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REVIEW ARTICLE - ENGINEERING (MISCELLANEOUS)

Machine Learning Algorithms and Their Effects on Crop Production in Agriculture: A Review

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Abstract

Agricultural production faces challenges, such as water scarcity, climate change, and the rising demand for food to feed the growing global population. Incorporating wireless sensor networks (WSNs), Unmanned Aerial Vehicles (UAVs), and Machine Learning (ML) enables an efficient Synergistic approach for crop monitoring, predicting, and managing. WSNs prefer environmental data instantaneously, UAVs provide data collection for large-scale aerial, and ML processes this data to make actionable decisions. The primary objective of this review is to explore the comprehensive effect of WSNs, UAVs, and ML in the agriculture sector, emphasizing crop yield, environmental sustainability, and optimizing resources. In addition, this review aims to detail the benefits and limitations of ML technology and its impact on farming. Integrating state-of-the-art technologies has expressed several key areas of significant potential, such as crop health monitoring, precision irrigation, yield prediction, disease and pest detection, and resource efficiency. Hence, the collaboration of recent technologies in modern farming significantly enhances monitoring and management in real-time, improves productivity and sustainability, and addresses global food security challenges. At the same time, this would shape agriculture's future through innovative promotion and more sustainable farming practices.

Publisher: Middle Technical University

Keywords: Agriculture; Collaborative System; Comprehensive System; ML.

1. Introduction

In ancient times, many socioeconomic and population growth factors were associated with food shortages [1]. In 2050, the increase in the world's population is estimated by the Food and Agriculture Organization and the United Nations Food and Agriculture Organization to be more than 30% and 70 %, respectively, in food production [2]. The World Food Summit defines food security as "a condition that exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food to meet their dietary needs and food preferences for a healthy and active life" [3]. It has been affected by multiple factors of water pollution, climate change, soil degradation, sociocultural development, market fluctuations, and government policies [4]. Due to these uncertainties, a challenge faced by agriculture is to improve quality and productivity while minimizing the anthropogenic greenhouse gas emissions, which currently account for 20% of all anthropogenic emissions that affect the environmental farming footprint [5]. Modern agriculture is considered the most significant economic domain in many nations. It is based on four key pillars to deal with the rising requirements: adequate services development, ecosystem conservation, managing the resources of optimal nature, and modern technology utilization [6].

Conventional methods of farming tend to be labor-intensive and lack the ability to monitor and maximize the production of crops. To encounter this, computer-based methods have emerged as transformative tools at every level of the agricultural production process, both in the pre-harvesting and post-harvesting processes [7]. Modern technologies, including Unmanned Aerial Vehicles (UAVs), the Internet of Things (IoTs), and Machine Learning (ML), are implemented in agriculture-based Wireless Sensor Network (WSN) devices to increase farming management costs and productivity [8].

Nomenclature & Symbols

WSN	Wireless Sensor Networks	P	Precision
UAV	Unmanned Aerial Vehicles	R	Recall
ML	Machine Learning	ERR	Error Rate
IoTs	Internet of Things	NB	Naïve Bayes
PA	Precision Agriculture	NDVI	Normalized Difference Vegetation Index
AI	Artificial intelligence	NN	Neural Network
IT	Information Technology	TP	True Positive
SL	Supervised Learning	FN	False Negative
Un-SL	Unsupervised Learning	FP	False Positive
Semi-SL	Semi-supervised Learning	TN	True Negative
RL	Reinforcement Learning	C	Confusion matrix
SVM	Support Vector Machine	n^+	TP+ FN
RF	Random Forest	N	TN+ FP
DT	Decision Tree	x_i,	Measured Values
KNN	K-Nearest Neighbor	y_i	Mean Values
SLR	Simple Linear Regression	$\dot{x}$	Predictive Values
PR	Polynomial Regression	MAE	Mean-Absolute-Error
P_0	actual agreement	MSE	Mean-Squared-Error
P_e	Chance Agreement by Hypothetical Probability	N	Total Number of Data Points
LR	Logistic Regression	R^2	Correlation Coefficient
BRT	Boosted Regression Trees	$F(x_i)$	Mass Function
LSTM	Long Short-Term Memory	i, and r	1,2,..n All in the Interval of [a,b]
CDF	Cumulative-Distribution-Function	MAPE	Mean-Absolute-Percentage-Error
RMSE	Root-Mean-Square-Error	CNN	Convolutional Neural Network

Precision Agriculture (PA)-based IoT devices are used at various stages of plant growth for sensing remotely and monitoring crop conditions. During the pre-harvesting stage, ML, WSNs, and remote sensing can enable farmers to track soil health, irrigate the land, anticipate pests, and determine crop harvests with ease [9]. UAVs, robotic harvesters, and Artificial Intelligence (AI)-oriented monitoring systems can be used during harvesting to support the timely pick-up of crops, reduce the number of employees, and lower the losses associated with over- or under-ripened products [10]. Computational techniques are also useful in post-harvesting processes, whereby computer vision, IoT-enabled storage systems, and predictive models are used to assess quality, sort products automatically, and predict the shelf-life of agricultural products [11]. Together, these computer-based approaches contribute to high productivity, more efficient use of resources, and sustainability, providing precision agriculture, which is responsive to environmental and market factors and data-driven.

Recently, global warming and irregular rainfall patterns have affected traditional agriculture methods, which depend upon reliability and elder experience. Whereas, the most common incoming data in the yield prediction were from remote sensing involving satellites and UAVs [12]. At the same time, MLs' computational power capacity can be exploited to edit, analyze, and interpret the vast data produced by digital resources called "big data" [13]. The advancement in ML enables the predictability of weather, irrigation choices, soil conditions, disease and pest occurrence, and other vegetation parameters [14]. Such advances can provide a proactive response and improved agriculture performance requirements during plant-grown levels, as detailed in Fig. 1. Accordingly, several challenges have been encountered in modern agriculture, including the rising call for food, due to climate change, the earth's population explosion, dietary alteration choices, natural resources depletion, as well as related to safety and health [15]. However, ML involves multiple algorithms, where the desired choice is necessary for a successful result [16]. In addition, resource unavailability, wrong data collection, unskilled people, biased data, no access to data, data privacy issues, and measurement problems may impact ML's power capabilities [17, 18].

This paper explores the types of ML, each with its usage in the agriculture field, through an assessment of their functional merits for improving sustainable agricultural efficiency. The paper reviewed ML technology in precision farming and how it can be employed with modern synergistic systems as collaborative and comprehensive systems, with their challenges.

This paper aims to provide an overview of ML technology used in the agriculture sector, while considering the following objectives:

- This paper estimates existing agricultural systems recruiting ML technology and explains their potential capabilities.
- A category of agricultural system methods is introduced, including conventional, cooperative, and comprehensive-based technologies. These categories are essential for farming professionals and scholars to stay updated and enable further developments and research efforts.
- A summary of previous studies in agriculture, emerging WSNs, and UAVs with ML technology is reviewed, emphasizing performance metrics. This summary allows researchers to choose appropriate technologies for agricultural usage and studies.
- This review outlines key challenges related to ML technology in agriculture, improving it to address shortcomings and modulate system usability.
- This paper comprehensively reviews recent agriculture technology applications, mainly based on ML, incorporated with WSNs and UAVs, and summarizes their advantages and challenges.

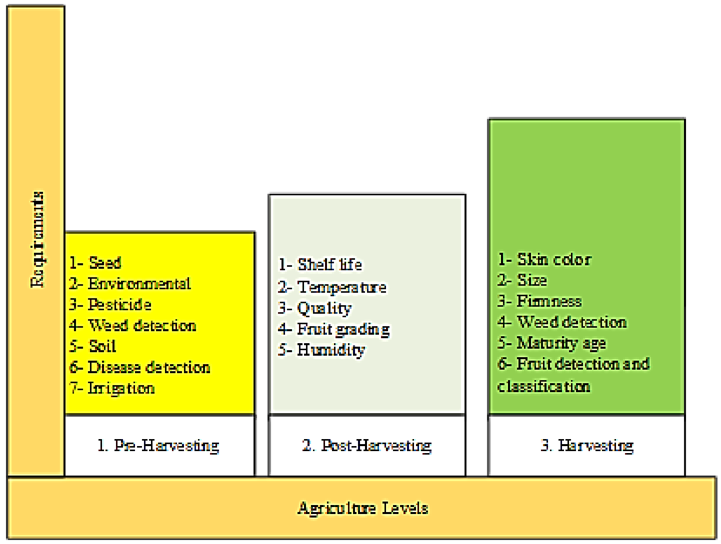

Fig. 1. Agriculture levels

2. Motivation Behind This Study

With the high interest worldwide in ML and its powerful impact on various agricultural domains, the motivation behind presenting a review bibliographic survey integrated with other recent technologies is the increase in population growth, which is expected to be 10 billion in 2050 [19], resulting in rising food demand. Adapting and mitigating the effects of climate change can be incorporated into food production through measures and policies. Utilizing digital technologies such as IoT, satellites, UAVs, WSNs, and robotics makes agriculture more sustainable and improves livelihoods and the economy. These technologies produce big data [20]. More annotative analysis techniques are required to exploit the accurate performance of big data. ML is considered a decision-making tool for predictive analytics, and it is used widely in many areas such as marketing, finance, medicine, and agriculture [21]. There is a request to study ML algorithms deeply, classify them, and analyze their relations and applications to address machine learning issues and specify the best solution path.

