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Machine learning in agriculture domain: A state-of-art survey

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A B S T R A C T

Food is considered as a basic need of human being which can be satisfied through farming. Agriculture not only fulfills humans' basic needs, but also considered as source of employment worldwide. Agriculture is considered as a backbone of economy and source of employment in the developing countries like India. Agriculture contributes 15.4% in the GDP of India. Agriculture activities are broadly categorized into three major areas: pre-harvesting, harvesting and post harvesting. Advancement in area of machine learning has helped improving gains in agriculture. Machine learning is the current technology which is benefiting farmers to minimize the losses in the farming by providing rich recommendations and insights about the crops. This paper presents an extensive survey of latest machine learning application in agriculture to alleviate the problems in the three areas of pre-harvesting, harvesting and post-harvesting. Application of machine learning in agriculture allows more efficient and precise farming with less human manpower with high quality production.

1. Introduction

Agriculture is considered an important pillar of the world's economy and also satisfies one of the basic need of human being i.e. food. In most of the countries it is considered the major source of employment. Many countries like India still use the traditional way of farming, farmers are reluctant to use advanced technologies while farming because of either the lack of knowledge, heavy cost or because they are unaware about the advantages of these technologies. Lack of knowledge of soil types, yields, crops, weather, and improper use of pesticides, problems in irrigation, erroneous harvesting and lack of information about market trend led to the loss of farmers or adds to additional cost. Lack of knowledge in each stage of agriculture leads to new problems or increases the old problems and add the cost to farming. Growth in the population day by day also increases the pressure on the agriculture sector. Overall losses in the agriculture processes starting from crop selection to selling of products are very high. As per the famous saying "Information is the Power", keeping track of information about the crops, environment, and market, may help farmers to take better decisions and alleviate problems related to agriculture. Technologies like blockchain, IoT, machine learning, deep learning, cloud computing, edge computing can be used to get information and process it. Applications of computer vision, machine learning, IoT will help to raise the production, improves the quality, and ultimately increase the profitability of the farmers and associated domains. The Precision learning in the field of agriculture is very important to improve the overall yield of harvesting.

Blockchain technology, cloud computing, internet of things (IoT), machine learning (ML) and deep learning (DL) are the latest emerging trends in the computer field. It has been already used in different domains like healthcare, cybercrime, biochemistry, robotics, metrology, banking, medicine, food etc. to solve the complex problems by the researchers. Many applications of machine learning, IoT in different domains are presented [1–5]. Deep learning algorithms are making machine learning more powerful and accurate. By using automated machine learning (AutoML) one can cut the demand of ML experts, automate the ML pipeline with more accuracy.

While performing agriculture tasks the steps as below is generally followed by farmers.

Step 1: Selection of Crop
Step 2: Land Preparation
Step 3: Seed Sowing
Step 4: Irrigation & fertilizing
Step 5: Crop Maintenance [use of pesticides, crop pruning etc.]
Step 6: Harvesting
Step 7: Post-Harvesting activities

As per the above algorithm, the agriculture related tasks are categorized in the for major sub areas. Fig. 1 shows these four sub-domains of agriculture tasks.

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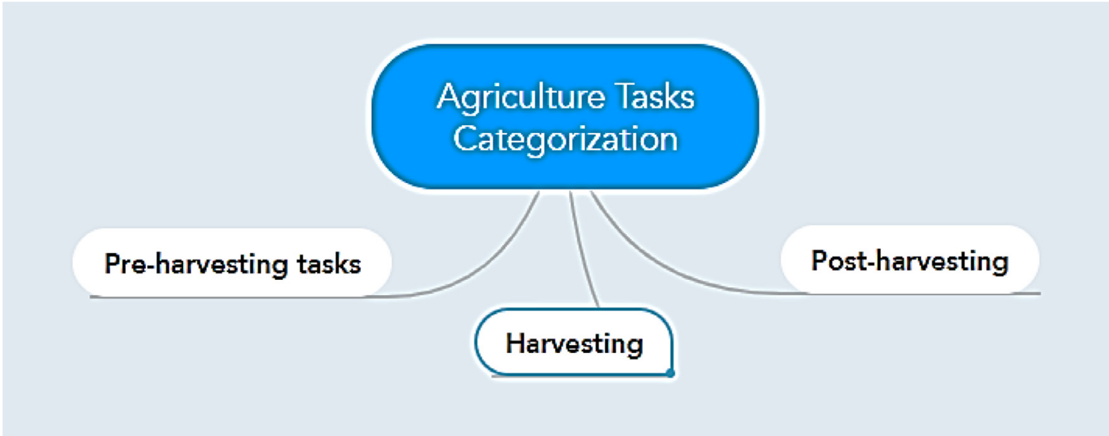

Fig. 1. General categorization of agriculture tasks.

