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Predictive modelling approaches in food processing: Future research strategies

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Abstract
Artificial neural network (ANN) technique is not very old as the application of this technique in the field of food engineering is only started in the late 1900's. Till date researchers only focused on validating the technology for decision-making using various technologies such as image processing, spectroscopy, and using physico-chemical properties of the commodity under study. The surge in the application of ANN is very recent as reported in the literature 2015-2020. The current decade is considered as the decade of industrial revolution 4.0 where ANN can play a major role in enhancing the efficiencies of various food processing operations. The available literature also highlights the non-availability of qualified graduates in the area of food processing thereby enhancing the need to develop new processes based on ANN for quick decision-making in the real-time scenario. This review paper presents a new way to apply the ANN for its application in the field of food processing.

Keywords: ANN, food, milk, dairy, AI, artificial

1. Introduction
Food processing is an activity across the globe that help in better handling of agricultural produce including dairy, meat, and fish. The operations carried out in the food industry include raw material quality authenticity; sorting and grading; processing into various products using thermal treatments – heating, freezing, and chilling; packaging; and storage at an appropriate temperature for enhancement of use by the date of the produce. All this is done to safeguard the food products and to ensure their distribution to the consumer. It can help in lowering the incidences of malnourishment, hunger, wastage of agricultural produce and can also help in the sustainable growth of the agricultural sector as well. Since, food composition includes carbohydrates, starches, proteins, minerals, sugars, and other cellular and extracellular materials, therefore, their behavior during processing and storage is very complex to understand. The process parameters such as heating temperatures, time of heating, heating rate, and rate of cooling /freezing during the processing operations decide the end-product quality. Another parameter i.e. moisture content, water activity, and acidity of the produce dictate the process parameters and shelf life of the end product. The microbiological load also decides temperature-time combinations for the processes where aim of the processing is to achieve the microbiological standard of the food items particularly in milk and milk products. The shelf-life is also dictated by the acidity and microbiological standards for most of the products although the enzymatic activity is also as important as any other parameters for achieving the shelf-life of the products. Other chemical reactions such as oxidation and Millard's reaction to occur during the storage of the product.
The approaches to develop predictive models based on mathematical or statistical tools or empirical models' development has been reported for various milk processing activities including plant maintenance and wastage (Yu & Gunasekaran 2005; Zhong & Daubert 2004; Simal S *et al*. 2001; Ndegwa *et al*. 2007) [60, 62, 43, 36]. The industrial processes can be controlled by knowing the properties of raw materials in relation to the processing parameters and the desired end product quality (Jorgensen & Naes, 2004) [23]. The recent approaches used by the researchers include techniques based on color images, spectrophotometric and hyperspectral analysis, artificial neural networks methods (white box model, black box model, grey box model, machine learning (ML) algorithms, and deep learning (DL) algorithms). Training of neural network (NN) was by using back propagation technique, multi-stage convolutional neural network (MS-CNN), Structural equation modelling (SEM) techniques, and artificial

neural network of the Support Vector Machine (SVM) type. No doubt process control and automation too require past data to design future process control models by appropriately selecting input parameters for desirable output. Such type of analyses approach eliminates the sample preparation time and also eliminates chemical residues produced in the conventional methods (Cruz *et al*. 2009) [9].

The application of engineering, sciences, medicine, food, and nutrition are improving with the use of artificial intelligence (AI). The upcoming 4th industrial revolution is said to be based on the application of AI, especially in the food industry where AI can play a pivotal role in the cleaning, manufacturing, and packaging areas (Mounika *et al*. 2022) [64]. There was a surge in the use of AI tools during 2015-2020 and the current decade is going to be in the same trend. Artificial intelligence is in the list of 4th industrial revolution technologies focusing on the development of intelligent machines which would work like humans. The sensor-based techniques help in problem identification after manufacturing and thus recalling the product for possible rectification (Nidhi *et al*. 2022) [65].

Stringent regulatory laws of the European Union (EU) and the United States Food and Drug Administration (U.S. FDA) for product tracing across the supply chain, combined with the declining number of graduates joining the food industry is posing a new threat where it is becoming impossible to replace the current generation of experienced dairy manufacturers. This concern is being addressed through the enhanced use of operator advisory and automated control systems. Such systems use predictive modelling. The next generation of dairy product manufacturers can be trained more efficiently using such systems (Roupas 2008) [42].

The focus of this paper is on the various studies pertaining to the use of spectra/images for the determination of the quality of agricultural produce and processing thereof, which is leading to the application of artificial intelligence tools such as ANN in decision-making. The period from 2000-2022 was chosen, as while going through the literature, it was found that during the early decade of twenty-first-century techniques of spectra/image analysis for determination of quality characteristics such as color, acidity, soluble sugar content, and °Brix was used for various commodities such as pomelo, watermelon, tomato, durian, banana, mango, apple, kiwi fruit, etc**. (**Churchart 2012; Duangchang 2009; Jaiswal *et al*. 2012; Jha & Matsuoka 2004; Jha & Garg 2010; Jha *et al*. 2010; Jha *et al*. 2011; Lapcharoensuk 2009; Onsawai & Sirisomboon 2015; Sirisomboon *et al*. 2009; Sirisomboon *et al*. 2012 (a); Sirisomboon 2012 (b); Theamprateep 2009) [8, 10, 16, 17, 20, 21, 22, 38, 45, 46, 47, 52]. During the second decade, the use of ANN models was reported for various agricultural commodities including milk and milk products (Cámara *et al*. 2009; Singh 2011; Golpour *et al*. 2015; Torkashvand 2017; Mezgec 2017; Ahn *et al*. 2019; Itakura 2019; Too *et al*. 2019) [44, 12, 54, 30, 1, 15, 53].

