DISSERTATION

ARTIFICIAL INTELLIGENCE POWERED PERSONALIZED AGRICULTURE

Submitted by

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ABSTRACT

ARTIFICIAL INTELLIGENCE POWERED PERSONALIZED AGRICULTURE

The integration of Artificial Intelligence (AI) in agriculture has shown the potential to improve crop selection and enhance sustainability practices. In this study, we aim to investigate the benefits and feasibility of using AI-powered personalized recommendations for crop selection and sustainability practices in the context of agroecology. We propose to lay the foundation for an agricultural recommendation engine that considers several parameters that influence yield and presents the best crop(s) to sow based on the model's output. We aim to examine this recommendation engine's impact on agriculture’s sustainability and to evaluate its effectiveness and accuracy. Our ultimate goal is to provide a comprehensive understanding of the potential benefits and challenges of using AI-powered recommendations in agriculture and to lay the foundation for the development of a practical, effective, and user-friendly recommendation engine that can help farmers make informed decisions about their crops and improve the long-term sustainability of agriculture.

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I want to express my special thank you to my wife, Mehar Lakshmi Tetala, who has been a rock in my life, constantly encouraging and supporting me throughout this journey. Her unwavering support and understanding have been invaluable, and I could not have achieved this without her. I would also like to acknowledge the role of my young children, Siri Sahithi Tetala and Abhiram Reddy Tetala, in my research. Their innate innocence and curiosity towards life as a boundless expanse of opportunities for exploration and discovery inspired me to approach this research with the same open-minded spirit of learning, experimentation, and creation. I extend my thankfulness to my parents, Appa Reddy Tetala and Subbalakshmi Tetala, for their encouragement and belief in me.

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Balancing doctoral research, full-time work, and parenthood has not been easy, but the love and support of my family and friends have made it possible for me to pursue my dreams. I extend my warmest thanks to my friends, Siva Sankar Yellampalli, Krishna Kishore Siddhareddy, Prashant Malladi, and Vinod Surapaneni, for their constant support. I am also thankful to my manager and friend, Ramakrishna Kondisetti, for his understanding and flexibility, which allowed me to balance my responsibilities at work and home.

PREFACE

As the world population continues to grow, the demand for food is rising at an unprecedented rate. Feeding a planet with over eight billion people is no small feat, and as such, agriculture has become one of the most important industries in the world. But with the growth in population, the challenges faced by farmers have increased manifold. Climate change, land scarcity, and labor shortages are just some of the daily challenges that farmers face.

As we continue to explore new ways to improve our agricultural practices, we must also recognize the delicate balance of nature and the importance of sustainable farming. Mother Nature has a way of resetting itself, providing for all the species on earth. However, as our population grows and climate change intensifies, the need for innovative and efficient farming methods becomes more urgent.

I am motivated by the belief that technology can play a pivotal role in solving this problem, and that is why I have focused my efforts on developing AI-powered personalized agriculture. This emerging field combines the latest advances in machine learning, computer vision, and robotics to create a more targeted, data-driven approach to farming that is tailored to the specific needs of individual crops, soil types, and environmental conditions.

My intention with this research is to provide a comprehensive overview of the emerging field of AI-powered personalized agriculture and to propose a holistic solution, based on analysis of available data, that brings together the latest research, insights, and best practices for designing, building, and deploying these systems in the real world. The potential impact of AI-powered personalized agriculture is immense, and my aim is to harness the power of these technologies to create a solution that benefits farmers, the environment, and society. Whether you are a farmer, a scientist, a technologist, or simply someone who cares about the future of our planet, I believe that this research will provide valuable insights and practical guidance for how we can use technology to create a more sustainable, efficient, and equitable food system for all.

At the same time, I am acutely aware of the potential pitfalls of technology and the ways in which it can be misused or abused if not developed and applied in a responsible and ethical manner. That is why I am committed to ensuring that the work I do in AI-powered personalized agriculture is guided by a strong ethical framework, and that the benefits of this technology are accessible to everyone, regardless of geography or socioeconomic status.

As we move forward, it is inevitable that AI-powered autonomous robotics will play a significant role in the future of agriculture. The ability to automate labor-intensive tasks and to monitor crops with precision has already led to a significant increase in efficiency and productivity. However, this is just the beginning. The rapid advancements in autonomous robotic technology are paving the way for a new era of farming – one where robots will be responsible for farming in both natural and controlled environments. In this research, we explore the intersection of technology and agriculture and how these developments can lead to a more sustainable future.

In conclusion, AI-powered personalized agriculture is not just a concept – it is a reality that is rapidly changing the world of farming. The combination of AI, data analytics, and robotics has the potential to revolutionize agriculture, and my goal with this research is to contribute to this transformation. By leveraging the power of technology, we can create a sustainable future for farmers, consumers, and the planet.

AUTOBIOGRAPHY

As I sit here working on my Ph.D. dissertation, I cannot help but reflect on the experiences that have brought me to this point. My passion for taking the technology beyond personalization and into the realm of need-based, practical applications, such as personalized agriculture, has driven my academic and entrepreneurial pursuits.

When I think about how I arrived at this point, I realize that my life experiences have played a significant role in shaping my research interests. My childhood was spent helping my cousins with their farms during school breaks. This instilled in me a deep appreciation for agriculture and its impact on our lives. As Steve Jobs once said, "you can't connect the dots looking forward; you can only connect them looking backward." This could not be more accurate for me, as my past decisions have led me to my current research topic

Throughout my education and career, I have gained a diverse set of skills and knowledge that have prepared me for my research. My background with an undergraduate degree in electrical and electronics engineering, a master's degree in electrical and computer engineering, another master's in business administration (MBA) in entrepreneurship and certifications in product strategy and management, and project management (PMP), have allowed me to feel comfortable when dealing with ambiguous situations, envisioning a product from the ground up and getting together a project plan and team to bring the product or system to life. I believe in Parkinson's Law, which means that the amount of time you give yourself to complete a task will determine how long it takes. I stay productive by breaking up my work into manageable pieces and setting deadlines for myself. However, I also make sure to take breaks and pursue my hobbies, such as practicing meditation, yoga, and philosophy, to help me maintain a balanced and healthy lifestyle.

Pursuing academic goals is no easy feat, but I have learned that it is all about perspective. When I began my Ph.D. journey at forty, I was balancing a demanding job and a young family with two children. It would have been easy to become overwhelmed and give up, but I knew that I had to prioritize and focus on what truly mattered to succeed. By focusing on what matters most and finding ways to adapt to our circumstances, we can overcome any obstacle and achieve our goals. Despite the challenges, I have made considerable progress and gained invaluable skills to help me in my future endeavors.

The COVID-19 pandemic and the shift to remote work was undoubtedly a challenging time for everyone. But for me, it was also an unexpected opportunity to excel. Working from home allowed me to better balance my work and personal life, allowing me to devote more time to my family and to my Ph.D. coursework and research. This extra time gave me the chance to be more productive, and I am proud of what I have accomplished.

As I look towards the future, I envision my research positively impacting the world. My proposed framework has been developed with all scenarios in mind, but there are still challenges that need to be addressed for the farmers to fully appreciate its advantages. The proposed system must be refined with collaborative efforts from local researchers, extension agents, companies, and government bodies, and in turn drive higher yields, greater profitability, and more sustainable farming practices. Who knows, one day, the system could provide recommendations that directly influence or even drive government policymaking.

Overall, my journey towards my Ph.D. has been challenging, but also incredibly rewarding. I am excited to see where my research takes me and the tangible positive impact it can have on the world.

DEDICATION

My grandfathers were farmers, as are many of my relatives, and I have seen firsthand the struggles they face with the uncertainty of crop yields. These experiences have inspired me to dedicate my research to improving yields and reducing uncertainty for farmers like my family. I hope my work will positively impact the lives of farmers and their families and pave the way for a more sustainable and prosperous future for the farming community.

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LIST OF ACRONYMS

The following abbreviations are used in this dissertation:

AI	Artificial Intelligence
ADSS	Agriculture Decision Support System
ANN	Artificial Neural Networks
AUC	Area Under the Curve
CNN	Convolutional Neural Networks
DL	Deep Learning
DNN	Deep Neural Networks
EPI	Environmental Performance Indicator
DSS	Decision Support System
DWS	Data Warehousing Systems
ESS	Executive Support Systems
ERD	Entity Relationship Diagram
GAN	Generative Adversarial Networks
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GUI	Graphical User Interface
HTTPS	Hypertext Transfer Protocol Secure
IAM	Identity and Access Management
IFMS	Integrated Fertilizer Management System
IOT	Internet of Things
IT	Information Technology

KBS	Knowledge-Based Systems
LSTM	Long Short-Term Memory
MAB	Multi-Armed Bandits
MCT	Mobile Communication Technologies
ML	Machine Learning
MLP	Multi-Layer Perceptron
NLP	Natural Language Processing
OSS	Operational Support Systems
RNN	Recurrent Neural Networks
SAM	Sustainable Agriculture Matrix
SDG	Sustainable Development Goals
SFA	Sustainable Food and Agriculture
SPS	Strategic Planning Systems
STCR	Soil Test Crop Response Studies
SVM	Support Vector Machine
TPS	Tactical Planning Systems
UAV	Unmanned Aerial Vehicles
UI	User Interface
UN	United Nations
UNDP	United Nations Development Programme
USDA	United States Department of Agriculture
UX	User Interface/User Experience
WAF	Web Application Firewall

CHAPTER 1: INTRODUCTION

The potential for Artificial Intelligence (AI) to revolutionize agriculture is immense, particularly for small farm holders in developing countries. Despite being a growing field of research and development for decades, recent advances in computing power and data storage have led to considerable progress in the application of AI in agriculture. With the ability to analyze vast amounts of data and make accurate predictions, AI can improve crop yields, reduce waste, and make farming more efficient and sustainable for small farmers. This dissertation will explore the use of AI-based recommendation systems to power personalized agriculture for small farm holders in developing countries

Background

AI-powered personalized agriculture refers to the application of artificial intelligence and machine learning techniques to provide tailored recommendations and solutions for farmers to optimize their agricultural practices. This involves the collection and analysis of data related to weather patterns, soil quality, crop growth, and other variables to provide personalized recommendations for planting, fertilizing, harvesting, and other agricultural practices. The goal of AI-powered personalized agriculture is to improve crop yield, reduce waste, and promote sustainable farming practices for small farm holders in developing countries. With AI-powered personalized agriculture, small farm holders can benefit from access to advanced technologies that would otherwise be out of their reach, resulting in more efficient and profitable farming practices. AI-powered personalized agriculture has the potential to transform the agricultural industry, making it more efficient, sustainable, and profitable.

Problem Statement

One area of AI that has garnered significant attention in recent years is the use of crop yields. These systems use various data sources, such as weather, and soil conditions, to calculate optimal crop yield precalculated and, provide recommendations for crop selection. Crop prediction is based on several parameters that influence crop yield. The farmers mostly rely on their experience or expert advice to determine the best crop to sow for maximum yield. Developing better techniques to predict crop choice and productivity in different conditions can assist farmers and other stakeholders in better decision-making.

However, the current research in this area has primarily focused on establishing which AI technique or ensemble predicts with the highest accuracy. While this is important, it is also essential to consider that the accuracy of these models can vary depending on the crop and region. Developing better techniques to predict crop choice and productivity in different conditions can assist farmers and other stakeholders in better decision-making. Moreover, these models often only take a few factors that farmers need to consider when making crop selection decisions, ignoring the complexities and sustainability factors involved in farm management.

Furthermore, this is particularly problematic for small-scale farmers, who often have unique and varied needs that one-size-fits-all recommendations cannot meet. As a result, there is a need to expand the use of AI in agriculture to provide personalized assistance to farmers. This could include developing more sophisticated recommendation systems that consider the unique needs and circumstances of each individual farmer, as well as addressing the ethical and social implications of using AI in agriculture. By doing so, we can help ensure that AI's full potential is realized in agriculture, leading to more efficient, sustainable, and profitable farming practices.

Purpose of the Study

The study aims to examine the feasibility and benefits of implementing AI-powered personalized recommendations for crop selection and sustainability practices in agriculture. The goal is to develop a scalable recommendation system that utilizes various input data, such as seed performance, soil type and quality, precipitation, irrigation, crop rotation, planting speed, tillage, and field weather, to provide farmers with accurate and relevant information to improve their crop management practices. The study aims to evaluate the impact of this recommendation engine on the sustainability of agriculture and the accuracy of the generated recommendations. The objective is to gain a comprehensive understanding of the potential benefits and challenges of utilizing AI-powered recommendations in agroecology, with the goal of developing a practical and effective recommendation engine that can assist farmers in making informed decisions about their crops, thus contributing to the long-term sustainability of agriculture.

Theoretical Framework

The theoretical framework for our proposed recommendation system will be built on a combination of machine learning algorithms, big data analysis, and extensive agroecological principles. Our goal is to provide farmers with personalized recommendations for crop selection, based on several key parameters that influence yield.

The first step in our framework will be to identify various parameters that influence crop yield and sustainability, including seed performance, soil type, soil quality, drainage, crop rotation, planting speed, tillage, field weather, and more. This data will be used to build a dynamic algorithm to determine the yield performance, sustainability, and profits for different crops under different scenarios.

Next, we will use machine learning techniques to analyze the data and provide personalized recommendations to farmers. These techniques will allow us to consider the unique conditions and constraints of each farm, as well as the specific needs and goals of each farmer, to provide the most accurate and relevant recommendations possible.

The last step in our framework will be to develop a user-friendly interface that allows farmers to access the recommendations and input their own data. Farmers can choose to provide their farm-specific data using various sensors or rely on aggregated data for their geographic region to get generalized recommendations. This will give farmers the flexibility and control to make informed decisions about their crops and yields.

Research Questions

The below research questions provide a framework for the research study, helping to shape the research design and ensuring that the research is focused and relevant to addressing the key challenges and factors that influence decision-making among small farmers and guide the development of an effective and sustainable system.

R1. How can a recommendation system be designed and implemented to address small farmers' specific challenges?

R2. What key factors influence small farmers' decision-making regarding crop cultivation, and how can a recommendation system account for these factors?

R3. What data sources are most useful for informing a recommendation system for small farmers, and how can data quality be ensured?

R4. How can a recommendation system be designed to accommodate small farmers' unique needs and resources in different regions and contexts?

R5. What are the potential benefits and drawbacks of using a recommendation system to guide small farmers' decision-making, and how can these be assessed?

R6. How can a recommendation system be integrated with existing agricultural extension programs and other support services for small farmers?

R7. What are the most effective methods for training small farmers to use a recommendation system, and how can these methods be scaled up to reach many users?

R8. How can a recommendation system be used to promote sustainable and regenerative agricultural practices among small farmers?

R9. What are the potential implications of using a recommendation system to guide small farmers' decision-making for broader issues such as food security, biodiversity, and climate change?

Research Hypotheses

The hypotheses below are derived from the research questions.

H1. A well-designed and implemented recommendation system can effectively address the specific challenges faced by small farmers.

H2. Small farmers' decision-making regarding crop cultivation is influenced by key factors, and a recommendation system that accounts for these factors can be more effective.

H3. Data quality and sourcing are important for developing a successful recommendation system for small farmers.

H4. A recommendation system can be designed to accommodate small farmers' unique needs and resources in different regions and contexts.

H5. A recommendation system can have benefits and drawbacks for small farmers, which must be carefully assessed to determine its effectiveness.

H6. A recommendation system can be integrated with existing agricultural extension programs and support services to provide additional benefits to small farmers.

H7. Effective training methods can help small farmers use a recommendation system, which can be scaled up to reach many users.

H8. A recommendation system can be used to promote sustainable and regenerative agricultural practices among small farmers.

H9. Using a recommendation system can have broad implications for food security, biodiversity, and climate change, which must be carefully considered.

Significance of the Study

The proposed study to develop and implement a recommendation system for small farmers has significant potential impact. Small farmers play a vital role in global food production, but they often lack the resources and information necessary to succeed. By providing small farmers with a well-designed and implemented recommendation system, tailored to address their specific needs and challenges, we can help level the playing field and improve their chances of success.

The recommendation system would provide guidance on cultivation techniques, seed variety selection, soil type, and crop rotation, leveraging data on weather, soil conditions, and other factors that influence crop growth. By doing so, it could help small farmers to improve their yields and profitability, which in turn could increase food production and contribute to global food security. Also, the proposed study would generate valuable insights into technology use to support sustainable and regenerative agricultural practices.

By providing small farmers with guidance on sustainable farming practices, the recommendation system could help reduce agriculture's environmental impact and contribute to efforts to mitigate climate change. Overall, the proposed study has significant potential to address existing inequalities in the agricultural sector, improve small farmers' ability to compete in markets dominated by larger producers, and contribute to sustainable and regenerative agricultural practices.

Definitions of Key Terms

The proposed study for developing a recommendation system for small farmers involves several technical and specialized terms that require definition to ensure clarity and understanding. The following are key terms and their brief descriptions:

Recommendation system - A software tool that provides personalized recommendations to users based on their interests and preferences.

Small farmers - Farmers who cultivate small plots of land and have limited resources and capital.

Cultivation techniques - Methods and practices used to grow crops, including planting, watering, fertilizing, and pest management.

Seed varieties - Different types of seeds that have unique properties and characteristics.

Soil types - Different types of soil that have distinct properties and characteristics, such as texture, pH, and nutrient content.

Crop rotation - The practice of planting different crops in a specific order in the same field to improve soil health and reduce the risk of pests and diseases.

Sustainable agriculture - A system of farming that emphasizes environmental, social, and economic sustainability.

Regenerative agriculture - A farming practice that focuses on improving soil health and biodiversity, increasing carbon sequestration, and reducing the use of synthetic inputs.

Data - Information collected and analyzed to generate insights and inform decision-making.

Weather data - Information about atmospheric conditions that affect crop growth and development, including temperature, precipitation, and wind.

Soil data - Information about soil's physical and chemical properties, including texture, pH, and nutrient content.

Artificial intelligence (*AI*) - A branch of computer science that focuses on developing intelligent machines and systems.

Machine learning (ML) - A subset of AI that involves training algorithms to learn from data and improve their performance over time.

Natural language processing (*NLP*) - A branch of AI that focuses on the interaction between computers and human languages.

User experience (*UX*) - The design and usability of software applications, websites, and other digital products.

User interface (*UI*) - The visual and interactive elements of software applications, websites, and other digital products that allow users to interact with them.

Cloud computing - A remote server system that provides on-demand access to computing resources and data storage.

Internet of Things (*IoT*) - A network of interconnected devices that can exchange data and communicate with each other.

Cybersecurity - The protection of computer systems and networks from unauthorized access, theft, and damage.

Precision agriculture - A farming practice that uses technology and data to optimize crop yields and reduce waste.

Remote sensing - The process of acquiring information about the environment from a distance, often using satellites or drones.

GIS (*Geographic Information System*) - A system for capturing, storing, analyzing, and managing geographical data.

Open data - Data that is freely available for anyone to access, use, and share.

Farm management software - Software tools designed to help farmers manage their operations, including crop planning, budgeting, and record-keeping.

Cloud-based software - Software hosted on remote servers and accessed via the internet rather than installed locally on a user's computer or device.

User feedback - Input and suggestions from a software application or digital product users.

Stakeholders - Individuals or groups interested in the proposed system, such as farmers, agricultural extension workers, software developers, and policymakers.

Prototyping - Creating an early version of a product or system to test its functionality and gather user feedback.

Usability testing - A process for evaluating the ease of use and user experience of a software application or digital product.

Natural resources - Materials and substances that occur naturally in the environment and are used by humans, including land, water, and air.

Sustainable development - Development that meets the needs of the present without compromising the ability of future generations to meet their own needs.

Agricultural extension - The practice of providing education and training to farmers to improve their knowledge and skills.

Summary

As the field of AI continues to advance, there is a growing potential for AI to revolutionize the way we approach agriculture. By leveraging data and technology to provide small farmers with the guidance and support they need to succeed, we can help to address some of the most pressing challenges facing the agricultural sector today. Whether it is improving yields, increasing profitability, or reducing the environmental impact of agriculture, a recommendation system can make a real difference in the lives of small farmers and the communities they serve. The proposed study to develop and implement a recommendation system for small farmers can significantly contribute to creating a more equitable, sustainable, and productive agricultural sector.

The dissertation is organized into the following chapters. Chapter 2 presents the state of agriculture and emergence of AI-powered agricultural practices. Chapter 3 introduces the recommendation system framework to power personalized agriculture. Chapter 4 thoroughly evaluates an AI-based application and suggests enhancements to demonstrate its potential as a prototype for the proposed personalized agriculture system framework. Finally, chapter 5 explores research opportunities and challenges using a recommendation system and concludes the dissertation.

CHAPTER 2: THE EMERGENCE OF AI-POWERED AGRICULTURE

The agriculture industry is facing unprecedented challenges in the 21st century, such as feeding a growing population, mitigating the impact of climate change, and ensuring food security. The integration of artificial intelligence (AI) in agriculture has emerged as a potential solution to address these challenges. AI-powered systems can assist farmers in decision-making, provide accurate predictions of crop yields, optimize resource utilization, and promote sustainable farming practices. As a result, the adoption of AI in agriculture has become increasingly popular, with both industry and academia investing in research and development in this field. This chapter presents a comprehensive review of the current state of AI-powered agriculture, examining the literature on the emergence of AI in agriculture, the several types of AI applications used in farming, and the potential benefits and challenges associated with their adoption. By presenting a detailed analysis of the existing literature, this study aims to provide insights into the impact of AI on agriculture and identify areas for future research.

The chapter is organized into several topics and subtopics. These topics include discussions on the current state of farmers and farming practices, technological advances in farming, the role of artificial intelligence in agriculture, and the significance of crop selection. Other topics include a thorough review of decision support systems, and recommendation systems and their application in agriculture. The chapter concludes with a discussion of the challenges and considerations surrounding the adoption of AI in agriculture, including building farmers' trust in smartphone applications for agriculture and responsible innovation.

Agriculture

Agriculture is an integral part of any country, and farming is a quintessential occupation. Approximately 3.4 billion people live in rural areas, which is 45% of the world's population.

Roughly 2 billion people (26.7% of the world population) derive their income and livelihoods from agriculture. In 2016, an estimated 53% of the population was economically active in agriculture [1]. In Asia and Africa, millions of small-scale and subsistence farmers, pastoralists, fishermen, and indigenous people produce most food consumed worldwide [2]. Small-scale farmers and family farms manage small farms (less than 2 hectares) and operate 87% of the world's agricultural land [3]. They work hard to ensure that they produce enough food to sell and make a profit, which can be reinvested into their farm operations or support themselves and their families. Appropriate return on investment (ROI) ensures sustained farming. One of the key United Nations' Sustainable Development Goals (SDGs) set by the Food and Agriculture Organization (FAO) is to achieve "zero hunger" by 2030 [1], which can be achieved by increasing agricultural productivity and reducing food waste and losses [4].

Goals of farmers

The goals of small farm farmers, both in developed and developing countries, depend on a variety of factors such as the economic, social, and environmental context in which they operate.

In developed countries, small-scale farmers often focus on producing high-quality, organic or specialty crops for local markets or direct sale to consumers. They may prioritize sustainable practices that promote soil health, biodiversity, and reduce environmental impacts. Additionally, small-scale farmers may strive to maintain a rural lifestyle and support their community by providing fresh, healthy food options.

In developing countries, small-scale farmers often focus on subsistence farming, producing enough food to feed their families and selling any surplus at local markets. They may prioritize sustainable practices that enable them to maintain the health of their crops and animals and preserve their land for future generations. Additionally, small-scale farmers may strive to increase their productivity and diversify their operations by investing in new farming techniques or value-added products.

The goals of a farmer may vary depending on their individual circumstances, values, and objectives, but producing high-quality food sustainably and profitably is always at the forefront of their mission.

Information required for farming

Farmers require various information to make informed decisions about planting, harvesting, and managing their land to optimize their operations and be successful in their business. These can be broken into three stages, as shown in Figure 1.

Stage	Typical Information Needed
Know-how	What are the new crop options? Are there higher value crops that I can grow?
Contextual information	When/how much should I sow? When should I harvest taking climate/soil into account? What are the best practices for my crop/soil?
Market information	What are the products prices? What are the market needs?

Figure 1*: Information, a farmer, needs at each stage*
Note: Adapted from Reference [5]

The information required throughout the agricultural cycle includes crop planning, buying seeds, planting, growing, harvesting, packing, storing, and selling, as depicted in Figure 2.

Agricultural practices

The traditional approach to agriculture is undergoing a fundamental transformation. Over the many centuries of our history, we have developed several forms of agriculture, 1.0 and 2.0, and are now moving towards 3.0 and 4.0 in the coming decades [6]. Today, all these versions are being practiced in various places on earth [7].

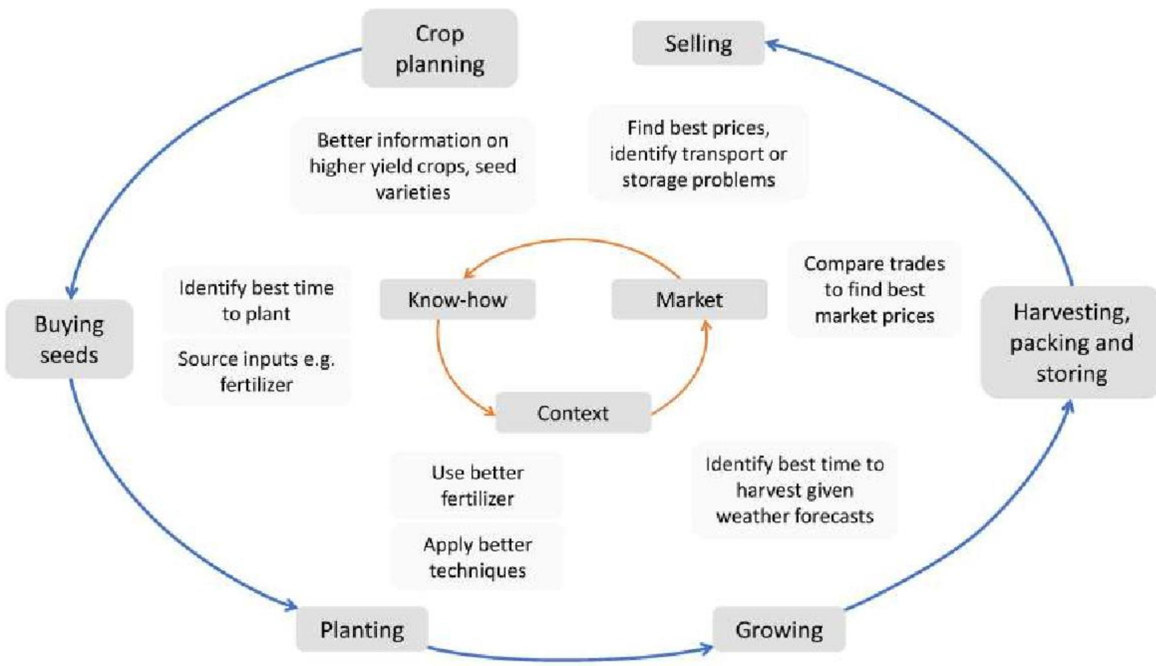

Figure 2: *Information required from farmers through the agricultural cycle*
Note: Adapted from Reference [5]

Agriculture **1.0** describes agriculture from ancient times to about 1920, when farming required substantial manual labor. It is still rooted in traditional ways. This model is locally adapted, labor-intensive, small, diverse, and very much at the heart of its respective communities and societies. Many family farms are part of this tradition as well [7].

Agriculture **2.0**, from 1920 to 2010 – machines, fertilizers, and better seeds helped farmers produce more with less effort. It was the era in which most of our parents operated; it began in the late 1950s when agronomic management practices and new tools like synthetic pesticides were allowed. This has created what we call agribusiness or industrial agriculture [7]. It has also pushed farming to the economic edge and produced cheap food. It had side effects, monoculture, glut pricing, soil depletion, etc.

