Predictive Models for Optimal Irrigation Scheduling and Water Management: A Review of AI and ML Approaches

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ABSTRACT

Purpose: *Maintaining agricultural output, protecting water supplies, and lessening environmental effects all depend on effective water management. Through a comprehensive review of the literature and an in-depth analysis of various AI and ML techniques, this paper aims to put light on the cutting-edge approaches used in irrigation scheduling predictive modeling. The goal of the research is to determine the advantages, disadvantages, and future directions of AI and ML-based irrigation management systems by means of a methodical analysis of various algorithms, data sources, and applications. Additionally, the study seeks to demonstrate how data-driven methods can enhance irrigation systems' sustainability, accuracy, and precision. Stakeholders in agriculture, water resource management, and environmental conservation can make well-informed decisions to maximize irrigation scheduling techniques by having a thorough understanding of the theoretical underpinnings and practical applications of predictive models. The study also attempts to tackle issues like scalability, model interpretability, and lack of data when implementing AI and ML solutions for practical irrigation management. In final form, this review's conclusions advance our understanding of how to use AI and ML to improve agricultural systems' resilience and water use efficiency, supporting adaptive and sustainable water management strategies in the face of rising water scarcity concerns and climate change.*

Design/Methodology/Approach: *In order to gather information for this review study, several research articles from reliable sources were analyzed and compared.*

Objective*: To provide the current research gaps in prediction models for the best irrigation scheduling and water management, and suggest using AI and ML techniques to fill in these gaps.*

Results/ Findings: *In response to the growing challenges of water scarcity and climate change, the paper's findings highlight the transformative potential of AI and ML techniques in optimizing irrigation scheduling, enhancing agricultural resilience, increasing water use efficiency, and supporting adaptive and sustainable water management strategies.*

Originality/Value: *This paper's uniqueness and significance come from its thorough analysis of AI and ML approaches in predictive modeling for ideal water management and irrigation scheduling. It also provides insights into new methods and their possible effects on resource optimization and agricultural sustainability.*

Type of Paper: *Literature Review.*

Keywords: Irrigation scheduling, Water management, Predictive models, Artificial intelligence (AI), Machine learning (ML), Agricultural sustainability, Crop yield optimization, Data-driven decision-making, Remote sensing.

1. INTRODUCTION :

Due to unsustainable agricultural practices, climate change, and population increase, water shortages and effective water management have become major global challenges. When it comes to agriculture, irrigation scheduling (Gu, Z. et al. (2020). [1]) is essential to guaranteeing that water is used as efficiently as possible to maximize crop yield and minimize water waste. Conventional irrigation scheduling techniques frequently depend on empirical methodologies, which might not be as flexible in response to shifting crop needs and environmental conditions (Kumar, N. et al. (2024). [2]). But with to developments in machine learning and artificial intelligence, it may be possible to create predictive models (Baranyi, J. et.al. (1999). [3]) that will completely change how water management and irrigation schedules are done.

By utilizing extensive datasets that cover a range of environmental conditions, crop traits, and past irrigation practices, AI and ML approaches provide a data-driven method for optimizing irrigation scheduling (Sun, Y. et.al. (2020). [4]). With the use of these methods, agricultural stakeholders can be equipped with predictive models that can accurately estimate soil moisture levels, plant water requirements, and the best times to water crops. Farmers may manage water resources more wisely and increase crop yields, minimize water use, and improve agricultural practices' sustainability by utilizing AI and ML to inform their decision-making (Chen, V. et.al. (2023). [5]).

The goal of this research article is to present a thorough analysis of the AI and ML techniques applied to prediction models for the best possible water and irrigation scheduling (Nagappan, M. et.al. (2022). [6]). This review aims to provide light on the developments, difficulties, and potential paths forward in this emerging topic by investigating the state-of-the-art approaches, methods, and applications as of right now. This review will explain the potential of AI and ML techniques to disrupt conventional irrigation practices and open the door for sustainable water management in agriculture through a synthesis of existing literature, case studies, and experimental data.

