, drying time, air temperature, airflow velocity, area difference, moisture content and final thickness, have an influence on the yield as well as the quality of the obtained dried vegetables and fruits. Moreover, scientific discoveries prove that the technology of drying fruits and vegetables supported by artificial intelligence offers an alternative in process optimization and quality control and, even in an indirect way, can prolong the freshness of food rich in various nutrients. In the future, the main challenge will be the application of artificial intelligence in most production lines in real time in order to control the parameters of the process or control the quality of raw materials obtained in the process of drying.

Keywords: artificial intelligence; machine learning; deep learning; convective drying; spray drying; fruit and vegetable

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1. Introduction

Human intelligence has been the subject of research and interest for many years for all of us [1]. Scientists strive to solve complex problems, trying to understand abstract terms [2]. They seek to find fast and effective answers to questions. They build up a knowledge base on the basis of experience and use methods to support working with the environment. The study on the mechanisms of human intelligence had an impact on creating the field of science called artificial intelligence (AI) [2]. When defining artificial intelligence, one could use a purely IT statement that it is an algorithm that processes information obtained from the environment with the intention of using it to make decision-making problems to effectively achieve a goal [2,3].

AI is widely used in various scopes, starting from industry through engineering and ending with medicine and agriculture. In food technology, AI also has practical applications; among others, it is used to preserve, improve, simplify, support or monitor raw materials or products obtained using numerous technological processes. Currently, AI in food technology makes it possible, among other things, to assess the quality of collected food samples by classifying them. AI manages food storage collections by sorting, packing and cleaning them. AI optimizes technological processes in order to increase the yield of raw materials that are obtained by improving operations to automate, among other things, quality evaluation of raw materials in real time (such evaluations will soon be available online). AI performs repetitive process tests to obtain homogeneous agri-food products. AI seeks appropriate methods to support microbiological safety for currently developed food products and optimizes the performance of many daily tasks, resulting in increased process efficiency and food safety and sustainability. AI is based on various methods such as decision trees [4], artificial neural networks, expert systems [5], machine learning [6] or hybrid models (LSTM-ALO, ANFIS-GBO, ELM-PSOGWO, LSSVM-IMVO, SVR-SAMOA, ANN-EMPA, ELM-CRFOA) [7–13], which allows for creating increasingly complex and advanced applications.

The origins of AI date back to the 1940s and 1950s [14], but the actual flowering of AI took place from 1956 to 1974 [15], when the two visions emerged: based on fuzzy logic and computer programs that solved some mathematical problems. With the advent of the 1980s, so-called machine learning (ML) gained much popularity [16,17]. The idea of machine learning is based on using computers that can analyze data and produce models that are adequate to the constantly posed phenomena and requirements. Machine learning algorithms can then be applied to predict the quality and shelf-life of food products, allowing better storage management [18].

ML can also be applied to identify; remove blemishes and contaminants; and monitor and realize data flow in industrial production between different machines, i.e., their sensors and cloud processing. ML will be able to analyze a considerable amount of data generated and use the skills gained to apply them (online) to food products. Finally, ML algorithms can be applied to optimize production processes, allowing increased productivity and efficiency in the food industry. In the next step, ML, through the mentioned activities, implemented them in food processing (Industry 4.0). In the future, in cooperation between man and machine (Industry 5.0), ML will make it possible to direct processes in such a way as to anticipate every next step. It will efficiently assess the shelf life of each food product during and after its production. Thus, it will translate into reduced waste and lower the scale of food waste.

The current smart reality offers solutions also using deep learning to recognize, identify, transcribe, optimize and predict the problems posed. The popularity of deep learning started to be noticeable at the beginning of the year 2010 [19]. Deep learning (DL) is defined as one of the subcategories of machine learning. The essence of the operation is the creation of artificial neural networks aimed at improving, for example, image recognition (commonly used in food, among other applications) or speech [20]. The process of learning is defined as deep learning because the structure of artificial neural networks consists of numerous inputs, outputs and hidden layers. Each layer also contains units that convert input data into information that subsequent layers can use to perform the prediction task. In this way, the machine learns by means of its own data processing. In the food industry, where deep learning is applied, it is of crucial importance to put special emphasis on subcategories responsible for image analysis and image recognition.

Considering the seasonal nature of fruits and vegetables, all methods that are aimed at preserving food and prolonging its shelf life are of fundamental importance. In view of the above, more active efforts are being made to search for methods supporting the preservation of food, especially those rich in nutrients [5,6]. It is worth knowing that changes in the metabolic transformation of vegetables and fruits are dependent on the action of high temperatures. Even room temperature affects the deterioration of vegetables and fruits by degradation of compounds, such as oxidation of vitamins, increased moisture and water activity leading to microbiological spoilage. When using the right method to fix the quality condition of vegetables and fruits, it is possible to eliminate their spoilage and the development of bacteria and other microorganisms [14,15]. Controlling water content will help extend their shelf life during storage (especially for fruits harvested seasonally).

Among those methods, the most important are the ones that allow the preservation of fruits and vegetables and guarantee that the obtained final products will have favorable forms. Drying allows for slowing down physiochemical changes, which translates into maintaining high-quality dried raw materials [2]. However, this process also sometimes triggers unfavorable chemical reactions such as the process of oxidization, non-enzymatic browning and vitamin transformation. It can also lead to structural changes (volume, porosity, density), sensory changes (taste, smell), textural changes, nutritional changes or visual changes (appearance, color). Nevertheless, drying has become very popular in the food industry, especially in the process of preserving food articles at the last stage of food production. Therefore, this process is often responsible for the final quality and properties of the product and can be shaped by an appropriate selection of parameters. Recently, the first fundamental progress in drying was made via applications of algorithms of machine learning, which allowed for optimizing the process of food drying [21]. This progress in artificial intelligence technology can substantially improve the food drying industry and ensure numerous benefits for both producers and consumers. The present review is based on studies to classify the quality of dried material and prediction drying kinetics using artificial intelligence.

2. Methodology

2.1. Multi-Layer Perceptron Technique

The structure of a multi-layer perception network is mainly based on one input layer, information processing elements (neurons) in the hidden layer and one output layer (Figure 1) [22,23]. In artificial neural networks (ANN) elements processing information, so-called artificial neurons are nothing else but the reflection of a real model of neurons (nerve cells), which is part of the nervous system responsible for processing and analysis of information in the human body. This information is processed inside the cells via inputs (dendrites). Then the processed signal is sent to other cells via axons. Information via inputs (dendrites) is processed inside the cell [24].

