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SMARTAGRI: An Intelligent Decision Support System for Smart Farming

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Thanks and appreciation

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Abstract

The most challenges facing sustainable development worldwide are the food shortage and the population growth. Therefore, recent technologies as artificial intelligence (AI), the Internet of Things (IoT), and the mobile internet offers many solutions to the challenges that are facing the world. Therefore, this work focuses on using the Artifical intelligence techniques to enhance smart farming practices.The intelligent system for smart farming presented in this paper utilizes case-based reasoning (CBR) to facilitate pest detection and management. The system aims to leverage historical data from past farming instances to inform decision-making in the present.

The case base serves as a repository of past farming cases, storing information on environmental conditions, farming practices, pest occurrences, and corresponding solutions. The retrieval phase identifies the most similar cases, which provide insights into potential solutions or actions.

The proposed intelligent system for smart farming, based on case-based reasoning, offers an effective approach to pest detection and management by leveraging historical farming experiences. By tapping into past knowledge, the system empowers farmers with valuable insights and informed decision-making, leading to optimized pest control strategies and improved agricultural outcomes.

Key words: Decision support system, Artificial intelligence, Smart Agriculture, case based reasoning .

ملخص

أكثر التحديات التي تواجه التنمية المستدامة في جميع أنحاء العالم هي نقص الغذاء والنمو السكاني. لذلك ، فإن التقنيات الحديثة مثل الذكاء الاصطناعي (AI) وإنترنت الأشياء (IoT) والإنترنت عبر الهاتف المحمول تقدم العديد من الحلول للتحديات التي تواجه العالم. لذلك ، يركز هذا العمل على استخدام تقنيات الذكاء الاصطناعي لتعزيز ممارسات الزراعة الذكية ، حيث يستخدم النظام الذكي للزراعة الذكية المقدم في هذه الورقة التفكير القائم على الحالة (CBR) لتسهيل اكتشاف الآفات وإدارتها. يهدف النظام إلى الاستفادة من البيانات السابقة من حالات الزراعة السابقة لإبلاغ عملية صنع القرار في الوقت الحاضر.

تعمل قاعدة الحالة كمستودع لحالات الزراعة السابقة ، وتخزين المعلومات حول الظروف البيئية ، والممارسات الزراعية ، وحدوث الآفات ، والحلول المقابلة. تحدد مرحلة الاسترجاع الحالات الأكثر تشابهًا ، والتي توفر رؤى حول الحلول أو الإجراءات المحتملة.

يقدم النظام الذكي المقترح للزراعة الذكية ، المستند إلى التفكير القائم على الحالة ، نهجًا فعالًا لاكتشاف الآفات وإدارتها من خلال الاستفادة من الخبرات الزراعية التاريخية. من خلال الاستفادة من المعرفة السابقة ، يمكّن النظام المزارعين من الحصول على رؤى قيمة واتخاذ قرارات مستنيرة ، مما يؤدي إلى تحسين استراتيجيات مكافحة الآفات وتحسين النتائج الزراعية.

كلمات مفتاحية : نظام دعم القرار ، الذكاء الاصطناعي ، الزراعة الذكية ، التفكير القائم على الحالة

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Chapter 1

General Introduction

1.1 Introduction

The agriculture sector is undergoing a transformation driven by new technologies, which seems very promising as it will enable this primary sector to move to the next level of farm productivity and profitability [1]. Precision Agriculture, which consist of applying inputs (what is needed) when and where is needed, has become the third wave of the modern agriculture revolution (the first was mechanization and the second the green revolution with its genetic modification [2]). Nowadays, it is being enhanced with an increase of farm knowledge systems due to the availability of larger amounts of data. The United States Department of Agriculture (USDA) already reported in October 2016 that Precision Agriculture technologies increased net returns and operating profits [3]. Also, when considering the environment, new technologies are increasingly being applied in the farms to maintain the sustainability of farm production. However, the adoption of these technologies involves uncertainty and trade-offs. According to a market analysis, the factors that would facilitate the adoption of sustainable farming technologies include better education and training of farmers, sharing of information, easy availability of financial resources, and increasing consumer demand for organic food [4]. When applying these new technologies, the challenge for retrieving data from crops is to come out with something coherent and valuable, because data themselves are not useful, just numbers or images. Farms that decide to be technology-driven in some way, show valuable advantages, such us saving money and work, having an increased production or a reduction of costs with minimal effort, and producing quality food with more environmentally friendly practices [5]. However, taking these advantages to the farm will depend, not only on the willingness of producers for adopting new technologies in their fields, but also on each specific farm potential in terms of scale economies, as profit margin increases with farm size. The USDA reported that, on average, corn farm operating profit of Precision Agriculture adopters was 163 dollars per hectare higher than for non-adopters, taking into account that the highest adoption rates for three technologies (computer mapping, guidance, and variable-rate equipment) were on farms over 1500 hectares [3]. Such margins can even go up to 272 dollars depending on the crop. A greater use of Smart Farming services is vital to not only improving a farm’s financial performance, but also to meet the food needs of an expanding population [3].

To tackle these challenges and ensure sustainable agricultural practices, there is a growing need for intelligent decision support systems that can assist farmers in making informed choices. In this context, Case-Based Reasoning (CBR) emerges as a promising approach due to its ability to leverage historical data and adapt past experiences to solve current problems.

The core principle of the system lies in its ability to retrieve relevant cases from the case base that closely match the current farming context. These cases represent similar farming situations, such as crop types, environmental conditions, disease outbreaks, or yield optimization strategies. By adapting and reusing the knowledge contained within these cases, the system generates intelligent recommendations and solutions tailored to the specific needs of the farmer.

The proposed intelligent decision support system for smart farming aims to empower farmers with real-time insights, recommendations, and solutions based on accumulated knowledge and data. By integrating IoT devices, sensor networks, the system collects and analyzes a wide range of farm-related information, including soil conditions, weather patterns, crop growth, and pest infestation levels. This wealth of data forms the foundation of the case base, which serves as a repository of past farming scenarios and their corresponding outcomes.

1.2 Objectives

We can say that The objectives of this thesis can be encompassed in three general purposes:

1. Study Decision Support Systems (DSS): The primary objective is to become familiar with the concepts, methodologies, and technologies related to decision support systems. This involves a thorough analysis of different existing models and approaches for decision-making in the context of disaster risk management.

2. Explore the artificial intelligence (AI) techniques for decision support systems. Presente the case-based reasoning as the primary method for designing the intelligent decision support system for smart farming. Case-based reasoning relies on the use of past knowledge and experiences to solve similar problems in the present. We will

explore the theoretical aspects of case-based reasoning and its steps of reasoning and advantageous.

2. Explore the field of smart farming: This includes examining best practices, regulations, international standards, and relevant conceptual frameworks. Focusing on various aspects of smart farming. These studies encompass diverse areas such as sensor technology, data analytics, machine learning, Internet of Things (IoT), and decision support systems. In addition, explore the use of sensors for monitoring soil conditions, weather patterns, and crop health, enabling real-time data collection and analysis.

3. Propose an intelligent system using AI: The central objective is to design an intelligent system that utilizes artificial intelligence (AI) techniques for smart farming . This involves identifying the specific needs of the domain, selecting appropriate AI methods such as case based reasoning and proposing a suitable architecture for the intelligent system.

4. Design and implement the proposed system: Once the design of the intelligent system is established, the objective is to proceed with its practical implementation.

1.3 Outline of the Thesis

This document is structured in 6 chapters:

1.3.1 Chapter 2:

The chapter highlights the significance and advantages of decision support systems (DSS) in facilitating decision-making across diverse domains, including IT service systems and customer service. It also emphasizes the rapid advancements in DSS and anticipates future enhancements in their capabilities.

1.3.2 Chapter 3:

The chapter presents the methodology of case-based reasoning (CBR) and its historical background, focusing on the four main stages of the CBR cycle: Retrieve, Reuse, Revise, and Retain. Additionally, it provides a comparative analysis of CBR with other techniques, discussing its advantages and limitations.

1.3.3 Chapter 4:

This chapter explores smart farming as a sustainable and efficient solution to meet the increasing global food demand, highlighting its benefits such as enhanced productivity, cost reduction, and improved sustainability through the use of technologies such as sensors, data analytics, machine learning, and automation. Explore the related works in the domain.

1.3.4 Chapter 5:

The architecture of the proposed model was exposed. The description of the design and the implementation of the decision support system based case-based reasoning (CBR) for smart farming, to leverage past knowledge and experiences. CBR is an artificial intelligence approach that uses previous cases as a knowledge base to solve new, similar problems.

1.3.5 Chapter 6:

The conclusion emphasizes the significance of implementing a comprehensive risk management system in smart agriculture to address the risks associated with technological advancements, and highlights the importance of collaboration, advanced technologies, and ongoing education for sustainable and resilient smart agriculture practices.

Chapter 2

Decision Support System

2.1 Introduction

Decision support systems (DSS) are computer-based tools designed to support decision-making processes. They can be used in a variety of settings, including business, healthcare, and government.

Overall, decision support systems can be powerful tools for improving decision-making processes in a variety of settings, but their adoption requires careful planning and consideration of organizational processes and needs.

2.2 Definition and History of Decision support systems:

A Decision Support System (DSS) is a computer-based information system that supports decision-making activities. DSSs are designed to help users make decisions in complex and unstructured situations by providing data analysis and modeling tools. The definition of a DSS is based on three common themes: problem structure, decision outcome, and managerial control. The benefits of using DSSs include improved decision-making, increased efficiency, and reduced costs. However, the limitations of DSSs include the need for accurate and timely data, the potential for errors, and the need for skilled users.The history of DSSs dates back to the 1960s when the first computer-based decision support systems were developed. These early systems were designed to support decision-making in the military and government sectors. In the 1970s, DSSs were developed for business applications, and by the 1980s, DSSs had become widely used in various fields, including healthcare, finance, and manufacturing.The five basic components of a DSS are data management, model management, knowledge management, user interface, and user. Data management involves the collection, storage, and retrieval of data. Model management involves the creation and management of models used in decision-making. Knowledge management involves the creation and management of knowledge used in decision-making. The user interface is the means by which users interact with the DSS. The user is the person who uses the DSS to make decisions.There are several categories and classes of DSSs, including model-driven DSSs, data-driven DSSs, knowledge-driven DSSs, communication-driven DSSs, and group DSSs. Each type of DSS has its own unique features and benefits, and the choice of DSS depends on the specific needs of the user [6].

2.3 Characteristics of Effective Decision Support System :

Effective Decision Support Systems (DSSs) have several characteristics that make them useful tools for decision-making processes.

One of the most critical characteristics is usability. DSSs should be user-friendly and easy to use, with clear and concise interfaces that allow users to access and analyze data quickly and efficiently.

Another important characteristic is accuracy. DSSs should provide accurate and reliable data to ensure that users can make informed decisions.

Additionally, DSSs should be flexible and adaptable to changing circumstances, allowing users to adjust their decision-making processes as needed [7].

Another characteristic of effective DSSs is their ability to integrate data from multiple sources. DSSs should be able to collect and analyze data from various sources, including internal and external databases, to provide users with a comprehensive view of the situation. DSSs should also be able to provide users with real-time data, allowing them to make decisions quickly and efficiently [8].

Finally, effective DSSs should be able to provide users with recommendations and insights based on the data analysis. DSSs should be able to identify patterns and trends in the data and provide users with actionable insights that can help them make better decisions [9].

Overall, effective DSSs should be user-friendly, accurate, flexible, able to integrate data from multiple sources, provide real-time data, and provide recommendations and insights based on data analysis. These characteristics make DSSs valuable tools for decision-making processes in various fields, including agriculture, healthcare, business, and finance [9] .

2. 4 Types of decision support system :

Decision support systems can be broken down into categories, each based on their primary sources of information.

