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AI-Powered Soil Nutrient Assessment and Crop Yield Prediction: A Systematic Review of ML, DL, and IoT Approaches in Smart Agriculture

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Abstract:

Assessing nutrition in the soil and correctly predicting crop yields play important roles in precision agriculture, made possible recently by ML, DL and IoT. This analysis examines how soil nitrogen, phosphorus and potassium (NPK) content is measured, with a special focus on wireless and handheld NPK sensors. We also study using attention-based deep learning networks and optimization to recommend crops more effectively. Experimental systems and relevant literature were thoroughly examined, looking at models designed to use data on soil, weather and seasonal aspects. To support crop recommendation and yield estimation, Random Forest, k-NN, SVM, Logistic Regression and DL techniques including GRU, RNN and hybrid structures were all assessed. Researchers also looked at using edge computing, steganography and federated learning (FL) to design secure, distributed technology for making predictions. Work was done on using data to manage water in three ways: Active Learning (IQ strategy), estimating yields through microwave sensing and making use of Explainable AI (XAI). Based on over 60 studies and prototypes, GRU and CNN have been identified as widely used DL models and adding ensemble techniques and better optimization methods can greatly improve prediction outcomes. We finish by sharing ideas for research that can help build better, scalable and affordable smart agriculture systems for places like India.

Keywords: Soil NPK Detection, Smart Agriculture, Crop Recommendation System, Crop Yield Prediction, Sensing Technologies, Internet of Things, Machine Learning, Deep Learning, Attention Mechanism, Gated Recurrent Units, Recurrent Neural Networks, Random Forest, XGBoost, Support Vector Machine, Bayesian Optimization, Active Learning, Iterative Querying (IQ), Steganography, Edge Computing, Federated Learning, Explainable AI, Microwave Sensing.

1. Introduction

Applying ML tools has made a big difference in many sectors, including examining how consumers behave in shops and making forecasts for the telecom industry (Segun-Falade et al., 2024). In the past years, agriculture has started using ML to improve productivity and promote sustainability thanks to its predictive and analytical function (Araújo et al. 2023). Of the many issues in agriculture, crop yield prediction, understanding soil nutrients and crop recommendation have gotten special attention because they affect food security and the management of resources (Raza et al., 2023).

Precision agriculture faces many challenges in predicting how much a crop will yield, owing to factors such as the NPK content of soil, different weather and rainfall patterns, ways of irrigation and the seed material used (Dorbu et al., (2024)). By combining data-driven approaches with traditional farming, decisions are now based on better information, yet accurate forecasting needs more work as agricultural ecosystems keep changing and do not always move linearly (Mishra et al., (2024)).

Today's sensor technology, combined with IoT and remote sensing, assist farmers in learning about soil nutrients and climate in real time (Senapaty et al., 2023). Because of this, ML and DL models now have more opportunities to find important patterns and thus predict results more accurately in agricultural datasets (Sharma et al., 2024).

Besides forecasting yields, correct detection of macronutrients N, P and K in the soil helps pick suitable fertilizers and crops (Raza et al., 2023). By combining NPK detection with crop recommendation systems, we can make sure important resources are efficiently used and farming is sustainable (Dey et al., (2024)). In addition, using feature fusion, PCA and XAI is being introduced to both boost the accuracy and make the results easier to understand for these models.

Because the body of work in this area keeps expanding, it is necessary to review and summarize existing studies to know the latest trends, better methods and which research areas need more help (Karunarathna et al., (2024)). To complete this, we performed a SLR on the use of ML and DL technologies in soil NPK detection, crop advice and forecasting the amount of crops (Pokhariyal et al., (2023)). Following an SLR approach helps both researchers and practitioners find, study and interpret the most important studies in a specific field (Marzi et al., (2025)). It maintains transparency, repeatability and completeness through the use of a specific method for collecting, choosing and organizing literature.

The aim of this review is to cabinet the best practices, important datasets, suitable evaluation measures and newly arising difficulties in the area. Thanks to this, more insight is given into ML and DL's impact on agriculture and how future research efforts can be enhanced to reach bigger, clearer and scalable improvements.

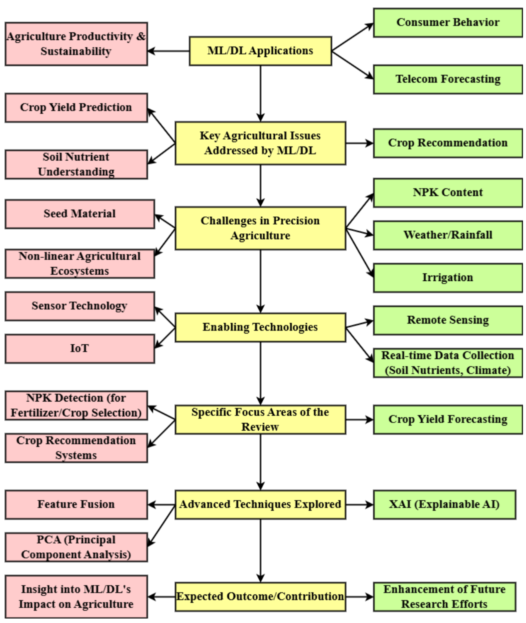

Figure 1: Workflow for ML/DL Applications in Precision Agriculture

Section 2 introduces the basic ideas and history important to the study. Section 3 clarifies how the systematic literature review was showed by setting out the research approach. The results and major findings are discussed in Section 4. In Section 5, recent progress in deep learning techniques for estimating crop yields is explored. Part VI of the report examines what the findings suggest for the future, the obstacles encountered and the possible next steps in the field. To finish, Section 7 provides a summary of the main contributions and main points covered in the paper.