Review of Literature

Artificial Neural Network (ANN)

The ANN approaches are to mimic the human ways of learning whereby the algorithms have been developed to train the machine on the basis of a large set of data and then revalidation these algorithms using a valid set of data and then calculating the error in the results of ANN model so developed and trained. The basic terminology used in ANN is artificial node or unit. Like the human neural network, these artificial nodes form a network and thus imitate the human neural network. These networks are similar to animal/human systems that they perform tasks collectively in parallel rather than subtasks assigned to them (Goyal & Goyal 2012) [13]. Owing to its ability to handle complex relations amongst the dependent and independent parameters the ANN is an advanced technique of modelling as compared to mathematical techniques of finite-elements or finite difference methods as it uses basic algebra only. On-line control systems are possible using ANN **(**Poonnoy *et al*. 2007) [40]. Fig.1. shows the various layers of an ANN model. The input layer and output layers are selected upon the target to be achieved and output required against the input parameters. The hidden layers may be more than one depending upon the complexity between the input and output parameters. The wights W_{ji} (extent of relations between the nodes) are adjusted to minimize the errors in the output against the input parameters. Researchers are generally dividing the data set in the ratio 70:30 for the training of the model and for the revalidation of the model respectively. The training set should be large enough to train the model with sufficient data points to infer the relation between the input parameters and output parameters with a minimum error during the revalidation of the model. The observed value and predicted values need to be compared using suitable statistical tools for error.

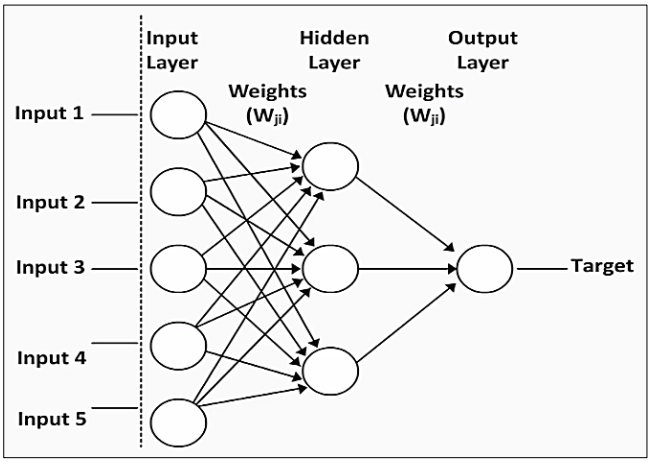

Fig 1: Depiction of various layers of an ANN

The function that consists of one input layer of input nodes and a hidden radial basis function with a linear output layer is known as a radial basis function network (Mateo *et al*. 2009) [28]. The input nodes forming the linear single neuron layer with static or dynamic character-depending upon the input delay whether '0' or greater than '0' these layers are classified as linear layers (Goyal & Goyal 2012) [13].

Image acquisition techniques and ANN

Wang & Lai (2020) [59] tried to develop a theoretical basis for research in commodity image recognition systems. Red, Green, and Blue space was used which have channel values ranging from 0 to 255 with 255 levels in each channel. The color values were obtained by adding the R, G, and B vector values. The cone angel i.e., 0-360 gave the hue value, where '0' was red. A Grey histogram was used to count the pixels in the image. Shape features of the commodity were divided into regional and boundary features. The developed model had more than 90% accuracy. It was reported that digital image

technology is being used for machine vision-based applications. The high-resolution images require a longer processing time. The developed algorithm used a sub-image to eliminate the undesired areas in the images (Minz *et al*. 2020) [32]**.** For the measurement of the color of mozzarella commercial color spectrophotometer was used. The study found that two-megapixel resolution was sufficient for color analysis. (Minz & Saini 2019) [31]. Results obtained by using a charge-coupled device (CCD) and complementary metal-oxide semiconductor (CMOS) showed the same results for color measurement. Technological advancement in webcam is making it possible to use this technology for computer vision systems (CVS). The methodology used for camera setup for image acquisition during the study was effective and it was reported that the system can be used for rapid and economical color measurement of cheese in the industrial setup (Minz & Saini 2021) [32]. QR code was used for the input and output data sets. A deep neural network algorithm was used for the detection of food items, their segmentation, and recognition. Of the total 149 types of dishes, 22,554 possible combinations were relied upon for the reliability output test. AI results confidence level was excellent for 39% of the dishes, whereas it was good for 19% dishes. To enhance the effectiveness of the method a sufficient number of photos of the items are required (Van *et al*. 2022) [55].

The change in color during the shelf-life estimation study on set-yogurt from full-fat and low-fat milk was digitized using a machine vision system (MVS). Data were subjected to a prediction model of ANN for yogurt shelf-life estimation. ANN was trained with back propagation method with one hidden layer and using the sigmoid function. Input parameters were pH; total aerobic, yeast, mold, and coliform counts; color values as acquired with the machine vision system; and yogurt storage period as output variable. The experimental and predicted data set were in high conformity having R^2 value of 0.9996, thereby confirming the reliability of the developed prediction model with a lesser number of parameters and shorter evaluation time. The use of ANN provides an inexpensive and easy technique for the evaluation of yogurt quality parameters (Sofu & Ekinci 2007) [48]. Segmentation and algorithm development, Edge-detection techniques, Digital morphology, Texture and, Thinning and skeletonization algorithms are the major grouping of image analysis algorithm types. Fig. 2 shows the percent accuracy of various segmentation techniques **(**Bhargav & Bansal 2021) [3]. The application of image processing for various commodities has been reported as given in table 1.

