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Artificial Neural Network and Their Applications in Food Materials: A Review

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ABSTRACT: This paper is a review of artificial neural network technique for the prediction of drying parameters of food materials. The meaning of ANN, the importance, areas that ANN could be applied, future prospects and summary of previous researchers work using ANN for the prediction of drying parameters were considered. These drying parameters are not limited to the following: thickness, temperature, velocity, moisture content, drying rate that are used in the prediction. Thus, ANNs hold a great deal of promise for modeling complex tasks in process control and simulation and in applications for food safety, preservation and quality control. This method eliminates the need for manual calculations and the ANN representing more tools for prediction drying parameters of food materials. This technique is preferred for large data set for robust, accuracy and less time consuming benefits. The method/leaning algorithm mostly used was Levenberg-Marquardt back propagation and the coefficient of determination (R^2) was above 0.9 and the moisture content was one of the key output parameter that was determined.

KEYWORDS: Artificial Neural network; drying; Modeling. Topology, Moisture ratio, Drying rate

1.0 INTRODUCTION

Artificial neural networks (ANNs) are a set of technologies often encompassed with artificial intelligence that attempt to simulate the function of the human brain (Huang *et al*., 2007). ANNs have a great deal of promise for modeling complex tasks in process control and simulation. Artificial Neural Network (ANN) is one such tool for prediction of outputs for nonlinear systems at various combinations. The process is based on learning of the network with the experimental values, thus knowing the system behavior, and then predicting the output values of the desired set of parametric combinations (Bhotmange and Shastri, 2011). Moreover, artificial neural network (ANN) is a technique of artificial intelligence derived from the neural networks found in the nervous system of humans. Simply put, ANN is set of interconnected simulated neurons which are made up of several input signals with synaptic weights. An ANN model simply sums the products of inputs and their corresponding connection weights (w) and then it passes it through a transfer or activation function to get the output of that layer and feed it as an input to the next layer. A bias term is added to the summation function in order to raise or lower the input which is received by the activation function. The activation function does the nonlinear transformation to the input making it capable to learn and perform more complex tasks.

Alexander Bain and William James independently examined brain functions and modeled these as a set of neuron activities which established the foundation for the modern ANN technology in the 19th century. (Jansson, 1991; Bain, 2004). It is established that Warren McCulloch and Walter Pitts in 1943 developed the first neural network model describing how human neurons might work (Huang *et al*., 2007). Their idea of mathematically simulating the human thinking process stimulated a huge amount of research in the past years which gave the foundation for others to delve in. The realization that neural network models do not provide a “mechanical brain” that can solve any complex calculation in a short time, as was the hope in the early 1960’s, and instead can only accomplish certain functions efficiently, has allowed rational and useful applications for ANN technology to be developed (Huang *et al*., 2007). The rapid development of learning algorithms as well as computer technology is ultimately the driving force for widely applying ANNs in research and routine life (Huang *et al*., 2007).

However, artificial neural network is the generalization model of biological nervous system. It is in essence an attempt to simulate the human brain. Thus, it is a modeling tool which is able to learn complex and non-linear input-output relationships and reproduce same from a given set of examples by the use of neurons. It requires no prior knowledge of the mechanism/principles or background underlying the process to be modelled. Ideally, a neural network consists of three distinct layers: input, hidden and output layers. The ability of an ANN to learn and approximate relationships between input and output is largely dependent on the size and complexity of the problem. The multilayer perceptron (MLP) is the most common amongst the types of ANN in which the data processing extends over more than one hidden layer. The hidden layer in MLP consists of layers of neurons. The ability of an ANN to learn input-output relationship depends largely on the number of datasets used in training the network. A sufficiently large amount of datasets will enable the network learn accurately the input-output relationship of any given process. (Offor and Alabi, 2016). Prior to training of the network, the dataset are brought to the same order of magnitude (pre-processed). There are several normalization techniques but the most common are min-max, z-score and scaling (Offor and Alabi, 2016).

