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Review Article

Agriculture 5.0 and Explainable AI for Smart Agriculture: A Scoping Review

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Abstract

The visionary paradigm of Agriculture 5.0 integrates Industry 4.0 principles into agricultural practices. Our scoping review explores the landscape of Agriculture 5.0, emphasizing the pivotal role of Explainable AI (XAI) in shaping this domain. Guided by the Preferred Reporting Items for Systematic Review and Meta-Analysis Scoping Review, we rigorously analyzed 84 articles published from 2018 to September 2023. Our findings highlight XAI's potential within Agriculture 5.0, recognizing its influence on intelligent farming. We propose a conceptual framework for integrating XAI, emphasizing its impact on model transparency and user trust. Despite transformative applications, existing literature often lacks XAI discussions. Our objective is to bridge this gap and provide a reference for academics, practitioners, policymakers, and educators in the field of smart agriculture that is both environmentally friendly and technologically advanced.

Keywords:

Explainable AI (xAI);
Agriculture 5.0;
Data-Driven Agriculture;
Smart Agriculture.

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1- Introduction

Agriculture has always been at the heart of human survival and prosperity, and its evolution has closely paralleled the advancements in industrial paradigms. From the dawn of mechanization during Industry 1.0 to the era of automation and data-driven decision-making in Industry 4.0, each industrial revolution has significantly impacted agriculture [1]. The adoption of electronic technology and major IT advancements in the Agriculture 3.0 phase have evolved into a more integrated approach with the introduction of precision farming approaches in the Agriculture 4.0 phase. Nonetheless, it is critical to recognize that the agricultural industry has specific constraints, such as a lack of experience and IT infrastructure, that impede the rapid adoption of technological breakthroughs. For example, space technologies are of utmost importance in enhancing soil quality, mitigating water wastage in irrigation practices, and facilitating the dissemination of agricultural knowledge among farmers. The collection, analysis, and use of geo-spatial data from many sources, including terrestrial, aquatic, and aerial sensors, as well as satellites and surveillance equipment, are imperative to implementing smart agriculture techniques [2], which include science, innovation, and space technology, to enhance the production and quality of agricultural outputs [3]. The agricultural and industrial revolutions are illustrated in Figure 1.

The historical progression of technological advancements in agriculture is examined by tracing their development from conventional food systems to Agriculture 5.0, which represents the post-industrial era characterized by the integration of robots, big data, and artificial intelligence systems [4–6]. Researchers have investigated the progression

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of industrial agriculture, considering the influence of the industrial revolution, i.e., the correlation between Agriculture 4.0 and Industry 4.0, specifically focusing on the enhancement of field work mechanization and machinery [7]. Moreover, developing countries require immediate implementation of data-driven technological advancements to boost their gross domestic product (GDP) and guarantee food security for their population [2]. With advancements in information technology, agricultural data analytics offers valuable and pertinent insights to farmers in the realm of intelligent agriculture, leading to enhanced yield security and significant improvements in crop output [8]. Additionally, these advancements will aid in conserving resources such as fertilizers, labor, seeds, and water [9], ultimately contributing to the stability of the food supply and alleviating poverty [10, 11]. Hence, timely use of automated and advanced technology such as the integration of drones, the use of precision technologies and equipment, the implementation of wireless sensor networks, the development of intelligent solar and wind energy systems, the application of artificial intelligence (AI)-based technology, and the adoption of large-scale desalination technology will undoubtedly be the future of smart agriculture. These technologies must possess predictive accuracy, user-friendliness (and interpretability), and the capability to facilitate decision-making that can be acted upon [12, 13]. To adequately address the issues in smart agriculture, it is essential to comprehend the agricultural ecosystems.

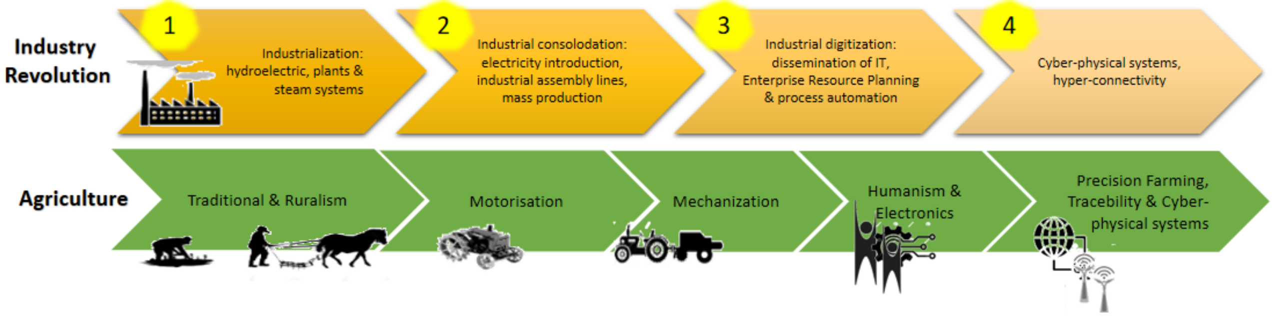

Figure 1. **Agriculture and Industrial Revolution**

Artificial intelligence (AI) and its subsets, i.e., machine learning and deep learning algorithms, have emerged as very influential and revolutionary advanced analytics tools that organizations may employ for making decisions [11]. Nevertheless, the accelerated progress of technology has increased the complexity and accuracy required to explain the principles of artificial intelligence (AI) and machine learning (ML) [14]. Numerous AI models that have achieved success are characterized by their opaqueness, rendering the comprehension of their internal mechanisms and decision-making procedures taxing. Hence, regulatory bodies are implementing new legislation aimed at mitigating the potential dangers pertaining to fairness, accountability, and transparency that are inherent in automated decision-making systems. Nonetheless, the use of black box models remains debatable due to their inherent transparency and lack of interpretability [15]. Only AI developers and those with specialized knowledge are able to comprehend the output of AI models, which constrains the potential of AI models in providing meaningful insights based on the input data and prediction as well as supporting decision-making processes involving different types of users [16].

Fernandez et al. [17] and Samek et al. [18] emphasize that Explainable Artificial Intelligence (XAI) involves a selection of technologies designed to reveal the working principles of black-box models and provide explanations for individual predictions. Compared to the word interpretability, explainability is more significant to present relevance, comprehensiveness, and accuracy of predictions that are produced by AI models or intelligent systems. Hence, XAI is more straightforward with a logical and transparent computational process to facilitate users in making sense of the patterns or relationships revealed by AI models [16, 19]. According to Montavon et al. [20] and Guidotti et al. [21], the outputs from the XAI models are more trustworthy to users since they can be easily understood, embody the principle of transparency [22], promote accountability according to ethical principles [23], and demonstrate efficacy in mitigating erroneous and biased decision-making [24].