Agriculture **3.0**. Now we have entered a new age. This is when high-tech sensors, cloud computing, specialized software, and the Internet of Things (IoT) are integrated into farming. In this new age of agriculture, data has become crucial. The data gathered will help farmers make more efficient use of their land, water, and fertilizer. Technologies and IoT have the potential to transform agriculture in many aspects.

Agriculture **4.0.** New techniques to produce differently using vertical farming (growing crops in vertically stacked layers in environment-controlled structures) [8], hydroponics (method of growing plants without soil, using mineral nutrient solutions in a water solvent), algae feedstock (algae farmed in aquaculture sites can become a substitute for feedstock and fishmeal), desert agriculture, seawater farming, etc., are disrupting the industry.

Sustainability in agriculture

Sustainable food and agriculture (SFA) are an FAO [9] initiative to holistically address all aspects of food security - availability, access, utilization, and stability - as well as the dimensions of sustainability: environmental, social, and economical. Sustainability in agriculture refers to farming that preserves the natural resources and biodiversity of the land for future generations while ensuring profitability. The FAO [10] has identified five fundamental principles of sustainability for food and agriculture:

1. *Productivity*: Sustainability requires increasing productivity in a way that does not degrade the environment or reduce the capacity of future generations to produce food.
2. *Resilience*: Sustainability requires adapting to and recovering from shocks, such as climate change and economic crises.
3. *Responsiveness*: Sustainability requires responding to changing consumer preferences and market demands.

4. *Inclusiveness*: Sustainability requires ensuring that all members of society, including women, youth, and smallholder farmers, have equal access to resources and opportunities.
5. *Transdisciplinarity*: Sustainability requires collaboration and cooperation across different sectors and disciplines to address the complex challenges facing food and agriculture.

The FAO advocates for SFA to achieve Zero Hunger and the United Nations Sustainable Development Goals (SDGs) worldwide. USDA [11] defines sustainable agriculture as farming in such a way as to protect the environment, aid and expand natural resources, and make the best use of nonrenewable resources. The key sustainable agricultural practices include:

1. *Conservation tillage*: Minimizing soil disturbance through no-till or reduced tillage helps improve soil health, reduce erosion, and increase water retention.
2. *Crop rotation*: Alternating different crops in a field can help to break pest and disease cycles and increase soil fertility.
3. *Cover crops*: Planting cover crops, such as clover or rye, can help to improve soil health and reduce erosion.
4. *Integrated pest management*: Using cultural, biological, and chemical methods to control pests rather than relying on synthetic pesticides alone.
5. *Water management:* Conserve and manage water resources through practices like precision irrigation, rainwater harvesting, and drought-resistant crop varieties.

The study [12], identified 30 sustainable agriculture practices in India, some focusing on specific aspects of agriculture (called "practices"), while others are more comprehensive and cover most aspects of agriculture (called "systems"). **Table 1** presents the sustainable agriculture practices and systems (SAPSs) from the study.

Table 1: Thirty identified sustainable agriculture practices and systems

System	Practice
Premaculture	Vermicompost
Organic farming	Drip irrigation/sprinkler
Natural farming	Crop rotation
System of rice intensification	Intercropping
Biodynamic agriculture	Cover crops
Conservation agriculture	Mulching
Integrated farming system	Contour farming
Agroforestry	Rainwater harvesting-artificial recharge of groundwater
Integrated pest management	Floating farming
Precision farming	Plastic mulching
Silvipastoral systems	Shade net house
Vertical farming	Alternate wetting and drying technique (for rice)
Hydroponics/Aeroponics	Saguna rice technique
Crop-livestock-fisheries farming system	Farm pond lined with plastic film
	Direct seeding of rice
	Canopy management
	Mangrove and non-mangrove bio-shields

Overall, sustainable agricultural practices aim to optimize the use of natural resources, minimize environmental impact, and promote biodiversity while maintaining or increasing agricultural productivity. Most nations employs a wide range of sustainable agriculture practices, but crucial data regarding their extent, distribution, and uptake is not available in either national or state databases and information systems.

Pressure on farmers

Farmers face various pressures, including financial pressures from rising costs and fluctuating market prices, environmental pressures from changing weather patterns and soil degradation, and regulatory pressures from government policies and trade agreements. Additionally, farmers may also face pressure from consumer demand for certain types of products or production methods.

Financial pressures can come from a variety of sources. For example, the cost of inputs such as seed, fertilizer, and fuel can be high and subject to market fluctuations. Additionally, the price farmers receive for their products may be low and subject to market fluctuations. This can make it difficult for farmers to make a profit and stay in business. Furthermore, small farmers may also need help accessing credit and other financial services, which can further exacerbate financial pressures.

Environmental pressures can also be significant for farmers. Climate change, for example, can lead to more extreme weather events such as droughts and floods, damaging crops and making it more difficult to produce food. Additionally, soil degradation and loss of biodiversity can also limit the productivity of farming operations.

Regulatory pressures can also be significant for farmers. Government policies and trade agreements can significantly impact the profitability of farming operations. For example, some policies may be designed to protect small farmers and limit the market power of giant agribusinesses, while others may promote exports and open new markets for farmers.

Consumer demand can also put pressure on farmers. For example, consumers are increasingly interested in buying organic and non-GMO products, which can be more expensive for farmers to produce. Additionally, consumers may all be interested in buying products made using sustainable or animal-friendly methods, which can be more costly for farmers to implement.

Technological Advances in Farming

Smallholder farmers, who make up a significant portion of the world's farming population, can benefit significantly from precision agriculture [13]. Here are five technologies that are driving precision agriculture for farmers [14]:

- *Mobile phones*: have become a crucial tool for smallholder farmers. They can be used for crop monitoring, weather forecasting, and market information, among other things. In addition, mobile phone-based extension services can provide farmers with the latest information on crop management, pests, disease control, and other vital topics.
- *Satellites*: provide detailed information on crop growth and can be used to monitor crop health and identify potential issues. They can also be used for weather forecasting and soil moisture monitoring.
- *Unmanned Aerial Vehicles (UAVs):* also known as drones, can be used for crop mapping, and monitoring crop health. They can also be used for crop spraying and soil sampling.
- *Sensors and Internet of Things (IoT):* can monitor crop health, soil moisture, and weather conditions. This information can be used to optimize irrigation and fertilization.
- *Robotics and Farm Automation*: can increase efficiency and reduce labor costs. For example, robots can be used for planting, harvesting, and other tasks.

Other technologies like Weather Monitoring, Soil Monitoring, Pest Surveillance, Disease Monitoring, Yield Monitoring, Smart Irrigation, and Precision Spraying are also used to optimize yields and improve efficiency.

Traditional vs. Precision vs. Personalization agriculture

Traditional agriculture, precision agriculture, and personalized agriculture are three different approaches to farming that have distinct characteristics, methods, and outcomes.

Traditional agriculture refers to farming practices passed down through generations and relies on traditional farming methods. This approach often involves more manual labor, such as tilling fields by hand or using animals to plow. This includes crop rotation, manual labor, and natural pest control. Traditional farming practices can be more sustainable than other methods but may not always be as productive or profitable. Examples of traditional agriculture include small-scale farming, family-run farms, and organic farming.

Precision agriculture, on the other hand, focuses on using technology to optimize crop production, reduce waste, and increase profitability. This involves using advanced technologies such as satellite imagery, drones, and GPS to monitor crops and optimize fertilizer and pesticide application. Precision agriculture is often used to manage large farms and can help reduce the amount of resources, including water and fertilizer, required to grow crops.

Personalized agriculture is a more recent approach to farming that combines the benefits of traditional and precision agriculture with advanced technology and data analysis. Personalized agriculture involves using data analytics, machine learning, and other technologies to tailor farming practices to specific crops and fields. This can include using sensors, GPS mapping, and machine learning algorithms to monitor crop growth and optimize irrigation, fertilizer, and pest control. Examples of personalized agriculture include vertical farming, hydroponics, and aeroponics.

All three types of agriculture have their unique advantages and disadvantages. Traditional agriculture is often more sustainable and can help preserve biodiversity and soil health, but it may not be as productive as precision or personalized agriculture. Precision agriculture can help improve efficiency and reduce waste, but it may be more expensive to implement. Personalized agriculture can provide tailored solutions for specific crops and fields, but it may require a significant investment in technology and data analysis. Both personalization and precision agriculture can help improve sustainability by reducing waste and optimizing crop production. However, they have different applications and benefits depending on the type and size of the farm. Personalization can be useful for small-scale farming operations, while precision agriculture is better suited for large-scale commercial farming.

In conclusion, traditional, precision, and personalized agriculture are three distinct approaches to farming that have different applications and benefits. Each approach has its strengths and weaknesses, and the best approach for a particular farm will depend on a range of factors, including the scale of the operation, the types of crops grown, and the local environment. The key to sustainable agriculture is finding the right balance of these approaches that consider the needs of the environment, the farmer, and the consumer.

Benefits of personalized agriculture applications

Personalized agriculture apps can provide a range of benefits to small farm holders, including:

Improved productivity: Mobile apps can provide small farm holders with access to personalized recommendations and insights about their farm, such as optimal planting schedules, nutrient management, and pest control. This information can help farmers to optimize their productivity and increase their crop yields.

Cost savings: Personalized agriculture apps can help small farm holders reduce costs by providing recommendations for more efficient use of resources, such as water and fertilizers. This can lead to significant savings on input and operational costs, which can be especially valuable for small-scale farmers who operate on limited budgets.

Better decision-making: By providing real-time data and insights, personalized agriculture apps can help small farm holders make informed decisions about their farming practices. This can help to mitigate risks and increase the likelihood of successful harvests.

Access to markets: Many personalized agriculture apps include features that help small farm holders connect with potential buyers and market their products more effectively. This can be especially important for small-scale farmers who may struggle to access markets and secure fair prices for their crops.

Customized recommendations: Personalized agriculture apps can provide small farm holders with customized recommendations based on their specific needs and circumstances. This can include factors such as soil quality, weather patterns, and crop preferences, allowing farmers to optimize their growing conditions and maximize their yield.

Enhanced sustainability: Personalized agriculture apps can also help small farm holders adopt more sustainable farming practices. By providing recommendations for eco-friendly pest control methods and nutrient management, these apps can help farmers reduce their environmental impact and improve the long-term health of their soil.

Improved record-keeping: Mobile apps can help small farm holders keep more accurate and up-to-date records of their farming practices, such as planting schedules and yields. This information can be useful for tracking performance, making future decisions, and meeting regulatory and certification requirements.

Access to expertise: Personalized agriculture apps can also provide small farm holders with access to a network of experts, including agronomists, horticulturists, and other specialists. This can be especially valuable for farmers who operate in remote areas or who lack local resources and support.

Increased efficiency: By providing real-time data and insights, personalized agriculture apps can help small farm holders work more efficiently and effectively. This can help to reduce the time and labor required for manual tasks, such as soil sampling and irrigation, and can free up time for other critical activities.

Overall, personalized agriculture apps can provide a range of benefits to small farm holders, from customized recommendations and sustainability improvements to enhanced record-keeping and access to expertise. By leveraging the power of technology and data, these apps can help farmers operate more efficiently, sustainably, and profitably.

Role of Artificial Intelligence

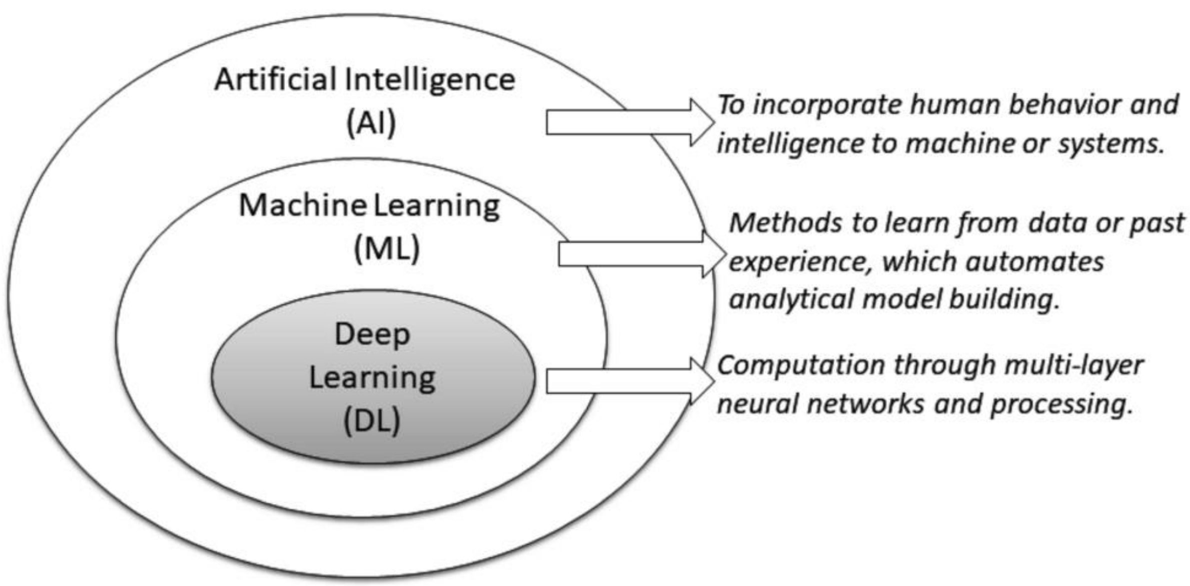

Figure 3: *An illustration of the position of DL, compared with ML and AI*
Note: Adapted from Reference [15]

Artificial Intelligence (AI) refers to the ability of a computer system to learn and make decisions based on data without being explicitly programmed. AI is a broad field encompassing many techniques and technologies, including machine learning and deep learning. The illustration in Figure 3 depicts their respective positions. Machine learning is a subset of AI that focuses on building systems that can learn from data, improve their performance over time, and make predictions or decisions without human intervention. On the other hand, deep learning is a subfield of machine learning based on deep neural networks (DNN), which are composed of multiple layers of artificial neurons.

Types of machine learning techniques

Machine Learning (ML) is a method of teaching computers to learn from data, without being explicitly programmed. It involves using algorithms to discover patterns and relationships in data automatically and then using those patterns to make predictions or decisions [16]. There are four main categories of machine learning: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. The popular two are depicted in Figure 4.

Supervised learning involves training a model on a labeled dataset where the correct output or label is already known. The model can then make predictions on new, unseen data based on the patterns it learned from the training data. Examples of supervised learning include linear regression, logistic regression, and support vector machines.

Unsupervised learning, on the other hand, involves training a model on an unlabeled dataset where the correct output or label is unknown. The model can then find patterns or structures in the data without prior knowledge of the correct output. Examples of unsupervised learning include clustering, principal component analysis, and anomaly detection.

Semi-supervised learning is a combination of supervised and unsupervised learning. It involves training a model on a partially labeled dataset, where only some of the data has the correct output or label known. The model can then make predictions on new, unseen data based on the patterns it learned from the partially labeled training data.

Reinforcement learning is a type of learning where an agent learns to make decisions by interacting with its environment. The agent is trained to perform a task by receiving rewards or penalties based on its actions. The agent learns to optimize its actions based on the feedback it receives, to maximize its rewards over time. Reinforcement learning is used in many applications, such as game playing, robotics, natural language processing, and control systems.

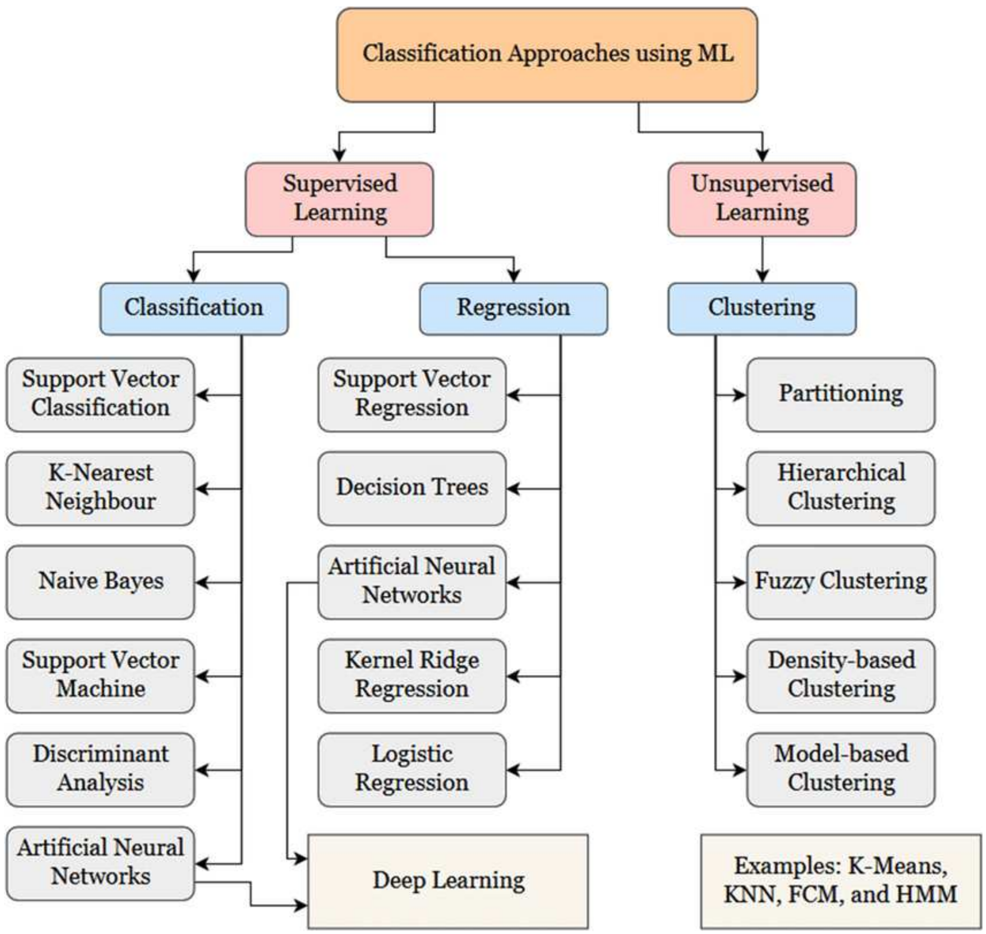

Figure 4: *An overview of machine learning classification and algorithms*
Note: Adapted from Reference [17]

Types of deep learning techniques

Deep Learning (DL) is a subset of Machine Learning, which uses neural networks with multiple layers to learn representations of data. Deep learning is particularly useful for tasks such as image and speech recognition, natural language processing, and decision-making. Deep learning classification algorithms classify data into predefined categories or classes. These algorithms are trained on large amounts of labeled data. They can learn complex patterns and features in data that are not easily captured by traditional machine learning algorithms. There are several main categories of deep learning classification algorithms:

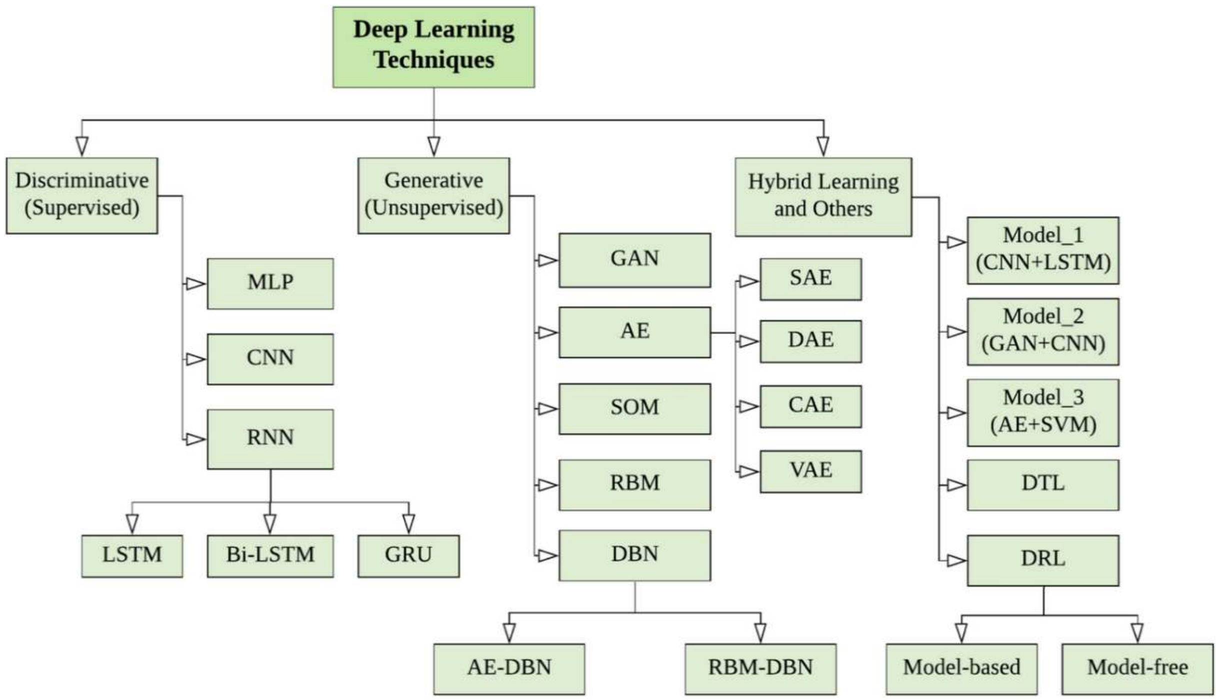

Figure 5: *A taxonomy of deep learning techniques*
Note: Adapted from Reference [15]

Convolutional Neural Networks (CNN): These are a type of deep learning algorithm that is particularly useful for image and video classification tasks. CNNs are composed of multiple layers of convolutional and pooling layers used to extract data features. They can use hierarchical representations of the data, allowing them to capture local and global features. The most popular applications are GoogleNet and AlexNet. AlexNet [18] is a large, deep network with eight layers, including 5 convolutional layers and 3 fully connected layers. AlexNet has been widely used as a base model for many other deep learning research since it is the first one that showed the potential of deep learning to achieve state-of-the-art performance on image classification tasks. GoogleNet

[19] is a deep CNN with 22 layers, and it is based on the "Inception" architecture, which is characterized by multiple filter sizes in the same layer. GoogleNet has been widely used as a base model for many other deep learning research since it was the first inception architecture that showed the potential of deep learning to achieve state-of-the-art performance on image classification tasks.

Recurrent Neural Networks (RNN): These deep learning algorithms are particularly useful for sequential data, such as speech and text. RNNs can capture temporal dependencies in the data by passing information from one time step to the next through hidden states. They are used in various applications, such as language modeling, speech recognition, and natural language processing.

Generative Adversarial Networks (GAN) [20]**:** These are a type of deep learning algorithm that is particularly useful for generating new data. GANs consist of two neural networks, a generator, and a discriminator, that are trained to generate new data like the training data. They are used in various applications, such as image synthesis, image-to-image translation, and text-to-speech synthesis.

Long Short-Term Memory (LSTM) networks [21]: These are a variation of RNNs that are effective for tasks such as natural language processing and speech recognition. LSTMs can remember information for more extended periods of time, making them useful for tasks involving sequences of data.

Autoencoder [22]: This deep learning algorithm is used for dimensionality reduction and feature learning. Autoencoder consists of an encoder and a decoder network. The encoder learns to compress the input data into a lower-dimensional representation, while the decoder learns to reconstruct the input data from this lower-dimensional representation.

Transformer: These are neural networks that are used to process sequences of data, such as natural language, and are particularly effective for tasks such as language translation and text summarization.

Role of artificial intelligence in farming

Artificial Intelligence (AI) is a rapidly evolving technology that can revolutionize how we farm. AI in farming can improve crop yields, reduce costs, increase efficiency, and sustainability. AI has significantly improved agricultural yield by helping farmers optimize their practices and make data-driven decisions. Here are a few examples of how AI is being used in agriculture today:

- *Crop monitoring*: AI can analyze images of crops and predict yields, identify potential issues such as pests or diseases, and optimize irrigation and fertilization.
- *Weather forecasting*: AI can analyze weather stations and satellite data to predict weather patterns and help farmers make more informed decisions about planting and harvesting.
- *Livestock monitoring*: AI can monitor livestock's health and behavior, which can help farmers identify potential issues and prevent them.
- *Autonomous vehicles*: AI can control autonomous vehicles such as tractors and drones, which can be used for planting, harvesting, and other tasks.
- *Precision agriculture*: AI can optimize crop yields and reduce costs by analyzing data from sensors, drones, and other sources to make more informed decisions about planting, irrigation, and other activities.
- *Inventory management*: AI can be used to optimize inventory management in the supply chain of farming by analyzing data on crop yields, weather patterns, and market prices to make more informed decisions about when to plant, harvest, and sell crops.

- *Predictive maintenance*: AI can analyze sensor data from farm equipment and predict when maintenance is needed, reducing downtime and repair costs.

In addition to these examples, AI can be used for other essential tasks such as soil analysis, crop breeding, and even predicting crop prices. As AI continues to evolve, it has the potential to transform the way we farm, making it more efficient, sustainable, and profitable.

Role of artificial intelligence in yield prediction

There are several algorithms used for yield prediction. In [16], the authors reviewed several algorithms used for predicting crop yields. One popular machine learning algorithm used for yield prediction is the decision tree. In [23], the authors present an architectural representation of ML models for addressing agricultural issues and discuss various ML algorithms for handling several types of data. The study highlights the potential of ML in improving processes such as water management, pest control, soil health detection, and crop yield forecasting. The decision tree is an algorithm that can be used for classification and regression tasks. It works by creating a tree-like model of decisions and their possible consequences. It can be used to identify patterns and relationships in historical data that are useful for predicting crop yields. Decision trees can accommodate a variety of input features, such as temperature and precipitation, and output a crop yield prediction. They are effective at crop yield prediction in some studies, but they can be less accurate than neural networks in some cases. Random forests, an ensemble of decision trees, can also be used for yield prediction and are often more precise than single decision trees, especially when trained on a large and diverse dataset. Random Forest and XGBoost combine multiple decision trees, where the output of multiple trees is connected to make a final prediction. These algorithms can improve the system's prediction accuracy by reducing the variance and bias of the individual trees.

Classification is a technique to predict a categorical outcome variable based on one or more input variables. It can be used in crop yield prediction systems to classify the crop based on the input provided. Regression is a technique used to predict a continuous outcome variable based on one or more input variables. It can be used to analyze historical data on crop yields and weather conditions and predict future crop yields. Clustering is a technique used to group similar data points. It can be used to analyze historical data and identify patterns and relationships helpful in making predictions.

Support Vector Machine (SVM)'s are supervised learning algorithms that can be used for classification and regression tasks. They can be trained on historical data to predict crop yields based on various input features. These models work by finding the best boundary between different data groups and are effective at crop yield prediction in some studies. However, the authors note that these models can be sensitive to the choice of kernel function and the amount of data used to train the model, which can affect the accuracy of the prediction.

Time series forecasting is an algorithm that relies on a temporal data stream for its predictive accuracy. When trained on a large dataset of historical data, these algorithms can achieve high accuracy in predicting future weather patterns, crop yields, and other variables necessary for farming and agriculture.

Neural networks, a type of machine learning model inspired by the structure and function of the human brain, are particularly effective at crop yield prediction. When trained on a large dataset of labeled images, these algorithms can achieve high accuracy in image-processing tasks, such as identifying crop types from satellite imagery. These models can be trained to recognize patterns in the data, and they have been used to predict crop yields with high accuracy in some studies.

Artificial Neural Networks (ANNs) are algorithms inspired by the human brain's structure and function. They are commonly used for pattern recognition and prediction. ANNs can be used in the crop yield prediction system to model the relationship between the input and output variables.

