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Automatic Learning in Agriculture: A Survey

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Abstract: Agriculture plays a pivotal role in the growth of any nation. Nowadays, with the advancements of information technologies, big data are generated and executed using faster computing techniques. machine learning techniques have been used to automate and improve agricultural activities for a long time. This paper presents a review of existing applications of machine learning in agriculture with a focus on the applications of Deep Reinforcement Learning techniques in agriculture. The conventional solutions for agricultural machine learning decision-making problems are using supervised approaches. In supervised learning, the machine needs to be trained on samples of inputs and outputs to support decision making. While, in reinforcement learning, sequential decision making happens and the next input depends on the decision of the machine. In this paper, we perform a survey of 49 publications of which 10 were secondary research efforts that discussed a variety of machine learning approaches applications in agriculture and 39 research efforts that used machine learning approaches to support the automation of agricultural activities.

Keywords: Smart Agriculture; Automation; Reinforcement Learning; Deep Learning; Machine Learning; Sustainability.

1. Introduction

Agriculture has a big impact on the living standards of people. It has many important roles; one of its roles is sustaining people's lives by supplying them with food needed to continue thriving. The supply of food for people and fodder for livestock depends on the agricultural sector. Generally speaking, agriculture is an important sector to make sure a stable chain of food supply exists and to ensure food security.

Some countries have very extreme resources' constraints. For instance, the Gulf Cooperation Council (GCC) countries have environments that are naturally unsuitable for farm production. The three main constraints related to the agricultural sector in this region are weather, water and arable land. In general, GCC countries have longer hot summers and shorter cool winters. For instance, Bahrain has an arid to an extremely arid environment, in which the average temperature exceeds 35-40 °C in the summer season (May to October) [1]. On the other hand, the main source of water in the region is groundwater which is mostly nonrenewable due to the limitation of rainfall which feeds the groundwater. Rainfall in this region is rare, with an average annual rainfall that ranges between 1-100 mm [2]. Moreover, according to Pirani and Arafat [3], less than 2% of GCC total land area is cultivable lands. In some countries, outsourcing agricultural production by acquiring lands abroad is considered a solution to face the extreme resource constraints. However, this solution does not assure self-sufficiency, efficiency and long-term sustainability. A possible practical solution for this problem is the use of Controlled Environment Agriculture (CEA) technologies.

CEA is about using technology to produce food, such that growing conditions are optimized and protection is provided throughout the crop lifecycle. Usually, in CEA, agricultural activities are held within an indoor farm or greenhouse. CEA methods include hydroponics [4], aeroponics [5], aquaponics [6] and aquaculture [7]. Generally, CEA focuses on optimizing resources such as water, energy, space and labor. For instance, vertical farms [8] are used to optimize space and hydroponics [4] are used to optimize water and nutrients.

CEA is already in use in several farms in GCC countries. Mostly these farms are inside a building or a greenhouse. Most of these farms are utilizing modern soil-less agricultural methods such as hydroponics. Some are even using vertical farming to efficiently utilize the space of the greenhouse. However, there is a shortage of studies in the literature discussing the application of CEA technologies in the GCC region. This might be justified by the fact that

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GCC countries are not agricultural. Though, greenhouse and indoor farms are used for a long time in almost all the GCC countries. This paper aims to focus on improving the monitoring and control of indoor/greenhouse farming activities.

Greenhouse farming is different from open-field farming. In a greenhouse, the variables related to farming can be controlled more efficiently, fully or partially. However, the optimization of crop growth and all CEA variables such as temperature, humidity, light, nutrients, acidity and pests is a multi objective problem with the presence of some uncertainty.

To come up with optimal solutions and unbiased opinion about the climate condition of a greenhouse, various measurements are required at many spots in the greenhouse. To accurately and precisely measure the different variables, a distributed sensing system is required. Using Wireless Sensor and Actuator Network (WSAN), developing a distributed monitoring and controlling system is achievable. A WSAN consists of a group of battery-powered sensing nodes that gather information about the environment as well as actuators, such as servos or motors, which communicate with them. All the elements in a WSAN interact wirelessly. The collected information from sensing nodes can also be transmitted wirelessly to a central base station which can store the data for future processing. Moreover, to make the best decision based on the collected data, AI can be used to learn rules directly from the real-life data instead of manually programming them.

The Problem Statement

We aim to survey current research efforts to explore the possibility of using deep learning and reinforcement learning techniques to propose an advanced Artificial Intelligence (AI) system for CEA that automates and optimizes certain greenhouse activities and functions which still rely heavily on manual intervention. Optimizing all the variables affecting a greenhouse environment is a complex task. Yet, many technological advancements in the last decade can make this task achievable.

Modern Machine Learning (ML) methods such as Deep Learning (DL) and Reinforcement Learning (RL) have achieved superior performance on a variety of tasks. In this paper, we are exploring the applications of ML, DL, and RL in agriculture. This paper present a survey of 49 publications of which 10 were secondary research efforts that discussed a variety of ML approaches applications in agriculture and 39 research efforts that used ML approaches to support the automation of agricultural activities.

A preliminary version of this work appeared in [9]. The main contribution of this research effort is to understand the various ML methods used in agriculture and their applications to specific agricultural issues. This work invites other researchers to use the results of this survey to build ML knowledge and solve some of the agriculture problems in Bahrain and the region.

The rest of this paper is structured as follows. Section 2 provides an overview of smart agriculture system components. Section 3 gives a theoretical background of reinforcement learning and deep learning. It discusses some basic definitions and notations. Section 4 discusses and compares related works to the one in hand. It provides a synthesis of ten secondary research efforts conducted in the last five years. The methodology used throughout this work is explained in Section 5. This is followed by an analysis of ML approaches in agriculture in Section 6. The analysis focuses on RL, DL, and other conventional ML approaches synthesized from research efforts conducted in the last five years. This is followed by a discussion of research challenges and future directions for research in Section 7. Finally, Section 8 concludes this paper.

2. Overview of Smart Agriculture

In recent times, a wide range of technologies have been used to make farming more efficient. For instance, farmers use Global Positioning System (GPS) and Global Navigation Satellite System (GNSS) [10] to optimize farming activities such as irrigation, harvesting, fertilizing and pest control. Other technologies used to support the monitoring and control of agricultural activities includeing Wireless Sensor and Actuator Network (WSAN) [11]–[14], robotics [15] and Unmanned Aerial Vehicles (UAVs) or aerial drones [10], [16]. Moreover, Variable Rate Technologies (VRT) were used to optimize farming activities such as irrigation and seeding [17].

CEA is an application of Precision Agriculture (PA). PA is about using technologies to enable farmers to electronically monitor, analyze and control soil, moisture and crop states. PA aims at optimizing the crop, taking into consideration factors such as weather, sun exposure, soil conditions and humidity. Almost two decades ago, Zhang et al. [18] provided a worldwide overview of the applications of PA technologies. Several studies about PA have been done in the Kingdom of Saudi Arabia, including [19]–[22]. What is common about these studies is the focus of field farming and the exclusion of greenhouse or indoor farming.

Modern greenhouses operate as systems. This is why a greenhouse is also referred to as a CEA system or a Controlled Environment Plant Production System (CEPPS). Shamshiri et al. [23] provided a review of the improvements in CEA technologies with a highlight on

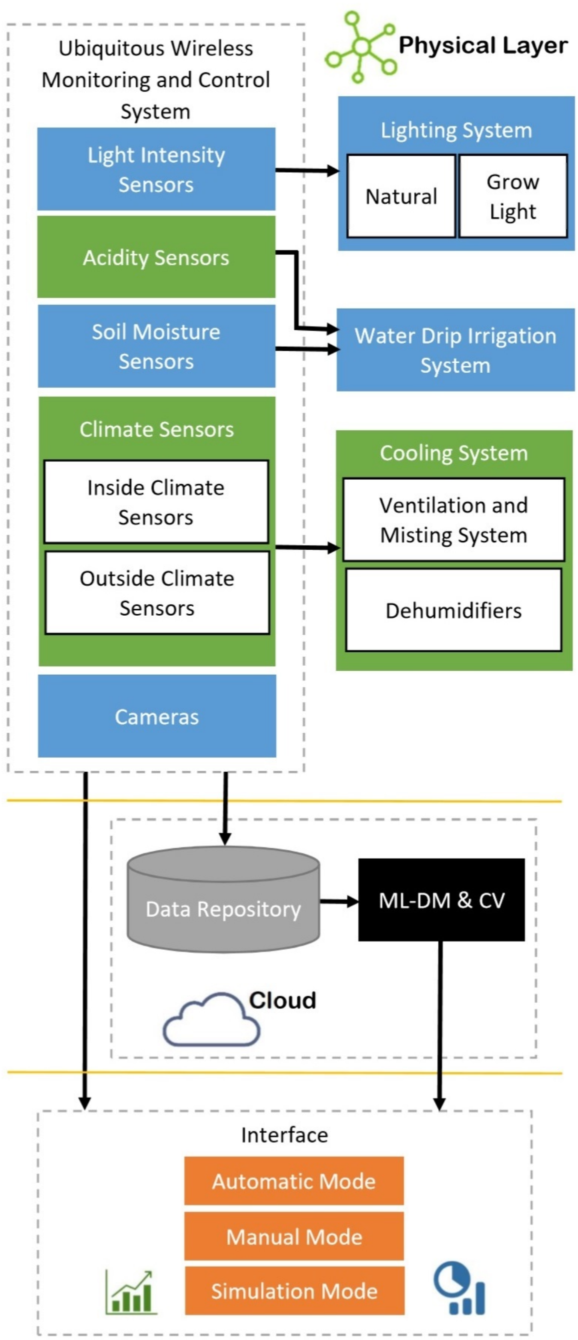


Figure 1. CEA Framework Overview

urban agriculture and a variety of its derivatives, including plant factories, rooftop farming and vertical farming. This study is focusing on soil-based greenhouse farming. Other varieties of CEA systems, such as soilless farming and vertical farming, are excluded and considered out of the scope of this study.

