Artificial Intelligence in Agriculture 6 (2022) 211–229

Contents lists available at ScienceDirect

Artificial Intelligence in Agriculture

journal homepage: http://www.keaipublishing.com/en/journals/artificial-intelligence-in-agriculture/

Deep learning based computer vision approaches for smart agricultural applications

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ARTICLE INFO

Article history:
Received 2 June 2022
Received in revised form 22 September 2022
Accepted 25 September 2022
Available online 30 September 2022

Key words:
Agriculture automation
Computer vision
Deep learning
Machine learning
Smart agriculture
Vision transformers

ABSTRACT

The agriculture industry is undergoing a rapid digital transformation and is growing powerful by the pillars of cutting-edge approaches like artificial intelligence and allied technologies. At the core of artificial intelligence, deep learning-based computer vision enables various agriculture activities to be performed automatically with utmost precision enabling smart agriculture into reality. Computer vision techniques, in conjunction with high-quality image acquisition using remote cameras, enable non-contact and efficient technology-driven solutions in agriculture. This review contributes to providing state-of-the-art computer vision technologies based on deep learning that can assist farmers in operations starting from land preparation to harvesting. Recent works in the area of computer vision were analyzed in this paper and categorized into (a) seed quality analysis, (b) soil analysis, (c) irrigation water management, (d) plant health analysis, (e) weed management (f) livestock management and (g) yield estimation. The paper also discusses recent trends in computer vision such as generative adversarial networks (GAN), vision transformers (ViT) and other popular deep learning architectures. Additionally, this study pinpoints the challenges in implementing the solutions in the farmer's field in real-time. The overall finding indicates that convolutional neural networks are the corner stone of modern computer vision approaches and their various architectures provide high-quality solutions across various agriculture activities in terms of precision and accuracy. However, the success of the computer vision approach lies in building the model on a quality dataset and providing real-time solutions.

Contents

Abbreviations: AI, Artificial Intelligence; ANN, Artificial Neural Network; BP, Back Propagation; C-GAN, Conditional Generative Adversarial Network; CNN, Convolutional Neural Network; COCO, Common Objects in Context; CV, Computer Vision; DCNN, Deep Convolutional Neural Network; DL, Deep Learning; DNA, Deoxyribo Nucleic Acid; RCNN, Region-based Convolutional Networks; FCN, Fully Convolutional Networks; FLDA, Fisher's Linear Discrimination Analysis; GAN, Generative Adversarial Network; GLCM, Grey Level Co-occurrence Matrix; GPU, Graphic Processing Units; HOG, Histogram of Oriented Gradients; KNN, K- Nearest Neighbour; LBP, Local Binary Patterns; LCTF, Liquid Crystal Tunable Filters; LDA, Linear Discriminant Analysis; LIDAR, Light Detection and Ranging; LSTM, Long Short-Term Memory; MHA, Multi Headed Attention; ML, Machine Learning; MLP, Multi-Layer Perceptron; NASNet, Neural Search Architecture Network; NLP, Natural Language Processing; OCR, Optical Character Recognition; PEAT, Progressive Environmental and Agricultural Technologies; PLF, Precision Livestock Farming; ResNet, Residual Network; RF, Random Forest; RGB, Red Green Blue; SegNET, Semantic Segmentation Network; SSD, Single Shot Multibox Detector; SVM, Support Vector Machine; UAV, Unmanned Aerial Vehicle; VGG, Visual Geometry Group; ViT, Vision Transformers; WSN, Wireless Sensor Network; YOLO, You Only Look Once.

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https://doi.org/10.1016/j.aiia.2022.09.007

1. Introduction

The UNDP 2021 report on "leveraging digital technology for sustainable agriculture" states that global food production needs to be increased by 98 percent to feed a burgeoning human population of 9.9 billion by 2050 (Burra et al., 2021). This target needs to be accomplished through the effective utilization of available resources viz land, labor, capital, and technology (Ranganathan et al., 2018). Present status on precision agriculture aims to define the decision support system for farm management by optimizing the output while consecutively preserving the resources applied. Constructively pointing out, the emerging trend of food security needs to be handled with data-driven farming that can increase productivity, efficiency, and profits. The key challenges such as food demand, labor shortage, water shortage, climate change (Badrzadeh et al., 2022; Elbeltagi et al., 2022a; Kaack et al., 2022) and increasing energy demands lead to the need for technology intervention. The opportunity offered by smart agriculture, which encompasses precision agriculture, digital agriculture as well as modern agricultural practices, needs prime validation at this point. Smart agriculture is primarily based on three platforms viz, science, innovation, and ICT (Information and Communication Technology) (Khanna and Kaur, 2019). The traditionally used information and knowledge management system for collecting and monitoring agricultural data is not only laborious but is also time-consuming and error-prone. Therefore, the technical advancement in remote sensing, digital applications, sensors, advanced imaging systems, cloud data storage along with intelligent data analysis using the decision support systems need to be well utilized in making the farming sector smarter (Fig. 1). Smart agriculture can leverage cutting-edge technologies like the Internet of Things, Machine learning, Cloud computing, Blockchain, *etc.*, and benefit from these opportunities in improving food production and addressing the emerging challenges in this sector (Sami et al., 2022).

Recently, the infiltration of computer/ mobile technology even to the most rural pockets, has provided an inimitable facility in connecting the rural producers with the city-consumers or the international investors, thereby facilitating better investments and knowledge transfer in agriculture (Aker, 2011; Karim et al., 2013). Artificial intelligence (AI) is a game-changing technology that already has proven track records across various industries, including agriculture (Adnan et al., 2021; Bhagat et al., 2020; Jamei et al., 2022b; Kumar et al., 2019; Subeesh et al., 2019). The use of machine learning, a subset of artificial intelligence, has been covered extensively by researchers in delivering innovative solutions for modelling complex relationships and further, making predictions on agriculture data (Bhavsar and Panchal, 2012; Heramb et al., 2022; Jamei et al., 2022c; Karbasi et al., 2022; Malik et al., 2022a; Rai et al., 2022; Rehman et al., 2019; Tantalaki et al., 2019). Computer vision, a field of artificial intelligence, is making a machine "see", using the modern technologies involving a camera and computer instead of human vision, empowering extensive automation capabilities to AI systems. Computer vision collects necessary visual data regarding crops, livestock, farm or garden, allowing us to identify, detect and track specific objects using visual elements and comprehend complex visual data for automation tasks. In the past decades, expert and intelligent systems based on computer vision technology have been well utilized for agricultural operations (Foglia and Reina, 2006; Gomes and Leta, 2012; Rico-Fernández et al., 2019). Further, the development of modern technologies and hardware supports like Graphic Processing Units (GPUs) and edge devices have diversified the application of computer

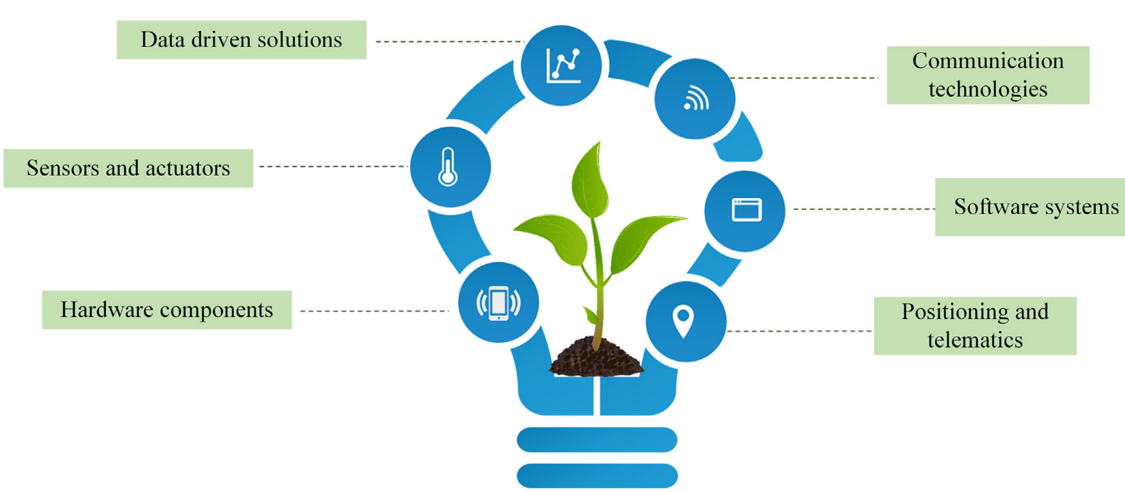

Fig. 1. Components of smart agricultural solutions.

vision, thereby making strands to efficient agricultural production (Li et al., 2019; Mochida et al., 2019; Rehman et al., 2019; Vázquez-Arellano et al., 2016). Modern computer vision techniques can help in the digital quantification of different morphological and physiological plant parameters along with the qualitative assessment of the same and are expected to rapidly improve the accuracy of plant phenotyping (Araus and Cairns, 2014; Ghanem et al., 2015). Further, combining the computer vision techniques with the high throughput molecular methodologies of DNA sequencing provides an opportunity for genome-wide exploration of useful genes and molecular modeling of the same to understand the complex traits such as plant yield and productivity, stress tolerance, biotic and abiotic stress management etc (Araus et al., 2018; Shakoor et al., 2017). Thus imaging with computer vision technology aided by various imaging sensors and algorithms can indeed play a major role in precision agriculture and in paving the way for smart agriculture (Araus et al., 2018). A data driven precision agriculture system architecture consists of sensors deployed on the fields (sensing layer), network layer that provides connectivity, storage and other services (service layer) and application layer consisting of the end user accessing the services through mobile/web-based applications (Fig. 2). Integrative and multi-mode Artificial Intelligence (AI) models can be deployed to predict crop behaviour under differing field conditions (Shrivastava and Marshall-Colon, 2018; Waldhoff et al., 2017). The yield performance of major crops in various regions, along with the field conditions for crop production, environmental impact and economic outcome, have been assessed using the algorithms of deep learning and machine learning (Tantalaki et al., 2019). Deep learning permits the computational models with multiple processing layers to indicate the data in multiple levels of abstraction (Schmidhuber, 2015). The main application of deep learning in the field of agriculture are building models to derive meaningful insights from agriculture data (Jamei et al., 2022a; Malik et al., 2022b), image analysis including classification and object detection, such as the detection of diseases, weed identification, soil analysis, plant disease detection, etc. (Kamilaris and Prenafeta-Boldú, 2018).