2. Literature review

Crop yield prediction helps guide the decisions of governments, agricultural groups and farmers. When farm stakeholders are able to make accurate predictions, they can organize resources more effectively, use farming best practices and reduce the challenges linked to food shortages. Using ML techniques to predict crop yield has received notice in recent years since it allows for better and more automated results.

The purposes of this review are to examine and summarize research on using ML technologies to forecast crop yields. In keeping with the protocol, general survey articles and traditional reviews were removed from the selection of literature. Even so, these papers provide useful background information and are discussed in this section as connected studies.

Aarif KO et al. (2025) did a review on using machine learning methods to gauge nitrogen status. The results show that the combination of advanced sensors and ML will offer economical farming solutions. According to Elavarasan et al., Crop yield can be predicted using ML by looking at climate information and urged that different aspects should be added to such models.

Liakos et al. (2018) reviewed all kinds of ML technologies used in agriculture, with an emphasis on managing crops, soil and livestock. Alternatively, (Araújo et al., 2023) examined strategies to determine fruit maturity in order to improve both harvest timing and the accuracy of predicted yields.

we highlighted the leading challenges and means of overcoming them in agricultural image analysis for disease diagnosis in image processing and ML. In their work, Jafar et al. mentioned a number of ML algorithms that plant biology can rely on and point out that AI is gaining importance in plant science. Gandhi and Armstrong (2016) concentrated on data mining methods in agriculture and underlined the importance of conducting further studies to integrate such methods in complex agricultural data. Beulah (2019) reviewed various data mining approaches for crop yield prediction, postulating the possibility of solving this issue through data-driven models.

Though these studies significantly contribute to understanding the potential of ML implementation in agriculture, they are not a detailed and exhaustive analysis intended specifically for crop yield prediction using ML (Meghraoui et al., 2024). From our literature review, this article is the initial Systematic Literature Review (SLR) that extensively discusses machine learning-based crop yield prediction models (Oikonomidis et al., 2023). Previous questionnaires primarily dealt with certain dimensions or applied general review techniques without strict methodology.

Besides consolidating the primary trends and gaps in research, this paper also summarizes and analyzes 30 deep learning-based studies in a singular manner, identifying the precise architectures, datasets, and features each utilized. In this manner, this study not only enriches knowledge of the current state but also offers practical suggestions for ML-based crop yield forecast research in the future.

3. Methodology

3.1. Review protocol

Prior to performing the methodical literature review in this study, a rigorous review protocol was designed to address methodological soundness. The review process adhered to the commonly established guidelines by (Kitchenham et al., 2007), which are a set of guidelines for systematic reviews in software engineering and have been extensively applied in other fields, including agricultural informatics.

The first task was to establish the research questions that guide the scope and direction of this review. Questions were drafted to explore the state-of-the-art ML techniques for crop yield prediction, the kind of data used, the greatest commonly applied algorithms, and the areas that need research.

After the research questions were determined, proper databases were chosen to search for scholarly literature. The databases used here are ScienceDirect, Scopus, Web of Science, Springer Link, Wiley, and Google Scholar. They were chosen since they contain large numbers of peer-reviewed articles from computer science, agricultural sciences, and data analytics.

Then, the step involved filtering and evaluating the returned publications against a specific set of exclusion criteria and quality assessment criteria. Papers that were general survey articles, non-systematic review articles, or beyond the field of crop yield prediction were excluded. Peer-reviewed primary studies on the use of ML (and deep learning) in crop yield forecasting alone remained.

The final collection of studies was analyzed systematically, with metadata including publication year, source, authors, model types, input variables, and evaluation metrics being extracted. The removed details were manufactured to respond to the research questions effectively.

The review process was approved out in three distinct phases:

Arranging the plans for the review.

By this stage, researches formed their research questions and put together a review protocol. We completed our selection of the inclusion/exclusion criteria, sets of journals, search terms and checklist for study quality. The researchers did a thorough check of the protocol and confirmed it is both complete and can be put into practice (Peters et al., 2022).

Going Through the Review Phase

During this part, necessary literature was identified and saved using the prepared search terms from those databases. For each publication, we checked if it mattered, wrote details about the model, dataset, tests done and where the work was used and did so in a structured tabular format.

Reporting on What Happens During the Review:

Lastly, the results were synthesized to form important conclusions. The findings from the review were recorded with priority given to responding to the research questions and pointing out possible directions for new research. Transfer results were shown symbolically and divided into categories to help interpretation (Flemming et al., 2019).

