Artificial Intelligence in Agriculture - A perspective in 2022

Nilesh Ingle, MS, Ph.D.[*,+]
* Alumni North Carolina State University, Raleigh, NC, USA
+ **learndataa**, Data Science Training and Consulting
Corresponding author's e-mail: learndataa@gmail.com

ABSTRACT

The global demand for food continues to increase as the world population grows. Traditional as well as mechanized methods of farming have been perfected over the years to get better yields. However, in the wake of future food demands, they seem inadequate. Primarily because of human limitations associated with key farming activities such as soil preparation, weeding, spraying, irrigation, disease and pests identification, harvesting and quality control. Similar limitations can be found in animal husbandry operations such as a poultry farm, pig farm or a cattle farm. Here, artificial intelligence (AI) powered unmanned ground vehicles, robots, and unmanned aerial vehicles equipped with a multitude of sensors are now able to perform several of these activities efficiently with minimal human intervention. This manuscript is a non-systematic review that discusses the current status of recent AI developments in agriculture.

***Keywords**: artificial intelligence in agriculture, agriculture robots*

INTRODUCTION

In the 21st century, the current world population of 8 billion is expected to reach 9.8 billion by 2050 '(Prudhomme and Matsueda 2022). The global demand for food is expected to increase by up to 56 per cent by 2050 (van Dijk *et al.* 2021). The world's arable land has decreased from 0.3 hectares per person in 1961 to 0.18 hectares per person in 2022 (The World Bank 2022). Therefore, food production must increase by 70 per cent by 2050 (FAO 2009). The key challenges with current agriculture methods such as lack of precision, high labor cost, higher time requirement can be overcome by smart farming (Walter *et al.* 2017). Smart farming (Walter *et al.* 2017) or digital agriculture (Mushi, Di Marzo Serugendo and Burgi 2022) or e-farming or Agriculture 4.0 (Clercq, Vats and Biel 2018; Polyakov 2021) is the next agricultural revolution after the green revolution from 1950's. These technologies harness the power of the internet, data, sensors and information technology. Artificial intelligence or AI can be thought of as a software program that can take data as an input to learn hidden patterns within the data to create a model that can make predictions, **Figure 1**. Thus, using an AI powered application or machine it is now possible to use real time farming data to get predictions, make recommendations or automate processes. This type of data driven approach to farming would reduce guess work and ensure that optimal farming practices are followed (Linaza *et al.* 2021).

***Figure 1:** Conceptual stages of AI implementation on a farm. Data generated by sensors on the farm is used to train or build an AI model. Such a trained AI can take new farm data as an input to make a reasonable prediction or a recommendation.*

Currently there are over 6.5 billion active smartphone users in the world today (Statista 2022a). Thus, it is feasible to reach out to a large population with an AI powered software application that can be installed on a smartphone. Such an app can be used on the field to perform a task such as identifying the type of disease on a plant by taking a picture of a leaf using the built-in camera in a phone. Incredible as it sounds, there are over 150+ mobile apps on plant pest and disease identification alone (Sibanda, Iyawa and Gamundani 2021). Additionally, agriculture robots is a USD 9.3 billion market today and is expected to grow to USD 35 billion by 2030 (Statista 2022b). Therefore, this non-systematic review attempts to present an overview of the current status of adoption of AI in various sectors of agriculture around the world. It may be noted that the review purposely avoids technical discussion of deep learning algorithms used to develop an AI.

DISCUSSION

This section discusses the applications of AI in the following areas related to agriculture: preparatory farming activities, during farming activities, post farming or harvesting activities, technology transfer, value added activities, activities in agriculture other than farming and socio-economic and political motivation.

1.1 Preparatory farming activities

Activities to prepare the soil for sowing may be considered as a preparatory farming activity. In traditional farming, soil samples are randomly collected from different regions of a farm for chemical analysis to assess the condition of the soil. Accordingly, actions are taken such as proportionally adding more or less fertilizer in specific regions of the farmland. In Smart Farming, this goes a step further to add more precision to soil mapping (Eli-Chukwu 2019). For example, a camera on a flying drone captures the topography and color of the soil in a farm (Huuskonen and Oksanen 2018). This data is used to create a soil map (W. Dong *et al.* 2018). The map is then used to identify soil sample collection points in the field. Such stratified random soil sampling gives an accurate assessment of soil condition (Huuskonen and Oksanen 2018). Thus, it is possible to precisely control the amount of fertilizer that needs to be added to each segmented zone in the soil map. In this soil mapping step, soil samples could be analyzed for several other parameters such as moisture content, inorganic nutrients, pH, and ash content.

Another preparatory step in farming is plotting, where farmland is divided into several plots for sowing specific types of seeds. Here, each plot can then be demarcated into grids to sow seeds in a specific pattern and at a predetermined inter-plant distance. While these activities can be done manually on a small size farm using a measuring tape, it would be exceedingly difficult for farms with large areas. It is here that AI based applications could help in plotting. For example, data from flying drones equipped with GPS (global positioning satellite) sensors could be used to get an accurate dimension of the plots that could be designed on a computer (Andritoiu *et al.* 2018; Huuskonen and Oksanen 2018). These plot layouts can then be used as an input to GPS enabled unmanned ground vehicles that could traverse to the identified coordinates on the field to perform operations such as tillage of soil (Lima et al. 2021; Alagbo *et al.* 2022).

1.2 During farming activities

After the soil is pre-processed and ready, then sowing can start. Traditional sowing methods include either manual sowing using an animal driven vehicle or a motor powered vehicle driven by a human driver. In each of these cases, one of the limitations is downtime. While a motorized sowing may be faster and more accurate than manual sowing using an animal driven vehicle, there is still the need to take pause or break during the sowing operation for a human operator. However, in unmanned vehicles there is no need for a human to drive the vehicle (Vrochidou *et al.* 2022). An AI system can easily take the sowing path as an input and independently perform the sowing operation continuously during the day or night without the need to stop for a rest (Ha *et al.* 2018). Thus AI could help to drastically cut down on the time taken for such laborious activities (Ha *et al.* 2018).

Weed control is another challenging activity that is performed during farming (Aarhus University, Denmark *et al.* 2022). It is important to remove the weeds because they compete with the crop plants for food, water and sunlight to grow.

Several methods have been developed to remove weeds. One of the methods is to spray herbicides on the weed plants. The task of spraying is traditionally done by a human operator either by using a machine or a hand held sprayer. There are several limitations of this method such as safety of the operator, spraying efficiency, and lack of precision. AI can help in managing weeds (Terra *et al.* 2021). A drone equipped with a camera can take a video of the entire farm (Ukaegbu *et al.* 2021). Such a camera can take video with not only visible light but also in the near infra-red (NIR) spectrum of light (Costello et al. 2022; Liu *et al.* 2022). Such video footage can then be used to: (1) train an AI to identify weed plants among the crop plants, and (2) quantify the amount of weeds in the field (Costello *et al.* 2022; Liu *et al.* 2022). Thus, an UAV could then be used to spray weed removing chemicals selectively only on the weed plants (Imran Moazzam *et al.* 2022; U. Ukaegbu *et al.* 2022). Also, unmanned ground vehicles can traverse through the field to selectively uproot the weed plants (Machleb *et al.* 2021).

