Review of Machine Learning Model Applications in Precision Agriculture

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Abstract. Over the past two decades, modern agriculture has made significant advancements. The methods used in farming have changed from conventional ways to digital technologies as a result of significant technology improvement. Advances in machine learning and artificial intelligence are being applied in this discipline to reevaluate farming practices in order to meet the demands of an expanding population. Throughout the entire cycle of planting, growing, and harvesting, machine learning is prevalent. It starts with the planting of a seed in the ground, goes through soil preparation, seed breeding, crop health monitoring, measuring water feed and concludes with the harvest being picked up by robots by using computer vision techniques.

For crop selection, yield prediction, soil classification, weather forecasting, irrigation system, fertilizer prescription, disease prediction, and determining the minimal support price, machine learning models are developed in the field of precision agriculture. In this article we will cover the different categories of precision agriculture applications and use of machine learning models in those different categories. Various models in precision agriculture include Artificial Neural Networks, Support Vector Machines (SVMs), Convolution Neural Networks (CNN), Random Forest (RF), K-Nearest Neighbor (KNN), K-Means Clustering. The ultimate solution to issues in agriculture rests in the efficient application of Machine Learning (ML). ML can bring about a paradigm change in nations like India where agriculture is the main source of employment. Since most Indian rural areas have adopted digitalization, ML and AI-related applications are gradually emerging in this sector.

Keywords: Machine learning · Crop yield · Disease detection · Support Vector Machine · K-Means Clustering · ANN · CNN · Precision agriculture

1 Introduction

Agricultural technology is evolving day by day and with such technological advancement, the digitization is taking the pace in agriculture with invention in precision agriculture applications. Precision agricultural management practices utilizes variety of

S. Tamane et al. (Eds.): ICAMIDA 2022, ACSR 105, pp. 916–930, 2023.
https://doi.org/10.2991/978-94-6463-136-4_81

machine learning technologies to analyze important factors such as soil and water for their effective management [1]. However, a number of problems, such as pests and diseases that harm crops, a lack of rain, floods, and unexpected weather changes, to name a few can influence agriculture. These problems, most of which are much unanticipated, combined with the unrestricted use of fertilizers and pesticides, insufficient government subsidies and corruption result in enormous economic losses on a worldwide scale. These factors alienate the farming community and lead to rising debt, which in turn leads to farmer suicides. Technological advancement like machine learning, deep learning, Image processing, IOT, UAV's can be used in the field. The precision agriculture activity starts with the planting of a seed in the ground, goes through soil preparation, seed breeding, crop health monitoring, water feed measuring, and concludes with the harvest being picked up by robots that use computer vision to determine when it is ripe [2, 3]. Applications of machine learning will help to increase the yield by making timely decisions which reduces the cost and increases the profitability.

ML, DL, natural language processing (NLP), swarm intelligence (SI), expert systems, fuzzy logic, and computer vision has many applications across different domains. Along with agriculture machine learning models are constantly used in healthcare, finance, automobile, robotics, e-commerce, security and the automation industry [4]. Machine learning techniques that are used effectively hold the key to solving agriculture's challenges. Machine learning has the potential to create a paradigm change in nations like India where agriculture is the primary industry. Machine Learning and Artificial Intelligence-related applications are steadily emerging in this field as most rural areas in India have adopted digitization. In agriculture the farmers follow certain steps which are listed by Vishal Meshram et al. [2]. These include choosing a crop, preparing the land, planting seeds, providing irrigation and fertilizer, crop maintenance, harvesting, and engaging in post-harvest activities.

The broad categorization of applications of ML in agriculture was done by Liakos et al. [5], where these generic categories are "crop management, water management, soil management and livestock management". In this article we will extend these categories and review the machine learning models/algorithms used in these categories.

The categories which are included in the study are Crop Yield prediction, Disease detection & Weed detection, Crop recognition, Crop quality, Drip Irrigation, Water quality, Soil properties, Weather conditions, Animal Welfare, Livestock Production, Harvesting techniques, Fertilizer Recommendation [2, 4, 5] and the machine learning models used in these applications are Support Vector Machines (SVMs), Convolution Neural Networks (CNN), random forest (RF), K-Nearest neighbors (KNN), K-means Clustering, XGBoost, AdaBoost. Applicability of machine learning models to the specific category is discussed in detail in coming sections.