Deep learning algorithms can also be used for yield prediction, such as neural networks and convolutional neural networks (CNNs). These algorithms can be trained on large amounts of data, such as images of crops and soil, to make predictions about crop yields.

Hybrid machine-learning algorithms combine multiple machine-learning techniques to create a more accurate and robust system. Using various algorithms can help mitigate the limitations of individual algorithms and improve the system's overall performance.

An efficient algorithm for predicting crop yields using historical data and pattern-matching techniques [24] can be developed using machine learning and data mining techniques. One approach is to use a time series analysis algorithm, such as ARIMA or LSTM, to analyze historical data on crop yields and weather conditions and identify patterns and trends. These patterns can be used to make predictions about future crop yields. Another approach is to use a data mining technique such as association rule mining or clustering, which can identify patterns and relationships in the historical data that are useful for predicting crop yields. The algorithm can be fine-tuned and validated using techniques such as cross-validation and bootstrapping to improve its accuracy. It is important to note that the accuracy of the prediction algorithm depends on the quality and quantity of historical data used for training the model and the pattern-matching technique used in the algorithm.

In [25], the authors consolidated a list of the most used ML algorithms. They are presented in **Table 2**.

Table 2: Most used machine learning algorithms

Most used machine learning algorithms	Number of times used
Neural Networks	27
Linear Regression	14
Random Forest	12
Support Vector Machine	10
Gradient Boosting Tree	4

Overall, various machine learning and deep learning algorithms can be used for yield prediction, and the choice of algorithm will depend on the specific problem and the available data. In [16], the authors argue that traditional methods of yield forecasting, which rely solely on historical data and weather predictions, are often inaccurate and fail to consider critical agricultural factors such as soil quality, irrigation, and crop management practices. The same study found that combining agricultural factors and machine learning models significantly improved yield predictions' accuracy compared to traditional methods. It is worth noting that the accuracy of these algorithms can be improved by fine-tuning the parameters using ensemble methods and other techniques.

AI-powered Personalization in Agriculture

In recent years, AI has gained significant attention in agriculture, particularly in crop yield prediction. Precision agriculture, which first emerged in the 1980s, has continued to evolve by incorporating newer technologies such as drones, sensor networks, and AI. However, the last three years have seen a significant increase in the number of publications on AI-based crop yield prediction, due to the Covid-19 pandemic. This section will provide an overview of AI-powered personalization in agriculture, with a particular focus on yield prediction and crop selection.

Yield Prediction

Yield prediction can benefit from the machine and deep learning AI algorithms. These algorithms can analyze large amounts of data, such as weather data, soil data, and data from sensors on farming equipment, to make predictions about crop yields. The algorithms or models have been used to forecast crop yields in crops such as wheat, corn, soybeans, cotton, and sugarcane.

The publication on forecasting yield by integrating agrarian factors and machine learning models [16] discusses the importance of accurate yield forecasting in agriculture, as it can help farmers make informed decisions about crop management and assist policymakers in developing policies to promote sustainable agricultural practices.

An intelligent decision support system for crop yield prediction [26] can be developed using a combination of machine learning algorithms. The system can use a hybrid approach that includes regression, decision tree, and artificial neural networks. The system can analyze historical data on crop yields, weather conditions, and other relevant factors to predict future crop yields. The system can also use a combination of supervised and unsupervised learning techniques, such as clustering and classification, to analyze the data and identify patterns and relationships that are useful for making predictions. Additionally, the system can use ensemble learning techniques such as Random Forest and XGBoost to improve prediction accuracy. The system can also be fine-tuned and validated using techniques such as cross-validation and bootstrapping to ensure the predictions are accurate.

The authors of crop yield prediction using machine learning [25] reviewed studies published between 1990 and 2018 and discussed the different machine learning techniques used in these studies, such as neural networks, decision trees, and support vector machines. They found that these techniques have been used to predict crop yields with varying degrees of success, with some studies reporting high accuracy, with others reporting lower accuracy. The authors also found that using remote sensing data in conjunction with machine learning models can improve the accuracy of crop yield predictions. Remote sensing data, such as images of the crop obtained from satellites or drones, can provide information on crop growth and development, which can be used as input for machine learning models. This is helpful because remote sensing data can provide a large amount of information quickly. Additionally, it can track crop growth and development at distinct stages, which can help the model adjust and make predictions more accurately.

Parameters influencing yield prediction

The forecasting yield by integrating agrarian factors and machine learning models [16] survey discusses various agrarian parameters that can impact yield, including weather conditions, soil properties, and crop management practices. The authors note that these parameters are often interdependent and can be difficult to predict, making accurate yield forecasting challenging. Based on the literature review of crop yield prediction using machine learning [25] publication, the top parameters used for yield prediction are listed in **Table 3**.

Table 3: Top parameters used for yield prediction

Parameters	**Number of times used**
Temperature	24
Soil Type	17
Rainfall	17
Crop Information	13
Soil maps	12

Temperature is one of the most critical parameters that influence crop yield. Different crops have different optimal temperature ranges for growth, and temperatures that are too high or too low can cause stress on the plants and reduce yield. For example, high temperatures can cause heat stress, which can cause the plants to wilt, stop growing, and reduce yield. Conversely, low temperatures can cause frost damage and reduce yield.

Soil type also plays a crucial role in crop yield. Different crops have different soil requirements and planting them in the wrong soil can lead to poor growth and reduced yield. The soil's pH level can also affect crop growth, as most crops prefer slightly acidic to neutral soils (pH 6-7). For example, rice and soybeans thrive in heavy clay soils, while others, such as corn and wheat, prefer well-drained sandy soils.

Rainfall is another crucial parameter that influences crop yield. Adequate rainfall is essential for the growth and development of crops, as it provides the necessary moisture for germination and growth. However, too much rainfall can lead to waterlogging, which can suffocate the roots of the plants and reduce yield. Conversely, too little rainfall can lead to drought stress, which can cause the plants to wilt, stop growing, and reduce yield.

Crop information is another critical parameter that influences crop yield. Different crops have different growth habits, nutrient requirements, and disease susceptibility, which can all affect yield. For example, some crops, such as corn and wheat, are more resilient to disease and pests than others, such as rice and soybeans, which are more susceptible. Knowing the optimal planting and harvesting times for different crops can also help maximize yield.

Soil maps can also be used to determine the suitability of a particular area for growing specific crops. These maps can provide information on soil type, pH level, and other crop growth characteristics. Also, measuring humidity and pH levels in the soil can help determine the soil's suitability for growing specific crops.

Parameters influencing sustainability

Sustainability measures in agriculture include using organic matter, the presence of beneficial insects and other wildlife, and the amount of water used. Additionally, reducing greenhouse gas emissions and conserving biodiversity can be used as indicators of sustainability.

Figure 6: *Sustainable Agriculture Matrix*
Note: Adapted from Reference [27]

The Sustainable Agriculture Matrix (SAM) in **Figure** 6 from the quantitative assessment of agricultural sustainability reveals divergent priorities among nations [27] publication in One Earth categories the parameters into three sections: Economic, Environmental and Social. Some commonly used parameters to measure sustainability [28] are:

1. *Organic matter*: Organic matter can be measured by taking a soil sample and analyzing it in a laboratory using methods such as loss on ignition or the Walkley-Black method. The unit of measurement is the percentage (%), and the measurement accuracy can vary depending on the method used and the technician's skill. A higher percentage of organic matter indicates better soil health and fertility.

2. *Biodiversity*: Biodiversity can be measured by conducting surveys of plants, animals, or insects on the farm, using techniques such as transects, quadrats, or pitfall traps. The unit of measurement is the number of species or individuals per unit area, and the accuracy of measurement can depend on the survey method used, the skill of the surveyor, and the time of year. Higher biodiversity indicates a more resilient ecosystem.
3. *Energy use*: Energy use can be measured by monitoring fuel consumption, electricity usage, and other energy inputs on the farm using techniques such as metering or monitoring devices. The unit of measurement is energy per unit of output (e.g., MJ/kg or KWh/ha), and the measurement accuracy can depend on the monitoring method used and the skill of the person collecting data. A lower energy use per unit of output and a higher proportion of energy from renewable sources indicate a more sustainable system.
4. *Water use:* Water use can be measured by monitoring irrigation systems, measuring water levels in wells or streams, or using remote sensing techniques such as satellites. The unit of measurement is water per unit of output (e.g., L/kg or m3/ha,) and the measurement accuracy can depend on the monitoring method used and the skill of the person collecting data. A lower water uses per unit of output and a higher proportion of water from renewable sources indicate a more sustainable system.
5. *Greenhouse gas emissions*: Greenhouse gas emissions can be measured by monitoring fuel consumption, livestock emissions, and other sources of emissions on the farm, using techniques such as emissions factors or life cycle assessment. The unit of measurement is CO_2 emissions per unit of output (e.g., kg CO_2/kg or t CO_2/ha), and the accuracy of measurement can depend on the monitoring method used and the skill of

the person collecting data. Lower emissions per unit of output and a higher proportion of emissions offset by carbon sequestration indicate a more sustainable system.

Overall, measuring sustainability in agriculture requires multiple indicators and techniques. It is essential to use appropriate methods and units of measurement and to interpret the results in the context of the specific agricultural system and the sustainability goals.

Significance of crop selection

Crop selection is an essential aspect of agricultural production as it determines what crops will be grown, affecting the farm's overall yield, income, and sustainability. Some of the factors that are considered when selecting crops are:

- *Climate and soil*: The climate and soil of a particular area are essential factors in determining which crops can be grown successfully. For example, certain crops may require specific temperature and rainfall conditions, while others may need soil types and pH levels.
- *Market demand*: The demand for a particular crop in the local and global market is another essential factor to consider. This can help farmers determine which crops will be most profitable and have the best chance of selling at a reasonable price.
- *Labor and equipment*: The amount of labor and equipment required to grow a particular crop should also be considered. Some crops may require more labor-intensive practices, while others may require specialized equipment.
- *Pest and disease*: The crop's susceptibility to pests and diseases is also vital to consider, as it can affect the yield and quality of the crop.
- *Crop rotation*: Crop rotation is also essential when selecting crops. This practice involves growing different crops in a specific order on the same land, which helps to

improve soil health, prevent pests and disease, and improve yields. For example, rotating between barely, corn and alfalfa shows a strong correlation between yields and best suited for soil health management in North Dakota [29].

By considering these factors, farmers can make informed decisions that can significantly impact the profitability and sustainability of a farm while minimizing risks.

Decision Support Systems in Agriculture

Decision Support Systems (DSS) are a type of computer system that supports decision making by providing relevant information and analysis to decision makers. A DSS may use any AI algorithms and techniques discussed above to analyze data, identify patterns and trends, and make predictions or recommendations to support decision making. These systems can be used in a wide range of industries, such as finance, healthcare, and retail, to improve efficiency, reduce costs, and increase revenue.

General framework and components of decision support systems

In [30], the authors conducted a review of thirteen Agricultural Decision Support Systems (ADSSs) and proposed a general framework for these systems as depicted in **Figure 7**. The framework emphasizes the importance of data in the decision-making process and suggests that data constraints should be evaluated to determine the necessary cleaning steps.

The ADSSs evaluated in the study consist of several modules, including crop models, irrigation models, and estimation models, which ingest data provided to the system. Each of these modules has its own set of constraints that guide the system in generating advice for farmers. The advice generated by the system considers both economic factors and environmental changes within the specified constraints. The goal of the ADSSs is to provide farmers with advice that will help them make informed decisions about their agricultural practices within the system constraints.

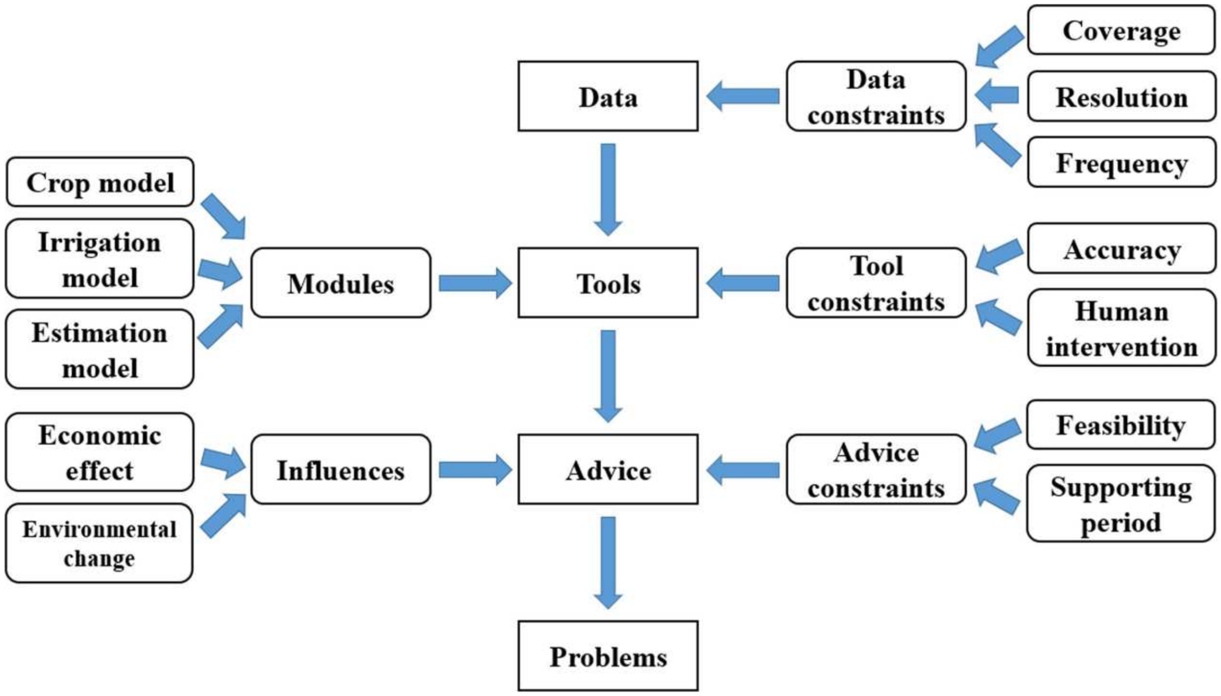

Figure 7: *General framework for agricultural decision support systems*
Note: Adopted from reference [30]

According to [31] and [32], the components of DSS are:

1. *Database*: A DSS relies on a central repository of data, which is usually stored in a database. The database is used to store and manage the data that the DSS uses to support decision making.
2. *Model base*: A DSS uses a variety of models to analyze and process data. These models may include mathematical and statistical models, simulation models, and optimization models.
3. *User interface*: A DSS must provide a user interface that allows users to access and interact with the system. The user interface should be intuitive and easy to use, and should allow users to input data, run analyses, and view results.

4. *Knowledge base*: A DSS may include a knowledge base that contains information and expertise relevant to the decision-making process. This knowledge may be in the form of rules, procedures, and best practices.
5. *Communication and dissemination*: A DSS should be able to communicate and disseminate the results of its analyses to decision-makers. This may be through automated reports, visualizations, or other formats.
6. *Software*: A DSS is usually implemented using specialized software designed to support the system's functions. This software may include databases, optimization and simulation tools, and programming languages.
7. *Hardware*: A DSS requires a combination of hardware and software to run. This typically includes servers, storage devices, and networking equipment and may also include specialized hardware such as high-performance computing clusters or geographic information systems (GIS) equipment.
8. *Security*: A DSS should have a robust security system to protect the data and decision-making process from unauthorized access. This may include encryption, access control, and authentication mechanisms.

These components work together to provide a comprehensive system that can support decision making by providing access to data, models, and knowledge.

Types of decision support systems

There are several different types of Decision Support Systems (DSS), each with their own unique characteristics and applications. Some common types of DSS according to [31], [32], and [33] include:

Executive Support Systems (ESS): These systems are designed to support high-level decision making by top management. ESSs typically provide access to a wide range of data, including financial, sales, and strategic information. They often use advanced visualization and modeling tools to help managers understand complex data and identify trends.

Strategic Planning Systems (SPS): These systems are used to support long-term decision making and strategic planning. They typically focus on external factors such as market trends and competition and use forecasting and modeling techniques to help managers anticipate future conditions.

Tactical Planning Systems (TPS): These systems are used to support medium-term decision making and planning. They typically focus on internal factors such as resource allocation and production schedules and use simulation and optimization techniques to help managers make trade-offs between competing objectives.

Operational Support Systems (OSS): These systems are designed to support day-to-day decision making and operations. They typically focus on real-time data and use rule-based systems, artificial intelligence, and expert systems to help managers make quick, accurate decisions.

Knowledge-Based Systems (KBS): These systems are designed to support decision making by providing access to an organization's collective knowledge and expertise. They use artificial intelligence techniques such as natural language processing and knowledge representation to help managers find and use relevant information.

Geographic Information Systems (GIS): These systems are designed to support decision-making by analyzing and visualizing geospatial data. They use advanced mapping and analysis tools to help managers understand the relationship between physical location and other data such as population, land use, and resource distribution.

Data Warehousing Systems (DWS): These systems are designed to support decision-making by providing a centralized repository of an organization's data. They use data mining and analysis techniques to help managers uncover patterns and trends in large data sets.

AI technologies used in decision support systems

1. *Machine Learning (ML):* ML is a subset of AI that involves training computer systems to learn from data and make predictions or decisions without being explicitly programmed. DSSs use a variety of ML algorithms, such as supervised learning, unsupervised learning, and reinforcement learning, as discussed above, to analyze data and identify patterns and trends.
2. *Natural Language Processing (NLP)* [34]**:** NLP is a field of AI that deals with the interaction between computers and humans in natural language. DSSs use NLP to analyze and understand unstructured data, such as text and speech. For example, a DSS in the healthcare industry might use NLP to extract information from medical reports and articles to support medical research and diagnosis. NLP techniques include tokenization, stemming, lemmatization, part of speech tagging, Named entity recognition, sentiment analysis, and many more.
3. *Expert Systems* [35]: Expert systems are a type of DSS that use knowledge-based techniques to mimic the decision-making process of a human expert. They are designed to guide decision makers in specific domains, such as medicine or finance. Expert systems use a combination of rule-based and case-based reasoning to make decisions. They use a knowledge base composed of facts, rules, and heuristics and a reasoning engine that applies the knowledge base to solve problems.

4. *Neural Networks* [36]: Neural networks are a type of machine learning algorithm inspired by the human brain's structure and function. DSSs use neural networks to process and analyze substantial amounts of data, particularly for images and video. They are used in image and video recognition, compression, and generation. They are particularly good at identifying patterns and features in data that are difficult for humans or other algorithms to detect.
5. *Genetic Algorithm and Evolutionary computation* [37]: Genetic Algorithms and evolutionary computation are optimization techniques based on the principles of natural selection and genetics. They are widely used in optimization problems such as scheduling, routing, resource allocation, and design optimization. DSSs use them to optimize decisions and find the best solutions to a problem. They are handy when the solution space is large, and the objectives are complex.

Types of decision support systems applications in agriculture

Decision Support Systems (DSS) have been applied to agriculture in several ways to improve the efficiency and productivity of farming. Some examples of how DSS have been used in agriculture include:

1. *Crop Yield Prediction*: DSS’s use machine learning algorithms to analyze data on weather, soil, and other factors to develop mathematical models of crop growth and development to simulate crop growth and predict crop yields. This can help farmers make more informed decisions about planting, fertilizing, and harvesting.
2. *Precision Agriculture:* DSS’s use technologies such as GPS and sensor networks to collect data on the condition of crops, soil, and weather. This data can be analyzed

using machine learning algorithms to optimize irrigation, fertilization, and other aspects of crop management.

3. *Livestock Management*: DSS's use sensor networks and machine learning algorithms to monitor the health and behavior of livestock. This can be used to optimize feed and breeding programs, and to detect and prevent disease outbreaks.
4. *Pest and Disease Detection*: DSS's use computer vision and machine learning algorithms to detect pests and diseases in crops. This can be used to identify outbreaks early, and to develop more effective pest control strategies.
5. *Climate-smart Agriculture* [38]: DSS's use machine learning algorithms and weather forecasting to predict and plan for weather changes. This can help farmers to adapt to changing climate conditions, reduce crop loss and increase overall productivity.
6. *Field Mapping and Management*: DSS's use satellite imagery, drones, and machine learning to map fields, monitor crop growth and identify issues such as pests, disease, or irrigation problems. This approach uses hydrological and hydraulic models to manage irrigation and drainage systems and optimize water resources.
7. *Economic DSS*: DSS's uses economic models and data to provide farmers with information about market prices, costs, and revenue, which can be used to make decisions about crop production, pricing, and marketing.

Smartphone applications of agricultural decision support systems

A systematic review of smartphone applications targeting precision agriculture practices [39] was recently published in the Journal of Sensors. The study included thirty-five articles published between 2010 and 2020 and covered several topics related to precision agriculture, including crop management, soil management, and weather forecasting. The review found that there are many precision agriculture apps available for smartphones. Still, most focus on a specific aspect of precision agriculture, such as crop or soil management. Additionally, many apps are tailored to particular crops or regions, which limits their usefulness for farmers in other areas.

In [40], the authors reviewed various apps developed to support the sustainable management of agricultural landscapes. The authors found a wide range of apps available, with varying levels of functionality and targeting different audiences. Many apps focus on providing farmers with information on best practices for sustainable agriculture, such as crop management, nutrient management, and pest control. Other apps offer tools for monitoring and reporting environmental indicators, such as water quality and soil health. Some apps also focus on providing farmers with market information, such as prices for crops and livestock.

Several more smartphone applications target increasing agricultural, or crop yields worldwide. Some examples include:

1. *FarmEasy* [41]: This is an intelligent platform designed to aid crop prediction and marketing. It utilizes machine learning algorithms to predict crop yields and assist farmers to make informed decisions about planting, fertilization, and harvesting. Additionally, the platform helps farmers market their crops by providing real-time data on crop prices and demand. The publication discusses the potential benefits of the platform for both farmers and consumers.
2. *AgroDSS* [42]: This is a decision support system for agriculture and farming. It is based on data analysis, modeling, and simulation techniques. The system uses data from various sources, such as weather forecasts, crop growth models, and satellite imagery, to provide farmers with information and recommendations for crop management, irrigation scheduling, and other farming activities. The system's accuracy can vary

depending on the quality and availability of data, but it is considered effective in helping farmers make informed decisions.

3. *Fruchtfolge* [43]: It is a crop rotation decision support system for optimizing cropping choices with big data and spatially explicit modeling. Crop rotation is a crucial factor in sustainable agriculture as it helps to improve soil health, reduce pest and disease pressure, and increase crop yields. The app considers a wide range of data sources, including weather, soil, and crop management data, as well as historical crop yields and spatially explicit modeling to optimize crop rotation choices. It then uses this data to generate spatially explicit crop rotation recommendations for farmers.
4. *Agrivi*: This app helps farmers plan and manage their crops, providing real-time data on weather, soil moisture, and crop growth.
5. *AgriBus-Smart: This app gives farmers information on weather, soil conditions, and crop growth and tools for creating planting and fertilization schedules.*
6. *AgriWebb*: This app helps farmers manage their livestock and crops, providing real-time data on animal health, feed and pasture management, and crop yields.
7. *Farm At Hand*: This app provides farmers with tools for tracking inventory, expenses, and crop yields, as well as weather forecasts and field mapping.
8. *Cropix*: This app uses AI and machine learning to analyze images of crops and provide farmers with information on crop health, pests, and yields.
9. *Cropio*: This app helps farmers plan and manage their crops, providing real-time data on weather, soil moisture, and crop growth. It also includes tools for creating planting and fertilization schedules and inventory and expense tracking.

10. *MyFarms*: This app helps farmers manage their land, livestock, and crops, providing real-time data on weather, soil conditions, and crop growth, as well as tools for creating planting and fertilization schedules.
11. *AgriApp:* This app provides farmers with crop-specific information, including recommended sowing and harvesting dates, pests and disease management, and market prices for their produce. It also offers weather forecasts and alerts for farmers to make informed decisions about their crops.
12. *Kisan Suvidha:* This app provides farmers with a wide range of information and services, including current market prices for agricultural commodities, weather forecasts, and information on government schemes and agrarian policies.
13. *Fasal:* This app uses artificial intelligence and machine learning to predict crop yields for farmers. It uses satellite imagery and weather data to analyze crop growth and identify potential issues like pests and diseases.
14. *CropIn:* This app uses digital farming techniques to help farmers increase crop yields and improve crop quality. It uses weather stations and satellite data to provide farmers with real-time crop monitoring and alerts for potential issues.
15. *AgroStar:* This app connects farmers with Agri-experts, who can provide personalized advice on crop management, including seed selection, fertilization, and pest control. The app also includes information on weather forecasts and market prices for agricultural commodities.

In conclusion, the use of smartphone applications in agriculture has grown rapidly in recent years, providing farmers with access to a wide range of tools and information to improve their crop management, increase yields, and support sustainable farming practices. While there are many agriculture apps available, most focus on a specific aspect of agriculture, and many are tailored to particular crops or regions, which limits their usefulness for farmers in other areas. As the demand for sustainable and efficient farming practices grows, smartphone applications will play an increasingly significant role in agriculture's future.

Challenges and limitations with agricultural decision support systems

In [30], the authors reviewed thirteen Agricultural Decision Support Systems (ADSSs) and examined five aspects of ADSSs are accessibility, scalability, interoperability, uncertainty and dynamic factors, and re-planning. The first aspect, accessibility, refers to the graphical user interface (GUI) of an ADSS, which is necessary for operators to manage agricultural activities more easily and efficiently. The second aspect, scalability, is the capability of ADSSs to process growing missions and add extra components for functionality. The third aspect, interoperability, emphasizes integration of functions and knowledge from heterogeneous components in an ADSS and its ability to work with external components or systems. The fourth aspect, uncertainty, and dynamic factors, refers to considering unexpected changes during runtime. The fifth and final aspect, re-planning, involves integrating mechanisms to enhance the robustness of decision supports by adjusting strategies or generating new ones.

The development of ADSSs holds great promise for the future of Agriculture 4.0. By overcoming the challenges faced by ADSSs, they can better serve the needs of farmers and industry. To achieve this goal, researchers must address the following key issues. In [30], the authors seven upcoming challenges in the field of Agriculture 4.0.

Primarily, it is crucial to simplify the graphical user interfaces (GUIs) of ADSSs. While many ADSSs already provide farmers with visual aids and monitoring tools, they often require a certain level of computer knowledge and optimization algorithms. This can be a barrier for many farmers who are not tech-savvy and may not want to spend a lot of time learning how to use the system. The GUIs of ADSSs should be user-friendly and easily accessible, making it easier for farmers to get started quickly. This can be achieved through data visualization in a variety of formats, such as maps, tables, charts, and diagrams, as well as through simple operations like clicking and dragging. Excessive text input and information about computation processes should be avoided, as this may be confusing to farmers. They are more interested in obtaining practical and efficient decision support for their agricultural activities.

Another important aspect of ADSSs is providing adequate decision support throughout the entire life cycle of Agriculture 4.0. This includes short-term, mid-term, and long-term planning. For example, short-term planning involves day-to-day decision-making tasks such as assigning tasks to machinery and scheduling irrigation activities. Mid-term planning should provide seasonal advice on fertilization, while long-term planning should focus on equipment replacement and maintenance. Currently, most ADSSs primarily focus on short-term planning and do not take mid-term and long-term planning into consideration. This needs to change to provide a complete and comprehensive decision support system for farmers.

Uncertainty and dynamic factors are a constant challenge in agriculture. Currently, few ADSSs take these factors into account. Climate change, changing conditions of farmlands, and economic effects from markets are just a few examples of the factors that can impact agriculture. ADSSs must be able to adapt to these factors and provide accurate decision support. For example, changes in temperature and soil moisture can affect the growth of crops and require different fertilization and irrigation practices. Similarly, fluctuations in market conditions can have a major impact on the price of agricultural products and must be considered.