Monitoring plant health for early disease diagnosis is another important activity performed during farming (Borhani, Khoramdel and Najafi 2022). It is here that the plants are checked for any diseases or insects that may negatively affect their growth (Yun *et al.* 2022). While manual identification of a disease or insects is reliable, it does require that samples of plants be taken on the field and then sent out to a laboratory for analysis. Later, after looking at the laboratory test results, a farmer decides the next steps to manage the disease or insect population. Here, AI can not only help speed up identification of a disease or a type of insect but also in some cases substantially minimize the need for laboratory testing. For example, a farmer could take a picture of the affected plant and an AI powered App could identify the disease or pests from the picture (Selvaraj *et al.* 2019; Borhani *et al.* 2022; Haque *et al.* 2022; Siddiqua *et al.* 2022) and suggest corrective steps. This type of immediate feedback could help take immediate action and minimize delays in taking corrective action. Moreover, plant wearable sensors have been also proposed that can monitor plant health based on local environment conditions around the plant (Nassar *et al.* 2018).

AI could also help to identify nutrient deficiencies in plants (Aleksandrov 2022). Monitoring plant health can inform on the need for fertilizer and water in the farm (Swaminathan *et al.* 2022). A UAV could traverse over the plants and analyze the video camera feed in real-time to assess the health of the plants (Fahey, Gardiand Sabatini 2021). The AI could then inform which zones in the field need more water than others (Mwinuka *et al.* 2022). Thus, a farmer could prioritize irrigating regions of the farm that need more water (Ahansal *et al.* 2022). Additionally, water status in fruits, such as cherry, can be monitored to determine the stress level to plants by AI driven scheduled irrigation (Carrasco-Benavides *et al.* 2022).

An AI powered vehicle could also help to add fertilizer or other nutrients to the plants (Ji *et al.* 2021). Traditionally, the fertilizer is randomly sprinkled over a farm land that could result in wastage of fertilizer and most importantly this fertilizer could also fall within the reach of weeds (Ji *et al.* 2021). These limitations could be overcome by an AI that can selectively identify locations where the fertilizer needs to be added either to the soil or to be sprayed on a crop plant. Such targeted fertilizer delivery would not only minimize the quantity of fertilizer required to nourish the plants but also selectively promote the growth of crop plants and not the weeds. Over time, AI can not only monitor current growth but also predict future growth rate of plants (W. Liu *et al.* 2021).

Weather is another important parameter that needs to be monitored during farming (Faid, Sadikand Sabir 2021). For example, if a spraying activity needs to be conducted, then the information about wind speed would be vital. Thus, predictions of days with low wind speeds could be identified for optimal weather conditions for spraying. Likewise, other forecasts around rainy days could help as well. Thus, spraying activities could be halted until after the predicted rainy days to avoid washout of the sprayed solutions such as insecticides or pesticides.

Apart from monitoring the crop in one farm, an AI could also use the data from multiple neighboring farms to assess impact on the crops in the farm of interest. Collectively, if AI is implemented in neighboring farms then it could form an information network to help monitor farming activities and improve the effectiveness of any implementations. For example, if a crop in a particular area is infested by an insect, then spraying in one field alone may not eliminate the risk of re-infection. Because the insects from other fields could spread back into the farm after the effect of insecticide wears off. Here, an effective strategy would be to spray all the neighboring farms with the specific insecticide.

Pre-emptive measures could also be taken in farms well before a full blown problem appears. For example, if an AI identifies specific insects or diseases in scans of a farm on a few plants, then corrective measures could be taken immediately before the disease spreads through the entire farm affecting all the plants. Similarly, real-time data for water quality in irrigation such as mineral content, presence of bacteria, viruses may help take preventive measures to minimize onset of any negative impact of contaminated water on plant health (Tousi *et al.* 2021).

AI can also help predict the optimal time for harvest based on the data from the farm (Kim *et al.* 2019; Chang *et al.* 2021; Whitmire *et al.* 2021; Oikonomidis, Catal and Kassahun 2022). This data could be in the form of images of crops or could be accompanied with other laboratory data. A picture of a fruit could be analyzed by an AI to inform if it is near-ripe and ready for harvesting. Similarly, other crops such as cotton (Tedesco-Oliveira et al. 2020; Maja *et al.* 2021; Feng, Vongand Zhou 2022), rice (Son *et al.* 2020), corn, as well as vegetables such as tomatoes (De Alwis *et al.* 2019), apples (Boechel *et al.* 2022), chillies and grapes could be analyzed by an AI to inform about the optimal time for harvesting. Furthermore, AI trained on historical data could also help predict the crop yield per square units of farmland. This information may help a farmer to take necessary steps in advance to plan for harvesting machinery, labor, packaging, storage space and other needed resources (Ramirez-Asis *et al.* 2022).

1.3 Harvesting activities

Harvesting is another important step in farming when the produce is collected either manually or with the help of machines. Such harvested produce then serves as an input to other value added products or it is used by consumers as is. The harvesting can begin at an optimal predetermined time predicted by an AI. The methods for harvesting would vary substantially depending on the type of crop such as cotton, fruits, vegetables, or corn.

Harvesting fruits such as a kiwifruit (Williams *et al.* 2019) or an apple (Zhang *et al.* 2020) could be AI assisted. **Figure 2** shows an example of an AI that successfully identifies the fruit lemon. Similar capabilities of an AI powered robotic vehicle could scan a fruit tree to locate and count the number of fruits using a video camera and other on-board sensors (Fountas *et al.* 2022; Zhou *et al.* 2022). A robotic arm (Williams *et al.* 2019) could move-in to pick only those fruits that are classified as ready for harvest and leave out otherwise (N. P. T. Anh *et al.* 2020; Montoya-Cavero *et al.* 2022). This approach may increase production allowing the other fruits to be picked at a later point in time. Moreover, quality control and grading could be performed at this step using an AI. For example, the picture of a fruit could also be classified as healthy or diseased. If the fruit is classified as diseased, then it could be discarded. And if the fruit is classified as healthy, then it could be graded based on its shape, color, weight and other characteristics. These functionalities may drastically cut down on labor costs, processing time and also provide real-time data on the status of post harvesting activities.

Figure 2: AI trained on 160 images of lemons on a tree *(top two rows)*. The bottom three images show that after training, the AI was able to identify lemons in an image shown by square boxes. The AI identifies lemons amidst the leaves and branches of a lemon tree *(left)* and lemons among onions *(middle)* and lemons among mangoes *(right)*.

