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Role of Explainable AI in Crop Recommendation Technique of Smart Farming

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Abstract: Smart farming is undergoing a transformation with the integration of machine learning (ML) and artificial intelligence (AI) to improve crop recommendations. Despite the advancements, a critical gap exists in opaque ML models that need to explain their predictions, leading to a trust deficit among farmers. This research addresses the gap by implementing explainable AI (XAI) techniques, specifically focusing on the crop recommendation technique in smart farming.

An experiment was conducted using a Crop recommendation dataset, applying XAI algorithms such as Local Interpretable Model-agnostic Explanations (LIME), Differentiable InterCounterfactual Explanations (dice_ml), and SHapley Additive exPlanations (SHAP). These algorithms were used to generate local and counterfactual explanations, enhancing model transparency in compliance with the General Data Protection Regulation (GDPR), which mandates the right to explanation.

The results demonstrated the effectiveness of XAI in making ML models more interpretable and trustworthy. For instance, local explanations from LIME provided insights into individual predictions, while counterfactual scenarios from dice_ml offered alternative crop cultivation suggestions. Feature importance from SHAP gave a global perspective on the factors influencing the model's decisions. The study's statistical analysis revealed that the integration of XAI increased the farmers' understanding of the AI system's recommendations, potentially reducing food insufficiency by enabling the cultivation of alternative crops on the same land.

Index Terms: Smart Farming; Machine Learning; GDPR; XAI; LIME; Dice_ml.

1. Introduction

The advent of smart farming has introduced a paradigm shift in agricultural practices, leveraging the power of machine learning (ML) and artificial intelligence (AI) to optimize crop production and management. The integration of these technologies has led to the development of sophisticated crop recommendation (CR) systems that analyze a multitude of variables, such as soil parameters, weather conditions, and historical yield data, to suggest the most suitable crops for cultivation. These systems aim to maximize agricultural output and profitability while minimizing resource consumption and environmental impact.

Despite the potential benefits, adopting AI-driven CR systems in agriculture faces a significant challenge: the opacity of ML models. Many of these models function as "black boxes," providing predictions without explanations. This lack of transparency can lead to skepticism and resistance among farmers, who are traditionally accustomed to making decisions based on empirical knowledge and experience. The inability to understand the rationale behind AI recommendations undermine trust and hinders the broader acceptance of smart farming solutions.

The need for model transparency is a matter of trust and a legal requirement under regulations such as the General Data Protection Regulation (GDPR), which mandates the right to explanation. This regulation underscores the importance of providing individuals with clear and understandable reasons for automated decisions that affect them. In the context of smart farming, this translates to the necessity for CR systems to elucidate the reasoning behind their recommendations.

Explainable AI (XAI) [1-4] is crucial in addressing these concerns. XAI aims to make the decision-making processes of AI systems interpretable and understandable to humans. By employing XAI algorithms, such as Local Interpretable Model-agnostic Explanations (LIME), Differentiable Counterfactual Explanations (dice_ml), and SHapley Additive exPlanations (SHAP), CR systems can provide farmers with insights into the factors influencing crop recommendations. These explanations can be local, offering justifications for individual predictions, or global, shedding light on the overall behavior of the model.

The theoretical underpinnings of XAI are rooted in the desire to bridge the gap between the growing adoption of AI in various domains and the critical need for accountability, fairness, and trust in AI systems. In smart farming, XAI facilitates a dialogue between farmers and AI systems, empowering farmers with actionable insights and enabling them to make informed decisions. This dialogue is about providing answers and allowing farmers to ask the right questions, fostering a collaborative relationship between human expertise and AI capabilities.

This paper aims to explore the role of explainable artificial intelligence (XAI) [5-8] in smart farming, with a particular focus on crop recommendation systems. The goals are to:

- Investigate the integration of XAI techniques within smart farming to address the gap between complex machine-learning models and the need for transparency in agricultural decision-making.
- Conduct experiments using XAI algorithms such as Local Interpretable Model-agnostic Explanations (LIME), Differentiable Counterfactual Explanations (dice_ml), and SHapley Additive exPlanations (SHAP) to generate explanations for crop recommendations.
- Assess the compliance of these systems with the General Data Protection Regulation (GDPR), which mandates the right to explanation.
- Analyze the effectiveness of XAI in enhancing the interpretability and trustworthiness of machine learning models in smart farming.
- Explore the potential of XAI to reduce food insufficiency by enabling the cultivation of alternative crops on the same land, contributing to food security.

Structure of the Paper
The paper is organized as follows:

- Literature Review: This section reviews the importance of XAI and various base papers related to XAI, highlighting the significance of XAI in enhancing the transparency and accountability of ML models, particularly in domains like smart farming.
- General Framework of Machine Learning & Explainable AI in Crop Recommendation System: This section describes the general framework of ML and XAI in the CR system, detailing the process from data preparation to model deployment and the role of XAI in providing explanations.
- Explainable AI Categories: The paper categorizes XAI based on scope, agnosticity, data type, and explanation type, providing a detailed explanation of each category.
- The Theory behind Explainable AI: This section delves into the LIME algorithm, its importance in crop recommendation systems, and other XAI techniques such as dice_ml and SHAP.
- Results and Discussions: The paper presents the experiment setup, basic model design steps, practical implications of current research, limitations and potential biases of the ML models, and experiment results, including data pre-processing, LIME Tabular explainer, counterfactual explanations, and SHAP summary plot.
- Conclusion: The conclusion summarizes the research findings, emphasizing the importance of model transparency and the ability to provide explanations for AI-driven decisions in smart farming.
- Future Scope and Applied Implications: This section discusses the limitations, potential biases, and future research directions, including integrating XAI into various smart farming activities and the need for education and training programs for farmers.

2. Literature Review

The literature review reviews the importance of XAI, and various base papers related to XAI. The literature review examines the significance of XAI and different base papers related to XAI.

2.1. XAI Literature Review

XAI plays a crucial role in enhancing the transparency and accountability of ML models, which is particularly significant in domains like smart farming, where model predictions impact critical decisions [1]. XAI techniques allow stakeholders to understand why specific recommendations or predictions are made by ML models [2]. For instance, when a recommendation suggests rice cultivation over other crops, XAI empowers farmers to inquire about the reasoning behind this decision [3].

XAI algorithms, such as LIME and dice_ml, have been employed to generate local and counterfactual explanations for crop recommendation datasets [4]. These explanations provide insights into model predictions and enable alternative crop cultivation suggestions, contributing to food sufficiency [5].

In a broader context, XAI methods have been widely explored and reviewed. These works highlight the importance of XAI across various domains, including healthcare, agriculture, finance, education, energy, and cybersecurity, emphasizing its role in ensuring model interpretability, fairness, and accountability.

Table 1 represents the XAI literature review from various journals like the Association for Computational Linguistics, Elsevier, and other important journal sources and analyzes the parameters and methods used in each article. One of the essential articles considered for explanations is Marco [6], titled "Why Should I Trust You?” while explaining any model.

Various ML models, such as glass box self-explanatory models (Decision tree, logistic regression) and black box models (SVM, Random Forest, and so on), are used for building crop recommendation systems. Building an explainable crop recommendation system required XAI algorithms like LIME, SHAP, etc. Further sections will discuss more XAI algorithms.

Table 1. XAI articles and sources

Publication Details	**Research Goal**	**Inference/Research Outcomes / Benefits**
Marco Ribeiro. et al. (2016) [1]	Explore the need for model explanations in smart farming recommendations.	Develop methods for explaining ML model predictions 1—the LIME algorithm presented for local explanations. The LIME goal is to provide explanations to the individual record to make an interpretable model. 2. Glass box and black box models are demonstrated by using LIME. SVM (support vector machine), DT (Decision tree), Logistic regression, and so on are demonstrated for explanations.
Linardatos P. et al. (2021) [2]	Provide an overview of ML interpretability methods.	1. Summarize existing ML interpretability methods 2. Model-independent techniques like LIME and SHAP are illustrated for various data formats, including pictures, text, and tabular data. 3. The study shows the importance and improvement of explanations for existing models.
Dutta, P et al. (2022) [3]	Investigate explainability in AI.	Survey on XAI in AI applications
Riccardo Galanti. et al. (2023) [4]	Develop an explainable decision support system for predictive analytics	Create an explainable system for predictive analytics
Wachter, S. et al. (2017) [5]	Explore GDPR requirements for model explanations.	Discuss counterfactual explanations and GDPR
Lynn Vonder Haar. et al. (2023) [6]	Analyze explainability methods for CNNs	Discuss the analysis of CNN explainability methods.
Adadi, A.; Berrada, M. (2018) [7]	Provide an overview of XAI.	1. Explains what XAI is, how to use XAI, when and where to use XAI, and cover the basics of XAI. 2. Counterfactual explanations are required to make an alternative decision. For example, the crop recommended for the farmer is rice. If there is a demand for the wheat crop, counterfactual explanations will provide suitable configurations to make the soil suitable for the wheat crop. 3. Explored model-specific and model Agnostic explanations. Model-agnostic explanations can be applied to any algorithm compared to model-specific explanations designed for a specific algorithm.
Guidotti, R et al. (2018) [8]	Survey various methods for explaining black box models	1. The importance of explanation for black box models is explored. 2. Model predictions may directly be learned from the explanations.
Gilpin, L.H et al. (2018) [9]	Offer an overview of ML model interpretability.	1. Deep neural networks(DNN) have complex architecture. Transparent explanations are required to understand the architecture of DNN. 2. Input data representation and explanations will make the DNN model interpretable.
Di Martino, F. et al. (2022) [10]	Examine XAI in clinical and health applications.	1. Explored applications of XAI for healthcare applications 2. Time series and tabular data explanations using XAI techniques are presented
Dang Minh [11]	To analyze the categories and challenges of XAI	1. Various XAI categories are presented 2. XAI challenges are presented
Ferraro [12], AI Review	Analyzing the importance of XAI in hard disk drive	1. Investigated the importance of XAI for hard disk drive maintenance. 2. Blackbox model explanations through XAI are investigated
El-Sappagh [13], AI Review	Analyzing AI in healthcare	1. Investigated how to build trustworthy AI models for medical applications
Rudresh Dwivedi. et al. (2023) [14]	Present core ideas and techniques of XAI	Explain the core concepts and techniques of XAI
Meike Nauta. et al. (2023) [15]	Conduct a systematic review on evaluating XAI	Summarize methods for evaluating XAI
Rawal, J. et al. (2022) [16]	Review recent advances in trustworthy XAI.	Summarize recent advances and challenges in trustworthy XAI.
Holzinger, A., Saranti, A., et al. (2022) [17]	Explore the role of AI in smart farming	Highlight the need for human-centered AI in smart farming

