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Assessment Of Machine Learning Adoption In The Agricultural Sector

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Abstract
The mounting pressures on the agricultural sector are population growth, climate change, shortage of resources, and the need to produce food sustainably. Though machine learning (ML) has the potential to transform the agricultural industry, especially in precision farming, yield prediction, pest management, and resource optimisation, it is not as widely implemented in these areas, especially in resource-starved areas. This paper evaluates the adoption of ML in terms of a systematic literature review of peer-reviewed articles and case studies across the world, and evaluates the application fields and practices, barriers to implementations, and results. The results indicate that there is extensive use of ML in crop, soil, water, and livestock management, resulting in greater productivity and sustainability, and constrained, however, by high infrastructural costs, data privacy, lack of technical expertise, and insufficient infrastructure. First and foremost, a faster process of adoption of ML requires stakeholder joint capacity building, low costs, and policy support to achieve its potential of resilient and knowledge-based agriculture.

Keywords: *Agriculture, data privacy, machine learning, sustainable.*

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I. Introduction

Agriculture is also known to be a foundation of human civilisation, where the people depend on the land to sustain their daily lives, and food security is the backbone of the economy in the country. The sector is the major food provider of a fast-growing world population, and in addition to sustaining billions, it contributes to huge segments of a national economy, especially in developing countries, where a huge portion of the workforce is employed. The importance of agriculture is also emphasised by the fact that agriculture has been used to solve more systematic problems in society, such as alleviating poverty, biodiversity preservation, and environmental management. The need to work harder to secure sustainability while maximising productivity has put agriculture as a priority issue on the international policy agenda and scientific research efforts in the context of unprecedented demographic pressures and environmental changes [1].

Generalisations about the industry indicate an era of radical change and exposure. The intensive production of agricultural products observed in the last few decades has played a significant role in preventing massive famine and promoting the development of the economy, but the gains are increasingly becoming jeopardised by multi-layered stressors. The population has been growing, which continuously increases food, fibre, and biofuels demand, and the climate variability brings uncertainty by causing changes in precipitation patterns, extreme weather, and changes in pests, causing dynamics. These factors are aggravated by resource limitations, such as the shrinking arable land, water scarcity and soil degradation, which require novel solutions that do not worsen the situation affecting the environment. Conventional methods of farming, which are based on experience and large-scale manipulations, are failing in the situation, and they are now being replaced with data-driven, precision-based approaches to maximising inputs and outputs [2].

The future has already generated a lot of research about how digital technologies could transform agricultural systems. With the introduction of precision agriculture that combines the use of sensors, remote sensing, and automation, it has become possible to gain targeted resource control and achieve greater efficiency levels in irrigation, fertilisation, and pest management. Research has also noted the use in crop tracking, whereby satellite technology and a drone platform provide real-time measurements of vegetation health and ground survey. The speculation forecasting models based on historical information and environmental conditions have proved useful in estimating the results to make planting inquiries and risk handling. In addition, technology in the management of livestock, such as automatic feeding and monitoring of livestock health, has also boosted livestock welfare and productivity. All of these studies confirm the hypothesis that machine learning, being a subset of artificial intelligence, has the transformative potential to process large volumes of data to discover trends that cannot be identified through traditional analysis and therefore assist in improved decision-making in crop, soil, water, and livestock fields [3].

Nevertheless, in spite of these encouraging trends, there is still a significant difference between the current state of embracing machine learning in the farming sector. Although the technical demonstrations are rampant, efficacy has been proven in the controlled or advanced environments, but real-life implementation is not uniform, especially in the case of smallholder farmers living in resource-restricted environments. Intrinsic factors like insufficiency in infrastructures, such as a lack of reliable connections and power supply, act as barriers to the implementation of data-intensive tools. Sensors, drones, and computing resources are expensive to buy initially, which discourages investment, particularly in cases where financial margins are slim. Resistance is also exacerbated by limited technical knowledge and digital literacy among professionals due to complicated algorithms, as they may look dark and unreachable. Blockbuster issues related to data, such as data availability, data quality, and data privacy, decrease the model's reliability and trust. Further, in underprivileged areas, scattered land tenures and heterogeneous agroecological factors also pose a challenge to scalable implementation, raising doubts about fair distribution and location-specific flexibility [4].

