Modern-age Agriculture with Artificial Intelligence: A review emphasizing Crop Yield Prediction

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Modern-age Agriculture with Artificial Intelligence: A review emphasizing Crop Yield Prediction

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Abstract: Agriculture is a key employment in several countries throughout the globe. AI is increasingly becoming a part of agriculture industry as traditional methods are insufficient to supply the massive survival needs of millions of people. AI, in form of machine learning and deep learning, is capable of providing a number of strategies that assist in the creation of more healthy seeds. This paper discusses significance of machine learning and deep learning that growers can use to gain access to increasingly sophisticated data and analytical tools, allowing them to make better decisions, improve efficiencies, and reduce wastes in food and bio-fuel production while minimizing negative environmental impacts. On the basis of critical parameters like temperature, rainfall, humidity, soil type, soil characteristics etc., ML and DL operate as recommenders and advise farmers to take the right action. Numerous AI applications in agriculture are addressed, with an emphasis on yield prediction. The article offers a comprehensive review of a variety of ML, DL and hybrid methodologies for correctly forecasting agricultural outputs that will promote the nation's economic growth.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Agriculture, Crop Yield Prediction.

1. Introduction

Agriculture has been the foundation of practically all ancient civilizations for the sole purpose of ensuring their survival. Agriculture is now a $2.4 trillion global business that is one of the most important contributors to the growth of developing countries[1)]. Agriculture has a paramount significance in world's economy. The agriculture sector will be under more strain due to endless progression in human population. Precision farming and agri-technology/digital agriculture[2)] are growing as modern scientific domains that make use of data-intensive methods to boost productivity in agricultural while lowering the impacts on environment[3)]. Agriculture, on the other hand, is prone to a variety of issues, the majority of which are highly unpredictable in nature, such as a lack of rain, floods, and blight, to mention a few. For the reasons stated, Artificial Intelligence must be introduced into the agricultural area in order to leverage statistical brilliance to give better harvests at reduced costs[4)]. In this vein, we propose a number of precision agriculture frameworks. Machine learning (ML) and deep learning (DL)[5)-81)] have evolved with technologies of big data, Internet of Things, and highly efficient computing to unravel, measure, and comprehend data-intensive processes in agricultural operations.

2. Article Organization

We give a complete examination of AI's importance in agriculture in this paper. The role of agriculture in a country's GDP is examined in detail in Section I. Some of the abbreviations will be revisited several times throughout the text that are described in Section III. Section IV delves into various application of artificial intelligence in agriculture. Section V focuses on the significance of machine learning and deep learning in crop yield prediction. The theory and technical parts of AI have been concluded at the very last.

3. AI Applications in Agriculture

3.1 Farm Harvesting Robots

Robots are being created that can handle bulk harvesting with more accuracy and speed, allowing the fruit to reach your kitchen table faster. These kinds of tools boost the productivity and reduces the crop waste from the field[6)].

3.2 Smart Chemical Spraying

Using computer vision and artificial intelligence, various companies have built robots that tracks and spray the weeds accurately[7]. By using these robots, approx. 80-85% chemicals are able to be removed that are sprayed on the crops, thereby and herbicides can be reduced up to 90%. These are called AI sprayers that can drastically lessen the proportion of pesticides being utilized in fields. This overall process improves agricultural productivity and also reduces cost.

3.3 Species Management

3.3.1 Identification of Species

A latest architecture[8] called leaf vein architecture is being used that provides more precise and efficient results. It holds the information about the leaf features, instead of the typical human tendency to compare leaf color and shape to classify plants.

3.3.2 Breeding of Species

This application is most useful as it is both sensible and unexpected, because harvest forecasting is taken into consideration at some point later. For some particular genes that impact the performance of nutrient content, water consumption, flavor, nutrient consumption, disease resistance, climate change adaptation and picking up of species is a time-consuming process. Deep learning[9] algorithms, for example, assess crop performance in a variety of conditions and develop new features as a result of the data. They can use this information to create a probability model that predicts which genes produces plants more frequently.

3.4 Crop Management

3.4.1 Crop Excellence

Crop quality traits may be accurately detected and classified, which can raise product prices and reduce waste. Machines, in compared to human specialists, can employ seemingly useless data and linkages to uncover new attributes that contribute to the overall quality of crops[10].

3.4.2 Prediction of Yield

Yield estimation is the most important matter of discussion in agriculture, which encompasses mapping of yield & prediction, demand matching, supply and management of crops[11)-14]. On the basis of historical data, state of art techniques can also be used along with computer vision.