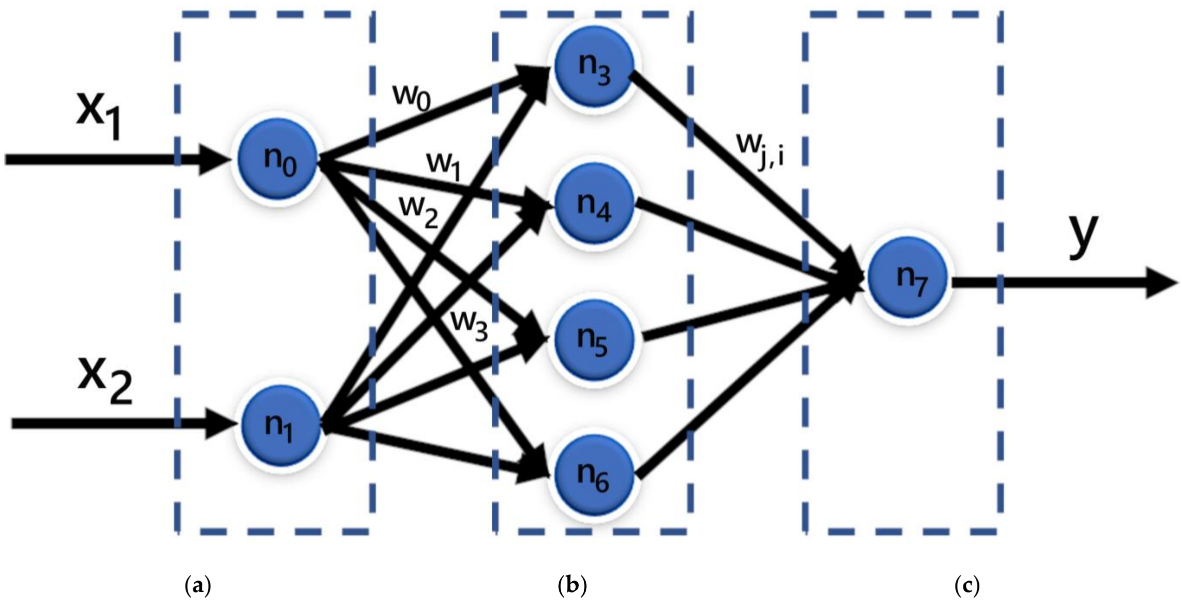

Figure 1. Structure of multi-layer perceptron (MLP): (**a**) input layer; (**b**) hidden layer; (**c**) output layer. Description: i—neuron index, n_i—an "i" index neuron, w_i—the weigh vector of "i" neuron connections, $w_{j,i}$—the weigh vector of connections from the previous layer with neuron from the present layer, x—input descriptors, y—output descriptors.

The most difficult stage seems to be determining the appropriate number of neurons in each layer. The characteristic of neurons determines both linear and non-linear dependency (logistic or hyperbolic, among others). A basic algorithm in supervised MLP learning is back propagation (BP) [25]. The algorithm is based on minimizing the error function or the sum of square errors, which is used to modify the vector of weights to determine the direction to decrease the errors made by the aforementioned network.

2.2. Radial Basic Function Technique

Radial basic function (RBF) was widely used in pattern classification, signal processing, non-linear system modeling and other areas because of its non-linear adaptability capabilities [26,27]. Networks with radial base functions consist of three layers [28], namely the input layer (linear neurons), the hidden layer (radial neurons) and the output layer (linear neurons). The flow of information proceeds without the exchange of information between neurons in a single layer. In the first stage of learning, base function centers are selected by determining values of weight for each radial neuron. The second stage allows for determining radial deviations, which is the process of determining the width of the activation function. The parameter determining the shape of the activation function is stored as the threshold value of the radial neuron. The third stage determines the values of weights in the output layer. The determination of centers, respectively, is used for comparison with the input vector to obtain a radially symmetric response. The elements of the learning set are divided into groups of derived elements [29]. It should be noted that the centers of gravity of each distinguished group are used as weights of radial neuron weights [30].

2.3. Deep Neural Networks Technique

Deep neural networks (DNN) are defined as artificial neural networks that are a collection of units, among which each neuron in a layer $-$n is connected behind each neuron n + 1 by a weighting factor [31]. DNN is a typical feed-forward neural network, which updates parameters such as network weighting and deviations via back-propagation of errors [32]. It is characterized by the ability to create mappings on the basis of dependencies in the training set, whereby the complexity of the decision-making boundary depends on the number of layers used. The input layer is used to feed the network with features related to the training target. The hidden layer usually consists of multiple layers of neurons stacked on top of each other with only adjacent layers of connected neurons. The output value is used to derive the training target. Data are transferred between the input layer, each level of the hidden layer and the output layer using the activation function, with the output of the previous layer used as the input for the next layer [32,33].

The network that is built up from two layers is characterized by better capabilities for determining decision-making boundaries. Networks with a number of layers n $\geq$ 3 are capable of mapping any relationship, with the number of layers and the number of neurons in each layer depending on the complexity of training data depicting the prediction or classification problem under consideration [24,34].

Factors that affect the choice of appropriate hyperparameters are the type of problem under consideration (whether the model is aimed at prediction or classification). Among the algorithms that are applied to minimize the value of the loss function, one can distinguish the methods based on the so-called Stochastic Gradient Descent (SGD) and on momentum or so-called Nestrov moments. These methods include, among others, “adam” [35], ”adadelta”, “adamax”, ”adagrad”, “nadam” and “RMSprop” [36,37]. The algorithm should be properly selected for the problem under consideration. In classification problems, it is common to encounter the use of the “adam algorithm” [16,38].

2.4. Convolutional Neural Networks Technique

Convolutional neural networks (CNN) are used for bitmap image analysis [31,39,40]. The concept has its basis in biological systems and refers to receptor fields present in the retinas of animal eyes. It should be noted that on the basis of the input tensor obtained in the result of uniform scaling with the coefficient of 1/255 of the image pixel values, the so-called convolutional window is cut out [41]. Convolution operation consists of mowing the convolution windows by a defied stride. Successive windows interlock by using a step size of 1. If the convolution stride is bigger than 1, then the whole process is called stride convolution. After extracting the convolution window, the resulting three-dimensional tensor of shape (window width, window height, window depth) is transformed through a tensor product with a tensor of weights called the convolution kernel into a feature vector of length corresponding to the predefined output depth. The output map of features is created by arranging the output vectors of features obtained from other convolution windows in two-dimensional space. Artificial convolutional neural networks entail creating models characterized by huge depth. In the case of very deep networks, one can observe the phenomenon of gradient disappearance, with the result that further deepening of the network for better performance becomes impossible. Thanks to the application of residual neural networks (ResNet) [42] architecture, it was possible to solve the problem of disappearing gradients. The principle of operation of this specific type of network is to pass the values returned from the layer with index n not only to the n + 1st layer but also to the n + k-th layer, where k is a natural number. In addition to the mechanism mentioned above, parcel normalization and other methods of modifying the operation of the network are also used. A specific type of ResNet network is a network type called densely connected convolutional neural networks (DenseNet) [43,44]. In DenseNets, each other convolutional layer receives, as augments, the output tensors from each previous convolutional layer [43].

2.5. Random Forest, k-NN, SVM, SVR Technique

Random forest (RF) is a classification or regression method that is based on the generation of multiple decision trees [45]. Currently, it is becoming an alternative to the methods used in classification problems. The idea of the RF algorithm is to build a base of random decision trees, where, unlike classical decision trees, random trees are built on the principle that a subset of analyzed features at a node is selected randomly [45]. The k-nearest neighbors (k-NN) algorithm is one of the machine learning methods [6]. This algorithm estimates the value of a point according to its neighborhood relative to the selected class, calculating the average distances between samples. The most similar samples belonging to the same class have a high probability [46,47]. The purpose of the kNN algorithm is to search the k nearest neighbors in the learning dataset and then predict them with the selected class among the k nearest neighbors [48]. The aforementioned qualities of learning the k-NN algorithm are heavily dependent on the k parameter [49,50]. At present, the specialized literature describes the application of the above algorithm as highly effective [49].

