Neural Computing and Applications (2024) 36:20011–20025
https://doi.org/10.1007/s00521-024-10208-z

ORIGINAL ARTICLE

Streamlit-based enhancing crop recommendation systems with advanced explainable artificial intelligence for smart farming

Yaganteeswarudu Akkem[1] · Saroj Kumar Biswas[1] · Aruna Varanasi[2]

Received: 2 October 2023 / Accepted: 12 July 2024 / Published online: 10 August 2024

Abstract
The main objective of this paper is to clarify the importance of explainability in the crop recommendation process and provide insights on how Explainable Artificial Intelligence (XAI) can be incorporated into existing models successfully. The objective is to increase the definition and transparency of the recommendations implemented by AI in smart agriculture, leading to a detailed analysis of the synchronization between crop recommendation systems and XAI that informs decisions as it has sustainable knowledge and practices in modern agriculture. It reviews state-of-the-art XAI techniques such as local interpretable model-agnostic interpretation (LIME), SHapley interpretation additive approach (SHAP), integrated gradients (IG), and level-wise relevance propagation (LRP). It focuses on interpretable models and critical features analysis, and XAI methods are discussed in terms of their applications, critical features, and definitions. The paper found that XAI methods such as LIME and SHAP can make AI-driven crop recommendation systems more transparent and reliable. Graphical techniques such as dependency plots, summary plots, waterfall graphs, and decision plots effectively analyze feature importance. The paper includes counterfactual explanations using dice ml and hearing with advanced techniques combining IG and LRP to provide in-depth narrative model behavior. The novelty of this study lies in a detailed investigation of how XAI can be incorporated into crop recommendation systems to address the "black box" nature of AI models. It uses a unique XAI technique and model approach to make AI-driven recommendations more meaningful and practical for farmers. The proposed systems and techniques are designed to consume agriculture, addressing the specific needs of intelligent systems, making this research a significant contribution to agricultural AI.

Keywords Smart farming · Machine learning · GDPR · XAI · LIME · SHAP

1 Introduction

Artificial intelligence (AI) integration in agriculture has ushered in a time of change, particularly in crop recommendation systems. These systems harness the power of machine learning algorithms to provide farmers with guidance appropriate to crop selection and consumption. The vague availability of AI models, often called "black boxes," raises concerns among farmers and agricultural experts about the reliability and trustworthiness of recommendations.

In response to these concerns, the field of artificial intelligence (XAI) has emerged as an important research area. XAI focuses on increasing the definition and transparency of AI-driven policies and enabling users to understand the logic behind decisions made by these models. This paper presents an in-depth analysis of convergence between the crop recommendation system and the XAI, shedding light on the critical importance of agricultural translatability.

The main objective of this paper is to clarify the importance of interpretability in the crop recommendation process and to provide insights on how it can be successfully incorporated into existing models. To achieve this goal, we discuss the main challenges associated with implementing AI-based cropping recommendations. By

✉ Yaganteeswarudu Akkem
yaganteeswarudu21_rs@cse.nits.ac.in

[1] National Institute of Technology, Silchar, India

[2] Sreenidhi Institute of Science and Technology, Hyderabad, India

going into the complexity of XAI methods, such as LIME, SHAP, IG, and LRP, we have a roadmap for researchers looking to increase the reliability of AI-powered cropping recommendations and for practitioners. As agriculture continues to evolve in the digital age, the fusion of AI and XAI has the potential to enable farmers to make recommendations that are not only accurate but meaningful. This, in turn, can promote informed decision-making, promote sustainable agricultural practices, and contribute to the broader goal of food security in the modern world. In the following aspects of this article, we examine the dynamic landscape of crop recommendation systems, their AI bases, and the evolving role of XAI in this regard.

2 Literature review

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

2.1 Explainable AI literature review

2.1.1 Interpretation methods and model transparency

Ribeiro et al. [1] provide users with a new interpretation method called LIME that searches for locally interpretable patterns around the forecast and interprets the forecast for each distribution fairly and realistically find a way to understand and validate model predictions, and contributes to the AI's transparency processes. Useful for improving AI recommendations through a better understanding of model decision processes. Rawal et al. [2] provide a comprehensive overview of XAI, including its development, challenges, and strategies for building reliable AI systems. This theory can reveal ways to make agricultural AI systems more transparent and better adapted by agricultural stakeholders. Sabrina et al. [3] developed a translatable AI framework for intelligent agriculture that can help farmers make better decisions about crop recommendations. It introduces transparent AI systems for agriculture; thus, farmers can rely on them in their decisions about growing crops that result in better yields.

2.1.2 Application of XAI in agriculture

Dwivedi et al. [4] discuss the basic concepts, different approaches, and solutions in XAI with the aim of shedding light on its basic concepts. This paper can define the underlying mechanisms by which agricultural AI systems can be adapted, thereby contributing to the preparation of crop recommendations that farmers can understand and trust. Minh et al. [5] provide an understanding of where XAI currently stands and how it can be further improved, which directly benefits the development of AI-based crop recommendation systems. Haar et al. [6] discuss CNNs, and since CNNs are commonly used in precision agriculture for tasks such as plant disease detection, rational approaches to interpretation can help build confidence and prepare recommendations on image-based agricultural systems.

2.1.3 Counterfactual explanations and argumentation in XAI

Antoniadi et al. [7] present findings on healthcare-related AI that can be translated to an agricultural context, as both industries require explicit AI to effectively guide critical decisions. Byrne [8] proposed that counterfactual theory can be utilized to elucidate AI-based crop recommendations, enabling users to comprehend the rationale behind preferring certain recommendations over others. Čyras et al. [9] suggest that employing argumentation processes in explainable AI (XAI) can enhance method recommendations within crop management systems by providing users with clear and comprehensible mechanisms, followed by validated improvements.

2.1.4 Social transparency and ethical considerations

Ehsan et al. [10] suggest ways to make AI systems in agriculture more socially transparent, encouraging adoption and trust among a wider community of stakeholders by addressing social implications and ethical considerations.

2.1.5 Training and education in XAI

Fiok et al. [11] the principles outlined in this research could apply to training programs for farmers and agricultural workers, equipping them to interpret better and utilize AI-driven crop recommendations. Gunning et al. [12] this paper could offer foundational knowledge key for integrating XAI into agricultural systems, potentially emphasizing the need for transparency in AI-driven tools used in crop management and planting strategies. Jiang et al. [13] address the issue of when explanations are needed and how to manage them, taking into consideration the user's understanding, or'epistemic uncertainty'. Markus et al. [14] presented on healthcare but the principles outlined could be applied to agriculture, offering a framework for ensuring that AI systems used in crop management are designed and evaluated with trustworthiness in mind. Tjoa et al. [15] this survey would offer insights that could be transferred to agriculture, where making informed decisions is equally critical and must be supported by systems that provide clear and informative explanations. Q. V. Liao et al. [16], the approach discussed in the design could be extremely useful in agricultural contexts, where users may need to question and understand crop recommendations to trust and act upon them. Szczesny et al. [17]. Real-time classification and explainability are valuable for precision agriculture applications, such as immediate disease detection or soil health monitoring, providing clear and actionable insights. Farrow [18] while focused on education, this paper might offer perspectives that could help understand the socio-technical dynamics of XAI as applied to agricultural education, including extension services and farmer training programs.

