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DESIGN PRINCIPLES FOR EXPLAINABLE AI IN SMART FARMING: INSIGHTS FROM AGRONOMISTS' PERCEPTIONS

Relatório de Dissertação do Mestrado em Engenharia de Software

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Resumo

Esta dissertação investiga o desenvolvimento de interfaces para apresentação de explicações geradas por técnicas de Explainable Artificial Intelligence (XAI), com o objetivo de maximizar a usabilidade e a compreensão dos utilizadores finais através da aplicação de princípios de Human Computer Interaction (HCI). O trabalho apresenta uma prova de conceito desenvolvida em parceria com a Associação de Viticultores do Concelho de Palmela (AVIPE), demonstrando um sistema inteligente de apoio à decisão para deteção de doenças em vinhas.

O desenvolvimento seguiu uma metodologia centrada no utilizador, iniciando com protótipos de baixa fidelidade e evoluindo para um protótipo funcional integrado na plataforma *AgriUXE*. Este processo iterativo incorporou sessões de *co-design*, garantindo que a solução respondesse às necessidades reais dos agrónomos.

Através de um estudo com utilizadores, foi avaliada a eficácia de três modalidades de explicação: cenário de controlo (apenas diagnóstico), explicações visuais com mapas de calor e explicações baseadas em exemplos similares. A avaliação utilizou métricas de confiança, carga cognitiva e satisfação. Os resultados revelam uma clara preferência pelas explicações baseadas em exemplos, consideradas mais intuitivas, diretas e eficazes na calibração da confiança. Esta modalidade permitiu que 33% dos participantes identificassem corretamente um diagnóstico incorreto do modelo.

A análise qualitativa, realizada a partir de sessões de *co-design* e do protocolo *think-aloud*, identificou requisitos essenciais para integrar explicações XAI no fluxo de trabalho de agrónomos. O estudo mostrou que estes profissionais valorizam ferramentas que atuem como uma "segunda opinião", apoiando processos de investigação ativa em vez de fornecer respostas absolutas.

Apesar de limitações relacionadas com o tamanho da amostra e as condições controladas do estudo, os resultados permitiram definir diretrizes práticas para o desenvolvimento de ferramentas que apoiem a tomada de decisão em contextos agrícolas, contribuindo para uma adoção mais informada e eficaz de soluções de XAI na agricultura inteligente.

Os resultados permitiram definir um conjunto de princípios de design para a criação de interfaces de XAI mais utilizáveis e confiáveis em contextos de agricultura de precisão. Trabalho futuro deverá alargar a avaliação a contextos agrícolas mais diversificados e analisar de que forma as explicações influenciam a precisão diagnóstica em condições reais de campo.

Palavras-chave: agricultura digital, XAI, HCI, suporte à decisão agrícola, usabilidade, design thinking, agronomia.

Abstract

This dissertation investigates the development of interfaces for presenting explanations generated by Explainable Artificial Intelligence (XAI) techniques, with the goal of maximizing usability and users' understanding through the application of Human Computer Interaction (HCI) principles. The work introduces a proof of concept developed in partnership with Associação de Viticultores do Concelho de Palmela (AVIPE), demonstrating an intelligent decision-support system for vineyard disease detection.

The development followed a user-centered methodology, starting with low-fidelity prototypes and evolving into a functional prototype integrated into the *AgriUXE* platform. This iterative process incorporated *co-design* sessions to ensure that the solution addressed the real needs of agronomists.

A user study was conducted to evaluate the effectiveness of three explanation modalities: a control scenario (diagnosis only), visual explanations using heatmaps, and example-based explanations. The evaluation considered metrics such as trust, cognitive load, and satisfaction. The results show a clear preference for example-based explanations, which were perceived as more intuitive, direct, and effective for calibrating user trust. This modality enabled 33% of participants to correctly identify an incorrect model prediction, which is a result not achieved by the other scenarios.

Qualitative analysis, based on *co-design* sessions and the think-aloud protocol, identified key requirements for integrating XAI explanations into the agronomists' workflow. The findings indicate that professionals value tools that operate as a "second opinion," supporting active investigation rather than providing definitive answers.

Despite limitations related to sample size and controlled study conditions, the results allowed the formulation of practical guidelines for developing tools that support decision-making in agricultural contexts, contributing to a more informed and effective adoption of XAI solutions in smart agriculture.

The findings informed a set of design principles for creating usable and trustworthy XAI-enabled interfaces for smart farming. Future work should expand evaluation to more diverse agricultural contexts and assess how explanations influence diagnostic accuracy in real field conditions.

Keywords: digital agriculture, XAI, HCI, agricultural decision support, usability, design thinking, agronomy.

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Acronyms

AI Artificial Intelligence. 1–3, 5–9, 12–14, 16, 17, 20, 21, 29, 30, 45, 47, 49, 50, 53, 59

API Application Programming Interface. 31, 38

AVIPE Associação de Viticultores do Concelho de Palmela. 4, 30, 59, II, III

CNN Convolutional Neural Networks. 2, 8, 11, 12, 16

DL Deep Learning. 2, 8, 11–14, 47

ESS Epworth Sleepiness Scale. 51

GANs Generative Adversarial Networks. 11

HAI Human-AI Interaction. 20

HCI Human Computer Interaction. 4, 5, 7, 17, 18, 20, 21, 26, 27, 29, 30, 45, II–IV

IoT Internet of Things. 1, 7, 8, 10, 15, 31

LIME Local Interpretable Model-agnostic Explanations. 16, 17, 31

ML Machine Learning. 4, 8–14, 16

NDVI Normalized Difference Vegetation Index. 30

PaSS Perceived Stress Scale. 51

RF Random Forest. 10, 12, 16

RNN Recurrent neural network. 11, 12

rrBLUP Regression best linear unbiased predictor. 12

SFT smart farming technologies. 8

SHAP Shapley Additive exPlanations. 16, 31

SVM Support Vector Machine. 10, 16

TXAI Trust in Explainable AI Scale. 51

UX User experience. 3, 26

XAI Explainable Artificial Intelligence. 1, 3–7, 13–17, 20, 29–31, 42, 45, 52, 56–59, II–IV

Chapter 1

Introduction

With technological advancements, the agricultural industry has undergone various transformations over the past decades. Currently, we are in the era of Industry 4.0, characterized by automation processes, digital integration, and the use of Internet of Things (IoT). This movement is not limited to factories but impacts various sectors, including agriculture [1]. In agriculture, the application of technologies in the sector, usually defined as digital agriculture, has revolutionized traditional practices. For instance, soil moisture and nutrient sensors enable a more efficient control of crop demands, significantly increasing crop yield and supporting sustainable resource management [2].

In digital agriculture, various technologies such as IoT (Internet of Things), Big Data, Artificial Intelligence (AI), cloud computing, and remote sensing are used to monitor plant health. While IoT and remote sensing technologies assist in monitoring characteristics such as height and soil conditions, drones are employed to capture images and data on plant growth. These technologies generate a significant amount of data, which can be processed and analyzed using Big Data, AI, and cloud computing techniques, providing support for efficient decision-making processes [3, 4].

Given the enormous amount of data generated by these technologies, the ability to interpret them in a clear and accessible way becomes essential. In this context, this dissertation investigates how to design interfaces that incorporate explanations generated by Explainable Artificial Intelligence (XAI), optimizing usability for end users. The study explores strategies for presenting these explanations, aiming to facilitate the interpretation of agricultural data and ensure that the information is understandable and useful for decision-making. Furthermore, it proposes the development of a web interface that allows for the visualization of satellite images, creation of areas of interest and markers, as well as sending images for disease detection, while integrating explanations in a clear and efficient manner to support vineyard owners in their strategic analysis.

1.1 Motivation

Agriculture faces significant challenges that threaten global food security. Rising food demand, driven by rapid population growth, is a critical concern. By 2010, the global population had already surpassed 6.9 billion, and United Nations projections estimate it could reach 9.15 billion by 2050 [5]. As illustrated in Figure 1.1, the rapid increase in population underscores the urgency of expanding food production to meet future demands. Meeting these demands will require key innovations in farm productivity, with digital technologies playing a pivotal role.

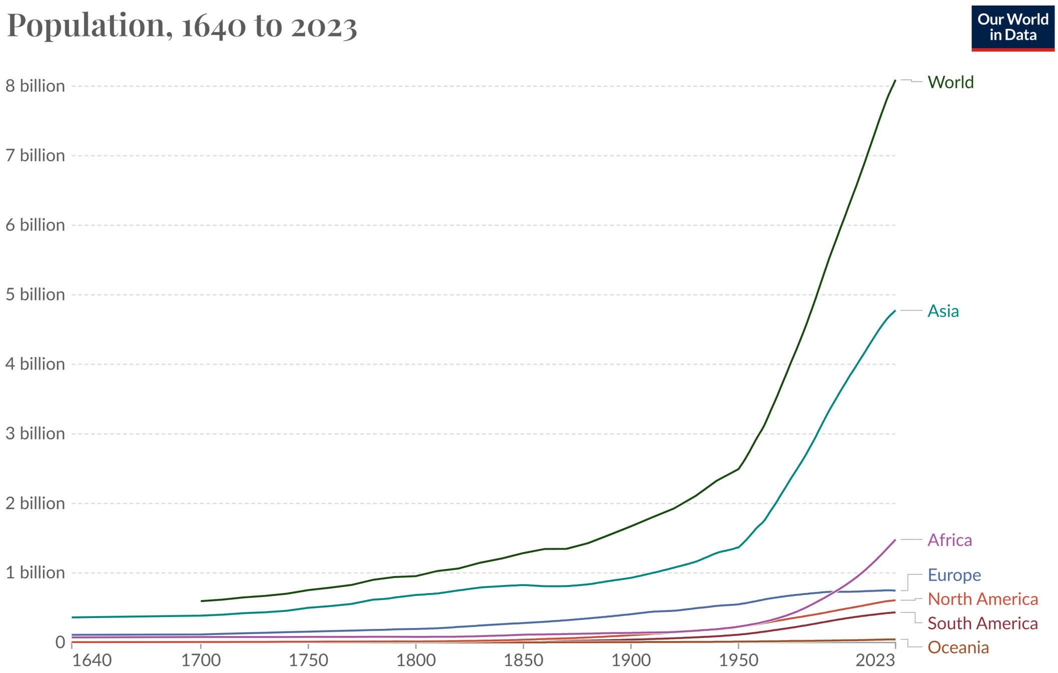

Figure 1.1: World Population Growth from 1950 to 2023 [6].

Compounding this issue are stagnant agricultural productivity for key crops, excessive reliance on chemical inputs with harmful environmental impacts, and climate change-induced risks such as extreme weather events and shifting growing conditions. Water scarcity, pest and disease outbreaks further intensify these challenges. To address these threats, agriculture must adopt sustainable practices to increase production while minimizing environmental degradation [7].

Digital agriculture has great potential to increase productivity in the agricultural sector. However, its implementation faces several obstacles. Among the main challenges are the high costs and lack of infrastructure in some regions, which hinder its adoption. Additionally, providing technical training is essential to ensure that farmers can use digital tools effectively. Ethical and security concerns also arise in this context, including issues related to privacy and the ownership of agricultural data [8].

In this context, effective plant disease control is essential for maximizing agricultural production. Traditional methods, such as chemical tests and visual recognition, although effective, are often time-consuming, labor-intensive, and require specialized technical knowledge [9]. Modern approaches leveraging Deep Learning (DL) models, such as Convolutional Neural Networks (CNN), have shown great potential in automating the detection and classification of diseases, offering faster and more efficient solutions [10]. However, the lack of transparency in how these AI systems generate their predictions can lead to distrust among end users, such as farmers and agricultural professionals [11]. This highlights the need for XAI techniques, which provide clear and interpretable explanations of the decision-making processes used by predictive models [12].

Despite these technological advancements, the adoption of such innovations in agriculture remains a significant challenge. Many farmers struggle with barriers that hinder the implementation of new technologies, including a lack of technical knowledge, resistance to change, financial constraints, and limited access to agricultural extension services. Additionally, factors such as age, education level, and prior experience influence their willingness to adopt modern practices, leading many producers to rely on traditional methods instead of investing in technologies whose effectiveness has yet to be fully validated in their specific contexts [13].

The integration of XAI in agricultural tools not only increases transparency but also opens up new opportunities for designing user-friendly interfaces that maximize usability. By studying how to effectively present XAI explanations—such as the logic behind disease classifications, model confidence levels, and potential errors—interfaces can be tailored to meet the needs of non-technical users. This approach ensures that farmers and agronomists can not only trust the results but also understand them and act with confidence. Ultimately, this research aims to bridge the gap between advanced AI technologies and their practical application in agriculture, promoting greater adoption and effectiveness of smart agricultural solutions.

1.2 Context Description

Despite the application of digital technologies for critical farm tasks like plant disease detection or early disease prediction, the existing solutions still face significant challenges [9]. Additionally, while constant plant monitoring is essential, efficiently managing the vast amount of data generated from monitoring systems, such as diverse input sources, environmental conditions, and growth patterns, remains a challenging task for farmers.

In this context, this work aims to explore how to design interfaces that incorporate XAI explanations in a way that maximizes usability for end users. The study focuses on creating a digital solution that not only facilitates the management of agricultural crops but also provides an intelligent system capable of detecting plant diseases and identifying early signs of disease emergence. Primarily intended for vineyard technicians and farmers, the goal is to support more efficient decision-making in crop management. To achieve this, the development of a web platform is proposed, leveraging AI and XAI for disease detection, ensuring that the interface remains intuitive and accessible.

The target audience for this solution includes agronomists and wine technicians, who often face challenges in efficiently managing crops and have time and resource constraints when monitoring and diagnosing diseases across large cultivation areas. By offering this solution, the goal is not only to reduce losses caused by pests and diseases in crops but also to provide more effective management of agricultural plots.

The application will be integrated with the AgriUXE platform, a multimodal and explainable solution designed to improve User experience (UX) in digital agriculture tools.

AgriUXE aims to enhance the interpretability and explainability of multimodal data and predictions generated by Machine Learning (ML) models, making the information more accessible and comprehensible for farm stakeholders.Therefore, the dissertation's context is bound to the AgriUXE, which is integrated in a PhD project being developed in the NOVA Laboratory for Computer Science and Informatics (NOVA LINCS).

Furthermore, the development of the application is based on the functionalities of AgriDash, a mobile application designed for viticulture that provides stakeholders with a digital solution featuring functions such as disease detection and satellite imaging, prioritizing usability and adaptation to user needs.

To ensure alignment with the end user's needs, the dissertation was developed in partnership with a vineyard cooperative, Associação de Viticultores do Concelho de Palmela (AVIPE). Founded in the 1980s by a group of grape growers from the Palmela region, AVIPE is dedicated to defending the interests of its members and promoting actions aimed at economic and social development. The association also engages in research, experimentation, demonstration, and dissemination of technical practices that contribute to the improvement of viticulture, as well as offering professional training to its members.

1.3 Objectives

The main objective of this dissertation is to study how to design interfaces that present XAI explanations in a way that maximizes usability for end users. The study will be conducted in the context of a web application for viticulture, facilitating efficient vineyard monitoring and assisting in plant disease detection. Integration with the AgriUXE platform will allow the uploading, processing, and analysis of leaf photos for diagnosis, but the primary focus will be on developing interfaces that make XAI explanations clear, intuitive, and highly usable.

The study will address how XAI techniques can be combined with user-centered design practices, utilizing Human Computer Interaction (HCI) methods to ensure that the explanations are understandable and relevant to end users, such as agronomists and farmers. The application will not only identify issues in plants but also provide detailed and accessible explanations of how decisions were made, highlighting the variables and processes involved. In this way, the project aims to promote more informed and reliable decision-making, while exploring design strategies that maximize the usability and effectiveness of XAI explanations in the context of viticulture.

Furthermore, the application will be designed to allow users to manage their crops areas, register and monitor different regions, and submit plant leaf photos for disease and pest analysis. This functionality will ease monitoring crop conditions over time, enabling rapid intervention when necessary and contributing to the mitigation of damage caused by diseases.

The interface development process will involve a partnership with AVIPE, following design thinking methodologies to incorporate end users into the development. This approach aims to address their real needs, ensuring the platform is functional and user-friendly. This collaborative approach will allow adjustments to the interface to align with the expectations and preferences of agronomists and farmers. As a result, the application will not only be effective in plant analysis and useful for field management, but also accessible and practical for daily use.

The following scenario illustrates a potential use case for incorporating the web application:

"It is the humid season, and John is walking through his vineyard, carefully inspecting the vines for signs of mildew, a common disease in vineyards. Instead of relying solely on traditional knowledge, John takes pictures of a few potentially infected leaves and heads back to his office. There, he uses the web application to submit the photos and activate the disease classification process. The application analyzes the images and outputs the unfortunate classification: "mildew," associated with one of the leaves. Unsure about the classification, John reviews the explanations generated by the system to understand how the decision was made. With a clear understanding of the AI's reasoning, John confidently proceeds with a treatment plan to address the predicted disease."