Hence, the objective of this review article is to examine the potential Explainable Artificial Intelligence (XAI) in the context of smart agriculture and specifically Agriculture 5.0. This review contributes to the existing literature as follows:

(i) Provide the focus or theme of earlier review studies between 2018-2023 related to smart agriculture, along with a brief description of the contribution of the reviews.

(ii) Propose a conceptual framework for the integration of XAI with Agriculture 5.0 based on the fundamentals of XAI and Agriculture 5.0.

(iii) Systematically analyze the literature on proposed XAI approaches for agriculture-related tasks using PRISMA-ScR and discuss the challenges of implementing XAI in the context of Agriculture 5.0.

The following section presents the review methodology, which is based on the Preferred Reporting Items for Systematic Review and Meta-Analysis Scoping Review (PRISMA-ScR) guidelines. Section 3 presents the results and discussions based on this review, while Section 4 presents the challenges of integrating XAI in the Agriculture 5.0 landscape. The last section concludes this review paper.

2- Methodology

The scoping review followed the PRISMA-ScR guidelines [25] to guide the search, selection, and analysis of articles. The research question guiding this review was: *"What is the current state of research on the integration of Agriculture 5.0 and Explainable AI for smart agriculture, and what are the challenges?"*

To identify relevant studies, an electronic search was conducted over the Scopus database for articles published within 2018 to September 2023 to ensure the recency of the scoping review. We applied a combination of search terms related to agriculture, artificial intelligence, and explainability. The Boolean operators AND and OR were used to refine the search queries. The search terms used are listed in Table 1.

Table 1. Search terms used for the literature search

Agriculture	farm*, digital, smart, agriculture 5.0, plant, crop, agricultur*, precision farming, precision agriculture
Explainable	XAI, explanation, explainability, interpret*, trust*, ethic*, causal*, understand*
Artificial Intelligence	AI, machine learning, machine intelligence, deep learning, transfer learning, neural network, convolutional, black box, classifier, prediction model, supervised learning, reinforcement learning, unsupervised learning, LIME, SHAP

The inclusion criteria specified for this scoping review include studies published in English as review papers, surveys, journal articles, and conference proceedings that are related to smart agriculture and explainable AI, focusing on the implementations, applications, challenges, and integration of both domains. The retrieved articles were independently screened by the authors for eligibility by analyzing the title and abstract based on the inclusion criteria. Non-relevant papers were omitted from this review. Discrepancies were resolved through discussion or by consulting the authors of this paper. Subsequently, a comprehensive evaluation was conducted by examining the complete text of the articles to exclude those that were not pertinent to this review, those that were excessively concise or generic, articles that did not sufficiently address the subject of agriculture and explainability, as well as those that lacked an easily accessible full text. Figure 2 illustrates the PRISMA-ScR flow diagram of the scoping review process.

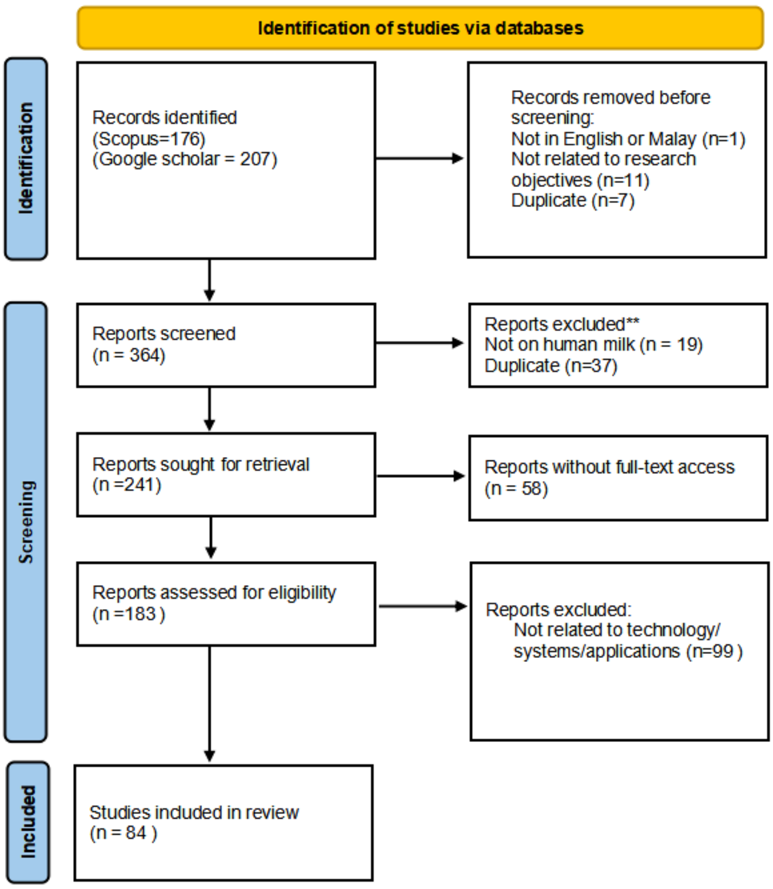

Figure 2. PRISMA-ScR flow diagram

Furthermore, relevant information was extracted from the potential studies, i.e., study objectives, methodology, key findings related to smart agriculture and XAI, as well as the implications for users. The data that was obtained was synthesized and thereafter presented through the use of descriptive and thematic analysis techniques. The present study identified and provided a summary of the key themes and patterns pertaining to the integration of Agriculture 5.0 and XAI in the context of smart agriculture. Furthermore, the objective of the scoping review was to offer a comprehensive summary of the existing body of research in this field. The present research demonstrates that there has been an increasing trend in the interest and attention given to the agricultural applications of artificial intelligence that employ approaches for explainability. Moreover, it is important to highlight that there is a clear focus on explaining the techniques used in deep learning models, considering their current dominance as the most often applied machine learning methods.

