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REVIEW ARTICLE - ENGINEERING

Wireless Sensor Network-Based Artificial Intelligent Irrigation System: Challenges and Limitations

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Abstract

As the global population and economy grow rapidly, the demand for accessible freshwater sources also increases to meet the rising consumption. However, this has resulted in several challenges, such as the global water crisis, drought, and scarcity of freshwater resources. To address this issue, many farmers worldwide rely on traditional irrigation systems despite their high water consumption. Therefore, there is a need to improve water usage efficacy in irrigated farming. This can be achieved by leveraging the Internet of Things (IoT) and advanced control technologies for better monitoring and managing irrigated farming. This article presents the findings of a comprehensive literature review on irrigation monitoring and sophisticated control systems, focusing on recent studies published within the last four years. The latest research on precision irrigation monitoring and cutting-edge control methods is highlighted. This study aims to serve as a valuable resource for those interested in understanding monitoring and advanced control prospects in the context of irrigated agriculture, as well as for academics seeking to stay up-to-date on the latest developments and identify research gaps that need to be addressed.

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Keywords: Artificial Intelligent; Challenges; IoT; Irrigation; Wireless Sensor Network.

1. Introduction

Due to rising global population levels and the subsequent need for more food production, agriculture now consumes more than 70 percent of the world's freshwater resources [1]. Poor water-use efficiency and low production are just two of the problems plaguing the traditional approach to irrigation management [2]. As a result, the quantity of precipitation that can be used to irrigate crops is dynamically influenced by global warming and climate change [3]. Sustainable targeted irrigation is a critical step toward achieving food security by mitigating the unpredictability of rainfall and the impact of water shortages caused by drought. To make up for water lost via evaporation, runoff, and deep percolation, accurate irrigation scheduling ensures that water is applied to plants precisely when and where it is required in the correct proportions[4]. Management of Irrigation Systems Saving water and the associated indirect energy consumption costs through careful monitoring and fine-tuned management will maximize efficiency and save money [5, 6]. Smart agricultural applications have achieved controlled monitoring of agricultural processes through the integration of wireless sensor network (WSN) technologies and the Internet of Things (IoT). This has resulted in a more significant comprehension of the dynamic changes in weather, soil, and crop conditions during the growing season, thanks to the rapid successes of remote sensing. Satellites, sensors on unmanned aerial vehicles (UAVs) [7], and mobile irrigation platforms such as lateral and center pivot moving machines are among the various examples of IoT-enabled sensors or equipment that may be used to continually pool real-time data from the desired area [8]. Therefore, intelligent decisions can be achieved by employing machine learning (ML) models by leveraging the massive amounts of geospatial data that varies over time and can be gathered and stored in multiple cloud servers [9]. ML provides a robust and adaptable framework for data-driven decision-making and in-depth system knowledge. Together, big data technologies and the ability of edge cloud computing to learn without being explicitly programmed have opened up a new way to make sense of and draw conclusions from the huge amounts of data that sensors collect [10]. These technologies will facilitate the conversion of raw data into useful information for making choices about irrigation and taking appropriate actions in the field or greenhouse. As a result, it saves money, reduces fatigue, and better uses energy and irrigation water [11, 12]. Furthermore, thanks to the development of climate- and environment-based paradigms for calculating crop water needs, farmers should be able to easily monitor and visualize the different metrics on smartphones or other computing systems to direct their choices, intelligently or manually. In addition, survey research has indicated that 90% of farmers favor using mobile and online apps to better control their irrigation systems to boost agricultural output [13, 14]. This study aims to summarize how AI and wireless sensor networks have been put to use in the irrigation industry. The structure of this paper is as follows: The current section provides an introduction. The second section explores the classification of AI techniques in irrigation systems. The third section reviews previous works on AI in irrigation.

Nomenclature & Symbols			
AIRA	Agricultural Irrigation Recommendation and Alert System	IoT	Internet of Things
ANNs	Artificial Neural Networks	k-NN	K-Nearest Neighbor
ANFIS	Adaptive Neuro-Fuzzy Inference Systems	LoRa	Long-Range
CNNs	Convolutional Neural Networks	LSTMs	Long Short-Term Memories
CWSI	Crop Water Stress Index	ML	Machine Learning
CU	Coefficient of Uniformity	MQTT	Message Queuing Telemetry Transport
DSS	Decision Support System	PSO	Particle Swarm Optimization
DL	Deep Learning	RF	Radio Frequency
DLiSA	Deep Learning for Precision Agriculture	RNNs	Recurrent Neural Networks
ES	Expert Systems	SIS	Smart Irrigation System
FL	Fuzzy Logic	SPDT	Single Pole Double Throw
GPRS	General Packet Radio Services	SWS	Smart Watering System
GSM	Global System for Mobile Communication	UAVs	Unmanned Aerial Vehicles
HTTP	Hypertext Transfer Protocol	USP	Universal Sensor Pole
IDSS	Irrigation Decision Support System	WSN	Wireless Sensor Network
KF-PID	Kalman Filter-Proportional Integral Derivative		

The fourth section explores the utilization of IoT in irrigation. In the fifth section, the limitations and challenges of implementing AI and IoT in irrigation are discussed. The sixth section presents a maturity evaluation, and finally, the paper is concluded in the seventh section.

2. Classification of Artificial Intelligent in Irrigation Systems

John McCarthy initially used the phrase "artificial intelligence" in 1956 at the Dartmouth Conference, defining it as the technology and engineering of creating intelligent machines or intelligent computer programs [15]. Machines can learn, comprehend, and respond appropriately thanks to artificial intelligence technology, which gives them computational intelligence. ML, Fuzzy logic (FL), natural language processing (NLP), swarm intelligence (SI), expert systems (ES), deep learning (DL), and computer vision (CV) are all types of artificial intelligence. Research into AI algorithms is widespread across many industries, including the agricultural sector [16, 17]. These days, artificial intelligence and the IoT are among the most popular innovative technologies used in agriculture. The sensors in the IoT-based smart farming system are meant to keep tabs on soil moisture and soil nutrients. The use of AI systems to compute the optimum soil watering needs is also being investigated [18]. Farmers may also discover answers to their questions and learn to use cutting-edge technology to boost crop yields. Because of this, AI and the IoT will be the two most important technologies in the agricultural sector [15, 19]. Here, we take a look back at the AI algorithms that powered the studies presented in this research (see Fig. 1).