Holzinger, A., Saranti, A., et al. (2022) [18]	Offer a brief overview of XAI methods	Summarize XAI methods
Masahiro Ryo (2022) [19]	Explore XAI in agricultural data analysis	Highlight XAI's role in agricultural data analysis
F. Sabrina, S. Sohail, et al. (2022) [20]	Present an interpretable AI-based smart agriculture system	Highlight the application of interpretable AI in smart agriculture
Lundberg, S. M. et al. (2020) [21]	Develop methods for making tree-based machine learning models more interpretable by shifting from local explanations to a global understanding of model behavior.	Techniques like SHAP can effectively provide local explanations that aggregate to reveal global model characteristics, thereby enhancing trust and transparency in critical fields such as healthcare and finance.
Jain, S. et al. (2020) [22]	Investigate whether attention mechanisms in neural networks truly offer reliable explanations for model predictions.	Attention weights do not necessarily correlate with model interpretability, challenging the notion that they can be directly used as justifications for model behavior, thereby prompting the need for alternative explanation methods.
Yaganteeswarudu Akkem. et al. (2020) [23]	Review the applications and impacts of artificial intelligence technologies in smart farming to enhance agricultural productivity and sustainability.	AI technologies are playing a crucial role in optimizing various agricultural processes, from crop monitoring to precision farming, thereby significantly improving yield and resource management.
Borrego-Díaz, J., Galán-Páez, J. (2022) [24]	Analyze XAI in data science.	Promotes the understanding of AI models in data science and facilitates better decision-making.
de Fine Licht, K. et al. (2020) [25]	Examine the role of transparency in the use of artificial intelligence within public decision-making processes.	Ensuring transparency in AI systems used for public decision-making is crucial for maintaining public trust and accountability, highlighting the need for clear and understandable explanations of AI-driven decisions to the general public.
Främling, K. (2020) [26]	Investigate the relationship between decision theory and XAI.	Explores the integration of decision theory and XAI for more interpretable AI systems.
Vassiliades, A et al. (2021) [27]	Survey the intersection of argumentation and XAI.	Provides insights into how argumentation can enhance the interpretability of AI systems.
Weiping Ding et al. (2022) [28]	Provide a comprehensive overview of AI explainability.	Offers a comprehensive understanding of AI explainability, including challenges and applications.
A. Hanif, X. Zhang, and S. Wood (2021) [29]	Survey XAI techniques and challenges.	Highlights various techniques and challenges in the field of XAI.
Yang, W., Wei, Y., Wei, H. et al. (2023) [30]	Survey XAI approaches, limitations, and applications.	Provides insights into different XAI approaches, their limitations, and application domains.
Zhang Y, Tiňo P, Leonardis A, Tang K. (2021) [31]	Survey the interpretability of neural networks.	Offers a comprehensive overview of interpretability in neural networks.
Arrieta AB, Díaz-Rodríguez N R, et al. (2020) [32]	Explore XAI concepts, taxonomies, and challenges.	Provides a foundation for understanding XAI concepts, taxonomies, and challenges in responsible AI.
Das A, Rad P. (2020) [33]	Investigate the opportunities and challenges in XAI.	Identifies opportunities and challenges in XAI, paving the way for further research and development.
Ooge J, Verbert K. (2022) [34]	Investigate the use of interactive visualizations for AI explanations.	Highlights the potential of interactive visualizations in explaining AI models.
Saeed W, Omlin C. [35]	Conduct a meta-survey on XAI challenges and future opportunities.	Provides an overview of the current challenges and future potential in the field of XAI.
Kotriwala A et al. (2021) [36]	Explore XAI applications, theses, and research directions in the process industry.	Provides insights into the application of XAI in the process industry and outlines research directions.
Albahri A et al. (2023) [37]	Evaluate the quality, bias risk, and data fusion in trustworthy and explainable AI in healthcare.	Assesses the quality and reliability of XAI in healthcare, considering bias and data fusion aspects.
Chaddad A, Peng J, Xu J, Bouridane A. (2023) [38]	Survey XAI techniques specifically in the healthcare domain.	Provides an overview of XAI techniques tailored for healthcare applications.
Tjoa E, Guan C. (2020) [39]	Investigate XAI's role in medical applications.	Offers insights into the application of XAI in medical contexts, promoting transparency and trust.
Gozzi N et al. (2022) [40]	Investigate XAI to explain EMG data in hand gesture classification.	Demonstrates the potential of XAI in improving the interpretability of prosthetic hand gesture classification.
Ahmed U et al. (2022) [41]	To enhance the transparency and interpretability of machine learning models in smart farming.	Providing explanations for crop recommendations to comply with GDPR and empower farmers with reasoning behind model predictions.

Palatnik de Sousa I et al.. (2019) [42]	To achieve interpretable results in the classification of lymph node metastases.	LIME is used to provide interpretable explanations for lymph node metastases classification, aiding in medical diagnosis.
Sarp S, Kuzlu M, Wilson E, Cali U, Guler O. (2021) [43]	To improve the interpretability of chronic wound classification using XAI.	XAI contributes to a more understandable and accurate classification of chronic wounds, aiding in medical assessments.
Gulmezoglu B. (2021) [44]	To enhance the transparency and interpretability of side-channel analysis in website fingerprinting attacks.	XAI techniques are applied to improve the understanding of side-channel attacks, aiding in cybersecurity.
Melo E, Silva I, Costa DG, Viegas CM, Barros TM. (2022) [45]	To provide interpretable insights into school dropout patterns using XAI.	XAI assists in the evaluation of school dropout, enabling targeted interventions in education.
Conati C, Barral O, Putnam V, Rieger L. (2021) [46]	To enhance the personalization and interpretability of intelligent tutoring systems using XAI.	Personalized XAI enhances the adaptability of intelligent tutoring systems, improving learning outcomes.
Omeiza D, Webb H, Jirotka M, Kunze L. (2021) [47]	To improve the transparency and safety of autonomous driving systems through explanations.	Explanations in autonomous driving contribute to safer and more understandable autonomous vehicles.
Machlev R et al. (2022) [48]	To enhance the transparency and efficiency of energy and power systems using XAI.	XAI techniques aid in optimizing energy and power systems, leading to more efficient energy usage.
Capuano N, Fenza G, Loia V, Stanzione C. (2022) [49]	To improve the transparency and security of cybersecurity systems through XAI.	XAI enhances the detection and understanding of cybersecurity threats, strengthening defenses.
Bussmann N et al. (2021) [50]	To provide interpretable insights into credit risk assessment using XAI.	Explainable ML aids in making more informed decisions in credit risk management, reducing financial risks.
Yilin Ning et al. (2022) [51]	To enhance the interpretability and transparency of ML models using Shapley Variable Importance Cloud.	Shapley Variable Importance Cloud improves model interpretability, aiding in better decision-making and insights.
Gramegna A, Giudici P. (2021) [52]	To assess the effectiveness of Shap and LIME in explaining credit risk predictions.	Shap and LIME contribute to more accurate and interpretable credit risk assessments, reducing financial uncertainties.
Mardaoui D, Garreau D. (2021) [53]	To evaluate the suitability of LIME for explaining text data predictions.	LIME is examined for its ability to provide interpretable explanations in the context of text data analysis.

2.2. Novelty and Research Contributions of the Paper

The key novelties and contributions are as follows:

- Integration of XAI in Smart Farming: The paper investigates the integration of explainable AI techniques within the context of smart farming, specifically focusing on crop recommendation systems. This novel approach addresses the gap between complex machine-learning models and the need for transparency and understandability in agricultural decision-making.
- Experimentation with XAI Algorithms: The study conducts experiments using XAI algorithms such as LIME, dice_ml, and SHAP. The application of these algorithms to generate local and counterfactual explanations for crop recommendations is a significant contribution, as it provides actionable insights for farmers.
- Compliance with GDPR: The research addresses the need for model transparency in compliance with the GDPR, which mandates the right to explanation. This legal compliance aspect is particularly novel in the domain of smart farming.
- Comprehensive Analysis of XAI Algorithms: The paper provides a detailed analysis of various XAI algorithms and their application in smart farming. It demonstrates how these algorithms can elucidate the reasoning behind crop recommendations and suggest configuration changes for alternative crops.
- Effectiveness of XAI in Trust Building: The results showcase the effectiveness of XAI [21-23] in making machine learning models in smart farming more interpretable and trustworthy. This contribution is crucial for adopting AI in agriculture, as it can enhance farmers' trust in AI-driven recommendations.
- Potential to Reduce Food Insufficiency: The study highlights the potential of XAI [25] to reduce food insufficiency by enabling the cultivation of alternative crops on the same land, which is a significant contribution towards achieving food security.

