Applications of machine learning in agriculture domain: A state-of-art survey

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3 authors:


Vishal Meshram
Vishwakarma Institute Of Information Technology, Pune


Kailas Patil
Vishwakarma Institute Of Information Technology, Pune


Dinesh Bhagwan Hanchate
Vidya Pratishthan's, College of Engineering, Baramati

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Applications of machine learning in agriculture domain: A state-of-art survey

Vishal Meshram[1], Kailas Patil[2] and Dinesh Hanchate[3]

[1]*PhD Scholar, Computer Department, Vishwakarma University, Pune, Maharashtra, INDIA*

[2]*Professors, S&T, Vishwakarma University, Pune, Maharashtra, INDIA.*

[3]*Associate Professor, VPKBIET, Baramati, Pune, Maharashtra, INDIA.*

[1] *E-mail* vismeshram1980@gmail.com, [2] *Email* kailas.patil@vupune.ac.in,

[3]*Email* dineshbhanchate@gmail.com

Abstract

Food is considered as a basic need of human being which can be satisfied through farming. Agriculture not only fulfils 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 [1]. 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 does 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.

Keywords: *Deep learning, harvesting, machine learning, post-harvesting, pre-harvesting, precision agriculture.*

1. Introduction

Agriculture is considered as 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 as 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, wrong harvesting and lack of information about market a trend lead to the loss of farmers or adds to additional cost [2]. 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 sectors. 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 IoT, machine learning, deep learning, cloud computing, edge computing can be used to get information and process it. Application of computer vision, machine learning, IoT will help to raise the production, improves the quality, and ultimately increases the profitability of the farmers and associated domains. The Precision learning in field of agriculture is very important to improve the overall yield of harvesting.

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Machine learning (ML) and Deep learning (DL) are the latest emerging trends in the computer field. It has been already used in different domain like healthcare, cybercrime, biochemistry, robotics, metrology, banking sector, medicine, food etc. to solve the complex problems by the researchers. Deep learning algorithms are making machine learning more powerful and accurate. By using automated machine learning (AutoML) we can cut the demand of ML experts, we can automate the ML pipeline with more accuracy.

While performing agriculture tasks the following flowchart is followed by farmers. :
Step 1: Selection of Crop
Step 2: Land Preparation
Step 3: Seed Sowing
Step 4: Irrigation
Step 5: Crop Maintenance
Step 6: Fertilizing
Step 7: Harvesting
Step 8: Post-Harvesting activities
As per the above algorithm, the agriculture related tasks are categorized in the for major sub areas. Figure 1 shows these four sub-domains of agriculture tasks.

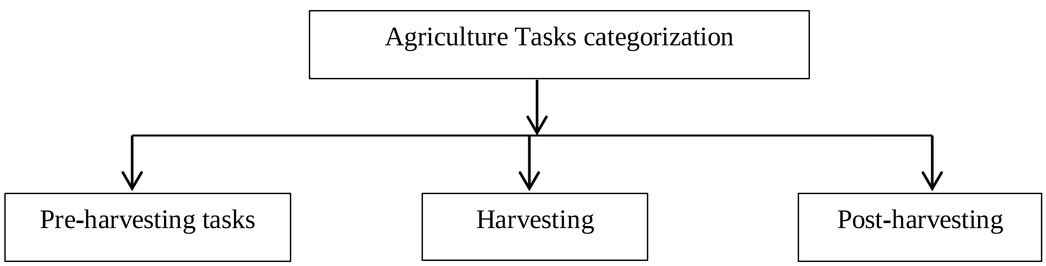

Figure 1. General categorization of agriculture tasks

In pre-harvesting tasks farmers are focused on selection of crops, land preparation, seed sowing, irrigation, crop maintenance and fertilizing. 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. Figure 2 shows the important factors should be considered in each stage of farming.

Table 1. Important factors to be considered in each stage

Sr. 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.	[3], [4]
2	Harvesting	Fruit/crop size, skin colour, firmness, taste, quality, maturity stage, market window, fruit detection and classification.	[4]
3	Post-harvesting	Factors affecting the fruit shelf-life such as	[4]

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		temperature, humidity, gases used in fruit containers, usage of chemicals in postharvest and fruit handling processes to retain the quality, fruit grading as per quality.	

