IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 11, No. 2, June 2022, pp. 753~763
ISSN: 2252-8938, DOI: 10.11591/ijai.v11.i2.pp753-763

A comprehensive review on machine learning in agriculture domain

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Article Info

Article history:

Received Sep 6, 2021
Revised Feb 14, 2022
Accepted Mar 3, 2022

Keywords:

Agriculture
Artificial neural network
Food security
Machine learning
Support vector machine

ABSTRACT

Agriculture is an essential part of sustaining human life. Population growth, climate change, resource competition are the key issues that increase food security and to handle such complex problems in agriculture production, intelligent or smart farming extends the incorporation of technology into traditional agriculture notion. Machine learning is a vitally used technology in agriculture to protect food security and sustainability. Crop yield production, water preservation, soil health and plant diseases can be addressed by machine learning. This paper has presented a compendious review of research papers that deployed machine learning in the agriculture domain. The observed sub-categories of the agriculture domain are crop yield prediction, soil management, pest management, weed management, and crop disease. The outcomes represent that machine learning provides better accuracy concerning classification or regression. Machine learning emerged with the internet of things, drones, robots, automated machinery, and satellite imagery motivates researchers for smart farming and food security.

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1. INTRODUCTION

Agriculture is a basic need for humankind to subsist. Continuous increment in population strains to feed the ever-growing population. Resources and food production management is required to cater for the augmented population. Agriculture production relies on many factors, such as soil type and quality, irrigation management, weather, and water. Agriculture is a basic need for humankind to subsist. Continuous increment in population strains to feed the ever-growing population. Resources and food production management is required to cater for the augmented population. Farming has become more intensified to maximize crop yields. To produce the sufficient amount of food, smart agriculture is required. Satellite data makes agriculture more accurate and predictive. Smart farming has evolved widely in the last few years to fulfil the food need.

Machine learning (ML) in consort with data analysis generates possibilities to understand and reconnoitre the field of agriculture more effectually. According to Tom Michael, ML is a set of computer instructions that learns from previous experience, concerning the task, and on the basis of previous experience and task, performance is measured and which improves with experience and task [1]. Samuel defines ML as a scientific domain of study which provides machines with the ability to learn without being specifically programmed [2]. With time, machine learning is being widely applied in many fields, including bioinformatics [3], anatomy [4], cheminformatics [5], economics [6], robot locomotion [7], speech recognition [8], information retrieval [9], and neuroscience [10]. In this research paper, machine learning algorithm in agriculture domain is deliberated [11].

The organization of the paper is: machine approach section has the description of machine learning methods, techniques, and algorithms, the literature review section contains the review of the identified areas of agriculture that have used machine learning, and discussion and conclusion section encloses the final findings, conclusion and discussion of the paper along with the advantages of application of machine learning in agriculture domain. ML is a process where the system or machine learns from experience and can improve performance. Statistical and mathematical models can measure improved performance. Set of examples can also be dictated as ML model or algorithms are trained using data sets. After the accomplishment of training, the trained model is used to identify, predict or classify new input data. Figure 1 illustrates the ML approach. ML algorithms explained below are not limited to the methods applied in papers used for this review process.