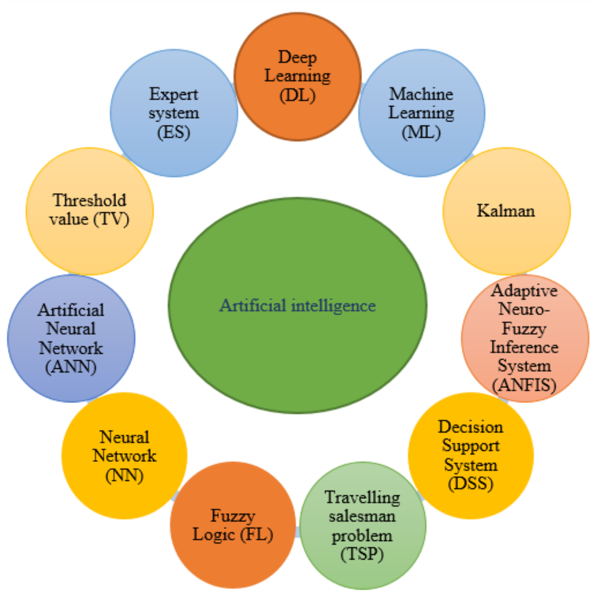

Fig. 1. Artificial intelligence techniques

2.1. Fuzzy logic algorithm

Irrigation is a complicated system with inherent nonlinearities, making it challenging to formulate the mathematical equation that explains the system. A fuzzy controller model could use rules in an "if-then-else" structure instead of a mathematical formula. This model would be based on experts' process knowledge [20]. By precisely estimating the quantity of irrigation and controlling the nonlinearity connected with the process, the fuzzy logic irrigation control algorithm serves as a valuable control mechanism for assuring irrigation accuracy and enhancing water usage efficiency [21]. The designer's familiarity with process (plant) dynamics is crucial to developing effective fuzzy rules and demonstrating their practicability via experimentally gathered long-term data, contributing significantly to the controller's efficacy and reliability [22].

2.2. Artificial neural network algorithm

Artificial neural networks (ANNs) are learning algorithms that build on how natural neural systems, such as the human brain, analyze data. The billions of neurons in the human brain constantly communicate with one another to process information [10]. ANN's nonlinearity features, input-to-output mapping capability, and ability to forecast several dependent variables make its artificial neurons functionally equivalent to the human brain's biological neurons [23]. Because of their propensity to learn and adapt to the changing factors impacting irrigation, ANN-based controllers have been employed in irrigation control systems [24]. ANN has also been used as an effective tactic for dealing with the challenge of developing mathematical models from fundamental principles. Nevertheless, the completeness with which the data input describes the system's behavior is crucial to the accuracy of the ANN-based prediction model or controller. Suitable and quality sensors should be used to capture data on required parameters, and a suitable sample time should be selected [22].

2.3. Machine learning algorithm

ML is a subfield of AI that enables machines to acquire new skills without being taught directly [25, 26]. ML aims to make computers carry out tasks on par with human intelligence by acquiring knowledge through experience [27]. Efficient intelligence-based decision support systems for the sustainable and equitable use of water sources in precision irrigation management have been demonstrated through the successful application of ML and deep learning models. Historically, farmers have relied on their knowledge and experience to decide whether or not to irrigate; however, recent advances in ML have made it possible to include forecasts of weather and soil conditions in irrigation choices. Knowing the water requirements, yield, and soil moisture content in advance allows for proactive response and improved management in irrigation planning, making prediction a crucial aspect of the process [28]. It is possible to achieve precision in irrigation activities by using ML techniques to automatically extract fresh information in the form of generalized decision rules. ML approaches, including federated learning, reinforcement learning, supervised learning, and unsupervised learning, have been more prominent in the area of precision irrigation management to address difficult problems like categorization and prediction [29]. In specific scenarios, the model can take care of the feature extraction work, a significant benefit of DL. DL models have helped many fields and businesses, and agriculture is no exception. DL models are often used in agriculture to process images and sounds. Most DL algorithms are ANNs with several hidden layers between the input and output layers. The use of supervised and unsupervised learning methods, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memories (LSTMs), can help with irrigation decision management [30, 31]. Particle Swarm Optimization (PSO) is a computational optimization technique inspired by bird flocking and fish schooling behavior. In an irrigation system, PSO can be used to optimize the water allocation process by minimizing water waste while maximizing crop yield.

PSO works by creating a particle swarm that represents potential solutions to the optimization problem. The position and velocity of every particle are modified by considering the particle's individual best solution and the swarm's overall best solution. These updates lead the particles to converge toward the optimal solution. In an irrigation system, PSO can optimize the allocation of water resources by determining the ideal quantity of water to be applied to each crop, depending on weather, soil moisture, and crop growth stage. Utilizing this technology can result in optimized water resource management and increased crop productivity [32].

2.4. Expert system algorithm

ES are computer-based tools that use knowledge and rules to solve complex problems in a specific domain. In an irrigation system [33], an ES can provide recommendations on irrigation management based on rules and knowledge about the crop, soil, climate, and irrigation system [34]. The ES algorithm in an irrigation system typically involves the following steps [35].

- Knowledge acquisition: Gather information from experts, scientific research, and other sources to develop a knowledge base of rules and information about the crop, soil, climate, and irrigation system.
- Rule-based reasoning: Use rules and logical reasoning to analyze the data collected from sensors and other monitoring tools and make recommendations on irrigation management.
- Inference engine: Use an inference engine to apply the rules to the data and generate recommendations based on the current state of the crop and irrigation system.
- User interface: Provide a user-friendly interface for farmers and irrigation managers to interact with the system, input data, and receive recommendations.
- Feedback: Monitor the results of the irrigation management decisions and use this information to refine the rules and knowledge base over time.