In order to characterize ANNs, three concepts are necessary to define: neuron, which is the basic computational unit in the network in question; architecture, the topological structure of how the neurons are connected; learning, the process that adapts the network in order to compute a desired function or perform an assignment. (Guine, 2019). One of the most commonly used models is at three-layer feed forward network (i.e Input to neuron (hidden layers) to output). ANN connection weights are coefficients used to determine the relative importance of the different inputs, and a number of equations are available to assess the relative importance based on the magnitude of the weights (Guine, 2019). The weights are positive or negative real numbers.

However, like all challenges, this one also comes with amazing and numerous opportunities too. One such opportunity is the genuine stride made in the development of new technologies to tackle it. The most current and by far the most pervasive technology that has crossover appeal across various industries is artificial intelligence. The reasons are not far-fetched. AI-based models offer numerous advantages. According to Bahiraei *et al.* (2019), AI-based models have the ability to learn from patterns and once learned can carry out generalization and estimation at great speed; they are fault tolerant in the sense that they are capable to handle noisy data and they are capable of finding the relationship among nonlinear parameters.(Agwu *et al.*, 2020). An artificial neural network corresponds to a technique of numerical estimation that allows simulation of the learning and memorizing process. It is a potent tool that learns based on the experimental input variables and finds the governing rules between the corresponding factors (Guine, 2019).

Worthy of note, networks trained with too small a sample size are generally not robust (or not repeatable) and have poor predictability for unknown patterns (Huang *et al.*, 2007). A network that is too small cannot account for the complexity of the data, while one that is too large often over-fits the data and has a poor generalization. Therefore, the ANN training in general requires a larger sample size (number of input-output patterns) than traditional methods to achieve an acceptable generalization (Huang *et al.*, 2007).

The aim of this paper is to review the application of artificial neural network models for predicting the drying parameters of food materials. The review will focus on the meaning of artificial neural network, importance of ANN, areas where it is applied, an overview of the current research, future trend of the applications of ANN technology and summary of some researchers work using ANN.

1.1 Benefits of ANN

This is done by migrating away from the old ways of tackling them and then gravitating towards revolutionary technology, one that would propel the drying operation in the direction that engenders greater improvements in performance, increase in productivity, effectiveness and efficiency. Therefore, a good understanding of the drying operation and how it affects the food materials gives the designer a better grip on the drying procedure.

Hence, if designer are going to effectively take charge of the drying operation and make informed decisions as regards the safety of equipment and personnel, they need accurate, measured and timely information insights along every steps taken. Therefore, proper planning and execution of drying operations, particularly the products that are not likely to be preserve for long period, require complete and accurate knowledge of the drying principles and skills. Nowadays, artificial neural networks are being applied to a lot of real world problems, such as functional prediction/approximation, system modeling (where physical processes are not well understood or are largely complex), pattern recognition, etc., with the ability to generalize while making decisions about imprecise input data (Offor and Alabi, 2016). The ANNs present many advantages, such as good adaptability characteristics, possibility of generalization and high noise tolerance, among others (Guine, 2019). ANNs can process more efficiently data comprising multiple input and output variables.

1.2 Areas Where ANN are Applied:

The Artificial Neural Networks (ANN) technology is used in process control, medical diagnosis, forensic analysis, weather forecasting, financial applications, and investment analysis. In food science, ANNs are useful tools for food safety and quality analyses, such as modeling microbial growth and from this predicting food safety, interpreting spectroscopic data, and predicting physical, chemical, and functional properties of food products during processing and distribution (Huang *et al.*, 2007). In other words, artificial neural networks have been successfully used in various areas, for example, business, finance, medicine, and industry, mainly in problems of classification, prediction, pattern recognition and control. In the food industry, food processing, food engineering, food properties or quality control, statistical tools (Guine, 2019)

