Development of a Fuzzy Case-Based Reasoning Decision Support System for Water Management in Smart Agriculture

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Abstract

This paper proposes a decision support system aimed at improving water management in smart agriculture, utilizing the Case-Based Reasoning (CBR) methodology. Given the increasing challenges of water resources and the need for their optimal use in agriculture, the application of advanced technologies for smart resource management has gained significant importance. The proposed system assists in better decision-making regarding irrigation timing and quantity by collecting data from various sensors, including information about environmental conditions, soil status, and plant water needs. As part of the system, the case-based reasoning model uses historical data and similarity comparison between current situations and previous cases to offer optimal water management solutions. The Internet of Things (IoT), as the main infrastructure of this system, facilitates the continuous and real-time collection of data, thereby enhancing the accuracy of decisions. The results obtained show that this system can optimize water consumption, reduce irrigation costs, and increase agricultural productivity. The key findings of this study suggest that this approach could serve as a sustainable solution for water efficiency in smart agriculture and optimal water resource management in the future.

Keywords: *Decision support system, smart agriculture, smart irrigation, case-based reasoning (CBR).*

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1. Introduction

Water resource management in agriculture, especially considering climate change and increasing food demands, has become one of the main challenges in the agricultural sector [1]. In this context, smart agriculture, as an innovative approach, utilizes advanced technologies such as the Internet of Things (IoT) to maximize resource efficiency and productivity [2].

The Internet of Things, by enabling the collection and real-time analysis of environmental data, provides significant opportunities for precise and intelligent water resource management [3-6]. Specifically, the use of sensors and networked devices for monitoring soil conditions and plant water requirements can lead to improved decision-making and reduced water consumption [7].

Moreover, Case-Based Reasoning (CBR), as an effective method for adapting and optimizing decisions based on past experiences, offers unique capabilities, especially in the domain of water resource management [8]. This method can assist farmers in making better and faster decisions regarding the timing and amount of irrigation [9].

This paper examines the design of a decision support system based on IoT and CBR for enhancing water management in smart agriculture. The proposed system, utilizing real-time data from various sensors and analyzing them through case-based reasoning, enables farmers to make more accurate water consumption decisions [10].

CBR, due to its effectiveness and strong reasoning capabilities, has been applied in various fields such as healthcare [11-13], error detection [14], emergency response [15, 16], and agricultural management [17-19]. Due to its strong reasoning abilities and ease of application, the CBR method has gradually been adopted in agriculture. This approach is used in areas such as plant classification, animal disease detection, pest management, irrigation planning, and more.

In the field of plant classification, Sharaf-Eldeen et al. (2012) employed the CBR method for classifying types of IRIS plants. Unlike traditional CBR systems, which only retrieve information, their proposal included domain adaptation rules to improve classification accuracy [19]. Similarly, Li and Yeh (2004) used this method to classify radar images with artificial resolution captured by multi-temporal satellites. They concluded that knowledge-based systems could serve as a suitable alternative to traditional classification methods, as these methods, like supervised classification, heavily rely on user skills and time-consuming training processes [20].

In the field of animal and agricultural product disease detection, Gebre-Amanuel et al. (2018) proposed an expert system combining CBR and Rule-Based Reasoning (RBR) for diagnosing animal diseases. Symptoms provided by users were treated as new queries, and solutions were retrieved from the case base [21]. Han (2019) examined the reasoning process in smart disease detection and knowledge acquisition related to animal diseases by combining CBR and RBR [22]. In pest management, Zhu and Yin (2019) designed a CBR-based decision support system for pest control and prevention. Plant diseases and insect pests were stored in an ontology model, and the features of this ontology were categorized and quantified using a similarity computation algorithm based on ontology mapping [23].

For irrigation planning, Gonzalez-Briones et al. (2019) proposed the design of a multi-agent system consisting of two agents: a "knowledge extraction agent" and a "CBR agent." The first agent used unsupervised learning techniques in cases where the data were unlabelled, while the second agent was responsible for generating solutions from stored CBR cases. Their proposal was tested in an agricultural environment aiming to optimize irrigation for corn crops [24]. Car and Moore (2011) modified the CBR method with a new interface that allowed users to select their desired parameters. In this context, the CBR-based decision support system did not impose limitations on decision input parameters or solution pathways. Their proposal was tested for daily irrigation planning in vineyards in southeastern Australia under drip irrigation systems [25].