The ES algorithm can help to improve irrigation management by providing accurate and timely recommendations to farmers and irrigation managers [36]. By optimizing irrigation management, the ES can help to reduce water waste, improve crop yield, and promote sustainable agriculture practices. However, it should be noted that the effectiveness of the ES may be influenced by factors such as data quality, rule accuracy, and system maintenance and may need to be calibrated to local conditions [37].

2.5. Threshold value algorithm

It is a simple, easy-to-understand algorithm that can monitor several irrigation-related factors and control the irrigation process. An SPDT (single pole, double throw) switch is used to switch between modes. In one setup, the tool is set only to track watering-related data. "Half-active mode" describes this state. In other settings, the utility monitors everything and regulates watering depending on relative humidity. "Full Active Mode" describes this state. When activated for the first time, the system checks the weather. The rain causes the machine to sleep for about half an hour; otherwise, it will connect to the nearest open WiFi network [38]. The general flowchart of the threshold value algorithm is shown in Fig. 2.

2.6. IrrSchedult algorithm

The irrigation scheduling algorithm IrrSchedult employs the crop water stress index (CWSI) to establish the ideal timing and quantity of water required for a crop. The algorithm works by monitoring the crop's water stress level using infrared thermometry and using this information to schedule irrigation events. The IrrSchedult algorithm consists of four main steps. First: determine the crop's baseline temperature using infrared thermometry. Second: Measure the crop's canopy temperature regularly and calculate the CWSI using the following formula: CWSI = (T_c –

T_{min}) / (T_{max} – T_{min}), where Tc is the canopy temperature, T_{min} is the minimum temperature, and Tmax is the maximum temperature. Third: use the CWSI to determine the crop's water stress level. If the CWSI exceeds a predetermined threshold, the crop is considered under water stress, and irrigation is scheduled. Fourth: Calculate the amount of water to be applied based on the crop's water use rate and the time until the next irrigation event. Using the CWSI to schedule irrigation events, the IrrSchedult algorithm can help optimize water use, reduce water waste, and improve crop yield. However, it should be noted that the algorithm's effectiveness may be influenced by factors such as soil type, weather conditions, and irrigation system efficiency and may need to be calibrated to local conditions. Fig. 3 shows a diagram describing the irrigation scheduling algorithm "IrrSchedule" [39].

2.7. Decision Support System algorithm

The Decision Support System (DSS) algorithm can help improve irrigation management's efficiency and effectiveness by providing real-time information and recommendations to farmers and irrigation managers. By optimizing irrigation management, the DSS can help to reduce water waste, improve crop yield, and promote sustainable agriculture practices. The DSS algorithm employs basic constructs such as "IF," "ELSE," and "IF-ELSE" to achieve its objective. Data from sensors is used to make decisions; it simplifies the code with increased softness, efficiency, and performance [40]. Fig, 4 shows a graph describing the general structure of the DSS algorithm.

