Machine Learning for Smart Agriculture: A Comprehensive Survey

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***Abstract*—As communication technologies and equipment evolve, smart assets become smarter. The agricultural industry is also evolving in line with the implementation of modern communication protocols, intelligent sensors, and equipment. This evolution is enabling large-scale agricultural production processes to operate independently, thus, securing the food supply chain for an ever-growing population. Data processing for such a system with multiple heterogeneous sources requires proper management for effective agricultural operations. Recognizing the advantages of Machine Learning(ML) in performing large-scale data processing, researchers are investigating the implementation of ML to design an effective intelligent agricultural architecture. The aim of this paper is to provide a thorough analysis of the state-of-the-art in smart agriculture, open challenges, and guidelines for the development of further enhanced smart agriculture systems. Specifically, we describe how ML is used to create intelligent agricultural systems supported by state-of-the-art technology.**

***Impact Statement*—The Internet of Things (IoT) in agriculture has the potential to completely transform the industry by enabling more streamlined and effective operations. Sensors based on the Internet of Things (IoT), such as temperature sensors, light sensors, pressure sensors, moisture sensors, and others enable the automation and simplification of a wide range of trustworthy user-oriented information, such as high-quality data, documented vulnerabilities, and appropriate measurement using artificial intelligence. The artificial intelligence of things (AIoT) aims to improve data management and analytics while increasing the efficiency of IoT operations. Furthermore, smart agriculture operations necessitate a solid understanding of local weather conditions, soil quality, crop monitoring, and preventive measures. The paper highlights recent research (2019-2023) on machine learning approaches (a subset of AI approaches)) and their prospective applications in smart agriculture. The article serves a number of purposes. It serves as a reference for AIoT-based research on agricultural health monitoring, crop yield estimation, crop disease identification, pest and weed detection for crops. Second, it provides insights into this field's open research areas and hurdles. Third, it seeks to stimulate new research ideas in smart agriculture.**

***Index Terms*—Crop monitoring, crop yield determination, deep learning, machine learning, pest and weed control, seed quality, smart agriculture, smart irrigation, soil condition.**

I. Introduction

The agricultural industry began with manual labor-based farming practices in the late 18th century and evolved into a machine-based industry in the present [1], [2]. In the first generation of the agricultural era, tools such as pitchforks and sickles were used for agricultural work, which eventually became a low-capacity practice. In the second generation of agriculture in the 20th century, fossil fuel-powered agricultural machinery was introduced to speed up food production processes. The development of the food supply chain was remarkable given the innovations in transport systems at the time. With the emergence of the third generation of the agricultural industry, software, and communication technologies are being introduced to increase production capacity through modern machinery and to make the agricultural system intelligent. In addition, the use of renewable energy sources such as solar, hydro, and wind energy is considered to develop green energy-based agricultural production systems. However, today's smart agricultural systems need to address food security for a large number of people, as the world's ever-growing population will increase demand for food over the next few decades [3]. Therefore, researchers are focusing on incorporating technologies such as big data [4], artificial intelligence (AI), which can consist of machine learning (ML) approaches [5], [6], [7], and blockchain to automate agricultural production processes [8]. In addition, agricultural production is closely related to communication technologies and especially wireless communications [9].

Nomenclature

AHA	Artificial Hummingbird Algorithm
AI	Artificial Intelligence
ALU-DL	Automatic Label Update Deep Learning
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive integrated Moving Average
BA	Bat Algorithm
Bayesglm	Bayesian Generalized Linear Model
BiGRU	Bidirectional Gated Recurrent Units
BiLSTM	Bidirectional Long Short-Term Memory
BN	BayesNet

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BP	Back Propagation
BPNN	Back Propagation Neural Network
BRT	Boosted Regression Trees
CART	Classification and Regression Tree
CNN	Convolutional Neural Network
ConvLSTM	Convolutional Long Short-Term Memory
CPS	Cyber-Physical System
DL	Deep Learning
DNN	Deep Neural Network
DT	Decision Tree
DTL	Deep Transfer Learning
ENSVM	Ensemble Support Vector Machine
EVI	Enhanced Vegetation Index
ExG	Excess Green
FPGA	Field Programmable Gate Array
FRC	Fused Representation-based Classification
FT-NIR	Fourier Transform Near-Infrared
GA	Genetic Algorithm
GaFPN	Global activated Feature Pyramid Network
GBDT	Gradient Boosting Decision Tree
GBM	Gradient Boosting Machine
GBRT	Gradient Boosting Regression Tree
GEE	Google Earth Engine
GLM	Generalized Linear Model
GMDH	Group Method of Data Handling
GMM	Gaussian Mixture Model
GPR	Gaussian Process Regression
GPU	Graphics Processing Unit
GRU	Gated Recurrent Units
GWO	Grey Wolf Optimization
HGS	Hunger Games Search
HMM	Hidden Markov Model
IOU	Intersection Over Union
KNN	K-Nearest Neighbor
KRLS	Kernel-based Regularized Least Squares
LAI	Leaf Area Index
LaRPN	Local activated Region Proposal Network
LASSO	Least Absolute Shrinkage and Selection Operator
LB	LogitBoost
LDA	Linear Discriminant Analysis
LR	Logistic Regression
LSTM	Long Short-Term Memory
LSWI	Land Surface Water Index
MAE	Mean Absolute Error
mAP	Mean Average Precision
MAPE	Mean Absolute Percentage Error
ME	Mean Error
ML	Machine Learning
MLP	Multilayer Perceptron
MNDWI	Modified Normalized Difference Water Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MSE	Mean Square Error
NB	Naive Bayes
NDVI	Normalized Difference Vegetation Index
NEAT	Neuroevolution of Augmenting Topologies
NFC	Near Field Communication
NN	Neural Network
NRMSE	Normalized Root Mean Square Error
NSE	Nash–Sutcliffe Efficiency
NSI	Narrow Strip Irrigation
PA	Pixel Accuracy
PLS-DA	Partial Least Squares Discriminant Analysis
PLSR	Partial Least Squares Regression
PNN	Probabilistic Neural Network
PSO	Particle Swarm Optimization
QANA	Quantum-based Avian Navigation optimizer Algorithm
QDA	Quadratic Discriminant Analysis
R^2	Coefficient of Determination
ResBiLSTM	Residual Network-Bi-directional-Long Short-Term Memory
ResNet	Residual Network
ResNet-50	Residential Energy Services Network-50
RF	Random Forest
RFR	Random Forest Regression
RGB	Red-Green-Blue
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
ROCKET	Random Convolutional Kernel Transform
RotFor	Rotation Forest
RPART	Recursive Partitioning and Regression Trees
RPIQ	Ratio of Performance to Interquartile Range
RVFL	Random Vector Functional Link
SARSA	State-Action-Reward-State-Action
SGD	Stochastic Gradient Descent
SMR	Stepwise Multiple Regression
SO-ANFIS	Seasons Optimization-based Adaptive Neuro-Fuzzy Inference System
SSA	Salp Swarm Algorithm
SSO	Social Spider Optimization
StoGB	Stochastic Gradient Boosting
SVM	Support Vector Machine
SVR	Support Vector Regression
TDNN	Time Delay Neural Network
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
VGG-16	Visual Graphics Group-16
XGBoost	Extreme Gradient Boosting

Fig. 1 depicts a potential architecture of a smart agricultural system. Autonomous tractors, sprinklers, drones, and satellites can be used for weed removal, harvesting, irrigation, pesticide application, and image capture for monitoring crops and crop field conditions. IoT sensors can also generate data related to crop health, and environmental and soil conditions and transfer this data to a data processing unit (or units) The data processing unit(s) perform data analysis to identify any issue(s) and make decisions accordingly. In the end, farmers can be notified to take the necessary action(s) with regard to farming practices.

A. Motivation and objective

As the agricultural industry continues to develop, so too will the amount of information that needs to be processed. As a

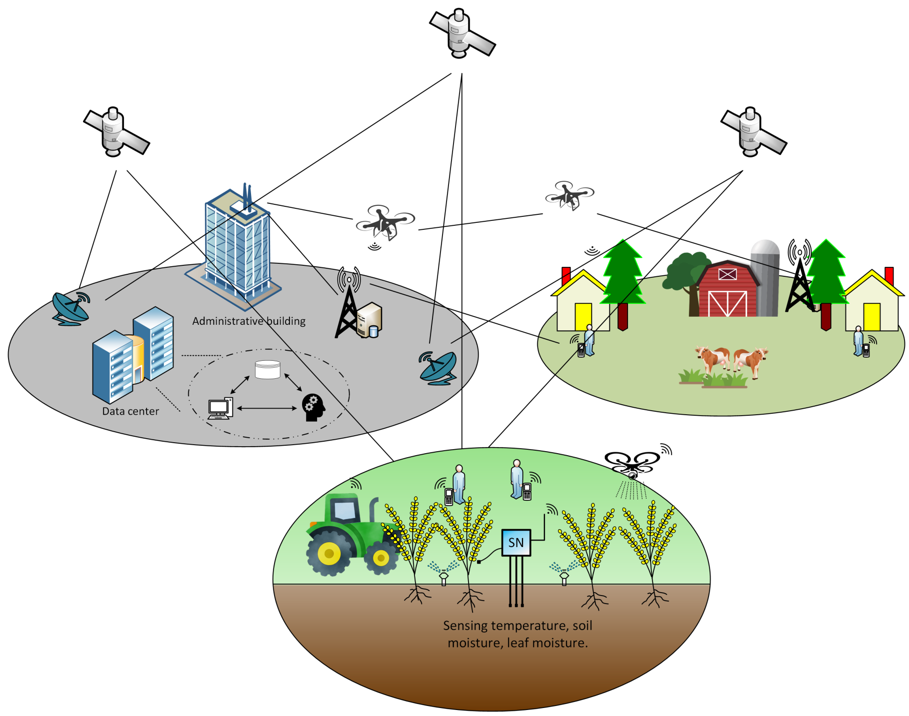

Fig. 1. Smart agriculture

result, processing a large amount of data using traditional approaches will be challenging and time-consuming. Approaches based on ML algorithms have shown their potential to handle large amounts of data and provide accurate information in a short time [10]. Recently, researchers have shown massive interest in incorporating ML algorithms to develop smart agricultural applications, as can be seen from Fig. 2. The "Scholarly Works" data are collected from well-known scholarly resources such as IEEE Xplore, Scopus, and the ACM Digital Library under the keywords "(Smart Agriculture OR Smart Farming OR Precision Agriculture) AND (Machine Learning OR Artificial Intelligence)". From these studies, we extract some useful information that is particularly applicable to new researchers or those just entering this field of study who plan to work on related topics. The aim of this paper is to provide a thorough analysis of the state-of-the-art in smart agriculture, open challenges, and guidelines for the development of further enhanced smart agriculture systems. Specifically, we describe how ML is used to create intelligent agricultural systems supported by state-of-the-art technology.