3. General Framework of Machine Learning & Explainable AI in Crop Recommendation System

3.1. General Framework of ML in CR System

ML in the CR system includes various activities, as shown in figure 1. Agriculture data sets are present from various sources like government websites, databases, comma-separated value (CSV) files, or other formats. Data preparation includes collecting data from multiple sources and performing basic checks on the data set to determine whether any null values exist or any outliers (unexpected) values exist, and so on. Feature selection includes selecting the best features from the given data set to improve the model's accuracy. In the further results section, the heatmap was discussed to select the best features from the dataset. Designing an ML model required a training dataset to train the model and a test set to evaluate the model using unseen data. CR is a classification model because the outcome of a CR model is a fixed set of values like rice, wheat, apple, and so on. Once classification algorithms are applied, the next step is to evaluate the model by using performance metrics and select the best model. Model design and performance evaluation results of the CR system are discussed in the further results section. Model predictions will help in making a decision or recommending a crop. When farmers expect explanations of the models, explainable AI is one solution to provide explanations of the models. Once the model is built and tested, it will be deployed in the production environment for customer access. When the model performance is degraded or reduced, a model rebuild will take place from starting data preparation to building the model.

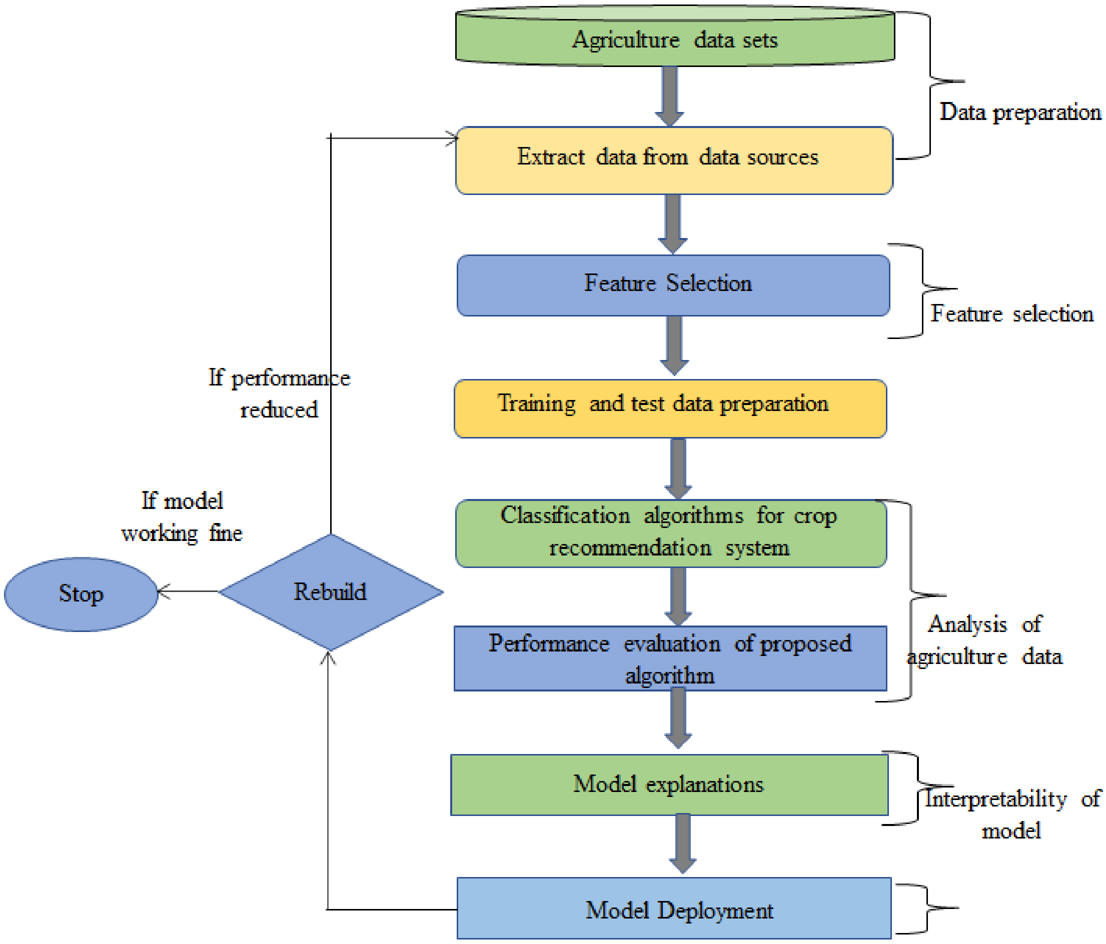

Fig.1. General Framework of ML in crop recommendation system

3.2. General Framework of XAI in CR System

Figure 2 represents the CR system [23] with XAI and without XAI general framework. ML model without XAI will start with data preparation and model building, and the final model will make decisions or recommendations for the crop. Whenever a user has questions about crop recommendation or an ML model without XAI, there are no explanations for those questions. For example, the farmer has questions about crop recommendations, like why rice crops are recommended. Why not wheat crops? How do you cultivate wheat instead of rice? Which parameter influences the cultivation of rice crops? There is no answer to these questions from the ML model without XAI. When the ML model is applied with XAI [14,15], XAI will explain the model, such as why the rice crop is recommended and whether it is due to rainfall, nitrogen content, humidity, etc. Which parameter influencing outcome will also be derived from XAI? When a farmer wants to cultivate wheat crop instead of rice crop or apple instead of watermelon, XAI will provide counterfactual(CF) explanations [16] like if the farmer changes nitrogen content by reducing it or increasing it or any other configuration changes will be suggested by XAI. More about XAI and categories will be discussed in further sections.

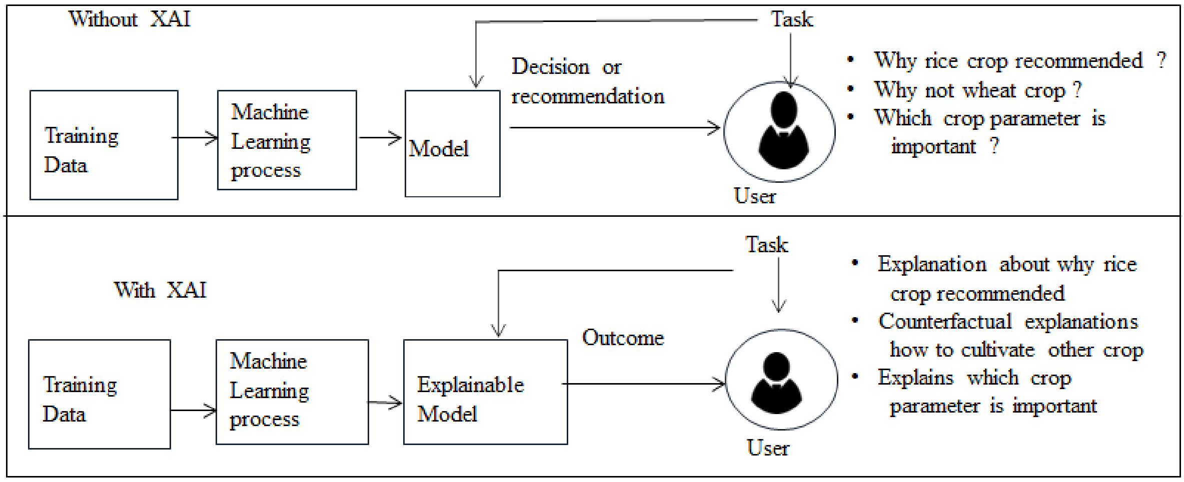

Fig.2. General framework of explainable AI in crop recommendation system

Sandra Wachter et al. [16] reviewed the importance of CF explanations. As per GDPR, it is the customer's right to know why a particular prediction happened. For example, if any loan is rejected, the customer has the right to ask why the loan was rejected and what should change to accept the loan. Counterfactual explanations will help to get the desired result from the current prediction. For example, suppose an apple crop is recommended for the farmer based on current soil properties, rainfall, humidity, and temperature. In that case, counterfactual explanations will provide configuration changes required to cultivate another crop in the farming land. CF explanations will describe the smallest configuration change that can achieve the desired outcome without explaining the internal details of the system.

3.3. *Explainable AI Categories*

Figure 3 represents various XAI categories. XAI is categorized based on the scope, Agnosticity, data type, and explanation type. XAI [24] is categorized into local and global explanations based on its scope. The local scope of explanations is defined as explaining every individual record and which parameter forces to recommend the crop for each record. Global explanations of the model will consider the entire model, not individual records. Parameter explanations that influence outcomes will be based on the entire model. Figure 4 represents the local explanation for record id 1. Each individual record will be explained in local explanations with corresponding parameter influence. Let us consider Figure 4, Soil fertility prediction. The actual outcome is that the soil is fertile, and the predicted outcome is that the soil is fertile. After observing Figure 4, for record id 1, sand, K, and silt are parameters which are influencing in predicting outcome as 0, but the majority of parameters like N . Clay, P, CaCO3, and so on make the model predict outcome as 1.

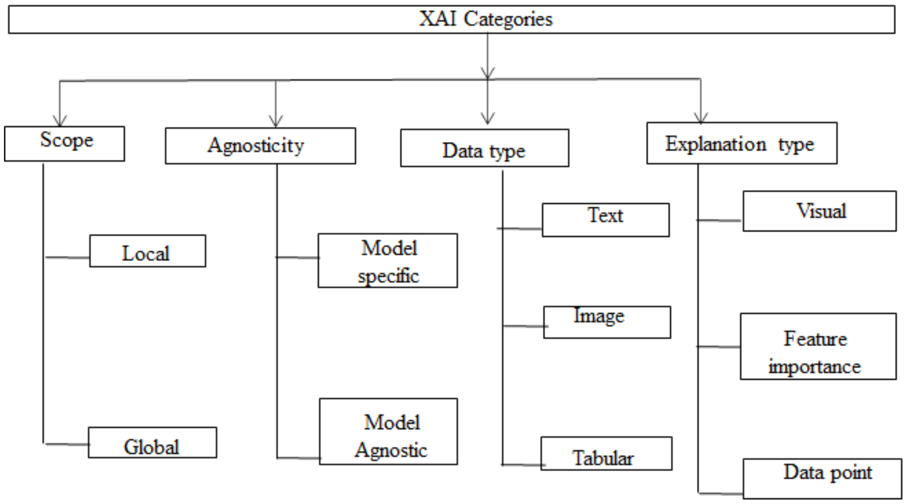

Fig.3. Explainable AI categories

Other categories of explanations include based Agnosticity, divided into model-specific and model agnostic. Model-specific explanations are designed for a specific model. For example, if explanations are designed for logistic regression (LR), those explanations will be applied only for logistic regression but not for any other model. Model agnostic explanations are designed to apply irrespective of a model like model agnostic explanations can be applied over LR, decision tree, random forest, or any other model. Based on the data type, explanations are divided into text, image, and tabular explanations. Crop recommendation data is usually tabular; each row represents a specific crop recommendation configuration, and the column represents a specific parameter. Image explanations or text explanations will explain what text or what feature of the image influences the predicted outcome. For example, if any image is categorized as a dog, XAI will provide details on which part of the image predicts a dog. If any paragraph text is categorized as agriculture text, XAI will explain which keywords contribute to categorizing it as agriculture. XAI is categorized as a visual, data point, and feature that is important based on the explanation type. A visual explanation will represent an explanation in various charts, the data point will consider individual record data points to explain the predicted outcome, and feature importance explains what features contribute to making the final prediction.