2.1.6 Role of explanations in user trust and satisfaction in decision making

Zhang et al. [19] the methods used in emergency control for power systems can be analogous to emergency or immediate response systems in agriculture, helping to manage unexpected changes or events affecting crop yields. Lundberg et al. [20] this research could illustrate methods to explain individual AI decisions in a way that reflects on the overall model behavior, which is essential for agronomy experts to trust the AI system as a whole. Kjersti et al. [21] in agricultural AI, understanding the interdependence of various factors affecting crop growth can significantly improve the precision of crop recommendation systems. Tintarev et al. [22] insights from this survey can inform the design of recommendation systems in agriculture, showing how explanations can affect user satisfaction, trust, and understanding. Tintarev et al. [23]. An evaluation framework discussed might inform the effectiveness of personalized crop recommendation systems, guiding adjustments for improved clarity and decision support for farmers.

2.2 Crop recommendation literature review

2.2.1 Machine learning and smart farming

Zeel Doshi et al. [24] introduced "Agricultural Consultants" a system that leverages machine learning algorithms to deliver intelligent crop recommendations. This system aims to assist farmers in making informed decisions about crop cultivation based on data-driven insights. Yaganteeswarudu Akkem et al. [25] The review discusses the application of various machine learning, deep learning, and time series analysis techniques to enhance the accuracy of algorithms used in smart farming. Akkem et al. [26]. The paper focuses on the importance of monitoring in farming and discusses using machine learning and MLOps to maintain and improve farming practices. Apat et al. [27] this research explores various ensemble learning approaches for crop prediction, highlighting their significance in improving predictive accuracy. Suresh et al. [28]. Developed an efficient crop yield recommendation system that utilizes machine learning techniques to optimize crop choices for digital farming.

The system is designed to help farmers increase productivity by recommending the most suitable crops based on various agricultural data inputs. Anantha Reddy et al. [29] the paper proposes a machine learning-based system to maximize crop yield in the Ramtek region by analyzing various agricultural parameters. Mamata Garanayak et al. [30] this research presents a crop recommendation system that utilizes various machine learning regression methods to provide agricultural advice. Rohit Kumar et al. [31] the study focuses on using machine learning techniques to develop a system that recommends crops to maximize yield. Sapna Jaiswal et al. [32] the paper discusses a collaborative recommendation system designed to enhance agricultural recommendations by leveraging collective knowledge.

Dhruv Piyus et al. [33] in this study present a crop recommendation system that uses machine learning and is accessible through the Flask API, focusing on the importance of defining features Pradeepa Bandara et al. [34] This study presents a crop recommendation system aimed at helping farmers make appropriate choices by analyzing various agricultural data Rubia et al. [35] The paper explores various machine learning approaches for smart agriculture, including crop recommendations, soil fertility, and water management. Zhang et al. [36]. The study examines the effect of biochar on soil microbial communities and antibiotic degradation, which have implications for soil health and crop production Tian et al. [37] This study uses satellite imagery and phenology-based algorithms to map winter crops, providing valuable information for agricultural planning and management Saeed, R. et al. [38] The study also includes sensors and machine learning for fish characterization, which are important for food safety and aquaculture.

2.2.2 Agriculture and IoT

Cheng et al. [39]. Paper explores dynamic service systems in IoT environments, which can be applied in smart agriculture for real-time monitoring and decision-making. Tong et al. [40] this study exemplifies the interactions between internal and external rural systems and provides insights into rural development and land use policies.

After reviewing various articles for crop recommendation, it is noted that explainability becomes especially crucial in the context of agriculture, where farmers and stakeholders need to make informed decisions based on AI-driven recommendations. Explainability is pivotal to ensure that farmers understand and trust the recommendations provided by the system. Explainability in ensemble models is essential to clarify how different models contribute to predictions and why certain recommendations are made. The focus on maximizing crop yield highlights the importance of transparency and explainability in ensuring that farmers adopt and follow AI-based recommendations. The use of machine learning in agriculture emphasizes the importance of explainability to ensure that farmers and agricultural experts trust AI-driven solutions.

2.3 Bibliometric analysis

Figure 1a displays the categorical distribution of reviewed articles, segmented into journals, conference proceedings, and book chapters. Figure 1b delineates the proportional distribution of reviewed articles sourced from major academic databases such as IEEE, Springer, Elsevier, and additional repositories. Figure 1c illustrates the percentage-wise allocation of articles across various subject areas, including machine learning, explainable AI, and other relevant methodologies.

Figure 1a–c collectively depicts the curated dataset of'Scholarly Works' aggregated from high-caliber academic repositories like IEEE Xplore, Scopus, and additional digital libraries, utilizing carefully selected keywords ("Smart Agriculture OR Smart Farming OR Explainable AI') AND ('Machine Learning OR Artificial Intelligence"). The primary objective of this data aggregation is to derive actionable insights that can benefit novices and emerging researchers within this domain. This manuscript offers a detailed review of these collected works, underlining their core strengths and contributions.

3 Explainable AI categories and its importance in crop recommendation systems

Figure 2 shows the basic categories of XAI, and each category supports other sub-categories. This article discusses important XAI categories that will impact the crop recommendation system.

Model-Agnostic Interpretability: Model-agnostic interpretability methods are techniques that can be applied to any AI model to generate explanations for their outputs without access to the internal structure of the model.

- Local interpretability: local interpretability methods aim to explain an individual prediction of a model. Techniques like LIME can be used to approximate the model locally and assess how different features affect a particular prediction.

