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Ontology-Based Smart Irrigation System: Enhancing Agricultural Water Management

Maher u Nisa, Muhammad Azam, Tanveer Rafiq^{*}, Mohsin Sattar, Aiman Zahra, Sana Zafar Chronicle Abstract

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Maher u Nisa is currently affiliated with the Department of computer science, institute of southern Punjab, Multan, Pakistan. Email: mehrunisa639@gmail.com

Muhammad Azam is currently affiliated with the Department of computer science, institute of southern Punjab, Multan, Pakistan. Email:muhammadazam.lashari@g mail.com

Tanveer Rafiq is currently affiliatedwith Department of computerscience, institute of southernPunjab, Multan, Pakistan.Email: tanveerrafiq07@gmail.com

Mohsin Sattar is currently affiliated with the Department of Clinical Psychologist, College Counselor, Cadet College Jhang, Pakistan. Email: mian_pgl@yahoo.com

Aiman Zahra and Sana Zafar is currently affiliated with the institute of southern Punjab, Multan, Pakistan. Email: aiman.zara2014@gmail.com Email: sanazafar198@gmail.com *Corresponding Author: We demonstrate a novel approach to agricultural water management with our smart irrigation system, which uses ontologies to streamline and improve decision-making. We build a comprehensive ontology suited to agricultural demands through iterative development using modeling languages like RDF and OWL, along with tools like Protégé and TopBraid Composer. This iterative procedure, which is continuously improved through expert discussions and literature reviews, guarantees that our ontology stays in line with domain-specific needs. Our system's scalability and interoperability with the current irrigation infrastructure are two of its main advantages. We provide smooth integration by using well-defined data formats, so farmers may take advantage of our system's benefits without having to make major changes to their present setup. We prioritize accuracy, efficacy, and relevance while choosing algorithms, making sure that each one is best suited for the task at hand. To increase performance and responsiveness to changing agricultural needs, regular changes are put into place. Precision, effectiveness, and expandability are examples of critical assessment criteria that are essential to our system's evaluation methodology. We make sure that our system maximizes water consumption efficiency while retaining efficacy and flexibility over time by giving these criteria priority. In the end, our intelligent irrigation system combines sophisticated ontology creation with exacting algorithmic selection and ongoing improvement procedures to offer a comprehensive response to agricultural water management issues. Our objective is to equip farmers with the necessary tools to maximize water consumption and improve agricultural output in a sustainable manner by giving priority to relevance, efficacy, and accuracy.

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Keywords: Smart irrigation system, soil moisture, ontology, sensor, model.

INTRODUCTION

The term "irrigation" is used to describe the process of artificially applying water to soil, which can be done in a number of ways (such as by trickle irrigation, sprinkler irrigation, or watering in pots). Irrigation is widely employed in places where rain falls intermittently (Patankar et al., 2021). Soil moisture sensors, microcontrollers, humidity sensors, temperature sensors, and GSM modules are all part of a sophisticated irrigation system. Use a soil moisture sensor to determine how much water is present in

the ground. The microcontroller acts as a communication hub, allowing the sensors to send and receive data. A temperature sensor is a device that can detect and record changes in temperature. Humidity sensors report on the relative humidity and air temperature. The GSM Module is a mechanism for mobile text messaging (Guo et al., 2023). Module for controlling power, measuring water levels, and detecting motion with a PIR sensor. Irrigation systems rely on relay modules to control water distribution. Use a pir movement detector to spot people or animals moving inside a certain area(Abdikadir et al., 2023). Therefore, it is crucial to constantly investigate and develop new agricultural techniques. The need to sustainably increase agricultural output highlights the importance of a smart irrigation system (SIS) and the problem of water efficiency. The process of watering a surface specifically so that vegetation might flourish there is known as irrigation. A body of water is guided by canals, ditches, pipelines, or even just the course of the water itself (Ndunagu, et al., 2022). In arid regions, proper water management is crucial. Because of the high water demand, agriculture is also negatively affected. To ensure the availability of water for food production and consumption in the face of the potential effects of global warming, adaptation measures are being considered.

Therefore, there has been a growing interest in studies that aim to reduce irrigation water consumption. Commercial sensors for agricultural irrigation systems are prohibitively expensive, making them out of reach for many smaller farmers. Manufacturers and customers alike are showing a growing interest in inexpensive sensors that can be used in conjunction with nodes to create irrigation control and agricultural monitoring systems(García, et al., 2020; Li et al., 2020). A smart irrigation system is a cutting-edge piece of technology that helps farmers save water and better manage irrigation for their crops by utilizing a wide range of sensors, weather data, and other inputs. The rising number of people living in the world has increased pressure on the planet's limited food supplies and freshwater systems. The agricultural sector is the largest consumer of water, accounting for around 70% of global water withdrawals used for irrigation(Simionesei, et al., 2020).

Soil moisture-based irrigation management

Estimating the water balance and the crop irrigation needs by measuring the soil moisture content (SMC) is a frequent practice. The use of sensor data to schedule irrigation at predetermined intervals is a common theme throughout the many research that have investigated irrigation monitoring approaches based on soil moisture sensing. The irrigation event is bypassed if the SMC is over the set limit. One study found that more accurate estimations for weekly citrus tree irrigation were obtained when soil sensor data was combined with weather information. In this part, we'll take a look at several different types of SMS-enabled smart irrigation systems (Qin, et al., 2021).

Cotton irrigation was planned using a low-cost radio frequency identification (RFID) system that wirelessly sent data from two soil temperature and three Watermark moisture sensors to a receiver. The crop field was outfitted with sensor nodes (soil sensors and RFID) and the central receiver was linked to a computer. The findings showed that the soil water tension was within acceptable ranges. However, the centre pivot irrigation system was slow to adapt to the crops' actual water requirements. It was proposed that a smart sensor array and a variable rate watering system be used to get around these technical hurdles(Blessy, 2021; Dharashive & Sawale, 2024). The water supply in an intelligent irrigation system was tracked with the help of a hygrometer and a temperature sensor wired to an Arduino Uno (Chengdu

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Ashining Technology Co., Ltd., China). If the soil's moisture level dropped below a predetermined threshold, the Arduino was programmed to turn on the water supply, and the farmer could access the data from their smartphone via a cloud server. Using a regression technique, farmers irrigated crops like wheat and beans with the use of Internet of Things (IoT) equipment that included humidity sensors or remote sensing (RS) (Wang, et al., 2021). Another study used a wireless robot that sprayed insecticide, detected wetness, and activated and deactivated electric motors using a Raspberry Pi 2 Model B. A camera was also interfaced with the Raspberry to keep an eve on the field and watch events unfold in real time. Recently, SMC was tracked during the chestnut's vegetative stage to determine the best time for irrigation. Good tree water status was ensured through the use of irrigation scheduling triggered by a tension value more than 100,000 Pa measured by a sensor buried in the soil between 30 and 60 centimeters (Ayodeji et al., 2023; Vellidis, et al., 2008). Studies have shown that Internet of Things (IoT)-based devices can effectively monitor soil moisture, temperature, and humidity. However, the efficiency with which these systems consume water is not frequently measured. Depending on the crop, studies have indicated that automated irrigation utilizing IoT-based sensors can reduce water usage by as much as 92% compared to conventional methods.

