International Journal of Biosciences | IJB |
ISSN: 2220-6655 (Print) 2222-5234 (Online)
http://www.innspub.net
Vol. 23, No. 5, p. 142-151, 2023

RESEARCH PAPER OPEN ACCESS

Artificial intelligence driven smart agricultural applications

Rubul Kumar Bania[*1], **Satyajit Sarmah**[2]

[1]*Department of Computer Science, Birangana Sati Sadhani Rajyik Vishwavidyalaya, Golaghat, Assam, India*

[2]*Department of Information Technology, Gauhati University, Assam, India*

Key words: Artificial intelligence, Machine learning, Smart agriculture, Agrotechnology

http://dx.doi.org/10.12692/ijb/23.5.142-151 Article published on November 10, 2023

Abstract

Agriculture serves as a cornerstone of the economy and a significant source of employment, particularly in developing countries like India. Within the realm of agriculture, there are three pivotal stages: pre-harvesting, harvesting, and post-harvesting. The emerging field of agrotechnology, often referred to as smart or digital agriculture, leverages data-intensive approaches to enhance agricultural productivity while minimizing its ecological footprint. Notably, the demand for artificial intelligence (AI) which includes machine learning (ML) and deep learning (DL) technologies has surged within the agrotechnology sector. This paper offers a comprehensive review of the latest applications of AI in agriculture, aiming to address challenges in the pre-harvesting, harvesting, and post-harvesting phases. It explores how AI and ML models can significantly assist farmers in decision-making processes across various domains and applications such as soil management, weed management, crop management, livestock management, water management etc. The findings of this study underscore the remarkable outcomes achieved by ML algorithms and models in resolving agricultural issues. In light of these findings, it is recommended that ML models be deployed in various real-time applications to provide valuable support to intended users, particularly farmers, in their day-to-day agricultural endeavours.

* **Corresponding Author:** Rubul Kumar Bania ✉ rubul.bania@gmail.com

Introduction

Agriculture stands as a cornerstone of the global economy, fulfilling a fundamental human necessity: nourishment. Across numerous nations, it serves as the primary source of employment. Even in countries like India, where traditional farming methods persist, many farmers hesitate to embrace advanced technologies due to factors like limited knowledge, high costs, or simply unawareness of the benefits that these innovations can bring. Insufficient understanding of soil types, crop yields, weather patterns, improper pesticide use, irrigation challenges, faulty harvesting practices, and a lack of market trend information contribute to financial losses for farmers and amplify operational costs (Khanna *et al*, 2019; Durra *et al.,* 2021). Each stage of agriculture, if not well-informed, generates new problems or exacerbates existing ones, adding to the overall expense of farming. Furthermore, the burgeoning global population places increasing demands on the agriculture sector.

The United Nations Development Programme's 2021 report on "Leveraging Digital Technology for Sustainable Agriculture" underscores the necessity of boosting global food production by a staggering 98 percent to adequately feed a projected population of 9.9 billion by 2050 (Durra *et al.,* 2021). This imperative goal can only be realized through the efficient utilization of available resources, encompassing land, labour, capital, and technology. Presently, precision agriculture strives to establish a decision support system for farm management, optimizing output while conserving essential resources. In this context, the emerging trend of food security must be met with data-driven farming practices to enhance productivity, efficiency, and profitability. Pervasive challenges such as rising food demand, labour shortages, water scarcity, climate fluctuations, and escalating energy requirements underscore the pressing need for technological intervention. Smart agriculture, which encompasses precision farming, digital agricultural techniques, and modern practices, holds tremendous promise and warrants substantial validation.

Smart agriculture predominantly relies on three fundamental pillars: science, innovation, and ICT- Information and Communication Technology (Simonyan *et al.,* 2014; Khanna *et al.*, 2019; Dhanya *et al.,* 2022). The conventional methods of information and knowledge management employed in gathering and overseeing agricultural data are arduous, time-intensive, and susceptible to errors. Consequently, it is imperative to harness technological advancements in remote sensing, digital applications, sensor technologies, advanced imaging systems, cloud-based data storage, and intelligent data analysis through decision support systems to usher in a more promising era for the farming sector (Islam *et al.*, 2017; Khamparia *et al.*, 2019; Bania, 2023). In Fig. 1, components of intelligent agricultural solutions are shown.