For this study, we have collected more than 100 research papers from scientific databases, including PubMed, Web of Science, and Scopus, in the area of deep learning-based computer vision. Further, we investigated all these works that leveraged deep learning-based computer vision technologies to address key agriculture tasks such as plant health monitoring, disease and weed identification, irrigation management, soil analysis, livestock management, yield estimation, etc. The main objective of this study is to evaluate the penetration of deep learning-based computer vision approaches in key agricultural problems, and this review is intended to be useful to agriculture researchers as well as general computer vision researchers who are interested in the application of computer vision solutions to automate and solve potential agricultural problems. The practical implications of these technologies along with major challenges in implementing large-scale applications were also constructively pointed out in this study.

2. Computer vision and deep learning models

Computer vision possesses dual and interrelated goals. In biological science, computer vision aims to represent the human visual system using computational models, and in the engineering perspective, computer vision attempts to create autonomous systems that can do tasks that often human visual systems cannot perform (Huang, 1993). Computer vision imparts visual capability to machines through cameras, data, models, and algorithms rather than retinas and the visual cortex. Optical character recognition (OCR) technology and intelligent character recognition were some major tasks that employed computer vision to accomplish tasks such as document and invoice processing, vehicle plate detection, etc. In the early stages of computer vision research, the main focus was to build algorithms to detect edges, curves, corners,

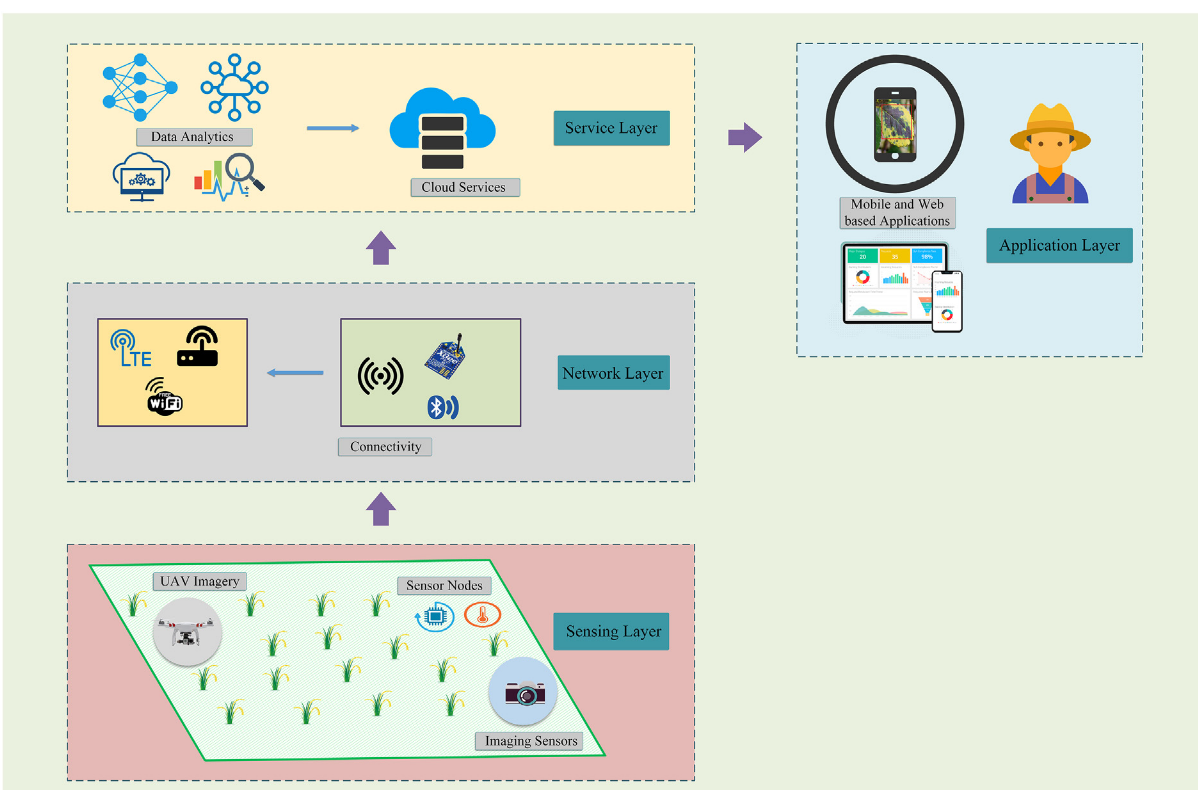

Fig. 2. Data-driven precision agriculture system architecture.

and other basic shapes. Before the era of deep learning, image processing relied on gray level segmentation and this approach wasn't robust enough to represent complex classes. Modern computer vision algorithms rely extensively on artificial neural networks that provide a dramatic improvement in performance and accuracy compared to traditional approaches for image processing. Deep learning-based computation models allow multiple processing layers to learn and infer complex patterns mimicking the human brain (O'Mahony et al., 2020; Schmidhuber, 2015; Zhong et al., 2016). It runs and inspects the data over several iterations until it discerns distinctions and identifies or recognizes the features in the images. The recent surge of interest in deep learning is due to the fact that it can handle massive amounts of heterogeneous data (visual, audio, text, etc.) and is capable of embedding solutions into several hardwares. DL allows automatic feature extraction and can be utilized in numerous image processing tasks and is well known for its effectiveness in handling vision-based activities like image classification, object detection, semantic segmentation, etc. In fact, these tasks are the backbone for modeling and automating agricultural activities such as disease identification, weed detection, yield estimation, etc (Jha et al., 2019; Subeesh and Mehta, 2021; Tian et al., 2020).

2.1. Image classification with CNN and Object detection models

Convolutional neural network-based deep learning architectures are popular for computer vision tasks like image classification. A convolutional neural network is a type of neural network architecture that takes input images and extracts relevant features to efficiently identify and classify images. CNN uses labels to perform convolutions and generate feature maps. The introduction of imageNet dataset that contained millions of tagged images had laid a foundation and benchmark for building advanced computer vision-based models (Kriegeskorte and Golan, 2019; Miikkulainen et al., 2019; Yoo, 2015). LeNet-5 was one of the earliest CNN proposed by Yann LeCun (LeCun et al., 1998), led to the development of various CNN models (Fig. 3). In 2012, AlexNet architecture (Krizhevsky et al., 2012a) was found promising for image recognition, and numerous new architectures such as VGGNet (Simonyan and Zisserman, 2015), ResNet (He et al., 2015), etc. were also introduced by researchers, reducing the error rate and improving the performance. Image segmentation approaches are quite useful for understanding what an image consists of, by dividing the images into several segments. Image segmentation creates a pixel-oriented mask for each object present inside the image. This eases the image processing tasks as the important segments alone can be considered for processing tasks.

The image classification mainly identifies the class, a specific image belongs to. The image classification approach is often not successful when there are multiple objects in the same image. Object detection aims to detect the location of objects in the image/video. Object detection task comprises two major components; class information and location information. The location information is described by bounding boxes around the target object. Object detection architectures such as YOLO (You Only Look Once) (Redmon et al., 2016), SSD (Single Shot Multibox Detector) (Liu et al., 2016), Faster-RCNN (Region Convolutional Networks) (Ren et al., 2016) are widely used for object detection and automation across different domains including agriculture.

2.2. Generative adversarial network (GAN) and Vision Transformers (ViT)

A generative adversarial network (GAN) is a special type of neural network used for unsupervised learning. GAN is an approach to generative modeling that can learn to mimic a given distribution of data. These models effectively reduce the data into its fundamental properties or generate new data points with varied properties. The application of GANs has achieved state-of-the-art performance in many image generation tasks, such as text-to-image synthesis (Xu et al., 2017), super-resolution (Ledig et al., 2017), and image-to-image translation

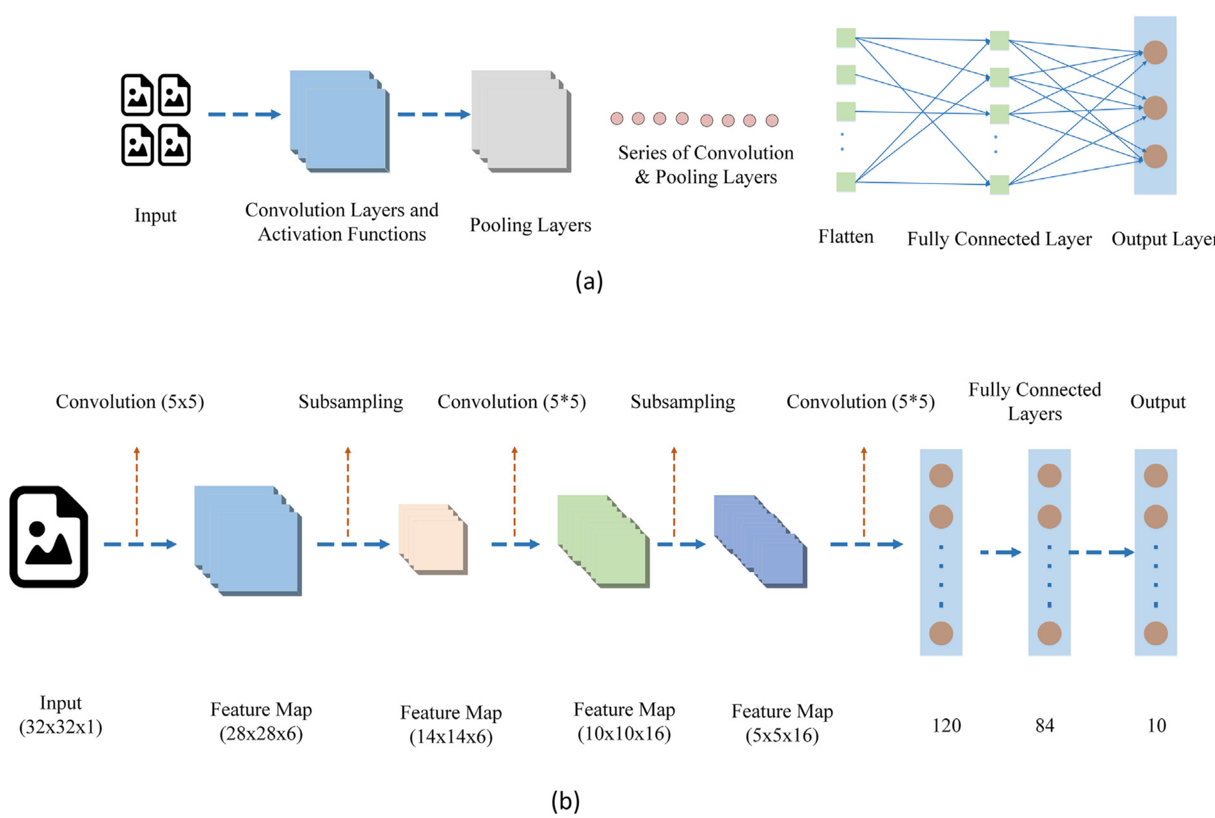

Fig. 3. Architecture of (a) Convolutional neural networks (b) LeNet-5 architecture.