In summary, it can be concluded that the CBR approach holds significant potential for modeling intelligent systems in agriculture. Moreover, complex agricultural problems can be efficiently and seamlessly solved using this approach. Therefore, CBR could be a suitable option for addressing irrigation planning issues. Case-Based Reasoning (CBR) is defined as the process of solving new problems by adapting cases that have previously been successfully managed. The CBR method simulates how humans reason and learn. Therefore, it appears to be a more valid psychological model of human reasoning [26]. This unique feature of CBR makes it a promising approach for building intelligent systems [27].

An Agricultural Decision Support System (ADSS) can be defined as a human-computer system capable of utilizing data from various sources such as weather, land use, and human labor. Its goal is to facilitate decision-making processes and provide useful suggestions to farmers regarding agricultural activities such as fertilization, irrigation, and pest management. With the help of sensor technologies and reasoning approaches, ADSSs can gather sufficient data (such as sensor measurements, meteorological data, infrared images) and generate evidence-based knowledge. CBR, as one of the most powerful reasoning approaches, has been employed by researchers in the field of agriculture for years. This paper aims to provide a comprehensive and practical model for the implementation of such systems, analyzing and reviewing these approaches, and its results can lead to significant improvements in water resource management in agriculture.

2. Methodology

The process of using existing knowledge and facts, along with the strategy adopted to solve new problems and achieve an acceptable (logical) outcome, is called reasoning. Generally, the reasoning methods used in computer systems are inspired by the reasoning methods employed by humans. Case-Based Reasoning (CBR), as one of the important techniques in artificial intelligence, is defined as the process of problem-solving by adapting and matching cases that have already been formed. CBR, as described by Watson and Marir (1994), appears to be a psychologically reasonable model of human reasoning by imitating human reasoning and learning processes. This unique feature makes CBR a promising approach for building intelligent systems. CBR has been applied effectively in various fields such as agriculture, robotics, medicine, and more due to its powerful and efficient reasoning capabilities. The main idea behind this method is to use older experiences, meaning that to solve a new problem, solutions from previously encountered, similar problems are utilized.

Case-Based Reasoning (CBR) can be organized in a 5R cycle, as outlined by Aamodt and Plaza (1994), which includes the stages of representation, retrieval, reuse, revision, and retention. A general workflow of CBR is presented in the following:

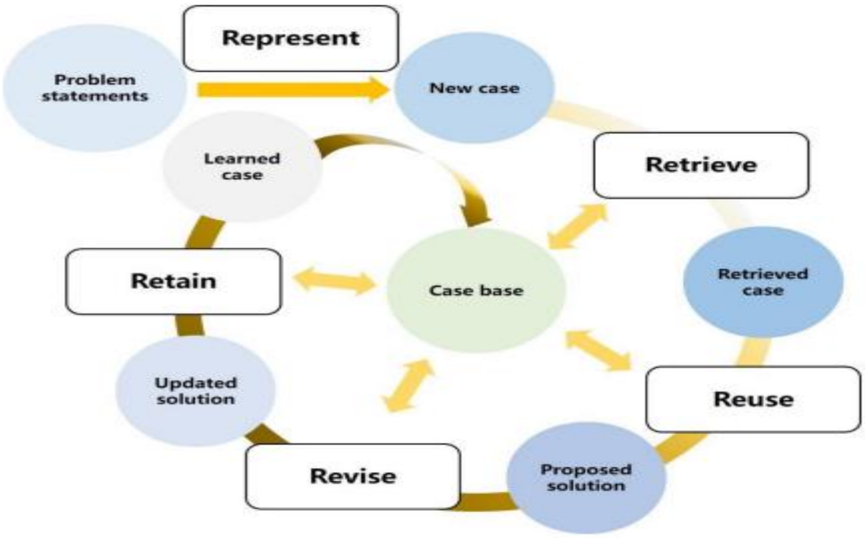

Figure 1. CBR System Workflow

This 5R cycle is essential for the effective implementation of a CBR system and is explained as follows:

• **Representation**: The initial definition of the problem and the identification of the relevant features of the case in the CBR case base.

• **Retrieval**: Finding and retrieving previously relevant cases from the case base that are most similar to the current problem.

• **Reuse**: Implementing or adapting the solutions of the retrieved cases to the new context, often with modifications to better suit the new problem.

• **Revision**: Evaluating the solution applied and generalizing it in response to feedback from the result; this may involve adjustments or corrections.

• **Retention**: Finally, the information gathered, and potentially a new case derived from experience, is added to the case base to serve as reasoning for future cases.