3- Results and Discussion

3-1- Agriculture 5.0 in Smart Agriculture

The advent of Agriculture 5.0 represents a unique and transformative phase. Basically, the need for smart agriculture arises from the need to address challenges such as population growth, resource scarcity, climate change, cost optimization, and labor efficiency. Resources such as water, land, and energy are limited and face increasing pressure due to population growth and climate change. Smart agriculture has the capacity to revolutionize conventional farming methods by incorporating cutting-edge technologies, resulting in more sustainable, efficient, and eco-friendly systems [26]. This fusion of cutting-edge technologies has ushered in a new era of precision farming, often referred to as smart agriculture or digital agriculture. By incorporating geographical and temporal variations into technological advancements and the data-driven decision-making process, smart agriculture facilitates accurate resource management, minimizes waste, and maximizes the efficient use of resources such as water, fertilizers, and energy [27, 28]. This eventually enhances economic efficiency while simultaneously minimizing resource inputs and environmental consequences [29–31]. Farmers will be empowered to make data-driven decisions based on events [32] at different stages of production, such as extreme weather, changing rainfall patterns, and the spread of pests and diseases, through optimized resource usage [33, 34] by utilizing robotics, automated control systems, and artificial intelligence methods [35], as well as integrating agricultural research and information to optimize the productivity and efficacy of the agriculture industry [36, 37]. Thus, farmers do not need to rely on manual labor for tasks such as planting, weeding, and harvesting, which enhances worker safety by minimizing exposure to hazardous conditions [38]. It also emphasizes collaboration and cooperation between humans and machines. The integration of robots and AI algorithms into data-driven farms, which enable seamless interaction between farmers, autonomous machinery, and data-driven algorithms, is known as Agriculture 5.0 [5, 9, 39]. The elements of Agriculture 5.0 are summarized in Table 2, and the concept of Agriculture 5.0 adopted from Polymeni et al. [40] is illustrated in Figure 3.

Table 2. Elements of Agriculture 5.0

Elements	Description
Connectivity and Data ubiquity	Agriculture 5.0 flourishes within an environment with extensive connectivity between devices and streams of data, wherein gadgets, machines, sensors, and instantaneous data streams. The advent of 5G technology, coupled with the Internet of Things (IoT), entails the widespread presence of data, leading decision-makers to possess a thorough and current comprehension of their agricultural systems.
Data-driven decision making	Optimize agriculture operations or processes by employing a fusion of advanced analytics, machine learning algorithms, and predictive modeling based on a thorough understanding of the data environment.
Robotics and Automation	Minimize harmful interventions such as chemical usage to promote and foster harmonious coexistence of human expertise and machine precision in executing tasks with precision and efficiency.
Precision ecosystem and Sustainable Practices	Ensure sustainable agricultural practices that hinder the environmental ecosystem from being compromised to provide lasting resources, including productive soils, uncontaminated water supplies, and flourishing ecosystems for future generations.

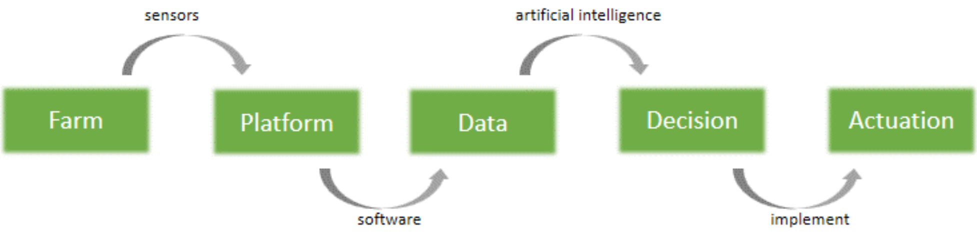

Figure 3. Agriculture 5.0 concepts

Smart agriculture provides a means to enhance agricultural output and efficiency to satisfy the increasing demand of estimated 9.7 billion people by 2050 [5]. By the year 2100, it is projected that over ten billion individuals would require food systems that exhibit carbon neutrality, resilience to catastrophic weather events, and the ability to provide culturally suitable nourishment in a financially viable manner, all while adhering to the limitations imposed by the planet. The resolution of this worldwide dilemma requires the implementation of a novel agricultural revolution that facilitates the integration of technology aimed at enhancing productivity while concurrently ensuring environmental sustainability. There is a pressing need for multidisciplinary and practical research and synthesis pertaining to food and farming systems to address the challenges faced by humanity. Similarly, it is necessary to use these understandings in manners that are culturally, economically, and politically suitable to guarantee the production and distribution of food in a manner that surpasses the current levels of economic and ecological efficiency [4].

Agriculture 4.0 is founded upon four fundamental pillars, namely data-driven management, the utilization of novel tool-based production methods, a commitment to sustainability, and the pursuit of professionalization [41]. The emergence of Agriculture 5.0 can be understood as a natural extension of the Agriculture 4.0 and Industry 4.0 principles into the realm of agriculture. Furthermore, the agricultural sector in European nations is now experiencing significant growth after the accessibility of GPS signals [42]. The integration of Agriculture 5.0 into the strategic plans of prominent agricultural equipment manufacturers is a prominent objective for the forthcoming decade, as highlighted by Saiz-Rubio and Rovira-Más [5]. Agriculture 5.0 is the envisioned paradigm shift in the future of smart agricultural practices. During that period, the prevalence of unmanned farming is expected to increase, hence offering advantages in situations where there is a scarcity of labor.

Agriculture 5.0 is more likely to produce more food with fewer inputs and less land with the implementation of cutting-edge digital technologies and biotechnologies [4]. Farm-to-fork traceability will be improved [26], allowing farmers to track the entire supply chain, ensure food safety, and provide transparent information to consumers [43, 44]. Moreover, studies on Agriculture 5.0 and food security observe that the application of artificial intelligence and robotics, along with machine learning (ML) and deep learning (DL), has the potential to forecast crop yields with a 75% probability [45, 46]. However, even though agriculture practices should increase productivity, the environment should not be compromised [5]. Strategies should be crafted to focus on gender empowerment, market accessibility, utilization of low-cost tools, minimizing food waste, and effective food distribution [4]. Hence, it is pertinent to contemplate the concept of Agriculture 5.0 in correlation with Industry 4.0 and Society 5.0, with the objective of advancing ecologically responsible technologies, establishing resilient smart cities, and safeguarding industrial progress as a fundamental measure of human welfare [47]. Moreover, the use of Agriculture 5.0 technology on the farm is important to facilitate precision farming and enable the realization of its full potential in sustainable global food systems [4]. At the core of this transformational process lies the incorporation of Explainable Artificial Intelligence (XAI), a technological advancement that not only equips farmers with sophisticated decision-making assistance but also guarantees the ethical foundations of AI-based agricultural systems. Table 3 summarizes reviews or surveys that have been published in relation to smart agriculture.