Moreover, due to the vital impact of flavor and aroma in food products, enormous efforts are made to evaluate these factors in both the research community and in the food industry. Sensory evaluation based upon panelist perceptions of food flavors has the problems of inconsistency, inaccuracy, and costliness. The results of sensory evaluation also strongly depend upon the experiences and skills of the panelists. The ANN technologies have been increasingly used as pattern recognition systems for electronic noses over the past decade .Electronic nose systems have been applied in quality analysis and classification of various food systems including beverages, fruit, oil, grain, fish, meat, and dairy products, which normally have a relatively strong smell. Electronic nose systems have also been used to evaluate the change in freshness and quality of fish as affected by storage time and fermentation time (Huang *et al*., 2007).

However, machine perception is one of the most promising application areas of ANNs in the field of food science with the most significant being machine vision and electronic nose, which have been embraced by some as a revolution in sensory analysis. Important sensory parameters such as the odor and appearance (including shape and color) of a food product can be detected by machine perception technologies, which can provide indications of overall food safety and quality. Applications of neural networks have been reported for predicting the functionality, rheological, physical, chemical and sensory properties of various food products (Huang *et al*., 2007). Therefore, ANN has been widely and successfully used in various fields to predict the influence of some targeted variables (inputs) on the investigated outputs.

1.3 ANN Implementation

Curves or graphs generated show the performance of the training, testing and validation datasets. The sequence of neural network modeling is to assume a set of weights initially, compute the outputs and the predict error, and then adjust the weights according to an error minimization technique until the prediction error falls to an acceptable level. This activity of finding optimal weight is called network training. Once the network is so trained, the black – box model is ready, and may be used to predict outputs for a set of new inputs, not originally part of those used in training (Bhotmange and Shastri, 2011). The activation function can be in various forms, generally non-linear. The four more commonly used activation functions are Binary (Step), Linear (Slope), Sigmoid (Logistic) and Tanh (Hyperbolic tangent) (Guine, 2019). The input layer corresponds to the independent variables while the output layer corresponds to dependent variables.

1.4 Reasons for ANN

A shift in paradigm is the application of artificial intelligence in the area of drying operation. Simulation will eliminate the time consuming. The used of ANN has been of interest to researchers over the past years. Artificial intelligence techniques can be applied as they have in recent time matured to a point of offering practical benefits in many of their applications. Artificial intelligence refers to the ability to mimic/replicate the human behavior/reasoning into machines and software using cutting edge techniques. One of such techniques is the artificial neural network (ANN), an intelligent data-driven modeling tool which is able to capture and represent complex and non-linear input/output relationships from a set of examples. (Offor and Alabi, 2016) The key challenge in the drying industry is the inability to predict most drying parameters, such as moisture content, moisture ratio, drying rate, among others. Thus, the most probable reasons for this technological and methodical shift by the food industry are attributable to: storage problems, easy transportation, preservation of the product, time consuming and faster prediction of the process conditions

With the use of artificial neural network technique being fairly popular have several advantages such as, for example: nonlinearity, adaptation, generalization, model independence, easy to use and high accuracy (Guine, 2019). Hence, if the food Engineers are going to effectively take charge of what happens in the course of drying operation, they need to make informed decisions as regards the safety of the product(s), they need accurate, measured and timely formation insights along every stage of drying.

2.0 METHODS OF DRYING

The essence of drying in the industries, especially processing and food industry cannot be overestimated. To achieve the expected drying of materials, several methods of drying have been developed and further researches are still been carried out. Each of the drying methods has its advantages and demerits, therefore the choice of method depends on individual and what you want to achieve. Some of these include but not restricted to the following listed (Inyang *et al*., 2019). The drying parameters are but not limited to these: air temperature, air velocity, relative humidity, thickness, moisture content, moisture ratio and temperature. The statistical measures that could be used in determining the goodness of fit for the model are in Inyang *et al*. (2019).

The valuable contributions by previous researchers using applications of artificial neural network to drying parameters prediction have been reported from literatures. A summary of the research efforts in using artificial intelligence techniques in predicting the drying parameter(s) of food materials are presented in Table 1.