4. The Theory Behind Explainable AI

4.1. LIME Algorithm

Marco [1] and Thilakarathne [11] discussed the value of explanations and how to determine whether or not to believe them. The LIME algorithm was proposed by Marco [1]. Marco [1] gives a simple explanation of the LIME algorithm's operation. LIME is a method used to explain the outcomes of ML models, especially when the models are viewed as "black boxes" and have complex internal workings. LIME offers local explanations by simulating the behavior of a complex model with a more straightforward, interpretable model centered on a particular instance of data.

The main idea behind LIME is to perturb the features of a specific instance and observe how the model's prediction changes. This perturbation analysis lets LIME determine which features most influence the model's decision-making process. The explanations generated by LIME are typically in the form of feature importances or weights assigned to each feature. LIME uses a proximity measure to determine the similarity between the instance of interest and the generated perturbed instances. The proximity measure is often based on a kernel function, such as the Gaussian kernel. The proximity measure can be represented as follows as equation1:

$$\mathrm{proximity}(\mathrm{a}, \mathrm{ai}) \;=\; \exp(-\mathrm{D}(\mathrm{a}, \mathrm{ai})2\ /\ \sigma 2) \tag{1}$$

Here, a is the instance of interest, a_i represents a perturbed instance, d(a, a_i) is the distance between a and a_i, and h is a bandwidth parameter controlling the spread of the kernel. The proximity measure quantifies how close each perturbed instance is to the instance of interest.

LIME assigns weighting coefficients to the perturbed instances based on their proximity to the instance of interest. These weights represent the importance of each perturbed instance in explaining the model's prediction. The weights are calculated by normalizing the proximity measures using a simple linear kernel as shown in equation 2:

$$\mathrm{weights}(\mathrm{a}) = \;[\mathrm{c}, \mathrm{proximity}\ (\mathrm{a}, \mathrm{a2}), \ldots, \mathrm{proximity}\ (\mathrm{a}, \mathrm{aN})] \tag{2}$$

Here, a stand for the relevant instance, a_1 through a_N for each perturbed instance, and N for all the perturbed instances. LIME fits a more straightforward interpretable model (such as linear regression or decision tree) on the perturbed instances and their accompanying predictions in order to explain the black box model's predictions. The weighted data, where the weights denote the significance of each disrupted occurrence, is used to train the local model. During model training, the weights are used as the sample weights. After the local model has been trained, LIME determines the importance or weights of each feature to show how each one affects the predictions made by the model. By looking at the coefficients or splitting rules of the trained local model, these feature importance can be determined.

LIME is a local interpretable model. rf is a recommender function for crops. The input term in equation 1 is crop recommendation input record. G is a set of complex models. For example, the CR system model constructed with all features and records is a complex nonlinear model. m is a simple model constructed from complex model G. Let us assume a simple CR system constructs its model using only N, P, or another simple model constructed by utilizing N, K, temperature, or combinations of other parameters or all parameters. So, m is a simple model constructed from a complex model M.

Figure 4 shows the general architecture of the LIME algorithm. Initial construction of a complex model (deep learning or random forest) M occurs for a given crop recommendation dataset. A data point was randomly chosen for the same dataset to apply LIME algorithm local explanations, as shown in Figure 4. We construct a simple model for nearest neighbors based on a distance metric and build a model to find predictions of the nearest neighbors of the chosen data point. Once you build a simple model around the data point, Local explanations will be derived for the chosen point, and the Results obtained are discussed in the results section.

Figure 5 represents the local explanation for record id 1. Each individual record will be explained in local explanations with corresponding parameter influence. In Figure 5, Soil fertility prediction. The actual outcome is soil is fertile, and the predicted outcome also the soil is fertile. After observing Figure 5, for record id 1, sand, K, and silt are parameters that influence predicting outcome as 0, but most parameters like N, Clay, P, CaCO3, and so on make the model predict outcome as 1.

Figure 6 represents global explanations of the model. Instead of considering individual records, the overall model will be considered to explain each parameter's importance. After observing Figure 6, Clay, CEC, Mn, CaCO3, P, and N impact the outcome to predict soil as fertile, whereas other features like sand and slit influence the model to predict the outcome as nonfertile soil.

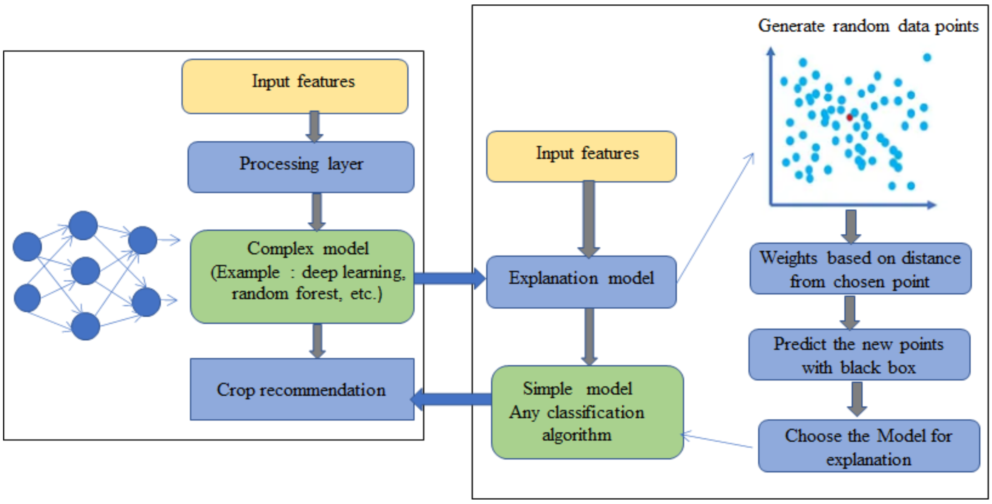

Fig.4. General architecture of LIME algorithm

Fig.5. Local explanations

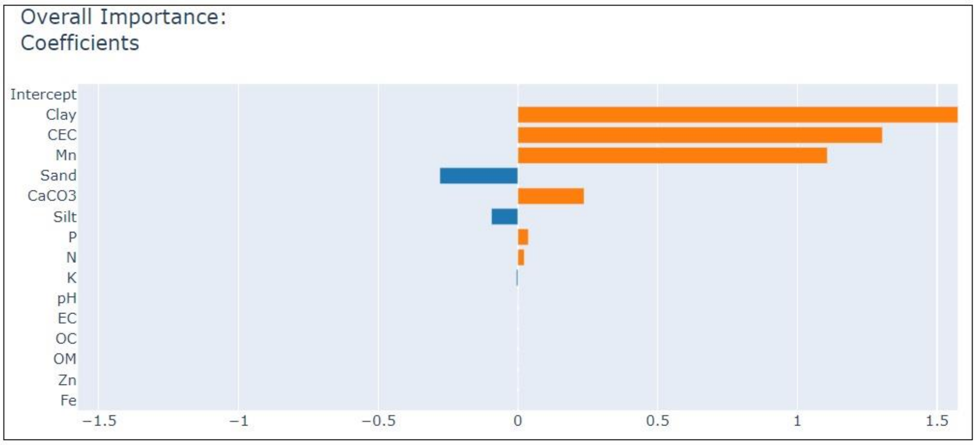

Fig.6. Global explanations

4.2. LIME Importance in Crop Recommendation Systems

- Interpretability: Crop recommendation models can be complex, making it hard for farmers to trust and understand their recommendations. LIME helps provide transparent, human-understandable explanations for specific crop recommendations.
- Trust and Adoption: Farmers are more likely to adopt AI-based crop recommendations if they understand why a particular crop was suggested. LIME bridges the gap between AI's predictive power and farmers' decision-making processes.
- Domain Expertise: LIME enables domain experts (e.g., agricultural scientists) to validate the recommendations. They can review the explanations to ensure they align with known agricultural knowledge and practices.
- Customization: LIME allows for the customization of recommendations based on specific factors, such as soil quality, climate, and crop history, by providing insights into which features are most influential.

4.3. Dice_ ml Algorithm

The ML library Dice ml provides a framework for creating CF for a given model prediction. Counterfactual explanations show how modifications to the input features will modify the model's output. While searching for inputs comparable to the original input but would provide a different model output, the Dice ml package employs a differentiable optimization technique. The Dice ml algorithm produces a set of hypothetical instances that show how altering the attributes of the input would modify the model's prediction. These counterfactuals can explain how the model behaves and provide suggestions for improving the model's work.

