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Review Paper

Machine learning for modern farming- a review

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ABSTRACT

Agriculture is vital to any country's economic growth. With a growing population, erratic weather patterns, and limited resources, feeding the current population has become a challenge. Hence the field of agriculture needs to be modernized and optimized to meet the growing food demands in the present and future era. Machine learning, a subset of artificial intelligence, holds great promise for knowledge-based farming. Agricultural researchers are currently using image processing to identify several plant species and diseases. This review discusses the various applications in machine learning and how agri-knowledge can enhance productivity and sustainability. Also, the paper provides a latest review demonstrating the work related to application of machine learning in agriculture. The modest contributions of ML illustrate the need for this article to identify the opportunities, challenges, and prospects for ML applications in agriculture.

Keywords: Agriculture, Applications, Artificial intelligence, Machine learning.

While global population continues to rise, the current state of modern agriculture faces numerous challenges, such as an ever-increasing demand for food, climate change (Thayer *et al*., 2020), the depletion of natural resources (Nassani *et al.,* 2019), shifting dietary preferences (Conrad *et al*., 2018), as well as concerns about food safety and health (Benos *et al*., 2020). In developing countries like India, agriculture serves as major contributors to economic growth. Agriculture accounts for 15.4% of India's GDP. India is already lagging behind in the production of its own food because of aberrant weather, in-efficient harvesting and traditional way of cultivation, improper irrigation methods, and poor livestock management. Aberrant weather conditions has caused dramatic shifts in weather patterns over the past few years**.** Climate conditions are uncertain because the Earth's average temperature has risen. Poor farmers face the greatest challenge from frequent droughts and heavy rainfall.

In order to address the aforementioned issues, which put stress on agriculture, it is urgent that agricultural practices be made more effective while also reducing their environmental impact. The advent of information and communications technology (ICT) and Internet-of-Things (IoT) has culminated in the fourth industrial revolution (4IR) and ushered in the big data era of artificial intelligence (AI)-enabled precision and personalization via the convergence of physical, biological, and digital technology (Ahmed *et al*., 2022). The basic concept of AI is to develop a technology which functions like a human brain.

Machine learning (ML) have opened new avenues for agricultural operations to analyze, quantify, and understand data-intensive processes. "Turing Test for Machine Intelligence" was written by Alan Turing in the year 1950, when he proposed the idea of learning machines. Artificial Intelligence (AI) or machine learning (ML) is a branch of science that allows machines to learn without being explicitly programmed (Samuel, 1959). Using machine learning, farmers can reduce their farming losses by receiving detailed recommendations and insights into their crops. Technological advances in the field of machine learning have aided in the improvement of agricultural gains. There is a huge potential in this industrialization of farming to ensure sustainability, maximum productivity, and a safe environment (Lampridi *et al*., 2019) by effective management of natural resources; conservation of ecosystem; growth of adequate services; and use of advanced technologies, which form the four main pillars that make up smart farming (Zecca, 2021). There are numerous uses for machine learning in agriculture. Researchers have recently discovered four generic categories in literature from the year 2004 to 2018 (Liakos *et al*. 2018) and included all the categories pertaining to crop, water, soil, and livestock management.

How machine learning works: Using data from the past, a machine learning system constructs prediction models and then uses those models to predict the outcome of new input data. The model's ability to accurately predict the output is directly correlated to the volume of data it has access to. An algorithm can predict the outcome of a complex problem simply by feeding data into a generic algorithm, which builds logic from this data and predicts what will happen. The working of algorithm in machine learning is illustrated in Fig. 1.

