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Machine Learning Overview in Agriculture

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Abstract: Today's agriculture industry makes extensive use of the promising field of machine learning (ML). There is not enough labour available for agriculture, and there are not enough skilled farmers. It is difficult to identify and stop crop diseases without a thorough understanding of the current situation. It is also frequently used in many aspects of agriculture, including managing soils, yields, water, diseases, and weather. The ML models allow rapid and actual decision-making. To anticipate correctness of the output, ML model uses training and testing. Species management, Disease detection, yield prediction, crop quality, water management, weed identification, increased productivity and better management of soil categorization are all aided by an application of ML in agriculture. By highlighting benefits and drawbacks of various ML methodologies put forth in the last five years, this article seeks to provide comprehensive information on them. Additionally, it contrasts several ML techniques employed in contemporary agriculture.

Keywords: Machine Learning, Sensors, Agriculture, Training Methods, Data Analysis.

1. Introduction

Today, agriculture is the primary industry everywhere in the globe and is essential to the international economy. Numerous funding and research projects are constantly being implemented using the newest technologies. Increasing crop output, automating crop-related tasks, reducing the need for human labour, lowering disease ratio by spotting early stages with already-available matching arrangements, and eventually harvesting with machinery in the shortest amount of time [1]. From planting to harvesting, ML is used in agriculture employing a variety of methods from several fields of technology, including data mining, drones, artificial intelligence (AI) and big data. Using these tools, existing data can be mapped to detect and address common issues. Using sensors detectors, define a machine with the associated setup based on moisture and weather location. Agriculture in its typical processing with manpower may have a number of issues, including a lack of expertise in crop complete processing, disease identification, the use of the proper pesticides in the early stages rather than spreading them throughout the crop, and the heavy reliance on manpower from sowing to harvesting. Knowing everything there is to know about crops and all of their varieties without any

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prior experience could have numerous negative effects. Thus, it is challenging for new crop workers to be fully informed. Using all available personnel has resulted in extremely high crop costs. Even today, many machines are used in agriculture, along with human labour, from planting to harvesting, however many crops cannot be automated since they are dependent on the environment and soil management [2].

The implementations of AI and deep learning (DL) algorithms are used to process ML algorithms. Automate a system using a combination of AI and DL. Utilizing DL in agriculture taught the system with sensors that served as intermediary data collection and processing points. Once the sensor has analysed the data on the current situation, it may then grasp how DL and AI based mapping work. The primary basis for ML in agriculture is the mapping of an existing dataset with a fresh data set produced by a sensor. DL is popular these days, even in agriculture. Utilizing the most recent image processing technologies along with data analysis of current models that match results and produce outstanding results [3]. These days, we can use DL mechanisms to address a variety of issues and challenges in various agricultural domains and food production. DL used to various crop fields along with speech recognition, natural language processing, and sensors to measure soil temperature based on a crop and meteorological conditions from seeding to mowing a crop [4]. When used in agriculture with use of information technology, ML enables farmers to gather knowledge and data in order to decide better conclusions for maximizing farm output [5]. Applications for ML algorithms in agriculture include crop recommendations based on plant pest detection, soil fertility, weed detection, crop yield cultivation, and plant disease detection based on disease identification at an initial stage that will recover plant and thereby surge crop. As food quality and human health are taken into consideration, it is crucial to reduce the use of pesticides. Intelligent agriculture must analyse how weather conditions affect the farm's environment and how long-term crop cultivation causes soil corrosion or alterations in soil structure in addition to monitoring environmental conditions on a farm. By limiting water management, we may conserve water and use it for another crop rather than wasting it. Crop productivity issues can be avoided by employing ML to monitor a farm [6]. Crop management, which includes everything from planting to harvesting, increases crop productivity.