Re-planning is also a major challenge for ADSSs. Unexpected issues and failures can arise during the execution of agricultural missions, requiring the system to adjust its strategy or generate a new solution. Additionally, as the mission is being executed, a better strategy may become apparent, and the ADSS must inform the farmer of this change. This requires the system to be flexible and able to adapt to changing circumstances.

Finally, knowledge from experienced experts is crucial for the development of effective ADSSs. While some researchers aim to create fully autonomous systems, current technology is not advanced enough to provide accurate decision support without human input. Therefore, agricultural knowledge from experts must be incorporated into the system to ensure that farmers receive reliable and practical advice.

In conclusion, overcoming these challenges will help to realize the full potential of ADSSs. By simplifying GUIs, providing complete decision support throughout the life cycle of agriculture, adapting to uncertainty and dynamic factors, considering re-planning components, and incorporating expert knowledge, ADSSs can better serve the needs of farmers and the industry.

Recommendation Systems in Agriculture

A recommendation system is an AI-based algorithm that uses data analysis and machine learning techniques to make personalized user recommendations, such as product or content recommendations. It helps users discover new options and make better-informed decisions. Setting up a recommendation system for crop selection can be evaluated by considering the factors influencing profitability and sustainability. Some of the characteristics overlap, but the context differs.

Components of the recommendation system

A recommendation system also referred to as recommender system is a specific type of DSS to generate recommendations. According to [44], the recommendation system comprises five key components as depicted in **Figure 8Error! Reference source not found.**.

Figure 8: *Components of a recommendation system*

1. *Data Preprocessing*: This component collects, cleans, and organizes the data needed for the recommendation system. This includes user-item interaction data, demographic information, and other relevant data that can be used to personalize recommendations.
2. *Model Building*: This component uses the processed data to build a model that can make personalized recommendations. This can include techniques such as collaborative filtering, content-based filtering, and hybrid techniques.
3. *Evaluation*: This component is used to evaluate the performance of the recommendation system. This can include metrics such as precision, recall, and AUC (Area Under the Curve) to evaluate the quality of the recommendations.
4. *Deployment*: This component is responsible for deploying the recommendation system in a production environment, making it available for real-world use. This can include integrating the system with a website or mobile app and scaling the system to handle substantial amounts of traffic.
5. *Maintenance*: This component includes monitoring the system's performance, updating the model as new data becomes available, and fine-tuning the system's parameters to improve performance.

Types of recommendation systems

According to [45], there are several types of recommendation systems. These include:

Content-Based Filtering [46]: This type of recommendation system recommends items to users based on their preferences and past behaviors. It works by analyzing the features of the items and the user's historical interactions with those features. It then recommends items with features that match the user's past preferences. This method is easy to implement, but it may be limited by the quality of the item’s features.

Collaborative Filtering [47]: This type of recommendation system recommends items based on the similarities between users' preferences. It works by analyzing the historical interactions of all users with all items and then identifies users who have similar preferences. It then recommends items that similar users have interacted with, but the target user has not. Collaborative filtering can be implemented in several ways, such as user-based, item-based, or matrix factorization-based methods. It can be complex to implement and may require significant computational resources, especially for large datasets.

Hybrid Recommender Systems [46], [48]: These systems combine multiple types of recommendation algorithms to improve recommendation accuracy. For example, a hybrid system might combine collaborative filtering with content-based filtering to take advantage of the strengths of both methods. Hybrid systems can be more accurate than single-method systems, but they may also be more complex to implement.

Demographic-Based Recommender Systems: This type of recommendation system recommends items based on demographic information about the user, such as age, gender, or location. It works by identifying items that are popular among users with similar demographic characteristics. This type of system is easy to implement, but it may not be as accurate as other methods, as it relies on generalizations about user behavior based on demographic data.

Knowledge-Based Recommender Systems: This type of recommendation system recommends items based on a user's explicit preferences and requirements. It works by providing users with recommendations based on their stated needs or criteria, such as a desired price range or a specific feature. This type of system can be useful for recommending items that are highly specific or specialized, but it may be limited by the accuracy of the user's input.

Context-Aware Recommender Systems: This type of recommendation system recommends items based on the user's current context, such as their location, time of day, or weather conditions. It works by combining information about the user's context with other recommendation methods, such as content-based or collaborative filtering. This type of system can be highly effective at providing highly personalized recommendations, but it may be more complex to implement and may require more data sources.

Reinforcement Learning-Based Recommender Systems: This type of recommendation system uses reinforcement learning algorithms to learn and adapt to user preferences over time. It works by providing users with a set of recommended items and then using feedback from the user's interactions with those items to adjust the recommendations for future interactions. This type of system can be highly effective at personalizing recommendations, but it can be more complex to implement and may require significant computational resources.

Knowledge Graph-Based Recommender Systems: This type of recommendation system leverages a knowledge graph, which is a database that represents entities and their relationships in a structured way. It works by identifying the user's interests and preferences, and then using the knowledge graph to recommend related entities. This type of system can be highly effective for recommending entities that are not related to the user's past interactions, but it may require significant domain-specific knowledge and resources to build and maintain the knowledge graph.

Session-Based Recommender Systems: This type of recommendation system focuses on making recommendations for a single session or visit, rather than long-term user preferences. It works by analyzing the user's interactions during the current session and recommending items that are likely to be of interest based on those interactions. This type of system can be highly effective for recommending items in real-time, such as for e-commerce websites, but it can be more complex to implement and may require real-time data processing.

Community-Based Recommender Systems: This type of recommendation system recommends items based on the preferences and interactions of a user's community or social network. It works by identifying users who are like the target user based on their social connections and past interactions, and then recommending items that are popular among those users. This type of system can be highly effective at providing personalized recommendations, but it may require access to social network data and can be limited by the size and activity of the user's social network.

Ensemble Recommender Systems: This type of recommendation system combines multiple recommendation algorithms or models to improve accuracy and coverage. It works by aggregating the recommendations from each model and providing a final set of recommendations that is more diverse and personalized than any single model. This type of system can be highly effective at providing accurate recommendations, but it can be more complex to implement and may require significant computational resources.

Matrix Factorization [49], [50]: Matrix factorization is a popular technique for building recommendation systems. In this approach, the preference matrix (also known as the user-item matrix) is factorized into two low-rank matrices, which represent the latent factors of the users and items. These latent factors are usually unobserved and represent underlying dimensions of user preferences and item characteristics, such as genre, artist, director, or rating. The predicted preference for a user-item pair is computed as the dot product of the corresponding user and item latent factors. Matrix factorization algorithms aim to learn these latent factors by minimizing a suitable objective function, such as mean squared error or cross-entropy loss. The learned latent factors can then be used to recommend items to users based on their predicted preferences.

Deep Learning [51]: Deep learning-based recommender systems use neural networks to model user-item interactions and predict preferences. These systems can learn complex non-linear relationships between user preferences and item features and can handle large-scale and high-dimensional data more efficiently than traditional techniques. There are several types of deep learning-based recommender systems, including:

1. *Multi-Layer Perceptron (MLP) based models*: These models use one or more layers of fully connected neural networks to model user-item interactions and make predictions. The input to the network typically includes user and item features, such as age, gender, genre, and rating.
2. *Convolutional Neural Network (CNN) based models*: These models use convolutional layers to learn spatial features from item features, such as image or text data, and predict user preferences based on these features.
3. *Recurrent Neural Network (RNN) based models*: These models use recurrent layers to capture temporal dependencies in user-item interactions, such as sequential data or time-series data.

4. *Autoencoder-based models*: These models use autoencoders to learn low-dimensional representations of the user-item interaction data, which can be used to predict user preferences or recommend items.

These are just a few examples of the types of deep learning-based recommender systems. These models require substantial amounts of training data and can be computationally expensive to train but have been shown to achieve state-of-the-art performance in many recommendation tasks.

Applications of recommendation systems in agriculture

Recommendation systems have been used in agriculture to improve yields, reduce costs, and increase sustainability. Here are a few examples:

Content-based recommendation systems: These systems have been used in precision agriculture to recommend crop-specific management practices based on soil data, weather patterns, and other environmental factors. For example, the AgroPad is a low-cost, handheld device that uses machine learning to analyze soil samples and recommend fertilizer and irrigation practices for specific crops based on their nutrient requirements and local conditions [52].

Collaborative filtering recommendation systems: These systems have been used in precision agriculture to recommend seed varieties based on a farmer's past yield data and the performance of similar farms in the region. For example, the startup Agrible has developed a platform called Morning Farm Report that uses collaborative filtering to recommend seed varieties and field management practices based on a farmer's location and historical yield data [53]. Another example, the agtech startup Hello Tractor has developed a platform that uses collaborative filtering to suggest inputs based on the historical purchases of farmers in the same region [54].

Reinforcement learning-based recommendation systems: These systems have been used to optimize irrigation practices and reduce water waste in precision agriculture. For example, the company CropX has developed a platform that uses sensors to collect soil moisture data and then uses reinforcement learning algorithms to recommend optimal irrigation schedules for different crops and soil types, reducing water usage by up to 50% [55].

Knowledge-based recommendation systems: These systems have been used to recommend crop varieties and management practices based on a farmer's specific requirements and preferences. For example, the company Indigo Agriculture has developed a platform that uses machine learning to analyze a farmer's soil and environmental data and then recommends seed varieties and management practices that are tailored to the farmer's specific goals and constraints [56]. Another example, the Farm to Market Alliance, a partnership between the UN World Food Programme and several private sector companies, has developed a knowledge graph-based tool that provides recommendations on sustainable farming practices, crop diversification, and market opportunities [57].

Community-based recommendation systems: These systems have been used to connect farmers with each other and share information about best practices, market trends, and weather conditions. For example, the social network Farmers Business Network (FBN) allows farmers to share data about seed and chemical prices, yield data, and other information that can be used to inform their decision-making [58].

Ensemble recommendation systems: These systems have been used to combine multiple sources of data to provide more accurate recommendations for crop management practices. For example, the company TerrAvion uses a combination of satellite imagery, weather data, and soil data to provide farmers with real-time recommendations for fertilizer and irrigation management, crop scouting, and other tasks [59]. Another example, the agtech startup AgroScout has developed an ensemble-based tool that combines data from satellite imagery, weather forecasts, and pest detection sensors to provide recommendations on the optimal timing and type of pest control interventions [60].

Profitability factors influence

When setting up a recommendation system to select the best crop based on profitability, several factors should be taken into consideration:

1. *Market prices*: The recommendation system should consider the current and projected market prices for different crops. Crops that are in high demand and command a higher price can be recommended for higher profitability.
2. *Yield*: The recommendation system should consider the yield of different crops. Crops that have a higher yield per unit area can be recommended for higher profitability.
3. *Production costs*: The recommendation system should consider the production costs for different crops, including the cost of seed, fertilizer, and labor. Crops that have lower production costs can be recommended for higher profitability.
4. *Pest and disease resistance*: The recommendation system should consider the differing pest and disease resistance of the selection of crops. Crops that are more resistant to pests and diseases can be recommended for higher profitability. Also, alternating between crops susceptible to various pests and diseases can help reduce the farm's overall pest and disease pressure. This requires a multiple crop, multiple year model for cost.

5. *Climate and weather*: The recommendation should consider the local environment and weather conditions, such as temperature, precipitation, and evapotranspiration, to recommend crops that are well-suited to the local environment.
6. *Harvest and post-harvest*: The recommendation system should consider the harvest and post-harvest process, such as how long it takes for a crop to mature, how it is harvested, and how it is stored. This helps farmers plan their work and can influence profitability.
7. *Market demand*: The recommendation system should consider the market demand for different crops to ensure that farmers can sell their produce at a reasonable price.
8. *Adaptation*: The recommendation system should consider the adaptation of the crops to the local climate and soil conditions, as this can influence the yield and profitability of the crop.

Sustainability factors influence

When setting up a recommendation system to select the best crop based on sustainability, several factors should be taken into consideration:

1. *Water usage*: The recommendation system should consider the water usage of different crops and the availability of water in the local environment. Crops that are well-suited to the local climate and require less water can be recommended.
2. *Pesticide and fertilizer requirements*: The recommendation system should consider different crops' pesticide and fertilizer requirements. Crops that require fewer pesticides and fertilizers can be recommended to reduce the environmental impact.
3. *Soil health*: The recommendation system should consider the impact of different crops on soil health and recommend crops that improve soil health. Crop rotation can help maintain soil health by reducing pest and disease pressure, improving soil

structure, and increasing nutrient availability. A crop rotation plan should consider the current state of the soil and the crops that are best suited to improve it.

4. *Nutrient management*: Different crops have different nutrient requirements, and a crop rotation plan should consider this. For example, alternating between crops with varying requirements of nutrients can help reduce the need for fertilizers and improve nutrient cycling in the soil.
5. *Biodiversity*: The recommendation system should consider the impact of different crops on biodiversity in terms of the direct effect on wild flora and fauna and the indirect impact on habitats and ecosystems.
6. *Carbon sequestration*: The recommendation system should consider the relative ability of different crops to sequester carbon from the atmosphere, which can help mitigate the effects of climate change.
7. *Adaptation*: The recommendation system should consider crop adaptation to the local climate and soil conditions. Crops adapted to the local environment will have a lower impact on the environment and will be more sustainable.
8. *Resilience*: The recommendation system should consider the resilience of the crops to environmental stress, such as droughts, floods, and extreme temperatures. Crops more resilient to environmental stress will be more sustainable eventually. For example, a diverse crop rotation plan can help reduce pest and disease pressure, improve soil health, and increase resilience to weather extremes.
9. *Harvest and post-harvest*: The recommendation system should consider the harvest and post-harvest process, such as how long it takes for a crop to mature, how it is harvested, and how it is stored. This can help reduce the environmental impact of farming.

It is important to note that profitability and sustainability factors are interrelated, and a balance should be struck between them to make the best recommendation. Additionally, a recommendation system should adapt to the changes in the conditions, and farmers should be able to input their observations and feedback to improve the system's accuracy.

Overall, recommendation systems can improve agricultural productivity and sustainability by providing personalized and data-driven recommendations to farmers. However, their implementation in agriculture may require significant investment in data collection, processing, and infrastructure, and collaboration between public and private sector stakeholders.

Challenges to Consider

The implementation of AI-powered personalized agriculture is not without challenges. This section highlights the challenges that could hinder the adoption of AI in agriculture and the importance of responsible innovation. As AI-powered agriculture is a new and emerging field, it is important to identify the potential roadblocks to its adoption and consider responsible innovation approaches.

Challenges to artificial intelligence adoption in agriculture

AI has the potential to transform agriculture, but there are several challenges that must be addressed for its widespread adoption. Here are some of the key challenges expressed by veterans of the agriculture sector [61] and [62]:

1. *Limited data availability and quality*: Agriculture produces a vast amount of data, but there is often a lack of standardization, and data quality can be inconsistent. Furthermore, many smallholder farmers do not have the tools or infrastructure necessary to collect and process data. This makes it challenging to develop AI models that are accurate, reliable, and scalable.

2. *Cost*: AI can be expensive to develop and implement, particularly for smaller farmers. The cost of hardware, software, and personnel can be prohibitive for some farmers, limiting their ability to take advantage of the benefits of AI.
3. *Technical expertise*: Farmers and other agriculture professionals may lack the technical expertise required to use and maintain AI systems. As AI technology continues to evolve rapidly, ongoing training and education will be necessary to keep pace with these changes.
4. *Connectivity and infrastructure: Many farms are in rural areas with limited connectivity and electricity, which can make it challenging to access cloud-based AI systems and other digital technologies.* This can also limit the ability of farmers to collect and transmit data in real-time, which is essential for effective decision-making.
5. *Ethical concerns*: As with any technology, there are ethical concerns associated with AI in agriculture. For example, there may be concerns around data privacy, the impact of AI on farm labor, and the potential for unintended environmental consequences.
6. *Regulatory hurdles*: There are a variety of regulatory and legal hurdles that can impact the adoption of AI in agriculture. For example, there may be restrictions on the use of drones for data collection, or regulations around the use of certain chemicals or pesticides that could limit the usefulness of AI-powered precision agriculture tools.
7. *Adoption and scalability*: While some farmers may be willing to adopt AI, scaling up these technologies to reach all farmers can be challenging. Factors that may affect adoption and scalability include trust in the technology, access to financing, and the ability to integrate recent technologies with existing systems.

8. *Cultural and social barriers*: Cultural and social barriers can also impede the adoption of AI in agriculture. For example, farmers may be resistant to change or may prefer traditional methods of farming. Furthermore, social dynamics such as gender and age can also play a role in adoption and use.
9. *Lack of government support*: Government support and regulations are crucial for successfully implementing and adopting agricultural technologies.

According to [63] the challenges in developed countries include the prohibitive cost of equipment and technology, limited understanding and knowledge, lack of government support and regulations, data privacy and security concerns, limited access to rural areas, and limited access to the internet and digital services. Developing countries face challenges, including a lack of infrastructure, limited access to technology and education, financial constraints, and culture and language.

Overall, addressing these challenges will be crucial for the successful adoption of AI in agriculture. Collaboration between farmers, technology companies, policymakers, and other stakeholders will be essential to overcome these obstacles and drive the widespread adoption of AI in agriculture.

Responsible innovation

Responsible innovation refers to the careful consideration of the potential positive and negative impacts of emerging technologies and ensuring that their deployment aligns with public values and societal goals. In agriculture, smart technologies, such as precision agriculture, robotic technology, and decision support systems, can lead to more efficient and sustainable farming practices. However, past technological revolutions have caused harm and controversies, and the use of AI and robotics may also lead to unintended consequences. Therefore, responsible governance of agricultural technology is necessary to ensure its positive impact on society.

To achieve responsible innovation, a systemic approach that encompasses all the different actors and innovations that contribute to sustainable agriculture is required. Responsible innovation frameworks need to consider the wider network of innovations that play a significant role in sustainable agriculture, including small farmer-led and community-led innovations, as well as low-tech sustainable agriculture solutions. A more systemic perspective on responsible innovation will enable innovators to consider interrelations between multiple innovations in sustainable agriculture and will promote more strategic levels of governance and coordination between public, private, and civil society actors.

The framework for responsible innovation proposed in [64] in the context of smart dairy farming, includes four dimensions of responsible innovation: anticipation, inclusion, reflexivity, and responsiveness. The first dimension, anticipation, means that the impacts of technological innovations must be predicted through techniques such as foresight exercises and scenario building. The second dimension, inclusion, requires that all affected actors be included in the responsible innovation process. The third dimension, reflexivity, calls for the creation of structures to guide the assessment of mutually beneficial trajectories. The fourth dimension, responsiveness, requires the ability of Agri-Tech innovators to respond to problems caused by recent technology.

However, responsible innovation frameworks need to broaden their notions of inclusion to encompass the voices of marginalized groups, such as small-scale farmers and indigenous communities. Including marginalized groups will help address public concerns about emerging science and technology and promote the cultivation of distributed responsibilities across the innovation ecologies. This will facilitate and demand more strategic governance and coordination between public, private, and civil society actors involved in steering innovations in the Agri-Tech revolution toward more socially responsible and humane ends.

To achieve this, we need methods that can map multiple innovations and track their emergence and interactions across fields of innovation in sustainable agriculture. This requires more systemic thinking, which demands methods capable of mapping and monitoring innovations and their interactions. Moreover, ethical considerations must be considered when implementing technologies in agriculture, and frameworks should be developed to mitigate risks and promote sustainable outcomes.

In [65], the authors discussed the need to broaden the idea of inclusion in responsible innovation to encompass the diverse ways societal actors engage with these modern technologies. Currently, the dominant approach in agricultural research is top-down and non-inclusive, with research institutions having the power to shape the trajectory of innovation design without consulting relevant stakeholders such as farmers. While proposals have been made to include stakeholders through methods like citizen forums and workshops, it is suggested that more than these methods are needed. There is a need to go beyond these methods and consider the existing ecologies of participation, the already existing forms of societal engagement with these technologies that can provide important sources of public concern, values, and actions that would otherwise be excluded from the responsible innovation process.

To address this, there needs to be a range of tools and methods for responsible innovation that can map diverse forms of societal engagement with emerging technologies across innovation systems. This can involve digital methods, issue mapping, systematic mapping, and comparative case studies. These methods can provide vital social intelligence about how farmers and the public interact with sustainable agriculture, from formal spaces like farmer networking events to informal areas like discussions on social media and low-tech forms of agricultural practice. This information is essential in creating a comprehensive responsible innovation framework that can map existing spaces of participation and enhance the reflexivity, anticipation, and responsiveness in responsible innovation frameworks.

In conclusion, responsible innovation in agriculture requires a comprehensive and systemic approach that considers the social and environmental benefits of technological advancements. The integration of smart farming technologies can improve agricultural production and provide social and environmental benefits. However, the potential consequences of technology should be carefully considered, and responsible governance of agricultural technology is necessary to ensure its positive impact on society. Responsible innovation frameworks need to broaden their notions of inclusion to encompass the voices of marginalized groups, and ethical considerations need to be considered when implementing innovative technologies in agriculture.

Building farmers' trust in smartphone applications for agriculture

Despite the abundance of smartphone applications available for agriculture, many farmers are hesitant to adopt them due to concerns over their longevity and continued support. In the study [66], the authors surveyed 261 farmers and found that factors like how useful the apps are and whether other people are using them affect how much the farmers use them. Farmers require apps that can be relied upon over multiple crop seasons, which requires app developers to take measures to ensure the trust and confidence of their user base. Some concerns are specific to the country or region. To address these concerns, here are some measures and considerations that app developers can take to ensure farmers can trust an app's longevity:

1. *Focus on user needs*: Developers should focus on creating apps that meet the specific needs of farmers. By addressing key concerns and providing real value, the app is more likely to be adopted and used over multiple crop seasons.
2. *Provide regular updates*: Developers should provide regular updates that address user feedback and ensure the app is up to date with the latest technological advancements. By keeping the app relevant, developers can build trust and demonstrate their commitment to long-term support.
3. *Provide customer support*: App developers should provide customer support to address any issues that arise and help farmers navigate the app. This support should be available via email or phone, and developers should respond promptly to inquiries.
4. *Build trust through transparency*: Developers should be transparent about their development process and plans for the app's future. This includes sharing information on the app's development roadmap, timelines for updates, and future features. This can help build trust and demonstrate the developer's commitment to the app's longevity.
5. *Foster a sense of community*: Developers should create a sense of community around the app, bringing together farmers to share knowledge and experiences. By creating a network of farmers who use the app, developers can build a strong user base that will support the app over the long term.
6. *Ensure data security and privacy*: Farmers may be hesitant to use agricultural apps if they are concerned about the security and privacy of their data. Developers should ensure that their apps comply with relevant data privacy laws and provide transparent information on how user data is collected, stored, and used. They should also

implement appropriate security measures to protect user data from unauthorized access or breach.

7. *Provide offline functionality*: Many farmers in rural areas may not have reliable access to the internet, which can limit their ability to use online agricultural apps. Providing offline functionality can help ensure that farmers can continue to use the app even when they are not connected to the internet. This can be achieved through offline data storage, synchronizing, and other features.
8. *Collaborate with local partners*: Developers can build trust and credibility with farmers by partnering with local agricultural organizations, extension services, and other stakeholders. By working with trusted local partners, developers can leverage existing networks and expertise to help promote the app and build awareness and trust among farmers.
9. *Offer a trial or freemium version*: Offering a free trial or freemium version of the app can help reduce the risk for farmers and encourage them to try the app. By providing a low-risk way to test the app, developers can help build trust and confidence among potential users. Additionally, freemium models can help ensure that the app remains accessible to farmers who may not have the resources to pay for a full version.

Therefore, to ensure farmers trust an app's longevity, developers should focus on meeting user needs, providing regular updates and customer support, building trust through transparency, and fostering a sense of community. By doing so, developers can create apps that are trusted and used over multiple crop seasons.

Summary

In summary, this chapter presented a comprehensive literature review of the state of agriculture and the role of AI in farming. The chapter has highlighted the importance of sustainability in agriculture and the several factors influencing selection and yield prediction. It has also emphasized the importance of responsible innovation and the need for addressing the challenges faced in the adoption of AI in agriculture.

The chapter has also explored the several types of recommendation systems used in agriculture and their applications, as well as the challenges and limitations of agricultural decision support systems. It has provided a detailed analysis of the various AI algorithms used in yield prediction and the role of responsible innovation in the adoption of AI in agriculture.

Overall, the emergence of AI-powered personalized agriculture represents a paradigm shift in the farming industry, where the use of advanced technologies and data-driven approaches can lead to more efficient and sustainable farming practices. With the help of AI, farmers can personalize their farming practices, from crop selection to pest control, by utilizing real-time data from sensors and satellites, weather forecasts, and soil conditions. This personalized approach can help farmers make informed decisions and optimize their yield while reducing waste and improving resource management. The integration of AI in agriculture has the potential to revolutionize industry, making farming more profitable, sustainable, and environmentally friendly. The emergence of AI-powered personalized agriculture is a promising development that could shape the future of the agricultural industry.

The chapter's findings provide a solid foundation for the development of AI-powered personalized agriculture and will serve as a valuable resource for researchers, practitioners, and policymakers in the field.

CHAPTER 3: PROPOSPED RECOMMENDATION SYSTEM FRAMEWORK

Farmers often face the challenge of unpredictable crop yields, despite the existence of various technological solutions (as discussed in Chapter 2). These solutions, however, tend to be generic, dispersed and location-specific, hindering access and utilization of the necessary information for informed crop selection and farm management. To address this, a personalized farming recommendation system framework is proposed, which considers both profitability and sustainability, offering farmers a comprehensive range of crop selection options. Implementing recommendation systems can revolutionize farming practices by utilizing data and machine learning to provide farmers with actionable insights on crop care and increased yields, while ensuring sustainability. This scalable framework builds upon previous research in the field, making it adaptable for farmers of all crops and locations.

In this chapter, the proposed recommendation system concept is broadly outlined. Next, the system architecture is presented followed by a level 1 entity relationship diagram. The remaining part of the chapter involves presenting the framework using various activity diagrams and entity relationship diagrams. The chapter ends with describing the attributes and limitations of the proposed framework.

Proposed Recommendation System Concept

The concept framework in **Figure 9** illustrates a system for recommending crops with high profitability for a specific region and identifying sustainable crop options. The first step for any AI driven system is to “connect local datasets” such as feasible crops, crop yields, crop nutritional requirements, weather historical and forecasts, soil, etc. to the system. This step involves preprocessing (collection, integration, cleaning, transformation, reduction, normalization, encoding, feature selecting and splitting) the data so that it can is easily consumed by the system.