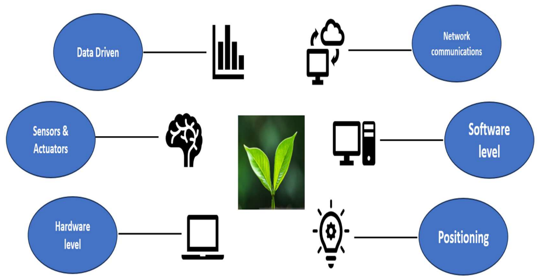

Fig. 1. Different components of smart agricultural solutions.

Smart agriculture has the potential to harness cutting-edge technologies such as the Internet of Things (IoT), ML, Cloud Computing, Blockchain, and more, reaping substantial benefits for enhancing food production and tackling the emerging challenges within the agricultural sector (Simonyan *et al.,* 2014; Zhao *et al.*, 2021; Dhanya *et al.,* 2022). Notably, the widespread adoption of computer and mobile technology, even in the remotest rural areas, has created an unparalleled opportunity for connecting rural producers with urban consumers and international investors. This connectivity, in turn, facilitates more robust investments and knowledge transfer in agriculture. AI emerges as a transformative technology, boasting a track record of success across various industries, agriculture included. Machine learning and deep learning, two subsets of AI, have garnered extensive attention from researchers due to their capacity to deliver innovative solutions for modelling intricate relationships and making accurate predictions based on agricultural data.

Computer vision, a subfield of artificial intelligence, equips machines with the ability to "see" by harnessing contemporary technologies that incorporate cameras and computers, thus negating the need for human imagination (Dhanya *et al.*, 2022; Bania, 2023). This capability empowers artificial intelligence systems with extensive automation capabilities. Computer vision collects essential visual data pertinent to crops, livestock, farms, or gardens, facilitating the identification, detection, and tracking of specific objects through visual elements. Moreover, it enables the comprehension of complex visual data to execute various automated tasks. The realm of computer vision technology encompasses a broad spectrum of solutions for farmers, including small AI-powered mobile applications for decision support, in-field imaging sensors, remote sensing technologies for data acquisition, and the deployment of drones and robots to automate a variety of agricultural processes.

The motivation and goals of this research cantered on investigating the substantial contributions that AI and ML models can make in empowering farmers to enhance their decision-making processes in diverse agricultural domains and applications, including soil management, weed control, crop management, livestock husbandry, water resource management, and more. The results of this study highlight the impressive outcomes attained through the application of ML algorithms and models to address agricultural challenges.

Background study

As per the renowned adage, "Information is Power", maintaining a comprehensive record of data concerning crops, environmental conditions, and market trends can empower farmers to make informed decisions and mitigate agricultural challenges. Utilizing technologies such as blockchain, IoT, ML, DL, cloud computing, and edge computing allows for the acquisition and processing of vital information (Samajpati *et al.*, 2016; Zho *et al.*, 2019). The applications of computer vision, machine learning, and IoT hold the potential to boost crop production, enhance quality, and ultimately elevate the profitability of farmers and related sectors. Precision learning in the realm of agriculture assumes paramount importance in the quest to optimize overall harvest yields. While performing agriculture tasks the steps as shown below in Fig. 2 is generally followed by farmers.

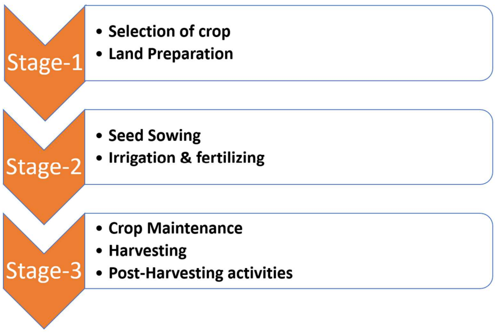

Fig. 2. Different stages in agricultural tasks.

