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A Review on the Current Trends in Crop Yield Forecasting Using Artificial Intelligence

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Abstract:
In the face of escalating global food demands and the increasing unpredictability of climate conditions, the importance of precise crop yield forecasting has never been more critical. This paper provides a comprehensive review of the current trends in leveraging Artificial Intelligence (AI) to enhance crop yield predictions, which is pivotal for strategic agricultural planning and ensuring food security. Our review covers a range of AI methodologies, including machine learning, deep learning, and hybrid models, that have been employed to predict crop yields with increasing accuracy.
Recent advancements have demonstrated that machine learning techniques, such as support vector machines and random forests, are effective in modeling complex agricultural data sets with a notable degree of precision. However, deep learning approaches, including convolutional and recurrent neural networks, have started to outperform traditional machine learning models, owing to their ability to process large-scale spatial-temporal data from remote sensing and IoT-based agricultural sensors. We also explore the emergence of hybrid AI models that combine the strengths of both machine learning and deep learning technologies, providing enhanced accuracy and robustness in yield prediction under varying climatic conditions.
Additionally, this review discusses the integration of AI with geographic information systems (GIS) and remote sensing technologies, which has significantly improved the spatial resolution of yield predictions. We highlight several key challenges that remain, such as data scarcity, the need for model generalization, and the integration of socioeconomic factors into yield prediction models.
In conclusion, AI presents transformative potential for crop yield forecasting. By harnessing cutting-edge AI technologies and addressing existing challenges, significant strides can be made towards more sustainable and efficient agricultural practices. This paper aims to inspire continued research and innovation in this critical field.

1. Introduction

1.1 Overview of the Project

The task of forecasting crop yields accurately is fundamental to enhancing agricultural productivity and managing food supply chains efficiently. With the global population projected to reach nearly 10 billion by 2050, the agricultural sector faces unprecedented pressure to increase yields and ensure food security. Traditional methods of yield prediction, heavily reliant on historical data and empirical observations, are increasingly proving inadequate due to their inability to accommodate the complexities of climate change and varied agricultural practices.
In this context, Artificial Intelligence (AI) has emerged as a revolutionary tool, offering new dimensions of accuracy and efficiency in predicting crop yields. Recent advances in AI, particularly

through machine learning and deep learning, have facilitated the analysis of vast and complex datasets, encompassing climatic variables, soil properties, and satellite imagery. This review paper critically examines a corpus of 40 recent research articles to explore the innovative methodologies and the effectiveness of AI applications in crop yield forecasting. Through this examination, we aim to highlight the transformative potential of AI in agriculture, identify current trends, and discuss future directions in this burgeoning field of research.

1.2 Motivation

The growing global population and the increasing volatility of environmental conditions demand more resilient and efficient agricultural practices. Crop yield forecasting is a critical component of agricultural management, influencing everything from on-the- ground farming decisions to national food policy. However, traditional forecasting methods often fall short in their accuracy and adaptability to changing climatic conditions and agricultural innovations.

Artificial Intelligence (AI) represents a promising frontier in addressing these challenges. AI's ability to digest and analyze vast arrays of data—from weather patterns and soil conditions to high-resolution satellite imagery—offers a significant leap in the precision of crop yield forecasts. This capability not only helps in maximizing yield outputs but also contributes to sustainable farming practices by optimizing resource use and reducing waste.

Given the rapid evolution of AI technologies and their increasing application in agriculture, there is a crucial need to systematically review and synthesize recent research findings. This paper aims to fill that gap by providing a comprehensive analysis of contemporary studies, thereby aiding stakeholders in understanding the current capabilities and future potential of AI in enhancing crop yield predictions. Through this endeavor, we seek to foster technological adoption and inform policy-making, ultimately contributing to more secure and efficient food systems globally.

1.3 Objectives

1. To systematically analyze and synthesize the methodologies employed in recent research articles on AI-based crop yield forecasting
2. To evaluate the practical implications and performance of AI models in real-world agricultural settings.
3. To identify gaps in the current research and suggest directions for future studies.

2. Theoretical Background

2.1 Artificial Intelligence:

Artificial intelligence (AI) is an interdisciplinary field focused on replicating human intelligence in machines to mimic human cognition and behaviors, such as learning and problem-solving. Researchers and extension specialists are increasingly utilizing AI to enhance agricultural productivity. AI can assist farmers in increasing yields by helping them select appropriate crop types, adopt better soil and nutrient management practices, control pests and diseases, estimate crop production, and forecast commodity prices. Techniques like deep learning, robotics, the Internet of Things (IoT), image processing, artificial neural networks, wireless sensor networks (WSN), and machine learning are employed to address agricultural challenges. These technologies enable real-time monitoring of farm variables like weather, temperature, water usage, and soil conditions, aiding farmers in making informed decisions.