Table 1: Summary of Drying of food materials using ANN Technique

S/N	Product	Drying Method Used	Model Topology/ Transfer Function	Input Parameter	Predicted property (Output parameter)	Model Performance	Method/ Learning Algorithm/ Ratio	Author (s)
1.	Bergamot	Hot air dryer	3 – 8 – 1 Tansig	3: (Drying time, Air velocity, Temperature)	Moisture Ratio	R^2 (0.99936) MSE(0.00006)	MLP Levenberg–Marquardt 60:15:25	Sharifi et al. (2012)
2.	Pistachio (Akbari v.)	Tray hot air dryer	3 - 8 – 5 - 1	2: (Temperature, Air velocity)	Moisture content	R^2 (0.9989) MSE(4.2E -06)	Levenberg–Marquardt	Omid et al. (2009)
3.	Pistachio	Infrared Assisted solar dryer	Radial basis 3 - 40 - 1	3; (Infrared dryer power, drying time, drying temperature)	Moisture content,	Training: R^2 = 0.999 RMSE = 0.0035 and Testing: RMSE = 0.0038, R^2 = 0.996	Levenberg–Marquardt back-propagation training algorithm 70:15:15	Mortezapour et al., (2017)
4.	Grated coconut	Parallelepiped fluidized bed dryer	9 – 4 – 1 Tanh	3: (Initial moisture of the product, Temperatures of dryer compartment, Final product temperature	Final moisture content	MSE (0.01) %Relative Error (0.35 – 0.34%)	Levenberg–Marquardt	Assidjo et al. (2008)
5.	Coconut	Mixed mode Solar Dryer	5 - 5 - 2 Logarithmic-sigmoid (logsig).	5: (Time, Relative humidity, Air temperature, initial moisture content and solar radiation)	Moisture content and Efficiency	R^2 = 0.99	FF-BP algorithm.	Subbian et al. (2016)
6.	Barberry fruit (*Berberis Vulgaris*)	Oven	4 – 20 – 1 4 – 25 – 5 – 1 Logsig 4 – 20 – 1 4 – 15 – 15 – 1 Tansig	4: (Pretreatment, Drying air Temperature, Drying Air velocity, Time)	Moisture content	MSE (0.00318) R^2 (0.993) MSE (0.001) R^2 (0.997) MSE (0.00293) R^2 (0.994) MSE(0.00130) R^2 (0.995)	Levenberg–Marquardt	Gorjiana et al. (2010)

7.	Carrot	Convection hot chamber	Tansig 4 - 4 -1	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	$R^2 = 0.97$	Feed forward Levenberg-Marquartd 70:15:15	Barroca et al. (2017)
8.	Carrot Cubes	Fluidized bed drying	4-1-2 Static ANN: Tanh	4: (Drying Time, Drying Temperature, cubes size, bed depth)	2: (Moisture Ratio, Drying rate)	Moisture ratio: MSE(0.00415) MAE(0.01408495) R^2 (0.992769) Drying Rate: MSE(0.000407) MAE(0.009897) R^2 (0.94929883)	Gradient Descent Feed forward propagation	Nazghelichi e al.(2011)
9.	Potato	Hot air convective dryer	4 - 8 - 4 – 1 Tangent Sigmoid	4;(Air temperature, air velocity, thickness, drying time)	3; Moisture kinetics (Moisture content, drying rate and moisture ratio)	P = 0.05 (%)	FF ANN method	Singh and Pandey (2011)
10.	Apple	Hot air convective dryer	2 - 25 -3	2: (Air velocity and air temperature)	3: (Color, total phenolic content, water holding capacity)	P = 2.4(%) Error < 2.4 %.	Hybrid ANN-Generic Algorithm	Scala et al. (2013)
11.	Dried Apple	Natural convection (drying air velocity), forced convection and fluidization	MLP 3-5-1 and MLP 3-4-1 Logsig	3: (Drying temperature, air velocity, rehydrating temperature)	Drying and Rehydration parameters	$R^2 = 0.988$ RMSE = 0.028	Back-stepwise Levenberg-Marquartdt 70:15:15	Gornicki et al. (2019)
12.	Apple	Natural convection (the drying air velocity), forced and	sigmoidal transfer function	4 (Drying air temperature, drying air velocity, rehydration temperature,	3: (Colour changes, volume ratio, and water absorption capacity).	Training, validation and test sets were 0.0014, 0.0019, and 0.0017, respectively.	Multi-Layer feed forward back propagation	Winiczenko, et al. (2018).