ML has become an innovative technology in the agricultural sector because it can solve complex and information-intensive management issues in various areas of agriculture, as shown in Fig 2. In crop management, the ML techniques can be used to predict yields, classify crops, and identify diseases and best infestations on crops early by analyzing multispectral images, weather information, and past production data. These strengths help in timely interventions, minimize losses on crops, and improve productivity without overusing agrochemicals. The growing access to high-resolution data provided by sensors and remote sensing platforms only enhances the efficiency of ML-based systems of crop monitoring. Additionally, ML is very important in water management to optimize the process of irrigation through the modeling of soil-plant atmosphere interactions, as well as forecasting crop water needs in different climatic conditions. Through the combination of data about environmental sensors, weather predictions, and crop development models, ML algorithms assist in the precise scheduling of irrigation, hence cutting down water usage and enhancing water-use efficiency. This is especially in areas with water shortages and climate change where sustainable water management is required to ensure agricultural sustainability in the long run. Additionally, ML applications are also very beneficial in soil management because soil properties are highly spatially and temporally varying, and are challenging to obtain through traditional approaches. To aid soil fertility, nutrient, and land suitability in the assessment, soil moisture, nutrient, soil salinity, and soil texture can be analyzed in ML models to assess soil moisture, nutrient content, salinity, and texture. Such insights are based on data, allowing site-specific soil treatment and fertilization plans, improving soil health, decreasing environmental impact, and boosting crop performance.

ML is used in the livestock management industry to promote better livestock health, productivity, and welfare by monitoring livestock and performing predictive analytics. ML algorithms can identify the early symptoms of disease, stress, or non-normal behavior, and thus the proactive management of health and decrease mortality rates through the processing of data collected by wearable sensors, imaging systems, and farm records. Moreover, optimized feeding practices, breeding initiatives, and forecasting production are assisted by ML-based models, resulting in more efficient and sustainable livestock practices.

Taken together, these applications show that ML offers a unified, intelligent, and scalable platform to operate agricultural systems faced with growing environmental, economic, and operating demands. The potential of ML to derive practical knowledge on heterogeneous and vast volumes of agricultural data has become a strong incentive to further studies and implementation of ML-based solutions to improve productivity, sustainability, and resilience in contemporary agriculture.

3. The Adopted Formal Inspection

The formal inspection of this study emphasizes the review of ML applications in agriculture with different integrations behind other recent technologies. The integration systems are categorized into conventional, integrated, and comprehensive within the agriculture field. The performance of conventional systems was compared while considering key practical parameters such as adopted ML, sensor type, field size, performance metrics, and limitations faced by each article to analyze each case study. By identifying the conventional studies' limitations, this review identifies other agriculture systems that emerged ML with UAVs and IOT or all coherent as a comprehensive system to provide a complete technological advancement. This systematic approach provides deep insights and understanding of ML applications behind one or more recent technologies to provide productive and sustainable agriculture practices.

4. Types of ML Algorithms Adopted in Agriculture

AI is an Information Technology (IT) sector that primarily works with machines that function similarly to humans. According to John McCarthy (AI's father), AI is ‘‘the scientific and technological understanding of building smart computer programs in particular [22]. ML is a subfield of AI that is defined as the scientific field, which enables machines to learn without being directly programmed [23]. ML has incorporated high computing performance and big data technologies to initiate a new chance to discover, quantify, and understand the environments of agricultural operations containing intensive processes of data [15]. ML algorithms are taxonomies into Supervised Learning (SL), Unsupervised Learning (Un-SL), Semi-supervised Learning (Semi-SL), and Reinforcement Learning (RL), depending on the computational techniques that are used for actionable knowledge [24], as shown in Fig. 3. These models use statistical and mathematical algorithms to identify field relationships, patterns, and trends to inform decision-making stages for precision agriculture.

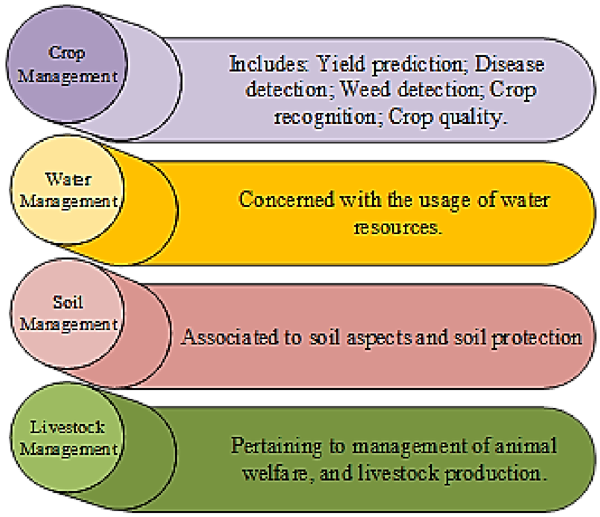

Fig. 2. The four main aspects of agriculture depend on the ML technique

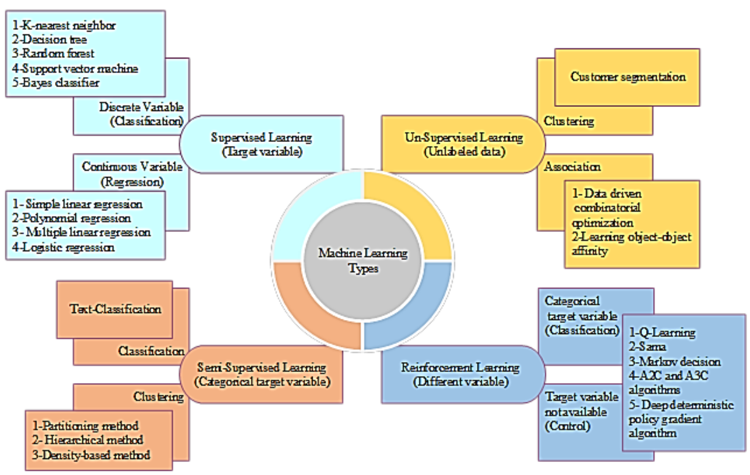

Fig. 3. ML techniques

4.1. SL algorithm model

In SL, the models require training-based labeled datasets, which equip the values of each input pair to the appropriate output through various generalized algorithms used for accurate prediction of the hidden [25]. These algorithms' procedures involve acquiring a dataset, data processing, identifying the target variable (If the variable type is discrete, then it is a classification problem; otherwise, it is a regression problem), splitting the dataset, training the model, hyperparameter tuning, and prediction [26].

SL is one of the most developed and popular paradigms of data-driven agriculture, due to the presence of historical data and its high predictive accuracy [27]. The applications of its use cover a wide area of pre-harvesting, harvesting, and post-harvesting, such as crop yield prediction, classification of diseases and pests, assessment of soil fertility, and quality grading of agricultural products [28]. SL models allow one to support accurate decision-making and early intervention that is vital in reducing losses and resource utilization, which is made possible by learning explicit mappings between labeled outputs and input features. The quality of SL, however, is highly reliant on the quality and representativeness of labeled data, which can only be labeled by experts and thus can be less scalable. This notwithstanding, SL has been used as a foundation of precision agriculture, especially where reliability, transparency, and validation are vital to ground truth data [29].

There are different types of SL algorithms related to the classification problem, such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbor (KNN), and Bayes Classifier [30]. Whereas, when the algorithm types related to regression problems involve Simple Linear Regression (SLR), Polynomial Regression (PR), Multiple SLR, and Logistic Regression (LR) [31]. SL models are widely used in agriculture, such as in classifying crop types, predicting crop yields, monitoring soil health, identifying diseases, and precision agriculture [32].

4.2. Un-SL algorithm model

Un-SL ML models are in themselves a learning technique used to provide patterns within input data without labels [33]. The required output is categorized into clusters and associations [34]. Regarding clusters, the output is grouped into similar identified data for a better and more accurate decision-making process [35].

Un-SL ML is a major part of agricultural data analysis because it allows one to explore data that is complex without requiring any labeled samples [36]. It has been used in fields such as crop and soil clustering, agricultural land segmentation, anomaly detection in sensor networks, and the detection of latent patterns in multisource data gathered by satellites, UAVs, and IoT devices [37]. The methods are especially useful in large-scale agricultural systems, where manual labeling is inconvenient, and there is a high heterogeneity of the data [38]. UN-SL can help generate hypotheses and discover knowledge, complemented by SL, by identifying intrinsic structures and relationships in data, and can be used as a preliminary step to SL modeling. Association algorithms provide the relationship between different parameters, which include different models such as data-driven combinational optimization, learning object-object affinity. Un-SL association algorithms are exploited in agriculture by analyzing irrigation scheduling, optimizing harvesting and fertilization, companion planting and crop rotation, crop and weather management, pesticide and fertilizer usage, and agricultural product analysis [39]. However, interpreting the results without supervision can prove to be difficult, and it may be necessary to have some domain knowledge to convert the computational pattern into an agricultural interpretation [40].