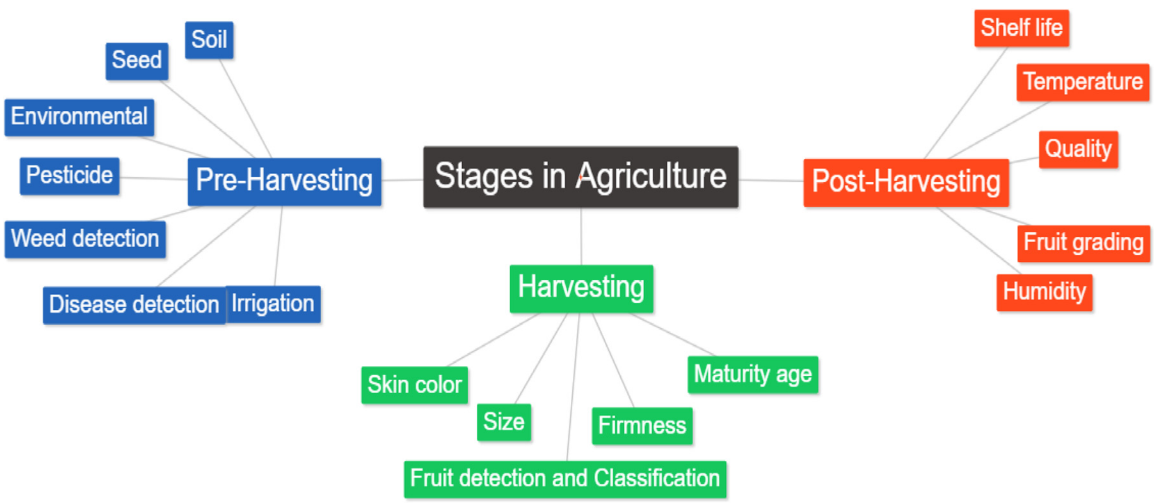

Fig. 2. Important parameters considered in each stage of farming.

Table 1
Important factors to be considered in each stage.

S. No.	Stage	Activities / Factors	References
1	Pre-harvesting	Soil, seeds quality, fertiliser/pesticide application, pruning, cultivar selection, genetic and environmental conditions, irrigation, crop load, weed detection, disease detection.	[6, 7, 9]
2	Harvesting	Fruit/crop size, skin color, firmness, taste, quality, maturity stage, market window, fruit detection and classification.	[7]
3	Post-harvesting	Factors affecting the fruit shelf-life such as temperature, humidity, gasses used in fruit containers, usage of chemicals in postharvest and fruit handling processes to retain the quality, fruit grading as per quality.	[7]

During pre-harvesting tasks farmers focuses on selection of crops, land preparation, seed sowing, irrigation, and crop maintenance which includes use pesticides, pruning etc. In yield estimation the farmers do the activities like yield mapping and counting the number of fruits so that they can predict the production and make the necessary arrangements required at the time of harvesting or post-harvesting. While harvesting farmers are focused on maturity of crops or fruits market need quality. Whereas in post-harvesting farmers are focused on post-harvest storage and processing systems. Fig. 2 shows the important factors that should be considered in each stage of farming. Table 1 summarizes few works in each stage of agriculture tasks.

The major branches of the agriculture are Agronomy, Horticulture, Forestry, Livestock, Fisheries, Agriculture Engineering and Economics. The scope of the paper is confined to use of machine learning in agriculture, specifically on fruits.

In the following sections, the review of the most recent techniques of machine vision systems used for classification and object detection in each stage of farming is presented. Section 2 explains the use of ML in the pre-harvesting stage. In Section 3, usage of ML in the stage of harvesting is explained and in Section 4 usage of ML in the post-harvesting stage is explained. Sections 5 and 6 focuses on discussion and challenges in use of the Artificial Intelligence (AI), ML, and DL.

2. Pre-harvesting

Pre-harvesting parameters play a key role in overall growth of crop/fruits. In pre-harvesting machine learning is used to capture the parameters of soil, seeds quality, fertilizer application, pruning, genetic and environmental conditions and irrigation. Focusing on each component it is important to minimize the overall losses in production. Here few important components in the pre-harvesting are considered and how neural networks and machine learning are used to capture the parameters of each component.

Table 2
Analysis of pre-harvesting parameter: Soil.