2. Literature survey

ML has recently grown in popularity as a research area in a field of AI. Wide-ranging AI research and application is currently being conducted by well-known Internet corporations, and ML, which includes picture and speech recognition, is one of these technologies. In particular, given the fast-paced development of big data, ML combined with big data can combine systems and algorithms in an efficient manner, enabling ML algorithms to operate contemporarily across numerous centers and practice large amounts of data that is also a current research direction in study of AI. Internet sector has grown quickly, offering not only the vast number of training illustrations for DL but also constant advancements, improvements, and innovation on the part of the industry [7]. Using ML in agriculture means growing a variety of crops. A prior work [8] uses robotics and a DL technique to explain date fruit orchard harvesting. AlexNet and VGG-16 are the two pre-learning CNN techniques. Creating a study machine imaginative and prescient system that is similarly dependent on a high-quality image collection with five data categories for every maturity stage. The recommended method successfully classifies data from a challenging dataset with a matching ratio. In future, a high-grade pixel picture data base will be used to enhance the mapping of various fruit plantations. Additional work [9] focused on construction of directed open-chain graphical representation, with a focus on thin linear additive references and suggested techniques to find the thin in part true additive form. This study updates findings as the case study and proposes a view that is extremely helpful for uncovering strengthened variables or stable based on short-term with appropriate output graphs. They suggested the technique for managing energy-efficient development. Nevertheless, different strategy is that a team developed was expected to be useful for numerous investigations that rely heavily on statistical methodologies. Here, they primarily concentrated on classifying normal additive samples, but their plan may be easily developed further and naturally involved arbitrary link models. In order to get the desired best results within the predetermined timeframe, they assumed the hill mountaineering strategy.

The branch of computer science known as ML allows computers to learn without explicit programming. (1959; Arthur Samuel) [10]. in 1950, Alan Turing published the manuscript titled "The Turing Test for Machine Intelligence" in which author suggested an idea of ML [11]. He conducted an experiment to determine whether the machine might exhibit intelligent behaviour that was comparable to humans. An AI system provides a framework for forecasting the future or making wise decisions by learning from data and extracting knowledge from it. As a result, the ML process may be broken down into three distinct phases: data input, model development, and generalization. The process of anticipating the outcome for inputs that the algorithm has not yet been trained on is known as generalization. The main applications of ML algorithms include detection of plant diseases, spam filtering, weather prediction, and pattern recognition. Today, ML algorithms are widely used by enterprises and academic communities to solve a wide range of challenges due to an accessibility of creative algorithms and vast data sets by internet. DL is a branch of the family of ML techniques that uses the artificial neural network (ANN) trained on huge datasets to generate intelligent judgements.

ML algorithms are categorized into three groups: reinforcement learning, unsupervised learning, and supervised learning. As name proposes, supervised learning involves studying with a teacher or supervisor. This group of algorithms uses a labelled data set, which means that there are outputs for every input. With this labelled data set as a foundation, an algorithm constructs the input-output relationship and then extrapolates/forecasts outputs for unknown inputs. Classification algorithms, the kind of supervised learning algorithm, are used to predict category values, and regression algorithms, a type of supervised learning algorithm, are used to predict numerical values. Unsupervised learning methods use unlabeled data to find unknown things by assembling related objects into groups. Unsupervised learning algorithms are extra challenging to develop than supervised learning algorithms meanwhile their purpose is to mine concealed information from a training data set. Another method that uses rewards and penalties to teach from the environment is reinforcement learning. World’s top chess-playing computer programme was defeated by DeepMind's reinforcement learning algorithm in the chess game Alpha Go [12].

ML is renowned for its capacity to maximize results on a variety of technology-based domains. The most effective analytical technique for fog computing applications is ML. In addition to modern accomplishments, ML applications and literature also play the significant part. Most recent knowledge hole describes fog computing. Accuracy, security and Resource management are three areas where ML research has made progress. In fog computing, ML is mostly used for resource management rather than accuracy and security. Cloud computing is one of the levels in ML. With these combinations, many issues and obstacles have remained unresolved. Even the majority of the difficult issues with the security measures applied in cloud computing. One of the well-known ML assignments is supervised learning in fog computing. The majority of applications in the healthcare sector use ML, and there are still numerous obstacles and problems with fog computing in ML [13]. Using robotic harvesting automation in agriculture, a previous learning [14] intended the strong and accurate algorithm for the novel machinery to analytically discover progress of vegetable. This programme uses a unique set of implementations and data mining techniques to uncover the exceptional components of the vegetable field. This process matches image pixels with vector elements to obtain the initial stage of the subsequent levels. Numerous yield results were used as feedback for testing and modelling an ending algorithm. This application's algorithm result is much effective for reaping vegetable. DL eliminates numerous diseases by recognizing them with the right data set and treating crop plants with a small amount of pesticides [15]. Another study [16] uses numerous methods, such as ANN, to explain crop prediction. Based on AI, determining the soil condition in relation to the weather and maximizing agricultural yield. In future, the study stated to roughly 40 inquiry based publications that were well-defined as the review on totally facets of agricultural ML. Reference articles on ML in agriculture published in reputable publications with significant citation counts and numerous implementations worldwide. Agricultural ML uses sensor data and AI with strong recommendations from planting to reaping. In a study [17], Rakesh Kumar, J.P. Singh, and Prabhat Kumar recommended seven ML techniques. Among the crop selection methods employed are GBDT, SVM, ANN, DT, RF, RGF and KNN. This method is meant to recover all sown crops and their developmental stages at a particular period of year. So, only the highest-yielding crops are chosen for planting. Additionally, the strategy suggests growing a series of crops to maximize output [18].