Fig. 1 represents what, generally, a CEA system consists of. A CEA system is a ubiquitous wireless monitoring and control system that interacts with several systems in the greenhouse. Moreover, the system consists of multiple sensors installed inside and outside the greenhouse. The coming subsections discuss the details of each subsystem within the greenhouse:

A. *Lighting System*

Since the GCC countries lie in the global sunbelt, natural sunlight is the main source of light in our greenhouse CEA system. Sunlight exposure intensity could be controlled by installing a shutter that opens or closes in response to light intensity sensor reading.

However, grow lights can be used to enhance the growth of some plants when needed. Many farmers, in the region, use grow lights to boost the rate of plant growth. During the day time, plants receive a sufficient amount of sunlight. To accelerate the growth of the plants at night, grow lights can be used by the farmers. Moreover, farmers use different colors of light to improve crop quality. Various colors, or wavelengths, of light play different roles for plant growth. The promotion of plant growth using a variety of artificial lights has been the focus of significant research and experimentation, as mentioned in [24]. For instance, the use of blue lights can increase the growth rate of plants more than other colors, hence it is preferable for farms nurseries to grow seedlings.

Light intensity Sensors are used to measure the intensity of light exposure inside the greenhouse. Had the values given by the sensors reach a specific threshold, a horizontal shutter will be used to shade the plants inside the greenhouse. This mechanism is only needed because of the arid and extremely hot weather of the region.

B. *Water Drip Irrigation System*

To use water efficiently and effectively a water drip irrigation system is used. The irrigation system allows the water to target plant roots. Two water tanks are used; one underground tank to store water from multiple sources, and another overhead tank which is connected to a network of irrigation pipes. A pump is also used to pump water from the underground tank to the overhead tank. Water, whatever its source is, is not used directly to irrigate the plants. Instead, it is stored in the underground tank. A sensor is used in each of the two tanks to measure the level of water. A microprocessor switch is used to switch off the pump once the overhead tank is filled and another microprocessor switch is used to switch off the valve feeding the underground water once the underground water is filled.

GCC countries are the world's poorest countries in natural freshwater resources [25]. Despite the freshwater shortage, people in the GCC countries have full access to clean drinking water and water for sanitation purposes. The majority of domestic water supply in the GCC countries rely mainly on costly desalinated seawater which is used either directly or blended with groundwater. To help improve the sustainability of water resources for the greenhouse, rainfall harvesting could be used to collect water during the rainfall seasons. The use of two tanks allows the storing of the harvested water.

The overhead tank is connected to a network of drip irrigation pipes and can be controlled using a valve. Multiple sensors are used to measure the soil moisture and soil acidity. Depending upon soil moisture and acidity values given by the sensors, the valves of the irrigation water pipe will open or close. The valves will automatically open if the soil moisture is below a specific threshold and close when moisture has reached a specific threshold.

Moreover, additional acidity sensors are used to measure the acidity of the water in the tanks to assure the quality of the water and its suitability for agricultural use.

C. Ventilation and Cooling Systems

The climate control of the greenhouse is done using two systems: ventilation and misting system and dehumidifying system. The ventilation and misting system consists of multiple fans and water pumps. Each fan is associated with a water pump. The fan can operate separately, without the water pump, if the purpose is to increase the level of ventilation of the greenhouse. However, if misting is the target, both the fans and associated water pumps will work together. On the other hand, the dehumidifiers are, most probably, needed in the very humid summers of Bahrain.

Temperature and humidity are monitored using multiple sensors. Two sensors that sense temperature and humidity, respectively, are installed inside the greenhouse. Similarly, two more sensors for temperature and humidity are installed outside the greenhouse. If the values reach a specific threshold the climate control systems will be switched on or off automatically.

D. Cameras

Multiple cameras will be installed inside the greenhouse using a rail-mount system to capture close up images of the plants and crops at different times and locations in the greenhouse.

3. Deep Reinforcement Learning

A RL problem represents the situation in which an agent that interacts with an environment has to learn through a process of trial-and-error. An RL problem is a combination of classical AI and Machine Learning (ML) techniques. Figure 2 is a graphical representation of the basic RL problem, in which an agent senses the current environment's state s_i and acts upon the sensed state with an action a_i. The action a_i, then is interpreted into a reward r_i and a transitioning state s_{i+1} which are both fed back into the agent. The agent then uses s_i and r_i for acting and for improving the agent's ability to behave optimally in the future to achieve the goal.

There are, generally, two categories of approaches for solving an RL problem. The first is to use a set of predefined actions, $A = (a_1, \ldots, a_n)$, and whenever the agent senses an environment state, s_i, it responds with an action a_i from the predefined set A. This approach is used in search techniques such as genetic algorithms. The second approach is to use statistical techniques to estimate and utilize the probability of the transition from a state s to another state s', given an action a. The focus of this paper is on the second set of approaches.

The basic RL problem is modeled as a Markov Decision Process (MDP). In subsection 3-A we introduce some basic definitions and notations for MDP. This is followed by introducing DL and discussing the reason for choosing it to solve the problem in hand, in subsection 3-B. After that, subsection 3-C discusses the possibility of combining RL Techniques with supervised or unsupervised learning Approaches of deep neural networks.

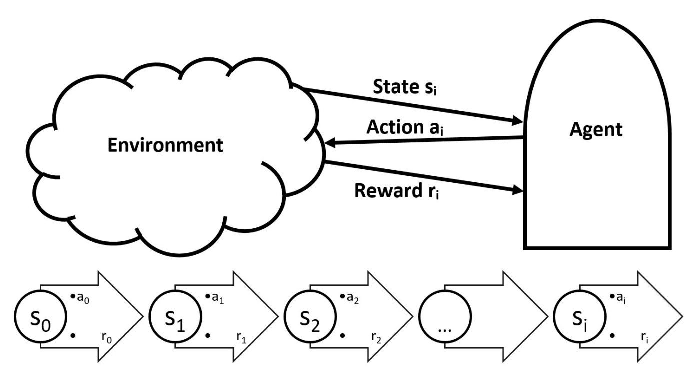


Figure 2. The basic Reinforcement Learning Problem

A. Markov Decision Process

MDP is a stochastic discrete-time control process. It is an extension of Markov chains; the difference is the addition of actions and rewards. An MDP is a quadruple (S, A, T_a, R_a), where:

- S is the state space, containing a finite set of environment states,
- A is a the action space, containing a finite set of agent actions,
- T_a is the state transition probability density function and it can be represented as follows:

$$T_a(s, s') = \Pr(s_{t+1} = s' \mid s_t = s, a_t = a) \quad (1)$$

  hence it is the probability that action a in state s at time t will lead to state s' at time $t + 1$.
- $R_a(s, s')$ is the reward function which represents the immediate reward received after transitioning from state s to state s', due to action a.

MDP provides a mathematical framework for modeling RL. In an RL problem, the task is to learn an optimal policy that maps states of the environment to actions of the agent, as follows:

$$\pi = S \rightarrow A \quad (2)$$

where S is a finite set of states $S = (s_1, \ldots, s_{\mathrm{m}})$ and A is a finite set of actions $A = (a_1, \ldots, a_{\mathrm{n}})$. At each time step in the learning task, the process is in some state s, and the agent may choose any action a that is available in state s. The process responds at the next time step by randomly moving into a new state s', and giving the agent a corresponding reward $R_a(s, s')$.

The agent has to find a policy π that specifies the action $a_t = \pi(s_t)$ at time t that will be chosen when in state s such that the chosen policy will maximize the expected total reward. It, possibly, can be calculated as the expected discounted sum over a potentially infinite time horizon. This cumulative function is also called the State-value function and it is represented as follows:

$$V_\pi(s) = \mathrm{E}[\sum_{t=0}^{\infty} \gamma^t R_{a_t}(s_t, s_{t+1})] \quad (3)$$

such that the expectation is taken over $s_{t+1} \sim P_{a_t}(s_t, s_{t+1})$ where E[.] is the expectation for the reward distribution and γ is the discount factor satisfying $0 \leq \gamma \leq 1$, which is usually close to 1. Because of the Markov property, the optimal policy for this particular problem can indeed be written as a function of s only. The discount-factor motivates the agent to favor taking actions early instead of postponing them indefinitely.

The probability that the process moves into its new state s' is influenced by the chosen action a. Specifically, it is given by the state transition function $P_a(s, s')$. Thus, the next state s' depends on the current state s and the agent's action a. But given s and a, it is conditionally independent of all previous states and actions; in other words, the state transitions of an MDP satisfy the Markov property.