1.4 Research Questions

This study is guided by the overarching goal of designing XAI-driven interfaces that enhance usability, trust, and decision-making in smart farming contexts. Despite the growing adoption of AI in agriculture, there remains a significant gap in how explanations should be presented to non-expert users such as agronomists and farmers to ensure they are understandable, trustworthy, and integrated into their workflows. To address this challenge, the following research questions were formulated:

- **RQ1:** How do agronomists perceive the usefulness of feature-based versus example-based explanations in their diagnostic workflow?
- **RQ2:** What factors contribute to an explanation being perceived as trustworthy, understandable, and actionable?
- **RQ3:** What design principles for XAI in smart farming can be derived from agronomists' perceptions and preferences?

1.5 Contributions

Following the general objectives, this dissertation's research will lead to the following contributions:

- **XAI-Driven Interface Design Grounded in HCI Principles**: A user-centred interface was designed to integrate feature-based and example-based explanations provided by AgriUXE into an agronomists' diagnostic workflow. This contribution demonstrates how HCI principles can be applied to present explanations in a clear, usable, and trust-enhancing manner, supporting more transparent decision-making in smart farming contexts.

- **Functional Web Application Prototype for Smart Farming**: A fully implemented web application was developed, enabling vineyard technicians to manage plots, view satellite information, upload leaf images, and access AI-generated diagnoses enriched with integrated XAI explanations. The prototype serves as a proof of concept illustrating how explainability can be incorporated into real agricultural tools in a practical and intuitive way.

- **Human Factors Study on Explanation Usefulness and Preferences**: A mixed-methods evaluation with agronomists was conducted to examine how different explanation modalities (no explanation, heatmaps, and example-based) influence trust, cognitive load, satisfaction, and critical interpretation of model outputs. The results highlight a clear preference for example-based explanations and reveal key requirements and design principles for developing usable and trustworthy XAI systems for agriculture.

- **Scientific Publication:** The results of this work were disseminated through the submission of the paper "Cultivating Trust: A Qualitative Study of How Agronomists Perceive XAI", R.P. Porfírio, J. Sequeira, P.A. Santos and R.N. Madeira, to the top conference ACM CHI conference on Human Factors in Computing Systems (ACM CHI'26).

1.6 Report Structure

Given the context and objectives of this research, this dissertation follows the following structure:

- **Introduction**: This first chapter presents the motivation, describes and contextualizes the problem to be addressed in this dissertation, outlines the main goals of the proposed solution, explains the expected contributions.

- **Research Context and Theoretical Foundations**: This chapter study different topics that were considered necessary and important for this dissertation. These topics include digital agriculture, precision agriculture, XAI, and AI.

- **General Approach**: This chapter provides an overview of the research methodology, including the research questions, general approach, previous work (AgriDash and AgriUXE), and the development of low-fidelity and functional prototypes.

- **Evaluation**:This chapter presents the evaluation conducted with agronomy professionals, including the study objectives, hypothesis, experimental design, participant recruitment, and interaction procedure using a think-aloud protocol. It also reports the collected quantitative and qualitative data (trust, cognitive load, satisfaction, and understanding), presents the main findings, and discusses their implications for designing effective XAI-powered tools in agricultural workflows.

- **Summary of the Work**: This chapter summarizes the key findings, discusses the main contributions and future work of the study, and outlines potential directions for future research and development.

Chapter 2

Research Context and Theoretical Foundations

This chapter establishes the context and essential theoretical foundation for this dissertation, exploring fundamental concepts related to digital agriculture and its role in addressing key farm tasks. Additionally, it explores the use of technologies such as Explainable Artificial Intelligence (XAI) and Human Computer Interaction (HCI), highlighting how these digital systems can be applied to enhance diagnosis, agricultural management, and user interaction with digital tools to support efficient decision-making.

2.1 Digital Agriculture

Digital agriculture is characterized by the digitization of agricultural activities, driven by data and technological advancements. Its primary purpose is to improve efficiency in farm practices, ensuring a more conscious use of resources, such as water and fertilizers, while reducing environmental impacts. By integrating data collection, transmission, and processing, digital agriculture enhances crop yields, optimizes resource management, and promotes sustainable practices [1, 14].

Furthermore, digital agriculture contributes to increased food safety and quality, fostering more efficient practices. The use of data enables more precise and informed decision-making, allowing farmers to respond proactively to challenges such as climate variability, pests, and market demands. These advancements not only increase productivity but also support the development of a more resilient and environmentally friendly farming system [15].

At its core, digital agriculture is realized through the use of technological resources, such as sensors, Internet of Things (IoT), and Artificial Intelligence (AI), to optimize input use and make agricultural processes more efficient and sustainable [16, 15]. The use of IoT allows for real-time data collection, enabling analyses that support decision-making. This contributes to the optimization of resources, such as water, and improves pest and disease control. Additionally, the technology enables the automation of field tasks, such as irrigation and monitoring, increasing operational efficiency [17] .

With the resources of digital agriculture, it is possible to collect and process large volumes of data coming from the field. The use of technologies such as IoT enables the reduction of human labor, allowing remote monitoring and control of crops. In this way, farmers can observe, understand, and manage the variability present in their production systems, adapting the application of inputs to achieve the desired results. This approach contributes to reducing production costs and, consequently, increasing profitability [18].

However, despite these developments, the adoption of digital agriculture still faces significant challenges. The main barriers include the high cost of implementation, the complexity of the technologies, and the lack of accessible and impartial knowledge about the benefits of using smart farming technologies (SFT) [19]. Many farmers remain skeptical about the application of SFT to support decision-making in farming, which limits their acceptance. Furthermore, concerns exist about the lack of technical support and the difficulty in interpreting SFT results. These factors, combined with inadequate digital infrastructure in some regions, create significant obstacles to the widespread adoption of digital agriculture.

There are several ways to apply digital agriculture to optimize processes and increase efficiency, promoting sustainability. Some common uses can be classified into the following categories [20]:

- **Crop Stress**: Digital tools such as drones equipped with sensors can capture high-resolution data on plant health, soil nutrition, and environmental conditions. When integrated with IoT networks, they enable the early detection of stress factors (e.g., water deficits, pests).
- **Pesticide Usage**: Machine Learning (ML) algorithms identify pest-affected areas, enabling targeted pesticide applications. Among these, Convolutional Neural Networkss (CNNs) can analyze real-time images to support selective spraying.
- **Disease and Pest Detection** The application of AI, using techniques like ML and Deep Learning (DL), enables the automatic identification of crop diseases and pest infestations. These models analyze satellite and drone imagery to detect abnormal patterns and perform automated segmentation of affected areas.
- **Yield Forecasting**: ML algorithms are applied to predict crop yield, helping farmers make informed decisions about planting and resource allocation.

There are several applications of digital agriculture that demonstrate its potential to optimize processes and increase sustainability. However, challenges still need to be overcome for an effective digital transformation, such as precision, interoperability, data storage, computational power, and farmers' reluctance to adopt new technologies [18].

2.2 Artificial Intelligence

AI is a field of computer science focused on developing systems and algorithms that mimic human-like reasoning by learning from data [21]. Unlike humans, AI algorithms do not 'think' in the traditional sense. Instead, they identify and generalize patterns from large datasets to support decisions and predictions. These systems are trained to process vast amounts of information, enabling the recognition of trends and correlations with high accuracy [22].

2.2.1 Machine Learning

Machine Learning (ML) is a subfield of Artificial Intelligence (AI), with the primary motivation being the development of algorithms that enable the training of predictive models. The goal of ML is to develop predictive models that learn from a dataset with minimal or no human intervention [23].

The workflow of ML can be divided into three main parts: data input, model training, and generalization, as illustrated in Figure 2.1 [24].

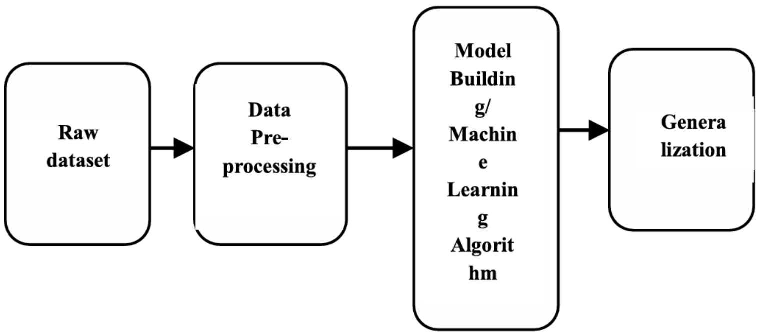

Figure 2.1: Traditional Machine Learning Flow [24]

According to [25], the main ML paradigms include supervised, unsupervised, reinforcement, semi-supervised, and self-supervised learning:

- **Supervised Learning**: This approach uses labeled datasets, where each input corresponds to a known output. The algorithm establishes a relationship between the input data and the corresponding outputs, later generalizing to unseen information.
- **Unsupervised Learning**: In this case, algorithms work with unlabeled data, discovering hidden patterns by organizing similar information into groups. The goal is to extract implicit knowledge from the dataset, making this approach more complex compared to supervised learning.
- **Reinforcement Learning**: This method is based on interaction with the environment, learning through a system of rewards and punishments to optimize decision-making.
- **Self-Supervised Learning**: In self-supervised learning, the algorithm learns from unlabeled data by automatically generating pseudo-labels. These pseudo-labels are used to pre-train the model, which can later be fine-tuned on labeled data for tasks such as classification or regression.

Regarding its application in agriculture, the use of ML offers the opportunity to provide more efficient predictions compared to traditional agricultural methods, even with smaller datasets. This is particularly relevant when combined with data collected by IoT sensors, which can continuously monitor soil quality, weather conditions, and other essential variables for agricultural production. Over time, this long-term data collection enables the training of ML models that are tailored to the agricultural context. These models can deliver precise analyses and accurate predictions, supporting strategic decision-making in the sector [26].

The use of ML in agriculture is constantly growing, being applied in tasks such as detection of crop diseases, weed identification, yield prediction, crop recognition, water management, animal welfare, and livestock production [27].

Related Work

Several studies have explored the use of ML techniques in agriculture, demonstrating their applicability in different contexts. For example, Viskovic et al. proposed a methodology that integrates satellite imagery with ML algorithms to classify agricultural crops [28]. In their approach, supervised models such as Random Forest (RF) were employed to distinguish seven crop types based on 15 spectral indices derived from satellite data. The reported performance included an accuracy of 0.8420 and a Kappa coefficient of 0.8157, metrics frequently adopted in remote sensing to assess classification quality. While accuracy and F1-score are often considered more representative in machine learning applications, the inclusion of the Kappa coefficient provides an additional perspective by accounting for agreement beyond chance.

Another relevant contribution is the recommendation system developed by Andayani et al. [29], which uses regression techniques to predict crop yields for rice, ragi, chickpeas, potatoes, and onions. To achieve this, weather and agricultural data were collected from the government of Andhra Pradesh, India, followed by preprocessing and feature selection steps. Algorithms such as linear regression, decision tree, RF, polynomial regression, and support vector regression were applied, and the majority voting method was used to combine the results of the models, forming an ensemble method. The system achieved an accuracy of 94.78%, demonstrating its potential to assist farmers in choosing the most suitable crops for their lands.

The detection of diseases in plant leaves has also been the subject of research, such as in the study conducted by Reddy et al. [30]. In this research, ML algorithms such as Support Vector Machine (SVM) and RF were applied to identify diseases in coffee and cotton leaves. The process involved image collection, preprocessing for noise reduction and standardization, segmentation to identify infected areas, and feature extraction based on edges and points. The Support Vector Machine (SVM) model achieved an accuracy of 88% in certain scenarios, demonstrating the value of automated techniques in reducing the time and cost linked to manual disease detection.

However, although ML offers many advantages and has significant potential in digital agriculture [27], it also presents several challenges:

- **Implementation costs**: The need for sensors and infrastructure can be a barrier to adoption.

- **Lack of knowledge**: Many farmers are unaware of the benefits of technology in agriculture.
- **Data quality**: Much of the data used does not reflect real-world scenarios, limiting the effectiveness of algorithms.
- **Algorithm limitations**: There is a need for more robust and efficient algorithms to handle complex agricultural data.
- **Environmental variability**: Data capture is complicated by factors such as lighting conditions and other environmental changes .

2.2.2 Deep Learning

DL is a subfield of ML that uses neural networks to extract patterns from data. These networks are designed to simulate the human brain's processing of information, with multiple layers of interconnected nodes that learn hierarchical representations of data. This approach enables deep learning models to effectively handle tasks such as image recognition and natural language processing [31]. Deep learning, a subfield of ML, employs neural networks with multiple processing layers to learn representations of data at various levels [31]. This allows the algorithm to process complex data, such as text, audio, and video, and solve advanced problems, such as facial recognition and medical diagnostics. DL is commonly applied through the use of neural networks such as CNN, Recurrent neural network (RNN), Generative Adversarial Networks (GANs), and, more recently, Transformers [32, 33].

- **RNN** RNNs process sequential data by using previous outputs as inputs for future steps, enabling them to capture dependencies over time. This memory capability, maintained by hidden layers, makes them ideal for tasks like natural language processing and time series analysis [34].
- **CNN** A CNN is a neural network architecture commonly used in supervised learning, where it adjusts its parameters using labeled data and backpropagation. Its architecture includes input, convolution, pooling, fully connected, and output layers, enabling the transformation of low-level features into high-level representations for effective data representation [35].
- **GANs**: GANs are a type of unsupervised learning model that uses two neural networks, a generator and a discriminator. The generator creates synthetic data, such as images, while the discriminator evaluates whether the data is real or generated. Through training, the generator improves its ability to produce realistic outputs, making GANs highly effective for tasks such as image generation, style transfer, and data augmentation [32].
- **Transformers**: Transformers are a deep learning architecture that relies on self-attention mechanisms to process sequential data. It consists of encoder-decoder

layers, multi-head attention, and positional encoding, making it highly effective for natural language processing tasks, such as translation and text generation [33].

In digital agriculture, the use of DL has grown significantly, aiming to optimize agricultural processes. Techniques such as CNN and RNN have been applied to various tasks, including plant species identification, plant disease classification, and pest detection, supporting more precise and efficient agricultural decision-making [36, 37].

Related Work

Several studies have explored the potential of DL in agriculture. An example is the study conducted by Sandhu et al., which investigated the application of DL to predict traits in spring wheat breeding programs [38]. The authors compared two DL algorithms: a custom CNN and a Multilayer Perceptron (MLP), with the Regression best linear unbiased predictor (rrBLUP). Using data from 650 wheat lines, the CNN achieved improved accuracy compared to rrBLUP, but the MLP performed slightly better than the CNN for some traits, reaching up to 5% higher predictive accuracy, demonstrating the promise of DL techniques for this purpose.

Another relevant contribution is the system proposed by Sunil et al. which uses CNN to monitor soil health in real-time [39]. The model was developed to analyze images captured by sensors, allowing the prediction of soil moisture, pH, and nutrient concentration with an accuracy of approximately 92%. This approach reduced the time required for traditional soil analysis by 80%. In addition, the model is scalable and can be adapted to different soil types and crops, making it an economical and efficient solution.

An additional study, conducted by Divya et al. proposed an approach for plant disease detection using ML techniques [40]. The process involved collecting a large dataset of leaf images, both healthy and infected, which was subjected to preprocessing steps for color, size, and orientation standardization. Then, relevant features, such as edges and textures, were extracted using advanced image processing techniques. These features were used to train classification models, including the VGG16 architecture, based on CNN, and the RF algorithm, both demonstrating high effectiveness in identifying complex patterns associated with different diseases.

DL in agriculture is quite promising but faces obstacles. Key challenges include [37]:

- **Data Availability:** Collecting and labeling data is time-consuming and labor-intensive. This is a challenge for any AI approach, but particularly critical for DL, which requires large datasets.
- **Adaptation to Different Regions and Environmental Conditions:** Adapting models to various regions and environmental conditions can be complex.
- **Interpretability and Transparency:** DL models often operate as "black boxes," making it difficult for agronomists to understand their decisions and reducing trust in the system's recommendations.

- **Vulnerability to Environmental Changes:** AI-based systems may lose accuracy when exposed to unforeseen environmental variations, such as climate changes or shifts in soil management.
- **Ethical Issues:** Ethical concerns related to the ownership and protection of data collected by DL models need to be addressed to ensure trust and security for users.

2.2.3 Explainable Artificial Intelligence

XAI is a subset of AI focused on providing explanations of AI system decisions, equipping end users with tools to assist in interpreting the system's decision-making process. By providing transparency on how decisions are generated, XAI has the potential to increase confidence in the results and allows users to manage and adjust the system more efficiently [41].

Although there is no universal consensus on the terminology of XAI, in this work we adopt the definition by Barredo Arrieta et al. [42], which describe XAI as a field of study encompassing methods and approaches aimed at making AI models interpretable and explainable to human users. This definition emphasizes transparency and supports the end-user's understanding of how AI systems generate decisions, providing a clear view of the model's behavior and enabling informed use.

