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Enhancing transparency and trust in agricultural decision-making through explainable artificial intelligence

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Abstract

The use of artificial intelligence in different software solutions applied in agriculture has significantly advanced data driven decision-making process in this field. The specific nature of many AI models, so called "black box", poses various challenges in terms of transparency, trust, and adoption of obtained results particularly among users with limited technical knowledge, skills, and expertise. These challenges can be addressed using explainable artificial intelligence, which makes model predictions more interpretable, understandable, and transparent. The main goal of this paper is to present the application of explainable artificial intelligence in seven critical agricultural domains: crop yield prediction, pest and disease detection, precision agriculture, soil health analysis, weather risk management, plant breeding and genomics, and market forecasting. For each of these domains, we examine how the use of different explainable artificial intelligence techniques, such as feature attribution, saliency maps, and rule-based explanations, can improve interpretability, increase user confidence, and support practical insights. In the same time, through the real case studies and prediction model analyses, we demonstrate how the use of explainability improves transparency, and leads to better-informed AI generated decisions, increased efficiency, and more sustainable farming practices. The obtained results show the great potential of using explainable artificial intelligence as a link between complex prediction algorithms and practical application in the field of agricultural production. At the same time, the application of such techniques promotes the responsible and inclusive use of artificial intelligence in the agri-food sector.

Keywords: *precision agriculture, feature attribution (SHAP, LIME), trust in AI*

1. Introduction

The agricultural production sector is experiencing a technological revolution driven by the use of data, automation and the use of artificial intelligence (AI). The use of AI offers the potential for resource optimization and increased productivity, starting from automated and precise irrigation to the detection of disease. However, many machine learning models and deep learning models are based on the black box principle. Although they can be very accurate, these models often do not have sufficient transparency in decision-making, which is a serious obstacle to the adoption of AI in every domain, including agriculture. Lack of transparency leads to skepticism among agricultural producers and agronomists, especially when it comes to important decisions such as pesticide application, fertilization or irrigation.

To bridge this gap, explainable artificial intelligence (XAI) has been used, to make predictive models more understandable even to non-experts. In terms of the application of XIA, interpretability refers to models whose inner workings are directly understandable, while explainability focuses on generating human-friendly explanations for complex or "black box" models. As AI tools applied in agricultural production are based on deep learning models and ensemble methods, explainability becomes crucial to ensure transparency and trust in the obtained results. For this reason, instead of simply displaying the results, XAI highlights the factors that influenced the decision-making process, the strength of those influences, and the reliability of the predictions. Increasing interpretability using XAI leads to shared decision-making

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between technology and agricultural stakeholders, with overall trust and facilitated information sharing (Antoniadi et al., 2021). The results of this study have several specific implications for the agricultural sector:

- For farmers: XAI enables farmers to make more informed decisions by uncovering the underlying factors that influence crop yield predictions, disease diagnoses, or irrigation recommendations. Interactive and visual explanations allow farmers to validate AI results against their field knowledge, reducing the risk of misapplication and fostering trust in digital tools.
- For policymakers: The application of transparent AI models in areas such as food safety planning, environmental regulation, and agricultural subsidies facilitates the formulation of evidence-based policies. In this context, XIA allows regulatory bodies to better understand the recommendations obtained from AI, thereby ensuring accountability and compliance.
- For researchers and developers: In order to integrate domain-specific explanations, multimodal data sources, and user-centered interfaces into AI systems developers need to have interpretability in mind. In this way, created AI models will be accurate and actionable in the same time. In addition, the use of XAI techniques provides better insights into data quality and prediction model issues, guiding further refinement and innovation.
- For extension services and agricultural advisors: Given that XAI tools can help agronomists convey complex insights from predictive models to farmers in a more accessible format, XAI can also be said to serve as an educational platform. This supports capacity building, knowledge transfer, and adoption of sustainable agricultural practices.

Globally, the application of XAI enables the transformation of artificial intelligence models from a "black box" into a reliable partner, providing full support in the decision-making process. In this way, the efficiency, sustainability and inclusiveness of the agricultural sector are promoted.