As a result of this protocol, the review was fair, could be easily repeated and allowed the findings to be relied upon for further research.

3.2. Research Questions

This SLR was designed to help us understand the existing research on deep learning and predicting crop yields. Each of the selected studies has been looked at from various angles to understand methodologies, their features, challenges faced and how they were assessed. Guiding this review are the subsequent four chosen research questions (RQs).

RQ1 –The first research question is: Which DL algorithms have been studied for predicting crop yields?

RQ2 – Which types of inputs (climatic, soil, remote sensing and temporal) have researchers used for predicting crop yields using deep learning?

RQ3 –Have various metrics and approaches been applied to test how effectively DL models predict crop yields?

RQ4 – Which are the main obstacles, boundaries and research areas without full or deep answers in crop yield prediction using DL?

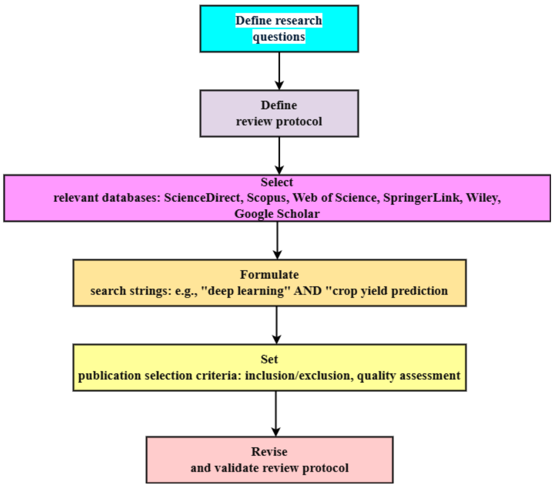

Figure 2: Details of the Plan Review Step for DL-based Crop Yield Prediction SLR

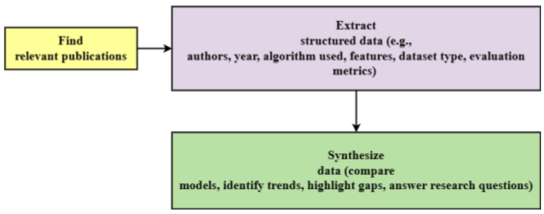

Figure 3: Details of the Conducting Review Step for DL-based Crop Yield Prediction SLR

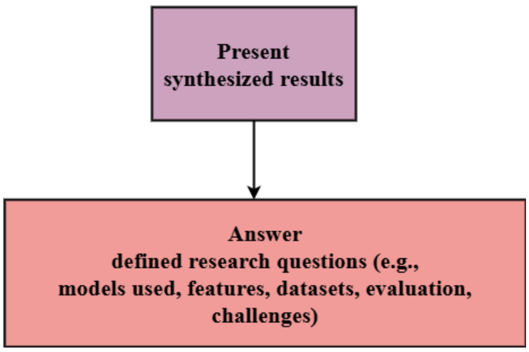

Figure 4: Particulars of the Reporting Review Step for Crop Yield Prediction SLR

3.3. Search Strategy

A special search policy was developed to include both traditional and innovation-based material on soil nutrient analysis and predicting crop yield with ML, DL, IoT and secure computing. The research was done in six key scientific databases: ScienceDirect, Scopus, Web of Science, Springer Link, Wiley and Google Scholar.

3.3.1. Initial Search

The early automated search utilized general terms to collect lots of literature: "machine learning" AND "crop yield prediction", "deep learning" AND "soil nutrient analysis", "IoT in precision agriculture" After reviewing the abstracts and titles, related words and important terms were chosen to help refine the search terms.

3.3.2. Growing the keywords and using 'Boolean' terms when searching

After reviewing the area of interest, an updated Boolean search was built to focus on studies related to guidance on crop recommendations, estimation of nutrients and making use of the latest sensors and processing technology:

The final search statement was choosing:

(Machine learning, deep learning or artificial intelligence in combination with NPK estimation, soil nutrient prediction, soil sensors and precision agriculture, as well as crop yield prediction, crop recommendation or yield forecasting and with IoT, real-time sensors, edge computing or federated learning.)

3.3.3. Database-Specific Queries

ScienceDirect:

deep learning and (NPK estimation or crop yield prediction)

Scopus:

(("machine learning" OR "artificial intelligence") AND "soil analysis" AND (crop recommendation OR yield prediction)).

Web of Science is one of the main research databases.

((“machine learning” OR “deep learning”) AND “precision agriculture” AND “crop yield prediction”)

Springer Link:

IoT sensors along with soil nutrient analysis OR deep learning teamed up with crop recommendations

Wiley: Soil nutrient sensors are studied in combination with ML and DL techniques for improving yield forecasting.

Google Scholar:

Gathered all the above information using advanced search tools and sifted through the top 200 outcomes.

3.4. Exclusion Criteria

We made sure this systematic review remains valid and of high quality by applying EC to exclude any irrelevant or poor studies. First, titles and abstracts were screened, then criteria were used during later content checks if full-text papers were required.