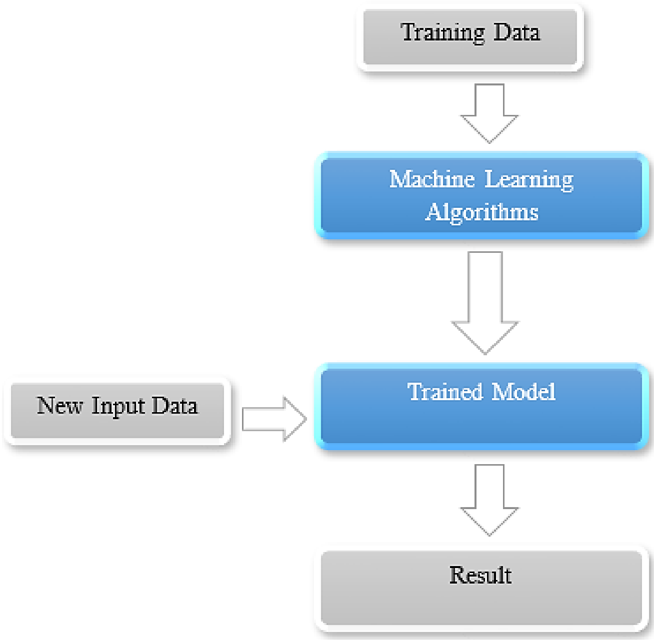

Figure 1. Machine learning approach

2. LITERATURE REVIEW
2.1. Research method

A systematic review methodology has been followed for the review conduction used in this research paper. The review process includes review planning, search string, and search criteria for Machine learning in agriculture. After completing the search, the paper selection is made based on inclusion and exclusion criteria. This section contains information about how the review is accomplished.

2.2. Planning of review

Machine learning has evolved in agriculture rapidly in past years. However, despite numerous research studies, the potential results for every field have not been identified yet. This review aims to provide an outline of the machine learning technology in the agriculture domain and in-depth investigation. The work analyses various sub-categories of the agriculture domain, techniques applied, observed features, and dataset resources used in the research.

2.3. Search string

To conduct the search string, some keywords are identified as agriculture machine learning, ML techniques agriculture, crop yield prediction machine learning, pest machine learning, crop disease machine learning, soil machine learning, and weed machine learning, with the main emphasis on keywords machine learning and agriculture. The authors performed an in-depth search to ensure the comprehensiveness of the study. A few known papers may not have been considered because of title mismatch with the identified keywords. Figure 2 represents the chosen search strings.

2.4. Selection criteria

The literature review follows pre-specified selection criteria for including and excluding the papers in the study. The inclusion criteria include the paper which matches the search string, and exclusion criteria excluded the papers by title and domain mismatch, abstract and text irrelevance. Figure 3 illustrates the paper inclusion and exclusion.

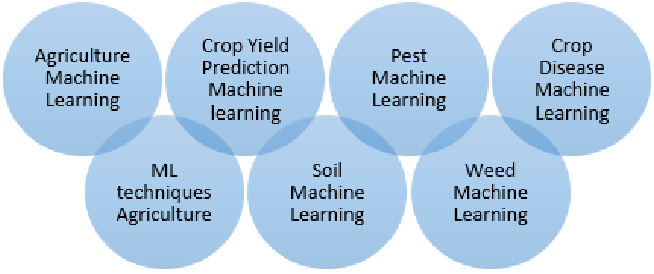

Figure 2. Search string

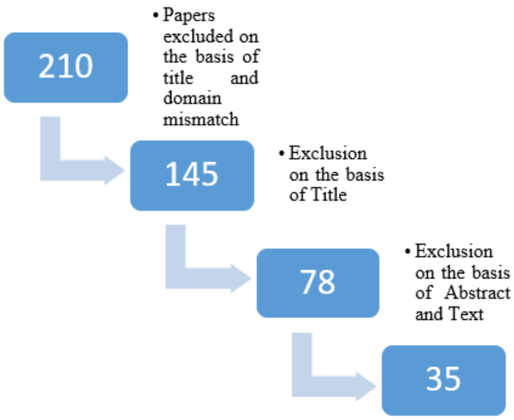

Figure 3. Inclusion and exclusion criteria

2.5. Review conduction

Machine learning is a game-changing technology and widely used in diversified fields. Machine learning has been applied in the agricultural domain throughout the crop cycle. It starts with soil management and ends with taking decisions about the crop's ripeness by the robot. In this review, articles have been classified into the following categories: crop yield prediction, soil management, pest management, weed management, and crop disease. The papers were searched using particular keywords for every selected domain of agriculture. Agriculture has many sub-areas, and all cannot be included in the review; considering this constraint, some areas are excluded. General abbreviations used in the paper are compiled in Table 1.

2.6. Categorical literature review

2.6.1. Crop yield prediction

In agriculture, crop yield, also known as agriculture output, is an essential component to complete the growing population's need. Agriculture crop yield or productivity depends on many factors, such as weather conditions, soil conditions, water, temperature, and rainfall. Therefore, ML can match the demand and supply of food without affecting the environment or natural resources.