3. Machine Learning In Agriculture

Using most recent methods, smart farming is being implemented in agriculture as part of the latest ML trend. Numerous modern techniques are being used in farming to determine soil moisture according to kind of crop grown, as well as for disease detection, pesticide selection, and crop management. ML comprises of five key components. These five key components are 1). Data collection from farm 2). Stored data 3). Data pre-processing 4). Train the model and 5). Performance metrics.

3.1 Data Collection From Farm

To gather information on soil fertility, crop yield, climate conditions, pest detection, and other topics, the majority of researchers used a variety of sensors, including temperature, water quality Sensor, passive infrared, humidity, GPS Sensor, soil moisture, pH, ultraviolet, gas sensors, barometric pressure, obstacle sensor, acoustic sensor. This data provides much exact answers, but it is more expensive, time-consuming, and challenging to gather. For the purpose of growing plants, a research [19] constructed a robot with multiple sensors that collects data on numerous environmental parameters that have an impact on the soil, like humidity, soil pH, soil temperature, sunshine intensity, soil wetness, etc.

Later, different research devised and created an optical transducer to assess primary nutrients in soil, like as potassium, phosphorus, nitrogen. In addition to possessing macronutrients and micronutrients, soil nutrients also depend on fundamental nutrients. In general, environmental conditions and soil fertility are linked [20].

Another study [21] used temperature, humidity, and UV sensors to build a smart irrigation system for agricultural. The key factors in creating a smart irrigation system are soil fertility, crop types, and weather conditions. In order to get more precise findings for judgments from the data analysis, it is therefore advisable to collect environmental parameters and the type of crop along with the soil nutrients. Hyperspectral Another study [22] used images of various crops to classify crops using hyperspectral cameras. Later, an investigation used an acoustic sensor to find nuisance insects beneath. The primary application of this sensor is the detection of pests in underground harvests such as potato, onions, taro, garlic, carrot, groundnuts, turmeric etc. Using the Canon EOS 80D camera, a study gathered [23] 652, 83, 16 and 260 colour photos in JPEG format from wheat planting in Shandong Province, China, to train and test the model for winter wheat leaf diseases, respectively.

3.2 Standard Data Repositories

The biggest advantage of using current data is that it saves the researcher money on data collection. Although easier to gather and requires less effort, this data is less reliable [24]. Particularly, this information may be found on numerous websites. The data analysis is done by the researchers using downloads from websites. Images, tables, text, graphics, audio files, and videos are among the several types of data. The datasets used by agriculture's ML algorithms for data analysis are mostly produced by the following industries. Live tree, China Agro, MIT, Kaggle, University of Arkansas. And data from GitHub, Open Government Data, OpenAg, and Economics. The World, Knoema, USDA-ARS, V2 Plant Seedlings Dataset, Food and Agriculture Data, Pesticide Use in Agriculture, and Soil Resources Development Institute all contributed data for the study.

As per research [25], soil-related information from an upazila in Bangladesh's Khulna district was utilised to categorize soil and recommend crops. Information was gathered from country's soil resources development institute. To identify rice plant illnesses, a second study [26] collected 3010 pictures of diseased rice plants from high-standard rice investigational field of Hunan Rice Research Institute in China.

In another study [27], 16652 pictures from Shandong Province, China, were divided into eight groups to help researchers identify 8 distinct illnesses that affect wheat winter harvests. Alternative research [28] gathered 1070 actual photos of mango tree leaves from the shri mata vaishno Devi University in Katra area of Jammu and Kashmir, in order to recognize fungus known as anthracnose. While this technique is low costly, cost effective, easier to collect, it has a high error rate and is not appropriate in all situations.

3.3 Data Pre-Processing

Real-time data has a lot of problems, especially with consistency, replication, missing values and noise. Such kind of dataset raises the error rate and is essential for process analysis. Data pre-processing is done on raw data to improve quality of data before further processing. Pre-processing data is a key stage in ML that helps to increase processing speed.