SVM is a two-class linear classifier [45,51]. SVM separates data along the decision-making border, called hypersurface [52]. In general, it outlines the border between classes and maps the input space formed by independent variables with non-linear transformation in accordance with the kernel function. If the learning vectors are separated without error by the optimal hyperplane, the expected value of the probability of error in the test is bounded by the ratio of the expected value to the value of the indicated vector and the learning vectors [51]. At present, SVM can also be applied in non-linear classification tasks [6,53,54]. Support vector machines are often used to classify points in Hilbert space with infinite dimensions [55,56].

However, three parameters determine the SVR algorithm, namely [51,57]:

- capacity (C), which presents a compromise between model complexity and size, to which deviations bigger than (C) are tolerated;
- epsilon (ε), which controls insensitive space, and ε is used to adjust training data;
- gamma (γ), which is the parameter of the kernel function.

The idea of the SVR algorithm is dependent on the epsilon parameter, which can have an impact on the number of support vectors used in constructing the regression function.

The bigger the value of epsilon, the fewer selected support vectors, which translates into less complex evaluations of the aforementioned regression and a shorter time of learning [45].

3. Results and Discussion

3.1. Multi-Layer Perceptron vs. Convective Drying

Recently changing consumer habits, food supply and economic aspirations require the optimization of processes and applications of modern technology aimed at preserving food and obtaining a high-quality index of finished food articles. High level of food waste causes food producers to lean towards ways of extending the shelf life of food articles. Efforts are being made to reduce industrial energy consumption in the process of food production via automatization, optimization and applications of artificial intelligence in individual processes. New ways of production management, production organization, processing, marketing and waste management are also applied. Therefore, it seems justified to apply artificial intelligence in the process of quality evaluation of the final product obtained in the process of drying (Figure 2) and during the process of kinetic control of drying parameters also online.

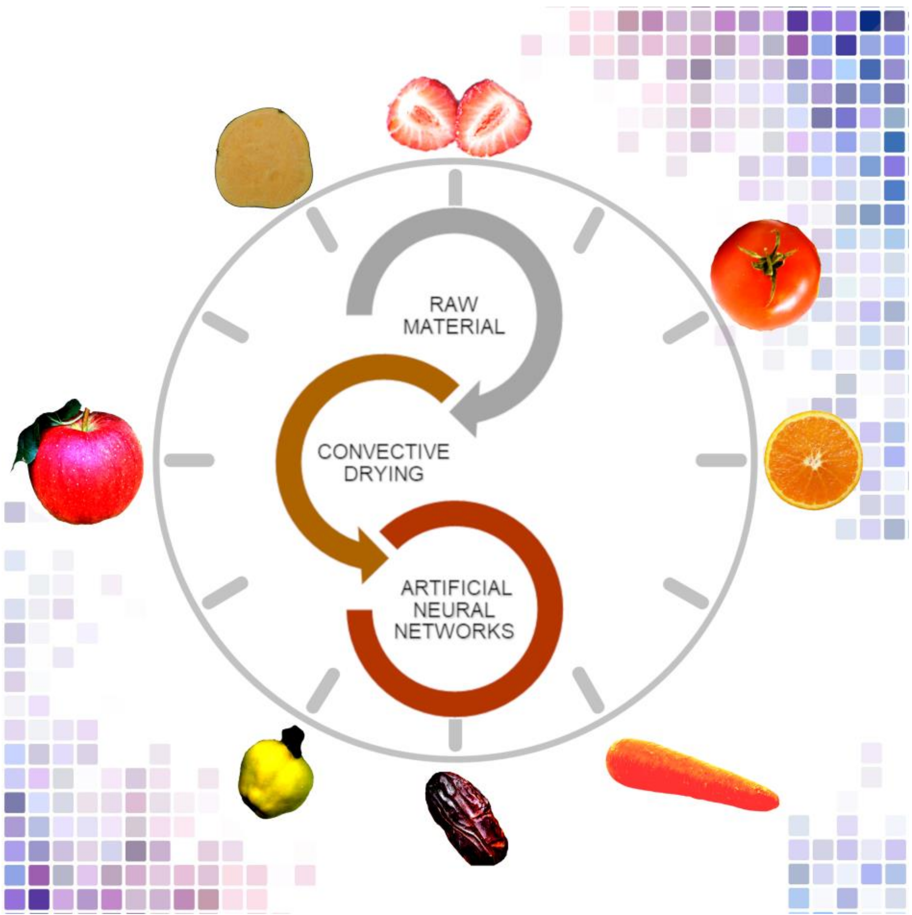

Figure 2. Convective drying supported by artificial neural networks.

Within the space of the last ten and twenty years, much research has been carried out related to the field of drying. This paper highlights the use of vegetables and fruits in convection drying. Convective drying is the most widespread method in the food industry. This technique is based on using drying agents such as hot air or gas, which have direct contact with the product during the drying process. The idea of drying kinetics is based on the simultaneous movement of mass and heat, i.e., the drying agent gives off heat to the moist raw material and simultaneously absorbs moisture from it [58].

Unfortunately, convective drying can have a negative impact on the quality of the obtained product because it leads to far-reaching physiochemical changes. At present, actions are taken to preserve food in a slow way in order to retain the content of bioactive compounds in dried fruits and vegetables and to keep a high-quality index [59]. That is why removing an appropriate amount of water from fruits and vegetables requires preparing an intelligent model of drying, allowing for determining optimal parameters of the drying agent, humidity, temperature and stream, among others, in order to obtain the highest possible quality index of the final product. Convective drying can be carried out with the implementation of recommended movement of the dried material. In such a situation, the raw material that is to be dried is in the direction with the co-current or counter-current of the drying agent [59]. Countercurrent-flow drying is used when raw material is characterized by properties that are highly resistant to high temperatures. Such material has direct contact with the drying agent throughout the whole process of drying. It translates into obtaining more dried fruits or vegetables than in the case of co-current drying. In co-current drying, the flow of raw material and the drying agent moves in the same direction. When the drying agent combines with raw material, it can have an impact on destroying the tissue structure of the latter. This method, as it was mentioned before, allows for obtaining products with higher humidity than the counter-current method because the drying agent emits thermal energy and increases its humidity while flowing.

As part of the research made by Przybył team et al., (2022) [60], an endeavor was made to create effective neural models with machine learning, i.e., multi-layer perceptron network (MLPN) (Table 1) and DL in the process of quality evaluation of slices of dried sweet potatoes. Sweet potatoes (named in Latin *Ipomoea batatas*) are one of the healthiest foods in the world [61], and it is recommended by NASA as a superfood used in space expeditions [62]. Experimental data were obtained by drying the slices of sweet potatoes (2 ± 0.1 mm) at four different air temperatures (60, 70, 80 and 90 °C) and a fixed air velocity value of 1.0 $m \cdot s^{-1}$. The results showed that the proposed MLP network using Gray Level Co-occurrence Matrix (GLCM)-based texture descriptors [63] did not meet the expected of classifying research samples. Therefore, Przybył team et al. (2022) [60] used the method of deep learning for comparison, which substantially improved the effectiveness of the classification of dried fruits and vegetables [60].