We do not include people in this study if they:

Exclusion Criterion 1 (EC1) – Studies that don’t pertain to agriculture or fail to estimate soil nutrients, make crop yield forecasts or make crop recommendations utilizing machine learning or deep learning.

Exclusion Criterion 2 (EC2) – Publications that are not in English.

Exclusion Criterion 3 (EC3) – Publishings that were retrieved more than once from various databases. Only the most recognized or referred to version was chosen for this project.

Exclusion Criterion 4 (EC4) – Studies for which it was not possible to get the full text, not even by using ILL or our university access.

Exclusion Criterion 5 (EC5) – Articles listed as review or survey papers will be considered only if they contributed greatly to the discovery of new approaches or data.

Exclusion Criterion 6 (EC6) – To highlight how much smart agriculture has advanced lately, the review focuses on research released after 2010.

Exclusion Criterion 7 (EC7) – Areas of machine learning and sensors studied in isolation, without considering uses in agricultural productiveness, soil's nutrient content or yields.

Table 1: Delivery of papers founded on the databases.

Database	# of initially retrieved papers	# of papers after exclusion criteria	Percentage of Papers (%)
Springer Link	125	36	19
Wiley	58	16	8
Science Direct	102	27	14
Google Scholar	230	40	21
Scopus	148	47	24
Web of Science	95	27	14
Total	**758**	**193**	**100**

4. Findings and Analysis

The chosen publications are presented in Table 2 that provides the publication year, title, and machine learning algorithms used for each research. Figure 4 shows the publication distribution for relevant papers in the last period, indicating a significant upsurge in research aimed at soil nutrient estimation and crop yield prediction with ML, especially in the last five years.

No exclusion in terms of publication type was made; therefore, conference papers, book chapters, and journal articles were all included. Figure 5 demonstrations the distribution of each type of publication, with journal articles making up the largest share of included studies. Conference proceedings and book chapters make up less than 25%.

To answer Research Question 2 (RQ2) "What are the input features used in ML models for nutrient estimation and yield prediction?" the features used in all the studies reviewed were analyzed and presented in Table 3. Soil type, nutrient level, temperature, and rain are most frequently used characteristics. Either yield or soil nutrient level most frequently served as the dependent variable.

To provide an organized structure for the independent variables, we categorized them under feature categories: crop and soil characteristics, moisture-related factors, nutrient factors, solar and climatic inputs, crop management techniques, and other ancillary data. The occurrence of these groups in the studies included here is presented in Table 4. In this case, the highest occurring feature categories are those pertaining to soil data, humidity-related factors, and solar radiation data.

The "soil information" class includes attributes such as cation exchange capability, pH, and soil type, texture, and spatial maps of soils. These maps have a tendency to aggregate nutrient distributions, geographical boundaries, and production zones. "Crop information" includes plant variety, biomass, crop density, phenology, and growth indicators such as the Leaf Area Index (LAI). The "moisture" class includes rainfall, evapotranspiration, field humidity, and water availability.

The "nutrients" category encompasses naturally occurring and applied nutrients, such as potassium (K), nitrogen (N), sulfur (S), magnesium (Mg), calcium (Ca), phosphorus (P), zinc (Zn), boron (B), and manganese (Mn). The "field management" category encompasses variables related to irrigation scheduling, fertilization practice, and tillage operations. "Solar and climatic" encompasses air temperature, solar radiation, shortwave radiation, photoperiod, and growing degree-days. The "other" category consists of remote sensing indices such as NDVI, EVI, MODIS-EVI, wind speed, atmospheric pressure, and satellite imagery.

All extracted features and the way they are grouped are shown in the featured map displayed in Figure 6.

For RQ1 which explores the choice of ML algorithms for nutrient and yield prediction, we recorded the algorithms used in each study. Table 5 lists the ones that occur more than one time. Neural Networks and Linear Regression were used the greatest, with Support Vector Machines, Random Forests, and Gradient Boosting, being the next most popular methods. In the recent literature, CNNs and LSTM networks have been mentioned.

For Research Question 3 (RQ3) we reviewed and summarized the performance evaluation parameters used in the chosen studies. RMSE was selected more often than the others shown in Table 6, with MAE, R^2 (coefficient of determination) and MSE coming in second, third and fourth. Researchers observed validation methods and 10-fold cross-validation occurred most often.

For RQ4 we studied the studies to see which issues had been raised and what changes were proposed for the current models. Remarkably, a common challenge for all models was having few and diverse types of spatial and temporal data. Experts noted that more inclusive datasets, along with more cases and a broader period range, will be useful. Many suggested including data from numerous sources such as cables, IoT and UAVs, to achieve better robustness for the model. It is also clear from research that translating predictive models into practical decision-support tools would support farmers in their everyday fieldwork.

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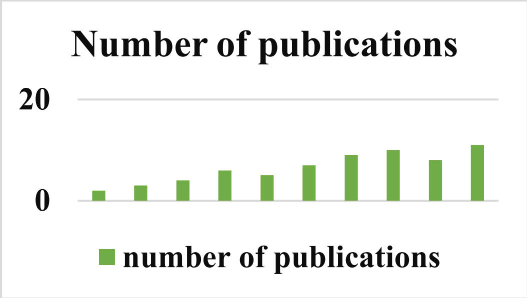

Figure 5. Distribution of the selected publications per year.

