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"MACHINE LEARNING FOR PRECISE CROP MANAGEMENT IN AGRICULTURE: A REVIEW"

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Abstract: Machine learning has emerged in conjunction with high-performance computing and big data technologies to open up new avenues for data-intensive science in the multidisciplinary agri-technologies domain. In this paper, we present a comprehensive review of research on machine learning applications in agricultural crop production management systems. The works analyzed on crop production management systems were categorized into (a) yield prediction (b) disease detection (c) weed detection (e) species recognition, and (f) crop quality. The filtering and classification of the presented articles demonstrate how machine learning technologies will benefit the crop production management system of agriculture. Farm management systems are evolving into real-time artificial intelligence-enabled programs that provide rich recommendations and insights for farmer decision support and action by applying machine learning to sensor data.

Index Terms **- Yield prediction, disease detection, weed detection, crop quality, and species recognition**

I. Introduction

Agriculture is crucial to the global economy. With the continued expansion of the human population, pressure on the agricultural system will increase. Agri-technology and precision farming, also known as digital agriculture, have emerged as new scientific fields that use data-intensive approaches to boost agricultural productivity while reducing environmental impact. Modern agricultural operations generate data from a variety of sensors, allowing for a better understanding of the operational environment (an interaction of dynamic crop, disease, weed, and quality conditions) and the operation itself (machinery data), resulting in more accurate and faster decision making.

Machine learning (ML) has emerged alongside high-performance computing and big data technologies to open up new avenues for unraveling, quantifying, and comprehending data-intensive processes in agricultural operational environments. ML is defined, among other things, as the scientific field that allows machines to learn without being strictly programmed (Samuel, 2000). ML is being used in an increasing number of scientific fields, including agriculture, bioinformatics, biochemistry, medicine, meteorology, robotics, aquaculture, food security, and climatology. The adoption of Information and Communication Technology (ICT), which is promoted by policymakers all over the world, is unquestionably a necessary prerequisite for modern agriculture.

In this paper, we present a comprehensive review of the use of machine learning in the crop production management system of agriculture. A number of relevant papers are presented, emphasizing key and distinguishing characteristics of popular ML models. Below are listed abbreviations used in related scientific works due to the large number of them. the abbreviations used in this work are classified as ML models and algorithms, statistical measures, and general abbreviations, respectively.

The remainder of this paper is organized as follows. The second section briefly describes the fundamentals and overview of ML. The third section includes the related work on the subject of the five generic categories for a better understanding of the scope of the current study. The fourth section examines the methodology used, as well as the inclusive criteria and search engines. This section also includes the main performance metrics that were used in the selected articles. The main results are shown in the fifth section in the form of bar and pie charts, while the main conclusions are drawn in the sixth section by also discussing the results from a broader perspective. Finally, all of the selected journal papers are summarized in Tables A1–A5 based on their field of application and presented in Appendix A, along with Tables A6 and A7 containing commonly used abbreviations, to avoid disrupting the flow of the main text.

AN OVERVIEW OF MACHINE LEARNING

Machine learning: Terminology and Definition

ML methodologies typically involve a learning process with the goal of learning to perform a task from "experience" (training data). In machine learning, data is made up of examples. Individual examples are typically described by a set of attributes, also known as features or variables. Nominal (enumeration), ordinal (e.g., A+ or B-), binary (i.e., 0 or 1), or numeric features are all possible (integer, real number, etc.). A performance metric that improves with experience is used to assess the ML model's performance in a specific task. Various statistical and mathematical models are used to calculate the performance of ML models and algorithms. The trained model can then be used to classify, predict, or cluster new examples (testing data) based on the experience gained during the training process. Figure 1 depicts a typical machine learning approach.

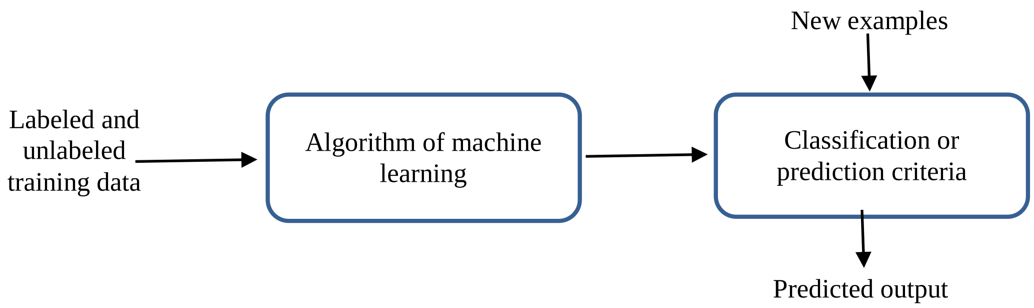

Figure 1. A typical machine learning approach

ML tasks are typically classified into broad categories based on,

(1) The type of learning (supervised/unsupervised),
(2) Learning models (classification, regression, clustering, and dimensionality reduction), or
(3) Learning models used to implement the selected task.

Task and Analysis of Machine Learning

ML tasks are divided into two categories based on the learning signal of the learning system: supervised learning and unsupervised learning.

(1) Supervised learning: The data is presented with example inputs and outputs, and the goal is to build a general rule that maps inputs to outputs. In some cases, inputs may only be partially available, with some target outputs missing or provided only as feedback to actions in a dynamic environment (reinforcement learning). The acquired expertise (trained model) is used in the supervised setting to predict the missing outputs (labels) for the test data.
(2) Unsupervised learning: There is no distinction between training and test sets, and the data is unlabelled. The learner processes input data in order to discover hidden patterns.

Dimensionality reduction (DR) is a type of analysis used in both supervised and unsupervised learning families to provide a more compact, lower-dimensional representation of a dataset in order to preserve as much information as possible from the original data. To avoid the effects of dimensionality, it is usually performed prior to applying a classification or regression model. The following are some of the most common DR algorithms: Principal Component Analysis (Pearson, 1901), Partial Least Squares Regression (Wold, 1985), and Linear Discriminant Analysis (Fisher, 1936).