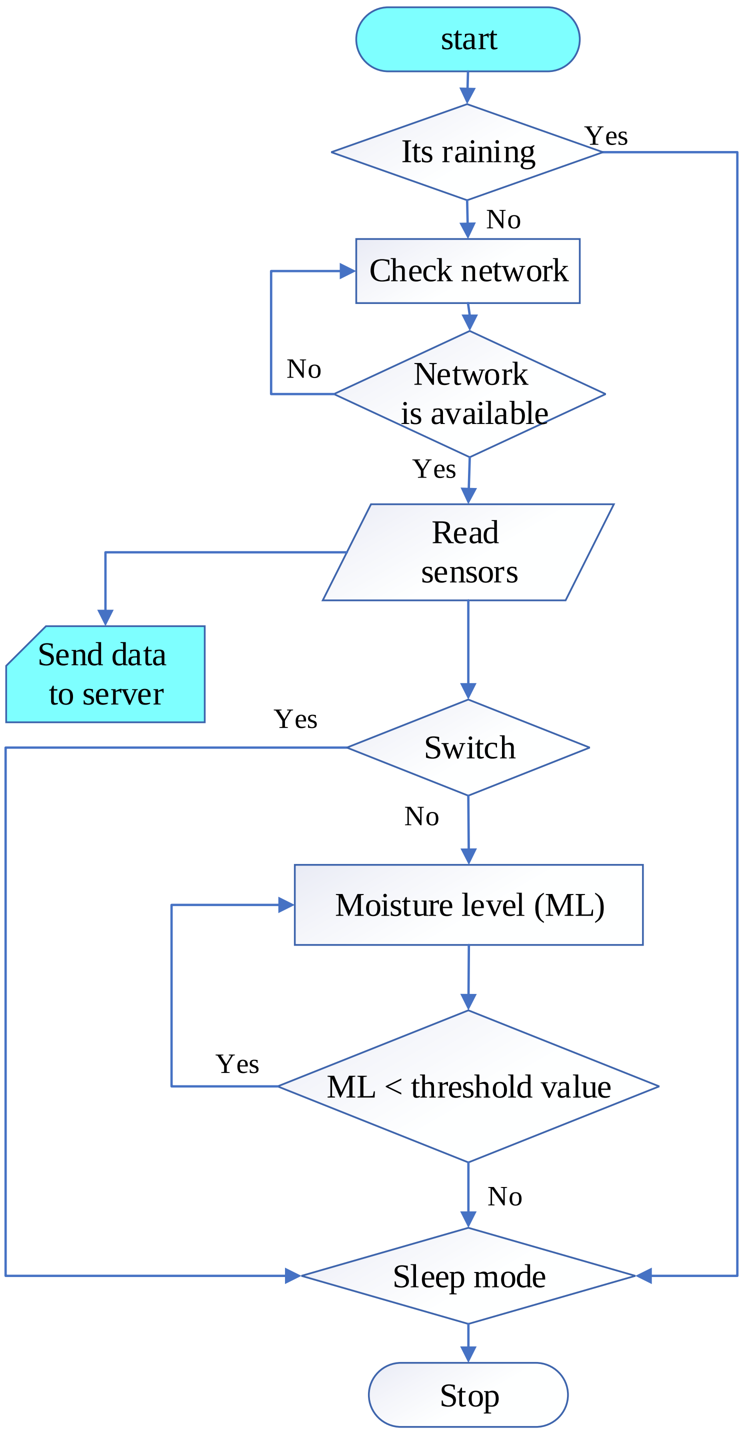

Fig. 2. General flowchart of threshold value algorithm

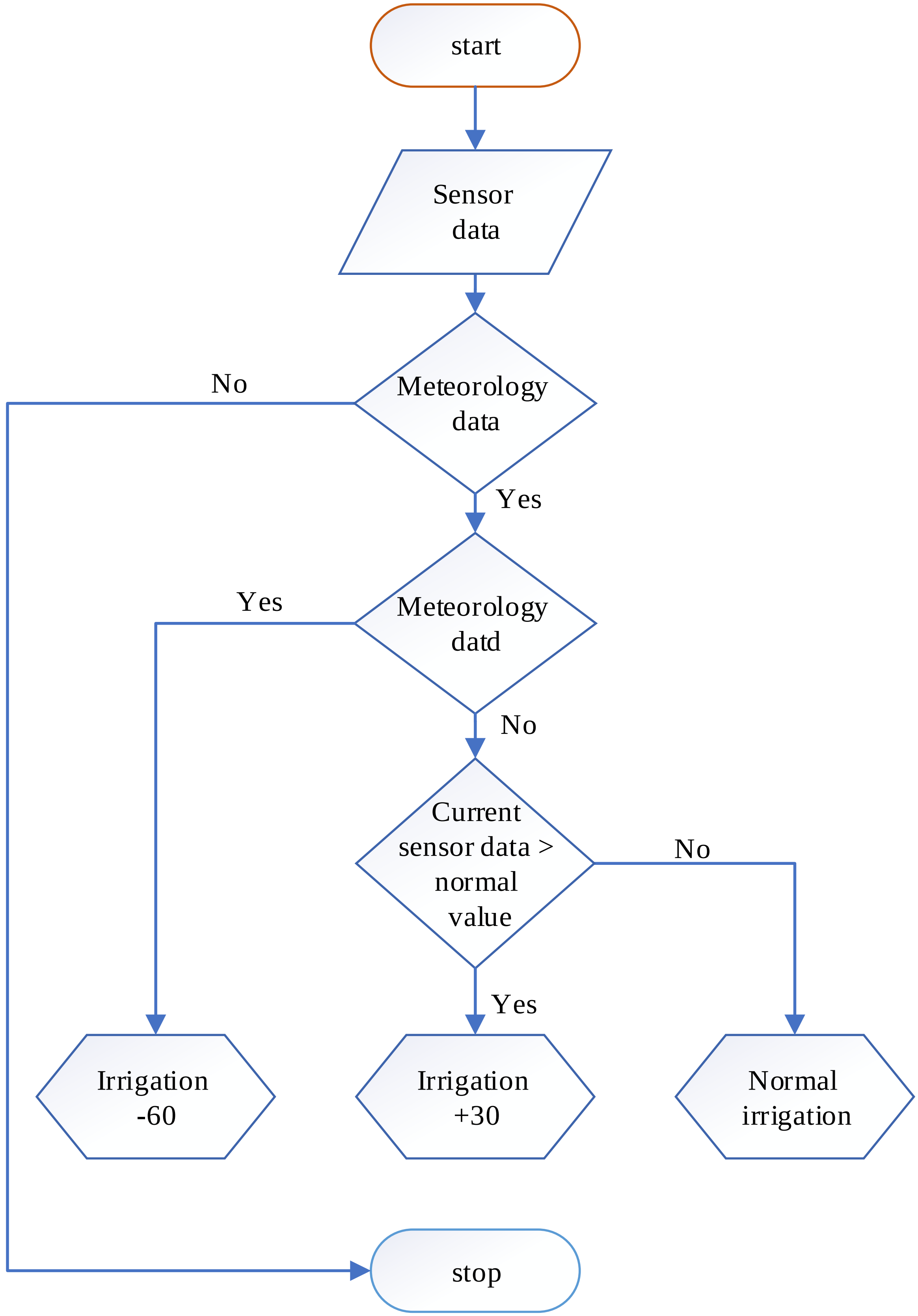

Fig. 3. Flowchart IrrSchedult algorithm [39]