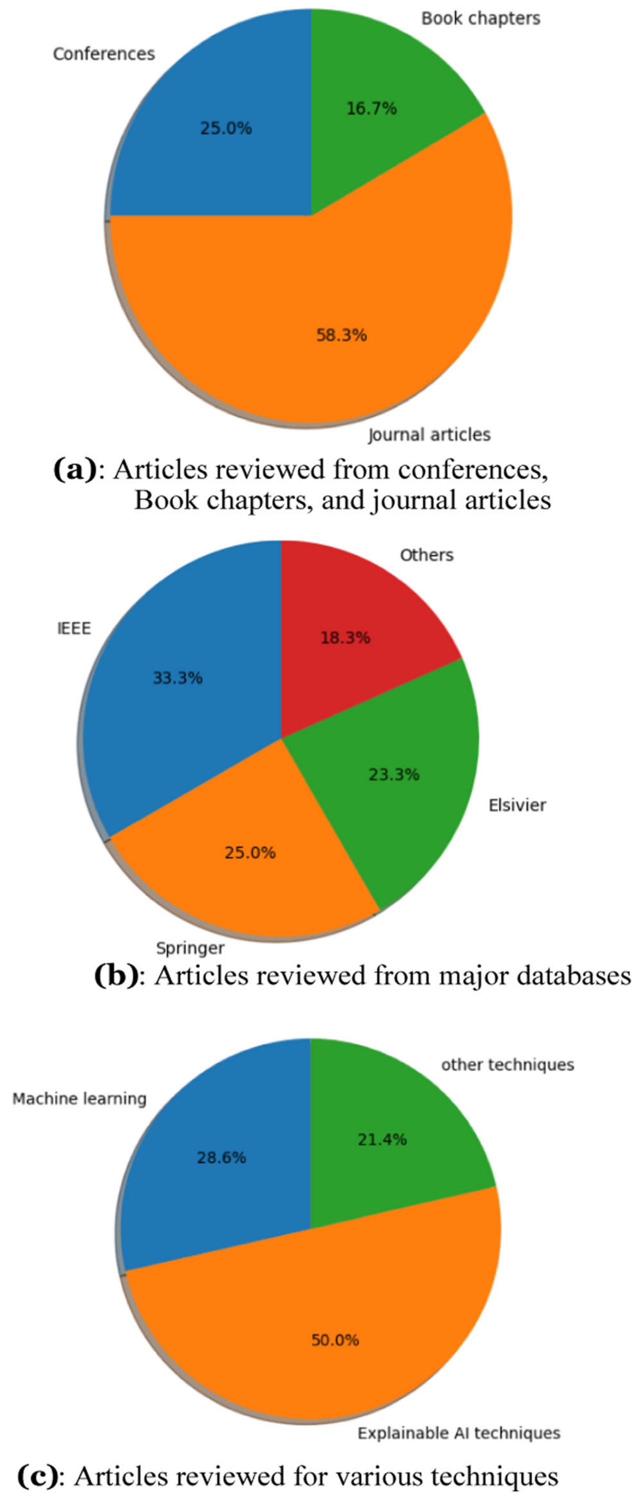


Fig. 1 **a** Articles reviewed from conferences, Book chapters, and journal articles. **b** Articles reviewed from major databases. **c** Articles reviewed for various techniques

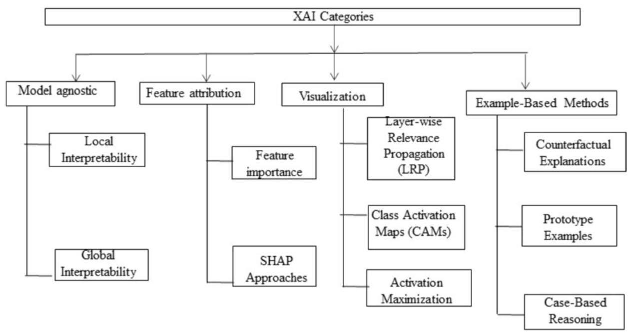


Fig. 2 Explainable AI categories

- Global interpretability: global interpretability techniques seek to provide an overall understanding of the model's behavior as opposed to explaining individual predictions. Methods such as feature importance ranking and partial dependence plots can be used for this purpose.

  Feature attribution: feature attribution is focused on determining which features are most influential in a model's prediction.
- Feature importance: various methods, including model-specific techniques like Gini importance or coefficients in linear models, assess the relative importance of different input features in the model's predictions.
- SHAP approaches: SHAP values consist of a game-theoretic approach to explain the output of machine learning models. SHAP assigns each feature an importance value for a particular prediction, making it one of the most comprehensive feature attribution methods, merging both local and global perspectives.

  Visualization: Visualization techniques present complex data or model behaviors in a visual context to make them more comprehensible.
- LRP: LRP is used to explain deep neural network decisions by backpropagating the prediction to the input layer, attributing relevance to each feature.
- CAM (Class Activation Mapping): CAM techniques highlight the regions of input (such as image pixels) that are important for a model, particularly convolutional neural networks (CNNs), to identify the class label of interest.
- Activation maximization: this involves finding an input that maximizes the activation of certain features or classes in a network. It helps to visualize what the network is looking for when making decisions.

  Example-Based Methods: Example-based methods use specific instances from the dataset to explain the model's behavior.
- Counterfactual explanations: counterfactual explanations present an alternative scenario that would have led to a different prediction. They essentially answer "what-if" questions, showing how altering some feature values changes the outcome.
- Prototypes: prototypes are instances that are representative of the model's behavior for a certain class or segment. Identifying and presenting these prototype examples can help explain what the model has learned.
- Case-based reasoning: case-based reasoning involves presenting past cases (examples) that are similar to the current instance to explain the model's decision. This method leverages analogical reasoning, where the AI refers to historical data points to make predictions.

4 Proposed architecture

4.1 Crop Recommendation parameters and their significance

Various crop recommendation parameters are used for visualization using XAI [41, 42] graphs with SHAP values. These parameters are critical factors that influence the decision-making process of AI-driven crop recommendation systems.

- Soil quality parameters (N, P, K): Nitrogen (N), Phosphorus (P), and Potassium (K) are primary nutrients essential for plant growth. The balance of these nutrients in the soil significantly affects crop yield and health. For instance, nitrogen is crucial for leaf growth, phosphorus for root development, and potassium for overall plant health and disease resistance. The importance of soil quality parameters in crop growth and the need for their careful management is highlighted in studies such as those by Gurunath Raddy et al. [29] and Yanli Bian et al. [38], which discuss spatial fertilizer recommendation mapping and residue extrapolation for pesticides in vegetable crop groups, respectively.
- Weather conditions (rainfall, temperature, humidity): rainfall, Temperature, and Humidity are climatic factors that play a vital role in determining the suitability of a crop for a particular region. Rainfall affects water availability, temperature influences growth rates and developmental stages, and humidity can impact plant diseases and pest prevalence. The impact of weather conditions on agriculture is explored in the work of Souryabrata Mohapatra et al. [39], which examines the heterogeneous climate effect on crop yield and associated risks to water security in India.
- Historical crop yields: these data are used to predict future yields based on past performance. This information helps in understanding the potential productivity of different crops in a given area. The use of historical data in enhancing agricultural practices is evident in the

research by Zeel Doshi et al. [24], which presents an intelligent crop recommendation system utilizing machine learning algorithms.

- Soil pH levels: this parameter will influence plant nutrient availability and uptake. Certain crops thrive in specific pH ranges, making this parameter crucial for crop selection. The significance of soil pH in crop production is discussed in the study by Andrew Tapiwa Kugedera et al. [40], which reviews integrated soil fertility management practices for improved crop production in semi-arid areas.