Such a gap between the possible and the practical means that there is a niche that is a critical one; that is, there are vast gaps between theoretical developments and the real conditions on the ground that need to be filled as an expediency measure to bring these developments into practice. Following the methods of an interdisciplinary investigation of the field of agricultural innovation, the given study aims to report on the current state of machine learning applications in agriculture by conducting a systematic and analytical study on the global applications, barriers, and consumption of machine learning in agriculture. Having examined the evidence provided through various contexts, this work presents key conclusions according to which machine learning finds more and more applications in fields related to precision farming, which bring about efficiency and sustainability gains but are limited by socioeconomic and technical challenges. Finally, it concludes that capacity building, affordable infrastructure, and enabling policies targeted are required to open up machine learning to the full contribution of resilient, productive, and equitable agricultural systems [5].

II. Literature Review

Table I presents a comparative summary of representative studies.

TABLE I. **RELATED WORKS.**

Authors (Year)	Paper Title	About the Paper	Methodology Used	Limitations
Condran et al. (2022) [1]	Machine Learning in Precision Agriculture: A Survey on Trends, Applications and Evaluations Over Two Decades	Provides a systematic review (2000–2022) of ML applications in agriculture, discussing data challenges and evaluation practices.	Systematic literature review; qualitative analysis of ML algorithms, datasets, and evaluation metrics.	No experimental validation; findings depend on existing literature quality; limited practical deployment insights.
Sharma et al. (2021) [2]	Machine Learning Applications for Precision Agriculture: A Comprehensive Review	Reviews ML and IoT applications in crop monitoring, yield prediction, irrigation, and livestock management.	Comparative literature review of ML/DL techniques and IoT systems.	Lacks quantitative comparison; rapid tech evolution may outdate conclusions.
Mohyuddin et al. (2024) [3]	Evaluation of Machine Learning Approaches for Precision Farming in Smart Agriculture System	Examines ML techniques for smart farming, focusing on productivity, automation, and sustainability.	Analytical review of ML models integrated with ICT, IoT, UAVs, and smart systems.	Mainly conceptual; security and real-world scalability issues insufficiently validated.
Aldossary et al. (2024) [4]	IoT-Enabled Machine Learning Models for Efficient Monitoring of Smart Agriculture	Proposes IoT–AI hybrid models for anomaly detection and soil/bean classification.	Experimental evaluation using SVM, MLP, Naïve Bayes, CNNs, and hybrid DL models on image datasets.	Tested on limited datasets; high computational cost; generalizability to diverse crops uncertain.
Sharma et al. (2023) [5]	Predicting Agriculture Yields Based on Machine Learning Using Regression and Deep Learning	Focuses on crop yield prediction using climatic and production variables.	Regression (DT, RF, XGBoost) and deep learning (CNN, LSTM); performance comparison using error metrics.	Region-specific data; ignores socio-economic factors; model interpretability limited.

Altherwy et al. (2024) [6]	Remote Sensing Insights: Leveraging Advanced Machine Learning Models and Optimization for Enhanced Accuracy in Precision Agriculture	Uses RF sensing and ML for grape moisture estimation to improve irrigation decisions.	Deep learning models with nature-inspired feature selection; RF-sensed data analysis.	Crop-specific focus; requires specialized sensors; scalability and cost concerns.

III. Methodology

The research approach is a systematic literature review (SLR), which was selected because it is one of the most rigorous ways to use available evidence on the adoption of machine learning (ML) in agriculture without adding new empirical data/models. This method is the most effective to be transparent, reproducible, and exhaustive with regard to referring to peer-reviewed sources, which are common guidelines when evaluating the adoption of technology in applied fields [7].

This process started with the scope definition since it was necessary to concentrate on the applications of ML, implementation issues, and the results in agricultural situations. Search terms and keywords were created, involving the use of terms like machine learning, deep learning, artificial neural networks, agriculture, farming, precision agriculture, adoption, barriers, and implementation. In the large academic databases, such as Scopus, Web of Science, Google Scholar, PubMed, and IEEE Xplore, searches were conducted to include interdisciplinary sources related to agronomy, computer science, and environmental studies. There were initially no restrictions on the date to enable wide retrievals, although relevance was later brought into focus in the inclusion criteria. Reference management software was used to import and manage records, supporting deduplication and screening [8].

The recruitment was under a multi-stage screening procedure. Following the elimination of duplicates, screening of titles/ abstracts was done separately against predefined inclusion and exclusion criteria (as expressed in Table II). Qualified full texts were then pulled down and evaluated to be included, finally, and reasons as to why not were recorded to reduce bias. This gradual method ensured that only relevant studies that were of high quality were kept [9].