II. REVIEW

On a first level, the reviewed articles on the crop applications of ML were classified into four generic categories: (a) yield prediction (b) disease detection (c) weed detection (e) crop quality, and (f) species recognition.

The search engines such as Google Scholar, Shodhganga, ScienceDirect, and Krishikosh were used. The chosen articles are based solely on works presented in journal research papers, articles, and review papers. Climate prediction, despite its importance for agricultural production, has not been included in the presented review, owing to the fact that ML applications for climate prediction are a separate field in and of themselves. Finally, all of the articles presented here cover the time period from 2000 to the present.

Crop management encompasses a wide range of aspects derived from the combination of farming techniques aimed at managing the biological, chemical, and physical crop environments in order to achieve both quantitative and qualitative goals (Yvos et al, 2020). Using advanced crop management techniques, such as yield prediction, disease detection, weed detection, crop recognition, and crop quality, contributes to increased productivity and, as a result, financial income. Precision agriculture's key goals are as follows.

2.1 Yield Prediction

In general, one of the most important and difficult topics in modern agriculture is yield prediction. An accurate model can assist farm owners in making informed management decisions about what to grow in order to match the crop to the current market's demands (Van et al. 2020). However, this is not a simple task, it entails several steps. Several factors, including environment, management practices, crop genotypic and phenotypic characteristics, and their interactions, can influence yield prediction. As a result, a fundamental understanding of the relationship between these interactive factors and yield is required. In turn, identifying such relationships necessitates large datasets as well as powerful algorithms such as ML techniques (Khaki and Wang, 2019).

2.2 Disease Detection

Crop diseases are a significant threat to agricultural production systems, reducing yield quality and quantity at the production, storage, and transportation levels. Reports of yield losses caused by plant diseases are common at the farm level (Harvey et al, 2014). Crop diseases are also a major threat to global food security. Identification of plant diseases at the right time is critical for effective management. Bacteria, fungi, pests, viruses, and other agents can all cause plant diseases. Wilting and color change, leaf and fruit spots, leaf curling, and other disease symptoms include physical evidence of pathogen presence and changes in plant phenotype (Jim isleib, 2012). Historically, disease detection was carried out by expert agronomists through field scouting. This process, however, is time-consuming and solely based on visual inspection. Recent technological advances have resulted in commercially available sensing systems that can detect diseased plants before symptoms appear. A large dataset of both healthy and diseased plant images is required for accurate image classifiers for disease diagnosis. In the case of large-scale cultivations, such automated processes can be combined with autonomous vehicles to detect phytopathological problems in real-time through regular inspections. Furthermore, maps of the plant disease's spatial distribution can be created, depicting the zones in the farm where the infection has spread. Furthermore, computer vision has made remarkable progress in recent years, particularly through the use of deep learning.

2.3 Weed Detection

Weeds typically grow and spread invasively over large areas of the field very quickly as a result of their prolific seed production and longevity, competing with crops for resources such as space, sunlight, nutrients, and water availability. Furthermore, weeds frequently emerge earlier than crops without having to contend with natural enemies, which has a negative impact on crop growth (Su et al, 2020). Weed control, either mechanical treatment or herbicide application, is an important management task to prevent crop yield reduction. Mechanical treatment is often difficult to perform and ineffective if not done correctly, so herbicide application is the most commonly used operation. Using large quantities of herbicides, on the other hand, proves to be both costly and harmful to the environment, particularly when a uniform application is made without regard for the spatial distribution of the weeds. Surprisingly, long-term herbicide use is very likely to make weeds more resistant, resulting in more difficult and costlier weed control. In recent years, significant progress has been made in the differentiation of weeds from crops on the basis of smart agriculture, with herbicide application becoming the most widely used operation.

2.4 Species Recognition

Crop recognition has gotten a lot of attention in a variety of scientific fields, including plant taxonomy, botanical gardens, and the discovery of new species. Plant species can be identified and classified through the examination of various organs such as leaves, stems, fruits, flowers, roots, and seeds (Bonnet et al, 2016; Seeland et al, 2017). The most common method appears to be leaf-based plant recognition, which involves examining specific leaf characteristics such as color, shape, and texture (Zhang et al, 2020). With the increased use of satellites and aerial vehicles for sensing crop properties, crop classification via remote sensing has grown in popularity.

2.5 Crop Quality

Crop quality has a significant impact on the market and is generally related to soil and climate conditions, cultivation practices, and crop characteristics, to name a few. High-quality agricultural products are typically sold at higher prices, providing farmers with higher earnings. For example, in terms of fruit quality, flesh firmness, soluble solids content, and skin colour are among the most commonly used maturity indices for harvesting (Papageorgiou et al, 2020). Harvesting timing has a significant impact on the quality characteristics of harvested products in both high-value crops and arable crops. As a result, developing decision support systems can assist farmers in making appropriate management decisions for increased production quality. Selective harvesting, for example, is a management practice that can significantly improve quality. Furthermore, crop quality is closely related to food waste, which is an additional challenge that modern agriculture must overcome, because if the crop deviates from the desired shape, colour, or size, it may be discarded. Similarly, to the preceding section, ML algorithms combined with imaging technologies can yield promising results.