2.6.2. Soil management

Machine learning implementation has been used to predict and identify based on soil characteristics such as valuation of soil moisture, condition, and temperature. A better prediction of soil condition can help to improve soil management. ML technologies can achieve a more accurate estimation of soil with less time and cost.

Table 1. General abbreviations

Abbreviation	Definition	Abbreviation	Definition
AMSR-E	Advanced Microwave Scanning Radiometer on the Earth Observing System	MODIS	Moderate Resolution Imaging Spectroradiometer
ANN	Artificial Neural Network	MPE	Mean percent error
AI	Artificial Intelligence	NB	Naïve Bayes
CNN	Convolutional Neural Network	NDVI	Normalized difference vegetation index
CP-ANN	Counter Propagation Artificial Neural Network	NN	Neural Network
DL	Deep Learning	PCA	Principal Component Analysis
DT	Decision Tree	PLSDA	Partial Least Squares Discriminant Analysis
EL	Ensemble Learning	PMNN	Perceptron Multilayer neural network
ELM	Extreme Learning Machine	RBF-NN	Radial Basis Function Neural Network
EM	Expectation Maximisation	RE	Relative Error
ERT	Extremely randomized tree	RF	Random Forest
LR	Logistic Regression	RMSE	Root mean square error
LS-SVM	Least Squares Support Vector Machines	SOM	Self-Organizing Map
LSTM	Long short-term memory	SVM	Support Vector Machine
ML	Machine Learning	SVR	Support Vector Regression
MLR	Multiple Linear Regression		

2.6.3. Pest management

Pest damages the crops and reduces production, which can rigorously affect the food supply and demand chain. Reduction of the crop damage and increment of the crop production compels the farmers to use chemicals to control and protect the field from pests. Even though utilization of chemicals is harmful to the environment, animals and human's health, ML algorithms can provide an efficient solution for pest management.

2.6.4. Weed management

Weed in farming is the most undesirable plant that rivals the yield. It makes harvesting difficult and includes impurity and moisture to crop. The negative effects of weeds on yields incorporate challenge to sunlight, water, space, complex harvesting, and devaluation of crop quality. ML can detect weed on the crop. Many articles have been presented here to detect and discriminate weed from the crop.

2.6.5. Crop disease

The rapidly increasing world population puts much pressure on agriculture resources. Crop Production is the essential component to maintain the population need as well as the economic system. Crop diseases are the primary source of plant damage, which affects crop production. Due to distressed climate and environmental situations, a manifestation of plant illnesses is at the upward thrust. There are numerous crop diseases and various symptoms containing spots/smudge appearing on plant leaves [12]. ML techniques accommodated to detect the disease in the plant at an early stage. The Table 2 shown in appendix represents the comparison of above-mentioned categories.

3. DISCUSSION

The review's primary focus is to brief the significant benefits of ML in the agriculture domain and possible research areas. The review analyses the existing machine learning tools and techniques deployed in the agriculture domain, including crop prediction, soil management, pest management, weed management and crop disease. Many international journals cover the advances in the development and applications of hardware, software, and related technologies for solving issues in the agriculture domain. The total number of research articles reviewed is 38. The review includes 3 conference and 35 journal articles, as shown in Figure 4. The presented articles here are from 2005 to till present, shown in Figure 5. The year-wise distribution of reviewed papers is demonstrated in Figure 5. The result clearly shows that there is significant work done in the last 3 to 4 years in agriculture using machine learning.

Analysis of the articles indicates that mainly nine ML algorithms are examined/adopted in the survey, shown in Figure 6. In crop prediction, Nine ML algorithms are deployed; further analysis of the surveyed articles indicates that ANN is the most popular algorithm applied in the field of crop prediction. In soil management, five ML algorithms are deployed where SVM and regression are mainly used. In the pest management category, five ML algorithms are deployed where SVM is majorly used. In Weed management, five ML algorithms are implemented and, SVM is most often used. In last, crop disease, four ML algorithms are implemented and, SVM is majorly used. Thus, the majority of work is done using ANN and SVM can be concluded from the reviewed literature.