B. Contributions of the paper

In this paper, ML-based intelligent agricultural systems are investigated and some research problems are addressed. It can be seen that a large number of academic papers related to this research area have been published in the last 5-6 years. We have classified these papers according to their type, number of citations, number of references, year of publication, main objective, enabling technologies, etc. The research articles were classified on the basis of crop classification, soil monitoring, intelligent irrigation systems, seed vigor and germination determination, crop health monitoring, weed, disease, and pest detection, and crop yield determination. ML will also be used to maintain data privacy and secure the overall system architecture against cyber-attacks.

Specifically, this paper provides a survey on the application of machine learning algorithms in smart agriculture systems. Its main contributions are highlighted below.

- Perform a systematic literature review to obtain knowledge on the state of the art in smart agriculture systems, the limitations of current research, and future work.
- Discuss enabling technologies for smart agricultural systems.
- A thorough discussion on recent research trends on ML-based smart agricultural systems and their outcomes.
- Identify the issues and challenges regarding the ML-smart agriculture systems.
- Guidelines for the development of improved smart agriculture systems.

C. Organization of the paper

The paper is organized as follows. Section II discusses the technologies that contribute to designing smart agricultural systems. Section III describes the data collection and processing for ML implementation on these data. Section IV describes the implementation of ML-based approaches in classifying the health, germination capacity, and types of crop seeds. Section V discusses the crop type classification approach over the cultivation areas by means of ML-based algorithms. Section VI highlights the use of ML-models for monitoring crop health and predicting crop yield. Section VII discusses the determination of soil conditions and water usage for irrigation with ML. Section VIII discusses the identification of crop diseases, weeds, and pests with ML algorithm-based

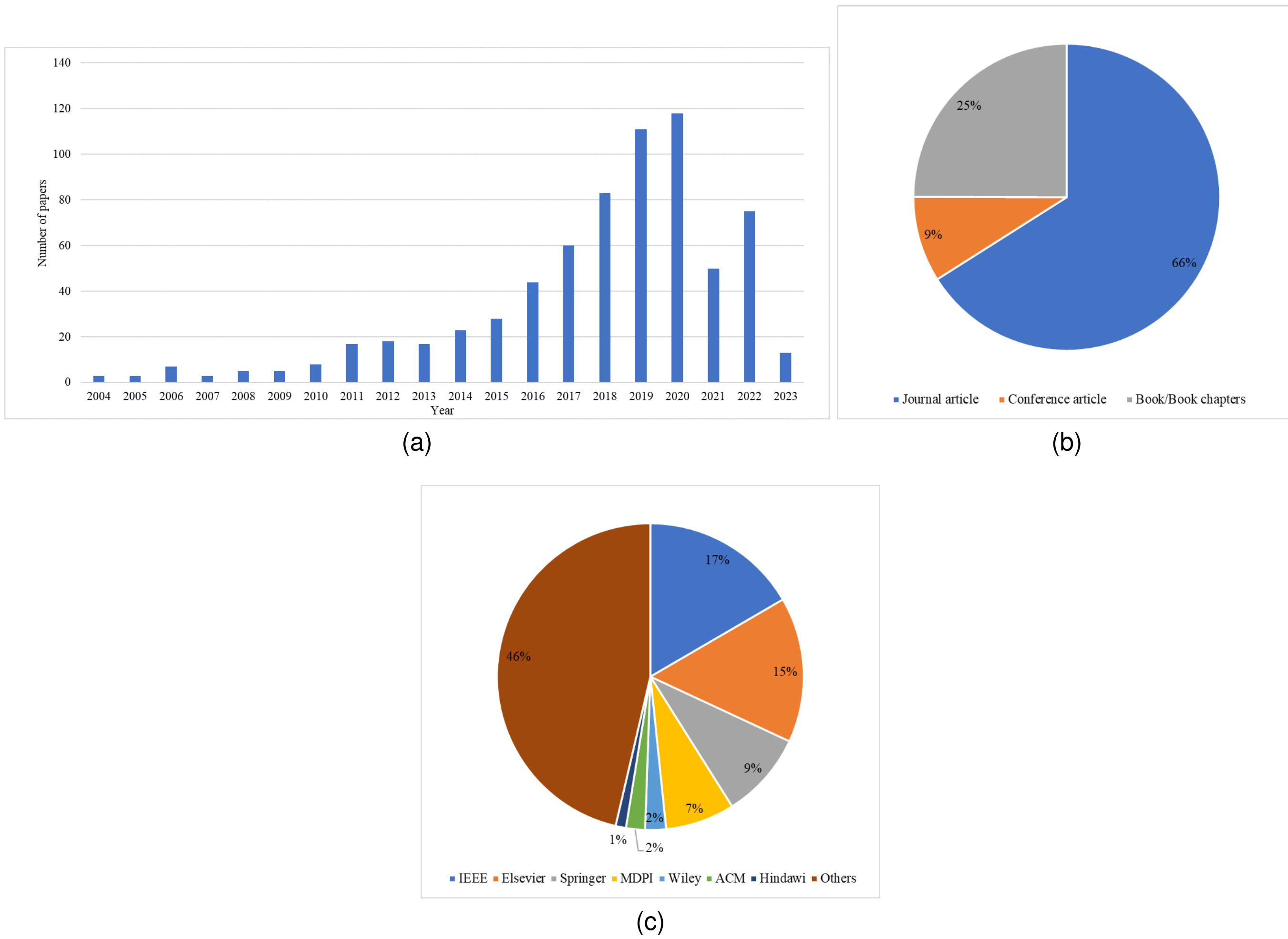

Fig. 2. Research trend on ML-based smart agriculture.

approaches to ensure effective agricultural production. Section IX focuses on issues in the deployment of ML-based smart agricultural systems and related future research scope. In the end, section X concludes the paper. The paper organization is illustrated in Fig. 3.

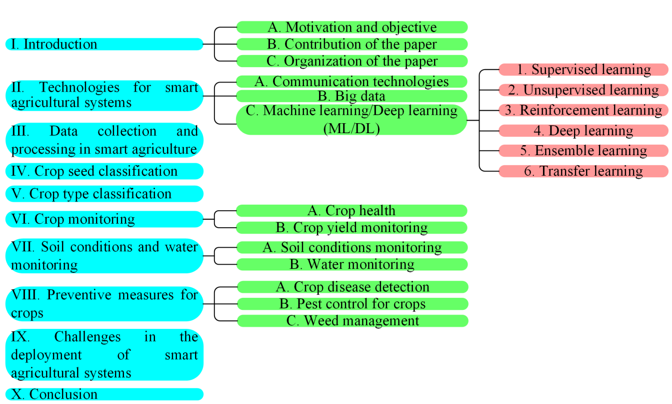

Fig. 3. Organization of the paper.

II. Technologies for Smart Agricultural Systems

This section provides a glimpse into the paradigms such as communication technologies used in smart agriculture, big data generated by smart sensors and cameras, and ML algorithms with examples.

A. Communication technologies

Effective transmission and reception of data for smart agriculture depend on wireless communication technologies, which have characteristics such as low power consumption, less delay, large connectivity, etc. [11]. From cellular networks to short-range and long-range network technologies, they are found to be relevant for agricultural purposes. However, there is a trade-off between power consumption and range [12], [13]. Communication protocols such as RFID and Near Field Communication (NFC) consume less power but have a limited range. ZigBee, BLE, and Wi-Fi offer low to medium-range transmission, but Wi-Fi offers high data rates at the expense of the high power consumption of the other two protocols. Cellular networks (2G-5G and beyond) offer long-range and high data rates at the cost of higher power consumption [14]. LoRa, SigFox, and NB-IoT also offer high coverage with low power consumption. However, these protocols offer a low data rate.

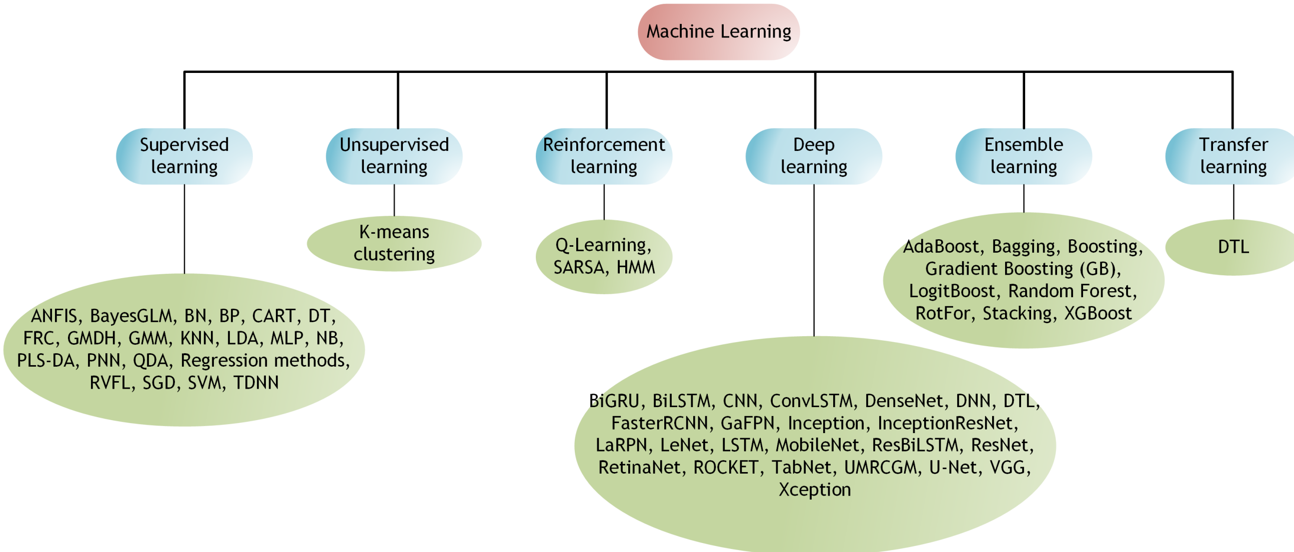

Fig. 4. Taxonomy of Machine learning/Deep learning.

The cost of implementing these communication technologies is also an important consideration for agricultural applications. For example, LoRa and NB-IoT offer low power consumption, but their implementation costs are high. Therefore, network coverage, power consumption, data rates, and implementation costs of communication technologies should be considered before developing a smart agriculture architecture.