4.3. Semi-SL algorithms model

It is a mixture of techniques between SL and Un-SL algorithms models, where the input data are categorized (labeled and non-labeled). It is used to improve accuracy for both clustering and classification, with a high accuracy level with few labeled data, making it low-cost and fast. Such a type of learning is vital for practical applications in future generations of wireless communication systems, especially in scenarios involving balanced resource allocations to cluster the cell-center users separately from the cell-edge users [41]. It could also be used with WSN and a smart agriculture system to split the field into clustered spots, with each spot containing plants with certain properties to establish a clustered precision agriculture system.

Semi-SL has been growing in popularity in the agricultural field, as it helps resolve the shortage of labeled data and the abundance of non-labeled data [42]. Its application domains are particularly eminent in the remote sensing-based classification of crops, plant phenotyping, and disease detection with image and spectral data, whereby acquisition of data is relatively cheap, and labeling is very costly and time-consuming [43]. Semi-SL models can use a small number of labeled samples and a large amount of unlabeled data to obtain better generalization, and significantly decrease the amount of annotation. This paradigm is especially beneficial in the field of real-life agriculture, where seasons and regions change, and it is not possible to label everything. Semi-supervised learning, as such, provides a viable tradeoff between performance and the cost of data collection in a model, which in turn increases the scalability of intelligent farming systems [44]. Semi-SL classification models can be investigated in agriculture applications such as crop disease detection, weed detection, and crop yield prediction. Additionally, the semi-SL clustering model includes a partitioning method, a hierarchical method, and a density-based method, which are used in the agriculture domain, such as in crop type clustering, land use classification, and pest-disease hotspot detection [45].

4.4. RL algorithm models

This branch of ML decision-making depends on the trial-and-error method, in which agents learn via interacting with an interesting environment, providing powerful outcomes [46]. RL finds more applications in the agricultural field, which needs to make adaptive decisions in dynamic and uncertain environments. The main areas of its use are irrigation, climate control in the greenhouse, fertilizing, autonomous harvesting, and robotic navigation [47]. In contrast to the conventional learning paradigm, reinforcement learning models develop optimal learning policies by engaging in constant interaction with the environment, and in this way, systems are able to adapt to new weather patterns, crop growth stages, and resource limitations. The RL is especially applicable to automation and intelligent control in contemporary agriculture due to its ability [48]. Nevertheless, there are issues of high computational cost, long training time, and safety concerns in application in the real world, which need to be well considered. Nevertheless, reinforcement learning has great potential to facilitate autonomous, resilient, and sustainable agricultural systems despite these limitations [49]. It involves various types of variables, including categorical and variables without a target, which are determined by some factors like action space, learning approach, policy representation, and value estimation [50]. The RL model has different types of algorithms, such as Sarsa, Q-learning, Markov decision, A2C, A3C, and the deep deterministic policy gradient algorithm. It is applied in agricultural applications like fertilization schedules, optimizing crop irrigation, controlling climate systems, and managing the health and feed of livestock [51].

5. ML Role in Agriculture

ML has been used in modern agriculture to solve complex biological, environmental, and production issues. ML algorithms facilitate accurate prediction, classification, and decision-making throughout the agricultural value chain through the combination of heterogeneous sources of data, such as climatic records, soil characteristics, remote sensing images, and sensor-based measurements [9]. RF and GB are widely used as SL methods to predict the yield of crops, soils, and animal productivity, owing to their ability to adapt to nonlinear and noisy data, whereas deep learning techniques, especially CNNs, have transformed applications to images, including crop diseases, weed detection, and animal welfare [52]. At the same time, Un-SL and clustering methods are applied to assist in precision agriculture by identifying management zones, field spatial heterogeneity, and reinforcement learning methods are being studied to assist in adaptive irrigation and resource optimization [53]. In general, ML improves agricultural productivity, sustainability, and resilience through timely, site-specific, and evidence-based management, thus responding to the increasing issue of food security, environmental protection, and climate change [54]. The functions of the most popular ML algorithms in each of the agricultural applications specified are illustrated in detail in Table 1.

Table 1. The role of ML algorithms in agriculture

ML type	Crop prediction	Disease detection	Weed detection	Crop recognition	Crop quality	Usage of water resource	Soil aspects	Soil protection	Animal welfare	Livestock production	Role
KNN	☒	☑	☒	☑	☒	☒	☑	☒	☒	☒	Regulate data distribution Make the relationships global [55].
GB	☑	☒	☒	☒	☒	☑	☑	☒	☒	☑	Minimize prediction error [56].
DT	☑	☑	☒	☒	☒	☑	☒	☒	☒	☒	Provides explicit decision rules [57].
RF	☑	☒	☒	☑	☒	☒	☒	☑	☑	☑	Reduces overfitting and handles noisy data and high-dimensional input data [58].
SVM / SVR	☒	☑	☒	☑	☑	☒	☒	☒	☒	☒	Effective with a limited sample size and high-dimensional input data [59].
Naïve Bayes	☒	☑	☒	☒	☒	☒	☒	☒	☒	☑	Probabilistic relationships with vigorous independence assumptions [60].
RL	☒	☒	☒	☒	☒	☑	☒	☒	☒	☑	taught the best practices through communication [61].
CNN	☒	☑	☑	☑	☒	☒	☒	☒	☑	☒	trained spatial features of images automatically [62].
Anomaly detection	☒	☒	☒	☒	☑	☒	☒	☒	☑	☒	Detect abnormal conditions [63].
Clustering Algorithms	☒	☒	☒	☑	☑	☒	☑	☒	☑	☒	Find concealed trends and areas of management [64].

6. Literature Survey of ML Applications in Agriculture

Due to the formidable challenges of climate change to agriculture, it is necessary to innovate intelligent approaches for efficient and sustainable farming practices. ML has been revealed as a pivotal technology in this scope, providing preceding solutions for forecasting, planning, and optimizing resources to alleviate environmental impacts. The following sections present a literature review on using different ML algorithms in agriculture for prediction, disease detection, and precision irrigation with a comparison.

6.1. DT algorithm

It is a widely used model type of ML for both regression and classification tasks. Understanding its decision is not required for feature scaling, as it handles both categorical and numerical values. It represents a decision-making process in a hierarchical tree structure with a node structure that includes internal nodes, branches, and terminal leaf nodes. It recursively divides the feature space based on splitting criteria (information gain, entropy, Gini impurity, and so on) and allows deriving explicit decision rules, which can be conveniently understood by domain experts [65]. Due to this level of transparency, DT has been widely used in fields where its explanation is paramount, such as agriculture, healthcare, and finance. Nevertheless, DT models are sensitive to the fluctuations and noise in data, which can lead to overfitting, especially when the tree is deep in growth. To overcome this weakness, pruning techniques, depth generalization, and extensions of ensembles like the RF and Gradient Boosting are generally used to improve the generalization performance [66]. A considerable number of researchers have studied this topic. For instance, Reddy et al. [67] presented a smart irrigation system to forecast the water needed for crop-based ML algorithms. The DT algorithm depended on limiting water usage to prevent future havoc caused by water scarcity. The system comprised temperature, humidity, soil moisture sensors, and a microcontroller with storage for the dataset (the author mentioned it as a sample in the paper), and to host the web server. The soil moisture type DHT11 sends the collected data to the Raspberry Pi, which processes it with a DT algorithm to predict accurate results. Finally, the results, which mean the decisions, were sent to the farmer by email via simple mail transfer protocol to inform him about the crop water requirements in terms of yes/no. The system helped the farmer to supply the crop with water at the right time. However, the system required the application of an automatic irrigation valve to go beyond the stage of the farmer providing the crop water by himself. In addition, Raju et al. [68] presented a decision-making agriculture irrigation system with the suggestion of developing a WSN architecture for monitoring and controlling fields based on IoT and hybrid ML. The proposed system consisted of user and cloud systems, one for collecting data and the other for storage and analysis. Sensors collected data and sent it to the Raspberry Pi, which acted as a gateway to pre-process data and sent it to the cloud and the farmer's application to inform him about field environment variables. The data is then analyzed in the cloud, and the ML methods LR, Multiple SLR, LR, and PR are applied and evaluated according to the measurement index. The results were categorized as normal healthy growth, alert, and emergency. The performance metrics of ML methods were indicated that the DT method has superior performance to other used methods, which resulted in (maximum accuracy of 98%), (minimum MAE of 0.07%), (MSE of 0.06%), (R^2 parameter of 99%), and (RMSE of 0.002%)—the results obtained via Thing-Speak cloud platform by application programming interface Key. However, the decision wags not applied to auto irrigation; it also sent an SMS or email to the farmer.