In the same year, Çetin [64] also conducted research aimed at improving the characteristic of convective drying and optimizing drying conditions for selected varieties of oranges, i.e., Valencia, Washington and Navel. As a result of the research [64], Çetin designed two structures for the MLP model, which became one of the methods of using machine learning in his research. The results showed the effective prediction of moisture ratio with MLPN in the case of Valencia, Washington and Navel varieties. Nevertheless, the Valencia variety obtained a higher determination ratio. The model structure characteristics for MLP learning consisted of five neurons in the input layer, three neurons in the hidden layer and one output layer responsible for moisture ratio. The coefficient of determination for the 5-3-1 MLP network was at $R^2 = 0.981$. For comparison, the author evaluated the drying rate (the deponent variable in the output player) in MLPN by modifying the independent variables in the input layer and in the hidden layer. As a result of the prediction for the second structure of the MLP 3-2-1 in orange fruit for the same Valencia variety, a lower rate was obtained than in the case of the Washington and Navel variety, and its value was $R^2 = 0.862$ (Table 1).

In his research, Dalvi-Isfahan (2022) [65] also evaluated and compared the effectiveness of two different methods of forecasting models for moisture ratio when drying apple slices. Golden Delicious variety was used as research material. The first stage required preparing raw materials for drying. Apples were washed and peeled, the cores were hollowed out, and the raw material was cut into $20 \times 20 \times 6$ mm cubes. Another step involved convective drying. Experiments were carried out at four different temperatures of drying using a drying agent (air) similar to the team of Przybył team et al. (2022) [60]. In the above research, there was no fiche airflow. The drying process was performed at different air speed levels in a convection dryer. As a result of the drying and forecasting process using the MLP in the work of Dalvi-Isfahan (2022) [65], the best results were obtained. The topology of the MLP 3-10-10-1 included two hidden layers, and the coefficient of determination was R^2 = 0.999 [65]. For comparison, the teams of Winiczenko et al. (2018) [66] and Nadian et al. (2015) [67], concerning apple fruit drying, developed dedicated solutions using an MLP-type network as well. Winiczenko et al. (2018) [66] experimentally researched the impact of drying temperate and air velocity on the quality parameters of apples based on the input data consisting of color difference, volume ratio and water absorption capacity in convective drying. On the other hand, Nadian et al. (2015) [67] devised MLPN as a non-invasive tool supporting fast evaluation and control of changes in the color and moisture of apples during drying. MLPN achieved a satisfying quality factor value higher than 0.92 [67] based on the changes in color and moisture of apple slices.

Another team consisting of Chasiotis et al. (2020) [68], in similar drying temperature conditions, carried out forecasting of moisture content for quince fruits. Quince (named in Latin (Cydonia oblong a Mill) is an edible fruit similar in shape to apples; it is also a yellow fruit with a slightly hairy peel. Quince, similar to apples, is used in the food industry to produce jams, jellies and preserves and can also serve as an addition to baked and dried food articles [69]. Quince are characterized by medicinal and antioxidant properties and are also rich in various polyphenolic compounds [70]. After the appropriate preparation of research material for drying, changes in the moisture ratio of quince slices were evaluated during convective drying with a thermo-convection dryer as part of the research. The obtained experimental data concerning moisture content as a function of drying time for nine measurements, i.e., from the group of drying air temperatures of 40, 50 and 60 °C and with the proper preset and supplied velocity of air flow at the level of 1, 2 and 3 $m \cdot s^{-1}$, respectively, made it possible to obtain the most optimal MLPN [68]. As a result of numerous configurations with MLPN, the best-performed ANN based on cross-validation contained two hidden layers and consisted of 90 artificial hidden neurons in each hidden layer. The predictions were found to be consistent with the experimental data and were noted, achieving a coefficient of determination (R^2) higher than 0.99.

In the same year, the team of Przybył et al. (2020) [71] used convective drying combined with innovation in the form of an acoustic wave to classify the obtained dried strawberry fruits. The growing interest in sound emission and the way of obtaining acoustic wave frequency spectrum was dependent on the availability of advanced electronic devices, including computer systems.

The data extracted from the sound required the construction of measurement and a research station beforehand. The utilitarian goal was to produce an artificial neural network MLP capable of classifying the qualitative state of the obtained dried fruit [71]. The research material consisted of two varieties of wild strawberry: the Chilean variety (*Fragaria chiloensis*) and the Virginian variety (*Fragaria virginiana*). In the study, strawberry fruits belonging to the ripe and overripe groups were dried: ripe and overripe. Fresh strawberry fruits were dried using a convective method at the temperature of the drying agent at 60 °C, with determined drying air velocity at v = 1.0 $m \cdot s^{-1}$ in co-current in a thin stationary layer.

In accordance with the author's original research methodology, in the next stage of the study, using a measuring and testing station that was designed to mimic the free fall of fruit during transport to the production line [71], sound measurements were carried out for the resulting dried strawberries. In the last step, the ANN consisted of an input layer, for which input variables such as frequency (Hz) were specified, and an output layer corresponding to the degree of quality of the strawberry (ripe or overripe). The research showed that the MLP 2:14:1 with 14 neurons in the hidden layer was characterized by the highest classification capabilities, and its classification rate was 98%. For comparison, one analysis of the wave spectrum shift of the acoustic signal was used as a basic method for the non-invasive evaluation of quality conditions in watermelon [72]. It proved to be an effective method, and its low evaluation cost made it possible to determine the quality class of watermelons efficiently using acoustic resonance. The efficiency of identifying watermelon ripeness was achieved at 95% [72].

Another interesting research was conducted by Marić et al. (2020) [73] and was based on the physicochemical properties of root vegetables after drying. It is worth noting that this method entailed applications of ANN using the MLP topology in convective drying in order to identify the above root vegetables. The research material comprised the following: celeriac root (*Apium graveolens*), fennel (*Foeniculum vulgare*), carrot (*Daucus carota*), yellow carrot (*Daucus carota*) (Petroselinum Hortense) and purple carrot (*Daucus carota*). Prior to conducting the experiment, a pre-treatment was performed; namely, the vegetables were washed, peeled and cut into slices with a diameter of d = 1.5–2 cm and thickness of h = 0.3–0.5 mm [73]. The process of convective drying was carried out at the temperature of T = 50 °C and T = 70 °C. After drying, a number of physiochemical analyses were carried out in order to design MLP-type neural networks. Marić et al. (2020) [73] devised two solutions with ANN. The first MLP model was aimed at predicting color parameters (Lab), the concentration of vitamin C and β-carotene, and the second MLPN model was to forecast the physical properties (completely dissolved solid substance and extraction effectiveness) and the chemical properties (i.e., the total content of polyphenols and antioxidant activity) of extracts of the aforementioned root vegetables [73]. The first model comprised data on the type of root vegetables and drying method in the input data, and the output data were responsible for parameters concerning color, vitamin C concentrations and β-carotene concentrations. The second MLP model aimed at forecasting physiochemical characteristics (information included in the output layer) consisted of the input data such as the type of root vegetables, drying method and the type of prepared extract. As a result of the learning process, the two optimal MLP networks were obtained with a high determination rate of R^2 = 0.887 for the first solution and R^2 = 0.878 for the second solution, respectively. MLPN effectively forecasted the way of drying and the type of prepared extract on the basis of the type of root vegetables [73].

In other research aimed at modeling neural networks based on MLP, the authors used a combination of various layers and neurons with different activation functions. Neural networks with one or two hidden layers were randomly selected with a pre-determined number of neurons (from 3 to 15 neurons) for each network. The next step entailed determining a network aimed at forecasting the moisture ratio for the research material, namely dried kiwi fruits [74].

