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Artificial intelligence applications in the agrifood sectors

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ABSTRACT

Food security is one of the priorities of every country in the World. However, different factors are making it difficult to meet global targets on food security. Some unprecedented shocks are encumbering food security at the global level. Various interventions have been applied toward food security and artificial intelligence is one of the modern methods that is being used in various stages of the food system. In this paper, the application of artificial intelligence in the whole food production ecosystem ranging from crop production, livestock production, harvesting/slaughtering, postharvest management, food processing, food distribution, food consumption and food waste management is assessed. The objective of this research is to assess the application of artificial intelligence systems in all the stages of food systems. A systematic review was conducted by analyzing 110 articles after the screening of 450 articles based on the inclusion and exclusion criteria. The results indicated that various artificial intelligence algorithms are being applied to all the stages of the food system from crop/livestock production up to food or agro-waste management.

1. Introduction

There is a continued increase in food insecurity at the global level since 2019, and 670 million people (8% of the global population) are projected to face hunger in 2030 [1]. This is despite the 2030 Agenda that has been in place since 2015 and various actions toward ending hunger. A majority of the food systems are not resilient which leads to food insecurity and the increasing population also contributes to food insecurity [2]. In 2021 11.7% of the world population was severely food insecure [1]. With the ever-rising world population, there is a need to implore technology in the food production ecosystem to make sure that the population is food secure. Artificial Intelligence (AI) has been proposed as one of the ways of fighting poverty among human beings through its applications in the field of agriculture where it has been proposed as a way of increasing the production of food [3]. Artificial intelligence applications play a major role in the improvement of the four pillars of food security namely accessibility, stability, utilization and availability [4]. Artificial intelligence is a combination of conventional science disciplines, scientific theories, and practices using mathematical logic, statistics, and probabilities, through computers to imitate the cognitive abilities of humans [5].

The major branches of AI include Machine Learning (ML), Computer Vision, Natural Language Processing, Artificial Neural Networks, Robotics and Expert Systems. These subsets of AI have been used to make decisions on different processes in the food chain ecosystem. ML can be divided into 2 and has its types and techniques as depicted in Fig. 1.

Artificial intelligence has brought some remarkable improvements in the field of agriculture including the production of crops, harvesting and marketing [6]. Artificial intelligence is a modernized technology that can be used in place of human intelligence in troubleshooting and decision-making. In combination with the Internet of Things (IoT) artificial intelligence can be utilized in the food system from agriculture to food waste management [7].

Reviews were conducted on the application of artificial intelligence on fruit and vegetable production [8,9], pre-harvesting and postharvest activities [10] and the supply chain of fruits and vegetables [11]. Mavani et al. [12] reviewed diverse AI apps in comparing their advantages, limitations and formulations as a guideline for selecting the most appropriate methods for enhancing future AI and food industry-related developments. They emphasized the integration of AI systems with devices such as electronic noses, electronic tongues, computer vision systems and near-infrared spectroscopy which will benefit both the

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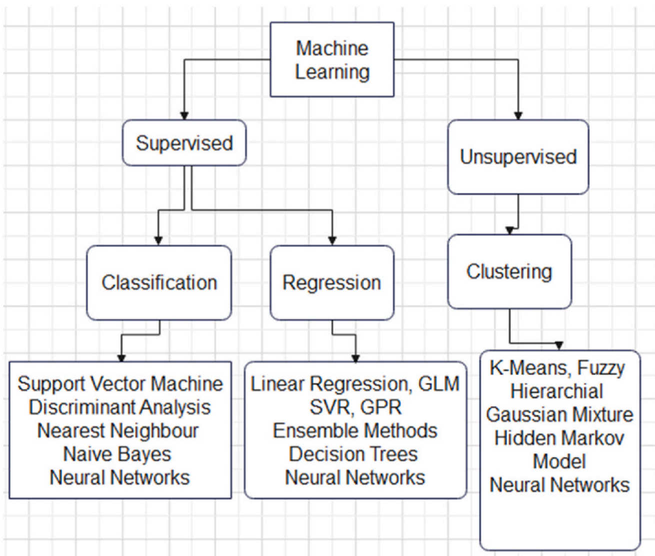

Fig. 1. machine learning techniques.

industry players and consumers. The reviews explained were focused on various stages of the food system but not on the entire food chain. There is minimal information available on Artificial Intelligence and its use in the entire food system, hence the need for a review that assesses the application of artificial intelligence in all the stages of the food system in one paper.

2. Methodology

A systematic review was conducted. Peer-reviewed research articles were collected from the internet through Google scholar and science direct. The main search terms included Artificial Intelligence/types of artificial intelligence systems and one or a combination of the following: agriculture, crop production, animal production, harvesting, post-harvest storage, postharvest handling, food processing, food distribution, food consumption, food waste management, and food system. The inclusion criteria considered the global location, field trials, laboratory trials, experimental designs, validation and comparisons of artificial intelligence-based systems. The exclusion criteria for the study included non-peer-reviewed research articles and research articles published before the year 2000.450 papers were downloaded from the internet based on their titles. These papers were first screened by removing 50 duplicates. Out of the remaining 400 articles, 102 articles were removed based on their relevance by assessing the abstracts of the papers. Of the remaining 298 articles 188 articles were removed based on the content of the entire paper. This review was constructed from the content of 110 journal articles based on the research objectives of this paper.

3. Artificial intelligence and the food system

3.1. Crop production

3.1.1. Pests and disease management

Low agricultural productivity has been experienced as a result of challenges in the accurate and early diagnosis of crop diseases by individuals. An intelligent mobile application that works on android mobile devices was developed to diagnose wheat diseases in Pakistan. The intelligent mobile application which utilizes a fuzzy interference system was validated by testing it on 100 genuine crop challenges and its accuracy was 99%. The system utilizes both English and the farmers' local language thus making it user-friendly [13]. An artificial intelligence system PhytAi was used to identify disease severity on pepper. It was applied to evaluate the biological activities of the bacteria *Pseudomonas lini* (PCA17) against Phytophillia blight disease in pepper. A comparison of the results of the AI system with visual scores indicated that the AI is accurate. The detection of the severity of the disease was based on the visual results of the plant [14]. A method that can be used for the earlier detection of pests in rice was developed. The unmanned aerial vehicle which is linked to the Imagga cloud utilizes python programming and AI to send information to the Imagga cloud. The information is sent in the form of pictures of the pests identified in the field. The Imagga cloud identifies the pest and the information is sent to the farmer for corrective or preventative action [15]. An 87% accuracy was recorded in the use of a Deep Convolutional Network to detect fall armyworm infestation on maize tassels, cobs and leaves [16].

Artificial intelligence can be used in crop disease identification in banana trees. Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) were combined resulting in Gated Recurrent Convolutional Networks. Banana tree images are captured using a camera that is located in the banana tree plantain. The system identifies any colour changes in the same manner as the human eye and it analyses what might have contributed to the changes through the use of CNN and Gated Recurrent Unit (GRU) which classifies and processes the images respectively. The model correctly classifies plantain tree diseases and detects plantain tree diseases at an early stage [17]. Artificial neural networks and remote sensing can be used in the approximation of the volume of the coffee tree. This was done to determine pesticide-spraying volume for an individual tree. This reveals the need for varying pesticide spraying volume as it varies among trees instead of the conventional way of using the fixed volume [18].