6.2. SVR

It is one of ML's algorithm models that deals with continuous numerical values, making it used for prediction in regression tasks. It is characterized by robustness to overfitting, works well with non-linear data, has high efficiency, and has good performance [66]. It is based on the statistical learning theory and is aimed at determining an optimum hyperplane that is most likely to maximize the gap between classes. The use of this margin-based principle allows SVM to realize good generalization, particularly in high-dimensional feature spaces, and in high-dimensional feature spaces with a small training set [69]. SVM can be used to model complex nonlinear relationships through the use of kernel functions such as radial basis function, polynomial and sigmoid kernel. However, the performance of the algorithm is strongly reliant on the hyperparameter tuning, especially the regularization parameter and coefficients unique to a specific kernel, and can be computationally expensive with large data sets [70]. SVR has been presented in several works of literature. The work by Vij et al. in [71] presented an IoT automatic irrigation system based on ML and developed a monitoring system to manage irrigation problems. SVR and RF regression methods were based on predicting soil moisture to provide sustainability. The data was collected by sensor nodes, which consisted of an Arduino Mega unit connected to multiple sensor nodes, where the collected data was sent to a Raspberry Pi 3, which ran a Python script to ensure different conditions in the data and then sent it to the cloud. The system permits a sustainable and efficient computational approach. However, the proposed system has different challenges, such as a limited dataset and region data, climate sensitivity, critical hardware installation, sensitivity to animal presence, limited dataset for crop water need, limited hyperparameters, and kernel type.

Nikdad et al. [72] presented a study to predict agricultural drought in Iran in different climates by locating the critical variables based on ML feature selection methods. The researchers depended on ML methods of SVR, which were developed with other feature selection methods to predict drought indicators. Emerging multiple products combined with three data sets to gain a lot of accuracy. The model was evaluated by computing performance metrics, resulting in an accuracy of 99.98% in precipitation data. It also exhibited higher accuracy when combining the data sets compared to ground-based measurements. However, the different variables' weight calculations were very complex due to different accumulation periods, which posed the main challenge.

Acharya et al. [73] presented soil moisture prediction in a crop field through the Red River Valley of the North to determine the ML performance-based observations of weather stations and the characteristics of the nearby areas under crop management. The effectiveness of ML methods used for evaluation included multiple-LR, Boosted Regression Trees (BRT), classification and regression trees, RF regression, artificial neural networks, and SVR. The ML models were carried out based on environmental software, and the entire dataset was separated into 70% for training and 30% for testing. After performance evaluation, boosted-regression-trees and random-forest-regression algorithms were the best, with the RMSE of $0.048 m^3 m^{-3}$ and $0.045 m^3 m^{-3}$, and the MAE of $< 0.040 m^3 m^{-3}$, respectively. In addition, SVR, RF regression, and BRT also scored high correlations between measured and predicted soil moisture by 0.65, 0.72, and 0.67, respectively. This helped predict large agricultural fields. However, the dataset used for training was structured from multiple sources, leading to susceptibility to certain types of inconsistencies.

6.3. KNN algorithm

It is a type of ML algorithm widely used for regression and classification tasks [74]. It is considered an unlearning model during training; thus, it is referred to as a lazy learner. KNN is exploited to predict new data points closest to other neighboring (query) points. In addition, KNN is used for classification and regression. This model has the advantages of simplicity, the ability to handle multiple classes for classification, and non-parametric properties [75]. However, the KNN algorithm is sensitive to the distance metric used, feature scaling, and the selected value of k; the latter greatly affects the accuracy of classification. Moreover, its computation and memory demands grow as the size of the dataset grows, and this drives the adoption of dimensionality reduction techniques and efficient indexing methods to enhance scalability. Li et al. [76] proposed a prediction method for wheat Fusarium head blight by combining KNN and an LR model. The feature selection of remote sensing factors considered the growth environment of the crops, which mainly reflected disease stress and crop nutrition. In contrast, the meteorological factors were selected according to the causes of changes in optical properties. The disease occurrence factor weights and prediction model of the development mechanism were expressed quantitatively by the regression model. Furthermore, the prediction factor was fused with factor weight as input for the KNN model to initiate a prediction with high precision for wheat Fusarium head blight with evaluation. The resultant accuracy has increased by comparing this proposal with others that do not suggest using disease mechanisms by approximately 13%. On the other hand, the overall accuracies were 0.88 and 0.92, while the F1 index was 0.86 and 0.94 for both mentioned dates, respectively. Accordingly, the prediction proposal based on logistic-KNN has higher accuracy and stability than other approaches that deal with just the KNN model. However, many other meteorological factors affect the occurrence of Fusarium head blight infection and cannot be ignored in certain circumstances.

Tace et al. [77] presented a smart agriculture proposal for a flexible and intelligent ML-based irrigation approach. A comparison of different methods, including KNN, SVM, neural networks, Naive Bayes, and LR, was used with the Node-RED platform to perform storage, supervision, and notification. Different sets of sensors were also used to acquire data, and the Mongo dataset was incorporated to manage the auto-irrigation system according to intelligent prediction. In a race of computerization, the proposed model is principle-based peer-to-peer, which provides data as “1” or “0” referring to pumping events. The data was standardized for accuracy and then separated into test and training data before implementing the models. Additionally, the neural network classification depends upon specific period numbers, where the accuracy and the lost data could be virtualized in each one. The accuracy and RMSE results after implementing the KNN, SVM, neural networks, Naive Bayes, and LR were (98.3%, 0.12), (96.7%, 0.17), (97.2%,0.16), (97%, 0.17), and (96.2%, 0.19), respectively. Accordingly, K-NN is the best method. However, very slow sampling with limitations to the calibrated region are realized when combining this model with techniques to analyze data.

6.4. Other ML types

This subsection presents other ML categories adopted in the literature. In this regard, Bakthavatchalam et al. [78] presented an IoT agriculture model for predicting high-yield crop-based ML algorithms. The SL methods used for classifying were decision tables, rule-based perceptron, and JRip classifiers to build a model for precision agriculture with high-yielding crops, where the decision was taken specifically for irrigation. The datasheet was taken from Kaggle, and the software program used for ML was Waikato Environment for Knowledge Analysis to implement crop irrigation decisions. The time required to build such a model was 8.05 s., and the accuracy of the selected classifier and characteristics of the average weight of the receiver operator were 98.2273% and 1, respectively. However, the module was limited to simulation, and at the same time, it was required to control an automatic valve for smart irrigation. Sambasivam et al. [79] demonstrated a high-performance model based on convolutional neural networks (CNN) to classify and detect cassava mosaics and diseases. Applying the sequence steps of acquiring a dataset, labeling, model training, and testing evaluation by k-fold cross-validation, where k = 3, resulted in an accuracy score of over 93%. However, the small dataset size, with five fine-grained 10000 categories of cassava leaf disease, low-resolution images, and limited labeling, was the main challenge of this proposed model.

Srinivas et al. [80] proposed the Krill-Herd-based-RF design to detect and crop disease accurately and enhance detection by optimizing the fitness function. The plant villa image dataset trained the system based on the net as a source, and Krill-Herd-based-RF was also designed. After pre-processing, which includes removing noise and errors, the images are converted from RGB into greyscale, followed by the segmentation process, which involves pixel value variation and feature extraction. Also, the affected parts in the crop were disclosed depending on the boundaries. Then, the crop diseases were detected in the classification layer using the krill herd fitness function in a random forest classifier. The proposal’s performance gained a good result after training on 100 images, and compared to other authentication techniques, it was concluded that the accuracy of the proposal in detecting disease is 99.55 %. On the other hand, the precision related to the crop affected region detection was about 99.85%, and the recall calculation, which was concerned with the accuracy of crop prediction disease, was 98.98%, the efficiency validation was 99.12%, and the execution time was 40 m sec. However, the article missed data sharing and analysis to take automatic actions upon detection. Patil et al. [81] elaborated an IoT system for precision irrigation-based ML to enhance crop production by limiting climate impact and water wastage. Data was collected from temperature, humidity, and raindrops, in addition to soil moisture sensors, which were placed in the soil, and all connected microcontrollers integrated with WiFi modules were used to send data to a database in the web host every minute. Then, the received data was processed with the ML, which used the LR method depending on previous usage of water, input parameters of soil water, and meteorological information. After that, the decision taken by ML was sent via Wi-Fi to ESP 8266, which controlled the water motor to irrigate the area when needed. Furthermore, all details about environmental parameters and decisions made using the ML method were deployed to specific applications on the farmer’s mobile to provide a full view of the field events. Accordingly, there was no need for farmer intervention, and efficient water usage had been investigated in the agricultural fields.

Singh et al. [82] exhibited an optimization of soil moisture estimation based on integrating WSNs with ML and DL exploration techniques. Amalgamating multiple data sources of WSN with climate and satellite data, aiming to obtain an accurate analysis of soil moisture resolution and irrigation management, made agricultural planning more efficient, and monitored the environment. Five ML models were selected, including SVM, LR, RF, DTs, and Long Short-Term Memory (LSTM) to train 80 % of the dataset and optimize weights and parameters for accurate predictions. ML models' performance was evaluated by the highest agreement scores with MSE and MAPE of 0.06 and 2.8%, respectively, related to the LSTM model over other ML models used. This study contributes to the technologies of soil moisture monitoring advancements, providing insights into a combination of WSNs, ML, and Deep Learning potential in agriculture and management of environmental practices. However, LSTM requires high training time, so computation is considered costly. Chen et al. [83] presented a hybrid-intelligent-evaluation model for the pollution risk of soil heavy metals based on laboratory chemical analysis for field sampling. The model was based on the Semi-SL Bayesian Regression model to predict the content of the heavy metal soil at unsampled points, which also requires at least 639 sets of samples. For prediction targets, 80 and 50 random samples were collected from Xinzhou and Huangpi cities, respectively, with a total area of 3.7×104 hm^2. A Multiple-Kernel-SVM model was used to evaluate soil pollution status. In contrast, the Artificial-Fish-Swarm-Algorithm determined the critical requirements of parameter combinations. The overall evaluation accuracy was 97.42%. Moreover, this novelty has investigated soil pollution with great practical significance, evaluating soil quality and other valuable work. However, the predicted results of this model may be affected by further important factors; hence, further in-depth research is required.