In the pre-harvesting phase, farmers concentrate on a range of tasks, including crop selection, land preparation, seed sowing, irrigation, and crop maintenance, which encompasses activities like pesticide application and pruning (Taheri-Garavand, 2021). In the context of yield estimation, farmers engage in activities such as yield mapping and counting the number of fruits. These efforts enable them to predict production levels and prepare for the necessary steps required during harvesting or post-harvesting activities. In the pre-harvest phase, machine learning is employed to capture and analyse a multitude of parameters encompassing soil quality, seed quality, fertilizer application, pruning practices, genetic traits, environmental conditions, and irrigation management. The objective is to meticulously address each of these components to minimize overall production losses and optimize agricultural output.

During the harvesting stage, farmers place a premium on factors such as the maturity of crops or fruits and align their efforts to meet market demands for high-quality produce (Dhanya *et al.,* 2022,). Following the comprehensive attention given to parameters in the pre-harvesting phase, encompassing aspects like soil quality, seed quality, and weed management, the harvesting phase assumes paramount importance within the spectrum of agricultural operations. Throughout this critical stage, it becomes imperative to give special focus to key parameters, including fruit or crop size, skin colour, firmness, taste, quality, maturity stage, market timing, as well as fruit detection and classification for precise harvesting purposes. The accuracy and effectiveness of the harvesting process bear a direct correlation to the overall profitability of the endeavour.

In the post-harvest phase, farmers redirect their attention towards the vital aspects of post-harvest storage and processing systems (Dhanya *et al.,* 2022). This phase stands as the final and most pivotal stage in agriculture, demanding heightened scrutiny. After successfully navigating through all the stages, ranging from yield estimation to harvesting, any lapse in the post-harvest phase can jeopardize the entire effort, leading to substantial losses for farmers. Key subtasks that warrant consideration during this phase include evaluating the shelf-life of fruits and vegetables, conducting postharvest grading, and preparing for export. It's worth noting that every country has its own set of standard rules and regulations governing the grading of fruits, ensuring quality and consistency in the agricultural produce.

Some of the promising application domains and areas

Machine learning makes agricultural applications incredibly efficient and simple. Data acquisition, model building, and generalization are the three stages of the machine learning process. In agriculture where AI including computer vision are in use as follows:

Seed quality analysis

The commercial seed industry is primarily focused on delivering high-quality seeds to farmers promptly and in the correct quantities. The process of distinguishing between low-quality and high-quality sources is not only labour-intensive but also demands advanced equipment, infrastructure, and time. Enhancing seed quality testing can be achieved through the integration of computer vision technology, which can extract morphological information from various seed lots and grade them in accordance with internationally recognized quality standards. Additionally, other seed testing modules can address factors such as physical purity, genetic purity, seed health, Vigor, and patterns of deterioration. These modules typically encompass characteristics that are visually discernible, such as seed length, shape, size, visual anomalies, and the presence of foreign matter, all of which advanced computer vision technology is adept at capturing. A study conducted by (Zhu *et al.*, 2019) highlighted the impressive effectiveness of combining spectroscopy and machine learning, particularly CNN models, in the realm of seed variety identification. The machine learning models showcased remarkable accuracy, surpassing the 80% mark when tasked with classifying cotton seeds based on features extracted using CNN and ResNet models. In another investigation conducted by (Li *et al.*, 2021) the SeedSortNet system, built upon computer vision CNN models, exhibited significant promise by achieving exceptional accuracy rates of 97.33% and 99.56% when sorting maize and sunflower seeds, respectively. (Garavand *et al.*, 2022) pioneered the development of models for the automated identification of chickpea varieties through the analysis of seed images captured within the visible spectrum. Furthermore, (Zhao *et al.*, 2021) employed seven distinct computer vision models to detect and identify surface defects with a high degree of precision, with the MobileNet-V2 model standing out for its exceptional accuracy when applied to the soybean dataset.

