Machine Learning Models for Smart Hydroponic Systems: A Systematic Review Toward an Optimal Hybrid Modeling Frameworks

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Abstract: Global food production is increasingly challenged by rapid population growth, climate change, declining soil fertility, and limited arable land, particularly in developing regions. These challenges have intensified interest in soilless farming systems such as hydroponics, which offer improved resource efficiency and controlled growing environments. When integrated with sensors, Internet of Things (IoT) technologies, and automation, hydroponic systems evolve into smart hydroponic systems in which machine learning (ML) enables data-driven monitoring, prediction, and autonomous control. However, existing studies are often fragmented, focusing on isolated algorithms or narrow applications, with limited attention to scalability, robustness, and hybrid learning strategies. The aim of this paper is to systematically review and critically examine machine learning techniques applied in smart hydroponic farming systems. A PRISMA 2020-guided systematic review methodology was adopted, covering peer-reviewed studies published between 2010 and 2025 and retrieved from major scientific databases. Eligible studies were screened, quality assessed, and analyzed using structured data extraction methods. The findings show that classical supervised models such as Decision Trees, Random Forests, and Support Vector Machines perform effectively in sensor-based monitoring and control tasks, achieving accuracies of up to 98%. Deep learning models, particularly Convolutional and Deep Neural Networks, consistently outperform classical approaches in image-based applications, with reported accuracies reaching 99.7%. Hybrid ML frameworks that integrate multiple models with IoT-enabled automation demonstrate enhanced adaptability and operational efficiency. This paper concludes that **while machine learning substantially improves the intelligence and performance of smart hydroponic systems, the adoption of robust hybrid frameworks, comprehensive environmental monitoring, and standardized evaluation metrics is essential for scalable, sustainable, and real-world deployment.**

Keywords: *Smart Hydroponic Systems, Machine Learning Models, Systematic Review, Model Limitations and Challenges, Hybrid Machine Learning Framework.*

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I. INTRODUCTION

Machine Learning (ML) is a core subfield of artificial intelligence concerned with the development of algorithms that enable computer systems to learn patterns from data and improve performance on specific tasks without explicit rule-based programming (Mitchell, 1997; Buczak & Guven, 2016). ML techniques leverage statistical inference, optimization, and computational learning theory to model complex, nonlinear relationships, making them particularly suitable for data-intensive and dynamic domains such as agriculture and controlled environment farming (Jordan & Mitchell, 2015).

Machine learning approaches are commonly categorized into supervised, unsupervised, and semi-supervised learning paradigms. Supervised learning relies on labeled datasets to train predictive models for classification or regression tasks and has been widely adopted in agricultural applications due to its high predictive accuracy when sufficient labeled data are available (Shahreza et al., 2011; Brownlee, 2016). Typical supervised models applied in smart agriculture include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and k-Nearest Neighbors (k-NN) (Li & Dong, 2014; Khodadadi et al., 2016). Unsupervised learning operates on unlabeled datasets

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and focuses on discovering inherent data structures, such as clusters or anomalies, using techniques including k-means clustering, hierarchical clustering, and principal component analysis (Parmar & Patel, 2017). Semi-supervised learning integrates both labeled and unlabeled data, offering a compromise between predictive accuracy and data acquisition cost, which is particularly relevant in agricultural systems where labeled datasets are often scarce or incomplete (Omar et al., 2013).

The adoption of ML in smart agriculture has accelerated in recent years due to advances in sensor technologies, Internet of Things (IoT) infrastructures, cloud computing, and data analytics platforms (Wolfert et al., 2017). ML models have been successfully applied to crop yield prediction, irrigation scheduling, nutrient management, pest and disease detection, climate impact assessment, and decision support systems (Kamilaris & Prenafeta-Boldú, 2018). In controlled environment agriculture, including greenhouses and soilless systems, ML techniques such as ANN, SVM, Random Forests, and deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been used for image-based plant disease detection, plant growth modeling, and time-series prediction of environmental variables (Ferentinos, 2018; Alipio et al., 2020).

Despite these technological advancements, global food systems remain under severe pressure. Food security continues to be a major global challenge, particularly in developing regions, due to rapid population growth, climate change, environmental degradation, urbanization, and socio-economic instability (FAO, 2010; Godfray et al., 2010). Climate change has intensified agricultural vulnerability through rising temperatures, altered precipitation patterns, extreme weather events, salinity intrusion, and increased pest and disease prevalence, all of which negatively affect crop productivity (FAO, 2020; IPCC, 2022). In sub-Saharan Africa, including Nigeria, food insecurity is further exacerbated by land scarcity, insecurity, population displacement, poverty, and disruptions to agricultural supply chains (Mudo et al., 2020).