Types of machine learning: Machine learning models work on the algorithms that are constructed with the aim of gaining a self-learning property. "ML algorithms" differ from "conventional computer algorithms" that work strictly according to the program created by its developer. "ML algorithms" interpret and analyze the input as well as the output (results) so that the accuracy of machine learning model will increase with this progression. The advantage of these methods is their less dependence on user instructions, unlike the conventional statistical methods. There are four main types of machine learning techniques which are as follows;

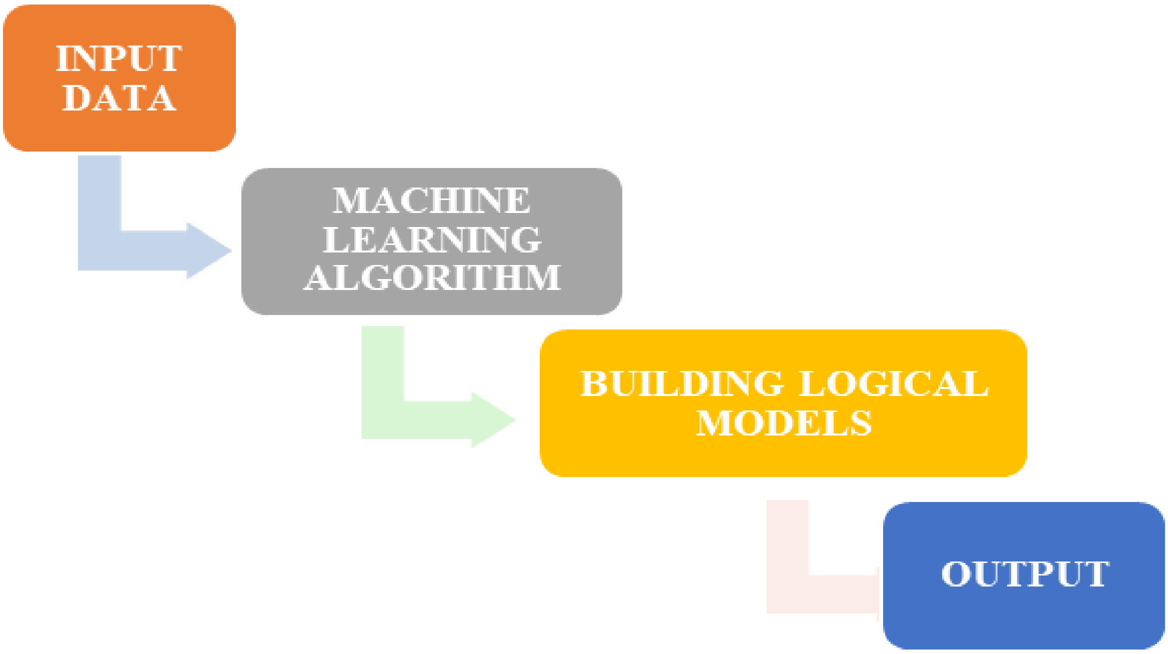

Fig.1 Illustration of Machine learning Algorithm (Ahmed and Nabi, 2021b)

Supervised learning: Supervised learning is the type of machine learning where an algorithm is provided with some training examples so that it can interpret and analyze the inputs and their corresponding outputs (Kaur, 2016). Supervised machine learning algorithms use labeled training datasets, and the model generates an inferred function from the relationship between output, and input parameters of the system (Khan and Samad, 2017). This type of model is ready and qualified after sufficient training and is able to work on new input. Moreover, there is a provision in modifying the model after comparing the results with the intended/correct results (Anonymous, 2020). Bayesian networks, decision trees, support vector classifiers, support vector machines, k-nearest-neighbor decision trees and more are all examples of supervised learning algorithms (Khatun, 2020). The following target values are present in the case of supervised learning (Ahmed and Nabi, 2021a):

i) If a "continuous target variable" is present, then it becomes the problem case of regression.
ii) If a "categorical target variable" is present, then it becomes the problem case of classification.

Unsupervised learning: In unsupervised machine learning the machine learning algorithm is not delivered with any target variable (Kaur, 2016; Khatun, 2020). As there are no labeled datasets or output vectors, the

ML model checks for similarities in the given dataset. The unsupervised machine learning algorithm discovers the hidden relationships and patterns among the variables (Khan and Samad, 2017). Algorithms involving clustering and association techniques belong to this category of ML (Kaur, 2016).

In general, there are two types of algorithms in unsupervised machine learning:

i) Clustering: This algorithm refers to the segregation or distribution of a dataset into a number of relatively small groups such that the dataset in 140. Data points with more similarities are grouped into a cluster and likewise, many clusters are formed.

ii) Association: This type of algorithm focuses on finding certain relationships between variables in large databases.