AI contributes to smart farming practices that minimize losses and maximize yields. It involves algorithms that learn from data and make predictions by dynamically linking input and output variables, providing solutions for various problems. AI-powered technologies are already prevalent in everyday life, from mobile face recognition to self- driving cars. While AI has significantly boosted productivity in many sectors, its impact on agriculture is becoming increasingly evident, driving the industry towards a digital transformation. AI applications in agriculture are vast, including precision agriculture which helps with watering, crop rotation, harvesting, crop selection, planting, and pest control using machine learning data.

The core idea of AI is that human intelligence can be described in ways that allow machines to replicate and perform tasks of varying complexity. AI aims to achieve learning, reasoning, and perception. Its impact is widespread, with every industry looking to automate specific tasks using intelligent machinery. In agriculture, AI has the potential to make significant improvements, Automating tasks and enhancing efficiency. By simplifying various processes, AI technology stands to revolutionize agricultural practices, leading to better productivity and sustainability.

2.2 Classification of AI Techniques

1. Machine Learning Models:

Machine learning techniques are foundational to AI-based crop yield forecasting. These methods involve training models on historical data to identify patterns and make predictions.

- Regression Analysis: Utilized for predicting continuous crop yield values based on various input features such as weather data, soil properties, and crop management practices. Common algorithms include:

Linear Regression, Polynomial Regression, Support Vector Regression (SVR).

- Decision Trees: Tree-based models like CART (Classification and Regression Trees) are used for their simplicity and interpretability.
- Random Forest: An ensemble of decision trees that improves prediction accuracy by averaging multiple trees.

Gradient Boosting Machines (GBM): Sequentially builds trees to correct errors made by previous ones.

- Support Vector Machines (SVM): Effective in high-dimensional spaces, SVMs are used for regression and classification tasks in crop yield prediction.
- K-Nearest Neighbors (KNN): A non-parametric method that predicts yields based on the closest data points in the feature space.

2. Deep Learning (DL) Techniques:

Deep learning techniques have revolutionized crop yield forecasting by leveraging large datasets and complex model architectures.

- Artificial Neural Networks (ANNs): Basic neural network structures used for capturing nonlinear relationships between input features and yield outcomes.
- Convolutional Neural Networks (CNNs): Primarily used for spatial data, CNNs are effective in analyzing satellite imagery and remote sensing data to predict crop yields.
- Recurrent Neural Networks (RNNs): Suitable for sequential data, RNNs and their variants like Long Short-Term Memory (LSTM) networks are employed for time series forecasting in agriculture.
- Auto encoders: Used for feature extraction and dimensionality reduction, improving the efficiency of crop yield prediction models.

3. Hybrid Models

Hybrid models integrate multiple AI techniques to leverage the strengths of each, often resulting in superior performance.

- ML + DL Hybrids: Combining traditional ML models with deep learning components, such as using CNNs for feature extraction followed by regression analysis for prediction.
- Multi-Model Approaches: Integrating different types of models (e.g., combining weather forecasting models with crop growth models) to capture various aspects of the crop yield prediction problem.
- AI + Domain Knowledge: Incorporating agronomic knowledge and process-based models with AI techniques to enhance prediction accuracy and interpretability.

3. Methodology of the Literature Review

In my review paper, I used a structured approach to search for relevant research papers. I looked at databases like ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar. Using keywords such as " Crop Yield Forecasting using Artificial Intelligence" and "smart agriculture" I found papers and was very selective about which ones to include. The papers had to be mostly about artificial intelligence in the field of agriculture, written in English, peer-reviewed, and available in full text. I have carefully read each selected paper to gather important information like the title, authors, publication year, publication venue, methods used, and key findings. This thorough process helped me compare and analyze the papers comprehensively.

To visualize the findings, I organized the data into tables and figures. Table 1 lists the articles distributed according to the source of download, such as ScienceDirect, IEEE Xplore and SpringerLink. Table 2 shows the articles distributed by the year of publication, highlighting trends and advancements in privacy-preserving techniques over time. In Figure 1, I have illustrated the PRISMA Flowchart, detailing the steps I took from identifying papers to deciding which ones to include in my review.