The use of short message service (SMS)-based drip irrigation for bananas resulted in a 20% water savings compared to manual drip irrigation, and the use of SMS in pear orchards resulted in a 50% water savings from irrigation while maintaining good crop output and quality. When developing an irrigation plan with SMS, it is crucial to establish the volumetric moisture content (VMC) threshold correctly. The medium VMC threshold setting has been shown to conserve water at a rate of up to 74% in some experiments, without sacrificing plant quality. Some studies looked at how to define the required water volume by crop growth phase using software run on IOS/Android-based systems, so that irrigation may be done in accordance with seasonal water requirements(Nawandar & Satpute, 2019).

ET controller-based irrigation management

ET estimates have emerged as a viable water-saving solution for scheduling irrigation (Davis & Dukes, 2009; Seagraves et al., 2010), complementing SMS for monitoring irrigation. The goal of this method of irrigation is to supply water in accordance with the ET needs of the crop. Multiplying ETO by a crop coefficient (Kc) that varies with crop type, development stage, and production environment yields ETC (Davis et al., 2007). ETc is the sum of soil-surface evaporation and transpiration via plant canopies. The crop water requirement (CWR) is the quantity of water needed to replace evapotranspiration (ET) (Anitha, et al., 2020). Weather characteristics (such as temperature, relative humidity, and wind speed), crop factors (such as crop type), and management and environmental factors (such as soil fertility) all play a role in determining ETcrop, or a crop's water demand (Kisekka et al., 2010b). Irrigation can be controlled using ET controllers (Isaya et al., 2009), which rely on weather data to make ET estimates (Anitha et al., 2020; Mousavi et al., 2021).

Significant water savings have resulted from the use of smart irrigation technology in residential settings for turf and landscape irrigation, particularly when combined with controllers based on soil moisture. The SMS group saved 44% of water compared to the ET group's 20% savings, as reported by Nautiyal et al. (2010). In addition, studies on papaya irrigation have shown that using soil water tracking or past ET data can result in significant water savings—approximately 65%—without compromising plant physiology or production attributes (Migliaccio et al., 2010). Furthermore, wheat and

tomato management have benefited from the deployment of ET-based irrigation controllers. Electronic modules, sensors, and digital controllers make up the system. A scientific program is developed and uploaded to the controller based on the local microclimate's ETc as determined by the modified Penman equation. There will be a 27% reduction in water usage because just the amount of water lost by the plants will be restored (Al-Ghobari & Mohammad, 2011) (Kovalenko et al., 2021; Rathore et al., 2021).

RS-based irrigation management

In order to conserve water with minimal outlay, using rain sensors. When a certain amount of precipitation is detected by one of these sensors, the solenoid valves will be disabled until the sensor dries up. Installing RS where it will receive unimpeded rainfall is recommended for best results. Runoff, deep percolation, weed pressure, and infections are all reduced or avoided with RS, as are wasteful irrigation events. According to the manufacturer (Cardenas-Lailhacar & Dukes, 2008; Dukes & Haman, 2002), RS have a lifespan of over 10 years and a 5-year warranty. According to research of Cardenas-Lailhacar et al. (2008) and Haley and Dukes, (2007), RS can reduce water use by 19%-34% under normal precipitation conditions in central Florida. Mini-Clik RS (Hunter Industries, Inc., San Marcos, CA) has been studied for its effect on water savings and turf quality with two different rainfall set points (3 mm and 6 mm) and three different irrigation frequencies (1, 2, and 7 days/week) (McCready et al., 2009). RS with different set points and irrigation frequencies resulted in water savings ranging from 7% to 30% with acceptable turfgrass quality. Similarly, it was discovered that the RS treatment applied less water per irrigation event than the SMS treatment when the irrigation frequency was 7 days per week and the set point was 6 mm (McCready & Dukes) (Bodkhe, Tanwar, Bhattacharya, & Kumar, 2022; Touil et al., 2022).

Optical sensors: Plant-based irrigation management

Specific hardware for wired and wireless connections to underground sensors is required for precision watering employing sensors. However, disconnection problems can cause these sensors to lose their signals (Al-Naji et al., 2021). In order to work around this problem, innovative methods have been implemented in irrigation management, such as the use of optical sensors such drones, UAVs, and RGB cameras (Ajith et al., 2018; Touil et al., 2022). Cost-effectiveness, ease of construction, simple transportation, high flexibility, short operating cycle, and relatively high resolution are just few of the reasons why UAV-based remote sensing technology has been widely embraced in smart irrigation (Boursianis et al., 2020; Shi et al., 2019). The crop canopy data obtained from UAV imaging is more applicable to in-field evaluations (Khalig et al., 2019) than that obtained from satellite images. Improved irrigation water use efficiency can be achieved by estimating the Crop Water Stress Index (CWSI) using the canopy temperature histogram produced from thermal infrared pictures acquired by UAVs (Bian et al., 2019). Therefore, the use of UAV-based remote sensing technology is a major advancement in smart irrigation management(Campoverde et al., 2021; Goap et al., 2018; Touil et al., 2022). The inefficiencies of usual irrigation techniques frequently lead to water waste and decreased agricultural productivity. The differences in soil moisture, weather, and crop water requirements are not sufficiently taken into account by techniques like flood irrigation and fixed schedule irrigation. Because of this, water is frequently used excessively or inappropriately, wasting this valuable resource. Environmental issues can be made worse by ineffective irrigation techniques, which can also lead to salinization, nutrient runoff, and soil deterioration. An ontology is a systematic depiction of concepts and their

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connections within a specific topic. A knowledge model specifies the set of concepts and categories that make up a domain, as well as the connections between those concepts and categories. Knowledge management, artificial intelligence, and computer science all use ontologies to better organize and reuse existing data(El-Gohary & El-Diraby, 2010). A set of concepts, relations, and axioms constitute an ontology. Objects, thoughts, and things in a domain are represented by concepts, the fundamental units of an ontology. Axioms are the logical principles that regulate the behavior of the ideas and relationships, while relationships indicate how the concepts are related to one another (El-Diraby et al., 2005; Zhou et al., 2022). More generic concepts are placed at the top of an ontology's hierarchy, while more specialized ones are placed at the bottom. A taxonomy is a classification system used to categorize and label terms within a certain field of study. [32] Different formal languages, such as the Resource Description Framework (RDF), the Web Ontology Language (OWL), and the Unified Modeling Language (UML), can be used to represent ontologies. The ontologies created with the help of these languages can then be used in a variety of contexts and applications because they all share the same standardized syntax and semantics (Papajorgji et al., 2009).