B. Deep Learning

DL uses deep neural networks of supervised and/or unsupervised learning algorithms to model high-level abstractions in data. It learns hierarchical representations in deep architectures for different tasks such as classification. DL models contain multiple layers of Artificial Neural Networks (ANN), such as convolutional layers. The input data, which is usually raw data, is fed into a network of multiple layers. The output of each layer is fed as an input to the next layer of the network. The output of the final layer can be used for classification. Each layer applies a nonlinear transformation on its input in order to extract underlying explanatory factors. Consequently, this process leads to learning a hierarchy of abstract representations.

DL is a very powerful tool in solving real problems. However, using deep networks with many hidden layers leads to having millions of parameters to learn. This imposes very high computational complexity. Fortunately, with the emergence of advanced parallel processing technologies like GPU this problem has alleviated somewhat.

DL algorithms allow the automation of feature extraction from the data. Feature learning is a key aspect of any ML task. Shallow ML techniques such as Support Vector Machines (SVM) depend heavily on feature learning. Feature engineering can use the knowledge of the domain experts in order to extract hand-crafted features and to reduce the dimensionality of features of the input data. The representations learned through the data are fed directly into deep networks without the use of human knowledge. This aspect of DL allows the machine to understand the world independent of expert knowledge and interference, which is the goal of AI.

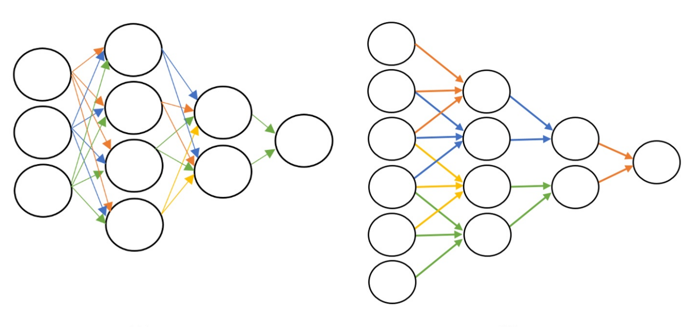


Figure 3. A generic architecture of traditional ANN and CNN

Convolutional Neural Networks (CNN) is a form of deep neural networks that are commonly used in different learning tasks, such as image recognition, image classifications and recommender systems. CNNs are special versions of an ANN. Like an ANN, a CNN consists of multiple layers. However, a traditional ANN usually consists of a fully connected network, that is, each neuron in one layer is connected to all neurons in the next layer, as demonstrated in Fig 3-A. A CNN, on the other hand, takes advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Fig. 3-B shows how in CNN, instead of a neuron being connected to all neurons of the previous layer they are connected to only neurons close to it. In CNN, only the last layer is fully connected. This enables nearby input elements to interact at lower layers while distant elements interact at higher layers. By stacking multiple convolution layers, a CNN can produce the hierarchical abstract representations of the input text.

C. *Deep Reinforcement*

Deep Reinforcement Learning (DRL) uses DL and RL principles to create more efficient algorithms. Implementing DL architectures with RL algorithms is capable of scaling to previously unsolvable problems.

4. Related Work

Table I, summarizes ten secondary research publications that cover the applications of ML in agriculture in the last 5 years (2016 - 2020). Eight out of the ten publications were regular Survey efforts, one is a meta-review, and one is a Systematic Literature Review (SLR).

The coming subsections discuss each of the ten works. Sections 4-A, 4-B, and 4-C discuss publications about the application of conventional ML, DL, and RL in agriculture, respectively, according to the analysis of the ten secondary research efforts listed in table I. We should note here that by conventional ML we mean ML approaches other than DL and RL.

A. *Conventional Machine Learning in agriculture*

Tripathi and Maktedar [26] focused on ML and Computer Vision (CV) to study the classification and detection of plant diseases so that the agricultural products can be improved by controlling those diseases. This research provided a survey of seven research efforts that used several ML techniques, such as K-Means, Artificial Neural Networks (ANN), and Support Vector Machine (SVM), for detecting and classifying agricultural diseases. Most of the techniques were based on CV and image processing approaches. SVM was considered the best in predicting and classifying agricultural diseases.

Similarly, Shinde and Kulkarni [27] focused on crop diseases. However, they focused not only on classifying and detecting crop diseases but also on predicting and forecasting diseases. This research provided a survey of six research efforts that used ML techniques and the Internet of Things (IoT) technology to forecast crop diseases.

Batra and Gandhi [30] focused on predictive modeling so that decision making can be improved in protected agriculture. This research highlights that in protected cultivation the micro-environment provided to the plants can help in controlling the negative effects of any factors. When predictive modeling is used in agriculture, it can help in proper water management and energy utilization. This research provided a survey of eleven research efforts and focused on two main ML algorithms, namely ANN and Bayesian Network (BN). ANN was the most common method used in predictions in greenhouses. Most of the surveyed works focused on the temperature control of the greenhouse and optimization of temperature maintenance costs.

B. *Deep Learning in agriculture*

Kamilaris and Prenafeta-Boldú [28] performed a survey of 40 research efforts that employed DL techniques to various agricultural and food production challenges. This review paper discussed a variety of agricultural applications that can utilize DL. Many DL techniques were discussed such as CNN, Long Short Term Memory (LSTM), and Gated Recurrent Units (GRU). The research compared the used dataset, the classes and labels, the techniques used for data pre-processing, data augmentation, and data splitting into training and testing datasets, and the performance metrics used in related work understudy. Furthermore, the research discussed the applications of CV in agriculture and popular techniques used for that. The agricultural problems discussed in this study include leaf classification, leaf disease detection, plant disease detection, land cover classification, crop type classification, plant recognition, plant phenology recognition, segmentation of root and soil, crop yield estimation, fruit counting, obstacle detection, weed identification, crop/weed detection and classification, prediction of soil moisture content, animal research, and weather prediction.

Ngugi et al. [35] provided a review of recent studies carried out in the area of automated leaf pest and disease recognition. They discussed the use of image processing techniques and DL methods to address this task. The scope of the study, though, is limited to image processing techniques employed in pest and disease recognition

TABLE I. Secondary research about ML applications in agriculture in the last 5 years

#	Ref.	Year	Country	Type	DL	RL	IoT	CV	CC	Application
1	[26]	2016	India	Survey	×	×	×	✓	×	Agricultural products disease detection and classification
2	[27]	2017	India	Survey	×	×	✓	×	×	Crop disease prediction
3	[28]	2018	Spain	Survey	✓	×	×	✓	×	Improving agriculture using DL
4	[29]	2019	India	Survey	✓	×	✓	✓	✓	Automating agriculture
5	[30]	2019	India	Survey	×	×	×	×	×	Predictive modelling in protected cultivation
6	[31]	2019	Indonesia	Survey	✓	×	×	✓	×	Plant disease detection and classification
7	[32]	2019	Brazil	Survey	✓	×	×	✓	×	Plants nutrition deficiencies detection
8	[33]	2020	France, Italy	Meta review	✓	×	✓	✓	✓	Remote sensing for agricultural applications
9	[34]	2020	India	SLR	✓	✓	×	✓	×	Improving agriculture supply chain using ML
10	[35]	2020	Egypt	Survey	✓	×	×	✓	×	Leaf pest and disease recognition

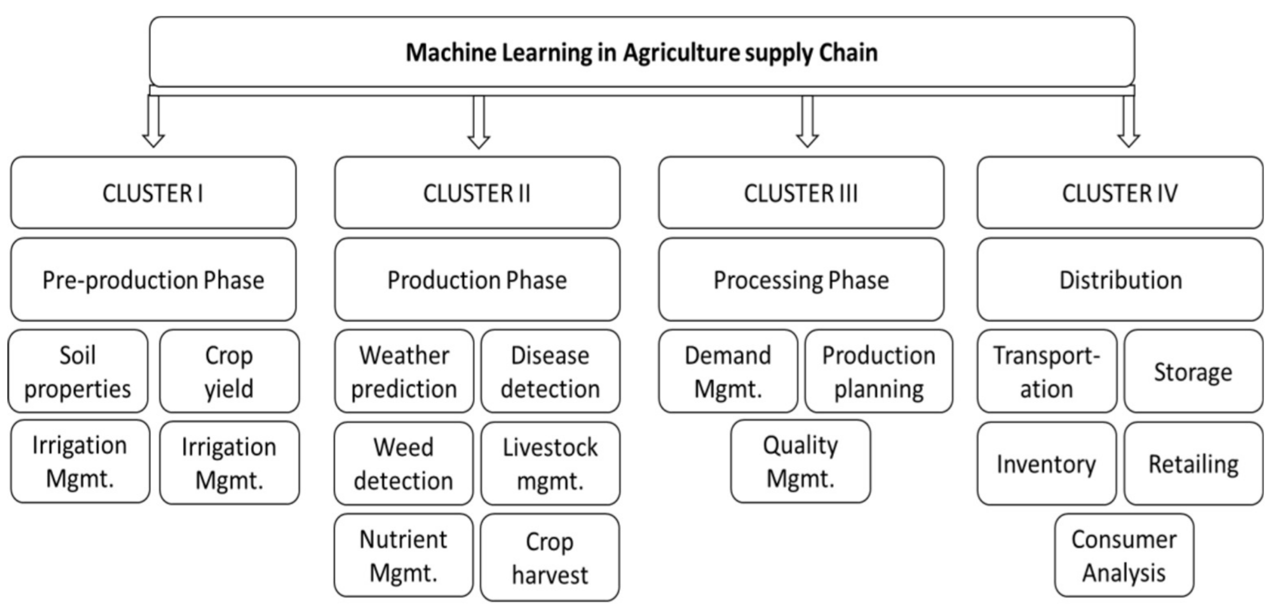


Figure 4. Classification of ML applications in agriculture by Sharma et al. [34]

using visible light (RGB) images. This study compared 17 works on leaf disease recognition using handcrafted feature extraction and shallow classifiers. Moreover, this study summarized 34 published studies in crop pest and disease recognition using DL algorithms. It also compared the results of ten CNN architectures used to solve the leaf disease recognition problem.