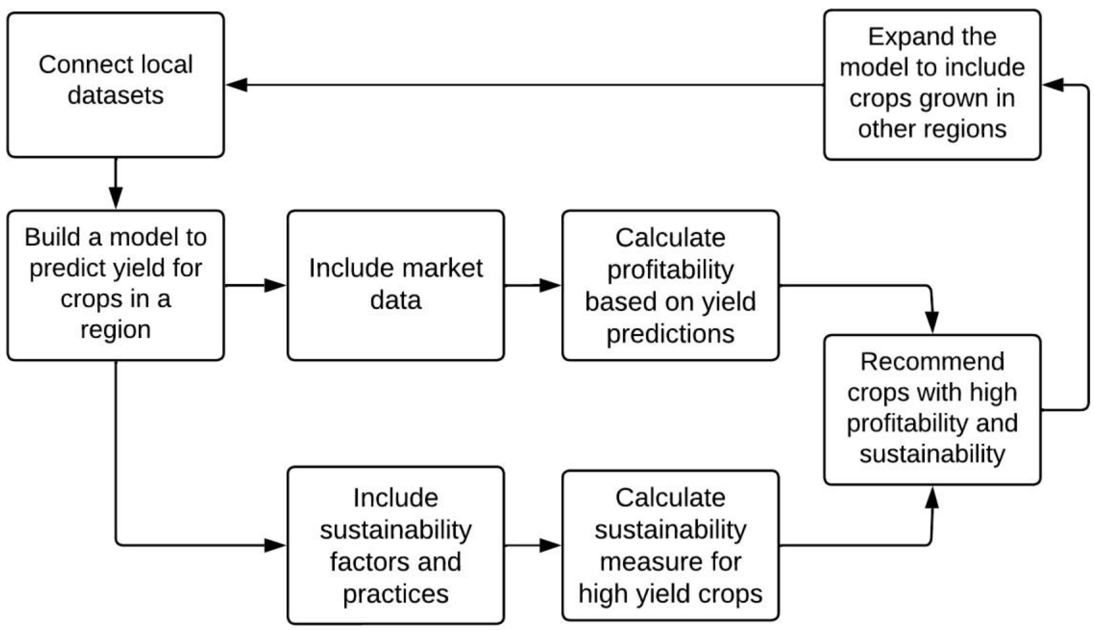

Figure 9: *Proposed recommendation system concept*

The first AI based block in the system concept is, "Build a model to predict yield for crops in a region," is to build a model comprising various machine learning and deep learning algorithms to predict how much yield a crop will produce in a specific region. As detailed above, this model considers multiple factors, such as weather conditions, soil health, and other environmental factors. The next block, "Include market data," incorporates market price, market demand and operating costs, if available, into the model. This includes current crop prices, demand for specific crops, and/or other relevant economic information. The third block, "Calculate profitability based on yield predictions," uses the yield predictions from the previous blocks to calculate the potential yield of growing a specific crop in the region.

In a parallel track, the system identifies crops with a lower environmental impact and better for the region's long-term health in the "Include sustainability factors and practices" block. This includes crops that require less water or fertilizer and/or those that positively impact soil health.

The step also includes crop rotation information to the model. Crop rotation is the practice of rotating the types of crops grown in a specific field to improve soil health and reduce pest and disease pressure, as discussed above. The matrix can be computed with DSS, as discussed in [43]. The next block, "Calculate sustainability measure for high-yield crops," evaluates the sustainability of crops identified as high-yield.

Both tracks' collective output is "Recommend crops with high profitability and sustainability." It aggregates all the predictions and calculations from the previous blocks to provide options to select a crop with relevant data for the farmer to decide on what crop to sow in that season. This step also includes a feedback system into the model to improve its accuracy over time. The feedback could include incorporating missing data from previous growing seasons, gathering feedback from farmers, and other information to improve the model's predictions.

The final block, "Expand the model to include crops grown in other regions," is to scale the model to incorporate data from other regions and make the model more universally applicable. The step feeds back to the start of connecting local datasets and running the data through the system.

Recommendation System Architecture

The recommendation system architecture presented in **Figure 10** is proposed taking design consideration from the data science handbook [67] and building a recommendation system [68]. The process is initiated by the user (farmer or extension agent) interacting with the system via the user interface (UI). The UI can be a web or mobile application or an interactive voice or text-based system. It is an essential system component that allows farmers to interact with the system, enter data, and receive recommendations.

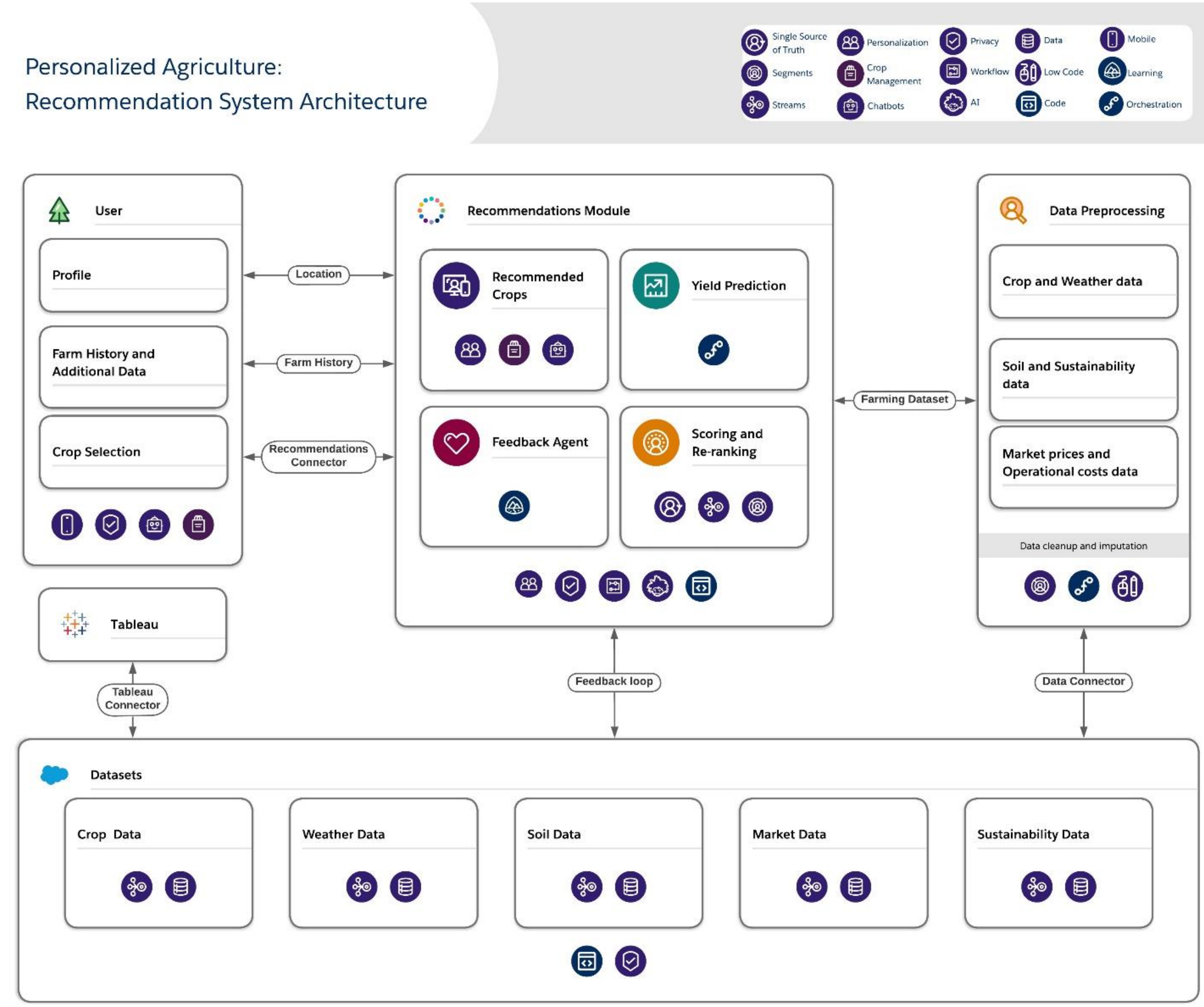

Figure 10: *Recommendation system architecture*

The first step in building a recommendation system is to collect data on weather conditions, crop yields, soil quality, and other relevant factors. This data can be collected from various sources such as weather stations, agricultural departments, and farmers. After collecting the data, the second step is to clean and transform the data into a format that the recommendation system can use. This step includes missing data imputation, data normalization, and feature engineering.

The next step is the recommendations module which has multiple blocks. It takes agricultural data input and generates recommendations as output. These primary components are:

- *Yield Prediction*: Once the data is preprocessed, it can be used to train a model that can make recommendations based on the weather forecast and other factors. Different models, such as content-based filtering, collaborative filtering, or deep learning models, can be used for this step. After training the model, it needs to be evaluated to see how well it performs on a validation set. This step includes splitting the data into training and validation sets and measuring the model's performance using evaluation metrics such as accuracy, precision, recall, and F1-score. Candidate generation and ranking as part of this process. It is an essential step in the recommendation process.
- *Scoring and Re-ranking*: Other agriculture data is used to score and re-rank the generated candidate. Re-ranking is the process of ordering the candidates based on their predicted relevance or usefulness to the farmland of the farmer.
- *Recommended Crops*: This is the output of the recommendation's engine. The farmer could evaluate the recommended crops and related parameters and select a crop to sow.
- *Feedback Agent*: A feedback loop is a critical component that allows farmers to provide feedback on the recommendations and allows the system to learn and improve over time. This can be done through an online survey or a direct feedback mechanism.

It is important to note that the system is designed to evolve as it is tested on different datasets in different regions. One way to address it is to use multiple models in the system and pick the best one that works for each dataset or each region. This concept is known as model ensemble described in [69], where multiple models are trained, and their predictions are combined to improve the overall performance of the recommendation system. There are several ways to combine the predictions of multiple models, such as:

1. **Model averaging** where the predictions of all models are averaged to produce the final prediction.
2. **Model stacking**: where the predictions of all models are used as input to a meta-model, which makes the final prediction.
3. **Model weighting**: where the predictions of all models are weighted according to their performance on a validation set.

These ensemble methods improve the recommendation system's performance by combining the strengths of different models and reducing their weaknesses. The following steps to implement an ensemble method for crop recommendations are included in the yield prediction of the recommendation module:

1. Preprocessing the data and preparing it for the models
2. Separately training and testing the different models
3. Evaluating the performance of each model using appropriate evaluation metrics
4. Combining the models' predictions using appropriate ensemble method
5. Evaluating the performance of the ensemble model using relevant evaluation metrics
6. Iterating the above steps with different combination of models and ensemble methods to find an optimal model

High-Level System Design

The high-level design using entity relationship diagram (ERD) notations illustrated in **Figure 11** depicts the relationship between various users (Farmer, Extension Agent/ Researcher, Local Administrator), profiles (Farmer Profile, Farmland Profile, Finances Profile, Sustainability Profile), and data connections (Weather, Crop, Market, Costs, Farm Practices) and yield prediction and recommendations (using AI).

The figure shows that users (Farmer, Extension Agent/Researcher, and Local Administrator) can create various profiles such as Farmer Profile, Farmland Profile, Finances Profile, and Sustainability Profile. These profiles contain information related to farmers, farmland, finances, and sustainability practices. The profiles are linked to Local Data Connections, which include several types of data such as weather, crops, market, costs, and farm practices. These data connections are used to generate yield predictions and recommendations using AI. Overall, **Figure 11** helps to visualize the relationships between different entities in the system and how they interact with each other to facilitate efficient and effective agricultural practices.

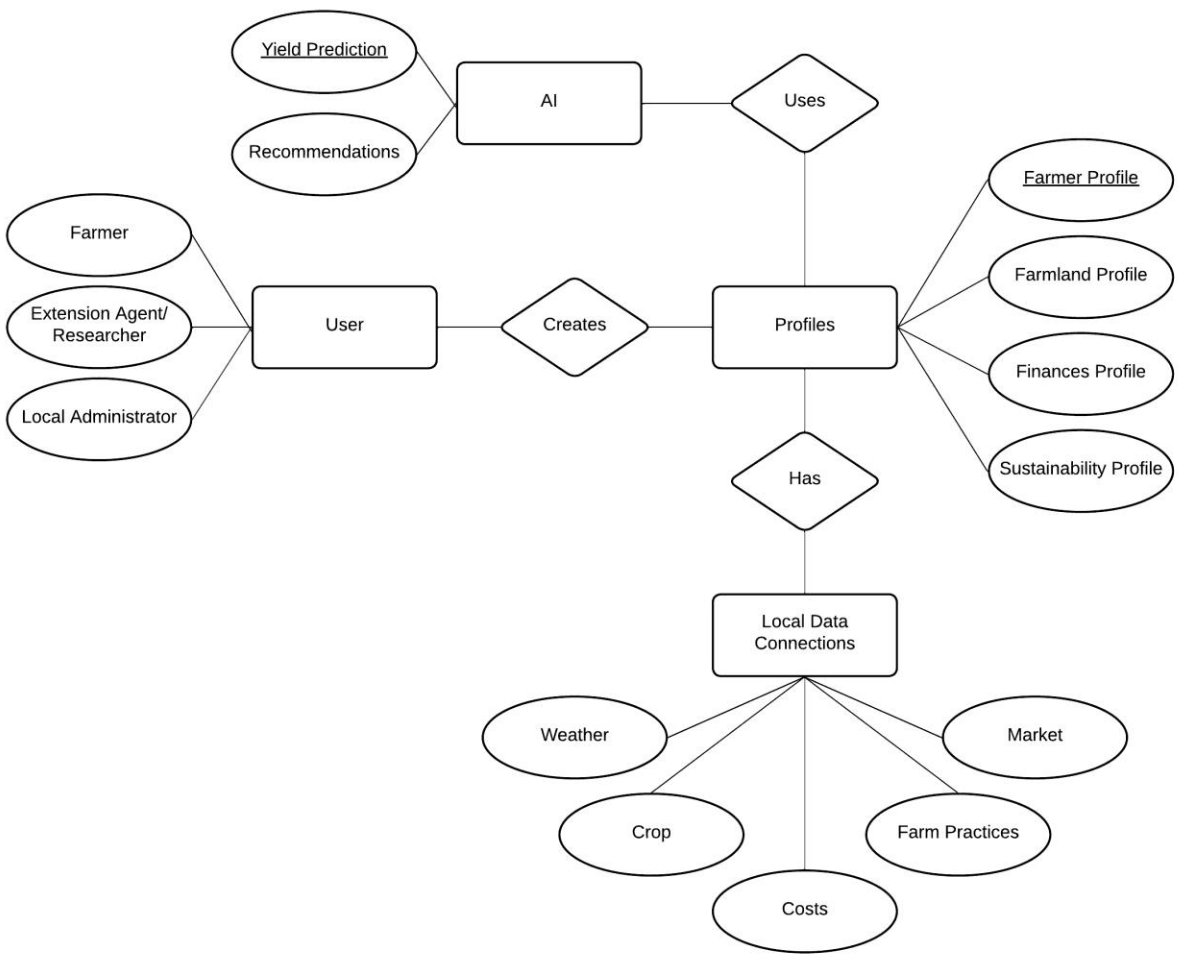

Figure 11: *High-level system design*

System User Roles

The proposed system requires three distinct user roles or types – Farmers, Extension Agents or Researchers, and Local Admin. The profiles of Farmer, Extension Agent and Researcher are depicted in **Figure 12**. The ERD helps to visualize the characteristics of the user roles and their profiles, making it easier to manage and access information related to farmers, extension agents, and researchers.

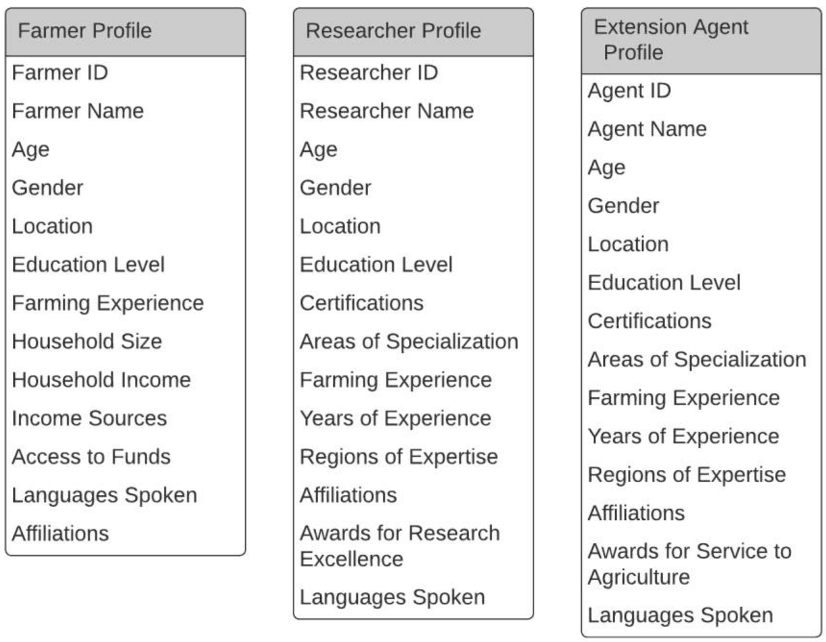

Figure 12: *System user role entities and associated fields*

The Farmer profile helps to identify and understand the characteristics of farmers, such as:

- *Education Level*: Indicates the level of formal education the farmer has received, which can influence their ability to access information, understand modern farming practices, and make informed decisions.
- *Farming Experience*: Reflects the number of years the farmer has been engaged in agriculture, indicating their level of knowledge and expertise.

- *Household Income*: Indicates the financial stability of the farmer's household, which can influence their ability to invest in farm inputs and equipment and engage in sustainable practices.
- *Income Sources*: Identifies the various sources of income for the farmer, which can provide insights into their financial priorities and constraints.
- *Access to Funds*: Shows whether the farmer has access to credit or financial services, which can impact their ability to invest in their farm and adopt modern farming practices.

Extension agents are experts or teachers employed by land-grant universities to serve the citizens of a particular state in various areas, including economics, agriculture, family, animal production, and nutrition. Their responsibilities include identifying and addressing issues in their area of expertise, developing, and executing educational programs, conducting research, answering questions from the community, and maintaining a prominent level of visibility. A bachelor's or master's degree in the subject area or agriculture and extension education is typically required, and extension agents are typically employed by state or county agencies. The Extension Agent profile helps to identify and understand the characteristics, such as:

- *Certifications*: Indicates whether the extension agent has acquired any relevant certifications, which can reflect their level of training and expertise in specific areas.
- *Areas of Specialization*: Reflects the specific areas in which the extension agent has specialized knowledge, which can help in matching farmers with the right extension agents for their specific needs.

- *Regions of Expertise*: Identifies the geographical regions where the extension agent has extensive knowledge, which can be useful in targeting extension services to areas with specific needs.
- *Awards for Service to Agriculture*: Recognizes the achievements and contributions of the extension agent to the agricultural sector, indicating their level of dedication and commitment.

Agricultural researchers or scientists conduct research and experiments related to the productivity and sustainability of crops and livestock, with a focus on environmental impact and conservation. They may specialize in areas such as soil, plants, or livestock and work in basic or applied research, examining the biological and chemical factors behind local agricultural productivity, and improving finished food products. They may also work on improving the nutritional benefits of existing food products or creating new ones in response to public demand for healthier options. Overall, the role is to develop and maintain the safety and quality of food products while promoting sustainability and environmental responsibility in agricultural production. The Researcher Profile helps to identify and understand the characteristics, such as:

- *Certifications*: Indicates whether the researcher has acquired any relevant certifications, which can reflect their level of training and expertise in specific areas.
- *Areas of Specialization*: Reflects the specific areas in which the researcher has specialized knowledge, which can help in identifying the right experts to collaborate with on specific research projects.

- *Regions of Expertise*: Identifies the geographical regions where the researcher has extensive knowledge, which can be useful in targeting research efforts to areas with specific needs.
- *Awards for Research Excellence*: Recognizes the achievements and contributions of the researcher to the agricultural sector, indicating their level of dedication and commitment to advancing knowledge and practices.

A local administration ensures that the system is effectively implemented and meets the specific needs of local users in different regions. In a system that serves users in different countries or regions, local administration is important because it can provide tailored support to users in specific locations. Local administration can provide support in areas such as user training, data collection, system customization, and troubleshooting. For example, they can help with data collection on local weather patterns, soil characteristics, and market trends to help users make informed decisions about their farming practices. Local administration can also help ensure that the system is optimized for the local environment, such as providing translations in local languages or customizing the system to work with local tools or technologies.

By providing this local support, the system can be more effective in meeting the needs of users in different regions and can be better integrated with local agricultural practices. This can help increase user adoption, satisfaction, and improve agricultural productivity and sustainability. Therefore, local administration plays a critical role in ensuring the success of a global system by tailoring its implementation to meet the specific needs of local users. In most circumstances, the Extension Agent or Researcher plays the role of the Local Administration.

System Behavior

The activity diagrams are used to represent the system behavior in the form of interactions between the user(s) and the system. The two primary users discussed in this section are the extension agent or researcher and the farmer. The activities in the diagram are connected in a specific order to ensure that the necessary information is gathered before moving on to the next step. The flow of activities in the diagram ensures that farmer profile and farmland profiles are created in a logical sequence and utilized to generate recommendations.

Extension Agent or Researcher – system interactions

The Extension Agent or Researcher activity diagram depicted in **Figure 13** provides a systematic and organized approach for agents to connect, validate, and update data within the system to provide evidence-based recommendations.

The initial step of accessing the web or mobile app and selecting between registration and login is critical to ensure that only authorized agents have access to the system. The steps involve creating or providing account details, selecting the appropriate agent role, and confirming the agent's location. The next step is to verify the agent’s credentials and authorization role. The verification of agent credentials and authorization role is essential to the integrity of the system, as it ensures that only qualified and authorized individuals have access to the data and can make changes. The agent or researcher can then view or update local agriculture data.

Once the agent has logged in, they can begin the process of improving local agriculture data by first ensuring the local datasets are connected to the system. The next steps involve validating the data, filling in any missing data, and supporting the system with data processing. The agent is also responsible for ensuring data is up to date.

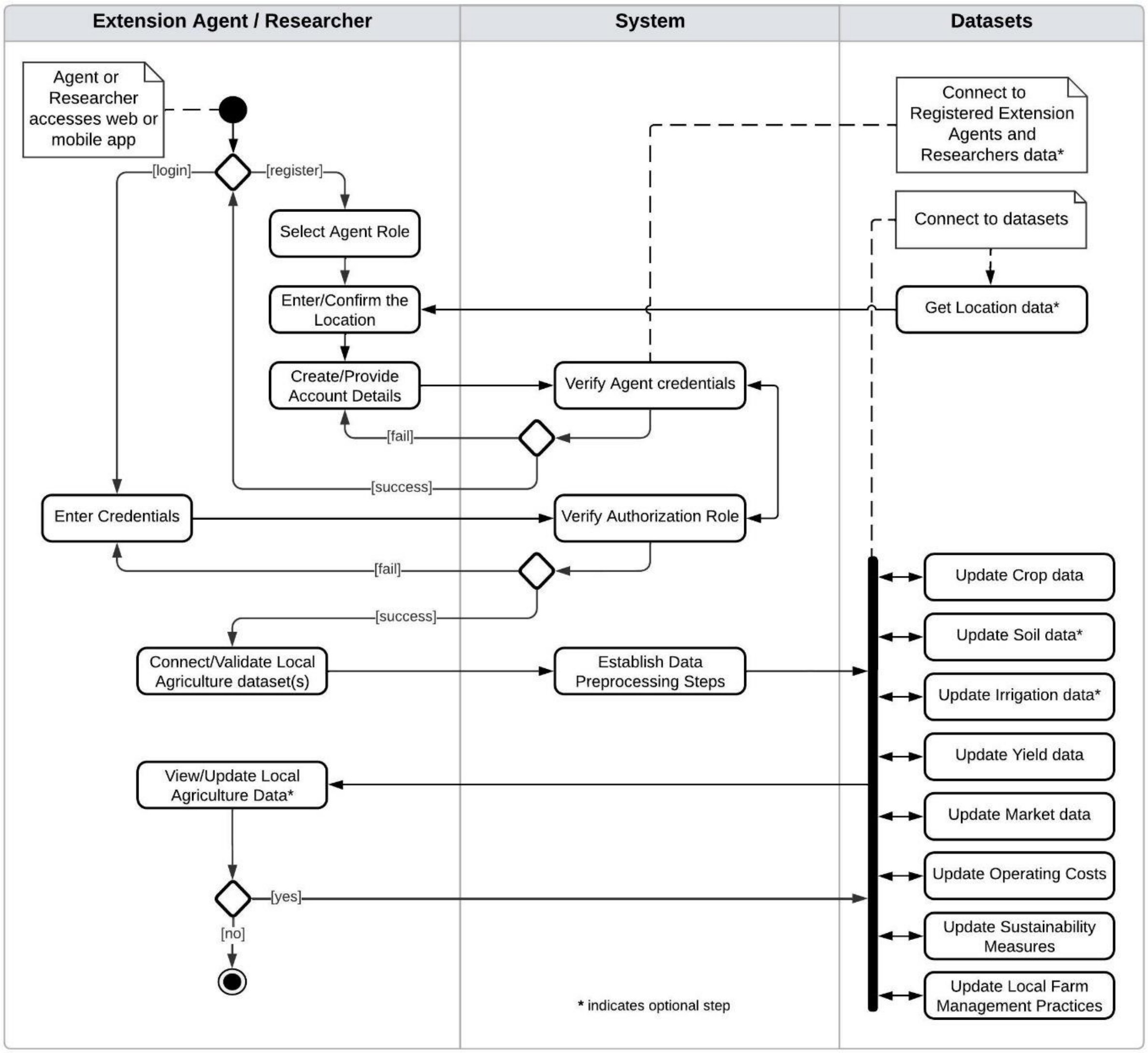

Figure 13: *Extension Agent or Researcher activity diagram*

The steps involving updating local farm management practices and sustainability measures are critical for promoting sustainable agriculture practices that protect the environment and promote long-term economic growth. By encouraging the adoption of sustainable farming practices, the agent can help ensure that local agriculture practices are environmentally sound and economically viable. These steps are particularly important in areas where there is an elevated risk of environmental degradation, such as in areas with fragile ecosystems or prominent levels of soil erosion. The steps involved in updating operating costs and market data are also significant, as they help to ensure that the agent's recommendations are financially feasible for farmers. By staying up to date on operating costs and market data, the agent can provide farmers with advice that is both economically viable and environmentally sound. Finally, the step involving validating local agriculture datasets is critical to ensuring the accuracy and relevance of the data used to inform recommendations. By validating local agriculture datasets, the agent can ensure that the system's recommendations are based on sound scientific principles and local conditions. This step is essential for providing evidence-based recommendations that are tailored to local conditions and can help to ensure the success of the system.

Farmer – System interaction

The farmer activity diagram outlines the various steps involved in providing personalized recommendations to the farmer. It comprises of the interactions between the farmer and the proposed system. It involves accessing location, weather, resources, irrigation, and soil data and creating various profiles such as farmer, farmland, weather, crop, etc. Using this data, the system generates crop candidates, predicts yield, adds sustainability practices, and identifies resource requirements to rank the crops based on their profitability and sustainability. The farmer can select alternate farming practices, growing seasons, operations, and resources and enter weekly crop data to personalize the recommendations further. These activities are depicted in two separate diagrams. **Figure 14** depicts the steps that result in the creation of farmer profile and their farm specific profiles, whereas **Figure 15** depicts the system activities for yield predictions and recommendations, enabling the farmer with personalized recommendations and actionable insights. The primary goal of **Figure 14** of the farmer activity diagram is to help the farmer create their profile and their farmland(s) profile by connecting to relevant local datasets and providing additional personal information.

