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TOPICAL REVIEW

Artificial Intelligence in Agriculture: A Systematic Review of Crop Yield Prediction and Optimization

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ABSTRACT Agriculture is key to global food security, and Artificial Intelligence is emerging as a catalyst for its modernization. This article explores how advancements are transforming resource management in agriculture and decision-making for crop yield prediction and agricultural optimization. It is based on a Systematic Literature Review (SLR) of 25 selected studies from an initial set of 776 to identify key algorithms, critical variables, and evaluation metrics. The bibliometric analysis reveals a recent increase in publications on the topic, with a focus on algorithms such as SVM, KNN, and XGBoost. Important variables considered include soil data, climate data, and crop characteristics. Challenges identified include model complexity, data quality, and the need for appropriate pre-processing methods. The ultimate goal is to optimize agricultural practices and improve productivity through accurate predictions.

INDEX TERMS Machine learning, crop yield prediction, agricultural optimization, feature selection, data analysis.

I. INTRODUCTION

Human well-being and global food security are increasingly intertwined. As the world's population continues its exponential growth, the pressure on the agricultural industry has intensified significantly to increase production and efficiency. The challenges involved range from the scarcity of natural resources to climate variability and the need to reduce environmental impact [1], [2], [3]

Advancements in Artificial Intelligence (AI) are optimizing the management of agricultural resources and improving the sustainability of crop production, particularly in response to contemporary agricultural challenges. AI technologies enable accurate predictions, efficient resource utilization, and improved decision-making, which are crucial for sustainable practices.

In this context, AI advancements have emerged as a key catalyst for the modernization and sustainable progress of agriculture. The adoption of cutting-edge technologies (AI models such as artificial neural networks, neuro-fuzzy logic, support vector machines, decision trees, random forests, and genetic algorithms) has transformed how agricultural resources are managed and how critical decisions are made [4], [5], [6]. The convergence of computing, electronics, and agricultural engineering has led to a technological revolution that promises to address many of the challenges posed by modern agriculture [7], [8].

This article analyses the current landscape of agriculture and the latest developments in AI applications for prediction in the agricultural sector. It focuses on reviewing research related to crop-related topics, including monitoring, water management, yield prediction, and agricultural practice optimization. A total of 776 studies were identified, and after applying exclusion criteria, 25 studies were analysed.

The article is structured into several sections, beginning with the methodology used, which follows the PRISMA protocol, detailing the inclusion/exclusion criteria and data collected. The next section presents the results of bibliometric analyses. Section IV analyses the AI technologies used, and Section V provides key conclusions.

II. METHODOLOGY

This section presents the review principles of the Systematic Literature Review (SLR), study selection criteria, and the quality assessment of the selected studies.

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A. PRINCIPLES OF REVIEW

This SLR was defined by [9] as a review using systematic methods to compare and synthesize the findings of studies in response to the research question, with detailed reporting of findings to ensure replicability.

The objective of this SLR was to analyse the current research landscape on Machine Learning (ML) algorithms applied to the optimization of crop yield prediction and estimation, identifying key algorithms, critical variables, evaluation metrics, and challenges. The methodological steps included identification, selection, eligibility, and inclusion. First, the research questions were defined, followed by the inclusion/exclusion criteria for studies. Relevant data were then extracted from scientific databases, and finally, the results were analysed to answer the research questions.

The SLR ensured clarity and transparency through a four-phase verification flowchart, adapted from [10]. This study aimed to expand knowledge on current research by focusing on AI applications in agriculture.

The research question: What is the current research landscape regarding the use of ML algorithms for optimizing crop yield prediction and estimation? led to four sub-questions on ML algorithms, variables, evaluation metrics, and challenges.