A possible way to solve the shortcomings of conventional irrigation techniques and develop intelligent irrigation systems is to use ontology-based technologies. Smart irrigation systems are able to incorporate data from multiple sources, such as weather forecasts, crop models, soil sensors, and watering schedules, by utilising ontologies, which are formalised knowledge about a niche. Irrigation procedures can be constantly modified based on crop needs and current conditions thanks to this integrated knowledge, which facilitates real-time decision-making. Ontologies also enable data sharing and interoperability among various agricultural systems and stakeholders, which promotes cooperation and creativity in water management.The smart irrigation system uses a range of measures to evaluate its precision, efficacy, and scalability, guaranteeing that it can improve agricultural water management techniques.

Accuracy Metrics

• **Soil Moisture Prediction Accuracy:** evaluates the system's prediction accuracy against ground-truth measurements of soil moisture content.

• **Crop Water Requirement Estimation Accuracy:** assesses how well the system is in predicting agricultural water needs based on crop features and environmental factors.

• Irrigation Recommendation Accuracy: evaluates the system's irrigation suggestions' correctness in relation to best irrigation techniques and crop responses that have been observed.

- Efficiency Metrics:
- Water Usage Efficiency: evaluates how effectively the system uses water to provide crops with the necessary amount while reducing waste.

• **Energy Efficiency:** assesses the irrigation system's energy efficiency while taking system automation and pump energy usage into account.

• **Time Efficiency:** evaluates how quickly the system can respond to changing environmental circumstances and provide irrigation suggestions. **Scalability Metrics**

• **Performance Scalability:** evaluates the system's capacity to continue operating at a certain level even when the amount of data and computing load grow.

• **Geographic Scalability:** assesses how well the system may be scaled to various geographic locations with diverse climatic conditions and farming methods.

• **System Resource Scalability:** evaluates the scalability of the system with respect to hardware and software resources, including processing power and server capacity.

By monitoring these parameters, the smart irrigation system can make sure that it is accurate, efficient, and scalable in order to promote sustainable agricultural water management practices. It can also continually assess its performance and pinpoint areas for development. We used a variety of tools, processes, and standards in the development of our ontology-based smart irrigation system in order to successfully define ideas, make connections, and integrate real-world data. First, we defined ideas and connections inside the ontology using ontology editors such as Protégé and TopBraid Composer, taking use of their user-friendly interfaces and features. We spoke with domain experts to verify that the ontology appropriately reflected agricultural water management. We used their knowledge to create concepts like crop kinds, soil types, and irrigation techniques. Furthermore, in order to compile the state of the art and industry best practices, we carried out extensive literature research.

In order to guarantee consistency and interoperability, our ontology design adhered to accepted techniques and included ontology design patterns. Relevance, granularity, and consistency were given top priority while establishing ideas to make sure they were in line with domain-specific language and closely connected to agricultural water management duties. In order to enable logical inference and reasoning inside the ontology, we concentrated on semantic consistency, transitivity, and symmetry while creating linkages. Utilizing sensor networks, standardized data formats, and data fusion techniques, real-world data integration involves gathering and combining information from many sources, including weather stations and soil moisture sensors. Overall, we created a strong ontology that may enhance agricultural water management techniques and promote wise irrigation decisions by carefully utilizing tools, methodologies, and criteria.

LITERTURE REVIEW

Using wireless sensor networks and an open-source IoT cloud computing platform named "ingspeak.com" for data gathering, archiving, analytics, and visualization, this research proposes a drip-based smart irrigation system (SIS). This method combines hardware and software to make irrigation decisions based on data from the internet, such as "weather.com" forecasts and soil-sample sensor readings. After collecting data, the edge server processes it and provides an update every 15 minutes. The irrigation schedule is used to determine whether or not to begin pumping water based on the threshold value. A web application was developed to monitor and control the system based on the data collected (Ndunagu et al., 2022). All forms of life, from plants to animals to humans, require water in order to survive. Although there is a lot of water on Earth, only around 1% of it is drinkable. As the world's population has increased, so has the need for water, elevating the price and importance of clean water. The agricultural sector consumes more than 70 percent of the world's fresh water supply. The agricultural sector not only uses the most water overall, but its workers are also the

least efficient, most wasteful, and most highly subsidized water users worldwide. Technology, such as smart irrigation systems, must be introduced to increase the amount of water used in agricultural irrigation. Such a system might be guite precise. but it needs information about the soil and climate of the area in which it would be used. In this study, we evaluate a smart irrigation system by integrating cloud computing, IoT, and other cutting-edge technologies. The system is designed to evaluate soil moisture and humidity, and it processes the data in the cloud using a variety of machine learning algorithms. The requirements pertaining to water content are communicated accurately to the farmers. Smart irrigation systems could help farmers save water (Phasinam et al., 2022). The global shortage of fresh water is a serious issue that is expected to worsen in the coming years. Precision farming and intelligent irrigation are the only viable solutions to the aforementioned issues. Due to developments in IoT and AI, smart irrigation and precision agriculture are now a viable business option. Improved productivity, lower costs, energy maximization, accurate forecasting, and user ease are just a few of the many benefits of the Internet of Things (IoT). When there are more systems and ways to process data, there is a greater potential for security issues.

The growth of the Internet of Things is being stymied by concerns over data privacy and security. This paper develops a system for detecting and classifying cyber attacks on IoT networks used in agriculture (Raghuvanshi et al., 2022). Through a series of astute corrective measures and management tactics, this study proposes a novel IoT-based architecture for regulating water guality and optimizing drinking water usage. By combining the strengths of knowledge graph technology and NRL, we were able to gradually map the WIN into a low-dimensional vector space, and it is constantly updated to account for changes/problems in the water zones under observation(Mezni et al., 2022). The Solar Power Smart Irrigation System (SPSIS) makes it easier for farmers to water their crops while also reducing the amount of labor required to irrigate and providing more precise regulation of watering times. Using solar energy for irrigation, decreasing the need for human intervention, and managing irrigation from a mobile device are all possible thanks to this reliable and efficient technology. This structured plan can aid agriculturalists with a wide range of problems. The purpose of this innovation is to reduce water and energy consumption in farming operations without sacrificing crop yields.