3.4.3 Detection of weeds

Weeds are the greatest serious hazard to crop yield, aside from diseases. The most difficult aspect of weed control is detecting and distinguishing them from crops. ML techniques[15] and computer vision can enhance the weed identification and discrimination at a minimal cost.

3.4.4 Detecting Diseases

Spraying insecticides equally across the cropping area is the most widely used technique of disease prevention. This strategy requires the use of enormous quantities of pesticides to be effective, which comes with a significant financial and environmental cost. Agrochemicals are sprayed at specified times, locations, and to specific plants using ML as part of a broader precision agriculture strategy[16].

3.5 Field Conditions Management

3.5.1 Management of Water

The hydrological, climatological, and agronomic factors are all affected by agriculture's water management. So far, the most developed machine learning based applications are related to regular evapotranspiration estimation, which allows more flexible irrigation system to use. Daily point temperature prediction aids in identifying the weather conditions, evaporation, and evapotranspiration to be expected[17].

3.5.2 Management of Soil

For agricultural scientists, soil is a diverse source of natural resources. Its temperature alone can reveal information about the impacts of climate fluctuations. ML approaches[18] seeks for temperature, soil moisture, and evaporation processes to understand the ecosystem statistics and their impact on agriculture.

3.6 Livestock Management

3.6.1 Animal Protection

In today's society, livestock is increasingly recognized as animals who are sad and tired of their farm lifestyles, rather of simply as food carriers. Chewing signals can be linked to the need for food changes, and animal behavior classifiers can identify how stressed an animal is by looking at their movement patterns, which include walking, eating and hydrating etc[19].

3.6.2 Livestock Management

Machine learning application, like crop management, enables precise prediction and farming parameters estimation for maximizing the effectiveness of animal production systems[20]. For an instance, weight estimation systems can forecast coming weights some days before slaughter. It permits the farmers to change environment and meals accordingly.

3.6.3 Farmer’s Little Assistant

A farmer always needs help for sorting through all of the options of crop management so that he can make a final selection. Companies are now concentrating their efforts on developing specialized chatbots that can talk with farmers and help them with essential statistics and data analysis to aid them[21]. Chatbots of farmers needs to be more intelligent than that of consumers i.e. such as Alexa because these chatbots will be able to provide data, analyze it, and consult farmers on challenging situations.

4. Machine Learning and Deep Learning in Crop Yield Prediction

Machine learning (ML) and Deep Learning (DL) techniques are widely employed in many fields, such as supermarkets for evaluating customer behaviour based on past purchases and for forecasting the typical smartphone usage time. Additionally, machine learning [22] is used continuously and globally. ML is extremely important in agriculture because there are so many different algorithms to use. ML is being used everywhere nowadays even in Agritourism for Sustainable Agriculture.

4.1 Selection Criteria of Crop Yield Prediction

Crop yield forecasting is a major source of worry for the world's food production. By making wise import and export decisions and depending on reliable forecasts, national food security is ensured. For finer variations, seed firms must estimate the performance of current mixed breeds in various environments. Growers use yield prediction's benefits for improved management and wiser financial choices.

The most challenging problem in precision farming[23] is predicting crop production, which has led to the development and validation of numerous models to date. Crop yield prediction requires the use of a variety of datasets because it depends on a number of variables, including weather, soil characteristics, fertilizer use, and seed type. That's why, Crop yield forecast[24] must be seen as a series of phases rather than a simple assignment. There are several crop yield prediction models that the farmer can use to determine the advantageous and desirable output, but a finer achievement is still valuable. Multiple uncertainties plague the farming industry, making it difficult for farmers to choose when to plan which crop because market prices often change regularly. As a result, some significant concerns occur. Furthermore, crops used to be damaged by harmful climatic conditions due to global warming[25].

Floods, groundwater, insufficient soil fertility, single crop failure owing to climatic variance, and a number of other issues all have a negative impact on farmers. Depending on certain geographic, climatic, financial, and organic elements, crop yield may be regarded as the most important component in agricultural financial terms. Depending on the locality and climatic conditions, the community advises the farmers to behave spiritedly in order to increase agricultural yield.

4.2 Machine Learning based Crop Yield Prediction

Machine learning is a part of AI that emphasizes on using data and several algorithms to imitate how human beings learn for a significant improvement in accuracy over time[26]. ML approaches permit various software applications to strengthen their prediction accuracy and are used to forecast new output values. Machine learning isn't some far-fetched notion. It is already being used by businesses across a variety of industries to enhance creativity and improve operational efficiency.