Conventional soil-based agriculture is increasingly constrained by declining soil fertility, limited arable land, inefficient water use, and environmental pollution, particularly in urban and peri-urban areas (Panwar et al., 2011). These constraints have intensified the need for alternative food production systems that are resource-efficient, climate-resilient, and adaptable to space-limited environments. As a result, soilless farming techniques have gained increasing attention as viable solutions for sustainable food production.

Hydroponic farming is a soilless cultivation technique in which plants are grown in nutrient-enriched aqueous solutions, allowing precise control over nutrient delivery and root-zone conditions (Resh, 2013). Compared to conventional agriculture, hydroponic systems offer higher water-use efficiency, reduced fertilizer losses, elimination of soil-borne diseases, and increased crop yields per unit area (Savvas & Gruda, 2018). These advantages make hydroponics particularly suitable for urban agriculture, arid regions, and areas with degraded or contaminated soils.

The integration of hydroponic farming with digital and automation technologies has led to the emergence of Smart Hydroponic Systems (SHS). A hydroponic system is considered “smart” when it incorporates sensors, actuators, communication networks, and intelligent data-processing algorithms to enable real-time monitoring, analysis, and autonomous control of the growing environment (Singh et al., 2016; Baras, 2018). Smart hydroponic systems continuously monitor key parameters such as temperature, relative humidity, pH, electrical conductivity, nutrient concentration, light intensity, and dissolved oxygen, and dynamically adjust system operations to optimize plant growth (Chinnasamy et al., 2021). IoT technologies facilitate real-time data acquisition and remote system management, while ML algorithms transform raw sensor data into actionable insights for predictive modeling, anomaly detection, and adaptive control (Borgia, 2014; Wolfert et al., 2017).

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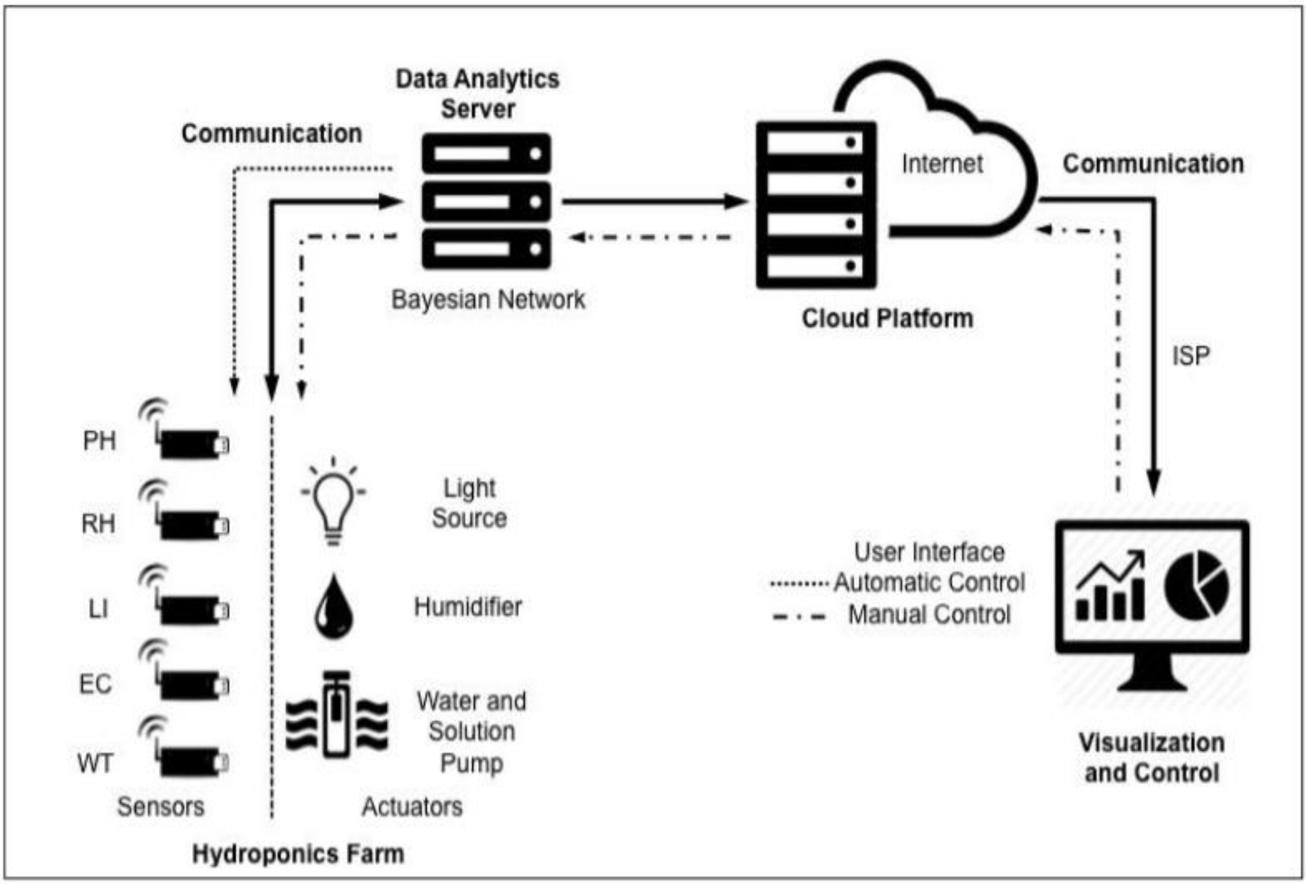