2 Model Generation and Testing Process Using Machine Learning

Machine learning model generation and analysis of a crop in a much complex process, which include huge input data in terms of image and text. Machine learning algorithms make it possible to get important information and insights from a large amount of data. The system will become intelligent and be able to provide definitive facts and make

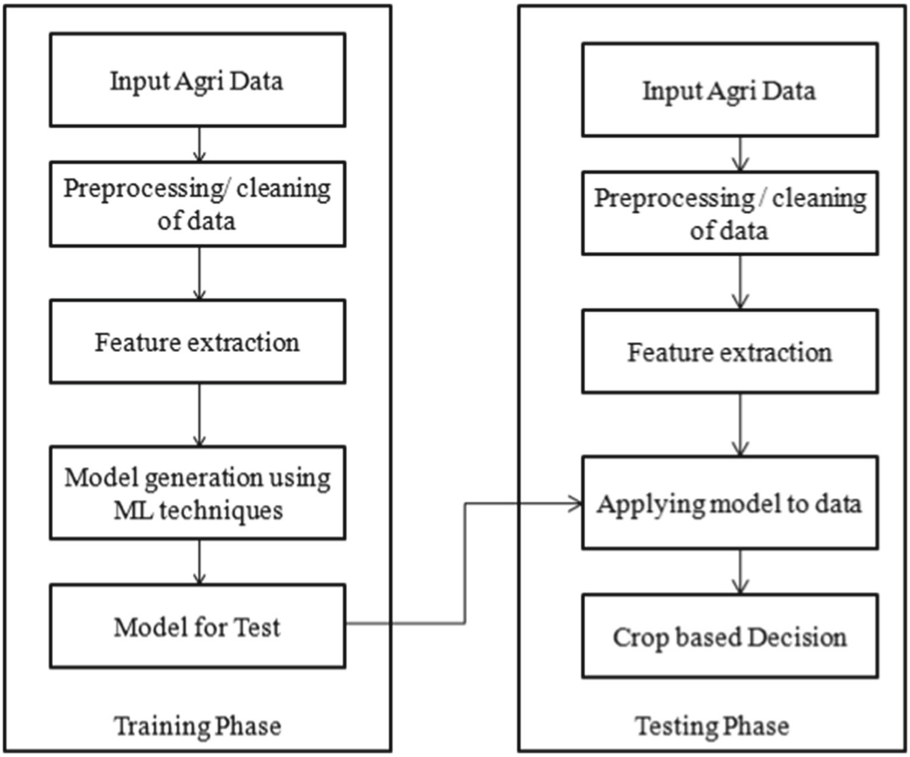

Fig. 1. Phases in Machine leaning model generation and testing

predictions as a result of the application of ML algorithms to data from various farm inputs [6]. Input data have to be preprocessed before it goes to the next step this is called as the cleaning of data. Mainly ML systems divided into two phases, namely the training phase and testing phase. The features which are extracted in the training phase of machine learning process are used like an experience learning. This experiential learning performance terminates when it reaches a certainbe used for decision making in the precision level (represented through statistical and mathematical correlations). The model that was created through the training process can then be applied to tasks requiring classification and prediction [7].

There are lots of challenges while creating and implementing machine learning model as getting data from government institutions requires a lot of procedure then selecting a relevant data, is another challenge and most importantly finding appropriate machine learning models which can map the relationship between the variables with maximum accuracy [6]. Depending on the quality of the available data, implementing a machine learning method can result in laborious and time-consuming processes. In general, two thirds of the data are used for the training dataset and one third for the validation dataset.

The process of machine learning model generation for agricultural data is shown in Fig. 1. It starts with agricultural data as input which is preprocessed/cleaned to remove inconsistencies in data items and data transformation procedures such as normalization