S. No.	Property	Important features	Classes defined in the work	Dataset used (Public / Own)	Total number of images used for training	Models / Method / Algorithms compared	Best model / method/ algorithm	Results	Reference
1	Soil	Village wise soil fertility indices of available Soil Reaction (pH), Organic Carbon (OC) and Boron (B), Phosphorus (P), and Potassium (K)	For P, K and OC three classes: Low, Medium, and High. For B six classes: Very Low, Low, Medium, Moderately High, High, and very High. For pH Four classes: Strongly Acidic (SA), Highly Acidic (HA), Moderately Acidic (MA), and Slightly Acidic (SLA).	public (reports available during the years 2014 to 2017)	NA	Extreme Learning Machine (ELM) with different activation functions like sine-squared, Gaussian radial basis, triangular basis, hyperbolic tangent, and hard limit	ELMs with Gaussian radial basis function	80% of accuracy	[10]
2		Soil Organic matter (SOM) and pH parameter	SOM and pH parameters	Own	523 soil samples	four Machine Learning models Cubist regression model (Cubist), extreme learning machines (ELM), least squares-support vector machines (LS-SVM), and partial least squares regression (PLSR)	ELM	R2 = 0.81	[11]
3		Moisture content (MC), organic carbon (OC), and nitrogen (TN)	Estimating moisture content (MC), organic carbon (OC), and nitrogen (TN)	Own	140 set	Cubist, partial least squares regression (PLSR), least squares support vector machines (LS-SVM), and principal component regression (PCR)	LS-SVM is best for MC and OC and TN is best by the Cubist	MC - RMSEP:0.457%, RPD:2.24 TN - RMSEP: 0.071 and RPD :1.96	[12]
4		soil moisture	Auto-regressive error function (AREF) combined with computational models	Own The soil moisture and density were determined by volumetric rings with 100 cm3 collected in eight positions along the plots, at depths from 25 mm to 75 mm	NA	One Neuro-Fuzzy model (ANFIS) and two artificial neural networks (a Multi-Layer Perceptron (MLP) and a Radial Basis Function (RBF)). Multiple linear regression (MLR) models with two and six independent variables	Neural Network with AREF	RMSE between 1.27% and 1.30%, R2 around 0.80, and APE between 3.77% and 3.75%	[13]
5		Soil Temperature	soil temperature (ST) at 6 different depths of 5, 10, 20, 30, 50 and 100 cm	Public (For Bandar Abbas, 10 years measured data sets for the period of 1996–2005 and for Kerman, 7 years measured data sets for the period of 1998–2004)	NA	ELM, SaE-ELM, genetic programming (GP) and artificial neural network (ANN)	SaE-ELM	MABE - 0.8660–1.5338 C R - 0.9084–0.9893	[14]

2.1. Soil

Liakos, et al. [8] and Sharma, et al. [9] presented a soil management survey with the application of ML techniques for prediction or identification of soil properties (estimation of soil temperature, soil drying, and moisture content). The categorization and estimation of the soil attributes help farmers in minimizing extra cost on fertilizers, cut the demand of soil analysis experts, increase profitability, and improve health of soil, whereas Suchithra and Pai [10] presented pH values and soil fertility indices classification and predication model. Yang, et al. [11] observed that important indicators of soil fertility are pH values and Soil Organic matter (SOM) and thus the authors have done prediction of SOM and pH parameters in paddy soil. Morellos, et al. [12] has predicted organic carbon (OC), nitrogen (TN), and moisture content (MC) parameters of the soil. The aim of study was to compare machine learning algorithms and linear multivariate algorithms on basis of their performance of prediction. As soil moisture is frequently associated with variability in yield, Johann, et al. [13] have estimated the moisture content of soil using with Auto-regressive error function (AREF) along with machine learning algorithms. Nahvi, et al. [14] developed a new model by employing Self-adaptive evolutionary (SaE) agent in extreme machine learning (ELM) architecture. This new model is used for the assessment of daily soil temperature (ST) at 6 different depths of 5, 10, 20, 30, 50 and 100 cm. The detail summary of work done by different authors on soli parameter is mentioned in Table 2.

2.2. Seeds

Seed germination is a vital factor for quality of seed, which is an important determining factor of yield and quality of production. Seed germination rate calculation is still done manually with the help of trained persons which is not only a tiresome process but also prone to error. Thus, various machine leaning and image recognition techniques have been proposed by different authors to automate the process of seed sorting and calculation. Various computer vision, machine learning techniques, Convolution Neural Network (CNN) methods have been presented in D. Sivakumar, et al. [15], Huang, et al. [16], Zhu, et al. [17]. Image recognition technique for seed sorting with high accuracy is developed by Young, et al. [18]. Ke-ling, et al. [19] used a multilayer perceptron neural network model for improving the accuracy of the classification method to separate pepper seeds of high-quality from low-quality. Uzal, et al. [20] and Veeramani et al. [21] used the deep neural network (DNN) model using CNN for the assessment of the quantity of seeds per pod in soybean and for sorting of haploid seeds on basis of shape, phenotypic expression, and the embryo pose. Nkemelu, et al. [22], built a model using CNN for plant seedlings classification into 12 species. Medeiros, et al. [23] assessed the proficiency of computer vision as an alternative to routine vigor tests to expedite the process of accurate evolution of seed physiological potential. Amiryousefi, et al. [24] used image analysis technique, principal component analysis (PCA), to save time and cost of placing seeds in different clusters by reducing the features to be considered for clustering. Vlasov, et al. [25], Kurtulmuş, et al. [26] used machine learning (ML) techniques for efficient seed classification. The detail summary of work done by different authors is mentioned in Table 3.

2.3. Pesticides and disease detection

In-time disease detection is the most important task to save crops from major loss. Some farmers regularly analyze 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. This section discusses bout disease detection using machine learning.

Alagumariappan, et al. [27], developed a real-time decision support system integrated with a camera sensor module for plant disease identification. In this work authors evaluated the performance of three machine learning algorithms namely, Extreme Learning Machine (ELM) and Support Vector Machine (SVM) with linear and polynomial kernels and observed that the performance of ELM is better when compared to other algorithms. Savary, et al. [28] studied how diseases cause the crop losses and their implications for global food production losses and food security. The objective of this work is to show that crop loss research is vital and should be consider as full branch of plant science.