B. Big Data

Big data can be referred to as a large volume of different types of data generated at a high rate [15]. In agriculture, this data can be generated by sensors, unmanned aerial vehicles (UAVs) or unmanned ground vehicles (UGVs) (with cameras installed), and satellites. Information such as soil moisture, electrical conductivity and pH of the soil, wind speed, atmospheric temperature and humidity, precipitation, etc. is usually obtained from smart sensors [16]. These sensors not only perform measurements but also pre-process and transmit the collected data to other devices for the extraction of valuable and interpretable information [13]. UAVs (with installed camera) are typically used to capture high-quality images for health monitoring, disease, pest and weed identification, crop yield estimation, etc. Remote sensing refers to the use of satellites to perform the above operations from a distance. In addition, variables such as Leaf Area Index (LAI), Land Surface Water Index (LSWI), Enhanced Vegetation Index (EVI), Normalised Difference Vegetation Index (NDVI), and Modified Normalised Difference Water Index (MNDWI) are determined from satellite imagery. The processing of these collected data is crucial, especially when data are collected from multiple sources (e.g. multiple satellites, UAVs and smart sensors, etc.) [17], [18], [19]. Therefore, it is a challenging task to integrate these multiple sources of data and generate useful information for agricultural applications.

C. Machine learning (ML)

Machine learning (ML) approaches predict outcomes from a given set of data after developing a mapping model [20]. In smart agriculture applications, multiple large volumes of data from IoT sensors, drones, and satellites are sent to the ML processing unit(s) to interpret the required information. ML can be divided into several categories, as shown in Fig. 4, which we discuss in the following.

1) Supervised learning: Supervised learning requires labeled datasets for training, as shown in Fig. 5. It determines the relationship between the labeled data with the help of simple mathematical functions, such as sigmoid, hyperbolic tangent function, etc. A general use case of such learning-based algorithms is classification/regression. Algorithms such as Discriminant analysis, SVM, KNN, etc. fall under this category.

2) Unsupervised learning: Fig. 6 represents the mechanism of unsupervised learning. It uses unlabeled data to search for their patterns. The training in this learning category aims at minimizing a given cost function [21]. The clustering of data is a use case of such learning-based algorithms. K-means clustering falls under this category.

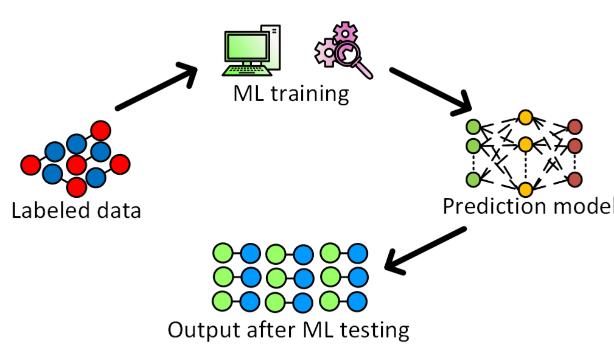

Fig. 5. Supervised learning

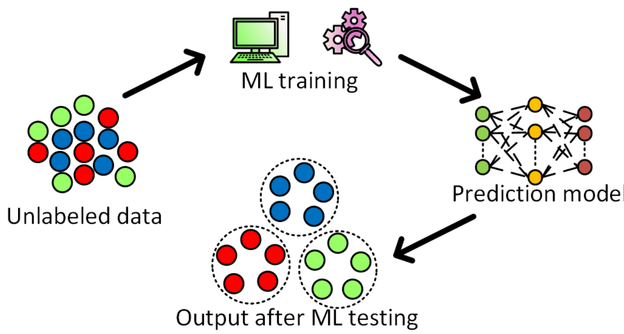

Fig. 6. Unsupervised learning

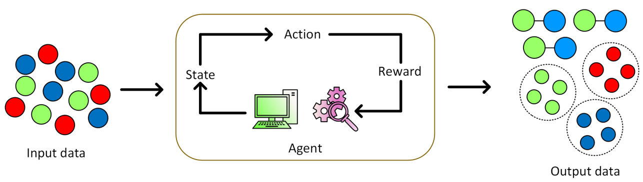

Fig. 7. Reinforcement learning

3) *Reinforcement learning:* Reinforcement learning aims at delivering optimum decisions on the basis of situations, actions, and rewards for the actions taken [22], [23]. As shown in Fig. 7, the agent analyses the state of the environment and takes action, which is evaluated by its reward value. This learning methodology aims to find the appropriate action so that maximum reward value is obtained. Algorithms such as Q-learning and State-Action-Reward-State-Action (SARSA) fall under this learning category.

4) *Deep learning:* Deep learning (DL) is the extension of ML due to its feature learning ability before developing the interpreting model [24]. Such learning architecture uses multiple layers, as shown in Fig. 8, to extract features of the provided data and perform functions similar to the above-mentioned learning methodologies. Algorithms such as CNN, VGG, ResNet, etc. fall under this learning category.

5) *Ensemble Learning:* Ensemble learning utilizes more than one ML algorithm to minimize the prediction error when a single ML algorithm is used. Fig. 9 demonstrates the ensemble learning mechanism. The individual learner is referred to as a base/weak learner, which produces weak results. Later, a combination approach is implemented to combine the outcomes of the weak learners and create a strong learning model. Boosting, bagging, and stacking are the most common approaches for creating a strong learner from weak learners [25].

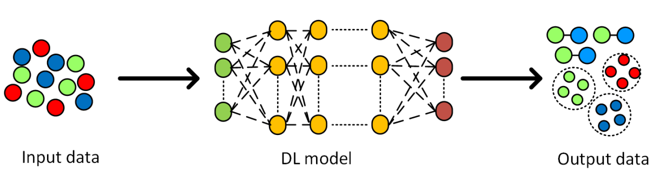

Fig. 8. Deep learning

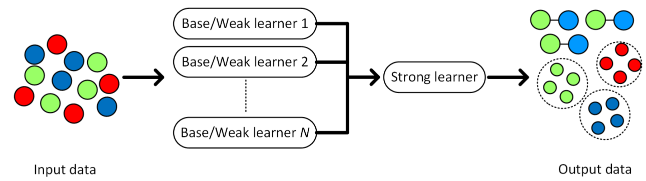

Fig. 9. Ensemble learning

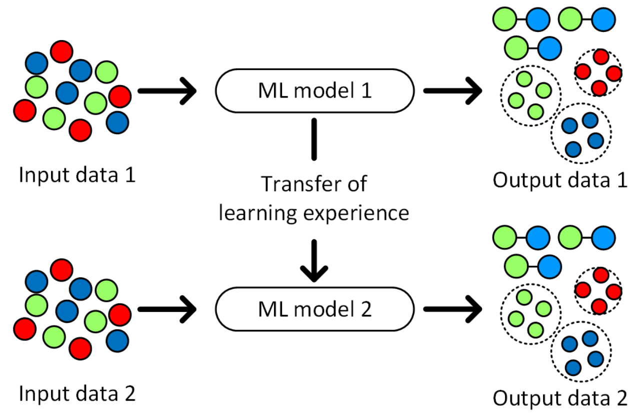

Fig. 10. Transfer learning

6) *Transfer learning:* Transfer learning takes the learning outcome(s) of one ML model (used in one application) and re-uses it/them for another similar application (Fig. 10) [26]. In particular, transfer learning allows for improving the learning of an ML algorithm by utilizing its own data in a given new domain and learning experience from a previous domain [27]. Such learning methodology is useful in a scenario where ML (supervised/unsupervised) training may suffer from training data shortage.

III. Data Collection and Processing in Smart Agriculture

For ML algorithm-based intelligent agricultural applications, data sources, and accumulation are of great importance. These data can be manually generated, collected from farmers, open access sources, journals/surveys, or collected from sensors, drones, or satellites. A number of features are extracted from these data to aid training and ultimately provide a satisfactory output. This section discusses data collection and processing for several smart agriculture research projects and applications. Fig. 11 demonstrates the flow chart of ML applications on the collected and processed data in the field of smart agriculture.

Samples such as soil, seeds, leaves, etc. can be collected from the study area of the field or from research laboratories. Traditional measurements and laboratory experiments are carried out to produce data sets for later use. Laboratory testing of seeds provides information on their health, composition, moisture content, and germination capacity. Biochemical methods or image-based methods (e.g. hyperspectral and multispectral, X-ray, CT scan, etc.) or both can be used to determine soil nutrient content, plant health, and crop yield. Farmers' declarations, surveys, and administrative databases are also

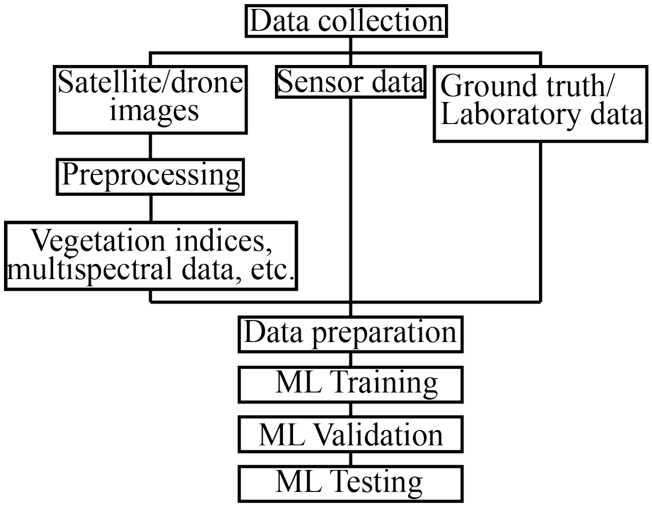

Fig. 11. Flow graph for ML applications in smart agriculture domain.

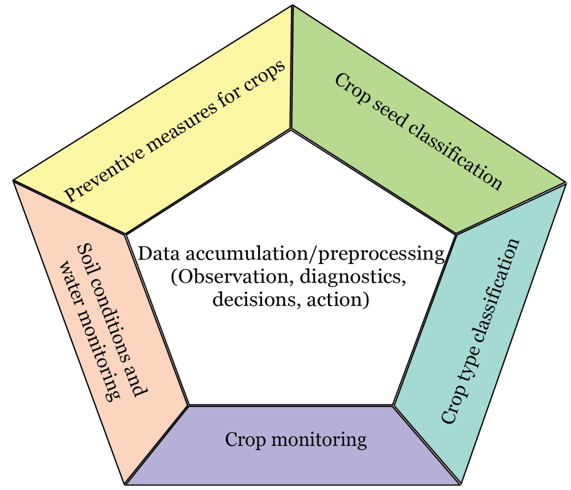

Fig. 12. ML applications in smart agriculture domain.

sources of agricultural data. For example, farmer validation is considered to develop crop type classification datasets [28]. Statistical data on climatic conditions, soil moisture, irrigation water source, and timing, and annual crop yield are available from several open-source databases, research articles, and surveys. [29], [30], [31], [32], [33], [34], [35], [36], [37]. Even images of pests and weeds are also available in these sources, which are utilized in training ML for respective applications [38], [39], [40], [41].