A distance metric in DiceML assesses how similar or unlike the original and alternative inputs are. Depending on the features and data being used, a certain distance metric should be selected. Euclidean distance, Manhattan distance, or customized similarity metrics particular to the problem domain are examples of frequently used distance metrics. An optimization method is used to create counterfactual justifications. The aim is to find substitute inputs that adhere to specified restrictions while differing from the original input. These restrictions frequently involve conforming to domain-specific standards, maintaining a particular distance from the original input, or altering certain traits or attributes.

The optimization process is guided by an objective function that balances multiple factors. The objective function minimizes the distance between the original and counterfactual inputs while satisfying the defined constraints. Additionally, it may incorporate other criteria such as interpretability, diversity of solutions, or user-defined preferences. DiceML emphasizes generating diverse counterfactual explanations to explore different decision scenarios. This is achieved by incorporating mechanisms that encourage exploration of the input space and promote variety in the generated counterfactuals. Diversity can be measured using metrics like the distance between counterfactuals, cluster analysis, or other domain-specific measures.

As shown in Figure 7, a machine learning model f uses the input data X to generate a prediction based on the features in X. By identifying other inputs X_c that result in a different outcome from the model f while still meeting specific constraints or requirements the dice ml technique subsequently creates CF. The model produces a new prediction f_c using the counterfactuals X_c. It generates an explanation E to assist users in understanding why the model made a specific prediction and how changing the inputs can lead to a different outcome.This explanation relies on the differences between the original prediction f and the counterfactual prediction f_c.

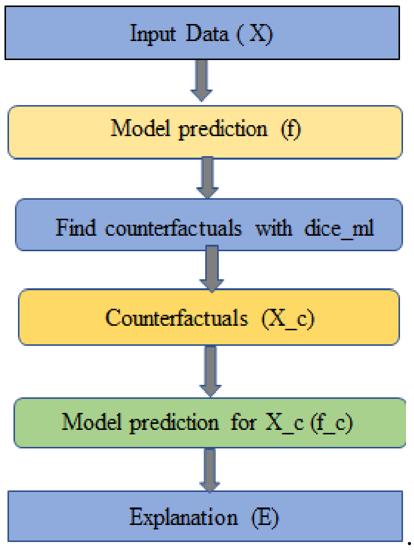

Fig.7. General architecture of dice_ml

4.4. SHAP (SHapley Additive Explanations)

The SHAP technique is used to evaluate how interpretable and explainable ML models are. It assigns each feature in a model's prediction an important value by calculating its contribution to the outcome. The crucial values are sometimes referred to as the Shapley values, which derive from cooperative game theory.

The Shapley value of a feature is calculated as the average marginal contribution of that feature across all possible coalitions. In the case of SHAP, the coalitions are subsets of features.

The SHAP value for a specific feature measures the contribution of that feature towards the expected prediction, taking into account all possible combinations of features. It is calculated by averaging the marginal contributions of the feature when added to all possible coalitions of other features.

General equation to calculate the SHAP value for a feature shown in equation 3:

$$\mathrm{SHAP(crop\_feature)} = \Sigma\,[\mathrm{P(coalition} \cup \mathrm{crop\_feature)} - \mathrm{P(coalition)}] \,/\, (\mathrm{N}-1)! \tag{3}$$

In the equation:

- SHAP(crop_feature) represents the SHAP value for the specific crop feature.
- P(coalition ∪ crop_feature) denotes the model's prediction when the coalition of features and the specific feature is present.
- P(coalition) represents the model's prediction when only the coalition of features (without the specific feature) is present.
- N is the total number of features.

By using SHAP values, we can understand how each feature contributes to the final prediction of a machine-learning model. These values provide a comprehensive explanation of the model's behaviour and aid in interpreting and validating its predictions.

4.5. SHAP Importance in Crop Recommendation Systems

Table 2 represents various articles reviewed to know the importance of SHAP in the CR system. SHAP values offer several advantages in the context of crop recommendation systems:

Table 2. Limitations, advantages, and importance of SHAP in crop recommendation

Author & Year	**Limitations of SHAP**	**Advantages of SHAP**	**SHAP for Crop Recommendation**
Ning, Y. et al. (2022)	1. Computational complexity may be high for certain models and datasets. 2. Interpretability may not always align with domain-specific knowledge.	1. Provides a comprehensive and interpretable feature importance analysis. 2. Offers insights into the impact of each feature on model predictions.	SHAP can be applied to crop recommendation models to explain the importance of various agricultural features (e.g., soil quality, weather data) in crop selection, facilitating informed decisions for farmers.
Gramegna, A. & Giudici, P. (2021)	Interpretability may require domain expertise for meaningful insights.	1. Enables the evaluation of discriminatory power in credit risk models. 2. Offers a transparent view of credit risk assessment.	In crop recommendation, SHAP can aid in assessing the discriminatory power of features in predicting crop outcomes, helping farmers and agricultural experts make informed choices.
Covert, I. & Lee, S.-I. (2021)	1. Potential limitations of KernelSHAP.	Practical Shapley value estimation using linear regression for improved interpretability.	SHAP can enhance crop recommendation models by providing interpretable insights into feature importance, enabling better crop selection and yield optimization.
Zhai, Y. et al. (2023)	The article does not discuss the limitations of SHAP.	Facilitates interpretable prediction of cardiopulmonary complications after surgery.	SHAP can be employed in crop recommendation systems to predict and explain potential complications or challenges associated with specific crop choices, aiding farmers in risk assessment.
Feldmann, C. & Bajorath, J. (2022)	Exact Shapley value calculations may be computationally intensive for certain models.	Enables the calculation of exact Shapley values for support vector machines with Tanimoto kernel, improving model interpretation.	SHAP can be used to interpret support vector machine-based crop recommendation models, providing insights into the contributions of different features to crop recommendations.
Siemers, F.M. & Bajorath, J. (2023)	The article does not discuss the limitations of SHAP.	Reveals differences in learning characteristics between support vector machine and random forest models using Shapley value analysis.	SHAP can be employed to analyze and compare different crop recommendation models (e.g., support vector machines vs. random forests) to understand their learning characteristics and decision-making processes.
Fan, H. & Zhao, Y. (2022)	The article does not discuss the limitations of SHAP.	Utilizes the Merton-Shapley model to identify systemically important banks and compares different indicators.	SHAP can be adapted to identify systemically important factors in crop recommendation models and compare the influence of various agricultural indicators on crop choices.

- Interpretability: SHAP values provide clear and intuitive explanations for why a particular crop was recommended. Farmers and agricultural experts can understand the role of each feature (e.g., soil quality, weather, location) in the recommendation.
- Feature Importance: By calculating SHAP values, you can identify which features significantly impact crop recommendations. This information can guide decisions on crop selection and farming practices.
- Model Accountability: SHAP values make the recommendation system more accountable. If a model recommends a particular crop, SHAP values can explain which features influenced that decision. This transparency is crucial for gaining trust in the recommendation system.

In the context of crop recommendation, SHAP values can be applied as follows:

- Identify the key features that influence crop selection, such as soil quality, climate, historical crop yield data, etc.
- Train a machine learning model (e.g., a decision tree, random forest, or neural network) for crop recommendation.
- For each recommendation, calculate the SHAP values for the features, showing how each feature contributes to the decision.
- Present these SHAP values to farmers or users and the recommended crop to help them understand and trust the recommendation.

5. Results and Discussions

5.1. Experiment Setup, Basic Model Design Steps and Practical Implications of Current Research

Implementing XAI in the CR system requires basic Python packages like Pandas, Scikit Learn, Dice_ML, LIME, and SHAP packages. Crop recommendation data sets can be collected from any database or Excel file based on user requirements. In current research datasets for crop recommendation datasets are collected from various data sources and websites like https://data.world/datasets/crops,https://github.com/topics/crop-recommendation, https://data.gov.in/sector/agriculture, https://agricoop.gov.in/en/CropSituation,https://iasri.icar.gov.in/. The input for the system is a CR data set, and the output is a classification of the dataset to any crop type like rice, wheat, and so on. In addition to classification, making the black model an explainable model is the main agenda of a current research article. For model design, use any ML algorithms like Logistic regression or stacking using ensembling or any other models. The main focus of this paper is to showcase how to provide explanations to the model designed.

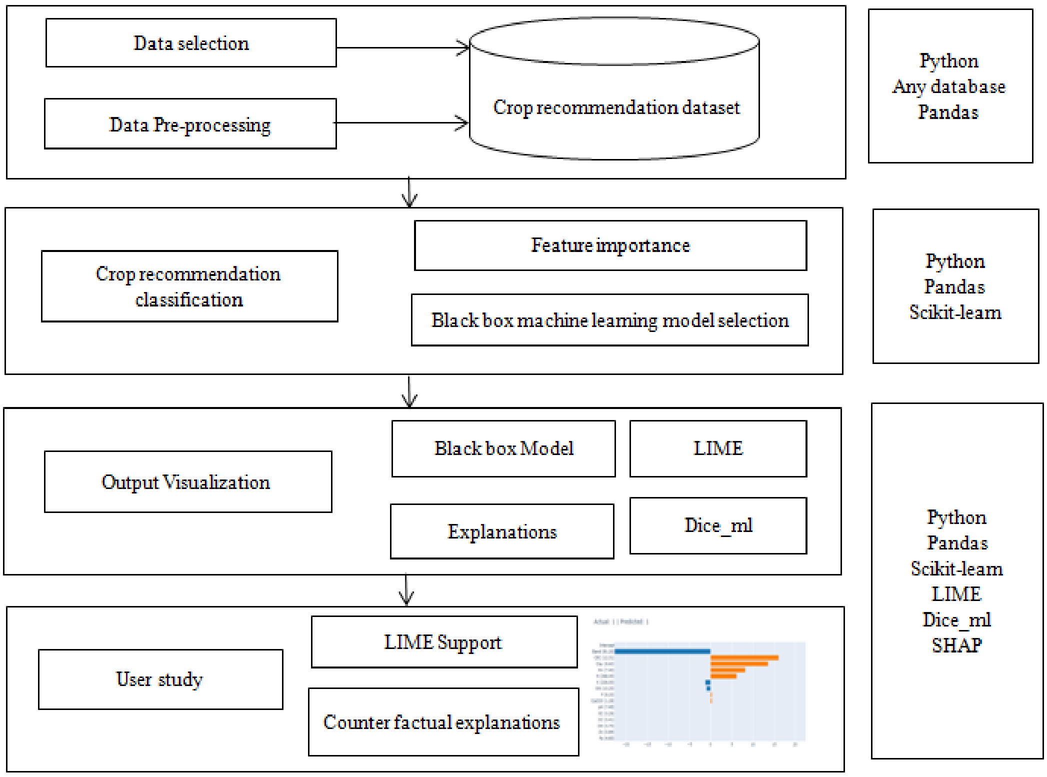

Fig.8. Experimental setup for crop recommendation explainable system

ML in the CR system includes various activities, as shown in Figure 8. Detailed discussion of every step as follows.