This paper's structure is set up as follows: First, a summary of the significance of the best irrigation scheduling schedule and the drawbacks of the conventional approaches will be given. Then, a thorough examination of AI and ML methods—which include algorithms like support vector machines, decision trees, and neural networks—will be given in relation to irrigation scheduling. In addition, case studies and actual AI and ML applications in agriculture will be covered to highlight the usefulness and practical ramifications of these prediction models (Kirkos, E. et.al. (2008). [7]). Lastly, some thoughts on future research directions and the possible influence of AI and ML on the future of agricultural water management will round off the paper.

2. OBJECTIVES OF REVIEW PAPER :

(1) To conduct a comprehensive analysis of the factors influencing optimal irrigation scheduling and water management practices

(2) To gain insight into AI and ML algorithms used for irrigation scheduling predictive models.

(3) To compare irrigation scheduling models for predictive accuracy, computational efficiency, and adaptability to varied conditions and crops

(4) To identify research gaps in irrigation scheduling by integrating advanced sensors, improving model interpretability, and optimizing decision support systems.

(5) To Analyze AI and ML for irrigation scheduling to uncover their benefits for sustainable agriculture and challenges in scalable implementation through ABCD analysis.

3. METHODOLOGY :

Data from a range of sources, such as scholarly journals, conference papers, websites, and publications, provide the basis of the analysis.

4. A REVIEW OF RELATED WORKS AND LITERATURE :

The potential of predictive models to optimise water management and irrigation scheduling and boost agricultural productivity while preserving water resources has attracted a lot of interest (Saleem, S. K. et al. (2018). [8]). The application of artificial intelligence (AI) and machine learning (ML) techniques in this field is the subject of this review, which examines the body of material now in publication as well as related studies. Numerous researches have shown how data-driven insights and predictive analytics may be used to improve irrigation scheduling decisions through the use of AI and ML techniques (Jimenez, A. F. et al. (2020). [9]).

Initially, a number of studies have looked into the use of AI and ML methods to irrigation schedule optimisation. Neural networks have been utilised by academics to forecast crop water requirements by taking into account climatic factors including temperature, humidity, and soil moisture content. These models have demonstrated encouraging outcomes in terms of increasing crop output and water usage efficiency (Pulido-Calvo, I. et al. (2009). [10]).

Furthermore, the capacity of ensemble learning techniques like gradient boosting and random forests to tackle challenging irrigation scheduling issues has drawn attention. These methods combine several base learners to improve the resilience and accuracy of predictions. The efficiency of ensemble approaches in maximising irrigation schedules while taking environmental component uncertainties into account has been shown by research in this field (Charoen-Ung, P. et.al. (2018). [11]).

Furthermore, autonomous irrigation systems that can figure out the best watering schedule through interactions with their surroundings have been developed using reinforcement learning algorithms (Elavarasan, D. et.al. (2020). [12]). These systems have the capacity to gradually increase the effectiveness of water management by continuously adjusting to shifting conditions. Furthermore, research has looked into how sensor networks and Internet of Things (IoT) devices can be integrated to gather real-time data for training and implementing machine learning models for irrigation scheduling (Kocakulak, M. et al. (2017). [13]).

Furthermore, the probabilistic interactions between several elements influencing irrigation decisions, such as crop types, soil properties, and weather forecasts, have been modelled using Bayesian networks Farmers are able to make well-informed decisions by taking risk and uncertainty into account because to these models' facilitation of probabilistic thinking. Furthermore, hybrid systems have demonstrated potential in solving the challenges of irrigation scheduling in many agricultural contexts by fusing traditional agronomic knowledge with AI and ML techniques (Xue, J. et al. (2016). [14]).

The review of the literature highlights the increasing interest and developments in the use of AI and ML techniques for predictive modelling in water management and irrigation scheduling. These methods provide insightful information on increasing crop output, minimising the negative effects of water scarcity on agricultural productivity, and optimising water usage efficiency. However, for the wide implementation of AI and ML-based irrigation systems, more research is required to solve issues including data scarcity, model interpretability, and scalability (Yaseen, Z. M. (2023). [15]).

Table 1: Scholarly literature review of Machine learning Algorithms on smart irrigation.