Smart IoT sensors are useful for collecting atmospheric temperature, humidity, sunlight intensity, soil temperature, and moisture content at a specific point in time. These sensors can be used in the agricultural sector for soil monitoring, irrigation status, crop health monitoring, disease identification, and pest control. The use of cameras with such sensors is also seen in the above applications. In [42], an intelligent energy-efficient crop monitoring system for greenhouse crops is being developed using light and camera sensors (which sense the light intensity and generate crop images), spectroradiometers, and intelligent control devices. For pest control applications, smart traps will be built in the study area of interest to capture images of the trapped pests and generate data sets [43], [44].

Sensors and cameras will also be installed on remotely operated vehicles, particularly aerial vehicles (UAVs/drones), to acquire thermal, hyperspectral/multispectral images and various vegetation indices. Identification of anomalous objects and dry parts of cultivated land is also a potential application of UAV-based monitoring systems [45], [46], [47]. The laboratory experimental data and the UAV sensor-based data can be combined for agricultural analysis using ML. For example, the mapping of seed composition data derived from laboratory experiments and various spectral features obtained from UAV image data will be studied to train the ML algorithm(s) [48]. A similar study can be done for crop yield estimation by combining nutrient content derived from laboratory experiments with data from hyperspectral imaging sensor(s) mounted on UAVs [49]. The accuracy analysis between ground truth data and UAV-based data helps to realize the scope of remote sensing-based data collection methods in smart agricultural fields [33], [50].

Satellite image-based approaches are being investigated by researchers for many agricultural applications, ranging from crop type classification to pest detection. Similar to UAV-based imagery methods, various vegetation indices, and other spectral information extraction are the motives for acquiring such satellite images. This information is also verified by human declarations or combined with in-field observations from UAVs, open source data, research articles, and surveys, [51], [28], [52], [53], [54], [55], [56], [30], [31]. Even multiple satellite data sets can be combined to generate usable images and extract the required information.

After combining this heterogeneous data from the multiple sources mentioned above, useful trainable datasets are prepared. The prepared datasets can also be divided into training, validation and test datasets. Using this training data, dedicated ML is trained. The effectiveness of the ML training is determined after validation and testing with the remaining datasets. In addition, new data sets can be provided to the trained ML-based architectures to determine the prediction accuracy. The application of ML-based approaches in intelligent agricultural applications (shown in Fig. 12) is discussed in later sections.

IV. Crop Seeds Classification

In this section, we discuss the classification of crop seeds on the basis of their vigor and varieties by applying ML algorithms for the sake of quality crop production. Table I provides a summary of ML-/DL-based seed classification methods.

In [57], the quality of peanut seed is attempted to be evaluated by assessing its characteristics, such as physical properties, pigments, and light reflectance. Quadratic Discriminant Analysis (QDA) is to classify the vigor of the seed lots. The protein level and oil composition in soybean and corn seeds are determined in [48] by analyzing hyperspectral and LiDAR data obtained from sensors incorporated in UAV. Gradient Boosting Machine (GBM) and Deep Neural Network (DNN) are used as data analyzers for seed quality assessment. Fourier Transform Near-Infrared (FT-NIR) spectroscopy and

TABLE I
ML ALGORITHMS FOR SEED QUALITY AND TYPE CLASSIFICATION.

Reference	Year	Research goal	Data for ML	ML tools	Research outcomes/Benefits
[57]	2022	Peanut seed quality evaluation in terms of seed vigor	Multispectral images	QDA	98% prediction accuracy is obtained by QDA with respect to laboratory experiment data.
[48]	2022	Soybean and corn seed nutrition value determination in terms of protein level and oil composition	UAV-hyperspectral images and LiDAR data (Lab experiments for validation of proposed method)	GBM and DNN	Better performance in terms of R^2, RMSE and relative RMSE is obtained compared to DRF, XRT, and GLM.
[58]	2020	Germination prediction and vigor determination of forage grass	FT-NIR spectroscopy and X-ray images	LDA, PLS-DA, RF, Naive Bayes (NB), and SVM with radial basis (SVM-r) kernel	LDA, PLS-DA, and RF showed higher germination and vigor determination accuracy compared to other ML models.
[59]	2021	Soybean seed classification on the basis of germination, stress tolerance, etc.	Autoflorescence-spectral images	ANN, SVM, and LDA	Compared to traditional laboratory tests, 99% seed quality classification accuracy is obtained by these ML models.
[60]	2021	Crambe seed quality determination based on internal tissue integrity, vigor, and germination	X-ray images	CNN-based deep learning (DL)	91 %, 95 %, and 82 % accuracy are achieved in terms of physical integrity, germination, and vigor classification respectively.
[61]	2020	Determination of viability and non-viability of pepper seeds	X-ray CT scanned images	PLS-DA, SVM, and KNN	PLS-DA provides better accuracy (88.7%) compared to other ML models.
[62]	2020	Determination of viability and non-viability of watermelon seeds	X-ray images	LDA, QDA, KNN and Deep Transfer Learning (DTL)	LDA provides 83.6% accuracy compared to traditional ML models, ResNet-50 provides 87.3% accuracy compared to other DL models.
[63]	2022	Identification and classification of crop seeds quality	Photonic sensor-captured images	Convolutional Neural Network (CNN) and VGG16, VGG19, InceptionV3, and ResNet50	98.31% accuracy is obtained with CNN and InceptionV3.
[64]	2020	Vigor, germination speed, and capacity of oilseed plant seed	X-ray images	LDA	Compared to traditional laboratory tests, 89.72%, 83.72%, and 94.36% accuracy in determining vigor, germination speed, and viability, respectively are achieved.
[65]	2020	Germination monitoring system experimented on tomato, pepper, Brassica, barley and maize seeds	Data and images generated by the proposed system	Deep learning (DL), Gaussian Mixture Model (GMM) and Stochastic Gradient Descent (SGD)	Proposed system is reported to be effective compared to the traditional method.
[66]	2020	Asian rice seed variety determination	Images of sample seeds	Logistic regression (LR), linear discrimination analysis (LDA), KNN, SVM, VGG16, VGG19, Xception, InceptionV3, and InceptionResNetV2	SVM and InceptionResNetV2 have displayed higher accuracy compared to other ML and DL models respectively.
[67]	2021	Maize seed variety determination	Images of sample seeds	Multilayer Perceptron (MLP), Decision Tree (DT), LDA, NB, SVM, KNN, and AdaBoost	SVM provides the highest overall classification accuracy (96.46%).
[68]	2021	Pumpkin seed variety determination	Images of sample seeds	LR, MLP, SVM and RF, and KNN	SVM provides the highest classification accuracy (88.64%).
[69]	2022	Wheat seed variety determination	Physical features from collected seed dataset	KNN, Classification and Regression Tree (CART), NB and ensemble machine learning	Ensemble ML provides highest accuracy (95%) compared to other ML models.
[70]	2020	Corn seed variety determination	Images of sample seeds	RF, BayesNet (BN), LogitBoost (LB), and MLP	MLP provides the highest accuracy (98.93%) compared to other ML models.

X-ray imaging techniques are studied in [58] for acquiring data to be processed by ML algorithms. Among the compared ML algorithms, LDA, Partial Least Squares Discriminant Analysis (PLS-DA), and Random Forest (RF) are reported to display high classification accuracy in classifying seeds of forage grass. In [59], autofluorescence-spectral imaging techniques and ML algorithms (Artificial Neural Network (ANN), SVM, or LDA) are combined to determine the quality of soybean seeds. Convolutional Neural Network (CNN)-based DL model is also used for seed classification in [60] by utilizing features obtained from X-ray images. In [61], [62], viability and non-viability of pepper seeds and watermelon seeds are considered as a classification problem, which is attempted to solve by means of ML algorithms by analyzing data from X-ray CT scan images. In [63], a laser backscattering, Deep Transfer Learning (DTL)-oriented photonic sensor is proposed to identify and classify the quality of crop seeds. InceptionV3 is shown to provide higher accurate results in classifying seed quality than other DTL methods, such as VGG16, VGG19, and ResNet50. Along with the seedling vigor, germination speed and capacity of the seed of an oilseed plant are studied in [64] with the help of X-ray images and LDA. In [65], a germination monitoring system of crop seeds, named "SeedGerm", is developed by using a cost-effective hardware system, open-source software, and ML-algorithm-based approaches. The monitoring capability of the system is applied to tomato, pepper, barley, and maize seeds. Correlation score greater than 0.98 is observed between the "SeedGerm" monitoring system and manual observation.

Apart from seed vigor and germination capability of seeds, ML algorithms are also used for seed variety classification. In [66], Asian rice variety classification by means of ML and DL-based algorithms is studied, which uses the physical characteristics of the seeds for classification. In [67], [68], similar studies are conducted on maize seed and pumpkin seed variety classification respectively by using traditional ML algorithms. In [69], an ensemble ML algorithm is used for wheat seed classification on the basis of their physical features. By analyzing statistical, spectral as well as geometrical information of the digital images of corn seeds, the ML-based classification approach for corn variety is studied in [70].

Brief Summary

Traditionally, seed quality and vigor assessments are usually carried out through laboratory tests and image inspections by humans, which are laborious, time-consuming, and error-prone. Therefore, automation by means of IoT devices and ML approaches (for analyzing the data generated by one/more types of IoT devices) eases the effort of seed classification. Several supervised ML, transfer, and ensemble learning models are studied for this operation. DL algorithms, according to some studies, are proven to be more successful in classifying seeds than ML algorithms.

V. Crop Type Classification

Classification of crop types helps to monitor agricultural productivity and ensure the availability of food and raw materials for goods produced in a given region. In addition, decisions about appropriate crops based on soil and climatic conditions depend on crop mapping. In this section, we discuss the role of ML in crop classification. We also summarise the discussions in the table II.

In [51], a hyperspectral imaging spectrometer-based image and ML and DL algorithms are used to classify and map crops such as soybean, hybrid maize, winter wheat, and sunflower over the cropped area. In [28], Sentinel-2-based time series data are used to train ML and DL algorithms for crop type classification. In [52], the time series EVI is determined from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data, and the Fused Representation-based Classification (FRC) algorithm is used for cotton pixel identification and cotton area mapping. The harmonic features of the annual time series EVI are obtained by applying the Fourier transform and later these features are provided as input to the FRC algorithm for classification of the area under cultivation. In [53], the ML algorithm uses the temporal variations within the tobacco crop and their correlation with other vegetation variations to provide better classification performance. The ML-based classifier uses the seasonal characteristics of winter wheat obtained from satellite data and a coarse-resolution map to update the ML label [54]. ML-based tools benefit not only farmers but also investors in agricultural finance. Crop identification and classification using ML tools and remote sensing technology can help them to be more efficient in providing loans for agricultural development [55].

Brief Summary

ML algorithms are explored to perform cropland identification and mapping by utilizing satellite imagery, to minimize the effort of physically conducted surveys and measurements. A decent correlation between statistical data and ML-based derived data is observed. Besides, DL algorithms both have shown high accuracy as well as geometric mean of the recall and precision scores in their respective studies.