Additionally, the system's functioning function is not complicated, thus it can be used by both experts and non-experts alike. Controlling Solar Energy Using a mobile phone as part of an intelligent irrigation system is preferable. The utilization of solar power, a renewable energy source that also happens to reduce running expenses, is the system's main selling point(Hussain et al., 2023). Present-day crop damage by wild animals has emerged as a critical socioeconomic issue. Sincere thought and an adaptable perspective are required. This endeavor is socially significant since it aims to solve the problem. Therefore, we designed a system that is easy to operate, has low energy requirements, and is dependent on ingeniously concealed agricultural security and spying. The primary objective is to protect agricultural lands from being destroyed by trespassers and wild animals. A system like this would aid farmers in protecting their land and belongings, save them money on farm preservation efforts, and cut down on unnecessary expenditures (Kanade & Prasad, 2021). In an effort to lessen the amount of water wasted during the irrigation process and increase its efficiency, a sensor-based autonomous irrigation program was developed. The study's goal is to improve water and resource efficiency. Increasing the effectiveness of irrigation could make agriculture more viable and competitive in the long run. The

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micro-controller learned how much water was in the soil thanks to data sent by the moisture sensor. It sent signals to the microprocessor to activate the water pump and irrigate the fields when the moisture level (water content) fell below a certain threshold (AI Mamun et al., 2021). The development of contemporary farming is greatly aided by the usage of networking technologies in agriculture. The effectiveness and consistency of agricultural output would increase, and water usage would be reduced, with the implementation of this strategy. The Internet of Things (IoT) will continue to develop in the future years, allowing for these systems to speed up, improve in capability, and decrease in cost. It's possible that in the future, the system may be able to foretell things like user movement, weather patterns, harvest seasons, animal incursions onto agriculture, and the broadcast of information to users via smart phones(Ramkumar et al., 2021). For future generations, the GSM Based Auto Irrigation System based on IOT project is seen as a less expensive, time-saving, and improved means of water conservation. The intelligent, automated labor provided by this system will be beneficial to the farmer. This technology allows for sustainable plowing in arid areas. Since this project employs a number of sensors, the required acreage will receive their water supply. This innovation reduces power consumption and necessitates less servicing.

The low energy use suggests that this setup may even be run on solar power. This method will provide the healthiest, most nutrient-rich harvest possible. Crop loss will be small, and in certain circumstances it may be eliminated entirely (Pithadiya et al., 2022). This internet-based irrigation system uses the SVM system as its data processor. The early agricultural pump actuator uses the forecast results as a guide for operating the pump. The MQTT protocol is used as the communication standard between the various nodes, gateways, and server estimations. For this prediction, the SVM achieved an accuracy of 95%, precision of 94.33%, recall of 91%, and F1-score of 92.73%. A recall of 82% is achieved for the 50% class, and a f1-score of 88% is achieved for the 50% class. The recall precision value and good f1 score used with the system in the 10% valve pump and 25% valve pump classes are significantly different. this is because only 50% of the training data came from actual classroom settings. For further research, the best possible datasets, gamma values, and c values will be generated (Sumarudin, Ismantohadi, Puspaningrum, Maulana, & Nadi, 2021). Three sensors were used to ensure adequate watering and fertilization. The sensors are successfully wired to the Arduino, and wireless communication has been established. This study offers a methodical approach to addressing the challenges of field irrigation, as deduced from analyses and empirical tests. An increase in crop yields and a decrease in water usage would result from implementing this technique in the field(Sruthi et al., 2021).

In a world where fresh water is both valuable and in high demand, water conservation is more important than ever. Irrigation systems require water, of course, but it is also critical that the available water be managed effectively. As a result, some sort of ingenious device is required to handle the situation. These papers describe an intelligent irrigation system built with the IoT. Because of their critical importance to plant growth, soil moisture, humidity, and temperature are constantly monitored by this system. Water is delivered to the field, and the farmer is updated in real time via smartphone(Avinash et al., 2021). Agriculture is the most prestigious and important industry in India. Agriculture is the main source of income for the vast majority of rural Indians. Intelligent irrigation systems are important for the development of any agricultural nation. About 16 percent of India's GDP and 10 percent of its exports come from the agricultural sector. In agriculture, water is essential. Water is a crucial

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commodity for farmers. Irrigation is one method of bringing water to people. They are wasting water because they are not following the correct schedules for this irrigation process. A wonderful method to save both time and water is with our IoT-powered smart irrigation system. As part of the smart irrigation system, we use a wide range of instruments, such as soil moisture sensors, humidity sensors, and temperature sensors. These sensors will detect the varying soil conditions and then irrigate the area automatically based on the soil moisture content. This means the engine will start up whenever the field needs water and shut down whenever it has enough. Users' devices will display the discovered parameters and the motor's status (Hafian et al., 2023). Sensor, Microcontroller, thing speak, plant knowledge based, plant detection and plant decision based comparison Table 1.

Table 1.

Sensor based comparison

Title / year	sensors	Microcontroller	Thing speak	Plant knowledge base	Plant detection	Plant Decision base
Arduino based machine learning and IOT smart irrigation system (Kanade & Prasad, 2021)	soil moisture, humidity, temperature,	yes	no	no	no	No
A Low Cost IoT Enabled Device for Monitoring Agriculture Field and Smart Irrigation System(Pokala & Bini, 2021)	soil moisture, humidity, temperature, PIR, water level	no	yes	no	no	No
PLC Based Automated Irrigation System(Ellahi et al., 2023)	soil moisture	no	no	no	no	Νο
Design and Development of an Automatic Prototype Smart Irrigation Model(Al Mamun et al., 2021)	soil moisture, Ultrasonic sensor	no	no	no	no	No
GSM Based Auto Irrigation System (Chauhan, Sah, & Khatri, 2022)	soil moisture	no	no	no	no	No
IOT and Raspberry-Pi Based Smart Irrigation System(Abdikadir et al., 2023)	soil moisture, temperature	no	no	no	no	No
MOBILE INTEGRATED SMART IRRIGATION SYSTEM USING IoT(CM, Girish,	soil moisture, temperature	yes	no	no	no	Νο