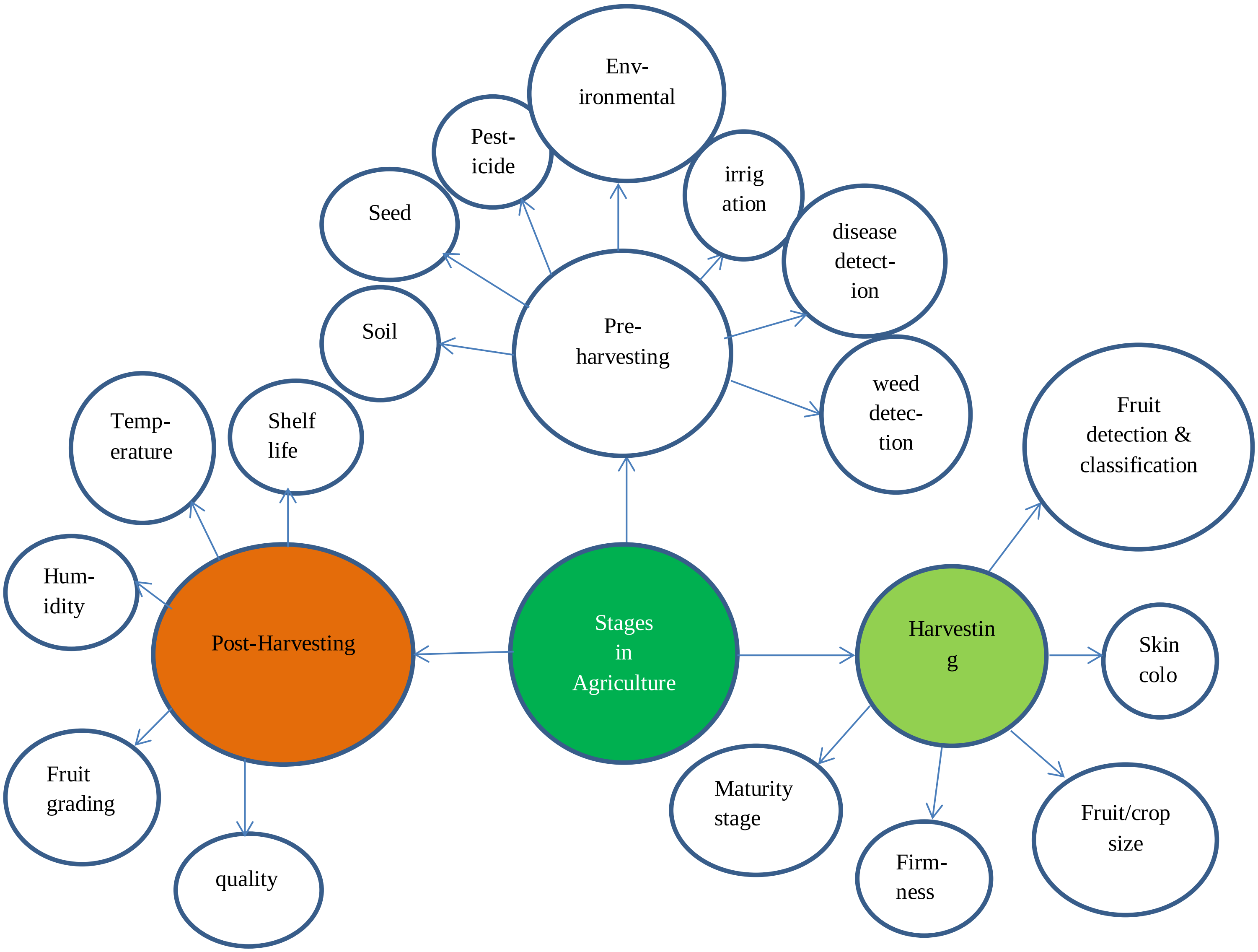

Figure 2. Important parameters considered in each stage of farming

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 Horticulture, 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 done. Section 2 explains the use of ML in

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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. Section 5 explains the Artificial Intelligence (AI), ML, and DL in detail.