Table 3. Smart agriculture-related reviews or surveys

Author (year)	Focus	Descriptions	Remarks
Kwaghtyo et al. (2023) [48]	General	• Investigates the implementation of supervised and unsupervised ensemble and deep learning techniques in predicting yield, irrigation, and environmental elements for smart farming. • Poor model performance is attributed to dataset quality and preprocessing issues. • The article suggests a machine learning procedure to mitigate dataset quality and preprocessing issues and emphasizes the potential of automation in agriculture.	• Narrative review • No reference to XAI
Otieno (2023) [26]	Security	• Highlights security concerns in smart agriculture, including unauthorized access and operational disruption, which are attributed to IoT devices and data communication, as well as farmers' security awareness to protect their data.	• Narrative review • No reference to XAI
Polymeni et al. (2023) [40]	Agriculture 5.0 and 6G-IoT	• Introduces the scope of Agriculture 5.0 and its impact on Quality of Service, security, and reliability in the 6G-IoT landscape. • Illustrates the potential of combining existing precision algorithm concepts with quantum sensing, robots, enhanced wireless networks, and artificial intelligence for Agriculture 5.0.	• Narrative review • No reference to XAI
Teeffelen (2023) [49]	Plant Disease Detection	• Summarizes the current state in the field of automatic plant disease detection and indicates that CNN models, particularly VGG models, exhibit superior performance in the domain of plant disease detection. Accuracy is the most employed performance metric. • Develop a VGG16 transfer learning model to analyze the influence of datasets on the outcomes of plant disease detection models. Three distinct datasets with varying features (small/large, in-situ/laboratory, raw/processed) are employed.	• Adopted tertiary systematic literature review methodology. • No reference to XAI

Mesias-Ruiz et al. (2023) [6]	Crop Protection	• Analyzed articles from 2010–2020 that have applied machine learning to crop disease before presenting a framework for the future of precision crop protection, emphasizing the scientific, agronomic, and industrial uses of traditional machine learning methods and current advancements in artificial neural network models. • The aim of the framework is to advance precision crop protection and align it with the emerging concept of Agriculture 5.0.	• Narrative review • No reference to XAI
Gardezi et al. (2023) [50]	Trust	• Analyzed and explored the obstacles and potential advantages of enhancing farmers' confidence in AI technologies for precision agriculture. • Emphasized the necessity of regulating and ensuring voluntary adherence to data ownership, privacy, and security to establish the acceptance and utilization of AI systems among farmers.	• Narrative review • Partly mentioned XAI to consider farmers training needs when engaging with XAI
Bwambale et al. (2022) [29]	Irrigation System	• Reviewed smart irrigation monitoring and control strategies to enhance water use efficiency in precision agriculture, including irrigation scheduling and monitoring the weather, soil, and plants.	• Narrative review • No reference to XAI
Vikrant et al. (2021) [51]	General	• Provided a brief overview of smart agriculture, focusing on Wireless Sensor Networks (WSN), IoT, and data analytics applications, benefits, challenges, and directions.	• Narrative review • No reference to XAI
Boursianis et al. (2022) [52]	IoT and UAV	• Described the use of intelligent sensors, IoT sensor types, networks, and protocols, as well as IoT applications and solutions in smart farming. • Highlighted the role of UAV technology in irrigation, fertilization, use of pesticides, weed management, plant growth monitoring, crop disease management, and field-level phenotyping.	• Narrative review • No reference to XAI
[53] Dara et al. (2022) [53]	Ethics	• Focused on fairness, transparency, accountability, sustainability, privacy, and robustness of AI in agriculture with the aims to address farmers' privacy concerns, ensure reliable AI performance, enhance sustainability in AI systems, and reduce AI bias.	• Narrative review • No reference to XAI
Sharma et al. (2022) [11]	Supply Chain	• Presented a systematic review of 93 research papers discussing machine learning (ML) applications in agricultural supply chains (ASCs) and highlighted the benefits towards sustainable ACS. • Proposed an ML application framework for sustainable ASC.	• Adopted the three-stage systematic literature review (SLR) methodology, comprising of the pre-operational, operational and post-operational stage. • No reference to XAI
Bacco et al. (2019) [54]	General	• Provides a survey of EU research projects and scientific literature in smart farming and categorizes them into four categories, i.e., sensing techniques and management systems, unmanned vehicles, IoT platforms, and decision support systems. • Identify threats and concerns in non-technical (incentives, investments, and innovative tools) and technical (data, networks, and information), and then look at existing and upcoming solutions to overcome those barriers in the EU research project.	• Narrative review • No reference to XAI
Jha et al. (2019) [8]	Artificial Intelligence	• Focuses on artificial neural networks, automation, wireless system networks, and the implementation of fuzzy logic in agriculture for flower and leaf identification and watering using IOT.	• Narrative review • No reference to XAI
Klerkx et al. (2019) [55]	Social Science	• Identify the relationship between digital architecture and farm diversity and examine the impact on business practices, value chain, food system, economy, and innovation system.	• No reference to XAI • Perform exploratory literature review with thematic clusters

3-2-XAI Methods

Modern technologies that employ deep learning, big data, and IoT architectures necessitate the extensive use of complicated computing technologies, which are normally known as black box models. User access is limited and depends on the tools employed. The comprehensibility of the outcomes generated by the models is also lacking, which presents a substantial obstacle to the adoption of AI-based decisions. In this context, Explainable Artificial Intelligence (XAI) is used to clarify these decisions [56] by converting complex systems into clear systems, allowing for understandable, interpretable, and transparent decision-making processes [57]. The value of human expertise should not be underestimated but rather complimented by AI, which utilizes formal modeling and reasoning approaches to solve real-world problems [56].

XAI techniques can be categorized into the explanation scope, which can either be local, focusing on specific predictions made by the model, or global, aiming to characterize the overall behavior of the model. Comprehensive explanations enhance comprehension of the overall behavior and logic of the model, hence leading to anticipated consequences. Local explanations refer to the provision of explicit justifications for a single prediction, explaining the rationale for the model's judgment for that case [16]. They can also be categorized based on their applicability to any machine learning algorithm (model agnostic) or their limited applicability to a specific machine learning algorithm (model specific). Model-specific techniques have specific constraints for the type of data or procedure employed, whereas model-agnostic methods are more flexible and can be applied in any situation [22].

Another categorization is based on the type of explainability model, either an intrinsic interpretable model or a post-hoc model. Intrinsic interpretable models, or transparent, are also known as white box/glass box approaches. The model's architecture and decision-making process are intentionally designed to facilitate human comprehension of its prediction methodology. These models are specifically designed using logical relations, statistical, or probabilistic frameworks to offer transparency and interpretability without requiring any supplementary post-hoc interpretation techniques. For instance, linear and logistic regression, decision trees, k-nearest neighbors, fuzzy inference systems, rule-based learners, general additive models, and Bayesian models fall under this category [16], with a similar perspective taken by knowledge-based systems. Nevertheless, their level of explainability, transparency, or interpretability is limited when high-dimensional scenarios are involved [58]. On the other hand, post-hoc models are additional features implemented on results or completed black-box models like random forests, support vector machines (SVMs), tree ensembles, and deep learning methods [22]. They are called post-hoc methods because they generate post-hoc explanations that are independent of the model used, in contrast to the approach of ante-hoc models. However, some of these methods may have certain requirements related to the data or structure of the model. Additionally, post-hoc procedures can be evaluated using quantitatively quantifiable metrics and human-centered evaluations [59]. Nevertheless, there is presently a lack of agreement over the criteria for assessing the interpretability of a model, the accuracy of an explanation, and the methodologies for comparing different approaches. Moreover, post-hoc explanations are subject to concerns over their dependability [60].