Sujatha, et al. [29], compared the ML algorithms (SVM, RF, SGD) with DL algorithms (Inception-v3, VGG-16, VGG-19) in terms of citrus plant disease detection and observed that DL methods performed much better. Karadağ, et al. [30] studied detection of healthy and fusarium diseased peppers (capsicum annuum) from the reflections obtained from the pepper leaves with the help of spectroradiometer. Artificial Neural Networks (ANN), Naive Bayes (NB) and K-nearest Neighbor (KNN) machine learning algorithms were used for classification. Authors claimed that leaf reflections can be used in disease detection. Pandya [31], presented data about different types of pesticides, their applications and impact on environment. Arsenovic, et al. [32] discussed the shortcomings of available DL models used for plant disease detections. A novel model is built which consist of two-stage architecture Disease Net, for classification of plant disease, which achieved 93.67% training accuracy. Barbedo [33], explored the new approach by using DL to identify plant diseases from individual lesions and spots instead of considering entire leaf. This approach helps to detect multiple diseases on the same leaf with 12% higher accuracy. Saleem, et al. [34], presented a detail review of DL models used to envision different diseases of plant. Many research gaps have been enlisted in the plant disease detection and suggested that advanced DL algorithms should be used to increase the accuracy.

Liu, et al. [36], Kour, et al. [37] studied the apple leaf diseases and apple fruit diseases respectively. A CNN model was proposed to classify apple leaf diseases into Brown spot, Rust, Mosaic, and Alternaria leaf spot. A new dataset was created consisting of 13,689 images of diseased leaves which was used to train the novel architecture based on AlexNet in [34]. For apple disease detection and classification in Kashmir Valley, another model called Fuzzy Rule-Based Approach for Disease Detection (FRADD) was proposed in [35]. Though the accuracy of the model is good, it takes into account only one disease known as scab and limited numbers of fruit types. Xing, et al. [38] proposed a new model called Weakly DenseNet-16, to overcome the limitations of pre-trained models which are trained on ImageNet dataset. A dataset consisting of 17 species of citrus pests and seven types of citrus diseases (9051 images of citrus pests and 3510 images of citrus diseases) was created. Weakly DenseNet-16 performed well with the accuracy 93.33% as compared to MobileNet-v1 (85.04%), MobileNet-v2 (87.82%), ShuffleNet-v1 (83.44%), ShuffleNet-v2 (83.21%), NIN-16 (91.66%), SENet-16 (88.36%), and VGG-16 (92.93%). Doh, et al. [39] proposed a solution to detect the citrus fruit diseases using their physical attributes such as the texture, color, structure of holes on the fruit and morphology. The proposed solution composed of K-Means clustering technique, ANN and SVM algorithms. Results show that the use of SVM with ANN helps in increasing disease detection and classification rate. The detailed summary of the published works is presented in Table 4.

3. Harvesting

After taking care of parameters in pre-harvesting stage like soil, seeds, weeds etc., when the fruits/vegetables are ready then harvesting is the most important stage. The important parameters should be focused in this stage are fruit/crop size, skin color, firmness, taste, quality, maturity stage, market window, fruit detection and classification for harvesting. Careful and right harvesting of fruit is directly correlated with the profit. In the survey, we observed that auto-harvesting robots, machine learning, deep learning techniques are achieving better results and helping farmers in reducing the losses in harvesting stage. This section presents the application of ML, DL algorithms in the harvesting.

Hua, et al. [40] presented a detail survey on automated fruit harvesting systems for sweet pepper, tomato, apple and kiwifruit as an example to demonstrate the recent advances in intelligent automatic harvesting robots in horticulture. The use automatic robots in field helps to increase the production, saves the harvesting time which ultimately increase the profits of the farmers. Kushtrim, et al. [41] developed a CNN model based on single shot detector (YOLO) algorithm for on-tree fruit detection. A dataset consisting of real and synthetic images of apple and pear trees was created. For labeling the images, open-source labeling tool called as BBox-Label-Tool was used. More than 5000 images of pear and apple fruits were used while training the model. Amazon cloud platform was used to train the model. The model achieved more than 90% accuracy for on-tree fruit detection. Two deep neural network models were investigated in the proposed work, a small CNN model and a VGG-16

Table 3
Analysis of pre-harvesting parameter: Seed.

Sr. No.	Property	Important features	Classes defined in the work	Dataset used (Public / Own)	Total no of images used for training	Models / Method / Algorithms compared	Best model / method / algorithm	Results	Model evaluation technique	Reference
1	Seed	color, shape, and texture	maze seed	Own	4000	ensemble learning, K-nearest neighbor (KNN), logistic regression, support vector machine (SVM), and Speeded Up Robust Features (SURF) algorithm to classify the extracted features, GoogLeNet, VGG19	GoogleNet	95%	Confusion Table, Training loss. Testing loss. Training accuracy. Testing accuracy	[16]
2	Cotton Seed		Jinxin5, Jinxi7, Shennongmian1, Xinjiangzaomian13, Xinluzao-mian29, Xinluzhong52 and Xinluzhong42	own, dataset collected from Shihezi, Xinjiang Uyghur Autonomous Region, China	13,160	SVM, PLS-DA, and LR models based on deep features extracted by self-design CNN and ResNet models	self-design CNN	80%	classification accuracy	[17]
3	pepper seeds	15 features (ten color features: R, G, B, L*, a*, b*, hue, saturation, brightness, and Gray, three geometric features: width, length, and projected area, seed weight and density)	germinated seed (1) and un-germinated seed (0)	Own	400 seeds	multilayer perceptron (MLP); BLR binary logistic regression, single feature models	multilayer perceptron and binary logistic regression	90%	classification accuracy	[19]
4	soybean pods	38 tailored features, geometrical characteristics (area, perimeter, major and minor axis length), shape features (density, elongation, ompactness, rugosity and axis ratio), first 4 Hu moments, and finally a 25 bins histogram of the profile of the pod straighten mask added along the short axis	2-SPP, 3-SPP, and 4-SPP	Own	18,178	tailored features extraction (FE) followed by a Support Vector Machines (SVM), CNN	CNN	86.20%	accuracy	[20]
5	haploid maize seeds	texture, morphology, color and shape	True-Diploid, True-Haploid	Own	4021	DeepSort, Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression (LR)	DeepSort	0.961	5-fold cross-validation	[21]