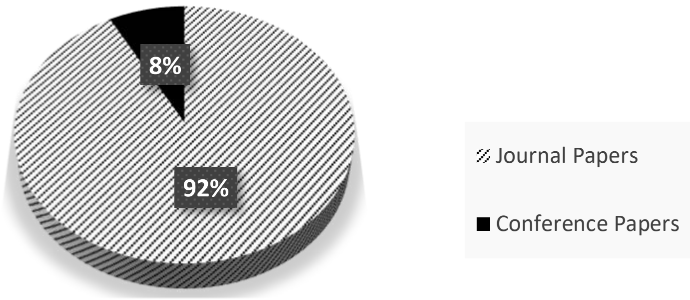

Figure 4. Categorization of papers

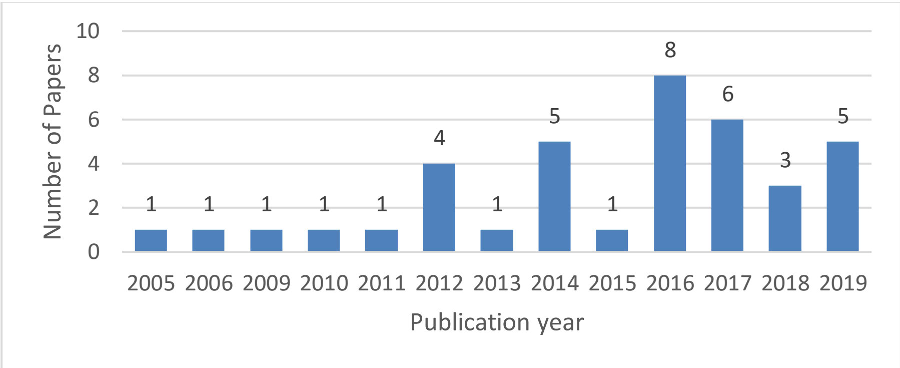

Figure 5. Number of papers published per years

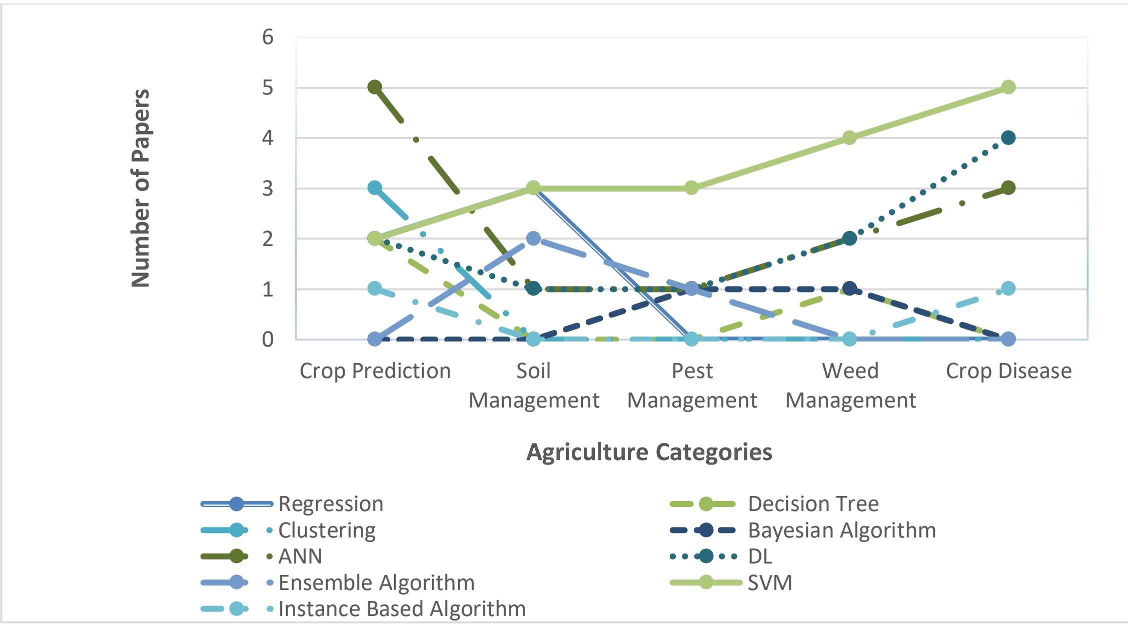

Figure 6. Utilization of ML algorithms in different categories

The analysis of figures indicates that SVM is majorly implemented because of its sequential approach, which incorporates several features to make a decision/ features into classes. SVM uses a kernel function to differentiate the nonlinear and separable data and generates a mapping relationship between the input vector and high-dimensional space vector through a hyperplane. SVM is preferred because of its sparse representation and absence of local minima. Machine learning has a significant impact on application areas of the agriculture domain. Results produced by ML are promising. Particularly DL is getting more acceptance because of its automatic feature extraction method in the agriculture sector, which can ease the process and support the stakeholders of the agriculture domain. DL architectures/algorithms are also vastly implemented in crop disease, weed management and crop prediction domains.