4.2 Proposed model architecture

Input data were collected from various data sources, including government websites and the Kaggle website. Government websites include https://dataverse.harvard.edu/dataset.xhml, https://www.indiastat.com/data/agriculture/commercial-crops, https://data.world/datasets/crops, https://ieee-dataport.org/documents/crop-recommendati on, and many other websites are visited and collected data for crop recommendation. Basic data cleaning was done, like a basic check of whether any null values exist in the dataset, and found that no null values exist in the dataset. A classification model was built for the crop recommendation system, and XAI techniques were applied to get explanations of the model. Figure 3 represents the basic architecture proposed in the current article. Further sections discuss visualizations of explanations and applications of XAI in crop recommendation.

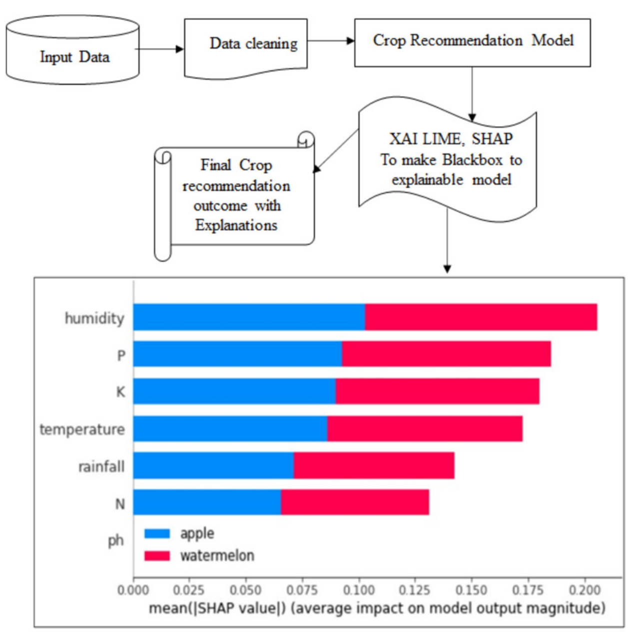


Fig. 3 Proposed model architecture

5 Visualization of crop recommendation parameters using XAI graphs with SHAP values

5.1 SHAP and SHAP graph's importance in crop recommendation

SHAP is a powerful tool in the field of XAI that provides interpretable explanations for the predictions made by machine learning models.

$$\phi i = \frac{\sum_{S\subseteq N\setminus i} \left|\text{subset}_f\right|!\left(n - \left|\text{subset}_f\right| - 1\right)!}{n!} \left[f_x\left(\text{subset}_f \cup i - f_x \text{subset}_f\right)\right] \quad (1)$$

where subset_f is a subset of features that do not include (i), φ shap value calculated for feature I, N is a set of all features, n is the number of all features, f_x (subset_f) is the prediction when only the features in (subset_f) are present.

In the context of crop recommendation systems, SHAP is particularly useful for several reasons:

- Feature importance: SHAP values help in identifying which features are most influential in the model's predictions. For instance, it can reveal the impact of soil quality, weather conditions, or historical crop yields on the recommendation of a particular crop. This is crucial for agronomists and farmers to understand the driving factors behind the model's decisions.
- Customized recommendations: by providing personalized explanations, SHAP enables farmers to see how specific conditions on their farm affect the crop recommendations. This level of customization is essential for farmers to make informed decisions that are tailored to their unique agricultural environments.
- Trust and transparency: the clear and understandable explanations provided by SHAP build trust between the users and the AI-based recommendation systems. When farmers comprehend the rationale behind a specific crop recommendation, they are more likely to follow through with the advice provided by the system.

Dependence plots: these plots show the effect of a single feature on the prediction outcome while accounting for the presence of other features. In crop recommendation, a dependence plot can illustrate how varying rainfall or temperature levels affect a crop's suitability for a given region, helping farmers make decisions about planting and irrigation.

Figures 4 and 5 represent dependence plots between different features. Figure 3 Dependence plot (DP) between N vs P and observed that for higher shap values of P, corresponding rainfall values are low in most of the cases. Similarly, the dependency of each parameter compared

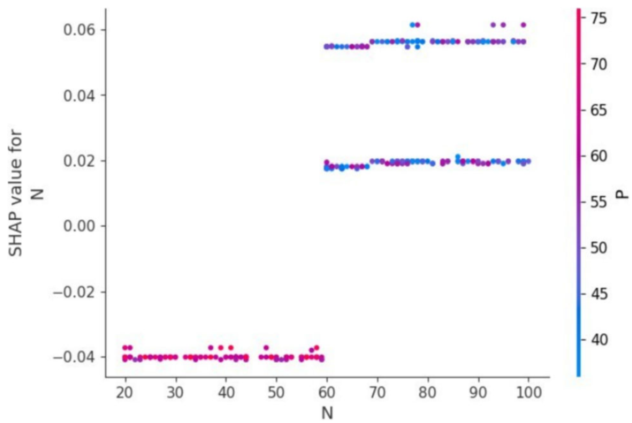


Fig. 4 Dependence plot N versus P

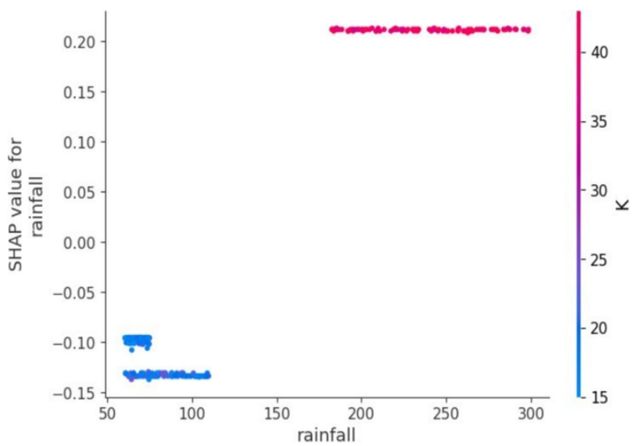


Fig. 5 Dependence plot rainfall versus K

with other parameters is presented in further figures. From all these graphs, it is clearly understood that each CR parameter depends on.

another parameter to decide the final crop.

Summary Plots: Summary plots provide a global view of feature importance and the impact of features on model predictions. In agriculture, this helps stakeholders prioritize which factors to focus on for improving crop yields and understand the overall behavior of the crop recommendation model.

Figure 6 represents a summary plot of CR data. Based on the SHAP values calculated for each parameter below the graph, it can be observed how each parameter will influence the model outcome.

Waterfall Graphs: Waterfall graphs break down the prediction for a specific instance by showing the cumulative contribution of each feature. This type of graph is particularly useful for explaining individual recommendations, allowing farmers to see the step-by-step contribution of each factor leading to the final recommendation. Figure 7 represents a waterfall plot for CR. The waterfall plot for CR data clearly indicates whether parameters contribute positively or negatively to deciding the outcome. From Fig. 6, it is observed that all parameters are contributing in deciding crop in a positive direction.

Decision Plots: Decision plots help visualize the model's decision-making process by showing how the prediction changes as different features are varied. For crop recommendations, these plots can demonstrate how the model differentiates between suitable and unsuitable crops based on various environmental and soil parameters.