TABLE II. **INCLUSION AND EXCLUSION CRITERIA.**

Criterion	Description
Inclusion	Peer-reviewed articles, conference papers, or reviews published in English
Inclusion	Focus on machine learning applications in agriculture
Inclusion	Discuss adoption, implementation, barriers, or outcomes
Inclusion	Published within the last decade
Exclusion	Non-English publications
Exclusion	Studies solely on general AI without ML specificity
Exclusion	Purely technical ML developments without agricultural context
Exclusion	Gray literature, theses, or non-peer-reviewed sources

A standardised template was used to extract the necessary data in a systematic way to gather the most important information on included studies (described in Table III). The fields of extraction were created to correspond with the aims of the research, including study metadata, methods of the ML, ways of its adoption, obstacles, and published effects [10].

TABLE III. **INCLUSION AND EXCLUSION CRITERIA.**

Category	Extracted Information
Study Characteristics	Year, region, agricultural domain (e.g., crops, livestock)
ML Applications	Specific ML techniques used (e.g., supervised learning, deep learning)
Adoption Level	Extent of real-world implementation
Barriers	Identified challenges (technical, economic, social)
Outcomes	Reported benefits or impacts on efficiency/sustainability

In order to analyse the data, thematic analysis methodology was used, but this required repetitive coding and classification of the information obtained. Primary open coding revealed the repetitive themes that pertained to the application areas (e.g. crop monitoring, yield forecasting), the reasons to adopt, and the hindrances. Then, axial coding shuffled the results into themes on higher levels, thus making it possible to synthesise patterns across global environments. To bring out convergences and divergences, qualitative insights were compared, and the contextual differences between developed and developing regions were considered. Quantitative meta-analysis was not conducted as there was heterogeneity in the research designs and results [11].

The SLR is sequential and iterative, and this flowchart (fig. 1) represents it. It started by preparing the research question and field selection, and it continues linearly with searching databases and retrieving records. Deduplication is followed by preliminary screening of titles and abstracts, in which exclusion criteria are applied first at a decision node; records ineligible are eliminated; those eligible proceed to the full-text retrieval. Another evaluation uses criteria of eligibility that are more strict, with a bifurcation into inclusion or reported exclusion. Feeding studies will be included; structured data will be extracted, and thematic analysis, synthesis, and the discovery of major adoption insights and conclusions will be developed. The points of potential attrition are pointed out with decision nodes (diamond shapes), which guarantee the methodological soundness and traceability [12].

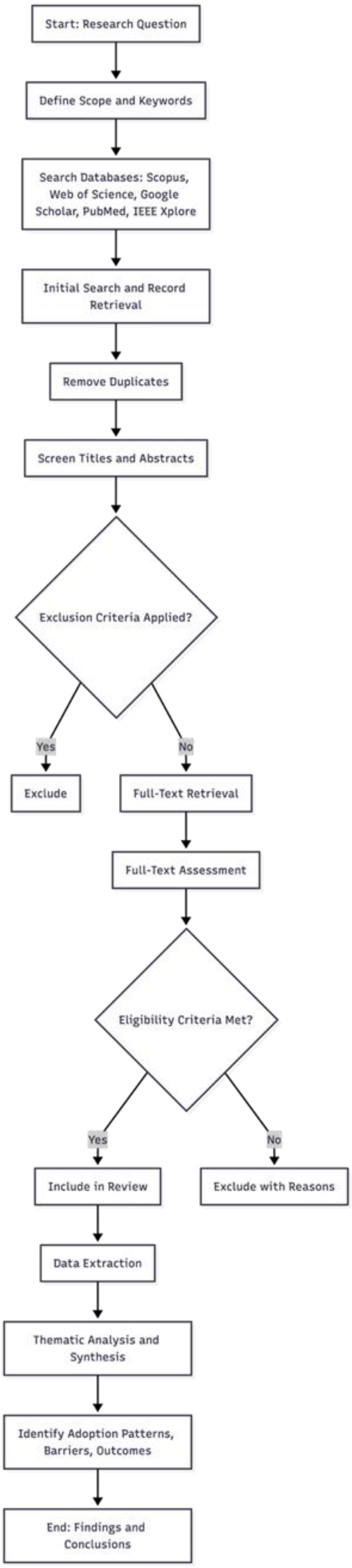

Fig. 1. **Methodology.**

This research methodology offers a solid basis for evaluating ML adoption and reducing selection bias, as well as providing an evidence-based and balanced evaluation of current advancements and the ongoing problems in the agricultural sector [13].