Hungilo et al. [31] argued that the role of agriculture is very important in the Tanzanian economy. However, in many cases the production of agriculture in Tanzania is poor. Climate change is one factor in this regard. Another factor is plant diseases which cause poor agricultural production in Tanzania. This research suggested that Tanzania can improve its agricultural production efficiency by early detection and classification of diseases. This research focused on the use of image processing and ML models for disease classification. The purpose here is to ensure that plant disease identification can be done on time and production can be improved. This research provided a survey of fifteen research efforts among which six research efforts used CNN and nine research efforts used conventional methods such as the K-Mean clustering algorithm.

Jha et al. [29] provided a survey of ten research efforts in which they discussed the importance of agricultural automation to all countries. They argued that the pressure on agricultural land is increasing with the increase in the world population. This means that the same amount of land now has to produce food for more people. This is possible only by using technology in the field of agriculture more aggressively. In this work, five main agricultural problems were addressed, namely plant disease infestation, lack of storage management, pesticide control, weed management, and lack of irrigation and drainage facilities. This work focused on integrating the technologies of conventional ML, DL, CV, IoT, AI, and Cloud Computing (CC) to automate agricultural activities and improve agricultural production and efficiency. Many DL and conventional ML algorithms were discussed in this work such as CNN, ANN, K-Nearest Neighbors (KNN), Fuzzy Logic, Neuro-Fuzzy Logic, and Expert Systems.

Weiss et al. [33] discussed that due to climate change, sustainable agriculture has become challenging. According to this research, remote sensing can be used in the evolution of agriculture in this situation. Information through remote sensing can be shared regularly with the stakeholders. According to this research, there are various variables in agronomics that can be studied through remote sensing. It also suggests several applications of remote sensing in agriculture such as phenotyping and breeding, monitoring of agricultural land usage, crop yield forecasting, optimization of short-term production, and the provision of ecosystem services related to soil or water resources as well as to animal or plant biodiversity. This research effort is a meta-review that focused mainly on remote sensing applications in agriculture. Moreover, it discussed the integration of ML, IoT, CV, and CC technologies to improve smart farming.

Barbedo [32] discussed that in recent times, digital images have been used to overcome agricultural challenges. ML has helped in identifying plant diseases and pests. Proximal images can provide more information including the situation of nutrients that are provided to the crops. This research provided a survey of 46 research efforts that used any kind of sensor imagery such as visible range, multispectral, hyperspectral, and chlorophyll fluorescence, provided that images were captured at close range. This work provided an analysis of classification and detection techniques such as linear regression, Naïve Bayes, CNN, KNN, SVM, Random Forest (RF), and Genetic Algorithm.

*C. **Reinforcement Learning in agriculture***

Sharma et al. [34] conducted an SLR on using ML to improve decision making in agriculture. Decision making can be improved due to the availability of data on the basis of which agricultural decisions can be taken. This SLR studied 93 papers that show that ML can help in the development of sustainable supply chains in agriculture. A framework dependent on ML is also proposed in this research. Many ML algorithms were addressed in this study such as BN, SVM, ANN, Decision Trees (DT), ensemble learning, regression analysis, clustering, genetic algorithm, and many deep learning algorithms. This study anticipated that the agricultural sector will continue to adopt ML techniques in the future. This SLR classified the agricultural problems that can utilize ML to four clusters as illustrated in Figure 4.

Although Rohit Sharma et al. [34] mentioned RL in the introduction of their SLR, the search keyword used to identify relevant publications did not include ”reinforcement learning” or any of the reinforcement learning algorithms such as Q-learning. It only included the Genetic Algorithm (GA) which is the closest algorithm to RL. GA was mentioned in 23 out of 93 surveyed papers. RL and GA operate on the same basic premise. They both try some action, receive a response indicating how good the action was. This is a reward for RL and a fitness score for GA, then try and do some other action to get a higher signal (reward or fitness). RL and GA solve the same class of problems which are usually containing finding solutions that maximize or minimize some function. However, they are different, in their aims and methodologies. GA work ends with finding an optimal solution while RL is a live-long learning mechanism where the agent can already explore the current state and learn as it goes.

In some problems, both RL and GA approaches can be combined. The agent, for instance, may start with a state that is already optimized by GA.

Knowing that RL was scarcely addressed in review research efforts motivates us to conduct this research effort which discusses ML techniques applications in agriculture with a focus on RL techniques. In the next section, we discuss our methodology to collect and analyze relevant publications.

5. Methodology

To get an initial idea about the current state of the research conducted in the field of ML applications in agriculture, a bibliographic analysis in the domain under study is conducted. The first step is to conduct a keyword-based search for conference papers and journal articles in three electronic databases:

1) ACM digital Library,
2) IEEE Xplore digital library, and
3) ScienceDirect digital library.

We used the following search commands distinctly:

”machine learning”.(agriculture+farming)
”deep learning”.(agriculture+farming)
”reinforcement learning”.(agriculture+farming)

where '.' corresponds to the Boolean *and* operator, and '+' corresponds to the Boolean *or* operator. The search commands were executed on the three databases mentioned above and the publication year was restricted to the range 2000 – 2020.

In the three libraries, a total of 794 papers about ML application in agriculture were published in the past twenty years. Figure 5 illustrates the steady growth of the number of publications during the last five years. Furthermore, Figure 6 gives a comparison of the number of publications conducted about the application of ML, DL, and RL in agriculture in the last 10 years. The general notice is that research effort addressing the applications of RL in agriculture is very minimal compared to other ML approaches.

The second step is to narrow the results to a shorter list of the most relevant papers. To do so we filter the results to papers published in the last five years only. Then we examined the shortlist particular problem they focused on and we ended having a list of 39 publications that we consider the most relevant to our study.

The third step, which will be discussed in the next section, is to analyze and compare the surveyed works based on the following:

- The agricultural problem
- The learning method employed
- The data source used
- The performance Evaluation methods

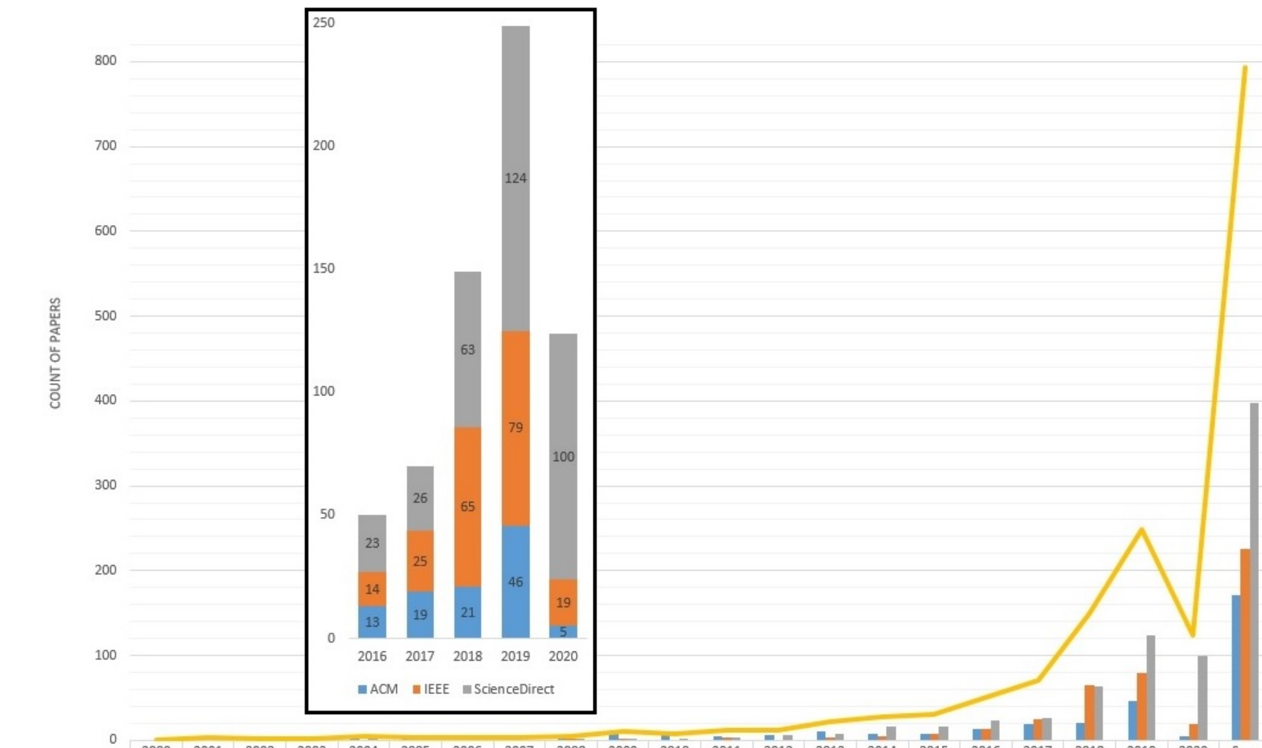
6. Analysis and Discussion

This section provides a comparative analysis of researches conducted about the application of ML, DL, and RL in agriculture. Sections 6-A, 6-B, and 6-C discusses in details the 39 surveyed publications about the applications of conventional ML, DL, and RL techniques in agriculture, respectively. This is followed by a summary of the main findings in this analysis, in section 6-D.