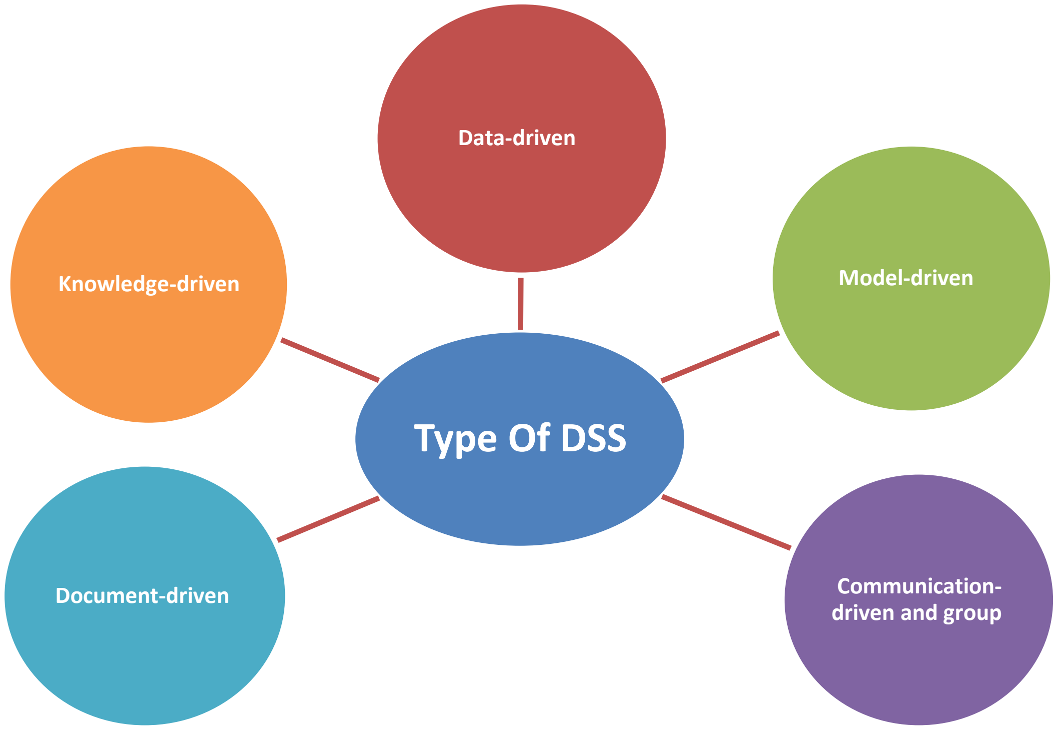


Figure2.1:Types of decision support system

2. 4.1 Data-driven DSS :

Data-driven DSS involves the access and manipulation of data that is structured and which includes time series functionality handling to fulfill the external and internal data requirements of organizations as the data is managed [13]. There are clear distinctions in the functionality of data in data-driven DSS. The file systems can easily be utilized through queries and retrieved through tools that have a lower functional level. The more comprehensive systems that are utilized by senior management such as the Executive Information Systems (EIS) allow the manipulation of data which are supported with tools that have been automated and have functionality that could be considered more comprehensive. Other applications of data-driven decision support systems arebusiness intelligence systems and Online Analytical Processing (OLAP) systems which provide the most significant support level for organizational decision makers[14]. The BI systems provide support to decision making in organizations through the use of technology which enable the access to the data and related analytics, and their presentation. More simply, the BI systems aid decision makers in formulating decisions when these are initiated, manipulating the data as needed, and analyzing the data and information that are in the databases [15]. A key aim of the use of BI and Analytic

Systems is to enhance the role of data and information in supporting decisions primarily through improved processing of data. The decisions are supported as the data-driven DSS enables the management through a significant volume of data which are typically complemented by the excellent level of quality of the primary data. The extent of success of DSS in this context is based on the ability of the systems to have access to error-free, well-structured and organized data and information which means that a deviation from these parameters may lead to an inefficient DSS [15].

2. 4.2 Model-driven DSS :

Power et al. [15] argues that a model-driven DSS leverages different elements of financial models, optimization models, and simulation models which are all integrated in the decision making support processes. A model-driven decision support systems is a specially designed model patterned after specific parameters and features defined by the users to include the property of support to decision making process through the analysis of given situations. The model-driven decision support systems does not require a large demand for data as there is minimal need for databases, if any with data and information only needed for specific data analysis requirements. The key feature in the design of a model-driven DSS is the integration of single or multiple qualitative models as part of the systems to provide increased efficiency in the analysis of solutions. The model-driven DSS leverages analytical tools and these are based on mathematical models that give the model-driven DSS the initial functional features which are required and utilized in the model-driven DSS applications. Typically, the mathematical models are designed as part of spreadsheets. In designing more complex models that are geared to provide decision making support, the model utilizes optimization programs and mathematical applications. An underlying feature of a model-drive DSS is that this would typically represent the interpretation of realism. Recently, the model-driven DSS has been utilized in expanded levels with a set of different models providing support for decision making across various parts of the supply chain including the manufacturing, planning and scheduling processes together with the logistics planning and management [15]. In addition, the model-driven DSS is used in various aspects of supply chain management (SCM) with the decisions supported by simulation models including the Monte Carlo simulation and other similar imitation methods such as agent and multi agent simulation, and visual simulation models [15].

2.4.3 Communication-driven and group DSS :

Typically, a communication-driven DSS relies on a network fusion and electronic methods to integrate core decisionmakers in given situations by consolidating the decision makers into one environment which has all the data, information and resources that are needed for decision making. These are shared and made available to the decision makers thereby enabling increased collaboration and communication among the group to facilitate improved decision making. This model is now formally referred to as Group Decision Support System (GDSS) following many years in which this model was initially referred to as group decision making (GDM), a sub category of in the subject of decision making. The GDSS involves many tools that are relevant for problem solving and problem structuring including planning and modelling tools. A different example of a communication-driven DSS is the Collaborative DSS (CDSS) which has elements of computer systems that enable engagement between decision makers with the increased interaction allowing the group to work together in defining solutions for the problems, even when these are novel problems or unstructured issues [16]. The collaborative DSS can be executed through a hybrid of IT equipment that already integrates modeling analysis tools thereby providing a platform that is easy for the users to leverage to identify solutions and execute decisions [16].

2.4.4 Document-driven DSS :

Previously, as organizations continued to operate and expand, document management became an important feature for organizations to manage and store relevant documents and other materials such as photos and images, and audio and video files. These resources including communications correspondences were increasingly stored electronically as technology developed. In recent years, large databases came into existence which supported the storing of these materials. With the continued development of Internet technologies, the document-driven DSS also came into fruition and evolved into an oft-used DSS for organizations [16]. There are many tools that have been developed that are utilized as part of document-driven DSS. Examples are search engines which are linked with document-driven DSS to aid organizations in decision making. The documents for the document-driven DSS are typically not uniform and not standardized in their patterns thus needing an approach to properly retrieve the data and information, and locate the documents from an extensive set of unstructured data groupings. There are good examples of information retrieval systems that are in the market including Infosys and Lexis- Nexis which provide structure to the documents and therefore make the documents much more usable as materials for decision making support in organizations. An alternative that is used in the retrieval of information is the text-based system which is also considered as effective in mining organizational data in identifying the location of documents [15].

2.4.5 Knowledge-driven DSS :

Another category for DSS is the knowledge-driven DSS which is considered to have started from intelligent decision support systems with a related perspective that these are linked to artificial intelligence [13]. Sander & Pearson [17] defined knowledge-driven DSS as “a computer-based reasoning system that provides information, comprehension and suggestions to users to support them in decision-making.”

The intelligent DSS emanated from the development of two generations:

1. Rule-based knowledge-based systems
2. Fuzzy logic, genetic algorithms, and neural networks [18].

The expert systems that are dependent on rules are largely utilized in processes which relate to scheduling in manufacturing activities. The expert systems are linked to heuristics and could be considered as methods that leads to the appropriate solutions to identified problems. The expert systems also inherently utilize the expert knowledge that are part of the databases in order to properly address the problems in organizations and effectively support decisions made [16]. With further development, the next generation shows increased capability with the integration of elements like fuzzy neural networks, genetic algorithms, and fuzzy logic which can involve linear programing models . These are utilized to execute unstructured tests with the identification of variables that support the location of the fitness function.

The systems which utilize genetic algorithm incorporates genes to result in values which have been revised and which are then used to support decision making processes. The objective in the use of knowledge-driven DSS is to identify specific data and information for knowledge development, and the relevant technologies and methods that can be helpful for the mining of the data. In recent years, organizations have taken actions to automate a larger part of organizational processes. The automation of the processes involves the management of data and information as these are necessary for supporting decision making. DSS requires data and information which have been reviewed and cleaned, and are located in the database. This means that the data has undergone the steps related to data mining and processing, and that the data has been converted to information and thence to knowledge [18].

2.5 Data Collection and Management for Decision Support Systems

2.5.1 Sources and Types of Data for Decision Support System:

Decision support systems (DSSs) are computer-based tools that provide timely, reliable, and useful information to enable management to make speedy, effective, and rational decisions. DSSs are one type of information system that plays a role in organizational hierarchy and decision-making processes [11] . DSSs have five basic components, including data and model management systems, a DSS knowledge base, and a user interface [20] . Data is an essential component of DSSs, and it can come from various sources, such as internal and external databases, surveys, and expert opinions. In addition to DSSs, other types of information systems, such as geospatial databases and GIS techniques, can also be used as decision-making tools in specific contexts, such as in landslide susceptibility assessment [19]. Clinical decision support systems (CDSSs) are another type of decision support system that is used to improve clinical practice. CDSSs use data from electronic health records, clinical guidelines, and other sources to provide clinicians with patient-specific recommendations at the point of care [10] . Data collection techniques and methods involve utilizing sensors to gather information. The data collection techniques rely on leveraging sensor readings to obtain accurate and reliable data.

2.5.2 Data Collection Techniques and Methods:

Data collection techniques and methods are used to collect data in a systematic way. The choice of data collection method depends on the research question, the type of data needed, and the resources available. Data collection methods can be broadly classified as self-reports, observation, and biophysiologic measures [21]. Examples of data collection techniques include interviews, questionnaires, scales, category systems and checklists, rating scales, and biophysiologic measures. In transportation planning, origin-destination (OD) studies are often used to determine the travel patterns of vehicles and goods in a particular area. Conventional and experimental techniques can be used for roadside station OD studies, and general recommendations can be made for the best OD study technique and data collection method, given the roadway characteristics and traffic conditions [21]. Privacy-preserving data mining techniques are useful for analyzing various information, such as Internet of Things data and COVID-19-related patient data. A method for privacy-preserving data collection that considers many missing values has been proposed, which uses differential privacy as a privacy metric [22]. In highway safety, many techniques have been utilized by state departments of transportation and local agencies to collect highway inventory data for other purposes. A comprehensive assessment of highway inventory data collection methods has been conducted to characterize the capability of existing methods for collecting highway inventory data vital to the implementation of the Highway Safety Manual [23]. Finally, unmanned aerial vehicles (UAVs) can be used as a reliable method of obtaining high-quality atmospheric data, such as temperature, humidity, pressure, and wind velocity, for meteorological research [24] .

2.5.3 Data Quality and Management for Decision Making:

Data quality and management are critical for decision making. High-quality data is necessary to perform management tasks, such as planning, managerial control, and decision support, and to ensure that management accountants can reliably fulfill their functions [25]. In addition, data management challenges, such as leadership focus, talent management, technology, and organizational culture for big data, are significant antecedents for big data decision-making capabilities, which play a key role in improving decision-making quality and environmental performance in public and private hospitals [26]. Digitalization of quality management can also improve the quality of strategic decisions by adding a tactical loop that tracks changes in events and using big data analysis to reflect the state of the control object [27]. However, the quality of data-driven decisions is not solely dependent on the data themselves but is also linked to the strategies employed for data collection and analysis [28]. Therefore, it is essential to employ appropriate data collection techniques and methods to collect accurate information and to manage data effectively to ensure data quality for decision making.