Based on this, the following sub questions were formulated:

- RQ1: What are the most commonly used ML algorithms in the literature for optimizing crop yield prediction and estimation? This question aimed to identify the types of ML algorithms employed in crop yield prediction studies, such as regression models, neural networks, decision trees, and other advanced methods.
- RQ2: What characteristics or variables are considered key in ML models for crop yield prediction? This question aimed to identify key variables, such as environmental conditions, soil properties, and farming practices, that influence yield prediction.
- RQ3: What approaches and metrics are used to evaluate the effectiveness of ML models in crop yield prediction? This question examined the metrics and approaches, such as RMSE, MAE, and cross-validation, used to assess the accuracy and robustness of the models.
- RQ4: What are the main challenges and limitations in applying ML for optimizing crop yield prediction? This question explored the difficulties in the field, including data quality issues, model scalability, and the influence of external factors on prediction accuracy.

To conduct the SLR, a specific search string was designed using keywords, synonyms, and Boolean operators, covering terms related to AI, agriculture, and specific applications. Based on the proposed research question regarding the application of AI in agriculture, it was structured as follows:

- Terms about artificial intelligence:

"Artificial intelligence" OR "AI" OR "machine learning" OR "neural networks" OR "genetic algorithms" OR "support vector machines" OR "random forests" OR "decision trees" OR "fuzzy logic"

- Terms about agriculture:

"agriculture" OR "farming" OR "crop production" OR "precision agriculture" OR "smart farming" OR "agricultural practices"

- Terms about specific applications:

"Yield prediction" OR "water management" OR "crop monitoring" OR "sustainability" OR "resource optimization" OR "environmental impact"

The search string was adapted for each database to align with its structure. In Scopus, the field tag TITLE-ABS-KEY was used to target relevant sections, for example ["machine learning" AND "agriculture" AND ("yield" OR "crop") AND ("prediction" OR "estimation") AND "optimization"]. IEEE Xplore used exact matches via quotation marks and Boolean logic, while Web of Science employed the TS= (Topic Search) to broadly capture results in titles, abstracts, and keywords.

This search string was adapted accordingly to the database in which the review was performed (Scopus, Web of Science, IEEE).

Inclusion/Exclusion criteria was also considered to further refine the results detailed below.:

Inclusion:

- Studies applying ML for agricultural performance prediction

- Research discussing variables, metrics, or challenges

Exclusion:

- Theoretical papers without empirical evidence

- Studies not focused on model optimization

Defining these criteria appropriately before conducting the search aims to ensure the inclusion of relevant and quality literature.

A four-phase verification flowchart adapted from PRISMA was followed. A total of 776 articles were retrieved, and after applying the exclusion criteria, 25 were included.

A structured data extraction form was created to collect:

- Bibliographic details (authors, title, source, year)

- ML algorithms used

- Features/variables included

- Evaluation metrics

- Reported challenges Two researchers extracted data independently and resolved discrepancies through discussion or consultation with a third reviewer to ensure accuracy.

III. RESULTS

The result reveals an increase in publications in recent years. This temporal pattern shows the current relevance and the constant evolution of knowledge in the field of interest (Figure 2).

The heat map emerges from the analysis of keywords used in the studies, where the words with the greatest strength are displayed, starting with Crop/Yield Prediction and ML (Figure 3).

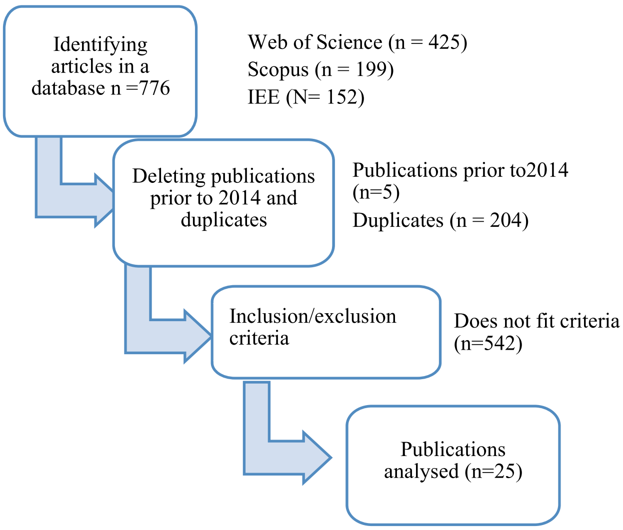

FIGURE 1. PRISMA diagram for study selection.