III. METHODOLOGY

3.1 Screening of The Relative Review of Literature

The search engines Google Scholar, ScienceDirect, Krishikosh, Shodhganga, and Web of Science were used to find relevant studies concerning ML in various aspects of agricultural management. Furthermore, keyword combinations of "machine learning" with each of the following: "crop management," "yield prediction," "disease detection," “weed detection”, “species recognition”, and “crop quality” were used. Our goal was to filter the literature using the same framework as, but only for the period 2015–2020. Once a relevant study was identified, the references of the paper in question were scanned to find studies that had not been discovered during the initial search procedure. This process was repeated until no relevant studies were found. Only journal papers were considered eligible at this stage. Non-English studies, conference papers, chapters, reviews, and Master's and Doctoral Theses were thus excluded. Following a discussion about the appropriateness of the selected papers, some were excluded if they did not meet the two main inclusion criteria, namely: (a) the paper was published between 2015- 2020, and (b) the paper referred to one of the categories and subcategories of field. In total, 510 journal papers were found. Figure 3 depicts the flowchart of the current review methodology, which is based on the PRISMA guidelines, as well as information about when each exclusive criterion was imposed, similar to recent systematic review studies such as [Akhigabe et al, 2021; Labarriere et al, 2020; Mostafa et al, 2019).

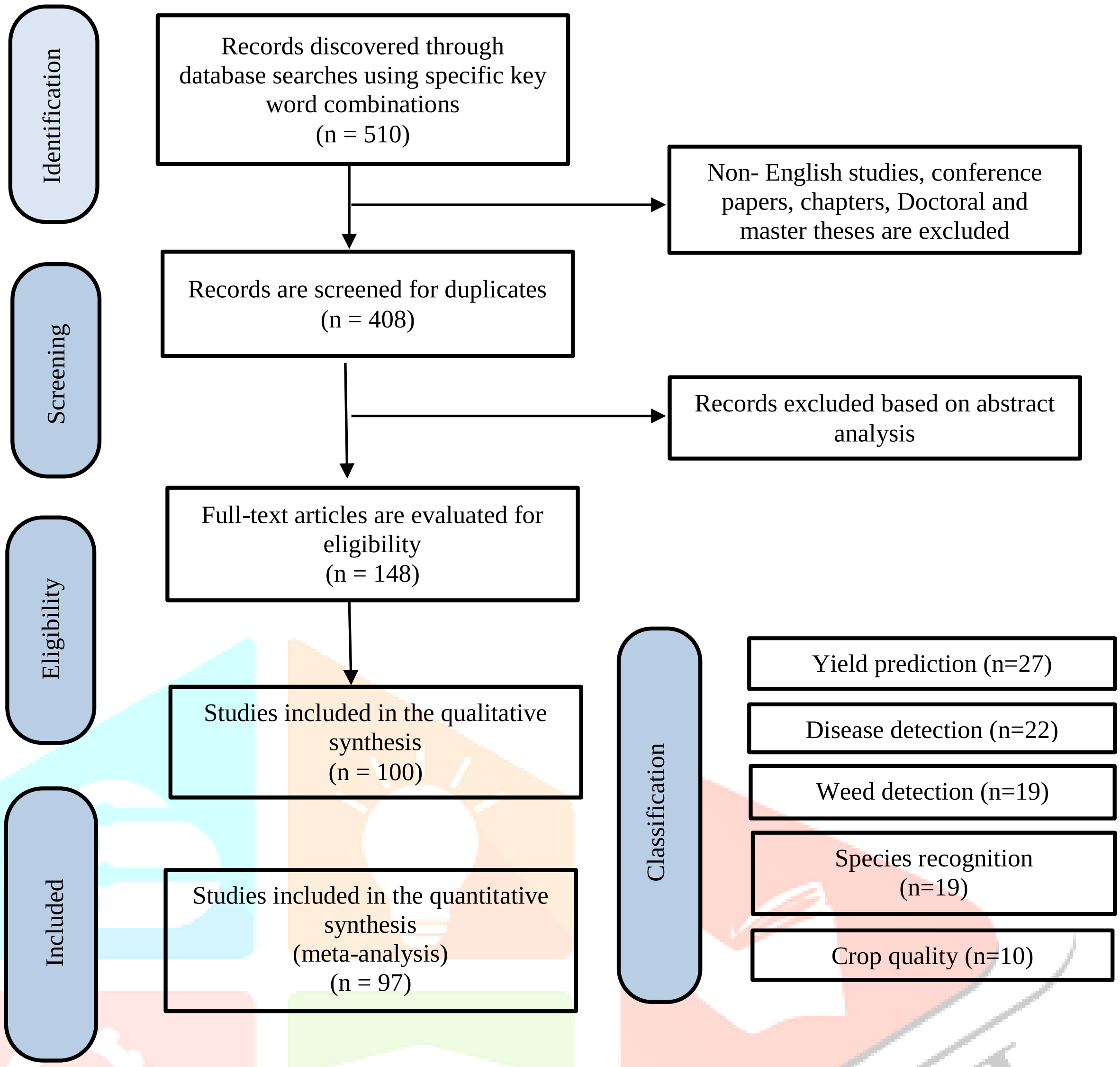

Figure 2: The methodology of the current systematic review, as well as the flow of information regarding the exclusive criteria, according to PRISMA guidelines

3.2 Definition of the Performance Metrics Commonly Used in the Reviewed Studies

In general, these metrics are used to provide a common metric for evaluating ML algorithms. The selection of appropriate metrics is critical because: (a) how the algorithm's performance is measured is dependent on these metrics, and (b) the metric itself can influence how the significance of several characteristics is weighted.

The confusion matrix is one of the most intuitive metrics for determining the correctness of a model. It is used to solve classification problems with at least two types of classes. Consider a simple example in which a target variable is labeled "1" when a plant is infected with a weed and "0" otherwise. In this simplified case, the confusion matrix (Figure 3) is a two-dimensional table with two dimensions, "Actual" and "Predicted," and its dimensions contain the results of the comparison between the predictions and the actual class label. In the simplified example above, this result can have the following values:

1. True Positive (TP): The plant has a weed infestation (1), and the model categorizes this case as weed infected (1).
2. True Negative (TN): The plant is weed infestation-free (0), and the model classifies this case as healthy (0).
3. False Positive (FP): Although the plant does not have a weed infestation, the model classifies this case as weed-infested (1).
4. False Negative (FN): Although the plant has a weed infestation (1), the model classifies it as a weed-free plant (0).