Pre-processing can include eliminating noise, adding missing values, selecting right data range, and mining functionality, among other things. Two-Dimensional Filter Mask Combined with Weighted Multistage Median Filter (2DFM-AMMF) was employed in a study [29] to reduce noise in photographs of rice plants. Segmentation and feature improvement are commonly employed in image-related operations to increase the quality of the data. Another study [30] improved an image quality to the 4-different crops and 2-weeds, Nutsedge and Paragrass which are selected for classification, by removing salt and pepper noise using Gaussian Median and Gaussian filter, correspondingly. In a different study [31], multicollinearity and dimensionality issues for projecting water supply in US West were eliminated using Principle Component Analysis.

4. Train the model by using ML algorithms

There are two classifications of ML algorithms i-e supervised learning and unsupervised learning. The classification of soil is one benefit of using ML in agriculture, along with a) soil classification b). Detection of diseases c). Species management d). Water Administration e). Yield Forecast f). Crop Excellence g). Detection of weeds.

4.1 Livestock production & management

In general, livestock production refers to the raising and management of cattle, including sheep, pigs, and other animals, for human consumption of their meat. Based on the farming criteria of these cattle, such as health, food, nutrition, and behaviour, livestock production and management are optimized in order to maximize the economic efficiency of this livestock. In the current environment, AI intelligence, Internet of Things (IoT), and block chain technologies [32] are widely investigated to improve the sustainability of livestock.

Analysis of their chewing habits, eating patterns, and movement patterns, such as standing and moving, drinking, and feeding habits, indicate the amount of stress the animal is going through, which in turn helps in predicting vulnerability to disease, weight gain, and livestock production. In addition, 90–180 days prior to the day of slaughter, an ML-based weight forecasting system can assist in estimating their body weight.

These analyses and projections suggest that farmers can modify their diets and living arrangements to help their livestock grow in terms of their health, behaviour, and weight gain, which will increase the economic efficiency of their livestock [33]. For precision sheep farming, Villeneuve et al. [34] develop a decision support system that uses both real-time data and expert knowledge. Animal welfare and livestock production are the two subcategories under the larger category of livestock management. Animal welfare normally focuses on the health and wellbeing of the animals; as a result, ML approaches are applied to their health monitoring feature with the goal of detecting diseases early. In contrast, livestock production uses ML to estimate a balanced livestock production in order to help farmers make money.

4.2 Weed Detection

The primary issue with any crop is weed detection; the final yield is determined by this. It poses a serious risk to the crop and has an impact on the output. The stage must be able to discern the age of the plant and weed. Weeds must be reduced for yield to be better; else, pesticides and fertilizers won't be effective on the crop. The weed's job is to use all of the soil's energy. Therefore, the crop will have a minimum yield by default. There are numerous ways for ML to identify the sort of weeds on each crop and in close proximity. In the research [35], Conventional Neural Network (CNN) and Support Vector Machine (SVM) were used to analyse photos and identify broad-leaf weeds in a pasture. Another study [36] employed CNN, SVM, and ANN to classify two different weeds and four different crops, but CNN produced the best results overall.

4.3 Crop Quality

Crop quality is a key to determining crop's financial performance. Quality of a crop and minimal wastage after harvest can be identified based on the ultimate yield quantity. We can define crop quality based on these factors and compare it to the dataset. In a research [37], various sensors were linked to a drone to assess crop condition. This drone can keep an eye on the crop and notify the farmer if there are any problems.

4.4 Yield Prediction

Each crop is supposed to be concentrated based on expected yields. The key definitions of yield prediction include plotting of harvest, demand based on crop results, and estimation. Earlier dataset may be used to define yield prediction and to determine what types of cutting-edge technologies are currently available and applicable based on a present crop, climatic conditions, and economic conditions for increasing revenue. For calculating the yield from a sorghum crop, the research [38] used Linear Regression and Tensor Flow with Convolutional Neural Networks.

4.5 Water Management

Every crop relies heavily on effective water management. We can utilize the water effectively using a ML technique so that any extra water may be used for another crop. We can supply the water daily, weekly, or monthly depending on the crop and soil type. In an automated water dripping system for agriculture, the research [39] employed pH sensors, moisture and soil temperature to determine level of soil water content. An autonomous irrigation system's key advantages are proper water use, energy efficiency, and time savings, but it costs farmers more money.

4.6 Species Management

Species breeding: choosing of species, which is dependent on the soil, local weather, and water related vitamins and flavors, is a crucial mechanism. Instead of making assumptions, existing patterns and data sets are mapped using DL techniques to address the myriad problems. The Cascaded SVM technique was used in a study [40] to classify nine different types of sunflower seeds.