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Manjunath, & Kumar, 2021)						
Smart Irrigation System in Agriculture (Vallejo-Gómez,	soil moisture, humidity	yes	no	no	no	No
Osorio, & Hincapié, 2023) Machine Learning Based Smart Irrigation System(Sami et	soil moisture, humidity, temperature	no	no	no	no	No
al., 2022) Microcontroller Based Automatic Irrigation and Fertilization System Using Soil Moisture Sensor and Ph Sensor(Sruthi et	Ph sensor,	no	no	no	no	No
al., 2021) IOT BASED SMART IRRIGATION SYSTEM BY EXPLOITING DISTRIBUTED SENSORIAL NETWORK (Faruk &	soil moisture, temperature, Ph	no	no	no	no	no
Debnath) Smart Irrigation System Using Intelligent Robotics (Türkler, Akkan, & Akkan, 2023)	temperature, conductive	no	no	no	no	no
Performance of Automatic Smart Irrigation System Using GSM(Zeeshan, Sundaraguru, Vijayakarthick, & Kumar, 2020)	soil moisture, humidity	yes	no	no	no	no
Microcontroller based smart irrigation system (Anitha et al., 2020)	soil moisture	yes	no	no	no	no
Design and development of solar powered automatic iriigation system for modernization of agriculture (Yatn	soil moisture	yes	no	no	no	no

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Dynamic Soil Moisture Control System for	soil moisture	yes	no	no	no	no
Irrigation Using GSM(Aminu & Sugathakumari, 2022)						

Smart irrigation systems rely on fixed irrigation schedules, simple sensors, and microcontrollers that don't understand the unique needs of individual plants. On the other hand, ontology-based smart irrigation system combines high-end sensors with powerful microcontrollers, and uses Thing Speak to monitor in real time. By using sophisticated image processing to accurately detect plants, plant ontology customises irrigation schedules to meet the demands of individual plants. The system's dynamic decision-making improves plant health and maximises resource utilisation based on real-time data and weather forecasts. It provides a scalable and adaptable solution for effective, precision agriculture.

The idea formulation, relationship building, and real-world data integration components of our ontology-based smart irrigation system work together harmoniously to form the core of the system's operation. Concept definitions include the fundamental components that symbolize important facets of agricultural water management, including crop kinds, soil moisture content, and irrigation needs. The intricate interdependence between many agricultural characteristics are captured by the connections between these ideas, which are based on well-established relationships. The ontology's ideas are linked to real-world data, which is gathered from sources such as weather stations and soil moisture sensors, enhancing the knowledge base with current environmental data. The system's decision support is based on this integrated data and ontology-driven reasoning and inference capabilities. The system may produce well-informed suggestions for the best irrigation scheduling, customized to particular soil conditions, crop varieties, and weather forecasts, by examining correlations between ideas and real-world data.

Sustainable agriculture depends on effective water management, especially in areas where there is a water shortage and drought. Conventional irrigation techniques, like flood irrigation and scheduled irrigation, frequently include inefficiencies that result in wasted water and lower crop yields. Attaining maximum water use efficiency is hampered by issues like nutrient leaching, soil erosion, and uneven water distribution. In addition, population expansion and climate change put additional strain on water supplies, calling for the implementation of more environmentally friendly irrigation techniques.

The drawbacks and restrictions of conventional irrigation techniques

The following obstacles and restrictions prevent traditional irrigation techniques from being as effective at managing water:

• Regardless of the true crop water requirements or soil moisture conditions, flood irrigation and fixed schedule irrigation techniques frequently provide water evenly throughout fields.

• Excessive irrigation can lead to waste of water, higher electricity bills, and higher production expenses.

• Impact on the environment: Overwatering can cause nutrient runoff, soil erosion, and water contamination, all of which worsen the state of the ecosystem.

• Uneven crop growth, lower yield quality, and heightened vulnerability to pests and illnesses can result from inconsistent water distribution.

• Ontology-driven decision support systems have been developed to help farmers choose the best crops, optimise irrigation schedules, and more efficiently manage water resources.

• The body of research indicates that ontology-based strategies have the ability to enhance agricultural water management techniques and overcome the drawbacks of conventional irrigation techniques.

Domain experts actively participated in the iterative process of ontology refinement and validation, which involved many phases of review, feedback integration, and validation exercises. We started by creating a draft ontology using reviews of the literature and current understanding. We then consulted domain experts in the disciplines of agriculture, water management, and allied subjects to confirm the content, organization, and language of the ontology. Experts gave insightful feedback on the complexities of agricultural water management through workshops and consultations, ensuring that the ontology appropriately represented pertinent ideas, linkages, and restrictions. We iteratively improved the ontology based on input from experts, changing concepts, connections, and definitions to better suit domainspecific knowledge and changing needs. The ontology's correctness, completeness, and consistency were evaluated using validation exercises that included methods including comparison against predetermined criteria, reasoning, and consistency checks. Experts in the relevant fields took part in the validation process, confirming that the ontology met domain-specific standards and was useful in realistic situations. The ontology was methodically improved upon and refined by incorporating feedback from validation exercises and expert consultations. Through this iterative approach, the ontology was kept strong, dependable, and in line with stakeholder needs, which improved its ability to assist wise irrigation decisions and agricultural water management techniques.

METHODOLODY

To create the ontology for our smart irrigation system, which would improve agricultural water management, we used a variety of approaches and instruments that were specific to the demands and intricacy of the work. Ontology editors and modeling languages were essential to this process since they shaped and depicted the knowledge base of the system. Interestingly, we used industry-standard ontology editors, such as Protégé and TopBraid Composer, which are well-known for their powerful features and adaptability in the ontology building process. These editors provide functionality and user-friendly interfaces for creating complex ontological systems. To represent the ideas, connections, and constraints of the ontology, we simultaneously used modeling languages like RDF (Resource Description Framework) and OWL (Web Ontology Language). We were able to successfully capture the subtleties of agricultural water management because to OWL's expressive semantics, while RDF made it easier to construct semantic links between different things. By skillfully using these tools and languages, we built an extensive ontology that forms the

basis of our intelligent irrigation system, enabling accurate decision-making and water-use optimization in farming environments.

PROPSED MODEL

Model for a smart irrigation system based on ontology's is proposed. Because they are more malleable, adaptable, and knowledge-driven than traditional smart irrigation systems, ontology-based irrigation management has the potential to boost smart irrigation's precision, efficiency, and efficacy. The model processes data from both visual and sensor sources in order to conduct some type of action. An analyzer receives the model's output and uses it to derive information about the incoming image. An evaluator receives this information from the analyzer and uses it to produce an output and deliver results. Computer vision, robotics, and automation are just a few examples of disciplines that might benefit from this kind of analysis and evaluation in order to carry out difficult tasks and make educated decisions based on data collected through sensors and images.