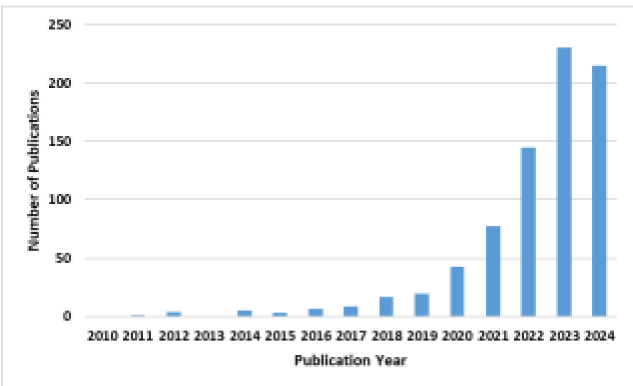

FIGURE 2. Publications by year (2010–2024).

Keyword	Frequency
Crop/Yield Prediction	27
Machine Learning	21
Optimization	13
Hybrid Models	5
ELM	3
Bagging	2
Boosting	2
A-Bi-LSTM-MFA	2

FIGURE 3. Keyword frequency heatmap extracted from selected studies.

In the search for an answer to the research question for this RSL, the selected sources describe how ML algorithms are increasingly used to optimize crop yield prediction and estimation.

The articles examine various ML and deep learning techniques to predict crop yield. Different algorithms (KNN, SVM, decision trees, random forests, etc.) are compared and hybrid models are proposed to improve the accuracy of predictions. The studies use data on soil, climate and other environmental variables to develop crop recommendation systems and predict yield, with the aim of optimizing agricultural practices and increasing productivity. Methods of data pre-processing and feature selection are also explored to improve model performance. Finally, some works present user interfaces to facilitate the application of the models to farmers.

A. ALGORITHMS ARE EMPLOYED FOR THE PREDICTION OF CROP YIELD

Below, we present the results obtained from various studies for crop yield prediction and crop recommendation. These algorithms have been applied with the aim of optimizing the accuracy of the predictive models, using a variety of climate, soil composition, and other relevant agricultural data. The performance evaluation of each algorithm was performed using key metrics such as R2, MSE, MAE, RMSE, and F1-score, allowing a detailed comparison of their effectiveness.

Table 1 summarizes the most relevant results, showing the algorithms most commonly used in modeling tasks. The algorithms include regression, classification, and ensemble methods, as well as neural networks and deep learning models. This diversity of approaches allows the evaluate of their strengths and weaknesses in different agricultural scenarios.

TABLE 1. Summary of ML algorithms used for crop yield prediction.

Algorithm	Amount	Author
Support Vector Machine (SVM)	8	[1], [3], [5], [8], [11], [12], [13], [14]
K-Nearest Neighbors (KNN)	5	[1], [3], [12], [15], [16]
X GBoost	4	[1], [8], [17], [18]
Decision Tree	4	[7], [8], [11], [12]
Random Forest	4	[7], [8], [11], [12], [19]
Linear Regression	3	[8], [11], [12]
Neural Networks	2	[20], [21]

Analysing the total number of unique algorithms in the consulted sources, we obtain a total of 39 different algorithms. KNN is employed as a flexible prediction approach, classifying a data point according to the majority of the classes of its K nearest neighbors [1]. Other algorithms such as LASSO regression are also used for prediction, with an L1 penalty for regularization [1]. Advanced Neural Networks and Activation Functions are mentioned [13]. The importance of BiLSTM networks is highlighted, which incorporate forward and backward LSTM layers to learn from data sequences, allowing to obtain past and future context [15]. The use of a hybrid DCNN algorithm with the Whale

Optimization Algorithm (WOA) is presented to improve the prediction performance [17].

B. VARIABLES USED

The data shown in Table 2 illustrate the key variables used in each model.

TABLE 2. Key features/variables used in crop yield prediction models.