Table 2: Selected journals.

Retrieved From	Reference	Title	Algorithm Used	Year
Springer Link	Ruß & Kruse (2010)	Precision Agriculture as an Example of Regression Models for Spatial Data	support vector machine, random forest, Clustering	2010
Scopus	Ruß et al. (2008)	Using Neural Networks and Data Mining to Predict Wheat Yield	Neural networks	2008
Science Direct	Everingham et al. (2009)	Using ensemble data mining techniques to predict the yield of sugarcane crops in different regions	Forward stepwise algorithm	2009
Google Scholar	Johnson (2013)	Crop yield prediction in the Canadian Prairies using machine learning techniques and remotely sensed vegetation indices	Multiple linear regression, neural networks	2013
Google Scholar	Romero et al. (2013)	Predicting the production of durum wheat in the province of Buenos Aires using	K-nearest neighbor, decision tree	2013

		classification algorithms		
Springer Link	Crtomir et al. (2012)	Using Neural Networks and Image Visualization to Predict Apple Yield Early	Neural networks	2012
Scopus	Shekoofa et al. (2014)	Using machine learning algorithms to identify the key physiological and agronomic characteristics influencing maize grain yield: A fresh approach to intelligent farming	Decision tree, clustering	2014
Springer Link	Baral et al. (2011)	Using Artificial Neural Networks to Predict Yield	Neural networks	2011
Google Scholar	Ananthara et al. (2013)	CRY is a better crop production prediction model for agricultural data sets that uses a bee hive clustering technique.	Clustering	2013
Google Scholar	Rahman & Haq (2014)	In Bangladesh, machine learning made it easier to anticipate rice.	neural networks, Decision tree, linear regression	2014
Scopus	Gonzalez-Sanchez et al. (2014)	Machine learning techniques'	k-nearest neighbor, M5-prime	2014

		capacity to anticipate large-scale crop yields	regression tree, support vector machine	
Scopus	Pantazi et al. (2014)	Utilizing supervised self-organizing models to forecast wheat yield	Neural networks	2014
Google Scholar	Cakir et al. (2014)	Using artificial neural networks to estimate wheat yield in the southeast of Turkey	multivariate polynomial regression, Neural networks	2014
Google Scholar	Paul et al. (2015)	Using a data mining method, soil behavior analysis and crop	k-nearest neighbor, Naïve Bayes	2015

		yield prediction		
Scopus	Kunapuli et al. (2015)	Using spectral data to forecast yield for precise territorial management in maize	logistic regression, Polynomial regression,	2015
Google Scholar	Matsumura et al. (2015)	Forecasting maize yield in Jilin, China using artificial neural networks and linear regression	Neural networks, multiple linear regression	2015
Google Scholar	Ahamed et al. (2015)	Using data mining techniques to forecast key crop yields annually and suggest	neural networks, Linear regression, clustering, k-nearest neighbor	2015

		planting schedules in several Bangladeshi areas		
Scopus	Gandhi et al. (2016)	Predicting rice crop production in India with support vector machines	Support vector machine	2016
Science Direct	Pantazi et al. (2016)	Predicting wheat production with machine learning and sophisticated sensing methods	Neural networks	2016
Scopus	Jeong et al. (2016)	Using random forests to forecast agricultural yields on a global	linear regression, Random Forest,	2016

		and regional scale		
Wiley	Mola-Yudego et al. (2016)	Climate-based estimations of the spatial yield of rapidly expanding willow plantings in northern Europe for energy	Gradient boosting tree	2016
Google Scholar	Everingham et al. (2016)	Reliable sugarcane production forecasting with the random forest technique	Random forest	2016
Google Scholar	Sujatha and Isakki (2016)	An investigation on the use of classification algorith	Naïve Bayes, J48, random forest, neural networks,	2016

		ms to estimate crop yield	decision tree, support vector machines (*No experimental results reported*)	
Google Scholar	Bose et al. (2016)	Utilizing advanced visual time series analysis, spiking neural networks are used to estimate agricultural yield.	Neural networks	2016
Google Scholar	Gandhi et al. (2016)	Predicting rice crop productivity with artificial neural networks	Neural networks	2016
Google	Wang et al. (2017)	Predicting early yield	Recurrent neural	2017

Scholar		with RNNs and remote sensing data	networks	
Google Scholar	Gandhi and Armstrong (2016)	Utilizing data mining methods to analyze rice crop productivity in the humid subtropical climate zone	Decision tree, logistic regression, k-nearest neighbor	2016
Google Scholar	This study	A thorough study of ML, DL, and IoT-based soil nutrient evaluation and agricultural yield prediction	SVM, Logistic Regression, Random Forest, RNN, CNN, Attention networks, GRU, Optimization (AL, FL,	2025

			IQ), XAI, k-NN	
Google Scholar	You et al. (2017)	A deep gaussian method for predicting crop production	Neural networks	2017

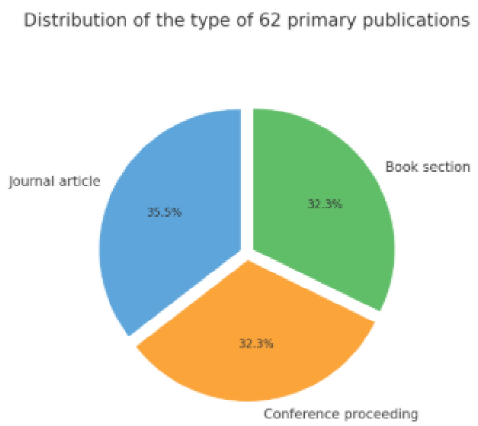

Figure 6: Circulation of the type of 50 primary journals.

