Deutsches Zentrum für Luft- und Raumfahrt
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Bridging Gaps between Farmers and AI with XAI

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Abstract: With the advent of technology, there has been observed a dramatic transformation in many of the industries across the.Surprisingly, agriculture, though being the least digitized, has seen momentum for the development and commercialization of agricultural technologies. Artificial Intelligence (AI) has begun to play a major role in daily lives, extending our perceptions and ability to modify the environment around us. Explainable AI (XAI) in agriculture provides transparency into how machine learning models make decisions. It is essential for modern farming because it replaces "black box" algorithms with clear, understandable reasoning, ensuring farmers can trust, verify, and safely act on AI-generated recommendations. Additionally, XAI supports regulatory compliance and fosters collaborative learning between farmers and agronomists by revealing how inputs influence outputs.

Why Explainable AI is Needed in Agriculture:

1. Building Farmer Trust and Buy-In
2. Farmers rely on generations of practical, hands-on knowledge. If an AI model simply tells them to "spray a pesticide on this block" or "stop watering," they are unlikely to follow it blindly.
3. XAI provides insights ,why a decision was reached—such as highlighting specific weather patterns or showing that soil nitrogen is low. This bridges the gap between traditional wisdom and modern technology.

State-of-the-art scientific results in agriculture: Most authors in XAI focus on post-hoc explainability rather than using intrinsically explainable models. Post-hoc methods explain decisions only after a prediction has been made, providing an after-the-fact interpretation that may not reveal the true internal reasoning. Our approach, however, is intrinsically explainable: the model itself is designed so that explanations arise directly during inference, allowing farmers to understand how input variables influence outcomes in real time.

