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Applications of Machine Learning Algorithms in Agriculture

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Abstract:
Machine learning(ML) makes machines independent and self-learning component. Researchers applying machine learning algorithms to solve various real word problems in various domains. Nowadays agriculture affects by various factors such as global warming, climatic changes, lack of manpower, etc. To help the farmers from the above factors and increase agriculture production, recently many machine learning techniques are utilized in the agricultural field. In this paper, we studied different applications of machine learning techniques in the agriculture domain. We classified applications of machine learning algorithms in agriculture by four categories namely, machine learning in plant monitoring, machine learning in soil analysis, machine learning in detection (or) prediction process in agriculture, machine learning in animal monitoring. We also analyzedthe important features of machine learning applications in agriculture.

***Keywords:** Machine learning, agriculture, smart farming.*

I. Introduction

Agriculture is one of the ancient businesses. Agriculture suffers due to various factors such as climatic change, unpredictable rainfall, pollution, lack of manpower, etc. Due to high population growth create a great demand for agriculture products [1]. To feed the world population, it is necessary to increase agriculture production. To increase agriculture production, researchers utilizing various technologies such as sensor networks [2], image processing [3], remote sensing [4], machine learning [6], etc. Machine learning is a fast-growing technique, which makes machines are intelligent also machines able to work without any instructions. The machine learning techniques are applied in various applications such as health care, smart cities, health care, automobile, etc [5].

Now a day's various machine learning algorithms are used in agriculture to solve various issues. In this paper, we studied applications of machine learning in agriculture field. The machine learning algorithms are used in various real-world agricultural applications; we classified these applications as machine learning in-plant monitoring, machine learning in soil analysis, machine learning in detection (or) prediction process in agriculture, machine learning in animal monitoring. The various agricultural applications of machine learning techniques are discussed in next section.

II. Machine learning in agriculture

The field of agriculture suffered due to various challenges, such as lack of water, excess rain, soil pollution due to plastics, synthetic fertilizer, etc. To helps the farmers from these issues, researchers applying machine learning in different fields of agriculture. The machine learning algorithms are mainly applied in the following four areas of agriculture such as plant monitoring, soil analysis, prediction (or) detection in the agricultural process, animal monitoring. The brief details about these applications are given below

A. Machine Learning in Plant Monitoring

Monitoring plants is one of the basic function of farming. Various machine learning techniques are applied to monitor plants. These plant monitoring techniques are given as follows:
In [6], the authors applied a sparse linear adaptive structure to monitor the plant growth in a plant factory. In [7], Ozbas et al. utilized ML algorithm