Features	Author
Soil data: Includes nitrogen (N), phosphorus (P), potassium (K), pH, electrical conductivity, organic carbon, soil moisture, soil temperature, water holding capacity, bulk density and porosity	[1], [3], [7], [20], [21]
Climate and environmental data: Include temperature (maximum, minimum, average), historical rainfall data, temperature, humidity, and the Southern Oscillation Index (SOI), humidity, wind speed, dew point, air pressure, climatic water deficit, actual and potential evapotranspiration, and solar radiation.	[1], [3], [8], [18], [20], [21], [22]
Crop characteristics: These include cultivated area, production, yield, crop type, crop season (Kharif, Rabi, Summer), crop year	[2], [8], [11], [14], [23]
Additional data: Considers the use of fertilizers (NPK), pesticides, geographic data (state, district), soil type, irrigation practices, and socioeconomic factors	[2], [8], [14]

These features are used in ML and deep learning models to predict crop yield, recommend suitable crops, and optimize agricultural practices. Data pre-processing, feature selection, and hyperparameter optimization methods are crucial to improve the accuracy and efficiency of these models.

C. EVALUATION METRICS

The metrics used in studies on crop prediction and agricultural optimization are detailed below:

- Common evaluation metrics: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-squared (R2), Mean Absolute Percentage Error (MAPE) [1], [2], [3], [6], [7], [8], [11], [13], [15], [24].

- Additional metrics: Accuracy, Recall (Sensitivity), F1-Score, Error Rate, Drought Index, Standardized Precipitation Index (SPI), Crop Moisture Index (CMI) [22], [25].

- Other indices: Willmott Index (WI), Nash-Sutcliffe Efficiency (ENS), Legates-McCabe (LM) [22].

The choice of evaluation metrics depends on the objective of the study and the characteristics of the data. Multiple metrics need to be considered to obtain a complete evaluation of the model performance. Hyperparameter optimization and feature selection are important steps to improve the model performance. Comparison with existing models is essential to demonstrate the superiority of the proposed model.

D. REPORTED CHALLENGES

Several authors report various challenges in the field of crop prediction and agricultural optimization:

- Shah et al. [3] and other authors [7], [8], [11], [18], [20], [26] mention the complexity of the crop prediction task, noting that there are significant variations in the performance of different ML approaches.

- Sridevi [7] indicates that the use of chemical fertilizers and climate changes are decreasing crop yield performance levels. In addition, farmers face obstacles in forecasting crops and weather based on soil nutrients and environmental factors. The author also mentions that feature selection and classification techniques are crucial in ML techniques and each technique has its pros and cons.

- Biswas [8] notes that existing models lack outlier detection and use data normalization techniques that cannot handle outliers properly. Furthermore, it highlights the importance of using more meaningful feature selection methods and other pre-processing tasks.

- Chauhan et al. [11] and other authors [3], [6], [7], [18], [23] emphasize the importance of accurate predictions for agricultural planning and sustainable decision making in farming practices.

- Jorvekar et al. [20] allude to challenges related to high labour costs for small farmers and inefficient agronomic water management practices. It also indicates that image acquisition is a risky process, and that there is a need to automate the use of EWT and cloud cover.

- Shetty et al. [13] review the strengths and limitations of different algorithms in accurately detecting crop diseases.

- Lahza et al. [23] highlight the challenges in developing high-performance forecasting models, including the selection of the best algorithm and the need for systems to be efficient in handling large amounts of data. Furthermore, it notes that factors such as soil type, climate, and harvesting techniques can vary from season to season, making accurate measurement of variants difficult.

- Sakib et al. [18] highlights the need for proper pre-processing of datasets and tuning of parameters in ML algorithms to improve the accuracy and interpretability of crop yield prediction models.

Challenges identified include the need for proper data pre-processing, parameter tuning, selection of appropriate algorithms, management of large amounts of data, consideration of variable factors such as climate and soil, detection of outliers, and improving the accuracy and interpretability of prediction models.

IV. DISCUSSION

Key points emerging from these papers include:

Importance of accurate crop yield prediction:

- Accurate crop yield prediction is crucial for global food security, sustainable agricultural planning, and economic growth, especially in developing countries [1], [2], [3], [4].