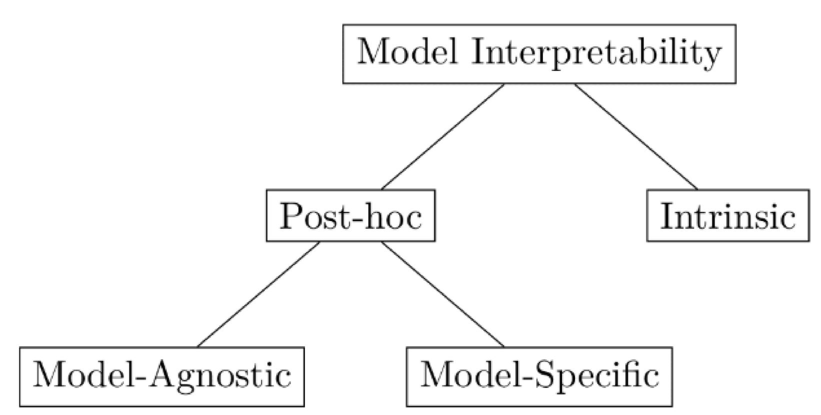

Figure 1: XAI divisions

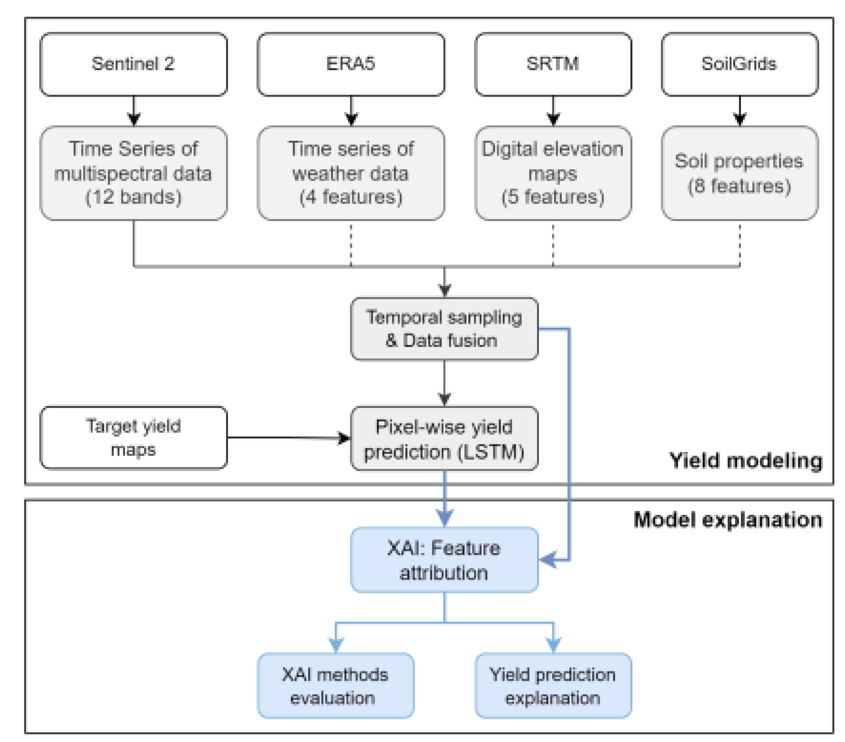

Figure 2: Example in post-hoc explainability ref [3]