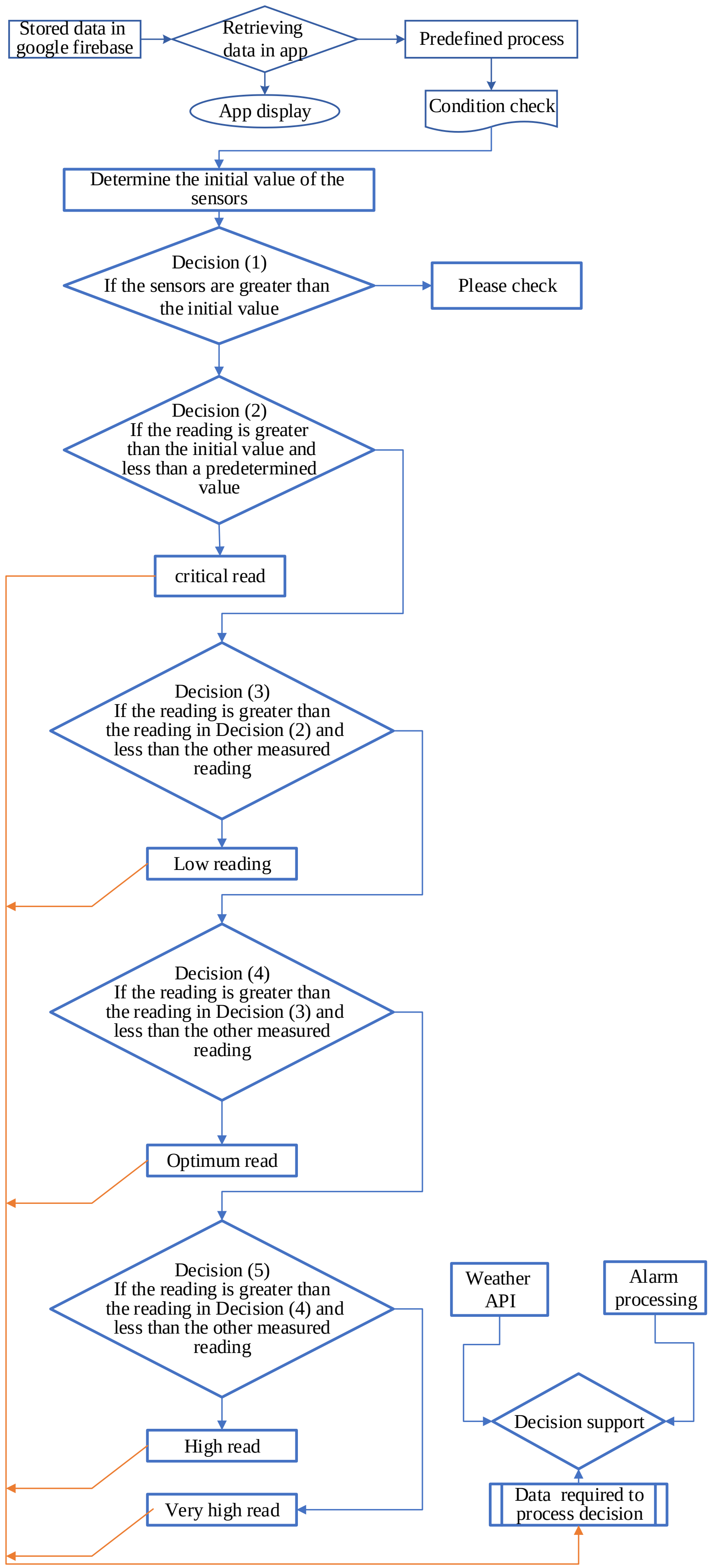

Fig. 4. General structure of DSS algorithm

3. Previous Works

With an emphasis on research from the last four years, this portion of the review examines the most recent advancements in intelligent irrigation systems. The recent works can be organized according to the adopted algorithm for irrigation systems as follows:

3.1. Previous works-based ANN

Using neural networks in irrigation systems allows for improved efficiency and precision in water management, leading to enhanced crop yields and resource conservation, as evidenced by various recent studies and developments built upon the ANN framework. Maroufpoor et al. [41] used a model to obtain the coefficient of uniformity (CU) values for the four sprinkler types: ZM22, ZK30, LUXOR, and AMBO. It is a reliable indicator for measuring water loss. The proposed design comprises a high-pressure electric pump, a water tank, a main pipe, regulator valves, a bypass pipe, gauges, a volumetric flow meter, a spray stand, sprinklers, and sample collection containers. ANN uses a coarseness index (nozzle sizes), average wind speed, and lateral spacing of the sprinkler to determine CU values. Experimental findings demonstrated that the suggested strategy lowers water loss. However, the magnitudes of the statistical indicators of the models used fluctuated significantly between the testing phases. Nawandar and Satpute.

According to the authors [42], a low-cost smart irrigation system was created that utilizes the Internet of Things to enable seamless communication and independent functioning of the devices employed in the system. The system consists of three units: An irrigation unit: which includes a water source, a water pump, and a pipeline. The control unit: It includes a soil moisture sensor, a moisture and temperature sensor, and a universal sensor pole (USP) that controls the sensors, sends data to the server, alerts the irrigation unit, and gets feedback from it. Moreover, it makes the decision based on the ANN. Remote monitoring module: It includes a message queuing telemetry transport (MQTT) broker that gets the sensor data sent by USP and an HTTP server for remote monitoring. The results showed that the proposed system saves water by 67% compared to traditional methods. However, the proposed system must manually enter the plant information and the soil type to create an irrigation schedule.

Kamyshova et al. [43] Suggested a way to improve agricultural irrigation effectiveness by integrating artificial neural networks and computer vision strategies. Eight IP cameras are connected via cable to a digital video recorder (DVR), connected to a laptop with an active internet connection on a center pivot irrigation. Build a database of ideal agricultural irrigation parameters and use neural network techniques to build dynamic maps of irrigation prescriptions to boost irrigation efficiency (ranging from layered artificial neural networks to pattern recognition and convolutional neural networks). Statistical evidence suggests improved efficiency in the use of water for irrigation. However, their implementation and maintenance costs are so exorbitant that their use is limited.

Veerachamy and Ramar [44] developed the Agricultural Irrigation Recommendation and Alert System (AIRA) to aid agriculture workers. The technology is designed to help agricultural engineers make the best irrigation choice possible by performing three primary functions. Several sensors, including a soil moisture sensor, an air humidity and temperature sensor, and a wind speed and intensity sensor, are used by the system to gather information from the field. Then, the gathered data undergoes processing in a hybrid classifier called k-N^4, which combines the k-nearest neighbor (k-NN) algorithm with ANN. The suggested k-N^4 algorithm is used to categorize the incoming data, alarm messages are created when water level and pressure are low, and a modified PSO algorithm based on gravity and fuzzy clustering is employed to arrive at the optimal irrigation option. In contrast, the M-RSA technique encrypts sensitive information while measuring low water levels. The findings indicated that the suggested method contributes to efficient water management, better data security, and future financial gains. However, the proposed system adopted soil, water, and climate data without any plantations in the field.