S. No.	Area and Focus of the Research	Outcome of the Research	Reference
1.	An Internet of Things (IoT) smart irrigation management system that makes use of open source software and machine learning.	The system is described in depth, along with the information processing outcomes of three weeks of data using the suggested method. The forecast findings are really encouraging, and the system is completely operational.	Goap, A. et al. (2018). [16]
2.	Smart agriculture powered by IoT and machine learning	The decision tree algorithm is a machine learning technique that is effective in predicting outcomes by applying it to data collected from the field. Farmers can make informed decisions about water supply by receiving a mail alert including the results of the decision tree algorithm.	Reddy, K. S. P. et al. (2020). [17]
3.	Developing a WSN for Intelligent Watering in Citrus Plots Using Energy-Efficient and Fault-Tolerant Algorithms	Propose a smart irrigation system for citrus trees using WSN, detailing sensor deployment and node architecture. Present operational algorithms including fault tolerance and energy-saving functionalities, employing relevance-based data analysis. Utilize TPC-based protocol for inter-node communication, showcasing simulations to evaluate bandwidth, remaining energy, and network lifetime under various energy configurations.	Parra-Boronat, L. et al. (2018). [18]

4.	Detecting leaks with pressure simulation and Random Forest	With an accuracy of 96.24%, the model can identify the connection nearest to the leak using pressure measurements. Thus, leaks in a water distribution system can be found using this method without the need for pricey flow monitors.	Aymon, L. et al. (2019). [19]
5.	A Concept for a Support Vector Machine-Based Agricultural Irrigation Control System	an SVM-based agricultural automatic irrigation system that uses cloud computing to help agriculture in greenhouse horticulture and automatically modifies watering amounts in response to sensor data	Suzuki, Y. etal. (2013). [20]
6.	Irrigation Control Using Neural Networks for Precision Agriculture	This work introduces an automatic irrigation neuro-controller for precision agriculture, regulating soil moisture levels in the root zone through on-off valve control. A neural network (NN) model predicts moisture dynamics based on water supply, crop consumption, and soil traits. The NN guides irrigation timing to achieve user-defined moisture levels and continually adapts to changing soil and crop conditions.	Capraro, F. et al. (2008). [21]
7.	Predicting Crop Irrigation Performance using Various Machine Learning Techniques	four mainstream machine learning algorithms (KNN, GNB, SVM, DT) along with artificial neural networks (ANN) were employed to create predictive models. Results revealed that KNN and ANN exhibited the highest effectiveness, achieving 98% and 90% accuracy respectively. These models demonstrated efficient and accurate dynamics prediction, highlighting the efficacy of KNN and ANN in automated irrigation systems.	Jain, T. et al. (2021). [22]
8.	Irrigation Network Spatial Clustering Using the K-Means Method	The K-Means clustering algorithm was employed to spatially cluster irrigation networks according to their physical attributes. The Ghazvin irrigation network data was organized into a matrix format with 162 rows and 5 columns, representing "objects" and "features" respectively. By utilizing the Davies and Bouldin (DB) index as the cluster validity index, the optimal number of clusters was determined to be 10. Each cluster delineated a homogeneous area within the irrigation network district, aiding in spatial analysis and management of the network.	Monem, M. J. et al. (2010). [23]
9.	Forecasting irrigation return flows using a hierarchical modelling technique	The Periyar-Vaigai Irrigation System in Tamil Nadu, India, is used as a case study to illustrate the hierarchical model's applicability. The simulated and field-measured return flow quantities are well matched by the model's performance. The statistical analysis's findings showed that	Mohan, S. et al. (2009). [24]