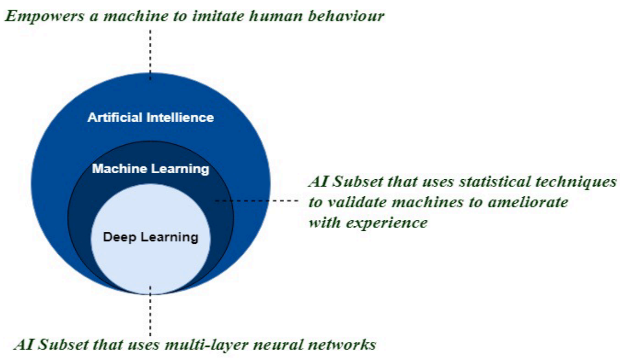

Fig. 1: AI, ML and DL

Machine learning is a learning process that aims to teach a computer how to complete a task through "experience" (training data). Data is made up of instances in machine learning. Some features/variables (a set of attributes) describe a specific instance. Numeric features or ordinal/nominal/binary measures can also be employed. To evaluate the performance of machine learning models, a performance metric is utilized that improves with experience. The performance of ML models and algorithms is calculated using a variety of statistical and mathematical methods. The integration of the Machine-learning based on the prosumer's EMS to address the uncertainty problem in the prosumer are explored.

When the learning process is finished, we can use the trained model in order to categorize, forecast, or cluster data. The classification of diverse sets of crop pictures using ML and computer vision is investigated in order to assess crop quality and production. By recognising reproductive trends, diagnosing eating disorders, and anticipating the behaviour of cattle using information from collar sensors, this technique can be used to increase livestock output[27].

Table 1: Various Machine Learning models in Crop Yield Prediction

Authors	**Year**	**Description**	**Model Used**	**Findings**
Seireg et al.[28)]	2022	Wild Blueberry Yield prediction using Ensemble ML techniques	LGBM, GBR, XGBoost	The best performance was demonstrated by SR, which outperformed CR and had the highest R-square (0.984) and RMSE (179.898).
Rasheed et al.[29)]	2021	National crop production planning by using a decision support framework	Decision aiding tool	2 case studies are used to address crop planning concerns and profit maximization: one involves a single farm with several fields, and the other involves many fields on multiple farms in various climatic zones.
Pant et al.[30)]	2021	Use of statistical ML techniques for analyzing agricultural crop yield prediction	GBR, DTR, RFR, SVR	The decision tree regression model predicts agricultural yield with a maximum degree of accuracy of 96%.
Raja et al.[31)]	2022	Use of various feature selection techniques and classifiers for predicting crop yield based of agriculture environment characteristics	BORUTA, RFE, MRFE	Comparing the ensemble technique to the current classification technique, it delivers greater prediction accuracy.
Lontsi et al.[32)]	2022	A case study of West African countries for predicting crop yield using ML models	DT, MLR, k-NN, hyper-parameter tuning + cross-validation	The decision tree performs well, with an R^2 of 95.3%, whereas the k-NN and logistic regression perform poorly, with R^2 of 93.15% and 89.78%, respectively.
Abdelraouf et al.[33)]	2022	Use of multi sensors remote sensing for predicting crop yields	Remote Sensing	Agricultural production is assessed using various methods: relied on determining the area of a particular crop from satellite images, evaluation of crop biophysical and biochemical parameters, estimating crop production using direct empirical statistical models.
Pantazi et al.[34)]	2016	Prediction of wheat yield by using ML and advanced sensing techniques	CP-ANN, XY-fused Network, Supervised Kohonen Network	High class accuracy increased to 83%, while medium class accuracy was determined to be 70%. The SKN model can be used to anticipate and categorise data into various 27yield potential zones.
Aghighi et al.[35)]	2018	Prediction of silage maize by using ML regression techniques for Time-Series Images of Landsat 8 OLI	SVR, BRT, GPR, RFR	BRT fared best in areas where its average R value exceeded 0.87.
Mariammal et al.[36)]	2021	Land suitability prediction for crops based on environmental and Soil characteristics by using MRFE & various	k-NN, NB, DT, SVM	Compared to other feature selection techniques, the MRFE technique performs well with 95% accuracy.