2.6 Decision Support System Architecture and Design

2.6.1 Components and Layers of Decision Support System Architecture:

The architecture of a decision support system (DSS) typically consists of five basic components: data management system, model management system, knowledge base, user interface, and user. The data management system is responsible for collecting, storing, and managing data, while the model management system is responsible for creating and managing models that can be used to analyze data and make predictions. The knowledge base is a repository of information that can be used to support decision-making, such as rules, procedures, and best practices. The user interface is the means by which users interact with the DSS, and the user is the person who uses the DSS to make decisions [6].

In addition to these components, DSS architecture can also include multiple layers, such as the strategic management layer, tactical management layer, and operational management layer, as in the case of a multi-agent architecture of a decision support system for human resource management [11]. The architecture of a decision support system for patients can also include transient and persistent application layers that support a general framework for patient decision support [29].

Overall, the architecture of a decision support system can vary depending on the specific application and context[30], but typically includes components such as data management system, model management system, knowledge base, user interface, and user, and can also include multiple layers to support decision-making in different contexts[8].

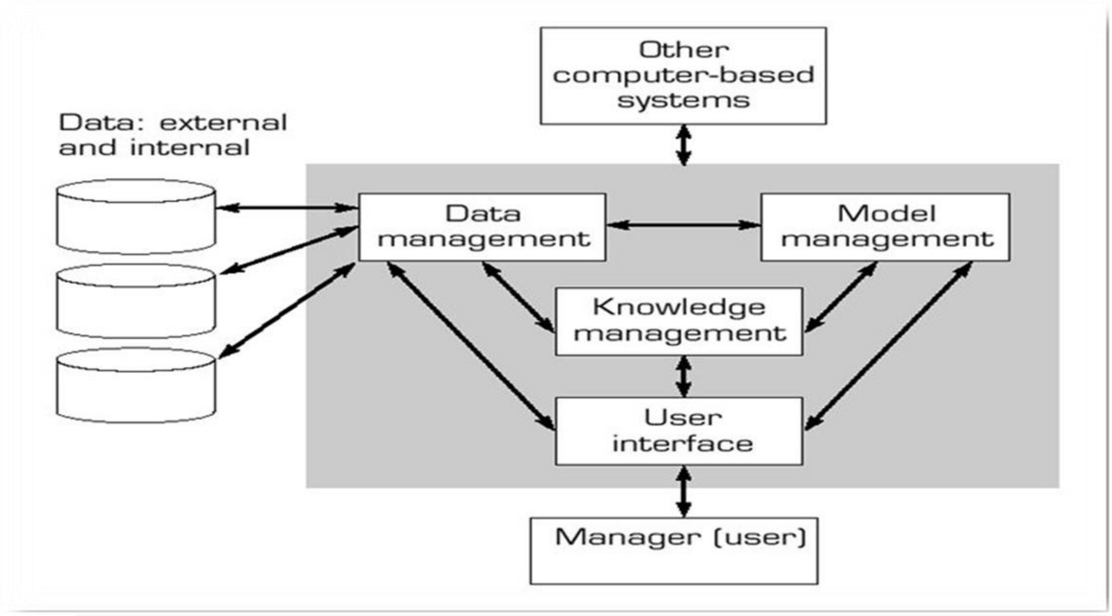


Figure2.2 : A Schematic View of DSS

2.7 Decision Support systems based artificial intelligence :

Artificial intelligence (AI) plays a crucial role in decision support systems (DSS) by providing intelligent decision support. AI techniques, such as data mining and machine learning, are used to analyze data and provide recommendations or guidance to users. The following are techniques of AI used in DSS:

Author	AI Tools	Description of IDSS
Kaszuba and Kostek (2012)	Fuzzy logic	Hand gesture classification for testing and monitoring patients with neurological conditions such as Parkinson Disease.
Lam et al. (2012)	Case-based algorithm Genetic algorithm	Warehouse cross-border delivery activities, such as palletization of the delivery goods according to regulation requirements.
Lao et al. (2012)	Fuzzy rule-based reasoning Case-based reasoning	Quality control of food inventories in the warehouse.
Kung et al. (2012)	Intelligent agents Neural network (back-propagation)	Predict and decide the debris-flow occurrence in Taiwan in disasters
Saed et al. (2012)	Particle Swarm Optimization (PSO) algorithm	Optimal design that satisfies quality requirements based on level of redundancy and trade-off between reliability and performance.
Lei and Ghorbani (2012)	Neural networks	Detection of fraud and network intrusion
Santos et al. (2011)	Intelligent agents incorporating affective characteristics (such as personality, emotion, and mood)	Decision aid to help improve the negotiation process.
Stathopoulou and Tsihrintzis (2011)	Neural network	Rapid and successful detection of a face in an image for automated face recognition system.
Buditjahjanto and Miyauchi (2011)	Genetic algorithm Clustering	Tradeoff between fuel cost (economic) and emission problems to achieve optimal decisions .
Kamami et al. (2011)	Fuzzy logic	Selection of sustainable wastewater treatment technologies
Dolsak and Novak (2011)	Expert system	Structural design analysis using a finite element method

Table 2.1 References about applications of intelligent decision support system(Gloria Ph-wen) [35] .

2.7.1 Case based resoning systems

A CBR-based decision support system (DSS) is a system that uses Case-Based Reasoning (CBR) to provide decision support. CBR is an AI technique that involves solving new problems by adapting the solutions of previously solved similar problems. The goal of CBR-based DSS is to develop a robust and general framework that supports the generation of a wide range of CBR systems using different approaches. The advantages of using CBR in DSS include domain independence, incremental learning, platform independence, fast retrieval algorithm, generality, and robustness [40] .

2.7.2 Artificial Neural Networks (ANNs) are computational models inspired by the brain's information processing

They consist of interconnected neurons that work together to solve problems. ANNs can represent any bounded continuous function with high accuracy. Neurons compute

a weighted sum of inputs and apply transformation functions. The weights are adjusted through iterative exposure to training data. Feedforward and recurrent networks are two common types of ANNs. They excel in decision support and pattern recognition tasks. ANNs learn through unsupervised, supervised, or reinforcement learning. Overfitting must be avoided to ensure generalization. ANNs can be seen as "black boxes" as their inner workings are not easily interpretable.

2.7.3 Fuzzy Logic for Intelligent Decision Support

Fuzzy Logic is a decision support approach that allows for the representation of uncertain inputs by assigning them a range of values between false and true. It offers flexibility, intuitive options, and the ability to handle uncertainty. Fuzzy logic can capture expert knowledge and be combined with neural networks for improved interpretation. It addresses the shortcomings of traditional neural networks by providing transparency and enhancing decision-making capabilities.

2.7.4 Expert Systems for Intelligent Decision Support

Expert Systems (ES) are computer systems that mimic the problem-solving abilities of human experts. They capture the knowledge of experts and use it to make decisions. ES consist of components such as a Knowledge Acquisition Module, Knowledge Base, Inference Engine, and Explanation Module. The ES collects knowledge from domain experts, stores it in a Knowledge Base, and allows users to access and utilize this knowledge for decision-making. ES provide a way to capture, infer, and transfer expert knowledge to support decision-making processes .

2.7.5 Evolutionary Computing for Intelligent Decision Support

Evolutionary Computing, inspired by natural evolution, involves the use of Genetic Algorithms (GA) for decision support. A population of individuals is initialized and evolves over generations to increase their fitness in relation to a specific goal. Individuals with higher fitness values are more likely to survive and become parents for the next generation. The population continues to evolve through techniques like crossover (swapping code between individuals) and mutation (small alterations in an individual's code). This process leads to a more fit and focused population over time.

2.7.6 Intelligent Agents for Intelligent Decision Support

Intelligent Agents (IA) are computer entities capable of autonomous action and decision-making in dynamic environments. They exhibit characteristics such as autonomy, reactivity, adaptiveness, proactiveness, social ability, communication, persistence, mobility, rationality, and learning. Multi-Agent Systems (MAS) are formed by teams of agents that can collaborate, coordinate, negotiate, and learn to achieve common goals. MAS are particularly suited for complex decision problems in uncertain environments. They involve communication, coordination, teaming agreements, and interactions with human decision makers. Learning is an important aspect of IA, making them more human-like. Recent research focuses on the Belief

Desire Intention framework, which incorporates an agent's beliefs, desires, and intentions in decision-making. Context and situational awareness play a crucial role in IA-based decision support systems.

2.8 Benefits and Applications of Decision Support Systems based on Artificial Intelligence:

Decision Support Systems (DSS) based on Artificial Intelligence (AI) have several benefits and applications. Here are some insights from the search results:
Benefits:

- Swift decision making: Timely information obtained through data warehousing assists management in swift decision making to avert situations leading to high business success [31] .
- Improved clinical care and strengthened health systems: AI-enabled technologies are poised to improve clinical care and strengthen health systems [32] .
- Comprehensive and holistic view of AI applications: A decision-making framework for guiding research and development efforts in AI applications can support a comprehensive and holistic view of AI applications [33] .
- Prioritization of research investments: A decision-making framework can help prioritize areas and techniques for research investments [33].
- Smart farming at AI : DSS based on AI can provide several benefits to smart farming, including better decision-making, improved resource usage, increased efficiency, sustainability, and a multi-agent approach .

Artificial Intelligence components, applications, and limitations are important pillars of ADSS However, there are also challenges that need to be addressed to develop and deploy similar innovations, especially in low- and middle-income countries. These challenges include improving data quality, equity in access to care, safeguards to minimize the harmful effects of bias, and supportive linkages within the health system.

Chapter 3

C.B.R(Case Based Reasoning)

3.1 Introduction

Introduction to AI Techniques: RBR, CBR, Machine Learning, Deep Learning, Rule-Based Systems, and Multi-Agent Systems

Artificial Intelligence (AI) has revolutionized numerous fields by enabling machines to perform tasks that traditionally required human intelligence. AI techniques encompass a wide range of methodologies and algorithms, each with its own unique characteristics and applications. In this introduction, we will explore some of the fundamental AI techniques, namely Rule-Based Reasoning (RBR), Case-Based Reasoning (CBR), Machine Learning, Deep Learning, Rule-Based Systems, and Multi-Agent Systems.

3.2 AI techniques:

3.2.1 Rule-Based Reasoning (RBR):

is an AI technique that utilizes a set of predefined rules to make decisions or solve problems. These rules are typically represented as if-then statements and are designed to capture expert knowledge in a specific domain. RBR is widely used in expert systems and knowledge-based systems, where it can effectively mimic human decision-making processes[36].

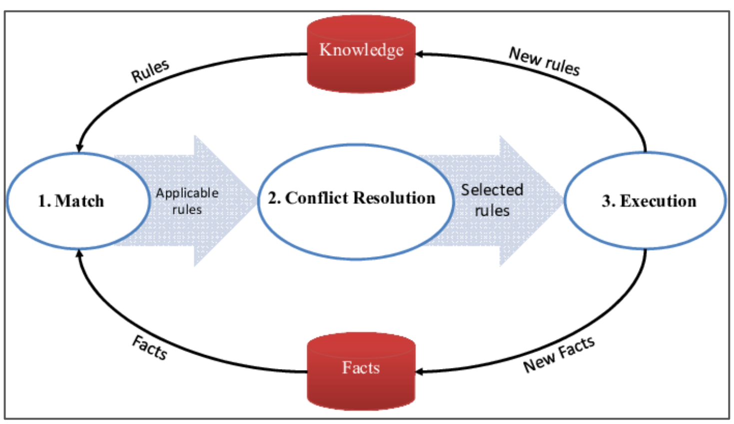


Figure 3. 1: The-rule-based-reasoning-process [45].

3.2.2 Case-Based Reasoning (CBR):

is an AI technique that solves new problems by leveraging solutions from previously encountered similar cases. CBR involves storing a database of past cases and using similarity measures to retrieve and adapt solutions. By learning from previous experiences, CBR enables systems to handle novel situations based on analogical reasoning [36].

3.2.3 Machine Learning:

is a branch of AI that focuses on developing algorithms and models that allow machines to learn and improve from data without explicit programming. Machine learning techniques involve training models on labelled datasets to make predictions or discover patterns and relationships within the data. These models can be used for various tasks such as classification, regression, clustering, and recommendation systems[36][37][38].