VI. Crop Monitoring

In this section, we discuss the use of machine learning in monitoring the nutrients and chlorophyll content and yield prediction, with summaries provided in Table III and Table IV.

A. Crop health

The use of satellites to monitor the morphological characteristics of a crop is preferable because of the high-resolution images that can be obtained. Using the images acquired by drones and satellites and ML algorithms, a remote monitoring system of sugarcane fields is proposed in [56]. The vegetation indices are obtained from the satellite data and the Gaussian process regression model is used to predict the biochemical components of the crop. Due to cloud cover, the optical images produced by the satellites have a high probability of being affected. In this case, in [17], satellites such as Sentinel-1 and Sentinel-3 are used to generate images of winter wheat. These images are then used to train the proposed DL model to determine LAI and chlorophyll content. However, the satellites take days to revisit the desired fields. Therefore, drone-based monitoring is a promising solution in an emergency situation. In [19], drones are used to generate vegetation indices, and IoT sensors are used to provide information on environmental status to determine its impact. ML algorithms (such as SVM, NB) and DL algorithms will be used to determine whether crops are healthy, under stress, or unhealthy. For an energy-aware greenhouse cultivation methodology, an intelligent horticultural lighting and crop monitoring system will be developed in [42]. The effective light intensity is provided to the lettuce

TABLE II
ML ALGORITHMS FOR CROP TYPE CLASSIFICATION.

Reference	Year	Research goal	Data for ML	ML tools	Research outcomes/Benefits
[51]	2023	Classification of hybrid corn, soybean, sunflower, and winter wheat	Satellite hyperspectral imaging	2-D WA-CNN, RF and SVM	CNN-based prediction model provide better accuracy compared to the other models.
[28]	2022	Crop type classification and segmentation	Multicountry benchmark dataset created by leveraging satellite imagery and ground truth data	Deep learning (DL) models (such as U-Net, LSTM, CNN, etc.)	Effectiveness of the dataset with DL is shown by accuracy, F1 and precision scores evaluations.
[52]	2021	Identification of cotton cultivated area	Satellite data	FRC	Compared to statistical data, the proposed method can identify cotton fields with R^2 score of 0.83.
[53]	2020	Tobacco crop detection from satellite data	Ground survey for training and satellite data for testing	ANN	95.81% of overall accuracy is obtained with the help of ANN and NDVI stacking.
[54]	2022	Winter wheat mapping	Satellite data for ML training and testing, field and statistical data for validation	Proposed ALU-DL, SVM, RF, U-Net and others	Higher overall accuracy and F1 score are achieved with the proposed model.
[55]	2022	Sugarcane crop identification with the help of ML-based software tool	Satellite data and ground survey for ML training and testing	Random Forests (RF), KNN, SVM, Neural Networks (NN) and Gradient Boosting	Higher F1 score is achieved with RF and KNN algorithms.

TABLE III
ML FOR CROP HEALTH MONITORING

Reference	Year	Research goal	Data for ML	ML tools	Research outcomes/Benefits
[56]	2022	Remote monitoring of sugarcane crop	Satellite, drone, and laboratory data for ML training and testing	GPR	Compared to laboratory experiment data, GPR-based model accuracy is evaluated in terms of R^2 score and normalized RMSE.
[17]	2022	LAI and chlorophyll content determination of winter wheat	Satellite data	Proposed deep learning model (UMRCGM), Partial Least Squares Regression (PLSR), RF and XGBoost	Proposed model provides better performance than other models in terms of R^2 score and RMSE.
[19]	2020	Crop health classification	Multispectral data from drones and climate parameters from IoT sensors	DNN, SVM and NB	Higher accuracy (98.4%) is achieved with the DNN model.
[42]	2023	Design of energy-efficient crop monitoring system	Amount of light received by the plant and images for plant growth monitoring in greenhouse setup	Multi-linear regression model (for controlling supplemental light controller)	The chosen model provides low energy usage of 28% than other studied mechanisms.
[71]	2021	Chickpea stress level classification due to water deficiency	Images of plants in laboratory setup under different stress conditions	ConvLSTM	DL with temporal analysis provides better stress classification than that with time-invariant analysis.
[72]	2022	Tomato seedling stress detection due to water deficiency	Chlorophyll fluorescence parameters and images under laboratory setup	LDA, SVM and KNN	Higher recognition accuracy (of 87.1%) is achieved with SVM.

crop by a combination of sunlight and LED light (which acts as a supplement). The supplementary light controller is controlled by a multi-linear regression model, which has a simple learning architecture with respect to the DT and RF algorithms and provides fairly accurate results. Compared to the time-scheduling mechanism, about 28% reduction in energy consumption per unit dry mass of lettuce is observed by the proposed horticultural lighting and crop monitoring system.

Image-based phenotyping is an emerging approach for monitoring the biotic as well as the abiotic stress levels in crops. ML algorithms can be used to detect stress levels at an early stage by performing analysis on the images. In [71], a CNN-Long Short-Term Memory (CNN-LSTM) algorithm-based approach is used to classify stress levels in chickpea due to water deficiency. In [72], a stress detection methodology due to water deficiency is proposed, which uses chlorophyll fluorescence parameters and corresponding images of tomato seedlings. These data are utilized by the LDA, SVM, and KNN to predict the stress level. Moreover, the authors in a recent paper evaluate the effectiveness of machine learning for mushroom growth monitoring [73].

B. Crop yield prediction

Crop yield estimation plays an essential role in ensuring proper crop monitoring, irrigation, and food supply management. The implementation of ML algorithms by processing data available from sensors and remote devices has been proven effective in various academic research. The application of ML algorithms in predictive crop yield estimation is reported as follows.

A yield estimation architecture is designed in [74], where data such as vegetation indices and meteorological and annual crop yield-related data are provided as input to the ML-based model for training. SVM, KNN, and GPR are studied to evaluate their performance in yield estimation. In [29], climate, irrigation, and soil moisture information are used to predict tomato and potato yield at the end of a season. DL models such as LSTM and Gated Recurrent Units (GRU) and their variants are used in this study for yield prediction with the given information. It is found that the bidirectional LSTM (BiLSTM) (Fig. 13) outperforms other models. A Gaussian Process (GP) is used in [30] for yield estimation of maize, soybean, and wheat, mainly using soil moisture and canopy greenness-related information. In [31], spectral vegetation indices extracted from satellite images are used for alfalfa yield estimation. Ridge Least Absolute Shrinkage and Selection Operator (LASSO), GPR, RF Regression (RFR), Boosted Regression Trees (BRT), and SVR are studied for developing inversion models that would perform alfalfa yield estimation. In [75], Bayesian regularisation with back-propagation algorithm is used to predict cotton yield by analyzing cotton boll opening. In another study [76], features such as canopy cover and height, vegetation index, cotton boll size and quantity, and irrigation-related information are used by ML models such as ANN, SVR, and RFR for cotton yield estimation. These algorithms are compared to determine which ML algorithm gives the best result. In [49], an RF-based algorithm is used to predict winter wheat yield using LAI and leaf nitrogen content obtained from UAV images. Information related to climate, satellites, soil parameters, and other data can be obtained from Google Earth Engine (GEE) and used by ML algorithms for wheat yield estimation, which is done in [77].

The DNN and RF models are reported to perform better than other ML models such as CNN and LSTM. In [78], UAV imagery is used to acquire the Excess Green (ExG) color feature, which is used to predict maize yield. Linear and non-linear regression models are investigated to develop ML prediction models. In [32], an attempt is made to determine the optimal stage of soybean crop development for the acquisition of multispectral images to be used for crop yield estimation. The MLP algorithm is used as the ML model for soybean yield estimation. In [33], a comparative study between Multiple Linear Regression, Stepwise Multiple Regression (SMR), Generalised Linear Model (GLM), Generalised Boosted Model (GBM), Kernel-based Regularised Least Squares (KRLS), and RFR is carried out for predicting sugarcane yield based on the data obtained from UAV imagery. Oil palm yield estimation is performed in [79] by the ML algorithms such as RF, LASSO, Extreme Gradient Boosting (XGBoost), Recursive Partitioning and Regression Trees (RPART), and NN; by analyzing a historical dataset of oil palm plantations and corresponding vegetation indices obtained from satellite imagery. The LAI and the canopy diameter of the coffee plant, collected by the camera mounted on the UAV, are considered two crucial parameters to estimate the coffee yield with the help of

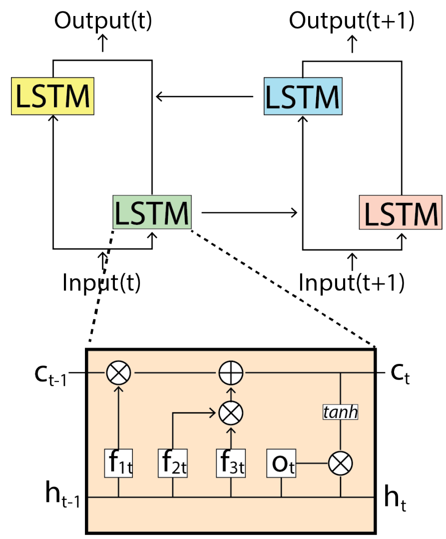

Fig. 13. Architecture of BiLSTM algorithm. Data sequences are transmitted in forward and backward order to the first layer and the second layer LSTM blocks respectively. Each LSTM block contains a forget gate (f_{1t}), an input gate (f_{2t}), a block gate (f_{3t}) and an output gate (o_t). The memory cell and the cell output at time t is denoted by c_t and h_t respectively.

SVM, GBR, RFR, PLSR, and Neuroevolution of Augmenting Topologies (NEAT) [50].

Brief Summary

Determining nutrients and chlorophyll content in crops by means of laboratory experiments is challenging at a large scale due to the requirements of many expert analysts, the use of chemicals, expensive equipment, and the time required for laboratory tests. Besides, manual on-field evaluation of crop yield is laborious and crop growth model, such as [80], requires a large volume of ground truth data for effective yield prediction. Therefore, supervised ML-based approaches in order to process data collected through satellites, drones, and IoT sensors have been considered for crop health monitoring and yield prediction. It has been found that DL models can analyze crop health more accurately than ML models. Furthermore, DNN and BiLSTM have shown better yield prediction performance than other ML-based algorithms.

VII. Soil conditions and water monitoring

With modern technology, farmers can monitor soil nutrient, water, and contaminant levels, monitor soil salinity and regulate irrigation water. Smart devices and ML algorithms can work together to initiate irrigation based on environmental and soil conditions, as well as plant water content. In addition, water quality assessment, efficient use of water, and classification of irrigation systems are also important concerns in the agricultural sector. In this section, we discuss the role of ML algorithms and IoT devices in monitoring soil conditions and developing intelligent irrigation infrastructure. We highlight the discussions in Table V and Table VI.