6.5. Comparison of previous works based on ML in agriculture

The literature survey over the last five years has been presented in the previous subsection, including the crucial applications of ML in the agriculture sector of disease detection, crop yield management, control of irrigation systems, and enhanced data gathering, among others. The precision decision has been taken according to accurate results, leading to smart automated agriculture offering farmer efforts. The highest accuracy is found in [72], which depended on the SVR model to predict drought indicators, resulting in an accuracy of 99.99%. In contrast, the CNN resulted in less accuracy of 93% in [79]. On the other hand, the most significant limitation that challenged the previous research was the data set, such as in [71, 73, 79]. Additionally, the integration of multiple types of ML resulted in latency, as seen in [82], which resulted in five types of ML models. To summarize, the comparative analysis used in Table 2 suggests that every ML algorithm has its own peculiar advantages and limitations in regard to data properties and the needs of the application. LR presents an interpretable and simple baseline model with easy computation, making it effective for separable problems linearly, but limited to nonlinear relationships. CNNs excel at image and signal processing tasks; however, they require significant computational resources and large labeled datasets. The high interpretability and easy-to-implement characteristics of DT models can be exploited without adequate control, leading to overfitting. SVMs are generalization machines that are very effective in large dimensionality spaces, but demand more careful parameter selection and increased computation time. KNNs are more flexible and simpler since they do not assume any prior knowledge of data distribution, but they are susceptible to feature scaling and the size of the dataset. Altogether, the comparison proves that no unique algorithm can be taken as universal, and the choice of computational efforts.

Table 2. Comparison of previous agriculture studies using ML

Ref./year	Type of ML	Types of sensors	Measurement parameter	Accuracy (%)	Limitation
[67]/ 2020	DT algorithm	Temperature, soil moisture, and humidity.	Temperature, soil moisture, humidity.	N/A	The irrigation decision wasn't applied automatically.
[71]/ 2020	SVR and RF Regression Algorithm	Temperature, humidity, water level, and MQ2 gas	Humidity, temperature, and weather conditions.	N/A	Limited dataset and region data, climate sensitivity, critical hardware installation, sensitivity to animal presence, crop water need, hyperparameters, and kernel type
[79]/ 2021	CNN	N/A	Classify and detect cassava mosaic and disease	93	The small size of the dataset, the resolution of the images, and the limited labeled
[73]/ 2021	SVR, RF Regression, and BRT	N/A	Weather parameters moisture	N/A	Datasets used for training were structured from multiple sources, leading to susceptibility to certain types of inconsistencies.
[76]/ 2022	KNN, and LR mechanism-based model.	N/A	Average of temperature, humidity, and precipitation, remote sensing, and meteorological factors	88 and 92	Many other meteorological factors affect the occurrence of Fusarium-head-blight infection and cannot be ignored in certain circumstances.
[77]/ 2022	KNN	Soil humidity, temperature, and rain	Soil humidity, temperature, and rain	98.3	Very slow sampling with limitations to the calibrated region when combining this model with other techniques to analyze data
[78] /2022	Decision table, perceptron rules-based, and JRip classifiers	Analytical sensors and specific sensors of temperature, Humidity, and rainfall	Temperature, Humidity, Rainfall, Nitrogen, Phosphorus, Potassium, and pH.	98.22	The module was limited to simulation. At the same time, it was required to control an automatic valve for smart irrigation.
[68]/ 2023	DT algorithm	Soil moisture, temperature, and humidity sensor, soil pH, and pi camera	Soil moisture, temperature, and humidity sensor, soil pH, and environment monitoring	98	The decision was not applied to auto irrigation; it also sent an SMS or email to farmers.
[83]/ 2023	Semi-BR	N/A	As Cd, Cr, Hg, Pb, Zn, Cu, and Ni.	97.42	This model may be affected by other important factors, requiring further in-depth research.
[80]/ 2024	RF	N/A	Disease detection and classification	99.5	Limited data sharing and analysis
[81]/ 2024	LR	Temperature, humidity, raindrops, soil moisture	Temperature, humidity, raindrops, soil moisture	N/A	The author didn't mention the percentage of the system's accuracy or the power supply for the system in the field that needed to be focused.
[82]/ 2024	SVM, LR, RF, DT, and LSTM	SMAP, PACD, and WSNs	Weather parameters moisture	N/A	High training time
[72]/ 2024	SVR	N/A	Precipitation root zone soil moisture, temperature, and potential evapotranspiration	99.99	The different variables' weight calculations were very complex due to the different accumulation periods

7. Performance Evaluation in Agriculture

In agriculture, ML techniques are used to analyze the collected sensed data. Accordingly, the performance of the experimental analyses must be evaluated numerically, as detailed in Table 3.

Table 3. Performance metrics evaluation details

No.	Performance metrics	Description	Mathematical expression	No. of Eq.
1-	Error-metrics K(Kappa)	It is the difference between actual and chance agreements in the confusion matrix and the exact computation at different or the same rating observers. It has two types: negative and positive, which refer to poor and perfect agreement. K(Kappa) is expressed in [84], as illustrated in (1)	$k\ (Kappa) = \frac{(P_0 - P_e)}{(1 - P_e)}$ where P_0 and P_e are denoted as actual agreement and chance agreement by hypothetical probability, respectively	(1)
2-	Histogram error	It is a validation of a proposed classification structure, which is the difference between the proposed structure and the output of resultant data, which is expressed in [85], as described in (2)	$Histogram\ error = target - output$	(2)
3-	Cumulative-Distribution-Function (CDF)	It is the density distribution of the probability mass function $f(x_i)$ Or finite variables x_i, where i, and r = 1,2,..n all in the interval of [a,b]. CDF is expressed in [85], as can be obtained in (3)	$F(x_r) = \sum_{i=1}^{r} f(x_i)$	(3)
4-	Root-Mean-Square-Error (RMSE)	It is the first function used to evaluate the accuracy and performance of prediction of the sensor network, where the smallest value refers to its high performance; RMSE is expressed in [68], as described in (4)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_j)^2}$ where P_0 and P_e are denoted to actual agreement and chance agreement by hypothetical probability, respectively	(4)
5-	Mean-Absolute-Percentage-Error (MAPE)	It is the average percentage of the absolute values of the prediction errors to the actual data. MAPE with low values indicates that the model has a high performance, and vice versa. The lower value of the MAPE is an indicator of the model's better performance. It is worth mentioning that the prediction model's indication performance is as follows: Highly accurate prediction, good prediction, Reasonable prediction, Inaccurate prediction when MAPE≤10%, 10% < MAPE ≤ 20%, 20% < MAPE ≤ 50%, and MAPE > 50%, respectively. MAPE is expressed in [86], as outlined in (5)	$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{x_i - y_i}{x_i}\right\rvert \times 100$ where x_i, y_i, and N are absolute values of prediction value, absolute values of actual value, and total number of data points, respectively.	(5)
6-	Correlation Coefficient (R^2)	It is an approach that evaluates a set of measured data predictions, with a value between 0 and 1, whereas the resultant closest to 1 indicates better performance. R^2 is expressed in [68], as provided in (6)	$R^2 = 1 - \frac{\sum(x_i - y_i)^2}{\sum(x_i - \dot{x})^2}$ where x_i, y_i, and $\dot{x}$ are the measured, mean, and predictive values, respectively.	(6)
7-	Mean-Absolute-Error (MAE)	It is the absolute weighted value of error degrees between individual observations. It can be obtained by removing the square root sign of RMSE, which is expressed in [87], as demonstrated in (7)	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert y_i - y_j\rvert$	(7)
8-	Mean-Squared-Error (MSE)	It is used as an evaluation metric to estimate the implementation of the model's performance, whereas the lowest value indicates good performance. It is expressed in [68], as provided in (8)	$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_j)^2$	(8)
9-	Confusion matrix	A misclassification matrix is represented as a figure or a frequency table of a two-way $C = (c_{ij})_{2\times 2}$, and it is possible to add a third column or row in aggregation cases. Indeed, it is an extraction from a testing dataset with a known ground truth value. In contrast, each class has been compared with the other to evaluate the classifier's performance by providing the number of misclassified samples. Confusion matrix C is expressed in [88], as presented in (9)	$C = \begin{pmatrix} TP & FN \\ FP & TN \end{pmatrix}$ where TP, FN, FP, and TN refer to true positive, false negative, false positive, and true negative, respectively	(9)

By using C, the Analytical properties measurement formula of the prediction accuracy can be obtained in a standard way via only using Positive and Negative as follows:

Accuracy: it is the ratio of True Positives and the Negatives to the total accounts classified, expressed in [89], as illustrated in Eq. 10.

$$Accuracy = \frac{TP+TN}{n^{+}+n^{-}} \tag{10}$$

n+ = TP+ FN and n- = TN+ FP.