2. Pre-harvesting

Pre-harvesting parameters plays 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 is important to minimize the overall losses in production. Here we considered few important components in the pre-harvesting and how neural networks; machine learning is used to capture the parameters of each component.

2.1 Soil

In [5], a soil management survey is presented in which the application of ML techniques for predication or identification of soil properties (estimation of soil temperature, soil drying, and moisture content) were reviewed. The categorization and estimation of the soil attributes helps farmers in minimizing extra cost on fertilizers, cut the demand of soil analysis experts, increase profitability, and improves health of soil. In [6], a pH values and soil fertility indices classification and predication model is presented. In [7], as per author an important indicators of soil fertility are pH values and Soil Organic matter (SOM) and thus the author has done prediction of SOM and pH parameters in paddy soil. In [8] author has done prediction of organic carbon (OC), nitrogen (TN), and Moisture content (MC) parameters of the soil. The aim of study is 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, in [9] author has estimated the moisture content of soil using with Auto-regressive error function (AREF) along with machine learning algorithms. In [10], author developed a new model by employing Self-adaptive evolutionary (SaE) agent in extreme machine learning (ELM) architecture. This new model is used to do the assessment of daily soil temperature (ST) at 6 different depths of 5, 10, 20, 30, 50 and 100 cm.

Table 2. Analysis of pre-harvesting parameter: Soil

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	Reference

ISSN: 2005-4238 IJAST

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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	[6]
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	[7]
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	[8]

ISSN: 2005-4238 IJAST

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%	[9]
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	[10]
6		soil drying	wetting/ drying	Public	NA	Classification trees, k-nearest-neighbors, and boosted perceptron’s	k-nearest-neighbor and boosted perceptron	91–94% accuracy	[11]

2.2 Seeds

Seed germination is vital factor for quality of seed, which is 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 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 [12, 13, 14]. Image recognition technique for seed sorting with high accuracy is developed by author of [15]. In [16], author has used multilayer perceptron neural network model for improving the accuracy of the classification method of separating pepper seeds of high-quality from low-quality. In [17], [18] the author have used the deep neural network (DNN) model using CNN, for an assessment of the quantity of seeds per pod in in soybean [17], and for sorting

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International Journal of Advanced Science and Technology
Vol. 29, No. 8, (2020), pp. 5319 - 5343

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of haploid seeds on basis of shape, phenotypic expression, and the embryo pose [18].In [19], author builds a model using CNN for plant seedlings classification into 12 species. The author of [20] have assessed the proficiency of computer vision as an alternative to routine vigour tests to expedite the process of accurate evolution of seed physiological potential. In [21], author have 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. In [22, 23] author have used machine learning (ML) techniques for efficient seed classification. The detail summary of work done by different authors is mentioned in table 3.

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	[13]
2	Cotton Seed		Jinxin5, Jinxi7, Shennongmian1, Xinjiangzaomian1, Xinluzaomian29, Xinluzhong 52 and Xinluzhong 42	own, dataset collected from Shihezi, Xinjiang Uyghur Autonomous Region, China	13160	SVM, PLS-DA, and LR models based on deep features extracted by self-design CNN and ResNet models	self-design CNN	80%	classification accuracy	[14]
3	noxious weeds	shapes, textures, sizes, and colors		132,428 sunn hemp seeds 164,973 weed						

ISSN: 2005-4238 IJAST

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				seeds						
4	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	[16]
5	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	2-SPP, 3-SPP, and 4-SPP	Own	18178	tailored features extraction (FE) followed by a Support Vector Machines (SVM), CNN	CNN	86.20 %	accuracy	[17]