A. Soil conditions monitoring

A soil nutrient estimation algorithm is proposed in [81] using a bat (BA) algorithm-supported ML learning model. The

TABLE IV
ML FOR CROP YIELD ESTIMATION

Reference	Year	Research goal	Data for ML	ML tools	Research outcomes/Benefits
[74]	2021	Estimation of crop yield	Satellite, recorded meteorological and annual yield data	SVM, KNN, and GPR, RF, Gradient Boosting Decision Tree (GBDT), LASSO, SGD and MLP	SVM, KNN and GPR provide better R^2 and RMSE than other ML models.
[29]	2021	Tomato and potato yield prediction	Historical data such as climate, irrigation and soil moisture	LSTM, Bidirectional LSTM (BiLSTM), GRU and Bidirectional GRU (BiGRU)	BiLSTM provide better performance than other ML models in terms of R^2 score and MSE.
[30]	2020	Corn, soybean and wheat yield estimation	Satellite and recorded meteorological data	Least square linear regression, RF and Gaussian process (GP)	GP provide better performance than other ML models in terms of R^2 score, low Mean Error (ME) and RMSE.
[31]	2022	Alfalfa yield estimation	Satellite data and recorded crop yeild	Ridge, LASSO, GPR, RF Regression (RFR), BRT, and Support Vector Regression (SVR)	Improved RMSE performance is achieved with GPR.
[75]	2021	Cotton yield estimation	UAV-based RGB and multispectral images and field sampling data	Bayesian regularization Back Propagation (BP)	Proposed model provides better performance than linear regression model in terms of R^2 score and MSE.
[76]	2020	Cotton yield estimation	Temporal and non-temporal features and irrigation status from drone data for yield prediction (recorded yield data from research area for drone method validation)	ANN, SVR and RF regression (RFR)	Proposed model performs better than other ML models in terms of R^2 score and MSE.
[49]	2021	Winter wheat yield estimation	LAI and nitrogen content data from UAV imagery (field and laboratory experimental data for UAV method validation)	RF	Compared to field and experimental approach, proposed ML model provides MAPE of 9.36%.
[77]	2021	Wheat yield estimation	Climate, satellite, soil parameters, etc. from GEE	RF, DNN, CNN, and LSTM	The RF and DNN models provide relatively better performance in terms of R^2 and RMSE than other models.
[78]	2020	Maize yield prediction from Excess Green (ExG) color feature	UAV-RGB images of the cultivated land (ground truth data for ML training and UAV method validation)	Linear and non-linear regression based ML models	The studied models provide R^2 values lower than 0.5 and MAPE within 6.2-15.1%.
[32]	2020	Soybean crop yield estimation	Data from drone-based multispectral images of cultivation area for ML training and testing	MLP	The performance of the proposed methodology with MLP is reported in terms of Spearman correlations.
[33]	2020	Sugarcane yield estimation	UAV-LiDAR data of cultivated area	Multiple linear regression, SMR, GLM, generalized boosted model (GBM), KRLS, and RFR	RFR provides better performance than other ML models in terms of R^2 score and RMSE.
[79]	2022	Oil palm yield estimation	Satellite imagery (mapped with historical data)	RF, LASSO, XGBoost, RPART, and NN	NN and RF provide better performance in terms of R^2, Nash–Sutcliffe Efficiency (NSE), RMSE and Mean Absolute Error coefficient (MAE).
[50]	2021	Coffee yield estimation from LAI and crown diameter of coffee crop	UAV-imagery based data of cultivation land	SVM, gradient boosting regression (GBR), RFR, PLSR, and NEAT	NEAT algorithm provides better performance than other ML models in terms of MAPE.

BA algorithm optimizes the maximum number of iterations and the weight reduction coefficient of a weak learner in the learning model. Besides, compared to other optimization algorithms, it also helps in speeding up the convergence speed of the learning model. A soil contamination estimation strategy is proposed in [82]. Effective information for estimating the level of pollutants in the soil is extracted from the soil hyperspectrum. Later, Tabular Learning (TabNet) and CNN are used to develop regression models. To ensure effective water use for irrigation, an estimation of soil water content is proposed in [34]. ResNet and LSTM learning networks are jointly used to extract the spatial and time series characteristics from the meteorological and crop growth stage data. In [83], [84], satellite data are used and processed with ML algorithms for soil moisture estimation. In both studies, RF achieved the highest prediction accuracy compared to the other benchmark ML algorithms.

B. Water monitoring

A groundwater salinity map is considered in [35] for groundwater quality assessment. ML algorithms such as Stochastic Gradient Boosting (StoGB), Rotation Forest (RotFor), and Bayesian Generalised Linear Model (Bayesglm) are studied to compare their predictive performance in determining the salinity level in groundwater. A water quality assessment methodology is proposed in [36] to determine its usability

TABLE V
ML FOR SOIL MONITORING

Reference	Year	Research goal	Data for ML	ML tools	Research outcomes/Benefits
[81]	2022	Soil nutrient estimation	Hyperspectral data of the collected soil samples in laboratory setup	Bat Algorithm (BA)-AdaBoost model	Higher accuracy and reliability is achieved by the proposed model than AdaBoost without BA.
[82]	2022	Soil pollution estimation	Data from soil hyperspectrum	Attentive interpretable tabular learning (TabNet) and CNN	The proposed model is evaluated in terms of R^2, root-mean-square error (RMSE) and Ratio of Performance to Interquartile Range (RPIQ).
[34]	2020	Soil water content determination from meteorological and crop growth stage data	Meteorological data and field survey	Residual Network (ResNet) and Bi-directional LSTM-based algorithm (ResBiLSTM), SVR, random forest (RF), MLP and CNN-LSTM-based approaches	ResBiLSTM provides better performance in terms of MSE, MAE, root mean squared error (RMSE), MAPE and R^2 score.
[83]	2021	Soil moisture estimation	Satellite data and field survey	SVR, RF, and Gradient Boosting Regression Tree (GBRT)	RF provides better performance than other models in terms of R^2 score and RMSE.
[84]	2021			Linear regression, ridge regression, kernel ridge regression, SVR and RF	RF provides lower MSE with tested data compared to other models.

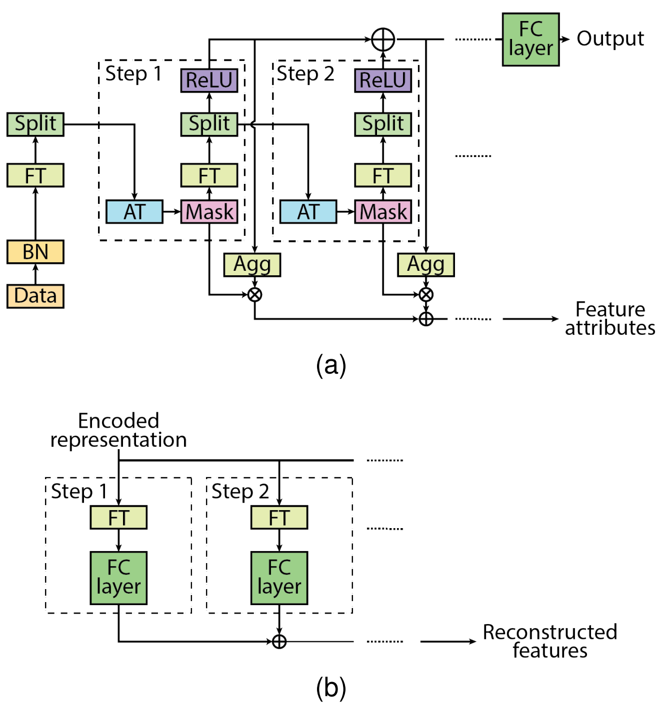

Fig. 14. Architecture of TabNet algorithm [(a) TabNet encoder (b) TabNet decoder].
Agg.: Aggregation. AT: Attentive Transformer (performing feature selection on the features obtained from split block, which divides data features into data to be utilized by AT and that to be utilized at the output). BN: Batch Normalization. FC: Fully Connected. FT: Feature Transformer (executing processing of data features). ReLU: Rectified Linear Unit.

for drinking and irrigation. ML algorithms such as RF, LR, and SVM are evaluated for water classification accuracy. In [85], a fused learning model, formed by random vector functional link network and group method of data handling model (RVFL-GMDH), is proposed to assess water quality for the aquaculture industry. Compared to ANN, SVM, RF, DT, and DenseNet, the proposed model has shown better prediction accuracy on the unseen dataset. Thus this model can also be explored in cropland irrigation application. In [37], supervised ML algorithms are used to classify different irrigation systems, such as drip irrigation, sprinkler irrigation, and flood irrigation. The proposed classifiers also identify whether an irrigation system is installed in the field. DL is shown to achieve the best classification accuracy. In [90], climate and irrigation-related parameters are used to predict the sap flow of crops using an ML algorithm-based approach. The prediction accuracy of several ML algorithms is studied and compared in the study. In [45], an intelligent selective irrigation system is proposed which identifies the dry parts of the cropland with the help of thermal images generated by the smart devices. The irrigation pattern is generated by an ML regression-based algorithm. To optimize the irrigation process, a methodology based on computer vision methods is proposed in [46]. The irrigation rate at the desired location of the crop field is determined by a trained NN. In [86] an irrigation water-saving scheme is proposed that uses temperature and humidity data to determine the rate of evapotranspiration with the help of ML algorithm. GNB, SVM, KNN, and ANN are studied to evaluate the prediction performance. In [87], improved versions of RVFL and RVM are implemented for evapotranspiration modeling. The influence of the artificial hummingbird algorithm (AHA) and the quantum-based avian navigation optimizer algorithm (QANA) on each of these algorithms are separately investigated. The study showed considerable improved performances by the hybrid prediction models compared to the base RVFL and RVM models. In [88], improvement of RVFL learning model by metaheuristic algorithms, such as particle swarm optimization (PSO), the genetic algorithm (GA), the grey wolf optimization (GWO), the salp swarm algorithm (SSA), the social spider optimization (SSO), and the hunger games search algorithm (HGS) are investigated for drought modeling. RVFL with HGS has shown better prediction results than the other RVFL models. In [89], two algorithms, namely Adaptive Neuro-Fuzzy Inference System (ANFIS (Fig. 15), developed from ANN and Fuzzy Inference System) and Seasons Optimisation-based ANFIS (SO-ANFIS) are implemented to predict the efficiency of water