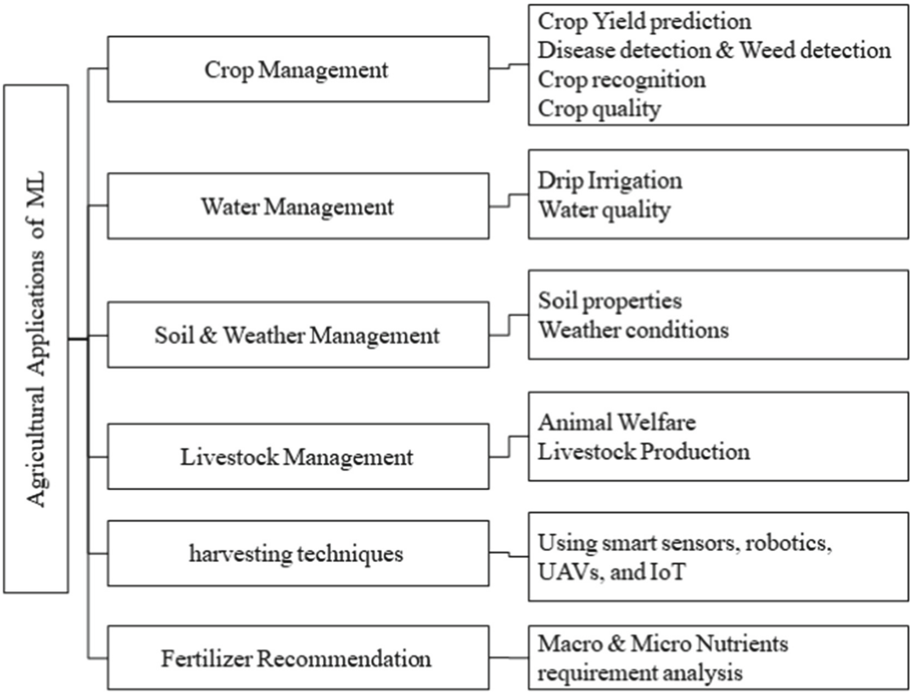

Fig. 2. Category wise machine learning model applications in precision agriculture

is performed to get a data which is consistent which will be given to the next step [8]. The feature extraction provides identifying important subset of features from all the available features which is used in the training phase to train the machine learning model [7]. The model created will be trained with 80% of the data and remaining 20% of the data is used for the testing. The output from this machine learning process is a prediction/classification which will be used for decision making in the precision agriculture applications.

3 Category Wise Machine Learning Model Applications in Precision Agriculture

Machine learning is being used in nevertheless every stage of precision agriculture [2]. As literature survey taken into account by Liakos et al. [5], four generic categories were identified which are crop, water, soil, and livestock management. In this article we will extend these categories/domains and review the machine learning models used in these categories (Fig. 2).

The crop management which again can be sub categorized into: Yield prediction, Disease detection & Weed detection, Crop recognition, Crop quality. The water management which again can be further sub-divided into: Drip Irrigation, Water quality. The Soil & Weather management which again can be further sub-divided into: soil properties, weather conditions. Livestock management applications are divided into: Livestock production, Animal welfare. Different Harvesting techniques using smart sensors, robotics, UAVs, and IoT and Fertilizer Recommendation is sub categorized into Macro & Micro Nutrients measurement, fertilizer requirement analysis.

4 Brief Description of Categories

4.1 Crop Management

Managing a crop involves taking into account qualitative and quantitative data which is used in agriculture. Using the crop management approaches such as yield prediction, disease & weed detection, crop recognition, and crop quality agriculture productivity can be increased and the cost can be reduced [3].

Yield Prediction. A potential study area is the prediction of crop yield based on environmental, soil, water, and crop characteristics. It is impossible to directly transfer the raw data to crop yield numbers in both a non-linear or linear fashion and the effectiveness of those models heavily depends on the quality of the characteristics that are extracted [9]. If a certain anomaly is not discovered in the early stages, it could significantly impact the crop yield prediction.

Maya Gopal et al. [10], used ML models such as ANN, SVR, KNN, RF to identify the yield in which RMSE, MAE, and R matrices is used for accuracy of yield prediction where RMSE is compared for different algorithms and RF algorithm is giving the highest accuracy. When using Multispectral data, CNN architecture performed better with RGB data than the NDVI data for combined model for wheat and barley yield prediction [11].

Disease and Weed Detection. Artzai Picon et al. [12], proposed Convolutional Neural Networks (CNN) based methods that uses contextual non-image meta-data such as crop information onto an image based Convolutional Neural Network. This lessens the difficulty of the disease classification tasks while learning from the complete multi-crop dataset. As CNN has shown their ability in the agronomy industry, particularly for assessing plant visual symptoms.

Disease-causing fungus, bacteria, and other microbes derive their energy from the plants they inhabit; this affects the production of agriculture. Farmers risk suffering a large financial loss if the problem is not discovered quickly. Farmers must spend a lot of money on pesticides to get rid of diseases and restore crop health. Overuse of pesticides also harms the ecosystem and has an impact on the agricultural land's water and soil cycle [4].