In simpler words, we can conclude that clustering is related to the grouping of the data points according to the relatively common attributes or similarities that they possess, when, on the other hand, association relies on the identification of patterns among data points that have a high degree of similarity (Khatun, 2020).

Table 1: Summary of machine learning applications in agriculture from year 2015-2020

Year	Application	Problem Description	Techniques used
2020	Disease Detection in leaves	A cucumber leaf disease detection using classification method	Sharifsaliency-based (SHSB) method, SVM, VGG-19 &VGG-M
2019	Selective Breeding	Used various segmentation technology to analyze plant quality.	K-means clustering; SVM; SFM; HOG descriptor
2019	Disease Detection using images	A model for disease detection using Deep Convolutional Neural Network architectures is developed.	CNN Dense net architecture Deep CNN
2018	Weed Detection	Inter-row weed is detected using a hybrid method.	Hough transform OBIA method Random forest classifier
2018	Weed Detection	Create a method for identifying weeds in sugar beet fields.	SVM Classifier ANN classifier Fourier descriptor
2018	Disease Detection	Through Convolutional Neural Network new model is developed.	CNN
2018	Species identification	The image thresholding method was used to identify features such as distinct background, noise, and contour.	Rectilinear derivations
2017	Selective Breeding	A method for automatically segmenting a plant image has been developed.	Image analysis pipelining Segmentation
2017	Disease Detection	The leaves of plants can be used to detect and classify plant diseases using an automated model.	Genetic algorithm Classification techniques.
2017	Agrochemical Production	Through the use of multiple fast networks, a convolutional neural network model was developed.	CNN
2016	Disease Detection	In order to identify and categorize fruit diseases, a model is developed.	Multiclass SVMK-means clustering
2016	Weed Detection	Because it's difficult to classify objects that touch rows of crops, we used a method for linear vegetation.	OBIAMETHOD
2015	Weed detection	Plant weed detection was made possible through the application of Convolutional Neural Networks.	CNN

Reinforcement learning: The feedback (i.e. reward or error) for every action is reflected to the algorithm, known as the reinforcement signal (Anonymous, 2020), and this cumulative feedback reinforces the performance and efficiency of the algorithm thus maximizing the advantages. Many reinforcement learning algorithms use dynamic programming techniques (Anonymous, 2020). Frequently used algorithms are genetic algorithms, Markov decision algorithms (Kaur, 2016), Q-learning (Wang *et al.*, 2007; Safavian and Landgrebe, 1991), etc.

Applications of machine learning in agriculture: AI has proven to be one of the effective and strategic solutions for the current world scenario of fewer resources and enormous demand. To a great extent, the expectations of farmers have been met, and the key reason is an increase in productivity. In the past, one could not have imagined that AI algorithms could precisely predict and galvanize an agricultural revolution (Intel, 2020). Smart farming powered by AI/ML high-precision algorithms keeps farmers at par with the technological world and has substantially contributed to the agricultural realm (Bagchi, 2020; Kharkovyna, 2020). Table 1 lists the application of machine learning in agriculture.

Some of the individual applications of AI and ML are elucidated (Fig. 2) and under the following headings:

Fig. 2: Application of machine learning in agriculture (Ahmed and Nabi, 2021a)

Soil management: Soil is a heterogeneous natural resource that is most essential in agriculture, and knowledge about soil is necessary for improving agricultural yield. There are processes involved in soil that are complex in nature as well as mechanisms that need strenuous efforts to understand. Hence, soil management becomes straightforward in order to avail maximum benefits for agricultural purposes (Liakos *et al*., 2018; Home, 2020). Soil availability data must be accurate if proper soil management is to be achieved. Predicting soil properties mainly involves forecasting soil nutrients, soil surface humidity, and weather conditions throughout the crop's lifecycle. Data on agricultural soil properties is fed to ML model which generates a reliable solution.