Figure 8 represents the decision plot for crop recommendation. Like a waterfall graph, a Decision plot will also give information about how each parameter will influence the model's outcome. Figure 6 shows that N has the highest importance, and K, humidity, and so on.

5.2 Application of SHAP in crop recommendation

The application of SHAP in crop recommendation systems can be illustrated through specific examples:

Soil quality parameters: SHAP can quantify the impact of soil nutrients like Nitrogen (N), Phosphorus (P), and Potassium (K) on crop recommendations. For example, a high SHAP value for nitrogen might indicate its critical role in recommending a nitrogen-loving crop like corn.

Weather conditions: SHAP can help farmers understand how different weather conditions influence the model's recommendations. A dependence plot might show that certain crops are recommended only when the temperature and rainfall are within specific ranges, which can guide farmers in selecting crops that are more likely to thrive in their local climate.

Historical crop yields: by analyzing historical yield data, SHAP can provide insights into the likelihood of success for different crops. This helps in making informed decisions based on past performance and expected future yields.

Soil pH Levels: SHAP values can reveal the importance of soil pH in the recommendation process. For instance, if a particular crop is recommended, a SHAP analysis might show that the soil pH aligns perfectly with the crop's optimal pH range, justifying the recommendation.

6 Importance of LIME and dice ml in crop recommendation

6.1 LIME algorithm

LIME is a technique that provides insights into the decision-making process of complex machine learning models at a local level. In the context of crop recommendation

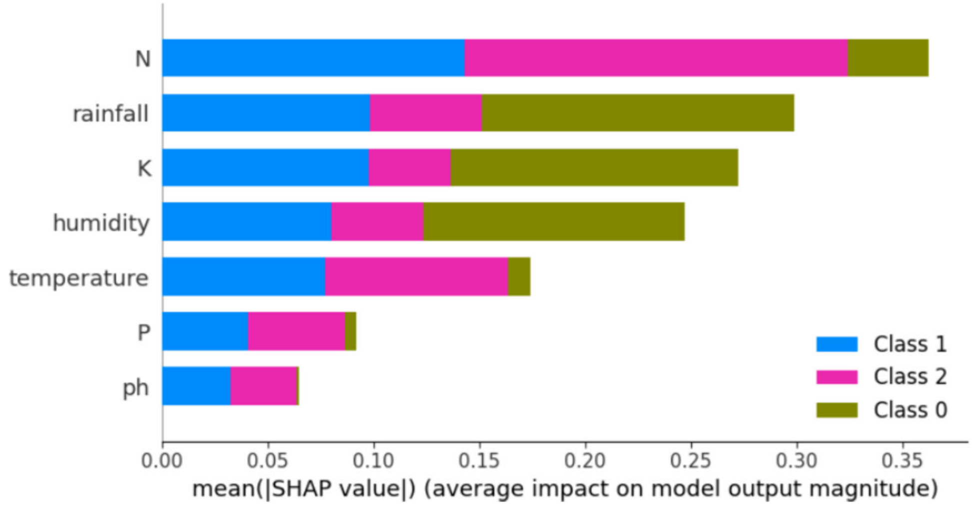


Fig. 6 Summary plot for crop recommendation

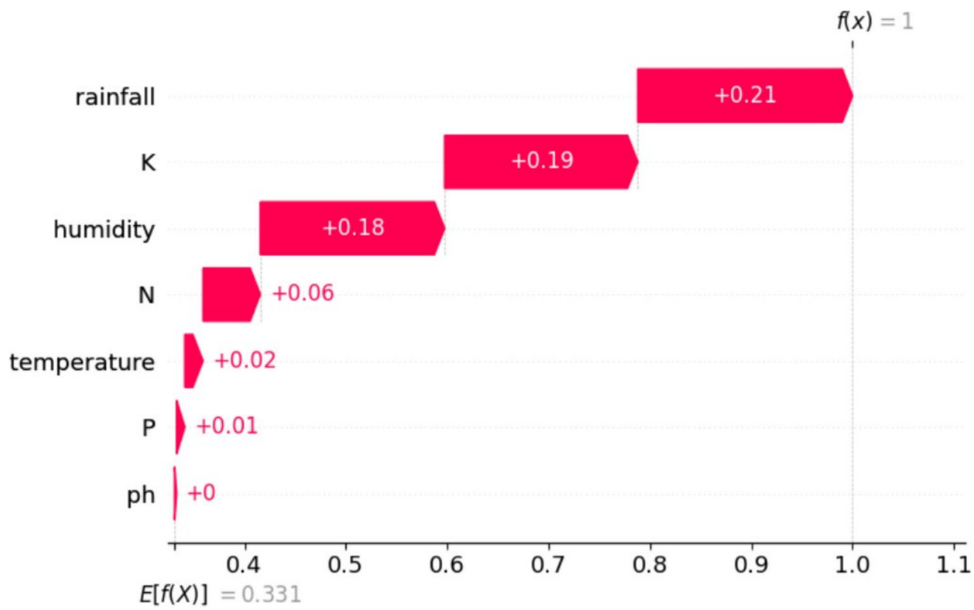


Fig. 7 Waterfall graph for crop recommendation

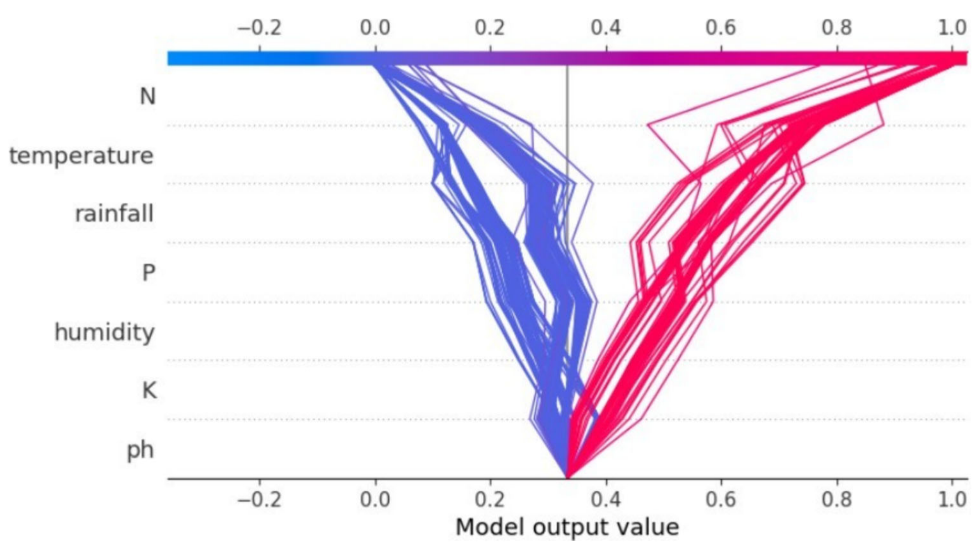


Fig. 8 Decision plot for crop recommendation data

systems, LIME is particularly useful because it allows for the interpretation of predictions for individual instances, which is critical for understanding and trusting AI-driven recommendations.