(Zhu et al., 2020b). Generally, GAN has two main building blocks (two neural nets) which compete with each other and are capable of capturing, copying and analyzing the variations in a dataset (Fig. 4). The two networks are usually called Generator and Discriminator. The generator neural network helps to generate new instances, while the discriminator neural network evaluates the authenticity of the generated images. The discriminator decides whether or not every instance of the data it evaluates belongs to the actual training set and penalizes the generator for generating implausible outcomes. The loss of the discriminator is used for improving the generator (Reimers and Requena-Mesa, 2020). The discriminator tries to identify the fake data from the real data, and both networks work simultaneously to learn complex data. GANs are a panacea for the data scarcity problem, which is a serious hurdle in developing robust deep neural network models (Hiriyannaiah et al., 2020). The realistic images produced by GAN that are different from the original training data are attractive in data augmentation of DL-computer vision to reduce the model overfitting.

Transformer models have become the de-facto status quo in text processing, and recently, the computer vision community has extended the concept of NLP (Natural Language Processing) transformer to apply to the image domain with slight modification in the implementation to process multiple modalities (*e.g.*, images, videos, etc.) using similar processing blocks (Dosovitskiy et al., 2021; Khan et al., 2021; Vaswani et al., 2017). Even though the general architecture used in both cases are similar, ViT uses different approaches for tokenization and embedding (Fig. 5). The overall architecture consists of 3 main components, viz., patch embedding, feature extraction by stacked transformer encoders and the classification head. In ViT, initially, the input image of shape (height, width, channels) is embedded into a feature vector of shape (n+1, d), using a set of transformations. The input image is split into a group of image patches. Later, these groups of image patches are embedded into encoded vectors and fed into transformer encoder network. The transformer encoder learns the features from the embedded patches using a stack of transformer encoders (Wu et al., 2021). The encoder mainly comprises multi-headed attention (MHA) and a 2-layer MLP with layer normalization and residual connections. The final MLP block, called the MLP head is used as an output of the transformer. In the case of image classification, a softmax on the output generates the classification outputs. ViTs are useful in several vision applications such as image classification, image-to-text, text-to-image generation, image segmentation, object detection, etc (Bazi et al., 2021; Li et al., 2022).

3. Deep learning driven computer vision – Application areas in agriculture

3.1. Seed quality analysis

The commercial seed industry is focused on the supply of the right quality seeds to the farmers at the right time in the right quantity. Filtering out low-quality of seeds from high-quality ones, is not only laborious, but it requires sophisticated equipments, infrastructure, and time (Kannur et al., 2011). The testing of seeds for their quality can indeed gain momentum by the use of computer vision technology which can extract the morphological information of different seed lots and grade it according to the internationally prescribed quality standards (Bao and Bambil, 2021). The different seed testing modules are likely to address their physical purity, genetic purity, seed health, vigour, patterns of deterioration etc., which in general may indeed cover the physical or visually attributable characters such as the seed length, shape, size, visual impairments, and presence of foreign bodies which can indeed be captured by the advanced computer vision technology (Granitto et al., 2005).

Performance issues of traditional computer vision have greatly been improved by deep learning-based computer vision, resulting in larger adoption for seed variety identification. The seed quality evaluation process using computer vision is shown in Fig. 6. Often, spectral imaging techniques are also merged with these approaches to enhance the accuracy (Qiu et al., 2018; Zhu et al., 2019). In a study conducted by Zhu et al. (2019), combining spectroscopy and machine learning – CNN models were found to be effective in identifying the seed varieties. The machine learning models showed an accuracy of more than 80% in classifying the cotton seeds based on the feature extracted by the CNN and ResNet models. In another investigation, SeedSortNet built from computer vision CNN models, was found to be promising, with accuracies 97.33% and 99.56% in sorting the maize and sunflower seeds (Li et al., 2021). CNN deep learning was also utilized for cognizing the viable and non-viable seeds and was found to be successful with 90% viability prediction accuracy for naturally aged seeds (Ma et al., 2020).

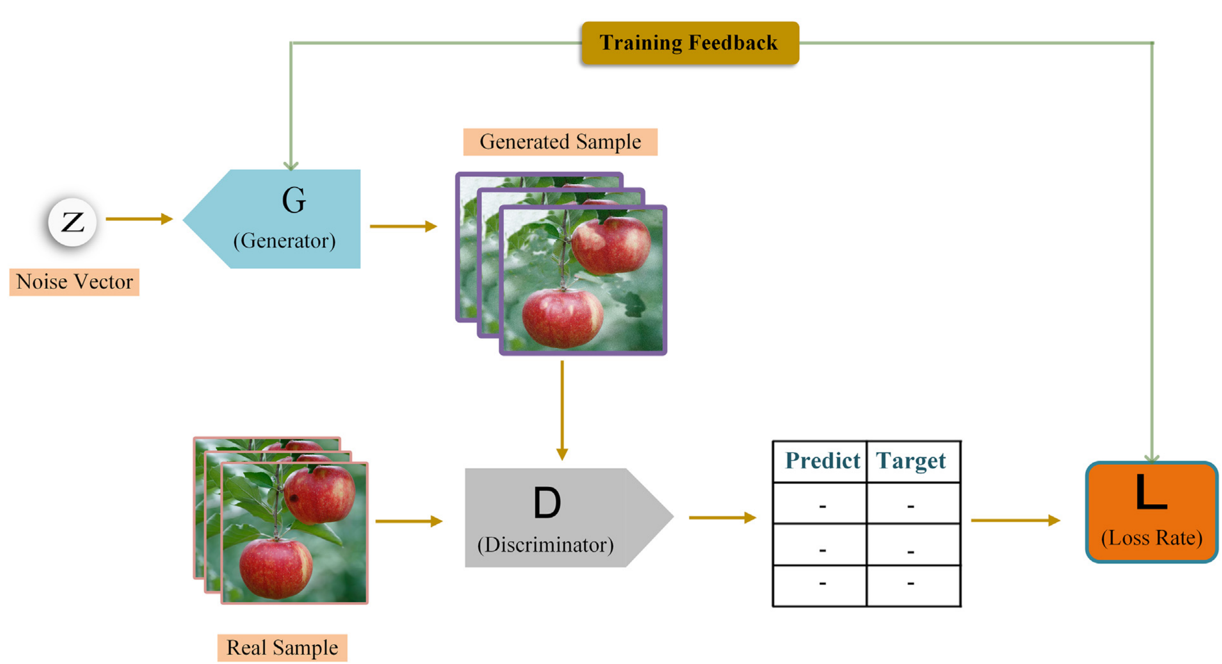

Fig. 4. Overview of training process in GAN (Generative Adversarial Network).

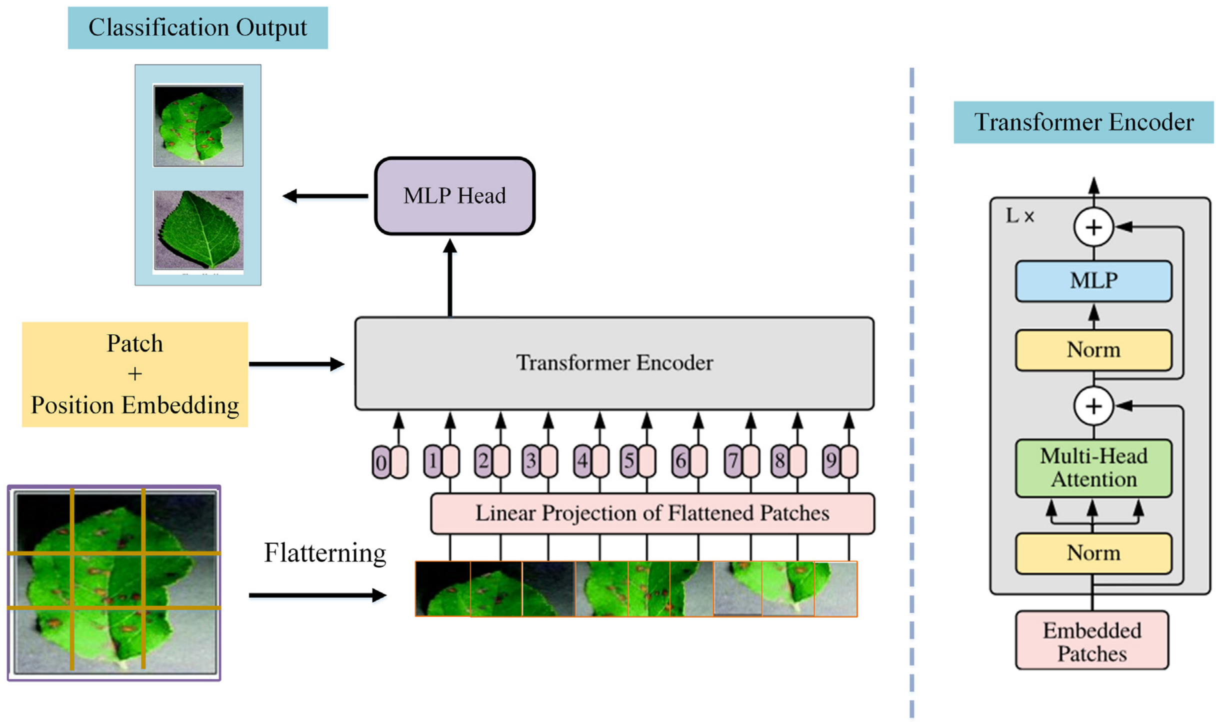

Fig. 5. The architecture of Vision Transformer Model for image classification (Dosovitskiy et al., 2021; Vaswani et al., 2017).

Taheri-Garavand et al. (2021) developed models for automatic identification of chickpea varieties using seed images in the visible spectrum. A modified VGG16 model was used for the identification purpose. As sorting high-quality seeds are vital for increasing yield in the breeding industry, Zhao et al. (2021) employed seven different computer vision models to accurately detect and identify surface defects. MobileNet-V2 model had shown excellent detection accuracy for the soybean dataset. There are numerous such studies done by various researchers and the seed industry is hugely getting benefited from advanced computer vision models, achieving a higher level of automation capabilities. Some of the studies in this area are precisely summarized Table 1.