Pesticides and disease detection

In-time disease detection is the most important task to save crops from major loss. Some farmers regularly analyse leaf or branches of tree while growing and identify the diseases or many times to avoid the diseases, they apply the pesticides on all the crops equally. Both the activities are based on human experience which is prone to errors and risky. Decision of which pesticide, when to apply and where to apply is totally dependent on type of disease, its stage and affected area. Application of unnecessary pesticide on all the crops may harm crops as well as farmer's health. Precision agriculture helps farmers for application of the right pesticide at right time at right place. Many works combined pesticides prediction with the detection of disease on plants.

The PlantVillage dataset has been extensively employed by various researchers to address disease identification challenges through the application of deep learning techniques. In their study, (Islam *et al.*, 2017) developed an image segmentation-based model for detecting potato leaf diseases, making use of the PlantVillage dataset. They subsequently employed a multiclass Support Vector Machine on the segmented images to classify the diseases, ultimately achieving an impressive accuracy rate of 95%. In a different approach, (Samajpati *et al.*, 2016) introduced a hybrid model for disease recognition in apples. The authors initiated the process by segmenting the images through k-means clustering and subsequently utilized the random forest algorithm for image classification. Furthermore, introduced a deep learning methodology aimed at classifying tomato leaf diseases and an additional 8 types of leaf diseases.

Soil analysis

The primary focus of agricultural soil management is to preserve and enhance the dynamic characteristics of soil, with the goal of increasing crop productivity. To achieve this, soil test reports serve as the cornerstone for assessing various crucial soil attributes, including village-specific indicators such as Available Phosphorus (P), Available Potassium (K), Organic Carbon (OC), Boron (B), and Soil pH levels. The classification and prediction of these soil parameters at the village level play a pivotal role in minimizing unnecessary expenditure on fertilizer inputs, boosting profitability, saving the valuable time of chemical soil analysis experts, promoting soil health, and improving environmental quality. In traditional soil texture analysis, soil samples are collected and transported to a laboratory, where they undergo a series of processes, including drying, crushing, and sieving, before analysis. However, computer vision-based methods revolutionize this approach by capturing soil images, whether they are dynamic or static, using cameras. Subsequently, computational models and programs are employed to classify and categorize these images, offering a more efficient and modern alternative to traditional soil analysis techniques.

Various machine learning techniques were employed for the prediction of soil nutrient content, soil type, and soil moisture (Reashma, 2017). In order to classify soil fertility indices and soil nutrient levels on a village-by-village basis, a comprehensive set of twenty classifiers, including RF, AdaBoost, SVM, neural networks, and bagging, were utilized. These classifiers were instrumental in assigning class labels, categorizing the soil conditions as low, medium, or high based on their respective numeric values (Sirsat *et al.*, 2017). The Bayesian network was applied to perform soil fertility rating with the pH value of soil and the soil nutrients like nitrogen, copper, iron, potassium, phosphorus, organic carbon and Zinc (Zia, 2010).

Irrigation management

Efficient irrigation water management plays a pivotal role in agricultural production, demanding significant attention to maintain a harmonious balance in hydrology, climate, and agronomy. To establish an effective irrigation regimen, it is imperative to accurately determine the precise water needs of the crops. Consequently, the utilization of computer vision technologies and the integration and implementation of automated systems for crop production management, plant irrigation, and yield assessment assume paramount importance in this context.

In their exploration of data collected from an experimental sustainable irrigation setup, as conducted by (Glória *et al.*, 2021), the introduction of a mobile application named "smart farm" has significantly expanded the capability for farmers to carry out tasks remotely, reducing the need for their physical presence on the farm.

In a related study by Zhang *et al.* (2018), the research delved into the identification and monitoring of center pivot irrigation systems. To optimize the allocation of irrigation water, the researchers employed a CNN approach. This study encompassed the development and comparison of CNNs with various structural configurations. To enhance the training process, they also devised and implemented data augmentation techniques alongside a well-defined sampling strategy. Furthermore, in (Zhang *et al.*, 2021), authors proposed an IoT-based environmental monitoring system with a distributed architecture. This system monitors parameters such as air and water temperatures, as well as dissolved oxygen. It utilizes an information perception layer, an information transmission layer, and system architecture designed for hydroponics and aquaculture management.