Table 1: Use of image processing and ANN

Commodity	Parameter	Reference
Peach	Cold injury	Pan *et al*. 2016 [39]
Tomato	Quality determination	Vazquez-Cruz *et al*. 2013 [56]
Kiwifruit	Color changes of dehydrated fruit	Fathi *et al*. 2011 [11]
Pistachios	Drying time prediction	Balbay *et al*. 2011 [2]
Apple	Drying	Khoshhal *et al*. 2010 [25]
Pineapple	Grading	Boonmung *et al*. 2006 [5]
Yogurt	Protein content	Khanmohammadi *et al*. 2009 [24]
Guava	Respiration rate	Wang *et al*. 2009 [59]
Banana	Phenolic compound and antioxidant activity	Guiné *et al*. 2015

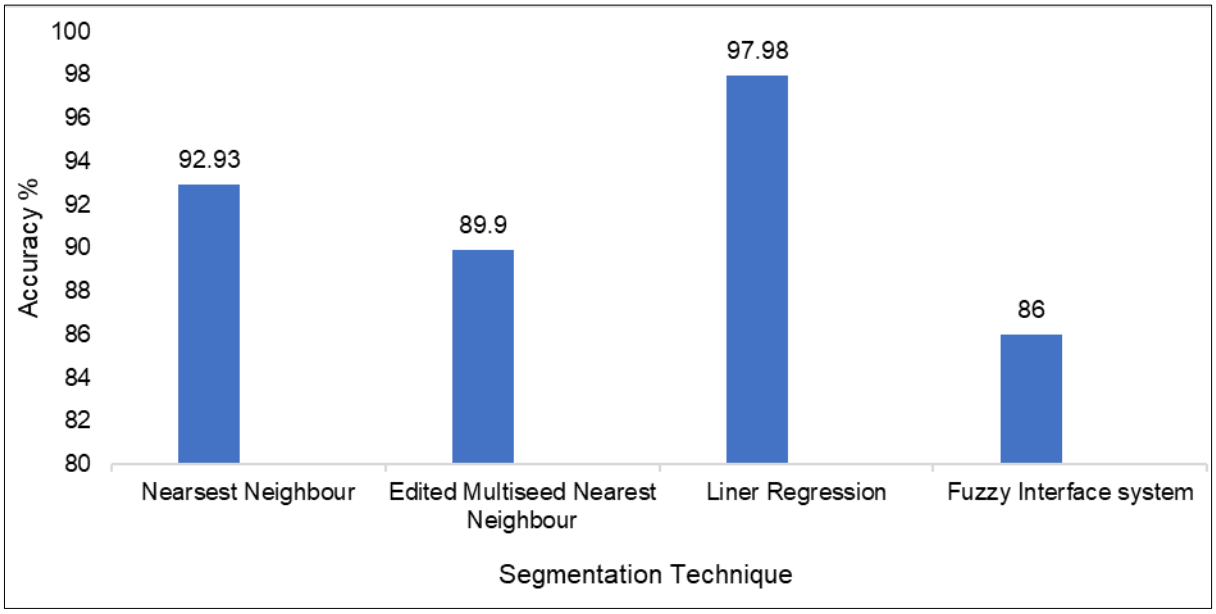

Fig 2: Efficiency for quality analysis of fruits and vegetables based on segmentation techniques

Spectroscopy techniques and ANN

Near infrared (NIR) and short wave near infrared (SWNIR) spectroscopy are emerging as important data acquisition techniques which are being accepted by industry and academia both (Jha *et al*., 2006, 2007; Jha & Gunasekaran 2010) [20] for measurement of total soluble solids, dry matter in a wholesome fruit, measurement of firmness (Carlomagno *et al*. 2004; Moons & Dardenne 1999; Sohn & Rae-Kwang

1999, 2000) [7, 34, 49, 50], sweetness (Jha *et al*. 2005; Jha & Garg 2010; Jha & Gunasekaran 2010) [20] of apple, mango, peach, and kiwifruit, but the prediction of maturity and quality parameters of banana were limited (Tarkosova & Copikova 2000) [51]. Jaiswal *et al*. (2012) [16] studied the banana fruit using NIRS for its pH, total soluble solids (TSS), dry matter (DM), and acid to Brix ratio prediction. The effect of ripening on color and texture was also reported and it was concluded that these properties were significantly affected by the ripening stage. Only color value 'b' was non-significantly affected by the ripening stage (Jaiswal 2014) [].

NIR spectra (1000-2500nm) were acquired during the coagulation of milk. The data were processed using PCA. Semi-empirical model for real-time data acquisition was used to develop an algorithm for the kinetics of the milk coagulation process. The whole milk coagulation with its phase wise coagulation process models shown the $R^2 > 0.99$ for the NIR data acquired during the study (Lyndgaard *et al*. 2012) [27]. NIR spectra (750-2498 nm) in reflectance mode was used for data acquisition of cheese samples. The data were acquired after 2nd and 4th week of storage at 41ºC. sensory analysis by trained panelists was done for nine sensory properties, Texture Profile Analysis (TPA) was used for five textural parameters whereas cheese meltability was recorded using a computer vision setup. Model to predict the instrumental texture and sensory parameters were developed using PLS on raw or pre-treated data. It was recommended that NIR in the reflectance mode can be used to assess the routine quality of processed cheese (Blazquez *et al*. 2006) [4].

Zhang *et al*. (2022) [61] concluded that combining UV-vis with ANN has possibility for accurately predicting the water quality parameters without the requirements of conventional quality testing infrastructure setup. It was presumed that after setting up of technological protocols no sample, as well as chemicals, would be required for analysis. Thus, reducing the analysis duration and chemical residues. This setup can be integrated with some central control system and model calculations can be performed where all parameters of interest can be monitored in real-time scenario. Véstias (2019) [57] reported CNN for quantification of cyanobacteria while predicting the water quality and water level. UV-visible spectrometer was used to acquire the data set, the spectrometer was equipped with 1 cm quartz cell for acquiring the data in absorbance mode. Data sets were analyzed using principal component regression (PCR) and partial least square (PLS) for multivariate analysis. Three-layer NN with back propagation was used. Table 2 indicates the nature of work undertaken by the researchers during the past using ANN and spectroscopy.