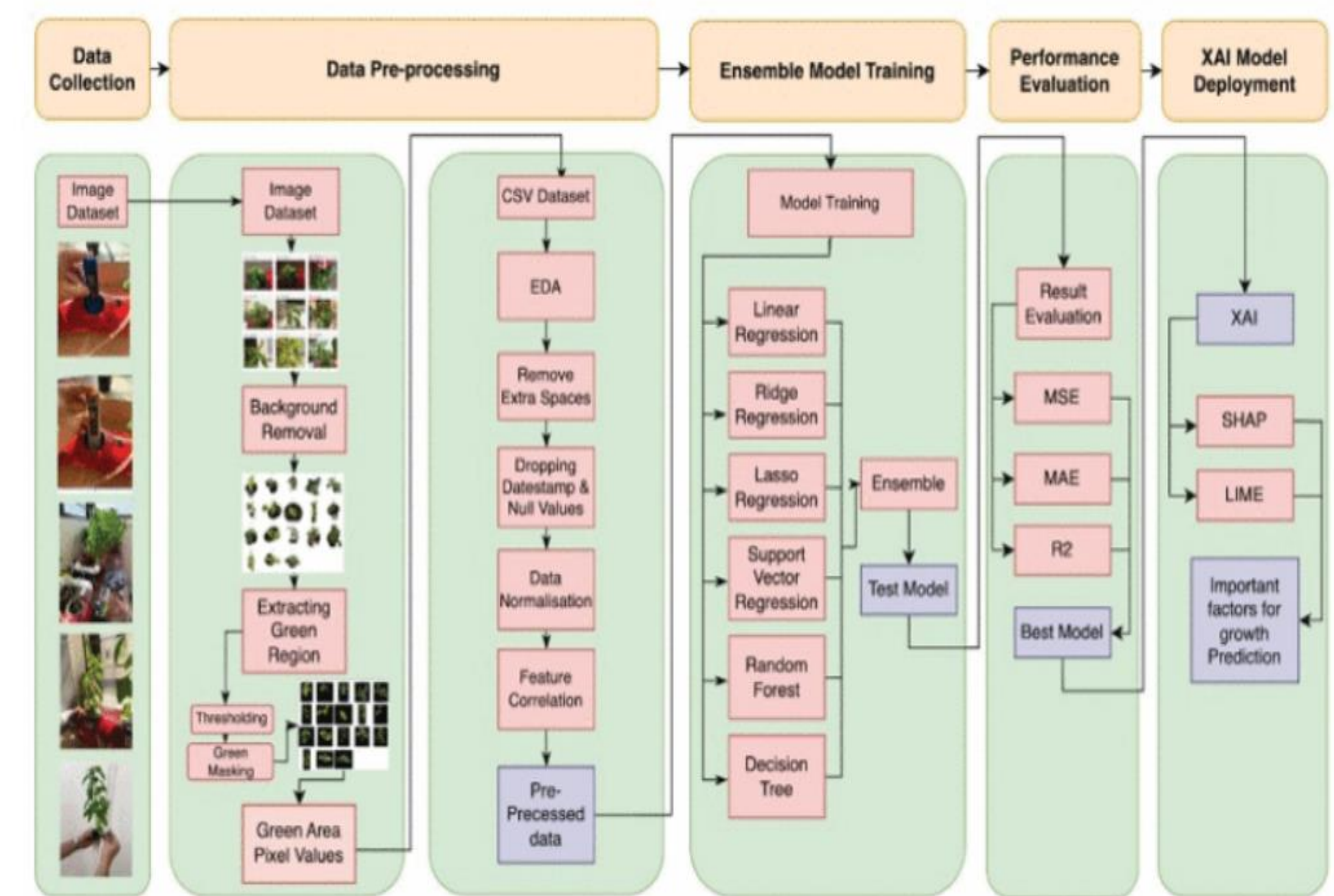

Figure 3: Example in post-hoc explainability ref[1]

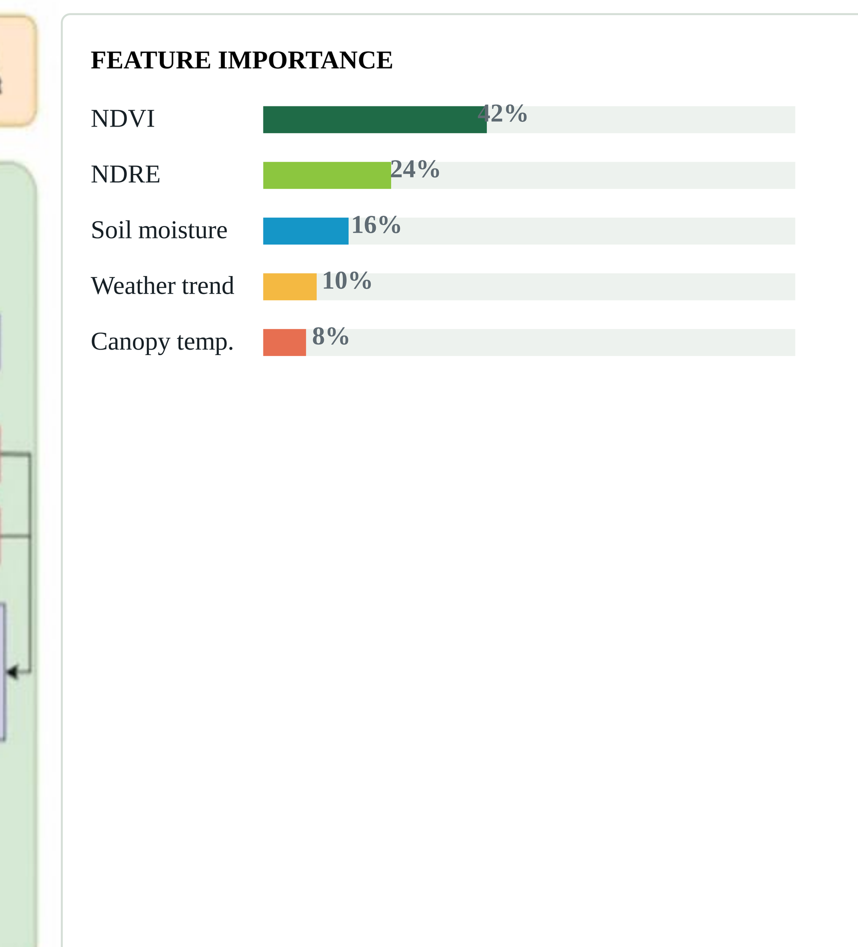

Figure 4:Feature importance score is a commonly used metric

RISCE, a DLR Spin-off project, aims to bridge the gap between end-users in agricultural practices and AI methods using XAI principles.