The capacities and efficacy of current irrigation infrastructure and technologies are increased by the seamless integration of the proposed ontology-based smart irrigation system with them. The ontology enables interoperability with a variety of irrigation equipment, including as sensors, controllers, and automated irrigation systems, by utilizing defined data formats and communication protocols. The smart irrigation system can obtain real-time data on crop water requirements, weather, and soil moisture levels by integrating with the current infrastructure. This allows for exact irrigation scheduling and optimization. Moreover, the ontology facilitates smooth communication and data sharing by offering a consistent semantic foundation for information representation and exchange across various irrigation system components. Through enhanced coordination and control of irrigation operations, this integration not only improves the efficiency of water utilization but also eventually leads to increased agricultural yield and sustainability. Furthermore, the system may be made to scale and adapt to future developments in irrigation technology and changing agricultural practices thanks to the ontology-based approach. Generally speaking, the smart irrigation system's connection with the current infrastructure improves irrigation operations' efficacy and durability, enabling more effective water management techniques in agricultural contexts.

Image and sensor-based Input

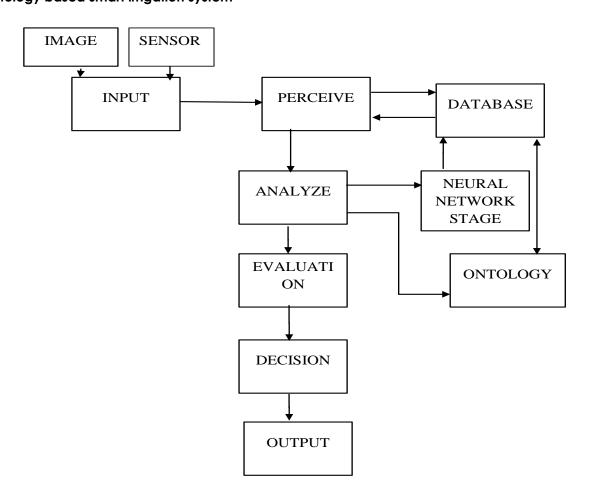
The process commences with the activation of an image sensor at the input stage. This sensor captures the prevailing environmental conditions in the form of an image, effectively converting real-world conditions into digital data. The captured image undergoes perception. This step involves interpreting and comprehending the image within the context of the smart irrigation system. It's the process of extracting meaning and understanding from the visual data, taking into account aspects such as soil conditions, plant health, and weather patterns.

ANALYSIS

Following perception, the image enters an analytical phase. This stage systematically processes the data, potentially employing algorithms tailored to the specific domain. The aim is to extract pertinent features or information, such as moisture levels, temperature, and plant conditions.

Figure 1.

The Asian Bulletin of Big Data Management Ontology based smart irrigation system



Database

The outcomes of the analysis are securely stored in a database. This structured repository ensures that processed data is organized and accessible for future reference and use. It serves as a reliable storage system for the valuable information derived from the analysis.

Perceive from Database

At a later stage, information is retrieved from the database for further processing. This re-introduction of data initiates another round of perception. It allows for additional insights or refinements based on updated sensor readings or historical data.

Neural Network Stage

The data then advances to a Neural Network (NN) stage. This is where advanced machine learning techniques may be employed to further refine and process the information, potentially uncovering intricate patterns or relationships.

Database Analysis

The data from the Neural Network stage is once again subjected to analysis after being sourced from the database. This step ensures the information remains dynamic and responsive to changing conditions, allowing the system to adapt and respond effectively.

Ontology-Based Smart Irrigation System Nisa, M,U et al. (2024) Ontology (Database to Ontology and Ontology to Database)

The analyzed information is systematically integrated into a structured knowledge framework known as an "ontology". This structure provides a conceptual map, organizing information for better understanding and relationship mapping. It serves as a structured representation of knowledge within the system. Data from the database is integrated into the ontology, enriching it with real-world data. This leads to a more comprehensive representation of knowledge within the system, incorporating relationships between factors like soil conditions, weather patterns, and plant health. Conversely, knowledge stored in the ontology is synchronized back into the database. This maintains the database's accuracy and relevance by updating it with the latest structured information, ensuring that the system operates with the most current and reliable data.

Analysis and Evaluation

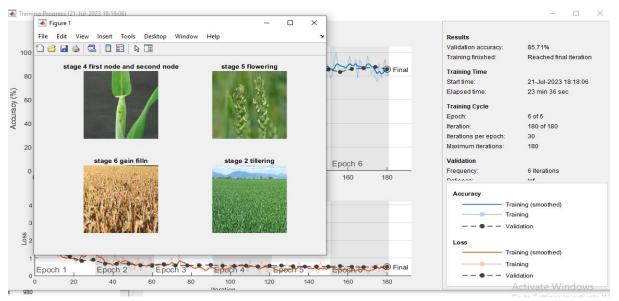
The information, now enriched by the ontology, undergoes another round of analysis. This step refines and enhances the data, leveraging the structured knowledge provided by the ontology. It allows for more sophisticated processing and understanding of the agricultural conditions. The refined information is subjected to evaluation. This involves making assessments or estimations based on predefined criteria or algorithms. For example, it may involve determining the optimal irrigation schedule based on plant needs and environmental conditions.

Decision and Output

Building on the evaluations, decisions are made regarding the irrigation strategy and water allocation. These decisions are influenced by factors such as plant requirements, soil conditions, and weather forecasts. It involves selecting the most effective course of action based on the evaluated information. Ultimately, based on the decisions made, the smart irrigation system generates a final output or result. This output represents the optimized irrigation plan, ensuring efficient water usage and promoting healthy plant growth. It is the meaningful insight or action derived from the initial captured image, showcasing the system's capability to make informed and beneficial decisions for irrigation management. Several important factors are taken into account when choosing algorithms for our smart irrigation system's analysis and evaluation phases. This ensures that the algorithms are appropriate for certain jobs, such picture recognition and feature extraction. First, algorithms are selected according to how well they match the goals that are being pursued and the type of data that is being handled. For example, machine learning methods such as convolutional neural networks (CNNs) are widely used for image perception tasks requiring satellite or drone footage because of their capacity to extract significant characteristics from visual input.

Furthermore, algorithms' scalability and computing efficiency are critical components, particularly when working with big datasets or real-time processing demands. Additionally, algorithms should be selected based on how well they handle different environmental circumstances, possible sources of noise or uncertainty, and accuracy and resilience. After selection, algorithms are subjected to task-specific optimization procedures that adjust designs and parameters to enhance efficiency and reduce computational overhead. Algorithms may be tuned to prioritize pertinent variables pertaining to crop health, soil moisture content, or irrigation needs, for instance, in feature extraction activities. Algorithms enhance the system's overall

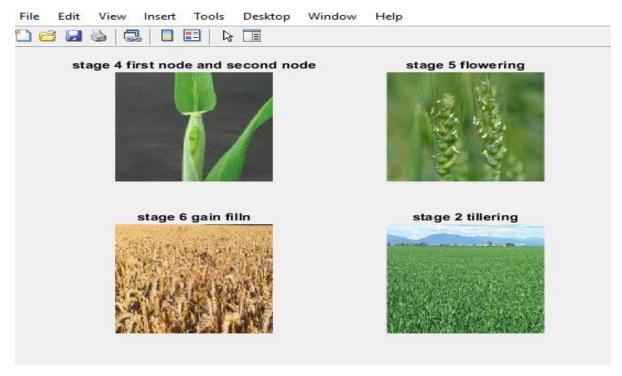
efficacy in data analysis and interpretation by means of meticulous selection and optimization. This results in the provision of significant insights that facilitate wellinformed decision-making about agricultural water management.