In this context, XAI primarily focuses on two fundamental concepts: interpretability and explainability. Interpretability refers to the extent to which a human can understand the internal mechanics of a model, while explainability concerns the ability to describe the reasons behind the decisions produced by the model [43]. These concepts are central to making AI systems more transparent and accessible to end users. The definitions of these concepts are:

- **Comprehensibility (or Intelligibility)**: Refers to the ability of a model to be understood by a human being without the need for detailed explanations about its internal structure. In ML models, it refers to the representation of the learned knowledge in an understandable way.
- **Interpretability**: Refers to the ability to assign meaning to the model's decisions, making them understandable to a human being. It is a passive characteristic, indicating how much an observer can understand a model by analyzing it.
- **Transparency**: A model is considered transparent when it can be understood directly, without the need for explanation techniques. It represents the opposite of the "black-box" approach, promoting an intuitive understanding of the internal functioning of the model.
- **Explainability**: Unlike interpretability, explainability is an active characteristic. It refers to any action or procedure, performed by the model itself or by external techniques, with the goal of clarifying, justifying, or detailing its internal functioning.

In the literature, a distinction is made between models that are interpretable by design (known as transparent models) and models that require external techniques to provide explanations, referred to as post-hoc explanation methods. The most common classification in the literature is therefore between transparent models and post-hoc explanation methods [44].

Transparent models are algorithms that possess some degree of inherent transparency, allowing their functioning to be understood directly without the need for additional techniques. Examples include linear regression, shallow decision trees, and association rules. Post-hoc methods are applied to complex and opaque AI models, often referred to as "black boxes," such as DL algorithms, which lack inherent transparency. These methods aim to increase the interpretability of the model's decisions by providing local, visual, or example-based explanations, bridging the gap between the user and the underlying model logic. [45].

Another way to classify XAI techniques is by looking at their dependency on the model. In other words, whether the technique can be applied to any algorithm or is designed only for specific cases. The literature usually groups this distinction into two main categories:

- **Model-agnostic techniques:** These techniques can be applied to any type of ML model, irrespective of its internal structure. They are particularly effective for black-box models, as they rely solely on the model's inputs and outputs to infer behavior, providing a consistent and interpretable way to generate explanations without accessing internal details [46].
- **Model-specific techniques:** These are designed to explain only certain types of ML algorithms and therefore cannot be applied to other models. The literature usually divides these specific techniques into two main categories [46, 42]:
  - Specific techniques for shallow models, such as decision trees, SVMs, and logistic regression;
  - Specific techniques for DL models, such as convolutional and recurrent neural networks.

The goal of XAI is to enhance transparency in AI systems by enabling technical interpretability and fostering user trust. This is achieved by revealing not only what decisions are made, but also how and why the model prioritizes specific patterns or features in its outputs. In this way, AI models are no longer treated solely as black boxes but instead operate as grey boxes, providing partial insight into the factors that drive decisions, even if full transparency is not achieved. It is also worth noting that there are white-box models, such as linear regression or shallow decision trees, which are inherently interpretable and therefore do not require additional XAI methods [12].

For XAI to be able to provide explanations about how a model works, different types of explanations are leveraged [42].

- **Textual Explanations**: Generate texts to make the model's output more understandable. This can involve creating a semantic mapping of the model, using symbols to represent its functioning, or producing a textual description that explains the model's behavior.

- **Visual Explanations**: Use images to make the model's functioning understandable. In some cases, techniques such as dimensionality reduction are applied to visualize complex patterns. These approaches help represent the model's internal behavior in a human-understandable way, often through heatmaps or activation maps, as illustrated in Figure 2.2.

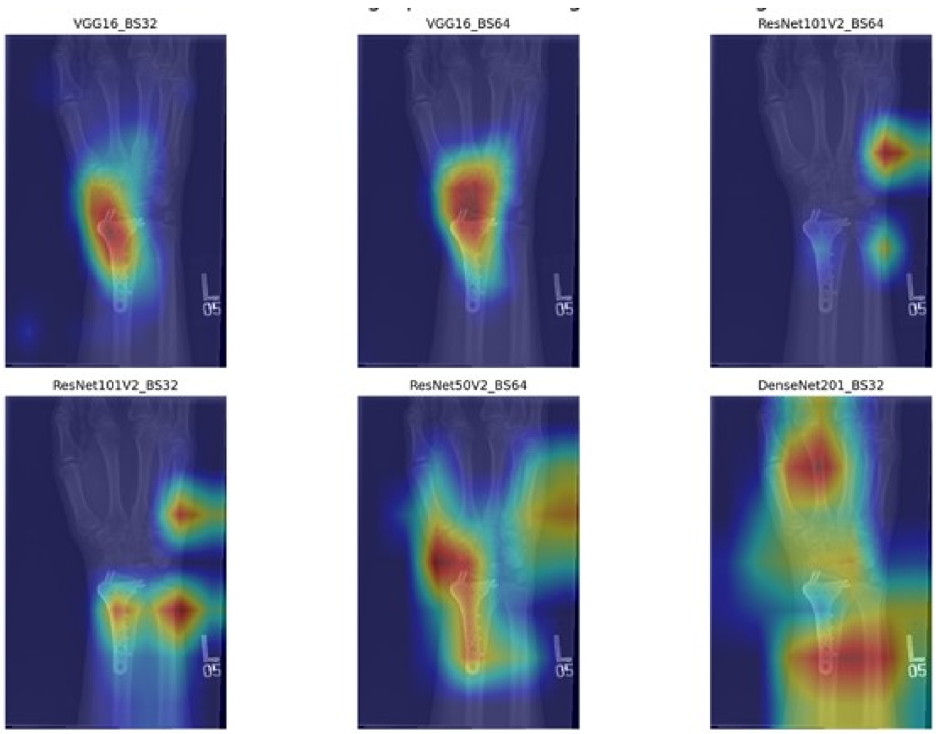

Figure 2.2: Visual explanation using a heatmap to highlight the most influential regions in the input image. [47]

- **Local Explanations**: These are used to provide an explanation for a specific instance, rather than generating a global explanation of the model.

- **Example-based Explanations**: Use data examples that have some relationship with the output generated by the model, often relying on visually similar instances in tasks involving image data. This category also includes counterfactual explanations, which show how small changes in the input could lead to a different model output.

The XAI approach is particularly relevant in critical areas such as medicine and agriculture, where decisions have a significant impact and therefore require a high level of reliability and transparency. . In recent years, XAI has been applied in various fields of natural sciences. In agriculture, XAI is being applied in crop yield estimation, crop type and trait classification, soil texture classification, disease detection, water flow and quality assessment, IoT-based smart farming systems, biomethane production, and agricultural land identification [48].

2.2.4 Feature-based Explanations

Feature-based XAI techniques assign importance to individual input variables of the system — such as pixels in an image or words in a text — in order to explain model decisions. Among the main techniques are [49]:

- **LIME (Local Interpretable Model-agnostic Explanations)**: An XAI technique designed to make the decisions of complex "black-box" models more understandable. It explains why the model produced a specific prediction for a given instance by generating perturbed variations of the input and observing the model's responses. A simple surrogate model (e.g., linear regression) is then trained to approximate the behavior of the original model in the perturbed region. This makes it possible to identify which features most influenced the decision. LIME is model-agnostic and local, but it suffers from drawbacks such as inconsistency between explanations (due to randomness) and sensitivity to parameter settings [50].
- **SHAP (SHapley Additive exPlanations)**: Based on Shapley value theory from cooperative game theory, SHAP assigns contribution values to each feature, evaluating how much each one influences the outcome compared to a baseline value. Unlike other methods, SHAP can be applied for both local (instance-level) and global (model-level) explanations, and it is model-agnostic. However, it has notable limitations, including high computational cost and reduced reliability in scenarios with strong feature collinearity [51].
- **GRAD-CAM (Gradient-weighted Class Activation Mapping)**: A method specifically designed for CNN, which leverages gradients to produce weighted activation maps. It computes the gradients of the target class score with respect to the feature maps of the last convolutional layer, weighting each channel by its impact on the prediction. The output is a heatmap overlaid on the original image, highlighting the regions most relevant to the model's decision. GRAD-CAM is widely used in computer vision applications, such as medical diagnostics, supporting transparency and user trust [52].

Related Work

In the work of Martin et al. an XAI-based system applied to digital agriculture was proposed, aiming to improve agricultural productivity and sustainability [53]. Using a large amount of data on climate, soil, and Indian crops, the study applied ML, such as XLNet, with the goal of generating precise recommendations for precision agriculture. Models such as SVM, RF, and neural networks were integrated with XAI techniques, such as Shapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), to promote transparency and interpretability in decisions. The results showed that the XLNet+SVM model had high accuracy in yield prediction, with a significant increase compared to traditional methods. The process of explaining AI decisions has the potential to increase farmers' trust and encourage the adoption of smart technologies.

In the work of Mehedi et al. a framework for detecting diseases in plant leaves was proposed, using transfer learning and XAI techniques [9]. The authors used three pre-trained models to identify 38 types of diseases in 14 plants. The study also used the LIME technique to explain the model's decisions, making the predictions more reliable and easier to interpret. The goal was to provide fast and accurate solutions for early disease detection. The framework proved to be efficient, with potential for application in agricultural systems.

XAI in agriculture is quite promising but faces obstacles. Key challenges include [54, 55]:

- **Imperfect Explanations**: AI explanations can be inaccurate, leading to incorrect interpretations, even when the predictions are correct.
- **Importance of Explainability in Decisions**: The effectiveness of XAI depends on providing explanations that are meaningful and useful for decision-making, ensuring that users can understand and trust the outputs of AI systems.
- **Limited Model Interpretability**: Many AI models remain complex and difficult for farmers to understand, which can reduce trust and hinder adoption.
- **Data Complexity**: Agricultural data includes geographic, sensory, and historical information, making implementations difficult [54].

2.3 Human-Computer Interaction

HCI is a field of study that analyzes how people interact with computers and how to develop technologies that facilitate these interactions, making them more intuitive and efficient. This field goes beyond usability, also encompassing cognitive, design, and economic factors [56].

Interaction occurs through user interfaces, which combine hardware and software to allow user input and system output. HCI focuses on the design, implementation, and evaluation of these interfaces, and is applicable to any domain involving interactions with computers [57].

HCI has both a theoretical and practical approach, covering concepts such as interface, interaction, impact of technology, user context, communicability, usability, accessibility, Gestalt, and interface design. Moreover, it applies evaluation methods such as questionnaires, brainstorming, interviews, "thinking aloud", usability testing, focus groups, observation, and surveys. These steps are fundamental for creating quality interfaces that meet user needs [58].

Some important aspects in the field of HCI, such as Prototyping, Design Thinking, and User Studies, guide the design process toward a more user-centered approach, ensuring that interface development aligns with the principles of usability, accessibility, and interaction.

2.3.1 Prototyping

The prototyping process plays a fundamental role in interface development and design, with approaches such as co-design and participatory design that directly involve users. Prototypes can be classified into two main categories: low-fidelity and high-fidelity, as illustrated in Figure 2.3 [59].

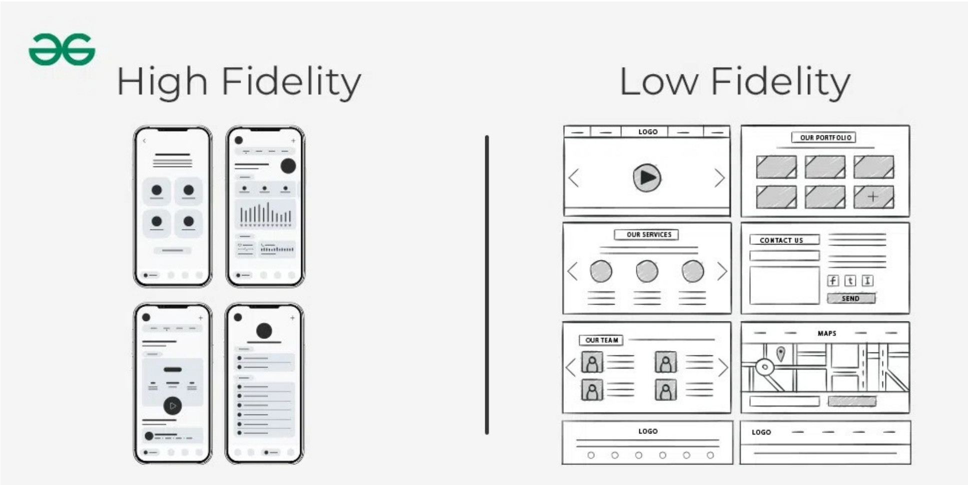

Figure 2.3: Low and High-Fidelity Prototypes

Low-fidelity prototypes are essential in the early design phases, as they allow a quick visualization of ideas and concepts without the need to develop a complex interface. They are usually created with simple materials such as paper, glue, and pen. This type of prototype is ideal for collecting user feedback and conducting usability tests and basic functionality evaluations, allowing quick and iterative adjustments. The "think aloud" protocol is often used, where users express their impressions and challenges during interaction. Furthermore, low-fidelity prototypes help validate storyboards and identify usability issues efficiently [60].

In contrast, high-fidelity prototypes are used in the final stages of the design process. These prototypes offer a more interactive version, closer to the final product. They are important for evaluating the usability and functionality of the design, representing the interface's appearance and behavior. Unlike low-fidelity prototypes, which are used to demonstrate concepts and ideas, high-fidelity prototypes implement visual elements and allow interaction, with clickable buttons and animations, enabling a more accurate assessment of the user experience. [61].

2.3.2 Design Thinking

Design Thinking is a general user-centered approach that can be applied to the development of applications, including in the context of HCI, where creative and rational thinking are used to solve problems. This methodology aligns user needs with what is technically feasible and economically sustainable. Consequently, Design Thinking proves to be an essential tool in HCI, where usability and user experience play a critical role [62].

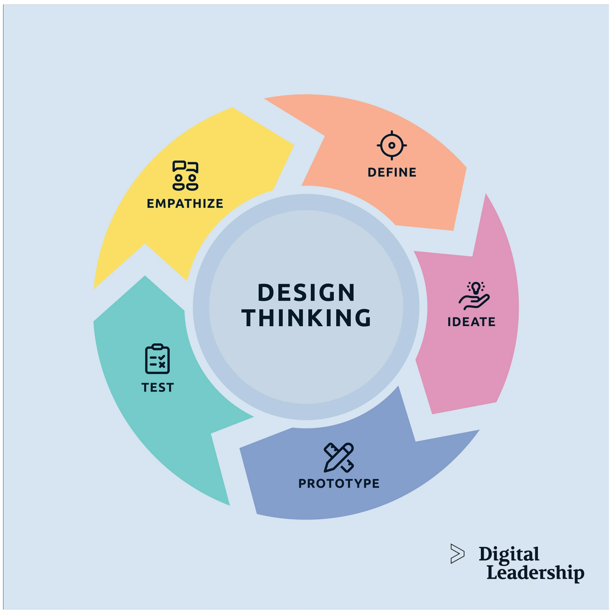

Figure 2.4: The five phases of the iterative Design Thinking process [63].

The process is typically structured in five iterative stages: Empathize, Define, Ideate, Prototype, and Test, as illustrated in Figure 2.4.

It is a collaborative and iterative process that involves the participation of various stakeholders such as designers, developers and end users. The process begins with the empathy stage, which seeks to deeply understand the users' needs, desires, and problems through research, interviews, and observation. Subsequently, in the definition stage, the collected data is analyzed and synthesized to identify the main problem to be solved. The next phase is ideation, in which the team generates a wide variety of ideas that are transformed into prototypes.

These prototypes allow the team to test and validate the proposed solutions. Finally, tests are conducted, where the prototypes are presented to users to collect feedback. It should be noted that the process is flexible, allowing previous stages to be revisited whenever necessary to refine the solutions [64].

2.3.3 User Studies

User Studies focus on evaluating systems or prototypes with real users. This phase involves testing and validation to ensure that the final design meets user expectations. By considering the user's perspective and using metrics defined in collaboration with stakeholders, user studies refine the design and address potential issues before implementation. This step is crucial for validating assumptions and ensuring that the product aligns with real-world user needs [65].

To achieve a comprehensive evaluation, user studies can employ both quantitative and qualitative approaches. Quantitative studies aim to measure user performance and system effectiveness using metrics such as task completion rates, error counts, and response times. These metrics provide statistical evidence of usability and efficiency, allowing comparisons between different interfaces and design iterations. In contrast, qualitative studies seek to capture users' subjective experiences, perceptions, and motivations through methods such as interviews, observations, think-aloud protocols, and focus groups. Qualitative data help explain why users behave in certain ways, offering deeper insights into their needs and challenges [66].

2.3.4 Bridging HCI and XAI

The use of XAI has the potential for fostering trust in decision-making systems based on artificial intelligence. To achieve this, the explanations generated by these systems must be communicated in a clear and accessible manner to the user. However, integrating AI-generated explanations into the interface presents significant challenges, such as technical complexity, increased cognitive load, risk of misinterpretation, and potential misuse of the provided information [67].