Smart irrigation system: Using AI-powered smart automated irrigation systems, soil conditions can be maintained at the desired level of precision and optimality. Increased yield and reduced water consumption are all results of this. In the long run, scientists believe that the careful use of water in these irrigation systems will have a significant global impact on water availability (Kharkovyna, 2020). It is necessary to estimate evapotranspiration to formulate and manage intelligent irrigation systems, but this is a difficult task to accomplish correctly. However, AI and ML algorithms can accurately estimate evapotranspiration and solve this issue.

Weather forecasting: Agriculture is highly dependent on favorable weather conditions, and any undesired alteration has dire consequences on productivity. Weather forecasts become immensely important so as to avoid any of the issues that can cause detrimental effects. The use of AI algorithms has greatly enhances the reliability of weather forecasting. Seasonal forecasting models improve agricultural accuracy and productivity. Such models were developed to predict weather patterns months in advance, helping farmers make better decisions. Forecasting the seasons is especially important for small farms in developing countries like India that are heavily reliant on rainy season rainfall.

Agricultural drones: Drones have applications in various sectors, including the agricultural arena. Data collection, field tracking, disease detection, and several Machine Learning (ML) driven agriculture practices like spraying inputs and surveillance are all made easier with the help of drones.

Precision agriculture: AI and ML have been an absolute driving force for the paradigm shift of “precision agriculture (PA)” into “Agriculture 5.0.”

Table 2 Some Smart Precision Farming Requirements and Providers (Ahmed and Nabi, 2021b)

Application	Company
Soil Analysis and Monitoring	CropIn, Bengaluru
Image Analysis	Intello Labs, Bengaluru
Predictive Analysis	Microsoft, India
Supply Chain Management	Gobasco, Lucknow
Crop Cycle Expertise	Gramophone, Indore
Farm Produce Aggregation	Jivabhumi, Bengaluru
Farmer Advisory	Agrostar, Pune

Real-time data, in combination with readily available data, provided to an AI or ML model produces many precise decisions for each specific purpose. When it came to certain tasks, these AI-powered machines outperformed humans. The use of computer vision in image analysis is one example of this. Some benefits of AI in PA include optimized and precise use of pesticides, insecticides, and other inputs, as well as the reduction in environmental degradation and overall cost reduction (Kharkovyna, 2020).

Agricultural robots: AI's primary goal has always been to reduce human labour requirements through the application of new technologies. Automation and smart devices that can perform tasks that previously required human intervention are critical in the agriculture industry, which is an important part of the global economy. Agricultural robots are being developed and programmed by companies to perform critical agricultural tasks, including harvesting crops at a larger quantity and faster pace than human labourers (Kharkovyna, 2020). John Deere's Blue River Technology (John Deere) developed a robot called "See & Spray" that reportedly uses computer vision and ML to monitor and precisely spray herbicide only where it is required. In addition, there is "RIPPA," a product that eliminates weeds and pests from the landscape (Anonymous. 2020b).

Reports claim that labor shortages in key farming regions have resulted in millions of dollars in revenue losses. Crop harvesting robots like "Harvest CROO Robotics" are one such example (Anonymous. 2020c). In order to assist strawberry farmers in the picking and packing of their crops, Harvest CROO Robotics created a robot. In a single day, the robot is said to be able to harvest the ripe strawberries from eight acres of land and thus eliminate the need for 30 human workers. On the other hand, PEAT, a Berlin-based agricultural tech farm has developed a deep learning based application, called Plantix which is capable of detecting potential defects and nutrient deficiencies in the soil in some efficient way.

Greenhouse: The use of artificial intelligence (AI) in greenhouse operations is critical. Speed breeding of crops is made possible with smart greenhouses regulating the photoperiods via LED lightings to shorten the time to flowering and fruiting. Automated vertical farms integrated with aquaculture have been adapted for urban farming to reduce the carbon footprint of transporting fresh produce (Ahmed *et al*., 2022). It's a time-consuming task to modify the greenhouse's temperature manually because Agriculture 5.0 has so many variables to take into account. High accuracy in temperature and humidity regulation is achieved through the use of techniques such as Artificial Neural Networks (ANN) and Fuzzy Logic Controllers (FLC).