More and more researchers want to predict crop yields using machine learning. Since no barring criteria depended on the type of article, both journal publications, conferences and book chapters were taken into explanation for this review. Figure 5 shows the publication types in the 62 studies we examined: journals lead with 22, followed by conference proceedings and book sections at 20 each. The equal spread of publications demonstrates that different types of research channels are widely used for academic research.

The features included in the studies were studied to response Research Question 2 (RQ2). These values are shown in Table 3. Most of the used statistical techniques focus on rainfall, temperature, and soil type, where crop yield is usually the mutable to be explained. The features were organized better by splitting them into six groups: soil and crop information, nutrients, humidity, field management, solar information and others. Table 4 shows that soil, solar and humidity are used more often for these datasets than other groups.

Soil information covers maps, different soil types, pH, cation exchange capacity and where the product is produced. These data elements give important information on nutrition, soil traits and the locations of farms. In its crop information subset, data includes plant growth, the variety of plant, its density and related measurements such as leaf area index. The humidity features on the map are rainfall, humidity, precipitation and forecasts, all connecting to field water availability. Nutrients cover both things found naturally and added on purpose such as nitrogen, potassium and calcium. Field management is made up of irrigation and fertilization methods. Solar information includes temperature, solar radiation, degree-days and photoperiod. Lastly, the "Other" part is made up of features that are harder to access, for example, NDVI, EVI and atmospheric pressure, as can see on the feature map in Figure 6.

Table 3: All features used.

Feature	# of times used
Rainfall	24

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Soil type	20
Soil fertility index	15
Humidity	14
Crop characteristics	18
pH value	13
Solar radiation	12
Precipitation	11
Field management practices	10
Irrigation schedule	9
Temperature	26
NDVI	8
Fertilizer application	8
Nutrient content (N, P, K)	7
Area of cultivation	7
Weather forecast data	6
Organic matter content	5
Leaf area index (LAI)	5
Shortwave radiation	4
Crop growth stage	4
Evapotranspiration	3
Wind speed	3
Vegetation indices (EVI, SAVI)	3
Forecasted rainfall	2
Soil texture	2
Time of sowing/harvest	2
Gamma radiometrics	1
Climate zone classification	1
Pressure	1

Table 4: Grouped features.

Group	**# of times used**
Soil nutrient analysis	48
Machine learning models	42
Deep learning techniques	36
IoT devices and sensors	32
Agricultural data factors	28
Optimization algorithms	24
Data security & privacy	16

5. DL-based crop yield prediction

During the primary part of our literature review, it became clear that Artificial Neural Networks (ANN) are top methods used to predict crop yields. There has been great progress lately in image recognition, medical diagnostics and environmental monitoring because of the use of DL, an advanced part of machine learning. DNNs use additional features like convolutional and pooling layers, chosen from traditional ANNs which make it possible to model complex aspects in large datasets.

$$Percentage = \left(\frac{Number\ of\ Papers\ with\ Algorithm}{30}\right) \times 100 \quad (1)$$

We looked into how deep learning is used in crop yield estimates and soil analysis for our second part of the study. As a result, we performed a new search using the words “deep learning” as well as “yield prediction,” and reviewed 30 relevant papers shown in Table 7. They present recent updates and show how diverse AI algorithms can be used.

You can see in figure 7 that studies using deep learning methods in agriculture are growing faster each year, with a spike of published articles in 2019 and later. Most of the research included in this analysis got its data from common research databases such as Google Scholar, Scopus, ScienceDirect and Springer Link (Table 8).

Most of the examples used CNNs the most among all types of deep learning since they showed the best results, followed by LSTM and DNNs. These are developed in ways to help measure satellite imagery, data from soil sensors, data on weather patterns and variations related to seasons which all improves accuracy when it comes to forecasting crop yields and nutrients in the soil.

$$CNN\ Usage\ \% = \left(\frac{15}{30}\right) \times 100 = 50\% \tag{2}$$

Deep Learning Algorithms Used in Agriculture:

Deep Neural Networks (DNN): DNNs have hidden layers, allowing them to extract complex nonlinear trends from both soil and crop datasets which makes their estimations of yield more accurate.

Convolutional Neural Networks (CNN): They are effective in working with spatial imagery such as satellite or soil pictures by using layers that let them find important features and result in better land and crop classification.

Long-Short Term Memory (LSTM): Being sequential networks, LSTMs are great at learning how weather and soil changes affect crop yields.