Precision (P): it is the ratio of the True Positive classified to the sum of the True Positive and False Positive classified, it can be expressed as outlined in Eq. 11 [90].

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

Recall (R): it is the ratio of the True Positive classified to the sum of the True Positive and False Negative classified, it can be expressed as clarified in Eq. 12 [69].

$$Recall = \frac{TP}{TP+FN} \tag{12}$$

F-score: it computes the combination of P and R results. It is expressed as demonstrated in Eq. 13 [91].

$$F - Score = 2 \times \frac{P \times R}{P+R} \tag{13}$$

Sensitivity: it is the accuracy of the True Positive classified rate, which is expressed as shown in Eq. 14 [92].

$$Sensitivity = \frac{TP}{n^+} \tag{14}$$

Specificity: it is the accuracy of the True Negative classified rate, which is expressed as clarified in Eq. 15 [92].

$$Specificity = \frac{TN}{n^-} \tag{15}$$

Error Rate (ERR): is the ratio of Actual Negatives classified to the total accounts classified. ERR is expressed as depicted in Eq. 16 [92].

$$ERR = \frac{FN+FP}{n^+ + n^-} \tag{16}$$

8. Challenges and Limitations of ML in Agriculture

In ML-assisted agriculture systems, ML algorithms are applied to solve complex problems at each agriculture level, including pre-harvesting, harvesting, and post-harvesting, and their importance has increased with the population increase. However, the advantages of implementing ML algorithms come with different challenges, as detailed below.

- Big data: This is the first requirement to build an ML model. It is defined as a vast data set that may cross the petabytes in some cases, where the management of database systems manages it. It can be categorized as structured data, where the original data can be analyzed directly; unstructured data sets, which refer to data that have no formatting and alignment; and Semi-Structured data sets, which refer to data between the types mentioned above [93].
- ML Adaptability: Due to the variety of smart agriculture systems, ML should be developed to adapt to the different data sizes. This resulted in structured data models that are sensitive to noise, requiring feature selection, careful preprocessing, and hyperparameter tuning. Additionally, over-adaptation can reduce generalization to unseen or new data [2].
- ML deployment models: absence of human skills, cost, size of models, real-time deployment, the complexity of real-world scenarios, limitation of platform hardware deployment (embedded boards, like Android phones), etc.[94].
- ML model training and testing: it is necessary to check the accuracy and the validity of the model before deployment, with the necessity of reducing the time of training [95].
- ML classification algorithm customization: the appropriate classification selection affected the efficiency of the algorithm's decision [96].
- ML Underfitting and overfitting: Underfitting refers to low variance and high bias, resulting in limited learning data, while overfitting refers to models that have been memorized with healthy training data but provide poor unused data to train them [97].

9. Integration Among WSNs, Drones, and ML in Agriculture

This section assesses the aspects of maintaining full integration among WSNs, UAV technology, and ML to establish intelligent agriculture infrastructure. The following subsections provide further details.

9.1. Collaborative Applications

IoT, UAVs, and ML are advanced technologies for monitoring and controlling devices worldwide. It can connect devices with living things. The collaborative systems of such technologies are making a significant mark in agriculture. Therefore, it is important to examine those technologies in this paper, taking into account the most interconnecting aspects of literature works that have examined those technologies as follows:

9.1.1. Crop prediction based on collaborative UAV and ML strategies

The following works generally examined the idea of crop prediction in agricultural systems based on ML techniques. Li et al. [98] presented hyperspectral image data acquired by UAV at a low altitude for the growth stages of the canopy of the winter wheat crop, with predicted yields based on ML. Hyperspectral images were collected by M600Pro, which were used as the flight platform equipped with Resonon Pika L nano-hyperspectral propulsion scanner for predicting the winter wheat yield based on SVM, linear ridge regression, Gaussian process, and RF. The evaluation results of the four yield prediction learner models based on decision-level fusion showed that the SVM was the best among the other used learner models that performed high accuracy with R^2 of (0.62 ~ 0.73) for all grown stages except the grain-filling stage, which resulted in R^2 of (0.78) based on Boruta's preferred characteristics. This study efficiently demonstrates using hyperspectral images to build an estimation yield model for winter wheat. However, yield estimation, which depends on hyperspectral data alone, still has some limitations.

Li et al. [99] presented an experimental study of above-ground biomass estimation and crop yield prediction for a two potato crop canopy stages-based RF regression method. The RGB and hyperspectral images were acquired by a UAV. The Relief feature selection algorithm was used to select the optimal predictor variables of 35 vegetation indices. The optimal selection was combined with the RF regression method to construct a prediction model of crop yield and above-ground biomass-based crop height, vegetation indexes, and imagery data gained after planting for about 90 days. That resulted in a correlation coefficient of ($R^2 = 0.63$) and ($R^2 > 0.90$), respectively. The Partial-Least-Squares regression model was also used to improve the multi-prediction model by demonstrating the full wavelength spectra, resulting in ($R^2 = 0.81$). This study has limitations on UAV battery lifetime and flight time. Yu et al. [100] demonstrated a study-based vegetation indices, field topographic metrics, crop height, soil properties, and UAV to collect multispectral imagery from a corn field in order to predict the nitrogen content of the crops. ML regression methods indicated the crops' nitrogen weight, an essential agricultural practice. SVR and RF models were used to evaluate the weight prediction of canopy nitrogen from 29 variables, resulting in better validation performance of RF than SVR, with a scored R^2 of 0.73 and RMSE of 2.21 g/m^2. However, limited Pix4D applications recognize and stitch crop canopy density at the middle and later growth stages.

9.1.2. Disease detection based on UAV-ML schemes

Several researchers have investigated adopting ML techniques to maintain crop classification and crop health monitoring as well as disease detection. For example, Lee et al. [101] suggested a method for cultivating crop recognition to optimize and improve the processing image of UAVs. SVM and RF classification algorithms were used to classify corn and other crops, while an error matrix evaluated the accuracy results. The dependent input variables, the explanation, and the image classification visualization results were provided by ArcGIS Pro software version 2.5. The results of applying farm map classification basis SVM and RF algorithms to UAV images for a wide area of 2700 ha were (81.68%, 96.58%), (75.09%, 92.27%,), (77, 0.94), and (0.78, 0.94), respectively, in term of producer's accuracy, user's accuracy, the Kappa coefficient and the F-measure, respectively. Additionally, the various crops in the cultivation environment were mixed, and the estimation of corn cultivation area was 96.54 ha and 98.77 ha with an accuracy of 90.27% and 92.36% by SVM and RF, respectively, which showed that the accuracy obtained with the RF method was more than that of SVM. However, linking satellite and UAV images was not easy to obtain; high resolution cannot be attained when the UAV's altitude is less than 5m from the ground due to the phenomenon of salt and pepper.

Abdulridha et al. [102] presented a study to detect early lesions of target-spot and bacterial-spot diseases based on a classification method and hyperspectral imaging in the range of (380–1020 nm). A UAV was used to collect data in the tomato field and the laboratory and field settings. Plant pathologists collected tomato leaves for indoor analysis by an indoor hyperspectral system, where the distance between the lens and the linear stage was 0.5 m, and the scans were done by Spectronon Pro software and analyzed by the post-processing data analysis software. Two classification methods were used to distinguish between diseases: a multilayer perceptron and stepwise discriminant analysis. As a consideration result and based on near infrared, the most suitable selection of wavebands, which the top values of spectral signatures reflectance acquired for all plant stages were (408–420 nm), (630–650 nm), and (730–750 nm) in terms of blue, red, and red edge, respectively. While the multilayer-perceptron accuracy resulted in 99% for both target-spot and bacterial-spot, with laboratory and field conditions (UAV-based), it was selected as a classification method in contrast to stepwise-discriminant analysis. However, there was a limitation on the flight time and battery life.

9.1.3. Collaborative UAV and ML for different applications in agriculture

Due to its importance, the parameters of the soils and the vegetation were considered in several works. For instance, Bertalan et al. [103] introduced a study of UAV efficacy-based multispectral and thermal cameras in soil-water-content mapping. Three types of pixel sampling and four ML algorithms were used to control accuracy, including General Linear Model, Elastic Net, RF, and Robust Linear Model with 3-fold cross-validation and 10 repetitions. Multispectral cameras were better than thermal cameras, where the results of R^2 and nRMSE were 0.97 and 0.71, 10% and 25 %, respectively. However, the spatial heterogeneities visualized have potential inaccuracies.

An evaluation study was provided by Cheng et al. [104] for UAV-ML-based multispectral imaging to specify the leaf-area-index of maize under various fertilizer stress and water conditions. Multispectral images were collected by UAV-based RedEdge-MX sensors for fertilizer and irrigation treatments at different growth stages of maize under five fertilizers and three water treatments. Also, the primary and secondary learners, which acted as a single ML method, scored R^2 and RMSE of 0.967 and 0.198, respectively, in 2020, and the test was repeated in 2021 for stability insurance, which scored 0.897 and 0.220, respectively. However, the visual information should be screened by other methods because the correlation between each of them and the leaf-area index was insignificantly different, and the results of R^2, which refers to accuracy, have not been improved. Moreover, Dilmurat et al. [105] presented a new framework showing the abilities of UAVs depending on the high resolution of LiDAR and hyperspectral data acquired from crops during the growing season. The framework used to estimate the oil compositions of corn, soybean, and the protein of seed-based automated ML and multisensory data fusion. To evaluate the performance of this Auto-ML model, the predicted results were referenced to ground truth values, which resulted in the selection of the best ML performance: Deep Neural Network and Gradient Boosting (GB) Machine. Additionally, based on a single sensor alone, the LiDAR and hyperspectral combination data prediction scored R^2 of 0.67 and 0.79 for corn oil and protein, and R^2 of 0.64 and 0.56 for soybean oil and protein. However, the features of the canopy structure derived from LiDAR point clouds were slightly poorer than the hyperspectral data.