Driverless tractors and crop sowing: Growers will eventually be able to carry over this century-old machine to robots due to recent advancements in software and "off-the-shelf" technologies such as sensors, radars, and GPS. There are many examples of smart tractors, such as the Blue River Technology (John Deere) (Bagchi, 2020). Sensors, radars, and GPS systems are used to automate tasks that would otherwise require human intervention. Artificial intelligence (AI) is primarily used in crop sowing to power predictive analytics that help determine when and how to plant. AI-assisted machinery can also be used to sow crops at equal intervals and at optimal depths.

Deciding the minimum support price (MSP): Typically, the MSP is the responsibility of the government in order to provide security to farmers, and this MSP varies from crop to crop. It is the minimum price that a crop will reap. In order to decide the MSP, there are numerous factors that influence this–specifically, total expenses in growing the crop, fluctuations in input costs, demand and supply, market price trends, inter-crop price parity, area specific costs like transportation, marketing costs, etc. This complex, big data formed from these factors need a rigorous analysis which conventional methods usually fail to perform.

Crop monitoring systems: An overall improvement in agriculture has been made by the use of AI and ML in crop monitoring practices. The following are just a few examples:

Crop selection and crop yield prediction: Choice of crops based on different factors such as topography, climate, soil type, soil composition, market trends, etc. is critical in determining yield. It is feasible to make multi-dimensional analyses using AI and ML to predict the best crop that will maximize yield. In modern farming, yield potential is among the most critical and challenging issues. An accurate model, for example, can help farmers make informed management decisions about what crops they should grow in order to meet the current market's needs. There are many steps involved in this process such as, environment, management practices, genotypic and phenotypic traits of the crop, and their interactions can all be used to predict yields. As a result, comprehensive datasets and powerful algorithms such as machine learning techniques (ML) are required for the detection of these kinds of connections. Predicting crop yields is a critical but challenging issue for sustainable intensification and efficient use of limited natural resources in agriculture (Phalan *et al*., 2014; Tilman *et al*., 2011). Farmers, agronomists, commodity traders, and policymakers are among the many people who benefit from accurate predictions of crop yields (Basso and Liu, 2019; Chipanshi *et al*., 2015). Numerous crop-specific variables, environmental factors, and management decisions impacts yield of crops but it is difficult to create a credible and comprehensible prediction model. Many methods have been used to forecast crop yield viz, field surveys, crop growth models, remote sensing, and statistical models. It is possible to estimate crop yields using remote sensing techniques that rely on satellite imagery (Lopez-Lozano *et al*., 2015). Crop yields can also be predicted using weather variables.

Disease detection: Significant development in smart precision agriculture has been in disease prediction accuracy. AI and ML techniques have a higher degree of accuracy than traditional statistical approaches because AI/ML models have been able to analyse diversified data (Mehra *et al*., 2016) and, consequently, input is aimed specifically in terms of time, place, and affected plants (Kharkovyna, 2020). The SVM technique was initially used for disease detection and classification (Rumpf *et al*., 2010). Other examples include the algorithms of ML that are used in Machine Learning (ML) for pattern recognition in detecting diseases by using images of the crop leaves.

Weed detection: Elimination of weeds from the field was traditionally done by sacrificing the environment. Crop farming is threatened by weeds, which grow rapidly, compete with the crop, and cause a variety of plant diseases, all of which reduce yields and profits for farmers. Presently, herbicides are the most widely used solution, but they also raise environmental and economic concerns. Also, weeds are becoming increasingly resistant to herbicides as a result of their ability to adapt and become resistant to chemicals over time. Instead of using herbicides to degrade the environment, an AI-based machine can better detect weeds and destroy them without harming the environment. Farmers' ability to detect weed infestations is about to undergo a major transformation due to advancements in machine learning. With a reduction in chemical consumption of 80%, the technology's results are astounding. See & Spray not only introduces precision farming, but also helps farmers identify persistent weeds, making customizing herbicide programmes easier and more convenient. Table 3 lists the frequently used machine learning algorithms with their description.