ISSN: 2005-4238 IJAST

International Journal of Advanced Science and Technology
Vol. 29, No. 8, (2020), pp. 5319 - 5343
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		profile of the pod straighten mask added along the short axis								
6	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	[18]
7	plant seedlings	color value	12 classes (black-grass, charlock, cleavers, common chickweed, common wheat, fat hen, loose silky-bent, maize, scentless mayweed, shepherds purse, small-flowered cranesbill, sugar beet)	provided by Aarhus University Signal Processing group with University of Southern Denmark,	4275	KNN, SVM, CNN (with attentation), CNN (with OpenCV background segmentation)	CNN (with OpenCV background segmentation)	92.6	Confusion matrix	[19]
8	pomegranate seed	nine image features and 21 physicochemical properties (morphological	20 classes in 3 clusters	own	NA	principal component analysis (PCA)	NA	66.67 % for cluster 1, 75% for cluster 2, and 50%	accuracy	[21]

ISSN: 2005-4238 IJAST

		parameters and color)						for cluster 3		
9	pepper seeds	color components	eight classes	own	832	MLP	MLP	84.94 %	Confusion matrix	[23]

2.3 Pesticides and disease detection

In time disease detection is the most important task to save crops. Mostly farmers assume the diseases and apply the pesticides on the crops equally. Some farmers regularly analyzing leaf or branches of tree and identify the diseases. Both the activities are based on human experience which is prone to errors and risky. Decision of which pesticide and when to apply is totally depends on type of disease and its stage. Application of random pesticide in random quantity on all the crops may harm not only crops but farmers also. Precision agriculture helps farmers for application of right pesticide at right time at right place. Many works combined pesticides prediction with the detection of disease on plants. So in this section we are presenting survey of disease detection using machine learning.

In [24], author elaborated in detail about how diseases can raise the crop losses individually and globally. He proposed three parts framework consists of crop losses and their measurement, emphasizing hidden consequences , multifaceted nature of crop losses, the nature of risks involved and avenues to address them and lastly a geographic and crop-based structure. In [25], detail study about types of pesticides and their applications in agriculture and bio-farming and impact on environment were presented. In [26], shortcomings of available DL models used for plant disease detections were discussed. Author built a novel model consisting of two-stage architecture Disease Net, for classification of plant disease, which achieved 93.67% training accuracy. In [27], author explored the new approach by using DL to identify plant diseases from individual lesions and spots instead of considering entire leaf. In [28], a detail review of DL models used to envision different diseases of plant was presented. Author suggests that advanced DL algorithms should be used to increase the accuracy. In [29], author used transfer learning using pretrained models for feature extraction and for further fine-tuning and the performance of nine plant disease detection DL models was evaluated. The objective of the study was to deploy plant disease detection model into android app. In [30], 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. For apple disease detection and classification in Kashmir Valley, another model called Fuzzy Rule-Based Approach for Disease Detection (FRADD) was proposed in [31]. Though the accuracy of the model is good, it takes into account only one disease known as scab and limited numbers of fruit types. In [32], author proposed his own model DenseNet-16, to overcome the limitations of pre-trained models which are trained on ImageNet dataset only. The proposed model is simple and effective as own dataset is used for the training. This model can be used in mobile devices because of its lightweight size. In [33], a model is presented to detect the citrus diseases by using their physical parameters like structure of hole (phenotypic nature), texture, color, vectors, and morphology. As per the author ANN performs better as compared to other algorithms for detection and classification. Result shows that the use of SVM with ANN helps in increasing disease detection and classification rate. The detail summary of the published works is presented in table 4.

ISSN: 2005-4238 IJAST

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	[26]
2	Plant disease	individual lesions and spots	Healthy, Mildly diseased, Moderately diseased , Severely diseased	Own (PlantDisease)	PDDB - 1575 XDB - 46,409	GoogLeNet CNN	GoogLeNet CNN	12% higher	Confusion matrices	[27]
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	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	[29]