Table 1: Article distribution by journal title

Journal Title	**No of Papers**	**%(approx.)**
IEEE	07	14
SpringerLink MDPI	03	6
ScienceDirect		
	23	46
Others		
	16	32
	01	2
Total	**50**	**100**

Table 2: Article distribution by publication year

Publication Year	**No of Papers**	**%(approx.)**
2024	11	22
2023	10	20
2022	03	6

2021	13	26
2018-2020	13	26
Total	**50**	**100**

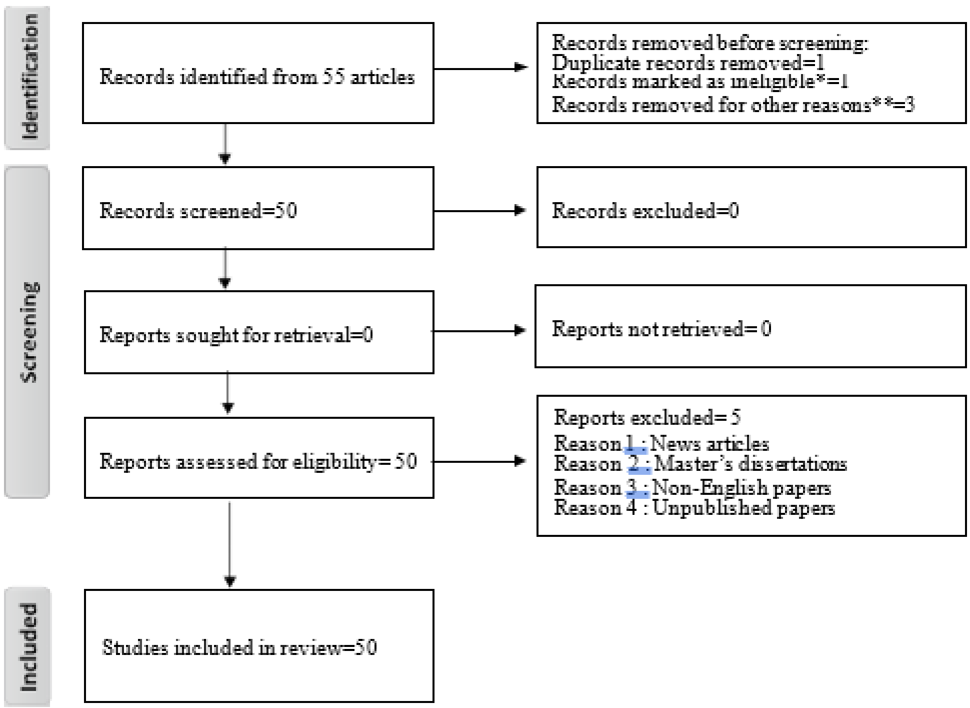

Figure 1: PRISMA flowchart of the inclusion and exclusion process. Abstract and content not suitable to the study: *The use or application of the system is not specified:**

4. Literature Review

In 2019, Gómez, D., Salvador, P., Sanz [1] developed a model to predict potato yield using satellite remote sensing to address limitations in traditional models. The model used images from Sentinel 2 satellites over three growing seasons, applying different machine learning models. Moreover Hemming, S., de Zwart, F., [2] made a comprehensive survey on international competition aimed to combine horticultural expertise with AI to improve fresh food production. Furthermore Adisa, O.M., Botai, [3] used crop modeling study using artificial neural network (ANN) models to predict maize production in major South African provinces. Climate variables like precipitation, temperature, and potential evapotranspiration were used. Here in Jha, K., Doshi, [4] surveys research on automation in agriculture and proposes a system for botanical farms. Traditional methods, such as harmful pesticides, are insufficient, causing land barrenness. Automation practices like IoT, wireless communications, machine learning, artificial intelligence, and deep learning can address issues like crop diseases, storage management, pesticide control, weed management, irrigation, and water management. Kim, N., Ha, K.J., [5] This paper compares six AI models for crop yield prediction in the Midwestern US, focusing on the July-August database. The optimized deep neural network model outperforms other models, indicating early corn and soybean yield forecasting.