Further categorizations can be established based on the way the output explanations are presented (such as textual, visual, or rule-based), the specific input data that is necessary, the problems to which they might be applied, or the method by which they are generated. According to Nauta et al. [61], XAI methods can be evaluated based on goodness checklists, explanation satisfaction scales, elicitation methods for mental models, computational measures for explainer fidelity, explanation trustworthiness, and model reliability. Figure 4 illustrates the most common approaches to the classification of XAI methods.

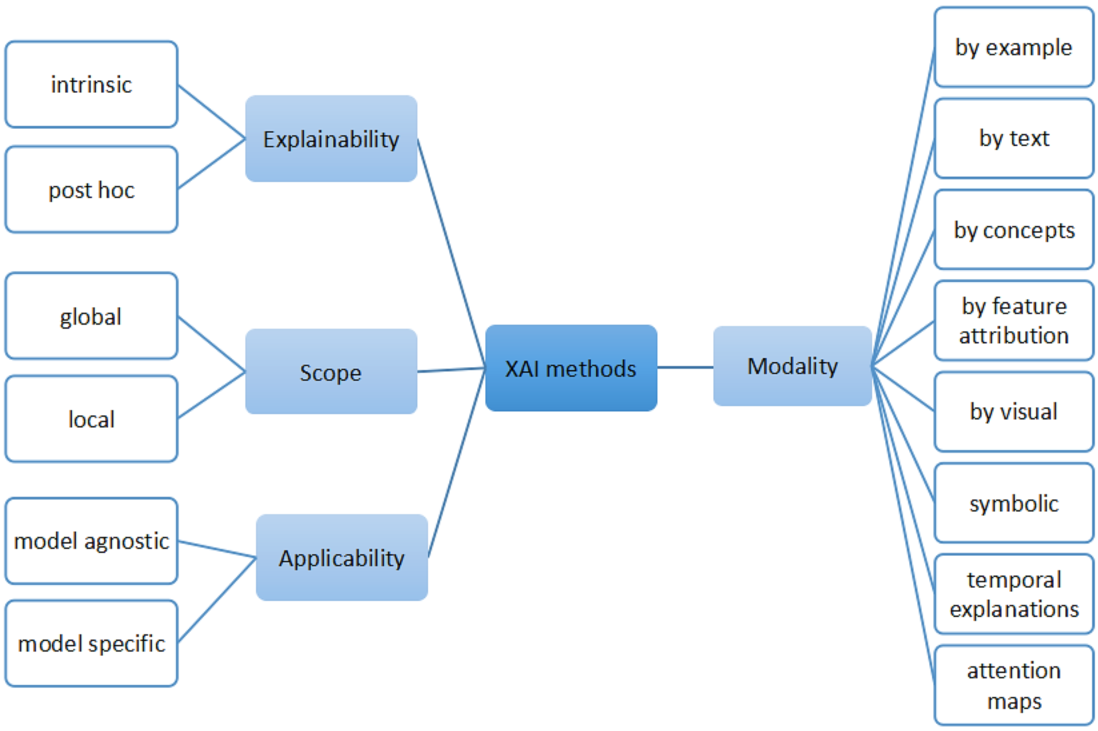

Figure 4. Common classification of XAI methods

3-3- Integration of XAI in Agriculture 5.0

Recent years have shown that XAI has gained attention for improving smart agriculture processes, including enhancing crop production, minimizing resource waste, reducing environmental impact, and improving overall profitability. This is attributed to the vast amounts of data acquired through sensors, drones, and satellite imagery [2, 62]. Analyzing this data using AI and data analytics helps farmers gain valuable insights, make informed decisions, and optimize farming practices for better outcomes [63]. For instance, data generated from continuous monitoring of crops, including factors like soil moisture, temperature, and nutrient levels, may help farmers detect crop stress, diseases, and nutrient deficiencies early on, allowing timely interventions and reducing crop losses [64, 65]. Based on the literature, XAI can be integrated into Agriculture 5.0 and XAI for enhancing decisions, enabling autonomous farming operations, and localizing decision-making [26]. It is an innovative approach to agricultural practices that leverages advanced technologies to optimize efficiency, productivity, and sustainability in farming operations [41, 48, 52, 66], leading to innovative applications that fulfill the basic requirements of Agriculture 5.0 [40]. A conceptual framework for the integration of XAI in smart agriculture is proposed and illustrated in Figure 5.