4. CONCLUSION

ML-based techniques have attracted much attention from researchers to improve the productivity in agriculture domain. This review summarises the implementation of the ML algorithm in the agriculture domain in the past few years. Though many algorithms are deployed, SVM and neural networks are the key techniques to be better and precise. However, the researcher can explore new techniques, new domain, and the inclusion of raw data to get more accurate results in the future. Deep learning is getting attention in the past 3-4 years. The review covers five major domains; however, further study is required to explore the other research areas of agriculture: rain management, weather Management, climate management, livestock production, and animal welfare.

APPENDIX

Table 2. Comparison among multiple agriculture domains *(continue)*

Reference No.	Agriculture Domain	Observed Features	Functionality	Applied Algorithms	Data Sources	Results
[13]	Crop prediction	Seven-band reflectance imagery	Remote sensing data used to train the model to predict the crop yield of one region. Then, another region prediction was performed using transfer learning	LSTM, regression	Moderate resolution imaging spectroradiometer satellite imagery	Trained and tested the model on soybean data of Argentina and predicts fine for brazil. Pre-trained model
[14]	Crop prediction	Soil moisture	Estimates crop yield and present comparison among many machine learning techniques	SVM, ERT, RF, DL	National Agricultural Statistical Service and United States of Department of Agriculture, National Aeronautics and Space Administration, European Space Agency, Climate Change Initiative and PRISM Climate Group	DL produced the highest accuracy among all
[15]	Crop prediction	Multiple features color, shape, texture and size	Detects each integral tomato fruit which incorporates mature, immature, and young fruits on a tomato plant	X-Means, DT	154 images were collected by conventional RGB digital camera at Tsukuba Plant Factory of the Institute of Vegetable and Tea Science, Ibaraki, Japan	Recall value: 0.80 Precision: 0.88 Recall of young fruit: 0.78
[16]	Crop prediction	Multilayer soil parameters	Predicts wheat yield for three isofrequency classes, namely high, medium and low	CP-ANN, XY-Fusion, Supervised Kohonen Network	Duck End Farm Field, Wilstead, Bedfordshire, U. K.	Accuracy: Supervised kohonen network: 81.65% CP-ANN: 78.3% XY-Fusion: 80.92%
[17]	Crop prediction	Geometrical features	Detects tomatoes from RGB images	K-Means, SOM, EM	RGB images of Spatial resolution acquired from unmanned aerial vehicles	K-means Precision: 0.723 Recall: 0.593 F-Measure: 0.652 SOM Precision: 0.730 Recall: 0.686 F-Measure: 0.707 EM Precision: 0.919 Recall: 0.606 F-Measure: 0.730