3.1.2. Crop water supply/irrigation

Different artificial intelligence algorithms namely Support Vector Machines (SVM), random forest RF, KNearest Neighbour (KNN) and adoptive boosting were used to predict crop evapotranspiration for sugar beet in semi-arid regions. The SVM method was identified as the most ideal method to estimate the evapotranspiration of sugar beet [19]. The estimation of crop evapotranspiration is significant for managing the water supply to the crops. This is very essential in crop irrigation management. The intelligent Internet of Things (IoT) was used in an irrigation system of 5911 fields. The IoT multiagent irrigation approach used multi-intelligent agents and cyber-physical agents for 11 pump stations that supplied water to the fields. The system managed the water supply using georeferenced field information and the results indicated an improved Irrigation water use efficiency. The system used robotic agents and software or virtual agents to monitor the fields. The water needed by the crops was determined by the agents and the distribution of irrigation water was also facilitated by the irrigation agents [20]. Canopy temperature, relative humidity and air temperature were used as the basis for the prediction of the crop water stress index using two artificial neural network models namely Unsupervised Kohenen Self Organizing Map and supervised Feed Forward Back Propagation. The Unsupervised Kohenen Self-Organizing Map had better results than the feed forward-back propagation [21]. The significance of the prediction of crop water stress index is that it enables efficient management of crop stress and can also be applied in irrigation scheduling.

Determination of watermelon irrigation depth and period can be easily carried out using Artificial Neural Network than Volumetric water balance [22]. Fuzzy Logic (FL) has been used for the FAO Penman-Monteith (FPM) method for optimizing irrigation and increasing crop yields [23]. FL can be used in combination with Wireless Sensor Network (WSN) and ZigBee, for experimental results verification in home gardens [24]. ANN-based systems have been used for evapotranspiration [25], where sensors are used to measure soil properties such that the irrigation process will be automated. ANN algorithms such as the Levenburg Marquardt and the Back propagation method have been used on the FPM method to decrease water evaporation by scheduling the use of water and electricity [26]. AI has also been used in smart agriculture for optimizing irrigation and application of herbicides

[27] to get maximum produce by applying automated spraying, irrigation and weeding methods.

3.1.3. Weed management

Machine Vision (MV) as an AI technique has been used for precision weed management using a smart sprayer on pepper and artificial plants. A smart sprayer with artificial intelligence and machine vision sprays precisely on the targeted weeds whilst avoiding other plants which are not the targeted weeds. This ensures that the agrochemicals are used effectively and it also reduces injuries to crops and it reduces agrochemical wastage. The weed detecting system is linked to the spraying system, which uses precision spraying, and these are linked to a system that is responsible for weed mapping. The results of this system showed that there were fewer agrochemical residues [28]. Destructive and non-destructive methods of weed control were integrated with an artificial neural network system for weed control. Machine learning analyzed and modeled the competition between weeds and crops. This enables the determination of the ideal method and timing of weed control. The experiments were conducted in the field in a region with an annual average rainfall of 673.9 mm and melon and sesame which are C3 crops were used for the experiment. Various species of weeds that attack melon/sesame were observed during the experiments [29]. The ANN can be used to determine the sustainable use of agrochemicals in a manner that is safe for humans as well as in a manner that improves productivity. The system can identify the current amount of agrochemicals and recommend the optimal amount [30]. ANN has mainly been used in weed control and weed identification to improve crop/-weed species discrimination [31].

Coupled with various other AI technologies and algorithms, drones have found themselves being used for pesticide spraying [32], crop monitoring and mapping using UAVs [33]. However, the use of drones has been attributed to high costs due to the use of cameras and sensors that have to be attached to them [27]. MV has also been used on autonomous weeding robots using high-powered lasers for intra-low weeding on sugar beet [34]. MV has been applied for robotic weed control using a mechanical and rotary hoe on sugar beet with a 92% accuracy [35]. By applying an electrical discharge, MV can be applied for weed control systems in lettuce [36].

3.1.4. Crop growth rate and yield

A method was developed for crop mapping in any region that has historical data on crop cover [37]. Artificial Neural Network is more accurate in the prediction of the growth rate of rice as compared to regression modes that are regression algorithms and gene-expression programming [38]. Artificial neural networks and genetic algorithms can determine the crop age thereby leading to the optimization of resources allocated to the crops as well as timely harvesting. Wheat images are captured in the field and the system evaluates the wheat crop nitrogen status. It also predicts crop yield [39]. Accuracy in the prediction of crop yields is imperative in crop production. Soybean crop yield prediction was accurately conducted using the Bayesian multi-modeling of deep neural networks [40]. For remote sensing, spectral-spatial classification and Bayesian Information criterion have been used for tomato sensing and segmenting tomato and non-tomato regions [41]. The use of drones in monitoring crops reduced the time spent carrying out the activities conducted by humans [42].

3.2. Livestock production

3.2.1. Dairy cow production

It was highlighted that there is no sufficient evidence of the impact of digital technology on livestock production in middle and low-income countries. In Kenya and India digital tools are used in various activities in dairy cattle and poultry production including extension, monitoring of flock/herd, management of pastures and artificial insemination. These digital tools have been manipulated for the management of cattle/dairy/goats/poultry and sheep. Farmtree is an application, which processes data entered by the farmer and gives output on total yield per lactation, days of peak yields and daily yields. It also calculates the profitability of the dairy cow [43] An automatic monitoring system was developed to identify a dairy cow and estimate the body condition score of the cow. This system is more advantageous for the monitoring of thin cows as compared to manual methods. The deep learning framework was used in the assessment of body conditions and identification of individual cows on an automated system. This method eliminated some errors that are encountered when conducting manual tasks [44]. Gharibi et al. [45], developed a quality index for dairy cattle was developed using fuzzy inference systems. 20 quality parameters were considered in the development. The fuzzy dairy cattle water quality index results were more comprehensive as compared to the national sanitation foundation for Iran. The fuzzy Dairy Cattle Drinking Water Quality Index (DCWQI) analyzed chemical quality (heavy metals, psychochemical properties and minerals) and microbial quality.

Deep neural network trials were conducted to predict the cows' production stage and daily milk yield based on features from mammary sonograms echotexture. The deep learning algorithm classified cows' daily milk yield as either no lactation or high lactation. It also classified the cows' productive stage [46]. Artificial neural networks were utilized to predict milk yield in dairy cows and the results were compared to Wood's models. The designed artificial neural network predicted the daily yields more accurately than Wood's model. The neural network that was developed is easier to use as it can give accurate results with datasets smaller than required by Wood's models and it doesn't require the satisfaction of meeting regression models assumptions [47]. Internet of the things-based device was used in a model named Moocare. This system forecasts the milk production of individual cows, assesses the cows and notifies the dairy farmer. The information provided to the farmer will enable timely planning and implementation of a nutritional plan for each cow. The model has 2 levels of notification and it is made up of a prediction engine, actuators and IoT sensors. Accurate calculations for the food quantities for each cow were performed by the system based on the lactation of each day [48].