Table 2: Use of spectroscopy and ANN for various commodities

Commodity	Parameter	Reference
Processed Cheese	Texture (sensory and instrumental)	Blazquez *et al*. 2006 [4]
Banana	Total soluble solids (TSS), dry matter (DM), pH, and acid-Brix ratio, colour L, a, B and Textural properties	Jaiswal *et al*. 2012 [16]
Water	Water quality, quantification of cyanobacteria	Zhang *et al*. 2022 [61]

ANN and physio-chemical techniques

Robin (2021) [41] study on predictive modeling of paneer based on physio-chemical and engineering properties have successfully predicted the textural, engineering and other physio-chemical properties using ANN model in Python. Samples were collected from 35 vendors, 30 unorganized and 5 organized. The samples were analyzed for fat, moisture, and ash along with instrumental texture properties, instrumental color properties, bulk density, porosity and thermal conductivity. Statistically, samples of unorganized and organized sector were found to be from the same population as the samples were non-significantly different. For development of prediction model, MLR analysis was carried out using the python programming language. A computer program was developed to predict the quality of paneer samples for hardness, adhesiveness, springiness, cohesiveness, gumminess, chewiness, resilience, L*, a*, b*, bulk density, porosity, and thermal conductivity. The error in various parameters was found to be less than 8 percent.

The pasteurized whole milk stored under refrigerated conditions was studied for its shelf-life with the help of a predictive model for quality loss. Parameters such as titratable acidity, pH, lipase, and protease activity were correlated with annual percent change (APC, index for defining shelf-life). The study has shown that it is possible in the future to develop colorimetric sensors for monitoring of spoilage of milk (Ziyaina *et al*. 2018) [63]. A total of 81 experimental data points were used for the study of specific heat (C_p), thermal conductivity (K), and density (ρ) of raw milk as a function of temperature, water, and fat content. Thermos-physical properties were predicted using 3-layer NN with the training of model with back-propagation algorithm and sigmoid transfer function. The data points were divided as 58 for training the model, 17 for validation, and 6 for generalization. The predicted values were compared using statistical tools. It was found that despite a good correlation coefficient obtained using regression analysis; the performance of ANN was better because of its ability to process noisy and large amounts of data. The study concluded that ANN can be an alternative to the polynomial regression methods for such studies (Mattar *et al*. 2004) [29]. The predictive model for *burfi* (an Indian traditional milk-based sweet) stored at 30ºC; the shelf-life prediction inputs were moisture content, titratable acidity, FFA, tyrosine, and peroxide value. The output variable was the overall acceptability score of the panelists. It was concluded that ANN can be excellent means of predicting the shelf-life of such products. (Goyal & Goyal 2012) [13]. A study on processed cheese shelf-life prediction model with 36 data observations at 30ºC storage temperature has shown an excellent correlation between observed and predicted values. The study concluded that the ANN model with the time-delay model was good for predicting the shelf-life of processed cheese.

Two varieties of bananas were studied for the impact of drying on their total phenolic compounds and antioxidant activity. The process variables were modeled, where 264 samples were used for training and validation of ANN for output for anti-oxidant activity; 277 samples for phenolic compound content as output. It was concluded that the ANN model can be used to predict the parameters under study

(Guiné *et al*. 2015) [14]. Peaches stored at 0º C and 5 ºC temperature conditions were analyzed for their firmness, juice content, soluble solids, titratable acidity, and chlorophyll content. The fruits were classified as normal and cold injured using their spectral responses. The correlation coefficient for predicted data ranges from 0.6979 – 0.9026. The predicted model used MLPANN (Pan *et al*. 2016) [39].

Future Strategies for Research

Present status of ANN vis a vis product characteristic

Based on the review of the past studies of the application of image processing, spectroscopy, NIR and UV-vis, and physico-chemical methods for assessment of various parameters such as shape, size, compositional analysis, shelf-life determination, etc. for developing various types of models and ascertaining use of ANN; it is certain that ANN has an advantage over the previous modelling techniques as data complexity can be resolved through the training of ANN for better prediction of the targeted results. Most of the studies have input either as an image, spectra, or from physico-chemical analysis only against the output as defined by the researcher himself.

Most of the quality parameters of fruits and vegetables can be defined based on the size, shape, and color in case of agricultural commodities as their maturity indices are well defined and that too cultivar-wise. The freshness of these commodities can be judged with a change in color or moisture loss and the appearance of blemishes on the surface, thus the day after the harvest can be correlated with such changes or the damage that occurred during the handling and transportation can be judged using such parameters.

In case of milk and milk products the physico-chemical changes such as pH, acidity, microbial load, and textural changes can be correlated with the freshness of the produce as well it can be segregated into various grades. The shelf-life of the milk products like cheeses, yogurt, and traditional Indian milk products *viz*. paneer, barfi, khoa, milk-cake etc. can be predicted. In developing countries where incidences of milk adulteration are there, adulterants can also be detected using such parameters.

Fig. 3 (a) and Fig 3 (b) Depict the concept of ANN being used in the current studies. It is a one-way approach similar to the situation where one can go across the river but can't return back. It has the drawback that it cannot be implemented in the field in its present form as the quality is a human sensory perception in combination with its economic value.