Costa et al. [106] delivered a novel methodology for citrus trees, which was used to determine the nutrient concentrations of leaves based on multispectral images gathered by UAV and AI. The database was generated depending on UAV, which relied on a five-band multispectral camera to collect the canopy reflectance's spectral measurements from four fields of trees. Multispectral bands were used by 80% for training, and a 5-fold cross-validation by 20% for validation. GB regression was used to improve the evaluation of several metrics, including mean-absolute-percentage-error, root-mean-square-error, mean-absolute-percentage-error-coefficient-of-variance ratio, and difference plot. This novel model specified macronutrients with high precision and the micro-nutrients in addition to moderate precision, less than 9% and 16%, average error of 17% and 30% for 'Hamlin' and 'Valencia' trials, respectively. In a summary, this UAV-AI methodology was used efficiently to specify the concentrations of nutrients and create nutrient maps in citrus orchards commercially, which could be carried out in other crop systems. However, the GB regression algorithm is suitable for small datasets (< 400 individuals).

9.2. Integrated systems

Multiple studies deal with comprehensive technology systems involving UAVs, WSNs, and ML to provide important applications required in agricultural aspects. Fig. 4 shows an example of an integrated system applied in previous studies, such as in Shafi et al. [107], who presented an integrated system for monitoring crop health based on the latest UAV, IoT, and ML technologies. The heterogeneity based on collecting data involves IoT-agri-nodes, which are used to collect environmental variables affecting crop health, and the UAV platform, which permits multispectral data used for Normalized Difference Vegetation Index (NDVI) to analyze the crop health. To gain the classification of crop health, SVM, Naïve Bayes (NB), and Neural Network (NN) were tested, resulting in a classification accuracy of 98.4% after basing the M4 model of NN, which was found to be the most suitable one. However, the proposed system has limited the environmental parameters related to group health.

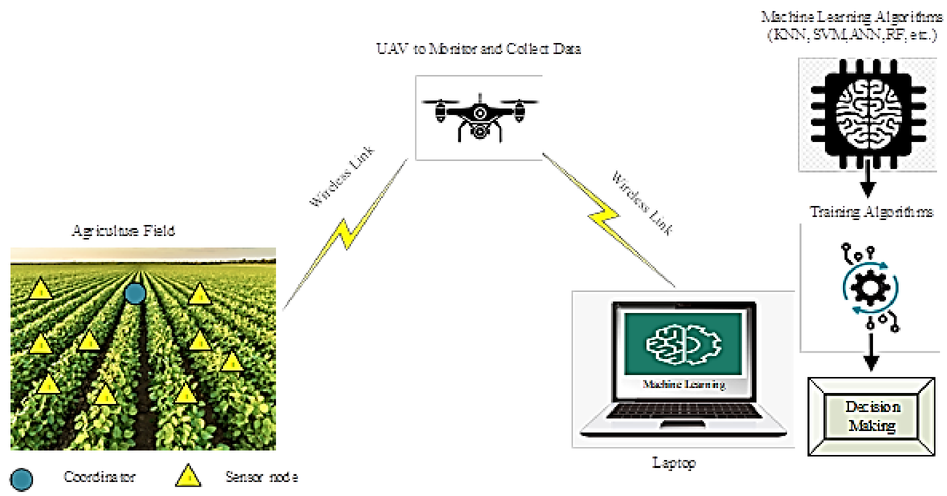

Fig. 4. Comprehensive technology system

Pukrongta et al. [108] developed an integrated agriculture system using UAV and IoT to enhance maize crop prediction-based ML. A UAV was used to monitor crops by collecting plant growth images. In contrast, IoT devices, including weather stations and soil analyzers, were used to collect relevant data on weather conditions, nutrients, vegetation indicators, and soil properties. LoRaWAN was used for efficient and reliable communication. Environmental data collected by IoT systems and by combining the homogeneity data and processing it, the PEnsemble 4 model, which is a combination of Huber and ML estimators, provided the maximum accuracy of 91% and 0.925427, 0.291894, 0.522753, and 0.723016 in terms of R^2, MAE, MSE, and RMSE, respectively. However, the data collection is about the effects of climate conditions, and the researchers needed to draw a causal correlation between the measurement factors and the study's objectivity. On the other hand, Bagha et al. [109] presented an IoT hybrid sensing platform for precision agriculture-based UAV, ground sensor nodes, and ML to improve the accuracy of the aerial data and reduce the cost of the farm sensor network. The data was collected by ground sensor nodes and sent to a Raspberry Pi via USB, which sends it to the IoT cloud platform via long-term evolution communication. At the IoT platform, ThingSpeak was used to calibrate and analyze the collected data using MATLAB. Statistical models and LR algorithms were used to validate and calibrate the hybrid sensing platform compared with ground sensor nodes. The comparison accuracy resulted in 34%, 51%, 66%, and 90% related to humidity, temperature, infrared data, and spectrometer, respectively. However, it was costly, had a limited coverage area, and tended to cause environmental damage.

Al-Naeem et al. [110] demonstrated a comprehensive monitoring crop system proposal with an efficient energy manner-based SVM, UAV for location management technique, and ground sensor nodes. To provide an efficient real-time monitoring process, the SVM algorithm was used for proper trajectory planning to make the UAV hover over desired sensitive locations in the fields and optimize the energy required for execution tasks. The proposed technique has improved results by comparing with other UAV techniques that control UAV movement, resulting in 34.5%, 6.5%, and 61.5% as agreement reduction in composite energy consumption, percentage of successful detection, and average delay, respectively. However, the proposed system is limited to simulation. Additionally, the work done by Ardakani et al. [111] presented the utilization of RL for remotely planning UAV routes for sensing in smart farms. Q-learning of location and energy was used to select/find best-fitted and/or cost-effective routes autonomously. Thus, an enhancement result was present, including minimized UAV power consumption, reduced data collection delay, increased number of samples, and reduced flight traversed distance. The improved Q-learning technique maximized data collection robustness and minimized UAV resource consumption, remote sensing latency, and traversed paths, especially in crowded and dense farms. However, this study was limited to simulation because it is costly to apply.

Sajid et al. [112] developed a framework of fog computing-based UAVs to collect data from IoT devices and drive it to fog sites to maintain the security of UAV-to-UAV communication by utilizing ML. A developed ML was used to detect the bad behavior of UAVs and make remarks on it. Data gathering and the offloading scenario were simulated using a simulation model developed in AnyLogic. At the same time, the ML processing proposed at the edge network was based on random forest, extra tree, XGBoost, DT algorithms for detection, and the K-means algorithm, a clustering technique for zero-day attacks. The performance metrics resulting from the XGBoost method are the most suitable, yielding 99.77%, 0.1055, and 99.81% in detection accuracy, F1, RMSE, and R^2 scores. The data set proposed for data training is CICIDS2017; however, it has limited features. Poudel et al. [113] characterized an efficient data collection algorithm of hybrid path planning based on UAV flights with collision-free paths in emergency environments. The shortest trajectory map has been designed using the probabilistic roadmap algorithm to improve the constraints of different paths in a three-dimensional climate. The generated path has been optimized by the artificial-bee-colony algorithm based on three types of bees: the employer bees, the onlooker bees, and the scout bees. The proposal has been compared with a probabilistic roadmap and a conventional artificial bee colony, resulting in higher energy consumption, longer flight time, and a path that outperforms. However, the proposed hybrid path planning simulation is limited to more complex cases and is required for dynamic obstacle cases.

10. Discussion of Collaborative and Integrative Systems

ML is revolutionizing the agricultural industry by facilitating the use of data to make decisions, predictive analytics, and automation of specific farming processes. Integrated ML with UAVs and WSNs offers considerable benefits compared to common ML methods used individually. The conventional ML methods, when applied independently, do not usually use data that is collected manually or limited, and they may not be able to effectively represent the spatial and temporal variation within an agricultural setting. Conversely, when combined with UAVs, IoT, and WSNs, the influence of ML can become even greater: UAVs can deliver high-resolution spatial data; IoT and WSNs can deliver real-time and continuous environmental and soil measurements. Coupled with ML, these data sources can be used to extract features automatically, achieve higher predictive performance, and make decisions adaptively to use in precision agriculture. Generally, the hybrid solution is more scalable, robust, and efficient, and the common methods of ML cannot process dynamic, large-scale, and heterogeneous agricultural data [114]. The synergy assists in the early identification of diseases or water stress, the optimal use of irrigation and fertilizers, and the sustainable management of resources.