Developments in animal health monitoring in terms of the use of artificial intelligence have also been documented. Themistokleous et al. [49], developed a machine learning-based fog computing-assisted system which is data-driven to detect lameness in cows with an accuracy of 87%. This system can detect lameness in cows 3 days before it can be visually identified by humans. This is an advantage in that the lameness can be treated earlier. It also reduces the probability of human subjective errors. Lameness in dairy cows was determined using a machine learning approach [50], though there is a need for further development to improve the performance of the system. The machine learning approach utilized tree induction and the lameness was detected remotely based on data that is consistently collected from the farm. Deep learning has been utilized to predict dairy cows' bovine tuberculosis using mid-infrared spectral profiles. The prediction is automated thus enabling farmers to have early management of the condition [51].

3.3. Poultry production

Poultry management refers to daily activities conducted by a poultry farmer along the short life cycle of broilers [52]. Neethirajan [53] developed a deep-learning model to track the movement of chickens in different environmental backgrounds through the use of cameras. The chicken activities (including their interactions with each other and the environment) were monitored. Artificial neural network systems were used to manage poultry through the use of sensors that record parameters on poultry management. This data is processed by machine learning technologies and action plans are drafted. The parameters that were managed/monitored by the ANN system are the broiler area(size), desired temperature, the internal temperature of broilers, the temperature of the broiler house, external climatic conditions of the broiler house, and age-day for input layers. The action plans developed were based on feed conversion ratio and average broiler weight [52]. An IoT system was developed to monitor livestock using their sounds. Identification of diseased birds was achieved through the design of a wearable device. The system monitored poultry as well as identified diseases through the monitoring of watering, feeding, cleaning, and bird data collection. A multisensory integrated collar band was utilized [54].

Reboiro-Jato et al. [55] designed a system to forecast the number of specific types of feed consumed per lot during its lifespan. The system utilized an ad-hoc algorithm and machine learning method. The system enables stock feed planning and management as it necessitates that there is no shortage of feed. A model that is based on fuzzy logic technology predicts egg production and is proven to be 100% accurate. The model utilizes SPSS in its first stage whilst the second and third stages utilize the fuzzy toolbox. The first stage is the correlational analysis of data which includes total egg production, chick body weight, age of chicks, feed quantities and feed quality. The second and third stages involve fuzzy model prediction and fuzzy model evaluation [56].

3.4. Crop harvesting and postharvest management

An algorithm that detects symmetry was used to detect the edge of tea on an image. It uses artificial intelligence to determine the grade of the tea based on the edge of the tea. This method was validated by comparing it to the three traditional methods of tea classification and it proved to be more accurate [57]. ANNlinear model is suitable for the determination of ripeness based on the firmness of watermelons through an acoustic impulse [58]**.** Support Vector Regression(SVR) application in the determination of banana quality indices based on colour was compared with ANN. It was concluded that the accuracy of quality prediction using SVR is improved as compared to ANN during banana storage [59]. FL has been used to automate the storage of cassava roots, potatoes and fruits in specialized areas for postharvest quality control [60].

Deep Learning has been applied on residual networks to automatically sort bananas [61] through a system that grades fruits where bananas were classified into healthy and unhealthy bananas using a DL-based RESNET-50 network with an efficiency of up to 90%. An electronic nose was used to detect fungal infection or the presence of Aspergillus during postharvest storage of Jasmine brown rice [62]. It was also used to detect grain mildew in Japonica rice [63] and fungal microorganisms due to spoilage-related aroma [64] during postharvest storage and drying. Artificial intelligence can be applied in the harvesting and postharvest processes of various plant-based foods (see Table 1)

Table 1
Artificial intelligence application for harvesting and postharvest management.

Crop	Description	Accuracy	Reference
Banana	Ripening was tested using light detection and ranging sensor laser scan. The laser sensor and fruit distance is 0.9 m.	Accuracy was 69% on the test set validation for visual classification. and 66% on the test set validation chlorophyll content classification.	[65]
Fuji apple	A robot that recognizes fruit through the use of an automated recognition vision system for locating the apples. The algorithm is based on a support vector machine.	The accuracy success rate in terms of apple fruit recognition is approximately 89%. The average time for recognition is 352 ms	[66]
Watermelon	A deep convolutional neural network was applied to acoustic resonance testing data. The system can be used in monitoring the extent of watermelon ripeness during postharvest storage.	A ripeness classification accuracy of 96% was recorded	[67]
Apple	Convolutional Neural Networks were used in the detection of apple spoilage during postharvest storage. The CNN Based systems which were either Deeplab or U-net model quantified the decay of the apples.	Accuracy was 99.99% for the Deeplab model and 99.71% for the U-net model	[68]
Maize	A decision tree machine learning algorithm was used in the estimation of stored maize grain damage by *Prostephanus trancatus*	The coefficient correlation was r = 0.93	[69]

3.5. Food processing

3.5.1. Raw material conversion to the product

A cyber-physical twin can be used to monitor food quality and packaging under various conditions during the food chain, particularly during transportation as well as food handling during and after packaging. The cyber-physical twin model that was developed takes into consideration some factors such as quality parameters, and these are sensory quality, chemical parameters, economical factors, and environmental factors. There is a need to develop a system that considers the microbiological aspects of the food [70].

The artificial neural network model was used in the production of flour from watermelon pomace through the dehydration/drying process. The solar air heater was connected to the data acquisition system. The artificial neural network accurately predicted the drying curve for the watermelon rind. The drying process in the production of flour from watermelon pomace can be optimized through the application of Artificial Neural Network modeling [71] Machine learning algorithms and deep learning can predict cattle beef carcass cut yields of both roasting cuts and grilling cuts. The system captures two-dimensional and three-dimensional images after slaughter. The yields that were predicted in the experiment were for grilling and roasting and these were validated using conventional methods [72].

3.5.2. Food analysis

Food quality is significant in the delivery of safe food and nutritious food thereby contributing to food security. Quality food is attained through the process of analyzing food within the processing stage. Biosensors have proven to be very significant in conducting food analysis. Biosensors have also proved to detect harmful microorganisms in food effectively. Pesticide residues can also be detected in foods through the use of biosensors. Heavy metals that contaminate water bodies are also detected by the use of biosensors [42]. The Internet of things (IoT) has resulted in a massive amount of streaming data which brings new opportunities to monitor food processes. The role of AI also includes food quality assessment using spectral methods and sensor fusion and food safety using gene sequencing and block chain-based digital traceability [73].

Three different machine learning algorithms namely support vector regression, multilayer perceptron and support vector regression are effective in the analysis of ascorbic acid and total phenolics The use of a machine learning algorithm-based system produced rapid results in the analysis of the dried apples. The multilayer perceptron is an ANN system [74]. Defects can be detected in an eggshell by the use of a vision system that scans the surface of the egg and analyses the scanned image to determine whether there are no defects in the egg. This vision system based on artificial neural networks was evaluated and it proved to have an efficiency of 97.5% [75]. Food adulteration was detected through the use of sound vibration artificial intelligence-based tools. Cheese and butter were tested in the experiment. The test accurately identified adulterated butter after comparison with unadulterated butter at room temperature [76]. Somatic cell count, milk urea nitrogen, fat lactose and protein can be accurately analyzed during milking through the use of a sensing system that utilizes Near Infrared spectroscope [77]. He et al. [78], used AI techniques for food identification from an image. The bag of visual words model (BOW) has been used to represent food images as visual word distributions [79]. Anthimopoulos et al. [80], used a support vector machine (SVM), artificial neural network and random forest classifications on 5000 food images organized into 11 classes described in terms of different bag-of-features. Ming et al. [81] proposed a photo-based dietary tracking system that employed deep-based image recognition algorithms to recognize food and analyze nutrition.