In other research, experiments on mulberry fruit drying were carried out at the temperature level of 50, 60 and 70 degrees Celsius and with air velocity at the level of 1.5, 2 and 2.5 $m \cdot s^{-1}$. MLPN with different thresholds and neurons, as well as the Levenberg–Marquardt algorithm and Tanh–Sigmoid threshold function, was used to model the drying quality. The results showed that the best type of neural network with a 3-12-3 structure and threshold function (Logsig i Purelin) obtained the best result in comparison with other topologies with the highest coefficient at the level of 0.9998 [75].

Between 2007 and 2010, several other MLP-assisted convection drying studies were conducted with sweet potatoes [76], beetroot and potatoes [77], and tomato, among others [78,79] (Table 1). In these studies, the results for MLPN were also promising and even provided an opportunity to be tried in further research experiments, as mentioned above.

In summary, in the works, the effect of changes in drying air temperature and speed shortened the drying time, while higher relative humidity prolonged the process itself. The speed and relative humidity of the drying air improved the energy indicators. The use of MLPN practically gave high efficiency in predicting and classifying the dried material and parameters in the drying process. The high determination rate can be translated into the high popularity of using just this topology in this research problem.

Table 1. Applications of multi-layer perceptron by using convective drying from 2007 to present.

No.	Application	Descriptors	Air Temp [°C]	Air Velocities [$m \cdot s^{-1}$]	Fruit and Vegetable	* Structure	R^2	Year	Ref.
1.	various temperatures evolution (classification of texture parameters)	GLCM texture feature	60, 70, 80, 90	1.0	sweet potato	6-11-4	0.55	2022	[60]
2.	moisture ratio	drying time, initial volume, area difference, moisture content, final thickness	50–60	0.5	orange Valencia	5-3-1	0.9811	2022	[64]
3.	drying rate	effective moisture diffusivity, moisture content, final volume	50–60	0.5	orange Valencia	3-2-1	0.8618	2022	[64]
4.	predict the moisture concentration changes during drying of apple	air temperature, airflow velocity, drying time	45, 50, 55, 60	0.75, 1.0, 1.25	apples	3–10–10–1	0.99	2020	[65]
5.	moisture content evolution (predictions)	temperature, flow velocity, time	40, 50, 60	1.0, 2.0, 3.0	quinces	3-90-90-1	0.99	2020	[68]
6.	classification (ripe and over-ripe fruits)	frequency (Hz) and the level of luminosity (dB)	60	1	strawberry	2-14-1	0.980	2020	[71]
7.	prediction of color parameters, vitamin C concentrations and β-carotene concentrations	type of root vegetables and drying method	50, 70	-	celery, carrot, fennel, purple carrot, parsley, yellow carrot	2-8-6	0.887	2020	[73]
8.	physical and chemical characteristics of the root, vegetable extracts prepared after different drying methods	type of root vegetables, drying method and the type of prepared extract	50, 70	-	celery, carrot, fennel, purple carrot, parsley, yellow carrot	3-10-4	0.878	2020	[73]
9.	optimization color difference (CD), volume ratio (VR) and water absorption capacity (WAC)	drying temperature, drying air velocity,	50–70	0.01–6	apple	2-5-3-3	0.98	2018	[66]
10.	prediction (moisture ratio)	drying temperature, drying time	50, 60, 70	-	kiwi slice	2-13-13-1	0.997	2017	[74]
11.	prediction	-	50, 60, 70	1.5, 2.0, 2.5	mulberry	3-12-3	0.9998	2017	[75]
13.	prediction (moisture ratio)	air temperature, air velocity, thickness, drying time,	50, 60, 70	1.0, 1.5, 2.0	apple	4-()-()-5	0.92	2015	[67]
14.	online predictions of moisture kinetics	temperature of heated air velocity of air, size of sample cube, drying time	50, 60, 70, 80, 90	1.5, 2.5, 3.5, 4.5, 5.5	sweet potato	4-8-4-1	0.9987	2010	[76]
15.	prediction (kinetics of drying)	the material moisture content in the previous step, process temperature and shape factor	50, 70, 90, 106	-	beetroot and potatoes	3-3-1	0.999	2010	[77]
16.	prediction (estimate the drying behavior)	air temperature, slice thickness, drying time	60, 80, 100, 120	-	tomato	3–17–5-1	0.992	2008	[78]
17.	predictions	power of heater, air velocity and time	43, 51.5, 56, 72	1.0, 1.9	tomato	3-4-1	-	2007	[79]

* Structure of artificial neural network: input layer-hidden layer (one and two)—output layer.

3.2. Multi-Layer Perceptron vs. Spray Drying

Spray drying is the most commonly used method of drying liquid products due to the possibility of obtaining a powder in one short operation and the relatively short time during contact between the product and the heating agent. The spray drying method started to be developed at the end of the XIX century. The method started to be used on a large scale in the second decade of the XX century to obtain, among other things, milk powder [80]. Next, it was applied to dry eggs and coffee [81]. Currently, this method is applied when drying food articles in the form of solutions and suspensions of milk [82], honey [83,84], juices and fruit concentrates, for example, strawberry [85], chokeberry [86], rhubarb [87] or raspberry concentrates [23,88,89].

In the process of spray drying, the direct parameters that affect the product obtained are the drying parameters that are properly selected, including drying air inlet temperature, drying air flow rate, liquid stream feed rate and spray air pressure. It is worth considering that the temperature of the drying air at the outlet; the droplet size; the drying capacity (product weight); and the physical properties of the dried product, e.g., particle size (size), moisture content, hygroscopicity and texture (texture consistency), also indirectly affect the quality of the resulting powdered product. The basic principle of the process is to increase the evaporation surface area of the spray-dried liquid, and the result is a rapid discharge of water in the form of steam. The raw material that undergoes the drying process is atomized in the drying chamber and takes the form of small, fine droplets. When a small area of material (droplets) is obtained, faster evaporation of water is possible. The atomized material droplets come into contact with the drying air. Dried fruits and vegetables obtained by this method are characterized by loose form, mostly powder and granules. A short evaporation time of water is obtained due to the high temperature of drying air. The drying time is 1–20 s [82,90,91].

Various carrier substances are used in the process of spray drying. They are one of the most important factors in spray drying because the raw materials that are rich in sugar, such as fruit and vegetable juices, are difficult to spray directly without a proper carrier [92]. In the case of drying fruit and vegetable juices, an additive in the form of carries such as starch [86] and its derivatives (maltodextrin [88], cyclodextrin), gum arabic [23], acacia senegal gum or protein substances (gelatin, milk proteins and soya proteins), can prevent glutinousness [93]. Starch and its derivatives are said to be good carriers in the process of spray drying. They are characterized by high molecular weight and high glass transition temperature but, unfortunately, have a low membrane-forming ability [94,95]. One of the less invasive methods of modifying starch grains that are also popular in the literature is physical modification [96–98]. Walkowiak and Przybył et al. (2022) [99] estimated the legitimacy of the physical modification of starch. The aim of the study was a non-invasive physical modification of native starch via the application of temperature changes and the evaluation of the impact of the above modification on the process of grueling and gelling of the samples, which were subject to analysis based on LF-NMR [99].