3.2. Soil analysis

The preservation and improvement of dynamic soil characteristics is the main emphasis of soil management in agriculture for increasing crop productivity (Kushwaha et al., 2022; Suchithra and Pai, 2020). Traditional soil texture analysis entails taking soil samples and bringing them to a laboratory, where they are dried, crushed, and sieved before being used. For coarse textured or sandy soils, sieving is the most typical laboratory analytical method, while for smaller textured particles, a hydrometer or pipette approach based on sedimentation theory is used (Kushwaha et al., 2022; Sudarsan et al., 2016).

With the advancement of image processing power and the development of image acquisition (e.g., cameras) systems in recent years, computer vision-based image analysis approaches have gotten a lot of interest in a lot of sectors, including soil science. This method collects soil images (dynamic or static) with cameras and then uses simple computer programmes to classify and categorise them (Fig. 7). For example, after matching textural patterns, the size of the soil particles might be estimated straight from the image. In several investigations, various image analysis-based computer vision approaches were tried.

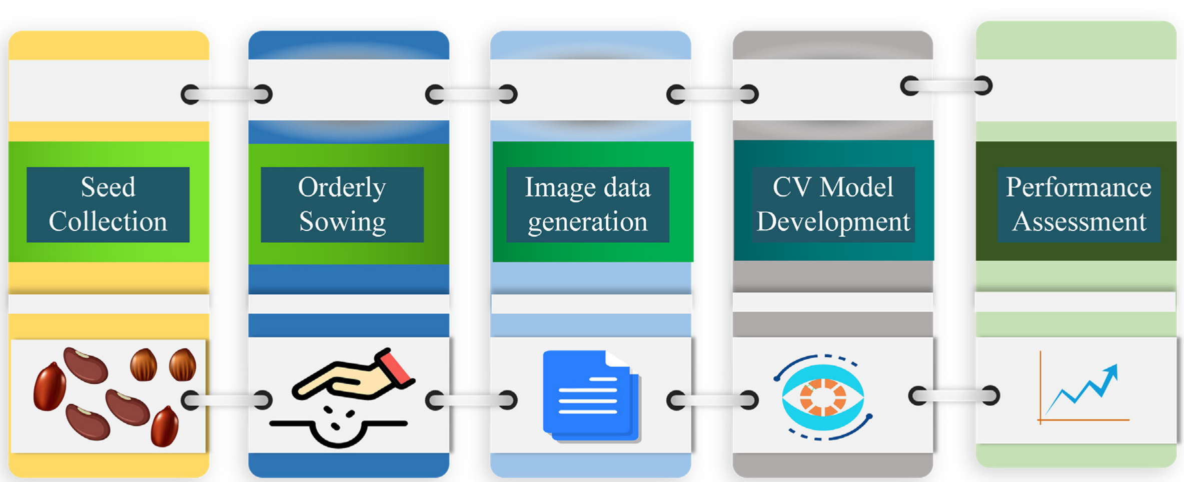

Fig. 6. Seed quality analysis using data-driven models.

Table 1
Previous studies on seed quality analysis through application of computer vision and deep learning.

Reference	Objectives and scenario of application	Methodology	Crop	Results
(Javanmardi et al., 2021)	Corn variety classification using 9 different varieties	CNN as a generic feature extractor. Classification using ANN, SVM, kNN, boosted tree, bagged tree and LDA	Corn	CNN ANN classification has a classification accuracy of 98.1%, precision 98.2%, recall 98.1% and F1 score of 98.1%.
(Qiu et al., 2018)	Variety identification in rice	KNN, SVM and CNN models	Rice	CNN outperformed other models with 89.6% accuracy on the training set and 87% accuracy on the testing set.
(Gulzar et al., 2020)	Seed classification using 14 types of seeds	VGG16 architecture for classification	-	99.9% accuracy over test set with 234 images
(Wu et al., 2019)	Variety identification in oats	DCNN model	Oats	99.19% accuracy on testing set.
(Gulzar et al., 2020)	Seed classification in maize and sunflower	CNN model	Maize and Sunflower	CNN based visual model - SeedSortNet developed with 97.33 percent accuracy on maize and 99.56% accuracy on sunflower dataset respectively.
(Liu et al., 2015)	Soyabean seed sorting	BP neural network	Soyabean	97.25% average recognition accuracy over 857 images of soybean seeds with pest and insect damage.
(Veeramani et al., 2018)	Corn seed defect detection	VGG 19 and GoogleNet	Maize	-
(Dolata and Reiner, 2018)	Varietal identification in barley	CNN	Barley	Increase in average classification accuracy by 0.6% and sensitivity by 2.3% with respect to view point ignorant architecture of the said study.
(Kurtulmuş, 2021)	Seed classification in sunflower	AlexNet, GoogleNet and ResNet	Sunflower	95% accuracy with GoogleNet algorithm for classification of 4800 sunflower seeds.
(Ni et al., 2019)	Seed grading in maize	DCNN	Maize	98.2% prediction accuracy for 408 test images in maize.

Haralick et al. (1973) attempted to classify images received from an aerial or satellite source using entropy and angular moment-based textural classification. Since then, the grey level co-occurrence matrix (GLCM) and its analogues have been used in a variety of remote sensing applications (Dell'Acqua and Gamba, 2003; Kuplich et al., 2005). However, the greatest resolution satellite can only provide a maximum resolution of 10 m/square pixel, which is insufficient to understand soil particle sizes. Riese and Keller (2019a) implemented three 1-dimensional (1D) convolutional neural networks: the LucasCNN, the LucasResNet and the LucasCoordConv. In addition, for the classification problem at hand, the study tweaks two existing 1D CNN techniques and compares the CNN techniques against a random forest classifier to see how well they do. Thereby, study uses the LUCAS topsoil dataset, which is freely available. The CNN method with the least amount of depth turns out to be the most effective classifier. In terms of average accuracy, the LucasCoordConv has the best results.

Similarly, Zhang et al. (Zhang et al., 2003) proposed a soil texture classification system that uses the wavelet transform approach to distinguish between different types of soil. Wavelet transform, which is a strong image and signal analysis method due to its multi-resolution capabilities, is used to extract features. A set of training instances is used to create a maximum likelihood (ML) classifier. This method of ML parameter estimation produces the best results. At the time of training and classification, the Fisher's Linear Discrimination Analysis (FLDA) is used to optimize and reduce the dimension of the vector. Soil textures such as clay, sand, and silt are employed for training and classification. Clay, sand, and silt have 60 percent, 100 percent, and 100 percent categorization rates, respectively. In instance segmentation, Zhang et al. (Zhang et al., 2020) suggested a mask refined R-CNN for refining object details. The goal is to figure out how semantic segmentation of high-level and low-level features affects instance segmentation. The COCO (common objects in context) and cityscapes datasets were used to collect the trial results. This approach is reported to be simple to use and effective. Some of the previous significant studies in soil analysis using DL computer vision have been summarized in Table 2.

3.3. Irrigation management

Irrigation water management in agricultural production necessitates considerable effort and is crucial in maintaining hydrological, climatological, and agronomic equilibrium. Several studies have thus been undertaken in gaining knowledge of the biophysical processes included in the uptake of water through the root zone of the soil and the processes of transpiration through the plant canopy (Elbeltagi et al.,

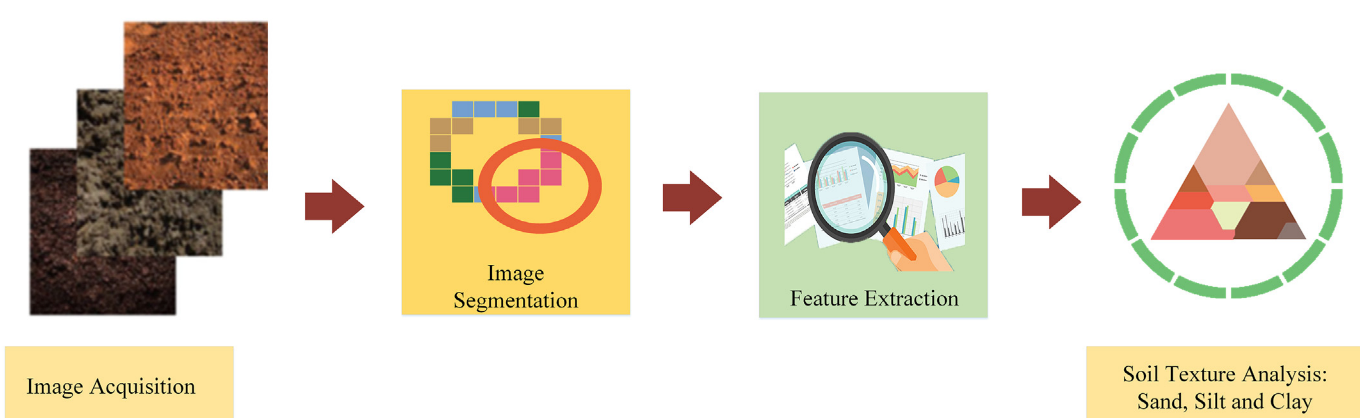

Fig. 7. Soil texture analysis using image processing.

2022b; Kushwaha et al., 2021). For an effective irrigation schedule, it is necessary to know the precise amount of water required by the crop (Kushwaha et al., 2016; Vishwakarma et al., 2022). The application of computer vision technologies, as well as the integration and deployment of automated crop production management, plant irrigation, and yield evaluation, thus become critical. Zhang et al. (Zhang et al., 2018) performed identification and monitoring of centre pivot irrigation systems using a Convolutional Neural Networks (CNNs) approach to the allocation of irrigation water. The CNNs with various structures were built and compared and for data augmentation,training, a sampling strategy was developed. In the testing region, the CNN with the best performance and the shortest training time was used. To further pinpoint the centre of each centre pivot system, a variance-based technique was presented. The proposed approach performed well in the centre pivot irrigation systems identification challenge, with a precision of 95.85% and a recall of 93.33% of the identification findings.

Similarly, Chang and Lin (Chang and Lin, 2018) developed a compact intelligent agricultural machine which is capable of autonomous weeding and variable watering on the cultivated ground, using a combination of computer vision and multitasking. The system classifies the plants and weeds in real-time so that it can weed and water while maintaining an average herbicidal rate of 90% and a deep soil moisture level of 80%. This strategy has a lot of potential because it allows for not only multitasking integration but also resource utilization in its entirety.