		classifiers		
Kumar et al.[37)]	2021	Plant disease prediction based on soil sensors using ML and exploratory data analysis and	ANN	Adam optimizer minimizes the binary cross-entropy loss function by 0.15 more than RMS-prop optimizer while converging more quickly than RMS-prop at higher epochs. All the optimizers have fared better than Adam.
Matteo et al.[38)]	2022	Incorporating CubeSat data into a crop model with early season prediction of within-field crop yield variability	CubeSat-based LAI + APSIM	With a significant correlation to measurements that were independently obtained, yield spatial variability was reasonably well reproduced (R^2 = 0.73 and RMSE = 12%).
Vlachopoulos et al.[39)]	2022	Crop health status evaluation by using UAS Multispectral Imagery	Multiple linear models, SVM, RF ANN	With a mean absolute error of 0.67 and an average relative root mean square error of 10.86%, random forests method was shown to be the best algorithm for GAI prediction. The average total accuracy is 94%.
Birrell et al.[40)]	1996	Sensor comparisons and various techniques for crop yield mapping	NA	Yield maps were created using various Kriging techniques and other mapping approaches were compared.

4.3 Deep Learning based Crop Yield Prediction

Deep learning is a subdivision ML and can be said as a 3-layer neural network[41)]. The purpose of neural networks is to imitate the human brain activities by permitting it to "learn" from huge data. A single-layer neural network may generate the predictions that are close, that's why some extra hidden layers can also be used to alter the accuracy.

Deep learning neural networks (Artificial Neural Networks) take advantage of data inputs that are: weights and bias and try to emulate the brain of a person. These collaborate with each other in order to identify, categorize and characterize items precisely in the data. DNN are union of several layers of linked nodes, each of which refine and improve the categorization or prediction. Two methods of propagation exist: (1) Forward propagation- The advancement of computations through the network. DNN's input & output layers are visible. The input layer accepts the data that needs to be for processed and while the output layer presents the concluded forecasts.

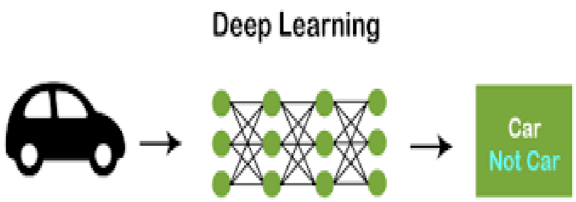

Fig. 2: Deep Learning

DNN are union of several layers of linked nodes, each of which refine and improve the categorization or prediction. Two methods of propagation exist: (1)

Forward propagation- The advancement of computations through the network. DNN's input & output layers are visible. The input layer accepts the data that needs to be for processed and while the output layer presents the concluded forecasts.

A different method called Backpropagation (2) can also be used to train a model that utilizes the gradient descent technique in order to compute errors found in prediction and then moves in backward direction by passing the layers to modify the inputs of the function. Both the kind of propagation operates collectively to enable a neural network to make predictions and to resolve the errors. The algorithm's accuracy keeps improving with time[42)].

Table 2: Various Deep Learning models in Crop Yield Prediction

Authors	**Year**	**Description**	**Models Used**	**Findings**
Kavita et al.[43]	2023	Estimate the crop output for five different crops in the Indian state of Rajasthan.	SVM, Gradient Descent, LSTM, Lasso regression	R2 Score - 0.963, RMSE - 0.035 and MAE-0.0251.
Kuradusenge et al.[44]	2023	Prediction of Irish potatoes and Maize	Random Forest, Polynomial Regression, and Support Vector Regressor	Random Forest performed the best with R^2 values of 0.875 and 0.817.
Elavarasan et al.[45]	2020	Prediction of crop yield with the use of deep reinforcement learning model	RNN + DQN	Accurate prediction with a realistic 93.7 percent.
Bose et al.[46]	2016	Use of spiking neural networks for estimating crop yield by analyzing image time series	Gaussian Process Model	Based on a nine-feature model, the method produced an average accuracy of 95.64%, an average prediction error of 0.236 t/ha, and a correlation coefficient of 0.801.
Saeed et al.[47]	2019	Prediction of crop yield using deep neural network	DNN	With a root-mean-square-error (RMSE) of 12% of the average yield and 50% of the standard deviation, the RMSE would be decreased to 11% of the average yield and 46% of the standard deviation.
Sun et al.[48]	2020	Prediction of crop yield using multilevel deep learning network	RNN+CNN, LSTM	Achieved R^2 value of 0.73 and RMSE of 1039.87 for 16 bins.
Qiao et al.[49]	2021	Prediction of crop yield from multi-spectral and multi-temporal remotely sensed imagery using recurrent 3D-CNN	3D CNN+RNN	With regard to handling multi-temporal multi-spectral data, SSTNN offers a lot of potential. can perform predictions more accurately than competing methods.
Kalaiarasi et al.[50]	2022	Prediction of crop yield using multi-parametric multiple kernel deep neural network	Multi-parametric DNN	The trials are carried out to determine the effectiveness of the MMKDNN for five distinct kinds of crops. withstands the enormous volume of data with ease.
Abbaszadeh et al.[51]	2022	Prediction of crop yield using bayesian multi-modeling of deep neural network	BMA	Predicts soybean crop yields more accurately and consistently than the 3DCNN and ConvLSTM networks.