Radial based Multiple Linear Regression (MLR) ANN technique has been used in dairy farming for predicting the shelf life of processed cheese at 30 °C by comparing the input parameters such as soluble nitrogen, standard plate count, pH, yeast count, mold and spore count. Using both single and multilayer perceptron *Time Delay Neural Network (TDNN)* networks, the shelf life of processed cheeses for 30 days was efficiently predicted as stated by Goyal et al., [82]. This radial basis of linear layer ANN was also used to detect the aroma, flavor, texture, moisture and free fatty acids of processed cheese. Computer Vision has been used on various types of cheese (blue, shredded, cheddar), to identify hole areas from cheese surfaces, free oil formation, shred size and shape [83], and gas hole formation [84]. Coupled with image analysis, Computer Vision has been used to monitor the quality of beer and wine in the alcohol production industry [85]. An electronic tongue has been used in the analysis of sensory perceptible properties of crayfish [86](Xu et al., 2020), honey [87,88], bacon [89](Du et al., 2021) and dry-cured pork [90].

3.6. Food marketing and distribution

Evolutionary ML has been used for efficient food distribution in supply chain optimization [91] to reduce costs in the supply chain and transport scheduled seafood and milk products. In combination with sensors and Zigbee-based networks, ML has been used to predict and tackle drought situations [92]. Bayesian Networks(BN) that are automated were used in integration with KNIME workflows to forecast the likelihood of liquid milk contamination in the milk supply chain. KNIME workflows extracted data automatically from sources within 6 European countries. The prediction was based on various indicators that are linked to food safety hazards. Alerts were automatically sent and saved whenever an anomaly was detected. The Bayesian network was run to predict the food safety hazard [93]. A Neural Network system was used In India to identify villages that lacked access to food based on specified food insecurity indicators and the study areas were classified into different levels of food insecurity [94].

3.7. Food consumption

Many applications have been focused on health and fitness. The instant development of AI technologies has enabled new food identification systems for dietary assessment which are significant for the prevention and treatment of chronic diseases [95]. The use of smartphones to track food consumption or compute the nutritional value of food has expanded due to the increasing number of food consumption tracking and recommended applications and the great potential of smartphones to be useful tools. Samad et al. [96], evaluated 473 applications of which 80 were selected for assessment based on exclusion and inclusion criteria. Their rating tool assessed consumption tracking and recommendations as well as their usefulness for general users. According to their assessment, most mobile applications in application stores do not satisfy the overall requirements for tracking food consumption and recommendations. Foodvisor is an application that can automatically recognize food items and compute the recommended volume and nutritional value of that item. For estimating an individual's food and calorie intake, the calculation of food portion size or volume is necessary, therefore different methods have been developed that can be used to estimate food volume from food images [97–99].

Artificial intelligence algorithms and machine vision systems were developed to aid in food preparation. The system monitors all the food cooking parameters and identifies if food is fully cooked based on the food colour. This system can stop the food cooking process to avoid food overcooking. The food status was classified as overcooked, cooked and uncooked. The food in the pot is stirred by a robotic arm [100]. A suggestion for a neural network and recommendation-integrated system which focus on Thai food was made. In addition to food choices, the system would pay attention to users' health. It would also assist consumers to make food selection decisions based on behavior, taste and eating history. A food recommendation system was built to recommend food for diabetic patients based on nutrition and food characteristics [96]. Natural Language Processing (NLP) has been used on digital menu boards to place orders employing a conversational chatbot [101]. AI techniques range from the use of mobile apps, decision support tools for nutrition and the use of telehealth for remote assessment of nutrition. The state of digital technology for clinical nutrition is still young though there is potential for growth [102].

3.8. Food waste management

Artificial intelligence applications can be used in the management of food waste both of plant and animal origin. Trials were conducted on the use of Artificial Neural Networks in the identification of ideal conditions for the processing of mackerel fish bone biofloculant and the efficiency of flocculation was 97.65%. Chicken compost was utilized as the major source of nutrients and the fish bones were collected from leftover mackerel fish [103]. Yasin [104] conducted experiments to compare the ANN and response surface methodology predictions of extraction of fatty acid methyl ester from fish waste. The comparison of the 2 models revealed that the use of ANN yielded a higher prediction efficiency as compared to the regression model and statistical analysis. The forecasting efficiency of machine learning was assessed on fresh fish demand to reduce the oversupply of fish in the market that often results in fish deterioration leading to increased food waste. The various models used proved to have a higher probability of fresh fish demand forecasting as compared to statistical and baseline models. These predictions help in reducing food losses at the retail level [105].

ANN and Central Composite Design were used in the modeling of alpha-amylase production from banana peel pieces as a substrate and the results showed that the use of ANN results in improved prediction and optimization as compared to the Response Surface Methodology [106]. An IoT-based system was designed for the separation and classification of dry waste from wet waste. Vegetable leaves, tomato slices and banana peels were some of the waste that was successfully classified and segregated from dry waste based on moisture content values [107]. The effective prediction of bioethanol yield from watermelon waste was conducted using ANN and Adaptive Neuro-fuzzy inference systems. The bioethanol was produced through the fermentation of watermelon waste by *Saccharomyces Cerevisiae* [108]. Biodiesel yields from waste vegetable oil were predicted using an artificial neural network, adaptive neuro-fuzzy inference system and response surface methodology and the ANFIS had the highest yield prediction accuracy of 99.3% followed by ANN with 99.1% [109]. Rice husk ash from a rice milling factory was added as a constituent for the production of concrete. Artificial Neural Network was applied in the prediction of tensile splitting and comprehensive strength and the results were in line with the standard traditional methods of determination [110].

4. Conclusions and future perspectives

This paper gives a review of the application of AI in agro-food systems and findings showed that various Artificial intelligence-based methods are being applied in all the stages of the agro-food system to help achieve SDG number 2. Among other reasons, AI helps in decision-making, the detection of crop and animal diseases. As an application in smart farming, AI can be used for soil monitoring, robocropping, weed management, crop diseases management, pest management and irrigation. It can be used to monitor the growth and productivity of livestock. Artificial intelligence can be used to monitor changes in agricultural produce during postharvest storage. In the food processing cycle, it can be used for the optimization of the food production processes, product sorting, packaging, and food analysis. On the consumer end where AI plays a major role, it can be used for customer satisfaction, recipes, food delivery, online services, automated ordering systems and food waste management. It is recommended that AI should be applied to diverse crops and livestock production to include even the underutilized crops.