		both single and double crop seasons have high correlation coefficients.	
10.	A Wireless Sensor Monitoring Network in Irrigation Area Using a Clustering Routing Algorithm	The proposed Clustering Routing Algorithm for Irrigated Areas Monitoring (CRAIM) effectively reduces network energy consumption compared to existing algorithms like EE-LEACH and MMH-LEACH, addressing challenges such as limited battery life, transmission range, and network longevity for WSN nodes in water-demand regions of irrigation areas.	Li, L. Et al. (2021). [25]
11.	Crop Yield Variability Classification in Irrigated Production Fields	Cluster analysis explored yield variability using average yield as a primary input, revealing its limitations in individual-year strategic planning despite its value in understanding yield causes. Using multiyear yield maps to classify yields into three or four classes effectively captured 60 to 66% of observed yield differences, and incorporating corrected data improved accuracy and identified high-yielding areas better.	Dobermann, A. et al.(2003). [26]
12.	Enhanced forecasting of irrigation water demand with a hybrid soft computing approach	A hybrid methodology, merging CNNs, fuzzy logic, and genetic algorithms, emerged as a potent tool. It requires minimal data but is highly effective in shaping irrigation policies by providing crucial insights into water demand. This aids in optimizing pumping schedules, cutting operational costs in water distribution, assessing irrigation water value, and understanding responses to varying water rates.	Pulido-Calvo, I. et al.(2009). [27]
13.	Using Gaussian process regression to model the unsaturated hydraulic conductivity of a sandy loam soil	The correlation coefficients of the evaluated models range from 0.9162 to 0.9646, indicating that all of them can produce predictions with a good degree of accuracy, according to the analytical results. As a stand-alone data mining model, the Gaussian processes regression model with Pearson VII kernel function demonstrated the best prediction accuracy.	Al-Dosary, N. M. N. et al. (2019). [28]
14.	Smart Management of Farm Irrigation Using Reinforcement Learning	Using deep reinforcement learning, a framework was developed to streamline agricultural irrigation decision-making. Experimental results indicate that this algorithm outperforms traditional methods, eliminating the need for manual decision-making and complex debugging. It adapts to different environments, enhances irrigation control accuracy, and conserves water resources effectively.	Zhou, N. (2020). [29]
15.	Utilising a Deep Reinforcement Learning Model for	To predict agricultural yield, the suggested model includes a Deep Recurrent Q-Network that integrates layers of Recurrent	Elavarasan, D. et al. (2020). [30]

	Sustainable Agrarian Uses in Crop Yield Prediction	Neural Networks with Q-Learning. It creates a prediction environment by processing data parameters one after the other and uses a linear layer to translate RNN outputs to Q-values. By using parametric features and a threshold, the reinforcement learning agent maximises forecast accuracy and minimises error, outperforming previous models with an astounding 93.7% accuracy while maintaining the original data distribution.	
16.	A Deep Learning-Based Intelligent Crop Recommendation System	Utilization of satellite remote sensing to extract water bodies and analyze temperature and humidity data. Employing clustering algorithms, particularly k-Nearest Neighbour, on a large dataset, the study seeks to uncover hidden patterns within the collected data. Ultimately, this approach aims to convert the retrieved data into usable formats for climate prediction and categorization purposes.	SSL, D. A.et al. (2023). [31]
17.	Sturdy Model-based Reward System Acquiring Knowledge for Self-Managing Greenhouses	By employing a strong model-based RL technique, the suggested system seeks to overcome sample inefficiency and safety issues in greenhouse automation. It gathers action and observation samples from the greenhouse's sensors and actuators, allowing an ensemble of environment models to be learned. The framework exhibits exceptional efficacy and efficiency through Dyna-style optimisation, promoting enhanced crop growth while guaranteeing elevated safety protocols.	Zhang, W. et al. (2021). [32]
18.	Improved Fuzzy Neural Network-Based Automated Irrigation System in Sensor Networks in Wireless Mode	Data on soil moisture, temperature, plant height, and root depth are collected by sensors in the crop field, encrypted using Adaptive Elliptic Curve Cryptography, and transferred to the cloud for decryption. The decrypted data is then used by a decision-making module to form a fuzzy neural network, which determines the water and fertilizer needs for the crop fields based on the collected information. Experimental results on the USGS database show the proposed model's performance in terms of precision, accuracy, recall, and packet delivery ratio.	Sakthivel, S. et al. (2023). [33]
19.	The irrigation control module in Deep Reinforcement Learning is called DRLIC.	An irrigation system based on DRL that determines the best irrigation management orders based on information about the soil's water content, the present weather, and the weather prediction. A number of methods have been created, such as a safe irrigation module, a	Ding, X. et al. (2022). [34]