With the increasing integration of AI into agricultural technologies, the concept of Human-AI Interaction (HAI) (Human–AI Interaction) has emerged as an evolution of traditional HCI. Designing for HAI involves addressing unique challenges, as intelligent systems can adapt, learn, and make autonomous decisions, which may sometimes lead to unpredictable behaviors. Effective HAI design requires rethinking conventional HCI approaches to account for uncertainty, autonomy, and the learning processes of AI systems, making AI an active and integral component of the interaction itself. This perspective is particularly relevant for XAI, as explanations must be presented in ways that foster understanding, trust, and collaboration between humans and AI [68].

Given these challenges, the application of HCI concepts becomes crucial for developing interfaces that effectively convey explanations. Well-designed interaction models can enhance user understanding of system decisions, thereby promoting trust in the AI and its outcomes [69].

According to Liao et al., user-centered XAI relies on three main roles [70]:

- Guiding technical choices based on users' explainability needs;
- Identifying limitations of current XAI methods and informing the development of new approaches;
- Providing conceptual frameworks that support explainability aligned with human cognitive capabilities.

However, there is no one-size-fits-all solution that addresses the needs of all stakeholders. XAI techniques must be adapted to the target audience, considering that explainability needs vary significantly depending on users' goals, level of expertise, and usage context.

Evaluating a XAI system presents several challenges, especially when using post-hoc techniques, as they do not always accurately reflect the model's decision-making process. This can compromise the transparency of explanations and introduce biases in user studies. To address this issue, the literature proposes the use of objective metrics that assess the effectiveness of explanations for human users. Some of the most commonly used metrics are [71]:

- **Explanation Goodness** – Evaluates the technical quality of the explanation by the researcher, considering attributes such as clarity, completeness, and usefulness of the generated explanation.
- **Explanation Satisfaction** – Measures the user's subjective satisfaction with the received explanations, assessing whether the user feels they have adequately understood the system after the explanation.
- **Mental Models** – Assesses the user's understanding of how the AI system works, measuring the accuracy and completeness of the mental model formed by the user.
- **Curiosity** – Evaluates the reasons motivating the user to seek explanations, classifying triggers of curiosity such as surprise, the need for prediction, or verification of understanding.
- **Trust Scale** – Measures the user's level of trust in the AI system, considering dimensions such as reliability, predictability, and perceived safety in using the system.
- **Human-AI Performance** – Assesses the performance of the combined human and AI system on a task, measuring effectiveness, efficiency, and the quality of human-machine collaboration.

2.3.5 User Study Metrics

In HCI, it is common to measure attitude-related data; user experience metrics are used to assess whether progress is moving in the right direction toward achieving goals, guiding product decisions. These metrics are generally collected on a small scale using timers and checklists. Some of these metrics include [72]:

- **Effectiveness**: Task completion rate, error rate.
- **Efficiency**: Time spent on the task.
- **Satisfaction**: User satisfaction, perceived ease of use, visual appeal, likelihood to recommend.
- **Error Rate**: Indicator of task success, representing the frequency of user mistakes or usability issues.

When conducting a user study in HCI, different metrics can be used depending on the study's goals. In this case, the study focused on evaluating cognitive workload and usability through subjective measures such as questionnaires. These metrics can be broadly divided into subjective measures (such as questionnaires) and objective measures (such as behavior analysis or physiological data). In this study, the main interest was in assessing the cognitive workload imposed by the system. Some commonly used subjective assessment tools include [73, 74]:

- **NASA Task Load Index (NASA-TLX)**: Questionnaire used to measure workload, evaluating six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. Subscales consist of horizontal lines divided into 20 intervals, with bipolar descriptions (e.g., "Low/High") and scale marks every 5 units, allowing scores from 0 to 100. Perceived workload can be analyzed with or without individual weighting of subscales (referred to as "Raw NASA-TLX").

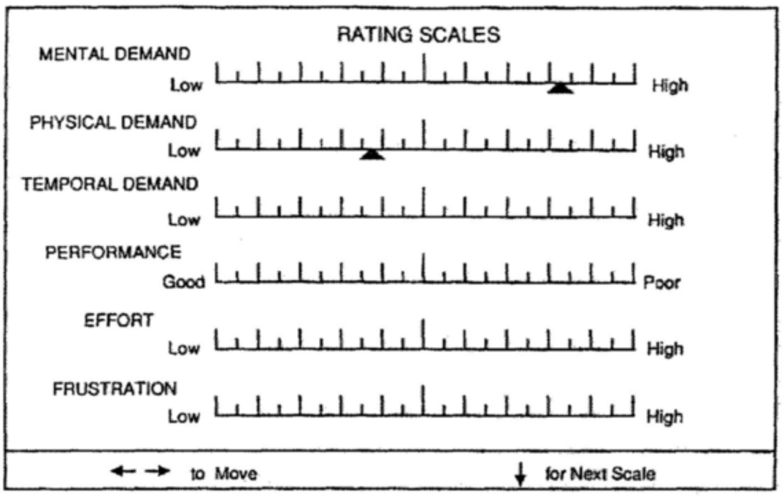

Figure 2.5: NASA Task Load Index [75]

- **Dundee Stress State Questionnaire (DSSQ)**: Used to measure stress related to cognitive load, considering three aspects: task engagement, distress, and worry. It employs 11 state factors associated with three dimensions: Task Engagement (Energetic Arousal, Tense Arousal, Hedonic Tone), Stress (Intrinsic Motivation), and Worry (Self-Attention, Self-Esteem, Confidence and Control, Concentration, Task-Related Cognitive Interference, Task-Unrelated Cognitive Interference). Each scale consists of eight items.

Factor	Scale	Example item	Scale α	3-week retest r[1]
Task Engagement	Energetic arousal	I feel... Vigorous	.80	.14
	Task Interest	The content of the task is interesting	.75	-
	Success Motivation	I want to perform better than most people do	.87	-
	Concentration	My mind is wandering a great deal (negative item)	.85	.52
Distress	Tension	I feel... Nervous	.82	.48
	Hedonic Tone (low)	I feel... Contented	.86	.42
	Confidence-Control (low)	I feel confident about my abilities	.80	.54
Worry	Self-Focus	I am reflecting about myself	.85	.41
	Self-Esteem	I am worrying about looking foolish (negative item)	.87	.66
	CI (task-relevant)	I have thoughts of... How much time I have left	.78	.37
	CI (task-irrelevant)	I have thoughts of... Personal worries	.86	.49

Note. CI = Cognitive Interference. [1]Data from Matthews et al. (1999a; *N* = 112).

Figure 2.6: Dundee Stress State Questionnaire [76]

- **Instantaneous Self-Assessment (ISA)**: A unidimensional subjective workload assessment technique. Participants rate their perceived workload at predefined intervals during task execution, enabling real-time evaluation. Participants are continuously asked to self-assess workload on a scale from 1 ('underutilized') to 5 ('overloaded').

Rating	*Workload*	*Description*
1	Under-utilised	Nothing to do. Rather boring
2	Relaxed	More than enough time for all tasks. Active on the task less than 50% of the time
3	Comfortably busy pace	All tasks well in hand. Busy but stimulating pace. Could keep going continuously at this level
4	High	Non-essential task suffering. Could not work at this level very long
5	Excessive	Behind on tasks; losing track of the full picture

Source: Adapted from Kirwan et al. (1997)

Figure 2.7: Instantaneous Self-Assessment [77]

- **Bedford Workload Scale**: A decision-tree-based scale estimating the user's available mental capacity. It consists of a hierarchical decision tree where participants are asked whether (1) the task could be completed, (2) the workload was tolerable, and (3) the workload was satisfactorily manageable without reduction. Depending on the decision, participants rate perceived workload on a scale from 1 ('negligible workload') to 10 ('task abandoned').

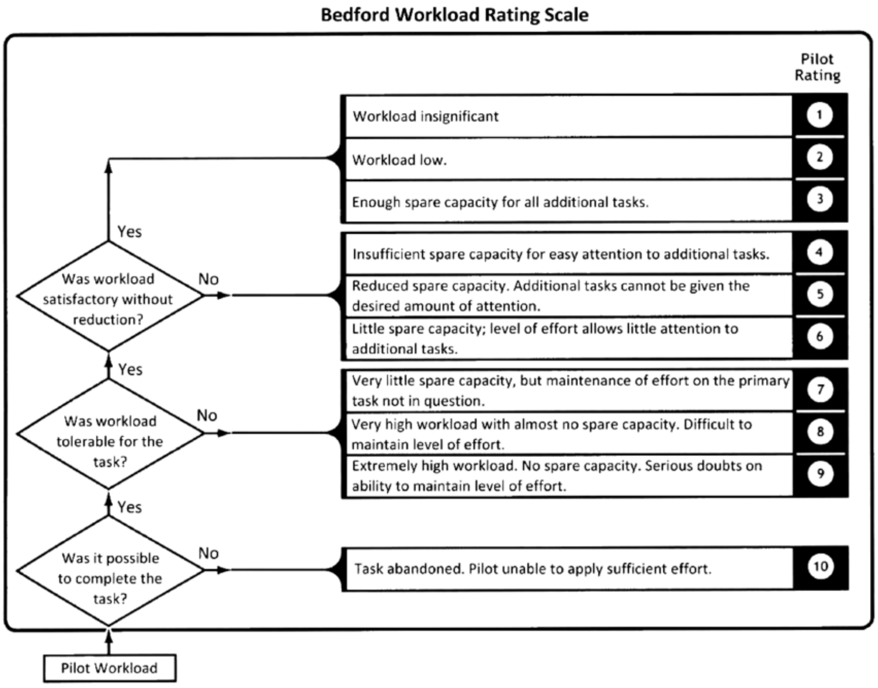

Figure 2.8: Bedford Workload Scale [78]

- **System Usability Scale (SUS)**: A usability metric; some studies use it as an indirect indicator of cognitive load. It is a ten-item questionnaire for subjective usability assessment. Each item is a statement (e.g., "I found the system unnecessarily complex"), and participants use five-point Likert scales (from 'strongly disagree' to 'strongly agree') to indicate agreement. The SUS has a predefined procedure to calculate a total score ranging from 0 to 100.

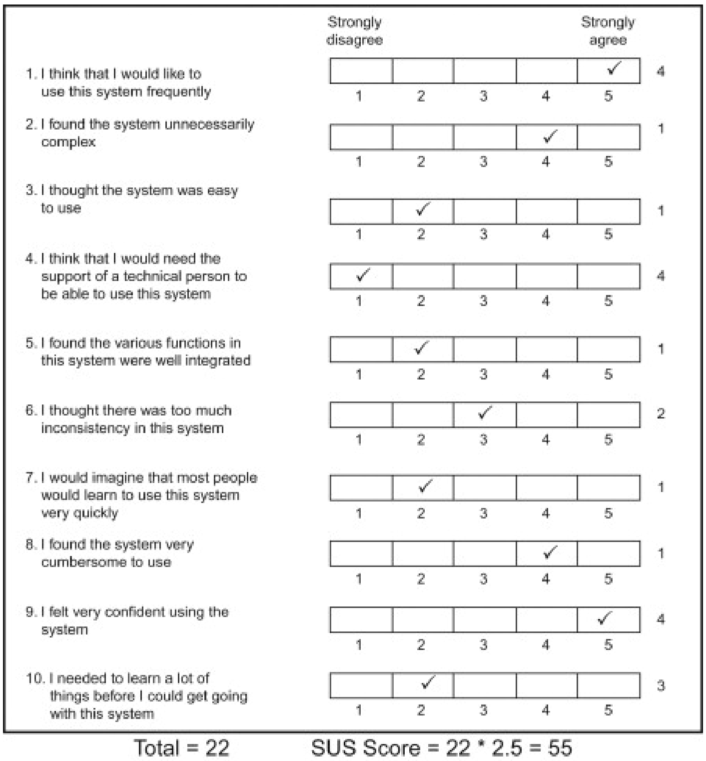

Figure 2.9: System Usability Scale [79]

- **Rating Scale Mental Effort (RSME)**: The RSME consists of a 150-mm vertical line with markings from 0 to 150 on the left side and nine workload levels labeled on the right. Participants rate their perceived workload on this scale and may exceed the predefined marks.

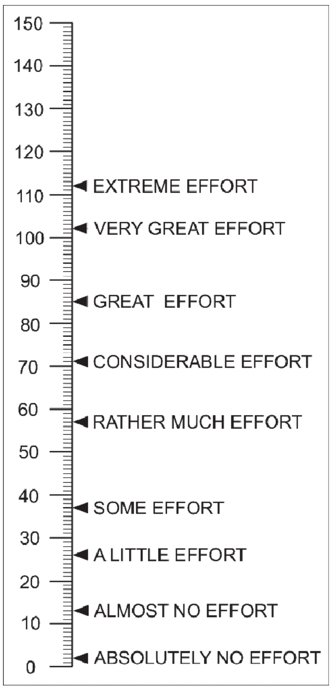

Figure 2.10: Rating Scale Mental Effort [80]

- **PaaS scale**: The PaaS scale is a subjective measure of mental effort during learning, used in Cognitive Load Theory. It consists of a simple scale where the user reports their perceived mental effort after completing a task.

In solving or studying the preceding problem I invested

1. very, very low mental effort
2. very low mental effort
3. low mental effort
4. rather low mental effort
5. neither low nor high mental effort
6. rather high mental effort
7. high mental effort
8. very high mental effort
9. very, very high mental effort

Figure 2.11: PaaS scale [81]

2.3.6 HCI in Agriculture

In digital agriculture, the use of HCI has seen increasing interest, integrating technologies into traditional processes. Interfaces designed for agriculture go beyond screens, including features that connect physical and virtual environments. This occurs, for example, through multimodal interfaces that use voice, gestures, and touch, facilitating farmers' interaction with systems. Additionally, these interfaces allow farmers to access real-time information about plant needs, assisting in decision-making and encouraging the adoption of new technologies [82].

The application of HCI to promote technology adoption in agriculture, with a focus on usability and User experience (UX), is particularly important for older farmers or those with limited familiarity with technology. Many face difficulties due to interfaces that are overly complex or disconnected from their practical needs. In this context, applying HCI concepts such as user-centered design, usability testing, and adaptation to specific contexts helps create more intuitive and accessible solutions. By reducing the learning curve and ensuring tools align with field demands, HCI not only facilitates technology adoption but also strengthens farmers' trust in digital innovations. This shift transforms resistance into engagement, boosting productivity and efficiency [83].

For instance, the work of Ibrahim et al. explores the integration between HCI and farmers, aiming to improve the user experience in the agricultural sector [84]. Through a literature review, the study identified trends, challenges, and research gaps in HCI applied to agricultural interfaces. As a result, the authors proposed key HCI design principles adapted to the characteristics of the agricultural environment:

- **Context-Aware Adaptability:** Tailor agricultural user interfaces to the context and environment in which they are used, considering factors such as weather conditions, location, and user preferences.

- **Sensory Integration:** Incorporate sensory cues, such as visual, auditory, and haptic feedback, to enhance user interactions with agricultural interfaces, ensuring effective communication of information even in noisy or visually challenging settings.
- **Task Efficiency and Simplification:** Streamline interface interactions to promote task efficiency, minimizing the cognitive load on users during complex agricultural activities.

To validate these principles, the literature review identified studies that employed surveys, interviews, and usability tests, gathering insights into user preferences and challenges. The study demonstrated the successful implementation of HCI in agriculture, leading to significant improvements in user engagement and task performance. Furthermore, the challenges associated with adopting HCI in agricultural environments were analyzed, providing practical insights for future developments in the field.

The study by Van de Zande et al. evaluates a precision irrigation tool based on HCI for resource-limited farmers [85]. The work highlights the need for affordable solutions to improve irrigation efficiency in regions such as East Africa and the Middle East and North Africa, where fully automated systems are unfeasible due to high costs and lack of infrastructure. To address this demand, the authors propose a model that combines automatic scheduling with manual operation, allowing farmers to use manual valves while receiving recommendations via mobile messages. Tests conducted in Kenya, Jordan, and Morocco demonstrated that this approach can enhance water and energy efficiency at a reduced cost, providing a viable alternative for small and medium-sized producers. The results indicate that the adoption of this technology can contribute to agricultural sustainability and facilitate the transition to more efficient irrigation practices.

Applying HCI principles in agriculture faces several challenges. Among the main obstacles identified in the literature are [86]:

1. **Heterogeneity of agricultural practices**: Agriculture presents significant variation in crop types and user profiles across different regions. This requires the development of interfaces capable of adapting to the specific needs of each user.
2. **Limited technological infrastructure in rural areas**: Infrastructure in rural environments can be unstable and difficult to access, limiting the development of interfaces that rely on real-time data.
3. **Demographic diversity of users**: The range of user profiles, from agronomists to farmers with lower technological literacy, makes it challenging to create intuitive and accessible interfaces for all.
4. **Low adoption of digital technologies**: Resistance to adopting digital tools constitutes a significant barrier to implementing new technologies in agriculture.
5. **Integration with existing systems**: Ensuring compatibility and interoperability with machinery and technologies already used by farmers represents a key technical challenge.

6. **Lack of standardized usability metrics**: The absence of consistent benchmarks complicates the objective evaluation of the effectiveness and efficiency of agricultural interfaces.