Table 4
Analysis of pre-harvesting parameter: Pesticides and disease detection.

Sr. No.	Property	Important features	Classes defined in the work	Dataset used (Public / Own)	Total no of images used for training	Models / Method / Algorithms compared	Best model / method / algorithm	Results	Model evaluation technique	Reference
1	Disease detection	color, shape, and texture	12 different species and 42 different classes (both healthy and diseased)	Own (PlantDisease)	79,265	AlexNet, VGG 19, Inception, DenseNet, ResNet, PlantDiseaseNet Object Detection: Two-Stage Methods - Faster R-CNN, Faster R-CNN with TDM, Faster R-CNN with FPN, One-Stage Methods - YOLOv3, SSD513, RetinaNet	PlantDiseaseNet	94%	TOP-1 Accuracy	[32]
2	Plant disease	individual lesions and spots	Healthy, Mildly diseased, Moderately diseased, Severely diseased	Own (Plant-Disease)	PDDB - 1575 XDB - 46,409	GoogLeNet CNN	GoogLeNet CNN	12% higher	Confusion matrices	[33]
3	Plant disease and pest detection	deep features	8 classes : 5 disease (Coryneum beijerinckii, Apricot monilia laxa, Peach monilia laxa, Cherry myzus cerasi, Xanthomonas arboricola); 3 pest (Walnut leaf mite ga, Peach sphaerolecanium prunastri, Erwinia amylovora)	Own	1965	extreme learning machine (ELM), support vector machine (SVM), and K-nearest neighbor (KNN), VGG16, VGG19, and AlexNet	ResNet50 model and SVM classifier	98%	accuracy, sensitivity, specificity, and F1-score, confusion matrix	[35]
4	Apple Leaf Diseases	edge, corner, color, shape and object,	4 classes: Brown spot, Rust, Mosaic, and Alternaria leaf spot	Own	13,689	AlexNet Precursor, VGG 19, Inception, DenseNet, ResNet, PlantDiseaseNet, SVM BP AlexNet GoogLeNet ResNet-20 VggNet-16 Our Work	AlexNet Precursor	97.62%	confusion matrix	[36]
5	Apple Fruit Disease	background and foreground pixels	4 classes: Poor, Average, Good, Excellent	Own (Two datasets)	NA	Fuzzy Rule-Based Approach for Disease Detection (FRADD)	FRADD	91.66	accuracy	[37]

fine-tuned model to classify the fruits by Hossain, et al. [42]. The first model was built with six layers while the second was fine-tuned visual geometry group-16 pre-trained DL model. Two datasets were used to evaluate the performance of the proposed models. Dataset-1 is publicly available and it consists of 2633 color images whereas dataset-2 consists of total 5946 images, distributed among 10 classes. It was claimed VGG-16 fine-tuned model achieved excellent accuracy on both datasets. Kirk, et al. [43] studied on improving network performance on unseen data through a structured approach and analysis of the network input. Instead of modifying network architecture and increasing depth of neural network, the fusion of features was chosen. Result shows that the model complexity for more accuracy and generalization capabilities can be avoided by using bio-inspired features. It is claimed that for the color centric data classes this approach shows more promising results with the robust DL model in real world. For this the work author created dataset consists of 6189 images over 2 months, August and September 2018, and manually annotated 150 of them. Altaheri, et al. [44] proposed a machine vision system to categorize date fruit images according their maturity stages which help in harvesting decision. A dataset of 8072 images were created consisting of five date types: Naboot Saif, Khalas, Barhi, Meneifi, and Sullaj with different pre-maturity and maturity stages. The images were captured in various angles, scales, illumination conditions, and there were few occluded images. Transfer learning from two famous CNN models AlexNet and VGGNet were used to build the three classification models to classify date fruit according to their maturity stage, type, and whether they are harvestable or not. Result shows that VGG-16 model outperformed with the accuracy of 99.01% in 20.6 msec. Bauer, et al. [45] developed a platform that chains up-to-date ML techniques, modern computer vision, and integrated software engineering practices to measure yield-related phenotypes from ultra-large aerial imagery named as AirSurf. Author claims that this platform help to increase the yield and crop marketability before the harvest. Zhang, et al. [46] developed a harvesting robot for autonomous harvesting which consists of low priced gripper and ML technique for detection of cutting-point. The purpose of the study was to develop an autonomous harvester system which can harvest any crop with peduncle rather than damaging to its flesh. Onishi, et al. [47] proposed a new system (robot arm) consisting of Single Shot MultiBox Detector (SSD) and stereo camera for autonomous detection and harvesting of fruits. The system was tested on apple tee called “Fuji”. Robot arm detects the harvestable fruit position and harvest it by twisting the hand axis. An experimental result shows that system was able to detect 90% fruits and took only 16 s for harvesting. Liu, et al. [48] proposed a novel pipeline consisting of segmentation, 3D localization and frame to frame tracking for accurately counting the fruits from order of images. This model was evaluated on orange and apple fruits dataset. Table 5, presented the detail summary of harvesting techniques.