Despite the fact that the research results regarding spray drying showed that efforts that were made to apply mathematical modeling aimed at supporting the process simulation, mass exchange and quality evaluation were part of successfully conducted research, it still seems that the above results are not satisfactory enough to determine physiochemical properties of the obtained powders successfully. In the specialist literature, Kwapińska and Zbiciński [100] made an endeavor to develop several ANNs based on shallow learning with only one hidden layer. Their solution applied in spray drying using ANN (Figure 3) was to predict the physical attributes of maltodextrin (17.5 DE) as a function of spray dryer operating parameters and feed conditions. The authors made use of the two-layer MLPN for predicting, for which the physical properties of powders were determined, namely the disintegration of particle size, bulk density, sedimentation density, apparent density, moisture content and morphology as a function of pre-drying and atomization of the powders [67]. Youssefi and others [101] presented comparative research between ANN and RSM in order to predict the quality parameters of spray-dried pomegranate juice. In the research, an endeavor was made to evaluate the type of carrier, concentration carrier, and crystallization of granulated cellulose for physiochemical parameters such as drying effectiveness, solubility, change in color and anthocyanin (in general antioxidant content and activity). In this particular case, ANN obtained better results than RSM [101]. Azadeh and others [76] presented a rather flexible approach to the meta-analysis of the prediction model with particle sizes being controlled by PLS-ANFIS and ANN in the process of spray drying. The PLS-ANFIS model resulted in being more effective and successful compared with a classical solution using ANN [76].

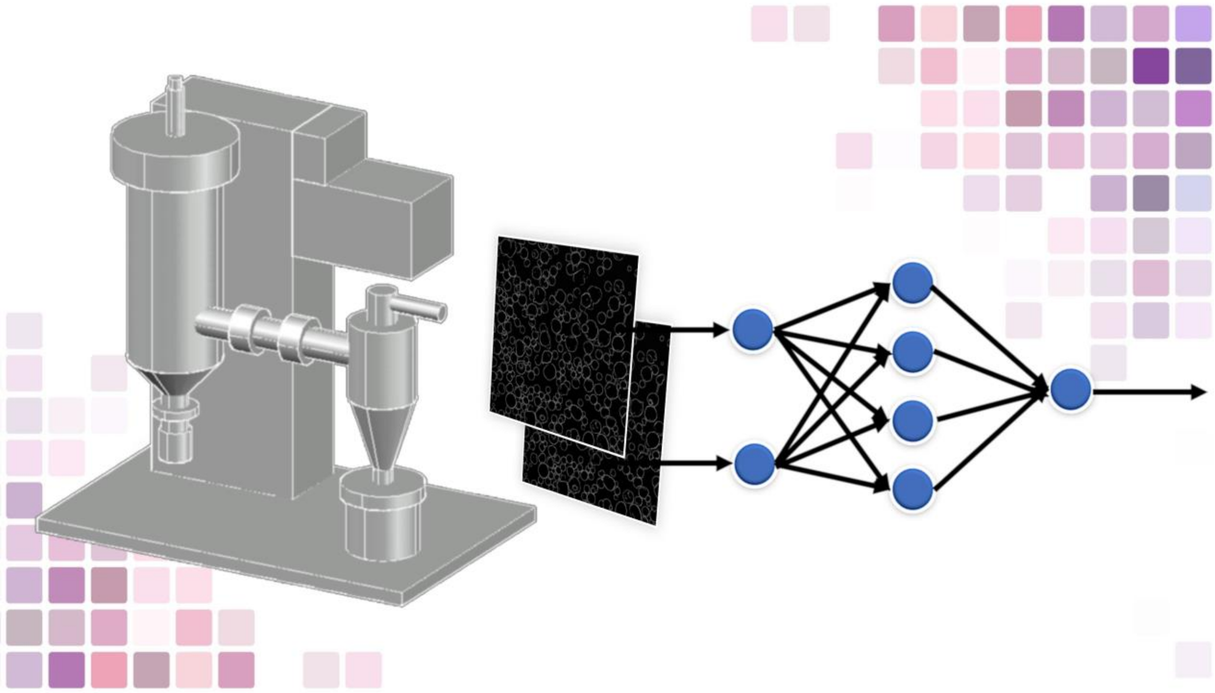

Figure 3. Spray drying supported by artificial neural networks.

Chegini et al. (2008) [102] researched the impact of the strength of the raw material flow, the temperature of the inlet air and the velocity of the sprayer in a semi-industrial dryer on the properties of orange juice. Seven performance indicators were studied, i.e., residual moisture content of orange juice powder, particle size, bulk density, average moisturizing time, insoluble solids, outlet air temperature and dryer performance. Supervised artificial neural network MLP trained by back propagation algorithms were developed to predict seven performance indicators based on three input variables (feed flow rate, atomizer speed and inlet air temperature).

Youssefi et al. (2009 [101] devised artificial neural networks in order to predict certain quality parameters such as the effectiveness of drying, solubility, color, total anthocyanin content and anti-oxidation activity of the spray-dried pomegranate juice. In developing predictive models, the type of carrier (gum arabic, maltodectin, wax starch) was determined. Spray drying was conducted at an inlet air temperature of 130 °C for all experiments [101]. The optimal MLP model (3-10-8-5) was compared with the RMS model because of its ability to model and predict. It turned out that the MLPN was more precise and accurate in predicting than the RMS, even with the limited number of experiments [101].

Przybył et al., 2018 [85], in this work, designed an innovative solution with electron microscopy, image analysis and artificial intelligence in order to differentiate the classes of fruit powders obtained in the process of spray-drying. The author made an endeavor to compare microscope images with digital images, including selected quality parameters such as color, shape coefficients and the coefficients of shape and image texture. The research material consisted of strawberry powders. The process of spray-drying was carried out at the same inlet air temperature of 165–170 °C for each class. It is worth noting that the same carrier, namely maltodextrin, was used in all the research to obtain strawberry powders. Learning sets were designed on the basis of the sets of representative characteristics, such as color and texture for images with a digital camera and color and texture for images with SEM. As a result, it was possible to create MLP neural networks characterized by a high determination ratio (Table 2). The first model consisted of 30 descriptors (12 parameters of

RGB and 18 parameters of GLCM) responsible for the color and texture of images; there were four neurons responsible for the classes of strawberry powders in the hidden layer. The MLP 30-19-4 network with 19 neurons in the hidden layer reached a quality rate at the level of $R^2 = 0.998$. For comparison, another MLPN, in which SEM image analysis was applied, determined the coefficients of shape such as (Circ), aspect ratio (AR), roundness (Round), solidity (Solidity), skewness (Skew), kurtosis (Kurt), Feret factor (Wsp.Feret), circularity factor W1 (W1) and area (Area) in the output layer. It should be noted that the MLP 9-9-4 model with nine neurons in the hidden layer reached the coefficient of quality at the level of 0.944. The last model with the MLP structure consisting of 12 neurons (selected texture parameters on the basis of GLCM matrix) in the input layer and 1 neuron in the hidden layer responsible for the same number of classes (the output layer), like the two previous models, reached the effectiveness of recognizing at the level of 0.944. Due to the fact that the above research showed a high ratio of recognizing fruit powders through coloring strength [86], it induced the researchers to conduct further research works on other solutions using artificial neural networks. The above research focused on analyzing the possibilities of applying computer image analysis and neural modeling in order to evaluate selected quality discriminants of the spray-dried chokeberry powders. Two imaging techniques were used using a digital camera and a scanning microscope. It was found that effective recognition of quality classes of juice from dried chokeberries occurs using color. The best color space model affecting the recognition ability of digital images turned out to be the YCbCr and RGB color space models (Table 2).