It is evident from the articles reviewed that AI can create more efficient production processes thereby making a huge impact on achieving the United Nations Sustainable Development Goals that are related to food systems. AI will impact the entire value chain from the farm-to-fork as there will be generated new opportunities for precision agriculture, real-time monitoring and management of crop fields whereas minimizing the adverse effects of these practices on the environment. With the use of AI-driven technologies that do not diminish natural resources, the global need for zero hunger and climate action will be met. Furthermore, AI technologies would be used to predict weather patterns, and evaluate farms for the presence of diseases or pests and inadequate plant nutrition. It enables an exceptional ability to analyze data and computationally discover complex relationships and patterns thus reducing time-wasting. AI is a potential tool to enable and facilitate a transition to sustainable and improved food systems such as school feeding programs. It can help ease the burden of administrative processes.

Due to the ever-changing climate conditions, there is likely to be a continual increase in demand and supply competition. This can potentially be mitigated by the application of AI to promote and maintain higher productivity and improve the quality of produce and sustainability. AI would allow real-time monitoring and analysis of agricultural processes to generate critical data to fine-tune strategies for optimum resource exploitation. The future of AI is aimed at the optimization of food production, food consumption, and value chains as well as minimizing negative environmental impacts. Adoption of AI in developing countries will, however, require policy recommendations that address data ownership, transparency and privacy issues. This will allow food and agricultural sectors to address bottlenecks such as farmers' incapacitation, data access and ownership, information leakage and cyber security. It also requires support for developing expertise and competencies to build resilient food and agricultural systems.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] I.F.A.D. Fao, UNICEF, WFP and WHO, The State of Food Security and Nutrition in the World 2022. Repurposing Food and Agricultural Policies to Make Healthy Diets More Affordable, FAO, Rome, 2022, https://doi.org/10.4060/cc0639en.
[2] M.L. How, Y.J. Chan, S.M. Cheah, Predictive insights for improving the resilience of global food security using artificial intelligence, Sustainability 12 (15) (2018) 6272.
[3] M.A. Goralski, T.K. Tan, Artificial intelligence and poverty alleviation: emerging innovations and their implications for management education and sustainable development, Int. J. Manag. Educ. 20 (3) (2022), 100662.
[4] R.M.S.R. Chamara, S.M.P. Senevirathne, S.A.I.L.N. Samarasinghe, M.W.R. C. Premasiri, K.H.C. Sandaruwani, D.M.N.N. Dissanayake, S.H.N.P. De Silva, W. M.T.P. Ariyaratne, B. Marambe, Role of artificial intelligence in achieving global food security: a promising technology for future, Sri Lanka J. Food Agric. 6 (2) (2020) 43–70.
[5] N.S. Redhu, Z. Thakur, S. Yashveer, P. Mor, Artificial intelligence: a way forward for agricultural sciences, in: Bioinformatics in Agriculture, Academic Press, 2022, pp. 641–668.
[6] N. Goel, Y. Kumar, S. Kaur, M. Sharma, P. Sharma, Machine learning-based remote monitoring and predictive analytics system for monitoring and livestock monitoring, in: Application of Machine Learning in Agriculture, Academic Press, 2022, pp. 47–67.
[7] P. Sharma, A. Vimal, R. Vishvakarma, P. Kumar, L. Porto de Souza Vandenberghe, V. K Gaur, S. Varjani, Deciphering the blackbox of omics approaches and artificial intelligence in food waste transformation and mitigation, Int. J. Food Microbiol. 372 (2022), 109691.
[8] N.C. Eli-Chukwu, Applications of artificial intelligence in agriculture: a review, Engineering, Technol. Appl. Sci. Res. 9 (4) (2019) 4377–4383.
[9] M.K. Tripathi, D.D. Maktedar, A role of computer vision in fruits and vegetables among various horticulture products of agriculture fields: a survey, Inf. Process. Agric 7 (2) (2020) 183–203.
[10] V. Meshram, K. Patil, V. Meshram, D. Hanchate, S.D. Ramkteke, Machine learning in agriculture domain: a state-of-art survey, Artif. Intell.Life Sci. 1 (2018), 1000010.
[11] B.B. Rodolfo, O.C.P. Rodrigo, G.L.Y. Jesus, Digital twins application in the post-harvest supply chain of fruits and vegetables: a systematic review of the literature, IEOM Soc. Int.Proc. Int. Conf.Ind. Eng.Oper. Manag.Istanb. (2022) 118–130.
[12] N.R. Mavani, J.M. Ali, S. Othman, M.A. Hussain, H. Hashim, N.A. Rahman, Application of artificial intelligence in food industry—a guideline, Food Eng. Rev. 14 (2021) 1–42, 2021.
[13] M. Toseef, M.J. Khan, An intelligent mobile application for diagnosis of crop diseases in Pakistan using fuzzy inference system, Comput. Electron. Agric. 153 (2018) 1–11.
[14] U. Ozyilmaz, Evaluation of the effectiveness of antagonistic bacteria against Phytophthora blight disease in pepper with artificial intelligence, Biol. Control 151 (2020), 104379.
[15] S.K. Bhoi, K.K. Jena, S.K. Panda, H.V. Long, R. Kumar, P. Subbulakshmi, H. B. Jebree, An Internet of Things assisted Unmanned Aerial Vehicle based artificial intelligence model for rice pest detection, Microprocess. Microsyst. 80 (2021), 103607.
[16] R. Prabha, J.S. Kennedy, G. Vanitha, N. Sathiah, M.B. Priya, Artificial intelligence-powered expert system model for identifying fall armyworm infestation in maize (*Zea mays L.*), J. Nat. Appl. Sci. 13 (4) (2021) 1339–1349.
[17] M. Nandhini, K.U. Kala, M. Thangadarshini, S.M. Verma, Deep Learning model of sequential image classifier for crop disease detection in plantain tree cultivation, Comput. Electron. Agric. 197 (2022), 106915.
[18] M.F. de Oliveira, A.F. dos Santos, E.H. Kazama, G. de Souza Rolim, R.P. da Silva, Determination of application volume for coffee plantations using artificial neural networks and remote sensing, Comput. Electron. Agric. 184 (2021), 106096.
[19] S.S. Yamaç, Artificial intelligence methods reliably predict crop evapotranspiration with different combinations of meteorological data for sugar beet in a semiarid area, Agric. Water Manag. 254 (2021), 106968.
[20] A.F. Jiménez, P.F. Cárdenas, F. Jiménez, Intelligent IoT-multiagent precision irrigation approach for improving water use efficiency in irrigation systems at farm and district scales, Comput. Electron. Agric. 192 (2022), 106635.
[21] N. Kumar, A.J. Adeloye, V. Shankar, R. Rustum, Neural computing modelling of the crop water stress index, Agric. Water Manag. 239 (2020), 106259.
[22] O.C. Rocha Neto, A.D.S. Teixeira, A.P. Braga, C.C. Santos, R.A. Leão, Application of artificial neural networks as an alternative to volumetric water balance in drip irrigation management in watermelon crop, Eng. Agric. 35 (2015) 266–279.
[23] P.J. Kia, A.T. Far, M. Omid, R. Alimardani, L. Naderloo, Intelligent control based fuzzy logic for automation of greenhouse irrigation system and evaluation in relation to conventional systems, World Appl. Sci. J. 6 (1) (2009) 16–23.
[24] A.R. Al-Ali, M. Qasaimeh, M. Al-Mardini, S. Radder, I.A. Zualkernan, ZigBee-based irrigation system for home gardens, Int. Conf. Commun.Signal Process. Appl. (2015) 1–5.
[25] S.M. Umair, R. Usman, Automation of irrigation system using ANN based controller, Int. J. Electr. Comput. Sci. 10 (2010) 41–47, 02.
[26] N. Karasekreter, F. Başçiftçi, U. Fidan, A new suggestion for an irrigation schedule with an artificial neural network, J. Exp. Theor. Artif. Intell. 25 (1) (2013) 93–104.
[27] T. Talaviya, D. Shah, N. Patel, H. Yagnik, M. Shah, Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides, Artif. Intell.Agric. 4 (2020) 58–73.