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called supervised algorithm for the production of hydrogen using biomass gases. Four ML classifiers such as Decision Tree, Bayesian, Neural Network, Random Forest applied to analysis the rainfall parameters to support the agriculture. The K-fold cross validation used to validate above-mentioned classifier, the result shows that Random Forest and Decision Tree classifiers provided remarkable performance [13]. In [16], the authors apply an automated multi-class classification approach for tomato ripeness estimation and ordering the distinctive development/ripeness stages. This methodology uses shading effects for grouping tomato ripeness stages. The methodology utilizes Principal Components Analysis (PCA) notwithstanding Support Vector Machines (SVMs) and Linear Discriminant Analysis (LDA) algorithms for feature extraction and arrangement. In [17], the authors demonstrated that machine learning algorithms dependent on morpho-colorimetric parameters and NIR examination independently were capable to classify leaves of 16 grapevine cultivars. Automated picture analysis for morphological and colour highlights extraction of checked leaves combined with ANN displaying rendered fast, exact and modest techniques to be utilized for ampelography/ cultivar characterization. In [20], the author features the estimation of long-term pest checking information and long-term natural information in understanding the spatial dissemination of Ceratitis capitata trap get in complexagrarian frameworks. This examination sets out a structure to spatially measure Ceratitis capitata trap catch into HCSs(hot-and bug spots) utilizing checking information from area-wide integrated pest management(AW-IPM) programs, empowering the examination of complex natural connections using ML algorithms. In [22], A tale computational insight vision detecting utilizing deep sparse extreme learning machines (DSELMs) combination and Genetic algorithm (GA) has been proposed to get plant pictures and estimate nutrient content in wheat leaves dependent on shading highlights of plant pictures caught on field with a critical variety of daylight forces. In [23] authors investigate the conceivable outcomes of phenological checking of paddy-rice, with regards to the directed arrangement, by considering the phenological organize estimations covering an entire development period to be utilized as a preparation dataset for ML classifiers. In [24], the authors utilizes AirSurf, a robotized and open-source diagnostic platform that consolidates present day computer vision, modern Machine learning, and secluded programming designing to measure yield-related phenotypes from ultra-enormous ariel imagery. To measure a large number of in-field lettuces obtained by fixed-wing light flying machines outfitted with normalised difference vegetation index (NDVI) sensors, they tweaked AirSurf by consolidating computer vision algorthims and a deep learning classifier prepared with more than 100,000 marked lettuce signals. In [39], the writers integrated some well-developed ML algorithms to predict silage maize yields from distinct time series. In [45], the classification of sugar beet and voluntary potato in uncontrolled agricultural settings was explored using Covoluation nural networks. This article first evaluates a learning process with three distinct pre-trained convolution neural network applications, and then evaluates the distinction in results among the six network architectures: VGG-19, ResNet-50, AlexNet, Inception-v3, GoogLeNet, and ResNet-101

B. Machine Learning in Soil Analysis

Soil is one of the vital element in agriculture. To increase the agriculture production, right soil should be used in agriculture. To help farmers in this aspects, researchers explored following technique.

Various soil parameters of agricultural land are classified by multiple ML classifiers such as bagging, boosting, decision trees, nearest neighbor classifier, etc. The experiment helps to identify the soil nature in Maharashtra, India [8]. In [21] author presented a viable land-cover change detection (LCCD) method that uses variety in radiometric

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estimations of flying pictures. In this T 2 monitoring plan has been used for LCCD and the weighted random forest (WRF) classifier has been connected to recognize the sort of progress. The outcomes show that the coordinated T 2-WRF is observed to be better in LCCD in contrast with other ordinarily utilized calculations. . In this study, the six soil (Sand, CEC, pH, complete N, OC and clay) were analyzed using CNN. The ML method was suggested in [31] by using VIS-NR spectroscopy to forecast soil properties such as complete nitrogen, organic carbon and humidity content. This article introduces an smart system to predict a field's irrigation demands using ground parameter sensing such as soil moisture, soil temperature, and environmental conditions along with Internet weather forecast information. A machine learning method was suggested in [34] to predict soil properties from unprocessed soil spectra to prevent dimensional reduction and pre-processing processes. The authors in [40] suggested a hybrid machine-based learning method with IoT-based intelligent irrigation architecture to predict soil moisture. In [41], the authors intended the soil drying ML algorithm that only needs precipitation and estimates of potential evaporatranspiration. This article uses three kinds of ML algorithms: algorithm k-nearest-neighbor (KNN), decision trees, boosted perceptron to predict the present soil situation. The applications of machine learning regression based techniques in the forecast of chosen microbial soil dynamics, including bacterial population (BP), phosphate solubilization (PS), and enzyme activity are addressed in [42]. In the forecast of soil microbial dynamics, this research uses the Wang and Mendel fuzzy inference systemWM-FIS and subtractive clustering SC)-FIS techniques. The self-adaptive evolutionary (SaE) algorithm is used to analyze the daily soil temperature in [43] to enhance the efficiency of extreme learning machine method. The technique mentioned in this research not only learns quicker than traditional algorithms, but also has a greater efficiency in generalization and predictive precision. In addition, randomness generated from the parameters of the random hidden layer in ELM is avoided. In [46], multiple machine learning algorithms such as bagged tree, k-nearest neighbour, Gaussian kernel based support vector machine (SVM) used to alanysis soil parameter. After analyzing soil, the system predict the soil parameter and also it suggested about related crop to the farmers.