Predicted \ Actual	**1**	**0**
1	**TP**	**FP**
0	**FN**	**TN**

Figure 3: Representative illustration of a simplified confusion matrix

Table 1. List of the tables appearing in the Appendix A related to: (a) the categories of the machine learning applications in agriculture (Tables A1–A5) and (b) the abbreviations of machine learning models and algorithms (Tables A6 and A7, respectively).

Table	Content
A1	Yield prediction
A2	Disease detection
A3	Weed detection
A4	Species recognition
A5	Crop quality
A6	Abbreviations of machine learning models/algorithms
A7	Abbreviations of Statistical measures and general words

IV. RESULT

4.1 Classification of The Studies Based on The Application Domain

Graphical representation of data related to the reviewed studies, such as bar chart, can provide an efficient approach to demonstrating and interpreting data patterns. The current methodology's flowchart (Figure 3) shows that the literature survey on ML in agriculture yielded 97 journal papers. Following that, these studies were classified into the four generic categories, as previously mentioned. The majority of the studies (27.83 %) were intended for yield prediction, while disease detection (22.68 %), weed detection (19.58 %), species recognition (19.58 %) and crop quality (10.30%) had nearly equal contributions in the current bibliographic survey. The former research field arose as a result of farmers' growing interest in making decisions based on efficient management that can lead to the desired yield. Disease detection, on the other hand, is critical, as diseases are a major threat to food security and quality assurance. Equal percentages (19.58%) were observed for weed detection and crop recognition, both of which are essential in crop management at the farm and in agricultural policy making.

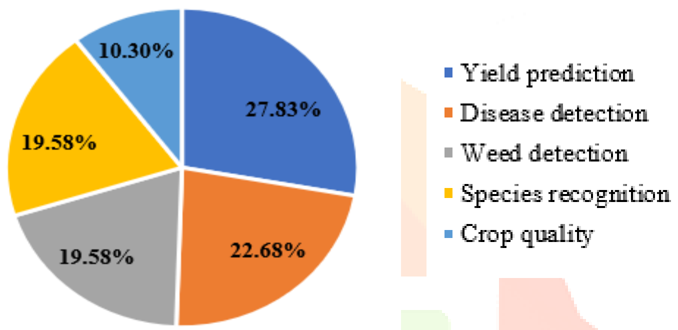

Figure 4: The classification of the reviewed studies according to the field of application of crop management system

4.2 Machine Learning Models Providing the Best Results

The selected studies used a diverse set of ML algorithms; their abbreviations are listed in Table A6 and A7. In the last two columns of Tables A1–A5, the ML algorithms used by each study, as well as those that produced the best results, are listed.

As shown in Figure 5, the most common ML model producing the best results was, by far, Artificial Neural Networks (ANNs), which appeared in nearly 32.72 % of reviewed studies. ANN models, in particular, produced the best results in the majority of studies involving all sub-categories. ANNs were inspired by the biological neural networks that comprise human brains (Chen et al, 2019), and they enable learning through examples from representative data describing a physical phenomenon.

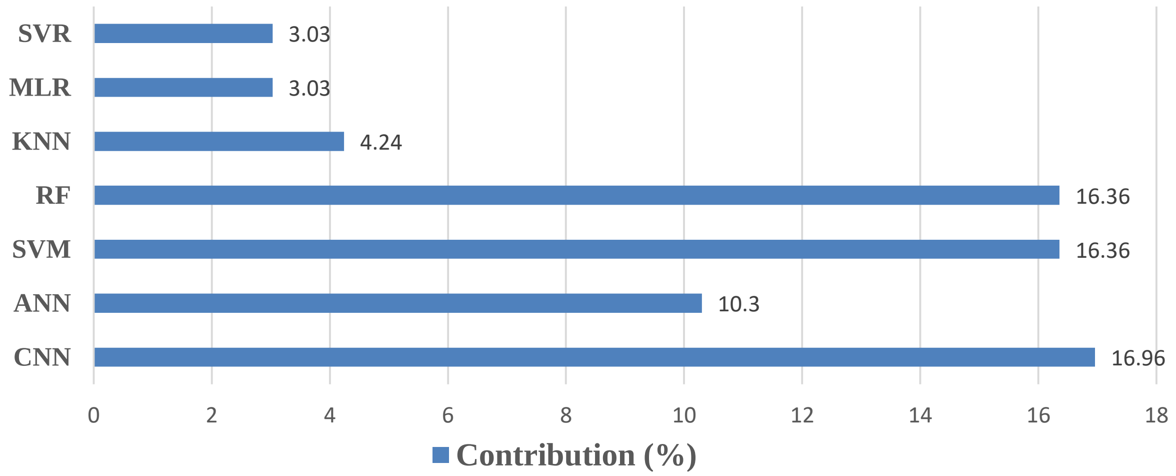

Figure 5: Contribution of different algorithms/models in review study

ANNs are distinguished by their ability to develop relationships between dependent and independent variables and thus extract useful information from representative datasets. ANN models have several advantages, including the ability to handle noisy data (Sadiq et al, 2019), which is very common in agricultural measurements. Deep Neural Networks (DNNs), which use multiple hidden layers between input and output layers, are among the most popular ANNs. Unsupervised, semi-supervised, and supervised DNNs are all possible. Convolutional Neural Networks (CNNs) are a common type of DNN, with layers that, unlike traditional neural networks, can arrange neurons in three dimensions (De Oliveira et al, 2018). In fact, CNNs were presented as the algorithms that produce the best results across all sub-categories, accounting for nearly half of the individual percentage of ANNs.