Chapter 3

Developed Solution

This chapter describes the user-centred methodology followed in the design of the interface supporting Explainable Artificial Intelligence (XAI) outputs in a smart farming context. It presents the design process, the considerations behind key interface decisions, and the iterative development of the prototype that was later evaluated with agronomists.

3.1 General Approach

This work was structured into two complementary strands: the development of a proof of concept (PoC) and the empirical investigation that employed this PoC to address the research questions. In the first strand, a web application was developed that incorporated explanations generated by XAI, applying concepts from Human Computer Interaction (HCI). In the second strand, the research focused on the use of the PoC as a platform, with an emphasis on co-design, enabling users to actively participate in the development process. This approach increased the likelihood that the resulting solution would effectively meet the needs of the target audience [87].

As a starting point, an application developed in previous work was used as a reference for creating the initial prototypes (see Section 3.2.1). This allowed identifying expected functionalities and better understanding the usage context. From these initial prototypes, a functional version of the system was developed, incorporating the main features and integrating the AgriUXE platform, responsible for detecting plant diseases through Artificial Intelligence (AI) techniques and generating explanations using XAI.

Based on this functional prototype, three distinct scenarios for presenting explanations were defined. The first scenario displays only the final output of the AI, serving as a control condition to assess how users interpret and trust the system when no explanation is provided. The second scenario presents visual explanations, such as heatmaps (e.g., Grad-CAM), which highlight the regions of the image that the model considered most relevant. This type of explanation was selected because it is widely used in computer vision and allows domain experts to verify whether the model's focus aligns with their own expertise. The third scenario employs example-based explanations, chosen for their alignment with case-based reasoning, where specialists often justify conclusions by comparing new instances with similar past cases. This scenario makes it possible to evaluate how contextualization through similarity influences user understanding and trust in AI outputs. After interacting with the three scenarios were presented to users in test sessions, where they could interact with the interface and experience the different explanation formats [88, 89].

After interaction, a post-task questionnaire was applied to evaluate perceived usability and user experience for each scenario. This questionnaire captured metrics such as trust in the AI decision, cognitive load, and satisfaction with the explanations provided. Finally, a collaborative design phase was conducted, in which participants, through a drag-and-drop supported tool, could assemble the explanation layout they considered most appropriate. This final activity allowed qualitative feedback to be collected directly from users about their preferences and expectations.

3.2 Previous Work

For the development of this dissertation, two previous projects served as a foundation. AgriDash is a mobile application designed for vineyard monitoring and developed based on HCI principles, while AgriUXE is a platform that integrates XAI techniques to generate explanations for agricultural predictions.

3.2.1 AgriDash

AgriDash is a mobile application developed based on HCI principles, in partnership with Associação de Viticultores do Concelho de Palmela (AVIPE) (Figure 3.1). Designed specifically for viticulture, this collaboration ensured a usability-focused interface, with a design tested and validated by agronomists and viticulturists, providing intuitive interactions. The application allows viewing fields through satellite images, with the possibility to overlay customizable data layers, such as the Normalized Difference Vegetation Index (NDVI) index, for monitoring vegetation health and soil conditions.

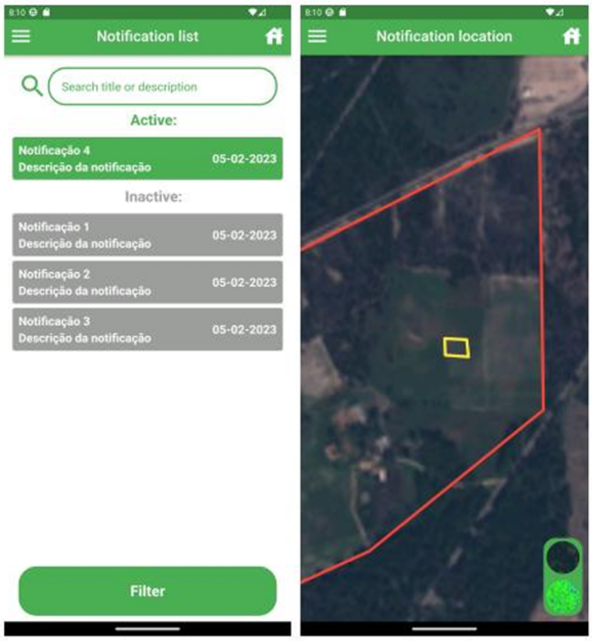

Figure 3.1: AgriDash: view of the mobile application showing the notification list and satellite imagery.

Additionally, AgriDash includes a real-time notification system to alert about issues such as pests or nutritional deficiencies, linking each alert to georeferenced areas on the map. For data analysis, the application provides interactive charts and tables, transforming raw data like climate forecasts from IPMA. The app also allows direct communication between agronomists and farmers via a text chat, facilitating clarification of doubts. In addition, agronomists can register treatments with detailed recommendations on inputs and quantities to be applied.

The application was developed in *Flutter*, allowing portability to both Android and iOS systems. The *backend* was implemented in Node.js with Express, providing an API to serve data to the application, while storage is handled in a PostgreSQL database

The disease detection feature was incorporated through integration with the AgriUXE platform, which enables efficient analysis of plant images to identify potential phytosanitary problems. This integration also allows presenting detailed explanations about the performed prediction, contributing to greater transparency in the diagnosis.

3.2.2 AgriUXE

For the XAI functionalities, the AgriUXE platform is used, which enables integration of explanations through an Application Programming Interface (API).

AgriUXE is a platform that uses multimodal data, such as Internet of Things (IoT) sensor data, satellite images, and weather records, combined with XAI techniques focused on multiple types of explanations: feature-level explanations (e.g., Shapley Additive exPlanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME) techniques), similarity-based explanations, and counterfactual explanations.

The platform architecture, illustrated in Figure 3.2, organizes itself into four main stages. Initially, multimodal data collection and storage from satellites, field sensors, and meteorological data occurs, where based on data volume, a defined set of pre-processing tasks is performed at the edge or sent directly to the cloud. The second stage comprises data analysis, generating insights through statistical reports and visualization techniques that form the Multimodal Data Explanations, in addition to the pre-processing required to make the data inference-ready.

In the third stage, inference and fusion, each unimodal data type is processed by a specific model, from which multiple explanations are extracted including model-agnostic approaches, model-specific approaches, transparent explanations, and post-hoc explanations. After all model predictions, final fusion explanations are computed, considering how data sources correlate and the prediction errors from each source, thus forming the Multimodal Inference Explanations.

Finally, all generated explanations are consolidated in the Explainability Orchestrator, where a dynamic complexity algorithm classifies each explanation into levels 0 to 5, from non-technical explanations ideal for farmers to detailed technical explanations for specialists. The output is an explanation dictionary with associated metadata, which is made available through an API for third-party systems, allowing filtered consumption of explanations by complexity, task, or multimodal type.

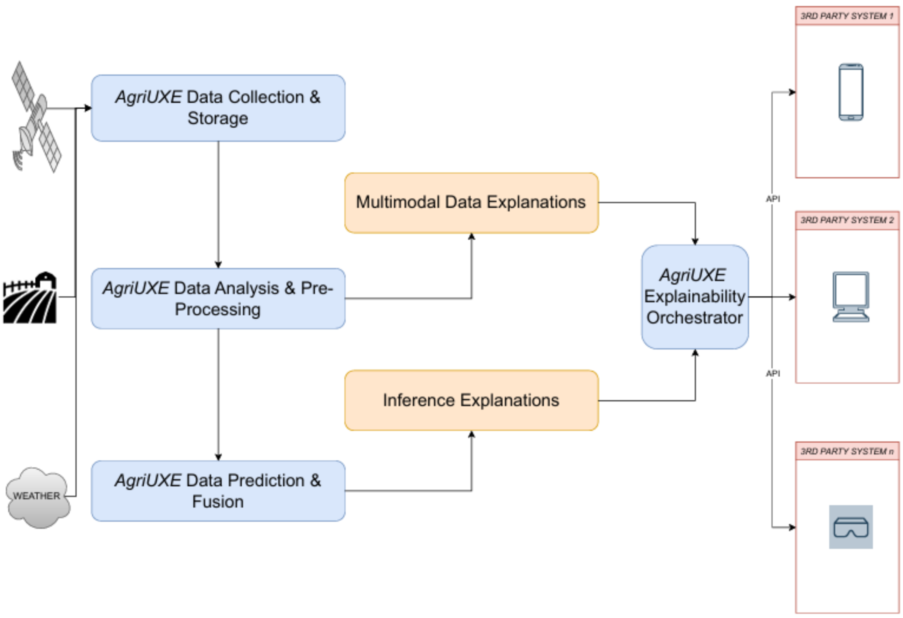

Figure 3.2: AgriUXE architecture

3.3 Low fidelity Prototypes

The development of the prototypes began with the system contextualization: the target audience was defined and its main functionalities established. This allowed obtaining a clear view of the most relevant interface features. During the requirements gathering process, the AgriDash application, a mobile app developed in previous projects, was used as a reference and baseline for development.

Initially, low-fidelity prototypes were developed with the goal of exploring and validating initial interface concepts. This type of prototype helps define the visual structure and layout, making it possible to analyze the interface flow before moving on to functional development.

For development, the program Figma[1] was used, a widely used interface design tool. Three distinct prototypes were created, each highlighting specific application features based on different approaches to organization and navigation.

To ensure accessibility and relevance of the application for agricultural stakeholders, the low-fidelity prototypes focused on the following (Figures 3.3a, 3.3b, 3.3c):

- **Prototype 1 (Fig. 3.3a):** A centralized interface, with all functionalities organized in a clear and accessible way, allowing quick access to the main tools. This includes satellite image visualization, sending these images for analysis, and a list of markers.
- **Prototype 2 (Fig. 3.3b):** Emphasis on satellite imagery visualization, providing a comprehensive view of crops for detailed monitoring.
- **Prototype 3 (Fig. 3.3c):** Vertical scrolling layout for broad field visualization, combined with a compact menu for rapid access to secondary functions.

[1]Figma is a collaborative interface design tool. Available at: https://www.figma.com

(a) Prototype 1: Centralized interface with quick access to tools.

(b) Prototype 2: Focus on satellite image visualization.

(c) Prototype 3: Vertical scrolling layout with compact menu.

Figure 3.3: Low-fidelity prototypes for the application's interface.

3.4 Functional Prototype

After analyzing the prototypes, the development of the functional prototype was based on Prototype 2 (Figure 3.3b), which stood out for emphasizing the platform's main functionality: monitoring agricultural areas through satellite imagery. Although the platform is intended for both farmers and agronomists, its design prioritizes agronomists, who are primarily responsible for analyzing and managing the monitored areas. For this reason, Prototype 2 was selected, as it gives greater prominence to the map feature, making geospatial data more accessible and easier to interpret. The interface also allows for the visualization and management of registered plots and markers, facilitating both the analysis and monitoring of agricultural areas.

The front-end was implemented using the Next.js framework, allowing server-side rendering (SSR) features that improve performance and scalability. Integration with the

AgriDash system's Node.js API enabled user management, authentication, and access to existing functionalities. The application was localized into Portuguese to ensure accessibility for agronomists in Portugal.

Figure 3.4 shows the overall system diagram, illustrating communications between the Node.js API and its connection with AgriUXE.

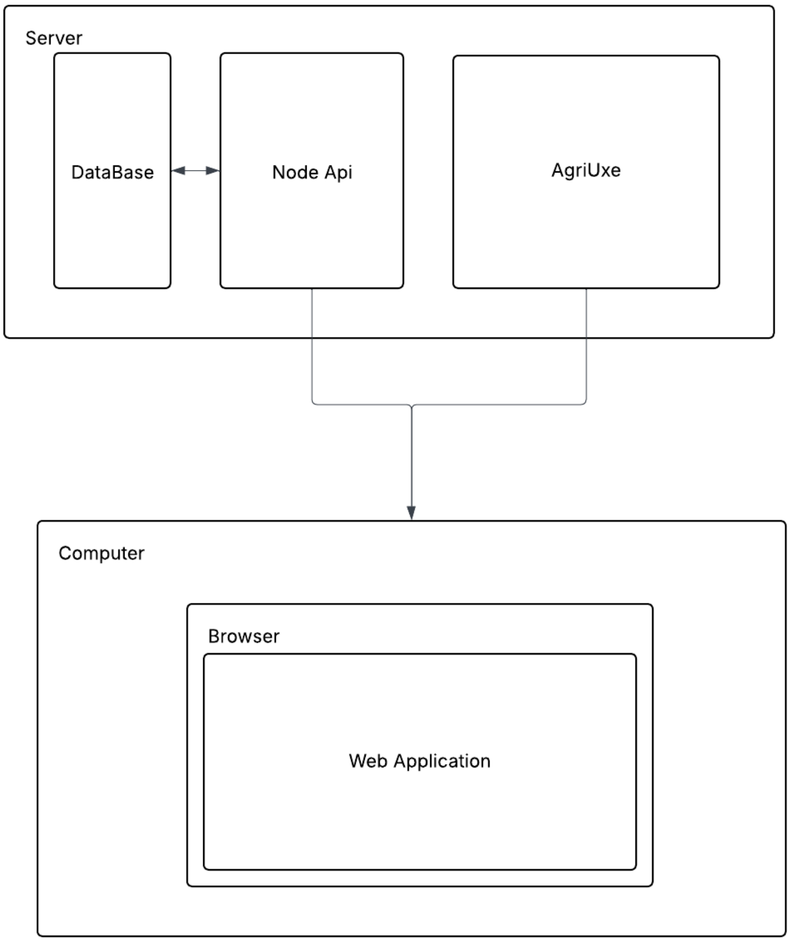

Figure 3.4: Overall system diagram showing main modules and integrations.

The functional prototype offers several features, including map visualization, user creation, marker listing, weather data, and pest and disease detection. Development was supported by an undergraduate student who was supervised during implementation.

3.4.1 Map and Marker Management

The map feature, shown in Figure 3.5, was implemented using the `react-leaflet` library, which provides interactive components for rendering maps in React applications. Tools for adding markers and drawing polygons were used, enabling the marking of areas of interest, such as plots and farms. Users can also switch between different map layers (satellite and street view), offering greater navigation flexibility.

To further enhance user experience, the component leverages the browser's geolocation data to automatically redirect the map to the user's current location. Additionally, if a user has a previously registered area in the database, the map uses the stored coordinates to set the initial focus, ensuring that relevant plots and farms are immediately visible.

The component also includes integrated features to assist agronomists, such as a coordinate search in the top-right corner to quickly locate an area. The map allows creating plots to highlight areas of interest, facilitating field management.

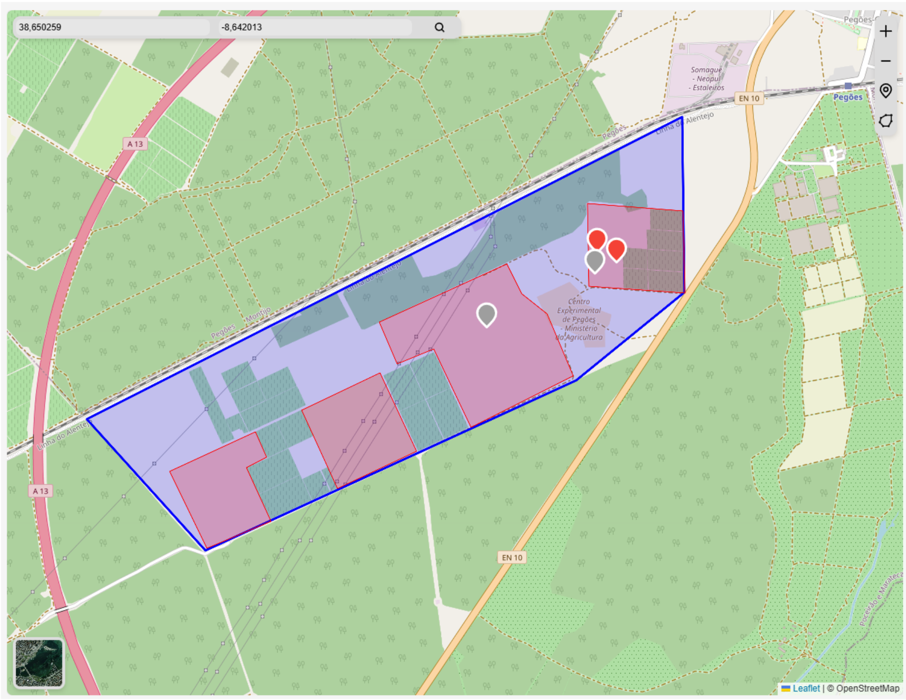

Figure 3.5: AgriDash Web Application: Map component with search, layer switching, and plot creation features.

To manage the data and interactions on the map, a dedicated `MapContext` was created in the front-end. This context handles state management for markers, farms, parcels, and regions, providing functions to:

- Fetch and filter markers using `GET /markers`.
- Create new markers with images via `POST /markers`.
- Toggle marker activity using `PUT /markers/status`.
- Retrieve farms and parcels (`GET /farms`, `GET /parcels`) and create new ones (`POST /farms/create`, `POST /parcels/create`).
- Obtain available regions with `GET /regions`.