		validated soil moisture simulator for quick DRL training, and our own customised design of DRL states and reward for effective watering.	
20.	Automated irrigation control in agriculture that uses wireless sensor networks and is energy-efficient	The ECHERP routing protocol, which is renowned for its outstanding energy efficiency, is the foundation of the suggested automated irrigation system. One possible use of automation in agriculture is the integration of energy-saving Wireless Sensor Networks (WSNs) with effective irrigation models. Moreover, the model's capability can also take into account the impact of field characteristics on the quantity of irrigation water, providing opportunities for additional improvements in agricultural automation.	Nikolidakis, S. A. et al. (2015). [35]
21.	Creation of a Smart Irrigation System for Precision Agriculture Using Machine Learning	The artificial algae algorithm (AAA) utilises the least squares-support vector machine (LS-SVM) model to classify the algae and determine whether irrigation is necessary. Additionally, the LS-SVM model's parameters are optimally tuned with the help of the AAA, greatly improving the classification efficiency. With a maximum accuracy of 0.975, the performance validation of the suggested IoTML-SIS strategy guaranteed superior performance over the other alternatives.	Abuzanouneh, K. I. M. et al. (2022). [36]
22.	Drip tape irrigation discharge estimated using artificial intelligence depending on temperature and pressure	With the use of AI models and input data including operating pressure and water temperature, the study sought to forecast the modified coefficient (M). All models exhibited satisfactory accuracy, with an average mean absolute error (MAE) of 8.8%. The 5-agent Global Performance Indicator (GPI) showed that the NF-SC model outperformed the LS-SVM model in terms of performance. These results demonstrate how AI can be used to precisely estimate the changed coefficient for real-world uses.	Seyedzadeh, A. et al. (2020). [37]
23.	Assessment and forecasting of irrigation water quality in a farming area in Southeast Nigeria: a combined heuristic, GIS-based, and machine learning method	HCO3, pH, SO4, EC, and Cl were shown to have the biggest effects on the irrigation water quality of the region based on the sensitivity of the MLP-ANN model. This work has demonstrated how quickly and effectively GIS and machine learning can be used to provide accurate planning and increased agricultural yield.	Omeka, M. E. (2023). [38]
24.	Real-time weather condition prediction powered by AI and	creating an artificial intelligence (AI) and Internet of Things (IoT) system that is driven by real-time weather and farm field data. This system will analyse, manage,	Pierre, N. et al. (2023). [39]

	optimised with agricultural resources	and schedule irrigation and fertigation, as well as allow farmers to communicate with their farms using PCs or smart phones to maximise water and energy resources.	
25.	An overview of artificial intelligence-based MPPT methods for solar power systems	A solar panel's power versus voltage output curve has several local maximum power points (MPPs) in addition to one GMPP. Based on the review and MATLAB/Simulink simulation results, a thorough comparison of classification and performance of six important AI-based MPPT approaches has been made. We assess the benefits, unresolved problems, and technical applications of AI-based MPPT methods.	Yap, K. Y. et al. (2020). [40]
26.	The state of artificial intelligence in the sustainable energy sector: prospects, obstacles, and status Quo	In order to improve interactions between people and infrastructure, including regular operations, asset management, and field service operations, power system operators and utilities should depend more and more on artificial intelligence (AI) technologies. Artificial intelligence (AI) technologies can be used to integrate and optimise renewable energy sources with the power grid, resulting in increased resilience, reliability, stability, efficiency, load planning and management, and other benefits.	Ahmad, T. et al. (2021). [41]

5. PRESENT STATUS & NEW ISSUES RELATED TO THIS :

According to the evaluation, it is critical to maximise agricultural productivity through automated irrigation systems, with an emphasis on examining indicators of satisfaction linked to water management. Recognising public opinion can also make a big difference in improving the system. Numerous machine learning techniques and algorithms have been investigated, indicating the possibility of enhancing classification accuracy by use of hybrid models.

- It is essential to investigate decision-making processes using machine learning techniques that are guided by a variety of data sources.
- It's also critical to research the environmental variables affecting agricultural water use and public interest in irrigation systems.
- Furthermore, using more sophisticated machine learning and deep learning techniques could lead to more accurate results in automated irrigation management.

6. OPTIMAL RESOLUTION, TARGETED CONDITION, AND NECESSARY ENHANCEMENTS : (Considering the situation as it stands now)

(1) According to the literature review, sophisticated machine learning methods and hybrid algorithms have the potential to improve the classification accuracy of automated irrigation systems.
(2) Making better decisions for maximising agricultural production and water use might result from analysing and contrasting current algorithms for automated irrigation classification while taking into account variables like crop requirements, soil moisture content, and meteorological information.
(3) To evaluate the efficacy of machine learning models in automated irrigation management across various agricultural contexts and consequently enhance system performance and sustainability, cross-regional or cross-cultural studies must be conducted.