Preprocessing: The gathered data should be cleaned and prepared. As part of this, missing values must be handled, numerical features must be normalized, categorical variables must be encoded, and the data must be divided into training and testing sets.

Feature Engineering: Extract meaningful features from the collected data that the machine learning model can use. Feature engineering can involve techniques such as creating derived features, aggregating data at different spatial or temporal scales, or applying domain-specific knowledge to enhance the model's predictive power.

Model Development: Choose an appropriate ML algorithm for the crop recommendation task. This could include decision trees, random forests, Logistic regression (LR), or deep learning models. Train the selected model using the preprocessed data. Many ML models are available to build models for CR systems. Here in this section, a brief introduction to LR is explained. The statistical model known as logistic regression is frequently utilized for binary classification tasks. It simulates the relationship between a collection of input factors (features) and the likelihood that a situation will fall into one of two categories. The logistic regression model uses a sigmoid (or logistic) function to convert a linear combination of input characteristics into a probability value between 0 and 1.

$$z = \beta_0 + \beta_1 * \text{rainfall} + \beta_2 * \text{temperature} + \ldots + \beta_p * \text{pH} \tag{4}$$

Where:

z is the linear combination of the input features and coefficients.

$\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ are the coefficients (also known as weights or parameters) associated with each input feature.

Rainfall, temperature, ..., and pH are the input features.

The linear combination (z) is then passed through the sigmoid function, which maps the linear combination to a probability value between 0 and 1:

$$p = 1 / (1 + e^{\wedge}(-z)) \tag{5}$$

Where:

p is the probability of the event or outcome belonging to the positive class.

e is the base of the natural logarithm.

A threshold (usually 0.5) is applied to the probability value to make predictions. If the probability is greater than the threshold, the instance is predicted as belonging to the positive class; otherwise, it is predicted as belonging to the negative class.

To train a logistic regression model, it is necessary to identify the ideal values for the coefficients (0, 1, 2,..., p) that minimize the discrepancy between the predicted probabilities and the actual class labels in the training data. This is often accomplished using maximum likelihood estimates or optimization methods like gradient descent. It is crucial to remember that logistic regression works under the premise that the input attributes and the event's log odds have a linear relationship. If the relationship is not linear, nonlinear patterns can be detected using polynomial features or feature transformations.

XAI Techniques: Use comprehensible AI methods to decipher and comprehend the model's decision-making process. Techniques like feature importance analysis, partial dependence plots, or LIME may be used in this. These methods illuminate the ways in which the model makes predictions by drawing on various features. CR is a classification model because the outcome of a CR model is a fixed set of values like rice, wheat, apple, and so on. Once classification algorithms are applied, the next step is to evaluate the model using performance metrics and select the best model. The further results section discusses the CR system's model design and performance evaluation results. Model predictions will help in making a decision or recommending a crop. When farmers expect explanations of the models, explainable AI is one solution to provide explanations of the models. Once the model builds and tested, it will be deployed in the production environment for customer access. When the model performance is degraded or reduced, model rebuilds will occur from starting data preparation to building the model.

5.2. Limitations and Potential Biases of the ML Models

Machine learning models, especially those employed in XAI applications, have several limitations and potential biases that need to be carefully considered. These limitations and biases can impact AI systems' interpretability, fairness, and trustworthiness.

Limitations of Machine Learning Models:

a) Complexity and Opacity:

- Complex Models: Some advanced machine learning models, like deep neural networks, can be highly complex and opaque. Interpreting their decisions can be challenging.
- Black Box: Models like deep learning are often referred to as "black box" models because they lack transparency in how they arrive at their predictions.

b) Data-Driven Biases:
- Bias in Training Data: ML models learn from historical data, which may contain biases present in the data collection process. The model can perpetuate these biases.
- Underrepresented Groups: Models may perform poorly on underrepresented groups, as they have less data to learn from.

c) Inherent Uncertainty:
- Probabilistic Nature: Many ML models produce probabilistic predictions rather than deterministic ones. This inherent uncertainty can be challenging to communicate and interpret.

d) Limited Context Understanding:
- Context Ignorance: Models may lack an understanding of context or domain-specific knowledge, which can lead to incorrect or nonsensical decisions.

e) Adversarial Attacks:
- Vulnerability: ML models can be vulnerable to adversarial attacks, where minor input modifications can lead to incorrect predictions. This can have significant consequences in critical applications.

f) High-Dimensional Data:
- Curse of Dimensionality: With high-dimensional data, models may struggle to generalize well and can overfit, making it harder to interpret their behavior.

g) Data Quality and Quantity:
- Insufficient Data: In some cases, insufficient data to train accurate models may lead to poor predictions.
- Noisy Data: Noise in the data can impact model performance and interpretability.

Mitigation Strategies:
To address these limitations and potential biases in ML models used in XAI, various strategies can be employed:

- Bias Detection and Mitigation: Implement algorithms and processes to detect and correct biases in training data, algorithms, and predictions.
- Explainability Techniques: Utilize XAI techniques like SHAP values, LIME, and rule-based models to provide transparent and interpretable explanations.
- Fairness-aware Models: Develop models that explicitly consider fairness constraints and aim to minimize bias in predictions.
- Data Pre-processing: Carefully pre-process and clean data, including addressing missing values and handling imbalanced datasets.
- Ethical Guidelines: Establish ethical guidelines and practices for AI development and deployment.
- Human Oversight: Incorporate human experts in the loop to review and validate AI recommendations.

5.3. Practical Implications and Insights Derived from this Research

- The GDPR in the European Union emphasizes the importance of transparency in AI systems. Crop recommendation systems in smart farming must explain to farmers why a particular crop is recommended. This ensures compliance with data protection regulations and builds trust between farmers and AI systems.
- CR systems should be designed with a user-centric approach, allowing farmers to inquire about the reasoning behind recommendations. Farmers should have the capability to ask questions and seek clarification, fostering a collaborative relationship between humans and AI.
- The introduction of XAI CR systems establishes accountability for AI-driven decisions. When farmers can understand the basis of recommendations, they can make more informed choices and hold the AI accountable for its suggestions.
- The use of XAI algorithms like LIME and dice_ml allows for the generation of local and counterfactual explanations. This means that farmers can receive explanations tailored to their specific situations, enabling them to explore alternative crop choices easily.
- Counterfactual explanations can play a vital role in reducing food insufficiency. By suggesting alternative crops for the same plot of land CR systems can contribute to diversifying crop production, which is essential for food security and reducing dependence on a single crop.
- Smart farming involves a combination of AI, agriculture, and data science. Collaboration between experts from various fields, including AI researchers, agronomists, and data scientists, is essential for successfully implementing XAI in CR systems.
- Ethical guidelines and considerations are paramount in developing and deploying AI systems in agriculture. Ensuring fairness, preventing bias, and protecting user data should be integral to the design and operation of crop recommendation systems.

5.4. Experiment Results

A. Data Pre-Processing for Crop Recommendation

To demonstrate the importance of XAI [28] in smart farming, we used Python as the programming language in CR systems, along with ML processes and XAI [29] algorithms like LIME and dice ML. Table 5 represents a sample dataset used in the CR system. Various features used are N (Nitrogen), P (Phosphorus), K(Potassium), temperature, humidity, the potential of hydrogen (pH), and rainfall. Plants get green colour by using chlorophyll molecule, which contains Nitrogen. Soil is phosphorus will help the development of the plant's growing tip and cell division. Potassium, often known as potash, improves fruits and Vegetables and aid in the water uptake and drought resistance of plants. Soil pH can limit plant growth, and crop yield will be affected if soil pH is very low or very high.

Table 3. Data setting for crop recommendation

N	P	K	temperature	humidity	ph	rainfall	label
75	49	15	21.53	71.5	5.91	102.4853	maize
91	94	46	29.36	76.24	6.14	92.82841	banana
43	50	48	28.28	91.37	6.63	179.2721	papaya

Figure 9 represents a heat map for the crop recommendation data set. Heatmap is available in the Python package seaborn. Each parameter correlates with other parameters represented in cells. Negative values in the heatmap indicate a negative correlation between parameters. For example, in Figure 6, row 1, N and P cell value is -0.23. A negative value indicates a negatively correlated means if N increases, P will decrease and vice versa. Using a heatmap makes it possible to find the best parameters to construct the ML model for the CR system.

By observing the heat map, you can examine how different parameters (rainfall, humidity, temperature, pH, K, etc.) interact. Correlations or dependencies between parameters may be evident through the spatial distribution of colors. Areas with similar color patterns might indicate a strong relationship between those parameters. By analyzing the colors and patterns in the heat map, one can gather insights into the relationships between various factors and identify favorable or unfavorable areas for specific crops. The heat map may display different soil properties, such as pH levels, organic matter content, nutrient levels (e.g., Nitrogen, phosphorus, and potassium), salinity, or moisture content. The colors on the map could help identify areas with favorable or unfavorable soil conditions for specific crops.