Kamyshova et al. (Kamyshova et al., 2022) proposed a computer vision-based technology for optimizing the watering process of crops utilizing a phyto indication system in low latency mode, the study suggested an algorithm-based system for obtaining a maize irrigation map. The system, which comprises 8 IP cameras coupled to a DVR connected to a laptop, can be mounted on a centre pivot irrigation system. There are three steps to the algorithm. Using an integrated excess green and excess red difference (ExGR) index during the image preprocessing stage. The application of the approach that the study chose based on the system's operational conditions is the categorization stage. A neural network trained using the Resilient Propagation method is utilised in the final stage to calculate the rate of watering of plants in the current sector of the sprinkler site. Plant identification accuracy was up to 93 percent, and growth stages were up to 92 percent. Low-cost cameras are now being used in all sectors of technology, particularly in agricultural applications. The soil water balance may be precisely assessed to enable accurate irrigation planning by acquiring relevant information on the growth of horticulture crops through photographs (Koech and Langat, 2018). Table 3 shows the irrigation water management through the application of computer vision and deep learning technologies.

3.4. Plant health analysis

With the advancement in computer vision and deep learning, new promising solutions for identifying overall health status of the plants were introduced. The intelligent decision support system for identifying crop diseases (Fig. 8), water stress, and nutrient deficiencies would lead to timely control of the panic situations and eradicating the huge losses, ultimately leading to improved plant quality.

Plant stress induced by biotic and abiotic factors is expressed in the plant canopy as multiple symptoms. In case of water stress, the plant closes stomata and delays photosynthesis and transpiration activities indicating colour changes in the leaf and temperature (Nilsson, 1995). Similarly, nutrient deficiencies-related symptoms are typically visible in leaves color and texture (Xu et al., 2011). Image analysis can detect these changes in a pattern quite effectively. Deep learning-based computer vision approaches are viable solutions in addressing timely disease identification and avoiding consultation of human experts. The availability of a large number of public image datasets such as PlantVillage (Hughes and Salathe, 2016), PlantDoc (Singh et al., 2020) have proliferated the research in the area of disease identification and many works have taken encouraging steps towards disease-free agriculture (Hassan and Maji, 2022; Ji and Wu, 2022; Nagasubramanian et al., 2019).

The PlantVillage dataset has been extensively utilized by various researchers for solving disease identification problems using deep learning (Amara et al., 2017; Brahimi et al., 2017; Ferentinos, 2018; Mohanty et al., 2016). Several studies reveal that pre-trained models quickly and accurately identifying the diseases in terms of precision, recall and F1 scores (Abbas et al., 2021; Chen et al., 2020b; Coulibaly et al., 2019; Mukti and Biswas, 2019; Thakur et al., 2021). Abbas et al. (Abbas et al., 2021) used synthetic images generated using the Conditional Generative Adversarial Network (C-GAN) to build tomato leaf disease detection. C-GAN can address the issue of data insufficiency and provide more generalization to the models (Mirza and Osindero, 2014). It is worth noting that some investigations were focused on the localization of the disease spots, giving precise information about the diseases (Cen et al., 2016; Liu and Wang, 2020; Mathew and Mahesh, 2022; Son, 2021). Several other studies reported research on DL-computer vision based identification of crop stresses, including water stress and nutrient deficiencies (Abdalla et al., 2021; Anami et al., 2020; Jahagirdar and

Table 2
Previous studies on computer vision and deep learning technologies for soil properties analysis and management.

Reference	Objectives and scenario of application	Methodology	Results
(Riese and Keller, 2019b)	Soil texture analysis	The CNN architectures LucasCNN, the LucasResNet and theLucasCoordConv Models	The CNN method with the least amount of depth turns out to be the most effective classifier
(Omondiagbe et al., 2022)	Soil texture prediction	Employed automated deep convolutional neural networks and population-based learning by replacing the random search with a Bayesian Optimization.	Results show improvements of 5% to 26% for all three soil properties such as sand, silt and clay.
(Pyo et al., 2020)	Estimation of heavy metal concentration	From the soil reflectance images, CNN with convolutional autoencoders was trained to estimate As, Cu and Pb metals.	The highest accuracies reported for As, Cu, and Pb estimates were with R^2 values of 0.86, 0.74, and 0.82.
(Zhong et al., 2021)	Soil properties	The DCNN architectures LucasResNet-16 and LucasVGGNet-16 models	When compared to a single-task DCNN model, the performance of a multi-task DCNN model created based on LucasResNet-16 was enhanced.
(Yu et al., 2019)	Soil Classification	Lquid crystal tunable filters (LCTF)-based system and three-dimensional convolutional neural network (3D-CNN) for soil classification	The overall accuracy of 99.59% for 3D-CNN-SD-PCA.
(Azadnia et al., 2022)	Texture Analysis	Portable smartphone-based machine vision system using CNN was developed. The features were extracted using CNN and classification is performed using ANN, SVM, RF and KNN classifiers.	Model accuracies at distances of 20, 40 and 60 cm were of 99.89, 99.81 and 99.58%,
(Azadnia et al., 2022)	Texture analysis	Deep learning models VggNet16, ResNet50, and Inception-v4 models were used to classify soil aggregates	Overall accuracy obtained for CNN networks was 96.2%, 97.1%, and 98.7%

Table 3
Previous studies on irrigation water management through application of computer vision and deep learning approaches.

References	Objectives and scenario of application	Methodology	Results
(Albuquerque et al., 2020)	Identification of malfunctioning in the irrigation systems	Mask R-CNN based segmentation on UAV captured images	Given dataset sizes, the results are satisfactory.
(Chen et al., 2020a)	Identification of water pollution for agricultural irrigation resources	Shallow CNN model in combination with decision tree algorithm trained on NIR data	Validation results were 25.47 of RMSEV and 0.914 of Rv.
(Zhang et al., 2018)	Monitoring and identification of canter pivot irrigation system to supply irrigation water	CNN based segmentation on UAV captured images	Precision and recall of 95.85% and 93.3 percent, respectively, were attained.
(Tang et al., 2021)	Monitoring the distribution of center pivot irrigation systems	Lightweight real-time object detection network (PVANET) based on GoogLeNet and Hough transform	Experiments with Sentinel-2 images achieved a precision of 95% and a recall of 95.5%,
(Kumbi and Birje, 2022)	Irrigation efficiency	Sun-flower Atom Optimization-based Deep convolution neural network (SFAO-DeepCNN) algorithm	Maximal accuracy of 92%, specificity of 91.2% and sensitivity of 94.1%
(Kim et al., 2022)	Water Level Estimation of Irrigation Channel	ResNet-50 image classification and U-Net segmentation models on irrigation canal's CCTV images	The image segmentation model showed a Dice score of 0.998 and predicted water levels showed R^2 of 0.97

Budihal, 2021). Table 4 shows the previous studies on deep learning based computer vision technology on plant health analysis.

3.5. Weed management

Weeds are among the major factors that affect agricultural production negatively. With the focus on improving agricultural productivity, it is evident that more and more chemicals are being dumped into the environment with the aim of managing the weed growth. But for improving the productivity, it also requires the optimum utilization of resources which can only be achieved by the precise spraying on weeds. The traditional robotic weeders generally function by detecting crop row patterns and they do not rely on crop recognition for the weeding operation. If the weed density and population are large, they may obscure the row pattern leading to reduced efficiency of the weeders. Computer vision approaches come to rescue at this point by accurately identifying the objects as precise spraying of weeds depends on the accurate identification and location of weeds. Recently, several studies were carried out by researchers on adaptability of computer vision technology for the agronomic classification of plant species at the field level, viz the classification of crops from weeds, off types etc. (Sau and Ucchesu, 2019; Sau et al., 2018; Subeesh et al., 2022). Detailed application of the same in the automatic identification of plant species based on the leaf recognition pattern has been proposed for preserving and cataloguing plant species (Putzu et al., 2016) along with the botanical characterization of germplasm (Lo Bianco et al., 2017). Methods of achieving weed detection at the field level mainly include the utilization of computer vision technology using the traditional image processing and deep learning. When, the conventional methods of computer vision are used, extracting the different features such as colour, shape, texture

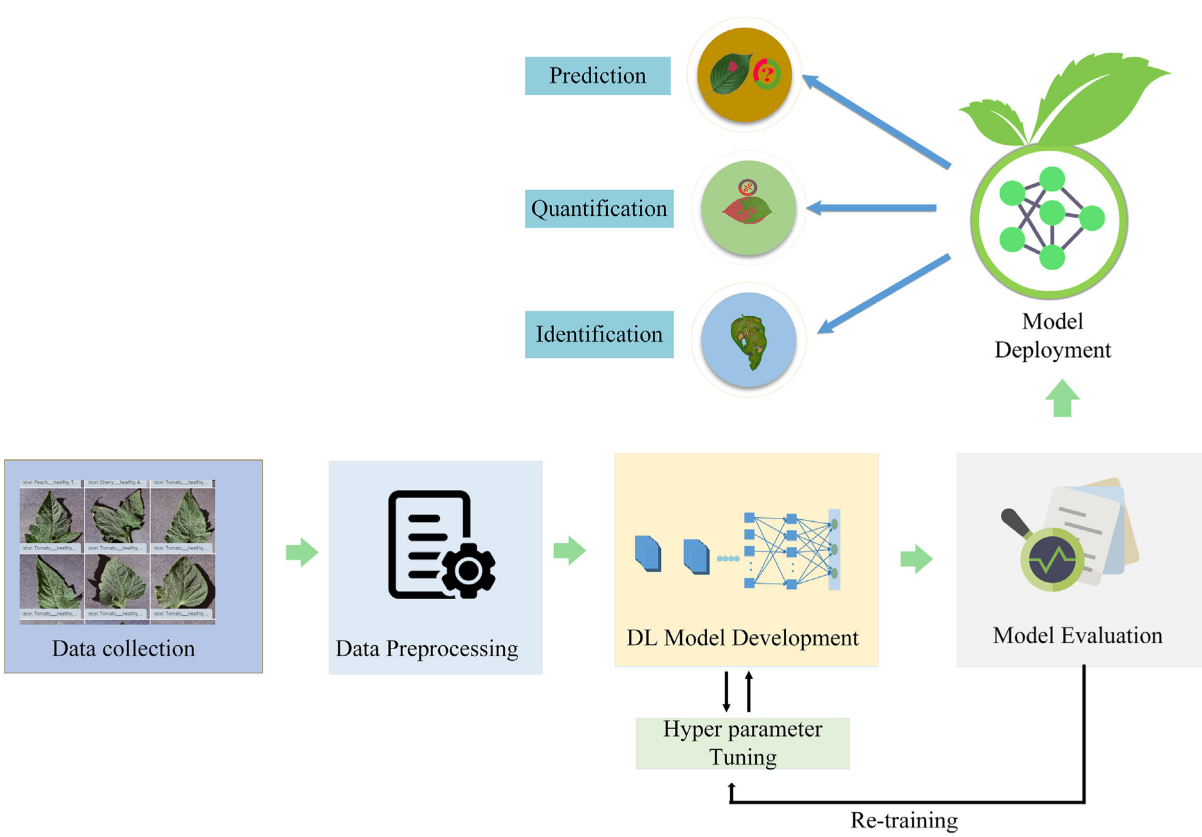

Fig. 8. Deep learning based computer vision approach for plant health analysis.