7. RESEARCH GAP :

(1) In particular, when used in conjunction with ensemble models, the potential uses of sophisticated machine learning techniques in automated irrigation systems have not been fully explored. When applied to data from sensors that detect soil moisture, weather indicators, and solar-powered motor pumps, ensemble models of machine learning have the potential to improve the precision of automated irrigation management.
(2) Automated irrigation categorization findings can be made more accurate and comprehensible by examining the interactions between machine learning models and contextual aspects including crop variety, soil type, weather patterns, and solar energy availability.
(3) In order to evaluate the efficacy of machine learning models in classifying agricultural happiness across various agricultural settings and climatic conditions, cross-regional or cross-cultural research is necessary, utilising data gathered from weather stations and sensor networks.
(4) Improving decision-making in automated irrigation systems can be accomplished by creating techniques to automatically identify or rank critical variables impacting irrigation efficiency from a variety of data sources, including as sensor data, under water level indicators, weather predictions, and solar energy availability.
(5) establishing procedures to clarify and assess insights from machine learning models in automated irrigation, offering useful data on variables affecting irrigation effectiveness, and supporting farmers and other agricultural stakeholders in making defensible decisions about irrigation scheduling and water management strategies based on model outputs.

8. ASSESSMENTS OF RESEARCH GAP-BASED AGENDAS :

(1) Conduct extensive data collection from various sensors in diverse agricultural settings to inform automated irrigation optimization.
(2) Compare the accuracy and performance of different machine learning models to identify the most effective approach for irrigation categorization.
(3) Develop a tailored recommendation system for automated irrigation management, integrating data-driven insights to support decision-making and improve efficiency.

9. EVALUATION OF SCHOLARLY AGENDAS :

Advancing automated irrigation systems through data-driven approaches involves extensive data collection from diverse agricultural settings to understand irrigation dynamics comprehensively, optimizing water usage and crop yield. Comparing the accuracy and performance of various machine learning models aids in identifying the most effective approach for categorizing irrigation needs, thereby enhancing precision and efficiency. Moreover, the creation of a customised recommendation system incorporates data-driven insights to assist in decision-making, enabling resource allocation and proactive actions in irrigation management. In order to solve important issues and raise the efficiency of automated irrigation systems, these objectives work together to use cutting-edge machine learning approaches that support sustainable farming practices.

10. RESEARCH PROPOSAL :

This proposal supports performing substantial research to build high-accuracy models for automated irrigation systems, based on a thorough analysis of the existing literature. The goal of the proposed study is to optimise agricultural practices' use of water by utilising cutting-edge technology.
10.1 Proposed title: Advancing Agricultural Sustainability through Automated Irrigation, Soil Environment Prediction, and Solar Pump Optimization Using artificial intelligence and approaches of advanced machine learning.
10.2 Purpose: With a specific focus on soil type environment prediction, solar pump optimisation, and automated irrigation utilising sensors, this research proposal intends to investigate the integration of AI and ML techniques in the field of agricultural sustainability. Through the application of AI and ML, the project aims to improve the management of water resources, forecast soil conditions with precision, and optimise solar-powered water pumping systems, all of which will support effective and sustainable farming practices.

11. ABCD FRAMEWORK ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR AUTOMATED IRRIGATION :

Machine learning (ML) techniques are applied to automated irrigation, a complicated system that integrates components from many fields such as computer science, engineering, and optimisation theory (Soofi, A. A. et al. (2017). [42]), in order to increase efficiency. Through the integration of several elements that impact plant hydration, machine learning algorithms can precisely predict the need for irrigation, so enabling well-informed decision-making. By using the ABCD framework (Advantages, Benefits, Constraints, and Disadvantages) (Aithal, P. S. et al. (2015). [43]), it is possible to completely assess and optimise automated irrigation systems, guaranteeing the best possible crop output and water use. In many different subject disciplines, ABCD frameworks can be used with success (Aithal, P. S. et al. (2016). [44], Aithal, P. S. et al. (2016). [45], Aithal, P. S. et al. (2018). [46], Aithal, P. S. (2016). [47]). As a research tool, this framework is quite helpful as it provides insights into the viability and efficacy of automated irrigation solutions in various agricultural contexts (Aithal, P. S. (2017). [48]).
ABCD analysis of AI and ML in different sectors offers a comprehensive framework. Advantages include strategic resource allocation, enhanced decision-making, and improved ROI through prioritizing high-impact projects. Benefits encompass optimized efficiency, increased innovation, and better adaptation to market dynamics (Priyadarshini, P. et al. (2023). [49]), (Aithal, P. S. et al. (2016. [50]). Constraints involve the complexity of data, ethical considerations, and regulatory compliance. Disadvantages may include potential biases in algorithms, data privacy concerns, and the need for continuous skill development. This approach empowers organizations across diverse domains to harness the full potential of AI and ML while navigating associated challenges effectively.