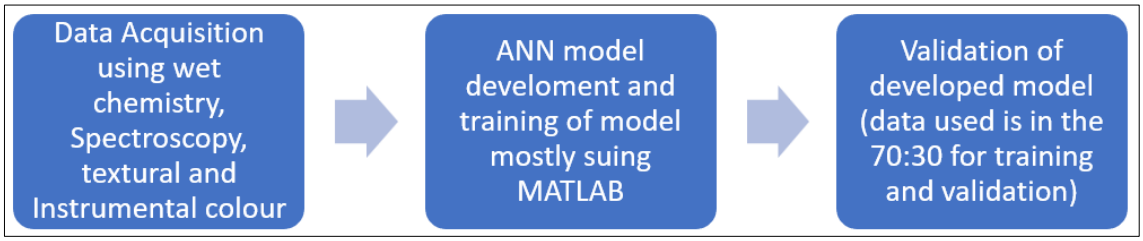

Fig 3(a): Concept of ANN used in the previous studies

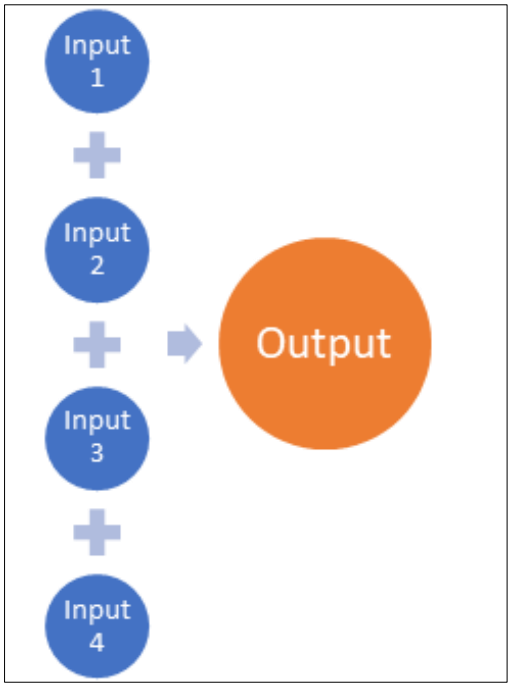

Fig 3 (b): The present approach of the ANN modelling

ANN and future approach

For the product traceability and to win over the consumer perceptions about the product quality, it is important to choose a reliable data acquisition technique for the various outputs as desired depending upon the type of the product under consideration. The ANN models should be developed in such a manner that single instrument-based data input should be able to determine the other quality parameters and

the shelf-life of the commodity under study rather than the wet chemistry methods that are time-consuming, pose environmental and health hazards. Certain instruments which require large sample size for analysis, in comparison to the wet chemistry methods, leads to sample wastage, large storage space requirements, and increase load upon the sewage treatment plants of the companies and institutes. The field testing of commodities can also be made possible with such systems. Fig. 4 (a) the future application of the ANN model for on-field real-time time decision-making.

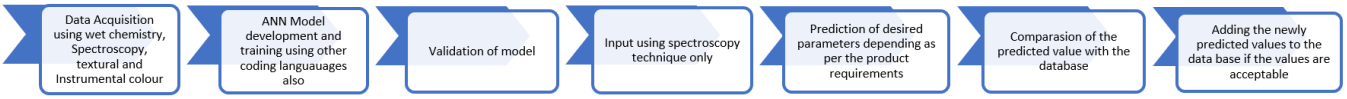

Fig 4 (a): Future strategies for the application of ANN

Fig 4 (a) presents more dynamic ANN model with the real-time application as the data acquired will be becoming part of the larger data set stored in a library. Such an approach, as shown in Fig 4 (b) will lead to less dependency on instrumental measurements for texture, viscosity, and color measurements. It would lead to a smaller sample size as only spectra would be required to predict the other values hence leads to saving on raw materials and chemicals otherwise used for experimentation during the research and new product development activity. It is further a researchable issue as how to combine the spectral acquisition techniques with the current development in smartphone technology as the quality is a human perception which is qualitative rather than quantitative.

Application areas of ANN prediction models

New product development: The prediction of quality characteristics of a new product development requires a considerable time and experimentation. It has been observed during the experimentations with the yogurt that experiments related to textural studies and rheology requires large sample size than the determination of acidity and pH owing to the minimum probe size and the travel of the probe inside the sample. This leads to the requirements for large amount of raw material as well as big size incubators. Using the prediction models for determination of such products would lead to small sample preparation, small size of sample holders and small size incubators. Also, the sample storage for the shelf-life study can be eliminated using such models based on ANN.

Environmental safety: Under current requirements the quality control personnel of each food factory is drawing samples at a specified time interval and then analyzing the same using wet-chemistry methods. This whole process leads to the wastage of samples as well as creation of chemical waste that must be treated before discharge to the main water streams or dumping for ground water recharge. The ANN based models can eliminate the requirements of chemical analysis or at least reduce the number of samples to be analyzed on day-to day basis.

Better decision making: After analyzing the samples in quality analysis laboratories, the decisions are conveyed to the production managers for possible changes required. All this requires a considerable time, hence, there is a time lag in the decision making; the use of ANN based model's cam increase the sample analysis efficiency as well as can minimize the time lag in decision making. The data generated after the analysis would also be automatically saved or conveyed to the higher-level decision makers almost instantly without failure.

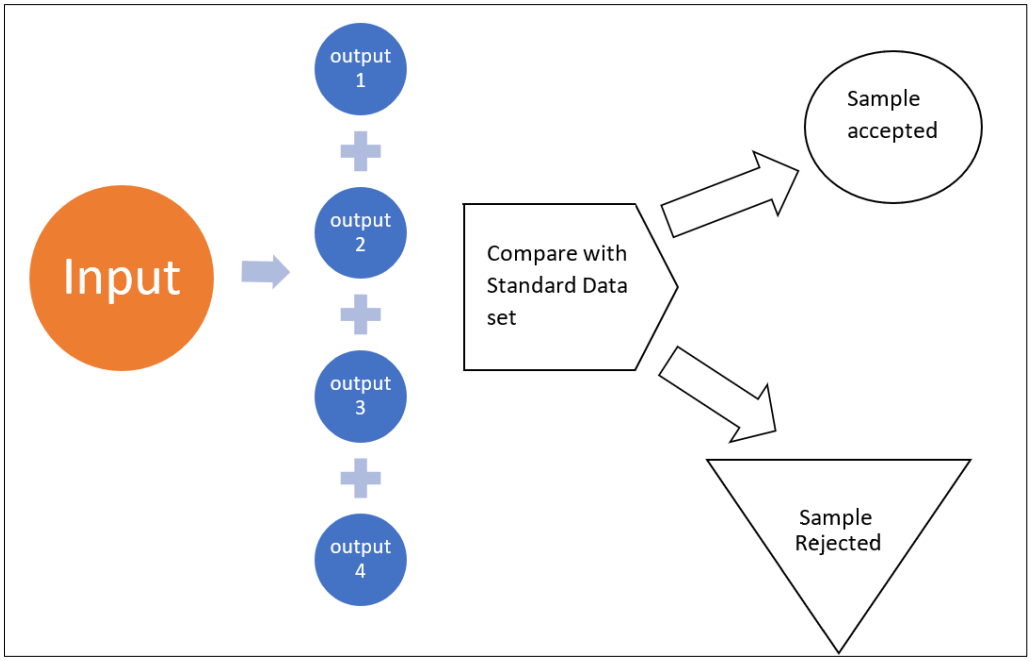

Fig 4(b): New approach to ANN modelling for real time data acquisition and decision making