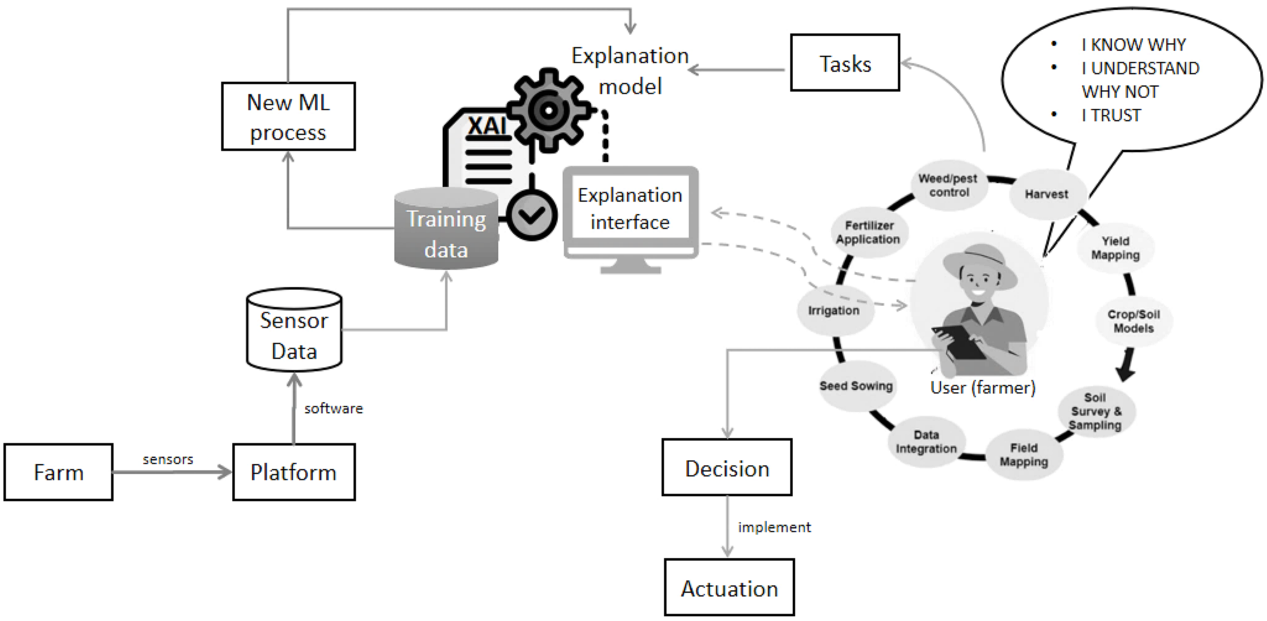

Figure 5. Agriculture 5.0 and XAI

Based on Figure 5, XAI requires a collection of diverse data sets from sensors or IoT devices in real-time using the Internet of Things (IoT), artificial intelligence (AI), data analytics, robotics, and remote sensing to create a comprehensive dataset for analysis. By utilizing a network of interconnected devices and sensors, farmers can collect real-time data on various factors, such as soil moisture levels, weather conditions, crop health, and pest infestations. This data is then analyzed to provide actionable insights, allowing farmers to make data-driven decisions and implement precise interventions [11, 51, 54, 55, 67].

The data is generally integrated into a platform for data cleaning and pre-processing to take place. Depending on the tasks at hand, feature engineering can be conducted to extract relevant information and enhance model performance [5]. Next, machine learning models will be trained for various agricultural tasks, including fertilizer application, weed or pest control, yield mapping, seed sowing, irrigation, etc., depending on the need. The XAI developer must ensure that the models are interpretable and explainable, even if they are complex. Moreover, the interpretability of the recommendations, which are supported by implementing visualizations and summaries from XAI techniques, may improve the transparency and accountability of decision-making. The model's performance will be assessed based on metrics that capture both accuracy and interpretability of the model and generalization across different scenarios. Besides, user-friendly interfaces that present AI-driven insights in a comprehensible manner to farmers and other stakeholders are a necessity to allow users to interact with the AI system, ask questions, and receive explanations for model predictions. Farmers and stakeholders will acquire a clear understanding of how AI-driven decisions are made. Eventually, they will be empowered to trust and harness AI-driven insights, making informed decisions that optimize crop yields, resource utilization, and sustainability as envisioned by Agriculture 5.0. As responsible innovation, it is essential to provide training programs for end-users to understand the basics of AI and the specific models used in Agriculture 5.0. The training should foster knowledge transfer between AI experts and farmers to enhance collaboration and address domain-specific challenges. There should also be mechanisms for continuous monitoring of model performance in real-world conditions where the models can be updated based on new data and feedback from users to ensure relevance and accuracy.

Guidelines and protocols for responsible AI use in agriculture should be developed to address ethical considerations related to data privacy, bias, and fairness in AI models. A collaborative ecosystem involving farmers, researchers, policymakers, and AI developers should be available to encourage knowledge sharing, feedback loops, and the cocreation of AI solutions that align with the needs of the agricultural community. Based on the literature, previous work has applied XAI in the context of smart agriculture. Table 4 outlines the focus of the work, describes the goals in brief, lists the tools or pre-trained models, provides the results of the best-performing model in the study, and classifies the type of explanation provided.

Table 4. XAI applications in smart agriculture

Author (Year)	Focus	Descriptions	Tools/ Pre-Trained Models	Evaluation	Type of Explanation
Chhetri et al. (2023) [68]	Cassava Disease	Combine vision models generated using deep learning with semantic models generated using ontologies and knowledge graphs. The fusion model was assessed based on prediction accuracy and latency, user-level explainability and understandability, as well as explanation usefulness.	RESNEXT50, EfficientNetV2S, and VOLO	Accuracy 90.5%	Text
Hu et al. (2023) [69]	Climate-crop Yield Relationship	Propose a Bayesian ensemble model (BM) that outperforms ElasticNet, Neural Network, MARS, SVM, Random Forests, and XGBoost in both predicting and explaining. BM was the only method for unveiling true relationships from synthetic data.	Bayesian ensemble model (BM)	Accuracy 99.2%; RMSE 0.50	Visual
Bandi et al. (2023) [70]	Leaf Disease	Identify and classify plant diseases based on the severity of the disease using deep learning networks, and offer appropriate treatments to stop the disease from spreading to other plant leaves. YOLOv5 is used to detect disease, and the vision transformer (ViT) is used for the classification.	YOLO5 and VIT	YOLOv5: F1 score 0.57 (conf. 0.2); ViT (with background): F1 score 0.758; ViT (without background): F1 score 0.908	Text
Chandra et al. (2023) [71]	Soil Fertility	Discuss the implementation of an XAI model based on a Random Forest classifier to predict the relative soil fertility of a given soil using its various physiochemical properties and explain the reasons behind the model's soil fertility indicator prediction using user-friendly graphs.	Random Forest, (SHAP)	Accuracy 97.02%; F1 score 0.87	Visual
Sahidullah et al. (2023) [72]	Fruit Classification	Combine ML methods, i.e., category boosting (CatBoost), extreme gradient boosting (XGBoost), support vector machine (SVM), k nearest neighbor (KNN), multi-layer perceptron (MLP), logistic regression (LR), and bagging methods with Local Interpretable Model-Agnostic Explanations (LIME), to classify different types of date fruits. MLP outperforms the other methods.	SVM, KNN, MLP, boosting, bagging, (LIME)	F1-score 0.90	Visual
Celik et al. (2023) [73]	Cotton Yield Prediction	Compared the performance of a glass box method known as Explainable Boosting Machine (EBM) to the traditional regression models (RLR and LASSO) and tree-based models (DT, XGBoost, and LightGBM) to predict cotton yield. The study findings showed that precipitation (P), enhanced vegetation index (EVI), and leaf area index (LAI) are the three most important dynamic features.	Explainable boosting machine (EBM)	MAE 87.41, RMSE 118.57, MAPE 0.10, and R^2 0.73	Visual
Bhat et al. (2023) [74]	Crop Yield	Develop Gradient Boosted Regression Tree (GBRT)-based deep learning surrogate models, combined with a Bayesian optimization (BO) algorithm to determine the most optimal hyperparameters for the deep neural network. The impact of each input parameter on the individual outputs is evaluated using explainable artificial intelligence (XAI).	GBRT-based hybrid DNN surrogate models	F1 score 1.0	Visual
Ryo (2022) [75]	Crop Yield	Compared permutation-based variable importance (global), pairwise interaction importance (global), partial dependence plot (global), and LIME local variable importance for all pre-trained models. Random forest is the best algorithm based on this approach.	Linear model with AIC stepwise variable selection, conditional inference tree, random forest, gradient boosting	RMSE 0.199; R^2 0.42	Visual
Kawakura et al. (2022) [76]	Workers	Demonstrate the capabilities of XAI techniques using wearable sensor data and questionnaires.	ELI5, PDPbox and Skater	Not provided	Visual