Table 4
Previous studies on computer vision and deep learning technologies for crop health analysis.

References	Objectives and scenario of application	Methodology	Crop	Results
(Hassan and Maji, 2022)	Plant disease identification	Novel lightweight CNN based on Inception and Residual connections with fewer parameters	Rice, Cassava	The testing accuracies of the proposed model is 99.39%,99.66% and 76.59% on Plantvillage, Rice, and Cassava dataset
(Hati and Singh, 2021)	Species Recognition (SR) and Identification of Healthy and Infected Leaves (IHIL)	Residual network (ResNet) based convolutional neural network (CNN) architecture	12 different plant species	Species identification: Precision 91.84%, Recall 91.67% and F191.49%. IHIL : Precision 84%, Recall 83.14% and F1 83.19%
(Ji and Wu, 2022)	Black measles disease identification in grape	Plant disease evaluation. Image segmentation using DeepLabV3 with ResNet50 backbone	Grape	Overall classification accuracy of 97.75% on the hold-out test dataset.
(Syed-Ab-Rahman et al., 2022)	Citrus diseases classification using leaf images	Two-stage deep CNN model	Citrus	Detection accuracy of 94.37% and an average precision of 95.8%.
(Li and Li, 2022)	Leaf disease identification	Vision Transformer-based lightweight apple leaf disease- identification model (ConvViT)	Apple	ConvViT achieved an accuracy of 96.85% on the apple leaf disease dataset
(Mkonyi et al., 2020)	Early identification of *Tuta absoluta* disease	Pre-trained CNN architectures VGG16, VGG19 and ResNet50 Models	Tomato	VGG16 attained the highest accuracy of 91.9%
(Azimi et al., 2021)	Stress level detection due to nitrogen deficiency	Custom Deep learning architecture with 23 layers.	Sorghum	8.25% better accuracy than traditional machine learning techniques
(Joshi et al., 2021)	Viral disease diagnosis	Convolutional neural network - VirLeafNet	Vigna mungo	Accuracies of VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3 were 91.234%, 96.429%, and 97.403%
(Shah et al., 2021)	Plant disease detection	ResTS Architecture with residual connection	14 crops	F1-Score: 0.991
(Singh et al., 2021)	Pest and disease detection	2D-CNN model with segmented images	Coconut tree	Accuracy of 96.94% with a Kappa value 0.91

etc., and combining them with the machine learning methods such as the SVM becomes necessary. But with the improvement in computing power, the deep learning algorithms can beneficially extract multidimensional and multi-scale spatial and semantic feature information of weeds through AlexNet, VGGNet, ResNet, etc due to their enhanced capability for image data expression thereby avoiding the disadvantages of traditional methods of feature extraction. The application of deep learning in agronomic classification of plant species has gained momentum after the outbreak of CNN and AlexNet (Krizhevsky et al., 2012b). Hall et al. (2015) have utilized the CNN architecture in classifying leaves of 32 species of crops and weeds by capturing nearly 1900 images of the same.

Utilization of CNN architecture in the classification and differentiation of weeds from different species of wheat, sugarbeet, corn, soybean, sunflower, etc. has been proposed by Kussul et al. (2017), while the modified version of VGG16 for the classification of barley, grass, oil crops and weeds have been proposed by Mortensen et al. (2016). Table 5 shows the previously applied computer vision technology for weed management.

3.6. Livestock management

Computer vision approaches are leveraged extensively in precision livestock farming (PLF), ensuring optimum output and health of each individual animal. Livestock monitoring systems provide real-time information and assist farmers in making strategic decisions (Fig. 9). The non-invasive computer vision technology has been widely researched for its use in recognition of livestock behaviour over the past few years (Bello et al., 2021; Kumar et al., 2017; Qiao et al., 2019a; Shen et al., 2020). Xiao et al. (2022) employed a modified Mask-RCNN model and trained a fusion of Mask-RCNN and SVM to identify cows in unconstrained barn. Hansen et al. (2018) trained a CNN to recognize pigs via the face using a data set with 1,553 images. The VGG-face model used in this study achieved an accuracy of 96.7%. Some of the

Table 5
Previous studies on computer vision and deep learning technologies for weed management.

References	Objectives and scenario of application	Methodology	Crop	Results
(Le et al., 2020)	Weed identification in Canola, corn and raddish	Filtered Local Binary Pattern withContour Mask and Coefficient k (k-FLBPCM), VGG-16, VGG-19,ResNet-50, Inception-v3	Canola, corn, radish	K-FLBPCM method outperformed other state of the art CNN models.
(Osorio et al., 2020)	Weed detection in lettuce	Compared Mask R-CNN with HOG SVM and YOLO V3	Lettuce	98% accuracy for Mask R-CNN
(Chavan and Nandedkar, 2018)	Weed identification in paddy field	Comapred SegNET with FCN and U-Net	Rice	92.7% accuracy for SegNet
(Chavan and Nandedkar, 2018)	Weed classification at field level	Comapred Hybrid network with VGGNet and AlexNet	Maize,wheat, sugarbeet	98.23% accuracy for Hybrid network
(Fawakherji et al., 2020)	Crop/weed segmentation using synthetic images	Synthetic image generation using GAN and segmentation models (UNET, BONNET,SEGNET, UNET-RESNET)	Sugar beet	All models were performed well with synthetic images generated using GAN and IoU increased drastically using synthetic dataset.
(Wang et al., 2020)	Weed detection in sugarbeet and oilseeds	FCN architecture employed	Sugarbeet and oilseeds.	Best MIoU value (pixel-wise segmentation) 88.91% and object-wise segmentation 96.12%
(Espejo-Garcia et al., 2020)	Detection of balck night shade and velvet leaf in tomato and cotton fileds	Compared Modified Xception, with Inception - ResNet, VGG-Net, MobileNet and DenseNet	Tomato and cotton	Combination of fine tuned Densenet and SVM.micro F1 score of 99.29%.F1 score ≥ 95% over repeated tests.
(Huang et al., 2020)	Weed in rice field	FCN	Rice	Highest accuracy- VGG Net based FCN
(Veeranampalayam Sivakumar et al., 2020)	Weed in soybean filed	Compared Single-Shot Detector (SSD), Faster R-CNN	Soybean	Faster RCNN as the best model for weed detection performance and inference time

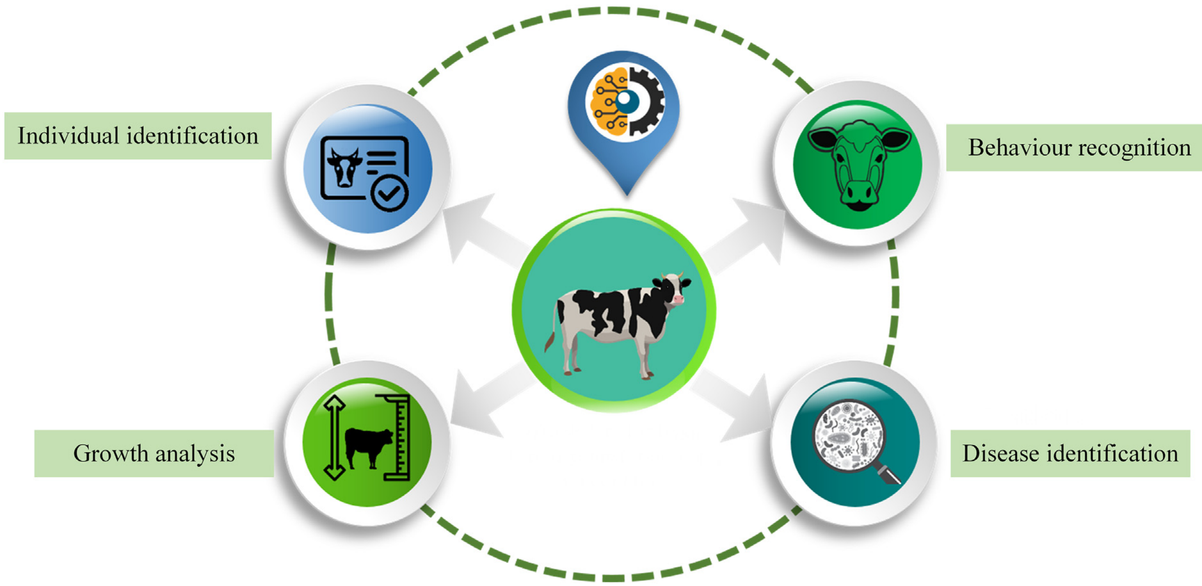

Fig. 9. Major applications of DL-Computer vision for livestock management

investigations relied on data collection using unmanned aerial vehicles to accurately detect and count the cattle (Andrew et al., 2019; Chamoso et al., 2014; Rahnemoonfar et al., 2019; Rivas et al., 2018). Such detection and counting approach problems, in general, have adopted either CNN-based probability heat map generation on the location of the animals or generation of bounding boxes for detection of the animals. An improved Yolo model called 'FLYOLOv3' (FilterLayer YOLOv3) based on Filter layer was introduced by Jiang et al. (2019) to ensure accurate detection of key parts of dairy cows. The performance of this approach was superior to the Faster-RCNN and Yolov3 algorithms.

Daily activity patterns, food intake, and ruminating are some key indicators closely bound to the health and productivity of dairy cows (Huzzey et al., 2007; Weary et al., 2009). Some recent studies underline that traditional methods of direct observation and time-lapse video recording are slowly getting replaced by computer vision approaches. Yang et al. (2018) used a Faster-RCNN model to identify individual pigs from a group and subsequently assess the feeding area occupation rate to identify their feeding behaviour. To improve the accuracy of feeding behavior analysis, identify and exclude the non-nutritive visits (NNV) to the feeding area, Alameer et al. (2020) developed a GoogLeNet-based approach. The detection of feeding behaviour was highly accurate with 99.4% accuracy. CNN architectures are also found to be promising for early cattle disease detection in the animal husbandry farm (Rony et al., 2021). Table 6 shows the previous studies on computer vision technology for livestock management.