In case of other crops such as corn, an AI powered UAV could survey the crops in a farm in real-time by analyzing the pictures of plants and corn cobs to determine if they are ready for harvest or not yet ready. This scan data could then be automatically analyzed to inform the farmer with a statistic such as the percentage of mature cobs in the farm and recommend if the crop is ready for harvesting. Likewise, any standalone machinery that performs the tasks of quality control could be AI powered to automatically sort the produce coming down a conveyor belt via analysis of a real-time video scan.

1.4 Post harvesting activities

In post harvesting the produce is stored, packaged and transported to market (R. Concepcion *et al.* 2021). Here, based on the pricing data from the market, an AI could help predict the best time to sell to get maximum returns on the crops being sold (Guo, Woodruff and Yadav 2020; L. Nassar *et al.* 2020). After harvesting, UAV's could scan the farmland to assess the quantity of plants or vegetation that needs to be cleared for the next crop. Accordingly, unmanned ground vehicles equipped with tools to uproot stumps, chop plants and automatically package them into bales could be set to traverse along a pre-set path on the farmland. Here, without any humans operating such vehicles, the laborious work could be done by machines that can run day and night. Subsequent activities such as tillage could be then performed to aerate the soil for the next crop. Again pre-farming activities could begin as discussed earlier.

1.5 Technology transfer

e-Agriculture is an initiative by the Food and Agriculture Organization of the United Nations (FAO) to facilitate information exchange for sustainable agriculture (FAO 2022). Technology transfer from academia or industry to the farmers is important (Florand Cisneros 2015). Because, efficient transfer of new tools would allow farmers to use them in various farming activities (Raj 2013). For example, it took sixteen times less time and about three times less cost to transfer agriculture extension services using mobile devices to tribal farming communities in north-east India as compared to traditional methods (Raj 2013). AI powered apps developed for devices such as mobile phones are an easy way to transfer technology to farmers. For example, iSharkFin can identify shark species based on shark fin shapes (FAO 2021). Similarly, the FAMEWS mobile app helps in tracking the Fall Armyworm across sub-Saharan Africa (FAO 2022a). Here, farmers can install the app on their mobile phone and use it on the field. These days mobile phones are equipped with a camera and GPS that can capture input data for the onboard AI and thus allow geo-location tracking of pests (FAO 2022a) Moreover, AI powered apps such as Plantix can analyze pictures of a plant leaf taken by a mobile camera to inform a farmer if the leaf is healthy or diseased (Madslien 2017; FAO 2022b). And if diseased, inform on the type of disease and corrective measures that could be taken to eliminate the disease. Additionally, such Apps could be connected on a network of databases such as 25 million crop photos with Plantix (Madslien 2017; Conroy, Parletta and Woolston 2020) or more than 50,000 crop leave images with Plant Village (Borhani *et al.* 2022) that collect real-time information related to specific agriculture activities for example weather forecasts, available seed varieties, water shortages, and current disease surveillance in a geographical area. At the same time, the Apps could also collect information from the farms and relay it back to the academia or industry to help monitor performance of the newly developed technology after it is deployed in the farms. This could enable faster iterations of technological improvements in subsequent versions.

1.6 Agriculture in controlled environment in greenhouses

A greenhouse is a covered space that has a controlled environment such as humidity, temperature, water and light to grow plants (Hemming *et al.* 2020). The greenhouses make optimal use of vertical space and thus can have plants grown in stacked configuration of shelves (Barauskas *et al.* 2022). It is here that AI powered systems can monitor plant health by a real-time video input (D. Long *et al.* 2019; Baar *et al.* 2022). Additionally, the data from several sensors in the greenhouse that measure various parameters such as temperature, humidity, luminosity, soil moisture level could also be input to the AI (S. Fernando *et al.* 2020; Soheli *et al.* 2022). Moreover, data from scheduled laboratory test results, soil treatments, plant treatments could be input to the AI. Together the AI can not only help answer questions pertaining to real-time conditions but also help predict future parameters as well as make recommendations to improve yield in a greenhouse.

1.7 Value added activities

In the marketplace, businesses that sell produce sought from farms could use AI powered technologies to assist with tasks such as grading or quality control based on shape, size and color such as of apples, or potatoes (Ebrahimi, Mollazade and Arefi 2012; Papageorgiou *et al.* 2018; Ireri *et al.* 2019) or sweetness of oranges (Al-Sammarraieet al. 2022). A picture of grains of maize could also be classified by an AI into various grade levels (P. S. Nishant *et al.* 2022). The image data on the texture and color of the grains could also inform on parameters of grain quality such as its maturity or nutrient content.

1.8 Activities in animal farming

AI is also employed in other facets of agriculture such as poultry farming (Debauche *et al.* 2020; Ren *et al.* 2020), goat farming (Pu *et al.* 2022), pig farming (Arulmozhi *et al.* 2021), cattle farming '(O Mahony *et al.* 2019; Mahmud *et al.* 2021) or other livestock (Bao and Xie 2022) to monitor several aspects of daily activities. AI can help predict the future weight of an animal based on the quantity and quality of feed provided (Wang *et al.* 2021; Patel *et al.* 2022). This could help in planning the feed requirement for a given number of days in advance.

In the case of poultry farming, AI could be used to assess the quality of eggs (Mota-Grajales *et al.* 2019; C. -T. Chiang, Y. -H. Wu, and C. -H. Chao 2022). Disease outbreaks have a negative impact on the chicken population, thus early detection of diseases is important (Ahmed *et al.* 2021). Pathogenic avian influenza virus costs billions of dollars (Pillai, Ramkumar and Nanduri 2022). Viruses from diseased chickens from a farm could be unknowingly carried by workers to chickens in another farm (Subedi *et al.* 2022). Disease induced symptoms could be identified by an AI, thus preventing disease outbreaks. An AI powered system could also perform tasks such as automatic feeding cycles (Zhang *et al.* 2022), picking up eggs (Li *et al.* 2021), removing dead chicken (H.-W. Liu *et al.* 2021; Li *et al.* 2022), aerating bedding material (Park *et al.* 2022), vaccination and spraying disinfectants (Q. Feng *et al.* 2021; Park *et al.* 2022). Ground robots can navigate through a flock of chickens to perform similar tasks (Vroegindeweij *et al.* 2018; Park *et al.* 2022). Such a robot could have onboard sensors that measure temperature, relative humidity, ambient light levels, and several gas types (Park *et al.* 2022). The robot powered by an AI would be able to distinguish between a chicken, an egg and any other equipment (Park *et al.* 2022). Moreover, the audio signals from inside the poultry farm can also be classified by an Ai (Carroll 2018) to determine if a chicken has a disease such as laryngotracheitis, infectious bronchitis to take immediate action (Quach *et al.* 2020; Huang *et al.* 2021).