3.2. Previous works-based fuzzy control

Integrating fuzzy control in irrigation systems enables intelligent and adaptive decision-making processes, resulting in optimized water allocation and improved agricultural productivity, as evidenced by several recent studies and advancements built upon fuzzy control techniques. Li et al. [45] developed a fuzzy inference system-based real-time irrigation decision support system (IDSS) with relevant software. The purpose of the IDSS was to evaluate its effectiveness in supplying guidance for real-time irrigation planning and forecasting the timing of alfalfa harvesting. There are three primary components to the IDSS structure: first, the model for alfalfa growth is responsible for determining alfalfa height and growth dependent on temperature, which has been used to forecast when to harvest alfalfa. Secondly, the soil water model, responsible for soil water (SW) and alfalfa water consumption estimates made using weather prediction information. Thirdly, the fogging inference system determines the amount of irrigation using soil moisture and the difference in clover height between the expected and observed values. After gathering the data, IDSS uses a Fuzzy inference algorithm to create the irrigation time and volume needed to real-time schedule water. According to the results, the IDSS determined the optimal time and amount of irrigation needed for the irrigation system to operate efficiently. However, water savings, crop productivity, and spatial variability are not focused on in the development of IDSS.

Mounir et al. [46] suggested a smart watering system (SWS) for small and medium-sized gardens and fields. The Android app supports it. It includes a soil moisture sensor, a light intensity sensor, and an air temperature and humidity sensor. The proposed SWS uses blockchain and fuzzy logic to evaluate data and define an irrigation plan. After a decision is made by a fuzzy logic system based on the values of the input variables, SWS engages the actuators to carry out irrigation activities, turning ON/OFF the water tunnels periodically. The results of the proposed system show that it is a reliable and safe tool for plant irrigation management. However, the mechanism created for watering the plants needs manual intervention by the farmer.

Jaiswal and Ballal [47] introduced an automated irrigation controller based on real-time fuzzy inference. It consists of three units: the sensor network, which consists of the water level sensor, the soil moisture sensor, the air temperature sensor, the humidity sensor, and the control unit, based on the fuzzy inference system. GPRS-based communication module and Weblogger built on the Laboratory Virtual Instrumentation Engineering Workbench (LabVIEW) platform. The fuzzy logic control determines the percentage of valve opening based on the preset values of soil moisture, humidity, the water level in the tank, and air temperature. The availability-based tariff (ABT)-based tariff system also enables scheduling irrigation at a low-tariff time. The results showed that the proposed method achieves 45% water savings compared to previous studies. However, the proposed system is expensive in terms of first-time installation.

Krishnan et al. [48] presented an intelligent irrigation system that enables farmers to water their crops With the support of the Global System for Mobile Communication (GSM). The system provides signals of acknowledgement regarding its functions, such as soil moisture content, ambient temperature, and motor status regarding mains or solar energy. The fuzzy logic controller generates the motor state outputs, calculating input factors, including soil moisture, temperature, and humidity. Additionally, the device shuts down the engine to conserve energy when rain is forecast. Hand immersion and Drip irrigation were contrasted with the suggested system. The comparison findings show that the suggested intelligent irrigation system conserves water and energy.

Jamroen et al. [49] Presented an intelligent fuzzy-based method for irrigation scheduling using a cheap WSN. The proposed irrigation scheduling method considered soil moisture and the crop water stress index. In addition to the wireless transmission of sensor data, the system is based on two sensor complexes, the first of which includes an Arduino Uno, soil moisture sensors, infrared temperature sensors, humidity sensors, temperature sensors, and light sensors. The second component is the control unit, which includes the Arduino DUE, pump drive unit, pump, and thermometer. The experimental results showed the effectiveness of the proposed irrigation scheduling system concerning its accuracy and efficiency in terms of water use and energy consumption. Agricultural production increased by 22.58%, water use decreased by 59.61%, and electricity use decreased by 67.35%. Although CWSI shows promise, several factors limit its practical use.

Benyezza et al. [50] Developed a low-cost smart network irrigation system based on zoning using the IoT to reduce water usage and energy consumption. The network comprises four regions, each equipped with a sensor node that includes an Arduino nano microcontroller, batteries, a soil moisture sensor, a humidity sensor, a temperature sensor, a valve, and a data transceiver unit. Through radio frequency (RF) communications, the data collected by the network is transmitted to a Raspberry Pi server. An irrigation decision is made by a fuzzy logic controller (FLC), which processes this data. A Human Man Interface (HMI) has been created under the Node-RED server to facilitate the monitoring and controlling of irrigation from any location and at any time through the developed system. The results indicate that the proposed system achieved water savings of 26.41% and energy consumption reductions of 65.22%. However, it should be noted that providing an exact percentage of improvement is problematic because it needs to be evaluated in various aspects.

In a study by Parrazales et al. [51], a design for an FLC was proposed to enhance the watering process for rose plants. The system incorporates two sensors that measure air humidity and temperature, with the latter and relative humidity serving as the primary control variables. The FLC and membership functions were developed using the Mamdani method and a programmable gate array (FPGA) in a domestic greenhouse that housed a cluster of rose plants. The results showed that water consumption was reduced to 0.2 liters per week or up to 10.4 liters per year compared to traditional manual irrigation. However, the proposed design is a case that cannot be generalized because only one plant species and specific variants were used.

Singh et al. [52] developed an innovative fuzzy logic irrigation control system to automatically control water pumps used in agricultural greenhouses and farms. It has an Arduino, a soil moisture sensor, an air humidity and temperature sensor, a DC pump, and solar panels, and it is serially connected to a laptop. These sensors, along with the solar radiation taken from the characteristics of the solar panel, provide information that the Simulink model uses to control the speed of the water pump, turning it on and off. The results showed that the system reduced water usage, reduced costs, and reduced energy consumption. However, the irrigation process is not automated for a variety of plants or soils.

3.3. Previous works-based ANFIS

The utilization of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in irrigation systems offers a hybrid approach that combines the advantages of neural networks and fuzzy logic, leading to enhanced water management, increased crop yields, and sustainable agricultural practices, as evidenced by numerous recent studies and advancements in ANFIS-based research. A fuzzy inference system was developed by Mendes et al. [53] that considers the field's geographical variability and uses sparse or ill-defined information on the crop's phenophase from satellite photos to determine whether to speed up or slow down the central pivot to the critical choice-making for precise watering. The program adheres to the guidelines for variable rate irrigation (VR). The volume of provided water varies as soon as the speed does by management zones. Experiments showed the pivot operation's potential efficacy. The rotation speed control, however, does not consider the volume of the water layer that will be applied. Water demand will fluctuate in areas where plant growth is variable.