Plant health analysis

With the continuous advancements in computer vision and deep learning, promising solutions have emerged for assessing the overall health of plants. Intelligent decision support systems designed to identify crop diseases, water stress, and nutrient deficiencies have the potential to enable timely responses to critical situations and reduce significant losses, ultimately leading to improved plant quality. Plant stress, whether induced by biotic or abiotic factors, manifests itself in various symptoms within the plant canopy. For instance, in cases of water stress, plants respond by closing stomata and slowing down photosynthesis and transpiration, resulting in observable changes in leaf colour and temperature. Similarly, symptoms related to nutrient deficiencies often manifest as alterations in leaf color and texture. Image analysis techniques can effectively detect these pattern changes. Deep learning-based computer vision approaches offer viable solutions for prompt disease identification, reducing the reliance on human experts for consultation. Qiu *et al.* (2021) pointed out that conventional method for monitoring nitrogen nutrient index (NNI) demand labour-intensive real field measurements, while alternative methods using red-green-blue (RGB) imagery from unmanned aerial vehicles (UAVs) can provide a more efficient approach. RGB or hyperspectral images can be employed to non-destructively detect nutrient deficiencies in the early growth stages of plants. In their investigation, (Backhaus *et al.*, 2011) explored the suitability of supervised approaches, involving classification models, to handle large datasets with significant variations, such as leaf age or pixel position within the leaf, for predicting plant nutritional status. Furthermore, in the study conducted by (Ghosal *et al.* 2018), individual soybean leaves exhibiting a range of deficiency symptoms, including potassium and iron deficiencies, were manually selected and collected in the field through destructive sampling. These leaves and associated data were meticulously recorded using a digital camera, resulting in the collection and labelling of 25,000 images to create a comprehensive dataset of leaf images. Bania *et al.* (2023) has developed a ResNet50 based CNN model with Principal component analysis (PCA) to classify tomato leaf diseases effectively.

Weed management

Weeds represent a significant detriment to agricultural production. Site-specific weed management in Precision Agriculture is becoming a popular topic among researchers and farmers. Weeds are native plants that grow naturally in crop fields. Weeds compete with the crops for resources such as moisture, air, light, and space causing potential yield loss. Therefore, weeds are not wanted in crop fields and must be controlled during crop production. As efforts intensify to enhance agricultural productivity, it's clear that an increasing quantity of chemicals is being introduced into the environment to combat weed proliferation. However, the pursuit of improved productivity also entails the efficient use of resources, a goal that can be best achieved through the precise application of herbicides on weeds. This is where computer vision approaches offer a solution by accurately identifying objects, as the targeted and detailed spraying of weeds hinges on the precise identification and localization of these unwanted plants. Support Vector Machine (SVM) is a machine learning algorithm that has been used for weed classification problems due to its high performance with an accuracy of over 97% (Ahmed *et al.* 2012; Zheng *et al.*, 2017). The fusion of different CNN models has also resulted in significant success to classify weeds from crop plants. For example, five multiple CNN models were fused extract the best features for weed classification tasks (Hoang *et al.*, 2020).

Livestock management

Computer vision approaches play a pivotal role in precision livestock farming (PLF), aiming to optimize the output and health of each animal in the herd. Livestock monitoring systems offer real-time insights, enabling farmers to make informed decisions strategically. Key indicators such as daily activity patterns, food intake, and rumination are closely linked to the well-being and productivity of dairy cows. Figure 3 illustrates various domains where AI-driven applications prove invaluable in the realm of livestock management systems.

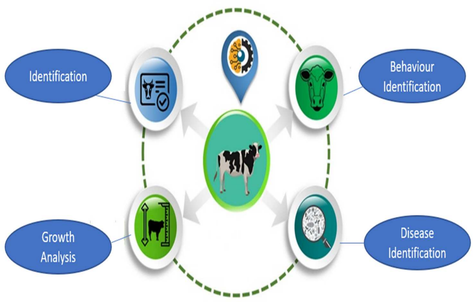

Fig. 3. Areas of AI-Computer vision for livestock management.