The approach has three major steps:

1) **Understanding XAI principles and tools**
2) **Analyzing current methods from an end-user's perspective**
3) **Evaluate the current methods in XAI**

Current remote sensing solutions for farmers: Several agri-software companies are using Earth observation data to bring crop health insights to farmers; however. Such approaches are limited only to large enterprises/farms. A user-friendly solution that 'talks to' farmers is still missing. For example, Pix4d, a agri- software company based sentinel-2 data and drone data to provide crop health insights.

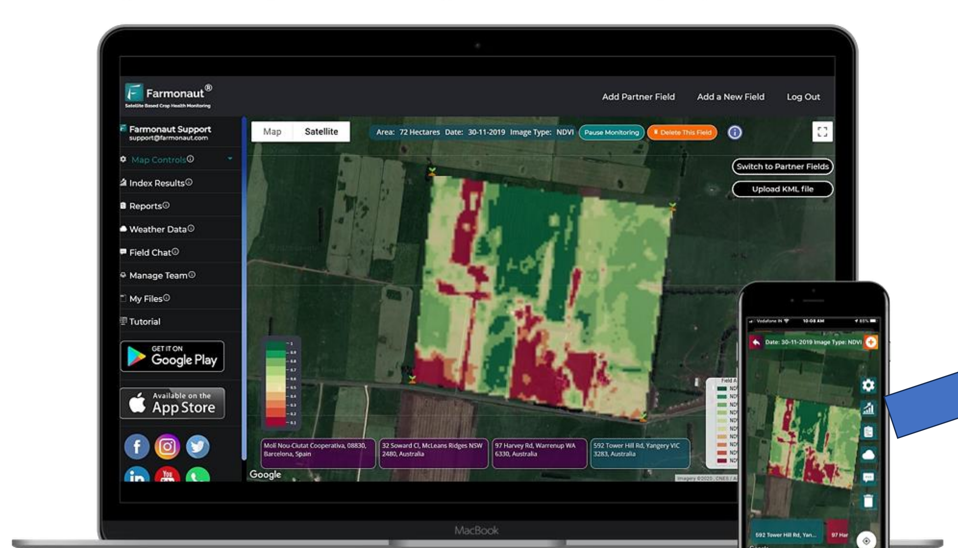

Figure 5: Crop monitoring UI of Farmnaur explains nothing, small famrers find it difficult

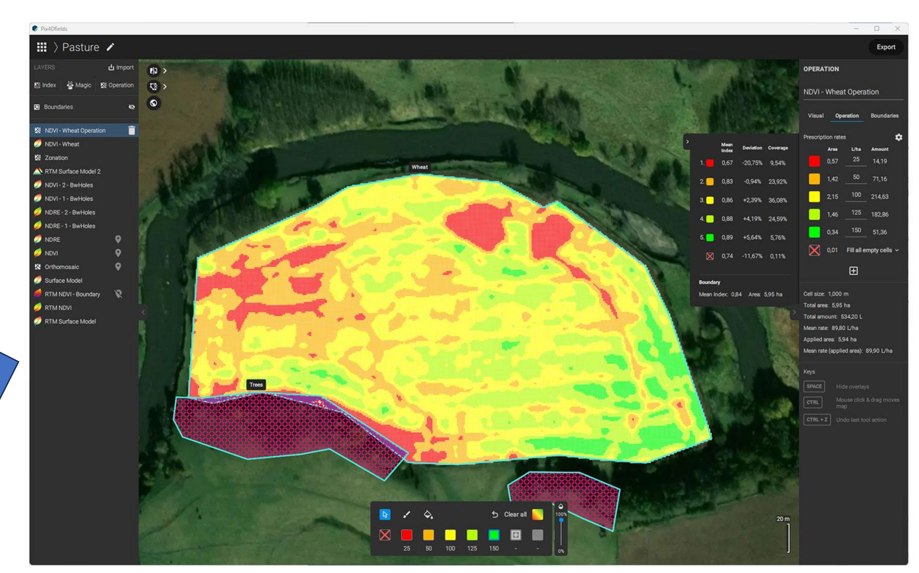

Figure 6: Crop monitoring UI of Pix4d explains nothing. Small famrers find it difficult.