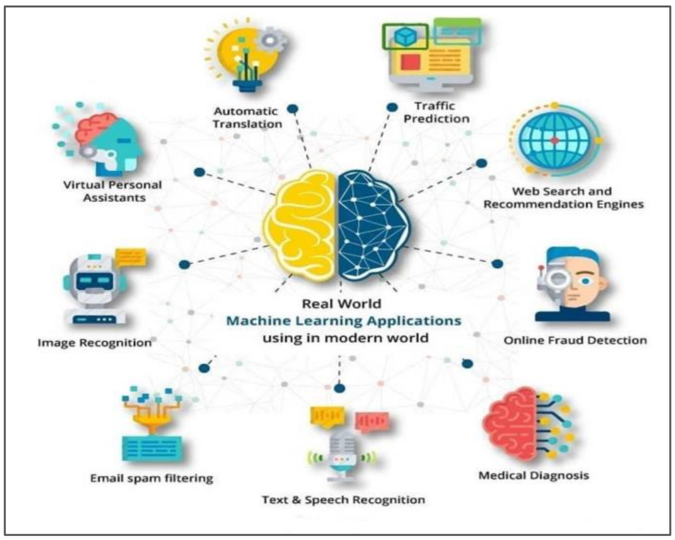


Figure 3.2: Machine learning applications

3.2.4 Deep Learning:

is a subfield of machine learning that deals with artificial neural networks inspired by the human brain. Deep learning models, known as artificial neural networks, consist of multiple layers of interconnected nodes (neurons) that process data. These networks excel at automatically learning hierarchical representations of data, enabling them to handle complex patterns and make high-level abstractions[36][39][40].

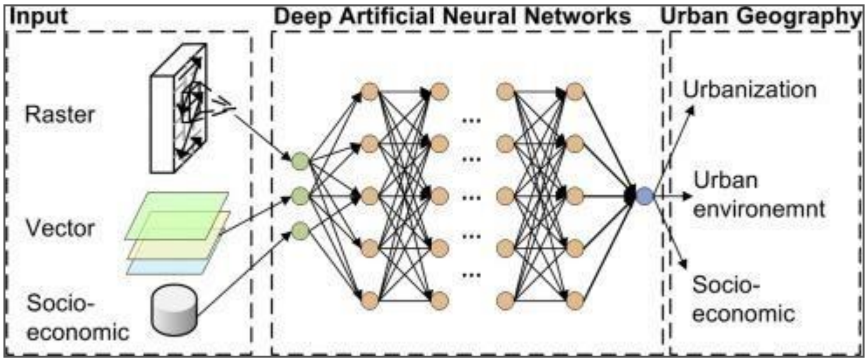


figure 3.3: S.N.N Simulated neural network [46].

3.2.5 Multi-Agent Systems (MAS):

Multi-Agent Systems (MAS) involve the interaction of multiple intelligent agents toachieve a common goal or solve complex problems. Each agent in a MAS possesses its own knowledge, capabilities, and decision-making processes. MAS leverage coordination, communication, and negotiation between agents to tackle tasks that are beyond the scope of individual agents. MAS have applications in areas such as robotics, traffic management, and social simulations[36].

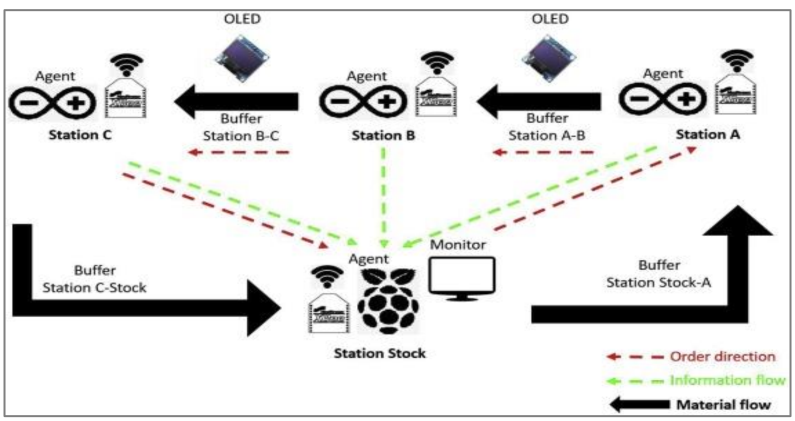


Figure 3.4: Multi-Agent-System-main-actors [47].

These AI techniques, RBR, CBR, machine learning, deep learning, rule-based systems, and multi-agent systems, have significantly contributed to the advancement of AI and have found diverse applications in various fields. As AI continues to evolve, these techniques will likely play a pivotal role in addressing complex challenges and creating innovative solutions for the benefit of society, we chose the CBR technique to implement it in our system,

3.3 C.B.R(Case Based Reasoning):

3.3.1 definition:

Case-based reasoning is a methodology in artificial intelligence that combines reasoning and machine learning techniques to solve problems based on past experiences or cases. When faced with a new problem, case-based reasoning involves retrieving similar past cases and reusing their solutions to solve the current problem. Learning methods can also be applied to enhance knowledge based on past experiences. It is a broad methodology applied in various industries and services, and it has been the focus of research in the field of artificial intelligence.

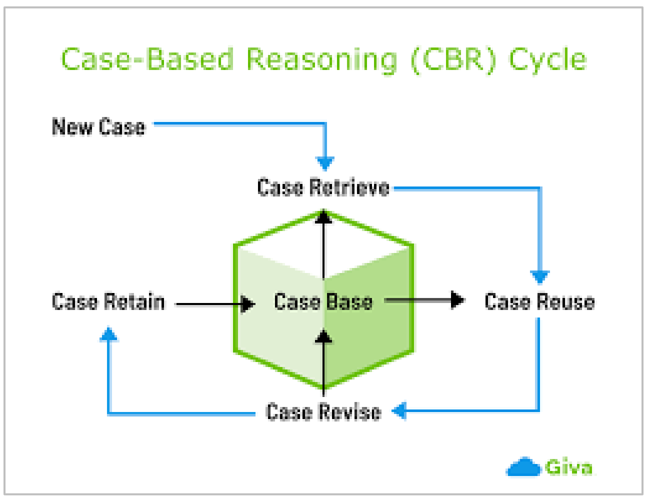


Figure 3.5: the case-based reasoning cycle [44].

3.4 The four Case-based reasoning phases:

3.4.1 Case Retrieval:

In CBR terminology, the retrieval task starts with a new problem description and ends when the best matching set of previous cases has been found. When we apply CBR to recommendation, this phase has the same purpose, but instead of retrieving similar problems, the system retrieves similar items. Thus, the retrieval task ends when the set of best matching previous items has been found

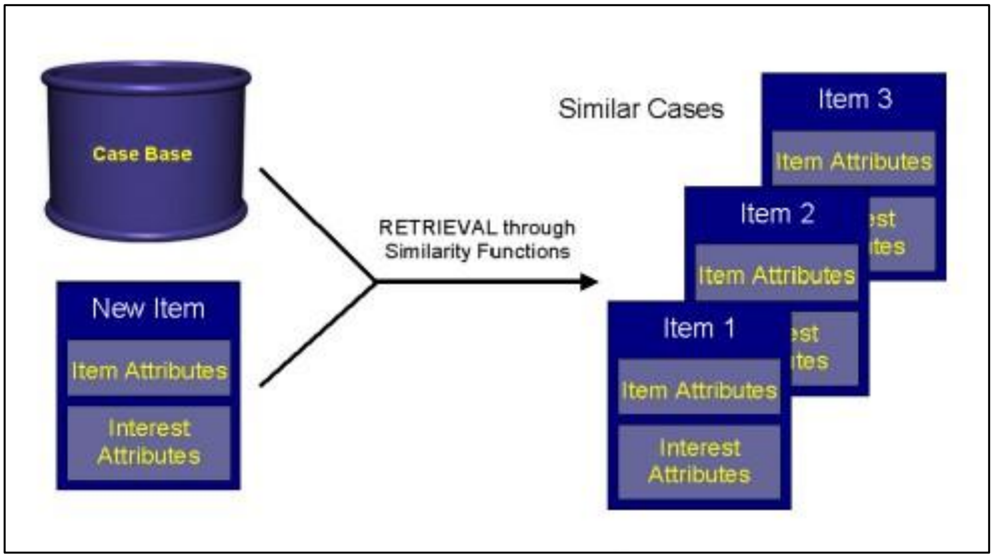


Figure3.6 Retrieve Phase[48].

- **Similarity Measure:**

  A measure of similarity is defined to retrieve relevant observations from the case database. The similarity measure calculates the similarity or distance between the current problem and the cases in the case database. Depending on the specific attributes and problem domain, you can use different distance metrics or similarity functions.

3.4.2 Case Adaptation:

Once a relevant past case is retrieved, it may not be directly applicable to the current problem due to differences in initial conditions or other factors. Case adaptation involves modifying the retrieved case to fit the current problem by making necessary adjustments.

3.4.3 Case Evaluation:

The adapted case is evaluated to determine its relevance and suitability in solving the current problem. This evaluation considers factors such as the similarity between the past and current cases, the quality of the solution in the past case, and other relevant criteria.

3.4.4 Case Storage:

After the solution derived from the adapted case is applied to solve the current problem, the case and its solution may be stored in a case library for future retrieval and reuse.

3.5 The Case Base:

A case-based reasoner is heavily dependent on the structure / representation and content of its collection of cases. In our approach, a case represents the user's experience concerning a certain item. Cases are split into two parts: the first, a set of objective attributes describing the item (the definition of the problem in CBR terminology) and the second, a set of interest attributes describing the user's interest in the given item (the solution to the problem in CBR terminology). Thus, given a set of item [13].

3.6 Case Representations

CBR's problem solving depends heavily upon the case representation that gives the important information for reasoning. Especially in complex problem domains, the cases need to be represented in a way that describes the sensible features of the problem that affect the solutions. Thus comparisons between cases can be carried out between source cases and target cases to find really reusable source case [49].

3.7 CBR Strengths

3.7.1 Knowledge reuse:

CBR's ability to reuse knowledge from past cases to solve new problems efficiently and effectively is one of its biggest strengths. This makes it particularly useful in domains where there is a large amount of domain-specific knowledge that can be leveraged to solve new problems.

3.7.2 Flexibility:

CBR is a flexible approach that can be applied to a wide variety of domains, including diagnostic systems, recommender systems, and decision support systems. It can also be combined with other AI techniques, such as rule-based reasoning (RBR) and machine learning (ML), to create hybrid systems that leverage the strengths of each approach[41].

3.7.3 Interpretability:

CBR is a transparent approach that allows users to understand how a solution was derived by examining the past cases that were used to solve the problem. This makes it particularly useful in domains where transparency and interpretability are important, such as healthcare and finance.

3.7.4 Accuracy:

CBR can lead to accurate solutions because it is based on real-world cases and experiences [42]. This means that the solutions generated by CBR are often practical and effective.

3.7.5 Standardization:

CBR can be standardized to ensure consistency in problem-solving approaches [42]. This can be particularly useful in fields like medicine, where standardized assessments are important for evaluating diagnostic reasoning skills [42].

3.7.6 Problem-solving mindset:

CBR's problem-solving mindset is another strength that sets it apart from other AI approaches. CBR emphasizes a knowledge-based perspective on the interpretation and reuse of experience that complements other problem-solving frameworks [43].

Chapter 4

Related works

Smart Farming Systems

4 Smart Farming Systems

4.1 Introduction:

The world's population is expected to reach 9.7 billion by 2050[78], which means that food production will need to increase by 70% to meet the demand [79]. However, traditional farming methods may not be sufficient to meet this demand, especially given the increasing challenges of climate change, water scarcity, and declining soil quality. Smart farming systems offer a solution to these challenges by using innovative technologies such as sensors, data analytics, and automation to increase agricultural efficiency, productivity, and sustainability.

4.2 What is smart farming?

Smart farming, also known as precision agriculture, is a modern approach to farming that uses advanced technologies to optimize crop yields, reduce costs, and improve sustainability. Smart farming systems rely on data analytics, machine learning, and other cutting-edge technologies to collect and analyze data from sensors and other sources, enabling farmers to make informed decisions about planting, irrigation, fertilization, and other aspects of agricultural management [50].