Over the years, technological advancements have greatly facilitated traditional farming activities. Specifically, in the realm of livestock production, it has become increasingly feasible to process the data collected on a daily basis pertaining to animal management. The application of ICT to the livestock sector has enabled the exploitation of this data to predict and describe behaviors associated with more efficient animal production. In one notable instance, (Hansen *et al.*, 2018) trained a CNN to recognize pigs by their facial features, using a dataset comprising 1,553 images. The VGG-face model employed in their study achieved an impressive accuracy rate of 96.7%. For the accurate detection and counting of cattle, ear tag-based identification methods are commonly employed in livestock farm management, as highlighted in (Kumar *et al.* 2016). These methods contribute significantly to understanding disease trajectories and controlling the spread of acute diseases. Daily activity patterns, food intake, and ruminating are among the key indicators closely linked to the health and productivity of dairy cows (Huzzey *et al.*, 2007). In this context, the Inception model, a cutting-edge Deep Learning (DL) model, has found extensive use in classification and detection tasks (Bania *et al.*, 2023). It has been particularly valuable in cattle farm management, where it plays a pivotal role in cattle identification and detection.

Discussion

This paper has conducted a comprehensive examination of the existing literature concerning the utilization of AI in agriculture. It encompasses a review of diverse state-of-the-art machine learning and deep learning models applied across various phases of agriculture, spanning pre-harvesting, harvesting, and post-harvesting stages within various agricultural domains. While the advantages of employing AI and ML in the field of agriculture are substantial, it is important to acknowledge that these benefits are accompanied by their own unique set of challenges.

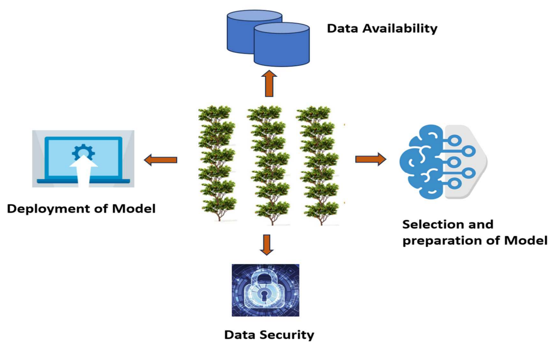

Fig. 4. Technology challenges in real time implementation.

In Fig. 4, few such challenges while implementing machine learning algorithms in agriculture domain are shown and details are as follows:

Availability and collection of data

Data serves as the foundational cornerstone for constructing machine learning models, and numerous researchers encounter various challenges in this regard. These challenges include issues such as data scarcity, unavailability of data in the required format, data of subpar quality, and the potential inclusion of extraneous features. Upon conducting a survey, it becomes evident that many researchers rely on data source platforms like Kaggle, Meandly, IEEE Dataport, and others to acquire the necessary data for model development. In instances where the requisite data is unavailable, researchers must undertake the task of creating their own datasets. Given the numerous complexities associated with data, individuals often find it necessary to employ diverse pre-processing techniques to render the data suitable for training, testing, and model validation. It's worth noting that this pre-processing phase can be time-consuming.

Selection and preparation of AI models

There exists a vast array of machine learning algorithms, making it challenging to pinpoint the most appropriate algorithm for customizing a machine learning model. Frequently, researchers resort to random selection or engage in a comparative analysis of results from multiple algorithms to determine the best-fit option. However, this trial-and-error approach can introduce delays into the model deployment process. The development of an accurate model necessitates an ample amount of training data. Additionally, testing and validation are critical to assess the model's accuracy prior to deployment. Crafting a model from the ground up to achieve the desired and feasible outcomes involves extensive training and repeated testing, both of which are notably time-intensive tasks. Furthermore, this endeavour demands high-performance hardware resources, expertise in the relevant domain, access to skilled programmers, testing tools, and more. Challenges like overfitting and underfitting commonly arise during the model-building process, further underscoring the complexity of this undertaking.