The cell structures of LSTM can control which parts of information are stored in long memory and which are discarded, resulting in memory optimization (Anagnostis et al, 2021). Furthermore, Multi-Layer Perceptron (MLP), Fully Convolutional Networks (FCNs), and Radial Basis Function Networks (RBFNs) appeared to perform the best in nearly 3–5% of ANNs. Finally, Back-Propagation Neural Networks (BPNNs), Modular Artificial Neural Networks (MANNs), and Deep Belief Networks were ML algorithms that belonged to ANNs with a low frequency (DBNs). Support Vector Machine (SVM) came next, accounting for approximately 16.36% of the studies. The SVM's strength stems from its ability to accurately learn data patterns while demonstrating reproducibility. Despite the fact that it can also be used for regression applications, SVM is a widely used classification methodology in a variety of data science settings (Pisner et al, 2020), including agricultural research.

V. DISCUSSION AND CONCLUSION

The current systematic review study focuses on ML in agriculture, which is a growing topic around the world. To that end, a thorough examination of the current state of the four generic categories identified in the previous review by (Liakos et al, 2018) was carried out. These are the categories for crop, water, soil, and livestock management. As a result of reviewing the relevant literature from the previous three years (2018–2020), several aspects were analyzed using an integrated approach. In conclusion, the following major conclusions can be drawn:

1. Several ML algorithms have been developed to deal with the heterogeneous data from agricultural fields. These algorithms can be divided into ML model families. ANNs were found to be the most efficient ML models. Nonetheless, in contrast to (Liakos et al, 2018), there has been a shift in interest toward EL, which can combine predictions from multiple models. SVM rounds out the top three most accurate ML models in agriculture due to several advantages, including its high performance when working with image data (Chandra and Bedi, 2021).
2. In terms of the most studied crops, maize was the most extensively studied, followed by wheat, rice, and soybean.
3. The demonstration of the input data used in the ML algorithms and the corresponding sensors was a significant outcome of the current review study. RGB images were the most popular choice, justifying the widespread use of CNNs due to their ability to handle this type of data more efficiently. Furthermore, a wide range of weather, soil, water, and crop quality parameters were used. Remote sensing, including imaging from satellites, UAVs, and UGVs, was the most common method of acquiring measurements for ML applications, though in situ and laboratory measurements were also used. As previously stated, UAVs are steadily gaining ground on satellites, owing to their adaptability and ability to provide high-resolution images in all weather conditions. Satellites, on the other hand, can provide time-series data over vast areas (Emilien et al, 2021).

Following significant advancements in ICT systems in agriculture, the accelerating rate of research interest in ML in agriculture is a result of a number of factors. Furthermore, there is an urgent need to improve agricultural efficiency while reducing environmental impact. This necessitates both accurate measurements and the handling of large amounts of data in order to provide a comprehensive picture of agricultural processes. The current technological outbreak has the potential to significantly strengthen agriculture in the direction of improving food security and meeting rising consumer demands. However, the majority of ICT requires upfront costs, namely high infrastructure investment costs, which frequently prevent farmers from adopting these technologies. This will be a pressing issue, particularly in developing economies where agriculture is an important economic factor. Overall, given the growing recognition of the value of artificial intelligence in agriculture, machine learning (ML) will undoubtedly become a behind-the-scenes enabler for the establishment of more sustainable and productive agriculture. It is expected that the current systematic effort will serve as a useful guide for researchers, manufacturers, engineers, ICT system developers, policymakers, and farmers, and thus contribute to more systematic research on ML in agriculture.

A1: Yield Prediction

Crop	References	Input data	Functionality	Algorithm /Model	Output data
Rice	PS, 2019	Irrigation, Weather data, Fertilization, Planting area	Evaluation of feature subsets for prediction of rice crop yield	ANN, SVR, KNN, RF	RF: RMSE = 0.085; MAE = 0.055; R= 0.93
Cotton	(Haghverdi et al, 2018)	Satellite spectral data	Yield estimation of cotton	ANN	(R = -0.2-0.60); ANN (R = 0.68)
Turmeric	Akbar et al, 2018	Soil fertility, Weather data	Forecasting oil yield	ANN	Multilayer-feed-forward NN: R^2 = 0.88
Wheat	Cai et al, 2019	Satellite spectral data	Prediction of wheat crop yield	SVM, RF, ANN	R^2 value: SVM: 0.74; RF: 0.68; ANN: 0.68
Rice	Gopal et al, 2019	Irrigation, Weather data, Fertilization, Planting area	Prediction of rice crop yield	ANN, SVR, KNN, RF	ANN-MLR: R = 0.99; RMSE = 0.051; MAE = 0.041
Sunflower	Wenzhi et al, 2018	Plant height and SPAD	Prediction of seed yield of sunflower	ANN, PLSR	ANN: RMSE = 0.66 t ha^{-1}; R^2 = 0.86 PLSR: RMSE = 0.93 t $ha^{-}1$; R^2 = 0.69
Rice	Yang et al, 2019	RGB and multispectral images from UAV	Estimation of rice grain yield	CNN	RGB images R^2 values: 0.424–0.499;
Maize	Kayad et al, 2019	Satellite spectral data	Prediction of maize crop yield	MLR, RF, SVM	RF: Yield: R^2 = 0.6; NDVI: R^2 = 0.48