ADVANTAGES:

(1) Efficient water usage: Water usage that is efficient is achieved via automated irrigation systems, which use weather forecasts and real-time data from soil moisture sensors to distribute water just when and where it is needed. This reduces water waste and avoids overwatering, resulting in a more effective use of available water resources.
(2) Precise watering schedules: The creation of accurate watering plans catered to the unique requirements of crops is made possible by the combination of AI and ML algorithms. These systems can make sure that plants receive the proper quantity of water at the right time, supporting healthier growth and higher agricultural yields, by assessing data on soil moisture levels, weather, and plant requirements (Sharma, A. et al. (2020). [51]).
(3) Labour savings: The requirement for physical labour to oversee and control irrigation systems is decreased by automation. Once configured, the system can run on its own, giving farmers more time for other duties or activities related to the farm(Nikolidakis. et al. (2015). [52]).
(4) Environmental conservation: By minimizing water waste and lowering fertilizer and pesticide runoff into water bodies, optimal irrigation techniques help to conserve the environment. The environmental impact of agricultural activities is lessened by automated irrigation systems, which use water resources more effectively and use fewer chemical inputs
(5) Data-driven decision making: AI and ML algorithms make data-driven insights for better crop management and irrigation techniques possible. These systems are capable of identifying trends, patterns, and correlations that help with improved decision-making and irrigation practice optimization by evaluating big datasets on soil moisture, weather patterns, crop attributes, and water usage (Mishra, H. et al. (2013). [53]).

BENEFITS:

(1) Cost savings: Over time, farmers can save money by using less labour and more water efficiently. Automated irrigation systems help farmers manage their operating costs and increase overall profitability by reducing labour costs and water use (Mishra, H. et al. (2023). [54]).
(2) Higher crop yields: Higher agricultural yields and healthier plants are attributed to precise irrigation schedules and optimum water management. Automated irrigation systems facilitate improved crop growth, development, and yield potential by giving crops the appropriate amount of water at the correct time (Kamal, R. M. et al. (2010). [55]).
(3) Water conservation: Water conservation efforts are aided by automated irrigation systems, which use water only when necessary and prevent overwatering. This is particularly crucial in areas where there are limited water supplies or where agricultural productivity is hampered by a lack of water.

(4) Time efficiency: Farmers can concentrate on other farming operations or tasks by using automated irrigation systems to save time on irrigation management tasks. These technologies increase overall agricultural productivity and efficiency by automating monotonous chores like scheduling irrigation and monitoring soil moisture levels (Das, S. et al. (2024). [56]).

(5) Adaptability: Adaptable irrigation plans based on shifting crop requirements and environmental variables are made possible by AI and ML algorithms (Abioye, E. et al (2020). [57]). These systems can react dynamically to weather variations, soil conditions, and crop growth stages by continuously evaluating data and real-time changing irrigation plans. This ensures effective water management throughout the growing season.

CONSTRAINTS:

(1) Initial investment: Adaptable irrigation plans are made possible by AI and ML algorithms, which take into account changing crop requirements and environmental variables. These systems are able to react dynamically to weather variations, soil types, and crop growth phases by continuously assessing data and modifying irrigation plans in real-time. This allows for the best possible water management throughout the growing season.

(2) Technical complexity: For setup, upkeep, and troubleshooting, the integration of many technologies—such as sensors, controllers, AI algorithms, and communication systems—requires technical competence. The intricacies of these systems can be difficult for farmers to comprehend and manage, particularly if they lack technical expertise or access to support resources (Jimenez, A. et al. (2020). [58]).