Kumar and Jayaraman [54] developed an adaptive neural fuzzy inference system (ANFIS)-PEGASIS-based irrigation system at a WSN using the IoT consisting of different sensors for monitoring environmental factors, including a light intensity sensor, a temperature and humidity sensor, and a soil moisture sensor. The best cluster head (CH) is chosen using a fuzzy inference system (FIS) method. The Sensor Information System (PEGASIS) power-efficient aggregation mechanism is used to collect data from irrigation systems, and the irrigation system relies on a decision-making strategy based on an ANFIS. The findings demonstrated the merits of the suggested technique in terms of energy utilization, packet delivery ratio, system life, throughput, and decreased waste of water. However, it has not been implemented in natural systems using sensor parameters, as it has only done simulations.

Liang et al. [55] utilized an adaptive prediction method to forecast the droplet infiltration effectiveness of sprinkler irrigation. The approach was implemented through an ANFIS model, and the irrigation system employed numerous components, including a fluid intensifier pump, charging controller, solar cell panel, storage battery, soil moisture sensors, irrigation pipe network, pressure valve, inverter, circuit controller, irrigation controller, strainer, check valve, and the main valve. The research findings indicate that maintaining a jetting pressure of 255.2 kPa, an impinging angle of 42.5, a water flow rate of 0.67 kg/min, and a continuous irrigation time of 32.4 min can ensure optimal and stable effectiveness prediction quality.

3.4. Previous works-based deep and machine learning algorithms

Integrating deep learning in irrigation systems enables the extraction of complex patterns from large-scale data, empowering accurate prediction and decision-making in water allocation, as demonstrated by several recent studies that have leveraged deep learning approaches. Kashyap et al. [56] suggested a smart irrigation system using IoT and deep learning for precision agriculture (DLiSA). The system consists of a rain gauge sensor, a soil moisture sensor, a sensor to measure air temperature and humidity, and a data router with Internet connectivity that make up the system. The volumetric soil moisture content, irrigation schedule, and water distribution throughout a given area are all predicted by DLiSA using a long-term memory (LSTM) network for the next day. For a year and a half, three locations were used to calibrate and test the proposed

DLiSA by adjusting the irrigation scheduling function. The results show a reasonably significant water saving with the proposed approach of up to 44.28%. However, a predictive irrigation plan that can also anticipate rainfall to maximize water availability using rainfall depths has not been developed.

Sami et al. [57] created an intelligent system based on long-term memory (LSTM) that utilizes predictive temperature, humidity, and soil moisture analysis to provide irrigation readings. This system also determines if a physical sensor is malfunctioning or transmitting incorrect values due to external factors affecting the system. The proposed solution is currently undergoing testing on a smart irrigation system (SIS) that includes physical sensors transmitting data on soil moisture, humidity, and temperature in the field. The physical sensors are replaced with a neural sensor, and the results demonstrate that the proposed neural sensor can predict essential values related to the SIS system successfully, aiding irrigation decisions and preventing system failures. However, a significant limitation of the deep learning-based neural sensors developed in this study is the requirement for large datasets during the training procedure. Additionally, there are few datasets available for farmers to use.

AlZu'bi et al. [58] developed a smart system that uses WSN to automate agriculture's irrigation process. The system includes a tank, a relay, a water pump, several cameras, a photo sensor, a raindrop sensor, an ultrasonic sensor, an Arduino Mega 2560, a breadboard, an ESP8266, a soil moisture sensor, a temperature and humidity sensor, and a light sensor. The proposed system aims to teach computers to see and understand information in various forms of media. The system relies on digital image processing (DIP) and the Internet of Multimedia Things to analyze images and determine when and where to make an irrigation decision. The experiments consisted of two distinct phases. Initially, a feature selection process was conducted to filter the relevant features for analysis. The CHI square feature selection method was employed to identify the top three features out of the initial set of eight. In the second phase, various classifiers were utilized to evaluate their performance in classification. This included the implementation of ANN, support vector machines, and random forests. Additionally, a convolutional neural network (CNN) was employed to address the classification problem. Remarkably, the CNN demonstrated superior performance compared to the other algorithms utilized in the study, showcasing its effectiveness in solving the classification task. According to the findings, the suggested method decreases water consumption and labour expenses. However, the suggested model takes a very long time to train.

Sanjeevi et al. [59] developed a smart irrigation system called Smart Irrigation System for Precision Agriculture and Farming (SIS-PAF) that utilizes the IoT and WSN for agriculture and farming in remote areas. The objective was to demonstrate the accuracy and intelligence of the system's devices, which enable decision-making for water management. The proposed system includes an Arduino UNO, humidity sensor, temperature sensor, soil feed sensor, ultrasonic sensor, light-dependent resistor sensor, transmitter, LCD, relay, and DC pump. The system is automated and operates in two stages: the first stage involves analyzing pre-loaded parameters on the server and making decisions on water supply using the ML algorithm. The water pump can also be controlled through web-based and mobile applications. While the proposed methodology has been shown to provide better performance for agriculture and water management in experimental settings, it requires real-time field monitoring to be effective.

Boursianis, et al. [60] presented a smart irrigation system named AREThOU5A. It uses cutting-edge technologies, including the Internet of Things and ML algorithm, for efficient water usage in diverse agricultural settings. The suggested method combines satellite data from the International Weather Forecast Services with wireless sensor network data from the field via temperature and soil moisture sensors. The user interface subsystem receives the gathered data online and uses it to make irrigation choices. The outcomes of the suggested strategy for managing irrigated water in agriculture were good. However, to assess its effectiveness, it must install a rectenna module in different IoT nodes inside an agricultural field.