Data security

The field of computer vision in agriculture is experiencing rapid growth, and the development of a resilient computer vision system hinges on several critical aspects, including the generation, transfer, and processing of high-quality data. Furthermore, robust security measures must be in place to safeguard against potential threats. The inherent diversity of resources in computer vision solutions introduces a host of security concerns, encompassing data integrity, privacy issues, and reliability, among others. Given that these solutions seamlessly integrate various digital technologies, ranging from the internet and IoT to cloud computing or edge computing, as well as wireless sensor networks, it becomes imperative for the system to incorporate security features that cater to the unique requirements of each technology. This entails ensuring the integrity of data and devices, maintaining data accuracy, and guaranteeing data availability throughout the entire ecosystem.

Deployment of models

The deployment phase stands out as the most formidable hurdle in transitioning models to production. This challenge is primarily attributed to factors such as a lack of deployment expertise, dependencies on third-party libraries, model size, intricate real-world scenarios, and hardware constraints associated with deployment platforms, which can range from Android phones to embedded boards, among others.

Conclusion

This paper has conducted an extensive review of the existing literature regarding the application of ML and DL in the field of agriculture. It has examined various cutting-edge machine learning and deep learning models utilized at different stages of agriculture, spanning pre-harvesting, harvesting, and post-harvesting phases across various agricultural domains. This survey underscores the pivotal role of machine learning within the agricultural domain, where researchers have consistently applied machine learning algorithms to address complex challenges. The contemporary imperative revolves around the development of precise and tailored machine learning models capable of rapid, automated analysis of extensive and intricate datasets. These models are instrumental in optimizing agricultural processes, ranging from classification to recommendations and predictions. However, it is important to acknowledge that despite the invaluable contributions of computer vision and AI to agriculture, notable challenges persist. These include issues related to data quality, the substantial computational power requirements, and other considerations. Additionally, the adoption rate of advanced agricultural technologies remains relatively slow, primarily due to the substantial initial investments required, a shortage of technical expertise, and mounting concerns regarding data privacy.

References

Khanna A, Kaur S. 2019. Evolution of Internet of Things (IoT) and its significant impact in the field of Precision Agriculture. Computers and Electronics in Agriculture **157 (34),** 218–231. https:// doi.org/10.1016/j.compag.2018.12.039.

Burra D.D, Hildebrand J, Giles J, Nguyen T, Hasiner. 2021. Digital Agriculture Profile: Viet Nam (Report). Food and Agriculture Organization of the United Nations.

Dhanya VG, Subeesh A. 2022. Deep learning based computer vision approaches for smart agricultural applications. Artificial Intelligence in Agriculture **6 (1)**, 211–229.

Simonyan K, Zisserman A. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv: 1409.1556.

Bania KR. 2023. Ensemble of deep transfer learning models for real-time automatic detection of face mask. Multimedia Tools and Applications 82, pages 25131–25153. https://doi.org/10.1007/s11042-023-14408-y

Khamparia A, Saini G, Gupta D, Khanna A, Tiwari S. 2019. Seasonal Crops Disease Prediction and Classification Using Deep Convolutional Encoder Network. Circuits System, and Signal Process **39**, 818–836.

M. Islam, Anh Dinh, Wahid K, Bhowmik, P. 2017. Detection of potato diseases using image segmentation and multiclass support vector machine, IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada, pp. 1-4. doi: 10.1109/CCECE.2017.7946594

Samajpati BJ, Degadwala S. 2016. Hybrid approach for apple fruit disease detection and classification using random forest classifier. International conference on communication and signal processing (ICCSP).
DOI: 10.1109/ICCSP.2016.7754302

Zhu S, Zhou L, Gao P, Bao. 2019. Near-infrared hyperspectral imaging combined with deep learning to identify cotton seed varieties. Molecules **24,** 3268. https://doi.org/10.3390/molecules24183268.

Li C, Li H, Liu Z, Li B, Huang Y. 2021. SeedSortNet: a rapid and highly efficient lightweight CNN based on visual attention for seed sorting. PeerJ Computer Science **7,** e639. https://doi.org/10.7717/peerj-cs.639.