Table 2. Comparison among multiple agriculture domains *(continue)*

Reference No.	Agriculture Domain	Observed Features	Functionality	Applied Algorithms	Data Sources	Results
[18]	Crop prediction	Soil properties	SBOCM used to predict different stages and yield of rice	SVM	Chinese Academy of Sciences	Middle-season rice Tillering stage: RE(%)=22.1 Heading stage: RE(%)=17.1 Milk stage: RE(%)=19.2 Early rice Tillering stage: RE(%)=20.5 Heading stage: RE(%)=15.8 Milk stage: RE(%)=8.5 Late rice: Tillering stage: RE(%)=21.0 Heading stage: RE(%)=16.5 Milk stage: RE(%)=11.1
[19]	Crop prediction	Irrigation water, rainfall, temperature	Crop yield prediction performed for two consecutive years	MLR, M5-Prime Regression Trees, PMNN, SVR, K-NN	Irrigation module of Santa Rosa [Agricultural Production Data and Weather information Data]	M5-Prime predicted with the best accuracy, followed by KNN, SVR and MLR.
[20]	Crop prediction	Vegetation indices	Determines the potential of hyperspectral data and ANNs	ANN	Emile A. Lods Agronomy Research Centre data obtained by Compact Airborne Spectrographic Image	RMSE (kg/ha)= 19.7
[21]	Soil management	N/A	Predict soil texture and stoniness based on γ-spectroscopy	SVM, ANN	Tuscany, Central Italy	RMSE: SVM Sand: 7.0 Clay: 5.9 Stoniness:0.10 ANN Sand:7.9 Clay:6.3 Stoniness:0.11
[22]	Soil management	N/A	Crop yield prediction based on soil salinity	Stepwise linear regression	Lower seyhan plane, berdan, seyhan, and ceyhan rivers	MPE: Wheat: 7.9% Corn: 8.8% Cotton:6.3% Crop Yield loss: Corn: 55% wheat: 28% Cotton: 15%
[23]	Soil management	N/A	AMSR-E data is consistently used to observe patterns of Global soil moisture	RF	Global change master directory and rural development administration	Coefficient correlation (r) South korea:0.71 Australis: 0.84 RMSE: South Korea:0.049 Australia: 0.05
[24]	Soil management	N/A	Uses near-infrared and visible bands to predict soil nitrogen, organic carbon, and moisture	LS-SVM, Cubist	Top soil layer from Premslin, Germany.	RMSE of prediction LS-SVM: Moisture content: 0.457% Organic carbon: 0.062%
[25]	Soil management	N/A	Predicts soil liquefaction susceptibility	SVM	Chi-Chi, Taiwan earthquake.	Performance: 77.65%

Table 2. Comparison among multiple agriculture domains *(continue)*

Reference No.	Agriculture Domain	Observed Features	Functionality	Applied Algorithms	Data Sources	Results
[26]	Soil management	N/A	Implemented digital soil mapping techniques to estimate the spatial distribution of numerous soil properties	Cubist, RF	Borujen region, Chaharmahal-Va-Bakhtiari Province, central Iran	soil organic carbon: RMSE: 0.33(RF) calcium carbonate equivalent RMSE: 9.52(Cubist) Clay: RMSE: 7.86(RF)
[27]	Soil management	N/A	Defines and assesses the efficiency of transfer learning to localize	CNN	LUCAS Soil database	RMSE Organic carbon: 10.5% Cation exchange capacity: 11.8% Clay content: 12.0% pH: 11.5%
[28]	Pest management	Color, Shape, Texture	Automated rice pest identification system	SVM	Live images with cameras	Accuracy 97.5%
[29]	Pest management	Area, Perimeter, sphericity, Eccentricity	Detect individual pest among other species	ANN	Sugar beet field in Shiraz, Iran	R=0.89
[30]	Pest management	Curve response and slope	Diagnosis of plant pest using Electronic nose.	SVM	Lancaster University, UK	Tomato (mildew) Linear: 95% Polynomial: 94% RBF: 96% Cucumber (wounded) Linear: 77% Polynomial: 82% RBF: 87% Cucumber (spider mite) Linear: 94% Polynomial: 88% RBF: 91% Pepper (wounded) Linear: 67% Polynomial:71% RBF: 92%
[31]	Pest management	58 attributes	Develop a method to forecast the result of pest monitoring.	AdaBoost, NB	Zespri International Ltd	Precision: AdaBoost: 98% Naïve Bayes: 95%
[32]	Pest management	N/A	Detects and classifies multi-class pests.	DL	88,670 images	Mean average Precision: 75.46%
[33]	Pest management	color indexes were: Hue, Saturation and Intensify	Automatically detects thrips and their position.	SVM	Tarbiat Modares University, Islamic Republic of Iran, Tehran	MPE of less than 2.25%
[34]	Weed management	Color, shape, texture and image orientation	Pynovisao software developed and used to detect weed in crop image and classified using CNN.	CNN	Images captured by unmanned aerial vehicle.	CNN: Precision 0.991 Sensitivity 0.991
[35]	Weed management	Nitrogen application rate: 60,120 and 250 kg N/ha	Weed classification performed w.r.t. nitrogen application rate	SVM	72-waveband compact airborne spectrographic imager (CASI), range: 408.73 to 947.07 nm	Effect of nitrogen and weed combined: 69.2% Effect of nitrogen:80.8 Effect of weed: 85.8
[36]	Weed management	Color and texture	Weed discrimination for different growing states of rice	DT	Rice and weed images from the internet of 1125*1500	Precision: 0.982 Recall: 0.977
[37]	Weed management	Spectral	Recognizes weed species based on hyperspectral sensing.	SOM, Mixture of Gaussian	Hyperspectral images using HSI.	Mixture of Gaussian- 31%-98% SOM- 53%-94%
[38]	Weed managemen	Color, moment invariant, size	Weed and crop were classified using digital images.	SVM	OLYMPUS FE4000 point-and-shoot digital camera	Accuracy- 97%