4. Post-harvesting

Post-harvesting is last and most crucial area in agriculture which require more attention. After successfully completing all stages starting from yield-estimation till harvesting, negligence in post-harvesting may spoil all the efforts and cause severe loss to farmers. The subtasks that

Table 5
Analysis of harvesting techniques.

Sr. No.	Property	Important features	Classes defined in the work	Dataset used (Public / Own)	Total no of images used for training	Models / Method / Algorithms compared	Best model / Method /Algorithm	Results	Model evaluation technique	Reference
1	Real-Time Fruit Detection within tree	fruit shapes, color and/or other attributes	apple and pear fruits	own	5000	Single-Shot Convolution Neural Network (YOLO)	YOLO	90%	confusion matrix.	[41]
2	fruit classification	NA	1st dataset: 15 classes, 2nd dataset: 10 classes	1st dataset: Public, 2nd Dataset: own	1st dataset: 2633, 2nd dataset:5946	2 deep learning Models : 1) light model of six CNN layers and 2)VGG-16 based architecture	VGG-16 based architecture	99.75%	Confusion matrix	[42]
3	Outdoor Fruit Detection	Bio-Inspired Features, fusion of features	3 classes: Ripe Strawberry, Unripe Strawberry, Both Classes	own (DeepFruit)	4219	Feature Pyramid Networks, Residual Neural Networks and RetinaNet	L*a*b*Fruits system	performance increase of 6.6 times	F1 score, the harmonic mean of precision and recall	[43]
4	Date Fruit Classification	local and spatial features and patterns	five date types in different pre-maturity and maturity stages: Naboot Saif, Khalas, Barhi, Menei, and Sullaj	own	8000	VGG-16, AlexNet	VGG-16	99.01%	Confusion matrix.	[44]
5	fruit harvesting robot	NA	apples Detected, Undetected	public	169	Single Shot MultiBox Detector (YOLO)	YOLO	0.9	precision, recall	[47]

can be consider in this stage are shelf-life of fruits and vegetables, post-harvest grading and export. Every country has their own standard rules and regulations for grading the fruits [49–51].

In [52], an information manual with directions for “Post-harvest management of mango for quality and safety assurance” was presented. This is very insightful for all the stakeholders of horticultural supply chain. Study showed that wrong post-harvest handling methods can affect the quality and quantity of fruits which increases the overall losses. 31% losses which are identified at retail level were caused by decay only. The other practices which add losses are poor harvesting, careless handling, and improper packaging and carriage conditions.

The wrong disease management during production causes the decay at high-level of pre-harvest infections. The decays in the form of anthracnose and stem end rot are very commonly observed. A training manual for “handling fresh fruits, vegetables and root crops” for Grenada was presented in [53], as a part of the “Agricultural Marketing Improvement” Project TCP/GRN/2901 which was implemented by Grenada Government and FAO. The goal of this project was to increase the profits for horticulture products and root crop growers through a well-organized agricultural marketing system. This document provides in detail study about all post-harvest stages with how to minimize the losses in every stage. Ucat, et al. [54] explored the use of image processing with deep leaning algorithm to classify Cavendish banana as per their grades. Python, OpenCV and Tensorflow were used to build the model to classify the bananas into different categories such as Class A big-hand or small-hand, Class B big-hand or small-hand and Cluster class (part of hand). Result shows that the model achieved more than 90% classification accuracy. Ireri, et al. [55] proposed a machine vision system for post-harvest tomato grading. The system works on RGB images given as an input to the system. Dataset was created by manually labeling the tomato images into four categories according to their defect, healthy and ripeness parameters. Four different models were built to classify image into one of the category according to the matching features, total 15 features were considered while taking the decision Result shows that RBF-SVM performed well as compared to others for category 1 i.e. healthy or defected with 0.9709 detection accuracy. Piedad, et al. [56] developed a system for banana (Musa acuminata AA Group ’Lakatan’) classification using ML techniques based on tier-based. A non-invasive tier-based technique was used in this study. ANN, SVM and RF classifiers were used to classify bananas into extra class, class I, class II and rejected classes. Result shows that the random-forest algorithm outperformed as compared to others with the 94.2% accuracy. Lia, et al. [57] studied and compared two hyper-spectral imaging technologies namely long-wave near infrared (LW-NIR) and short-wave near infrared (SW-NIR) for early identification of Bruise of ‘Pinggu’ peaches. An improved watershed segmentation algorithm based on morphological gradient reconstruction and marker extraction was developed and tested on multispectral PC images in this study. Experimental result shows that a proposed algorithm accurately classified 96.5% of the bruised and 97.5% of sound peaches respectively. An automated real–time grading system with quality inspection for apple fruit was developed by Sofu, et al. [58]. The developed system comprises a roller, transporter and class conveyors joined with an enclosed cabin with camera, load cell and control panel units. System not only classifies the apples on the basis of color, size and weight parameters but also identifies defective apples. The proposed system took only 0.52 s to capture the apple image and process. Average 15 apples per seconds were sorted by the system. Author claims average sorting accuracy between 73 and 96% and the system can be used to sort different fruits like orange, potatoes and so on. A grading and sorting system based on machine vision for date fruit was developed by Ohali [59]. The system was able to categorize the date fruit into three classes (grade 1, 2 or 3) from the given RGB image as an input. A back-propagation algorithm was tested in the study which showed 80% accuracy. Fruits and vegetables quality depends on their parameters like shape, size, texture, color and defects. Different methods needs to apply in order to classify the fruits and vegetables according to their quality parameters like data collection, pre-processing of data, image segmentation, feature extraction, and finally classification. Bhargava, et al. [60] presented a detail survey to compare the various algorithms used in every stage of the fruits and vegetables quality inspection. Meshram, et al. [61] proposed a new framework called “MNet: Merged Net” to reduce the fruits misclassification problem. Author created his own dataset of top Indian fruits consists of 12,000 images with