Fig 1: Overview of Typical Smart Hydroponic System (Alipio *et al*, 20200

Machine learning therefore constitutes a critical intelligence layer in smart hydroponic systems, enabling predictive analytics, optimization, and autonomous decision-making. ML techniques have been applied to nutrient optimization, yield forecasting, disease and stress detection, sensor fault diagnosis, and adaptive environmental control in hydroponic environments (Khodadadi et al., 2016; Alipio et al., 2020). However, existing studies often focus on individual algorithms or narrowly defined tasks, with limited attention to model generalizability, robustness to noisy data, scalability, real-time deployment constraints, and integration of multiple learning paradigms. Supervised, unsupervised, semi-supervised, and hybrid ML approaches exhibit varying strengths and limitations depending on data availability, system complexity, and operational objectives (Brownlee, 2016; Omar et al., 2013).

This paper presents a systematic review of machine learning techniques applied in smart hydroponic farming systems. The review critically examines existing ML models, their application domains, performance metrics, and inherent limitations. By synthesizing current research trends and identifying methodological gaps, this study aims to provide insights toward the development of robust hybrid machine learning frameworks capable of enhancing the efficiency, adaptability, and sustainability of smart hydroponic systems in addressing global food security challenges.

The rest of this paper is organized as follows: Section II describes the methodology employed for this systematic review, including the search strategy, selection criteria, data extraction, and quality assessment of the included studies. Section III presents the results and discussion, synthesizing the application of machine learning models in smart hydroponic systems, analyzing performance trends, and critically evaluating the advantages and limitations of supervised, unsupervised, semi-supervised, and hybrid approaches. Finally, Section IV concludes the study by summarizing the key findings, highlighting practical and research implications, and providing recommendations for the development of robust hybrid machine learning frameworks in smart hydroponic farming.

II. METHODOLOGY

This study employed a systematic review approach to critically analyze the application of machine learning (ML) techniques in smart hydroponic systems, with a particular focus on hybrid machine learning frameworks. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor, transparency, and reproducibility (Page *et a*l., 2021). The primary objective was to identify, synthesize, and evaluate empirical studies that applied ML models for monitoring, prediction, optimization, and control in smart hydroponic environments.

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A. Search Strategy

A comprehensive literature search was conducted across multiple electronic databases, including Scopus, Web of Science, IEEE Xplore, Google Scholar, ScienceDirect, and Springer, covering publications from 2010 to 2025. Keywords were carefully selected to capture relevant studies and combined using Boolean operators to optimize retrieval. Terms such as "machine learning," "artificial intelligence," "predictive modeling," "smart hydroponics," "controlled environment agriculture," "soilless farming," and "hybrid" were used in various combinations. Additionally, reference lists of selected articles were manually screened to identify further studies not captured in the database search. Only peer-reviewed studies published in English were considered to maintain methodological rigor and accessibility.

B. Eligibility Criteria

Studies were included if they reported the application of machine learning models—whether supervised, unsupervised, semi-supervised, or hybrid—in hydroponic or controlled-environment agriculture systems. Inclusion required sufficient methodological detail regarding the dataset, ML models employed, and evaluation metrics, as well as reported outcomes such as predictive accuracy, yield optimization, nutrient management, disease detection, or environmental control. Excluded studies comprised review articles, editorials, commentaries, and studies focusing exclusively on soil-based agriculture without hydroponic or controlled-environment applications. Additionally, studies lacking adequate methodological detail or performance results were excluded.