3.7. Yield estimation

Early and accurate yield estimation is essential for farmers and other stakeholders in making strategic decisions on post-harvest planning, policy-making and crop management (Al-Gaadi et al., 2016; Chlingaryan et al., 2018; Wei et al., 2020). Some of the studies underline that yield estimation using deep learning-based computer vision on aerial images is superior to traditional approaches. In a study conducted by Yang et al. (2019) rice grain yield from low-altitude remote sensing data was used to estimate the rice grain yield using convolutional neural networks. The models were trained on both RGB and multispectral images collected by UAV, and results showed that the CNN trained on these images outperformed the VIs-based traditional regression models for grain yield estimation at the ripening stage.

You et al. (2017) employed a combination of convolutional neural networks and recurrent neural networks based on the remotely sensed images to predict the soybean yield. Another investigation carried out by Russello (2018) utilized satellite images in combination with convolutional neural networks for crop yield prediction. In case of orchard crops like citrus, computer vision approaches are quite straightforward (Fig. 10). The yield can be estimated by directly counting the number of flowers or fruits prior to the harvesting stages (Cheng et al., 2017; Dorj et al., 2017; Kanwal et al., 2019). With an objective of estimating yield from citrus orchards, Apolo-Apolo et al. (Apolo-Apolo et al., 2020)developed a Faster-RCNN model for the fruit detection. The data collected through UAV was used for the model development. In their study, based on the count, yield from orchards was modelled using the Long Short-Term Memory (LSTM) model. An attempt was made by Zhou et al.(Zhou et al., 2020)to deploy the yield estimation models in smartphones as android applications. In his investigation, four different computer vision models; SSD with MobileNetV2, quantized MobileNetV2, InceptionV3, and quantized InceptionV3 were trained and converted to TensorFlow Lite models. As reported by studies, fruit occlusion caused by leaves and twigs and varying illumination conditions are some challenging factors in implementing fruit yield estimation systems based on computer vision (Maheswari et al., 2021). Table 7 shows the previous studies on computer vision technology for yield estimation.

4. Practical implications

Despite being late for digitization, the agriculture sector has finally seen good momentum for the practical implementation of several artificial intelligence applications, including deep learning-based computer vision approaches. Computer vision-powered disease identification applications merge the expertise of genetic resources and artificial intelligence, allowing farmers and extension workers to act quickly and rescue the crop. This disease detecting computer vision-enabled software is also being installed inside greenhouses, drones, and other equipment to identify the issues and provide a faster response in taking preventive measures. Advancement in computer vision technology has been used by agricultural startups for building solutions that assist farmers in harvesting, plant health monitoring, pest-weed control, etc. For pesticide application, blue river technology (Blue river technology) developed a see and spray' technology that works based on camera

Table 6
Previous studies on computer vision and deep learning technologies for livestock management.

References	Objectives and scenario of application	Methodology	Livestock	Results
(Qiao et al., 2019b)	Cattle Segmentation and Contour extraction	Mask R-CNN based cattle instance segmentation and contour line extraction	Cattle	Cattle segmentation performance with 0.92 Mean Pixel Accuracy (MPA)
(Achour et al., 2020)	Identification and feeding behavior monitoring	CNN coupled to Support Vector Machine (SVM)	Cow	Accuracy 97% for individual identification of cows using multi-CNN.
(Xu et al., 2020)	Livestock classification and counting	Mask RCNN based segmentation on UAV captured images	Cattle and Sheep	Classification Accuracy: 96% and Counting accuracy: 92%
(Jung et al., 2021)	Cattle Vocal Classification and Livestock Monitoring	Convolutional neural network (CNN) based cattle vocal classification	Cattle	Accuracy of 81.96% after the sound filtering.
(Qiao et al., 2022)	Behaviour classification	C3D-ConvLSTM based cow behaviour classification using video data	Cow	Classification accuracy of 90.32% and 86.67% in calf and cow datasets of 30-frame video length
(Abu Jwade et al., 2019)	Breed Classification	VGG16 model for breed classification	Sheep	Maximum classification accuracy of 95.8% with 1.7 standard deviation.
(Shojaeipour et al., 2021)	Automated Muzzle Detection and Biometric Identification	Two-stage YOLOv3-ResNet50 algorithm	Cattle	Muzzle detection accuracy was 99.13% and biometric identification of 99.11% testing accuracy
(Brand et al., 2021)	Pregnancy status prediction from mid-infrared spectroscopy	Genetic algorithm and DenseNet model	Cow	DenseNet was superior over GA with prediction sensitivity 0.89, specificity of 0.86, and prediction accuracy of 0.88%.
(Ayadi et al., 2020)	Rumination behavior identification	Convolutional Neural Networks	Cow	Average accuracy, recall and precision were 95%, 98% and 98% respectively
(Riekert et al., 2020)	Position and posture detection	Faster R-CNN object detection	Pig	Pig position detection: Average Precision (AP) 87.4% Pig position, and pig position and posture: mAPof 80.2%.

inputs and computer vision algorithms. The algorithm can distinguish weeds from plants and perform targeted pesticide applications. The startup, cromai (Cromai) developed AI-driven land and crop diagnostic information. They provide a technological solution for georeferenced identification of weeds in the sugarcane field using advanced artificial intelligence approaches. Harvesting robots are widely used in open field conditions, integrating with machine visions and achieving improved precision. Harvest CROO robotics (Harvest croo robotics) developed a fully autonomous harvester, employing a harvester-mounted LIDAR system to avoid collisions and accurate navigation. The computer vision system scans each berry on the plant and determines the ripeness and health before harvesting. 'Plantix', the crop damage diagnosis mobile application (Plantix) developed by German startup PEAT (Progressive Environmental and Agricultural Technologies), uses deep learning and computer vision to help farmers to combat pests and diseases (Goncharov et al., 2018; Tibbetts, 2018). The application's functionality enables the end-user to upload crop images and get guidance on the disease affected, symptom descriptions, treatment information, preventive measures, etc. With the same objective of identifying a large number of plant diseases, other applications such as Agrio (Agrio) were also introduced to the farming community. Several technology-driven solutions were introduced into precision livestock farming to ensure optimal health and output of animals also. The technology startup Cainthus (Cainthus) offers a computer vision-driven AI system for dairy farmers to monitor their cows and send timely alerts and reports via associated applications. Smart cameras are deployed to watch over the activities of the cows to provide the right amount of feed available on a timely basis. Similar to this, Piguard (Piguard), an innovative livestock management software, leverages deep learning-based computer vision approach to monitor the health status and behavioral patterns of animals.

Computer vision technology covers a broad spectrum of solutions for farmers, from small AI-enabled mobile apps for decision support, over in-field imaging sensors and remote sensing technologies for data collection, and to drones and robots for the automation of processes. Across the globe, farming community has realized the potential of digital technologies and for the past few years, there has been an increase in its adoption. Some of the key factors influencing the transformation of farms into digital farms include farm characteristics, operator characteristics, interactions, institutions, attributes to technology, and

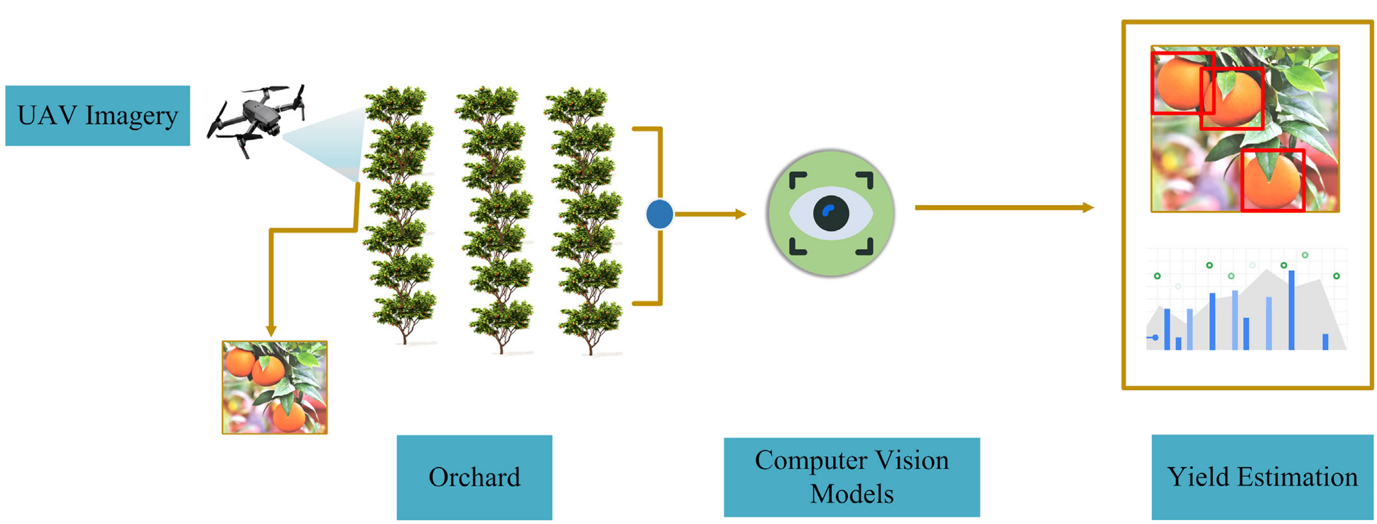

Fig. 10. Orchard yield estimation using computer vision.

Table 7
Previous studies on computer vision and deep learning technologies for yield estimation.