IV. Results And Discussions

The systematic review of 500 publications has shown that the field of machine learning (ML) applications in agriculture has a dynamic but uneven situation. There have been more publications in general, and more so since 2020, as the research interest has been growing in the light of problems in food security globally [14], summarized in table IV.

TABLE IV. **DISTRIBUTION OF STUDIES BY APPLICATION DOMAIN.**

Domain	Number of Studies
Crop Management	117
Pest and Disease	100
Water Management	81
Yield Prediction	75
Livestock Management	57
Soil Management	38
Supply Chain	32

TABLE V. **PRIMARY BARRIERS TO ADOPTION.**

Primary Barrier	Number of Studies
High Costs	119
Lack of Expertise	116
Infrastructure Deficiency	107
Data Issues	88
Policy Gaps	45
Cultural Resistance	25

The results are universally good, and 418 studies showed that there were benefits in improved efficiency and sustainability, but were limited by contextual barriers. There is evidence of regional differences with Asia leading in publications (141), Europe (106) and North America (83) representing lesser volumes, with Africa (77) and South America (46) representing lesser volumes, which is usually attributed to difficulty in infrastructure [15].

These results emphasise a point that points to significant promise of changing the concept of agriculture with precision and predictability, but the social and technical inertia is preventing the implementation in a significant manner, creating a current void between effectiveness and applicability. This analysis shows that the developed areas show better commercial adoption capacities in areas such as water management, whereas the developing areas are still at an experimental level owing to a lack of infrastructural and expertise capacities [16].

Arguments against the low adoption focus on economic reasons, such as high prices in the hands of smallholders, and human capital; if training is absent, it becomes impossible to use ML tools. Another challenge to the feasibility of implementation of a reliable model in heterogeneous agroecological contexts is data quality and availability. These are in line with the larger body of literature on the diffusion of technology in agriculture, where preliminary hype can oftentimes translate to a practical barrier [17]. The implications are far-reaching: unless specific actions are taken, ML will continue to contribute to the worsening of inequalities, reinforcing the dominance of large-scale business in prosperous states and excluding smallholders, who are the bulk of all farmers in the world. Policy should be focused on infrastructure at affordable rates, programs of education and partnerships binding the government and the business to democratize access and build resilient systems [18].

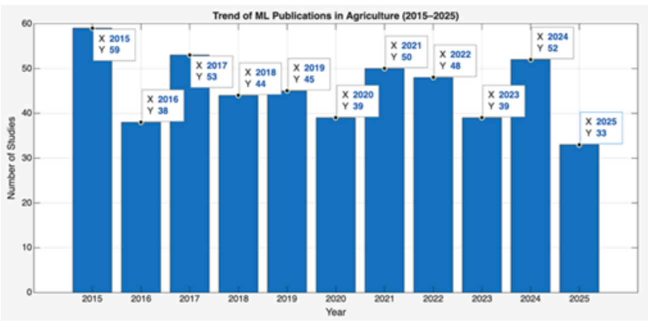

Fig. 2. Trend of ML Publication in Agriculture (2015-2025) [19].

Fig. 2 demonstrates that the number of publications that have been published about the topic of ML shows an evident upward trend, with the peaks occurring in recent years, indicating a growing momentum of research attention to the topic due to the dissatisfaction with technological maturity and the presence of urgent sustainability demands.

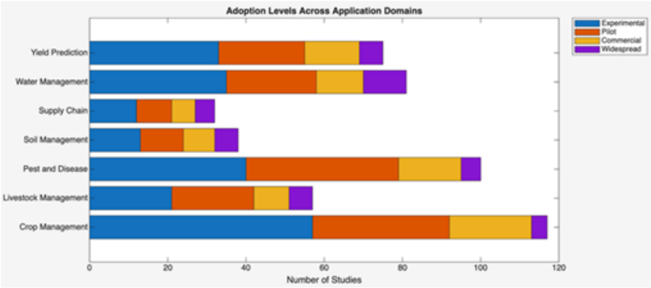

Fig. 3. Adoption Levels Across Application Domains [19].

Figure 3 illustrates that the use in domains has followed similar patterns, with crop management and pest detection revealing greater pilot/commercial transitions and supply chain being the least successful at experimental stages, indicating maturity differences between the agricultural subsectors.