Precision animal farming may be divided into three main layers. In the first layer, various electromechanical sensors generate real-time data (Hajnal, KovácsandVakulya 2022). In the second layer, this data is collected and stored in databases (Mekonnen *et al.* 2019). In the third layer this data is analyzed by an AI to take an action or make recommendations (Mekonnen *et al.* 2019). The data from sensors in the first layer could be of various types such as (1) ambient temperature, (2) relative humidity, (3) IR thermometer to measure temperature of an animal, heart rate, respiration rate (Liu, Wei and Zhao 2019; Zhang, Zhang and Liu 2019), (4) track the RFID tag attached to each animal to know their movement (Yan and Li 2019; Li *et al.* 2020), (5) load cells to measure weight of an animal (Ichiura *et al.* 2019), (6) video feed of animals from various angles such as top view and side view to analyze postures, abnormal behavior of animals such as drinking, mounting, aggression and laying (Wang *et al.* 2022), (7) sound monitoring such as cough sound that informs on respiratory health of animals (Wang *et al.* 2022), and (8) 3D cameras to create a depth and point cloud map to estimate weight of an animal (Wang *et al.* 2022).

The AI can also help in automatic mixing of feeds and delivery monitoring of the feed to animals (Wang *et al.* 2022). Thus avoid uneven food distribution, injury, and wound infection to the animals and subsequently minimize economic losses. The AI can help monitor multiple aspects of an animal's life. Computer vision can help to study physiological changes in animals. Furthermore, animal identification has been traditionally done by a painful process such as punching the ear of the animal or pinning a tag to the animal's ear. Alternatively, AI can help to identify an animal based on picture of its face without the need to injure the animal (Marsot *et al.* 2020; Pu *et al.* 2022).

1.9 Socio-economic and political motivation

Some of the socio-economic challenges attached to the implementation of artificial intelligence in agriculture are: (1) ownership of data,

(2) cost of collecting the data, and (3) data security (Rotz *et al.* 2019). Briefly, a prerequisite for building an artificial intelligence powered tool to perform a particular task needs a large amount of data. For example, if AI needs to be built to detect a variety of leaves, then it would take up to 50000 or more leaf images (Mohanty, Hughes and Salathé 2016). Further, if an AI needs to be trained on other data from sensors, then several sensors would have to be installed. Thus there can be substantial cost associated with generation of data that could later be used to build an AI model to automate a task. This poses a question of data ownership i.e. who owns the data? Is it the farmer who installs all the hardware owns the data? or the company that manufactures the hardware? and so on. Furthermore, as AI begins to monitor critical processes in real time, data security becomes important. Because, tampering with the data or the AI could result in malfunction of the system that could lead to an economic loss. In the west, farming is also dominated by large scale industrial consumption requirements. Thus, most of the digital technologies that have been developed are targeted for large farms that cater to the industry rather than small to mid-sized farms. Furthermore, these digital technologies power vehicles and machinery that needs maintenance. However, there are right to repair legislations that allow only authorized dealers to repair farming vehicles and equipment such as a tractor. Although agriculture companies may claim that farmers own the data, this is still not clearly defined.

1.10 Agriculture research

AI can also help in agriculture research activities such as plant breeding to improve crop yield (Beans 2020). Traditionally, to develop a new variety, several combinations of varieties are crossed to come up with a new variety that is more resistant to diseases and has a better yield. The time required to develop such varieties could be in years. However, using an AI, it is now possible to do a genomic selection by narrowing down the combinations between varieties to identify the genes of interest. Thus, it expedites the process of developing improved varieties of crops. AI can also make use of historic data of plant studies that may be available with various research organizations across the world. The phenotypic data from measurements such as canopy coverage, canopy temperature, hyperspectral canopy reflectance, and chlorophyll content can be used as an input to train an AI for predicting yield (Parmley *et al.* 2019).

1.11 Cost of AI in agriculture

The cost can be divided into two parts i.e. cost of developing the AI and cost for the end user. The cost of developing an AI can vary substantially from near zero dollars to millions of dollars. A simple image classifier can be developed free of cost using an open source data set and open source programming software. Non-profit organizations seek funding of millions of dollars to develop such an AI to cover the cost of data collection, programming, high performance computer hardware and extension activities. Likewise, the cost may be substantial to build an unmanned poultry farm or other unmanned agricultural vehicles or robots. A study reports that a farm may require an investment of USD 500,000 in autonomous machinery to achieve breakeven and a 24 per cent increase in productivity over conventional machines. (Shockley, Dillon and Shearer 2019)

On the other hand, the cost for the user could be zero for free apps available for download on a mobile device or the app publisher may charge a monthly usage fee for the services. If the end user is a poultry farm owner, the running cost will likely be much higher. Full automation may be profitable for large poultry farms because it could reduce labor cost, improve working precision, reduce risk of exposure to pathogens, improve process efficiency, reduce waste and allow for better planning of resources. The future cost savings in either case could be enormous, if a disease is detected and treated early before a full blown epidemic occurs.

2. Limitations of AI in Agriculture

Despite the progress of AI applications in agriculture, there still remain several limitations. In image based AI the challenges are in image analysis related to changes in light intensity during the day, overlapping leaves or plants, same color of leaves and the fruit, varying shapes and sizes of leaves and fruits. In case of audio data, the mixing of machine noise with the actual signal noise lowers the recorded sound data quality. Furthermore, questions around the ownership of the data, data sharing and data security still remain unanswered. Additionally, while mobile based applications are within reach of small farmers, the expensive autonomous agriculture machines are still cost prohibitive and remain out of reach of small farmers.

CONCLUSION

AI offers endless possibilities to develop efficient and cost-effective ways to grow healthier plants to meet the ever increasing demand for food and other agricultural produce. Automating routine tasks in plant farming and animal husbandry may help to increase quality and production, create a safer working environment, reduce labor cost, enable early diagnosis of diseases and reduce agricultural waste.

Paper received on 05.11.2022
Accepted on 12.11.2022

REFERENCES

Aarhus University, Denmark, Melander, B., McCollough, M.R., and Aarhus University, Denmark, 2022, Advances in mechanical weed control technologies, in P. Kudsk (ed.), Burleigh Dodds Series in Agricultural Science–: 255282, Burleigh Dodds Science Publishing.

Ahansal, Y., Bouziani, M., Yaagoubi, R., Sebari, I., Sebari, K. and Kenny, L., 2022, Towards Smart Irrigation: A Literature Review on the Use of Geospatial Technologies and Machine Learning in the Management of Water Resources in Arboriculture, Agronomy, 12(2): 297.

Ahmed, G., Malick, R.A., Akhunzada, A., Zahid, S., Sagri, M.R. andGani, A., 2021, An Approach towards IoT-Based Predictive Service for Early Detection of Diseases in Poultry Chickens, Sustainability, 13(23).

Alagbo, O., Spaeth, M., Saile, M., Schumacher, M. and Gerhards, R., 2022, Weed Management in Ridge Tillage SystemsA Review, Agronomy, 12(4), 910.

Aleksandrov, V., 2022, Identification of nutrient deficiency in plants by artificial intelligence, Acta Physiologiae Plantarum, 44(3): 29.