4.3 Advantages of smart farming systems:

Smart farming systems offer numerous benefits over traditional farming methods. These benefits include:

4.3.1 Optimized working parameters:

Smart farming systems use computerized assistance to optimize working parameters, which results in qualitative indices of lifting, comfort, and safety in the process of increased work for the user, low fuel consumption and manpower, and low negative impact on the environment.[50]

4.3.2 Precision agriculture:

Smart farming involves adjusting inputs in the agricultural system (seeds, fertilizers, pesticides) to distribute all where it is needed just as long as it takes. This results in more efficient use of resources and can lead to higher yields [50].

- **Real-time information:** Smart farming systems provide complete and accurate information on the processed surface, fuel consumption, seed, fertilizers, pesticides, or quantities harvested in agricultural harvesting machines in real or centralized time [50].

- **Remote access:**Smart farming systems can be accessed remotely, allowing end-users to gather uninterrupted information from numerous IoT systems for remote access of agricultural fields of varying sizes. This data can be used to enhance decision-making and create and test sophisticated prediction algorithms [51].
- **Low cost and energy independence:**IoT sensors used in smart farming systems are low cost and energy independent, making them helpful in water-scarce, remote Places [52].
- **Improved crop prediction:**Smart farming systems can use ESP8266 sensors to track temperature, humidity, moisture, and even the movement of animals that could damage crops in an agricultural field. If any discrepancy is detected, the system can send a notification to the farmer's smartphone as well as a notification on the application that was created for the purpose. Through an android application, the system's duplex communication link, which is based on a cellular Internet interface, enables data examination and irrigation scheduling programming [52].
- **Improved animal welfare:**Smart farming systems can provide major welfare advantages through life-long health monitoring, delivery of individual care, and optimization of environmental conditions. However, it is important to prioritize high welfare standards within smart farming systems to ensure that animals are not adversely affected by the technology [53].

4.4 Smart farming technologies:

Smart farming systems rely on a variety of technologies to collect, analyze, and act on data. Some of the key technologies used in smart farming include:

4.4.1 Sensors:

Sensors are an essential component of smart farming systems, as they are used to collect data on a wide range of variables, including soil moisture, temperature, and nutrient levels, as well as weather conditions. These sensors can be embedded in the soil, attached to plants, or placed in weather stations, and they transmit data wirelessly to a central hub or cloud-based system for analysis. Sensor data is critical to enabling farmers to make informed decisions about crop management, irrigation, and fertilization [54].

4.4.2 Internet of Things (IoT):

IoT technologies are used to connect sensors and other devices in a smart farming system, allowing them to communicate with each other and with cloud-based data analytics systems. IoT devices can include weather stations, soil moisture sensors, drones, and even livestock monitoring devices. The data collected by these devices is transmitted to a central hub for analysis, providing farmers with real-time information about their crops and enabling them to make data-driven decisions [55].

4.4.3 Data analytics

Data analytics tools are used to analyze the data collected by sensors and other devices, providing farmers with insights into crop health, soil quality, and other factors that can impact crop yields. Data analytics can help farmers to identify patterns and trends in the data, which can be used to optimize farming processes and increase efficiency. For example, data analytics can be used to determine the optimal time to plant crops or to identify areas of the field that require additional fertilizer [56].

4.4.4 Machine learning:

Machine learning algorithms are used to analyze large amounts of data and identify patterns and trends that can be used to optimize farming processes. Machine learning can be used to predict crop yields, identify potential pest and disease outbreaks, and optimize irrigation and fertilization schedules. By using machine learning, farmers can make more informed decisions about crop management and increase their crop yields while reducing costs [81].

4.4.5 CBR techniques:

CBR (Case-Based Reasoning) is a problem-solving technique that involves solving new problems by adapting solutions to similar past problems. In smart farming, CBR can be used to analyze data from past farming seasons and adapt solutions to current problems. For example, if a farmer is experiencing a pest problem, CBR can be used to analyze past data on similar pest problems and recommend a solution based on the successful outcomes of those past cases. Similarly, CBR can be used to analyze past data on crop yields and recommend solutions to improve crop yields in the current season. Overall, CBR can be a useful technique in Precision Farming to improve decision-making and optimize farming practices [80].

4.4.6 RBR techniques:

Rule-based reasoning (RBR) can be used in smart farming to develop intelligent systems that assist farmers in managing farming operations.

4.4.7 Automation:

Automation technologies such as robotics and drones are used to perform tasks such as planting, harvesting, and irrigation, reducing the need for manual labor and increasing efficiency. For example, automated irrigation systems can be programmed to water crops at specific times, based on data collected by soil moisture sensors. Similarly, drones can be used to survey crops and identify areas that require additional irrigation or fertilizer.

These technologies can help farmers improve efficiency, reduce waste, and increase yields. However, there are also challenges to adopting smart farming technologies, such as cost, lack of knowledge or training, and concerns about

data privacy and security [57][58][59].

4.5 Applications of smart farming:

Smart farming systems can be applied to a wide range of agricultural activities, from crop cultivation to livestock management. Some of the key applications of smart farming include:

4.5.1 Precision planting:

Precision planting is a key application of smart farming technologies, which involves the use of data analytics and machine learning to optimize crop yields by planting seeds with a high degree of precision. In this section, we will explore some of the key precision planting technologies in more detail.

4.5.1.1 Precision spraying:

Precision spraying is used to control pests, diseases, and weeds using precisionspray techniques or alternative measures. This can help reduce the use of conventional plant protection products and produce high-quality products, this technique is showing in Figure4.1 [60].

Figure4.1:precising spraying technique

4.5.1.2 GPS-guided tractors:

GPS-guided tractors are a key technology for precision planting, allowing farmers to plant crops with a high degree of accuracy. GPS-guided tractors use satellite navigation systems to guide the tractor along predetermined planting patterns. This technology allows farmers to plant seeds with a high degree of precision, reducing seed waste and improving crop yields[61].

Figure4.2 : GPS-guidedtractors technique

4.5.1.3 Variable rate planting:

Variable rate planting is another key precision planting technology, which involves adjusting the planting rate of seeds based on soil conditions and other factors. Variable rate planting uses data collected by sensors, such as soil moisture sensors and soil nutrient sensors, to determine the optimal planting rate for each location. This technology allows farmers to optimize seed usage and improve crop yields [62][63].

4.5.1.4 Seed monitoring:

Seed monitoring is a technology that involves using sensors to monitor the quality of seeds during planting. Seed monitoring sensors can detect issues such as seed damage, seed size, and seed spacing, allowing farmers to adjust their planting patterns to optimize crop yields. Seed monitoring technologies can also be used to detect seed diseases and other issues that can affect crop growth [64].

4.5.1.5 Automated planting systems:

Automated planting systems are another key precision planting technology, which involves using robots and other automated systems to plant crops. Automated planting systems can be programmed to plant seeds with a high degree of precision, reducing seed waste and improving crop yields. These systems can also be used to plant crops in challenging environments, such as steep terrain or areas with high labor costs[65].

Figure4.3: Automated planting system technique

4.5.1.6 Data Analytics:

Data analytics is a critical component of precision planting, as it allows farmers to analyse data collected by sensors and other technologies to optimize planting patterns. Data analytics can be used to identify patterns in soil moisture, temperature, and other factors that can affect crop growth. This information can be used to optimize planting patterns and improve crop yields[56].

4.5.2 Irrigation management:

Irrigation management is a critical application of smart farming technologies, as water is a scarce resource in many agricultural regions. Smart irrigation technologies use sensors and data analytics to optimize water usage, reducing waste and improving crop yields. In this section, we will explore some of the key smart irrigation technologies in more detail.

4.5.2.1 Soil Moisture Sensors:

Soil moisture sensors are one of the most important smart irrigation technologies, as they provide real-time information about soil moisture levels. This information can be used to optimize irrigation schedules and reduce water usage. Soil moisture sensors can be placed at different depths in the soil, providing data on water availability at different levels[66][67].

4.5.2.2 Automated irrigation systems:

Automated irrigation systems are another key smart irrigation technology, allowingfarmers to control water usage based on real-time data. Automated irrigation systems can be programmed to deliver water at specific times of day, based on data collected by soil moisture sensors and weather stations. By using automated irrigation systems, farmers can optimize water usage and reduce the risk of overwatering [68][69].

Figure4.4 :Automated irrigation system technique

4.5.2.3 Evapotranspiration sensors:

Evapotranspiration sensors are used to measure the amount of water lost from crops through evaporation and transpiration. This information can be used to calculate the water requirements of crops and optimize irrigation schedules. Evapotranspiration sensors are typically combined with soil moisture sensors and weather data to provide a comprehensive picture of crop water needs.

4.5.2.4 Weather Stations:

Weather stations are used to collect data on weather conditions, such as temperature, humidity, and rainfall. This information can be used to predict water requirements for crops and optimize irrigation schedules. Weather stations can be used in combination with soil moisture sensors and evapotranspiration sensors to provide a complete picture of crop water requirements [70].

Figure4.5 : Weather stations

4.5.2.5 Drip Irrigation:

Drip irrigation is a smart irrigation technology that delivers water directly to the rootsof plants, reducing water waste and improving crop yields. Drip irrigation systems can be controlled using data from soil moisture sensors and weather stations, allowing farmers to optimize water usage and reduce the risk of overwatering [73].

Figure4.6 : Drip irrigation technique

4.5.3 Fertilizer management:

Fertilizer management is an essential component of smart farming systems that ensures efficient and sustainable use of fertilizers. Fertilizers are an important input for crop production, and their proper management can significantly improve crop yields, reduce input costs, and minimize environmental impact.

Smart farming systems use various technologies and tools to manage fertilizers effectively. For instance, precision agriculture technologies such as sensors, drones, and GPS-based systems can be used to collect real-time data on soil nutrient levels, crop growth patterns, and environmental conditions. This data can be analysed to determine the optimal amount and timing of fertilizer application for each crop, thereby reducing waste and increasing efficiency.

Additionally, smart farming systems can use data analytics and machine learning algorithms to optimize fertilizer management. By analysing large datasets of soil and crop information, these systems can generate recommendations for fertilizer application that are tailored to specific crops, soil types, and weather conditions [74].

Another important aspect of fertilizer management in smart farming systems is the use of alternative fertilizers. Traditional chemical fertilizers can have negative impacts on the environment and human health, so many smart farming systems are exploring alternative fertilizers such as organic and bio-fertilizers. These fertilizers are derived from natural sources such as animal manure, compost, and microbial cultures, and can provide similar benefits to traditional fertilizers without the negative environmental impacts [75].

Overall, fertilizer management is a critical component of smart farming systems that can significantly improve crop yields, reduce input costs, and minimize environmental impact. By using advanced technologies and alternative fertilizers, smart farming systems can optimize fertilizer use and promote sustainable agriculture practices.

4.5.4 Crop monitoring:

Crop monitoring is a crucial aspect of smart farming systems, as it allows farmers to track the growth and health of their crops in real-time. By monitoring crops regularly, farmers can identify potential issues such as pests, diseases, and nutrient deficiencies before they become severe and take timely action to address them.

Smart farming systems use various technologies and tools to monitor crops effectively. For instance, sensors can be used to collect data on soil moisture, temperature, and nutrient levels, which can help farmers adjust their irrigation and fertilizer practices accordingly. Similarly, drones and satellite imagery can provide high-resolution images of crops, which can be analysed using machine learning algorithms to detect anomalies and predict crop yields.

Crop monitoring also involves the use of crop health monitoring tools such as disease detection systems and pest monitoring sensors. These tools use sensors and cameras to detect signs of disease and pests in crops, allowing farmers to take timely action to prevent crop damage [76].

Another important aspect of crop monitoring is yield monitoring, which involves the use of sensors and other tools to measure crop yields in real-time. This data can be used to optimize harvest schedules and inform future planting decisions [77].