The first stage in CBR-based implementation is representation and determination of case models. Here, a case is a snapshot of the environment at a specific moment from the perspective of an agent equipped with CBR. Since the information in a case is based on the internal state (beliefs) of this agent, this agent is referred to as the reference agent. The basic definition of a case consists of two parts: the problem description, which corresponds to the state and environmental conditions, and the solution description, which specifies the actions or sequences of actions the agent must perform to solve the problem.

Case retrieval is a crucial step in Case-Based Reasoning (CBR). In this stage, from the cases stored in the case base, a case is selected that seems to have the greatest similarity to the new problem. Below, the stages of case retrieval in CBR are explained:

1. **Indexing**: Initially, cases in the case base must be properly indexed. This indexing involves extracting important features from the cases, such as demographic features, characteristics, and other relevant information.
2. **Similarity Calculation**: Then, the similarity between the new case and the existing cases in the case base is assessed. This similarity can be calculated based on various criteria, such as distance or correlation.
3. **Case Selection**: The case that is most similar to the new problem is selected. This selection might be based on a similarity threshold or a specific prioritization method.
4. **Retrieval and Solution Application**: The solution from the selected case is retrieved from the case base and applied to the new problem. This may involve specific modifications or adaptations.
5. **Evaluation and Updating**: The results of applying the solution to the new problem are evaluated. If necessary, the case base is updated to improve performance in future similar cases.
6. **Learning**: The information derived from the reasoning results is added to the case base to enable better future reasoning.

Proposed Decision Support System Model

Figure 2 shows the overall model of the proposed Fuzzy Case-Based Reasoning (FCBR) approach. Before discussing the details of all the sections of the model, the definitions used in this model are examined. The first stage in the CBR-based implementation is representation and determination of case models. A case here is a snapshot of the environment at a specific moment from the perspective of an agent equipped with CBR. Since the information in a case is based on the internal perception (beliefs) of this agent, it is referred to as the reference agent. The basic definition of a case consists of two parts: the problem description, which corresponds to the state and environmental conditions, and the solution description, which specifies the actions or series of actions that the agent must take to solve the problem.

The model observed in the figure is designed based on Fuzzy Case-Based Reasoning (Fuzzy CBR). Fuzzy Case-Based Reasoning combines two main approaches: Case-Based Reasoning (CBR) and Fuzzy Logic. In this approach, the system uses past experiences (stored cases) and fuzzy rules to make decisions for new problems. In CBR, the system uses past similar cases to solve new problems. Fuzzy logic helps manage uncertainty and imprecision in data, enabling the system to work with uncertain data and continuous values. Based on this concept, each of the sections shown in the figure can be explained in terms of this method:

1. **Inputs**: In this section, new data or new problems are input into the system. These data can be imprecise or fuzzy (i.e., data that are not fully specified or precise). The inputs can include the features of a new problem that the system needs to solve.
2. **Initial Input Layer**: In this layer, the newly input data are processed. This includes converting raw data into fuzzy values. Data may be converted using fuzzy membership functions into values between 0 and 1 to account for their imprecision.
3. **Secondary Processing Layer**: In this layer, the data are evaluated to find similarities with existing cases in the case base. The fuzzy system calculates the degree of similarity based on each feature's membership degree (determined by fuzzy membership functions).
4. **Fuzzy Case Base**: In this section, there is a database containing fuzzy cases. Each case is a past problem, stored along with its solution. In CBR, the system attempts to find the similarity between the new problem and the cases in this database. Fuzzy logic is used here to calculate similarities, selecting the cases that have the closest fuzzy match to the new problem.
5. **Retrieved Case**: After searching the database, the system retrieves one or more cases that resemble the new problem. In fuzzy case-based reasoning, the degree of similarity is represented as a fuzzy

number between 0 and 1, indicating the proximity of the retrieved case to the new problem.

6. **Case Adaptation**: In this stage, if the retrieved case is not exactly similar to the new problem, case adaptation occurs. Fuzzy logic is used to adapt existing cases. The system adjusts the previous solution according to the features of the new problem to reach a suitable solution.
7. **Revised Solution**: The final solution is obtained after adaptation and is proposed to the system as the revised solution. This solution may be presented to the user or applied automatically in control systems.
8. **Returned Case**: After applying the solution, the result is returned to the system for evaluation to determine if the solution was successful. This feedback is returned to the case base so that, if necessary, the case database can be updated.
9. **Reuse**: If the solution is successful, it is added as a new case to the fuzzy case database for future use. Otherwise, the revised solution is re-evaluated, and after corrections, it is added to the case database.
10. **Output Layers**: Finally, the output of the system consists of the solutions provided after analysis. These solutions can be presented to the user or sent to control systems. Since the system uses fuzzy logic, the outputs may also be fuzzy, for example, "80% probability for Solution A," rather than a definitive answer.
11. **Outputs**: Ultimately, the final output is produced based on data analysis and processing and presented to the user or control system. These outputs can be fuzzy decisions, predictions, or suggestions.