TABLE VI
ML FOR WATER MONITORING

Reference	Year	Research goal	Data for ML	ML tools	Research Outcomes/Benefits
[35]	2020	Groundwater salinity mapping for water quality assessment	Electrical conductivity of water, collected from management company	StoGB, RotFor, and Bayesglm	StoGB provides better salinity prediction and the other algorithms provides higher Kappa values.
[36]	2022	Water quality assessment for drinkability and irrigation	Dataset collected from other studies	RF, LR, and SVM	LR and SVM provide better drinking and irrigation water quality assessment respectively.
[85]	2021	Determination of water quality	Images of water samples with labels	RVFL-GMDH, ANN, SVM, RF, DT and DenseNet	Higher prediction accuracy is achieved by the proposed model.
[37]	2022	Classification of irrigation systems	Satellite data and field survey of crop land	Residual Network (ResNET), Time series forest and Random Convolutional Kernel Transform (ROCKET)	ResNET provide best classification performance.
[45]	2023	Selective irrigation of dry part of the crop cultivation land	UAV-based thermal images	KNN, SVM, RF, and NN	RF model provides lowest MSE in predicting sprinkler parameters.
[46]	2022	Water usage optimization for irrigation on the basis of crop identification and growth stage	In-field computer monitoring system	Support Vector Machine (SVM), CNN, and Back Propagation Neural Network (BPNN)-based algorithms	BPNN and CNN with resilient propagation training accurately identify crop and growth stage and regulate irrigation accordingly.
[86]	2022	Irrigation water conservation scheme	Evapotranspiration estimation from in-field IoT sensors	Gaussian NB (GNB), SVM, k-Nearest Neighbours (KNN), and ANN	KNN provides better evapotranspiration prediction than the other ML algorithms
[87]	2023	Evapotranspiration modeling	Minimum and maximum climate temperatures and extraterrestrial ratiation	Hybrid models (RVFL-AHA, RVM-AHA, RVM-QANA, RVFL-QANA), base RVFL and base RVM	Considerable improved RMSE, MAE, R^2, and NSE scores are achieved with the proposed hybrid models
[88]	2021	Drought modeling in terms of standard precipitation index (SPI)	Collected monthly precipitation data	RVFL-PSO, RVFL-GA, RVFL-GWO, RVFL-SSO, RVFL-SSA, and RVFL-HGS	RVFL-HGS has shown better performance in terms of RMSE, MAE, R^2, and NSE scores than the other models.
[89]	2022	Water usage efficiency and yield determination	Field studies for climate, soil parameters, irrigation, fertilizers and yield data	ANFIS, SO-ANFIS, GPR, and RF	SO-ANFIS provides better water usage efficiency and yield predictions for Narrow Strip Irrigation (NSI) based cultivation system

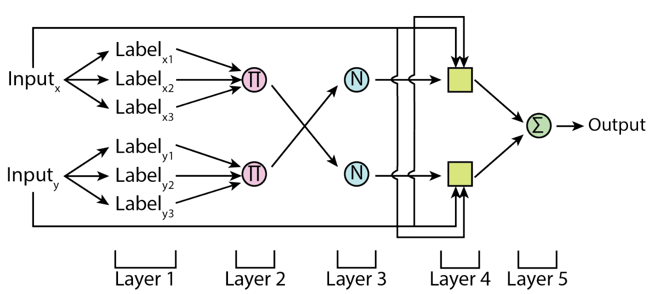

Fig. 15. Architecture of ANFIS, a five layered network-based algorithm. The first layer determines the level of dependence of each input data on different fuzzy domains. The second layer aims in obtaining the weight of the rules from the product of each node's input values. The third layer computes the importance of regulations through normalization of the weight of the rules. The fourth layer generates a rules layer by performing mathematical operations on the input data. The fifth layer generates the output of the network.

use during irrigation. Improved performance is achieved over state-of-the-art water use efficiency estimators.

Brief Summary

Algorithms such as BA-AdaBoost, TabNet, ResBiLSTM, and RF have shown improved performances for soil nutrients, pollution, and water content by analyzing different types of data such as hyperspectral, meteorological, satellite, UAV, and field data. Other than RF, StoGB, LR, SVM, ResNet, BPNN, CNN, RVFL, GMDH, KNN, and SO-ANFIS are proposed for use cases such as drinking and irrigation water quality assessment, irrigation system classification, identification of selective irrigation soil, and water usage efficiency. These proposed schemes not only aim at mitigating human effort but also at providing high prediction performances.

VIII. Preventive Measures for Crops

In this section, we discuss the preventive measures for crops with ML-based systems in terms of crop disease prediction, and detection of pests, and weeds with ML. We also highlight the discussions in Table VII-Table IX.

A. Crop Disease detection

Farmers' efforts to detect crop diseases can be facilitated with the help of smart IoT devices and ML-based disease detection systems. In [91], a real-time crop monitoring system is designed to analyze the data collected by IoT sensors. SVM and CNN-based algorithms are proposed to analyze the

TABLE VII
ML FOR CROP DISEASE DETECTION

Reference	Year	Research goal	Data for ML	ML tools	Research outcomes/Benefits
[91]	2021	Leaf disease identification	IoT sensors and cameras for cropland environmental data and images	Ensemble SVM, SVM, CNN, Naïve Bayes (NB)	The ENSVM and CNN-based approaches perform better in terms of recall, specificity, accuracy, and precision scores.
[92]	2020	Crop disease prediction	Cameras installed in crop land	CNN	The proposed CNN-based framework provides 99.24% detection accuracy.
[93]	2020	Disease detection in citrus plants and fruits	Images collected from a dataset [94]	Deep CNN, K-means clustering and simple NN classifier	The proposed deep CNN model provide better performance in terms of detection accuracy, amount of required training parameters and execution time.
[95]	2022	Tomato leaves disease detection	Images from NIR camera	CNN, SVM, MLP, TDNN and ANFIS	The CNN performs better than the other models in terms of Intersection Over Union (IOU) and Pixel Accuracy (PA).
[96]	2021	Rice blast prediction	Recorded weather data (such as, air and soil temperatures, mean relative humidity, and sunlight) and corresponding event of rice blast	MLP, SVM, RNN, and PNN	The PNN-based model performs better in terms of accuracy, precision, recall and F-measure scores than the other models.

TABLE VIII
ML FOR PEST DETECTION FOR CROPS

Reference	Year	Research goal	Data for ML	ML tools	Research Outcomes/Benefits
[43]	2021	Energy-efficient pest controlling system	Images from IoT sensors and camera in indoor setup	LeNet-5, VGG16 and MobileNetV2	VGG16 provide marginally better accuracy with recall, precision, and F-scores than the other two algorithms.
[44]	2020	Pest classification, localization, and severity determination	Dataset containing HD images (captured by a camera inside pest trap) and expert validations	Global activated Feature Pyramid Network (GaFPN) and Local activated Region Proposal Network (LaRPN)	GaFPN provides better Mean Average Precision (mAP) than the other two models, i.e., Faster R-CNN and FPN.
[38]	2021	Pest detection with fast computational speed	Images from smartphones, traps, search engines, and photo sharing platform (especially for dataset generation for ML training)	FasterRCNN, SSD, and RetinaNet for detection; VGG, ResNet, DenseNet, and MobileNet for feature extraction	FasterRCNN with MobileNet provides better accuracy and execution time than the other models.
[97]	2021	Determination of the severity of locust and damages caused by them	Satellite imagery for data input and ground data for validation	Proposed HMM and the Autoregressive Integrated Moving Average (ARIMA) model	HMM provides better overall accuracy and Kappa score than the ARIMA model.

TABLE IX
ML FOR WEED DETECTION IN CROP FIELDS

Reference	Year	Research goal	Data for ML	ML tools	Research outcomes/Benefits
[39]	2022	Mitigation of overlapping and occlusion of leaves and image illumination problem	Dataset collected from [98], [99]	Proposed model with Visual Graphics Group-16 (VGG-16), Residential Energy Services Network-50 (ResNet-50) and Inception-v3	The proposed model provides better accuracy, precision score, recall score, F1 score, false positive and negative scores with respect to state-of-the-art models.
[47]	2020	Quick detection of a visual object such as weed	Images from the online source	Proposed DTL with k-means++ algorithms	The proposed model provides better recall and precision score than the DTL with k-means clustering algorithm.
[40]	2019	Crop row detection as an aid for weed detection, sowing seeds, and harvesting	UAV-based RGB images	Proposed CNN-based algorithm	The proposed model provides higher recall, precision, F-score and IoU than other state-of-the-art models.
[41]	2019	Weed species classification	Images from a developed database, reported in [100]	DNN powered by Field Programmable Gate Array (FPGA)	Proposed scheme reduces power consumption by 7 times and computes 2.86 times faster than DNN with GPU.

collected data for leaf disease identification. In [92], a cyber-physical system (CPS) for crop monitoring is designed where crop images are analyzed using CNN to predict disease(s). The proposed system is also evaluated for tracking of irrigation along with crop disease prediction. In [93], disease detection in citrus plants and fruits is performed using a three-module learning architecture. The ML architecture includes deep CNN, K-means clustering, and a simple NN classifier. In [95], IoT and ML-based intelligent agricultural systems are developed, where a sensor records environmental data and

TABLE X
ADVANTAGES, LIMITATIONS AND EFFECTIVE USE CASE OF ML ALGORITHMS IN SMART AGRICULTURE.

Algorithms	**Advantage(s)**	**Limitation(s)**	**Effective use case(s)**
ANFIS	• Quick learning capabilities and identifying non-linear input-output relationship. • Low memorization errors	• Requires expert knowledge in designing algorithm for new data • Requires large datasets for effective performance [101]. • Curse of dimensionality	Water monitoring
BiLSTM	• Predicts future data on the basis of time-series data. • Learns forward and backward features from the given data	Consumes high training time [102].	Crop yield estimation
CNN	Identifies data features automatically [103]	• Requires large datasets for effective performance. • Prone to overfitting. • Extensively computationally demanding.	Seed monitoring, crop type classification, crop disease detection, weed detection.
DTL	• Saves training time due to the ability of data feature transfer • Address training issue with small data	Negative transfer can cause low accuracy if the source and target learners are not well related [104].	Weed detection
Ensemble Learning	• Effective performance with large or lack of data by combining multiple weak learners to create a strong learner • Better performance and enhanced precision over individual learners • Minimize the likelihood of overfitting and underfitting.	• Ensembling is not easily interpretable, making it difficult to anticipate and explain the output of the combined model[105]. • Combining multiple models into one is costly in terms of both time and memory usage. .	Seed monitoring.
FPN	• Inherits the advantages of DL algorithms. • Able to identify small objects.	Requires large datasets for effective performance	Pest detection.
GP	• Easy to define signal and noise ratio in kernel function. • Address black box issue in other ML algorithms.	Sensitive to high data ranges, causing potential inaccuracy with test data	Crop health monitoring, crop yield estimation.
KNN	Allows addition of new data without affecting the model accuracy	Consumes high execution time [106].	Water monitoring
MobileNet	• Optimizes CNN-based classifiers without compromizing accuracy for mobile device compatibility. • Fewer parameters compared to other CNN models, low-latency, low-power models	• Requires large datasets for effective performance. • Less accurate than larger CNNs. • Requires larger training time.	Pest detection
PNN	• Higher classification accuracy than that of NNs. • Relatively insensitive to outliers. • Faster than NNs.	• Slow execution time • Requires high memory space [107]	Crop disease detection
ResNet	• Improved accuracy over traditional DNNs. • Faster convergence. • Can be used for Transfer learning. • Identifies data features automatically.	• Requires large datasets for effective performance. • Prone to overfitting. • Higher complexity than conventional DNNs	Water monitoring
RF	Has the advantages of ensemble methods with a high tolerance for data faults. Address collinearity and overfitting issues	Feature extraction depends on human judgement, leading to potential inaccuracy [108]	Soil monitoring
RVFL	Less training time than iterative tuning-based ML algorithms	Manual assignment of parameters is required.	Water monitoring
TabNet	Same as other DL models and is effective in handling tabular data		Soil monitoring
UMRCGM		Large datasets for effective performance, large training time	Crop health monitoring
VGG-16	Identifies data features automatically		Weed detection