2. XAI in agricultural domains

XAI is a subset of AI research focusing on making AI models transparent without significantly losing performance (Gunning et al., 2019). From one side, traditional statistical models like linear regression offer interpretability, but from the other side, modern AI models like random forest, gradient boosting, convolutional neural networks (CNNs) are characterized as opaque. In the process of agricultural production, environmental variability, as well as the complexity of biological processes, constantly challenge the prediction results obtained using AI prediction models. For this reason, users of software systems need not only accurate but also explainable solutions and prediction results. Such results can be achieved using techniques such as feature attribution (e.g. SHAP values, LIME), visual interpretability tools (e.g., saliency maps in image classification), and rule-based systems. From an agricultural production perspective, for example, the use of such solutions can indicate which weather variables have the greatest impact on crop yield forecasts, or which image features have led to the detection of plant diseases. Some of the most relevant applications of XAI in the field of agricultural production are described below.

Crop yield recommendation and prediction

Explainable artificial intelligence in agriculture enhances decision-making by providing transparent insights into crop recommendations. While using machine-learning models to analyze data, XAI ensures that farmers understand the rationale behind created suggestions, thus fostering trust and improving crop production and resource management. Artificial intelligence models can integrate data from different sources, such as high-resolution images, historical weather data, soil composition data, as well as the existing farming practices, all with the aim of more accurately predicting crop yields and producing safe food, planning markets and optimizing resource allocation. While these models can have very high accuracy, they are often characterized by poor explainability. Use of XAI aims to address this by for example ranking the variables that influence the predicted yield. For example, the use of SHAP analysis can show that the amount of precipitation in the first days of vegetation can contribute to 40% of the prediction variance, while the amount of fertilizer explains an additional 25%. This insight into the prediction results allows agronomists and agricultural producers to better analyze the approach of the AI prediction model in relation to experience in the field. In practice, explainability feature enables scenario planning. For example, a farmer can input hypothetical changes such as delayed planting or altered irrigation schedules, and see how the model's forecast changes, making yield prediction an interactive decision-support tool rather than a static report. XAI-based crop recommendation system can offer a significant advancement in agricultural technology by combining high predictive accuracy with needed transparency, providing farmers with understandable and trustworthy insights for optimal crop selection and resource management.

Pest and disease detection

The occurrence of plant diseases and pests can greatly affect the yields of cultivated plants. In conditions of intensive agricultural production, yield losses caused by the occurrence of diseases or pest attacks can amount to 20% to 40%. Software solutions based on computer vision or convolutional networks very effectively classify the health status of plants based on images of plants obtained from the field. However, despite the high accuracy, users of such systems cannot be sure that the model's decision is correct. For example, the use of the Grad-CAM XAI technique in this case can highlight certain parts of the plant leaf image that were significant for the classification itself, which will increase the user's confidence in the results obtained. The use of such a technique aims to highlight the part of the leaf on which the user can clearly see the appearance of disease symptoms, which is directly related to the classification result. This serves two purposes:

- Validation – Farmers and plant pathologists can confirm that the diagnosis is based on legitimate symptoms.
- Trust-building – Reduces skepticism about AI “guessing” the answer.

Moreover, by storing and reviewing explanation maps over time, extension services can track the evolution of disease symptoms, potentially catching outbreaks earlier and minimizing crop losses.

Precision agriculture

The focus of precision agriculture is on a specific area, a specific location, or even a specific plant species. In this regard, agricultural processes such as irrigation, fertilization, and pesticide application are adapted to the cultures grown in the observed area. The artificial intelligence models used in this case generate, for example, pesticide maps based on multispectral images obtained by drones flying over the production area, as well as on sensor data from the field. Without XAI, these maps can seem arbitrary to farmers. By integrating XAI, the reasoning behind each zone’s classification becomes transparent. For example, an explanation might show that a given area was marked for increased nitrogen because of low NDVI values from drone imagery, coupled with low soil nitrate measurements. Such clarity fosters better adoption rates farmers are more likely to implement recommendations when they understand the underlying reasoning. Additionally, agricultural input suppliers can use XAI-derived insights to design more sustainable application strategies, reducing environmental impact.