Table 3: Machine Learning Algorithms

Algorithm	Description
Regression	Predicting the numerical value of an unknown input based on its relationship to the training data is the goal of regression algorithms, a class of supervised learning algorithms.
K-NN (K-Nearest Neighbor)	Classification algorithms such as K-NN are easy to implement and use. An initial step in this algorithm involves classifying the labelled dataset according to its results. This process continues indefinitely.
SVM (Support Vector Machine)	SVM is a multi-dimensional boundary-building algorithm for classification and regression. The SVM predicts the output based on the training data divided into classes.
RNN (Recurrent Neural Network)	RNN is a feed-forward neural network with input-output feedback. The network has self-loops.
ELM (Extreme Learning Machines)	ELMs are multi-layer feedforward NNs. It can solve real-time regression and classification problems without iterations.
Random Forest	An ensemble-based model that combines decision tree classifiers. The expected majority class is used to determine an object's final class.
CNN (Convolutional Neural Network)	The most common deep neural network is CNN. Including at least one of the network layers, convolution is used instead of matrix multiplication.

POTENTIALS: Using ML data-driven techniques will provide new insights, which could ultimately lead to:

Better yield for both crop and livestock: Achievable through accurate disease diagnosis and management, location-specific soil analysis, improve seed variety analysis.

Improved linkages along the value chain: Achievable through ease integration of the various actors from input, farmers, finance, extension agent to market.

Reduction in production cost: Achievable through adoption of more insightful cost-effective technique in every step of the production.

A Path to sustainability and self-sufficiency in agriculture: Achievable through high-profit margins which will lead to more production and increased farming participation thus, creating a self-sufficient nation in agricultural produce that will continue to cater to the nation’s growing population.

Increased agriculture contribution to the nation’s GDP: Achievable through high production, employment, and newly spring up MSMEs in Agro-tech, Agro-processor, etc.

Global leadership in ML technology advancement: Achievable through the adoption of ML technologies in agriculture. This will lead to more local researches, ML idea incubation labs capable of propelling the country into the forefront of ML advancement in the world.

CHALLENGES: Despite the enormous advantages inherent in the use of machine learning applications in Agriculture, myriads of challenges constitute a stumbling block for its achievement. These challenges can be classified as personnel, infrastructural and technical. They include

i) Availability of enough and quality dataset: The two basic factors that can affect the effectiveness of any machine learning application are bad algorithms, bad data, or a combination of both. Early ML applications developers for Agriculture will have a problem of availability of enough and/or poor quality datasets to train and feed their algorithm due to the infancy. Thus, they might have to create their data and might likely lead to overfitting.

ii) Poor infrastructure: In rural areas, where most farming is done, telecommunications and electricity infrastructure are lacking or underdeveloped. These infrastructures should be required for many modern ICTs to perform optimally and achieve desired goals. They are mostly built around cities, and even here, the infrastructure is often lacking. Low bandwidth issues necessitate enhancing the Internet backbone.

iii) High rate of illiteracy in rural areas: Lack of literacy is a major impediment to participation in the For the most part, illiteracy in rural areas is due to lack of access to text-based information. Deprived of basic skills to harness the benefits of ML technologies. Intermediaries like extension agents may be needed.

iv) Privacy and security issue: Due to the lack of clear policies and regulations surrounding the use of AI in general, precision agriculture and smart farming raise many legal questions that often go unanswered. Cyber-attacks and data leaks pose serious risks to farmers. Sadly, many farms are at risk.

CONCLUSION

Varied machine learning algorithms allow farmers resolve issues. Unwittingly or not, everyone today uses machines. We can use computer vision to create brain-like models or systems. Smart agriculture relies on digital image processing, AI, and the internet of things. So we tried to illustrate various researchers' ideas and algorithms in this paper. Machine learning has made machines self-sufficient and helps farmers optimize time by reducing constant field vigilance. Researchers in this field have made much advancement, but more are required, such as selecting the correct data set for machine training. In conclusion, machine learning algorithms have numerous applications and will continue to be a dynamic research field with various developmental options. Precision farming uses technology to maximize output from precise inputs. So far, these are just a few of the major agricultural technological advances. These components help collect data in real-time and make decisions without human input. Automation of intelligent behaviour benefits both our planet and humans.

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