The context ensures that all interactions with the API are centralized, and any changes to the data are automatically reflected in the map component without requiring page reloads, providing a seamless and interactive user experience.

Markers can be created on the map to register points of interest, allowing farm stakeholders to pinpoint relevant locations in their crops by filling in a title, description, and disease, as well as attaching images to document important information (Figure 3.6). Once submitted, the marker data is sent to the backend via an API, which stores the information in the database, associating each marker with the user's registered region. This ensures that markers are persistently saved and correctly linked to the relevant plots or farms.

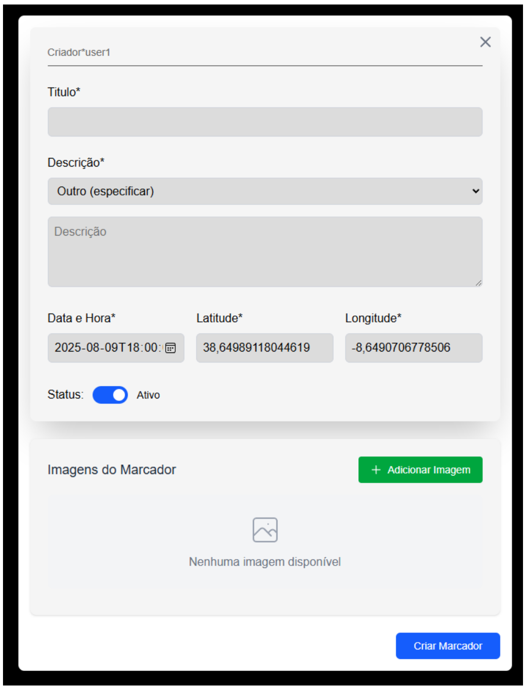

Figure 3.6: Form for creating and editing markers on the map.

The marker list is connected to the backend via API. Users can apply filters by time range, status, or disease type, which dynamically update both the list and the map, hiding markers that do not meet the criteria. Selecting a marker from the list automatically centers and zooms the map on that location, providing quick access to detailed information. This functionality enhances usability, allowing users to efficiently manage and navigate a potentially large number of markers.

Figure 3.7: Marker list with filters and map navigation.

The marker list component leverages the `MapContext` to access the markers already fetched for the map. This approach allows the list to display, filter, and navigate markers without making additional API calls, ensuring consistency between the map and list views and improving performance. Any updates made to markers—such as creation, editing, or status changes—are automatically reflected in both the map and the list, thanks to the centralized state management provided by the context.

3.4.2 Weather Data

The weather data component (Figure 3.8) shows IPMA[2] weather forecasts updated daily via an API. Users can select precipitation or evapotranspiration metrics and filter by location—currently, the application supports Setúbal, Palmela, and Torres Vedras. Data is presented in line charts, enabling long-term analysis.

[2]https://api.ipma.pt/

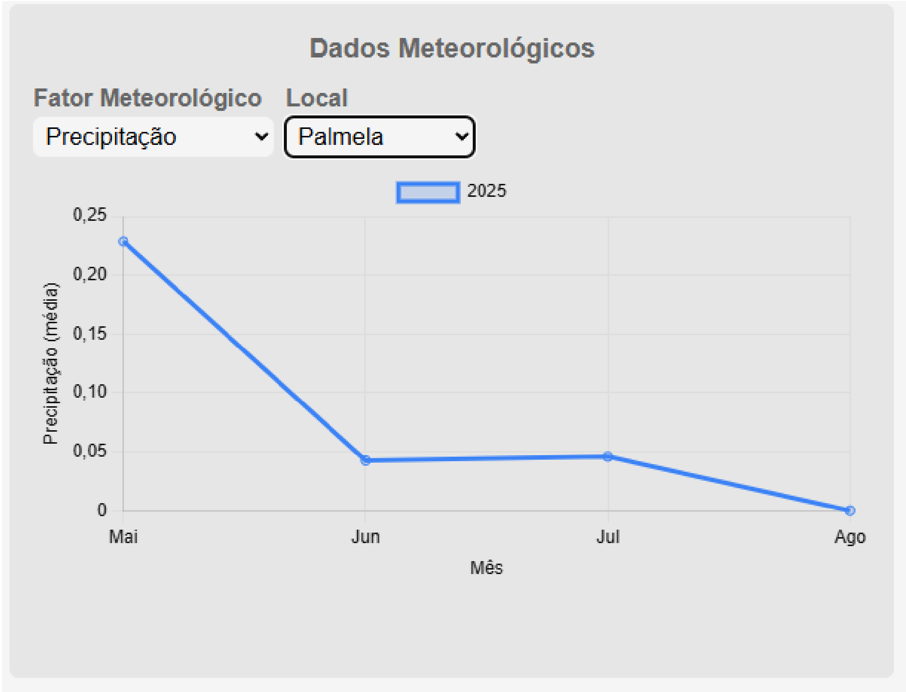

Figure 3.8: Graphical visualization of weather data by location and type.

The weather data component consumes information from the existing Node.js API, which provides precipitation and evapotranspiration values for specific locations. The main endpoints used are:

- **Setúbal**:
  - `/data/setubal/precipitation` – precipitation data
  - `/data/setubal/evapotranspiration` – evapotranspiration data
- **Palmela**:
  - `/data/palmela/precipitation` – precipitation data
  - `/data/palmela/evapotranspiration` – evapotranspiration data
- **Torres Vedras**:
  - `/data/torres-vedras/precipitation` – precipitation data
  - `/data/torres-vedras/evapotranspiration` – evapotranspiration data

These endpoints are accessed through the `MeteorologyContext`, which centralizes the fetching and state management of weather data. By using the context, the component can update the charts dynamically and provide a consistent user experience without redundant API calls.

The Node.js API runs an automated routine every 24 hours to fetch the latest meteorological data directly from the IPMA service. This routine downloads the CSV files corresponding to the supported regions (Setúbal, Palmela, and Torres Vedras), processes their contents, and stores the parsed data in the local database. Maintaining a local copy of the information ensures fast access, reduces dependency on external requests, and preserves historical records for long-term analysis.

3.4.3 User Management

User registration was adapted based on information from the AgriDash system, prioritizing compatibility with the existing API. Since not all farmers have email, registration is performed using a username, password, and role (farmer or agronomist), as illustrated in Figure 3.9. Upon submission, the registration data is transmitted to the backend via the API, where it is validated and stored in the database.

Figure 3.9: User registration screen with fields for name, password, and role.

User registration is processed through the endpoint `POST /users/create`, which receives the user's name, password, and role (farmer or agronomist) and stores the information in the database after validation. The front-end uses the `UserContext` to manage authentication and registration state, ensuring that a newly registered user can log in immediately without redundant API calls.

The front-end also leverages the `UserContext` to manage the user state, including login, logout, and registration. After login, the user's data is stored in a cookie called `token`, which allows session persistence even after closing the browser. Thus, when returning to the site, the user remains authenticated without needing to log in again, until the token expires or is manually removed.

A Next.js middleware was implemented to control access to routes based on authentication status. It checks for the presence of the `token` cookie and applies redirections according to the route type. Public routes (`/login`, `/register`) are accessible without authentication, while private routes require the user to be logged in. When an unauthenticated user attempts to access a private route, the middleware automatically redirects them to the login page. Conversely, authenticated users trying to access public routes are redirected to the home page, preventing access to the login and registration pages after authentication. This mechanism ensures both security and coherent navigation throughout the application. The middleware works in conjunction with the `UserContext`, which manages the authentication state in the front-end, ensuring a consistent and secure user experience.

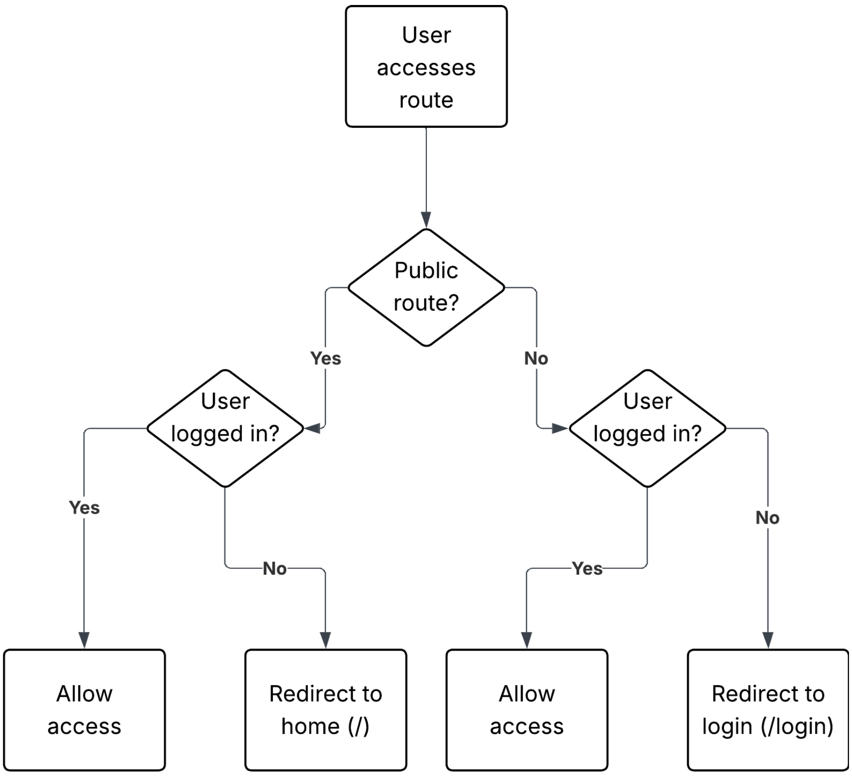

Figure 3.10: Flow of authentication and route redirection managed by the Next.js middleware.

Furthermore, there is a functional distinction between user roles. Agronomists have full access to the system, being able to create and manage parcels and agricultural regions, while farmers have restricted access, being able only to view registered areas and create markers. This distinction ensures appropriate permission control and reflects the hierarchy of responsibilities in using the platform.

3.4.4 Disease Detection with AgriUXE

For disease detection, the platform was integrated with AgriUXE, allowing users to upload crop images for automated analysis and result interpretation. The interface includes a drag-and-drop component for image submission, as illustrated in Figure 3.11.

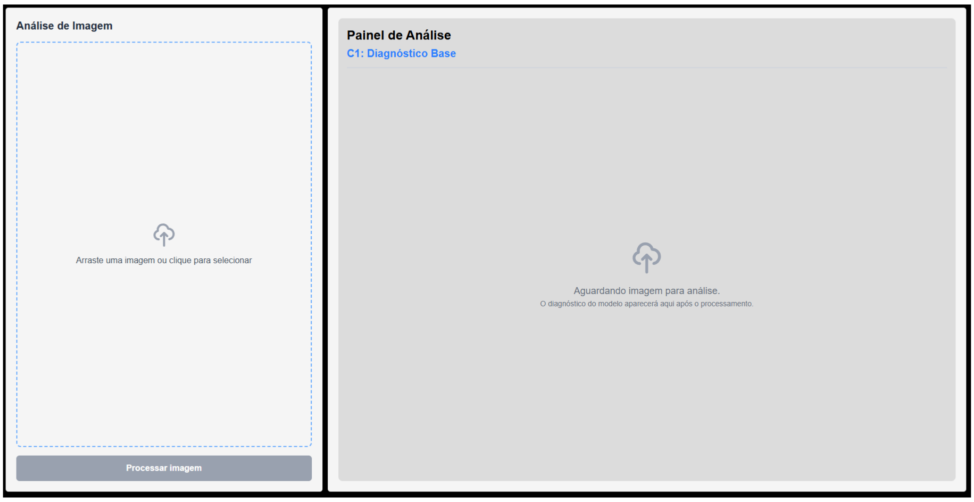

Figure 3.11: Analysis component with image upload and display of detection and explanation results.

After submission, the image is processed by the *Next.js server-side API*, which converts it to *Base64* format and publishes it to a Kafka topic managed by AgriUXE. The platform then performs disease prediction and generates associated explanations using XAI techniques.

AgriUXE returns these explanations in *JSON* format, containing multiple types of information tailored to different user profiles (*stakeholders*), such as farmers, agronomists, and machine learning experts. Each JSON entry specifies the explanation type (*inference*, *visualization*, *statistics*), the modality (*text*, *image*), the technique used (e.g., Prediction, LIME, GradCam), and the explanation content (descriptive text, numeric value, or image), allowing detailed and personalized interpretation of the results.

By centralizing communication and processing on the server side, the client (*client-side*) remains lightweight and focused solely on presenting the results. Figure 3.12 summarizes the complete workflow, from image submission to explanation visualization, highlighting the interaction between the front-end, the *Next.js server-side*, and the AgriUXE ecosystem.

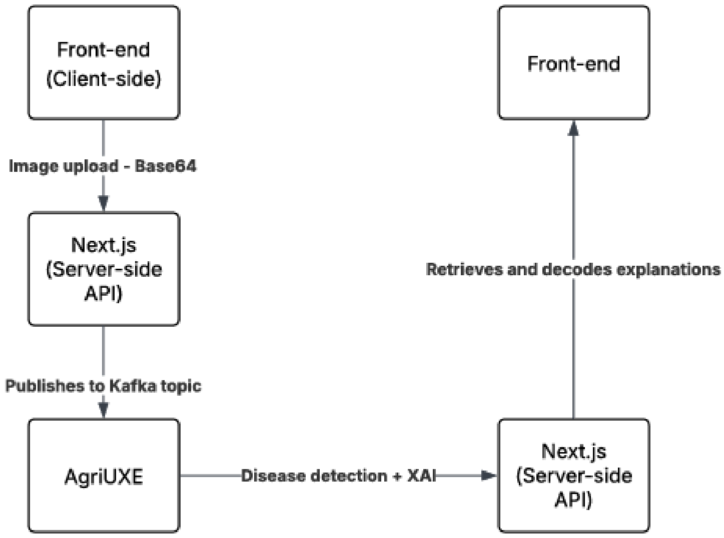

Figure 3.12: Workflow of disease detection and retrieval of explanations with AgriUXE integration.

This architecture provides several benefits, including a lightweight and responsive front-end, secure handling of external communications via the *server-side API*, persistent storage of explanations for future analysis, and seamless integration of disease detection results into the platform's overall interface.

3.4.5 Integrated Functional Prototype

As shown in Figure 3.13, the functional prototype interface integrates the map, marker list, filters, and weather data, providing a comprehensive view for the user. From this prototype, different explanation presentation scenarios were defined for the next research stage.

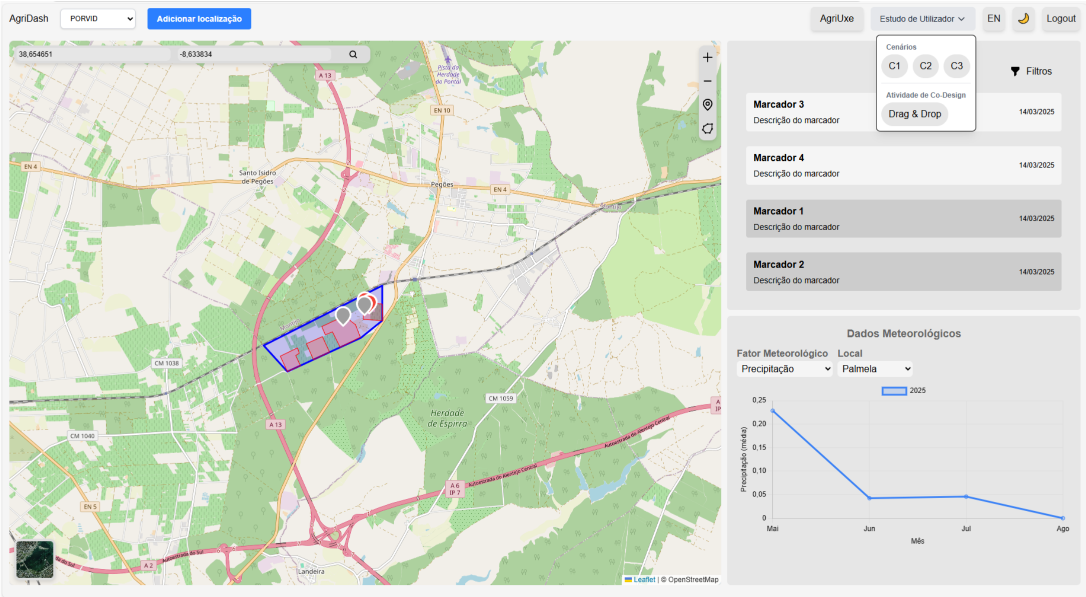

Figure 3.13: General interface of the functional prototype integrating main features.

Chapter 4

Evaluation

This chapter presents the evaluation conducted to investigate the impact of different explanation techniques generated by XAI on trust, reasoning, and decision-making among farm domain stakeholders. The study aimed to assess how the proposed system supports decision-making in real agricultural workflows, providing insights into the usability and interpretability of the explanations.