C. Study Selection Process

The study selection followed the PRISMA 2020 flow diagram framework, incorporating searches across databases, registers, and other sources (Page et al., 2021). Initially, duplicates were removed from the retrieved records. The remaining articles were screened by title and abstract to identify potentially relevant studies. Full-text screening was subsequently conducted to assess eligibility based on the criteria outlined above. Discrepancies during the selection process were resolved through discussion and consensus among the reviewers (U.J.O, O.U.A & E.F). The selection process is summarized in a PRISMA 2020 flow diagram (Fig. 2), showing the number of records identified, screened, excluded, and included in the final analysis.

D. Data Extraction

For each included study, data were extracted using a structured narrative approach, capturing bibliographic information, type of hydroponic system, crop species, machine learning paradigms applied, dataset characteristics, performance metrics, application domains, and reported limitations. The extraction process aimed to ensure consistency and comparability across studies, enabling a detailed synthesis of ML techniques, trends, and methodological gaps.

E. Quality Assessment

The methodological quality of the included studies was evaluated using a modified Critical Appraisal Skills Programme (CASP) checklist suitable for quantitative and computational studies. Quality assessment focused on the clarity of objectives, appropriateness of ML model selection, dataset description, evaluation metrics, reproducibility of results, and consideration of limitations. Each study was categorized as high, moderate, or low quality, providing a framework for interpreting findings and assessing the reliability of conclusions drawn from the review.

III. RESULTS AND DISCUSSIONS

A. Results

Table 1 summarizes the application of machine learning models in smart hydroponic systems as reported in the reviewed studies.

Fig. 3 illustrates a comparison of the reported accuracy of different machine learning models applied in smart hydroponic systems.