Zhao G, Quan L, Li H, Feng H, Li S. 2021. Real-time recognition system of soybean seed full-surface defects based on deep learning. Computers and Electronics in Agriculture **187**, 106230. https://doi.org/10.1016/j.compag.2021.106230

Taheri-Garavand A, Nasiri A, Fanourakis D, Fatahi S, Omid M, Nikoloudakis N. 2021. Automated in situ seed variety identification via deep learning: a case study in chickpea. Plants **10**, 1406. https://doi.org/10.3390/plants10071406.

Jia HY, Chen J, Yu HL, Liu DY. 2010. Soil fertility grading with Bayesian Network transfer learning. In proceedings of IEEE International conference on machine learning and cybernetics **3**, 1159–63. DOI: 10.1109/ICMLC.2010.5580915

Reashma SJ, Pillai AS. 2017. Edaphic factors and crop growth using machine learning—A review. In: International conference on intelligent sustainable systems (ICISS). IEEE, 270–274.

Sirsat MS, Cernadas E, Ferna´ndez-Delgado M, Khan R. 2017. Classification of agricultural soil parameters in India. Computers and Electronics in Agriculture **135(6),** 269–279.

Glória A, Cardoso J, Sebastião P. 2021. Sustainable irrigation system for farming supported by machine learning and real-time sensor data. Sensors **21**, 3079.

Zhang S, Li S, Ke Z, Zhao H, Guo, Y. 2021. Investigation on environment monitoring system for a combination of hydroponics and aquaculture in greenhouse. Information Processing in Agriculture **13(2),** 12-19.

Ahmed F, Al-Mamun HA, Hossain Bari ASM, Hossain E, Kwan P, 2012. Classification of crops and weeds from digital images: a support vector machine approach Crop Protect, **40**, 98–104, https://doi.org/10.1016/J.CROPRO.2012.04.024.

Zheng Y, Zhu Q. 2017**.** Maize and weed classification using color indices with support vector data description in outdoor fields, Computers and Electronics in Agriculture **141**, 215–222. https://doi.org/10.1016/j. compag.2017.07.028.

Hoang Trong V, Gwang-hyun Y, Thanh VuD, Jin-young K. 2020. Late fusion of multimodal deep neural networks for weeds classification. Computers and Electronics in Agriculture **175**, 105506. DOI: 10.1016/j.compag.2020.105506.

Qiu Z, Ma F, Li Z, Xu X, Ge H, Du C. 2021. Estimation of nitrogen nutrition index in rice from uav rgb images coupled with machine learning algorithms. Computers and Electronics in Agriculture **189**, 106421. DOI: 10.1016/j.compag.2021.106421

Backhaus A, Bollenbeck F, Seiffert, U. 2011. Robust classification of the nutrition state in crop plants by hyperspectral imaging and artificial neural networks. 3rd Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS). IEEE, 1–4.

Ghosal S, Blystone D, Singh AK. 2018. An explainable deep machine vision framework for plant stress phenotyping. Proc. Natlional. Academy Science 115, 4613–4618.

Kumar S, Singh SK, Dutta T, Gupta HP. 2016. A fast cattle recognition system using smart devices. Proceedings of the 24th ACM International Conference on Multimedia, pp. 742–743. DOI: 10.1145/2964284.2973829.

Zhang C, Yue P, Di L, Wu Z. 2018. Automatic identification of center pivot irrigation systems from landsat images using convolutional neural networks. Agriculture 8, 147. https://doi.org/10.3390/agriculture8100147.

Hansen, M.F, Smith, M.L, Smith, L.N, Salter. 2018. Towards on-farm pig face recognition using convolutional neural networks. Computers in Industry98, 145–152. https://doi.org/10.1016/j.compind.2018.02.016.

Huzzey JM, Veira DM. 2007. Prepartum behavior and dry matter intake identify dairy cows at risk for metritis. Jurnal Dairy Science **90**, 3220–3233. https://doi.org/10.3168/jds.2006-807.

Bania RK, Dey S, Buragohain N. 2023. Hybrid ResNet50-PCA based deep transfer learning approach for classification of tomato leaf diseases. Journal of Biodiversity and Environment Science **42 (2),** 42-48.

C. Szegedy *et al.*, 2015. Going deeper with convolutions. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, USA, pp. 1-9. DOI: 10.1109/CVPR.2015.7298594.