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Authors' contributions
AS: Conceptualize and write the MS
RC: Guided the and study
PP: Collect the relevant review and helped in preparing the structure of the MS
DV: Collected relevant review and format the MS

Abbreviations

Abbreviation	Full name
Instrumental techniques, modelling, and statistical methods	
AI	Artificial intelligence
ANN	Artificial neural network
APC	Annual percent change
DL	Deep learning
DM	Dry matter
EU	European Union
ML	Machine learning
MS-CNN	Multi-stage convolutional neural network
MVS	Machine vision system
NIR	Near infrared
NN	Neural Network
PCR	Principal component regression
PLS	Partial least square
SE	Structural equation modelling
SVM	Support vector machine
SWNIR	Short wave near infrared
TPA	Texture profile analysis
TSS	Total soluble solids
U.S. FDA	United States Food and Drug Administration

Conclusions
The review of the literature available clearly indicates that the researchers focus till date was on the verification of various techniques such as image processing, spectral acquisition including NIR and UV-Vis for the determination of quality parameters, process parameters, and their relation to end produ1ct quality, shelf-life prediction using mathematical, statistical and ANN models. But till date, no real-time product has been developed based on ANN for field application. Although few researchers have indicated the potential and possible use of such tools. Now it is high time that these tools i.e. image/spectral analysis shall be clubbed with the ANN tools to develop new generation analysis tools in line with the concept of sustainable development that also includes the environmental factors in consideration so that chemicals used for wet chemistry analysis can be minimized thus reducing the loads on waste treatment plants. These new-generation analysis tools would also help in reducing the sample size of the commodity for laboratory analysis. It would be a futuristic approach if these tools can be further clubbed with smart mobile phones through some software/hardware development for their real-time application in the field for quality check and traceability of the product.

References
1. Ahn D, Choi JY, Kim HC, Cho JS, Moon KD, Park T. Estimating the composition of food nutrients from hyperspectral signals based on deep neural networks. Sensors. 2019;19(7):1560.
2. Balbay A, Şahin Ö, Karabatak M. An investigation of drying process of shelled pistachios in a newly designed fixed bed dryer system by using artificial neural network. Drying Technol. 2011;29(14):1685-1696.
3. Bhargava A, Bansal A. Fruits and vegetables quality evaluation using computer vision: A review. Journal of King Saud University-Computer and Information Sciences. 2021 Mar 1;33(3):243-57. https://doi.org/10.1016/j.jksuci.2018.06.002
4. Blazquez C, Downey G, O'Callaghan D, Howard V, Delahunty C, Sheehan E, *et al*. Modelling of sensory and instrumental texture parameters in processed cheese by near infrared reflectance spectroscopy. Journal of Dairy Research. 2006 Feb;73(1):58-69. doi: 10.1017/S0022029905001536. https://pubmed.ncbi.nlm.nih.gov/16433962/ available on 24.12.2022
5. Boonmung S, Chomtee B, Kanlayasiri K. Evaluation of artificial neural networks for pineapple grading. Journal of texture studies. 2006 Oct;37(5):568-79.
6. Camara M, Torrecilla JS, Caceres JO, Sanchez Mata MC, Fernandez-Ruiz V. Neural network analysis of spectroscopic data of lycopene and β-carotene content in food samples compared to HPLC-UV-Vis. Journal of agricultural and food chemistry. 2010 Jan 13;58(1):72-5.
7. Carlomagno G, Capozzo L, Attolico G, Distante A. Non-destructive grading of peaches by near-infrared spectrometry. Infrared Physics & Technology. 2004 Dec 1;46(1-2):23-9.
8. Churchart S. Evaluation of lycopene and soluble solid content (sweetness) in cut watermelon (Kinnaree variety) at different harvesting using near infrared spectroscopy. Master thesis, King Mongkut's Institute of technology Ladkrabang, Bangkok; c2012.
9. Da Cruz AG, Walter EH, Cadena RS, Faria JA, Bolini HM, Fileti AF. Monitoring the authenticity of low-fat yogurts by an artificial neural network. Journal of Dairy Science. 2009 Oct 1;92(10):4797-4804.
10. Duangchang J. Study on the composition of the peel essential oil of Kao Nam Pueng pomeloes at different harvesting date and storage duration using near infrared spectroscopic technique. Master Thesis, King Mongkut's Institute of technology Ladkrabang, Bangkok; c2009.
11. Fathi M, Mohebbi M, Razavi SM. Application of image analysis and artificial neural network to predict mass