- It helps farmers make informed decisions about what, when, and how much to plant, optimizing resource allocation and maximizing profitability [1], [5], [6], [7].
- Policy makers also rely on accurate predictions to assess yield, make import and export decisions, and strengthen national food security [1], [8].

Factors influencing crop yield:

- Various factors influence crop yield, such as weather conditions (temperature, rainfall, humidity), soil composition (pH, nutrients), pesticide application, irrigation practices, topography, climate, and external factors such as pests and diseases [1], [6], [11], [21], [27].
- Weather conditions, in particular, have a significant and often non-linear impact on crop yield, making accurate predictions difficult [17].

Understanding these complex relationships is essential for developing accurate predictive models.

ML techniques for crop yield prediction:

- ML models can analyse large historical data sets, identify complex patterns and relationships, and make predictions with remarkable accuracy [1], [15], [26].
- Various ML algorithms, including decision trees, support vector machines, random forests, and neural networks, have been successfully used to predict crop yield [1], [3], [5], [7].
- Feature selection is crucial to identify the most influential factors for crop yield and improve model accuracy [7], [17].
- Ensemble learning techniques, such as combining multiple models, can further improve predictive accuracy [1], [7], [11], [15].

Importance of parameter optimization:

- Fine-tuning the hyperparameters of ML models is essential to optimize their performance.
- Nature-inspired optimization algorithms, such as the crayfish optimization algorithm, have been used to fine-tune recurrent neural network models for multivariate time series forecasting of crop yield

Emerging trends and future directions:

- Integration of advanced technologies, such as remote sensing, geographic information systems (GIS), and Internet of Things (IoT) sensors, with ML enables real-time monitoring, more accurate analysis, and personalized recommendations.
- Deep learning models, such as convolutional neural networks (CNNs) for image analysis and recurrent neural networks (RNNs) for capturing temporal dependencies, are gaining traction in crop yield prediction.
- Future research focuses on improving the interpretability of ML models, addressing data challenges such as sparsity and noise, and developing more robust and adaptable systems for diverse agricultural environments.

Benefits of ML in agriculture:

- ML-based crop yield prediction systems enable farmers to optimize crop selection, fertilizer and pesticide application, irrigation practices, and other management decisions, leading to increased productivity, reduced costs, and sustainable farming practices.
- These systems also help address challenges related to climate change, pests and diseases, and soil degradation, contributing to global food security and sustainable agricultural development.

The use of ML algorithms to optimize crop yield prediction and estimation is a rapidly evolving area of research with significant potential to revolutionize agricultural practices and improve productivity. As technology advances and more data becomes available, ML models will become more sophisticated and accurate, enabling farmers to make more informed decisions and contribute to a more sustainable and resilient global food system.

The most commonly used algorithms, key variables, and challenges in crop yield prediction have been identified. However, there are limitations in their studies.

V. CONCLUSION

AI-based prediction models can help farmers make informed decisions about which crops to plant, when to plant them, and how to manage resources (water, fertilizers, etc.). This can increase productivity and reduce costs.

However, these models need to be accessible and easy to use, especially for smallholder farmers with limited resources. This review suggests the development of user-friendly interfaces and mobile applications that enable farmers to access these tools.

Accurate crop yield predictions can help governments plan more effective agricultural policies, such as subsidy distribution, food reserve management, and import and export decisions.

This review highlights the need for collaboration between researchers, governments, and farmers to implement these technologies effectively and equitably.

Future research areas include:

- Improving Data Quality: Future research should focus on improving data collection and pre-processing, using technologies such as IoT and remote sensing.
- Generalizable Models: Models need to be developed that can be applied in different regions and crop types, incorporating universal variables and cross-validation.
- Integration of Socioeconomic Factors: It is crucial to include socioeconomic variables in the models to improve their accuracy and practical relevance.
- Interpretability of Models: Work should be done to create more interpretable models, especially for farmers and policy makers who do not have technical experience.

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