3. Findings and Results

The Fuzzy Case-Based Reasoning (Fuzzy CBR) model enables the system to utilize past experiences and similar cases to solve new problems, leveraging fuzzy logic to manage uncertainty and imprecise data. This method is particularly useful in problems where the data is imprecise or involves uncertain complexities. Case retrieval in CBR depends on the type of problem, similarity criteria, and the structure of the case base. Optimizing these steps and validating the selected cases are key points in enhancing the efficiency of the CBR system. The case structure, in its simplest form, is formally defined as a pair:

Case = (Problem, Action)

Table 1. Problem Features

Problem Features	Soil Moisture	Soil Acidity	Air Temperature	Rainfall Level
Values	Low, Medium, High	Low, Medium, High	Low, Medium, High	Low, Medium, High

Table 2. Actions

Symbol	a0	a1	a2	a3
Actions	irrigOFF	irrigON	irrigDEC	irrigINC

The problem description section corresponds to a set of features that describe the current state of the environment from the perspective of the reference agent. In the domain of smart agriculture, the most relevant features for describing the environmental state are presented in Table 1. In the solution description section, the solution to a case corresponds to an action or a series of actions that the CBR agent must perform, as shown in Table 2. A = (a0, a1, a2, ...)

An example of a case constructed in the above structure is as follows:

({'conditions': {'soil_moisture': 'low', 'temperature': 'high', 'light_intensity': 'medium', 'rainfall': 'low', 'wind_speed': 'high', 'soil_ph': 'acidic'}, 'action': 'Irrigation'})

In this work, the features are considered fuzzily. This is a strategy to strengthen the system when dealing with noisy data, uncertainty, imprecision, and vagueness. Each of these features, which are linguistic variables, consists of three terms or sets: "low", "medium", and "high". Therefore, three fuzzy membership functions exist.

The Euclidean distance measure is initially designed for numerical data and is typically applied to points in a Euclidean space. This measure may have limitations if the features contain fuzzy information or uncertainty. Fuzzy features are usually described by probabilistic distributions that are not represented in Euclidean space. Therefore, directly using the Euclidean distance measure may lead to errors and issues. To calculate the distance between fuzzy features, measures specifically designed for fuzzy variables, such as fuzzy distance measures or fuzzy set interactions, can be considered. These measures are best suited to fuzzy concepts. Some fuzzy distance measures include the Fuzzy Minkowski Distance, Zadeh's Fuzzy Distance, and Hamming Fuzzy Distance. These measures are used to calculate distances between fuzzy feature sets and are more consistent with fuzzy concepts. Of course, fuzzy distance and similarity measures may vary in their use and definition in different references and sources.

Based on Zadeh's concept of difference between two fuzzy sets, the Zadeh fuzzy distance for two fuzzy sets A and B is defined as follows:

$$D_{ZF}(A,B) = \max_i \left(\min(A_i, B_i)\right)$$

The fuzzy case retrieval algorithm is implemented as follows. This algorithm uses the FuzzyWuzzy library to calculate fuzzy similarity:

```
pip install fuzzywuzzy
from
fuzzywuzzy import fuzz
class IrrigationSystem:
  def __init__(self):

def should_add_to_case_base(new_case, existing_cases, threshold):
    for existing_case in existing_cases:
        similarity = calculate_similarity(new_case, existing_case)
        if similarity > threshold:
            return True
    return False
```

Some case-based systems use this mechanism to enhance diversity and combine a variety of cases. By adding new cases that are more similar or aligned with the existing cases, they can somewhat expand the dataset and add new information to the decision-making system. This can be useful when the system quickly adapts to new changes and matches new situations. Adding new cases with greater similarity might allow the system to more easily respond to new states and inputs that resemble previous ones. This may lead to early convergence, especially if the number of cases is large and each quickly matches existing ones. Early convergence may result in the loss of diversity and new information, causing the system to reach a stable and repetitive state.