		fluidized bed drying		rehydration medium)		R^2 = (0.9778 – 0.9829		
13.	Apple	Convective hot air dryer	2 - 8 – 6	2: (Variety and temperature)	6 :(Moisture, Acidity, Hardness, Springines s, Cohesiven ess, Chewiness)	$R^2 \geq 0.99$	Feed-forward model with L-M algorithms	Guine et al. (2014)
14.	Codfish	Convective dryer	Sigmoid function	4: (Drying time, Air velocity, Temperature and Relative Humidity)	Moisture content	Standard error = 0.96%, average error = 2.93% and average relative deviation = 3.70	Levenberg-Marquardt	Boeri et al. (2011)
15.	Gingko biloba seed	Microwave Dryer	2 – 1 - 1	2:(Microwav e Power, Drying time)	Moisture ratio	Correlation coefficient > 0.9056	Levenberg-Marquardt	Bai et al. (2018)
16.	Grains and Legumes	Oven (Moisture sorption isotherms)	4-2-1 Sigmoid	3: Product type , (Sorption state (adsorption or desorption), temperature and equilibrium moisture content)	Equilibriu m relative Humidity	R^2 = 0.984 MSE = 0.009	Levenberg-Marquardt	Al-Mahasneh et al. (2014)
17.	Tomato	Tray hot air dryer	3 - 1 – 1	3: (Power heater, Air velocity and drying time)	Moisture ratio	P = 1.18 (%)	Back propagation training algorithm	Movagharne jad and Nikzad, (2007)
18.	Tomato	Multi-tunnel greenhouse with a polyethylen e cover	7-10-7-5-2 and 7-10-8-5-2	Leaf area, Plant height, fruit number, dry matters of leaves, stem, fruit, growth degree days	Fresh fruit yield and Aerial dry matter	Substrate (R = 0.97, MSE = 0.107, error = 12.06%) and Soil (R = 0.94, MSE = 0.049, error = 13.65%), respectively	Levenberg-Marquardt	López-Aguilar. et al. (2020)
19.	Thyme	Microwave Drying	Log Sigmoid function	2 (sample mass, Microwave power).	Moisture content	R^2 = 0.9999 MAPE (%) = 4.0937 and RMSE = 0.025	Multilayer Perceptron(M LP)	Sarimeseli et al. (2012).
20.	Shelled corn	Fluidized bed dryer assisted by microwave heating	hyperbolic tangent sigmoid	3 Microwave power, drying air temperature and grain	Drying time	Random errors within a range of ±5%.	Resilient back propagation	Momenzade h et al. (2011).