A. *Conventional Machine Learning*

Table II shows the six surveyed publications that utilized conventional ML in different agricultural applications. The first three papers theoretically proposed an architectural design of systems to monitor, control, and/or automate farm activities. The other three papers provided evidence of experiments with some datasets to predict some features related to farm activities or detect and classify some plant diseases.

Several studies suggested utilizing several information technologies to fully or partially automate farm activities. Joshi et al. [36], for instance, suggested the use of a bot to provide help and assistance in small scale farming. The bot can be used by the farmer who is planning to plant something in the backyard or in the garden. With the use of various machines, the bot can take over the process of farming from planting sees to watering and weeding out the other plants in the field which are not required. Using sensors, the bot can sense the qualities that the soil has and it can also understand the weather of the area. This research utilized Bayesian Networks to automate farm activities. In a similar context, Kaburuan et al. [37] highlighted the problems that agriculture faces in Indonesia. Climate change is one important issue that creates extreme weather conditions that can damage crops. The effect of the same is felt of the plant quantities and quality. The use of a technology-based monitoring system can improve the situation. This research presented an indoor micro-climate which has an electronic sensor to monitor the performance of horticulture. Sensor reading is collected regularly into a database that is linked with the data of meteorological agency. This research suggested the future of agriculture will depend more on ML. On the other hand, Vadivel et al. [38] focused on the monitoring and control of hydroponics. Various sensors are applied in this case using various algorithms of ML such as Simple Linear Regression to monitor and control hydroponics.



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Sum
ACM	0	3	2	0	3	1	2	4	2	9	6	5	6	10	7	7	13	19	21	46	5	171
IEEE	0	0	0	1	0	2	0	0	1	1	0	3	0	4	5	7	14	25	65	79	19	226
ScienceDirect	1	0	0	1	2	0	2	0	2	1	2	4	6	8	16	16	23	26	63	124	100	397
Sum	1	3	2	2	5	3	4	4	5	11	8	12	12	22	28	30	50	70	149	249	124	794

Figure 5. Number of publications in ML applications in Agriculture in the last 20 years

TABLE II. Conventional ML applications in agriculture

#	*Ref.*	*Year*	*Country*	*Type* [a]	*IoT*	*CV*	*CC*	*Application*
1	[36]	2017	India	D	✓	✓	✓	Farm activities automation
2	[37]	2019	Indonesia	D	✓	×	×	Monitoring the performance of indoor micro-climate horticulture
3	[38]	2019	India	D	✓	×	✓	Monitoring and controlling hydroponics
4	[39]	2019	Brazil	B	✓	×	×	Productivity and soil fertility prediction
5	[40]	2018	Thailand	E	✓	×	×	Hydroponic farm lettuce quality prediction
6	[41]	2019	Bangladesh	E	×	✓	×	Plant leaf disease detection and classification

[a]D: Architectural Design, E: Experimental Research, B: Both

The focus of this research was the use of ML to suggest the optimal use of chemicals. Live data was harvested from the proposed system. The system is semi-automated so part of the data was entered manually. The data storage from this hydroponics system would be stored remotely which would help the consumers in knowing if the product is organic or not.

Conventional ML techniques and other computational technologies, such as image processing, have been used

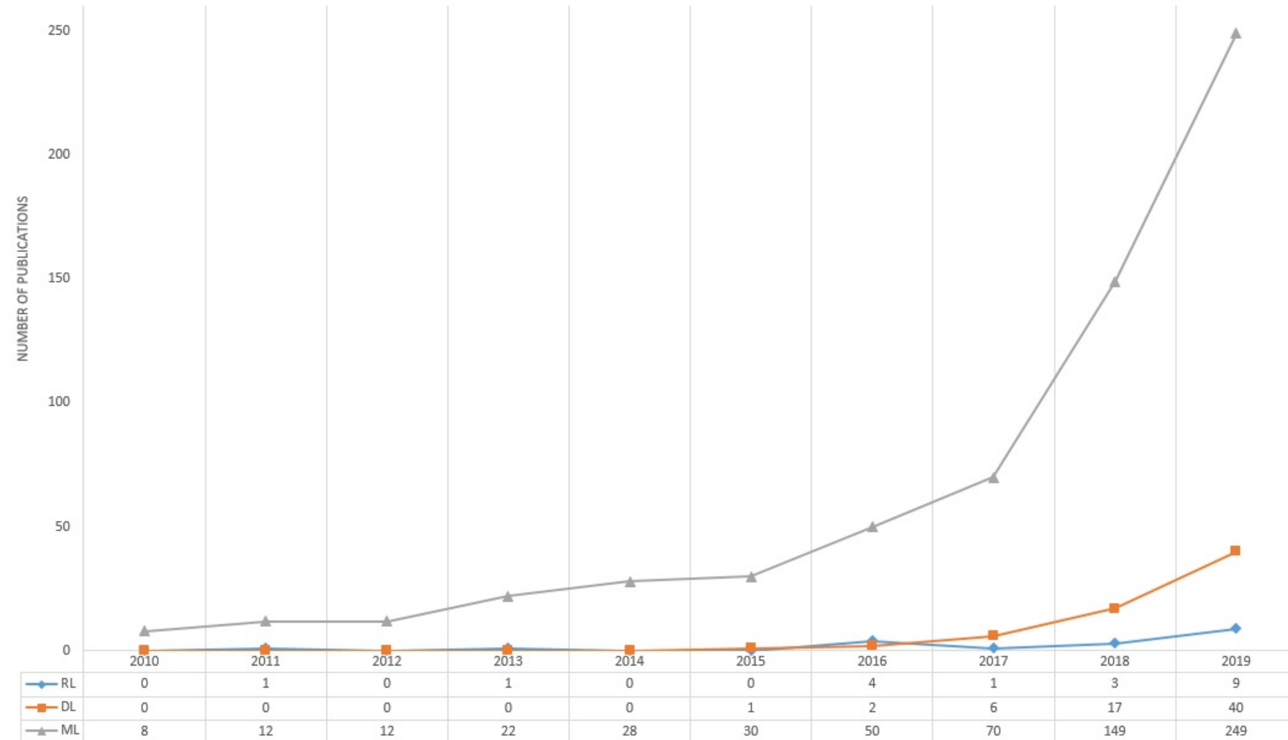


Figure 6. A comparison of the number of publications conducted about the application of ML, DL, and RL in agriculture in the last 10 years

in literature to experiment with datasets and predict or detect some features related to the quality of the agricultural activities and products. Helfer et al. [39], for instance, discussed the use of ubiquitous computing in agriculture. They suggested that highly sophisticated sensors can be used to study the soil properties and to predict productivity and soil fertility. This research focused on wheat farms and studied different climatic events that had an impact on the overall production of the wheat crop between 2001 and 2015. This research used the Partial Least Squares Regression. Similarly, Gertphol et al. [40] discussed the importance of yield forecasting in agriculture. However, this research is focused on Thailand agriculture where hydroponic lettuce farms were studied with excessive use of IoT. Several models were created to predict lettuce quality including linear regression, Support Vector Regression (SVR), Multiple Linear Regression (MLR), and ANN. The dataset used in this study contained 326 samples gathered in 19 months. Variables included in the dataset are of two types. First, weekly gathered variables such as the number of leaves, the plant's height and width, and the stem's diameter. The other group of variables is gathered during the harvesting season such as the fresh weight, dry weight, nitrate content, and vitamin c content of the harvested crop. Additionally, Hossain et al. [41] focused on plant leaf diseases and the use of ML and CV to mitigate this threat. KNN classifier is proposed in this paper for disease detection and classification. The dataset used to train the model contained 237 images of leaf disease collected from 2 larger datasets. The images were labeled with five leaf-disease classes. The experiment proved successful in almost 96% of cases.

B. *Deep Learning*

Table IV put together the 25 surveyed research papers that utilized DL techniques in different agricultural applications. The general notice is that in the majority of sampled publications DL, CV, and data processing are used to analyze images datasets related to different agricultural activities and products. Moreover, Convolutional Neural Network (CNN) techniques have proved their value in the classification of objects in agricultural fields in a lot of experiments in the surveyed sample.