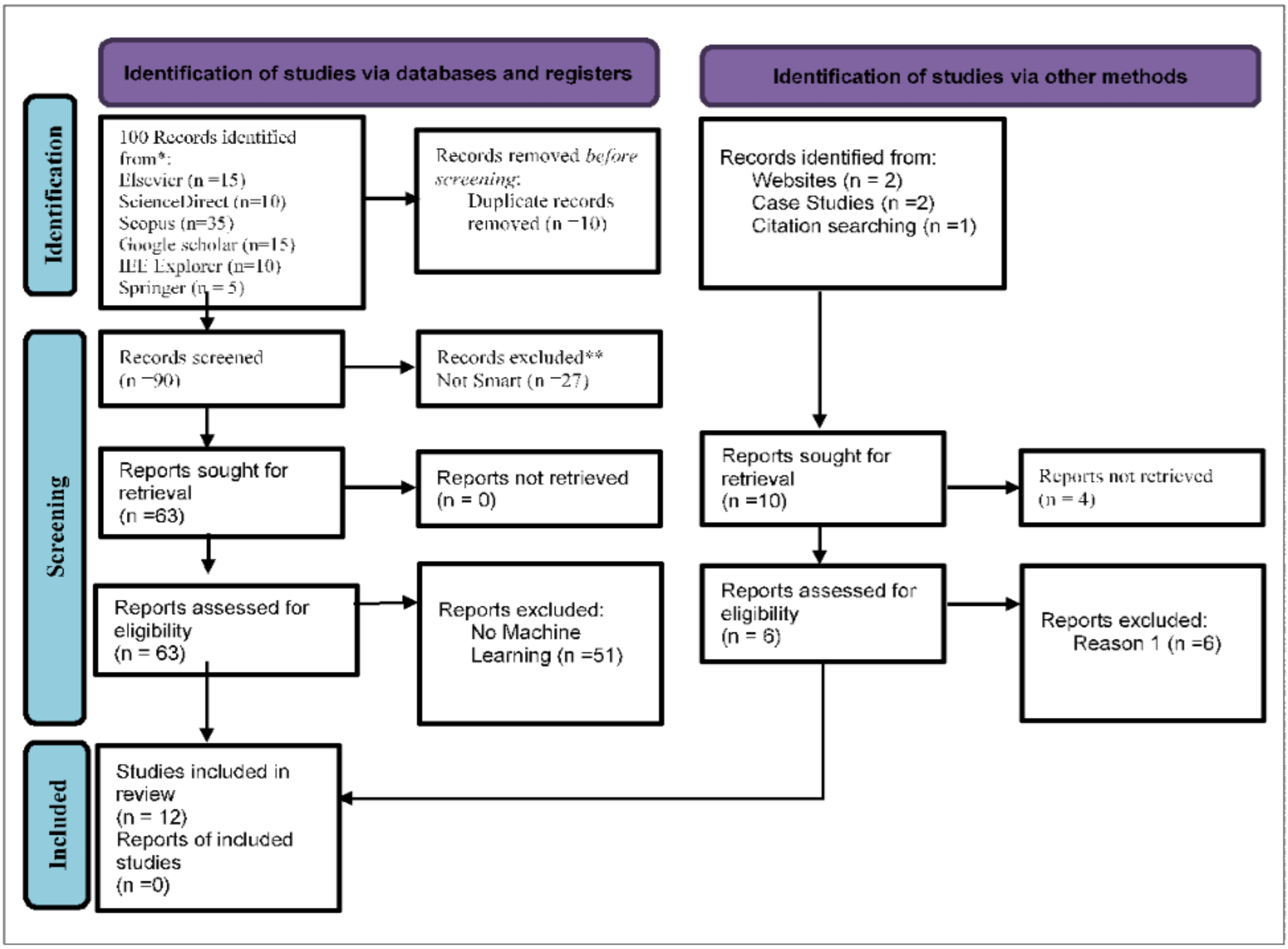

Fig. 2: PRISMA 2020 flow diagram for the study which included searches of databases, registers and other sources. (*Source:* Page et al., 2021)

Fig. 2 presents a total of 12 studies published between 2017 and 2024 were reviewed to evaluate the application of machine learning (ML) in smart hydroponic systems. The studies span various ML paradigms, including classical supervised learning algorithms, deep learning architectures, and hybrid frameworks, applied to tasks such as plant growth prediction, disease detection, nutrient optimization, and automated environmental control.

Table 1: Summary of Machine Learning Models Applied in Smart Hydroponic Systems

Study	Hydroponic System	ML Model(s)	Dataset	Application	Performance Metrics	Key Findings	Limitations
Wongpatikaseree et al., 2018	Hydroponic vegetables	Decision Tree (J48), Naive Bayes, MLP, Deep NN	Image data	Freshness detection	Accuracy: 98.12% (DT best)	DT outperformed others in detecting fresh vs. withered vegetables	Limited to image-based freshness, no yield optimization
Alipio et al., 2017	Smart hydroponics with sensors & actuators	Bayesian Network	Sensor values (pH, EC, temp, RH, light)	Automated environmental control	Yield: +66.67% vs manual	BN minimized sensor fluctuations, improved yield	CO_2 & O_2 not controlled, limited security & traceability
Asy'ari et al., 2023	Hydroponic farm	ARIMA (2,2,1)	Time-series data, 8 days	Plant growth forecasting	RMSE: 0.97, MAE: 0.94, MAPE: 0.04	ARIMA provided accurate growth forecasts	Short data collection period, no external

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							factors considered
Raju et al., 2022	AI-SHES with IoT	Deep CNN	Sensor & image data	Nutrient prediction, disease detection	Accuracy: 99.29%, F-measure: 99.23%, Precision: 99.38%, Recall: 98.58%	High performance in disease detection & nutrient prediction	CO_2/O_2 not controlled, high energy consumption, security concerns
Rajkumar & Chachadi, 2021	Automated hydroponic farm	Decision Tree	Sensor data	Environmental control	Maintained pH, EC, Temp, Humidity	Autonomous remote monitoring effective	Accuracy not reported, intrusion & disease detection not considered
Bulut & Hacıbeyoğlu, 2023	Smart hydroponics using water/wastewater data	SVM, K-NN, Naive Bayes, Logistic Regression, DT, DNN, CNN, ANN, RNN	Sensor database	Plant growth monitoring	DNN: 99.7%	DNN outperformed other methods, >80% accuracy overall	Yield, intrusion, and disease detection not addressed
Rajkunwar et al., 2024	Hydroponic plant disease & nutrient detection	CNN	Image dataset (16,504 train; 2,064 val; 2,070 test)	Disease & nutrient deficiency detection	Accuracy: 96% disease, 87% nutrient	Real-time supervision & intervention	No real-time environmental control
Tambakhe & Gulhane, 2022	Hydroponic spinach	SVR, Linear, Lasso, DT, Ridge, RF	Sensor & growth data	Crop growth monitoring	RF: 95% accuracy, DT: R^2=0.86, SVR: MAE=12.65, RMSE=21.31, Lasso: MSE=4.51	Real-time continuous monitoring effective	Limited to spinach, CO_2/O_2 not monitored
Idoje et al., 2023	Smart hydroponic farm	DT, RF, SVM, ANN	Sensor data	Plant growth prediction	Not explicitly reported	Provided insights on algorithm strengths/limitations	Yield optimization & environmental control not addressed
Mehra et al., 2018	IoT hydroponic tomato farm	DNN	Sensor data via Arduino/Raspberry Pi	Real-time growth control	Accuracy: 88%	DNN improved growth control efficiency	Compared only with BN, limited crop types
Devi et al., 2024	IoT hydroponics system	ML algorithms (not specified)	Real-time sensor data	Optimal condition prediction & automated nutrient/water control	Not explicitly reported	Enhanced yield, sustainable resource use	Specific performance metrics not reported