Pang et al.[52]	2020	Spectra and image-based prediction of Corn seeds using deep learning and hyperspectral imaging and rapid vitality estimation	CNN, Hyperspectral Imaging	On raw data, 1DCNN performs best, however 2DCNN performs with a faster convergence rate.
Alebele et al.[53]	2021	Prediction of crop yield using combined Optical and SAR Imagery with Gaussian Kernel Regression	Bayesian Linear Regression, Gaussian Kernel Regression	In comparison to probabilistic Gaussian regression and Bayesian linear inference, Gaussian kernel regression performs better. The optical red edge differential vegetation index (RDVI1) (R^2 = 0.65, RMSE = 0.61 t/ha) improved forecast accuracy.
Martínez et al.[54]	2021	Prediction of crop yield using interpretability With Gaussian processes	Gaussian Process Model	GP model uses a composite covariance to take different scales, non-stationary processes, and nonlinear processes into account and gives the ability to pinpoint climate extremes, anomalies, and their corresponding causes that affect crop productivity.
Qiao et al.[55]	2021	Prediction of crop yield using 3D CNN and Multikernel Gaussian Process	MKL	Using a kernel-based approach, the probability distribution of the prediction outcomes is derived. The effectiveness of the suggested strategy is assessed using estimates of China's wheat yield.
Sivanantham et al.[56]	2022	Prediction of crop yield using quantile correlative deep feedforward multilayer perceptron	Quantile regression	In comparison to existing studies, the proposed technique increased prediction accuracy and precision by 6% and 9%, respectively, and decreased prediction time by 32%.
Zhenwang et al.[57]	2022	Prediction of crop yield using multi-source satellite data across Northeast China	Linear regression, ensemble model	When satellite data and environmental data were combined, variability of maize, rice, and soybean yields was found to be 72%, 69%, and 57%, respectively,
Gupta et al.[58]	2021	Prediction of crop yield using big data depending upon weather conditions	Map-reduce + K-means	Amalgamation of MapReduce and k-means clustering gives the mean produce for a group of crops.
Liu et al.[59]	2022	Prediction of plant disease using IOT & ML	MLR+IOT	Implemented model demonstrates the disease's occurrence could have been

				predicted with up to 91% accuracy from 2015 to 2019.
Udutalapally et al.[60]	2021	Prediction of crop yield, plant disease, crop selection and irrigation in Internet-of-Agro Things	CNN	The proposed plant disease prediction framework achieves an accuracy of 99.24%.

4.4 Hybrid Methods

In order to get best results, the machine learning and deep learning techniques are executed in order to predict the best crop production[61]. The current atmosphere, the soil along with its constituents i.e.the climatic and soil parameters are taken into consideration. Deep learning is used to achieve numerous successful calculations as it is used to get the best suitable crop in case a number of options available. By using this technique, crops are predicted accurately. The output collected after applying ML algorithms is further passed to deep learning algorithms.

Table 3: Various Hybrid models in Crop Yield Prediction

Authors	**Year**	**Description**	**Models used**	**Findings**
Agarwal et al.[62]	2021	Predicting crop yield by using ML and DL algorithms	SVM, LSTM, RNN	The model foresees the ideal crops. Crop prediction is carried out utilizing SVM, LSTM, and RNN. Attained accuracy is 97%.
Bodapati et al.[63]	2022	Analyzing crop yields by using ML and DL	CNN	By adding neural networks as a tool, the CNN model outperforms the prior one.
Mopideviet al.[64]	2022	Predicting plant growth and crop yield by using ML and DL Algorithms	CNN, LSTM	Support Vector Regression and Random Forest Regression performed the best.
Swarnakanthaet al.[65]	2022	ML and Image Processing based decision making framework for precision agriculture	Image processing	Performed effectively for predicting yield, future market and intermediate buying selling prices, identifying pests and administering effective treatments, fertilizer plan and water delivery according to soil type.
Bhansali et al.[66]	2022	Predicting crop yield and disease detection	DT, NB	SVM or NN techniques are used to identify the type of disease.
Nancy et al.[67]	2022	Image based plant disease detection along with classification using ML & DL	Computer vision, image processing	The technique makes it simpler to categorize crop disease images and anticipate illness.