In 2020, Kakani, V., Nguyen, [6] This review explores computer vision and AI technologies in the food industry, focusing on sustainability and their potential in real-time farming. It discusses challenges, recommendations, and the role of 4.0 IR technologies in sustainable food production. A study of Abbas, F., Afzaal, [7] Proximal sensing techniques can help survey soil and crop variables affecting crop yield. Combining precision agriculture technologies with machine learning algorithms can extract useful information for controlling crop yield. Four ML algorithms were used to predict potato tuber yield in Atlantic Canada, with SVR models outperforming others. Work by Abraham, E.R., Mendes dos Reis, [8] uses Artificial Neural Networks (ANN) to predict soybean harvest area, yield, and production in Brazil. ANN is the best approach for predicting soybean yield, while classical linear function remains effective for yield. It helps stakeholders anticipate the world soybean offer. Again Han, J., Zhang, [9] did a study in China focuses on predicting wheat yield using multi-source data and machine learning techniques. The study uses climate, remote sensing, and soil data from four time windows. Results show models can accurately predict yield 1~2 months before harvesting, than 10% error. Work by Talaviya, T., Shah [10] reviews the use of artificial intelligence in agriculture, including irrigation, weeding, and spraying, using robots and drones. It discusses the benefits of these technologies, including reduced water usage, soil fertility, and improved productivity. The paper also explores drone implementation and crop monitoring. Van Klompenburg, T., Kassahun [11] did a study which analyzed crop yield prediction studies using machine learning algorithms. The most common features were temperature, rainfall, and soil type, with Artificial Neural Networks being the most applied algorithm. Deep learning algorithms like Convolutional Neural Networks were also widely used. Again Nevavuori, P., Narra, [12] did UAV-based remote sensing is gaining popularity for agricultural and environmental monitoring. Finland's researchers evaluated spatio-temporal deep learning architectures for crop yield time series modelling and prediction using RGB time series data. Elavarasan, D. and Vincent, [13] work presents a Deep Recurrent Q-Network model, combining reinforcement learning and deep learning, to predict crop yield based on environmental, soil, water, and parameters. The model efficiently predicts crop yield with an accuracy of 93.7%, outperforming existing models and preserving the original data distribution.

In 2021, Hara, P., Piekutowska, [14] study Forecasting crop yields is crucial for farmers, policymakers, and food processing plants. Artificial neural networks (ANNs) can be used to predict yields, with environmental variables like climatic data and plant productivity indices being valuable predictors. This technology aids precision agriculture. Moreover Sagan, V., Maimaitijiang, [15] highlighting its innovative use of satellite imagery and deep learning for accurate agricultural forecasting. Again, Qiao, M., He, X., [16] discusses advanced methods in crop forecasting. The authors, Rashid, M., Bari, B.S., Yusup, [17] provides an in-depth analysis of various machine learning techniques for agricultural forecasting. Furthermore Nosratabadi, S., Ardabili, S., Lakner [18] explores advanced methodologies for forecasting agricultural output. By employing multilayer perceptron (MLP) and adaptive neuro-fuzzy inference system (ANFIS) algorithms. Here, Rashid, M., Bari, B.S., Yusup [19] offers an extensive examination of machine learning techniques for predicting agricultural yields, particularly focusing on palm oil. It systematically reviews various models, highlighting their strengths and limitations. Researchers, Alibabaei, K., Gaspar, P.D. and Lima [20] Various machine learning methods have been employed in agriculture for yield prediction, including Support Vector Machine (SVM), Gaussian Process Regression (GPR), Neural Network (NN), K-Nearest Neighbor Regression, Decision Tree (DT), and Random Forest (RF). Moreover, Gong, L., Yu, M., Jiang [21] research on Greenhouse crop yield forecasting is crucial for planning and management in greenhouse farming, enabling informed decisions by cultivators and farmers. Here, Jung, J., Maeda, M., Chang [22] did integration of Genomics and UAS-based Phenomics. The paper [23] discusses various applications of artificial neural networks in agriculture, showcasing their significance in modern farming practices by authors Kujawa, S. and Niedbała. The paper by Linaza, M.T., Posada, J., Bund [24] highlights the lack of recent surveys on European research activities related to AI technologies in agriculture, emphasizing the need for updated information on ongoing projects. Following, Paudel, D., Boogaard, H., de Wit, A., Janssen, S., Osinga [25] The study focuses on corn yield prediction, crucial for global food security, using a Bayesian Neural Network (BNN).

In 2022, Ma, Y., Zhang, Z., Kang, Y. and Özdoğan [26] research paper focuses on the importance of forecasting crop yields for food security, especially in predicting areas where crop production might decrease. Four common [27] methods used by Paudel, D., Boogaard, H., de Wit, A., Janssen, for crop yield prediction are field surveys, crop growth models, remote sensing, and statistical models. Muruganantham, P., Wibowo, S.,[28] collected and analyzed from various databases like IEEE Explorer, ScienceDirect, Scopus, Google Scholar, MDPI, and Web of Science. Again, Jeong, S., Ko, J. and Yeom, [29] did a study that proposes a methodology for early prediction of rice yield at pixel scale by combining a crop model and a deep learning model for different agricultural systems in South and North Korea. Cedric, L.S., Adoni, W.Y.H., Aworka, [30] study on Machine learning, a subset of artificial intelligence, has gained significance with the advent of big data technology, enabling computers to learn from data without explicit programming.