Table 6
Analysis of post-harvesting works.

Sr. No.	Property	Classes defined in the work	Dataset used (Public / Own)	Total no of images used for training	Models / Method / Algorithms compared	Results	Model evaluation technique	Reference
1	POSTHARVEST GRADING CLASSIFICATION OF CAVENDISH BANANA	4 classes	own	1116	Python OpenCV and Tensorflow	0.9	accuracy	[54]
2	Defect discrimination and grading in tomatoes	4 classes: category 1, 2, 3, and 4. depends upon defect, healthy, and ripeness (red color intensity)	own	8000	linear-SVM, quadratic-SVM, cubic-SVM, and radial basis function (RBF-SVM), ANN, decision tree, and random forest	0.9709	Confusion matrix	[55]
3	Postharvest classification of banana (Musa acuminata)	extra class, class I, class II and reject class	own	1164	artificial neural network, support vector machines and random forest	0.942	Classification Accuracy, F-Score, Confusion matrix	[56]
4	Automatic apple sorting system	small, normal, large, light and dark, defective and non-defective	own	183	K-means, C4.5 decision tree	0.79	statistical test	[58]
5	Date fruit grading	3 classes: grades 1, 2 and 3	own	1860	back propagation neural network (BPNN)	0.8	Confusion matrix	[59]

six classes. Table 6, presented the detail summary of post-harvesting works.

5. Discussion

This paper has extensively reviewed the available literature on application of machine learning and deep learning in agriculture. Different state-of-the-art machine learning and deep learning models in different stages of agriculture, including pre-harvesting, harvesting and post-harvesting in different domains were reviewed. Deep learning technology is becoming mature day-by-day. This survey shows that use of CNN in agriculture is huge and it is also getting remarkable results. By exploiting depth, other structure and hardware support, the learning capacity and accuracy of the CNN is significantly improved. Still there are challenges like dataset creation, time required for training and testing, hardware support, deployment of big models on small devices like boards or android phones, user awareness etc.

A popular technique called “Transfer Learning” is often used to mitigate the problems of small dataset, time required for training and to improve the accuracy of the model. Internet of Things (IoT) systems combined with machine learning provides a beneficial solution to improve farming gains. Real time parameters of the farms are gathered using IoT, and the collected data is used by machine learning algorithms either to predict or for recommendations to farmers for improvements in farming. From the survey it is also observed that Single-Shot Convolution Neural YOLO (You only look once) is a state-of-the-art, real-time object detection system which must be used for detection and localization to increase the classification accuracy.

Automated machine learning (AutoML) is the latest approach which can be used to build highly efficient, more accurate, high quality ML models in a less time [62,63]. AutoML is used to automate the entire ML pipeline shown in the Fig. 3, starting from data cleaning to model selection and hyperparameters tuning. These are time-consuming and iterative tasks of machine learning model development. As compared to traditional ML model development which is time-consuming, resource-intensive, need domain expertize, AutoML can accelerate the complete process to get production-ready model in less time without requiring domain expertise. In depth surveys on automated machine learning (AutoML) is presented in [64–69].

6. Challenges and recommendations

From this survey one can comprehend the importance of machine learning in the agriculture domain. In each phase of agriculture starting from pre-harvesting to post-harvesting, researchers have applied machine learning algorithms to solve the complex problems. Today’s need is to develop precise and customized machine learning models which can perform fast, automatically analyze bigger, more complex data and help to optimize the agriculture processes like classification, recommendations or predications.