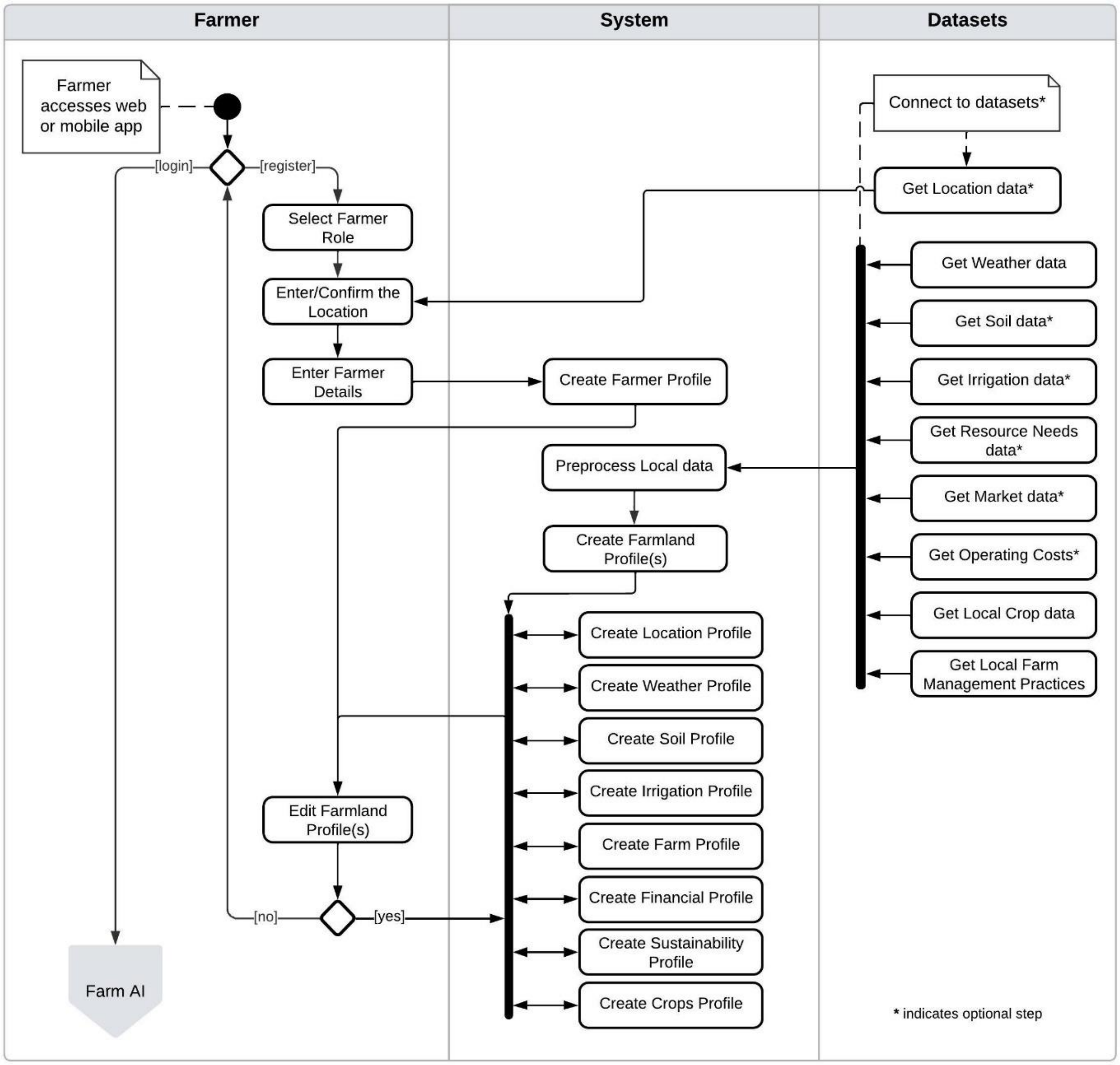

Figure 14: *Farmer activity diagram*

These datasets provide information about various aspects of the farmland and include:

1. *Location data*: This dataset provides information about the geographic location of the farmland, including latitude, longitude, and altitude. Examples of typical datasets for location data include GPS coordinates, topographic maps, and satellite imagery.
2. *Weather data*: This dataset provides information about the weather patterns of the location, including temperature, precipitation, and wind speed. Examples of typical

datasets for weather data include historical climate data, weather station data, and satellite imagery.

3. *Resource Needs data*: This dataset provides information about the resource needs of crops and farmland, including water, fertilizer, and pest control. Examples of typical datasets for resource needs data include soil testing results, water quality reports, and pest monitoring data.
4. *Irrigation data*: This data set provides information about the irrigation needs of the crop and farmland, including the type of irrigation system used and the scheduling of irrigation. Examples of typical datasets for irrigation data include water usage data, crop water requirements, and irrigation system performance data.
5. *Soil data*: This dataset provides information about the soil types on the farmland, including pH levels, nutrient content, and soil structure. Examples of typical datasets for soil data include soil testing results, soil maps, and satellite imagery.
6. *Operating Costs*: This dataset provides information about the costs associated with running the farm, including labor, equipment, and inputs such as fertilizers and pesticides. Examples of typical datasets for operating costs include financial statements, invoices, and receipts.
7. *Market data*: This data set provides information about the market demand and prices for the crops grown on the farmland. Examples of typical datasets for market data include market reports, price histories, and supply and demand data.
8. *Local Farm Management Practices*: This dataset provides information about the farming practices used on nearby farms, including crop rotations, tillage practices, and

pest management strategies. Examples of typical datasets for local farm management practices include surveys, interviews, and observation data.

9. *Local Crop data*: This dataset provides information about the types of crops grown on nearby farms and the typical yields for those crops. Examples of typical datasets for local crop data include crop yield data, crop rotation data, and satellite imagery.

Overall, these datasets are critical for creating the various profiles needed to optimize crop production and manage the farmland effectively. By analyzing and processing these datasets, the resulting profiles are created:

Location Profile: The location of farmland is a crucial factor that determines the type of crops that can be grown and the environmental factors that will influence crop growth. The Location Profile includes information such as latitude, longitude, altitude, and proximity to other farms. This information is significant in determining the climate and weather patterns, soil types, and irrigation needs of the farmland.

Weather Profile: Weather patterns, such as temperature, rainfall, and wind, have a significant impact on crop production. The Weather Profile provides information about the weather patterns of the location, including average temperatures, precipitation levels, and other weather-related data. This information is important for crop selection and planning, and for determining the irrigation and other resource needs of the farmland.

Farm Profile: The Farm Profile provides detailed information about the farm, such as the size of the farm, the type of crops grown, and the farming practices used. This information is crucial for planning crop rotations and determining the resource needs of the farm. The Farm Profile can also provide information about the history of the farm, including previous crop yields and production data.

Irrigation Profile: Irrigation is critical for maintaining crop growth and production in areas where rainfall is insufficient. The Irrigation Profile provides information about the water sources available, the type of irrigation system used, and the irrigation scheduling. This information is essential for planning irrigation needs and optimizing water use efficiency.

Soil Profile: The Soil Profile provides detailed information about the soil types, including pH levels, soil structure, and nutrient content. This information is essential for crop selection, determining the nutrient and fertilizer needs of the farmland, and improving soil health. The Soil Profile can also provide information about any soil constraints, such as erosion or compaction, that need to be addressed to maximize crop production.

Financial Profile: The profile provides information about the financial aspects of farming, such as the costs of production, the expected returns on investment, and the sources of financing. This information is important for determining the profitability of the farm and making decisions about resource allocation.

Sustainability Profile: The profile provides information about the environmental and social impacts of farming. This includes factors such as the use of pesticides and other chemicals, the impact of farming practices on soil and water quality, and the impact of farming on local communities. This information is crucial for ensuring that farming practices are sustainable and environmentally friendly.

Crops Profile: The profile provides information about the types of crops grown on the farmland, including the planting, and harvesting dates, the expected yields, and the market demand. This information is crucial for crop selection and planning and for making decisions about resource allocation and market opportunities. The Crops Profile can also provide information about the historical crop yields data, which can be used for analysis and planning purposes.

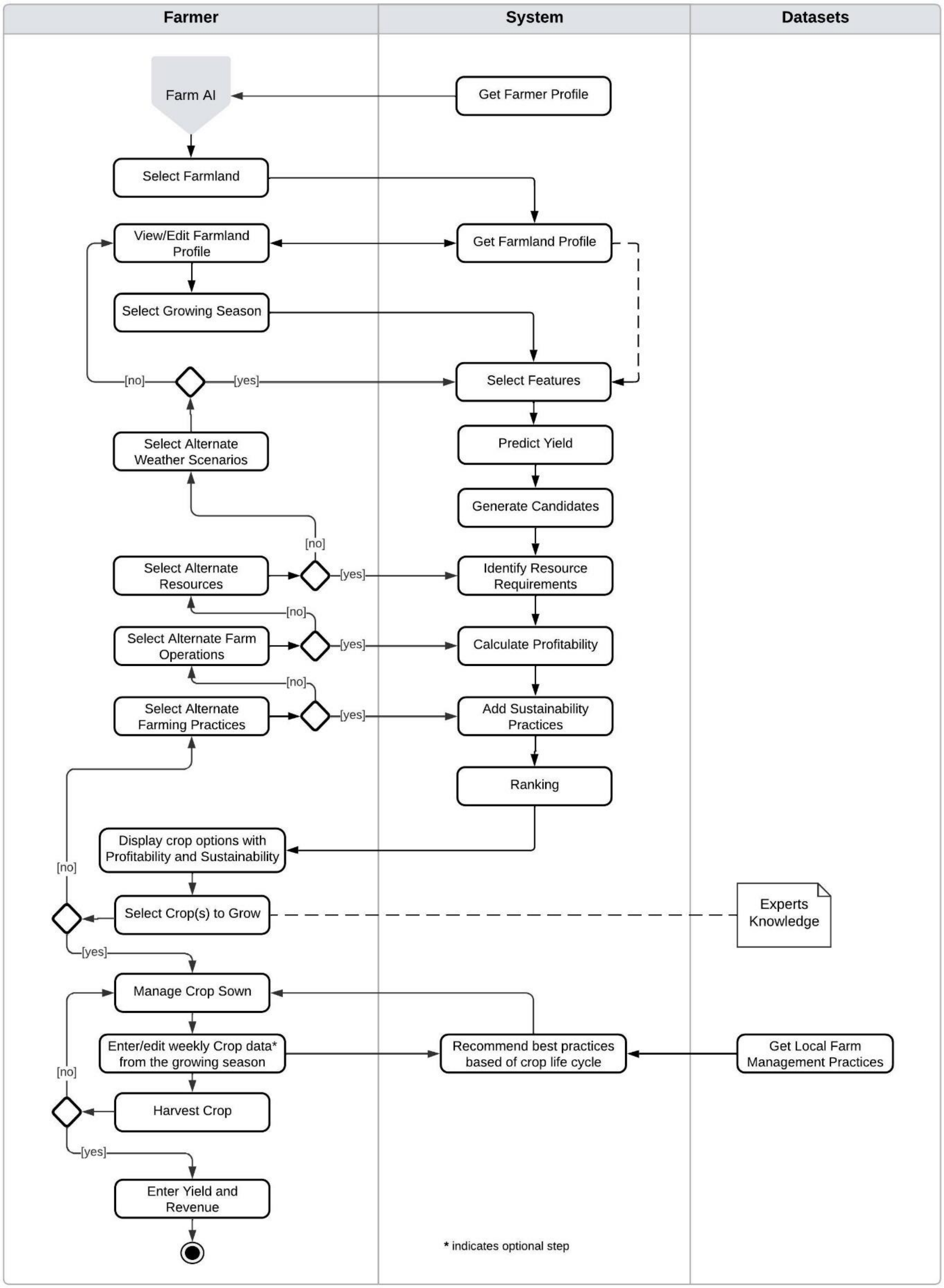

Figure 15: *Farmer activity diagram continuation with AI components*

Once the profiles have been created, the next step is to analyze the data and provide insights on the farm's performance and recommendations based on farmer's specific needs. These activities are depicted in **Figure 15**. The farmer logs in to the system via the user interface and selects the farmland they want explore and the season under consideration. Getting farmers' and farmland profiles and related data is a crucial first step in initializing the system. The profiles and data can help the system understand the farmer's goals, resources, constraints, and the characteristics of their farmland. This information can be used to generate customized recommendations tailored to the farmer's specific needs and circumstances. The key activities for the proposed recommendation system are:

Select Features: Feature selection is a key step in the yield prediction algorithm as it helps to identify which variables or features are most relevant and informative for predicting crop yield accurately. In general, a feature can be any measurable or observable aspect of a crop, such as weather conditions, soil properties, resource availability, or cultural practices. There are several methods for feature selection, including filter methods, wrapper methods, and embedded methods. Filter methods involve selecting features based on statistical metrics such as correlation, mutual information, or chi-squared tests. Wrapper methods use a model to evaluate subsets of features and choose the most predictive ones based on performance measures such as accuracy or AUC. Embedded methods integrate feature selection into the model-building process, such as regularization or decision tree algorithms.

Predict Yield: This activity is a crucial system component, enabling farmers to make informed decisions about crop management practices, resource allocation, and market strategies. The system estimates a crop's expected harvest, given environmental and management conditions. The system uses a combination of historical crop data, environmental variables, and management practices to predict the expected yield for a given crop and growing season. The system takes selected features from the previous step and uses a machine learning algorithm to train a model on historical data. The trained models can then predict future yields based on new inputs. The system also incorporates real-time data on weather conditions, soil moisture, and other relevant factors to refine yield predictions throughout the growing season. By accurately predicting crop yields, the system can help farmers optimize their farming practices, reduce costs, and increase profitability while maintaining sustainability.

Generate Candidates: This activity refers to the process of selecting a set of candidate crops that are likely to perform well on a given farmland based on yield prediction and other relevant factors. This step is critical in the recommendation system as it helps to narrow down the list of potential crops for the farmer to grow and make personalized recommendations based on the specific needs and goals of the farmer. The candidate's list is generated based on the yield prediction earlier activity. Once the candidate crops are generated, the system can move to the next steps of the recommendation system, which involves selecting the most appropriate crops for the farmer to grow based on the specific needs and goals of the farmer. Overall, generating candidates is a critical pre-step in the recommendation system as it helps narrow down the list of potential crops for the farmer to grow and make personalized recommendations based on the specific needs and goals of the farmer.

Identify Resource Requirements: This activity refers to the various inputs needed to grow a crop, such as water, fertilizer, and labor. These requirements can vary depending on the crop, location, and other factors. After generating candidate crops, the system can suggest the resource requirements for each crop. To incorporate resource requirements, the recommendation system can use predictive models to estimate the resource needs for each crop. These models can consider factors such as soil type, weather conditions, and historical yields to provide accurate estimates of the resources needed to grow a particular crop. Once the resource requirements for each crop have been estimated, the Farm AI system can use this information to help farmers make informed decisions about which crops to grow. For example, if a farmer has limited access to water or fertilizer, the system can recommend crops that require less of these resources.

Calculate Profitability: This activity refers to the potential return on investment for each crop, which is influenced by a variety of factors such as market demand, crop yield, and input costs. After generating candidate crops and identifying resource requirements, the system can estimate the potential profitability of each crop by considering market prices, yield estimates, and input costs. This is done by using predictive models and historical data to estimate the expected revenue and costs associated with each crop. To incorporate profitability, the recommendation system can provide farmers with a list of the most profitable crops based on the estimated revenue and input costs for each crop. This list can be sorted by profitability, allowing farmers to quickly identify the crops that are likely to generate the highest returns.

Add Sustainability Practices: This activity refers to a range of agricultural practices that aim to minimize negative environmental impacts and promote long-term productivity and ecosystem health. After generating candidate crops, the system includes various sustainability practices that can be incorporated into the farming operation. These practices may include reducing the use of synthetic fertilizers and pesticides, improving soil health through cover cropping and reduced tillage, and optimizing water and nutrient use efficiency. To incorporate sustainability practices into the recommendation system, the system uses environmental performance indicators (EPIs) to evaluate the sustainability of different crop options. EPIs measure various aspects of environmental performance, such as water use efficiency, soil erosion, and greenhouse gas emissions, and can be used to rank potential crop options based on their environmental impact. By incorporating sustainability practices, the recommendation system can help farmers optimize their farming operation to increase profitability and reduce negative environmental impacts. This can lead to long-term sustainability and resilience for the farming operation and the broader ecosystem.

Ranking: After generating candidates, identifying resource requirements, estimating profitability, and assessing sustainability practices, the system ranks the list of crops based on these factors to provide farmers with personalized recommendations. The ranking process involves assigning a score to each crop based on its performance across multiple factors. The scores can be weighted based on the farmer's preferences, available resources, and other factors specific to their farming operation. The scores can also be updated based on the latest information, such as changes in market prices or weather conditions. Once the scores have been assigned to each crop, the system ranks the crops based on their overall score. The top-ranked crops can be presented to the farmer as personalized recommendations, considering their individual preferences and available resources.

Display Crop Options with Profitability and Sustainability: Once the potential crop options have been identified, the system presents them to the farmer through the user interface, along with information on the crops' profitability and sustainability. The farmer can then select the crops they wish to grow based on their preferences and farming goals. This helps the farmer to make an informed decision about the crop selection and to optimize their profits.

The system allows for the farmer to explore other scenarios via the user interface. The "what if" scenarios are a way to evaluate the impact of various changes that can be made to farming practices, growing seasons, operations, and resources.

Here are some examples of “what if” scenarios that can be checked in the system:

Select Alternate Farming Practices: The farmer can choose different farming practices, such as changing the irrigation method, altering the crop rotation, or adopting a different fertilizer application method. For example, the farmer could consider using a drip irrigation system instead of a sprinkler system, potentially reducing water usage and increasing crop yield.

Select Growing Season: The farmer can select different growing seasons based on weather and crop conditions. For example, the farmer could choose to grow a summer crop during the rainy season or a winter crop during the dry season, depending on the local climate.

Select Alternate Farm Operations: The farmer can choose different farming operations, such as changing the planting density or using different machinery. For example, the farmer could consider using a no-till farming method, potentially reducing soil erosion, and improving soil health.

Select Alternate Resources: The farmer can select different resources, such as seeds, fertilizers, and pesticides. For example, the farmer could consider using organic fertilizers instead of chemical fertilizers, potentially reducing environmental pollution and improving soil health.

By evaluating these what-if scenarios, farmers can make informed decisions about which practices, operations, seasons, and resources will result in their farms' most sustainable and profitable outcomes. The recommendation system can help the farmer to compare the different scenarios and choose the one that best meets their needs and goals. Once the farmer is satisfied, they select the crop to grow.

Select Crop(s) to Grow: This activity involves the farmer selecting the crop(s) from the list of recommended crops. They can opt to take experts' help to understand the recommendations, and pick a crop based on their specific constraints and tolerance to risk. The selected crops can then be managed using the best practices recommended by the system. By adopting best farming practices, farmers can benefit from the knowledge and experience of other farmers in their community and adapt to the local climate and soil conditions. They can use this knowledge to manage their crops and work towards meeting or exceeding yield and profitability measures predicted by the system.

It is recommended that the farmer provide regular (weekly) updates for the selected crop during the growing season, resources use, farm management practices followed, harvest status, yield, price, etc. Entering growing data for crop sown provides several benefits to the system. Primarily, the farmer can use the system to monitor the crop's health and identify any potential issues or diseases. The system can then provide recommendations for addressing these issues and preventing future problems. Most importantly, the growing data from the selected crop can help the system to provide more personalized recommendations to the farmer over time. Secondly, the data can help the system to improve sustainability by identifying the most resource-efficient and environmentally friendly growing practices.

In conclusion, the activities in the farmer activity diagram provide farmers with a comprehensive tool for managing their crops and optimizing their farm's performance. Ultimately, this system aims to provide farmers with accurate, personalized recommendations to help them improve their yield, sustainability, and profitability.

System Entity Relationship Diagrams

The System ERD is a powerful tool for planning, designing, and implementing efficient and effective systems that can improve business processes and operations. It is a diagram that illustrates the relationships among different entities in a system. It is used to design, analyze, and communicate the structure of a system, and provides a graphical representation of the data flow, processes and entities that make up a system. As an essential component of system documentation, it is used to detail out several profiles. They are grouped into four crucial profiles: farmland profile, crop profile, financial profile, and sustainability profile.

Farmland profile

The Farmland as depicted in **Figure 16**, contains several entities that capture vital information about the farmland, its location, the soil, irrigation and irrigation management, transportation, and storage.

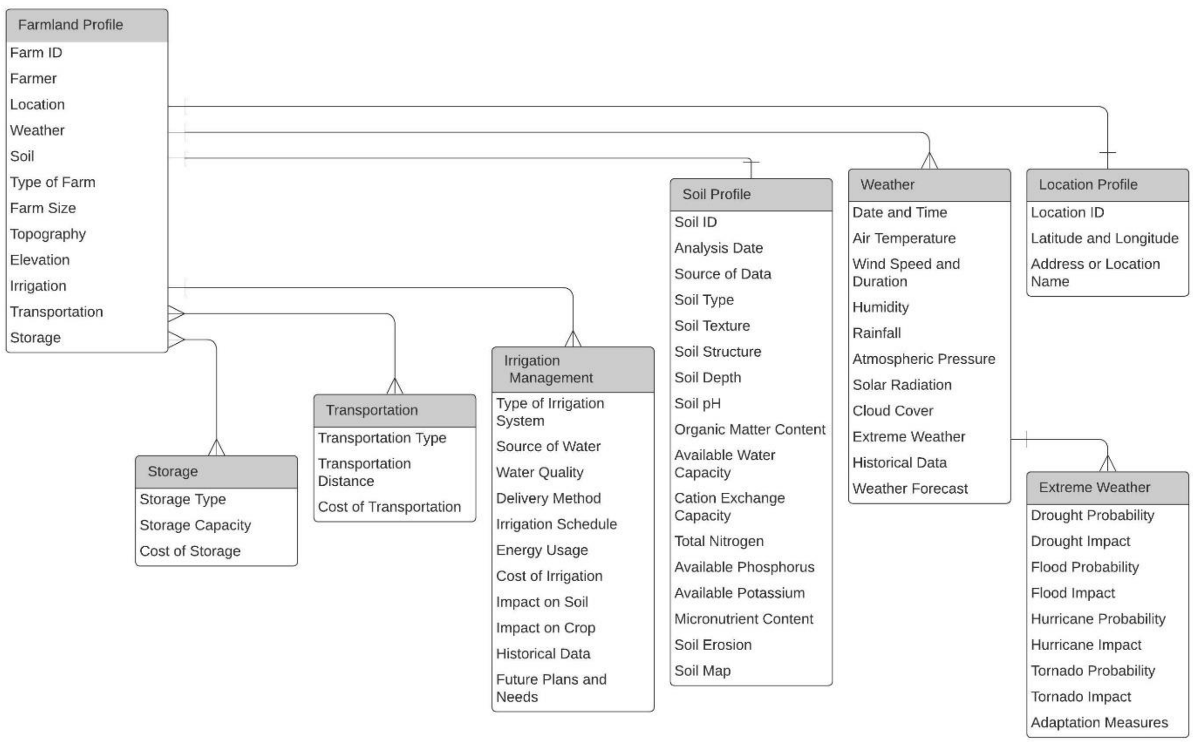

Figure 16: *Farmland profile entities and related fields*

The Farmland Profile entity contains the core fields that describe the farm. The Farm ID is a unique identifier for each farm that can be used to track the farm and its details. The Location field captures the physical location of the farm. It is important to know the location because it has a significant impact on the type of crops or livestock that can be raised. The Weather field provides information about the average weather conditions in the farm's location, which is critical for planning crops and livestock production. The Soil field is another crucial field in the Farmland

Profile entity that captures information about the soil type, texture, structure, depth, pH, and organic matter content. The Soil field is important because it affects the crop yield and quality. The Type of Farm field provides information about the type of crops or livestock raised on the farm, which is essential for managing the farm efficiently. The Farm Size field captures the total land area of the farm in acres or hectares, which is necessary for planning the use of the farm's resources. The Topography and Elevation fields capture important physical characteristics of the farm's land, which is critical for understanding the environmental factors that impact crop and livestock production. The Irrigation field captures the method used to irrigate the farm, which is essential for maintaining proper moisture levels in the soil and achieving optimal crop yields.

The Location Profile entity contains fields that capture information about the location of the farm. The Location ID field is a unique identifier for each location, which is important for managing information about the location. The Latitude and Longitude field captures the coordinates of the location, which is important for geospatial analysis and understanding the environmental factors that impact crop and livestock production. The Address or Location Name field captures the street address or name of the location, which is important for managing the logistics of farming.

The Soil Profile entity contains fields that provide information about the soil at the location. The Soil ID field is a unique identifier for each soil type, which is important for managing information about the soil. The Analysis Date field captures the date the soil was analyzed, which is important for tracking changes in the soil over time. The Source of Data field captures the source of the soil analysis data, which is important for understanding the quality of the data. The Soil Type field captures the general classification of the soil, such as clay, loam, or sand, which is important for understanding its properties. The Soil Texture field captures the relative proportions of different-sized soil particles, such as sand, silt, and clay, which is important for understanding its water-holding capacity and nutrient content. The Soil Structure field captures the arrangement of soil particles into aggregates, which is important for understanding the soil's ability to retain water and nutrients. The Soil Depth field captures the thickness of the soil layer, which is important for understanding its ability to support root growth. The Soil pH field captures the acidity or alkalinity of the soil, which is important for understanding its ability to support several crops. The Organic Matter Content field captures the amount of organic matter in the soil, which is important for understanding its fertility and nutrient content.

The Irrigation Management entity contains fields that provide information about irrigation management on the farm. The Type of Irrigation System field captures the irrigation system used, which is important because different crops require various moisture levels. The Source of Water field captures the source of water used for irrigation, which is important for managing water resources efficiently. The Water Quality field captures the water quality used for irrigation, which is critical for ensuring that the soil and crops are not contaminated with harmful substances. The Delivery Method field captures the method used to deliver water to the crops, which ensures that water is distributed evenly across the farmland. The Irrigation Schedule field captures the schedule for watering the crops, which is critical for maintaining proper moisture levels and achieving optimal crop yields. The Energy Usage field captures the energy used for irrigation, which is important for managing costs and ensuring that the irrigation system is sustainable. The Cost of an Irrigation field captures the cost of the irrigation system, including water and energy costs, which is important for managing costs and ensuring that the farm is profitable. The Impact on Soil and Impact on Crop fields capture the effects of the irrigation system on the soil and crops, respectively, which is important for managing the farm's long-term sustainability.

The Transportation entity contains fields that capture information about the transportation of crops and livestock from the farm to other locations. The Transportation Type field captures the type of transportation used, such as truck, rail, or air, which is important for managing transportation. The Transportation Distance field captures the distance between the farm and the destination, which is important for managing the cost and efficiency of transportation. The Cost of Transportation field captures the cost of transportation, including fuel, maintenance, and other expenses, which is important for managing costs and ensuring that the farm is profitable.

The Storage entity contains fields that capture information about the farm's storage of crops and livestock. The Storage Type field captures the type of storage used, such as silos, barns, or refrigerated storage, which is important for managing logistics. The Storage Capacity field captures the maximum number of crops or livestock that can be stored, which is important for managing inventory and planning production. The Cost of Storage field captures the cost of storage, including maintenance, utilities, and other expenses, which is important for managing costs and ensuring that the farm is profitable.

The Farmland ERD is important because it captures critical information about the farm, its location, the soil, irrigation, transportation, and storage. This information is essential for managing the farm efficiently, optimizing crop and livestock production, and ensuring long-term sustainability. By using a database to store and manage this information, farmers can make data-driven decisions about how to manage their resources, reduce costs, and maximize profits. The ERD also facilitates communication between different stakeholders, such as farmers, agronomists, transportation companies, and storage providers, by providing a common language for discussing the farm's resources and operations. Finally, the ERD can be used to monitor changes in the farm's resources and operations over time, which is essential for identifying trends, adjusting, and planning for the future.

Crop profile

The Crop Profile shown in **Figure 17** helps organize and maintain vital information necessary for efficient crop management. The crop entity relationship diagram includes entities such as Crop Profile, Farming Practices, Fertilizer Management, Sowing Practices, Pest Management, Climate Requirements, Soil Requirements, Crop Variety, and Market Demand.