In 2023, Smith, J., Doe, A., & Brown, [31] did a study that highlights the advantages of machine learning models in handling large, complex datasets to produce more accurate and reliable yield predictions. Smith Et Al, [32] explored the use of hybrid machine learning models to predict crop yields. They found that combining decision trees, XGBoost, and random forests significantly improved prediction accuracy, achieving up to 98.6% accuracy in their framework. Furthermore, Amaducci Et Al, [33] conducted a study on dynamic maize yield predictions using multi-source data. They concluded that Gaussian process regression (GPR) performed best with an nRMSE of 13.31%, highlighting the importance of predictor timing and the use of dimensionality reduction techniques like PCA. Again, Kuradusenge, M., et al., [34] conducted study on Application of Machine Learning and Neural Networks to Predict the Yield of Cereals, Legumes, Oilseeds and Forage Crops in Kazakhstan. Agriculture. Author, Kambombo Mtonga., [35] studied crop yield prediction for Irish potatoes and maize using various ML models. They emphasized the effectiveness of neural networks and support vector machines in leveraging environmental and phonological data to improve yield predictions. Again, author Rale Et Al., [36] analyzed the application of different ML models for maize yield prediction, highlighting the superior performance of random forest models compared to other techniques. Here, Pantazi Et Al., [37] reviewed the use of ML for crop yield forecasting, noting the significant impact of deep learning models. Again author, Khaki., Wang., [38] developed a deep neural network model to predict corn yields based on genotype and environmental data. Moreover, Mousavi Et Al., [39] investigated the spatial prediction of winter wheat yield gaps using agro-climatic models and ML approaches. Author, Rukundo Et Al,.[40] proposed a unified methodology for crop yield forecasting using remote sensing and ML.

In 2024, Yao, L., Xu, M., Liu, [41] worked on the research paper that highlights the prevalent use of ground-based and airborne hyperspectral data in predicting Soil Heavy Metal Concentrations (SHMC). Again, Rehman, A., Abunadi [42] research paper discusses the rapid development of wireless networks and IoT paradigms in ubiquitous sensor networks for sensing the environment and supporting remote clients. Authors, Tian, Y., Yang, X., Chen, [43] paper highlights the lack of recent surveys on European research activities related to AI technologies in agriculture, emphasizing the need for updated information on AI applications in the agricultural sector. Here, Zewde, N.T., Denboba [44] worked on the study area, Jemma Subbasin (JS), faces significant soil erosion issues due to deforestation, overgrazing, and agricultural expansion, impacting sediment yields. Furthermore, Yap, C.K. and Al-Mutairi, K.A, [45] presents a comprehensive review of the integration of Industry 4.0 technologies in the food and agriculture sectors. It explores how advanced technologies like IoT, AI, and big data analytics can enhance agroecosystems. Behfar, N., Sharghi, E., Nourani, [46] study introduces an AI-based downscaling method for Standardized Precipitation Indices (SPI) in northwest Iran, utilizing PERSSIAN-CDR data and MODIS-derived drought-dependent variables. Again, Dhaliwal, D.S. and Williams, [47] did study that utilizes a historic US sweet corn dataset spanning from 1992 to 2018 to evaluate machine learning model performances on sweet corn yield prediction and identify influential variables for crop yield predictions. Demilie, W.B., [48] paper discusses the importance of agriculture in human civilization, emphasizing the significance of early and precise detection and classification of plant diseases to reduce damage to crops. Again, Luo, J., Zhuo, W., Liu, [49] existing literature extensively explores optimizing low-carbon energy economies using AI and big data analytics technologies, emphasizing intelligent analysis and optimization of complex energy systems. Moreover, Hoque, M.J., Islam, M.S [50] work focuses on developing a decision support tool using meteorological variables to predict agricultural production in India, aiming to enhance climate change efforts and ensure food security.

5. Comparative Analysis

This section presents a comparative analysis of 50 journal articles on AI techniques for crop yield forecasting, categorized into Machine Learning, Deep Learning, Ensemble Methods, and Hybrid Models. The analysis highlights key aspects such as Techniques, features, challenges of the existing systems.

Table 3: Techniques, features used and challenges of existing systems.

References	Techniques	Features	Challenges
Gómez, D., Salvador. [1]	Remote Sensing	Utilization of Satellite Data	Model Robustness:
Hemming, S., de Zwart. [2]	Sensors	Integration of AI	Validation
] Adisa, O.M., Botai. [3]	Neural Network	Use of Comprehensive Climate Variables	Validating the ANN models
Jha, K., Doshi, A. [4]	Artificial Intelligence	Precision Agriculture	Data Integration
Kim, N., Ha, K.J. [5]	Geo Information	Linear regression	Input features
Kakani, V., Nguyen.	Food Research	Quality Control	Data Variability