transfer kinetics and color changes of osmotically dehydrated kiwifruit. Food Bioprocess Technol. 2011;4(8):1357–1366.
12. Golpour I, Chayjan RA, Parian JA, Khazaei J. Prediction of paddy moisture content during thin layer drying using machine vision and artificial neural networks. J Agr Sci Technol. 2015;17(2):287-298.
13. Goyal S, Goyal GK. Radial basis (exact fit) and linear layer (design) ANN models for shelf life prediction of processed cheese. International Journal of u-and e-Service, Science and Technology. 2012 Mar;5(1):63-70.
14. Guiné RP, Barroca MJ, Gonçalves FJ, Alves M, Oliveira S, Mendes M. Artificial neural network modelling of the antioxidant activity and phenolic compounds of bananas submitted to different drying treatments. Food Chem. 2015;168:454–459.
15. Itakura K, Saito Y, Suzuki T, Kondo N, Hosoi F. Classification of soymilk and tofu with diffuse reflection light using a deep learning technique. Agric. Eng. 2019;1(2):235-245.
16. Jaiswal P, Jha SN, Bharadwaj R. Non-destructive prediction of quality of intact banana using spectroscopy. Scientia Horticulturae. 2012 Feb 24;135:14-22.
17. Jha SN, Matsuoka T. Non-destructive determination of acid–brix ratio of tomato juice using near infrared spectroscopy. International journal of food science & technology. 2004 Apr;39(4):425-30.
18. Jha SN, Kingsly AR, Chopra S. Non-destructive determination of firmness and yellowness of mango during growth and storage using visual spectroscopy. Biosystems Engineering. 2006 Jul 1;94(3):397-402.
19. Jha SN, Chopra S, Kingsly AR. Modeling of color values for nondestructive evaluation of maturity of mango. Journal of Food Engineering. 2007 Jan 1;78(1):22-6.
20. Jha SN, Garg R. Non-destructive prediction of quality of intact apple using near infrared spectroscopy. Journal of food science and technology. 2010 Mar;47:207-13.
21. Jha SN, Gunasekaran S. Authentication of sweetness of mango juice using Fourier transform infrared-attenuated total reflection spectroscopy. Journal of Food Engineering. 2010 Dec 1;101(3):337-42.
22. Jha SN, Jaiswal P, Narsaiah K, Singh AK, Kaur PP, Sharma R, *et al*. Prediction of sensory profile of mango using textural attributes during ripening. Food Bioprocess Technol. 2011;6(3):734-745. doi:10.1007/s11947-011-0720-6
23. JÖrgensen K, Næs T. A design and analysis strategy for situations with uncontrolled raw material variation. Journal of Chemometrics: A Journal of the Chemometrics Society. 2004 Feb;18(2):45-52.
24. Khanmohammadi M, Garmarudi AB, Ghasemi K, Garrigues S, de la Guardia M. Artificial neural network for quantitative determination of total protein in yogurt by infrared spectrometry. Microchemical Journal. 2009 Jan 1;91(1):47-52.
25. Khoshhal A, Dakhel AA, Etemadi A, Zereshki S. Artificial neural network modeling of apple drying process. Journal of food process engineering. 2010 Feb;33:298-313.
26. Lapcharoensuk R. Evaluation of internal and external properties for exporting pomelo at different storage duration by non-destructive method using near infrared spectroscopy. Master Thesis, King Mongkut's Institute of technology Ladkrabang, Bangkok; c2009.
27. Lyndgaard CB, Engelsen SB, van den Berg FW. Real-time modeling of milk coagulation using in-line near infrared spectroscopy. Journal of Food Engineering. 2012 Jan 1;108(2):345-52.
28. Mateo F, Gadea R, Medina A, Mateo R, Jiménez M. Predictive assessment of ochratoxin an accumulation in grape juice based-medium by Aspergillus carbonarius using neural networks. J of Appl Microbiol. 2009;107(3):915-927.
29. Mattar HL, Minim LA, Coimbra JS, Minim VP, Saraiva SH, Telis-Romero J. Modeling thermal conductivity, specific heat, and density of milk: a neural network approach. Inter J of Food Prop. 2004;7(3):531–539.
30. Mezgec S, Koroušić Seljak B. Nutrinet: A deep learning food and drink image recognition system for dietary assessment. Nutrients. 2017;l9(7):657.
31. Minz PS, Saini CS. Evaluation of RGB cube calibration framework and effect of calibration charts on color measurement of mozzarella cheese. J of Food Meas and Charact. 2019;13(2):1537-1546.
32. Minz PS, Saini CS. Comparison of computer vision system and colour spectrophotometer for colour measurement of mozzarella cheese. Appl Food Res. 2021;1(2):100020. https://doi.org/10.1016/j.afres.2021.100020
33. Minz PS, Sawhney IK, Saini CS. Algorithm for processing high-definition images for food colourimetry. Measurement. 2020;158:107670.
34. Moons E, Dardenne P. Determination of internal apple quality by non-destructive visible and near infrared spectroscopy. InNIR99, Proceedings of the 9th International Conference on Near Infrared Spectroscopy, Verona, Italy. Chichester, West Sussex, UK. NIR Publications, 1999, 785-789.
35. Addanki M, Patra P, Kandra P. Recent advances and applications of artificial intelligence and related technologies in the food industry. Appl Food Res, 2022¸ 100126.
36. Ndegwa PM, Wang L, Vaddella VK. Potential strategies for process control and monitoring of stabilization of dairy wastewaters in batch aerobic treatment systems. Process Biochem. 2007;42(9):1272-1278.
37. Mavani NR, Ali JM, Othman S, Hussain MA, Hashim H, Rahman NA. Application of artificial intelligence in food industry—a guideline. Food Eng Rev. 2022;14(1):134–175.
38. Onsawai P, Sirisomboon P. Determination of dry matter and soluble solids of durian pulp using diffuse reflectance near infrared spectroscopy. J Near Infrared Spectrosc. 2015;23(3):167-179.
39. Pan L, Zhang Q, Zhang W, Sun Y, Hu P, Tu K. Detection of cold injury in peaches by hyperspectral reflectance imaging and artificial neural network. Food chemistry. 2016 Feb 1;192:134-41.
40. Poonnoy P, Tansakul A, Chinnan M. Artificial neural network modeling for temperature and moisture content prediction in tomato slices undergoing microwave-vacuum drying. Journal of food science. 2007 Jan;72(1):E042-7.
41. Robin K. Prediction modelling for quality of paneer using engineering properties, physio-chemical properties and sensory evaluation. Master thesis, College of Dairy