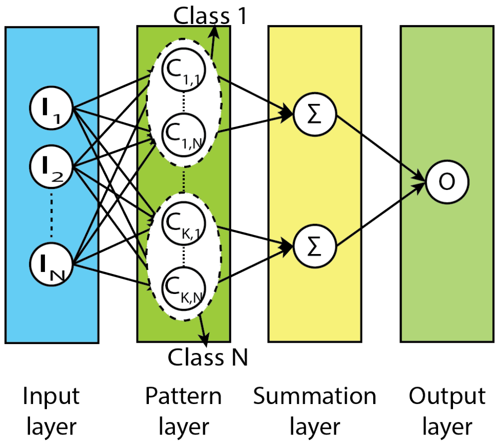

Fig. 16. Architecture of PNN (4-layered network) algorithm. Pattern layer computes a vector from the Euclidean distance between training data (found in the input layer) and radial center in a defined class. The summation layer contains the added result of each class. In the end, the output layer contains the weighted sum of the results determined in the summation layer.

soil moisture, and an ML algorithm such as CNN is used to identify diseases in foliage plants. To improve the rice blast occurrence prediction performance of the ML model by considering soil temperature as a factor along with the other environmental parameters such as air temperature, sunlight and relative humidity, a probabilistic neural network (PNN)-based prediction model is proposed in [96]. The proposed model has shown higher prediction performance than MLP, SVM and RNN models.

B. Pest control for crops

ML algorithms must be designed to identify anomalous objects so that detection devices can perform the necessary operations using these approaches. In [43], a pest control system using energy-efficient devices is proposed. Compatible CNN-based algorithms are proposed to perform the detection and classification of foreign objects. Although VGG16 provides better accuracy, recall, precision, and F-score performance than LeNet-5 and MobileNetV2, low energy is consumed by the LeNet-5-based pest control system. In [44], a two-stage DL algorithm is proposed for pest classification and severity determination. The first stage algorithm extracts the features of the pest, and the second stage determines the location of the pest. Several CNN-based ML algorithms are analyzed in [38] not only in terms of pest detection accuracy but also in terms of computational speed. In [97], the Hidden Markov Model (HMM) is used to analyze time series data (obtained from satellites) to determine the severity of pests such as locusts and to estimate the damage caused by such pests.

C. Weed management

DL has received much attention in weed detection from camera sensor-generated images due to the ability of such algorithms to learn image features. Taking this advantage into account, a CNN-based learning model is developed in [39]. A three-CNN feature extractor architecture is implemented to address issues such as overlapping and occluding foliage and the image illumination problem. In [47], a DTL is implemented for fast detection of visual objects, which would reduce the computational load. Also, an improved version of k-means clustering is proposed to increase clustering performance. In [40], the detection of crop rows is considered a measure to guide autonomous agricultural machines for operations such as weed detection, seeding, and harvesting. Row detection in agricultural fields is performed using CNN and Hough transform. DNN networks, usually trained on a graphics processing unit (GPU), can provide the desired performance at the cost of high power consumption. Therefore, a DNN network powered by a Field Programmable Gate Array (FPGA) is studied in [41] and compared with the DNN powered by GPU. The study shows that the FPGA-driven DNN is more energy efficient than the GPU-driven DNN, which can motivate the designers to design an energy-efficient robotic weed management system.

Brief Summary

Several ML learning models are explored for disease and pest detections for crops as well as weed detection by analyzing data collected from surveys, satellites and IoT devices, to shift the dimension of these use cases from traditional labor-based approaches to automation-based approaches. DL-based schemes have outperformed other supervised and unsupervised learning-based schemes in a study for crop disease prediction. Evaluation of several DL learning models is also conducted for pest and weed detection-related studies to determine the best DL models for respective applications. Table X highlights the advantages, limitations of the ML algorithms and their effective usage in smart agriculture.

IX. CHALLENGES IN THE DEPLOYMENT OF SMART AGRICULTURAL SYSTEMS

Smart devices, communication protocols, and ML algorithms have promising applications in agriculture, as can be seen from the above discussions. However, the practical implementation of smart agricultural systems raises several issues. We discuss such issues/challenges in this section.

a) Affordability and durability of smart IoT sensors and equipment: Farmers have to take out loans to buy fertilizer, tractors, etc. to run their farms. The cost of smart IoT sensors will be an additional burden for them: the availability, import, and quality of these sensors determine their market price, which can be very high. Therefore, high initial and operational costs will discourage farmers from installing these sensors in their fields. The operational life of these sensors is another major concern. Battery-powered sensors with low-power backup raise reliability issues due to the hindrance of continuous data generation. A battery charging/replacement planning strategy needs to be developed to address this issue. Special care must be taken when installing sensors to protect them from extreme weather conditions.

b) Data accumulation: As stated in Subsection II-B, multiple IoT sensors, UAVs/UGVs, and satellites can be integrated into a smart agriculture architecture, generating heterogeneous data. The accumulation and processing of these large amounts of data require a huge effort to obtain useful information to accelerate agricultural production tasks. Even the use of ML algorithms can be inefficient in terms of accuracy and computational resources. Therefore, it is crucial to design ML algorithms in such a way that satisfactory accuracy is achieved in less time and the computational burden is minimized.

c) Universality of ML: Another issue with ML-based smart agriculture applications is their universality. A smart agriculture tool developed with ML for a specific application in one region may prove to be effective. However, it is not guaranteed to provide accurate information when applied in another region. The reason for this is that environmental conditions and the characteristics of farmland vary from one region to another. Therefore, it will be difficult to construct statistical information for designing effective ML algorithms. This raises the issue of the scalability of the ML smart agriculture architecture.

d) Lack of farmers' education/training: Education/training is essential for farmers to use smart technologies for agricultural applications. However, in developing countries, most agricultural activities are carried out by farmers without formal education or training. It is therefore difficult for them to learn about new and emerging technologies and apply them to improve their agricultural production. The operation of devices such as smartphones, UAVs/drones, smartphone applications, etc. requires skilled manpower. Farmers will not be able to operate these devices or use the information they receive, or both, if they are not properly trained. Collaborative efforts between government and private organizations can ensure effective training of farmers to adopt smart agricultural innovations and increase their productivity.

e) Lack of synchronization among the farmers and the researchers: The success of ML-based intelligent agricultural models depends on the accuracy of their formulation of agricultural problems as decision models. This is possible if the ML model developers are aware of the problems that occur in agricultural production processes. However, it is generally not possible for them to learn about such problems themselves. Therefore, in order to build effective ML model(s) for intelligent agricultural application(s), it is important to include information collected from farmers and professionals in agricultural fields together with information from other sources (sensors, satellites, etc.). The synchronization between farmers, professionals, and ML model developers can ensure an effective architectural model construction of ML-based smart agriculture.

f) Effective network connectivity: Farmland is mostly located in rural areas where network access is limited. This limits the use of intelligent agricultural systems, as these systems use network connections to transmit information. Data such as atmospheric temperature, moisture levels, nutrient levels in crops and soil, high-quality leaves, images of crops and farmland, etc. need to be transmitted quickly and reliably, which requires uninterrupted network connectivity at high data rates. As mentioned in Section II-A, it is necessary to use communication technologies that offer high network coverage and data rates with low power consumption and implementation costs.

g) Data privacy and security: While developing ML models for predictive operations in agriculture-related operations, data privacy and security must be considered as one of the major concerns. The heterogeneity of various agricultural production-related data creates challenges in maintaining privacy, especially when the data contains any information related to farmers [2]. ML algorithms such as federated learning (FL) can be implemented in such a scenario as they allow the sharing of ML parameters without sharing the real data [10]. Another issue is the security of the overall smart agricultural system architecture against various cyber threats. ML algorithms have been explored to discover their potential to detect any intrusion from unwanted devices. Therefore, research interest in the use of such learning models in smart agriculture is no exception.

X. Conclusion

The agricultural sector is about to be revolutionized by the introduction of new communication, device, and computing technologies. Various smart IoT sensors, UAVs, and satellites are being used to monitor land management and agricultural production processes. These heterogeneous data generated from different sources require proper management for efficient agricultural operations. ML algorithm-based approaches are discovered as promising measures to interpret the required information from a large amount of data generated by the aforementioned sources. Therefore, the implementation of ML models in intelligent agricultural applications is of massive research interest.

First, we discuss the evolution of the agricultural industry. We present research trends in ML algorithm-based intelligent agricultural systems over several years. Later, we describe the enablers for future smart agricultural systems and elaborate on the collection of agricultural data from different sources and their processing. We also discuss recent studies on ML algorithms for different agricultural use cases and their results. Several issues may arise in the deployment of ML-based approaches in large-scale agricultural applications, which we highlight at the end. Based on the discussions, we realize the following future research possibilities. To address the issue of ML universality, appropriate determination of environmental and farmland characteristics of the cultivable region is required to determine, which will be utilized by the ML algorithms. DL-based approaches are advantageous in this case due to their capability of learning features from such data. However, some DL algorithms consume high memory during computation time, which limits their implementation. Therefore, compatible DL algorithms are required to be designed for running on devices with limited computation and memory resources. Furthermore, prediction models based on algorithm such as RVFL have shown better performance than some ML algorithms in water monitoring applications, which opens the door for exploring the compatibility of such algorithms in other agricultural application. In general, ML algorithms are accelerated by GPUs, which typically consumes high electrical power and consequently is challenging for the deployement of GPU-powered ML based portable and resource-constrained AIoT systems. Therefore, the implementation of ML algorithms on energy-efficient and fast computing-supported neural accelerators (e.g. FGPA) for such systems is another research direction. To end with, the aim of this review is to provide an overview of current research practices and potential research areas in the field of agriculture.

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