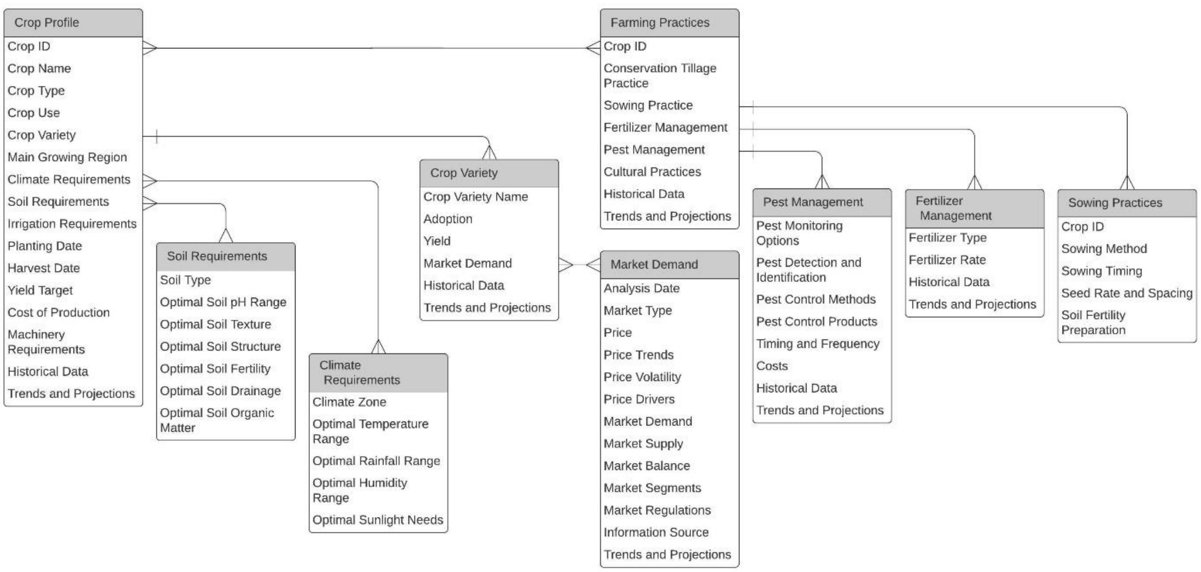

Figure 17: *Crop profile entities and related fields*

The Crop Profile entity in the ERD captures critical information about a specific crop. The Crop ID attribute is a unique identifier that helps distinguish one crop from another. Crop Type attribute determines the type of crop being grown, which could be vegetables, grains, or fruits. The Crop Use attribute provides information about how the crop will be used, such as for consumption or for commercial purposes. The Crop Variety attribute is vital because it helps to determine the best variety of the crop to grow in a particular location or climate. The Main Growing Region attribute is crucial as it determines the region where the crop can be grown successfully. Climate

Requirements attribute specifies the necessary climate conditions for the crop to thrive, including Optimal Temperature Range, Optimal Rainfall Range, Optimal Humidity Range, and Optimal Sunlight Needs. The Soil Requirements attribute specifies the type of soil in which the crop can grow best, including Optimal Soil pH Range, Optimal Soil Texture, Optimal Soil Structure, Optimal Soil Fertility, Optimal Soil Drainage, and Optimal Soil Organic Matter. The Irrigation Requirements attribute specifies the amount of water required for the crop's growth. The Planting Date and Harvest Date attributes provide essential information on when to plant and harvest the crop to maximize yield. The Yield Target attribute specifies the expected amount of yield. The Cost of Production attribute indicates the cost of producing the crop. Machinery Requirements attribute specifies the type of machinery required to grow and harvest the crop. Historical Data attribute captures the historical data about the crop's growth and production over a specific period. Trends and Projections attribute helps to predict the crop's growth and production based on historical data and current trends.

The Farming Practices entity in the Crop ERD includes attributes such as Crop ID, Conservation Tillage Practice, Sowing Practice, Fertilizer Management, Pest Management, Cultural Practices, Historical Data, and Trends and Projections. The Conservation Tillage Practice attribute specifies the type of conservation tillage practice used for growing the crop. The Sowing Practice attribute specifies the method of sowing and the timing for sowing the crop. The Fertilizer Management attribute specifies the type of fertilizer used, the rate of application, and historical data and trends for fertilizer usage. The Pest Management attribute captures information on the pest monitoring options, pest detection and identification, pest control methods, pest control products, timing and frequency of pest control, costs, and historical data and trends on pest management. Cultural Practices attribute captures valuable information on the cultural practices used in growing the crop. Historical Data attribute captures historical data on crop management practices, while Trends and Projections attribute helps to predict the crop's growth and production based on historical data and current trends.

The Fertilizer Management entity in the Crop ERD includes attributes such as Fertilizer Type, Fertilizer Rate, Historical Data, and Trends and Projections. The Fertilizer Type attribute specifies the type of fertilizer used for crop production. The Fertilizer Rate attribute specifies the rate of fertilizer application. Historical Data attribute captures historical data on fertilizer use, while Trends and Projections attribute helps to predict fertilizer use based on historical data and current trends.

The Sowing Practices entity in the Crop ERD includes attributes such as Crop ID, Sowing Method, Sowing Timing, Seed Rate and Spacing, and Soil Fertility Preparation. The Sowing Method attribute specifies the method of sowing used for the crop. The Sowing Timing attribute specifies the optimal timing for sowing the crop. The Seed Rate and Spacing attribute specifies the rate at which the seeds should be planted and the spacing between them. The Soil Fertility Preparation attribute specifies the necessary steps taken to prepare the soil for sowing the crop.

The Pest Management entity in the Crop ERD includes attributes such as Pest Monitoring Options, Pest Detection and Identification, Pest Control Methods, Pest Control Products, Timing and Frequency, Costs, Historical Data, and Trends and Projections. The Pest Monitoring Options attribute specifies the methods used to monitor pest infestations. The Pest Detection and Identification attribute specifies the steps taken to detect and identify pests. The Pest Control Methods attribute specifies the methods used to control pests. The Pest Control Products attribute specifies the products used for pest control. The Timing and Frequency attribute specifies the timing and frequency of pest control measures. The Costs attribute specifies the cost of pest control measures. Historical Data attribute captures historical data on pest management practices, while Trends and Projections attribute helps to predict pest management practices based on historical data and current trends.

The Climate Requirements entity in the Crop ERD includes attributes such as Climate Zone, Optimal Temperature Range, Optimal Rainfall Range, Optimal Humidity Range, and Optimal Sunlight Needs. The Climate Zone attribute specifies the region's climate zone in which the crop can grow. The Optimal Temperature Range attribute specifies the optimal temperature range for the crop's growth. The Optimal Rainfall Range attribute specifies the optimal amount of rainfall required for the crop's growth. The Optimal Humidity Range attribute specifies the optimal humidity range for the crop's growth. The Optimal Sunlight Needs attribute specifies the optimal amount of sunlight required for the crop's growth.

The Soil Requirements entity in the Crop ERD includes attributes such as Soil Type, Optimal Soil pH Range, Optimal Soil Texture, Optimal Soil Structure, Optimal Soil Fertility, Optimal Soil Drainage, and Optimal Soil Organic Matter. The Soil Type attribute specifies the type of soil in which the crop can grow. The Optimal Soil pH Range attribute specifies the optimal soil pH range for the crop's growth. The Optimal Soil Texture attribute specifies the optimal soil texture for the crop's growth. The Optimal Soil Structure attribute specifies the optimal soil structure for the crop's growth. The Optimal Soil Fertility attribute specifies the optimal soil fertility for the crop's growth. The Optimal Soil Drainage attribute specifies the optimal soil drainage for the crop's growth. The Optimal Soil Organic Matter attribute specifies the optimal amount of soil organic matter required for the crop's growth.

The Crop Variety entity in the Crop ERD includes attributes such as Crop Variety Name, Adoption, Yield, Market Demand, Historical Data, and Trends and Projections. The Crop Variety

Name attribute specifies the name of the crop variety. The Adoption attribute specifies the rate of adoption of the crop variety. The Yield attribute specifies the yield of the crop variety. The Market Demand attribute specifies the demand for crop variety in the market. Historical Data attribute captures historical data on the crop variety, while Trends and Projections attribute helps to predict the crop variety's growth and production based on historical data and current trends.

The Market Demand entity in the Crop ERD includes attributes such as Analysis Date, Market Type, Price, Price Trends, Price Volatility, Price Drivers, Market Demand, Market Supply, Market Balance, Market Segments, Market Regulations, Information Source, and Trends and Projections. The Analysis Date attribute specifies the date when the market analysis was conducted. The Market Type attribute specifies the type of market, such as local or international. The Price attribute specifies the price of the crop in the market. The Price Trends attribute captures the trends in crop prices in the market. The Price Volatility attribute captures the volatility in crop prices in the market. The Price Drivers attribute specifies the factors that drive crop prices in the market. The Market Demand attribute specifies the demand for the crop in the market. The Market Supply attribute specifies the supply of the crop in the market. The Market Balance attribute specifies the balance between the supply and demand of the crop in the market. The Market Segments attribute specifies the different segments of the market, such as wholesale or retail. The Market Regulations attribute specifies the regulations that govern the crop market. The Information Source attribute specifies the source of market information. The Trends and Projections attribute helps to predict the future trends in crop prices and demand based on historical data and current trends.

The Crop ERD is an essential tool for crop production planning and management. The entities and their attributes help to provide information on the crop, its growth and production, and market trends. This information can help farmers to make informed decisions about crop production, including selecting the right crop variety, using the right farming practices, managing pests and diseases, and accessing the market. The Crop ERD is, therefore, a valuable tool for identifying crop production efficiency and profitability.

Farmer financial profile

The Farmer Financial profile ERD depicted in **Figure 18**, provides a comprehensive view of a farmer's financial health, and enables the farmer to make informed decisions about their operations. Additionally, the information in the Farmer Financial profile ERD can be useful for external stakeholders, such as lenders and investors, who may want to assess the financial health and potential of a farm before providing funding or making investment decisions.

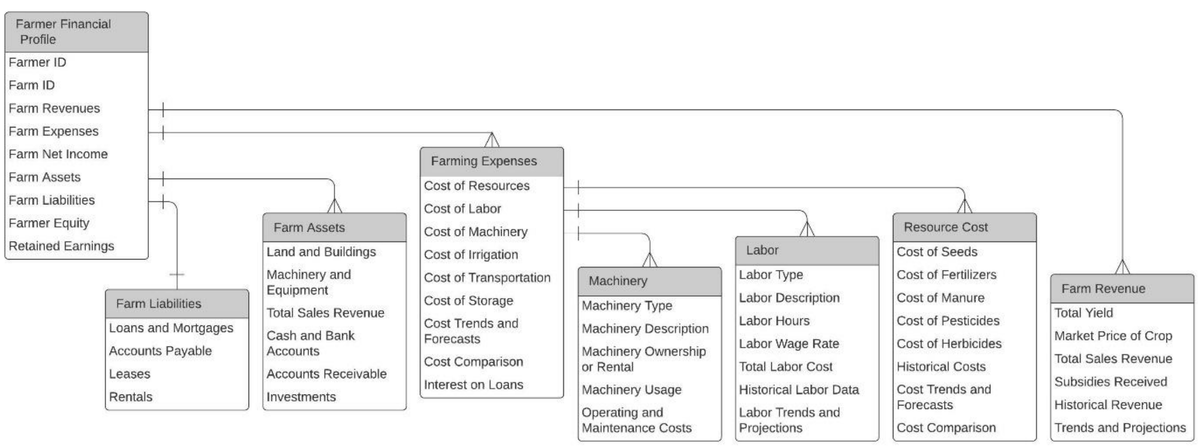

Figure 18: *Farmer financial profile entities and related fields*

The Farmer ID and Farm ID are unique identifiers that help to organize and track financial information for a particular farmer and farm. The Farm Revenue entity provides insight into the farm's revenue streams, including subsidies and historical trends, which can be useful in projecting future revenue potential. The Farming Expenses entity provides information about the farm's cost structure and can be used to identify areas where cost-cutting measures can be implemented to improve profitability. The Farm Revenues and Farm Expenses entities provide insight into the amount of money the farm is making and spending, respectively, while the Farm Net Income entity calculates the difference between revenues and expenses. The Farm Revenue entity provides insight into the farm's revenue streams, including subsidies and historical trends, which can be useful in projecting future revenue potential. The Farming Expenses entity provides information about the farm's cost structure and can be used to identify areas where cost-cutting measures can be implemented to improve profitability. The Farm Revenues, Farm Expenses, and Farm Net Income fields provide key financial metrics that allow farmers and external stakeholders to assess the profitability of a farm. By comparing these metrics over time and between farms, it is possible to identify areas of strength and weakness and develop strategies to improve profitability.

The Farm Assets entity includes information about the assets that the farm owns, such as land, buildings, machinery, equipment, and investments. The Farm Liabilities entity, on the other hand, includes information about any outstanding debts or loans that the farm owes, such as loans and mortgages, accounts payable, leases, and rentals. The difference between the farm's assets and liabilities is known as Farmer Equity. The Farm Assets and Farm Liabilities entities provide insight into the farm's overall financial position and can be used to assess the farm's ability to withstand financial shocks or take advantage of growth opportunities. The Farm Assets, Farm Liabilities, and Farmer Equity fields provide insight into the financial health of the farm and the farmer's stake in the business. By monitoring changes in these fields over time, farmers can track their progress towards financial stability and identify areas where additional investment may be needed to achieve their goals.

The Machinery entity includes information about the machinery owned or rented by the farm, such as the type, description, ownership or rental, usage, and operating and maintenance costs. The Labor entity includes information about the types of labor used on the farm, labor hours, wage rates, total labor costs, historical labor data, and labor trends and projections. The Machinery entity provides information about the farm's capital equipment and can be used to identify areas where efficiency improvements can be made, for example, by improving maintenance practices or investing in more advanced machinery. This information can be used to identify areas where several types of labor are needed and to compare the costs and benefits of using distinct types of labor.

The Resource Cost entity includes information about the cost of seeds, fertilizers, manure, pesticides, herbicides, historical costs, cost trends and forecasts, and cost comparisons. The Resource Cost entity provides insight into the cost of inputs required for crop production and can be used to identify areas where cost savings can be achieved, for example, by using alternative or more efficient inputs. The Cost of Resources, Cost of Labor, Cost of Machinery, Cost of Irrigation, Cost of Transportation, and Cost of Storage fields provide insight into the cost structure of the farm. By tracking changes in these fields over time and comparing them to industry benchmarks, farmers can identify areas where cost savings can be achieved and develop strategies to improve efficiency.

The relationships between these entities are important because they help to provide a more comprehensive view of a farmer's financial health. For example, the relationship between the Farm Revenue and Farming Expenses entities can be used to calculate the farm's net income, while the relationship between the Farm Assets and Farm Liabilities entities can be used to calculate the farm's equity. The Total Yield, Market Price of Crop, and Total Sales Revenue fields provide information about the revenue generated by the farm. By comparing these metrics to historical trends and industry benchmarks, farmers can identify areas where revenue growth can be achieved and develop strategies to improve profitability.

In summary, the Farmer Financial profile ERD provides a comprehensive view of a farm's financial health, enabling farmers and external stakeholders to make informed decisions about farm management, funding, and investment. By understanding the entities and relationships in this ERD, farmers can identify areas where cost savings and efficiency improvements can be achieved, and plan for the future by projecting revenue potential and assessing financial risk.

Sustianability profile

The sustainability entity includes attributes related to the overall sustainability of a farm or agricultural operation, as depicted in **Figure 19**.

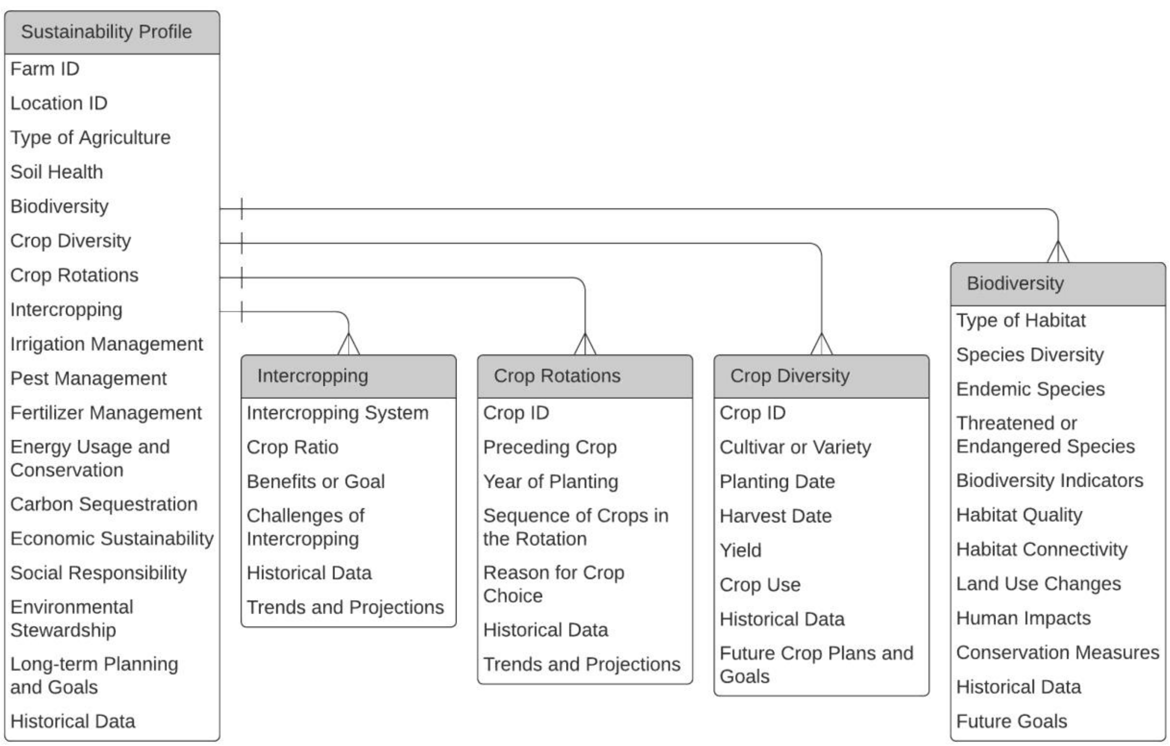

Figure 19: *Sustainability profile entities and related fields*

The Sustainability profile entity plays a crucial role in providing a comprehensive overview of the farm or agricultural operation's sustainability practices. The various attributes provide information about the farm's environmental, social, and economic sustainability practices, as well as its long-term goals and historical data. This information can be used to identify areas for improvement and develop strategies to enhance sustainability over time.

The Biodiversity entity includes attributes related to biodiversity, such as Type of Habitat, Species Diversity, Endemic Species, Threatened or Endangered Species, Biodiversity Indicators, Habitat Quality, Habitat Connectivity, Land Use Changes, Human Impacts, Conservation Measures, Historical Data, and Future Goals. The Biodiversity entity plays a crucial role in monitoring and conserving biodiversity on a farm or agricultural operation. The various attributes provide information about the types of habitats and species present, the health and quality of those habitats, and the potential threats and impacts that could harm them. This information can be used to design and implement conservation measures and set goals for the future.

The Crop Diversity entity includes attributes related to crop diversity, such as Crop ID, Cultivar or Variety, Planting Date, Harvest Date, Yield, Crop Use, Historical Data, and Future Crop Plans and Goals. The Crop Diversity entity plays a crucial role in monitoring and maintaining crop diversity on a farm or agricultural operation. The various attributes provide information about the types of crops grown, the timing of planting and harvesting, the yield of each crop, and the intended use of each crop. This information can be used to identify opportunities to introduce new crops and maintain a diverse crop portfolio. Crop Diversity entity is related to the Sustainability Profile entity because crop diversity is an important aspect of overall sustainability.

The Crop Rotations entity includes attributes related to crop rotations, such as Crop ID, Preceding Crop, Year of Planting, Sequence of Crops in the Rotation, Reason for Crop Choice, Historical Data, and Trends and Projections. The Crop Rotations entity plays a crucial role in improving soil health, reducing pest pressure, and improving yields over time. The various attributes provide information about the types of crops grown in each rotation, the timing of planting and harvesting, the reason for selecting each crop, and historical data and projections. This information can be used to design and implement crop rotation strategies that optimize soil health and crop yields. The Crop Rotations entity is related to the Crop Diversity entity because crop rotations are a way to maintain and improve crop diversity.

The Intercropping entity includes attributes related to intercropping, such as Intercropping System, Crop Ratio, Benefits or Goal, Challenges of Intercropping, Historical Data, and Trends and Projections. The Intercropping entity plays a crucial role in improving soil health, reducing pest pressure, and improving yields over time. The various attributes provide information about the types of intercropping systems used, the ratio of crops grown in each system, the benefits and goals of intercropping, and the challenges associated with intercropping. This information can be used to design and implement intercropping strategies that optimize soil health and crop yields. The Intercropping entity is related to the Crop Rotations entity because it can be used to rotate crops and improve soil health.

Limitations

Recommendation systems inherently have some limitations that are worth mentioning. These include:

1. *Cold Start Problem*: This occurs when a recommendation system is unable to provide personalized recommendations for new users or items, because there is not enough data available to make accurate recommendations.
2. *Scalability* [70]: As the number of users and items increases, the recommendation system's computational complexity also increases, making it difficult to scale the system to handle substantial traffic.

3. *Data Sparsity*: This occurs when there is not enough data available to make accurate recommendations, which can lead to mediocre performance of the recommendation system.
4. *Bias and Discrimination*: Recommendation systems are prone to reproduce and reinforce biases present in the data used to train them. This can lead to discriminatory recommendations, which can be harmful to specific groups of users.
5. *Privacy and security*: recommendation systems may also raise privacy and security concerns because of the sensitive nature of the data they collect and store.
6. *Lack of transparency*: Some recommendation systems operate as black boxes, meaning that it is difficult to understand how they make recommendations. This can make it difficult to trust the recommendations provided by the system.

Recommendation systems for crop selection based on profitability and sustainability can be limited in several ways. First, such systems consider the unique conditions of a particular farm or region, such as soil type, weather patterns, and available resources. This wide range of data can be collected from various sources, such as weather stations, soil sensors, and other monitoring devices, as well as from farmers and other stakeholders. The system may need access to the local data or need more infrastructure and resources for data collection. Additionally, farmers may need more resources or technical expertise to collect and share the data. This can make it challenging to gather the detailed and accurate data required to fully consider the unique conditions of a particular farm or region. This can lead to recommendations that need to be better suited to the local environment, which can negatively impact crop yields and profitability.

Second, these systems may be based on limited or outdated data, which can lead to inaccurate or unreliable recommendations. For example, if data is only collected at certain times of the year, it may not accurately reflect the conditions of the farm or region throughout the entire growing season. Additionally, if a system uses data from the past, it may not consider changes in the market or technological advances that have occurred since that time. For instance, new crop varieties or farming techniques may have been developed that could make a crop more profitable or sustainable than it was in the past. If the system is not based on the latest data, it will not be able to consider these new developments and make appropriate recommendations. Another limitation is that if the data is not collected frequently enough it may not accurately reflect the current conditions of the farm or region. For example, if data on weather patterns is only collected once a month, it may not accurately reflect the weather conditions that a crop is currently experiencing.

Third, these systems may not fully consider the sustainability of the crops being recommended. Sustainability is a complex and multi-faceted concept, and it can be difficult to generalize and quantify it in a way that is useful for crop selection. For example, there are many distinct aspects of sustainability that can be considered when evaluating a crop, such as its environmental impact, its social impact, and its economic impact. These various aspects of sustainability are often interrelated, and it can be challenging to separate them and assign them quantitative values. Additionally, the definition of sustainability is context-dependent and can vary depending on the region, culture, and other factors. For example, what may be considered sustainable in one region may not be in another. Another area for improvement is that sustainability indicators are often based on a set of assumptions and are only sometimes able to consider the unique characteristics of a specific crop or farming operation. For example, an indicator that measures the use of pesticides may not consider the unique pest pressures of a particular crop or the practices that a farmer uses to manage pests.

To overcome these limitations, it is essential that AI-powered personalized agriculture systems be developed using a multidisciplinary approach that incorporates data from a wide range of sources and incorporates the perspectives of farmers, researchers, and other stakeholders. This will ensure that the recommendations generated by the system are well-suited to the local environment and consider the social and environmental impact of crop selection.

Delimitations

There are several delimitations to building an AI-powered personalized agriculture system that consider profitability and sustainability to recommend a crop for selection. As the framework is still a proposal, several of these delimitations can be addressed during implementation. Some of the delimitations of the system include:

Availability of Data: The accuracy and availability of data on which the system relies may be limited by data sources, data quality, and data access. The system relies heavily on the availability and accuracy of local agriculture datasets. The system's recommendations may be less effective or even misleading if these datasets are incomplete or inaccurate. Therefore, it is essential to ensure that the local agriculture datasets are up-to-date and reliable.

Human Resource Availability: The system requires trained and qualified extension agents or researchers to input, update, and validate data. In areas with a shortage of qualified human resources, the system may not be effective or practical to implement. Additionally, creating a network of volunteers to manage the system at the local level is challenging unless the local governing bodies promote the technology.

Cultural and Social Factors: The system's recommendations must be tailored to local cultural and social factors. These factors may vary significantly from region to region, making it difficult to develop universally applicable recommendations. This particularly applies to the farm management practices that differ between regions and countries. To overcome this delimitation, local farmers and agricultural experts should be involved in developing and implementing the system to ensure that it considers local cultural and social factors. Use participatory approaches to engage local communities and understand their needs, preferences, and constraints. Consider the diversity of farm management practices and design the system to be flexible and adaptable to local conditions.

Economic Factors: The cost of implementing the system, including hardware, software, and personnel, may limit its applicability in some areas. In areas where resources are limited, the cost of implementing the system may be prohibitive. To overcome this delimitation, develop cost-effective solutions that minimize hardware and software requirements should be developed using open-source technologies to reduce licensing costs. Explore public-private partnerships, government subsidies, and other funding opportunities to support the implementation of the system. Provide training and support to farmers and extension workers to maximize the benefits of the system and ensure its sustainability.

Human factors: The success of the system may also depend on human factors such as the farmer's willingness to adopt new practices, their ability to understand and interpret the recommendations, and their access to necessary resources such as equipment, labor, and capital. To manage this delimitation, user-friendly interfaces and training materials that are accessible and easy to understand should be provided. Involve farmers in the development of the system and solicit their feedback on its usefulness and usability. Provide incentives and rewards to encourage farmers to adopt new practices and measure the impact of the system on their productivity, profitability, and sustainability.

Technical: The performance and accuracy of the system may be limited by technical factors such as computational power, algorithm design, and software bugs. The system's effectiveness may be limited by technical factors such as hardware or software limitations, network connectivity issues, or compatibility issues with other systems. To overcome this delimitation, it is important to ensure that the system is designed to be compatible with a wide range of hardware and software platforms. This may involve using standard protocols and interfaces or providing user-friendly installation and configuration tools. Additionally, the system should be designed to handle network connectivity issues or other technical problems, using caching or offline modes.

User: The system's effectiveness may be impacted by the user's level of technical expertise, ability to understand the recommendations, and willingness to adopt the recommended practices. To manage this delimitation, the system should be designed with a user-friendly interface that is easy to understand and navigate. This may involve incorporating instructional videos, tutorials, or other training materials to help users understand how to use the system. Additionally, the system should be designed to provide users with clear and actionable recommendations that are easy to follow and implement.

Time: The system may only be effective within a certain period, such as a growing season or specific crop cycle. To manage this delimitation, the system should be designed to give users recommendations appropriate for the specific growing season or crop cycle. This may involve using real-time data and analysis to provide up-to-date recommendations that reflect the current state of the crop or providing users with a timeline or schedule for implementing specific practices. Also, the system should be designed to provide users with recommendations appropriate for the specific growth stage of the crop.