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			ga, Peach sphaerolecanium prunastri, Erwinia amylovora)							
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	[30]
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	[31]
6	Citrus Pests and Diseases	Input features (H, W, C)	17 species of citrus pests and seven types of citrus diseases. ((a) citrus anthracnose , (b) citrus canker, (c) citrus melanose, (d) citrus scab, (e) sooty mold, (f) leaf miner, and)	Own	12561	ShuffleNet-v1, ShuffleNet-v2, MobileNet-v1 , MobileNet-v2 , VGG-16, SENet, NIN-16, WeaklyDenseNet-16	Weakly DenseNet	99.83	accuracy	[32]

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7	CITRUS FRUIT DISEASE DETECTION	vectors, color, texture, morphology, structure of hole (phenotypic nature)	6 classes: Anthracnose, Black spot, Canker, Citrus Scab, Melanose, Greening	Public (Kaggle)	NA	K-Means clustering technique, ANN and SVM	SVM	93.12	true positive rate (TPR), false positive rate (FPR), precision and average classification accuracy (ACA)	[33]

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 colour, firmness, taste, quality, maturity stage, market window, fruit detection and classification for harvesting. Careful and right harvesting is directly correlated with profit. In the survey, we found that auto-harvesting robots, machine learning, deep learning techniques are achieving better results and helping in reducing the losses in harvesting stage.

In [34], authors presented detail survey on smart automatic fruit harvesting robots. The use automatic robots in fields helps to increase the production and ultimately profits of the farmers. Authors in [35] developed a CNN model based on single shot detector (YOLO) algorithm for on-tree fruit detection. The training dataset was created by manually labeling 5000 images of pear and apple fruits. The result shows that model achieved more than 90% accuracy for on-tree fruit detection. In [36], two deep neural network models with different architectures were proposed to classify the fruits. First model was built with six layers while the second was fine-tuned visual geometry group-16 pre-trained DL model. In [37], a strawberry fruit detection system was developed based on DNN like Feature RetinaNet, Residual Neural Networks and Pyramid Networks. The benefit of this system was it can be trained in an hour with a less number of input images. A more accurate machine vision system was proposed in [38], to categorize the date fruit images according to their different parameters. 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. Own dataset was created consisting of 8000 dates images of five verities of dates in different maturity and pre-maturity stages. To conduct the PA practices with objective of increasing the yield and crop marketability before the harvest, authors in [39] were 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. In [40], a harvesting robot was developed for autonomous harvesting which consists of low priced gripper and 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. In [41], a new system consists of Single Shot MultiBox Detector (SSD) and stereo camera was proposed for autonomous detection and harvesting of fruits. The experiment was conducted on apple tree called “Fuji”. For accurately counting the fruits from order of images authors in [42], proposed a novel pipeline consists of segmentation, 3D localization and frame to frame tracking. This

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model was evaluated on orange and apple fruits dataset. Table 5, presented the detail summary of harvesting techniques.

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.	[35]
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	[36]
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	[37]
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	own	8000	VGG-16, AlexNet	VGG-16	99.01 %	Confusion matrix.	[38]

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5	Fruit and Vegetable Harvester gripper	NA	NA	NA	NA	Mask Region-based Convolutional Neural Network (Mask R-CNN)	Mask R-CNN	93%	precision-recall curve	[40]
6	fruit harvesting robot	NA	apples Detected, Undetected	public	169	Single Shot MultiBox Detector (YOLO)	YOLO	0.9	precision, recall	[41]

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 may cause severe loss to farmers. The subtasks we can consider in this stage are a) shelf-life of fruits and vegetables b) post-harvest grading c) export. [43, 44, 45] shows that for grading the fruit every country has their own standards.

In [46], an information manual with direction for “Post-harvest management of mango for quality and safety assurance” was presented. This was 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 by author in [47], 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.

The DL based classifier to classify Cavendish banana grade was explored in [48]. A model was developed using Python OpenCV and Tensorflow. The model achieved more than 90% classification accuracy. In [49], a machine vision system for post-harvest tomato grading was proposed. The system works on RGB images given as input to the system. Own dataset were 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. In [50], author developed a system for banana (Musa acuminata AA Group 'Lakatan') classification using ML techniques based on tier-based.