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Table 1 highlights the type of hydroponic system, machine learning algorithms employed, dataset characteristics, application domains, and reported performance metrics such as accuracy, precision, recall, and F-measure. Classical supervised models including Decision Trees, Random Forests, and Support Vector Machines were widely used for environmental control, growth monitoring, and plant growth prediction. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), were predominantly applied for image-based tasks such as plant disease detection, nutrient deficiency recognition, and crop quality assessment. Hybrid approaches integrating machine learning with IoT-based monitoring and automation demonstrated enhanced operational efficiency and predictive performance compared to standalone models. The table also identifies limitations reported by the studies, including unmonitored critical parameters (e.g., CO_2 and O_2), energy consumption, security and traceability issues, and limited generalizability across crop types.

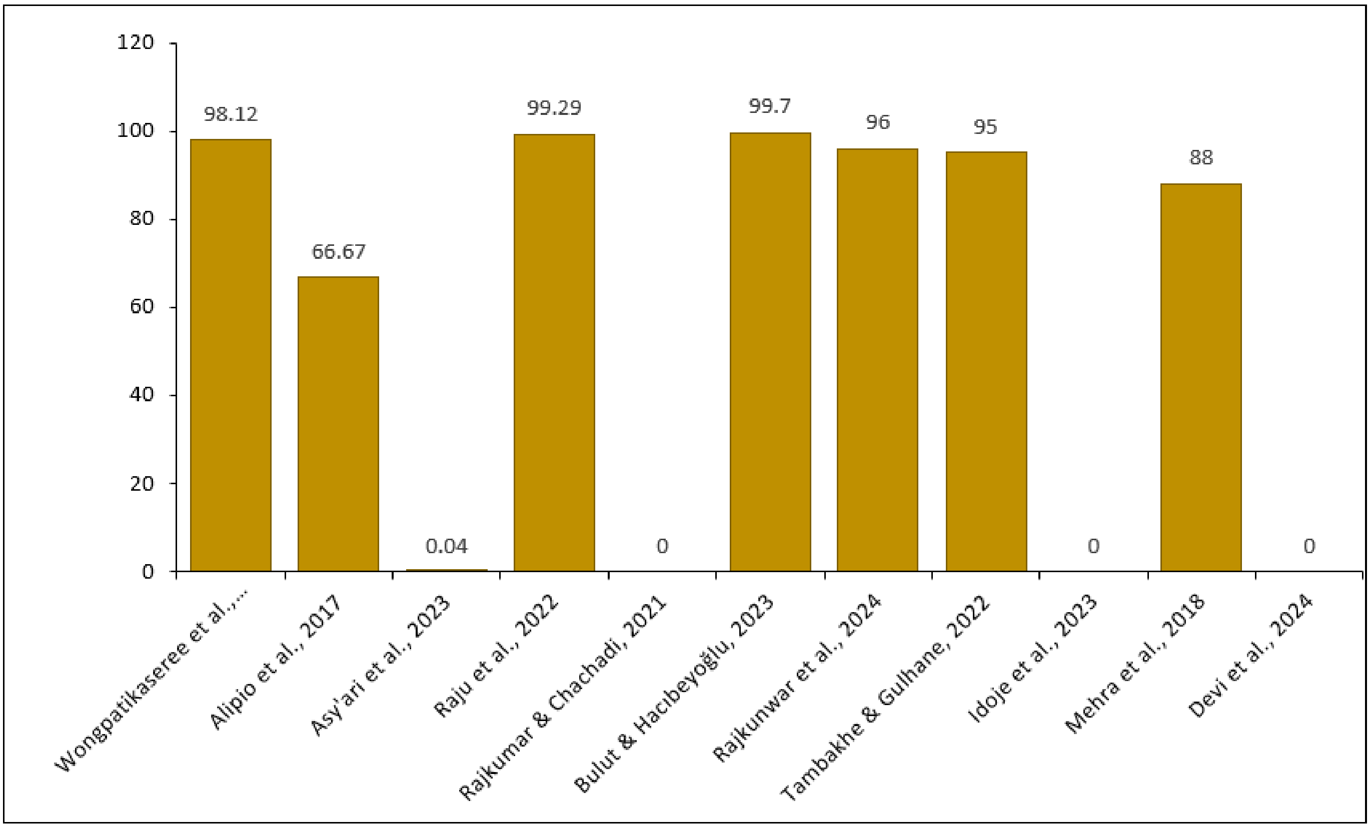

Fig. 3: Accuracy Comparison of Machine Learning Models in Reviewed Smart Hydroponic Systems.

Figure 3 showed that classical algorithms such as Decision Trees, Random Forests, and SVM achieved accuracy values ranging between 80% and 98%, while deep learning models, including CNNs and DNNs, generally outperformed classical models, reaching accuracies of 96% to 99.7%. The figure emphasizes that hybrid and deep learning-based approaches tend to offer superior predictive performance, particularly in tasks involving complex or image-based datasets. It also highlights that several studies did not report accuracy metrics for their models, reflecting gaps in reporting standards and comparability

B. *Discussion of Findings*

The reviewed works provide a comprehensive overview of the application of machine learning (ML) in smart hydroponic systems (Fig. 2). These studies span classical supervised learning models, deep learning architectures, and hybrid frameworks, applied to tasks such as plant growth prediction, disease detection, nutrient optimization, and automated environmental control. The review highlights the increasing integration of ML with Internet of Things (IoT)-enabled hydroponic systems, demonstrating the transformative potential of data-driven approaches in precision agriculture (Kamilaris & Prenafeta-Boldú, 2018; Wolfert et al., 2017).

➢ *Performance of Classical Machine Learning Models*