The imaging techniques' data from melon leaves was used to train models including LRA, SVM, and ANN, which categorize new samples as "healthy or infected". This classification is effective when small portion (5–7%) of the leaves area is affected [13].

In most cases, weeds spread rapidly across large fields, competing with crops for resources like air, sunlight, nutrients, and water supplies. Weed control, either mechanical treatment or the administration of herbicides, is a crucial management technique to prevent crop production decline. A snapshot mosaic hyperspectral camera was tested for classifying weeds on maize using the popular and effective Random Forests (RF) method. Utilizing a snapshot mosaic hyperspectral image sensor, RF was evaluated for its ability to construct classifiers with various spectral feature combinations [3, 14]. Recent research has demonstrated the importance of discriminative features in weed detection from sensor data. The identification of agricultural plants and weeds at various vegetative phases using image segmentation and digitization, followed by classification, is a promising strategy [18].

Crop Recognition. Crop classification by remote sensing has grown in popularity, including the use of satellites and airborne vehicles to detect crop attributes. A two step approach First, the Google Earth Engine cloud computing platform was used to pre-process and evaluate time-series metrics based on Landsat that capture within-season phenological variation. Each crop's developmental stage was modeled using a harmonic function. The output of the model was also used to create training samples automatically. Second, tests were conducted on a number of classification techniques (support vector machines, random forest, and decision fusion). Sentinel-1 and Landsat image composites were used as input data for crop classification. Accurate crop mapping is very important for sustainable crop management [15].

Also three-dimensional (3D) convolutional neural networks (CNN) based method that automatically classifies crops from spatio-temporal remote sensing images can be used, comparative study of SVM and CNN gives us the result that CNN will give us more accurate result in cases where spatio-temporal remote sensing images are used [16].

Crop Quality. Crop quality, which is typically determined by elements like soil and climate conditions, cultivation methods, and crop traits, to name a few, has a significant impact on the market. Agricultural producers often make more money when selling high-quality products because they can command higher prices. For example, in terms of fruit quality, soluble solids concentration, flesh hardness, and skin color are some of the common maturity indices used for harvesting [3].

The date of harvest has a significant impact on the quality of both high value crops' (tree crops, grapes, vegetables, herbs, etc.) and arable crops. Therefore, creating decision support systems can help farmers make wise management choices for higher-quality output. For instance, one management strategy that may significantly improve quality is selective harvesting. Additionally, crop quality and food waste are strongly related, which presents another difficulty for modern agriculture. If a crop does not conform to the ideal shape, color, or size, it may be thrown away. Similar to the aforementioned part, using ML algorithms to imaging technology can produce promising outcomes [17].

ML regression algorithms are compared for biophysical parameter retrieval with neural networks (NNs) and random forests (RFs). Several state-of-the-art convolutional neural network (CNN) architectures with region suggestions have been trained using transfer learning to automatically recognize seeds within petri dishes and predict whether the seeds germinated or not. Using CNN has higher performance compared to conventional and manual methods for measurement of quality [19].

Individual seeds were used to gather FT-NIR spectroscopic data and radiographic pictures, and the models were built using the following algorithms: Support vector machines (SVM), naive bayes (NB), random forest (RF), and linear discriminant analysis (LDA).

The LDA method and the utilization of X-ray data demonstrated significant promise as a practical alternative to aid in the quality classification [20].

4.2 Water Management

Water management is required in agriculture industry as a large amount of fresh water is needed for the farming and intern effective water management will increase the availability and water quality intern by reducing the water pollution [21].

Irrigation of the water is widely studied area using the machine learning models to optimize the use of water by dividing the farm fields into different management zones so as to control rate of irrigation by using variable rate irrigation [22]. Thus by using effective water management techniques drip irrigation, controlling the water quality will accomplish optimizing water resource and intern optimization of yield.

Drip Irrigation. As fresh water is a scare resource proper utilization of it is necessary to make production cost effective. In contrast to sprinkler systems, drip irrigation is based on a low-pressure watering technique, which increases the system's energy efficiency for real-time prediction and decision-making in smart irrigation systems, which takes into account the data gathered by the sensors and IoT enabled devices, historical data is used as an input [23, 24].