In addition to these technologies, smart farming systems can also use data analytics and machine learning algorithms to analyse large datasets of crop and environmental data to predict crop growth patterns and optimize farming practices [77].

Overall, crop monitoring is a critical component of smart farming systems that can significantly improve crop yields, reduce input costs, and promote sustainable agriculture practices. By using advanced technologies and analytics tools, farmers can monitor crops more effectively and make data-driven decisions that optimize their farming practices.

4.5.5 Livestock management:

Livestock management is an important component of smart farming systems that involves the use of advanced technologies and data analytics tools to optimize animal health, nutrition, and productivity. By using smart farming technologies to monitor livestock, farmers can improve animal welfare, reduce input costs, and promote sustainable livestock production practices.

One important aspect of livestock management is the use of sensors and monitoring tools to track animal health and behavior. For example, wearable devices such as GPS trackers and bio-sensors can be used to monitor animal movement, body temperature, and heart rate, allowing farmers to identify early signs of disease or injury. Similarly, smart feeding systems can provide animals with precise amounts of feed and supplements tailored to their nutritional needs, ensuring that they receive the right balance of nutrients for optimal health and productivity [78].

Another important aspect of livestock management is the use of data analytics and machine learning algorithms to analyse large datasets of animal health and behavior data. By analysing this data, farmers can identify patterns and trends that can help them optimize their livestock management practices. For example, data analytics can help farmers identify the optimal time to breed animals, the best feed ratios for different stages of growth, and the most effective disease prevention and treatment strategies.

Smart farming systems can also use advanced technologies such as robotic milking machines and automated feeders to increase efficiency and reduce labor costs in livestock management. Robotic milking machines can monitor milk production in real-time and adjust milking schedules accordingly, while automated feeders can provide animals with food and water on a schedule, reducing the need for manual feeding [79].

Overall, livestock management is an essential component of smart farming systems that can significantly improve animal health, productivity, and welfare. By using advanced technologies and data analytics tools, farmers can optimize their livestock management practices and promote sustainable livestock production practices.

4.6 Conclusion

In conclusion, smart farming systems offer numerous benefits for the agriculture industry, including increased productivity, reduced input costs, and improved sustainability. Precision agriculture technologies such as crop monitoring, irrigation management, precision planting, and fertilizer management have revolutionized the way farmers manage their land and crops. Additionally, livestock management has also been improved through the use of wearable devices, smart feeding systems, and data analytics.

With the advancements in technology and data analytics, smart farming has become an increasingly important tool in modern agriculture. It allows farmers to make data-driven decisions, optimize resources, and improve overall efficiency. The implementation of smart farming technologies has the potential to significantly reduce waste, improve crop yield, and ensure sustainable food production for future generations.

As the world's population continues to grow, it is imperative that the agriculture industry finds ways to increase food production while minimizing its impact on the environment. Smart farming systems provide a sustainable and efficient way to achieve this goal. Therefore, it is important for farmers, researchers, and policymakers to continue to work together to further develop and implement these technologies in the agriculture industry.

Chapter 5

Design And Implementation

5.1 Introduction

In the following diagram, we have shown how our system, the Smart Decision Support System for Smart Agriculture, works.

In general, the framework of the Intelligent Decision Support System for Smart Agriculture is designed to help decision makers in agriculture make better decisions through the use of artificial intelligence technologies.

5.2. The proposed architecture

The proposed architecture includes three layers, as suggested in [82].

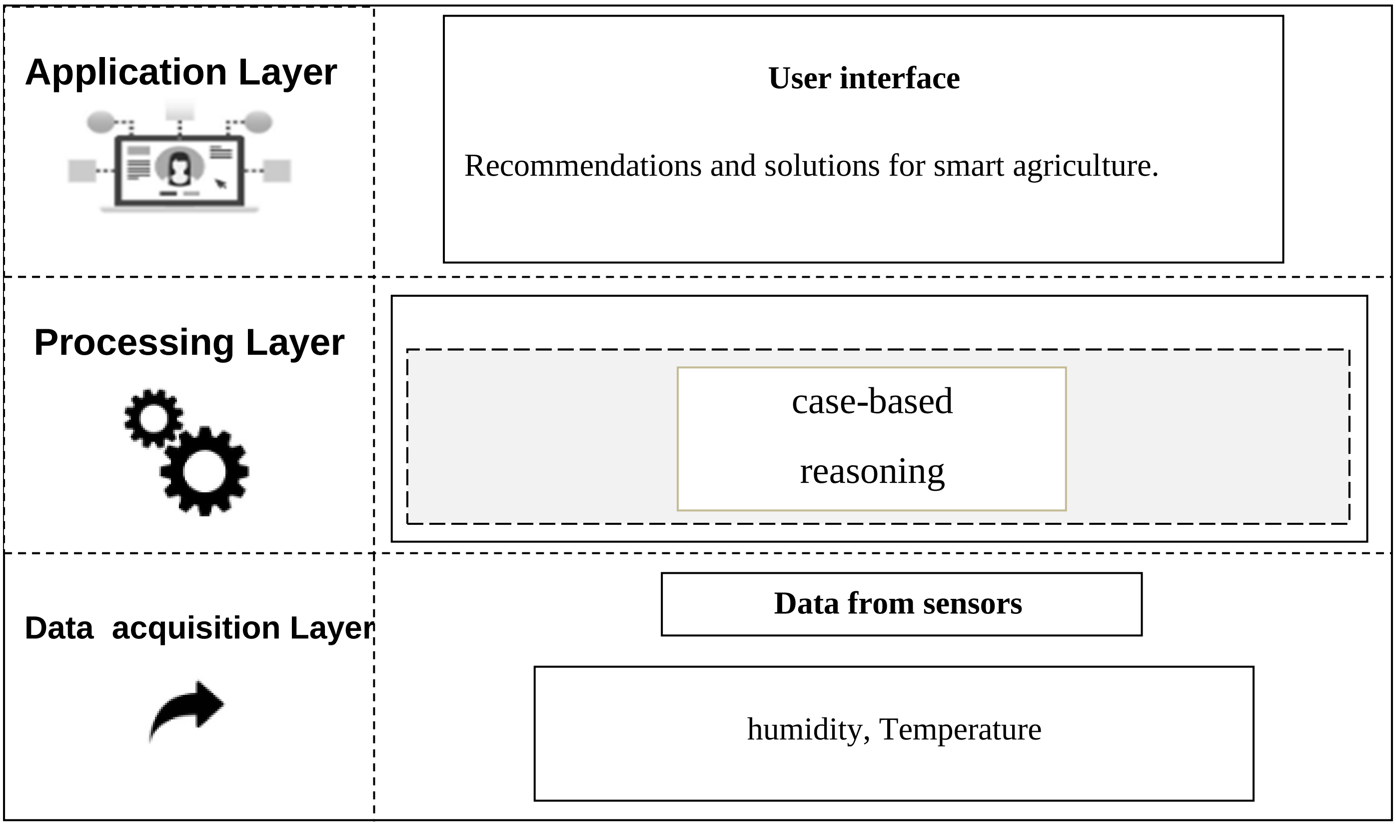


Figure 5.1: The framework of the An Intelligent Decision Support System for Smart Farming

5.3.1 Data Acquisition Layer

Risk management in smart farms involves the identification, assessment, and mitigation of potential risks in agricultural operations using advanced technologies and data-driven approaches. Similar to the factors found in the COPD text, several influencing factors play a role in the risk management system of smart farms:

.

5.3.2 Reasoning and Application Layers

The reasoning layer forms the foundation of smart agriculture systems. It involves collecting, processing, and analysing various data inputs to generate meaningful insights and recommendations.

The application layer focuses on the practical implementation of recommendations and solutions generated by the reasoning layer. It involves the deployment of technologies and tools on the farm to achieve the desired outcomes.

Both the reasoning layer and the application layer are interconnected and work together to create an integrated smart agriculture system. The reasoning layer analyses data and generates recommendations, while the application layer implements those recommendations using various technologies and tools. This synergy between the two layers enables farmers to make data-driven decisions, optimize resource usage, and improve overall farm productivity and sustainability.

5.4 Case-based reasoning (CBR)

CBR is an AI application that for technical environments is becoming an important user support tool that can be used in systems that help the user to solve problems and make decisions on the spot [82-83]. The CBR approach offers a solution to new problems arising from previous situations. The similarity measure allows determining the similarity between the cases and allows the most similar solution(s) of the case(s) to be reused or adapted to the new case under consideration [84,85]. According to [84], the CBR cycle consists of four phases, the so-called 4Rs: recovery, reuse, verification and retention. During the research phase, when a new situation or problem is detected, the CBR-based computer system starts searching for similar cases in its knowledge base. Once a solution is found, it can be reused or adapted to solve similar processes to determine a solution to the problem in the reuse phase. The solution obtained by the system can be corrected in the review phase and finally the new experiences are recorded in the case database of the maintenance phase. An important feature of the CBR system is its ability to learn. When a new issue is fixed, corrected, or changed, it is saved in the database and remains available for solving similar issues in the future. As a result, knowledge of the CBR system is constantly updated and it can be learned based on new cases [84]. According to the CBR approach, a case is a unit of knowledge that stores all the information about the situations or problems of a solution. A case thus represents a problem situation that has already been recognized and solved.

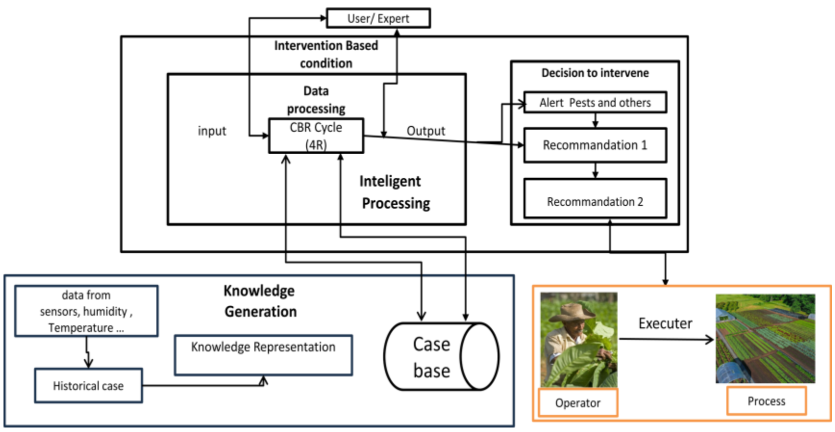
5.5 Proposed method

The purpose of the proposed system is to support decision-making regarding Building an intelligent decision support system for smart farming using case-based reasoning, humidity and temperature sensors, to recommend pest alerts, and other recommendations to farmers.

The proposed method is based on: Creating a case format that stores information about historical farming data, sensor readings from humidity and temperature sensors, pests information type and density, and case studies related to previous pest infestations, the corrective measures done and recommendations.

A proposal for building a CBR-based system is shown in Figure 5.2.

Figure 5.2. The PROCESS OF the intelligent decision support system for smart farming



5.6 knowledge representation

The case can have different content and presentation depending on the scope and purpose of the justification for the information. This information should be implementation specific, but the minimum structure a case should have is a description of the problem and its solution [84]. Cases can be represented in a variety of ways. Figure 5.3 shows the frame format that can be used for the case in smart farming case base.

CASE		
case description	**Problem description**	**Solution description**
CaseID	Pestquantity ; Peststage; Infectedarea ; Growthstage ; Plantingdensity ; Temperature_min; Temperature_max; Humidity; Rainfall; Sunlight; Windspeed	Alert1 Recommendation1 Recomendation2

Figure 5.3 Structure of a case describing a nonconformance in a process

5.6.1 Description of the case

This field gives the unique identification code, the date of the case, and the identification code of each case is important and linked to the recovery phase and the indexing concept to facilitate or speed up the search in the database for cases of similar situations.

5.6.2 Description of the problem

Cases in the case base need to be represented in a structured format that captures the relevant information for problem-solving. The problem description represents the characteristics and attributes of a specific farming scenario or situation. In the case of an intelligent system for smart farming using case-based reasoning with temperature and humidity sensors, the problem description may include the following elements:

-Temperature: The temperature readings obtained from the sensor at a particular time or interval.