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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 showed that the random-forest algorithm outperformed as compared to others with the 94.2% accuracy. In [51], two hyper-spectral imaging technologies long-wave near infrared (LW-NIR) and short-wave near infrared (SW-NIR) were studied and compared for early identification of Bruise of 'Pinggu' peaches which cause a major quality loss. An improved watershed segmentation algorithm was developed and tested on multispectral PC images in this study. An automated real–time grading system with quality inspection for apple fruit was developed in [52]. The developed system comprises of 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. A grading and sorting system based on machine vision for date fruit was developed in [53]. The system was able to categorize the dates into three classes (grade 1, 2 or 3) from the given RGB image as an input. A back-propagation algorithm 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 has 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. In [54], a detail survey to compare the various algorithms used in every stage of the fruits and vegetables quality inspection was presented. Table 6, presented the detail summary of post-harvesting works.

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	[48]
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	[49]
3	Postharvest classification of banana (Musa acuminata)	extra class, class I, class II and reject class	own	1164	artificial neural network, support	0.942	Classification Accuracy, F-Score, Confusion	[50]

ISSN: 2005-4238 IJAST

					vector machines and random forest		matrix	
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	[51]
5	date fruit grading	3 classes: grades 1, 2 and 3	own	1860	back propagation neural network (BPNN)	0.8	Confusion matrix	[52]

5. Overview of AI, ML, and DL

Figure 3 explains how the AI, ML and DL are related with each other. Even though DL is the subset of ML and which is also the subset of AI, still there is difference between these technologies [55]. First time the "AI" term was coined by John McCarthy, an American computer scientist, back in 1956. According to John McCarthy, AI is *"The science and engineering of making intelligent machines, especially intelligent computer programs"*. The term Machine Learning was coined back in 1959 by Arthur Samuel, an American innovator in the field of computer gaming and AI and stated that, *"it gives computers the ability to learn without being explicitly programmed"* which means ML algorithms automatically learns from the knowledge without being automatically programmed. Machine learning follows the certain steps to produce the output. The steps involved are data collection, feature extraction, model building based on the data available, and choose the cost function, optimization, and hyperparameters tuning, training, testing, deployment. Deep learning is the subset of ML which helps to increase the accuracy of ML algorithms. DL takes data from higher level i.e. from ML and processes it. DL technology mimics the network of neurons in a brain. It is called DL because it works on ANNs, consists of number of layers of NN increases with time in the training phase [56].

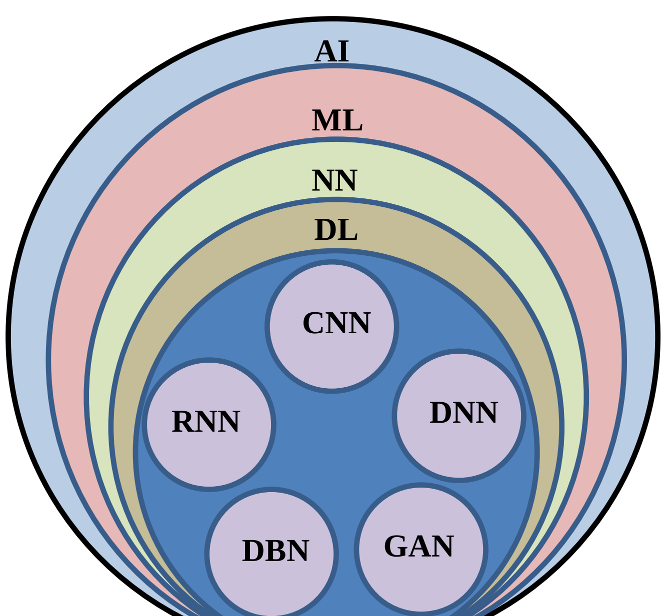
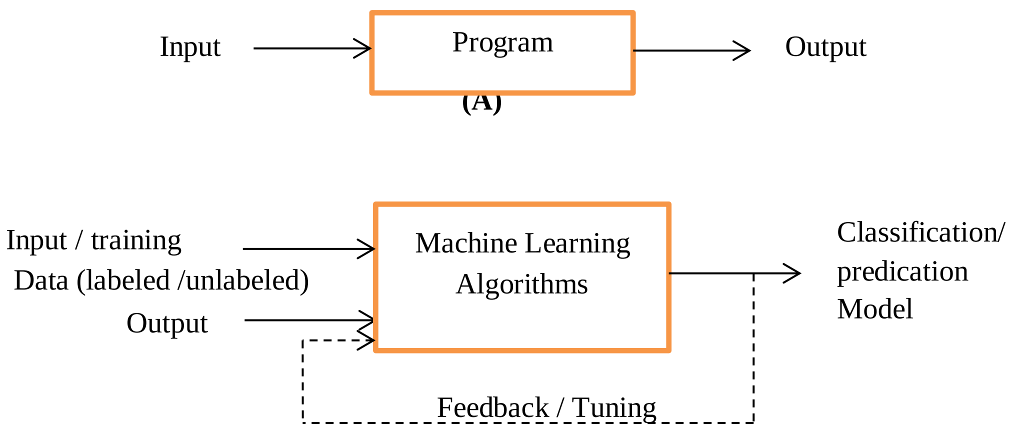