Table 2. Applications of multi-layer perceptron by using spray-drying from 2007 to present.

Application	Descriptors	Inlet Air Temp. [°C]	Carrier	Fruit and Vegetable	* Structure	R^2	Year	Ref.
classification	Circularity (Circ.), Solidity, Round, Feret factor, AW (water activity), MC (moisture content), W1, W2	80	maltodextrin, gum arabic, inulin	raspberry	8-44-9	0.999	2021	[88]
classification based on color features	RGB, YCbCr, HSV and HSL	-	Maltodextrin used during the research has dextrose equivalent (DE), respectively: “H”—DE 26 and “L”—DE 12	rhubarb	46-11-10	0.91	2020	[87]
classification	YCbCr	150, 160, 170	maltodextrin	chokeberry	15-25-3	0.994	2019	[86]
classification	RGB	150, 160, 170	maltodextrin	chokeberry	15-10-2	0.999	2019	[86]
classification	GLCM feature	165–170	maltodextrin	strawberry	12-1-4	0.944	2018	[85]
classification	shape factors	165–170	maltodextrin	strawberry	9-9-4	0.944	2018	[85]
classification	color coefficients	165–170	maltodextrin	strawberry	30-19-4	0.998	2018	[85]
prediction	Yield (%) Solubility (%), Antioxidant activity (%), Total anthocyanin content (mg = L), Color (DE)	130	maltodextrin, arabic gum, waxy starch	pomegranate	3-10-8-5	0.87	2009	[101]
predict	feed flow rate, atomizer speed, inlet air-temperature	110, 130, 150, 170, 190	maltodextrin, liquid glucose, and methylcellulose	orange	3-14-10-7	0.966	2008	[102]

* Structure of Artificial Neural Network: input layer-hidden layer (one and two)—output layer.

However, another research concentrated on the analysis of rhubarb powders [87]. The aim of the above research was to classify spray-dried powders based on graphic data obtained from bitmap obtained in the process of spray-drying.

The neural model was developed with a multi-layer perceptron topology. There were variables expressed in the form of 46 image descriptors in the input layer, i.e., RGB, YCbCr, HSV (B) and HSL color models [103–105]. As a result of the learning process, it was possible to create MLPN 46-11-10, which was characterized by a high coefficient of quality at the level of 0.91. The aforementioned ANN consisted of 11 neurons in the hidden layer and 10 neurons in the output layer. The results allowed for demonstrating that color characteristics have an impact on the effective differentiation of the research material consisting of the spray-dried powder from rhubarb juice with different powder content: 30, 40 and 50% and high ("H") and low ("L") level of saccharification of the selected carrier (maltodextrin).

In 2021, research was conducted to test the effectiveness of fruit recognition at low inlet temperatures in spray drying. Based on the experience of previous work and using scanning microscopy techniques, image analysis, artificial neural networks, as well as modeling changes in water activity, Przybył et al. [23,88,89] carried out additional experiments on raspberry fruits. In one of the research, an endeavor was made to evaluate the impact of the type of carrier (maltodextrin, arabic gum and inulin) with dry mass content at the level of 50, 60 and 60% on the quality of raspberry powders [88]. Different types of powders were compared, taking into consideration the structure of micro-particles, water activity and moisture. It should be added that modern methods were applied in this research, such as low-temperature spray-drying and artificial intelligence with visual technique supported by an electron microscope. The aim of the study was to monitor the process of spray-drying in order to obtain raspberry powders characterized by high-quality properties. As a result of the research, it was possible to create the MLPN, for which the output layer of the network defined a nine-state variable, i.e., raspberry powder samples with different proportions and types of carriers. The MLP 8-44-9 network (Table 2) was determined from a set containing 8 neurons in the input layer (circularity, solidity, round, feret, W1, W2, water activity, moisture content) and 44 neurons in the hidden layer (Table 2).

In summary, the qualitative assessment of the obtained powder, in terms of customer requirements, requires a wide range of physicochemical determinations. Producers of fruit and vegetable powders struggle with the problems of repeatability of nutritional properties of powders both between batches and within one production batch. Appropriate selection of input parameters in the MLPN resulted in high efficiency of quality assessment of fruit and vegetable powders, considering the amount and type of carriers. In order to obtain homogeneous powders, it is necessary to monitor the quality and drying parameters of food powders (including the selection of the amount of carrier) online using artificial intelligence.

3.3. Other Algorithms in Artificial Intelligence vs. Drying

The most well-known neural model has become the MLP-type network. The choice of the model is identified by a simple structure with which any computational operation can be effectively implemented. This has also translated into the use of this topology, most often in convection spray drying. At present, there is little work using other artificial intelligence learning methods in spray and convection drying. Table 3 shows other methods of learning that appeared in the last few years. In 2020, Khaled et al. [54] conducted a study to predict the moisture ratio in persimmon fruit. Persimmon fruit is characterized by a high content of bioactive components; it contains fiber, phenolic compounds and minerals, among others. The above features make persimmon fruit a preferred choice for healthy eating [106,107]. It is worth noticing that apart from the MLP network, the support vectors method (SVM) and k-nearest neighbors (k-NN) were also applied. The SVM tool, as a method of computational intelligence, gave better results compared to ANN and k-NN. SVM helped give a view of a wider range of experimental data. Khaled et al. (2020) [54] claimed that ANN was limited to determined experimental conditions in most cases. Application of SVM, for which the aforementioned determination reached the ideal level of R^2 = 1.00, presented an alternative modeling method of behavior during the process of drying the slices of persimmon fruit [54].

For comparison, the application of the k-NN method, for which the coefficient of determination was R^2 = 0.9591, served as one of the regression models, which were created for the needs of predicting moisture ratio in date fruits. Date fruits are one of the most popular fruits, especially in Iran, both in fresh and dried forms [108]. Date fruits are rich in fiber, vitamins, minerals and antioxidants [109–111]. Date consumption can prevent atherosclerosis development, which translates into a lower risk of other cardiovascular diseases. A dried date has similar nutritional values, which is why the process of date fruit drying turned out to be so important [108]. In the above case, the researchers used both methods using the k-NN random forest algorithm, for which it was possible to obtain coefficient R at the level of R^2 = 0.959. Three RF models were trained with different sets of parameters. In order to optimize the above method, on account of the bigger number of parameters of the RF method than in the k-NN model, Keramat-Jahromi et al. (2021) [108] proposed the combination of calculations obtaining approximately 4000 possibilities.

Simulations of the drying process were also based on RBF neural network topology. Dalvi-Isfahan (2022) [65] compared the learning results of MLP with RBF. In RBF, as in MLP, the input variables were air temperature, air velocity and drying time, and the output variable was the moisture concentration of the apple slice. The number of neurons is based on the input and output parameters. The coefficient of determination using RBF to evaluate apple slice moisture reached a value of R^2 = 0.98.