More than a third of the surveyed sample of publication is utilizing DL to detect or classify some sort of disease or pest affecting plants or crops. Wan et al. [42] stated that the economic value of food loss with reference to plant disease is in billions in China only. If the food loss in other parts of the world is considered the economic loss is much bigger. They argued that food loss in the world should be controlled and that the use of technology is highly recommended for pest control and disease control. By utilizing the right detection methods for plant diseases, the production of agriculture can be improved. In this work, the researchers experimented using a dataset that contained 36,258 pictures with 10 different kinds of crops. The images were labeled with 59 different crop states (healthy or suffering from certain diseases). A CNN model was developed that achieved an accuracy of 87.99% in the classification task. Similarly, Jain et al. [43] suggested that the utilization of ML methods and the provision of a cloud-based system can help farmers in understanding if their crop is healthy or not. The study argued that using CNN, not only plant diseases can be studied but the use of pesticides and chemicals can also be controlled. In this research, a dataset of manually obtained images of firecracker and pomegranate plants from southern India was used. The images in the dataset were classified as diseased or healthy. Two models were used, CNN and SVM, in the plant classification task, and the CNN classifier outperformed SVM with an accuracy of 93.40%. Another research on a related topic is done by Saravan and Perepu [44]. According to this research, if the detection of various issues related to plant production can be done earlier, the crop yields can be better. When the farmers know more about the diseases of the plants and they check for the issues sooner, they can save their crops. This research presents social media as a source of information for the farmers. The texts and images from the fields can be shared on social media to generate in-depth knowledge about the disease. Two datasets were used in this study. The first consisted of users' replies to the query uploaded by other users with the identified disease name and its corresponding image solution. This dataset was collected by crawling 150 solutions posted by the users with the disease names and images. The second consisted of 1,200 diseases with 54,300 images and solutions ranked in order of effectiveness. In this study, CNN was employed to identify plant disease from images, and rank regression was used to rank solutions from social media. The created model in this paper reached a classification accuracy of 92.00%. Likewise, according to Alfarisy et al., [45] Paddy production in Indonesia is harmed greatly by pests and diseases. The automatic identification of pests and diseases is still a challenge in paddy production in Indonesia. By applying DL, the task of paddy pest and disease recognition can be resolved. For this purpose, this study used a dataset that consisted of 4,511 images collected from the internet. The dataset was collected using a query of pests and diseases name in different languages that represent the majority of paddy producers in the world, such as Chinese, English, Japanese, and Indonesian. The dataset, then, was annotated by agriculture experts from Indonesia into 13 classes. CaffeNet which is a CNN model was used for the recognition task and 87% accuracy was achieved in this experiment. In a similar manner, in the research by Xu et al. [46] the focus was on the recognition of one disease that affects one plant, which is the Zanthoxylum Armatum rust. A dataset consisting of 22,937 images was used in this research. The dataset had a total of 19 kinds of leaf diseases and it was labeled as healthy or rust. Experiments were conducted using GoogLeNet, which is a CNN model. Best recognition accuracy reached 91%. In a similar way, Bhatt et al. [47] stressed that the timely diagnosis of plants nutrients deficiencies and plant disease helps improve yield. Low cost, reliable and quick diagnoses are needed. This research developed a participatory application for sensing using smartphones. Farmers can scout their fields and assess crop health in this way. CNN is used to classify plant images. Also, transfer learning used to calculate the features of the images for classification. The dataset used for this task consisted of 3,750 images. The images are consisting of a subset collected by a mobile application merged with a subset of a publicly available dataset. The images were labeled using 6 classes with one class of healthy leaves and the other 5 classes with different diseases to predict the disease. This research presented a classification accuracy of 99.7%. Picon et al. [48] used also used CNN for multi-crop plant disease classification. Cell phones acquired images in the field were taken in real field wild conditions. In this study, 17 diseases were studied in five crops. Diseases were in many stages and more than 100,000 pictures were taken with the phone. Different CNN models were used and the highest recorded accuracy reached 98%. Coulibaly et al. [49] also stressed that classification is important in agriculture and DL can be effective in this case only if transfer learning is applied. The accuracy of results in small datasets was quite impressive in this research. This research aimed to identify mildew disease in pearl millet crop. CNN with transfer learning was used to achieve this task. The model in this study achieved a classification accuracy of 95%. In like manner, Kim et al. [50] argued that image based-monitoring system for agricultural fields can monitor crops automatically. Onion fields were monitored in their experiment. Monitoring was done by PTZ camera and wireless transceiver as well as a motor system and a module for image logging. CNN model was utilized to detect onion downy mildew disease. Images used as input to the model were captured onion images using the filed monitoring system. Finally, as per Ale et al. [51] in smart agriculture, DL is a smart approach. In this research, a Densely Connected Convolutional Networks (DenseNet) was proposed for transfer learning. Computing resources were utilized to identify plant diseases. A dataset consisting of images of corps with diseases was used. Input sizes were reduced to ensure that cost can remain within affordable limits. This research showed that the proposed model provided an identification accuracy of 89.70%.

Another issue that concern farmers is the effective control of bird pest in agriculture. Lee et al. [52] focused on detecting pest birds in the fields of agriculture. It is considered to be difficult to identify birds in the dynamic background. The objects that mostly confuse bird detection in agriculture environments are flying things, trees, and clouds. Also, the size of the object has an impact on accuracy where tiny birds had less detection accuracy. To increase efficiency in this case, DL was used. DL, however, proved to be slow as the computation costs are very high. This research used a Gaussian Mixture Model to extract moving objects. Then a Region-based Convolutional Neural Network (R-CNN) was used for the classification task. The results showed that by applying the model to specific areas of the image, accuracy can be better than applying it to the whole frame. A database of a huge number of images was used. The images were classified into 7 classes, bird and six non-birds. Each of the 7 classes consisted of 10,000 images.

Another factor that can cause lower plant productivity in farming is related to poor weed control. That is why many efforts were dedicated to utilizing DL and other computational technology for weed identification and detection. As discussed by Miao et al. [53] to handle weed effectively, it is important to have a clear distinction between crops and weeds. Modern agriculture has relied more on CV and image processing in recent times. Other technologies used are DL and the results have been good. Based on this background, Miao et al. [53] introduced a CNN to classify weed and crop by using images from an open dataset. The images were first manually annotated as one of 3 categories, crop, weed, or ground. The accuracies of classifying crop, weed, and ground reached 63%, 69%. and 99.9%, respectively. Another research that focused on weed control is the one conducted by Suh et al. [54]. They stressed that weed control can have a direct impact on the yield. The focus of there experiment was to classify sugar beets and volunteer potatoes. Sugar beets weed, which is called volunteer potato, are not just an unsightly nuisance in sugar beet, they are highly competitive, whereas sugar beet is quite the opposite, being relatively uncompetitive during its early growth stages. Volunteer potatoes can be controlled using smart bots. CNN is used in this study to classify sugar beet and volunteer potato. DL can be costly as training a whole network is not easy but transfer learning can work in such cases. In this experiment, AlexNet was applied in three different ways and the difference of performance was studied in six networks. Transfer learning proved to be very effective in classification. The highest classification accuracy reached was 98.7%. A dataset of 1,100 plant field images was used. Images were collected using a camera that was mounted at a height of 1 meter and perpendicular to the ground. Moreover, another huge dataset of 1.2 million labeled training images and 50,000 test images for transfer learning. As per do Santos Ferreira et al. [55] the use of UAVs and unsupervised DL algorithms can prove to be cost-effective. In this study, image recognition with CNN was used for weed discrimination. For this clustering task, two datasets were used. The first dataset was captured in a soybean plantation in Brazil and discriminates weeds between grass and broadleaf. The second dataset consists of 17,509 labeled images of eight nationally significant weed species native to Australia. Transfer learning was used in this study. The model reached an accuracy of 97%. Similarly, Fawakherji et al. [56] focused on the use of robotics in agriculture for taking care of weeds. For this purpose, the CNN technique is used to classify weeds and crops. A pixel-wise labeled dataset of RGB images acquired by a farming robot on a sunflower field is used for the classification task. The images were binary classified as crop or weed. The classification of both weed and sunflower achieved an accuracy of 90%.

Remote sensing and satellite imagery are widely used in the field of agriculture. As per Zhou et al. [57] CNN can help in classifying different land covers using Remote Sensing Images (RSI). This research focused on the comparison of the spatial distribution of crops in a county in China using Sentinel-2A RSI. The satellite imagery contained spectral information and temporal information. Labels were obtained in situ were location information of different crops recorded in 2017 by a ground survey experiment. The images were labeled as one of four categories, rice, corn, peanut, or other. This was done to compare classification using CNN and SVM models. The result showed that the accuracy of crop classification using CNN was 95.6% which was better than SVM. In a similar manner, Sidike et al. [58] proposed a model based on CNN for mapping heterogeneous agricultural landscape through remote sensing. A deep Progressively Expanded Network (dPEN) was proposed in this paper. A data set of satellite imagery was used. Moreover, a field survey to visually identify and label crop/weed type and crop developmental stage resulted in manually outlining 19 classes. The model achieved a classification accuracy of 86.06%. Also, as discussed by Shuangpeng et al. [59], for estimation of yields of grain, farmland mapping is vital. In this research, a Deep Feature Aggregation Net (DFANet) was used to recognize the farmlands. DFANEt is a CNN architecture. The model was tested using a dataset consisting of 6 images, whose dimensions are 8,000 x 8,000 pixels each. 5 images were used for training and 1 for testing. Each of the 6 images was divided into small images of a size of 512 x 512 pixels with a step of

128 pixels. The aim is to classify the central pixel as farmland or not. The model outperformed the baseline models. Furthermore, Xin and Adler [60] discussed the role of grasslands in agriculture as well as in ecology. They used a 3-layers fully connected CNN with Long Short-Term Memory (LSTM) to classify or detect Miscanthus. The dataset used contained high resolution multispectral, spatial, and temporal remote sensing imagery representing geographic data of Miscanthus fields. The images were labeled with a binary class, yes or no. The accuracy obtained by this model was 98.8% which is much higher than the 92% usual accuracy.