Nonetheless, there are still a number of challenges: these systems usually demand a significant capital input, a well-developed connectivity infrastructure, and highly qualified staff, which may be costly, particularly to smallholder farmers. Besides, UAVs and sensors need to be combined and processed, which is computationally expensive and complicated [115]. The lifetime of the system is also constrained by the battery life of UAVs and the energy constraints of sensor nodes and energy management. On the ML side, a great deal of predictive models is implemented as a black box, so farmers cannot trust or make sense of the recommendations, and this may be a barrier to adoption. There is also the issue of security and data privacy to consider because networks and cloud infrastructure might be susceptible to unauthorized access or abuse of data. Altogether, whereas the combination of ML to UAVs, IoT, and WSNs has enormous potential to improve agricultural efficiency and sustainability, to achieve the full potential, it is necessary to address financial, technical, and social obstacles [116]. However, successful monitoring and automation implementation in a sensing environment is challenged by different obstacles that must be addressed. Such challenges are the accurate and precise data collection of monitoring systems and automated sensors, which are affected by climate conditions, calibration issues, and sensor drift [117]. Also, the heterogeneity of data gathering is very difficult due to the complexity of the fusion of the various formats, quality, and resolutions. Furthermore, development, including automation technologies in areas of restricted resources, is costly. Indeed, the advancement in digital farming is hindered by farmers' low literacy rates and difficulties in the acquisition of digital skills [118]. On the other hand, the limitation of internet connectivity leads to minimizing access to cloud storage and service with missing information and other transmission problems of outliers, duplication, and data breach integrity. Also, high energy consumption with limited resources and the accuracy of predictive issues, which include the classification module, are other challenges that must be addressed [9].

11. Research Gaps

Despite the remarkable success of ML in the Agri-industry, several significant knowledge gaps remain, which may be attributed to technological shortcomings and the complexity of agroecosystems. The fact that there are only very few large and high-quality labeled datasets of the scale needed by standalone ML systems is an inherent limitation; a disconnect exists between the data-driven models and the variability of the real world in agricultural settings. Similarly, the inaccessibility of real-time and edge-deployable ML models also demonstrates the difficulty of translating these theoretical advances into practical and field-deployable instruments, which are dynamic to the continuously changing waves of environmental and biological dynamics. These technical constraints are not the only limitations to the epistemic credibility of the application of ML by farmers, agronomists, and policymakers, as there are also philosophical concerns about whether or not more automation is better than human judgment in decision-making.

Partly integrated or collaborative systems, such as ML and UAVs, UAVs with simple sensors, or ML and WSNs, provide some advantages over independent solutions, but are not complete. This type of system can be used to improve spatial or temporal tracking, provide partial real-time analytics, or support specific management tasks; however, they are weak in terms of data fusion, interoperability, and system performance. Using the example of the ML-UAV, it can process aerial data but may fail to provide valuable soil or other environmental information that can be provided by WSNs, reducing the level of predictive accuracy and strength. Similarly, UAV-WSNs and ML are not able to automatically generate the insights to be used, and ML-WSN and UAV can inject large-scale spatial variations. These violations show that even good part integration, as useful as it is, is not sufficient to deal with the multidimensionality of agricultural systems.

Full-fledged ML-UAV-WSN systems, however, have the potential of offering comprehensive, dynamic, and accuracy-oriented agricultural control. These solutions can provide in-depth, real-time decisions, following the environment with resilient aerial imagery, continuous monitoring, and smart information analysis. Nonetheless, they have their own set of challenges, which encompass energy efficiency, computational and storage demands, multimodal data fusion, environmental variability, cost, and scalability. The strength of edge and cloud computing solutions and the standard information protocols, coupled with dynamic ML algorithms, can solve these problems with the capability to process heterogeneous information in real-time and at various agricultural settings. Accordingly, there are the incremental strengths of standalone ML and partially connected systems, but until someone arrives at full integrated ML-UAV-WSN systems, thus an incomprehensive, scalable, and robust system is required to address contemporary agriculture. The research should be directed to fill the gaps in the future on data fusion, real-time computing, model interpretability, and system interoperability to make computational intelligence practical for agricultural practices.

12. Future Architecture Technology Trends in Agriculture

By adopting WSN, UAV, and ML-assisted technologies, future agriculture systems can become more efficient, sustainable, and resilient to climate and resource challenges. Predictive AI can guide climate resilience strategies, providing adaptive measures represented by crop diversification, soil conservation, and optimized water management. Water usage in agriculture can be further optimized by integrating IoT and AI-driven smart irrigation. This is possible by analyzing real-time soil moisture and weather data to reduce the waste generation while enhancing crop yields. In addition, productivity could also be enhanced by AI-powered soil health monitoring and disease detection, as it would lead to better recommendations of fertilizers based on the composition of the regional soil. In addition, future agriculture systems could benefit from ML-assisted crop prediction that is drought-resistant. Identifying high-yield and low-water crops could help farmers adapt to climate variations. Moreover, satellites and UAV-based remote sensing could provide real-time insights into crop health, soil conditions, and pest infestations, leading to early threat detection, identification, and yield protection.

In the future, agriculture systems such as smart greenhouse automation could depend on AI-controlled climate systems assisted with UAV and WSN to optimize indoor farming. Such control systems assist in mitigating extreme weather effects. Specifically, AI-powered pest diagnoses and detection of plant diseases could play a vital role in preventing large-scale losses affecting key crops and improving general resilience. Future precision agriculture systems could benefit from renewable energy-powered smart farms to support sustainability. In particular, rural and remote farming communities could also adopt AI-driven solar irrigation to reduce their dependency on fossil fuels. Crop selection quality can also be enhanced by AI-driven market forecasting, which in turn minimizes post-harvest losses and highly boosts economic outcomes. It is worth mentioning that it is vital to analyze the previous papers that tackled agricultural national Iraqi diseases, such as rice blast, and other Iraqi palm tree diseases, as the main direction of the current review was to focus on the applying ML and other technologies in agriculture in Iraq, and to evaluate the role of ML and AI algorithms in the field of agriculture. Thus, it is recommended to include such matters in future research efforts. Finally, localized WSN and UAVs assisted with AI models tailored to specific agricultural landscapes can ensure more accurate and practical solutions for future agriculture precision systems.

13. Conclusions

The review summarized the role of ML in agriculture and how it can contribute, not only as a single tool, but also when deployed alongside other technologies that enable its application, including UAVs and WSNs. ML alone is useful in solving a broad spectrum of agricultural problems, such as crop yield prediction, disease detection, soil analysis, and resource management. Such techniques are especially useful because they are relatively easy to compute, can be easily interpreted, and are less computationally and infrastructurally intensive. Nevertheless, their practicality is usually constrained by stagnant datasets, lower spatial-temporal coverage, and reliance on manual data gathering or periodic data gathering, which might not remain contemporary to the dynamic character of agricultural settings.

ML, UAVs, and WSNs, have the potential to transform the way agricultural systems, are handled into intelligent, data-driven, and autonomous systems. UAVs can be used to get high-resolution aerial images and quick field coverage, whereas the WSNs can be used to monitor the environment and soil conditions on the ground continuously. These heterogeneous streams of data can be used together with ML algorithms to promote advanced analytics, real-time decision-making, and accurate intervention strategies. These systems are very adaptive, scalable, and robust, thus using them is very appropriate to precision agriculture and large-scale farming activities where variability and uncertainty dominate.

In the practical sense, the implementation of the ML-based and integrated ML-UAV-WSN systems has real advantages to farmers, such as optimal irrigation and fertilization, early-stage identification of crop stress and diseases, lower operating costs, and yield stability. These technologies help in decision-making based on the data, increase risk management in the conditions of a changing climate, and make the farming practices more sustainable and environmentally responsible.

In the future, a few research directions are found that are important to the development of ML-driven agricultural systems. These are the establishment of effective data fusion methods to combine multisource data, light and energy-efficient ML models that can be used in edge and fog computing, and better generalization methods to be able to make them robust across different crops, regions, and climatic conditions. Moreover, future research ought to deal with the problems of data privacy, system interoperability, interpretability of complex models, and especially deep learning architectures. Other potentially successful opportunities to improve the intelligence and responsiveness of the system include the integration of the emerging technologies (IoT, 5G/6G communication, China, and digital twins) with the frameworks of ML-UAV-WSN.

To sum up, although standalone ML is still a worthy and applicable solution to numerous uses in agriculture, its integration with UAVs and WSNs can be used as a more comprehensive and potent solution to fulfill the needs of contemporary agriculture. The future of ML-based agricultural systems has the potential to make a great contribution in terms of productivity, sustainability, and resilience due to the integration of computational intelligence with sensing, communication, and automation technologies, thus benefiting the world’s food security and environmentally friendly farming operations.

Authorship Contribution Statement

Nada M. Khalil Al-Ani: Conceptualization, Resources, Methodology, Investigation, Writing - Review and Editing. **Sadik Kamel Gharghan:** Formal analysis, Writing- Original draft, Supervision. **Ziad Qais Al-Abbasi:** Visualization, Investigation, Writing - Review & Editing, Project administration. **Razan Alenezi:** Writing - Review & Editing, Project administration. **Muhammed Abdelhameed:** Writing - Review & Editing, Project administration.

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