Sugarcane	Murali et al, 2020	Monthly precipitation data	Forecasting of sugarcane yield	RNN	RMSE = 0.31 t ha^{-1} MAE = 0.39 t ha^{-1} MAPE = 5.18%
Soybean	Eugenio et al, 2020	Multispectral images from UAV	Yield estimation of soybean	MLP	R = 0.92
Maize, Soybean	Sayago et al, 2018	Satellite spectral data	Estimation of corn and soybean yield	MLR, ANN	Maize R^2 values: ANN: 0.92 Soybean R^2 values: ANN: 0.90
Potato	Abrougui et al, 2019	Soil parameters and tillage treatments	Forecasting of organic potato yield	MLR, ANN	MLR: R^2 = 0.894, RMSE = 0.431, MAE = 0.327; ANN: R^2 = 0.95, RMSE = 0.431, MAE = 0.327
Rice, Millet	Khosla et al, 2020	Weather data	Prediction of various kharif crops yield	MANN, SVR	Overall RMSE = 79.85%
Maize, soybean	Saranya et al, 2020	Satellite spectral data	Forecasting of maize and soybean yield	MLR, ANN	Corn: RMSE = 4.83-8.41, R = 0.91- 0.99; Soybean: RMSE = 5.1-7.7, R = 0.79-0.99
Maize	Kim et al, 2020	Satellite spectral and weather data	Prediction of maize yield	DNN	Drought case: R = 0.954; Heatwave case: R = 0.8-0.9
Maize	Mwaura et al, 2021	Satellite spectral and weather data	Estimation of maize yield	DLS	R^2 = 0.76; RMSE = 0.038 t ha^{-1}
Cotton	Leo et al, 2021	Topographic, weather, soil, satellite spectral data	Within-field yield prediction	RF, GB	RF: RMSE = 0.20 t ha^{-1}; CCC = 0.50–0.66
Rice	Wan et al, 2020	Multispectral images from UAV	Prediction of rice grain yield	RF	RMSE = 62.77 kg ha^{-1}; MAPE =0.32
Potato	Salvador et al, 2020	Weather, irrigation, and satellite spectral data	Forecasting of yield in potato fields at municipal level	RF, SVM	Winter cycle: R^2 = 0.757, RMSE = 18.9;
Sugarcane	Rahman et al, 2020	Satellite spectral data	Prediction of sugarcane yield	MLR	R^2 = 0.92–0.99
Cotton	Ashapure et al, 2020	Multispectral images from UAV	Estimation of cotton yield	ANN, SVR, RFR	ANN: R^2 = 0.9
Rice	Elavarasan et al, 2020	Soil and weather data	Forecasting paddy yield	RF, DT, GBM	RF: MSE = 0.07, R^2 = 0.67
Maize	Guo et al, 2020	Multispectral images from UAV	Yield prediction of maize	SVM, RF	SVM: RMSE = 1.099, MAE = 0.886
Wheat	Zhou et al, 2021	Multispectral images from UAV	Prediction of wheat grain yield	LR, RF, SVM, ANN	LR: RMSE = 972 kg ha^{-1}, R^2 = 0.62
Soybean	Da Silva et al, 2021	Multispectral images from UAV	Prediction of wheat grain yield	DT	RMSE = 196 kg ha^{-1}
Potato	Li et al, 2020	Hyperspectral data from UAV	Yield prediction at two growth stages	RF, PLSR	R^2 values: RF: 0.63; PLSR: 0.81
Carrot	Wei et al, 2020	Satellite spectral data	Carrot yield mapping	RF	R^2 = 0.82, RMSE = 2.64 Mg ha^{-1}

A2: Disease Detection

Crop	References	Input data	Functionality	Algorithm /Model	Output data
Tomato	Fuentes et al, 2018	RGB images	Recognition of diseases and pests in tomato	CNN	Recognition rate = 96%
Avocado	Abdulridha et al, 2018	Hyperspectral images	Detection of Laurel wilt disease	DT, MLP	Accuracy = 100%
Maize	Wu et al, 2019	RGB images from UAV	Detection of leaf blight in maize	CNN	Accuracy = 95.1%
Wheat	Zhang et al, 2019	Hyperspectral images from UAV	Detection of yellow rust in wheat plots	CNN	Accuracy = 0.85
Rice	Ramesh et al, 2020	RGB images	Classification of rice infected leaves	ANN, KNN	Accuracy = 90%, Recall = 88%
Onion	Kim et al, 2020	RGB images	Detection of downy mildew in onion	WSL	mAP@0.5 = 74.1–87.2%
Cotton	Wang et al, 2020	Hyperspectral images from UAV	Disease classification of cotton root rot	KM	Accuracy = 88.39%
Soybean	Karlekar et al, 2020	RGB images	Diagnosis of soybean leaf diseases	CNN	Accuracy = 98.14%
Papaya	Habib et al, 2020	RGB images	Diagnosis of five papaya diseases	SVM	Accuracy = 90%, Precision = 85.6%
Potato	Abdu et al, 2020	RGB images	Identification of early and late blight disease	NB, KNN, SVM	Accuracy = 99.67%
Tomato	Lu, et al, 2018	Spectral measurements form spectroradiometer	Detection of bacterial spots and late blight in tomato	KNN	Accuracy values: Healthy leaves: 100%, Asymptomatic: 100%, Late stage: 100%
Citrus	Sharif et al, 2018	RGB images	Detection and classification of citrus diseases	SVM	Accuracy values: 1st dataset: 97%; 1st & 2nd dataset: 89%;
Soybean	Kaur et al, 2018	RGB images	Detection and classification of three leaf diseases in soybeans	SVM	Accuracy Downy mildew =79%; Frog eye = 95.9%; leaf blight = 90%
Millet	Coulibaly et al, 2019	RGB images	Identification of fungal disease (mildew) in pearl millet	CNN	Accuracy = 95.00%, Precision = 90.50%, Recall = 94.50%, F1 score = 91.75
Grape	Cruz et al, 2019	RGB images	Detection of grapevine yellows in red grapes	CNN	Sensitivity = 98.96% Specificity = 99.40%
Maize	Wiesner et al, 2019	RGB images from UAV	Detection of northern leaf blight in maize	CNN	Accuracy = 0.9979, F1 score = 0.7153
Sugar beet	Ozguven et al, 2019	RGB images	Detection of diseased leaf spots in sugar beet	CNN	Accuracy = 95.48%
Grape	Pantazi et al, 2019	RGB images	Detection of diseased vine on leaves	SVM	Accuracy = 95%
Wheat	Picon et al, 2019	RGB images	Identification of three leaf diseases in wheat	CNN	Accuracy values: (1) Septoria: 100%; (2) Tan Spot: 99.32%; (3) Rust: 99.29%
Tomato	Agarwal et al, 2020	RGB images	Identification of various diseases in tomato	CNN	Accuracy values: (1) PV dataset: 98.4%; (3) Field data: 86.27%
Rice	Li et al, 2020	RGB images, videos	Video detection of brown spot in rice	CNN	Brown spot: Recall = 75.0%, Precision = 90.0%;
Tomato	Karthik et al, 2020	RGB images	Detection of early blight	CNN	Accuracy = 98%