Bias: The delimitation of bias is a common concern. Bias limitations refer to the potential for systematic errors or inaccuracies in a research study, which can affect the validity and reliability of the findings. In the context of the proposed system, bias could arise if the data used to train the model is not representative of the full population, or if there are inherent biases in the way the data is collected or labeled. One way to manage bias is to carefully select and preprocess the data used for training. This can involve techniques such as stratified sampling, where the data is divided into groups based on specific characteristics, to ensure that each group is represented in the training data. Additionally, data preprocessing techniques such as data cleaning and normalization can help to reduce the effects of outliers or errors in the data, which can introduce bias into the model. Another way to manage bias is to monitor the model's performance over time, and to retrain the model using updated or corrected data as needed. This can help to identify and correct any biases that may arise due to changes in the data or in the population being served by the model.

Finally, it is important to engage in ongoing ethical reflection and evaluation of the model's use and impact, to ensure that the model is being used in a responsible and equitable manner. This can involve regular review of the model's performance and impact, as well as ongoing consultation with stakeholders and affected parties to identify potential biases or other ethical concerns.

Advantages and Limitations of AI-Based Agricultural Advice for Smallholder Farmers

The proposed AI system is designed to provide advanced and personalized advice to smallholder farmers, including recommendations for crops, inputs, and other important decisions. One of the main advantages of our system is that it can analyze large amounts of data and generate recommendations that a human advisor may not have considered. For example, our system can analyze weather patterns, soil conditions, and other factors to recommend specific varieties of crops or optimal planting times. In addition, our system has the potential to reach and benefit more farmers than a human advisor, as it can be easily accessed through a cell phone or other digital device. This is particularly important in remote or underserved areas where access to human advisors may be limited. Furthermore, our system can provide personalized recommendations to farmers without requiring them to provide the same information every time they seek advice. This is because the system can store and analyze previous data and use it to make more accurate and relevant recommendations in the future. In contrast, a human advisor may need to ask for the same information repeatedly, which can be time-consuming and burdensome for the farmer.

While AI can provide valuable recommendations for smallholder farmers, it's crucial to remember that these recommendations should be viewed as a complement to human expertise, rather than a replacement for it. As with any decision-making tool, there are limitations and potential risks associated with relying solely on AI recommendations. There is always the risk that a recommendation made by the AI system could result in unintended consequences if not properly vetted and evaluated by an expert in the field. Therefore, it's important that any recommendations made by the AI system be thoroughly reviewed by human experts at regular intervals for system calibration to ensure that they align with best practices and consider any unique contextual factors that may not have been captured by the algorithm. This approach would ensure that smallholder farmers have access to the most comprehensive and accurate advice possible, while still benefiting from the efficiency and scalability of AI technology.

Ethical Assurances

When developing a recommendation system for crop selection, it is vital to consider the ethical implications of the technology. There are several ethical considerations that need to be addressed to provide assurance to the farmer:

1. *Privacy*: The recommendation system must be designed to protect the privacy of farmers and other individuals whose data is used to train the model. This includes ensuring that personal information is kept confidential, and that the data is used only for the purposes for which it was collected.
2. *Fairness*: The recommendation system should be designed to ensure that it does not discriminate against any group of farmers or crops. This includes avoiding bias in the data used to train the model and ensuring that the recommendations are based on objective criteria.
3. *Transparency*: The decision-making process of the recommendation system should be transparent so that farmers understand how the recommendations are made and can evaluate the system's performance.
4. *Explain ability*: The recommendation system should be able to explain its reasoning for its recommendations so that farmers can understand why a particular crop or rotation plan is recommended.
5. *Human-in-the-loop*: The recommendation system should be designed to work with human expertise rather than replacing it. Agricultural experts should validate the recommendations and adjust them accordingly to the local conditions.

To ensure that these ethical considerations are met, it is essential to involve experts from diverse fields, such as computer science, agriculture, ethics, and sociology, during the development of the recommendation system to ensure that all potential ethical issues are identified and addressed. Also, it is vital to keep farmers and communities involved and informed throughout the system's development and deployment.

Summary

The proposed personalized recommendation system framework for agriculture could revolutionize how farmers make decisions about their crops. The framework is based on machine learning techniques that analyze data about a farmer's crops, such as soil conditions and weather patterns, to make tailored recommendations. This can help farmers make more informed decisions and optimize their crop yields, resulting in better economic outcomes.

However, there are challenges that need to be addressed to fully realize the system's potential. The accuracy and reliability of the recommendations must be ensured, as incomplete or inaccurate data, changes in environmental conditions, and technical limitations can affect the system's predictions. To address these challenges, the machine learning algorithms need to be refined and best practices in data management and processing must be employed.

Another important consideration is scalability, as the system needs to be able to handle substantial amounts of data and a growing number of users. Conducting user testing and research on the user interface and overall user experience of the app can help address adoption challenges. It is important to ensure that the UI is intuitive and easy to use, and that the workflow is streamlined and efficient, to encourage farmers to adopt the system and utilize its recommendations.

Overall, the chapter provides a useful starting point for developing a personalized recommendation system for agriculture, but additional work is necessary to fully realize its potential. It is important to note that, even though the proposed system can make recommendations based on the data, it is essential to have agricultural experts validate the recommendations, as they have knowledge of the local conditions and can adjust the recommendations accordingly.

CHAPTER 4: IMPLEMENTATION AND EVALUATION

The proposed recommendation system framework for small farmers' decision-making was developed in the previous chapter. This chapter aims to outline the implementation and evaluation of the framework in practice. The implementation section will cover the potential challenges, solutions, and best practices for deploying the system to different regions and contexts. The evaluation section will provide an overview of how the system can be evaluated and measured to ensure its effectiveness and impact on small farmers' decision-making. Through the implementation and evaluation of the proposed framework, we aim to provide insights and guidance for practitioners and researchers interested in adopting this system in their region or country.

A Roadmap for Implementation

The farming community has been inundated with a plethora of ADSS applications that ultimately fizzle out within a few months or years due to a lack of ongoing support or regular enhancements. This trend highlights the need for a real plan for adoption beyond merely testing or validating the AI model. Furthermore, there are numerous studies and apps aimed at calculating bits and pieces of the proposed framework. But there is a conspicuous absence of a holistic approach that addresses the end-to-end needs of farmers throughout the year.

We believe that a comprehensive approach that caters to the entire spectrum of a farmer's requirements is essential to provide a sustainable and long-term solution that benefits the farming community as a whole. Our decision is to concentrate on developing a framework and collaborating with other regional researchers rather than building yet another app is the best path forward.

Collaborating with researchers who are already researching and maintaining some of the existing apps provides a unique opportunity to leverage their expertise and insights. By integrating the proposed framework's capabilities into their existing apps, we can test it on their existing user base of farmers. This collaborative effort will dramatically speed up the time frame to bring this framework to fruition and increase product/feature offerings to existing user base of farmers.

By taking this approach, we can reduce the time it takes to bring our idea to the market while ensuring that our solution is practical and effective. Ultimately, our goal is to create a solution that meets the needs of farmers and provides long-term benefits to the farming community. We firmly believe that this is the best path forward for creating a sustainable solution that will positively impact the lives of farmers for years to come.

With this notion, we picked Krishi Mitr (farmer friend) Android mobile application to start with as an example of such an effort, and evaluate the enhancements required to transform it as a prototype for the proposed framework.

Implementation Case Study: Krishi Mitr

The Krishi Mitr [71] mobile application is designed to provide personalized crop recommendations to farmers in India. The mobile app evaluates the compatibility of different crops and varieties with specific agricultural and financial variables unique to each farmer and assigns scores to them.

System design and development

The Krishi Mitr mobile application is designed to help farmers select the optimal crop for their farm based on several variables. The application generates a user profile with four components: location profile, farm profile, weather profile, and crop profile. The first stage of the crop-selection algorithm is the Natural Resources module, which calculates the performance of various crops based on factors like soil type and climate and eliminates incompatible crops. The Agricultural Inputs and Technologies module determines the quantity of fertilizers, pesticides, and labor required for the selected crops, while the Agricultural Finances module calculates the total cost of cultivation and the potential revenue based on market prices. The final recommendations are based on the scores in the Natural Resources module and the income estimated by the Agricultural Finances module, and the optimal crops and varieties are presented to the farmer.

Data collection and processing

The Krishi Mitr application uses a range of data sources to provide accurate and relevant recommendations to farmers. These sources include the Local Government Directory [72], Soil Health Card [73], TerraClimate data [74], OpenWeather API [75], Agriculture Contingency Plans [76], ICAR-Soil Test Crop Response Studies [77], List of Fertilizers [78], Integrated Fertilizer Management System [79], Cost of Cultivation/Production & Related Data [80], Package of Practices [81], API for Current Daily Price of Various Commodities from Various Markets, and Variety-Wise Prices of Various Agricultural Commodities. These data sources provide information on factors such as soil health, climate, fertilizer management, cultivation costs, crop varieties, and commodity prices, which are used by the application's algorithm to generate personalized crop recommendations for farmers.

System infrastructure

The Krishi Mitr application has been developed and deployed as an Android application, with compatibility maintained for API levels 23 and above. To ensure scalability, the application uses a serverless architecture with AWS Lambda as the primary processing resource. AWS Lambda uses DynamoDB to store and process data, and communication between the server and the application is facilitated through a RESTful API. This approach enables the system to expand its services to multiple types of clients in the future.

Data privacy and security

Given that the application handles sensitive personal data, including mobile numbers and farm equipment information, several security measures have been implemented to ensure user privacy. The APIs are secured using HTTPS protocol, which encrypts all messages. The requests are processed by Amazon's API Gateway, which, when combined with AWS Web Application Firewall (WAF), prevents exploitative attacks that may try to steal user information. Each service in the REST API framework operates with its own identity and access management (IAM) profile, which ensures that each module's work is compartmentalized so that an exploited module cannot perform tasks outside its intended use.

The entire cloud architecture works on a virtual private network to prevent unauthorized access. Only the Lambda instance, which resides inside the virtual private network, can communicate with the databases, and no external requests can be made to any system components.

Best practices

The algorithm prioritizes sustainable cultivation by recommending crops that require minimal chemical fertilizers. The farmer is also provided with additional information about cultivation practices that can facilitate better productivity. Additionally, the application plans to integrate additional data sources in the future to enhance the accuracy and relevance of its recommendations.

User engagement and training

The Krishi Mitr mobile application requires minimal user-data entry, making it accessible for semi-literate and literate farmers in India. The application supplements the farmer's information with data from Krishi Mitr's cloud databases. The Krishi Mitr application can be used by agricultural extension services, NGOs, FPOs, and individual farmers to determine the profit-maximizing crop based on soil, climate, and other factors, leading to sustainable increases in profit margins and accelerating the agricultural sector's development.

Challenges and solutions

According to the authors in [71], the algorithm used in the Krishi Mitr application addresses only three of the five factors determined for crop selection. Integrating policy and household factors can further enhance the accuracy of recommendations. To improve the accuracy of crop yield prediction, the application can employ machine learning with remote sensing data and convolutional neural network (CNN) linked with long short-term memory (LSTM) networks. As soil testing data quality and frequency improves, the accuracy of recommendations provided by the application will also increase.

Suggestions for improvement

There are several enhancements that could be made to Krishi Mitr to achieve the goal of AI powered personalized agriculture and to fill the gap between your proposed framework and the current state of the Krishi Mitr. Here are a few suggestions:

1. *Expand user roles to include extension agents*: Extension agents play a crucial role in providing information and advice to farmers, and by including them in the user roles of the Krishi Mitr system, they could not assist the farmers but also provide feedback on the accuracy and usefulness of the recommendations.
2. *Implement a feedback loop*: The Krishi Mitr system could benefit from a feedback loop that allows farmers and extension agents to provide feedback on the accuracy and

usefulness of the recommendations. This would help to refine the system and improve its performance over time.

3. *Include "what-if" scenarios evaluation*: The Krishi Mitr system could be enhanced to include the ability to evaluate "what-if" scenarios, allowing farmers to explore the potential outcomes of different agricultural practices and crop choices. This could help farmers make more informed decisions and improve their yields and profitability.
4. *Incorporate regional languages*: To make the Krishi Mitr system more accessible to farmers who may not be fluent in English, an app or user interface in regional languages could be developed. This would help to expand the user base and ensure that the system is accessible to farmers across different regions.
5. *Include farmer preferences*: The Krishi Mitr system could be enhanced to include information on farmer preferences, such as preferred crops or farming practices. By incorporating this information, the system could provide more personalized recommendations that are better suited to individual farmers' needs and preferences.
6. *Partnerships with agri-businesses*: Krishi Mitr could partner with agri-businesses to provide farmers with access to modern technology and inputs, such as improved seed varieties, fertilizers, and pesticides. These partnerships would provide farmers with the resources they need to implement the recommendations provided by the platform.
7. *Machine learning models*: Krishi Mitr could work with local extension agents to individually focus on specific regions and crops to develop region-specific and crop-specific machine learning models that are tailored to the unique environmental and economic conditions of each farmer. The models could also consider the farmer's past performance and success rate with different crops.

By implementing these enhancements, Krishi Mitr could become a more powerful and effective tool for supporting farmers in making informed decisions about their crops and farming practices, while also aligning with the goals of your proposed framework.

Summary

The Krishi Mitr application, with its foundational elements, has already proven to be a promising solution for addressing some of the challenges faced by farmers in India. However, by expanding the application's features and capabilities as suggested, the potential for the application to fully implement the proposed system in a short time is enormous.

One key aspect of the proposed system is the integration of machine learning algorithms to provide personalized recommendations to farmers based on their specific needs and the characteristics of their farms. With the addition of these algorithms, the application can provide even more tailored advice and recommendations to farmers, considering a wide range of factors such as weather conditions, soil quality, crop health, and more.

Another feature that could be added to the application is the use of drones and other sensors to collect real-time data about crops and environmental conditions. By incorporating this data into the system, the application could provide even more accurate recommendations and help farmers make more informed decisions about their farming practices.

Finally, Krishi Mitr application can not only validate the proposed system but also refine the AI powered personalized agriculture system so that it can be adopted in other countries and have an even greater impact on the lives of farmers around the world. We would also like to expand our collaboration to other interested researchers to expand the framework’s viability beyond one app.

CHAPTER 5: IMPLICATIONS, RECOMMENDATIONS, AND CONCLUSIONS

The proposed framework and study on designing and implementing a recommendation system for personalized agriculture have several implications, recommendations, and conclusions that can inform both practice and research in the context of sustainable and regenerative agriculture. The implications highlight both the positive and negative effects of using a recommendation system for small farmers. The recommendations aim to enhance the accessibility and effectiveness of the system, while the conclusions emphasize the potential benefits of a recommendation system for small farmers and the need for further research to evaluate its impact on broader issues such as food security and ecological sustainability.

Implications

The proposed framework on designing and implementing a recommendation system for small farmers has several implications. This section presents both positive and negative implications for each research question (identified in chapter 1) and used as a guide throughout the study.

Research Question 1: Designing for Small Farmers

How can a recommendation system be designed and implemented to effectively address the specific challenges faced by small farmers?

Positive implications: A well-designed and implemented recommendation system can provide small farmers with tailored recommendations that account for their specific needs, resources, and constraints. This can help improve their crop yields, reduce input costs, and increase their profits.

Negative implications: However, the implementation of a recommendation system may require significant investment in technology and infrastructure, which may not be feasible for small farmers with limited resources. Additionally, the system must consider the unique cultural, social, and economic contexts of the farmers to ensure it is effective and well-received.

Research Question 2: Factors in Decision-Making

What are the key factors that influence small farmers' decision-making regarding crop cultivation, and how can a recommendation system account for these factors?

Positive implications: Understanding the key factors that influence small farmers' decision-making can help design a recommendation system that provides tailored recommendations that are more likely to be accepted and adopted by the farmers. This can lead to increased yields, improved profits, and more sustainable practices.

Negative implications: However, the factors that influence small farmers' decision-making may vary widely depending on their socio-economic and cultural contexts. As such, the system must be flexible enough to account for these differences and provide recommendations that are relevant and acceptable to the farmers.

Research Question 3: Best Data Sources

What data sources are most useful for informing a recommendation system for small farmers, and how can data quality be ensured?

Positive implications: A recommendation system that is informed by high-quality data can provide accurate and reliable recommendations to small farmers, leading to improved crop yields, reduced input costs, and increased profits.

Negative implications: However, small farmers may not have access to the necessary data sources or the technical expertise to ensure data quality. It is also important to consider issues of data privacy and security, particularly in areas where data infrastructure and regulations may be weak.

Research Question 4: Unique Needs and Contexts

How can a recommendation system be designed to accommodate small farmers' unique needs and resources in different regions and contexts?

Positive implications: A recommendation system that is designed to be adaptable to the unique needs and resources of small farmers in different regions and contexts can improve the system's effectiveness and relevance. This can lead to increased adoption and improved outcomes for the farmers.

Negative implications: However, designing and implementing a flexible and adaptable system may be more complex and require additional resources. The system must also consider the specific cultural, social, and economic contexts of the farmers in each region to ensure it is effective and well-received.

Research Question 5: Benefits and Drawbacks

What are the potential benefits and drawbacks of using a recommendation system to guide small farmers' decision-making, and how can these be assessed?

Positive implications: A well-designed and implemented recommendation system can provide small farmers with tailored recommendations that account for their specific needs and resources, leading to improved crop yields, reduced input costs, and increased profits. It can also promote more sustainable agricultural practices and help improve food security.

Negative implications: However, the system may require significant investment in technology and infrastructure, and small farmers may not have access to the necessary resources or technical expertise to use the system effectively. Additionally, there may be concerns around data privacy and security, as well as the potential for the system to displace traditional knowledge and practices.

Research Question 6: Integration with Services

How can a recommendation system be integrated with existing agricultural extension programs and other support services for small farmers?

Positive implications: Integrating a recommendation system with existing agricultural extension programs and support services can help increase the system's reach and effectiveness. It can also help promote more sustainable practices and improve the overall quality of support services for small farmers.

Negative implications: However, integrating the system with existing programs and services may require significant coordination and resources. Additionally, there may be concerns around the potential displacement of traditional knowledge and practices, as well as issues around data privacy and security.

Research Question 7: Training Methods and Scalability

What are the most effective methods for training small farmers to use a recommendation system, and how can these methods be scaled up to reach many users?

Positive implications: Providing effective training to small farmers can help ensure that they can use the recommendation system effectively, leading to improved crop yields, reduced input costs, and increased profits. It can also help promote more sustainable agricultural practices and improve overall access to agricultural knowledge and resources.

Negative implications: However, providing effective training may require significant resources and coordination. Additionally, the training must consider the unique cultural, social, and economic contexts of the farmers to ensure it is effective and well-received. Finally, scaling up the training to reach many users may be challenging and require additional resources.

Research Question 8: Promoting Sustainable Agriculture

How can a recommendation system be used to promote sustainable and regenerative agricultural practices among small farmers?

Positive implications: The use of a recommendation system can provide small farmers with recommendations that promote sustainable and regenerative agricultural practices, such as reducing the use of chemical inputs, conserving soil health, and increasing biodiversity. This can lead to improved soil quality, increased crop yields, and long-term environmental and economic sustainability.

Negative implications: However, the implementation of sustainable and regenerative practices often requires additional resources and knowledge, which small farmers may not have access to. Moreover, it is important to ensure that the recommendations provided by the system align with the cultural and socio-economic contexts of the farmers.

Research Question 9: Implications for Broader Issues

What are the potential implications of using a recommendation system to guide small farmers' decision-making for broader issues such as food security, biodiversity, and climate change?

Positive implications: A well-designed and implemented recommendation system can help small farmers make informed decisions that increase crop yields and enhance food security, while promoting practices that maintain or enhance biodiversity and reduce the carbon footprint of farming. This can contribute to addressing broader societal issues such as climate change and food insecurity.

Negative implications: However, the use of a recommendation system may also lead to increased dependence on technology and reduce farmers' autonomy and traditional knowledge. It is also important to ensure that the recommendations provided by the system align with local socio-economic and cultural contexts and do not contribute to further marginalization of small farmers.

Recommendations

Based on the proposed framework and study, there are several recommendations for both practice and research in the context of designing and implementing a recommendation system for small farmers.

Recommendations for Practice

For practice, it is recommended that agricultural extension programs and support services consider integrating a recommendation system into their existing programs to enhance their impact and reach. The system can provide personalized recommendations on cultivation techniques, seed varieties, soil types, and crop rotation, among other factors. To ensure that the system is accessible and effective, it is important to consider the unique needs and resources of small farmers in different regions and contexts. Also, effective training methods and scalable digital platforms can be used to ensure that the system is user-friendly and accessible to many users. Below are additional details for recommendations for practice:

1. *Gather and integrate data*: Collect data on crop yields, prices, weather conditions, soil quality, pests and diseases, and other relevant factors. Integrate this data with information on local regulations and farmer preferences.
2. *Develop a multi-disciplinary team:* Assemble a team that includes agriculture, machine learning, and environmental science experts. This will ensure that all relevant perspectives are considered when developing the recommendation system.
3. *Validate the model*: Test the recommendation system using field trials and real-world data. This will help ensure that the system is accurate and effective.

4. *Continuously improve*: Continuously monitor and evaluate the performance of the recommendation system. Use this feedback to improve the system over time.
5. *Engage and educate farmers*: Engage with local farmers about the recommendation system's benefits. This will help to ensure that the system is widely adopted and used effectively.
6. *Decision-making process*: Consider the farmer's decision-making process and how they want to use the system. This is crucial for the scalability and adaptability of the system.
7. *Understand the trade-offs*: Understand the trade-offs between profitability and sustainability and ensure the system can optimize for both.
8. *Make the system user-friendly*: Make the system easy to use and understand for farmers, so they can easily access recommendations and make informed decisions. Consider expanding to other languages and integrating text-to-speech functionality.

Recommendations for Future Research

For research, it is recommended that further studies are conducted to evaluate the effectiveness of recommendation systems for small farmers. This includes examining the system's impact on crop yields, soil health, and ecological sustainability, and assessing the potential benefits and drawbacks of using such a system. Also, research can be conducted to identify the most effective data sources for informing the system and develop methods for ensuring data quality. Furthermore, research can explore the potential implications of using a recommendation system for broader issues such as food security, biodiversity, and climate change. Below are additional details for recommendations for future research:

1. *Incorporating local and regional weather forecast data*: Use real-time weather forecast data to consider the local and regional weather conditions for more accurate crop selection recommendations.
2. *Incorporating precision agriculture techniques:* Incorporate precision agriculture techniques such as sensor data, drones, and satellite imagery to gather data on crop growth, soil quality, and pests and diseases. Provide a straightforward way to synchronize data from these sensors in real time.
3. *Developing models for crop stress prediction*: Develop models that can predict crop stress caused by weather conditions, pests and diseases, and soil quality.
4. *Optimizing for multiple objectives*: Develop methods to optimize for various objectives, in addition to profitability, and sustainability considerations.
5. *Incorporating farmers' knowledge*: Incorporate local farmers' knowledge and expertise into the recommendation system to ensure that recommendations are context-specific and tailored to the unique needs of each farm.
6. *Investigating the system's impact:* Investigate the recommendation system's long-term impact on crop yields, profitability, and sustainability.
7. *Consider the social and economic context:* Consider farmers' social and economic context when developing the system. This will help to ensure that the system is accessible and valuable for farmers regardless of their socio-economic status.
8. *Combining with other decision support systems:* Combine with other decision support systems that can assist farmers in making informed decisions during growing season such as machine vision applications for integrated pest management and crop management.

9. *Incorporating data from other domains:* Incorporating data from different disciplines, such as market prices, trade data, and economic indicators, to understand how the recommendation system can be affected by the global economic situation.
10. *Distributed architecture:* The agricultural mobile apps enable use of technologies in the field and are designed to be user-friendly, with simple interfaces and clear instructions. However, the data connectivity is spotty in the agricultural fields where the population density is low. The severely hinders the farmers' ability to utilize the full capabilities of the application. The apps should be designed such that they can work online and offline and synchronize up to the cloud infrastructure when the connectivity is strong. Future research should focus on understanding how farmers use these apps and adapt it to architecture of the mobile application.

Overall, the recommendations for both practice and research aim to enhance the effectiveness and impact of a recommendation system for small farmers, while also contributing to the broader goal of promoting sustainable and regenerative agricultural practices.

Next Steps: Collaboration and Automation

There are two major research focus areas for improving the recommendation system for agricultural practices and sustainability measures.

The first area involves collaborating with an existing mobile application research team as discussed in Chapter 4 to test the viability of the framework. The goal is to enhance the existing agricultural practices database and recommendation system by incorporating user feedback and re-architecting the system as need be to allow for online and offline operation, as well as distributed computing. By doing so, we can validate the core system framework

The second area of focus involves automating the incorporation of local farmers' knowledge and expertise into the recommendation system, as well as their social and economic context. This requires the transformation of unstructured data from sources such as agricultural forums and discussions into structured data that can be easily incorporated into the recommendation system. By doing so, we can ensure that the system is tailored to the unique needs and experiences of local farmers, providing them with personalized recommendations that take into account their specific context and circumstances. This approach can improve the effectiveness and relevance of the recommendations, ultimately leading to better adoption of sustainable practices and increased productivity and profitability for farmers.

Conclusions

The research study and proposed framework for AI powered personalized agriculture aimed to design and implement a recommendation system that addresses the specific challenges faced by small farmers. The conclusions drawn from the study include the following:

1. The proposed recommendation system can effectively guide small farmers in making informed decisions regarding crop cultivation. The system can provide recommendations on cultivation techniques, seed varieties, soil types, seasons for a crop, and crop rotation.
2. The key factors that influence small farmers' decision-making regarding crop cultivation have been identified and accounted for in the design of the recommendation system. These factors include local weather conditions, availability of resources such as water and labor, market demand, and individual farmer preferences.
3. The data sources most useful for informing the recommendation system include weather data, soil quality data, market data, and data on previous crop yields. The

quality of these data sources can be ensured through rigorous data cleaning and validation processes.

4. The recommendation system is designed to accommodate the unique needs and resources of small farmers in different regions and contexts. The system can be customized to consider local crop varieties, cultural practices, and available resources.
5. The potential benefits of using a recommendation system to guide small farmers' decision-making includes increased crop yields, improved soil health, and reduced resource waste. The drawbacks include the cost of implementing and maintaining the system, and potential privacy and security concerns.
6. The recommendation system can be integrated with existing agricultural extension programs and other support services for small farmers to enhance the reach and impact of these programs.
7. Effective methods for training small farmers to use the recommendation system should include in-person training sessions, user manuals, and online tutorials. These training methods can be scaled up to reach many users through digital platforms and cloud-based software.
8. The recommendation system promotes sustainable and regenerative agricultural practices among small farmers by providing recommendations that prioritize soil health, biodiversity, and ecological sustainability.

Lastly, the use of a recommendation system to guide small farmers' decision-making would have broad implications for issues such as food security, biodiversity, and climate change. By promoting sustainable agricultural practices, the system can contribute to the long-term resilience of local food systems and ecosystems.

Summary

Through a thorough analysis of the key factors that influence small farmers' decision-making, the study provides valuable insights into how a recommendation system can be designed to provide effective recommendations on crop cultivation, soil health, and ecological sustainability.

The study highlights the potential benefits of using a recommendation system, such as increased crop yields and reduced resource waste, while also acknowledging the potential drawbacks, such as bias, ongoing refinement of the machine learning algorithms, and privacy concerns. The study also emphasizes the importance of integrating the recommendation system with existing agricultural extension programs and support services to enhance their reach and impact. The study also presents the path to implementation and validation of the proposed framework, while also exploring ways to incorporate local knowledge and context through the automated transformation of unstructured data.

Overall, the study provides a valuable contribution to the field of sustainable agriculture by demonstrating the potential of a recommendation system to support small farmers in making informed and sustainable decisions that have a significant impact on small farming communities worldwide and can contribute to the long-term resilience of local food systems and ecosystems.

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