To convert four fuzzy states (irrigation, no irrigation, increased irrigation time, and decreased irrigation time) to a non-fuzzy state, a conversion function can be used. Below is a simple example of a conversion function implemented using Python.

```
def defuzzify_action(fuzzy_action):
    # تابع تبدیل احتمالات فازی به مقادیر غیر فازی


    # حالت‌های فازی ممکن
    fuzzy_states = ["آبیاری", "عدم آبیاری", "افزایش زمان آبیاری", "کاهش زمان آبیاری"]


    if fuzzy_action == fuzzy_states[0]:
        return "آبیاری"
    elif fuzzy_action == fuzzy_states[1]:
        return "عدم آبیاری"
    elif fuzzy_action == fuzzy_states[2]:
        return "افزایش زمان آبیاری"
    elif fuzzy_action == fuzzy_states[3]:
        return "کاهش زمان آبیاری"
    else:
        # اگر حالت فازی مشخص نباشد، یک پیام خطا یا مقدار پیش‌فرض را بر می‌گردانیم
        return "حالت نامشخص"
```

In four scenarios, eight date palm trees of the same age were irrigated using four different irrigation methods, and their data were collected through environmental sensors and an Arduino platform. Each irrigation method was assigned to two separate trees, ensuring equal environmental conditions for all the trees. The four irrigation models in this study include: flood irrigation or surface irrigation every 10 days, conventional reactive drip irrigation every 3 days in spring, every 2 days in summer, every 7 days in autumn, and once in winter; CBR-based non-fuzzy drip irrigation; and CBR-based fuzzy drip irrigation, where "CBR-based thinking" refers to AI-based intelligent decision-making dependent on the conditions.

Upon a thorough review and considering figures of the fuzzy CBR drip irrigation method, this approach consumes less water compared to the other methods. Additionally, based on the trees' water needs, irrigation is performed intelligently and adequately at the appropriate times. The average water consumption is the lowest, with a small deviation from the mean, indicating less variability in water use. There are relatively smaller changes in water consumption across months. Reactive drip irrigation also consumes less water compared to flood irrigation. However, since it is pre-scheduled and automated, it is unable to accurately assess the trees' water needs and optimize the irrigation timing. As a result, it consumes slightly more water compared to the CBR-based thinking method and may also be less efficient in terms of irrigation quality, as the irrigation schedule is changed solely based on seasonal programming. The deviation is higher, indicating greater variability in water consumption.

The surface water consumption chart in Figure 3 clearly shows how much water needs to be extracted from underground aquifers for irrigation using each method in order to achieve a similar level of agricultural land coverage and sustain irrigation for a date palm orchard. Finally, the trend charts in Figure 4 indicate that although water consumption decreased across all four methods due to seasonal changes from summer to winter, the CBR-based drip irrigation method shows a consistently lower trend. Particularly, the chart for the fuzzy CBR method (FCBR) proposed here demonstrates lower water consumption across all months of the year compared to the other methods, confirming the validity and effectiveness of the proposed method.