[28] V. Partel, S.C. Kakarla, Y. Ampatzidis, Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence, Comput. Electron. Agric. 157 (2019) 339–350.
[29] A.L. Monteiro, M. de Freitas Souza, H.A. Lins, T.M. da Silva Teófilo, A.P.B. Júnior, D.V. Silva, V. Mendonça, A new alternative to determine weed control in agricultural systems based on artificial neural networks (ANNs), Field Crop. Res. 263 (2021), 108075.
[30] E. Elahi, C. Weijun, H. Zhang, M. Abid, Use of artificial neural networks to rescue agrochemical-based health hazards: a resource optimization method for cleaner crop production, J. Clean. Prod. 238 (2019), 117900.
[31] A. Tobal, S.A. Mokhtar, Weeds identification using evolutionary artificial intelligence algorithm, J. Comput. Sci. 10 (8) (2014) 1355–1361.
[32] A. Garre, M.C. Ruiz, E. Hontoria, Application of Machine Learning to support production planning of a food industry in the context of waste generation under uncertainty, Oper. Res.Perspect. 7 (2020), 100147.
[33] P. Psirofonia, V. Samaritakis, P. Eliopoulos, I. Potamitis, Use of unmanned aerial vehicles for agricultural applications with emphasis on crop protection: three novel case-studies, Int. J. Agric. Sci. Technol. 5 (1) (2017) 30–39.
[34] T. Bakker, K.V. Asselt, J. Bontsema, J. Müller, G.V. Straten, An autonomous weeding robot for organic farming, in: Field and Service Robotics, Springer, Berlin, Heidelberg, 2006, pp. 579–590.
[35] B. Åstrand, A.J. Baerveldt, An agricultural mobile robot with vision-based perception for mechanical weed control, Aut. Robots 13 (1) (2002) 21–35.
[36] J. Blasco, N. Aleixos, J.M. Roger, G. Rabatel, E. Moltó, AE—automation and emerging technologies: robotic weed control using machine vision, Biosyst. Eng. 83 (2) (2002) 149–157.
[37] C. Zhang, L. Di, L. Lin, H. Li, L. Guo, Z. Yang, G.Y. Eugene, Y. Di, A. Yang, Towards automation of in-season crop type mapping using spatiotemporal crop information and remote sensing data, Agric. Syst. 201 (2022), 103462.
[38] L.W. Liu, X. Ma, Y.M. Wang, C.T. Lu, W.S. Lin, Using artificial intelligence algorithms to predict rice (Oryza sativa L.) growth rate for precision agriculture, Comput. Electron. Agric. 187 (2021), 106286.
[39] A. Sharma, M. Georgi, M. Tregubenko, A. Tselykh, Enabling smart agriculture by implementing artificial intelligence and embedded sensing, Comput. Ind. Eng. 165 (2022), 107936.
[40] P. Abbaszadeh, K. Gavahi, A. Alipour, P. Deb, H. Moradkhani, Bayesian multi-modeling of deep neural nets for probabilistic crop yield prediction, Agric. For. Meteorol. 314 (2022), 108773.
[41] J. Senthilnath, A. Dokania, M. Kandukuri, K.N. Ramesh, G. Anand, S.N. Omkar, Detection of tomatoes using spectral-spatial methods in remotely sensed RGB images captured by UAV, Biosyst. Eng. 146 (2016) 16–32.
[42] K.S. Balan, Robotic-based agriculture for rural renais-sance: drones and biosensors, Compr. Anal. Chem. 74 (2016) 363–375, 2016.
[43] T. Daum, T. Ravichandran, J. Kariuki, M. Chagunda, R. Birner, Connected cows and cyber chickens? Stocktaking and case studies of digital livestock tools in Kenya and India, Agric. Syst. 196 (2022), 103353.
[44] S. Yukun, H. Pengju, W. Yujie, C. Ziqi, L. Yang, D. Baisheng, L. Runze, Z. Yonggen, Automatic monitoring system for individual dairy cows based on a deep learning framework that provides identification via body parts and estimation of body condition score, J. Dairy Sci. 102 (11) (2019) 10140–10151.
[45] H. Gharibi, M.H. Sowlat, A.H. Mahvi, H. Mahmoudzadeh, H. Arabalibeik, M. Keshavarz, N. Karimzadeh, G. Hassani, Development of a dairy cattle drinking water quality index (DCWQI) based on fuzzy inference systems, Ecol. Indicat. 20 (2012) 228–237.
[46] M. Taneja, J. Byabazaire, N. Jalodia, A. Davy, C. Olariu, P. Malone, Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle, Comput. Electron. Agric. 171 (2020), 105286.
[47] W. Grzesiak, P. Błaszczyk, R. Lacroix, Methods of predicting milk yield in dairy cows—predictive capabilities of Wood's lactation curve and artificial neural networks (ANNs), Comput. Electron. Agric. 54 (2) (2006) 69–83, 2006.
[48] R. da Rosa Righi, G. Goldschmidt, R. Kunst, C. Deon, C.A. da Costa, Towards combining data prediction and internet of things to manage milk production on dairy cows, Comput. Electron. Agric. 169 (2020), 105156.
[49] K.S. Themistokleous, N. Sakellariou, E. Kiossis, A deep learning algorithm predicts milk yield and production stage of dairy cows utilizing ultrasound echotexture analysis of the mammary gland, Comput. Electron. Agric. 198 (2022), 106992.
[50] D. Warner, E. Vasseur, D.M. Lefebvre, R. Lacroix, A machine learning based decision aid for lameness in dairy herds using farm-based records, Comput. Electron. Agric. 169 (2020), 105193.
[51] S.J. Denholm, W. Brand, A.P. Mitchell, A.T. Wells, T. Krzyzelewski, S.L. Smith, E. Wall, M.P. Coffey, Predicting bovine tuberculosis status of dairy cows from mid-infrared spectral data of milk using deep learning, J. Dairy Sci. 103 (10) (2020) 9355–9367.
[52] R. Ribeiro, D. Casanova, M. Teixeira, A. Wirth, H.M. Gomes, A.P. Borges, F. Enembreck, Generating action plans for poultry management using artificial neural networks, Comput. Electron. Agric. 161 (2019) 131–140.
[53] S. Neethirajan, ChickTrack–a quantitative tracking tool for measuring chicken activity, Measurement 191 (2022), 110819.
[54] R. Mohanty, S.K. Pani, Livestock health monitoring using a smart IoT-enabled neural network recognition system, in: Cognitive Big Data Intelligence with a Metaheuristic Approach, Academic Press, 2022, pp. 305–321, 2022.
[55] M. Reboiro-Jato, J. Glez-Dopazo, D. Glez, R. Laza, J.F. Gálvez, R. Pavón, D. Glez-Peña, F. Fdez-Riverola, Using inductive learning to assess compound feed production in cooperative poultry farms, Expert Syst. Appl. 38 (11) (2011) 14169–14177.