A3: Weed Detection

Reference	Input data	Functionality	Algorithm /Model	Output data
Ahmad et al, 2018	RGB images	Classification of monocots and dicot weeds	AdaBoost with NB	Accuracy values: Original dataset: 98.40% expanded dataset: 94.72%
Bah et al, 2018	RGB images from UAV	Detection of weeds in bean, spinach fields	CNN	Accuracy values: Bean field: 88.73% Spinach field: 94.34%
Barrero et al, 2018	RGB images from UAV, multispectral images	Detection of Gramineae weed in rice fields	ANN	Best system: 80% < M/MGT < 108%, 70% < MP < 85%
De Castro et al, 2018	Multispectral and RGB images from UAV	Weed mapping between and within crop rows, cotton and sunflower	RF	Accuracy: Cotton: 84% Sunflower: 87.9%
Sabzi et al, 2018	RGB images	Classification of potato plant and three weed species	ANN	Accuracy = 98.1%
Teimouri et al, 2018	RGB images	Estimation of weed growth stage (18 species)	CNN	Maximum Accuracy = 78% Minimum Accuracy = 46% Average Accuracy = 70%
Kounalakis et al, 2019	Grayscale images from UGV	Recognition of Broad-leaved dock in grasslands	CNN, SVM	Accuracy = 96.8%
Partel et al, 2019	RGB images	Evaluation of weed detection and spraying system. Two Scenarios: (1) artificial weeds, (2) real weeds	CNN	Scenario: (1) Accuracy = 91%, Recall = 91%; (2) Accuracy=71%, Precision =78% (for plant detection and spraying Accuracy)
Kamath et al, 2020	RGB images	Weed and crop discrimination in paddy fields	MCS, SVM	Accuracy values: Right channel (76.62%), Left channel (85.59%)
Osorio et al, 2020	Multispectral images from UAV	Weed estimation on lettuce crops	SVM, CNN	F1 score values: (1) SVM: 88%; (2) CNN-YOLOv3: 94%; (3) Mask R-CNN: 94%
Gao et al, 2018	Hyperspectral images	recognition of three weed species in maize crops	RF	Mean correct classification rate: (1) Zea mays: 1.0; (2) Convolvulus arvensis: 0.789
Gao et al, 2018	RGB images from UAV	Detection of weeds in early season maize fields	RF	Overall Accuracy = 0.945, Kappa = 0.912
Akbar et al, 2018	Multispectral images	Classification of corn (crop) and silver beet (weed)	SVM	Precision = 98%, Accuracy = 98%
Knoll et al, 2019	RGB images	Classification of weeds in organic carrot production	CNN	Plant-based evaluation: Accuracy = 94.6%, Precision = 93.20%, Recall = 97.5%, F1 Score = 95.32
Lambert et al, 2019	Multispectral images from UAV	Mapping of Black-grass weed in winter wheat fields	CNN	Baseline model: AUC = 0.78; Weighted kappa = 0.59; Average misclassification rate = 17.8%
Dadash et al, 2020	Videos recordings	Classification of two weeds species in rice field	ANN, KNN	Accuracy values: Right channel (76.62%), Left channel (85.59%)
Kamath et al, 2020	Gray-scale and RGB images	discrimination in carrot field	RF	Accuracy = 94%
Le et al, 2020	Multispectral and RGB images	Discrimination of weed and crops with similar morphologies	CNN	Accuracy = 98.6%
Lam et al, 2021	RGB images from UAV	Weed mapping of Rumex in native grasslands	CNN	VGG16: Accuracy = 92.1%, F1 score = 78.7%