Given a complex model (*f*) and an instance (*x*) to explain, LIME generates a new dataset of perturbed samples around (*x*) and computes the corresponding predictions using the complex model. LIME then weighs these samples according to their proximity to (*x*) and fits a simple interpretable model (model$_S$) to this new weighted dataset.

$$\xi(\text{instance}_x) = \underset{\text{model}_s \in \text{model}_C}{\text{argmin}} L(f, \text{model}_s, \pi\text{instance}_x) + \Omega(\text{model}_s) \quad (2)$$

where instance$_x$ model instance, model$_S$—simple model constructed for Complex model, model$_C$—family of models, *f*—complex model, Ω—is a measure of the complexity of the model (models). *L* is a measure of fidelity, indicating how unfaithful (models) is at approximating (*f*) in the locality defined by (πinstance).

LIME is important in Crop Recommendation due to several reasons.

- Understanding complex decisions: crop recommendation systems often involve complex algorithms that take into account a multitude of factors, such as soil characteristics, weather patterns, and historical yield data. LIME helps in breaking down these complex decisions by providing interpretable models that approximate the predictions of the original model for individual instances.
- Tailored recommendations: each farm has unique characteristics, and a one-size-fits-all approach is not practical in agriculture. LIME's local explanations allow for recommendations that are specific to individual cases, taking into account the particular conditions of a farmer's field.
- Identifying key features: LIME can identify which features are most influential for a particular prediction. This is crucial for agronomists and farmers to understand the driving factors behind the model's decisions and to focus on the most relevant aspects of their farming practices.
- Facilitating informed decision-making: by providing explanations for each recommendation, LIME empowers farmers to make informed decisions. They can understand why a certain crop is suggested and what changes could potentially lead to different recommendations.
- Local explanations generated by LIME are particularly important in crop recommendation systems because they provide a detailed understanding of the model's behavior for individual predictions. This is essential when dealing with tabular data, which is common in agriculture, where each row represents a different set of conditions for a particular field or season.

Figure 9 represents the local explanation for record id 2. Each individual record will be explained in local explanations with corresponding parameter influence.

The tabular explainer in LIME is designed to handle this type of data effectively. It perturbs the input data around the instance being explained and observes the changes in the model's predictions. This process results in a simpler, interpretable model that provides insights into the original complex model's behavior for that specific instance. For example, a tabular explainer could reveal that for a particular field, the recommendation of a certain crop is heavily influenced by the soil pH and nitrogen levels. This information is valuable for a farmer who might be considering amendments to the soil to improve crop yield. Figure 9 represents the LIME tabular explainer for the crop recommendation dataset. The visualization of the tabular explainer clearly explains why a particular crop is recommended and why not other crops. For example, a crop is precited as watermelon but not black gram or, mungbean or muskmelon. Figure 10 clearly indicates that the crop is not predicted as blackgram because N, K, P, humidity, and temperature values are in the opposite directions of blackgram.

6.2 Dice ml

Dice-ml is a Python library used to generate diverse counterfactual explanations for machine learning models. Counterfactual explanations describe a possible alternate reality close to an observed outcome, especially for classification or regression tasks. They answer"what-if" scenarios, explaining how input features might be altered to achieve a different, usually more desirable, prediction. In the context of crop recommendations, dice-ml can be particularly valuable when the recommended outcomes from a predictive model are not satisfactory or when the user desires to understand how they might achieve different results. Below is how dice-ml and counterfactual explanations can be useful for crop recommendation:

Understanding influential factors: counterfactual explanations can help farmers or agricultural researchers understand which factors are most influential in delivering a specific crop recommendation. For instance, if the model suggests a particular fertilizer mix does not yield optimal results, dice-ml can reveal what changes could lead to a better outcome.

Scalability for multiple scenarios: users can generate multiple counterfactuals from a single query with dice-ml. In agriculture, this means exploring a variety of scenarios

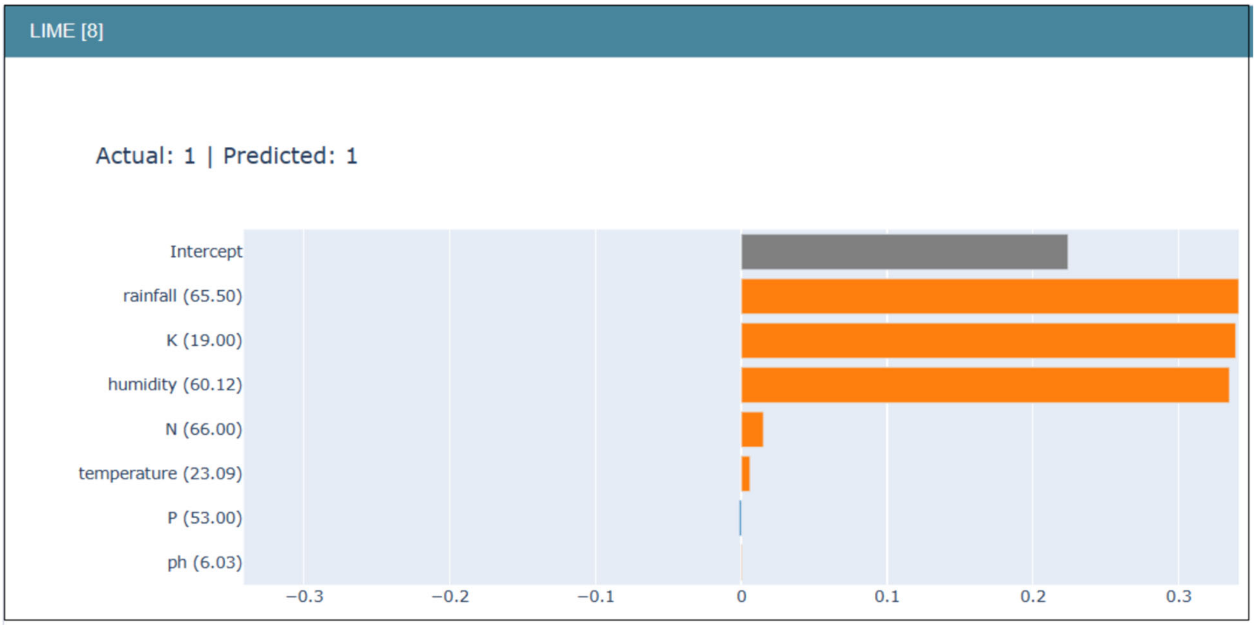
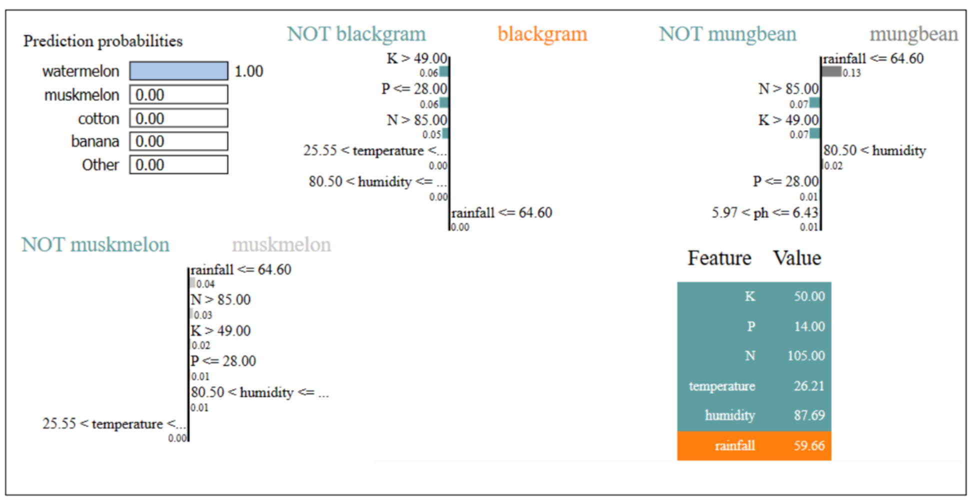