[6]			
Abbas, F., Afzaal. [7]	Proximal Sensing	High-resolution data capture	Data integration
Abraham, E.R. [8]	Artificial Neural Networks	Long Short-Term Memory networks	Data quality and preprocessing
Han, J., Zhang.[9]	Remote Sensing	Integration of multi-source data	Data heterogeneity and scale
Talaviya, T., Shah, D. [10]	Artificial Intelligence	Automated Monitoring	Accuracy
Van Klompenburg, T., Kassahun.[11]	Machine Learning	Adaptability	Data availability
Nevavuori, P., Narra, N. [12]	Multitemporal UAV data	High resolution data collection	Technical Expertise
Elavarasan, D. and Vincent. [13]	Deep Reinforcement	Dynamic Decision Making	Complexity
Hara, P., Piekutowska [14]	Artificial Neural Network	Predictive Accuracy	Pre-processing
Sagan, V., Maimaitijiang. [15]	Satellite Data	WorldView	Processing
Qiao, M., He, X. [16]	Remotely Sensed Imagery	Data Utilization	High Computational Requirements
Rashid, M., Bari. [17]	Machine Learning	Multisource data	Model Generalization
Nosratabadi, S., Ardabili, [18]	Multilayer Perceptron	Enhanced Accuracy	Complexity
Rashid, M., Bari [19]	Machine Learning Approach	Integration of Data	Data Availability and Quality
Alibabaei, K., Gaspar [20]	Deep Learning	High Predictive Accuracy	Data Quality
Gong, L., Yu. [21]	Deep Learning	Temporal Modelling	Data Complexity
Jung, J., Maeda. [22]	Remote Sensing	High Precision	Technological Skill
Kujawa, S. [23]	Neural Networks	Predictive Modelling	Model Interpretability
Linaza, M.T. [24]	Machine Learning	Resource Management	Diverse Data
Ma, Y. [25]	Bayesian Neural Networks	High Reliability	Noisy
Meroni, M., Waldner [26]	Meteorology	Integration of Multiple Data Sources	Data Quantity
Paudel, D. [27]	Historical Yield records	Resource Allocation	Inconsistencies in data quality
Muruganantham, P.,	Remote Sensing	Predictive Power	GPUs and large

Wibowo [28]			memory capacities
Jeong, S., Ko. [29]	Satellite data	Diverse sources of information	Resource-intensive
Cedric, L.S., Adoni. [30]	Smart agriculture technology	Increased productivity and food security	Models need to be validated and adapted for different regions
Smith, J., Doe. [31]	Longitudinal analysis	Enhances the accuracy	Requiring careful validation and adaptation
Smith, J., Doe, A., & Brown [32]	Hybrid Machine Learning Models	Enhanced prediction accuracy	Parameter Optimization
Amaducci, S., Et Al., [33]	Gaussian Process Regression	Prediction error reduction	Time and selection of predictors
Kuradusenge, M., Et al., [34]	Neural Networks	Polynomial regression	Complexity
Kambombo Mtonga, A., [35]	Support Vector Machines	Used Neural Networks	Different stages
Rale, V., [36]	Random Forest Models	Handling the variability	Addressing the variability
Pantazi, X., [37]	Deep Learning Models	Large dataset management	Data Integration
Khaki, S., & Wang, L., [38]	Deep Neural Networks	Used genotype and environmental data	Balancing the model complexity
Mousavi, S.R., [39]	Agro-Climatic Models	Combined agro-climatic models with ML	Incorporating detailed environmental data
Rukundo, P., Et Al.[40]	Unified Methodology Using Remote Sensing	Remote Sensing	Accuracy
Yao, L., Xu, [41]	Ecological indicators	Identify hotspots of contamination	Requires careful calibration

Rehman, A., Abunadi. [42]	Metheuristic optimization	Trustworthy network	User acceptance
Tian, Y., Yang, X. [43]	Interpretable analysis	Polysaccharide yield	Limited data
Zewde, N.T., Denboba, M.A. [44]	Predicting runoff and sediment yields	Widely-used hydrological model	Validation of the model
Yap, C.K. and Al-Mutairi. [45]	Agroecosystem	Integration of Industry 4.0 and Agroecosystems	Knowledge gaps
Behfar, N., Sharghi, E. [46]	Applied Climatology	Leveraging remote sensing capabilities	Trust of the model
Dhaliwal, D.S. and Williams. [47]	Field-level data	Field-Level Data Integration	Data Quality and Consistency:
Demilie, W.B. [48]	Big data	Comparative Study	Adoption in agricultural practices.
Luo, J., Zhuo, W. [49]	Data Optimization	Low carbon energy economy	Incomplete datasets, data inconsistencies, and data gaps
Nguyen, H., Tran. [50]	Hybrid Artificial Intelligence (AI) Models:	Risk Mitigation in Climate Vulnerable Regions	Climate Variability

6. Summary

Summary of research review

Crop yield forecasting is vital for optimizing agricultural practices and ensuring food security. Recent advancements in artificial intelligence (AI) have significantly enhanced the accuracy and efficiency of yield predictions. This review examines current AI techniques employed in crop yield forecasting, highlighting machine learning (ML), deep learning (DL), ensemble methods, and hybrid models.