-Humidity: The humidity measurements captured by the sensor concurrently with the temperature readings.

-Crop Type: The specific crop or plant being cultivated in the farming system.

-Growth Stage: The current growth stage of the crop, such as seedling, vegetative, flowering, or ripening.

-Environmental Factors: Additional environmental parameters that may influence crop growth, such as sunlight, rainfall, or wind speed.

5.6.3 Description of the solution

The solution represents the recommended course of action or decision based on the problem description. It provides guidance on how to address the specific farming scenario. In the case of the intelligent system, the solution may include the following elements:

- Recommended Actions: Specific actions to be taken by the farmer or user based on the problem description. This may include adjusting irrigation levels, applying fertilizers or pesticides, altering planting density, or implementing specific cultivation practices.

- Best Practices: Established farming practices or techniques that have proven effective in similar situations.

- Previous Outcomes: Information about the outcomes or results achieved in past instances where similar problem descriptions were encountered. This helps in understanding the potential consequences of different actions.

5.6.4 Results

The result field contains recommendation based on the adapted cases, the DSS would generate recommendations for the farmer. These recommendations could include appropriate pest management strategies, such as the type and timing of pesticide application, pest-resistant crop varieties, or cultural practices to control pests in specific temperature and humidity conditions.

By combining the problem description and the solution, the intelligent system can retrieve relevant historical cases from the knowledge base that match the current problem description. It then applies the solutions provided in those cases to offer informed recommendations and decisions to optimize farming practices in real-time.

5.7 CBR implementation

The COLIBRI platform was used to implement the CBR-based system, an academic software whose main purpose is to provide the necessary infrastructure for the development of CBR systems and related software components. COLIBRI aims to provide a collaborative environment where users can share their efforts in implementing CBR applications [83].

Offering a well-defined architecture for designing CBR systems, the COLIBRI includes the jCOLIBRI platform and several development tools that make it easy for users to share CBR components.

COLIBRI Studio is a superior implementation of the COLIBRI platform. It provides the graphical tools needed to generate CBR systems without dealing directly with the source code, thus allowing the assembly of its CBR components.COLIBRI Studio is integrated with the popular Eclipse IDE and therefore leverages the launch and project management capabilities of Java, as shown in Figure 6. CBR system modelling tool COLIBRI Studio creates a CBR model that can be used in other applications of the same knowledge, with only minor modifications [83].

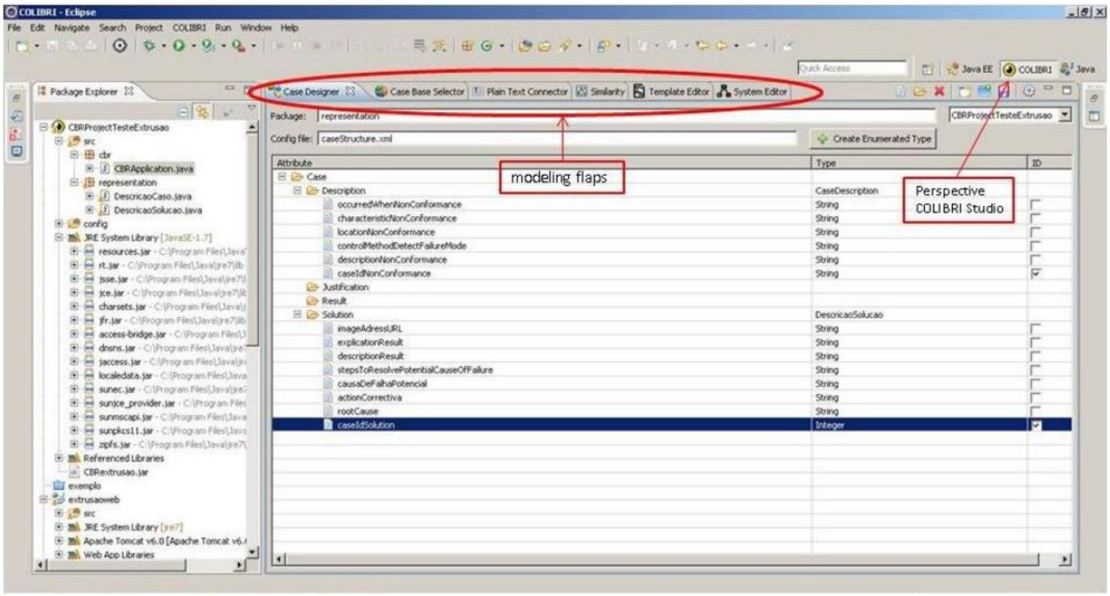
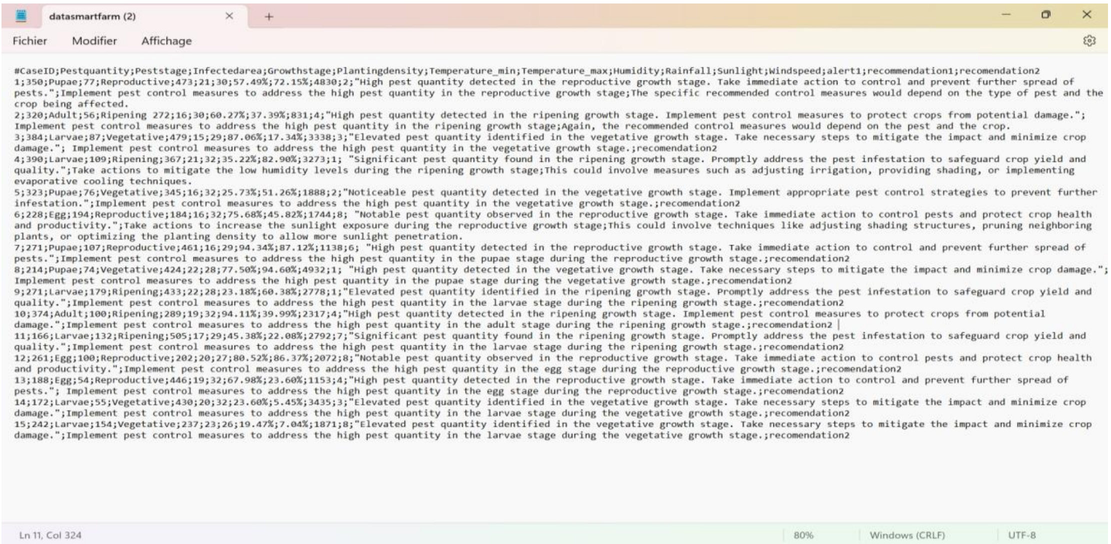


Figure 5.4: COLIBRI Studio's plug-in in the Java Eclipse IDE

5.7.1 Case-base




```
#CaseID;Pestquantity;Peststage;Infectedarea;Growthstage;Plantingdensity;Temperature_min;Temperature_max;Humidity;Rainfall;Sunlight;Windspeed;alert1;recommendation1;recomendation2
1;350;Pupae;77;Reproductive;473;21;30;57.49%;72.15%;4830;2;"High pest quantity detected in the reproductive growth stage. Take immediate action to control and prevent further spread of pests.";Implement pest control measures to address the high pest quantity in the reproductive growth stage;The specific recommended control measures would depend on the type of pest and the crop being affected.
2;320;Adult;56;Ripening 272;16;30;60.27%;37.39%;831;4;"High pest quantity detected in the ripening growth stage. Implement pest control measures to protect crops from potential damage."; Implement pest control measures to address the high pest quantity in the ripening growth stage;Again, the recommended control measures would depend on the pest and the crop.
3;384;Larvae;87;Vegetative;479;15;29;87.06%;17.34%;3338;3;"Elevated pest quantity identified in the vegetative growth stage. Take necessary steps to mitigate the impact and minimize crop damage."; Implement pest control measures to address the high pest quantity in the vegetative growth stage.;recomendation2
4;390;Larvae;109;Ripening;367;21;32;35.22%;82.90%;3273;1; "Significant pest quantity found in the ripening growth stage. Promptly address the pest infestation to safeguard crop yield and quality.";Take actions to mitigate the low humidity levels during the ripening growth stage;This could involve measures such as adjusting irrigation, providing shading, or implementing evaporative cooling techniques.
5;323;Pupae;76;Vegetative;345;16;32;25.73%;51.26%;1888;2;"Noticeable pest quantity detected in the vegetative growth stage. Implement appropriate pest control strategies to prevent further infestation.";Implement pest control measures to address the high pest quantity in the vegetative growth stage.;recomendation2
6;228;Egg;194;Reproductive;184;16;32;75.68%;45.82%;1744;8; "Notable pest quantity observed in the reproductive growth stage. Take immediate action to control pests and protect crop health and productivity.";Take actions to increase the sunlight exposure during the reproductive growth stage;This could involve techniques like adjusting shading structures, pruning neighboring plants, or optimizing the planting density to allow more sunlight penetration.
7;271;Pupae;107;Reproductive;461;16;29;94.34%;87.12%;1138;6; "High pest quantity detected in the reproductive growth stage. Take immediate action to control and prevent further spread of pests.";Implement pest control measures to address the high pest quantity in the pupae stage during the reproductive growth stage.;recomendation2
8;214;Pupae;74;Vegetative;424;22;28;77.50%;94.60%;4932;1; "High pest quantity detected in the vegetative growth stage. Take necessary steps to mitigate the impact and minimize crop damage."; Implement pest control measures to address the high pest quantity in the pupae stage during the vegetative growth stage.;recomendation2
9;271;Larvae;179;Ripening;433;22;28;23.18%;60.38%;2778;1;"Elevated pest quantity identified in the ripening growth stage. Promptly address the pest infestation to safeguard crop yield and quality.";Implement pest control measures to address the high pest quantity in the larvae stage during the ripening growth stage.;recomendation2
10;374;Adult;100;Ripening;289;19;32;94.11%;39.99%;2317;4;"High pest quantity detected in the ripening growth stage. Implement pest control measures to protect crops from potential damage.";Implement pest control measures to address the high pest quantity in the adult stage during the ripening growth stage.;recomendation2
11;166;Larvae;132;Ripening;505;17;29;45.38%;22.08%;2792;7;"Significant pest quantity found in the ripening growth stage. Promptly address the pest infestation to safeguard crop yield and quality.";Implement pest control measures to address the high pest quantity in the larvae stage during the ripening growth stage.;recomendation2
12;261;Egg;100;Reproductive;202;20;27;80.52%;86.37%;2072;8;"Notable pest quantity observed in the reproductive growth stage. Take immediate action to control pests and protect crop health and productivity.";Implement pest control measures to address the high pest quantity in the egg stage during the reproductive growth stage.;recomendation2
13;188;Egg;54;Reproductive;446;19;32;67.98%;23.60%;1153;4;"High pest quantity detected in the reproductive growth stage. Take immediate action to control and prevent further spread of pests."; Implement pest control measures to address the high pest quantity in the egg stage during the reproductive growth stage.;recomendation2
14;172;Larvae;55;Vegetative;430;20;32;23.60%;5.45%;3435;3;"Elevated pest quantity identified in the vegetative growth stage. Take necessary steps to mitigate the impact and minimize crop damage.";Implement pest control measures to address the high pest quantity in the larvae stage during the vegetative growth stage.;recomendation2
15;242;Larvae;154;Vegetative;237;23;26;19.47%;7.04%;1871;8;"Elevated pest quantity identified in the vegetative growth stage. Take necessary steps to mitigate the impact and minimize crop damage.";Implement pest control measures to address the high pest quantity in the larvae stage during the vegetative growth stage.;recomendation2
```

Figure 5.5: knowledge base XML

The data that we will deal with in our system will be the vital indicators in which the measurement process takes place using sensors such as temperature, humidity, location, and others. We will deal with digital data primarily, and the analysis process is completed and the appropriate solution is included for each case.