Soil health analysis

Soil health is a key determinant of long-term agricultural productivity. Predictive models use laboratory analyses (e.g., organic matter, pH, nutrient content), and remote sensing indicators to evaluate soil quality. However, without explanation, AI outputs like “low fertility risk” or “high salinity warning” lack actionable context. XAI can break down the relative influence of each factor. For example, a model might show that soil organic matter contributed 50% to the fertility classification, while potassium deficiency accounted for 30%. This enables targeted remediation, so farmers can amend specific nutrient deficiencies rather than applying broad-spectrum fertilizers. Furthermore, historical explainability data allows trend monitoring which provides tracking whether specific parameters (e.g., soil organic matter) are improving or declining over time, supporting sustainable land management policies.

Weather risk management

Weather variability is one of agriculture’s greatest uncertainties. The application of AI to create meteorological models is based on the use of historical meteorological data, satellite images and climate simulations, all with the aim of more accurately predicting precipitation, temperature and the occurrence of extreme weather conditions such as early autumn and late spring frosts, drought and ice. As in previous applications, the problem of explainability of the obtained results affects user confidence. XAI can be used to provide insight into what influenced the forecast result. For example, the prediction that there will be a heat wave can be based on the formation of an abnormal high pressure system over a certain region, as well as a drop in relative humidity. Agronomists and agricultural producers can make decisions in advance about the crop to be grown, sowing density, irrigation schedule, as well as the expected harvest date, based on this information. In addition to agricultural producers, such information is also of great importance to government agencies in order to issue warnings about the formation of hazardous phenomena, as well as to plan yields at the state level.

Plant breeding and genomics

Modern plant breeding relies on genomic selection models that analyze vast datasets of genetic markers to predict desirable properties such as drought tolerance or pest resistance. The complexity of such models is very high, precisely because they work with thousands of variables, each of which has an impact on the outcome of the model. The task of applying XAI techniques is to highlight which specific genes or genomic regions contribute most to the predicted trait. In this way, breeders can focus on these regions when crossing plants. Such targeted crossing speeds up the breeding process and allows the development of new species in as few growing cycles as possible. In addition, the use of XAI can help identify unknown genetic associations, translating complex genetic insights into understandable displays and rankings.

Market forecasting

The agricultural market is influenced by various factors, starting from the supply and demand of agricultural products, through climatic conditions, trade policies, as well as geopolitical events. The application of artificial intelligence models is reflected in the integration of all available variables in order to predict the movement of agricultural product prices on the market. At the same time, an increase or decrease in demand for some agricultural products can be monitored, as well as a possible shortage of the same on the market. The application of XAI in this domain is reflected in the fact that the obtained forecasts are not taken for granted, but are understood and trusted. For example, the increase in the price of wheat can be explained by a combination of low inventory (40%), projected drought in the regions that are the world's largest wheat producers (35%), as well as increased transportation costs (25%). The level of detail created in this way supports risk management strategies, as well as deciding whether it is wiser to store the crop and wait for a higher price or sell it immediately. In a similar way, XAI can be used to plan interventions in the world market or agricultural subsidies.

3. XAI techniques and their role in agriculture

Explainable AI techniques transform complex model predictions into transparent, interpretable insights that can be understood by domain experts and non-technical stakeholders alike. In agriculture, where the user base spans from data scientists to smallholder farmers, these methods serve as a communication bridge between algorithmic complexity and practical decision-making. The most relevant techniques include:

- Feature attribution methods - such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), quantify the contribution of each input variable to a model's output. For instance, in a crop yield prediction model, SHAP values might indicate that early-season rainfall accounts for 38% of the variance in yield estimates, while soil nitrogen levels contribute 25%. This information allows agronomists to verify that the model's logic aligns with agronomic principles and helps farmers prioritize interventions on the most influential factors.
- Visual interpretability tools - Visual explanations are particularly important for image-based tasks, such as pest and disease detection or crop health monitoring via drones. Techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) and saliency maps highlight the specific image regions that influenced a model's classification. For example, if a CNN detects a fungal infection in tomato leaves, Grad-CAM may reveal that the network focused on discolored edges rather than unrelated background pixels. The visual transparency created in this way increases user confidence and reduces the likelihood of misdiagnosis due to irrelevant visual cues.
- Counterfactual explanations: This type of reasoning is characterized by the fact that small changes in input parameters can greatly affect the model's output. From the perspective of agricultural production, such models are used for so-called "what if" analysis. For example, if irrigation is increased by 15%, the model could show a yield improvement of 10%. Such scenario planning empowers farmers to evaluate alternative management strategies before implementing costly changes, supporting evidence-based decision-making.
- Rule-Based explanations - Rule-based systems, such as decision trees or association rule mining, produce outputs in human-readable conditional statements. For example, a rule might state that if soil pH is below 5.5 and rainfall exceeds 800 mm annually, then the probability of nutrient leaching is high. This form of explanation is particularly suitable for smallholder farmers or policymakers who require straightforward, actionable insights without advanced statistical interpretation skills.
- Temporal and spatial explainability: Many agricultural decisions are time-sensitive and location-dependent. XAI methods that incorporate temporal and spatial dimensions such as heatmaps over geographic maps or time-series decomposition, allow stakeholders to understand how predictions vary over time and across regions. For instance, in precision irrigation, spatial explanations can show why specific field zones require more water based on soil moisture maps and evapotranspiration rates, while temporal explanations can indicate how changing weather patterns influence irrigation needs over a growing season.

Benefits of XAI in agricultural contexts

- Trust and adoption: Farmers are more likely to follow AI-driven recommendations when they understand the underlying rationale.
- Error detection: Stakeholders can identify when models are relying on incorrect or irrelevant factors, allowing for corrective retraining.
- Knowledge transfer: Insights generated by XAI can inform training programs, bridging the gap between data science and traditional agricultural expertise.
- Regulatory compliance: Many agricultural AI applications, particularly those related to environmental impact or food safety, may be subject to regulations requiring explainability.

In summary, XAI techniques not only demystify AI models but also turn predictive analytics into collaborative decision-support systems. By enabling transparency, they allow AI to function as a trusted partner in agricultural management rather than as an opaque "black box," ultimately supporting more sustainable, efficient, and inclusive farming practices.

4. Case studies and practical examples

Authors in the paper (Kumar et al., 2024) presented a novel crop recommendation system underpinned by XAI, aimed at augmenting decision-making in agriculture. The created system is based on machine learning algorithms that are used to identify the most suitable crops for cultivation in a given geographical area based on various input data such as soil characteristics, climate variables and market dynamics. What characterizes this methodology is explainability. The application of XAI provides clear insight and justification for the given cultivation recommendations, thereby increasing the level of trust and understanding between agricultural producers and artificial intelligence models. The integration of XAI into crop recommendation systems has significantly revolutionized agricultural practices, promoting data-informed decision-making that enhances crop yields and optimizes resource utilization. Nonetheless, the inherent opacity and interpretive limitations of these models often impede their practical application. Authors investigate XAI-oriented methodologies, such as LIME and SHAP, to elucidate model outputs and underscore the salient features that shape predictions. Their empirical investigations reveal that XAI contributes to the clarity of machine learning models, and assists in the enhancement of model efficacy through judicious feature selection, and model modifications. The models they proposed attain the highest predictive accuracy utilizing the KNN algorithm, while the BiLSTM model also demonstrates commendable accuracy levels.

In one of the papers (Linheiro et al., 2023) authors specifically focuses on the application of AI, with a particular emphasis on XAI, within the agricultural sector. The aim is to address the complexities and challenges by making AI systems more transparent and understandable, thereby bridging the knowledge gap and fostering better adoption of advanced technologies by farmers. In essence, the authors highlight agriculture's critical role, the challenges it faces, and how advanced technologies like AI, particularly XAI, are crucial for sustaining and improving agricultural activities by providing clearer insights and reducing the technology-farmer knowledge divide. More specifically, the paper focuses on XAI. In this paper, the main goal of applying XAI techniques is to make complex AI systems more understandable, which is especially important for agricultural producers, as this approach reduces the gap between technical experts and agronomists.