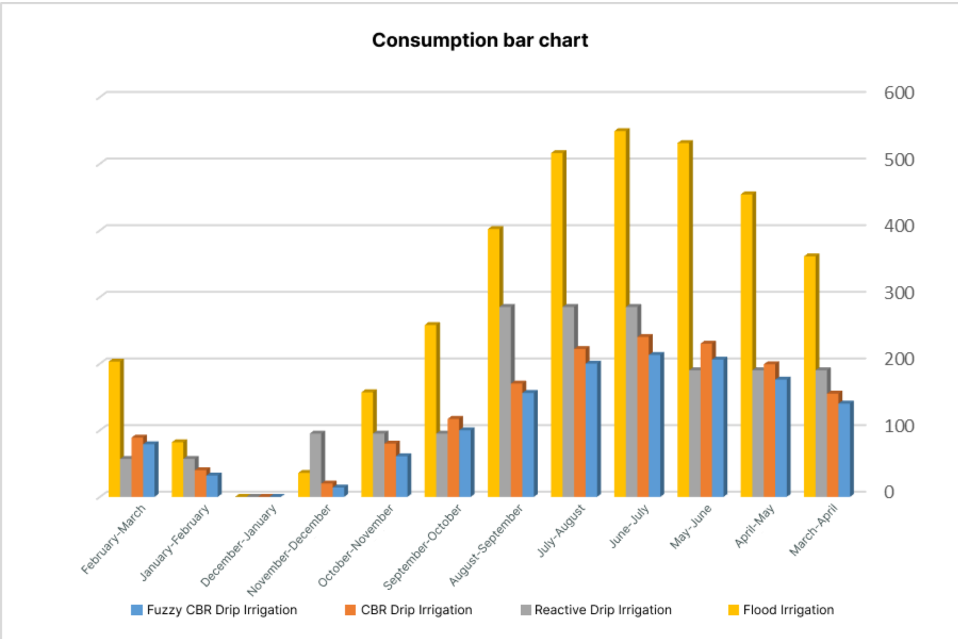

Figure 2. Monthly Water Consumption of Four Irrigation Methods

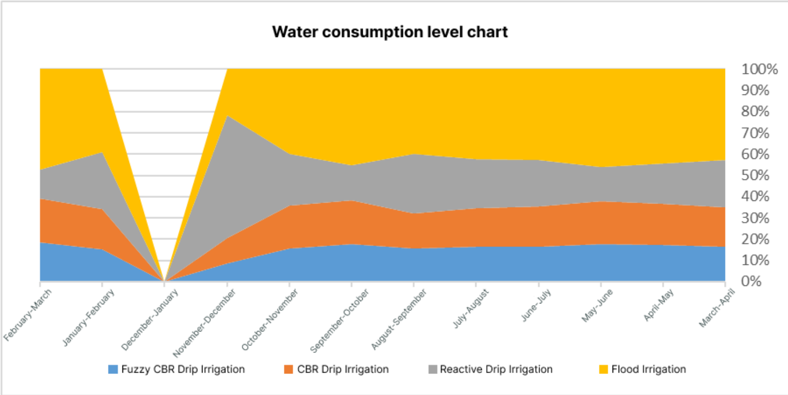

Figure 3. Comparison of Water Surface Area Requirements for Four Irrigation Methods

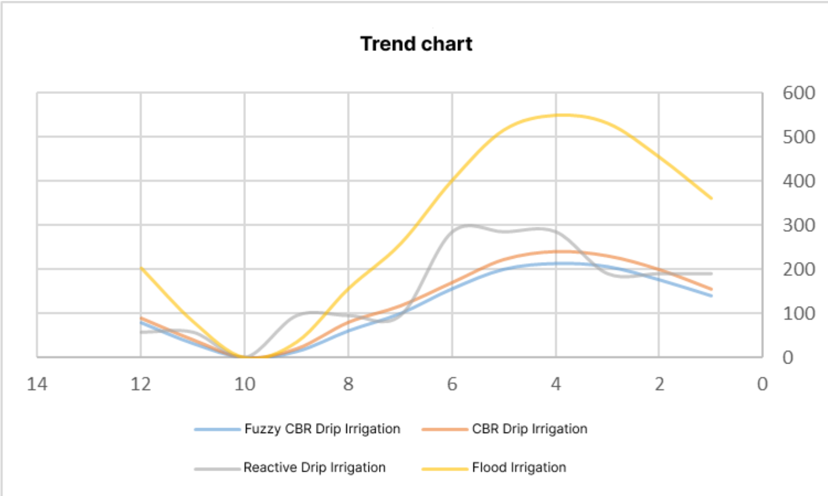

Figure 4. Trend Comparison of Water Consumption across Four Irrigation Methods from Months 1 to 12

4. Discussion and Conclusion

Case-Based Reasoning (CBR) works by selecting a case from previously stored cases in the knowledge base (case base), where the selected case is most similar to the current problem being addressed. This method is similar to how experts reason when solving various problems. The proposed intelligent irrigation model, which utilizes artificial intelligence and information technology, could be one of the best smart irrigation methods, as it can perform similarly to an expert agricultural consultant. This approach can lead to optimal water resource use, which is crucial for the development of sustainable agriculture, soil conservation, orchard development, reduction of human labor, and enhancement of both the quantity and quality of the product using available resources. This intelligent irrigation system, with the use of sensors and smart data, can analyze and manage the water needs of orchards, ensuring that water is efficiently delivered to the trees at the appropriate times. The results, on a small scale, indicate the efficiency of using water resources in agriculture with the proposed decision-making engine. The Agriculture 5.0 approach, considering future challenges and opportunities, can promote the improvement and optimization of smart agriculture and help farmers address challenges such as the future water crisis.

The proposed fuzzy CBR-based drip irrigation method shows lower water consumption compared to other methods, confirming the validity and efficiency of the proposed approach. This method significantly outperforms traditional flood irrigation methods, saving more than 50% of water. As future work, our proposed model can be integrated with other artificial intelligence methods, such as reinforcement learning, neural networks, and others, to enhance the model across different phases.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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