Torres-Sanchez et al. [25] presented an irrigation management decision-support system for citrus fields in southeast Spain. Smart sensors are used in the proposed model to track water usage from the previous week, meteorological information, and soil water status. To develop the irrigation decision support system, three regression models namely SVM, RF, and Linear regression were then trained on this data. RF forecasts the optimal outcome with a significantly lower prediction error.

Different irrigation recommendation models were built using three ML approaches: one traditional linear regression approach and two nonparametric approaches, Gradient boosted regression trees (GBRT) and boosted trees classifiers (BTC). In comparison to linear regression, GBRT and BTC models needed fewer adjustments to account for non-linear relationships between variables. The generated model can greatly assist agronomists in their irrigation planning [26].

Water Quality. The study was done to evaluate recent developments in water quality remote sensing, identify shortcomings in the system as it is, and suggest changes for the future.

Multivariate regression methods like PLSR, SVR, deep neural networks (DNN), and long short-term memory (LSTM) are common among the techniques currently employed. Using PLSR, a linear method, three principal components relating to absorbance, refraction, and light scattering that were used in modeling for both the proximate and satellite datasets were demonstrated to be the most effective. The employed SVR model (Sagan, V. et al.) Deep learning in the field of remote sensing for water quality uses a linear kernel and a Bayesian optimization function, which have grown in popularity. Additionally, a feed forward DNN with five hidden layers and a learning rate of 0.01 was developed. Bayesian regularized back propagation was used to train the model [27].

Hyperspectral data from the satellites cannot be used to find all the water quality variables such as nutrient concentrations and microorganisms/pathogens [4, 27]. Using deep learning methods, DNN and LSTM produced intriguing results that showed excellent overall model accuracies.

4.3 Soil and Weather Management

Soil management deals with the problems of soil/land degradation due to natural cause or overuse of fertilizers. To keep the soil fertile there is a need to make an effort to balance the crop rotation to stop the soil from erosion [28].

In soil management we can manage soil properties and according to weather prediction mechanisms use the proper crop rotation. Soil properties include texture, organic matter, and nutrients content. Soil spatial variability can be studied using sensors for soil mapping and remote sensing for which ML techniques are used.

Soil Properties. Depending on the soil properties which intern depends on climatic conditions and geography of land in use, the crop is selected for the harvest. Predicting the accurate properties of the soil is an important step which decides the "selection of crop, land preparation, selection of seed, crop yield, and selection of fertilizers". The geography and climate of the location affect the qualities of the soil. Predicting soil qualities mostly entails foreseeing soil nutrients, soil surface humidity, and meteorological conditions during the crop's lifecycle. The nutrients present in a specific soil determine how well crops develop. Electric and electromagnetic sensors are mostly used to monitor soil nutrients [29]. Based on the nutrients in the soil, farmers choose the appropriate crop for the area.

Partial least squares regression (PLSR) and the Cubist tree model were used to build the prediction models. Additionally, when using a deep learning model, convolutional neural networks (CNNs) are used to feed spectral data to them in either one- or two-dimensional (2D) forms (as a spectrogram). According to a study, the CNN model predicts improvements on average compared to the PLSR model [30]. To forecast the top soil parameters, such as soil organic carbon (SOC), calcium carbonate equivalent (CCE), and clay content, digital soil mapping was utilized to correlate environmental variables. Non-linear models included Cubist (Cu), Random Forest (RF), Regression Tree (RT), and a Multiple Linear Regression (MLR) [31].

Weather Prediction. Weather events such as rain, heat or cold waves, dew point temperature impacts the everyday agriculture practices, Gaitán [32] have provided the study of these weather events.

The dew point temperature is an important factor that is especially necessary in numerous hydrological, climatological, and agronomical research studies. To predict the daily dew point temperature, an extreme learning machine (ELM)-based model is utilized. ELM provides superior prediction capabilities compared to SVM and ANN models, allowing it to predict daily dew point temperature with extremely high accuracy [33].

J. Diez-Sierra and M. D. Jesus [34], In order to predict long-term daily rainfall using atmospheric synoptic patterns, generalized linear models and a number of machine learning techniques (support vector machines, k-nearest neighbors, random forests, k-means clustering, and neural networks) are examined.

4.4 Livestock Management

Livestock management includes tasks related to their health, nutrition, and growth monitoring. Machine learning is used in these activities to examine the animals' chewing, eating, and movement behaviors (such as standing, moving, drinking, and feeding habits), which reveal the level of stress the animal is under and, thus, aid in predicting their propensity for sickness, rate of weight gain, and level of production. These analyses and projections suggest that farmers might alter their dietary habits and lifestyles for improved growth in terms of behavior, health, and weight gain, which will enhance the economic viability of the production [35].