Table 2. Comparison among multiple agriculture domains

Reference No.	Agriculture Domain	Observed Features	Functionality	Applied Algorithms	Data Sources	Results
[39]	Weed management	Shape, Fourier descriptor, moment invariant	Weed detection using shape features	SVM, ANN	960×1280 pixels, Shiraz university.	Accuracy: ANN: 92.92% SVM: 95.00%
[40]	Weed management	RGB-NIR imagery	Detect sugar beet plant and weed-based on vision classification	CNN	UAVs equipped with vision sensors	Accuracy 95%
[41]	Weed management	Size, length, and fourier	Classification for small-grain weed species concerning cirsium arvense and galium aparine	SVM	Red (580 nm) and infrared (>720 nm) spectrum	Overall accuracy: 97.7%
[42]	Crop disease	Hyperspectral imaging with 2.8 mm spectral resolution, pixel size is 6.45×6.45 µm	Detecting sclerotinia sclerotiorum on oilseed rape stems	PLSDA, RBF-NN, SVM, and ELM	farm of Zhejiang University	Sample set 1: Average spectra: PLSDA: 100 RBFNN: 97.50 ELM: 100 SVM: 92.50 Pixel-wise Spectra: PLSDA: 94.80 RBFNN: 98.80 ELM: 99.40 SVM: 99.00 Sample set 2: Average spectra: PLSDA: 92.50 RBFNN: 87.50 ELM: 97.50 SVM: 90.00 Pixel-wise Spectra: PLSDA: 96.60 RBFNN: 98.70 ELM: 99.50 SVM: 99.30
[43]	Crop disease	Leaf, stem, and fruits	Detect real-time disease along with the class and location of the plant	DL	Images using a digital camera from farms of the Korean peninsula	Mean average precision 83.06%
[44]	Crop disease	Spectral vegetation indices	Detects and classifies plant diseases in sugar beet	SVM	Cercospora leaf spot, leaf rust and powdery mildew	Cercospora Leaf spot: 89.69 Sugar beet rust: 83.60 Powdery mildew: 92.46
[45]	Crop disease	Coloured, greyscale and segmented	Detects plant disease using images	CNN	PlantVillage Public dataset	Overall accuracy- 99.35%
[46]	Crop disease	75 features by wavelet decomposition	Healthy and fusarium diseased pepper leaves were detected	KNN	GAP Agricultural research (GAPTEAM), şanlıurfa, Turkey	KNN: Statistics of wavelet coefficient: 99% Wavelet Coefficient: 100%
[47]	Crop disease	Grayscale	Detect and classify potato disease by visible symptoms	CNN	Images captured by cameras	Dataset split: 90%-train and 10%-test provides accuracy - 0.9585
[48]	Crop disease	Shape, texture, and grey level	Identification of plant disease by visual symptoms	SVM	The University of Georgia, USA	Accuracy 93.1%
[49]	Crop disease	Leaf properties	Classifies the disease based on symptoms visible	CNN	Plant village	Accuracy 99.18%
[50]	Crop disease	Color, texture, gray level co-occurrence matrix, and wavelet transform	Detects disease in apple fruit	ANN, SVR-rbf, and SVR-Poly	ANN, SVR-RBF, and SVR-Poly	RMSE: ANN: 0.53 SVR-Poly: 0.42 SVR-RBF: 0.2

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