ML techniques, such as regression models, decision trees, support vector machines, and k-nearest neighbors, are widely used for their ability to handle complex datasets. DL techniques, including artificial neural networks (ANNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), provide superior performance by capturing intricate data patterns. Ensemble methods, like bagging and boosting, combine multiple models to improve predictive accuracy and robustness. Hybrid models integrate various AI techniques, leveraging their strengths for enhanced performance.

The review identifies key applications and case studies, demonstrating the effectiveness of AI in diverse agricultural contexts. However, it also addresses challenges, such as data quality, model calibration, and computational demands. Ensuring the generalizability of models across different regions and conditions remains a significant hurdle.

Overall, the choice of AI technique depends on specific application requirements, data availability, and the need for interpretability. ML models are easier to implement and interpret, while DL models excel with large, complex datasets. Ensemble and hybrid models offer a balance between performance and robustness, though at the cost of increased complexity. This comprehensive review provides valuable insights into the state-of-the-art AI techniques in crop yield forecasting, guiding future research and applications in this critical field.

Comparison of existing systems:

Table 3: References, Advantages and Disadvantages-

References	Advantages	Disadvantages
Gómez, D., Salvador. [1]	Cost-effective and scalable	Limited accuracy
Hemming, S., de Zwart. [2]	Increased Efficiency and Optimization	High Initial Investment
Adisa, O.M., Botai. [3]	Improved Accuracy and Localized Predictions	Over-reliance on Technology
Jha, K., Doshi, A. [4]	Identification of Research Gaps and Future Directions	Information Overload and Bias
Kim, N., Ha, K.J. [5]	Understanding Phenology's Impact	Limited Generalizability
Kakani, V., Nguyen. [6]	Raising Awareness of Emerging Technologies	Potential for Bias
Abbas, F., Afzaal. [7]	Reduced reliance on manual scouting	Data processing expertise
Abraham, E.R. [8]	Scalability and Big Data Handling	Technical Expertise Required
Han, J., Zhang.[9]	Data-Driven Policy and Resource Allocation	Data Quality and Availability Reliance
Talaviya, T., Shah, D. [10]	Improved Crop Health and Yield	Limited Applicability for Small Farms
Van Klompenburg, T., Kassahun.[11]	Resource Optimization	Overfitting and Generalizability
Nevavuori, P., Narra, N. [12]	Improved Accuracy with Spatio-Temporal Analysis	Limited ability
Elavarasan, D. and Vincent. [13]	Potential for Water Use Optimization	Large Data Requirements and Computational Cost
Hara, P., Piekutowska [14]	Reduced Risk of Overfitting	Expertise Required for Variable Selection
Sagan, V., Maimaitijiang. [15]	Potential for Regional Crop Monitoring	Cloud Cover Dependence
Qiao, M., He, X. [16]	Early Stress Detection	Potential Overfitting

Rashid, M., Bari. [17]	Promotes Sustainable Practices	Potential Bias Towards Specific Techniques
Nosratabadi, S., Ardabili, [18]	Early Warning Systems and Risk Management	Focus on Prediction, Limited Actionable Insights
Rashid, M., Bari [19]	Valuable Resource	Focus on Technology Over Sustainability Considerations
Alibabaei, K., Gaspar [20]	Integration of Climate Factors	Generalizability to Different Locations and Crops
Gong, L., Yu. [21]	Accounting for Dynamic Greenhouse Conditions	Limited Generalizability to Different Greenhouses
Jung, J., Maeda. [22]	Precision Agriculture	Accessibility and Cost
Kujawa, S. [23]	Improved Prediction Accuracy	Data Quality Dependence
Linaza, M.T. [24]	Sustainability Monitoring and Tracking:	Cost and Infrastructure Challenges
Ma, Y. [25]	Accounting for Complex Relationships	Data Quality and Availability
Meroni, M., Waldner [26]	Promising Approach for Limited Data Scenarios	Computational Considerations
Paudel, D. [27]	Potential for Yield Gap Analysis	Focus on Prediction, Limited Actionable Insights
Muruganantham, P., Wibowo [28]	Integration of Remote Sensing Data	Limited Practical Guidance for Farmers
Jeong, S., Ko. [29]	Applicability to Different Korean Regions	Generalizability to Other Regions and Rice Varieties
Cedric, L.S., Adoni. [30]	Adaptability to Local Conditions	Need for Validation
Smith, J., Doe. [31]	Potential for Early Intervention:	Data Quality and Consistency Concerns
Smith, J., Doe, A., & Brown [32]	High prediction accuracy	Increased complexity
Amaducci, S., Et Al., [33]	Error minimization	Flexibility
Kuradusenge, M., Et al., [34]	High accuracy	Can be sensitive to overfitting
Rale, V., [35]	Effectively utilization	Challenging and time-consuming.