Livestock management deals with animal welfare and livestock production activities; in precision livestock farming, real-time monitoring of animal health is taken into account which includes identifying warning signs and enhancing early-stage productivity. By using such a decision support system and real time monitoring of the livestock the quality policies can be implemented regarding living condition, food plan, vaccination etc. [36].

Animal Welfare. Monitoring animal behavior, which can be influenced by illnesses, emotions, and living situations, as well as disease analysis in animals, chewing habit monitoring, and living conditions analysis that may reveal physiological conditions are all part of the field of animal welfare.

Riaboff, L. et al. [37], has given a review of algorithms such as SVM, RF, Adaboost algorithm which is used for monitoring livestock behavior and XGB algorithm. The best prediction was reached with XGB in their study to predict livestock behaviors with accelerometer data.

Sensors and a range of machine learning methods, such as random forest (RF), support vector machine (SVM), k nearest neighbors (kNN), and adaptive boosting, can be used to continuously track eating behavior. In order to accurately classify the features, several elements retrieved from signals were graded according to how important they were for grazing, ruminating, and non-eating habits [38]. As a function of the method utilized, the location of the sensor, and the quantity of information used, a variety of performance metrics were taken into account while comparing classifiers. Additionally, sensors are utilized to monitor changes in animal movement, water or food consumption, and other factors Table 1.

Livestock Production. The goal of the precision livestock farming (PLF) method is to totally automate and continuously monitor and manage animal care. The farmers will become aware of the specific animals that require their assistance to address a problem, thanks to the use of contemporary PLF technology (cameras, microphones, sensors, and the internet) [39].

The main focus of livestock management is the raising of cattle, including sheep, pigs, and other animals, for human consumption of their flesh. ML techniques can

Table 1. Application Category and ML models

Sr. No.	Applications in Precision Agriculture	Various Models/ Algorithms used	Reference/ Paper
1	Crop Yield prediction	ANN, SVR, KNN, RF, CNN	Maya Gopal et al. [10] Nevavuori, P et al. [11]
2	Disease detection & Weed detection	LR, SVM, ANN, CNN, KNN, RF	Artzai Picon et al. [12] Pineda, M. et al. [13] Ramesh, S. et al. [14] Gao, J. et al. [18]
3	Crop recognition	SVM, RF, DF, CNN, SVM, KNN	Ghazaryan, G. et al. [15] Ji, S. et al. [16]
4	Crop quality	RF, ANN, CNN, LDA	Wolanin, A. et al. [17] Genze, N. et al. [19] Medeiros, A.D.D. et al. [20]
5	Drip Irrigation	ANN, LS-SVM, RF, GBRT, MLR,BTC	Torres-Sanchez *et al.* [25] Goldstein, A. et al. [26]
6	Water quality	LSTM, PLSR, SVR, DNN	Abhinav Sharma et al. [4] Sagan, V. et al. [27]
7	soil properties	PLSR, Cu, CNN, RF, RT, MLR	Ng, W. et al. [30] Zeraatpisheh, M. et al. [31]
8	weather conditions	SVM, KNN, RF, Kmeans Clustering, NN, ELM	K. Mohammadi et al. [33] J. Diez-Sierra & M.D. Jesus [34]
9	Animal Welfare	RF, SVM, KNN, XGBoost, AdaBoost, RF	Riaboff, L. et al. [37] Mansbridge, N. et al. [38]
10	Livestock Production	MLR, ANN, SVR, BN, CNN	Alves, A.A.C. et al. [40] Tian, M. et al. [41]
11	harvesting techniques	Single-Shot Convolution Neural Network (YOLO), KNN, SVM, SURF	Vishal Meshram et al. [2] Kushtrim B et al. [43]
12	Fertilizer Recommendation	k-NN, Naive Bayesian model, Linear SVM, TPF-CNN	L. Kanuru et al. [6] Tanmay Thorat et al. [44]

increase livestock production efficiency by using livestock management techniques for feeding the animal. Precision livestock farming is used by using the sensors to monitor the multiple animals at the same time with accuracy [3].