Science and Technology, Guru Angad Dev Veterinary and Animal Sciences University, Ludhiana, Punjab, India; c2021.
42. Roupas P. Predictive modelling of dairy manufacturing processes. Int Dairy J. 2008;18(7):741-753.
43. Simal S, Sánchez ES, Bon J, Femenia A, Rossello C. Water and salt diffusion during cheese ripening: Effect of the external and internal resistances to mass transfer. J of Food Eng. 2001;48(3):269–275.
44. Singh NJ. Neural network approaches for prediction of drying kinetics during drying of sweet potato, Agr Eng Int: CIGR J. 2011;13(1).
45. Sirisomboon P, Tanaka M, Kojima T, Williams P. Nondestructive estimation of maturity and textural properties on tomato 'Momotaro'by near infrared spectroscopy. Journal of Food Engineering. 2012 Oct 1;112(3):218-26.
46. Sirisomboon P, Lapcharoensuk R. Study of physical and mechanical properties of intact pomelo (Kao Num Peung variety) during storage. In47. Kasetsart University Annual Conference, Bangkok (Thailand), Mar 2009, 17-20.
47. Sirisomboon P, Thanapase W, Lapcharoensuk R. Identification of different storage of Pomelo (Kao Num Peung variety) by near infrared spectroscopy using PLS-DA. The 3rd Asian Near Infrared Symposium (ANS2012) Amari Watergate Hotel, Bangkok, Thailand. (14-18 May 2012); c2012.
48. Sofu A, Ekinci FY. Estimation of storage time of yogurt with artificial neural network modeling. J Dairy Sci. 2007;90(7):3118–3125. doi:10.3168/jds.2006-591
49. Sohn MR, Cho RK. Development of calibration equation for firmness and determination of cell wall components in apple fruit using near infrared reflectance spectroscopy. In: Davies A, Giangiacomo R (Eds.) NIR99 Proceedings of the 9th International Conference on Near Infrared Spectroscopy; c1999.
50. Sohn M, Cho R. Possibility of nondestructive evaluation of pectin in apple fruit using near-infrared reflectance spectroscopy. J Korean Soc Hortic. Sci. 2000;41(1):65-70.
51. Tarkosova J, Copikova J. Determination of carbohydrate content of banana during ripening and storage by near infrared spectroscopy. J Near Infrared Spectrosc. 2000;8(1):21–26.
52. Theamprateep C. Non-destructive evaluation of Pummelo (Kao Numpung Variety) maturity by near infrared spectroscopic technique. Master Thesis, King Mongkut's Institute of technology Ladkrabang, Bangkok; c2009.
53. Too EC, Yujian L, Njuki S, Yingchun L. A comparative study of fine-tuning deep learning models for plant disease identification. Comput and Electron in Agric. 2019;161:272–279.
54. Torkashvand AM, Ahmadi A, Nikravesh NL. Prediction of kiwifruit firmness using fruit mineral nutrient concentration by artificial neural network (ANN) and multiple linear regressions (MLR). Journal of Integrative Agriculture. 2017 Jul 1;16(7):1634-44.
55. Van Wymelbeke-Delannoy V, Juhel C, Bole H, Sow AK, Guyot C, Belbaghdadi F, *et al*. A cross-sectional reproducibility study of a standard camera sensor using artificial intelligence to assess food items: the FOODINTECH project. Nutrients. 2022;14(1):221. https:// doi.org/10.3390/nu14010221
56. Vazquez-Cruz MA, Jimenez-Garcia SN, Luna-Rubio R, Contreras-Medina LM, Vazquez-Barrios E, Mercado-Silva E, *et al*. Application of neural networks to estimate carotenoid content during ripening in tomato fruits (Solanum lycopersicum). Scientia Horticulturae. 2013 Oct 23;162:165-71.
57. Véstias MP. A survey of convolutional neural networks on edge with reconfigurable computing. Algorithms. 2019 Jul 31;12(8):154.. https://www.mdpi.com/1999-4893/ 12/8/154
58. Chen R, Wang M, Lai Y. Analysis of the role and robustness of artificial intelligence in commodity image recognition under deep learning neural network. PLoS One. 2020 Jul 7;15(7):e0235783.. https://doi.org/10.1371/journal.pone.0235783
59. Wang ZW, Duan HW, Hu CY. Modelling the respiration rate of guava (Psidium guajava L.) fruit using enzyme kinetics, chemical kinetics and artificial neural network. European Food Research and Technology. 2009 Jul;229:495-503.
60. Yu C, Gunasekaran S. Modeling of melt conveying and heat transfer in a twin-screw cheese stretcher. Journal of food engineering. 2005 Sep 1;70(2):245-52.
61. Zhang H, Zhang L, Wang S, Zhang L. Online water quality monitoring based on UV–Vis spectrometry and artificial neural networks in a river confluence near Sherfield-on-Loddon. Environmental Monitoring and Assessment. 2022 Sep;194(9):630.
62. Zhong Q, Daubert CR. Kinetics of rennet casein gelation at different cooling rates. Journal of colloid and interface science. 2004 Nov 1;279(1):88-94.
63. Ziyaina M, Govindan BN, Rasco B, Coffey T, Sablani SS. Monitoring shelf life of pasteurized whole milk under refrigerated storage conditions: Predictive models for quality loss. Journal of food science. 2018 Feb;83(2):409-18.
64. Mounika A, Ilangovan B, Mandal S, Yashwant WS, Gali SP, Shanmugam A. Prospects of ultrasonically extracted food bioactives in the field of non-invasive biomedical applications–A review. Ultrasonics Sonochemistry. 2022 Sep 1;89:106121.
65. Nidhi Dahiya S, Kumar A, Duhan S, Goyat MS. Single-pot hydrothermal derived TiO2/SBA-16 cubic mesoporous nanocomposite for humidity sensing. Journal of Materials Science. 2022 Feb;57(5):3441-51.