Case iD	Pest quantity	Pest stage	Infected area	Growth stage	Planting density	Temper _min	Temper _max	Humidity	Rainfall	Sunlight	Wind speed	Solution
1	350	Pupae	77	Reproductive	473	21	30	57.49%	72.15%	4830	2	-
2	320	Adult	56	Ripening	272	16	30	60.27%	37.39%	831	4	-
3	384	Larvae	87	Vegetative	479	15	29	87.06%	17.34%	3338	3	-
4	390	Larvae	109	Ripening	367	21	32	35.22%	82.90%	3273	1	-
5	323	Pupae	76	Vegetative	345	16	32	25.73%	51.26%	1888	2	-
6	228	Egg	194	Reproductive	184	16	32	75.68%	45.82%	1744	8	-
7	271	Pupae	107	Reproductive	461	16	29	94.34%	87.12%	1138	6	-
8	214	Pupae	74	Vegetative	424	22	28	77.50%	94.60%	4932	1	-
9	271	Larvae	179	Ripening	433	22	28	23.18%	60.38%	2778	1	-
10	374	Adult	100	Ripening	289	19	32	94.11%	39.99%	2317	4	-
11	166	Larvae	132	Ripening	505	17	29	45.38%	22.08%	2792	7	-
12	261	Egg	100	Reproductive	202	20	27	80.52%	86.37%	2072	8	-
13	188	Egg	54	Reproductive	446	19	32	67.98%	23.60%	1153	4	-
14	172	Larvae	55	Vegetative	430	20	32	23.60%	5.45%	3435	3	-

The table 5.1 the case base showing how data will be arranged in the case base

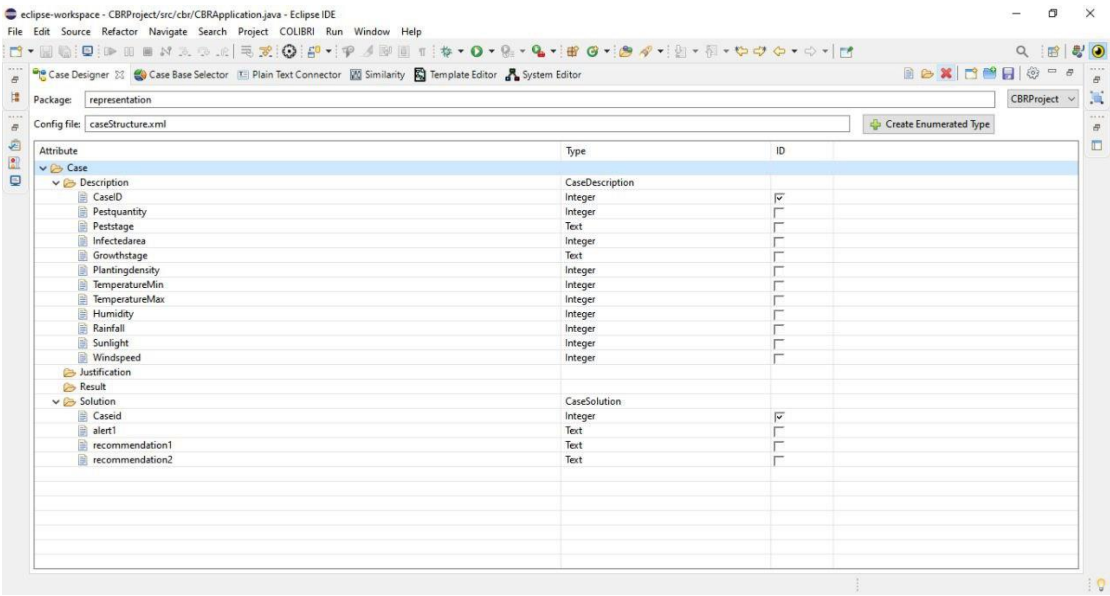


Figure 5.6 : Representation of the case structure.xml

The DSS would have a knowledge base containing historical and contextual data related to temperature, humidity, and pests. This information could include the ideal temperature and humidity ranges for different crops, the impact of temperature and humidity on pest prevalence, and successful pest management strategies employed in the past

5.7.2. Similarity Measure: To retrieve relevant cases from the case base, a similarity measure is defined. The similarity measure calculates the similarity or distance between the current problem (current environmental conditions, farming practices) and the cases in the case base. Various distance metrics or similarity functions can be used, depending on the specific attributes and problem domain.

5.7.3. Retrieval: The retrieval phase involves searching the case base for the most similar cases to the current problem. This is done by applying the similarity measure to compare the current problem with the cases in the case base. The retrieval process identifies a set of similar cases that are potentially relevant to the current problem.

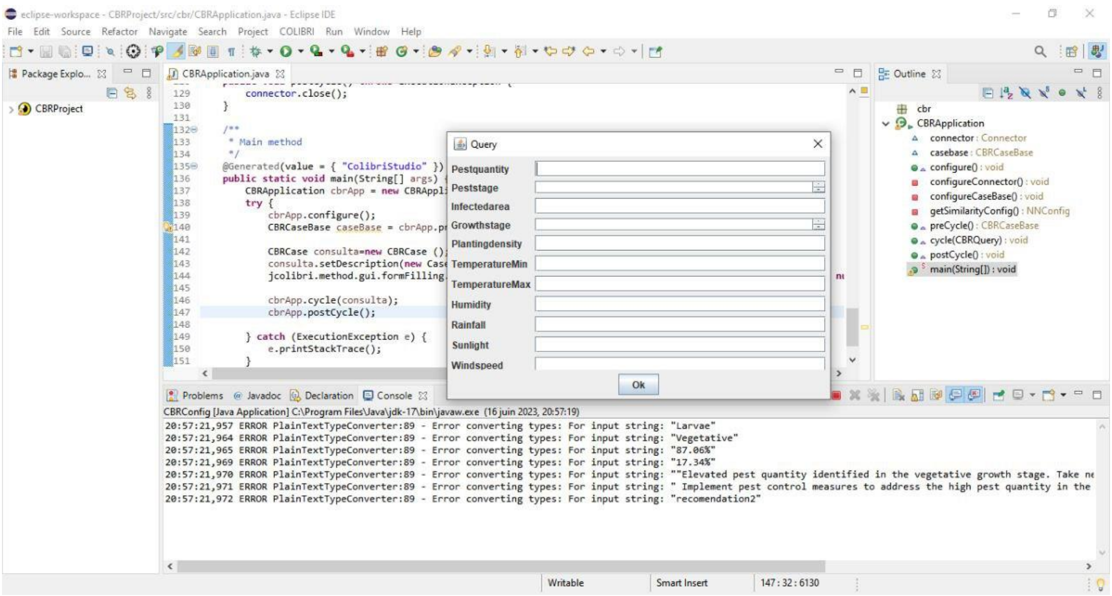


Figure 5.7: the retrieval phase with the case of the knowledge xml

The CBR system continuously learns and improves its problem-solving capabilities by leveraging past experiences stored in the case base, making it a valuable approach for intelligent systems in smart farming.

5.8 Discussion of results:

In view of the results obtained through the use of the Smart Agree system in dealing with sensor data such as expressed in the table, it analyses the measurement results and compares them with its own database. Obtaining higher quality results and lower costs compared to other systems, as it maintains the same environment and variables, that is, it is not in line with sudden changes, which may cause danger about basic resources such as the quality of soil and plants.

Among the most important strengths of our system, which proved its effectiveness is its ability to monitor and continuously follow up on various variables such as biomarkers such as temperature, humidity, soil moisture, etc., and its positive results are reflected in the study that took place on the rice plant, as the difference of one degree Celsius in temperature from the normal situation necessary for the plant causes a delay in harvesting the crop for two full weeks, which leads to many losses, the most important of which is the increase in costs for the farmer as well as the shortage in the market side, which leads to inflation Prices and many more, our system in this case was to alert to move or make the appropriate reaction to any unexpected change as well as another example about predicting diseases through biomarkers, as each disease has symptoms that are manifested in the plant, so the degree of moisture of the soil around the natural plant is not the same with a diseased plant, as well as the temperature of the soil varies from here we can diagnose the disease condition earlier and find the appropriate solution to this case.

5.9 Conclusion

The intelligent system for smart farming presented in this paper uses case-based reasoning (CBR) to facilitate pest detection and management. The system aims to leverage historical data from past farming instances to inform decision-making in the present. The core components of the system include a case base, case representation, similarity measurement, retrieval, reuse, revise, retain, and revisit.

Chapter 6

General Conclusion

General Conclusion

In conclusion, this work has examined the importance of implementing a robust decision support system in smart agriculture. The rapid advancements in technology and the integration of smart devices and sensors in agricultural practices have revolutionized the industry, leading to increased efficiency, productivity, and sustainability. However, with these advancements come inherent risks that can significantly impact the success and stability of smart agriculture operations.

Through an in-depth analysis of existing literature, case studies, and expert interviews, this study has identified key risk factors in smart agriculture, including technological failures, data security breaches, weather-related risks, and market volatility. These risks can result in financial losses, crop failure, compromised food safety, and reputational damage for farmers and agribusinesses.

In conclusion, the integration of temperature and humidity sensors, along with the case based reasoning technique; in an intelligent decision support system for smart farming holds great promise in enhancing agricultural practices. By harnessing real-time environmental, this system can provide invaluable insights and support to farmers, leading to improved efficiency, productivity, and sustainability in the agricultural sector.

Firstly, the incorporation of temperature and humidity sensors allows for precise monitoring of environmental conditions crucial to plant growth and animal well-being. These sensors provide accurate and continuous data on temperature and humidity levels, enabling farmers to make informed decisions regarding irrigation, ventilation, and climate control. By maintaining optimal environmental conditions, crop yields can be maximized, and the risk of disease or stress can be minimized, ensuring healthier and more resilient plants.

Moreover, the intelligent decision support system analyzes the data collected from sensors , integrating it with other relevant information such as weather forecasts, historical data, and crop-specific knowledge. By employing artificial intelligence and case based reasoning, the system can generate accurate predictions, offer actionable recommendations, and assist in decision-making processes. This not only saves farmers time and effort but also enables them to make more precise and effective choices in resource allocation, crop protection, and overall farm management.

Overall, an intelligent decision support system that combines temperature and humidity sensors. It harnesses the benefits of advanced technology, and data-driven insights to optimize agricultural operations, promote sustainable practices, and enhance productivity. By empowering farmers with real-time information and intelligent recommendations, this system has the potential to revolutionize the way farming is conducted, leading to more efficient and environmentally friendly food production.

Perspectives :

The perspective of the intelligent decision support system (DSS) for smart farming lies at the intersection of agriculture, technology, and data analytics. It represents a transformative approach to farming by harnessing the power of advanced technologies to optimize agricultural practices and improve productivity:

1- Precision Agriculture: The DSS embodies the principles of precision agriculture, which focuses on site-specific management of crops and resources. It enables farmers to make precise, data-driven decisions tailored to the specific needs of individual plants or sections of their fields. This approach maximizes resource efficiency, minimizes waste, and ensures optimal crop growth.

2- Data-Driven Decision Making: The DSS leverages data analytics and artificial intelligence to provide valuable insights and recommendations. By analyzing vast amounts of data from various sources, it helps farmers gain a deeper understanding of their farms, enabling them to make informed decisions based on real-time and historical data. This data-driven decision-making approach enhances efficiency and productivity.

3- Real-Time Monitoring and Intervention: The DSS enables real-time monitoring of farm conditions, including crop health, soil moisture, and weather patterns. This allows farmers to detect and respond to changes or issues promptly. By providing alerts and notifications, the system empowers farmers to take immediate action, preventing potential crop losses and optimizing yields.

4- Risk Mitigation and Resilience: The DSS helps farmers mitigate risks associated with crop failures, pests, diseases, and adverse weather conditions. By providing accurate weather forecasts, early pest detection, and disease monitoring, it allows farmers to implement preventive measures and take timely corrective actions. This enhances the resilience of farming operations and reduces financial losses.

7- Accessible and User-Friendly Technology: The DSS aims to make advanced farming technologies accessible and user-friendly for farmers. User-friendly interfaces, mobile applications, and simplified visualizations enable farmers to easily interact with the system and understand the insights and recommendations provided. This ensures that technology adoption is not a barrier and empowers farmers of all backgrounds to leverage the benefits of smart farming.

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