In one of the papers (Turgut et al., 2024) investigate the integration of emerging technologies such as IoT, ML, and XAI in order `to enhance efficiency and productivity in agriculture. Their proposed system, AgroXAI, is an edge computing–based explainable crop recommendation framework designed to suggest the most suitable crops for specific regions by analyzing local weather and soil parameters. The proposed system combines techniques such as ELI5, LIME, and SHAP within machine learning models. In this way implemented system provides both global and local explanations for results generated as a result of AI prediction models. Furthermore, counterfactual explainability is incorporated to generate alternative crop suggestions at the regional level. Through this design, AgroXAI aims to promote crop diversification and support the development of next-generation agriculture. The study employed an agricultural dataset from Kaggle containing 2,200 records with seven features: nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall. This data set targets 22 crop types. Some of them are apple, banana, coffee, and cotton, among others. Multiple ML algorithms were evaluated for crop classification. The most significant ones are including K-Nearest Neighbors (KNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), LightGBM (LGBM), and Multilayer Perceptron (MLP). The interpretability methods ELI5, SHAP, and counterfactual explainability were applied to analyze the decision processes of the ML models, particularly RF and LGBM. The results show that for both models, humidity and rainfall emerged as the most influential features. From the angle of nutrients potassium was especially important for RF and phosphorus for LGBM. The AgroXAI framework achieved high accuracy in crop recommendation. The authors concluded that the integration of XAI techniques is vary important in order to enhance transparency and interpretability of the AI models. In this way models provides both global and local insights into feature relevance and enable alternative crop recommendations. The increase in prediction accuracy indicates the advantages of applying the model and AI, which greatly affects the optimization of agricultural production. The research results, however, show that the KNN model lacks transparency, which greatly affects its practical application in the decision-making process.

The use of artificial intelligence in tools that provide assistance to agricultural producers is increasingly prevalent precisely because of the increasing accuracy of the models used (Konda et al., 2024). In order to overcome the aforementioned problem of non-transparency of KNN models, the authors in this paper propose the integration of XAI methods. They place special emphasis on saliency maps. The authors used silent maps and interactive control tables to improve the transparency of prediction models for predicting crop yields. The authors also conducted a survey among farmers in order to analyze the impact of this approach on trust, understanding and acceptance of AI recommendations based on artificial intelligence. The study used SHAP to identify critical variables that influenced the prediction result. In this way, transparency, interpretability and accessibility were prioritized. The overall study was conducted with the aim of supporting agricultural producers in the process of resource management and creating sustainable practices and long-term resilience.

The research described in (Ngo et. al., 2022) aimed to introduce a knowledge map model and an ontology-based XAI framework in the process of agricultural data analysis. The created solution is called OAK4XA, and is characterized by emphasizing the semantics of the knowledge dimension by applying ontology and knowledge map models as basic modules. Based on the applied algorithms and concepts, the approach provided more consistent mining of agricultural data. During the research, the researchers developed an agricultural computational ontology called griCom. The created ontology is characterized by encompassing a wide range of concepts and transformations relevant to agricultural production and computing. Such an ontology contributes to more transparent knowledge management in precision and digital agriculture.

Agricultural eXperience Enhanced through eXplainability (AgriUXE), a digital platform, was created as a platform that integrates multimodal data with XAI techniques. The goal of this platform is to generate user-friendly explanations in the domain of precision agriculture (Porfirio et al., 2024). AgriUXE, as a platform, is connected to IoT sensors in the field, which enables remote sensing and data collection. The processing of such data allows for predictions tailored to the needs of different agricultural producers. The platform is designed to allow connectivity to different applications, thereby increasing transparency and supporting more informed decision-making during the agricultural production process itself. Complementing this platform, the study presents AgriDash, a practical application focused on viticulture, which improves vineyard management.