RESULTS AND DESCUSION

Figure 2.

This Figure 2. shows that MATLAB 2019ain which model is trained for wheat stages detection, transfer learning is performed by using a pre-trained model Alexnet is done by adjusting hyper parameters are 6 epochs with batch size 10, validation accuracy received at the end 85.71%. Program was utilized, and the wheat dataset included 1400 pictures taken at seven different stages.





Nisa, M,U et al. (2024)

After training is completed, Alexnet performs stages classification, showing the model validity. This image predicts four stages.

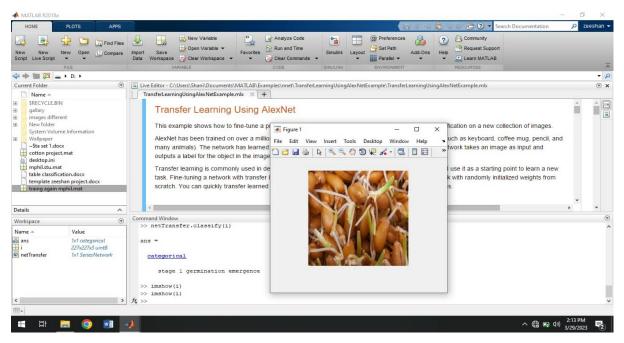


Figure4. Stage 1

Wheat seeds enter the germination stage when they begin to sprout and develop into seedlings. At this point, the embryo within the seed begins to grow and develop into a new plant as the seed takes water and nutrients from the earth.

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Figure 5. Stage 2

Completed the training performance of model is evaluated by testing. This image shows the code for classifying the picture and the results shows in command window and in picture form. seedling stage begins once the seed has germinated. The earliest leaves and roots of the plant will appear during this two- to three-week period. The

plant keeps taking in water and nutrients from the ground, and it starts making its own food through a process called photosynthesizing.

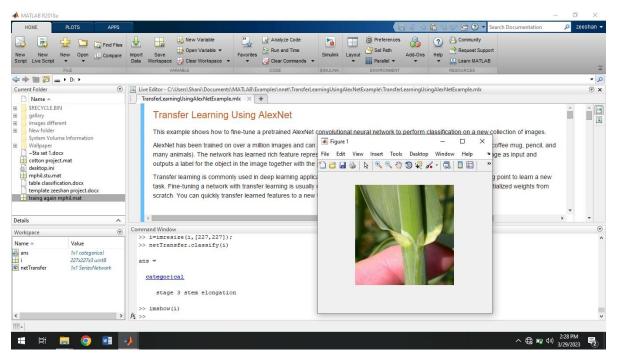
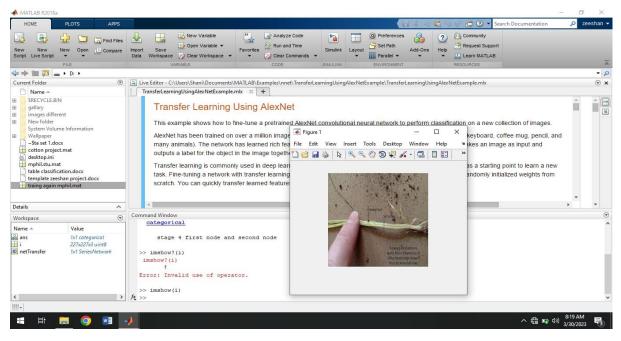


Figure 6. Stage 3

Another image is testing after completed the execution of model is evaluated by testing is done. This image shows the code for classifying the picture and the results shows in command window and in picture form, the tillering phase of a plant's life cycle follows the seedling phase and typically lasts for three to four weeks. In this growth phase, the plant sends out new branches from its main stem; these are called tillers. These tillers have the potential to develop into more wheat heads, so increasing the plant's production.





Nisa, M,U et al. (2024)

Also another images training completed the execution of model is evaluated by testing. This image shows the code for classifying the picture and the results shows in command window and in picture form, the stem begins to lengthen and grow taller during the stem elongation stage. During these two to three weeks, the stem grows rapidly, sometimes reaching heights of several feet. Extra leaves are produced by the plant at this time as well.

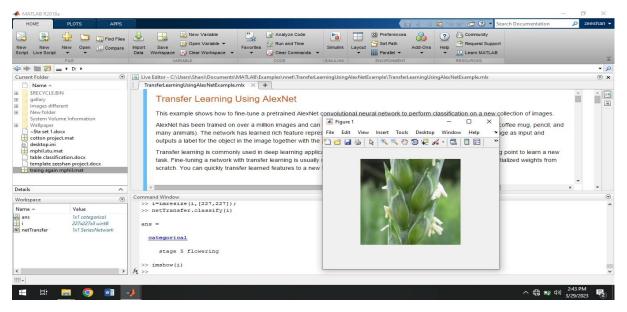
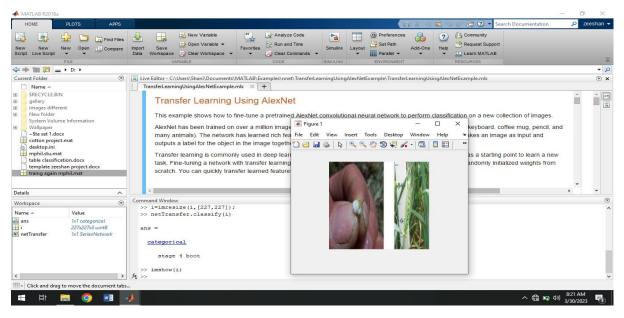


Figure 8. Stage 5

Training is completed the execution of model is evaluated by testing. This image also shows the code for classifying the picture and the results shows in command window and in picture form, during the booting phase, a protective covering known as the boot forms around the emerging wheat plant head. The plant's head is most susceptible to harm from pests and the elements during this time period, which lasts for roughly a week to two weeks.





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The training performance of model is completed testing .This image shows the code for classifying the picture and the results shows in command window and in picture form, the flowering stage, also known as anthesis, begins once the booting stage is complete. At this point, the wheat plant has developed enough to produce its blooms, which act as both sexes in the plant's reproduction cycle. Wheat grain growth begins when pollen from the male organs fertilizes the female organs.