Fig. 9 Local explanations for record actual and predicted are 1

Fig. 10 LIME tabular explainer



regarding weather conditions, soil properties, or irrigation schedules, thereby offering farmers a range of actionable changes to improve crop yield or health.

Decision support and risk management: farmers can use counterfactual explanations to understand how to avoid poor crop outcomes. By considering recommendations on what not to do (derived from negative counterfactuals), they can make more informed decisions to mitigate risks.

Optimization of resource utilization: counterfactuals can guide farmers in adjusting agricultural inputs (like water usage, pesticide applications, or soil amendments) to optimize resource utilization and, thus, achieve better outcomes without overusing resources.

7 Recent advancements in XAI: integrated gradients and layer-wise relevance propagation

7.1 Integrated gradients

The integrated gradient (IG) is a method to show that the prediction of neural networks is causally derived. Particularly useful in models where the input has an obvious physical or functional meaning, such as pixels in an image or words in a text document, IG works by comparing model predictions with input data compare actual insertion to a baseline or input (which typically represents the absence or neutrality of an object) over an insertion condition). Along the way, it calculates the gradient of the output of the model with respect to the input features. The integral of these gradients is taken to obtain an attribute score for each feature. In the crop recommendation process, IG can be used to understand how soil type, climate, historical yield data, and various other inputs contribute to the model recommendation, e.g., It can help to identify crops to recommend.

For a given input (x), baseline input (x'), and model (f), the Integrated Gradient for the (i)-th feature is computed as:

$$\mathrm{IG}_i(\mathrm{input}_x, x') = \left(x_i - x_i'\right) \times \int_0^1 \frac{\partial f(x' + \alpha \cdot (\mathrm{input}_x, x'))}{\partial x_i} d\alpha \tag{3}$$

where IG_i—is the integrated gradient for feature (i) of input (x). Input_X—given model input, x'—baseline input, $\int_0^1 \frac{\partial f(x' + \alpha \cdot (x - x'))}{\partial x_i} d\alpha$ computes the average value of the gradients over all points along the path from baseline input to actual input. The integral (∫) effectively computes the average gradient of the model's output with respect to the features along the straight-line path from the baseline input to the actual input. This path is parameterized by α, which ranges from 0 to 1.

7.2 Layer-wise relevance propagation

LRP is another technique that explains the predictions of complex models, especially deep neural networks. LRP works by backpropagating the prediction output through the network layers, distributing the prediction value to each neuron so that the sum of the contributions is equal to the original prediction. This backward mapping continues until it reaches the input layer, providing a relevance score for each input feature that indicates its contribution to the final decision.

LRP is particularly useful for hierarchical feature extraction models, such as convolutional neural networks (CNNs) used in image recognition tasks. In agriculture, LRP could be applied to models that analyze satellite imagery for crop health monitoring or disease detection, providing insights into which aspects of the image led to a particular diagnosis or recommendation.

$$R_j^{(l)} = \sum_k \frac{Z_{\mathrm{jk}}}{\sum_{j'} Zj'K} R_k^{(l+1)} \tag{4}$$

where l is the number of layers, R is the relevance score for layer (l) and neuron (j), R_j is the relevance score for neuron j in the current layer. R_k is the relevance score for neuron k in the previous layer. Z_{jk} represents the contribution (e.g., weighted activation) of neuron j to neuron i in the next layer, k typically represents a neuron in the next layer (closer to the output layer) of the network, j typically represents a neuron in the current layer (closer to the input layer) of the network, j' Represents all neurons in the current layer in the context of a summation.

Figure 11 represents the basic architecture of LRP consisting of an input layer and hidden layers. The input layer consists of various nodes with inputs. Let us assume ai aj are input nodes, and the final output is calculated. Based on the final output, relevance scores are calculated Ri, Rj, and based on the relevance scope, input features can be selected. The relevance score indicates how much the features depend on the output value.

7.3 Integration of IG and LRP with LIME and SHAP

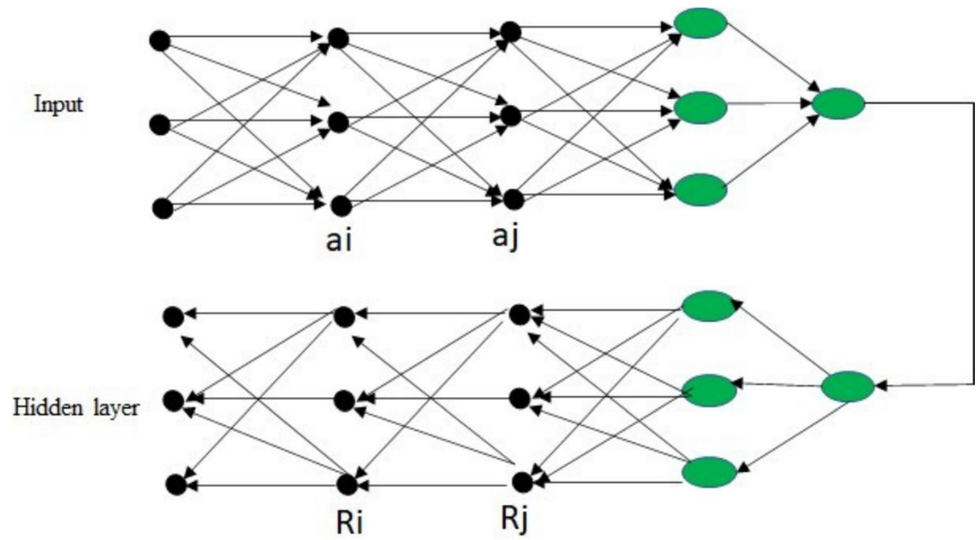
Both IG and LRP offer complementary insights to LIME and SHAP. While LIME provides local explanations and SHAP offers consistent and additive feature attributions, IG and LRP can provide more detailed insights into the inner workings of deep learning models. IG can highlight the importance of features across the entire path from a baseline to the actual input, and LRP can reveal the contribution of each layer and neuron in the network to the final prediction.