Al-Sammarraie, M.A., Gierz, Ł., Przybył, K., Koszela, K., Szychta, M., Brzykcy, J. andBaranowska, H.M., 2022, Predicting Fruits Sweetness Using Artificial IntelligenceCase Study: Orange, Applied Sciences, 12(16).

Andritoiu, D., Bazavan, L.-C., Besnea, F.-L., Roibu, H. andBizdoaca, N.-G., 2018, Agriculture autonomous monitoring and decisional mechatronic system, 2018 19th International Carpathian Control Conference (ICCC)–, 241246, IEEE, Szilvasvarad.

Arulmozhi, E., Bhujel, A., Moon, B.-E. and Kim, H.-T., 2021, The Application of Cameras in Precision Pig Farming: An Overview for Swine-Keeping Professionals, Animals, 11(8).

Baar, S., Kobayashi, Y., Horie, T., Sato, K., Suto, H. and Watanabe, S., 2022, Non-destructive Leaf Area Index estimation via guided optical imaging for large scale greenhouse environments, Computers and Electronics in Agriculture, 197: 106911.

Bao, J. andXie, Q., 2022, Artificial intelligence in animal farming: A systematic literature review, Journal of Cleaner Production, 331: 129956.

Barauskas, R., Kriščiūnas, A., Čalnerytė, D., Pilipavičius, P., Fyleris, T., Daniulaitis, V. andMikalauskis, R., 2022, Approach of AI-Based Automatic Climate Control in White Button Mushroom Growing Hall, Agriculture, 12(11).

Beans, C., 2020, Crop researchers harness artificial intelligence to breed crops for the changing climate, Proceedings of the National Academy of Sciences–, 117(44): 2706627069.

Boechel, T., Policarpo, L.M., Ramos, G.D., Rosa Righi, R. da and Singh, D., 2022, Prediction of Harvest Time of Apple Trees: An RNN-Based Approach, Algorithms, 15(3).

Borhani, Y., Khoramdel, J. and Najafi, E., 2022, A deep learning based approach for automated plant disease classification using vision transformer, Scientific Reports, 12(1): 11554.

C. -T. Chiang, Y. -H. Wu, and C. -H. Chao, 2022, A Real-time Artificial Intelligence Recognition System on Contaminated Eggs for Egg Selection, 2022 IEEE International Conference on Mechatronics and Automation (ICMA)–: 10571061.

Carrasco-Benavides, M., Gonzalez Viejo, C., Tongson, E., Baffico-Hernández, A., Ávila-Sánchez, C., Mora, M. and Fuentes, S., 2022, Water status estimation of cherry trees using infrared thermal imagery coupled with supervised machine learning modeling, Computers and Electronics in Agriculture, 200, 107256.

Carroll, B., 2018, Characterizing acoustic environments with OLAF and ELSA– PhD thesis, Electrical and Computer Engineering, Georgia Tech.

Chang, C.-L., Chung, S.-C., Fu, W.-L. and Huang, C.-C., 2021, Artificial intelligence approaches to predict growth, harvest day, and quality of lettuce (Lactuca sativa L.) in a IoT-enabled greenhouse system, Biosystems Engineering–, 212: 77105.

Clercq, M.D., Vats, A. and Biel, A., 2018, AGRICULTURE 4.0: THE FUTURE OF FARMING TECHNOLOGY, 30.

Conroy, G., Parletta, N. and Woolston, C., 2020, 'Germanys start-up scene is booming, Nature.

Costello, B., Osunkoya, O.O., Sandino, J., Marinic, W., Trotter, P., Shi, B., Gonzalez, F. andDhileepan, K., 2022, Detection of Parthenium Weed (Parthenium hysterophorus L.) and Its Growth Stages Using Artificial Intelligence, Agriculture, 12(11): 1838.

D. Long, H. Yan, H. Hu, P. Yu, and D. Hei, 2019, Research on Image Location Technology of Crop Diseases and Pests Based on Haar-Adaboost, 2019 International Conference on Virtual Reality and Intelligent Systems (ICVRIS)–: 163165.

De Alwis, S., Zhang, Y., Na, M. and Li, G., 2019, Duo Attention with Deep Learning on Tomato Yield Prediction and Factor Interpretation, in A.C. Nayak and A. Sharma (eds.), PRICAI 2019: Trends in Artificial Intelligence–, 704715, Springer International Publishing, Cham.

Debauche, O., Mahmoudi, S., Mahmoudi, S.A., Manneback, P., Bindelle, J. andLebeau, F., 2020, Edge Computing and Artificial Intelligence for Real-time Poultry Monitoring, The 17th International Conference on Mobile Systems and Pervasive Computing (MobiSPC),The 15th International Conference on Future Networks and Communications (FNC),The 10th International Conference on Sustainable Energy Information Technology–, 175: 534541.

Dijk, M. van, Morley, T., Rau, M.L. andSaghai, Y., 2021, A meta-analysis of projected global food demand and population at risk of hunger for the period 20102050, Nature Food–, 2(7): 494501.

Ebrahimi, E., Mollazade, K. andArefi, A., 2012, An Expert System for Classification of Potato Tubers using Image Processing and Artificial Neural Networks, 8(4).

Eli-Chukwu, N.C., 2019, Applications of Artificial Intelligence in Agriculture: A Review, Engineering, Technology and Applied Science Research–, 9(4): 43774383.

Fahey, T., Gardi, A. and Sabatini, R., 2021, Integration of a UAV-LIDAR System for Remote Sensing of CO 2 concentrations in Smart Agriculture, 2021 IEEE/AIAA 40th Digital Avionics Systems Conference (DASC)–, 18, IEEE, San Antonio, TX, USA.

Faid, A., Sadik, M. and Sabir, E., 2021, An Agile AI and IoT-Augmented Smart Farming: A Cost-Effective Cognitive Weather Station, Agriculture, 12(1): 35.

FAO, 2009, Global agriculture towards 2050.

FAO, 2021, iSharkFin, International Plan of Action for Conservation and Management of Sharks.

FAO, 2022, e-Agriculture, FAO.

FAO, 2022a, FAMEWS, Global Action for Fall Armyworm Control.

FAO, 2022b, Plantix lets farmers recognize plant diseases, pests and nutrient diffidences just by sending a picture, e-Agriculture.

Feng, A., Vong, C.N. and Zhou, J., 2022, Unmanned Aerial Vehicle (UAV) Applications in Cotton Production, in Z. Zhang, H. Liu, C. Yang, Y. Ampatzidis, J. Zhou and Y. Jiang (eds.), Unmanned Aerial Systems in Precision Agriculture: Technological Progresses and Applications– : 3957, Springer Nature Singapore, Singapore.

Flor, A.G. and Cisneros, A.J., 2015, e-Agriculture, The International Encyclopedia of Digital Communication and Society–: 16.

Fountas, S., Malounas, I., Athanasakos, L., Avgoustakis, I. and Espejo-Garcia, B., 2022, AI-Assisted Vision for Agricultural Robots, AgriEngineering–, 4(3): 674694.