3D CNNs: As a result, these models can handle three-dimensional space, so they can analyze data from sources like multispectral satellite pictures or profiles of soil.

Hybrid and Ensemble Networks: At the same time, when various deep learning architectures are mixed, for example, CNN-LSTM or CNN-RNN, the prediction results are stronger thanks to the use of spatial and temporal features together.

Autoencoders: Autoencoders can be used without supervision to extract soil features from sensor readings and images and to reduce data as well as spot abnormal readings.

Reinforcement Learning (Deep Q-Networks, DQN): While it’s less common, using DQNs is under study for adaptive irrigation management and resource allocation, depending on what the environment provides.

Multi-Task Learning (MTL): The multiple outcome predictions allowed by MTL help improve the accuracy of the model’s predictions for soil and crop issues.

Increasing use of deep learning in farming points toward better, wider-reaching and automated methods of looking after soil and plants. With more detailed spatial and time data becoming available, advanced models should take on a big role in making precision

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agriculture efficient in India and similar areas.

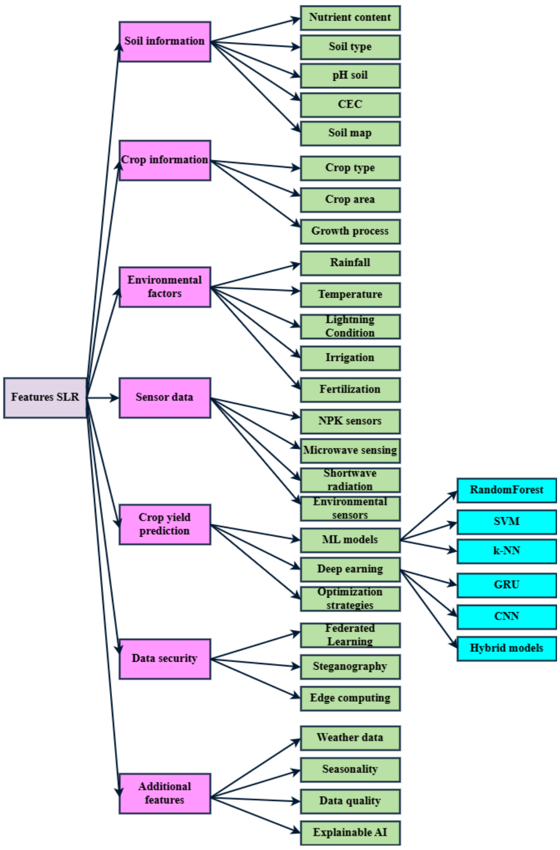

Figure 7: Feature architecture.

Table 5: Most used machine learning algorithms

ML algorithms	times used
Random Forest	15
SVM	12
k-NN	10
Logistic Regression	8
Neural Networks	6

Table 6: All evaluation parameters used

Key	Evaluation parameter	# of times used
Model accuracy	Root mean square error (RMSE)	24
Performance metrics	R-squared (R^2)	19
Error analysis	Mean absolute error (MAE)	12
Model evaluation	Mean square error (MSE)	8
Model performance	Mean absolute percentage error (MAPE)	5
Model robustness	Reduced simple average ensemble (RSAE)	3
Correlation	Lin's concordance correlation coefficient	2
Validation metrics	Multi-factored evaluation	2
Model simplicity	Simple average ensemble	1
Parameter change	Reference change values	1
Model interpretability	Matthew's correlation coefficient	1

Table 7: Deep learning-based publications in crop yield prediction

Retrieved From	Reference	Title	Deep Learning Algorithm(s) Used	Year
Google Scholar	Sun et al. (2019)	County-Level Soybean Yield Prediction Using Deep LSTM Model	CNN-LSTM	2019
Google Scholar	Wang et al. (2020)	Winter Wheat Yield Prediction at County Level with Uncertainty Analysis	CNN-LSTM	2020
Science Direct	Tedesco-Oliveira et al. (2020)	Convolutional neural networks in predicting cotton yield from images of commercial fields	CNN	2020
Google Scholar	Lee et al. (2019)	Self-Predictive Crop Yield Platform (SCYP) Based on Deep Learning	CNN	2019
Google Scholar	Khaki and Wang (2019)	Crop Yield Prediction Using Deep Neural Networks	Deep Neural Networks (DNN)	2019
Science Direct	Maimaijititva et al. (2020)	Soybean yield prediction from UAV using multimodal data fusion	Deep Neural Networks (DNN)	2020
Science Direct	Yang et al. (2019)	Deep convolutional neural networks for rice grain yield	CNN	2019