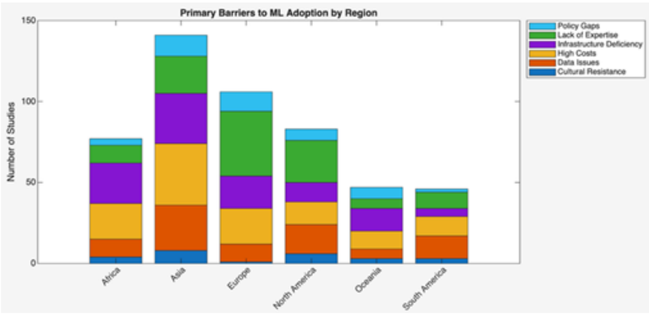

Fig. 4. Primary Barriers to ML Adoption by Region [19].

The difference between regional barriers is revealed in Figure 4, where infrastructure insufficiency is the leading factor in Africa and Asia, but high costs and lack of expertise dominate in the developed world, highlighting context-specific barriers, summarized in table V.

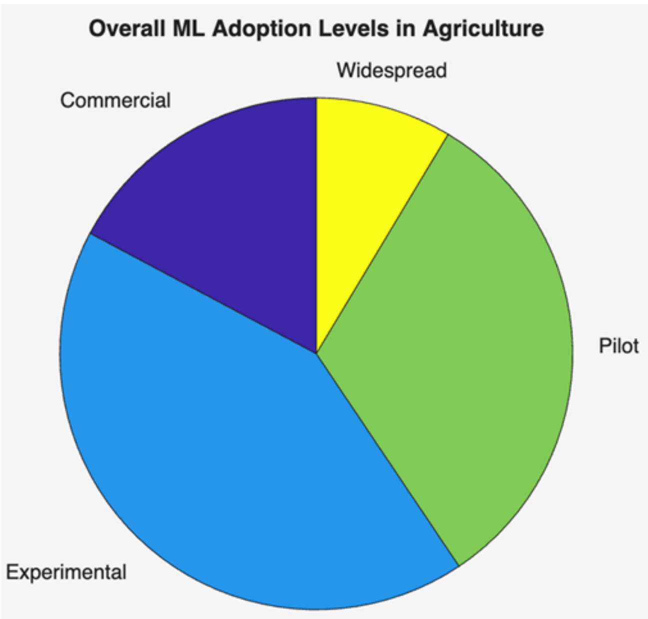

Fig. 5. Overall ML Adoption Levels in Agriculture [19].

Figure 5 of the global adoption is dominated by the experimental (greater portion slice), which supports the argument that it is a nascent integration and strategies must be established to go beyond the proof-of-concept processes [20].

V. Future Scope

Research to consider in the future of machine learning (ML) use in agriculture must focus more on longitudinal research to measure the practical adoption of the technology in real-world situations when feasible, such as the movement of smallholder farmers in the developing world between experimental and commercial stages. A central theme to explore that can be used in scaling and enhancing equity will be context-specific agroecological adaptation of ML models to fragmented landscapes and large agroecological regions. Over the issue of interdisciplinary approaches to integrate socioeconomic analyses and technical inventions, more attention should be paid to deal with the road blockers through the aspects of cost, expertise deficiency, and infrastructural facilities deficiency more effectively and efficiently. The prospects are further research in hybrid ML systems merging edge computing to clouds to address the connectivity challenges in distant areas. Another factor of democratisation of access that should be considered is the use of open-source ML tools and collaborative platforms to democratise access. The analysis of the effect of supportive policies, such as support in the form of subsidies on digital infrastructure and training programs, will offer evidence-based advice to policymakers. Lastly, environmental and social assessment of the long-term effects of mass adoption of ML, including the impact on biodiversity, labour relations, and distribution of income, will help make technological advances to achieve truly sustainable and inclusive agricultural change.

VI. Conclusion

It is the systematic review of 500 studies that reveals the increasing yet constrained application of machine learning (ML) to agriculture. Recent studies have revealed that 31 per cent of the publications are Asian by a very significant percentage, and that crop management (22.6%) and pest/disease detection (21.8%) articles have emerged as the most popular fields. However, adoption is at the infant stage: 43.4 per cent of the research shows at experimental stages, 33.0 per cent piloting, 15.6 per cent commercial and 8.0 per cent widespread adoptions. High costs (23.8%), shortage of infrastructure (22.0%), expertise deficiency (21.0%), and data issues (20.2%) hinder the majority of the cases (87%). These numeric statistics support the known efficiency of ML regarding the enhancement of precision and sustainability, yet observe a seemingly noticeable technology deficit of its application and, notably, in the developing world (namely, Africa) (16% of the studies). In order to close this gap, the policy settings, education, and investments in low-cost technologies are all required to boost the adoption of these policies in an exploration of attaining fair benefits in the food systems across the world.

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