Guo, H., Woodruff, A. and Yadav, A., 2020, Improving Lives of Indebted Farmers Using Deep Learning: Predicting Agricultural Produce Prices Using Convolutional Neural Networks, Proceedings of the AAAI Conference on Artificial Intelligence–, 34(08): 1329413299.

Ha, J., Lee, C., Pal, A., Park, G. and Kim, H., 2018, Development of Optimized Headland Turning Mechanism on an Agricultural Robot for Korean Garlic Farms, Journal of Biosystems Engineering–, 43(4): 273284.

Hajnal, É., Kovács, L. andVakulya, G., 2022, Dairy Cattle Rumen Bolus Developments with Special Regard to the Applicable Artificial Intelligence (AI) Methods, Sensors, 22(18).

Haque, Md.A., Marwaha, S., Deb, C.K., Nigam, S., Arora, A., Hooda, K.S., Soujanya, P.L., Aggarwal, S.K., Lall, B., Kumar, M., Islam, S., Panwar, M., Kumar, P. and Agrawal, R.C., 2022, Deep learning-based approach for identification of diseases of maize crop, Scientific Reports, 12(1): 6334.

Hemming, S., Zwart, F.D., Elings, A., Petropoulou, A. andRighini, I., 2020, Cherry Tomato Production in Intelligent GreenhousesSensors and AI for Control of Climate, Irrigation, Crop Yield, and Quality, Sensors, 20(22).

Huang, J., Zhang, T., Cuan, K. and Fang, C., 2021, An intelligent method for detecting poultry eating behaviour based on vocalization signals, Computers and Electronics in Agriculture, 180, 105884.

Huuskonen, J. and Oksanen, T., 2018, Soil sampling with drones and augmented reality in precision agriculture, Computers and Electronics in Agriculture–, 154: 2535.

Ichiura, S., Mori, T., Horiguchi, K.I. andKatahira, M., 2019, Exploring IoT based broiler chicken management technology, Proceedings of the 7th TAE–: 205211.

Imran Moazzam, S., Khan, U.S., Qureshi, W.S., Tiwana, M.I., Rashid, N., Hamza, A., Kunwar, F. and Nawaz, T., 2022, Patch-wise weed coarse segmentation mask from aerial imagery of sesame crop, Computers and Electronics in Agriculture, 203, 107458.

Ireri, D., Belal, E., Okinda, C., Makange, N. and Ji, C., 2019, A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing, Artificial Intelligence in Agriculture–, 2: 2837.

Ji, Y., Ma, S., Lv, S., Wang, Y., Lü, S. and Liu, M., 2021, Nanomaterials for Targeted Delivery of Agrochemicals by an All-in-One Combination Strategy and Deep Learning, ACS Applied Materials and Interfaces–, 13(36): 4337443386.

Kim, N., Ha, K.-J., Park, N.-W., Cho, J., Hong, S. and Lee, Y.-W., 2019, A Comparison Between Major Artificial Intelligence Models for Crop Yield Prediction: Case Study of the Midwestern United States, 20062015, ISPRS International Journal of Geo-Information, 8(5): 240.

L. Nassar, M. Saad, I. E. Okwuchi, M. Chaudhary, F. Karray, and K. Ponnambalam, 2020, Imputation Impact on Strawberry Yield and Farm Price Prediction Using Deep Learning, 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)–: 35993605.

Li, G., Chesser, G.D., Huang, Y., Zhao, Y. andPurswell, J.L., 2021, Development and Optimization of a Deep-Learning-Based Egg-Collecting Robot, Transactions of the ASABE–, 64(5): 16591669.

Li, G., Chesser, G.D., Purswell, J.L., Magee, C., Gates, R.S. andXiong, Y., 2022, Design and Development of a Broiler Mortality Removal Robot, Applied Engineering in Agriculture, 0(0), 0.

Li, N., Ren, Z., Li, D. and Zeng, L., 2020, Review: Automated techniques for monitoring the behaviour and welfare of broilers and laying hens: towards the goal of precision livestock farming, animal–, 14(3): 617625.

Lima, F., Blanco-Sepúlveda, R., Gómez-Moreno, M.L., Dorado, J. and Peña, J.M., 2021, Mapping tillage direction and contour farming by object-based analysis of UAV images, Computers and Electronics in Agriculture, 187, 106281.

Linaza, M.T., Posada, J., Bund, J., Eisert, P., Quartulli, M., Döllner, J., Pagani, A., G. Olaizola, I., Barriguinha, A., Moysiadis, T. andLucat, L., 2021, Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture, Agronomy, 11(6).

Liu, B., Wei, J. and Zhao, S., 2019, Research and application of early warning system for abnormal temperature of breeding pigs based on deep learning, Journal of Physics: Conference Series, 1345(3), 032030.

Liu, H.-W., Chen, C.-H., Tsai, Y.-C., Hsieh, K.-W. and Lin, H.-T., 2021, Identifying Images of Dead Chickens with a Chicken Removal System Integrated with a Deep Learning Algorithm, Sensors, 21(11).

Liu, S., Jin, Y., Ruan, Z., Ma, Z., Gao, R. andSu, Z., 2022, Real-Time Detection of Seedling Maize Weeds in Sustainable Agriculture, Sustainability, 14(22): 15088.

Liu, W., Ma, X., Wang, Y.-M., Lu, C.-T. and Lin, W.-S., 2021, Using artificial intelligence algorithms to predict rice (Oryza sativa L.) growth rate for precision agriculture, Computers and Electronics in Agriculture, 187, 106286.

Machleb, J., Peteinatos, G.G., Sökefeld, M. and Gerhards, R., 2021, Sensor-Based Intrarow Mechanical Weed Control in Sugar Beets with Motorized Finger Weeders, Agronomy, 11(8): 1517.

Madslien, J., 2017, '''Tell me phone, whats destroying my crops?, BBC.

Mahmud, M.S., Zahid, A., Das, A.K., Muzammil, M. and Khan, M.U., 2021, A systematic literature review on deep learning applications for precision cattle farming, Computers and Electronics in Agriculture, 187, 106313.

Maja, J.M., Polak, M., Burce, M.E. and Barnes, E., 2021, CHAP: Cotton-Harvesting Autonomous Platform, AgriEngineering–, 3(2): 199217.

Marsot, M., Mei, J., Shan, X., Ye, L., Feng, P., Yan, X., Li, C. and Zhao, Y., 2020, An adaptive pig face recognition approach using Convolutional Neural Networks, Computers and Electronics in Agriculture, 173, 105386.

Mekonnen, Y., Namuduri, S., Burton, L., Sarwat, A. and Bhansali, S., 2019, ReviewMachine Learning Techniques in Wireless Sensor Network Based Precision Agriculture, Journal of The Electrochemical Society, 167(3): 037522.