The research conducted by Mohan et al. included the application of AI and XAI methods to predict crop yields and analyze climate variables on the agricultural production process (Mohan et al., 2025). The research conducted in this way provided new insights into the complex relationship between climate, climate change, and agricultural production, all with the aim of minimizing the impact of climate change on global food security. The authors applied exploratory data analysis (EDA) which showed that air temperature change is one of the most influential variables in terms of crop yields. In addition to air temperature, the analysis showed that the amount of precipitation, as well as the availability of micronutrients, also have an impact on crop yields. From the perspective of AI techniques, it can be concluded that advanced regression techniques such as decision tree regressor, random forest regressor, and LightGBM regressor were used. The aforementioned high-accuracy prediction methods are enhanced by integrated XAI methods such as SHAP and LIME. The results of the research show that combining high-accuracy prediction methods with methods that provide transparency and interpretability provides a scalable framework for precision agriculture. In this way, decisions can be made that will help in the process of mitigating the negative impacts of climate change on cultivated plants.

The authors of the study described in (Martin et. al., 2024) used a dataset obtained from sources in India. The dataset used consisted of meteorological variables, variables that carry information about the soil and crops in a certain area. The selected dataset was used to extract features from it using pre-trained algorithms in combination with the Enhanced Barnacles Mating Optimization (EBMO) algorithm. In this way, the problem of data dimensionality and computational complexity was successfully solved. The following machine learning models SVM, Random Forests, Neural Networks and Decision Trees were applied to the selected prediction attributes. The mentioned models were used to generate recommendations in the field of precision agriculture. The used hybrid model XLNet+SVM showed significant performance in prediction compared to other models. This model was tested on several types of crops. Interpretability is achieved by integrating SHAP and LIME techniques, which enables transparency and easier interpretation of prediction results. In this way, the authors proposed a smart agricultural system based on a combination of AI and XAI techniques to improve prediction accuracy. This implementation provides a scalable solution for increasing productivity and supporting informed decision-making in agricultural production.

5. SWOT analysis of XAI in agriculture

The application of XAI in agricultural production can be better understood through a SWOT analysis. By applying a SWOT analysis, the strengths and limitations of XAI can be highlighted, as well as the external opportunities and risks. Some of the most important SWOT characteristics are listed in Table 1.

Strengths: The strength of XAI lies in the ability of the techniques to increase the transparency of AI systems, which increases user confidence in the results of the system. Compared to traditional "black box" models, XAI techniques delineate why a certain prediction was obtained. Such information can be crucial for important agricultural decisions, such as pesticide use, irrigation, or disease diagnosis and prognosis. The interoperability of the applied techniques supports the process of regulatory compliance, given the fact that financiers and government authorities require transparency in software solutions used in agricultural production. XAI not only provides transparency and results, but also trains agricultural producers and agronomists on the fundamental factors that influence the agricultural production process, which is another of its great strengths.

Table 1. SWOT analysis

Strengths	Weaknesses	Opportunities	Threats
Improves trust and transparency in AI predictions	Explanations may be too technical for farmers	Higher adoption of AI tools in farming communities	Over-reliance on explanations without critical evaluation
Supports regulatory compliance and accountability	Adds computational cost to models	Integration with IoT, robotics, and precision farming	Data privacy and ownership concerns
Facilitates knowledge transfer between developers and users	Trade-off between accuracy and interpretability	Encourages data sharing and collaboration	Misinterpretation of explanations could lead to poor decisions
Strengthens decision-making through transparency	Limited real-time scalability in the field	Supports sustainability and food security goals	Unequal adoption may increase the digital divide

Weaknesses: Like any technique, XAI techniques have some weaknesses in addition to their advantages. The weaknesses of these techniques are that although they are very powerful, they are still difficult for the non-technical users to interpret. For example, farmers may have problems with SHAP diagrams or saliency maps. For this reason, they are often translated into simple context-aware insights. In addition to this weakness, the use of XAI methods very often leads to additional costs in terms of computing time. This is especially important when it comes to environments that need to work in real time or with limited resources. Examples of such environments are IoT sensors in the field, as well as mobile devices. The possible trade-off between accuracy and interpretability introduces another limitation, which is that simpler models are easier to explain but are less precise, while complex models are more demanding in terms of explanation, but for this very reason can seem unclear to end users.