Cartolano et al. (2022) [77]	Crop Cultivation	Demonstrates the use of LIME and SHAP in recommending crops to cultivate based on XGB, MLP, and SVM classifiers. XGB obtained the highest accuracy with SHAP's TreeExplainer.	Extreme Gradient Boosting (XGB), Multi-Layer Perceptron Neural Network (MLP), Support Vector Machine (SVM)	Accuracy: XGB 99.32 Linear SVM: 98.64 MLP: 97.05	Visual
Feldkamp et al. (2022) [78]	Data Farming Output	Evaluate the suitability and applicability of different black-box algorithms using real data. Also, we applied XAI-based data farming output analysis using permutation feature importance. Quadratic Discriminant Analysis (QDA) and Random Forest are preferred for subsequent XAI analysis of the data farming output.	Gaussian Naïve Bayes, Quadratic Discriminant Analysis, Random Forest, Nearest Neighbor,Ada-Boost, Artificial Neural Network, Support Vector machine (SHAP)	QDA and RF: Accuracy 99.994%; average prediction time 0.12 seconds	Text
Mehedi et al. (2022) [79]	Leaf Disease	Used the transfer learning approach for detecting leaf diseases with EfficientNetV2L. The approach outperforms MobileNetV2, and ResNet152V2.	LIME	Accuracy 99.63%	Visual
Kawakura et al. (2022) [80]	Workers	Applied XAI to analyze time series data from workers who perform specific tasks, including acceleration and angular velocity.	SHAP, LIME, and LightGBM	Not provided	Visual

Most of the work highlighted the importance of interoperability and seamless integration of various components within the agricultural value chain. This included the integration of IoT devices, cyber-physical systems, and automated machinery into farm operations. Since Agriculture 5.0 promotes a symbiotic relationship between farmers with advanced technologies, the studies also stressed the need for human oversight and decision-making alongside automated processes. The reviewed studies repeatedly highlighted the significance of transparency in decision-making processes powered by AI in the field of agriculture [22, 69, 78, 81]. Besides that, the concept of XAI was found to be particularly relevant in agriculture practices, where autonomous systems can make real-time decisions based on local conditions and the principles of precision agriculture [46]. This encourages the localization of decision-making and fosters human-machine collaboration. The utilization of models, frequently employing decision trees, rule-based systems, or local explanations, has been seen as crucial in establishing confidence in the suggestions generated by AI [82, 83]. XAI methods aim to make machine learning models more interpretable, allowing farmers and stakeholders to understand why certain decisions are made. Additionally, visualization tools and dashboards that present AI-generated insights in a comprehensible manner were commonly mentioned. These interfaces allow farmers to monitor crop health, weather forecasts, and equipment status easily.

4- Challenges in XAI for Agriculture

The scoping review revealed that while XAI holds promise for agriculture, it is not without challenges. Agriculture 5.0 concepts such as interoperability, human-machine collaboration, and decentralized production, along with XAI methodologies that prioritize openness, have the potential to lead to more efficient, sustainable, and yield-optimized agriculture practices. However, XAI is only meaningful in certain instances when the decision made by AI can be elucidated on an individual basis. Ultimately, this scoping review provides a fundamental reference for researchers, practitioners, policymakers, and educators who are interested in the intersection of Agriculture 5.0 and XAI for smart agriculture to consider tackling the related difficulties in their work.

4-1- Real-time Data

Agriculture involves diverse and complex data types, including geospatial data, sensor data, and historical records. The fairness of decisions produced by XAI systems relies on the data provided to the machine learning algorithms. In their work, Mehedi et al. [79] reported challenges in acquiring adequate data and infrastructure for detecting plant diseases using pre-trained models and improving reliability using LIME. Reliable connectivity is essential to avoid signal delay and loss in acquiring data from multiple sensors. In addition, integrating data from different types of sensors, which involve different data requirements like format, size, and structure, is also an important challenge to address prior to developing any predictive AI models. In addition, farmers also find it difficult to optimize crop yield, manage production and inventory according to customer demands, and optimize their work schedule, which could lead to labor savings and high crop production [84]. Insufficiency of available data may cause gaps in the training data, model, and objective function of the system.

With the growing emphasis on data in agriculture, the matter of data privacy and security becomes a crucial problem. The widespread accumulation and dissemination of delicate agricultural data, ranging from harvest quantities to soil condition, presents difficulties with data ownership, consent, and safeguarding. Farmers and stakeholders must confront inquiries over data ownership, storage, and sharing, as well as the possible hazards associated with data breaches. Adhering to ethical protocols for data management and implementing strong cybersecurity measures are essential to safeguarding the integrity and confidentiality of agricultural data.

To explain the reasoning of a machine learning model, it is important to possess the data necessary to train the model. Nevertheless, the data may be exclusive or classified, making it not possible to be disclosed to the users. Since there is a possibility of exposing confidential details in the underlying data, precautions and preventive measures need to be implemented to maintain data privacy and security. Further research on safeguarding organizations from security attacks that could impact AI models explainability for Agriculture 5.0 should consider developing areas like edge computing, microservices, and 5G connections.

4-2- Ethical Considerations

The understanding of XAI is highly influenced by the context in which it is being examined [85]. Dara et al. [53] present a framework for ethical AI in agriculture that includes six measures, i.e., fairness, transparency, accountability, sustainability, privacy, and robustness. XAI models are susceptible to biases present in the data and the algorithms employed for analysis. Algorithmic bias refers to the occurrence of AI systems generating findings that are distorted, ranging from showing preference for specific crops or agricultural methods to sustaining disparities among diverse farming groups. Additionally, the functioning and training of XAI systems rely on parameters that are determined by developers. The level of complexity of an algorithm's context directly correlates with the difficulty of XAI. Various technologies, such as LIME, SHAP, and Grad-CAM, can be employed to elucidate the models. However, these technologies are tailored for particular model types or datasets, and certain tools can be intricate and challenging to operate [59]. Furthermore, these technologies suffer from scalability and coverage limitations. The selection of algorithms can provide different outcomes for distinct individuals [86, 87].