C. Machine Learning in Prediction or Detection

Most of the times the farmers need to detection (or) predict varios plant diseases. The following machine learning techniques are used in predicition or detection process in agriculture.

In [9], extreme learning machine algorithm used with acoustic signal processing in order to detect damaged wheat kernels. The result shows that, the system able to classify various damages in wheat. The authors [10], used multiple classifiers such as K-nearestNeighbor (KNN), Naive Bayes (NB) and Artificial Neural Networks (ANN) to detect pepper fusarium disease in pepper plants. In [11], multiple ML algorithms such as boosted regression trees (BRT),ν-support vector regression (ν-SVR), Gaussian process regression (GPR) and random forests regression (RFR) to detect wheat leaf rust disease. Machine learning classifiers such as support vector machine, K-nearest neighbours, stochastic gradient descent classifiers used to classify rapeseed. The ML classifiers applied with computer vision technology in order to classify rapeseed [12]. In [14], the authors used ML technique with hyperspectral image to estimate mango fruit maturity. Genetic algorithm and brute force algorithm applied with ML technique in for optimization technique. In [15], The authors recommend that yearling fleece, compliance and well being attributes alongside field and atmosphere information can be used by ML algorithms to precisely and correctly anticipate grown-up fleece development and quality characteristics. Among the ML algorithms BG (Bagging) and MT (Model Tree) were best for foreseeing grown-up fleece generation and quality dependent on a wide scope

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of logical factors. Despite the fact that BG seemed prevalent in its precision of expectation, there were no noteworthy contrasts from the exhibition of MT. Expectation models created in this investigation will be joined with other choice help instruments in ASKBILL to help sheep ranchers to improve the gainfulness of sheep undertakings. In [18], the authors select the best strategy between Artificial Neural Network (ANN) and Support Vector Machine (SVM) to assess three unique factors incorporate inside air, soil and plant temperatures (Ta, Ts, Tp) and also energy exchange in a polyethylene greenhouse. The authors utilized 13 diverse training algorithms for ANN models (MLPRBF). In light of K-fold cross validation and Randomized Complete Block (RCB) technique, the best model was chosen. The outcomes demonstrated that the sort of training algorithms and kernel function are significant factors in ANN (RBF and MLP) and SVM model execution, individually. Looking at RBF, MLP and SVM models demonstrated that the exhibition of RBF to anticipate Ta, Tp and Ts factors is better. In [26] convolutional neural system models were created to perform plant malady identification and conclusion utilizing basic leaves pictures of healthy and infected plants, through deep learning methodologies. In [27] the authors tried four distinctive machine learning algorithms to anticipate rectal (Tr), skin-surface (Ts), and hair-coat surface (Th) temperatures of piglets dependent on natural information. From the four algorithms considered, deep neural networks gave the best expectation to Tr with a blunder of 0.36%, inclination supported machines gave the best forecast to Ts with a mistake of 0.62%, and random forests gave the best forecasts to Th with a mistake of 1.35%. These three calculations were strong for a wide scope of sources of info. The fourth algorithms, generalized linear regression anticipated at higher mistakes and was not strong for a wide scope of data sources. This examination bolsters the utilization of machine learning algorithms to anticipate physiological temperature reactions of piglets. In [28] this examination is to apply, approve and think about the presentation of ML techniques in precisely classifying seriousness of occupational injury results in different agribusiness ventures in the Midwest of the United States utilizing to an informational index with over 33,000workers' pay guarantees in. In [29] author applyed multiple machine learning algorithms to foresee month to month power and water utilization on Irish dairy farms using information identified with milk generation, stock numbers, infrastructural hardware, administrative procedures and natural conditions. In [30] athors investigates the use of machine learning techniques in two different ways. Right off the bat, how linear regression decides significant highlights for expectation. Also, the use of neural systems and support vector machine in foreseeing the qualities. The mango tree deficiency predictied by anlysing mango tree leaf [47]. To identify the nutrient deficiency of mango tree, image processing technique integrated with machine learning technique. The clustering algorithm such as K-means clustering used to detect deficiency in mango tree. In [48], the authors combined image processing and machine learning technique to detect nutrient deficiency in the plant. The supervised machine learning algorithm used to detect the nutrient deficiency. The system able to detect the six nutrients deficiencies such as Calcium, Nitrogen, Potassium, Phosphorous, Magnesium and Sulphur. In [49], the authors compared the baseline algorithm which used color line and decision tree ensemble (DTE) in precision agriculture. The objects in vineyard are identified using baseline and DTE. The result shows that DTE identifies object with high accuracy.