Opportunities: The application of XAI techniques enables new application possibilities in agriculture. First, these techniques make the results of artificial intelligence more understandable, which leads to easier acceptance of the obtained results by agricultural producers. Second, the integration of XAI techniques with other technologies used in precision agriculture and IoT platforms, creates the possibility of providing explainable recommendations in real time. Recommendations created in this way can be used, for example, for the scheduling of irrigation, fertilization, or the control of diseases and pests. An accurate recommendation can lead to a timely response aimed at increasing yields and economic profit, as well as environmental sustainability. In this way, XAI shows its potential in the domain of data exchange between agricultural producers, agronomists, researchers and government authorities.

Threats: There are several threats that hinder the widespread adoption of XAI in agriculture. One of the main risks is the overreliance of system users on explanations generated by artificial intelligence. For example, if agricultural producers or government agencies take the obtained results as absolute truth, they may overlook something that exists in the data or methodology. Another threat is data privacy. This is especially important if the explanations require access to sensitive information, which may lead to farmers not allowing access to the data for fear of misuse. The last but not least threat is the misinterpretation of data. Because no matter how clearly the explanation is defined, there is a possibility that the system user, due to poor information, misinterprets the explanation itself. Global inequalities also pose a threat. Such advanced solutions are easily adopted in developed countries, while in less developed countries, agricultural producers may be disadvantaged due to poor infrastructure, further widening the gap in digital agriculture adoption.

6. Challenges and future directions

The integration of XAI into agricultural production faces various obstacles. While the benefits of use are very significant, the technical, social and ethical obstacles that software engineers must address in order to fully exploit the advantages offered by XAI cannot be ignored. Properly understanding these challenges as well as identifying development directions can help in creating further integration paths into digital agriculture (Hsieh et. al., 2024).

Data quality, bias, and availability: A characteristic of agricultural data in large datasets is that the data is often heterogeneous and collected from different sources. Some of the sources are weather stations, drone images, IoT sensors, and internal records of agricultural producers. This way of collecting data often leads to incomplete data, which is full of outliers. For example, remote sensing data may be affected by cloud cover, while soil sampling may be too sparse to represent entire fields. Such inconsistencies can lead to biased explanations that misguide farmers. In developing regions, the lack of digital infrastructure further limits access to reliable datasets.

Future directions include:

- Building federated learning systems that allow farmers to contribute data without sharing sensitive information.
- Developing bias detection algorithms that identify and correct misleading patterns in agricultural datasets.
- Promoting open data initiatives supported by governments and international organizations to improve data accessibility.

Complexity and interpretability of explanations: While XAI seeks to make models transparent, many existing techniques (e.g., SHAP or LIME visualizations) still produce explanations that are too technical for farmers, extension agents, or policymakers with limited AI knowledge. A farmer may not easily interpret a SHAP value chart that shows rainfall contributing 35% to yield variance. Without appropriate translation, the risk of misunderstanding or misuse increases.

Future research should focus on domain-specific explanation interfaces that convert complex metrics into simple, farmer-friendly language or visuals. For example, explanations could be delivered as "traffic light systems" (green = healthy, yellow = moderate risk, red = critical) or through natural language summaries. Training programs and participatory design workshops will also be key in ensuring that explanations align with users' literacy and cultural contexts.

Trade-off between accuracy and interpretability: There remains a fundamental tension between model accuracy and interpretability. Deep learning models such as CNNs and RNNs often outperform simpler models in disease detection, yield forecasting, and weather prediction. However, these models require the application of complex explanatory techniques. On the other hand, predictive models such as linear regression can be more easily interpreted but may be less accurate in terms of data variability. The solution lies in the development of hybrid models that combine good predictive capabilities and interpretability. One example of such models is neuro-symbolic artificial intelligence, which integrates neural networks with symbolic reasoning. In addition to neuro-symbolic artificial intelligence, there are also attention-based models that are used to highlight the most important features.