Phenology is important because it affects whether plants thrive or survive in their environments and it is important because our food supply depends on the timing of phenological events. Yalcin [61] focused on monitoring the phenology to improve precision in the field of agriculture. When phonological changes in plants can be identified quickly, the yield output and harvesting time can be predicted accurately. Visual data can help in identifying the phenology. CNN used in this case to recognize plant phenology. It proved to be much accurate as compared to other ML algorithms with an accuracy of 87.14%. The database used in this study was collected through a government-supported project in Turkey. The database covered 6 plant classes, namely, wheat, barley, lentil, cotton, pepper, and corn.

Another important application of DL in agriculture is the detection of farm crops. Santos et al. [62], for instance, used CNN for grape detection and segmentation. The same technology is used in segmentation and tracking too. The dataset used in this study contained 408 grape clusters from images taken on a trellis-system based vineyard. The F1 score achieved through this method for segmentation was 91%. Another related research is conducted by Habaragamuwa et al. [63]. They discussed that generic algorithms are needed in agriculture to detect and classify objects. In this experiment, DL was utilized to study the mature and immature strawberries by classifying them using CNN and greenhouse imagery. Three-labels classification was used to classify objects in the greenhouse to mature strawberry, immature strawberry, and background. The accuracy reached 88.03% for mature strawberry and 77.21% for immature strawberry.

Designing and implementing smart solutions to monitor and control farms and optimize farming activities is an important research topic. Carvalho et al. [64] proposed an edge solution for farming. They discussed that edge computing, IoT, and CC can help in making smart agriculture possible. And they argued that to create smart agricultural solutions the integration of ML algorithms is needed such as Deep neural networks (DNN), CNN, Recurrent neural network (RNN), and Genetic Algorithm (GA). Moreover, Mehra et al. [65] stressed on the fact that modern farming techniques need to rely on the latest technologies such as aeroponic and hydroponic. This research highlights that the use of IoT and ANN and other ML algorithms helps in controlling hydroponics systems. The researchers experimented with a DNN model. The dataset used in this research consisted of 5,000 instances of real-time collected data about the hydroponic system including pH, temperature, humidity, light intensity, and water level. The instances were labeled with 8 classes of control action. And the model created reached an accuracy of 88.50%.

Crop yield prediction is important in developing countries so that agriculture can be developed sustainably. The current technology that is commonly used in this regard is expensive. Remote sensing and satellite imagery can provide a much cheaper option. Wang et al. [66] developed a model based on LSTM and regression to predict soybean yield in Argentina. For experimentation, annually updated satellite reflectance and temperature imagery were used to identify cropland from non-cropland. Moreover, statistics about county-level and province-level soybean crop yields in Argentine and Brazil were used as ground truth. Each crop yield of a particular region for a particular harvest was paired with a sequence of reflectance and temperature images from the months preceding the harvest. The Argentine dataset contained 1,837 harvests, and the Brazilian dataset contained 336 harvests. Moreover, the large volume of data from Argentina and the country's geographical proximity to Brazil inspired the use of transfer learning to improve predictive performance.

C. *Reinforcement Learning*

Table III illustrates the seven surveyed research efforts that discussed the utilization of RL techniques in agriculture. Generally speaking, research efforts related to this topic is very limited.

The use of autonomous farm vehicles and machinery, such as Unmanned Aerial Vehicles (UAVs) and rovers, to achieve agricultural tasks is increasing. RL can be used to optimize the use of such machines. Some research efforts recently focused on this topic. For instance, Boubin et al. [70] explored the use of autonomous UAVs, edge computing, and cloud offloading in precision agriculture. They designed a system that employed RL to manage flight actions that include fly north, south, east, west, and land. They tested the system with a dataset that consists of over 10,000 12-megapixel images captured by UAVs over a corn field. Images were captured at 3 points in the growing season. The results were evaluated based on error, energy demand, and compute and labor costs. Multiple models were used to obtain better predictive performance and the error was estimated using an ensemble modeling approach. Similarly, Zhang et al.

TABLE III. RL applications in agriculture

#	Ref.	Year	Country	Type[1]	IoT	CV	CC	Application
1	[67]	2019	SriLanka	D	×	×	✓	Optimizing pesticide spraying using a swarm of drones
2	[68]	2019	China	D	✓	×	✓	Improving smart agriculture using deep reinforcement learning
3	[69]	2017	USA	S	×	×	×	Improving disintermediation behaviour in a food supply network
4	[70]	2019	USA	B	×	✓	✓	Improving precision agriculture autonomy using EC, CC offloading and UAVs
5	[71]	2019	China	S	×	×	×	Optimizing tracking performance of agricultural rovers
6	[72], [73]	2018	China	S	×	×	×	Optimizing the usage of agricultural resources and machineries
7	[74]	2019	Qatar	C	×	×	×	Exploring risks on the water-food nexus for outdoor agricultural operations

[71] utilized RL to develop a path-tracking algorithm for agricultural crop scouting and phenotyping rovers. The algorithm is based on the Double-Deep Q network (DQN). The aim was to optimize the tracking performance using a reward function learned in a simulated virtual environment. The DQN trained by driving a rover in a simulated environment and tested in both simulation and on a grass-field to follow paths with multiple sharp turns. The performance was compared with that of a Pure-Pursuit Control (PPC) algorithm. The results of the DQN outperformed the results of the PPC method. Amarasinghe et al. [67], also discussed the usage of RL to optimize the use of drones. They discussed a solution to efficiently spray pesticides using a swarm of autonomous drones. The manual Spraying of pesticides takes huge e time and requires large manpower. This work is formatted as a white paper that briefly proposed a solution to optimize safe pesticide usage with minimum human intervention. RL is introduced in this solution to optimize safety spraying.

Not only the use of autonomous machines can be optimized using RL but also conventional Machines. Jiang et al. [72] established an agricultural resource allocation model. The model aimed to minimize the total distance traveled of all agricultural machinery and keep the variance of distance traveled by each machine as small as possible at the same time. They used empowered Q-Learning with immune optimization to improved a Reinforcement-Immune Algorithm (RIA). More details about the development of the algorithm are available in [73].

Challenges related to agricultural supply chains can also be addressed. Craven and Krejci [69], for instance, described an agent-based model (ABM) that incorporated the Q-learning algorithm to study disintermediation behavior in a food supply network. The study aimed to design a decision support tool for food hub managers. RL allowed producer agents to use a heuristic trial-and-error approach to optimize decision policies over time. A simulation with different service rates was conducted to validate the model and no real-life data from the food system was used.

Risks related to agriculture can also be managed and optimized using RL. Govindan and Al-Ansari [74] discussed how to enhance the resilience of the energy, water, and food nexus in risky environments. As a case study, they used outdoor agriculture in Qatar. They used two databases. The first consisted of the meteorological measurements from a weather station near the farm under study. The second consisted of remote sensing imagery acquired over the farm from the NASA Earth Explorer database. The researchers did not validate the method due to the inability to access the farm and test the optimal strategies as suggested by the model, hence the studies carried thus far are purely theoretical.

Deep reinforcement learning uses deep learning and reinforcement learning principles to create efficient algorithms applied to different areas such as robotics, computer vision, and transportation. Bu and Wang [68] compared recently developed deep reinforcement learning models and algorithms. Their work aimed to present a smart agriculture system based on deep reinforcement learning. However, there is no evidence in the study of actually proposing one. Instead, a very helicopter view description is given for the smart agricultural system. The framework of the system consists of four layers. The first layer consists of sensors to collect the data. The second layer is the edge layer which aims to reduce the bandwidth of transferred data. The third layer is the data transmission layer. And the final layer is the cloud

TABLE IV. DL applications in agriculture

#	Ref.	Year	Country	Type [2]	IoT	CV	CC	Application
1	[64]	2019	Ireland	D	✓	✓	✓	Edge solution for farming
2	[65]	2018	India	B	✓	×	✓	Controlling hydroponics system
3	[44]	2018	India	E	×	✓	×	Plant disease identification and social media solutions ranking
4	[42]	2020	China	E	×	✓	×	Plant disease classification
5	[43]	2017	India	E	×	✓	✓	Plant disease classification
6	[61]	2017	Turkey	E	×	✓	×	Plant phenology recognition
7	[46]	2019	China	E	×	✓	×	Recognition of Zanthoxylum Armatum rust
8	[45]	2018	China	E	×	✓	×	Paddy pests and diseases recognition
9	[59]	2019	China	E	×	✓	×	Farmland recognition
10	[60]	2019	USA	E	×	✓	✓	Identifying Miscanthus
11	[66]	2018	USA	E	×	✓	×	Crop yield prediction with remote sensing data
12	[47]	2017	India	E	×	✓	×	Crop health assessment
13	[53]	2019	China	E	×	✓	×	Crop weed identification
14	[57]	2018	China	E	×	✓	×	Crop classification
15	[52]	2019	Korea	E	×	✓	×	Bird identifying from other moving objects
16	[51]	2019	USA, China	E	×	✓	×	Plant disease detection
17	[56]	2019	Italy	E	×	✓	×	Crop and weeds classification
18	[54]	2018	Netherlands	E	×	✓	×	Sugar beet and volunteer potato classification
19	[63]	2018	Japan	E	×	✓	×	Greenhouse strawberries detection and classification
20	[49]	2019	France	E	×	✓	×	Mildew disease identification in pearl millet crop
21	[62]	2020	Brazil	E	×	✓	×	Grape detection and segmentation
22	[58]	2019	USA	E	×	✓	×	Mapping heterogeneous agricultural landscape
23	[50]	2020	Korea	E	×	✓	×	Onion downy mildew disease detection
24	[55]	2019	Brazil	E	×	✓	×	Weed discrimination
25	[48]	2019	Spain, Germany	E	×	✓	×	Multi-crop plant disease classification

computing layer. The paper also provided a presentation of different deep reinforcement learning algorithms that can be used in agriculture.