				moisture content)				
21.	Apple	Freeze drying	Fermi transfer function	5 (Drying time, pressure, sample thickness, chamber temperature, sample temperature, and relative humidity).	Moisture content, Moisture Ratio and Drying Rate	R^2, *RMSE* and *MAPE* for *MC*, *MR* and *DR*, as 0.999, 0.0078895, 0.2668459, and 0.999, 0.0001099, 0.2968427 and 0.999, 0.0000008, 0.2703797, respectively.	Levenberg–Marquardt (LM) Back-propagation	Menlik et al. (2010)
22.	Mushroom	Freeze drying.	Tansig 6-13-1 70 : 15 :15	Primary Drying, Temperature, Secondary Drying, temperature, drying time, Pressure, Initial moisture content, and sample thickness.	Water activity	$R^2 = 0.97$	Feed-forward-backpropagation Levenberg-Marquardt	Tarafdar et al. (2018)
23.	Mushroom	Microwave-hot air dryer	3-6-7-1 Tangent-sigmoid (tansig) and purelin	Air temperature, Microwave power density and microwave power	Moisture content	$R^2 = 0.9914$ RMSE = 0.2179	Levenberg-Marquardt	Omari et al. (2018)
24.	Cocoa	Solar Drying	Tansig and logsig	Relative Humidity and Time	Moisture content	$R^2 = 0.99$.	Multilayer perceptron	Karidioula et al. (2018)
25.	Celeriac (Apium graveolens L.)	Vacuum Drying	Hyperbolic tangent sigmoid transfer function 3-6-9-1	Temperature, Pressure and Time	Moisture Content	$R^2 = 0.9999$)	Multilayer feed forward back propagation	Beigi and Ahmadi (2019)
26.	Bengkulu's local durian	microwave oven	5-10-1-1 Logarithmic-sigmoid (logsig)	Sample mass, temperature, diameter, Thickness, time	Moisture content	RMSE = 3.97% MSE = 0.16% $R^2 = 98.47\%$	Levenberg–Marquardt Back-propagation	Husna and Purqon (2015)

27.	Onion	fluidized bed dryer	hyperbolic tangent sigmoid 2 - 5 - 1	Drying temperature and airflow velocity	dynamic drying behavior	$R^2 = 0.9999$ RMSE = 0.004157	Levenberg–Marquardt Feed forward–back propagation	Jafari et al. (2015)
28.	Green bell Pepper	fluidized bed dryer	hyperbolic tangent sigmoid transfer function 2-5-1	Drying temperature and airflow velocity	Moisture ratio	R = 0.99828 MSE = 0.000055	Levenberg–Marquardt Feed-Forward-Back-Propagation network	Jafari et al. (2015)
29.	Banana	Convective drying (Lyophilization was made using a Freeze Dryer)	Tansig 4-10-1	Variety, state/dehydration method, extract type and extract order	2: (Antioxidant activity and phenolic compounds contents)	$R^2 = 0.98$	Feed forward Levenberg-Marquartd 70:15:15	Guine et al. (2015)
30.	Banana	Convective hot dryer	4-8-1 Sigmoidal tangent function	Air temperature, Air velocity, Drying time, and thickness	Moisture content	RMSE = 0.01122 $R^2 = 0.9983$	Multi-Layer Perceptron	Ebrahimi et al. (2011)
31.	Potato cubes	laboratory oven	3-10-1 Logig	3: (Drying time, drying air and Temperature)	Moisture ratio	$R^2 = 0.997$	Back propagation 70:30	Yaghoubi et al. (2013)
32.	Green Pea	Fluidized bed dryer	Logsig	3:(Drying air temperature, and green pea moisture conten)t	Drying Time	$R^2 = 0.981$ MAE = 0.436 RMSE = 0.586	Resilient backs propagation 80:20	Momenzadeh et al. (2012)
33.	Kiwi	Convective hot-air dryer	Tansig 2-2-1	2: (Time and temperature)	Moisture ratio	$R^2 = 0.997$	Feed forward 70:15:15	Mahjoorian et al. (2017)
34.	Kiwi Juice Pomace	Microwaved-assisted extraction	Tansig 2-13-13-1	Temperature, Extraction time, solvent composition, solvent-solvent ratio	Total phenolic compounds	$R^2 = 0.99$	Feed forward back propagation Levenberg-Marquartdt 60:20:20	Carbone et al. (2020)
35.	Dried Savory leaves	Forced conductive dryer.	4 - 2 – 1 Hyperbolic tangent sigmoid	4: (Air temperature, air velocity, relative humidity, drying time)	Moisture content	Hybrid FFNN-GA MSE= 0.000094606 $R^2 = 0.9992$	Hybrid FFNN-GA	Taheri-Garavand, et al. (2018)