Classical supervised learning algorithms, including Decision Trees (DT), Random Forests (RF), and Support Vector Machines (SVM), were widely applied in structured sensor-based hydroponic systems. Wongpatikaseree et al. (2018) reported that a Decision Tree classifier achieved the highest accuracy (98.12%) in detecting fresh versus withered vegetables, outperforming Naive Bayes, MLP, and shallow deep neural networks. Tambakhe and Gulhane (2022) similarly demonstrated that Random Forest achieved 95% accuracy for crop growth monitoring, with complementary metrics provided by SVR, Lasso, and Decision Tree Regression. These findings reinforce the robustness and reliability of classical ML algorithms for structured data tasks where environmental variables are clearly defined (Shahreza et al., 2011; Li & Dong, 2014).

➢ *Performance of Deep Learning Models*

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), consistently outperformed classical approaches in high-dimensional and image-based applications. Raju et al. (2022) achieved 99.29% accuracy using a deep CNN for disease detection and nutrient prediction, with precision, recall, and F-measure all exceeding 98%. Bulut and Hacıbeyoğlu (2023) reported a DNN accuracy of 99.7% for plant growth monitoring, outperforming classical algorithms. Rajkunwar et al. (2024) used CNNs to detect plant diseases and nutrient deficiencies with accuracies of 96% and 87%, respectively. These findings demonstrate the strength of deep learning in capturing nonlinear relationships, extracting complex features, and enabling real-time monitoring in image-rich hydroponic systems (Ferentinos, 2018; Alipio et al., 2020).

➢ *Hybrid Machine Learning Approaches*

Hybrid approaches that integrate multiple ML models or combine ML with IoT-based monitoring and automation exhibited superior operational efficiency and predictive performance. Alipio et al. (2017) employed a Bayesian Network with automated actuators and sensors to optimize environmental parameters, achieving a 66.67% higher crop yield compared to manual control. Devi et al. (2024) demonstrated that hybrid ML with IoT-enabled nutrient and water management improved yield, resource efficiency, and sustainability. These findings are consistent with recent evidence that hybrid ML frameworks often outperform single-model approaches, providing enhanced robustness, generalizability, and adaptive control in complex, dynamic agricultural environments (Ukoba et al., 2025; Kamilaris & Prenafeta-Boldú, 2018).