On the other hand, carrot is a type of vegetable that is well-known for their high content of β-carotene. Β-carotene plays an important role in the human diet due to its high content of vitamin A [112]. It is also known for its antioxidant activity, which involves the physical and chemical scavenging of free radicals [73,113]. In the study, different types of drying and different drying conditions were used, as a result of which six groups of samples were obtained, among others, in the process of convective drying. It is worth adding that in this case MobileNet architecture was applied in the process of learning, which was based on separate convolutions [114]. On the basis of the experiment that was carried out, it can be concluded that effective discrimination of the objects contained in digital images, i.e., dried carrots samples, is possible using CNN. The best results were observed precisely in the differentiation of dried carrots obtained by convective drying (R^2 = 0.998).

Huang et al. (2022) [115] carried out an experiment on apples in the process of convective drying. The process of drying was performed at the temperature of about 50, 60 and 70 °C with the air velocity of 1, 2 and 3 $m{\cdot}s^{-1}$. As a result, a deep neural network (DNN) was developed based on 4526 groups of apple slice drying data. It was used to predict changes in moisture ratio (MR), for which R^2 = 0.998, and dry matter (DBMC), where R^2 = 1.00.

As it was mentioned before, Çetin, 2022 [64] conducted a number of studies aimed at predicting the moisture ratio in the drying process of the two varieties of oranges. Apart from the aforementioned typology, the author took advantage of the other methods of learning, such as support vector regression (SVR), gaussian processes (GP), random forest and k-NN. Each of the above algorithms demonstrated a high coefficient of prediction effectiveness of dried orange fruits. The results of predicting the speed of drying showed that k-NN obtained the highest levels of R^2 at the level of 1.0000 and 0.9954 for the Navel and Valencia varieties, respectively.

Przybył et al. (2022) [60], as mentioned above in this study, used deep artificial neural networks to improve classification performance using image texture based on GLCM. In this case, the network analyzing the images was expressed in eight-bit grayscale, and this translated into achieving 100% four-class classification quality. This leads us to believe that the deep applied networks with MobileNet architecture seek solutions to the classification problem within the boundaries defined in the considered hyperspace by the training set. This increases the reliability of the results returned by the obtained models. MobileNet (grayscale) for four-class classification also achieved high values of testing and validation quality. In the test set, the best-discriminated class was class 4 (with a temperature of 90 °C during drying), for which 83% of cases were classified correctly. The remaining 18% of misclassified cases were evaluated by the network as class 3 (including drying temps of 80 °C). For the validation set, 78% of the validation cases belonging to class 3 were classified correctly, and the mistaken cases were evaluated as belonging to classes 1 and 2. Seventy-two percent of the cases belonging to class 2 were classified correctly, while twenty-two percent were mistaken for class 3. This indicates some similarity in the texture of the cases from classes 2 (drying temp. equals 70 °C) and 3. Only 6% of the cases were falsely assigned to class 1 (drying temp. equals 60 °C). Seventy-eight percent of cases belonging to Class 1 were classified correctly, while seventeen percent were falsely assigned to Class 2. Only 6% were misclassified as Class 3.

Table 3. Other methods of AI in drying.

Application	Descriptors	Air Temp. [°C]	Air Velocities [m·s^{-1}]	Fruit and Vegetable	Type	R^2	Year	Ref.
various temperatures evolution (classification of texture parameters)	GLCM texture feature by vegetable image	60, 70, 80, 90	1.0	sweet potato	MobileNet	0.778	2022	[60]
moisture ratio	drying time, initial volume, area difference, moisture content, final thickness	50–60	0.5	orange Valencia	k-NN	0.9898	2022	[64]
moisture ratio	drying time, initial volume, area difference, moisture content, final thickness	50–60	0.5	orange Valencia	Random Forest (RF)	0.9840	2022	[64]
moisture ratio	drying time, initial volume, area difference, moisture content, final thickness	50–60	0.5	orange Valencia	GP	0.9435	2022	[64]
moisture ratio	drying time, initial volume, area difference, moisture content, final thickness	50–60	0.5	orange Valencia	SVR	0.9803	2022	[64]
prediction (moisture ratio (MR))	the weights of the apple slices, drying time, drying temperature, drying air velocity and infrared radiation distance	50, 60, and 70	1.0, 2.0, 3.0	apples	DNN	0.998	2022	[115]
prediction (dry basis moisture content (DBMC))	the weights of the apple slices, drying time, drying temperature, drying air velocity and infrared radiation distance	50, 60, and 70	1.0, 2.0, 3.0	apples	DNN	1.000	2022	[115]
classification included both the type of drying process and the quality of drying for binary division on account of the applied parameters	the vegetable image	-	-	carrot	MobileNet	0.998	2022	[116]
predict the moisture concentration changes during drying	air temperature, airflow velocity and drying time	45–60	0.75–1.25	apple slices	RBF	0.98	2022	[65]
prediction (moisture ratio)	the fruit image and the environment variables, including temperature and air velocity	25, 35 and 60	0.5, 1.0, and 1.5	date fruits	Random Forest (RF)	0.976	2021	[108]
prediction (moisture ratio)	the fruit image and the environment variables, including temperature and air velocity	25, 35 and 60	0.5, 1.0, and 1.5	date fruits	k-NN	0.959	2021	[108]
prediction (moisture ratio)	temperature, thickness and drying time	50, 60, 70	1.10	persimmon fruit	SVM	1.000	2020	[54]
prediction (moisture ratio)	temperature, thickness and drying time	50, 60, 70	1.10	persimmon fruit	k-NN	0.9327	2020	[54]

In summary, the above research confirms the high efficiency of matching various AI methods, which translates into obtaining excellent forecasting or classification results obtained as a result of drying vegetables and fruits.

The value of the fit coefficient below 0.7 would mean that the discrepancies between the results of the designed AI methods and the model results for the network are not fully satisfactory in research work. A fit quality factor below 0.6 would mean that the fit of the model is not sufficient for ANN methods to be able to independently decide on the qualification of dried vegetables and fruits with sufficient accuracy.

4. Perspectives of AI Conclusions

Machine learning and artificial neural networks are definitely the future of the modern world because it is a continuously developing technology. AI is more and more widely applied in many sectors of the economy. The development of artificial intelligence was obtained, among others, from the availability of computers. Their adequate computing power and unlimited disk capacity resources allowed for setting new standards in many decision-making processes. The above creates greater possibilities for conducting this kind of research in a wider social circle, which ensures further AI development. Different research is directed at ensuring that artificial intelligence itself will be more and more often replacing processes at different stages of the technological food process. Artificial intelligence applied in food drying will be used to automate and optimize the conditions of drying. Food drying can become more productive and efficient and can ensure a better quality of dried food.

One challenge is the limited availability of supercomputers in many research centers and academic institutes. Artificial intelligence requires appropriate programming and supervision using supercomputers in order to ensure its effectiveness, verification and validation. Another issue is the appropriate selection of input and output parameters when designing AI algorithms. It is possible that unlimited data collection will allow the use of artificial intelligence even in real time during the process of convective and spray drying.

Generally speaking, the application of AI in food drying ensures substantial benefits, including an improvement in productivity, accuracy and food safety. It could expect more and more innovative applications and further revolution in how food is preserved and stored. It is highly likely that neural networks combined with the farm and food industry will soon have a huge impact on the automation of processes and productivity in the process of producing raw materials and food processing.

In the future, it will be possible to imagine automated farm and food machines, drones monitoring the condition of production lines processing raw materials or even intelligent quality control of vegetables and fruits, among others, via the quick activity of visual devices.

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