36.	Apple slices	convection drying (CD) and microwave drying (MD).	CD: 2 – 10 - 10-1 MD: 2-15-10-1	2;(drying time, and drying chamber inlet air temperature)	Moisture Ratio	R^2 = 0.9993 and 0.9990, for CD and MD respectively. RMSE (0.0335) ; MSE (0.00059)	Levenberg-Marquartd Combining CFBF and FFBF network	Sharabiani et al. (2021)
37.	Orange juice powder	Spray Dryer	3-14-10-7.	Feed flow rate, inlet-air temperature, and atomizer speed	Residual moisture content of orange juice powder, particles size, bulk density, average time of wet ability, insoluble solids, outlet air temperature and dryer yield	RMSE = 0.042, $R^2 \geq 0.93$,	Back propagation algorithm	Chegini et al. (2008)
38.	Dill Leaves	Convective dryer	3 -45 - 1 Logsig and Purelin transfer function	Air Temperature, Air velocity and drying rate.	Moisture ratio	R^2 = 0.9998	Levenberg-Marquardt	Motevali et al. (2013)
39.	Quince Fruit	Oven dryer	Tangent sigmoid 60 : 20 : 20 5 – 8 - 1	Values of textural features at constant temperature	Moisture content	R^2 = 0.994 MSE = 0.12%	Feed-forward back-propagation Levenberg-marquardt	Bakhshipour, et al. (2011)
40.	Sweet potato (*Ipomoea batatas* L.)	Infrared drying	Logsig	3: (Thickness, drying temperature and drying time.	shrinkage and dimensionless moisture content	$R^2 \geq 0.95$.	Multilayer perceptron (MLP)	Onwude et al. (2018)
41.	white mulberry	Infrared–convective drying	Tansig Logsig Purelin 3–20-20-1 3–10-10-1	Temperature, Velocity and Infrared Power	diffusivity or specific energy consumption	R^2 = 0.9972	Levenberg-Marquardt Feed and cascade-forward back-Propagation neural systems	Golpour et al. (2020)
42.	Gari granules into thick paste	Reconstitution of gari into paste	Log sigmoid for Input	Temperature and time, particle size	Convective heat and mass transfer	0.00044% MSE, 0.0103% MAE and 0.22% SSE .R^2 = 0.974	Back propagation network algorithm	Sobowale, et al. (2014)

			while pure-Line	and air flow velocities	coefficients.			
43.	Blanched field pumpkin	Laboratory scale convective hot air dryer.	2 – 18 - 1	2: (Air Temperature and drying time)	Moisture Ratio	MRE = 0.000966%	Back propagation algorithm	Mokhtarian *et al.* (2012)
44.	Eggplant	Microwave-convective drying.	4-7-6-2 Logarithmic-sigmoid (logsig), Tangent-sigmoid (tansig).	Air temperature, Air velocity, Microwave power, Drying time.	Moisture ratio and drying rate.	MSE = 0.00011 R^2 = 0.9989	Levenberg-Marquardt	Chayjan and Kaveh, (2016)
45.	Pumpkin	Fabricated convective dryer,	Logsig 70 ; 30	3:(Temperature, thickness and time)	Moisture ratio	R^2 = 0.992 RMSE=0.036 SSE = 0.207	Back-propagation algorithm	Onwude et al. (2016)
46.	Yam slices	Hot air convective dryer	Sigmoid function ANFIS	drying time, air temperature, air velocity, and yam slice thickness	Moisture ratio	R^2 = 0.98226 RMSE= 0.01702	Levenberg-Marquardt algorithm Back-Propagation (BP)	Ojediran et al. (2020)
47.	Cantaloupe, Potato, Garlic	Convective hot air dryer.	Tansig 4:15:15:1	Air temperature, air velocity, drying time Product type	Moisture ratio, Drying rate	MR: R^2 = 0.992 MSE = 0.0005 DR; R^2 = 0.984 MAE = 0.0018	Feed forward Back propagation Levenberg-Marquartdt 75:25 (MR) Cascade forward back propagation Bayesian regulation (DR	Kaveh et al. (2018)
48.	Peeled bittim nuts	Designed dryer system (Convective hot air dryer)	Log-sigmoid	3: (Temperature and flow rate of the drying air)	Moisture content	R^2=0.9977	Back propagation	Balbay et al. (2012)
49.	Kiwi	convective-infrared system with heat recovery	Fermi transfer function	Surface temperature, inlet temperature, velocity, time weight, relative humidity	Energy consumption, moisture content	R^2 =0.99, RMSE = 0.001 MAPE = 0.34,	Back-propagation learning algorithm with Levenberg–Marquardt	Ozdemir et al. (2017)