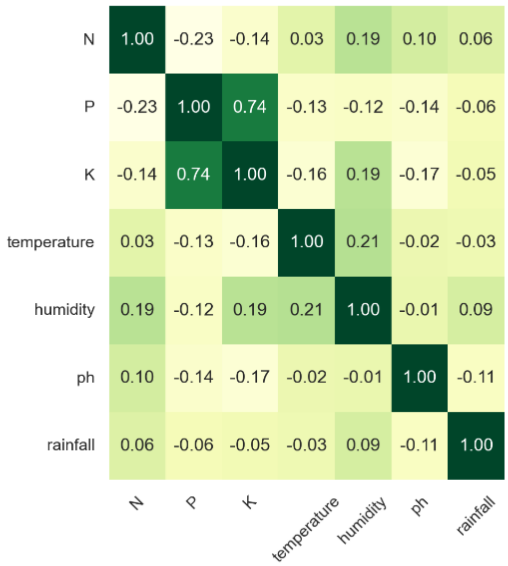

Fig.9. Seaborn package heat map to select the best parameters

B. LIME Tabular Explainer for Crop Recommendation

Figure 10 represents the LIME Tabular explainer for a crop recommendation record. In the figure, various features represented (features 0 to 6) are N (0), P (1), K(2), temperature (3), humidity (4), pH (5), and rainfall (6). The actual class of the record is watermelon, and the predicted class is also watermelon. Figure 7 shows the various features that predict watermelon. Figure 10 shows that all features (feature 0 to feature 6) contribute to predicting the record as watermelon. In the same figure 10, we observe that many features predict something other than an apple or papaya. We will use these explanations to answer the farmer's questions, such as why watermelon and apple are not recommended. LIME tabular explainer identifies the most important features contributing to a prediction. By highlighting the influential features, LIME can help farmers gain insights into the key factors the crop recommendation system considers. This information can be valuable for decision-making, such as understanding which soil properties, weather conditions, or historical data influence the recommendations.

C. Counterfactual Explanations for CR

Table 4 represents various features and configurations for recommending a watermelon crop. After recommending a watermelon crop, farmers have a question: How can apple crops be cultivated instead of watermelon to make more profit? Applying ML algorithms makes recommending a crop or making a decision possible, but counterfactual explanations are not possible. By applying the XAI dice_ml algorithm, it is possible to provide counterfactual explanations. In Python, a package called dice_ml is available to provide counterfactual explanations. Below is the sample code for counterfactual explanations for Table 5, watermelon crop, to cultivate apple crop. Line 1 contains a code to apply dice_ml on crop data. Line 3 contains a code to read input data points and specifies how many counterfactual explanations. In the current example, code total_CFs=2 will return output with two counterfactual explanations, as in Table 7. For example, to cultivate land with an apple instead of a watermelon, if the farmer changes Nitrogen from 91 to 7, P No changes required, K from 46 to 153, temperature no modifications required, humidity no changes necessary, pH no changes required, rainfall no changes needed as shown in row1 of table 4.

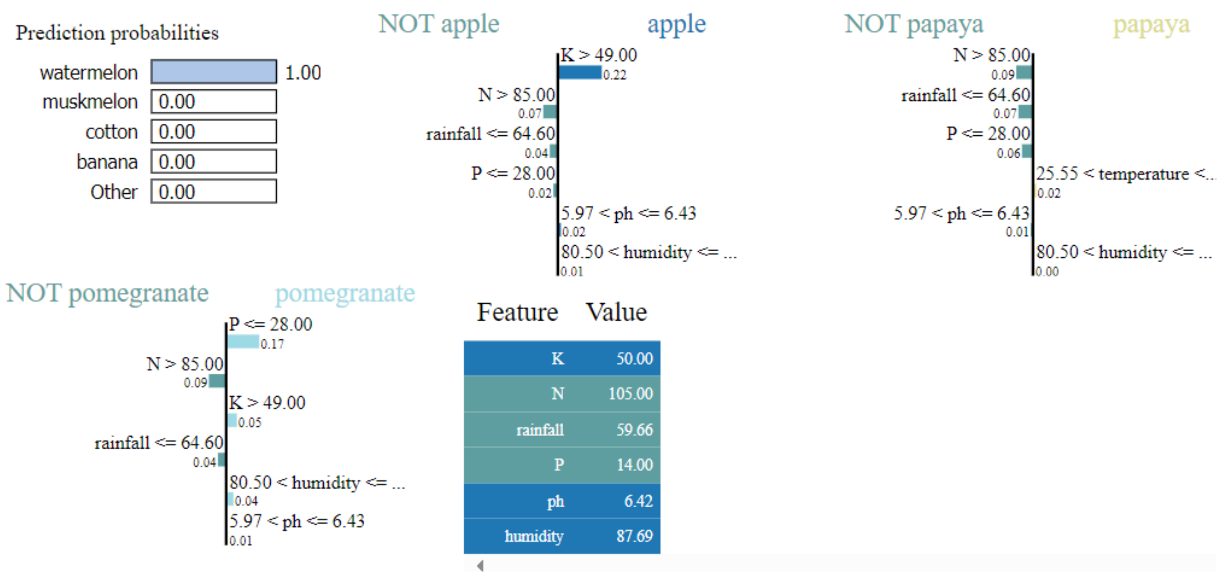

Fig.10. Lime Tabular explainer for crop recommendation system

```
Line 1: data_dice = dice_ml.Data(dataframe=crop_data, continuous_features=[N, P, K, temperature, humidity, ph,
Line 2: 'rainfall'], outcome_name='label')
Line 3: cf = explainer.generate_counterfactuals(input_datapoint, total_CFs=2, desired_class= ‘ apple’)
```

Table 4. Crop recommendation input record for counterfactual explanations

N	P	K	temperature	humidity	ph	rainfall	label
91	12	46	24.64	85.49	6.34	48.32	watermelon

Table 5. Counterfactual explanations outcome to cultivating the apple crop instead of the watermelon crop

N	P	K	temperature	humidity	ph	rainfall	label
7	12	153	24.64	85.59	6.34	48.32	apple
16	12	114	24.64	85.59	6.34	48.32	apple

D. SHAP Summary Plot for Crop Recommendation

We must determine the SHAP values for each input feature and display their magnitudes in order to generate a summary plot for the importance of crop recommendations. The relative value of various features in the crop recommendation model is better understood thanks to this figure. Equation 2 should be used to calculate the SHAP values for each crop characteristic. Determine the feature's absolute mean SHAP value across all dataset instances. The crop suggestion model's average relevance of each characteristic is shown here. Place the features on the y-axis and the important values that correspond to them on the x-axis. A horizontal bar whose length reflects the value of that feature's importance depicted each feature. The bars are ordered with the most significant feature at the top and in descending order.

Figure 11 shows the SHAP summary plot, and the plot provides a concise visual summary of feature importance in the crop recommendation model. It allows us to identify the most influential features and their impact on the model's predictions. The longer the bar for a feature, the more significant its contribution to the crop recommendation.

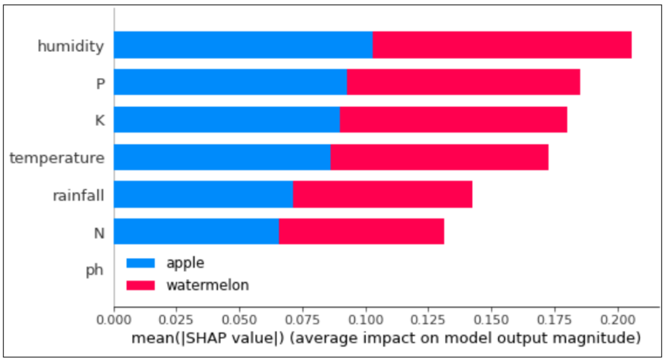

Fig.11. SHAP summary plot

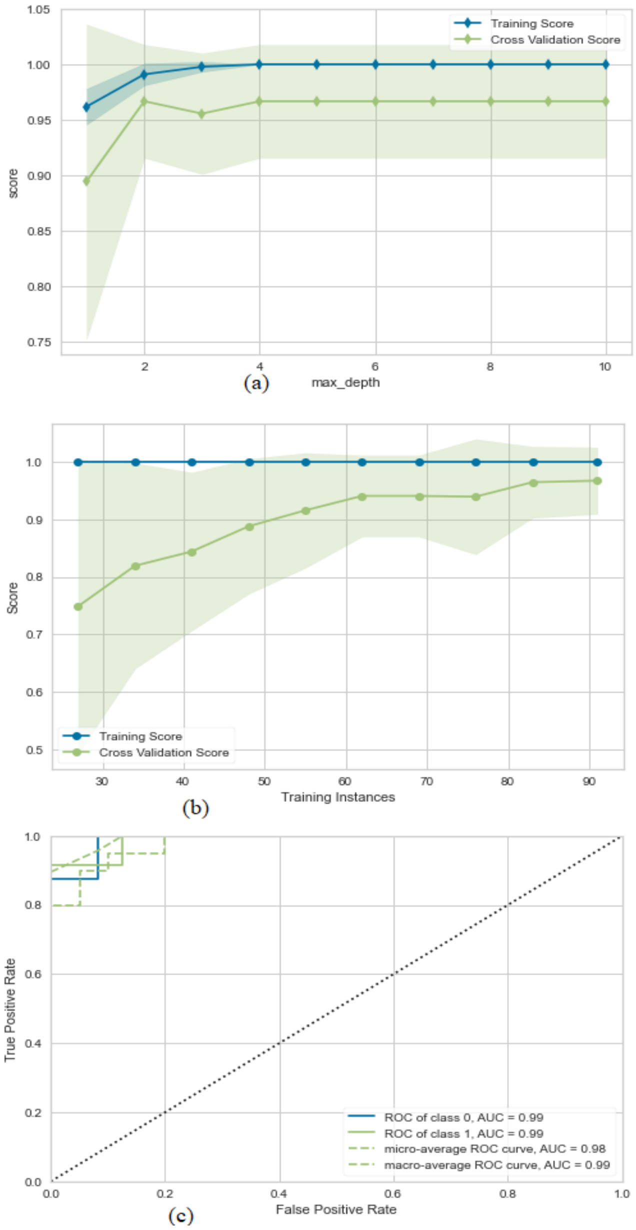

Fig.12(a). validation curve for CR data set. 12 (b). Learning Curve for CR dataset. 12(c). ROC AUC Curve for CR dataset

E. Performance Analysis of the XAI Model

Figure 12 (a) validation curve for CR data set. Yellowbrick is a Python library that allows for the visualization of ML models. The model_selection module in Scikit-learn provides tools for model selection and evaluation. One useful function in this module is validation_curve, which helps determine the optimal values for hyperparameters in a machine learning model. The validation_curve function generates a curve that depicts how the performance metric of a model changes with variations in hyperparameter values. It employs k-fold cross-validation on the training set using different hyperparameter values and returns each value's training and validation scores. The relationship between them can be visualized by plotting these scores against the hyperparameter values. Yellowbrick provides a convenient wrapper for the validation_curve function, making it easy to visualize the results using different types of plots, such as line plots or scatter plots. These plots can help identify the optimal hyperparameter value by observing the relationship between the performance metric and the hyperparameter value. In summary, Yellowbrick's model_selection validation_curve is a powerful tool for visualizing the relationship between hyperparameters and model performance, which can assist in model selection and optimization.