D. Machine Learning in Animal Monitoring

To monitor animals following machine learning techniques are applied. By using the indices from routine blood testing, the writers in [35] suggested an strategy based on machine learning to define the status of glyphosate toxicity in rats. This paper used an improved Fuzzy k-nearest neighbor

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(FKNN) model for particle swarm optimization approach (PSO) to define glyphosate poisoningstatus in rats. In [44], the researchers suggested a profound learning (SBDA-DL)-based real-time sow behavior detection algorithm to monitor the three distinct behaviors, drinking, urinating, and mounting. It is discovered that compared to the frequently used deep learning target detection network model, the SBDA-DL detection algorithm can keep the category accuracy to the same level but with a much quicker detection Speed.

E. Anonmous Agriculture Applications

Few researchers applied machine learning in unique agricultural applications such as biogas production and monitoring, rainfall analysis, etc. These kind of applications are given below.

In [7], Ozbas et al. utilized ML algorithms such as linear regression (LR), support vector machine regression (SVMR), decision tree regression (DTR) and K nearest neighbors (KNN) for production of hydrogen using biomass gases. Four ML classifiers such as Decision Tree, Bayesian, NeuralNetwork, RandomForest applied to analysis the rainfall parameters to support the agriculture. The K-fold cross validation used to validate above mentioned classifier, result shows that RandomForest and Decision Tree classifiers provided remarkable performance [13].

The novel method based on machine learning, ensemble feature ranking algorithm was created to define the cause of shellfish closure and predict the closure in [32] as well. In[36], the authors suggested to use Kernel Extreme Learning Machines to define the odors of six fruits: onion, lemon, banana, apple, plum and garlic. And the findings are compared to the current algorithms and it is discovered that in terms of high test precision and quick reaction, KELMs generated excellent odor identification output. The various important fearutes of machine learning (ML) algorithms are given in Table I.