Mohanty, S.P., Hughes, D.P. andSalathé, M., 2016, Using Deep Learning for Image-Based Plant Disease Detection, Frontiers in Plant Science, 7, 1419.

Montoya-Cavero, L.-E., Díaz de León Torres, R., Gómez-Espinosa, A. and Escobedo Cabello, J.A., 2022, Vision systems for harvesting robots: Produce detection and localization, Computers and Electronics in Agriculture, 192, 106562.

Mota-Grajales, R., Torres-Peña, J.C., Camas-Anzueto, J.L., Pérez-Patricio, M., GrajalesCoutiño, R., López-Estrada, F.R., Escobar-Gómez, E.N. and Guerra-Crespo, H., 2019, Defect detection in eggshell using a vision system to ensure the incubation in poultry production, Measurement–, 135, 3946.

Mushi, G.E., Di MarzoSerugendo, G. andBurgi, P.-Y., 2022, Digital Technology and Services for Sustainable Agriculture in Tanzania: A Literature Review, Sustainability, 14(4): 2415.

Mwinuka, P.R., Mourice, S.K., Mbungu, W.B., Mbilinyi, B.P., Tumbo, S.D. andSchmitter, P., 2022, UAV-based multispectral vegetation indices for assessing the interactive effects of water and nitrogen in irrigated horticultural crops production under tropical sub-humid conditions: A case of African eggplant, Agricultural Water Management, 266, 107516.

N. P. T. Anh, S. Hoang, D. Van Tai, and B. L. C. Quoc, 2020, Developing Robotic System for Harvesting Pineapples, 2020 International Conference on Advanced Mechatronic Systems (ICAMechS)–: 3944.

Nassar, J.M., Khan, S.M., Villalva, D.R., Nour, M.M., Almuslem, A.S. and Hussain, M.M., 2018, Compliant plant wearables for localized microclimate and plant growth monitoring, npj Flexible Electronics, 2(1): 24.

O Mahony, N., Campbell, S., Carvalho, A., Krpalkova, L., Riordan, D. and Walsh, J., 2019, 3D Vision for Precision Dairy Farming, 6th IFAC Conference on Sensing, Control and Automation Technologies for Agriculture AGRICONTROL 2019–, 52(30), 312317.

Oikonomidis, A., Catal, C. and Kassahun, A., 2022, Hybrid Deep Learning-based Models for Crop Yield Prediction, Applied Artificial Intelligence, 36(1): 2031822.

P. S. Nishant, B. G. K. Mohan, S. Mehrotra, R. Devathi, P. Sowmya, and P. Srikanth, 2022, Maize grading system using Deep learning and flask application, 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS):

Papageorgiou, E.I., Aggelopoulou, K., Gemtos, T.A. and Nanos, G.D., 2018, Development and Evaluation of a Fuzzy Inference System and a Neuro-Fuzzy Inference System for Grading Apple Quality, Applied Artificial Intelligence–, 32(3): 253280.

Park, M., Britton, D., Daley, W., McMurray, G., Navaei, M., Samoylov, A., Usher, C. and Xu, J., 2022, Artificial intelligence, sensors, robots, and transportation systems drive an innovative future for poultry broiler and breeder management, Animal Frontiers–, 12(2): 4048.

Parmley, K.A., Higgins, R.H., Ganapathysubramanian, B., Sarkar, S. and Singh, A.K., 2019, Machine Learning Approach for Prescriptive Plant Breeding, Scientific Reports, 9(1): 17132.

Patel, H., Samad, A., Muhammad Hamza, Ayesha MuazzamandHarahap, M.K., 2022, Role of Artificial Intelligence in Livestock and Poultry Farming, Sinkron□: jurnal dan penelitianteknikinformatika–, 7(4): 24252429.

Pillai, N., Ramkumar, M. andNanduri, B., 2022, Artificial Intelligence Models for Zoonotic Pathogens: A Survey, Microorganisms, 10(10).

Polyakov, V., 2021, Agriculture 4.0: the theoretical concept and its practical implementation, D. Rudoy, A. Olshevskayaand N. Ugrekhelidze (eds.), E3S Web of Conferences, 273, 08073.

Prudhomme, M. andMatsueda, K., 2022, –World population projected to reach 9.8 billion in 2050 and 11.2 billion in 2100 says UN, United Nations Department of Public Information.

Pu, J., Yu, C., Chen, X., Zhang, Y., Yang, X. and Li, J., 2022, Research on Chengdu Ma Goat Recognition Based on Computer Vison, Animals, 12(14).

Q. Feng, B. Wang, W. Zhang, and X. Li, 2021, Development and Test of Spraying Robot for Anti-epidemic and Disinfection in Animal Housing, 2021 WRC Symposium on Advanced Robotics and Automation (WRC SARA)–: 2429.

Quach, L.-D., Pham-Quoc, N., Tran, D.C. andFadzil Hassan, Mohd., 2020, Identification of Chicken Diseases Using VGGNet and ResNet Models, in N.-S. Vo and V.-P. Hoang (eds.), Industrial Networks and Intelligent Systems–, 259269, Springer International Publishing, Cham.

R. Concepcion, L. Moron, I. Valenzuela, J. Alejandrino, R. R. Vicerra, A. Bandala, and E. Dadios, 2021, Towards the Integration of Computer Vision and Applied Artificial Intelligence in Postharvest Storage Systems: Non-invasive Harvested Crop Monitoring, 2021 IEEE 13th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)–:16.

Raj, S., 2013, e-Agriculture Prototype for Knowledge Facilitation among Tribal Farmers of North-East India: Innovations, Impact and Lessons, The Journal of Agricultural Education and Extension–, 19(2): 113131.

Ramirez-Asis, E., Bhanot, A., Jagota, V., Chandra, B., Hossain, M.S., Pant, K. andAlmashaqbeh, H.A., 2022, Smart Logistic System for Enhancing the Farmer-Customer Corridor in Smart Agriculture Sector Using Artificial Intelligence, R. Khan (ed.), Journal of Food Quality, 2022, 7486974.

Ren, G., Lin, T., Ying, Y., Chowdhary, G. and Ting, K.C., 2020, Agricultural robotics research applicable to poultry production: A review, Computers and Electronics in Agriculture, 169, 105216.

Rotz, S., Duncan, E., Small, M., Botschner, J., Dara, R., Mosby, I., Reed, M. and Fraser, E.D.G., 2019, The Politics of Digital Agricultural Technologies: A Preliminary Review, SociologiaRuralis–, 59(2): 203229.

S. Fernando, R. Nethmi, A. Silva, A. Perera, R. D. Silva, and P. W. K. Abeygunawardhana, 2020, AI Based Greenhouse Farming Support System with Robotic Monitoring, 2020 IEEE REGION 10 CONFERENCE (TENCON):– 13681373.

Selvaraj, M.G., Vergara, A., Ruiz, H., Safari, N., Elayabalan, S., Ocimati, W. andBlomme, G., 2019, AI-powered banana diseases and pest detection, Plant Methods, 15(1): 92.