Figure 3. Relationship between AL, ML and DL

5.1 Machine learning overview

This section discussed about the high level of the ML techniques. Many researchers have attempted to define machine learning. Few of the notable findings are listed below According to [57], *"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E* " . According to [58], *"Optimizing a performance criterion* using example data and past experience."

The difference between the way we do traditional programming and ML programming is shown in Figure 4:



(B)

Figure 4. (A) Traditional programming model (B) Machine Learning programming model

The ML algorithms are broadly categorized into three types namely, supervised learning, unsupervised learning and reinforcement learning (RL) [59]. In supervised learning the input also called as training data and output is provided to ML algorithm to construct the classification or prediction rule that mapped input to outputs. Classification or regression algorithms are considered as supervised algorithms. In unsupervised learning, however, only training data is provided to ML algorithm with the objective that algorithm should able to find out the hidden patterns. Therefor in unsupervised learning algorithm learn from the training data and try to classify or cluster or group them. Reinforcement learning is a learning method concerned with how software agent take actions to maximize a specific reward function. According to [60], a *policy*, a *reward function* and *value function* are the three main components of reinforcement learning.

ISSN: 2005-4238 IJAST

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Learning Models in the ML are regression models, Bayesian models, dimensionality reduction, instance based models, decision tree, clustering and neural networks. The model evolution techniques for performance analysis used in ML are confusion matrix, accuracy, f1- score, ROC curve – Receiver Operating Characteristics, Bias-variance tradeoffs, Goodness of Fir – R2, Mean Squared Error (MSE), Error rate. For model tuning the techniques used in ML are cross-validation, hyperparameters, early stopping (Regularization), overfitting, underfitting, bootstrap, bagging.

5.2 Deep learning overview:

Deep Learning is the fast growing branch of AI and playing key role in AI applications. Application of DL methods dramatically improved the results in computer vision, image, speech, video and audio processing, object detection, object classification [61]. As shown in the figure 4, DL is the subclass of ML. The basic components of DL are neural network consists of multiple layers, which progressively extracts the feature in each layer from raw input [62]. The different available DL architectures which are very popular are deep neural network (DNN), Convolutional Neural Network (CNN), Long Short Term Memory (LSTM)/Gated Recurrent Unit (GRU) Network, Deep Belief Network (DBF), Recurrent Neural Network (RNN), Auto-Encoder (AE), Restricted Boltzmann Machine (RBM), Deep Stacking Network (DSN), Generative Adversarial Networks (GANs). Out of these CNN and RNN are two basic and most commonly used approaches [56,63, 64]. From the surveyed literature we observed that CNN approached was used by maximum researchers either for classification or for predication. CNN models performed well on image datasets. CNN model consists of convolution layers, pooling layers, and activation functions which are arranged together to build the architecture [65]. According to [66], the performance of the CNN models is depends upon size of labeled input dataset, number of layers used in the architecture, training duration (epochs). Well known pre-trained models based on CNN architecture for image classification are listed in table 7:

Table 7. Pre-trained models for image classification

Sr. No.	Name of the Pretrained Model	Year	No of total layers	Evaluated on Dataset	Ref
1	AlexNet	2012	8	ImageNet	[67]
2	VGG	2014	19	ImageNet	[68]
3	GoogLeNet	2014	22	ImageNet	[69]
4	ResNet	2015	18 -152	ImageNet, CIFAR-10	[70]
5	SqueezeNet	2016	10	ImageNet	[71]
6	ResNeXt	2016	50/101	ImageNet-1k, ImageNet-5k, CIFAR-10, CIFAR-100 and COCO datasets	[72]

ISSN: 2005-4238 IJAST

International Journal of Advanced Science and Technology
Vol. 29, No. 8, (2020), pp. 5319 - 5343

7	DenseNet	2017	103	CIFAR-10, CIFAR-100, SVHN, and ImageNet	[73]
8	ShuffleNet V2	2018	50 / 26	ImageNet, MS COCO	[74]
9	MobileNet V2	2018	28	ImageNet, COCO, VOC	[75]

In [76], author presented an analysis on deep neural models. Building a new model from scratch is time consuming need high end hardware support. Dataset plays the crucial role in building highly accurate model. More the clean and equally distributed input dataset, more accuracy you will achieve. To overcome the problems of time required for training, high end hardware requirement, and large dataset "Transfer Learning" is used. Transfer learning helps to build accurate models in less time. Transfer learning has shown remarkable results in image classification. According to [77], transfer learning is defined as "Given a source domain *DS* and learning task *TS*, a target domain *DT* and learning task *TT* , *transfer learning* aims to help improve the learning of the target predictive function *fT* (·) in *DT* using the knowledge in *DS* and *TS*, where *DS* _= *DT*, or *TS* _= *TT* ".

CNN model layers are categorized into two parts: feature extraction layers and classification layers. Feature extraction layers are also called as convolution layers which are comprises of convolution layers and pooling layers. Classification layers are composed of fully connected layers. According to [78, 79], based on this fact you can apply transfer learning in following scenarios: a) train the entire model: use the pre-trained model and train it on own dataset b) fixed convolution layers: take a pre-trained model, freeze the feature-extraction layers and modify classification layers as per your need c) Fine tune the ConvNet: use the pre-trained model and freeze few layers of convolution instead of all and retrain the model on your dataset.

6. Discussion and Conclusion:

[4, 5, 36, 54, 80, 81, 82, 83] presented in depth surveys of application of machine learning in agriculture. 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. In this survey we observed that, steps shown in figure8 have been followed in most of the work.

Deep learning technology is becoming mature day-by-day. Survey shows that use of CNN in agriculture is huge and it 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. We have also discussed the technique called "Transfer Learning", which are 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 we 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.

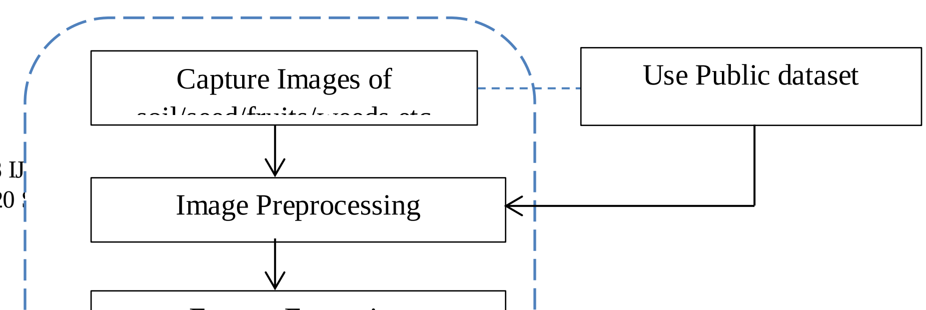

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Figure 5. Steps of Machine Learning used in literatures

In the context of application of machine learning in agriculture domain this review provides a comprehensive stat-of-art review for those who want to explore this new area in their future research endeavours.

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