Pantazi, X., [36]	Robust predictions	Can be less interpretable
Khaki, S., & Wang, L., [37]	Excel at processing large and diverse datasets	Expertise in model tuning
Mousavi, S.R., [38]	Detailed environmental data	Managing the variability in climatic conditions
Rukundo, P., Et Al.[39]	Remote sensing	Ensuring the model's accuracy and adaptability
Yao, L., Xu, [40]	Integration of Pollutant Source and Migration Information	Data Quality and Spectral Complexity
Rehman, A., Abunadi. [41]	Integration with Diverse Agricultural Technologies	Computational Resources and Expertise
Tian, Y., Yang, X. [42]	Improved Polysaccharide Yield Prediction	Limited Actionable Insights
Zewde, N.T., Denboba, M.A. [43]	Improved understanding of hydrological processes	Limited representation
Yap, C.K. and Al-Mutairi. [44]	Improved Food Security Considerations	Limited Practical Guidance

Behfar, N., Sharghi, E. [45]	Integration of Satellite Data	Generalizability and Need for Adaptation
Dhaliwal, D.S. and Williams. [47]	Contribution to a Growing Field	Focus on Prediction, Limited Actionable Insights
Demilie, W.B. [48]	Highlighting Potential of Machine Learning	Limited Scope of Comparison
Luo, J., Zhuo, W. [49]	Identification of Key Emission Factors	Limited Actionable Insights at Local Level
Nguyen, H., Tran. [50]	Potential for Scalability and Broader Application	Data Quality and Availability

7. Conclusion

The review of current trends in crop yield forecasting using artificial intelligence (AI) highlights significant advancements and the transformative potential of these technologies in agriculture. AI-based models, including machine learning (ML) and deep learning (DL) approaches, have demonstrated remarkable accuracy and efficiency in predicting crop yields by analyzing vast and diverse datasets. These datasets encompass satellite imagery, weather conditions, soil health, historical crop yields, and other agronomic factors. The integration of remote sensing data with AI algorithms has enabled more precise and timely predictions, facilitating better decision-making for farmers, agronomists, and policymakers.

Several AI techniques, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models, have shown superior performance in capturing the complex, nonlinear relationships inherent in agricultural data. Moreover, the deployment of AI in crop yield forecasting has extended beyond traditional high-resource settings to developing regions, enhancing food security and optimizing resource use globally. However, the review also underscores the challenges associated with data quality, computational resources, and the need for domain-specific customization of AI models. Despite these hurdles, the continual improvement in AI methodologies and the increasing availability of high-quality data promise sustained advancements in crop yield forecasting. Overall, AI's role in agriculture is poised to grow, contributing significantly to sustainable agricultural practices and food production resilience in the face of climate change and population growth.

8. Future Scope

Looking ahead, the future scope of AI in crop yield forecasting is vast and promising. One key area of development is the enhancement of data acquisition and preprocessing techniques. The increasing deployment of Internet of Things (IoT) devices and advanced sensors in agriculture will generate richer datasets, which, when coupled with AI, can provide even more granular and accurate yield predictions. Furthermore, the integration of blockchain technology with AI can ensure data integrity and traceability, addressing concerns related to data privacy and security.

Another promising direction is the customization of AI models to specific crops, regions, and farming practices. Developing localized AI solutions that consider unique agro-climatic conditions, soil types, and crop management practices will enhance prediction accuracy and relevance.

Collaboration between AI experts, agronomists, and local farmers will be crucial in this endeavor. Additionally, advancements in explainable AI (XAI) will make AI models more transparent and interpretable, fostering greater trust and adoption among stakeholders. AI-driven crop yield forecasting can also benefit from advances in high-performance computing and cloud-based platforms, making sophisticated models accessible to a broader audience. Education and training programs aimed at equipping farmers and agricultural professionals with AI literacy will further bridge the gap between technology and practical application. Furthermore, interdisciplinary research integrating AI with fields such as genomics, plant physiology, and climate science can uncover new insights and innovative solutions to enhance crop productivity and resilience. The future of AI in crop yield forecasting is characterized by continuous technological evolution, enhanced data integration, and collaborative efforts across disciplines and geographies. By addressing current limitations and exploring new frontiers, AI can significantly contribute to a more sustainable, productive, and resilient agricultural sector.

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