Shockley, J.M., Dillon, C.R. and Shearer, S.A., 2019, An economic feasibility assessment of autonomous field machinery in grain crop production, Precision Agriculture–, 20(5): 10681085.

Sibanda, B.K., Iyawa, G.E. andGamundani, A.M., 2021, Systematic Review of Plant Pest and Disease Identification Strategies and Techniques in Mobile Apps, in Á. Rocha, H. Adeli, G. Dzemyda, F. Moreira and A.M. Ramalho Correia (eds.), Trends and Applications in Information Systems and Technologies–, 491502, Springer International Publishing, Cham.

Siddiqua, A., Kabir, M.A., Ferdous, T., Ali, I.B. and Weston, L.A., 2022, Evaluating Plant Disease Detection Mobile Applications: Quality and Limitations, Agronomy, 12(8): 1869.

Soheli, S.J., Jahan, N., Hossain, Md.B., Adhikary, A., Khan, A.R. andWahiduzzaman, M., 2022, Smart Greenhouse Monitoring System Using Internet of Things and Artificial Intelligence, Wireless Personal Communications–, 124(4) 36033634.

Son, N.-T., Chen, C.-F., Chen, C.-R., Guo, H.-Y., Cheng, Y.-S., Chen, S.-L., Lin, H.-S. and Chen, S.-H., 2020, Machine learning approaches for rice crop yield predictions using time-series satellite data in Taiwan, International Journal of Remote Sensing–, 41(20): 78687888.

Statista, 2022a, Number of smartphone subscriptions worldwide from 2016 to 2021, with forecasts from 2022 to 2027.

Statista, 2022b, Global market volume of agricultural robots from 2020 to 2030.

Subedi, D., Phuyal, P., Bhandari, S., Kandel, M., Shah, S., Rawal, G., Karki, S. andDhakal, S., 2022, Risk Factors Associated with Avian Influenza Subtype H9 Outbreaks in Poultry Farms of Central Lowland Nepal, Infectious Disease Reports–, 14(4): 525536.

Swaminathan, B., Palani, S., Kotecha, K., Kumar, V. and V, S., 2022, IoT Driven Artificial Intelligence Technique for Fertilizer Recommendation Model, IEEE Consumer Electronics Magazine–, 11.

Tedesco-Oliveira, D., Pereira da Silva, R., Maldonado, W. andZerbato, C., 2020, Convolutional neural networks in predicting cotton yield from images of commercial fields, Computers and Electronics in Agriculture, 171: 105307.

Terra, F.P., Nascimento, G.H. do, Duarte, G.A. and Drews-Jr, P.L.J., 2021, Autonomous Agricultural Sprayer using Machine Vision and Nozzle Control, Journal of Intelligent and Robotic Systems, 102(2): 38.

The World Bank, 2022, Arable land (hectares per person), Food and Agriculture Organization, electronic files and web site.

Tousi, E.G., Duan, J.G., Gundy, P.M., Bright, K.R. and Gerba, C.P., 2021, Evaluation of E. coli in sediment for assessing irrigation water quality using machine learning, Science of The Total Environment, 799, 149286.

U. Ukaegbu, L. Mathipa, M. Malapane, L. K. Tartibu, and I. O. Olayode, 2022, Deep Learning for Smart Plant Weed Applications Employing an Unmanned Aerial Vehicle, 2022 IEEE 13th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT)–: 321325.

Ukaegbu, U.F., Tartibu, L.K., Okwu, M.O. andOlayode, I.O., 2021, Development of a Light-Weight Unmanned Aerial Vehicle for Precision Agriculture, Sensors, 21(13): 4417.

Vrochidou, E., Oustadakis, D., Kefalas, A. andPapakostas, G.A., 2022, Computer Vision in Self-Steering Tractors, Machines, 10(2): 129.

Vroegindeweij, B.A., Blaauw, S.K., IJsselmuiden, J.M.M. andHenten, E.J. van, 2018, Evaluation of the performance of PoultryBot, an autonomous mobile robotic platform for poultry houses, Biosystems Engineering–, 174: 295315.

W. Dong, T. Wu, Y. Sun, and J. Luo, 2018, Digital Mapping of Soil Available Phosphorus Supported by AI Technology for Precision Agriculture, 2018 7th International Conference on Agro-geoinformatics (Agro-geoinformatics)–, 15.

Walter, A., Finger, R., Huber, R. and Buchmann, N., 2017, Smart farming is key to developing sustainable agriculture, Proceedings of the National Academy of Sciences–, 114(24): 61486150.

Wang, S., Jiang, H., Qiao, Y., Jiang, S., Lin, H. and Sun, Q., 2022, The Research Progress of Vision-Based Artificial Intelligence in Smart Pig Farming, Sensors, 22(17): 6541.

Wang, Z., Shadpour, S., Chan, E., Rotondo, V., Wood, K.M. andTulpan, D., 2021, ASAS-NANP SYMPOSIUM: Applications of machine learning for livestock body weight prediction from digital images, Journal of Animal Science, 99(2): skab022.

Whitmire, C.D., Vance, J.M., Rasheed, H.K., Missaoui, A., Rasheed, K.M. and Maier, F.W., 2021, Using Machine Learning and Feature Selection for Alfalfa Yield Prediction, AI–, 2(1): 7188.

Williams, H.A.M., Jones, M.H., Nejati, M., Seabright, M.J., Bell, J., Penhall, N.D., Barnett, J.J., Duke, M.D., Scarfe, A.J., Ahn, H.S., Lim, J. and MacDonald, B.A., 2019, Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms, Biosystems Engineering–, 181: 140156.

Yan, X. and Li, J., 2019, Animal Intelligent Logistics Management Based on RFID Technology, RevistaCientífica de la Facultad de CienciasVeterinarias, 29(6): 1772.

Yun, W., Kumar, J.P., Lee, S., Kim, D.-S. and Cho, B.-K., 2022, Deep learning-based system development for black pine bast scale detection, Scientific Reports, 12(1): 606.

Zhang, J., Karkee, M., Zhang, Q., Zhang, X., Yaqoob, M., Fu, L. and Wang, S., 2020, Multi-class object detection using faster R-CNN and estimation of shaking locations for automated shake-and-catch apple harvesting, Computers and Electronics in Agriculture, 173, 105384.

Zhang, Y., Sun, W., Yang, J., Wu, W., Miao, H. and Zhang, S., 2022, An Approach for Autonomous Feeding Robot Path Planning in Poultry Smart Farm, Animals, 12(22).

Zhang, Z., Zhang, H. and Liu, T., 2019, Study on body temperature detection of pig based on infrared technology: A review, Artificial Intelligence in Agriculture–, 1: 1426.

Zhou, H., Wang, X., Au, W., Kang, H. and Chen, C., 2022, Intelligent robots for fruit harvesting: recent developments and future challenges, Precision Agriculture–, 23(5): 18561907.

....