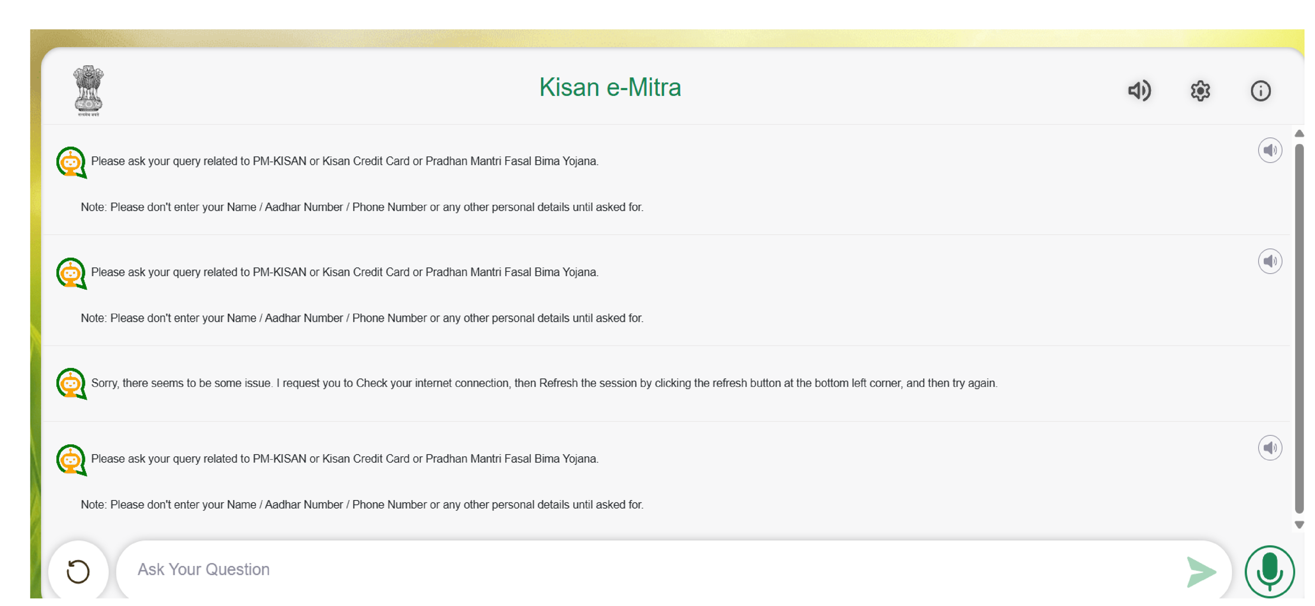

Figure 7: chatbot offered by Kisan e-Mitra, an Indian Govt initiative for farmers, only has textual information