D. Summary

TABLE V. Learning algorithms in the surveyed sample

Algorithm / Method	***Publications***
Regression	[40] [66]
Linear Regression	[38]
Rank Regression	[44]
Partial Least Squares Regression	[39]
Bayesian Network	[36]
Support Vector Machine	[44] [43]
K-Nearest Neighbors	[41]
Ensemble Learning Models	[70]
Artificial Neural Networks	[40]
Deep Neural Network	[65] [64]
Convolutional Neural Network	[44] [42] [64] [43] [61] [46] [45] [59] [60] [47] [53] [57] [52] [51] [56] [54] [63] [49] [62] [58] [50] [55] [48]
Long Short-Term Memory	[60] [66]
Recurrent neural network	[64]
Unsupervised Deep Clustering	[55]
Genetic Algorithm	[64]
Q-learning Algorithm	[69]
Double-Deep Q network	[71]
Agent-Based Model	[69]
Immune Algorithms	[72]
Memory Q-Network	[68]
Transfer Learning	[66] [51] [54] [49] [55]
Time Series Analysis	[74]

Figure 7 illustrates the variety of agricultural problems that research efforts in the surveyed sample addressed. The most common problem discussed in research is related to disease and pest identification and classification. However, there are agricultural problems that are scarcely tackled by the research community although these problems can be solved using ML techniques.

Table V shows all the learning techniques used in the publications in the survey sample. It seems that the research community has exhausted the use of CNN in agricultural applications. The utilization of transfer learning is, also, gaining an increasing interest. Still, RL methods, such as Q learning, are hardly utilized in agricultural solutions.

7. Research Challenges and Future Direction

CEA can provide the perfect environment for the plants but it is not possible without human intervention. To implement fully autonomous greenhouse wireless technology sensors and communication protocols can be used. Robots can be used for seeding, planting, fertilizing, irrigation, weeding, spraying, and harvesting.

As a future direction, the research community should aim to study the motivation towards, barriers for, and impact of implementing fully-automated agriculture. According to Jha et al. [29], demographic differences of farmers affect their investment in automation. It is worthy, as a starting point, to aim at understanding the actual motivations of farmers toward automation. This will greatly increase the validity of any developed model and improve its usefulness. Interviews and questionnaires can be developed to study the behaviors of farmers and decision-makers and their motivation towards the utilization of computational technology and automation of agriculture. Such studies can help to identify various barriers and dependencies for implementing ML in agriculture. The identification of the driving barriers will help in accelerating the ML implementation. Additionally, by interviewing decision-makers, the environmental, economical, and social impact of utilizing ML in agriculture can be measured. This can provide guidelines on how ML can be deployed to enhance agricultural activities.

Future studies should, also, aim at collecting live images from farms in different seasons and incorporate other forms of data such as geographic location, disease history, and weather trends, This can help improve the results of current systems. However, for the settings which are short of data, another direction is to effectively apply transfer learning methods. Cloud computing could, also, be used to improve the learning process efficiency for large-scale learning, especially for complex tasks. Finally, future studies could focus on multi-task and multi-agent learning in smart agriculture.

At the same time, we noticed that majority of plant disease research are focusing on one type of disease and one type of plant. We believe, it is worthy to develop models which can combinedly classify multiple numbers of plants, and detect multiple numbers of diseases on different kind of plants. Furthermore, most of the studies focused on leaf and crop disease. A future direction for plant disease could be the recognition of disease on other parts of the plant such as flowers and stems which has not been extensively addressed by researchers. Moreover, research efforts can focus on estimating the severity of the disease.

In our point of view, deep reinforcement learning suits the agricultural problem. However, the full automation of agriculture is a very complex problem. The problem is

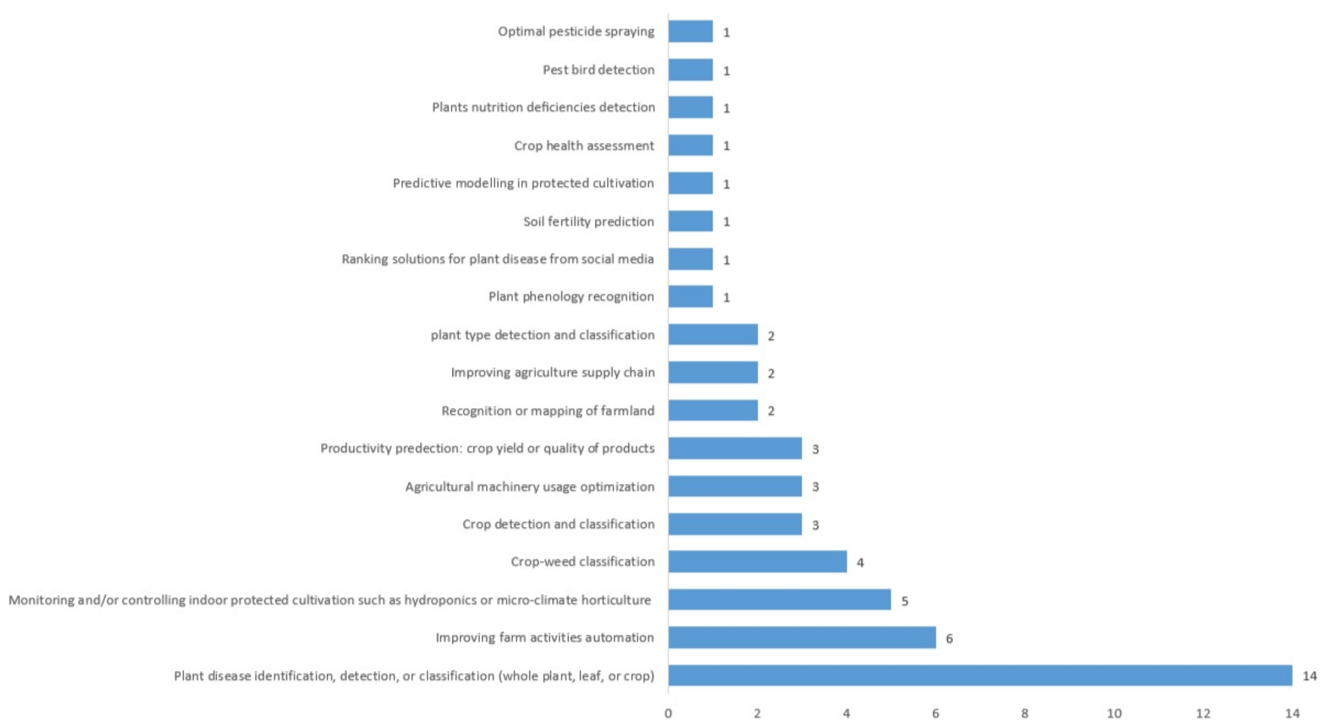


Figure 7. Agricultural applications utilizing ML in surveyed sample

composed of multiple tasks, multiple agent and sensors are needed to fully automate agriculture. Although deep reinforcement learning algorithms, such as Deep Q-learning (DQL), has shown great progress that exceeds the human-level in fields such as game playing, it cannot yet achieve the human-level performance in solving complex tasks such as agriculture. RL algorithms can be used in CEA for robots, rovers or drones navigation, general machine skill acquisition, and real-time decision-making. In the future, efforts can be made on deep reinforcement learning to improve its performance in dynamic environments for CEA.

8. Conclusion

The present work, aims at complementing previous efforts by surveying 49 publications of which 10 were secondary research efforts that discussed a variety of ML approaches applications in agriculture and the remaining 39 publications are primary research efforts that used ML approaches to support the automation of agricultural activities. The review reveals that the agricultural applications of reinforcement learning, compared to other machine learning techniques, are in an infancy stage. This survey is not exhaustive by any means as literature is being published very frequently.

This paper discusses and compares the research efforts on the basis of various criteria, including the techniques used, the application of ML techniques in agriculture, the accuracy of results. Gap analysis in the existing literature is also conducted. Section 7 highlights and shows some possible future research directions.

Reinforcement learning has the potential to be an effective tool for improving the autonomy of CEA. This survey aims to motivate more researchers to employ reinforcement learning to solve various agricultural problems.

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