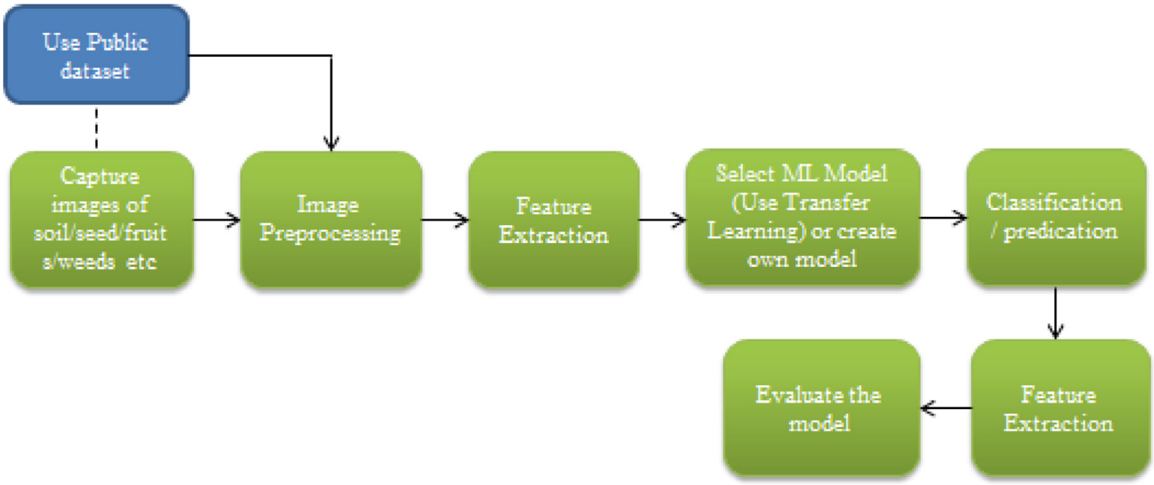

Fig. 3. Steps of Machine Learning used in literature.

The benefits of machine learning in agriculture domain are enormous. However, the benefits come with its challenges. Few such challenges while implementing machine learning algorithms in agriculture domain are listed as follows:

1) *Data:* Data is the most fundamental requirement to build the machine learning models. Many researchers faced the challenges regarding data like lack of data, unavailability of data in required format, poor quality of data, data may contain extraneous features etc. From this survey it is observed that, many researchers use data source sites like Kaggel, Meandly, IEEE Dataport etc. to get the data to build models. If the required data is not available then researchers need to build their own dataset [70–75].
2) *Pre-processing of the data:* As there are lot of problems associated with data, one has to apply the different pre-processing techniques to make the data suitable for training, testing, and validation testing the model. This might be time consuming process.
3) *Selection of machine learning algorithms:* Wide list of machine learning algorithm is available which make it difficult to find out more suitable algorithm to build the customize machine learning model. Many times, it is required to do random selection or after comparing results of multiple algorithms one can come to conclusion for best suitable algorithm. This trial-and error technique may delay the model deployment process.
4) *Training and testing of the machine learning model:* Building the accurate model needs huge data for training. Testing and validation are also important to check the accuracy of the model before its deployment. Building a model from scratch for best desired and possible outcomes needs long training and multiple time testing which are very time-consuming tasks. It needs high configuration hardware resources; domain knowledge programmers, testing tools etc. Overfitting and underfitting are the common challenges faced while building the models.
5) *Deployment of models:* This is the most challenging phase to bring the models in the production as there is absence of deployment skills, third party library dependencies, size of models, complex real-world scenarios, deployment platform hardware limitations, (like android phones, embedded boards) etc.

Some more challenges are important to make a note of:

1) Understanding the business need and identification of problem.
2) Understanding user and their interaction with technology
3) User friendly application design.
4) Performance of models in the real-word scenarios.
5) Power consumption by model and battery limitations to run the model on the devices.
6) For computer vision models camera configurations at user end.

The applications of machine learning and deep learning in the field of agriculture are huge with many challenges. After this in-depth survey following are a few recommendations to make the implementation process more fast, accurate, smooth and deployable.

1) Focus to build a machine learning model to solve specific problem like classification or recommendation.
2) For training the model try to create own dataset and make this available to other researchers through open platform like Kaggel, Meandly, IEEE Dataport etc.
3) For testing and validation of the models use publically available dataset.
4) To reduce the time required for training a model use the “Transfer Learning” techniques.
5) AutoML is the state-of-the-art approach which can be used to build more accurate, high quality ML models in a less time.
6) Deployment of the model in real-time application is recommended to help the intended users in their mundane work.

7. Conclusion

In this paper an in-depth survey of applications of machine learning algorithms in agriculture domain is presented. According to this review, agriculture activities are broadly categorized into three major areas as pre-harvesting, harvesting and post harvesting. Important parameters to be considered in each stage are shown in Fig. 2 and Table 1. Machine learning algorithms/techniques used in each stage are reviewed and presented in Tables 2,3,4,5 and 6 respectively. Machine learning is the state-of-art technology which is used to solve complex problem in the agriculture and helping farmers to reduce their losses. In this survey it is seen that machine learning algorithms have obtained remarkable outcomes to solve agriculture related problems.

Our study indicated that there is need to follow the machine learning pipeline with standard experimental methods. Researches should create their own dataset and make this available to others through different platforms, so that others can use it for testing and validation of their own models. This comprehensive survey of various machine learning algorithms used in different stages of agriculture will be more helpful to other researches who are working in this field.

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Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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