4.1 User Study

User studies play a pivotal role in HCI, as they aim to systematically analyze and understand how different design aspects can influence participants' perception, reasoning, and behavior under controlled conditions. As experimental methods carried out in controlled environments, these studies provide high internal validity, ensuring that the observed results indeed reflect the effects of the manipulations rather than external factors. The primary focus lies in the systematic comparison of different conditions, such as alternative forms of presenting feedback or visual explanations. Furthermore, they offer empirical evidence to validate (or challenge) early-stage interaction concepts [90].

4.2 Objective and Hypothesis

The primary objective of the user study was to understand how different XAI techniques affect and influence reasoning, trust, and the integration of the system into the workflow within an agricultural context. The intention was to collect data that would support the design of an interface capable of meeting the needs of the target audience, while also improving the clarity and transparency of the outputs produced by XAI-powered solutions.

The guiding hypothesis was that certain forms of explanation, such as saliency maps or example-based explanations, could enhance trust in the diagnosis, and assist participants in more appropriately calibrating their confidence in the predictive model, as the reasoning process of the AI becomes more transparent and interpretable.

4.3 Experimental Design

The study was designed to collect and integrate both qualitative and quantitative data, as the initial intention was to obtain objective evaluations—such as those regarding the clarity and usefulness of the explanations—alongside subjective insights related to participants' understanding, trust, and perceived usability of the system-provided explanations. However, since the number of participants was not sufficient to support a robust statistical analysis, the focus of the evaluation was primarily qualitative. Each participant interacted with all experimental conditions, which were presented in a counterbalanced order using a Latin square design to mitigate potential order effects.

Participant	**C1 (Control)**	**C2 (Feature-based)**	**C3 (Example-based)**
P1	Image A	Image B	Image C
P2	Image B	Image C	Image A
P3	Image C	Image A	Image B

Table 4.1: Distribution of experimental conditions per participant (3x3 Latin square).

4.3.1 Mixed-Methods Study Design

In scientific research, studies can generally be classified as quantitative or qualitative, depending on the type of data collected and the methods used for analysis. Quantitative studies focus on numerical data and employ statistical analyses to identify patterns and trends. In contrast, qualitative studies emphasize understanding experiences, perceptions, and contexts, using descriptive data such as interviews, observations, and participant reports to explore meanings and interpretations. These approaches are complementary, and many studies combine quantitative and qualitative methods to gain a more comprehensive understanding of the phenomenon under investigation [91].

- **Quantitative Studies**: Collect numerical data, use statistical analyses, and allow generalization from samples to populations.
- **Qualitative Studies**: Collect descriptive data, explore perceptions and contexts, and use interpretative analyses to identify patterns and meanings.

4.3.2 Recruitment and Participants

Participants were recruited through partner institutions with which established research collaborations were already in place. The target audience was defined based on the practical application of the tool, directed toward agronomists, so that it could be efficiently integrated into their daily workflow. Accordingly, professionals in the field of agronomy with appropriate academic training and relevant practical experience were selected. The study was initially planned to include approximately 20 volunteers, a number justified by the qualitative nature of the research, whose objective was to achieve thematic saturation, the point at which new data no longer provide additional insights, given the homogeneity of the group and the narrow focus of the investigation [92].

Recruitment resulted in a group of nine qualified experts. The participants had extensive professional experience in agronomy, averaging 7.3 years in relevant roles. The sample was composed predominantly of Agronomists/Agricultural Engineers (7 out of 9), complemented by one Agricultural Researcher and one Agricultural Technician. Among the main benefits reported by participants were the opportunity to directly influence the development of new tools for their professional domain and early access to innovative technologies. In addition, it was ensured that a detailed and anonymized summary of the results would be made available to all participants and their respective institutions, thereby promoting transparency and knowledge sharing.

4.3.3 Instantiated Use Case in the Prototype

The study was conducted using the functional prototype integrated within the web application. The interface was localized into Portuguese to facilitate usability and correspond to the native language of the participants. The platform simulated a Deep Learning (DL)-based tool for plant disease diagnosis.

The explanations used in the study were cached by the AgriUXE platform, in order to avoid potential issues related to network connectivity and latency. This strategy ensured a smoother experience for participants, keeping their attention focused on the core aspects under investigation, namely the quality and usefulness of the explanations.

Three main experimental conditions were evaluated:

Scenario 1 — No explanation: In this scenario, the interface shows only the analysis result performed by the AI, displaying the detected disease name on the plant without any visual or textual justification of how the decision was made. This scenario serves as a control, allowing assessment of user perception in the absence of explainability.

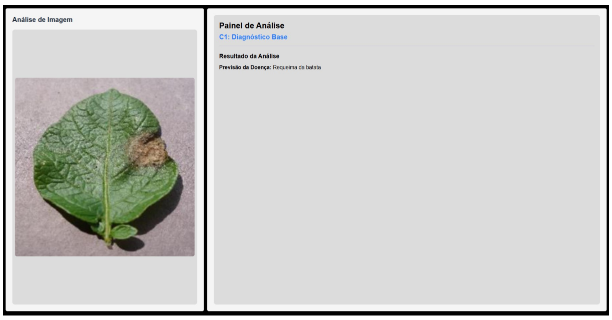

Figure 4.1: Image from Scenario 1, showing disease detection without visual explanation.

Scenario 2 — Visual explanation (heatmap): Here, the interface displays an output image with a heatmap overlaid on the plant photo. This heatmap is generated using the Grad-CAM (Gradient-weighted Class Activation Mapping) technique and highlights the regions of the image that most influenced the model's decision, allowing a visual interpretation of the AI reasoning process.

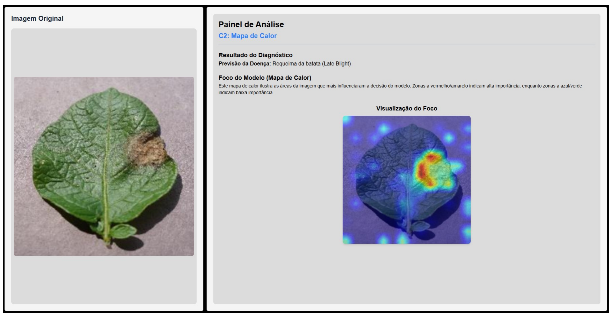

Figure 4.2: Image from Scenario 2, showing disease detection without visual explanation.

Scenario 3 — Example-based explanation: In this scenario, besides the analysis result, the interface presents a reference image used by the model to justify its decision. The displayed image corresponds to another similar case previously identified with the same disease. This exemplifies a similarity-based explanation, a type of example-based XAI approach, where the model provides a comparable instance to help the user understand its reasoning. This allows the user to visually compare the current input with a similar case and better interpret the model's decision.

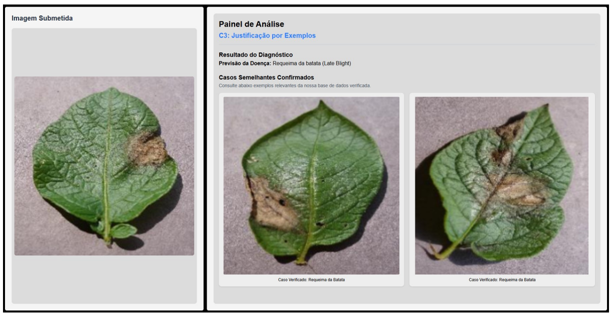

Figure 4.3: Heatmap overlaid on the plant image, highlighting regions most relevant to the model's decision (Scenario 2).

Three plant images were used: a grape leaf with black rot, a potato leaf with late blight, and an apple leaf. During the explanation generation process, for each image, a case was created in which the model produced an incorrect classification. These predictions were employed in a confidence calibration scenario, allowing for the assessment of how participants would react to error conditions—that is, whether they were able to identify and reject an incorrect prediction.

(a) Healthy apple leaf (b) Potato leaf with late blight (c) Grape leaf with black rot

Figure 4.4: Examples of leaves used in the analysis during the user study.

4.3.4 Procedure

The study was conducted remotely, lasting approximately 45 minutes per session. All interactions were recorded in both audio and video format, with the consent of the participants. Experimental scenarios were presented in a counterbalanced order to reduce potential biases. The procedure was structured into the following stages:

1. **Onboarding (5 min)**: introduction to the study, signing of the informed consent form, and a brief tutorial on the system.

2. **Experimental tasks (approx. 7.5 min per condition)**:

   - Interaction with each case was conducted remotely, with screen sharing of the prototype enabled only during the execution of the scenarios. Participants did not share their screens while completing the questionnaires, thus avoiding external pressure on their responses.
   - In each scenario, participants were provided with an image of a plant showing signs of disease. They accessed the web application and uploaded the image into the corresponding scenario.Upon clicking to process image the AI produced a diagnosis, which was either presented alone or accompanied by an explanation, depending on the experimental condition (e.g., saliency map or similar examples).
   - During the interaction, participants verbalized their reasoning using the *think-aloud* protocol. The facilitator asked probing questions (e.g., "What are you observing?", "How does this explanation affect your confidence?", "How could this result be integrated into your workflow?") to gather additional qualitative insights.
   - At the end of each condition, participants completed a short questionnaire, including measures of trust, cognitive load, and satisfaction with the explanation.

3. **Final comparison (5 min)**: Participants ranked their preferences among the explanations used in the study.

4. **Co-design (10 min)**: In the final stage, participants were provided with a co-design tool composed of pre-created components (e.g., "AI Prediction," "Visual Explanation," and "Chat with Assistant") along with free-drawing features. They could drag and drop components to build their ideal interface or sketch custom elements. The entire process was accompanied by the *think-aloud* protocol. To further explore design motivations, the facilitator posed non-directive probes (e.g., "I noticed you did not include [component]"). This process allowed for a deeper understanding of the reasoning behind participants' design choices.

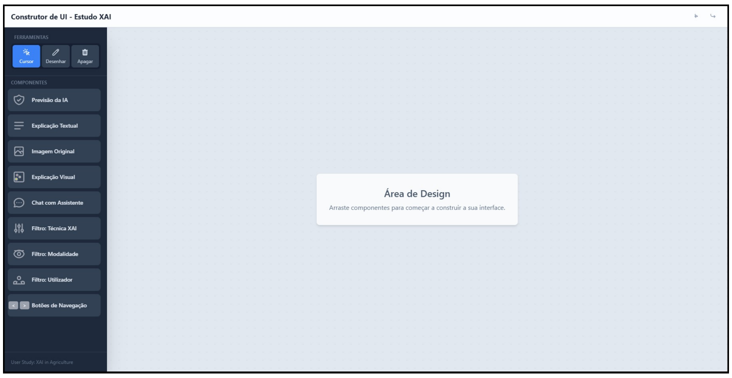

Figure 4.5: Co-design tool provided to participants, including pre-created components and a free-drawing area.

5. **Debrief (1 min)**: participants were thanked for their contribution, and any remaining questions were addressed.

All collected data were anonymized to ensure participants' privacy. Recordings were later transcribed for qualitative analysis through thematic analysis techniques, while questionnaire data were analyzed quantitatively.

4.4 Questionnaires

To evaluate participants' perceptions and understanding of the AI explanations, several standardized questionnaires were administered throughout the study:

- **Demographics Questionnaire (Form 1)**: Collected participants' age, gender, education, professional role, experience in agriculture, familiarity with digital tools and AI concepts, and comfort using technology in agricultural contexts. This contextual information helped interpret subsequent responses and ensured the sample represented the target population.

- **Scenario-specific Questionnaires (Forms 2–4)**: After each experimental condition, participants completed a questionnaire assessing trust, confidence, perceived system reliability, explanation satisfaction, cognitive load, and objective understanding. These instruments included:

  – Likert-scale items adapted from Trust in Explainable AI Scale (TXAI), Perceived Stress Scale (PaSS) Cognitive Load Scale, and Epworth Sleepiness Scale (ESS).
  – Forward simulation questions (e.g., predicting how the system would behave under slightly different conditions) to evaluate mental models and comprehension of the AI reasoning.
  – Open-ended questions allowing participants to verbalize thoughts, perceptions, and difficulties encountered.

- **Final Comparative Ranking**: At the end of the study, participants ranked the three explanation types (no explanation, visual/heatmap, and example-based) according to preference, perceived usefulness, and clarity. This informed which explanation methods were most effective in supporting trust and understanding.

The questionnaires were designed to provide both quantitative and qualitative data. Quantitative metrics allowed calculation of averages and standard deviations for trust, cognitive load, explanation satisfaction, and confidence, while qualitative responses captured participants' reasoning and subjective experiences.

Data Analysis

The study was originally designed to collect and integrate both qualitative and quantitative data, aiming to obtain objective evaluations—such as clarity and usefulness of the explanations—alongside subjective insights related to participants' understanding, trust, and perceived usability of the system-provided explanations. However, the number of participants was not sufficient to support robust statistical analysis, and therefore the focus of the evaluation was primarily qualitative.

Quantitative measures were still collected to provide contextual information and descriptive statistics, while qualitative responses offered deeper insights into participants' perceptions, reasoning, and experiences. The collected data were analyzed using a sequential explanatory strategy, in which quantitative analysis provided an initial overview and qualitative interpretation guided a more detailed understanding of user interactions.

The following metrics were employed:

- **Trust (Trust in Explainable AI - TXAI)**: This scale was used to assess how different types of explanations influence participants' trust in automated decisions, ensuring the notion of "appropriate trust," where users know when to trust the system and when to exercise caution.

- **Cognitive load (Paas Scale, short version)**: This scale was used to assess the perceived mental effort of using the interface or interpreting the system's explanations, verifying whether they facilitate or hinder understanding.

- **Explanation satisfaction (Explanation Satisfaction Scale - ESS)**: This scale was used to evaluate the user's perception of the usefulness, clarity, and understanding of the explanations generated by the AI system.

- **Objective understanding (mental model questions)**: This was used to assess whether participants truly understood the AI's reasoning, ensuring that the subjective perception of understanding corresponded to actual comprehension.
- **Final preference (comparative ranking)**: This was used to identify which types of explanations users prefer, guiding future design decisions to promote greater acceptance, trust, and understanding.

In addition, qualitative data were gathered through the *think-aloud* protocol, enabling participants to verbalize their perceptions of the interface and explanations. Semi-structured interviews were also conducted, allowing the identification of factors relevant to trust, understanding, and design preferences.

The questionnaires captured preference rankings and responses to mental model questions, as well as assessments of cognitive load and explanation satisfaction. This enabled a clearer understanding of how participants might react if some of the predictions presented unexpected results.

Data analysis followed a sequential explanatory strategy. Descriptive statistics were first generated from the questionnaires, providing a quantitative overview to guide the qualitative interpretation. This integration allowed participants' perceptions to be contextualized with greater precision.

Thematic analysis followed the approach proposed by Braun and Clarke [93]. The recordings were transcribed and reviewed to identify relevant excerpts. These excerpts were grouped into code sets, which were subsequently labeled, checked, and refined until the final themes were consolidated.

4.5 Results and Discussion

This section presents the findings of the user study conducted with agronomy professionals, along with their discussion. The aim was to evaluate the perception and usefulness of different XAI explanation modalities, specifically heatmaps and example-based explanations, within agricultural diagnostic workflows, analyzing their impact on trust, cognitive load, and decision-making.

4.5.1 Participant Characterization

The study included nine participants, mostly Agronomists or Agricultural Engineers, aged between 23 and 48 years ($\bar{x} = 32.4$). Professional experience ranged from 0.5 to 21 years ($\bar{x} = 7.3$), with vineyards being the primary crop for seven out of the nine participants.

Participants self-assessed their technological proficiency as high ($\bar{x} = 5.8$ on a 1–7 scale). Familiarity with artificial intelligence was moderate ($\bar{x} = 4.0$ on a 1–5 scale), while specific knowledge of XAI ranged from low to moderate ($\bar{x} = 2.4$). These findings suggest that the group possesses strong digital skills but remains at an early stage of being familiar with explainable AI techniques, making it particularly suitable for this study (Figure 4.6).

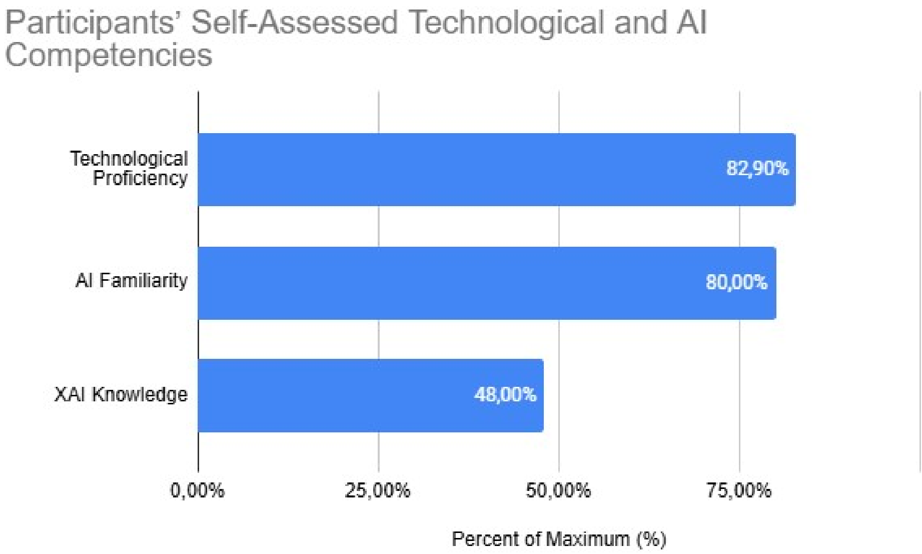

Figure 4.6: Self-assessed technological proficiency, familiarity with AI, and knowledge of explainable AI among participants.