Figure 12 (b) Learning Curve for CR dataset. Yellow brick offers a Learning Curve plot that assesses machine learning model performance by plotting training and cross-validation scores against the number of training samples. It helps identify issues like overfitting or underfitting. Yellowbrick's LearningCurve visualizer requires input from a trained model and dataset, helping determine the optimal training set size. The plot typically shows two lines for training and cross-validation scores, with training samples on the x-axis and model performance on the y-axis. Shaded areas around the lines represent variability in scores. Analyzing the plot provides insights into the model's learning behavior, overfitting or underfitting, and potential improvement with more training samples. The LearningCurve plot in Yellowbrick is a valuable tool for assessing machine learning model performance and making informed decisions for model optimization.

Figure 12 (c) ROC AUC Curve for CR dataset. The Yellowbrick library, a Python package for visualizing machine learning model performance, contains the yellowbrick.classifier module. The Receiver Operating Characteristic (ROC) curve and the Area Under the ROC Curve (AUC) calculation methods for binary classifiers are provided by the ROCAUC class in the yellowbrick.classifier module. The true positive rate (sensitivity) versus false positive rate (1 - specificity) trade-off is depicted on the ROC curve, and the AUC is a metric for classifier performance, with a larger AUC indicating better performance.

F. Results Comparison with Existing Research:

The LIME algorithm, which was initially introduced by Ribeiro et al. (2016) [1], has been widely adopted for local explanations in different domains, including healthcare, finance, and cybersecurity. The application of LIME in our research to provide interpretable explanations for individual crop recommendations echoes its use in other studies where understanding the decision-making process of complex models is crucial. Similarly, SHAP values have been employed across various studies to quantify the contribution of each feature in a model's prediction. The study's focus on model transparency and the right to explanation is in line with GDPR requirements, as discussed by Wachter et al. (2017) [5]. The application of counterfactual explanations using dice_ml aligns with the research by Wachter et al. (2017) [5], which highlighted the importance of counterfactuals under GDPR. The current research demonstrates how these explanations can be generated for crop recommendation systems, providing actionable insights for farmers. This research contributes to the literature by providing practical examples of how XAI can be used to comply with such regulations in the context of smart farming. The use of XAI in agriculture has been explored in various studies, such as those by Holzinger et al. (2022) [17] and Masahiro Ryo (2022) [19], which emphasize the need for human-centered AI and the role of XAI in agricultural data analysis. The current research supports these findings by demonstrating the application of XAI algorithms like LIME and dice_ml in crop recommendation systems. The research aligns with studies like those by Pradeepa Bandara et al. (2020) [47] and Thilakarathne et al. (2022) [48], which focus on developing crop recommendation systems using various features and machine learning algorithms. The current research extends this by providing explanations for the recommendations, addressing a common limitation noted in these studies—the lack of model explanations. The use of LIME for local explanations and SHAP for global explanations is consistent with the work of Marco Ribeiro et al. (2016) [1] and Lundberg et al. (2020) [21], which introduced these methods. The current research applies these methods to the specific domain of smart farming, showcasing their effectiveness in making ML models more interpretable for farmers. The work by Ning et al. (2022) [52] and Covert & Lee (2021) [53] demonstrates the utility of SHAP in providing a comprehensive feature importance analysis, which is directly applicable to our research in understanding the factors influencing crop recommendations.

6. Practical Solutions for Different Use-cases in Smart Farming Using Explainable AI

- Crop Recommendation for Resource Optimization

Use-Case: A farmer needs to decide which crop to plant in the upcoming season to maximize yield and profit while considering resource constraints such as water availability and soil nutrients.

Practical Solution: Implement an AI-based crop recommendation system that uses XAI techniques like LIME or SHAP to provide transparent recommendations. The system analyses historical data, soil conditions, weather forecasts, and crop market trends to suggest the most suitable crops. XAI explanations help the farmer understand the reasoning behind each recommendation, ensuring that the decision aligns with their knowledge and experience.

- Disease Detection and Prevention

Use-Case: Early detection of plant diseases can prevent widespread crop damage. Farmers need a way to identify potential disease outbreaks before they become unmanageable.

Practical Solution: Develop a machine learning model that uses image recognition to detect signs of disease in crops. Employ XAI methods to explain the features that led to the detection, such as discoloration or leaf shape changes. This allows farmers to take targeted action, such as applying the appropriate treatment only to affected areas, thus saving resources and reducing chemical use.

- Water Management for Irrigation

Use-Case: Efficient water use is critical in regions with limited water resources. Farmers need to optimize irrigation schedules to conserve water without compromising crop health.

Practical Solution: Use AI to analyse weather data, soil moisture levels, and crop water requirements to create dynamic irrigation schedules. XAI can provide explanations for irrigation recommendations, helping farmers understand when and why to water their crops, leading to more efficient water use and potentially lower water bills.

- Fertilizer and Nutrient Management

Use-Case: Overusing fertilizers can lead to environmental damage, while underusing can result in poor crop yields. Farmers need precise guidance on fertilizer application.

Practical Solution: An AI system can recommend optimal fertilizer types and quantities based on soil tests, crop needs, and environmental considerations. XAI can explain these recommendations by highlighting the soil nutrient levels and how they match the crop's requirements, helping farmers apply the right amount of fertilizer for efficient nutrient management.

- Alternative Crop Cultivation Suggestions

Use-Case: Farmers may want to explore alternative crops to diversify their production or adapt to changing market demands.

Practical Solution: Use counterfactual explanations from XAI algorithms like dice_ml to suggest what changes in farming practices could lead to the successful cultivation of alternative crops. For example, suppose a farmer typically grows watermelon but wants to switch to an apple. In that case, the system can provide specific adjustments in nitrogen content or irrigation practices needed for this change based on the counterfactual explanations.

- Yield Prediction and Market Analysis

Use-Case: Predicting crop yields and understanding market trends can help farmers plan their production and sales strategies.

Practical Solution: Create a predictive model that forecasts yields and analyzes market data to predict future price trends. XAI can explain the predictions by identifying the key factors influencing yield and market prices, such as weather patterns or global supply chains. This information helps farmers make informed decisions about what and how much to plant, and when to sell their produce.

7. Conclusions

Smart framing crop recommendation with XAI provides a comprehensive analysis of the application of XAI in smart farming, particularly focusing on crop recommendation systems. The study emphasizes the importance of model transparency and the ability to provide explanations for AI-driven decisions, which is crucial for building trust among farmers and ensuring the broader acceptance of smart farming technologies.

The use of XAI algorithms such as LIME, dice_ml, and SHAP has been shown to be effective in making machine learning models more interpretable and trustworthy. These algorithms provide local, global, and counterfactual explanations that offer actionable insights into the decision-making process of AI systems. The research also addresses the need for compliance with the GDPR, which mandates the right to explanation, thereby aligning smart farming practices with legal requirements.

8. Future Scope and Applied Implications

Despite the promising results, the study acknowledges several limitations and potential biases inherent in machine learning models. These include the complexity and opacity of advanced models, biases in training data, the probabilistic nature of predictions, limited context understanding, vulnerability to adversarial attacks, and the curse of dimensionality. The research also highlights the need for bias detection and mitigation strategies, using fairness-aware models and incorporating human oversight to address these limitations.

The theoretical implications of this research suggest a continued exploration of XAI methodologies to enhance the interpretability and fairness of AI systems. Future research could focus on developing new algorithms that provide more accurate and domain-specific explanations, as well as methods to quantify and validate the correctness of these explanations.

From an applied perspective, the integration of XAI into various smart farming activities, such as disease detection, water management, and fertilizer management, presents a significant opportunity for advancement. The research suggests that future smart farming systems should be designed with a user-centric approach, allowing farmers to inquire about and understand the reasoning behind AI recommendations.

Additionally, there is a need for education and training programs to help farmers and agricultural stakeholders effectively use AI-powered crop recommendation systems. The development of user-friendly interfaces and clear documentation will be essential for disseminating knowledge and ensuring the successful adoption of XAI features in smart farming.

In the future, farmers can explore XAI in various smart farming activities, such as disease detection, water management, fertilizer management, and many more.

Source Code and Data Availability

The source code can be found at https://github.com/Yaganteeswarudu940. Users can view suitable code for explainable crop recommendations like counterfactual explanations or local and global explanations code based on user requirements. Based on user requirements, data can be shared, and currently, GitHub contains sample code.

Declarations

Conflict of interest - The authors affirm that they have no known financial or interpersonal conflicts that would have seemed to have an impact on the research presented in this paper.

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