References	Objectives and scenario of application	Methodology	Crop	Results
(Khaki et al., 2020)	Image-based corn kernel counting and yield estimation	Truncated VGGNet backbone and semi supervised deep learning.	Corn	MAE and RMSE of 41.36 and 60.27 respectively.
(Apolo-Apolo et al., 2020)	Yield map Generation	Region-CNN (RCNN) Model using UAV imagery	Apple	R-squared value: 0.86, MAE: 10.35 and RMSE: 13.56
(Palacios et al., 2020)	Detection of flower at bloom for yield estimation	CNN SegNet architecture with a VGG19 network encoder	Grape	A determination coefficient (R2) of 0.91 between the actual and detected flowers.
(Faisal et al., 2020)	Intelligent harvesting decision system based on date fruit maturity level.	VGG-19, Inception-v3, and NASNet Models	Date	Performance metrics of IHDS were 99.4%, 99.4%, 99.7%, and 99.7% for accuracy, F1 score, sensitivity (recall), and precision, respectively.
(Yang et al., 2019)	Rice grain yield forecasting using UAV images	CNN models with RGB and multispectral datasets	Rice	Prediction accuracy: MAPE: 20.4%, RMSE: 0.658 and R-squared: 0.585
(Tedesco-Oliveira et al., 2020)	Yield estimation using object detection models	Faster RCNN, SSD and SSD Lite Models	Cotton	Mean percentage error of 8.84%
(Chen et al., 2019)	Yield prediction by counting number of flowers and maturity analysis, using aerial ortho images	Faster RCNN model	Strawberry	The average deep learning counting accuracy was 84.1% with average occlusion of 13.5%.
(Bargoti and Underwood, 2017)	Yield Estimation using fruit detection and counting	CNN and Watershed algorithm	Apple	The count estimates using CNN and WS with R-squared value of 0.826
(Zhou et al., 2020)	Real-time fruit detection and yield estimation through smartphones.	Single shot Multibox Detector with MobileNetV2, quantized MobileNetV2, InceptionV3, and quantized InceptionV3 Models	Kiwi	MobileNetV2, quantized MobileNetV2, InceptionV3, and quantized InceptionV3 obtained TDR of 90.8%, 89.7%, 87.6%, and 72.8%, respectively.
(Rahnemoonfar and Sheppard, 2017)	Fruit counting based on deep simulated learning	Modified version of the Inception-ResNet Model	Tomato	91% average test accuracy on real images and 93% on synthetic images

psychological factors (Shang et al., 2021). Larger farms are more likely to adopt these technologies by taking advantage of economies of scale, and they can afford the higher initial investment cost. Use of complementary technologies can also lead to better adoption of technologies. For example, the variable rate technology and yield mapping are interrelated, and farmers who are using variable rate technologies are more likely to adopt yield mapping technologies. Operator characteristics such as end user's education level, age, on-farm digital device such as computer usage are also significant (Isgin et al., 2008). Operators having higher education levels and innovativeness could adopt the new technologies faster (Aubert et al., 2012). Isgin et al. (2008) found significant evidence relating to the impact of urban influences on adoption of precision farming technologies in their empirical analysis. Mohr and Kühl (2021) investigated the behavioral factors influencing the acceptance of artificial intelligence technologies using a theoretical framework. The results showed that behavioral control and personal attitude of the farmers are the two most influential factors in the acceptance of artificial intelligence in agriculture.

5. Challenges and way forward

Deep learning for computer vision, the spearhead of artificial intelligence, is perhaps one of the most promising technologies for meeting the ever-growing food demand. Several intractable problems in agriculture are being solved with the support of DL-computer vision. However, high innovation capability always comes along with some challenges. One major challenge in computer vision using deep learning includes the requirement of massive processing power, and most deep learning applications are data-intensive. A possible solution to this is the adoption of cloud-based solutions that offer auto-scaling, load balancing, easier maintenance, and high availability features. However, cloud solutions limit real-time processing due to the latency in access and retrieval of the data from the cloud. The increased cost of immense data processing and privacy issues are also other concerns. Advanced edge devices with accelerators are capable of analyzing real-time video inputs and providing inferences in near real-time. Deployment of the computer vision solutions in edge devices can reduce the latency limitations. Sophisticated computer vision models in a variety of agricultural use cases often do not perform as expected in the production environment. To ensure that a promising model is not becoming a costly liability, several aspects like data quality check, code inspection, hyperparameter tuning, code versioning, setting up the right deployment environment, rigorous training and re-training, etc, need to be closely evaluated.

Quality of data is another major concern for developing efficient data-driven solutions (Cai and Zhu, 2015; Carletto, 2021). Programmatically generating synthetic data is one of the approaches for enhancing the data quality in deep learning-based computer vision solutions (Fig. 11). Generative adversarial networks and their variations like CGAN can generate synthetic data for agricultural applications quite effectively (Cui et al., 2021; Olatunji et al., 2020; Zhu et al., 2020a). The performance of a DL-CV model relies heavily on the right hyperparameter configurations. There are no simple ways to set hyperparameters such as learning rate, batch size, momentum, weight decay, etc, and it demands expertise and extensive trial and error to achieve the best performance. The process of configuring the hyperparameter in a high-dimensional space is not a trivial challenge. Computer vision problems, more specifically object detection approaches face practical implementation challenges such as viewpoint variation, deformation, occlusion, varying illumination conditions, complex backgrounds, and speed. Viewpoint variation is very common in object detection, and segmentation problems, as the object may look at different viewing angles. For e.g., a crop may look different when captured from different angles. The additional complication appears due to the occlusion.

In fruit yield estimation systems, this is a major concern and causes sharp declination in the overall accuracy of the system. Varying illumination conditions and extraction of data from complex overlapped and textured backgrounds also make the computer vision task challenging. In real-time video applications, performance in terms of detection speed and accuracy are crucial for detecting objects in motion. Research in computer vision is growing at a faster pace in the agriculture domain. Building a robust computer vision system requires quality data generation, transfer, and processing. The system should have adequate security to block attacks. Heterogeneity of resources involved in CV solutions introduces a lot of security concerns, such as data integrity, privacy issues,

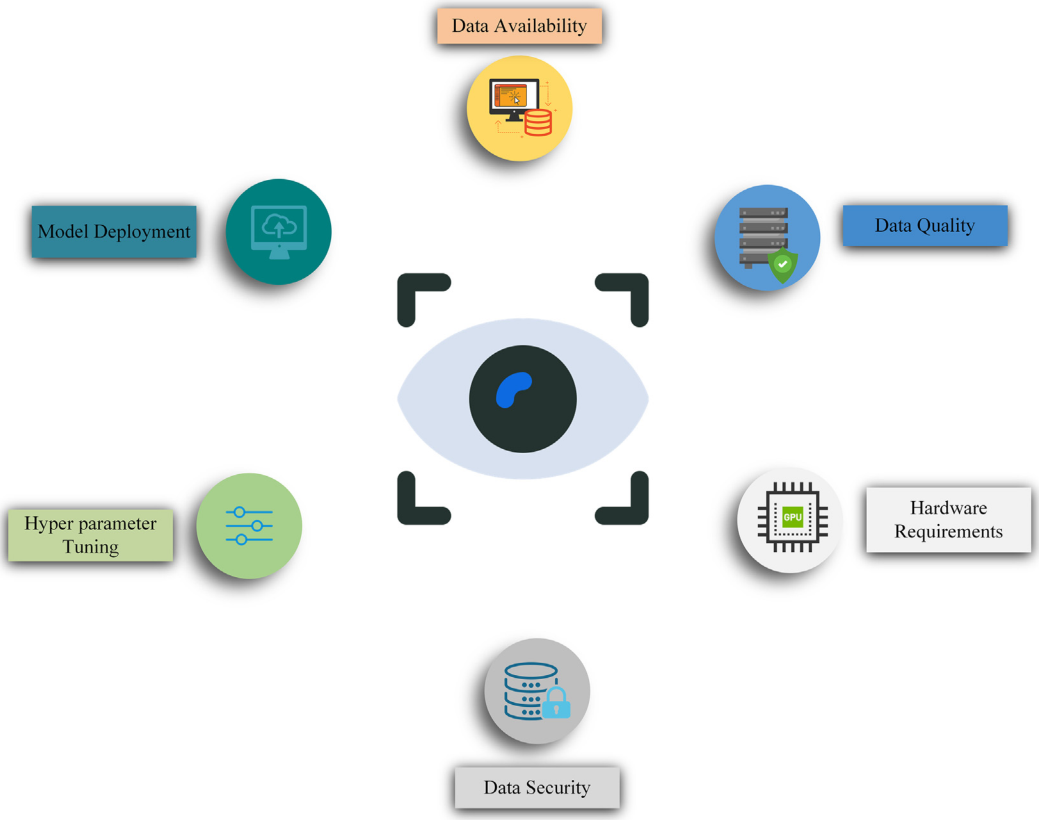

Fig. 11. Challenges in implementation of deep learning based computer vision.

reliability, etc. As these solutions integrate several digital technologies starting from the internet, IoT, cloud computing or edge computing, and wireless sensor networks, the system should accommodate security features for all these technologies and ensure data and device integrity, data accuracy, and availability. From land preparation to harvesting, different stakeholders are leveraging new ways to improve the ability to derive insights from images, object detection and tracking, etc. Deep learning - computer vision models will undoubtedly continue to expand and become more innovative and intelligent, handling more complex computations in agriculture with utmost precision. Above all, for obtaining efficient and desirable outputs, strong business cases with the capability to scale on a larger scale is necessary.

6. Conclusions

The surge of deep learning coupled with computer vision over the past few years has brought automation capabilities to traditional agriculture practices. In this paper, we have extensively discussed the role of deep learning-based computer vision in different agriculture applications. More specifically, the paper emphasizes seven different application areas such as seed quality analysis, soil analysis, irrigation management, plant health analysis, weed management, livestock management, and yield estimation. Review of the application of deep learning particularly, the assessment and planning of water resources revealed that the water sector would continue to embrace deep learning at an accelerated rate, and it will play a significant role in the future of water-related research and the wide range of application areas. Technologies powered by deep learning have created a myriad of application and research opportunities that have the potential to change hydrological science and workflow. Recent advances in deep learning-assisted image analysis involving algorithms for image classification, object detection, segmentation, etc., have expanded their applications across different pre-and post-harvesting activities in agriculture.

The following conclusions can be drawn from the study.

- Deep learning-based computer vision has tremendous automation capabilities across different applications such as automated plant health monitoring, weed detection, irrigation management, livestock management, yield estimation, etc.
- Integration of the deep learning computer vision approaches with the UAV, and spectral data can help in building advanced-intelligent solutions.
- Despite the benefits computer vision and deep learning brought to agriculture, significant challenges do remain, especially the data quality issues, the computation power requirement, etc.
- The extensive automation across various agriculture activities will continue to attract the interest of the deep learning research community in the years to come.

The adoption rate of advanced technologies in agriculture is relatively slow, owing to the high initial investment required, lack of technical expertise, and growing concerns about data privacy. However at present, the rate of the adoption of these digital solutions has seen a rising curve, thus suggesting that these would not be concerns in moving forward.

Declaration of Competing Interest

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

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