A4: Species Recognition

Crop	References	Input data	Functionality	Algorithm /Model	Output data
Rice, Soybean	Ji et al, 2018	Satellite spectral data	Classification of various crops	CNN, SVM, KNN	Overall accuracy = 0.939, Kappa = 0.902;
Various crops	Xu et al, 2018	Satellite data, phenological, in situ data	Classification of various crops	NB, DT, KM	KM: Overall accuracy = 92.04%, Kappa = 0.7998
Cabbage, Potato	Kwak et al, 2019	RGB images from UAV, in situ data	Classification of potato and cabbage crops	SVM, RF	SVM: Overall accuracy = 90.85%
Rice	Cinar 2019	Morphological data	Classification of two rice species	LR, MLP, SVM	LR: Accuracy = 93.02%
Soybean	Tan et al, 2019	Hyperspectral data, seed properties	Discrimination of 10 soybean seed varieties	PLS-DA, BPNN	TS-FFNN in terms of identification accuracy, stability, computational cost
Cotton	Zhu et al, 2019	Hyperspectral data, seed properties	Identification of seven cotton seed varieties	PLS-DA, LGR, SVM, CNN	(1) Full spectra: CNN-SoftMax: 88.838%; (2) Effective wavelengths: CNN-SVM: 84.260%
Cotton, Rice	Bhuyar 2020	Satellite spectral data	Crop classification	RF, KM	RF: Accuracy = 95.06%
Maize, Soybean	Xu et al, 2020	Satellite spectral data	Crop classification	RF, MLP, LSTM	LSTM: confidence interval = 95%
Rice	Zhang et al, 2020	Satellite spectral data	Crop classification	CNN, SVM, RF	CNN: Accuracy = 93.14%, F1 score = 0.8552
Various Crops	Abad et al, 2018	Satellite spectral data	Classification of early-season crops	RF	Beginning of growth stage: Accuracy =97.1%, kappa = 93.5%
Various Crops	Nemmaoui et al, 2018	Satellite spectral data, in situ data	Identification of crops growing in greenhouses	DT	Overall Accuracy = 75.87%, Kappa = 0.63
Various Crops	Paul et al, 2019	Satellite spectral data	Classification of various crops	SVM	Overall Accuracy = 94.32%
Various Crops	Piedelobo et al, 2019	Satellite spectral data, in situ data	Classification of various crops in large areas	EBT, DT, WNN	EBT: Overall Accuracy = 87%
Maize, Canola, Wheat	Sun et al, 2019	Satellite spectral data, in situ data	Classification of various crops	RF, ANN, SVM	RF: Overall Accuracy = 0.93, Kappa = 0.91
Maize, Peanut, Soybeans, Rice	Wei et al, 2019	Satellite spectral data, in situ data	Prediction of different crop types	FCN, SVM, RF	Best crop mapping: FCN: Accuracy = 85%, Kappa = 0.82
Various Crops	Zhao et al, 2019	Satellite spectral data, in situ data	Classification of early growth crops	CNN, RNN, RF	Highest Kappa: 1D CNN: 0.942
Zea mays, Canola, radish	Le et al, 2019	Grayscale testbed data	Classification of the crops	SVM	Precision = 91.87%, Recall = 91.85%, F1 score = 91.83
Various crops	Shelestov et al, 2019	Satellite spectral data	Crop classification	SVM	SVM (RBF): Accuracy values: (1)2016: 88.3%; (2) 2017: 91%
Banana, Sugarcane Cotton	Mandal et al, 2020	Satellite spectral and in situ data	Crop classification	SVM	Overall Accuracy = 89%

A5: Crop Quality

Crop	references	Input data	Functionality	Algorithm /Model	Output data
Apple	Papageorgiou et al, 2018	Flesh firmness, soluble solids, fruit mass, and skin color	Classification of quality: very poor, poor, medium, good and excellent	ANFIS, FIS	FIS: Accuracy values: (1) 2005: 83.54%; (2) 2006: 92.73%;
Soybean	Wolanin et al, 2019	Satellite spectral and soil data	Estimation of gross primary productivity	ANN, RF	ANN: R^2 = 0.92, RMSE = 1.38 gC dm^{-2}
Pepper	Tu et al, 2018	RGB images, Color, mass and density of peppers	Recognition of pepper seed quality	MLP, BLR	Predicted germination = 79.1%, Predicted selection rate = 90.0%
Millet, rye	Genze et al, 2020	RGB images captured in laboratory	Assessment of grain crops seed quality	CNN	(1) Millet: mAP =94.3%; (2) rye: mAP = 94.2%
Wheat	Yang et al, 2019	RGB images captured by UAV	Estimation of aboveground nitrogen content combining	PSO-SVR, PLSR	PSO-SVR: R^2 = 0.9025, RMSE = 0.3287
Various legumes	Baath et al, 2020	Spectral data from spectroradiometer	Estimation of legume forage quality	SVM, GP, PLS	Accuracy SVM: = 0.92–0.99, IVTD: = 0.42–0.98
Forage grass	Medeiros et al, 2020	X-ray imaging	Prediction of vigor and seed germination	RF, NB, SVM, LDA	Germination accuracy Fast: 82.08%, Slow: 76.00%,
Jatropha	De Medeiros et al, 2020	X-ray imaging	Prediction of vigor and seed germination	LDA	Accuracy values: Vigor: FT-NIR: 0.61, X-ray: 0.68, Germination: FT-NIR: 0.82, X-ray: 0.86,
Tomato	Lee et al, 2020	RGB images	Dimensions for quality inspection	CNN	Precision = 99.7%
Peach	Yang et al, 2020	Hyperspectral images	Estimation of soluble solids content	SAE-RF	R^2 = 0.9184, RMSE = 0.6693

Table A6: Abbreviations of Machine Learning Models/ Algorithms

Abbreviation	Models/ algorithms
ANFIS	Adaptive-Neuro Fuzzy Inference Systems
ANN	Artificial Neural Networks
BLR	Binary Logistic Regression
BPNN	Back-Propagation Neural Networks
CNN	Convolutional Neural Network
DLS	Damped Least Squares
DNN	Deep Neural Networks
DT	Decision Trees
EBT	Ensemble Bagged Trees
FCN	Fully Convolutional Network
FIS	Fuzzy Inference System
GBM	Gradient Boosting Model
GP	Gaussian Processes
KM	K-Means
KNN	k-Nearest Neighbor
LDA	Linear Discriminant Analysis
LGR	LoGistic Regression
LR	Linear Regression
LSTM	Long-Short Term Memory
MANN	Modular Artificial Neural Network
MCS	Multiple Classifier System
MLP	Multi-Layer Perceptron
MLR	Multiple Linear Regression
NB	Naïve Bayes
PLS-DA	Partial Least Squares Discriminant Analysis
PLSR	Partial Least Squares Regression
RF	Random Forest
SAE	Stacked AutoEncoder

SVM	Support Vector Machine
SVR	Support Vector Regression
WNN	Weighted Nearest Neighbors
WSL	Weakly Supervised Learning

Table A7: Abbreviations of Statistical Measures and General Words

Abbreviation	Statistical measures
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Squared Error
CI	Crop Indices
mAP	mean Average Precision
NDVI	Normalized Difference Vegetation Index

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