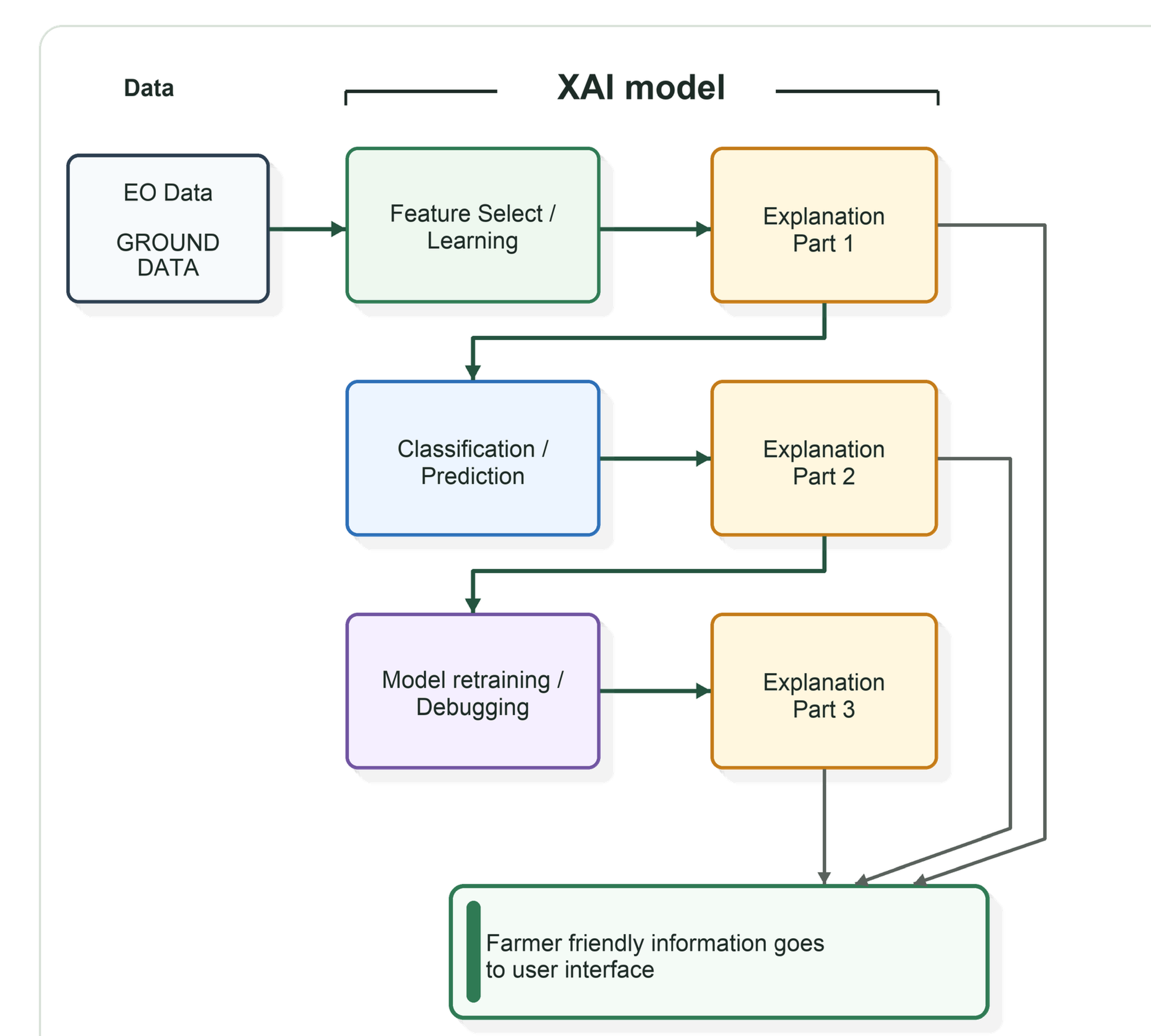

Figure 8: Our method of using intermediate explainations in a farmer-friendly manner

RISCE's interview with Solawi farmers and findings:
The non-profit association **Netzwerk Solidarische Landwirtschaft e.V. (Network for Community-Supported Agriculture)** serves as the central development partner for Community-Supported Agriculture (CSA) in Germany. In this capacity, it supports its members and the broader CSA movement. The association achieves this objective through networking, consulting, education, research, and the provision of various services. Furthermore, it acts as the voice of the CSA sector in Germany, serving as the primary point of contact for the general public and the press. It collaborates with partner organizations at both national and international levels.RISCE interviewed 12 SoLaWi farmers to understand how model explainability should be communicated.

EXPECTED VALUE

- Farmers see the reason behind the alert.
- Researchers see which evidence and model stage need debugging.
- The interface can ask for missing ground truth only when it is useful.