For crop recommendation systems that use deep learning models, integrating IG and LRP could enhance the explainability of the system by providing a more nuanced understanding of the model's behavior. This could lead to better trust and adoption of AI-driven recommendations by farmers and agricultural experts, as they would have a clearer picture of how the model arrives at its conclusions.

8 Results and discussion

In SHAP and LIME, in the previous section already demonstrated the importance of LIME local explanations, tabular explanations, and SHAP various graphs like dependence plot, waterfall graph, summary plot, and many other plots.

Table 1 represents inputs like N62, P 22, K 93, temperature 10.64, humidity 26.49, pH 10.34, and rainfall 259.32, for which the crop is predicted as corn. If the farmer wants to grow a wheat crop instead of a corn crop, then dice ml will help the farmer by suggesting suitable configuration changes. Table 2 represents the configuration changes required to grow wheat crops instead of corn crops. As per the user's request, dice ml can provide multiple suggestions for the user. For example, in Table 2, there are 2 counterfactual explanations. In Row 1, if the farmer changes configuration like N from 62 to 68, P from



$$R_j^{(l)} = \sum_k \frac{z_{jk}}{\sum_{j'} z_{j'k}} R_k^{(l+1)}$$

Fig. 11 General architecture of LRP with deep learning

Table 1 Crop recommendation input record for counterfactual explanations

N	P	K	Temperature	Humidity	PH	Rainfall	Label
62	22	93	10.64	26.49	10.34	259.32	Corn

Table 2 Counterfactual explanations of the outcome to cultivating the wheat crop instead of the corn

N	P	K	Temperature	Humidity	PH	Rainfall	Label
68	23	32	39.64	85.59	6.34	48.32	Wheat
92	97	53	20.64	64.59	10.34	22.32	Wheat

Table 3 LRP output

Feature	Relevance scores
Nitrogen	0.25
Phosphorus	− 0.1
Potassium	0.15
Temperature	0.3
Humidity	− 0.05
pH	0.2
Rainfall	0.05

22 to 23, K from 93 to 32, and so on, then the land will be suitable for the wheat crops. Still, a lot of research is required, and validations are required to prove that the provided counterfactual explanations are correct.

Table 3 represents LRP output for various crop parameters and their relevance in crop recommendation. This output suggests that 'Temperature' and 'Nitrogen' have the most positive relevance, meaning they contribute positively towards the model's prediction. Conversely, 'Phosphorus' and 'Humidity' might have negative relevance, indicating a suppressive effect on the prediction.

Streamlit Dashboard.

Streamlit is a lightweight Python framework, and web applications can be easily built with it. This article aims to build a streamlit dashboard where users can enter required parameters and visualize various graphs from XAI to know the importance of each feature that contributed to the final crop recommended. Figure 12 represents a streamlit 'application with required crop parameters as input and visualizations of XAI for the crop recommended.

9 Conclusion and future scope

The integration of AI into agriculture, mainly via crop recommendation systems, has marked a tremendous advancement in farming practices. These AI-driven structures utilize sophisticated machine studying algorithms to provide farmers with customized steerage on crop choice and management, thereby optimizing agricultural productiveness and sustainability. However, the opacity of AI models, frequently referred to as the" black box," poses an assignment in setting up consideration among farmers and agricultural specialists. XAI has become a critical area of research for mitigating this problem. This paper has

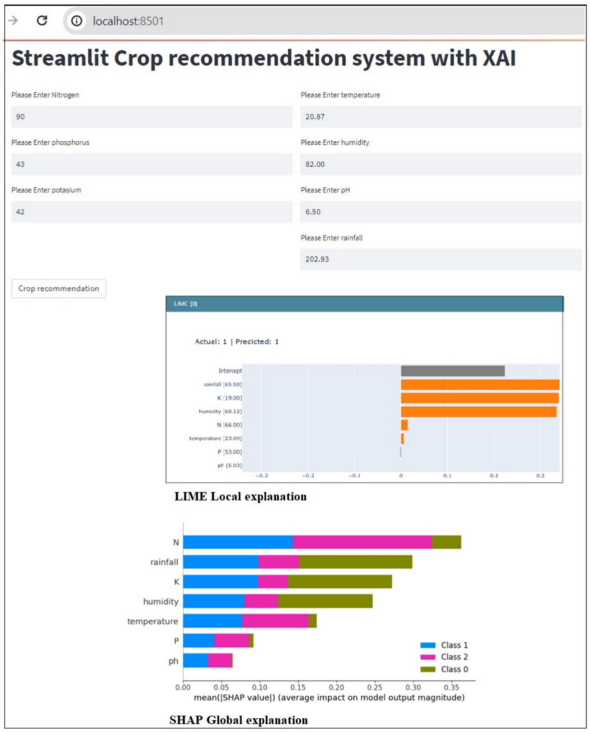


Fig. 12 Streamlit dashboard for farmers

provided a complete examination of the intersection among crop recommendation structures and XAI, emphasizing the essential importance of explainability inside the agricultural region. LRP is instrumental in explaining the predictions of complicated fashions, mainly deep neural networks, by way of backpropagating the prediction output via the community layers and attributing relevance to every input feature. This method is especially useful for fashions containing hierarchical function extraction and those studying satellite imagery for crop fitness tracking or sickness detection. By providing relevance scores for each enter function, LRP contributes to deeper information on the version's selection-making process, which is crucial for the adoption and acceptance as true within AI-driven recommendations. SHAP and LIME are demonstrated to provide more explainable models to farmers.

The future scope of research in XAI for agriculture is vast and promising. Further research could focus on various improvements in agriculture. Combining the strengths of various XAI techniques, such as LIME, SHAP, IG, and LRP, with machine learning algorithms to create hybrid models that offer both predictive accuracy and explainability. These models can serve as a bridge between data-driven insights and user comprehension. Conducting extensive validation studies to ensure that the counterfactual explanations provided by tools like dice-ml are accurate and practical for real-world agricultural scenarios. Exploring the integration of XAI into agricultural education and extension services to equip farmers and agricultural workers with the skills needed to interpret and utilize AI-driven crop recommendations effectively. Investigating the social and ethical implications of AI in agriculture to ensure that AI systems are designed and deployed responsibly, considering the diverse needs and values of stakeholders in the agricultural community. Since model fairness is important, as part of the future scope, building a feedback system where users directly interact with the system and provide feedback so that more reliable models can be built.

Data availability The data supporting the findings of this study can be obtained by requesting the corresponding author. Based on user request code will be available on repositories.

Declarations

Conflict of interest The authors affirm that they have no known financial or interpersonal conflicts that might have looked to have influenced the research presented in this study.

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