[56] T.G. Omomule, O.O. Ajayi, A.O. Orogun, Fuzzy prediction and pattern analysis of poultry egg production, Comput. Electron. Agric. 171 (2020), 105301.
[57] M. Jiang, Z. Chen, Symmetry detection algorithm to classify the tea grades using artificial intelligence, Microprocess. Microsyst. 81 (2021), 103738.
[58] J. Mao, Y. Yu, X. Rao, J. Wang, Firmness prediction and modeling by optimizing acoustic device for watermelons, J. Food Eng. 168 (2016) 1–6, 2016.
[59] A. Sanaeifar, A. Bakhshipour, M. De La Guardia, Prediction of banana quality indices from color features using support vector regression, Talanta 148 (2016) 54–61.
[60] V. Sahni, S. Srivastava, R. Khan, Modelling techniques to improve the quality of food using artificial intelligence, J. Food Qual. 2021 (2021), 2140010.
[61] A. Helwan, M.K. Sallam Ma'aitah, R.H. Abiyev, S. Uzelaltinbulat, B. Sonyel, Deep learning based on residual networks for automatic sorting of bananas, J. Food Qual. 2021 (2021) 1–11.
[62] A. Jiarpinijnun, K. Osako, U. Siripatrawan, Visualization of volatomic profiles for early detection of fungal infection on storage Jasmine brown rice using electronic nose coupled with chemometrics, Measurement 157 (2020), 107561.
[63] J. Zhang, B. Zhang, J. Dong, Y. Tian, Y. Lin, G. Fang, S. Wang, Identification of mouldy rice using an electronic nose combined with SPME-GC/MS, J. Stored Prod. Res. 95 (2022), 101921.
[64] A. Makarichian, R.A. Chayjan, E. Ahmadi, S.S. Mohtasebi, Assessment the influence of different drying methods and pre-storage periods on garlic (*Allium Sativum L.*) aroma using electronic nose, Food Bioprod. Process. 127 (2021) 198–211.
[65] K.K. Saha, M. Zude-Sasse, Estimation of chlorophyll content in banana during shelf life using LiDAR laser scanner, Postharvest Biol. Technol. 192 (2022), 112011.
[66] W. Ji, D. Zhao, F. Cheng, B. Xu, Y. Zhang, J. Wang, Automatic recognition vision system guided for apple harvesting robot, Comput. Electr. Eng. 38 (5) (2012) 1186–1195.
[67] D. Albert-Weiß, E. Hajdini, M. Heinrich, A. Osman, CNN for ripeness classification of watermelon fruits based on acoustic testing, in: Proceedings of the Virtual 3rd International Symposium on Structural Health Monitoring and Nondestructive Testing, 2020, pp. 25–26.
[68] N. Stasenko, M. Savinov, V. Burlutskiy, M. Pukalchik, A. Somov, Deep learning for postharvest decay prediction in apples. IECON 2021–47th annual conference of the, IEEE Ind. Electron.Soc. (2021) 1–6.
[69] T. Nyabako, B.M. Mvumi, T. Stathers, S. Mlambo, M. Mubayiwa, Predicting Prostephanus truncatus (Horn)(Coleoptera: bostrichidae) populations and associated grain damage in smallholder farmers' maize stores: a machine learning approach, J. Stored Prod. Res. 87 (2020), 101592.
[70] R. Accorsi, M. Bortolini, M. Gamberi, B. Guidani, R. Manzini, M. Ronzoni, Simulating product-packaging conditions under environmental stresses in a food supply chain cyber-physical twin, J. Food Eng. 320 (2022), 110930.
[71] M.P. Fabani, J.P. Capossio, M.C. Román, W. Zhu, R. Rodriguez, G. Mazza, Producing non-traditional flour from watermelon rind pomace: artificial neural network (ANN) modeling of the drying process, J. Environ. Manag. 281 (2021), 111915.
[72] D. Matthews, T. Pabiou, R.D. Evans, C. Beder, A. Daly, Predicting carcass cut yields in cattle from digital images using artificial intelligence, Meat Sci. 184 (2022), 108671.
[73] N.N. Misra, Y. Dixit, A. Al-Mallahi, M.S. Bhullar, R. Upadhyay, A. Martynenko, IoT, big data and artificial intelligence in agriculture and food industry, IEEE Internet Things J. 9 (9) (2020).
[74] N. Çetin, C. Sağlam, Rapid detection of total phenolics, antioxidant activity and ascorbic acid of dried apples by chemometric algorithms, Food Biosci. 47 (2022), 101670.
[75] R. Mota-Grajales, J.C. Torres-Peña, J.L. Camas-Anzueto, M. Pérez-Patricio, R. G. Coutiño, F.R. López-Estrada, E.N. Escobar-Gómez, H. Guerra-Crespo, Defect detection in eggshell using a vision system to ensure the incubation in poultry production, Measurement 135 (2019) 39–46.
[76] G. Lymen, G. Tanriver, Y.Z. Hayirlioglu, O. Ergen, Artificial intelligence-based identification of butter variations as a model study for detecting food adulteration, Innovat. Food Sci. Emerg. Technol. 66 (2020), 102527.
[77] S. Kawamura, M. Kawasaki, M. Tsukahara, K. Itoh, H. Nakatsuji, M. Natsuga, Milk-quality monitoring by near-infrared spectroscopy for artificial intelligence in dairy farming, IFAC Proc. Vol. 37 (2) (2004) 22–27.
[78] Y. He, C. Xu, N. Khanna, C.J. Boushey, E.J. Delp, Analysis of food images: features and classification, IEEE Int. Conf.Image Process. (2014) 2744–2748.
[79] G.M. Farinella, M. Moltisanti, S. Battiato, Classifying food images represented as bag of textons, IEEE Int. Conf.Image Process. (2014) 5212–5216.
[80] M.M. Anthimopoulos, L. Gianola, L. Scarnato, P. Diem, S.G. Mougiakakou, A food recognition system for diabetic patients based on an optimized bag-of-features model, IEEE J.Biomed. Health Inf. 18 (4) (2014) 1261–1271.
[81] Z.Y. Ming, J. Chen, Y. Cao, C. Forde, C.W. Ngo, T.S. Chua, Food Photo Recognition for Dietary Tracking: System and Experiment, International Conference on Multimedia Modeling, 2018, pp. 129–141.
[82] S. Goyal, G.K. Goyal, Radial basis (exact fit) and linear layer (design) ANN models for shelf life prediction of processed cheese, Int. J.u-and e-Service Sci. Technol. 5 (1) (2012) 63–70, 2012.
[83] S. Gunasekaran, Cheese quality evaluation, in: Computer Vision Technology for Food Quality Evaluation, Academic Press, 2016, pp. 487–524.
[84] J. Dias, P. Lage, A. Garrido, E. Machado, C. Conceição, S. Gomes, A. Martins, A. Paulino, M. F Duarte, N. Alvarenga, Evaluation of gas holes in "Queijo de Nisa" PDO cheese using computer vision, J. Food Sci. Technol. 58 (3) (2021) 1072–1080.