5. Discussion

In order to synthesise and extract the features and methods that have been utilised to estimate agricultural yields in research, a thorough evaluation of the literature is undertaken in this study[68)-72)]. A few carefully chosen studies are examined, their methodologies are examined, and features are applied. The characteristics that are most frequently used include soil type, temperature, rainfall, and humidity. We came to the conclusion that Random Forests, Decision Trees, Neural Networks, and Deep Learning is the most often used machine learning algorithms after reviewing a number of machine learning

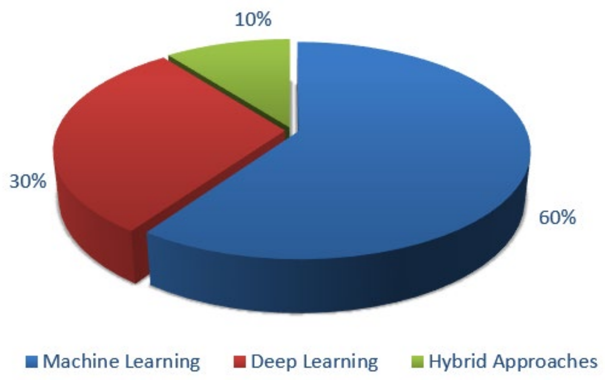

Fig. 3: Article Distribution

literature. Additionally, CNN, DNN, and LSTM are the most often used deep learning techniques[73)-75)] in this research, with DNN coming in second. The literature review is conducted for several approaches used for crop prediction based on ML and DL and hybrid methods.

Figure 3 shows the count of papers taken into consideration during the literature survey of aforementioned topic. Various kind of techniques are used for the prediction of crop yields in the articles surveyed. Figure 3 represents the distribution of various techniques.

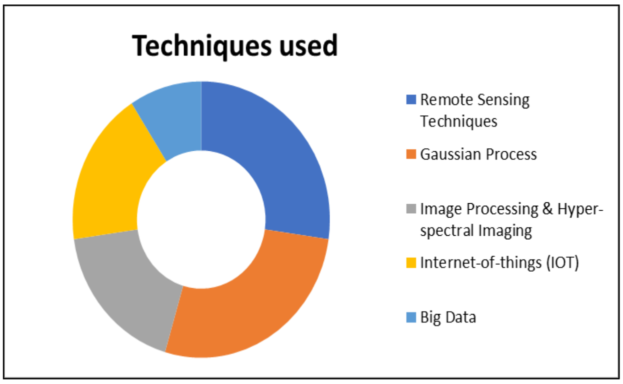

Fig. 4: Techniques used in surveyed articles

6. Conclusion

Cultivation has been metamorphosed with the use of technology as the time goes by. Also, the technological breakthroughs have had a number of effects on the agriculture industry. Artificial intelligence is entrenched on the assumption that it can define the human intelligence in a fashion that a computer can mimic it while performing several tasks (simple/complex both). Learning, thinking, and perception are all goals of artificial intelligence. Farming has become digital farming, thanks to the use of numerous sophisticated models (machine learning and deep learning methodology). By integrating ML with sensor data, systems for farm management are maturing into complete artificial intelligence systems, offering wealthy recommendations and perceptions for upcoming verdicts and actions with the eventual aim of enhancing the production. The study concluded various implications of machine learning and deep learning models to be more prevalent in the future for the creation of integrated and practical solutions with a lot of potential as advanced data analysis and image processing approaches.

Nomenclature

PA	Precision Agriculture
ML	Machine Learning
NB	Naive Bayes
DT	Decision Tree
RF	Random Forest
RFR	Random Forest Regression
MLR	Multi-Linear Regression
SVM	Support Vector Machine
SVR	Support Vector Regression
k-NN	k-Nearest Neighbor
DL	Deep Learning
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
DNN	Deep Neural Network
DQN	Deep Q-Network
LSTM	Long Short-Term Memory
RFE	Recursive Feature Elimination
MRFE	Modified Recursive Feature Elimination
BMA	Bayesian Model Averaging
MKL	Multiple Kernel Learning
IOT	Internet of Things

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