4.5.2 Quantitative Results

Table 4.2 presents the average values for the key metrics evaluated in each scenario.

Metric	**C1 (Control)**	**C2 (Heatmap)**	**C3 (Examples)**
Decision Confidence (1–7)	5.10	5.60	**5.90**
Composite Trust (1–5)	3.65	3.89	**3.98**
Cognitive Load (1–9)	2.78	2.89	**2.56**
Preference (1st Choice)	0	2	**7**

Table 4.2: Comparative results across the three explanation scenarios.

The data reveal a clear preference and higher perceived performance for Scenario 3 (Example-based Explanations). This scenario achieved the highest scores in both Decision Confidence and Composite Trust, as well as the lowest cognitive load, indicating that participants found this type of explanation easier to understand and use. This perception is further supported by the fact that 7 out of 9 participants (77.8%) selected C3 as the most useful, while C1 (Control) was not chosen as the first option by any participant (Figure 4.7).

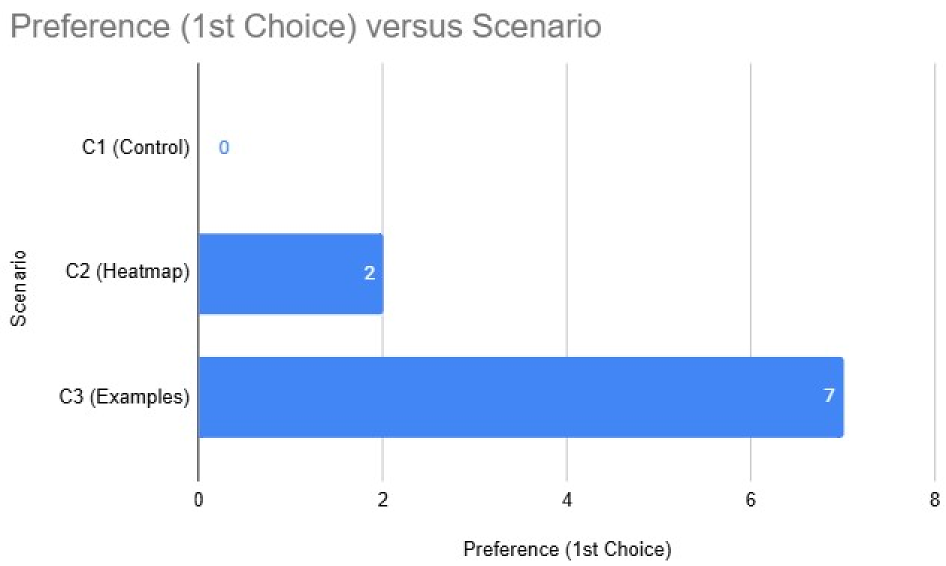

Figure 4.7: Participants' preferences across the three explanation scenarios.

The analysis of participants' perceptions suggests that the tool functioned as a support system rather than an oracle, reinforcing prior knowledge and enhancing diagnostic confidence. This interpretation is corroborated by participant P8, who explicitly linked their confidence to the perceived quality of the example database. Thus, case-based explanations not only make the model's reasoning more transparent but also serve as a complementary resource to validate the agronomist's decision-making process.

This type of explanation is often applied in high-stakes domains such as healthcare and law [94]. The user study demonstrates its promising potential in the agricultural context, particularly by incorporating visual attributes into the explanations.

An important feature of explanations is their ability to help users identify when the model is incorrect. To assess this, misleading diagnoses were introduced in one of the scenarios.

- In **Scenario 1 (Control)**, **0%** of participants correctly rejected the incorrect diagnosis.
- In **Scenario 2 (Heatmap)**, **0%** of participants correctly rejected the incorrect diagnosis. The visual explanation apparently did not effectively indicate that the diagnosis was wrong.
- In **Scenario 3 (Examples)**, **33%** of participants identified and rejected the incorrect diagnosis. Presenting similar examples allowed some participants to question the model's suggestion, demonstrating a notable improvement in confidence calibration.

4.5.3 Qualitative Results and Thematic Analysis

The integrated analysis of quantitative and qualitative data enabled the consolidation of three central conclusions that directly address the research objectives. The qualitative analysis followed a systematic approach based on the reflexive thematic analysis method proposed by Braun and Clarke (2006)[93]. All session recordings were fully transcribed to allow for a detailed examination. Through the review of these transcripts, an initial codebook was developed by identifying and labeling relevant excerpts with descriptive codes. These codes were then iteratively grouped into related topics through a collaborative process and subsequently refined and synthesized into the final overarching themes presented in the results.

Within this analytical strategy, the quantitative data collected through questionnaires were used to contextualize and complement the qualitative insights. Descriptive statistics derived from these instruments served to illustrate and add precision to the qualitative narrative, thereby enriching the interpretation.

Key Findings 1: Diagnosis as a Starting Point for Action

Participants consistently interpreted the system's output not as a final verdict, but as the **beginning of an investigation and intervention process**. As P1 summarized: *"the disease has been identified, now what are we going to do?"*. For most participants, the main value of the tool lay in guiding subsequent agricultural management actions, rather than merely providing a diagnosis. This need for **actionability** became evident during the *co-design* sessions, where several participants emphasized the need for practical recommendations to support the treatment or prevention of identified issues.

Key Findings 2: Example-Based Explanations Improve trust Calibration

The data revealed a significant difference in the effectiveness of the explanations. Example-based explanations were perceived as more intuitive and aligned with the agronomists' cognitive process, being described as a *"complementary opinion"* that validated their own reasoning. This was reflected in tangible results: Scenario 3 was the only one in which users successfully identified incorrect diagnoses (33% correct rejection),indicating potential preliminary evidence of the effectiveness of this type of explanations for trust calibration.

In contrast, Scenario 2 (heatmaps) proved prone to **misinterpretations** (e.g., P8 interpreted it as a temperature map) and potential **automation bias**, where visually persuasive explanations may lead users to accept errors without sufficient critical evaluation. This highlights the limitations of explanations that focus on *"where"* the model looks rather than *"why"*.

Key Findings 3: The Importance of an Interactive and Exploratory Approach

The co-design process made it clear that users do not desire a passive system, but rather an interactive investigative tool. There was consensus on the importance of forming an initial independent opinion before using AI to question, refine, and deepen their conclusions. Experienced users emphasized that static explanations alone are insufficient; trust is built through **active dialogue** with the system. This finding highlights the need to design not a mere answer provider, but an **exploration environment**.

Actionability and Workflow Integration

The qualitative analysis revealed that participants did not perceive the AI diagnosis as a final verdict, but rather as a decision support tool integrated into a broader and contextual diagnostic process.

- **Actionable Next Steps:** The value of an explanation was judged by its ability to guide subsequent actions. The need for **treatment recommendations** emerged as the main utility criterion, with participants such as P1 asking, "*the disease has been identified, now what should we do?*" and P2 suggesting the inclusion of "*recommendations [...] for example, warning that this is a rapidly spreading disease*".
- **Integration into Existing Workflow:** The typical process consisted of: 1) generating a **personal hypothesis**, 2) using the AI as a **second opinion**, 3) assessing severity in the field, and 4) deciding on a treatment. The tool was seen as a quick first screening or a "*second opinion*" (P3, P6) that accelerates and confirms the initial steps, but not as a substitute for the final contextual evaluation and user decision-making.
- **Recommendation for Co-Design:** Participants expressed interest in an interactive tool that allowed them to actively consult the model, e.g., requesting "*more example images*" (P1). The implementation of an **AI chatbot** (P1, P3, P4, P5, P6) was proposed as a central mechanism to provide additional information that participants felt was missing, such as specific treatment recommendations.

4.6 Design Implications

The results outline a clear path for designing future XAI-powered solutions in agriculture, guiding them toward a more effective decision support workflow. Based on the results of the user study at hand, four design principles are proposed as follows:

4.6.1 P1: Support Active Investigation and Dialogue

The system should be designed as a second opinion rather than an oracle. This can be achieved through:

- **Conversational Interfaces:** Integrate chatbots that allow users to ask, "give me more example images, because I wasn't satisfied with these", question "if it indicated what had been the, the area that, like in the previous case" or inquire "with this problem, what could I do?", as expressed by participants during testing.
- **Data Exploration:** Allow filtering, comparing, and navigating examples in a non-linear manner.

4.6.2 P2: Anchor Explanations in Domain Context

Explanations should be enriched with critical contextual data for the expert:

- **Agricultural Metadata:** Automatically integrate information about weather conditions, crop phenological stage, field treatment history, etc., alongside examples or diagnoses.

4.6.3 P3: Prioritize Actionability over Pure Explanation

The system should bridge the gap between diagnosis and actionable outcomes.

- **Integrated Recommendations:** Automatically link each diagnosis to relevant treatment options, recommended products, dosages, or preventive actions.

4.6.4 P4: Favor Intuitive and Robust Explanations

Explanation design should avoid modalities that, despite technical popularity, are prone to misinterpretation (such as opaque heatmaps). Priority should be given to:

- **Example-Based Explanations:** Results indicate a tendency toward the effectiveness and user preference for example-based explanations, suggesting their potential as a primary modality in similar contexts.
- **Simplicity and Clarity:** Ensure that explanations remain self-explanatory and understandable without requiring specialized AI knowledge.

4.7 Limitations and Future Work

It is important to acknowledge the limitations of this study. The sample size (N=9), although qualitatively rich, restricts the statistical generalization of the results. Nevertheless, the data obtained allowed for the identification of significant trends in users' behavior and preferences regarding XAI explanations. Future research should involve a larger and more diverse group of participants, including different experience levels, technological profiles, and geographic regions, to validate and extend the applicability of the identified design principles.

Additionally, the scenarios were conducted in a controlled environment, which may not fully reflect the complexity and conditions of a real-world agricultural workflow, such as time pressures, variable technological infrastructure, and environmental distractions. Future investigations should evaluate the interface and explanations in real-world, long-term contexts to better understand the practical effectiveness and utility of the proposed solutions.

Another relevant point is the limited scope of explanations tested in the scenarios. The study focused on three types of explanations (example-based explanations, heatmaps, and control outputs), but other types of explanations may reveal additional insights and have significant potential in supporting decision-making. Future work could explore different explanation modalities, combinations of interfaces, and adaptive approaches that tailor explanations to the user's profile and context.

Finally, developing a functional prototype that incorporates multimodal data and interactive or conversational features will allow a more robust validation of the usability and utility of XAI interfaces, promoting greater adoption and trust in smart farming tools.

Chapter 5

Conclusions and Future Work

This chapter presents the main conclusions of the dissertation, revisits the research questions, and summarises the insights obtained from the design and evaluation of the prototype. It also reflects on the study's limitations and outlines opportunities for future research and system development.

5.1 Summary of the Work

The work developed in this dissertation aimed to investigate how explainable interfaces can be designed and organized in smart farming systems to support agronomists in interpreting AI-generated diagnoses. To explore this question, a web application was developed in collaboration with AVIPE and integrated with the AgriUXE platform, enabling the presentation of different explanation modalities within a realistic vineyard disease-detection workflow.

The prototype was evaluated with nine agronomists, whose feedback provided valuable insights into how explanatory components can be structured to improve usability, clarity, and trust. The study showed a consistent preference for example-based explanations, which were viewed as more intuitive and helpful for understanding and validating the model's reasoning. These explanations also contributed to lower cognitive load and enabled some participants to detect incorrect predictions, suggesting they can support better decision-making. Heatmaps were perceived as useful in specific cases but were generally considered less clear and more cognitively demanding.

In addition to the interpretation of explanations, participants contributed suggestions through a co-design activity, helping refine how explanatory elements can be organized within the interface. Their input informed a set of practical guidelines for designing future XAI-enabled tools in agriculture.

Overall, this dissertation demonstrates the importance of combining explainability with user-centred interface design to promote the adoption of AI in agricultural decision-making. The developed prototype and the insights obtained through the user study form a foundation for further refinement and broader evaluation of XAI approaches in agronomic contexts.

5.2 Revisiting the Research Questions

This dissertation was guided by three research questions focused on understanding how agronomists perceive different types of explanations, what factors influence their trust and understanding, and how these insights can translate into design principles for XAI-driven tools. The findings provide clear answers to each of these questions.

RQ1. How do agronomists perceive the usefulness of feature-based versus example-based explanations in their diagnostic workflow? The findings show that agronomists consistently perceive example-based explanations as more useful and intuitive than feature-based ones. Example-based explanations were described as familiar, easier to interpret, and better aligned with real diagnostic reasoning. Feature-based explanations were valued for transparency but often seen as visually dense and requiring more cognitive effort to interpret. Overall, agronomists reported greater confidence and clarity when interacting with example-based explanations.

RQ2 — What factors contribute to an explanation being perceived as trustworthy, understandable, and actionable? Four main factors emerged from the analysis. First, clarity and cognitive load played a major role: explanations that required minimal interpretation effort were preferred. Second, alignment with mental models influenced trust, with agronomists favouring explanations that matched the reasoning patterns they use in the field. Third, perceived reliability mattered, especially when explanations corresponded to recognisable symptoms or patterns. Finally, actionability was essential: explanations were considered useful when they supported the next step in decision-making rather than simply revealing internal model behaviour.

RQ3 — What design principles for XAI in smart farming can be derived from agronomists' perceptions and preferences? The study revealed several design principles for creating explainable interfaces that support agronomists' work. These include prioritising example-based explanations as the primary explanation mode; avoiding unnecessary visual complexity; aligning explanatory content with established agronomic reasoning; presenting information in layers to balance clarity and depth; and structuring explanations so they directly assist decision-making. Together, these principles provide practical guidance for developing XAI-driven tools that are both usable and trustworthy in agricultural settings.

5.3 Design Principles Derived from the Study

From the perceptions and preferences expressed by agronomists, several design principles emerged that can guide the development of explainable agricultural decision-support tools:

- **Use example-based explanations as the default**: These were consistently preferred for clarity, recognisability, and alignment with agronomists' reasoning.
- **Avoid unnecessary visual complexity**: Dense feature overlays and heatmaps should be used sparingly, as they increase cognitive load.

- **Align explanations with agronomic mental models**: Explanations should map onto familiar diagnostic patterns and terminology.
- **Provide layered levels of detail**: A high-level explanation should always be accessible first, with deeper information available on demand.
- **Support decision-making explicitly**: Explanations should contribute to actionable insights rather than simply reveal internal model behaviour.
- **Ensure consistency between explanation formats**: Switching between explanation types should not disrupt workflow continuity.

These principles synthesise the empirical findings into actionable guidance for future XAI interface design.

5.4 Limitations

Although the study generated valuable insights, several limitations must be acknowledged. The number of participating agronomists was relatively small, limiting the generalisability of the results. All sessions were conducted outside real vineyard conditions, meaning that environmental pressures and real-world decision constraints were not fully captured. The prototype implemented fixed explanation modalities, preventing exploration of hybrid or adaptive approaches.

Additionally, the evaluation relied primarily on self-reported perceptions; objective performance metrics such as task accuracy, decision speed, or error detection were not systematically measured. Finally, the study focused on a single disease-detection scenario, which may not represent all agricultural contexts.

5.5 Future Work

Although the results are promising, several directions could strengthen future research:

- **Implementation of Design Principles and Re-Evaluation:** Update the developed application by integrating the design principles identified during the user study. Following these improvements, conduct a new user study with agronomists to evaluate the updated system and validate whether the design changes enhance usability, trust, and explanation clarity.
- **Integration of Multimodal Data:** Expand the integration with AgriUXE by incorporating sensor data (e.g., soil moisture, weather stations) to provide more contextual and dynamic explanations.
- **Interactive and Conversational XAI:** Develop a chatbot or dialogue-based interface that allows users to ask questions, request additional examples, and explore the model's reasoning in an interactive manner.

- **Expansion and Diversification of User Studies:** This study involved only nine participants, which, while providing meaningful qualitative insights, limits the generalizability of the results. Future research should include a larger and more diverse group of agronomists, covering different educational levels, age groups, and levels of technological familiarity.

- **Completion of the Functional Prototype and Full Integration with AgriDash:** Expand the current prototype by implementing the AgriDash features that were not included in this initial version, including compatibility with map-based index visualizations such as NDVI and other vegetative indicators. Completing additional functionalities, such as real-time notifications and full management of treatments, will enable evaluation of the system in a fully operational scenario, supporting usability studies in real contexts, longitudinal analyses, and validation of the system's scalability.

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