3.0 PRACTICAL APPLICATION

The predicting technique using artificial neural network could be applied for all food material products as well as offer an attractive possibility for control design that results in a controller with a higher level of robustness due to information contained in the model. However, with the ANN model, the time spent carrying out the compositional analysis can hopefully be reduced and reallocated man to other high value-added tasks. The functionality of the developed ANN model is for the prediction of the drying parameters such as moisture content, drying rate and others. This involves the incorporating of the model into the software of drying to help in predicting the parameters. This unique modelling technique and the model it evolved represents a huge step in the trajectory of achieving full automation of drying parameters estimation. This method (ANN) eliminates the need for surface measurement equipment, while at the same time, representing more accurately the inputs parameters at any given conditions say air flow velocity, air temperature, among others.

4.0 FUTURE PROSPECTS

In future, the application of ANN will be diverse in application since it gives accurate calculation and less time consuming. This will be done when the Artificial Neural Networks and Fuzzy Systems have proved their speed competitive potentials and expandability.. The intelligent modeling approach of models employing Artificial Neural Network in combination with other data analysis systems is able to solve a very important problem - processing of scarce, uncertainty and incomplete numerical and linguistic information about multivariate non-linear and non-stationary systems as well as biotechnological processes (Bhotmange and Shastri, 2011). For future work, developing hybridize ANN model that optimizes the prediction of more parameters of the food materials will be necessary.

In years to come, the use of ANN will continue with enormous interest in using neural networks as problem solving algorithms which in performing mapping, regression, modelling, clustering, classification and multivariate data analysis. ANN modeling can be suitably applied in different emerging technologies in food processing such as high-pressure processing, pulsed electric field treatment, high intensity pulse light technology, radio frequency electric fields, irradiation, ultrasonic assisted food freezing, and cold plasma treatment (Raj and Dash 2020), Considering the flexibility of ANNs which makes them ideal to solve highly non-linear problems and deal with any kind of data due to its adaptability in emerging areas or fields and ANN methods have been successfully employed by numerous researchers. Hence, scientific activities in this field should therefore be intensified. Furthermore, they concluded that the major advantage of ANN models over empirical equations, besides accuracy, was their generalizing applicability. ANN models can describe a wide range of experiments while the empirical equations are only valid to a specific experiment.

5.0 CONCLUSION

From the reviewed so far, it could be seen that most of the method/leaning algorithm was Levenberg-Marquardt back propagation and the coefficient of determination (R^2) was above 0.9. Also, the moisture content was one of the key output parameter that was determined. This was to assess the level of moisture in the food products to avoid deterioration.

The performance of an ANN is sensitive to parameters such as the network topology, learning rate and the weight and bias. The optimal combination of these parameters can be found using evolutionary techniques such as genetic algorithm which have good global search ability. This will give the advantage of memory conservation and reduce the number of unnecessary parameters.

In-spite that, the ANNs have proven to be particularly adequate to solve many different problems in the food processing, food engineering and food properties domains. Therefore its usage has become quite frequent and in general the results collaborated the fact of being a powerful tool, very practical and less time consuming.

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