➢ *Comparison of Model Accuracy*

Figure 3 provides a comparison of reported accuracies across ML models in smart hydroponic systems. Classical algorithms such as DT, RF, and SVM achieved 80–98% accuracy, whereas deep learning and hybrid models consistently reached 96–99.7%. The figure clearly shows that hybrid and deep learning-based approaches offer superior predictive performance, particularly for image-based and complex sensor datasets. However, several studies did not report accuracy metrics, highlighting inconsistencies in performance reporting and the need for standardized benchmarking across studies (Brownlee, 2016; Omar et al., 2013).

➢ *Identified Limitations and Research Gaps*

Despite the high accuracy of ML models, several limitations were identified. Critical environmental parameters such as CO_2 and oxygen were frequently unmonitored, limiting optimal growth and yield (Alipio et al., 2017; Raju et al., 2022). Security, traceability, and energy efficiency were rarely considered in IoT-integrated systems, potentially affecting long-term sustainability. Moreover, most studies focused on short-term experiments or single-crop setups, restricting generalizability across hydroponic crops and environments. The inconsistent reporting of standard performance metrics, particularly in hybrid and IoT-enabled systems, further hampers cross-study comparisons.

➢ *Implications for Smart Hydroponic Systems*

The findings demonstrate that ML significantly enhances monitoring, prediction, and control capabilities in smart hydroponic systems. Classical algorithms are effective for structured, quantitative tasks; deep learning models excel in image-based and high-dimensional datasets; and hybrid ML frameworks integrating multiple models with IoT enable the highest operational efficiency. Addressing gaps such as multi-parameter monitoring, energy-efficient operations, security, and generalizability will be critical for advancing scalable, real-world smart hydroponic systems capable of contributing to sustainable food production and food security (FAO, 2020; Wolfert et al., 2017; Ukoba et al., 2025).

IV. CONCLUSION AND RECOMMENDATION

This systematic review highlights the transformative potential of machine learning (ML) in smart hydroponic systems for precision agriculture. The reviewed studies, spanning classical supervised algorithms, deep learning architectures, and hybrid frameworks integrated with IoT-enabled monitoring, demonstrate that ML can effectively support plant growth prediction, disease and nutrient deficiency detection, environmental control, and yield optimization. Classical algorithms such as Decision Trees, Random Forests, and Support Vector Machines performed well in structured sensor-based tasks, achieving accuracies up to 98%. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), consistently outperformed classical models in image-based applications, with accuracies ranging from 96% to 99.7%. Hybrid ML approaches integrating multiple algorithms with IoT-enabled automation provided the highest operational efficiency, predictive performance, and adaptability to dynamic hydroponic environments (Kamilaris & Prenafeta-Boldú, 2018; Ukoba et al., 2025).

Despite these achievements, several limitations and gaps were identified. Critical environmental parameters such as CO_2 and oxygen are often unmonitored, potentially compromising yield optimization. Security, traceability, and energy efficiency remain largely unaddressed in IoT-enabled systems, raising concerns about long-term sustainability and scalability. Furthermore, many studies focused on single crops or short-term datasets, limiting the generalizability of ML models across different hydroponic setups. Inconsistent reporting of standard performance metrics, particularly for hybrid frameworks, complicates benchmarking and hinders reproducibility. Addressing these gaps is essential for advancing ML-enabled smart hydroponic systems from controlled experimental setups to practical, large-scale applications.

Based on the findings of this review, several recommendations are proposed:

- ➢ Integration of Critical Environmental Monitoring: Future systems should incorporate real-time monitoring and control of essential parameters such as CO_2, oxygen, and nutrient concentrations to maximize plant growth and yield.
- ➢ Security and Energy Efficiency: IoT-enabled hydroponic systems must prioritize cybersecurity, data traceability,

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and energy-efficient operations to ensure sustainable and resilient smart farming solutions.

- Hybrid and Adaptive ML Frameworks: Researchers should develop and validate hybrid ML models that combine the strengths of classical and deep learning algorithms. Such models can improve prediction accuracy, robustness, and generalizability across diverse hydroponic crops and environmental conditions.
- Standardized Performance Reporting: Adoption of standardized performance metrics, including accuracy, precision, recall, F-measure, and energy/resource efficiency, will facilitate comparability and reproducibility of ML applications in hydroponics.
- Scalability and Multi-Crop Studies: There is a need for long-term, multi-crop studies that evaluate ML models under varying environmental conditions to enhance the scalability and practical applicability of smart hydroponic systems.

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