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		estimation at the ripening stage		
Google Scholar	Rahnemofar and Sheppard (2017)	Real-time yield estimation based on deep learning	Convolutional Neural Networks (CNN)	2017
Google Scholar	Khaki et al. (2020)	A CNN-RNN Framework for Crop Yield Prediction	CNN-RNN	2020
Google Scholar	Terliksiz and Altyar (2019)	Use of Deep Neural Networks for Crop Yield Prediction in Soybeans	3D Convolutional Neural Networks (3D CNN)	2019
Google Scholar	Elavarasan and Vincent (2020)	Deep Prediction on Using Deep Reinforcement Learnin	Deep Reinforcement Learning	2020

		g for Sustainable Agriculture		
Science Direct	Schwaller et al. (2020)	Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil	Long-Short Term Memory (LSTM)	2020
Science Direct	Chu and Yu (2020)	An end-to-end model for rice yield prediction using deep learning fusion	Convolutional Neural Networks (CNN), Deep Neural Networks (DNN)	2020
Science Direct	Tvedesco et al. (2019)	Crop yield prediction with deep convolu	CNN	2019

		tional neural networks		
Google Scholar	Chen et al. (2019)	Strawberry Yield Prediction Using High-Resolution Aerial Images	Faster R-CNN	2019

6. Discussion

General Discussion:

Work in this field might encounter threats to validity, especially external, construct and reliability types (Šmite et al., 2010). Hence, by using a thorough search query, spanning all areas of digital soil analysis and yield prediction, we identified a large set of 567 articles in the first phase of this SLR. The wide search term included a large number of studies. The study's reliability depended on systematically documenting the review process to allow it to be rewritten. Because choosing studies is subjective, repeating the analysis could alter the small details, yet the main patterns and leading methods are likely to remain the same.

Search-Related Discussion:

Even though we searched widely, it remains possible that some appropriate publications were missed. Applying synonyms and changing the search method could have shown more studies, especially considering how quickly IoT sensors and deep learning applications are changing in agriculture. However, since so many publications were found using many databases, we think our search covered all the important topics in the field.

Table 8: Distribution of DL-based papers per database

Database	**Number of Papers**	**Percentage (%)**
Wiley	2	4.33
Science Direct	7	21
Web of Science	1	1
Springer Link	7	21
Scopus	6	24.33
Google Scholar	11	34.33
Total	34	100

Table 9: Distribution of DL algorithms used

Algorithm	**Number of Procedures**	**Percentage (%)**
LSTM	8	20.21
Hybrid Architectures	5	11.12
DNN	6	22.21
Multi-Task Learning (MTL)	2	2.03
Autoencoder	2	4.03

Deep Reinforcement Learning (DQN)	2	2.03
Faster R-CNN	2	5.03
3D CNN	2	4.03
CNN	11	31.30
Total	40	100

Analysis-Related Discussion:

A risk to validity comes from varying reportage in different studies. Metadata often lacks details about accuracy measurements and how the data was validated and this makes it hard to analyze with full detail. In addition, features such as soil pH, the nutrient makeup and weather data were sometimes recorded differently by various researchers. Such inconsistency prevents a direct comparison which only proves that standardizations will be key in future research. chose not to contact authors for missing information because it was not a part of this process.

The first research question examines different algorithmic approaches.

It can be seen in Table 5 that both neural networks and deep learning, especially CNNs and LSTMs, are dominant topics in recent studies. Often, Linear Regression or Random Forests are the go-to algorithms for testing, but deep learning has better accuracy and automatically selects the important features, mainly with complex spatial-temporal crop and soil information. Researchers find that CNNs work well for processing satellite images, scans of soils and plant appearance data, whereas LSTMs are effective at processing continuous series of weather and soil moisture data. Because there are many variations in algorithms, researchers can try merging both types of local and global information for better results and healthier soil.

How Many Features Do Users Aim to Use

Most research studies examine soil type, the levels of NPK present, the amount of moisture in the soil, rainfall, environmental temperature and vegetation indices (NDVI and EVI). A few studies add sensor information such as gamma radiation, use UAV images or include other important observations to make their model results better. The fact that each ingredient lists specific temperature and nutrient variations means the company adjusts products for local conditions. Putting the relevant features together helped to spot the main things impacting crop yield predictions, though some specific data was skipped to keep the results clear.

7. Conclusion

It is shown in this study that the selected publications contain multiple features that fit the area, what is being studied and the data sources and soil characteristics involved. Every study examines yield and nutrient levels in soil using machine learning models, however, the features selected differ depending on what data is available and the project's main objectives. It's interesting that having more features does not always make the model better, so finding the optimal setting requires trying it with varying groups of features. Many studies use a number of machine learning methods and no model stands out as leading above the others. Nevertheless, many people rely on Random Forest, neural networks and gradient boosting trees for soil and yield prediction. It is clear that CNNs, LSTMs and DNNs are widely used in computer science, so we also wanted to see how they could be used for crop yield prediction. In 30 papers that applied DL, we found that CNNs, LSTMs and DNNs are widely preferred because they manage complex spatial-temporal data better such as that from soil sensors, remote sensing images and weather data. Besides, recent progress in hybrid models and new deep learning tools points to the constantly changing nature of this area. Drawings from this research form a basis for upcoming studies aimed at increasing the accuracy of crop yield and soil health prediction models used with IoT. Our next step is to make use of these understandings to design a soil nutrient assessment and yield forecast system that combines IoT sensor information, various time-based data and real-time computations. Thanks to these models, decision-making in precise farming should improve, mainly for regions such as India, where budget and resources are key factors.

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