MODEL EVIDENCE -> FARMER LANGUAGE

Model signal		User message
NDVI is a highly important feature in the crop-health prediction.	➡	**Low greenness in this area may indicate stress. Please inspect the vines and upload plant photos.**

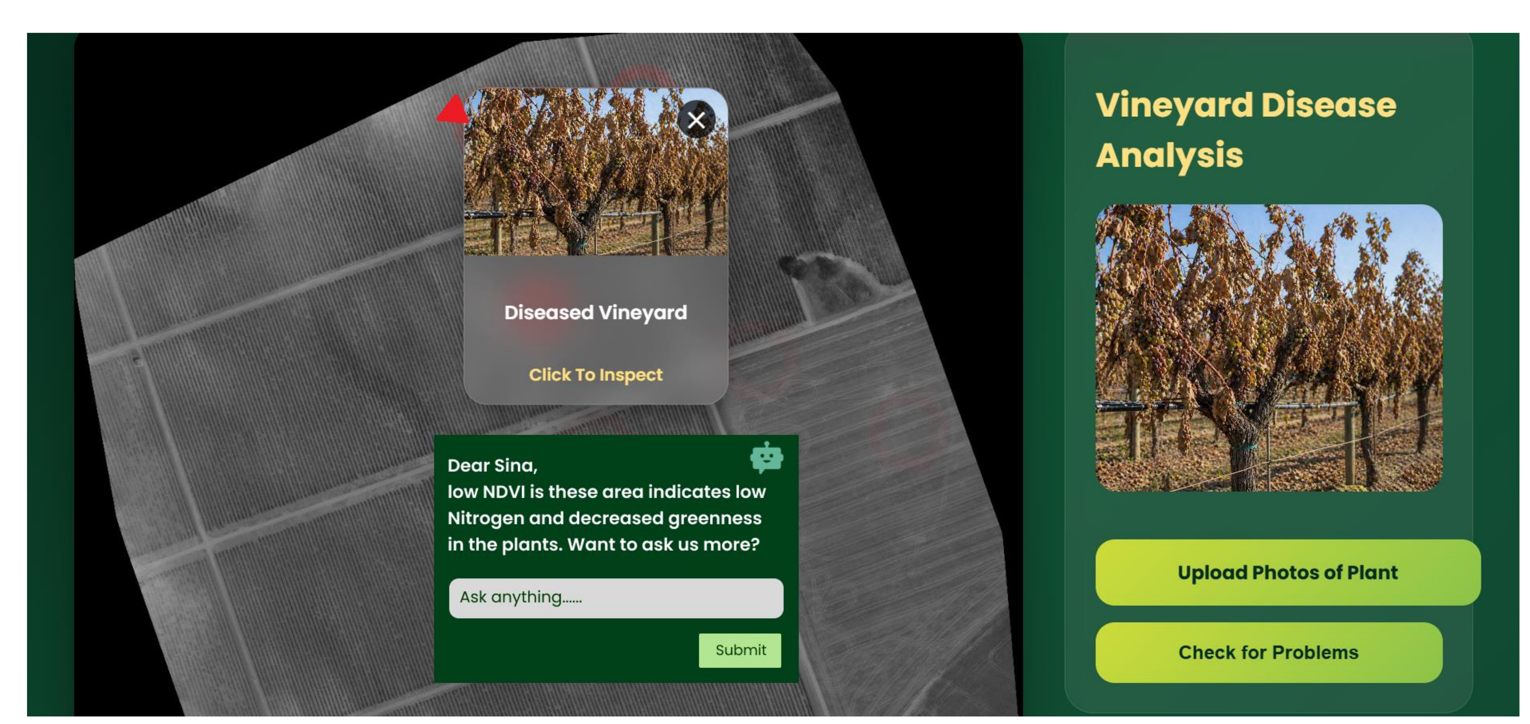

Figure 9: NDVI had a high feature importance, and RISCE says it in a farmer's way

References:
[1] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah, "Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides," *Artificial Intelligence in Agriculture*, vol. 4, pp. 58–73, 2020.
[2] R. Grati, N. Fattouch, and K. Boukadi, "Ontologies for Smart Agriculture: A Path Toward Explainable AI," *IEEE Access*, vol. 13, pp. 72883–72905, 2025.
[3] R. Grati, N. Fattouch, and K. Boukadi, "Ontologies for Smart Agriculture: A Systematic Literature Review," *IEEE Access*, vol. 13, pp. 72883–72905, 2025.

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