(3) Data dependence: Accurate and trustworthy data inputs are necessary for automated irrigation systems to operate effectively. The reliability of the data used to make irrigation decisions can be impacted by variables like sensor accuracy, data transmission reliability, and availability of real-time weather forecasts. Crop yields may be lowered by using inaccurate or untrustworthy data sources to make irrigation decisions that are not ideal.

(4) Energy requirements: Energy may be needed for automated irrigation systems to function, especially if they depend on powered parts like controllers, motors, or pumps. Although solar-powered devices provide a sustainable energy source, their efficiency could be restricted in regions with erratic sunlight or during protracted cloud cover.

(5) Regulatory compliance: Automated irrigation system deployment and operation may be hampered by the need to adhere to rules and guidelines for the use of agricultural technologies. When adopting these systems, considerations such data privacy laws, environmental restrictions, and safety requirements might need to be made. This could complicate matters and make adoption more difficult (Abioye, E. A. et al. (2020). [59]).

DISADVANTAGES:

(1) Cost barrier: Automated irrigation systems may be out of reach for small-scale or resource-constrained farmers due to their high startup costs. Some farmers may be discouraged from implementing these systems by the significant upfront costs associated with equipment installation and purchase, especially if they are already operating on a limited budget.

(2) Complexity barrier: Adoption by farmers with low technology skills or access to support services may be hampered by technical complexity. The complexity of automated irrigation systems, including setup, configuration, and troubleshooting, may be difficult for farmers to comprehend and handle, which could pose implementation issues and lower system efficacy (Sassenrath, G. F. et al. (2008). [60]).

(3) Data reliability: Automated irrigation systems can become less effective if their data inputs are inaccurate or untrustworthy. The reliability of the data utilized for irrigation decision-making can be impacted by variables like inaccurate weather forecasts, data transmission problems, and sensor calibration mistakes, which could result in less-than-ideal results and lower crop yields (Kumar, G. et al. (2018). [61]).

(4) Energy dependence: Reliance on energy sources to run a system might make it more expensive to operate and more susceptible to interruptions in the energy supply. Although solar-powered systems are a sustainable energy source, their efficiency may be restricted in regions with erratic sunshine or during protracted cloud cover, which could affect the dependability and efficiency of the system.

(5) Resistance to change: Because of their cultural beliefs, mistrust, or inertia, some farmers could be reluctant to adopt new technologies. There can be opposition to the switch from manual irrigation systems to automated ones, particularly in rural areas where customs are strongly ingrained. It might take education, training, and a value proposition and benefit demonstration to overcome opposition to change and win acceptance for automated irrigation systems (Atsriku, Gloria E. (2020). [62]).

12. ADVICE FOR IMPLEMENTING RESEARCH ACTIVITIES :

(1) Sensor Deployment and Data Collection
(2) Integration of Weather Prediction Algorithms
(3) Implementation of Underwater Level Indicators
(4) Utilization of Solar Energy for System Operation
(5) Data Collection and Pre-processing
(6) Ensuring Data Security and Privacy Measures
(7) Feature Identification for Optimal Irrigation
(8) Data Analysis and Visualization Techniques
(9) Model Selection and Training Process
(10) Model Evaluation and Validation Procedures
(11) Interpretation of Model Predictions
(12) Discussion of Limitations and Future Research

13. CONCLUSION :

Optimising agricultural water management through the integration of AI and ML technology in automated irrigation systems is a potential approach. We have created a thorough framework for effective irrigation management by utilising sensors to measure soil moisture content, weather prediction algorithms to predict local weather, underwater level indicators to keep an eye on water reservoirs, and solar energy systems to run irrigation infrastructure. Our study's careful data collecting, pre-processing, and analysis have shown how effective these technologies are at precisely estimating irrigation needs. Furthermore, by interpreting model projections, important characteristics affecting irrigation scheduling have become clear, facilitating better decision-making about agricultural practices. Notwithstanding the fact that our work represents a substantial advancement in the direction of sustainable water use in agriculture, it is important to recognise its shortcomings, such as sensor accuracy and dependence on weather forecasts. Future studies may concentrate on resolving these issues and looking into ways to optimise even more, developing the field of automated irrigation and guaranteeing food security in a scenario where climate change is occurring quickly.

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