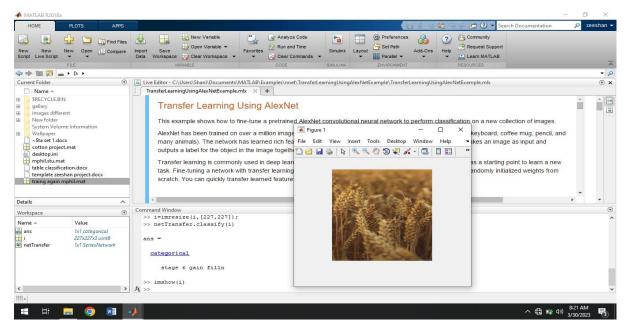


Figure 10. Stage 7

Training is complete the execution of model is evaluated by testing. This image shows the code for classifying the picture and the results shows in command window and in picture form, Wheat takes roughly three to four weeks to ripen, the ultimate stage of its growth and development. At this point, the wheat grain has fully developed, changing color from green to a rich golden brown. Grain goes dormant and is ready for harvest as the plant dries out.

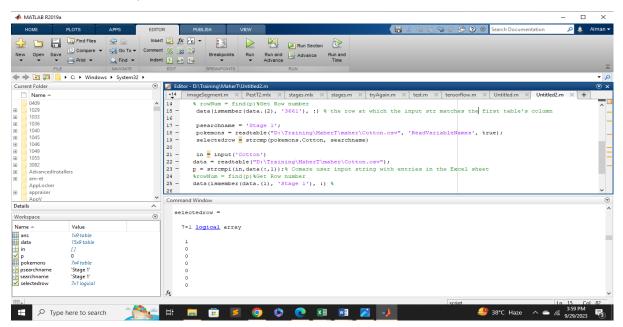


Figure 11.

Nisa, M,U et al. (2024)

This image shows that our model fetches information regarding wheat stage from the database, this information above is fetched from the short-term memory the data states the location of wheat stage.

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Figure 12.

This image displays the information that is extracted through Ontology by analyzing the problem and then finding solution to solve it. To fetch the information for stage 1 ontology analyzed the agricultural environment and made relationships with objects in the environment. Wheat stage 1, its duration and water requirements are analyzed in this environment.

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Figure 13.

The information regarding the environment has been extracted from knowledge base and now decision will be made on the basis of that information by evaluation. The image above shows the complete knowledge of an area of wheat 2.96(ha) which requires 3661(ha) water forirrigation (IN) along with crop water needs (ET) which is 10,836 and then comes the water requirement on the basis of soil. Five soil conditions

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are fixed, the soil which requires 0% water is properly watered by the farmer or maybe due to rainfall so there is no need to water it anymore, then comes the soil which requires 25% water due to rainfall it has fulfilled the most portion of water but only it needs 25% more water. Soil which is partially dry and partially moist needs 50% of water whereas the soil which is almost dry needs to be watered 75% and then there is extremely dry soil which requires 100% water as no rainfall has been there

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Figure 14.

This image displays the ontology of cotton, NN performs classification and then this classification results are sent towards ontology where it analyzes the situation and recalls the cotton stage from memory.

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Figure 15.

After getting connected with the environment the relationships are made, here the display of cotton crop along with Stage 1 duration and IN and no of irrigation are relationships being made to fetch data for Stage 1 cotton.

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Figure 16.

After making relationships, the information is evaluated and then final verdict is made. This picture displays the specific area of the cotton producing land, total irrigation needed for it, crops water requirement and then soil water needs are depicted starting from soil 1 to soil 5, where soil 1 is the soil which is rightly watered at time and do not require more water, soil 2requires 25% water as it is a little moist due to rainy weather, then soil 3 requires 50% water as it is half moist, soil4 requires 75% water as it is quite dry because the weather has been extremely hot and then comes the soil 5 which needs 100% water as soil has been very dry due to no rainfall and extreme summers.

DISCUSSION AND LIMITATION

The use of Smart Irrigation Systems has the potential to improve agricultural irrigation methods. However, they may not be appropriate for all crops and growth situations, and they demand a hefty initial investment and regular upkeep. Therefore, farmers should weigh the pros and downsides of these systems thoroughly before incorporating them into their operations. Smart irrigation systems do have their drawbacks, though. The price tag is a major obstacle. Installation and upkeep of smart irrigation systems can be costly, and they may need periodic calibration and software updates to ensure precise readings and optimum performance. Small farmers may not be able to afford this technology because of the price tag.

The dependency on technology is another drawback of smart irrigation systems. Irrigation schedules could be disrupted if these systems had power failures, malfunctions, or other technical concerns. If a problem arises with a farmer's smart irrigation system, the farmer may not be able to water his crops. In order to improve agricultural irrigation methods, ontology-based smart irrigation systems use ontology, a formal description of knowledge that facilitates intelligent reasoning. A device like this can assist farmers in optimizing irrigation by ensuring that the plants receive the optimal amount of water at the optimal time. Knowledge about the crops, the soil, the weather, and other aspects are compiled in a database in an ontology-based

smart irrigation system. This body of information is utilized to infer when and how much water should be provided to the crops.

CONCLUSIONS AND FUTURE WORK

The use of ontologies to describe knowledge about crop irrigation, soil moisture levels, weather patterns, and other pertinent aspects is a new area of study known as ontology-based smart irrigation systems. These systems use AI and ML to evaluate data and determine the optimal times and amounts to irrigate crops, with the goal of minimizing water waste while maximizing crop yields. There are many potential avenues for further study that might help make ontology-based smart irrigation systems even more efficient. Some examples are: Including Internet of Things gadgets: Soil moisture sensors, weather stations, and crop monitoring systems are all examples of Internet of Things (IoT) gadgets that can supply real-time data useful for informing irrigation decisions. The precision and timeliness of irrigation recommendations could be enhanced by integrating these tools with ontology-based smart irrigation systems. Including information about certain crops: Water needs vary among crops and even within a single species, as well as between stages of development.

Improve the accuracy of irrigation recommendations and lessen water waste by incorporating crop-specific knowledge into ontology-based smart irrigation systems. In order to ascertain efficacy and find areas for development, it is necessary to conduct an evaluation of the performance of ontology-based smart irrigation systems in real-world settings. Performing experiments in the field and analyzing data on crop yields and water use could be part of this process. Smart irrigation systems that are ontology-based hold great promise for lowering water usage and raising agricultural yields. Integration of Internet of Things devices, assimilation of crop-specific knowledge, and evaluation of system performance are all anticipated to progress as research in this area continues.

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Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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