Table 1. Comparative description of applications ML in Agriculture

Reference, Year & Country	*Machine Learning Algorithm*	*Features*	*Real Time Implementation*
[6], (2019), Japan	Sparse regularizationML	Plant growth control	✓
[7], (2019), Turkey	Supervised ML	Hydrogen gas production	✓
[8], 2017, India	Multiple ML classifiers	Agriculture land soil parameter analysis	✓
[9], 2019, China	Extreme learning machine algorithm	Detection of demaged wheat	✓
[10], 2019, Turkey	Multiple ML classifiers	Pepper fusarium disease detection	✓
[11], 2019, Iran	Multiple ML algorithms	Wheat leaf rust detection	✓
Reference, Year & Country	*Machine Learning Algorithm*	*Features*	*Real Time Implementation*
[12], 2014, Turkey	MultipleML classifiers	Classification of rapeseed mixture	✓
[13], 2018, India	MultipleML classifiers	To analyse rainfall parameters	✓
[14], 2019, Spain	ML algorithm for filter selection	To detect mango fruit maturity	✓
[15]2018, Australia	ML algorithms	Prediction of adult wool traits.	✓
[16], 2015, Egypt	Automated multi-class classification approach	Tomato ripeness measurement	✓
[17], 2018, Australia	ML algorithms	Grapevine cultivars classifications	✓
[18], 2018, Iran	MultipleML algorithms	Predecting greenhouse simulation	✓
[19], 2019, Australia	MultipleML algorithms	Variables affecting production of Pawn in Ponds	✓
[20], 2019, South Africa	ML algorithms	Ceratitis capitata trap catch	✓
[21]2019, Saudi Arabia	Weighted random forest algorithm	Detecting land cover change	✓
[22], 2018, UK	deep sparse extreme learning machines (DSELM) fusion and genetic algorithm	nutrient content in wheat leaves	✓
[23], 2016, Turkey	ML classifiers	Paddy-Rice Phenology Classification	✓
[24], 2019, UK	Airsurf	commercial lettuce production	✓
[25], 2019, China	Counting Convolutional Neural Network	Pig counting	✓
[26], 2018, Greece	convolutional neural network models	plant disease detection	✓
[27], 2018, United States	MultipleML algorithms	predict core, skin, and	✓

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Reference,Year & Country	*Machine Learning Algorithm*	*Features*	*Real Time Implementation*
		hair-coat temperatures of piglets	
[28], 2019, USA	ML algorithms	predicting injury severity	✓
[29], 2018, Ireland	MultipleML algorithms	predicting on-farm direct water and electricity consumption	✓
Reference, Year & Country	*Machine Learning Algorithm*	*Features*	*Real Time Implementation*
[30], 2018, India	MultipleML algorithms	Predecting wine quality	✓
[31], 2016, Germany	MultipleML techniques	To predict soil properties	✓
[32], 2015, Australia	Novel ensemble feature ranking algorithm	To predict the shellfish closure	✓
[33], 2018, Turkey	Epsilon-SVR	To predict tree-bark volume	✓
[34], 2018, Australia	CNN, deep learning	To analyse soil properties	✓
[35], 2018, China	Fuzzy k nearest neighbour algorithm	To identify the glyphosate poisoning status in rats	✓
[36], 2017, Turkey	Kernel Extreme Learning Machines	To design an android electronic nose	✓
[37], 2018, Belgium	Random forest ML algorithm	To recognize weeds in maize crops	✓
[38], 2019, USA	MultipleML techniques	For segmentation of soyabeans plants	✓
[39], 2018, Iran	MultipleML techniques	To predict theyield of Silage maize	✓
[40],2018, India	-	To predict soil	✓
Reference,Year & Country	*Machine Learning Algorithm*	*Features*	*Real Time Implementation*
		moiture	
[41], 2014, US	k-nearest-neighbor (KNN) algorithm, decision trees, boosted perceptron	To test the soil conditions	✓
[42],2018, Viet Nam	ML based regression methods	To predict soil micbrobial dynamics	✓
[43], 2019, Iran	Self-adaptive evolutionary (SaE) algorithm in ELM	To estimate Soil temperature	✓
[44],2019, China	Sow Behavior Detection Algorithm based on Deep learning (target detection method baded on Deep learning)	To test the sow behaviour(drinking, urination, mounting)	✓
[45], 2018, The Netherlands	Transfer Learning	volunteer potato control in sugar beets	✓
[46], 2018, Bangladesh	Bagged tree, k-nearest neighbour, Gaussian kernel based support vector machine	Soil Classification	✓
[47], 2018, India	K-means clustering	Nutrient deficiency detection	✓
[48], 2018, India	Supervised ML algorithm	Nutrient deficiency detection	✓
[49], 2018, Switzerland	Decision tree ensemble (DTE)	Precision algorithm	✓

III. CONCLUSION

Machine learning techniques are applied in various fields of agriculture. We studied various applications of machine learning algorithms in agriculture and also classified these applications into four categories. Various features of agricultural machine learning techniques are discussed

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