Multiple linear regression (MLR) was selected as the benchmark method because it has been widely utilized in animal science studies to predict carcass features and commercial meat cuts in lambs using non-invasive in vivo measures. MLR can be used with or without the stepwise procedure for feature selection. Artificial neural networks (ANN), support vector machines (SVM), and Bayesian networks were suggested as alternative modeling methodologies in this paper (BN) [40]. Tian, M. et al. [41], Constructs CNN model that learns the mapping from image feature to density map, the number of pigs in the entire image can be determined by integrating the density map, even if they are partially obscured in different views.

4.5 Harvesting Techniques

Pre-harvest, harvest, and post-harvest difficulties can all be resolved using machine learning. To minimize human interference, smart harvesting uses robotics, UAVs, IoT systems, and smart sensors. The autonomous harvesting and picking robots are among the most used robotic devices in agriculture because of the speed and accuracy having greatly improved recently [42]. Better crop understanding is provided by smart harvesting, which also enables farmers to harvest their crops to their full potential and so boost productivity. When compared to conventional harvesting methods, smart harvesting systems have many benefits, including reduced labor requirements, optimum crop output, greater crop insight, lower harvesting costs, and cost-effective production. [4].

The crop calendar enables a farmer to select the ideal planting and harvesting dates for the plant. So before the actual harvest the farmer has to prepare the crop calendar which involves the decision about the seed selection, preparation of a land for sowing, fertilizing and all these decisions are dependent on the season and the timing of harvest. Accordingly the dependent variables in machine learning model changes and helps in achieve better prediction accuracy [47].

R-CNN (Region-based Convolutional Neural Networks) and Mask R-CNN, two CNN-based models, are employed for object detection. These models start by employing a region proposal network to produce regions of interest, which are subsequently passed through the pipeline for object categorization and regression. The method You Only Look Once (YOLO) learns from the image and does classification same as Single Shot MultiBox Detector (SSD) method [43].

The most important phase is harvesting when it comes to the fruits or veggies are ripe. Soil, seeds, weeds, and other pre-harvesting factors need to be analyzed too. The critical elements that need to be concentrated on at this stage are fruit/crop size, skin color, hardness, flavor, quality, maturation stage, time to the market, fruit detection, and categorization for harvesting [2].

4.6 Fertilizers Recommendation

By utilizing fertilizers, the necessary nutrients are added to the soil, where they are then transported by the roots to the plants. Fertilizers like potassium (K), phosphorus (P), and nitrogen (N) are three of the main macronutrients that plants require in order to remain healthy. However, excessive use of insecticides and fertilizers in farming puts human health at risk; as a result, it is important to control these practices in order to ensure healthy crop production. A soil NPK sensor is used to do soil nutrient analysis, and fertilizer recommendations are made in accordance with the results of the analysis [44].

In order to reduce fertilizer waste and enable cost savings for farmers and healthier food for consumers, the recommender is required to anticipate the type of fertilizer depending on the region and the crop type [6].

Additionally utilized in this context are the Naive Bayesian, Linear Supporting Vector Classification, and K Nearest Neighbor Algorithms. The pesticide recommendation operation is effective and compact because to the TPF-CNN dual operator technique. When compared to other methods like KNN, SVM, and ANN, TPF-CNN performs about 20% better [44].

5 Conclusion and Future Work

Applications of ML along with sensors, robotics, Drones, IoT is ever increasing use in precision agriculture. In this paper we have taken into consideration the broad categories of applications in precision agriculture, which are Crop Yield prediction, Disease detection & Weed detection, Crop recognition, Crop quality, Drip Irrigation, Water quality, soil properties, weather conditions, Animal Welfare, Livestock Production, harvesting techniques, Fertilizer Recommendation.

Model generation and testing process in machine learning is discussed which is used to create the precision agriculture models using the methods such as Support Vector Machines (SVMs), Convolution Neural Networks (CNN), random forest (RF), K-Nearest neighbor(KNN), Kmeans Clustering, XGBoost, AdaBoost. A single models is used across the many categories of precision agriculture activities.CNN and various modification/ improvements done over it are the most used algorithm/ model in precision agriculture.

For the future scope, the robust recommendations systems can be developed to make the timely decisions at the categories of application in the precision agriculture which will increase the efficiency for the farmer. Needs to create the large amount of crop dataset which can be used as an input to machine learning process to train the model. Along with harvesting stage, pre-harvesting and post harvesting stages can be studied in detail to apply the machine learning models to automate the activities. More Efficient techniques can be developed and used for solving complex agricultural problems using machine learning.

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