4.7 Species Recognition

The colour, age, and shape of the plant's leaves can all be used in the manual selection of plants. The initial stage of crop will be choosing of a plant, with consideration given to the age and colour of the veins on the leaves of the plant. A study [41] classified five kinds of species i-e stem, fruit, leaf, leaf san and Flowers using three diverse classifiers, including SIFT-based, Color-Shape-Pixel and Texture. Another study [36] combined Object Oriented Classification (OOC) and Feature Band Set (FBS) to categorize various crops by means of hyperspectral images.

4.8 Disease Detection

Disease is mostly influenced by climatic conditions and weather, soil properties, and plant hardiness. Disease management involves both simultaneous disease management and disease detection based on climatic circumstances and viral diseases, which are generally pests.

Additionally, disease detection compares with a dataset according to the plant's age and environmental variables. The research [42] matched two ML algorithms, including grouping of fuzzy C-means and k-means clustering (FCM-KM) + faster region convolutional neural network (R-CNN) and faster Region Convolutional Neural Network (R-CNN), for detecting rice plant diseases like sheath blight, bacterial blight and rice blast. It was found that faster Re (R-CNN).

Identification of rice plant diseases on a big scale is not appropriate for this technology. Another study [43] evaluated five different ML methods for identifying various illnesses in various crops, including Conventional Neural Networks (CNN), Fuzzy, SVM, K-NN and ANN. The findings of Conventional Neural Network categorization, one of these five ML methods, are more accurate and it can be used for more crops. Another study [38] classified eight different leaf diseases, including normal leaf, mechanically damaged leaf, stripe rust, leaf rust, bacterial leaf blight, bacterial leaf streak, Cochliobolus heterostrophus and powdery mildew, using the ML algorithm known as matrix-based convolutional neural network (M-bCNN).

4.9 Soil Classification

According to its strength and capacity to aid in crop growth, soil is categorized. Former employs a system of soil classification to forecast soil behaviour. Soil can be categorized and given names based on physical and chemical characteristics of its layers. Based on the kind of soil, soil classification can be used to determine better crops and fertilizer types. Along with water management, climate change has a significant impact on soil management. Using ML approaches, offers related steps and temperature-related moisture techniques. For soil classification, the research [44] used ML algorithms like Bagged Trees, Gaussian kernel-based SVM and k-NN. However, suggested Gaussian kernel-based SVM based technique outperforms Bagged Trees and k-NN.

4.10 Performance Metrics

The accuracy is used to choose the optimal method. The best method is the one with the most accuracy. Better selections can be the result of models that are more accurate. Different ML methods used in agriculture are displayed in Table 1 along with their level of accuracy.

Table 1- Comparison of different ML algorithms used in agriculture.

S.No	Domain	Crop	Algorithm	Accuracy	Ref No.
1	Disease Detection	Wheat	Matrix based CNN	92.43	[5]
2	Disease Detection	Cotton	SVM	91.55	[10]
3	Disease Detection	Sugar cane	FNN	95.00	[12]
4	Weed Detection	Pasture	ANN & CNN	CNN best	[15]
5	Weed Detection	Cotton	Naïve Bayes	90.89	[16]
6	Weed Detection	Cotton	Logistic Regression	88.86	[18]
7	Species Breeding	4-specie	Sift based	91.20	[20]
8	Species Recognition	5-speciess	RF	96.11	[21]
9	Yield Prediction	Sorghum field	Linear Regression	86.21	[22]
10	Yield Prediction	Rice	J-48	98.72	[23]
11	Yield Prediction	Maize	XGboost	76.23	[25]
12	Soil Classification	-	SVM	80.98	[26]
13	Soil Classification	-	SVM	87.25	[28]
14	Soil Classification	-	SVM	92.44	[29]

5. Conclusion

In contemporary agriculture, ML is frequently applied. With ML, robotics, AI, DL and much more is needed to automate nearly everything from sowing to harvesting crops in order to reduce the need for human labour and manual errors. Detecting the type of crop and choosing the appropriate pesticides in relation to the dataset mapped using the most recent technologies and techniques for reducing manual errors Agriculture benefits from the use of ML in a variety of subfields, including weed identification and processing, crop quality, water management, disease detection, yield prediction, species management and soil classification. Our goal in this study is to deliver the thorough overview of numerous ML algorithms which have been simulated to several aspects of contemporary agriculture. This article compares and contrasts several ML algorithms in great depth.

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