Scalability and real-time applications: The decision-making process in agricultural production requires real-time operation. As already discussed, XAI methods are very expensive operations in terms of computing time, which affects their application, for example, on edge devices or within IoT systems implemented on productive agricultural areas. Further development and research directions should focus on creating XAI methods that are lightweight and energy-efficient on the one hand, while at the same time being optimized for operation on edge devices. This can be achieved by using simpler models, so-called surrogate models, in the process of providing explanations when working in real time, while significantly more complex models would be used within centralized systems.

Ethical, social, and policy considerations: The privacy of agricultural data and the use of XAI over this data raises questions about ethics, data ownership, and liability in the event of misuse. It is for these reasons that farmers are very often reluctant to grant access to the data they collect in the field. For example, if a predictive model makes a recommendation that will lead to crop failure or lower yields, the question of liability undoubtedly arises. In this case, on the one hand, it may be the fault of the agricultural producer who followed the advice received from the system, or on the other hand, the fault may lie with the data scientist who trained and integrated the model into the system. In order to avoid such problems, clear governance frameworks must be established that will regulate data ownership, consent for its use, and responsibility for decision-making in agricultural production supported by artificial intelligence. In such systems, all information needs to be logged, both audit trails and the explanations created (Vale et al., 2022). Ethical frameworks must be set up so that the benefits obtained from the use of artificial intelligence are fairly distributed, thus avoiding that corporations benefit in absolute terms, while small producers are left behind.

Integration with human expertise: The challenge facing agricultural producers is that the explanation obtained by artificial intelligence-based systems does not necessarily lead to a better decision. What decision the obtained explanation will lead to depends largely on the knowledge and experience of the agricultural producer. For example, two agricultural producers or two agronomists, based on the same explanation of the occurrence of a disease, may recommend different treatments (Ali et. al., 2023). Collaboration between humans and artificial intelligence is key in the future development of the system. In this regard, XAI can be used to transfer knowledge and expertise, allowing users to validate, refine or even refute predictions, thereby actively working on improving the model. This approach leads to more relevant explanations.

Data quality, interpretability, scalability, ethics, and human collaboration are some of the challenges facing the application of XAI techniques in agricultural support systems. However, everything indicates that future directions of development lead to more usable and sustainable systems. The evolution of XAI from a research concept to a practical tool must be farmer-centered, ethical governance, and technical innovation to produce a tool that supports global food security and sustainable agricultural practices.

7. Conclusion

In order to bridge the gap between modern computer models and traditional agricultural practices, it is necessary to integrate XAI techniques. Traditional artificial intelligence approaches are characterized by high accuracy when it comes to predicting crop yields, diagnosing and forecasting diseases and pests, and assessing market trends for agricultural products. The way these traditional models work is often accompanied by low trust, understanding, and adoption by users. XAI, as a new approach in artificial intelligence, offers a solution to these problems by introducing transparency and interoperability to traditional models. This approach allows agricultural producers to understand why the model made a certain prediction, as well as whether it is necessary to react in accordance with the obtained predictions.

The application of XAI in agricultural production demonstrates its capacity, starting from soil health analysis to plant genotypes. The application of XAI in each of the seven areas analyzed has shown improvements in decision-making, increased trust, accountability, and inclusiveness in digital agriculture. Trait attribution, saliency maps, and rule-based explanations are just some of the methods that can be used to provide clarity and help agricultural producers and agronomists validate decisions obtained by AI systems and integrate them into daily practice.

However, some challenges remain. The design and management of XAI systems are constrained by issues of data quality, interpretability complexity, computational time costs, and contextual uncertainties. The future development and future progress of such systems will depend on the implementation of simple, user-friendly methods of explanation, which operate on the basis of data protection and equitable access.

The great advantage of using XAI systems is reflected in the possibility of transforming agricultural production from a technology-driven sector to a knowledge-driven sector. This is only possible if people and artificial intelligence collaborate in a transparent and sustainable way. The use of XAI techniques ensures the development of responsible digital innovations that will contribute to global food security, environmental sustainability, and all by using artificial intelligence models that are not only accurate but also understandable.

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