Decisions are also made by considering a sophisticated interaction of data and perhaps several algorithms. During the process of converting this information into a form that a wider audience can comprehend, the developer also makes subjective choices that may be up to debate due to inherent biases. Moreover, a singular explanation would not suffice to account for all decisions made by an algorithm. Therefore, to mitigate the bias, it is crucial to meticulously evaluate the data sources and algorithms employed in these systems. Cartolano et al. [77] focused on improving the explainability of single-class classification by utilizing the visualization features of SHAP and LIME. Mehedi et al. [79] used pre-trained weights from ImageNet datasets to customize EfficientNetV2L, MobileNetV2, and ResNet152V2 to avoid algorithm bias among the models. Moreover, inaccurate or highly biased domain knowledge can also act as a bottleneck. Therefore, even though Chhetri et al. [68] recommend the incorporation of domain knowledge in the models, it should be done with extreme caution, and multiple domain experts should be involved to eliminate or reduce bias.

Ensuring equity in AI-powered decision-making is not just a moral obligation but also a pragmatic requirement to avert unexpected repercussions and inequities in agricultural results. Although Agriculture 5.0 prioritizes sustainability and environmental care, there are apprehensions that the extensive implementation of technology could unintentionally result in environmental harm. For example, the utilization of self-governing machinery and unmanned aerial vehicles might result in environmental consequences, and over dependence on technology may lead to the erosion of conventional farming methods. Ethical problems also include the displacement of rural labor caused by automation and the possible consolidation of power among technology providers.

4-3- Collaboration and Responsible Innovation

The responsible adoption of Agriculture 5.0 with self-governing systems and decision support powered by artificial intelligence requires well-defined boundaries of authority and accountability in case of AI faults, malfunctions, or misinterpretations of suggestions from AI models. Collaboration efforts between academia, industry stakeholders, and government in building appropriate frameworks for interdisciplinary cooperation that promote ethical deployment of AI in Agriculture 5.0 need to be strategized effectively. All stakeholders must anticipate and prepare for the potential implications of XAI on the decision-making process in the context of Agriculture 5.0. For instance, how they affect labor arrangements, knowledge production, and the distribution of benefits and workload among farmers. The stakeholders must be able to adapt and respond to new information or changes in context as agricultural systems evolve with the integration of AI and robotics [5]. This is supported by the meta-analysis by Velten et al. [88], which underscores the success factors for collaborative groups, emphasizing the need to define priorities, address trade-offs, and recognize agency within collaboratives. Furthermore, Maryono et al. [89] reviewed multi-stakeholder partnerships in agricultural research projects, emphasizing the complexity of participatory research and the importance of involvement across research contexts and phases. Hermans et al. [90] recognize the role of social networks and effective stakeholder communication in agricultural innovation and achieving sustainability goals. It is challenging to elucidate the functionality of the algorithms in a comprehensive manner and to clarify their distinct results. Different stakeholders may have diverse expectations and demands about the concept of explainability [91].

Responsible innovation must take precedence, ensuring that technology is utilized to the advantage of everyone, with a particular emphasis on fair access and sustainability. This includes efficient use of resources, reducing pollution, and the conservation of ethical farming practices [5] while minimizing negative impacts on natural resources [92, 93].

It involves designing technologies that align with farmers' values, cultural practices, and environmental stewardship. Key dimensions of responsible innovation include anticipation, inclusion, reflexivity, and responsiveness. For instance, Chhetri et al. [68] employ the microservices architecture to deploy the vision model, semantic model, and decision engine for the reusability of cassava disease classification. The BentoML and the semantic classifier REST (REpresentational State Transfer) Service were utilized for this purpose.

4-4- Decision Support

The synergy between XAI techniques and real-time data from IoT devices and sensors, facilitated by Agriculture 5.0, ensures that the decisions made by AI models are understandable and justifiable by the users [94]. The combination of XAI techniques and real-time data from IoT devices and sensors enhances the capacity of farmers to harness AI-driven insights effectively, thereby optimizing resource management and crop yields. Analyzing the data can help in providing better services, predicting trends, and timely decision-making for industries [95].

Besides, it is vital to prioritize work aimed at enhancing the accessibility and affordability of AI and XAI for all types of farmers to ensure fairness throughout the agriculture industry. Generally, XAI operates under the assumption that the general user possesses a particular level of expertise. Nevertheless, it is important to acknowledge that many individuals may lack this expertise and, hence, may not be able to accurately evaluate the fairness or justice of a decision made by an AI system. Certain users may lack the requisite foundational knowledge to completely grasp the supplied explanations [58]. Hence, XAI systems must be specifically designed to offer explanations that are customized to the requirements and levels of knowledge of various user groups. This may involve incorporating visual aids, interactive interfaces, or other tools to aid users in comprehending the rationale behind AI decisions [84, 96]. Furthermore, AI models are always being improved to meet the changing needs of stakeholders. Complex machine learning models that involve a multitude of parameters and complex structures, such as deep neural networks, require more calculations as the explanations must scrutinize and decipher the intricate linkages and patterns acquired by the model. Hence, it causes high computational costs, which may limit the applicability of XAI in the actual environment. On the other hand, in order to create models that are easier to understand, there is frequently a trade-off that requires sacrificing accuracy [58, 88, 89].

5- Conclusion

The scoping review analyzes 84 articles from 2018 to September 2023 which offers insights on XAI's potential impact on crop production, resource conservation, and yield security for the future of farming. Key findings include the recognition of XAI's pivotal role within Agriculture 5.0, emphasizing model transparency and user trust. By bridging the gap in existing literature, this review provides a reference for environmentally friendly and technologically advanced smart agriculture. The proposed conceptual framework for integrating XAI serves as a practical guide for informed decision-making. As we move toward a data-driven agricultural landscape, the timely adoption of automated and advanced technologies such as drones, precision equipment, wireless sensor networks, and AI-based systems will undoubtedly shape the future of farming. These technologies must prioritize predictive accuracy, user-friendliness, and actionable decision support. However, the challenges related to the complexity of agricultural data, scalability concerns, educational obstacles, and the trade-off between interpretability and performance must be tackled cautiously. Overall, this review contributes significantly to sustainable food production, resource conservation, and poverty alleviation, positioning smart agriculture as a powerful force for global well-being. In summary, the conclusion effectively encapsulates the review's key findings and underscores their implications for advancing agriculture into a more efficient, transparent, and resilient era.

6- Declarations

6-1- Author Contributions

Conceptualization, S.F.A.R.; methodology, S.F.A.R. and S.Y.; investigation, S.F.A.R., S.Y., M.S.S., and M.I.F.M.D.; resources, M.S.S.; writing—original draft preparation, S.F.A.R. and S.Y.; writing—review and editing, S.F.A.R. and M.S.S. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available in this article.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6-4- Institutional Review Board Statement

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6-5- Informed Consent Statement

Not applicable

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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