[85] J. Lukinac, K. Mastanjević, K. Mastanjević, G. Nakov, M. Jukić, Computer vision method in beer quality evaluation—a review, Beverages 5 (2) (2019) 38.
[86] X. Xu, C. Sun, B. Liu, Q. Zhou, P. Xu, M. Liu, A. Wang, H. Tian, W. Luo, Q. Jiang, Flesh flavor of red swamp crayfish (Procambarus clarkii Girard, 1852) processing by GS-IMS and electronic tongue is changed by dietary animal and plant protein, Food Chem. 373 (2022), 131453.
[87] B. Lozano-Torres, M.C. Martínez-Bisbal, J. Soto, M.J. Borrás, R. Martínez-Máñez, I. Escriche, Monofloral honey authentication by voltammetric electronic tongue: a comparison with 1H NMR spectroscopy, Food Chem. 383 (2022), 132460.
[88] T. Yin, Z. Yang, N. Miao, X. Zhang, Q. Li, Z. Wang, C. Li, X. Sun, Y. Lan, Development of a remote electronic tongue system combined with the VMD-HT feature extraction method for honey botanical origin authentication, Measurement 171 (2021), 108555.
[89] H. Du, Q. Chen, Q. Liu, Y. Wang, B. Kong, Evaluation of flavor characteristics of bacon smoked with different woodchips by HS-SPME-GC-MS combined with an electronic tongue and electronic nose, Meat Sci. 182 (2021), 108626.
[90] X. Tian, Z.J. Li, Y.Z. Chao, Z.Q. Wu, M.X. Zhou, S.T. Xiao, J. Zeng, J. Zhe, Evaluation by electronic tongue and headspace-GC-IMS analyses of the flavor compounds in dry-cured pork with different salt content, Food Res. Int. 137 (2020), 109456.
[91] A. Cheraghalipour, M.M. Paydar, M. Hajiaghaei-Keshteli, Designing and solving a bi-level model for rice supply chain using the evolutionary algorithms, Comput. Electron. Agric. 162 (2019) 651–668.
[92] G. Arvind, V.G. Athira, H. Haripriya, R.A. Rani, S. Aravind, April. Automated irrigation with advanced seed germination and pest control, IEEE Technol. Innovat. ICT Agric.Rural Dev. (2017) 64–67.
[93] N. Liu, Y. Bouzembrak, L.M. Van den Bulk, A. Gavai, L.J. van den Heuvel, H. J. Marvin, Automated food safety early warning system in the dairy supply chain using machine learning, Food Control 136 (2022), 108872.
[94] K.N. Priyadarshini, M. Kumar, K. Kumaraswamy, Identification of food insecure zones using remote sensing and artificial intelligence techniques, the International Archives of Photogrammetry, Rem. Sens. Spatial Inf. Sci. 42 (2018) 659–664.
[95] W. Min, S. Jiang, R. Jain, Food recommendation: framework, existing solutions, and challenges, IEEE Trans. Multimed. 22 (10) (2019) 2659–2671.
[96] S. Samad, F. Ahmed, S. Naher, M.A. Kabir, A. Das, S. Amin, S.M.S. Islam, Smartphone apps for tracking food consumption and recommendations: evaluating artificial intelligence-based functionalities, features and quality of current apps, Intell. Syst.Appl. 15 (2022), 200103.
[97] J. Dehais, M. Anthimopoulos, S. Shevchik, S. Mougiakakou, Two-view 3D reconstruction for food volume estimation, IEEE Trans. Multimed. 19 (5) (2016) 1090–1099.
[98] A.E. Maxwell, T.A. Warner, F. Fang, Implementation of machine-learning classification in remote sensing: an applied review, Int. J. Rem. Sens. 39 (9) (2018) 2784–2817.
[99] B.D. Meyer, W.K. Mok, J.X. Sullivan, Household surveys in crisis, J. Econ. Perspect. 29 (4) (2015) 199–226.
[100] C.S. Lin, Y.C. Pan, Y.X. Kuo, C.K. Chen, C.L. Tien, A study of automatic judgment of food color and cooking conditions with artificial intelligence technology, Processes 9 (7) (2021) 1128.
[101] M. Lasek, S. Jessa, Chatbots for customer service on hotels' websites, Inf. Syst. Manag. 2 (2) (2013) 146–158.
[102] B.N. Limketkai, K. Mauldin, N. Manitius, L. Jalilian, B.R. Salonen, The age of artificial intelligence: use of digital technology in clinical nutrition, Curr. Surg. Rep. 9 (7) (2021) 1–13.
[103] U. Suparmaniam, N.B. Shaik, M.K. Lam, J.W. Lim, Y. Uemura, S.H. Shuit, P. L. Show, I.S. Tan, K.T. Lee, Valorization of fish bone waste as novel bioflocculant for rapid microalgae harvesting: experimental evaluation and modelling using back propagation artificial neural network, J. Water Proc. Eng. 47 (2022), 102808.
[104] N.H. M Yasin, N.H. Mat, A.S. Fakhrudin, A.W.A.A. Hadi, M.H. M Khairuddin, N.R. A. Sepian, F.M. Said, N. Zainol, Comparison of response surface methodology and artificial neural network for the solvent extraction of fatty acid methyl ester from fish waste, Int.J. Mod. Agric. 9 (3) (2020) 1929–1942.
[105] V.L. Miguéis, A. Pereira, J. Pereira, G. Figueira, Reducing fresh fish waste while ensuring availability: demand forecast using censored data and machine learning, J. Clean. Prod. 359 (2022), 131852, https://doi.org/10.1016/j.jclepro.2022.131852.
[106] A. Prabhakar, G.M. Madhu, Statistical optimization and neural modeling of amylase production from banana peel using *Bacillus subtilis* MTCC 441, Int. J. Food Eng. 6 (4) (2010) 1–12.
[107] A. Das, A. Shukla, R. Manjunatha, E.A. Lodhi, IoT based solid waste segregation using relative humidity values, in: 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 2021, pp. 312–319.
[108] A. Jahanbakhshi, R. Salehi, Processing watermelon waste using *Saccharomyces cerevisiae* yeast and the fermentation method for bioethanol production, J. Food Process. Eng. 42 (7) (2019), e13283.
[109] A.N. Amenaghawon, N.I. Evbarunegbe, K. Obahiagbon, Optimum biodiesel production from waste vegetable oil using functionalized cow horn catalyst: a comparative evaluation of some expert systems, Clean Eng. Technol. 4 (2021), 100184.
[110] M.A. Getahun, S.M. Shitote, Z.C.A. Gariy, Artificial neural network based modelling approach for strength prediction of concrete incorporating agricultural and construction wastes, Construct. Build. Mater. 190 (2018) 517–525.