3.5. Previous works-based other algorithms

Applying other algorithms, including threshold-based methods, Kalman filtering, PSO, and more, in irrigation systems provides diverse approaches for efficient water management, crop yield optimization, and sustainable agricultural practices, as evidenced by numerous recent studies and advancements in this field. Borah et al. [38] Created a lightweight, low-cost, and energy-efficient IoT-based irrigation control system using the threshold value algorithm. Measuring soil irrigation variables using a moisture sensor, a soil temperature sensor, and a moisture and air temperature sensor. In addition, using the ESP-12F8266 as the primary microcontroller for irrigation system tracking and management, cloud-based data monitoring and storage are free and open source. A 12-volt lithium-ion battery is charged using solar energy. The results show that the proposed threshold value algorithm improves energy efficiency while reducing water loss by up to 60% compared to traditional irrigation methods. However, this technique was not used in large fields and was only active during one growing season yearly.

Arshad et al. [40] Established a Decision Support System (DSS) system using WSN, an Android application, and a long-range (LoRa)-based platform to automate environmental parameters to produce optimal crops and reduce water loss. The core components of the proposed model are a controlled fertilizer unit, a smart irrigation system, and a smart sensor unit. The smart sensor module includes a temperature sensor, a soil moisture sensor, a humidity sensor, a soil conductivity sensor, a nutrient, phosphorous, potassium (NPK) sensor, and a pH sensor, all of which stats can be transmitted to the cloud via serial peripheral interface SPI-based communication (LoRa) over the Internet. Using accurate field data, smart device decisions can now be made in real time. The results showed that the system helped reach long-term economic goals by improving production and reducing water waste in agriculture. However, the prototype is compatible in certain areas with a small range and cannot extract parameters from encoder sensors.

Karunanithy and Velusamy [61] created Efficient Scalable Data Collection Scheme (ESDCS) employing WSNs . to estimate how much water with fertilization a crop will need. The smart irrigation system with fertilization consists of several parts: a data collection drone, a microcontroller, storage, I/O interfaces, communication modules (Zigbee, WiFi, GSM), soil moisture sensors, air temperature sensors, air humidity sensors, sensors for wind speed and sunlight, and water pumps. The study's findings revealed that, in comparison to the existing irrigation system, the suggested approach only utilizes 25.08% of the water. System restrictions on high consumption of fertilizers as a result of improper fertilizer application and placement. Mannan et al. [39] developed an IoT-based smart irrigation system to decrease labour, energy, and water use for irrigation. It is built with various sensors that measure wind speed, water, humidity, temperature, soil moisture, and light to gather information about agricultural fields and store it in the cloud to calculate irrigation schedules. The results showed that this system reduced labour costs, electricity consumption, and water consumption by up to 18.7%. However, executing in a small agricultural area with various crops is not easy.

Scarlatache et al. [62] presented an innovative hybrid method for managing irrigation system pump motors. The primary aim of this approach is to minimize the power required to pump 1,000 cubic meters of fluid. Make irrigation decisions with the help of an ES, a computer program that can handle large amounts of high-quality data and use that information to mimic the judgment of a human expert. MATLAB was used to design and build the hybrid approach, which has a pumping array of five pumps rated at 160 kW. The results indicated that the proposed approach is the most effective means of managing irrigation systems in terms of reducing energy use. However, the scenario with all five pumps running was not studied because the experimental station did not use all the pumps during the field measurements.

Abioye et al. [63] demonstrated the practical application of the Kalman filter-proportional integral derivative (KF-PID) controller for a subsurface fibrous capillary irrigation system. Using their approach, a substantial decrease in water consumption was observed compared to other irrigation methods. The proposed approach involves various modules, including a soil moisture sensor, a water level sensor, a camera, a Node MCU, and a Raspberry Pi for the sensor module, a water tank, a pump, and an ultrasonic sensor to measure the water level in the tank for the water supply module, and an Internet of Things-based weather station. The data collected from these modules is transmitted to the cloud for irrigation decisions. The results indicated that the application of the KF-PID controller in the proposed approach led to a water saving of 56.3% hand an increase in productivity. Nevertheless, the capillary movement of water through fibrous materials can lead to the accumulation of salts in the cultivation medium, thereby increasing soil salinity.

Table 1 shows several intelligent irrigation technologies, the types of sensors used, the types of data transmission devices, and the types of algorithms used to control the irrigation process, as well as the percentages of water saved and the problems with each of the earlier works.

Table 1. Comparison between previous works on irrigation systems

Ref/ year	Sensor type	Method of transfer sensing data	Platform	Method of irrigation	Algorithm	Water saving (%)	Limitation
[41]/2019	Weather station sensors	N/A	Sprinkler water distribution	Sprinkler	ANN	N/A	The magnitudes of the employed models' statistical indicators oscillate noticeably between the test phases.
[42]/2019	Soil moisture sensors temperature and humidity sensor	MQTT and HTTP	Intelligent watering system	Automatic irrigation	ANN	67%	The system needs to manually enter the information of the plant to be planted and the soil type to create an irrigation schedule.
[45]/2019	Weather websites	Wireless data	Real-time irrigation decision support system	Pivot irrigation	Fuzzy	N/A	water savings, crop productivity, and spatial variability are not focused on in the development of IDSS
[46] / 2019	Soil moisture sensor, a light intensity sensor, and an air temperature and humidity sensor	Wi-Fi Module ESP 8266–01	Smart watering system (SWS)	Irrigation schedule	Fuzzy	N/A	The mechanism created for watering the plants needs manual intervention by the farmer.
[53]/ 2019	Soil moisture, canopy temperature, and vegetation index,	Satellite images	Variable rate irrigation	Pivot irrigation	ANFIS	N/A	Does not consider the volume of the water layer that will be applied. Water demand will fluctuate in areas where plant growth is variable.
[58] / 2019	A raindrop sensor, an ultrasonic sensor, a soil moisture sensor, a temperature and humidity sensor, and a light sensor	ESP8266	Efficient employment of the Internet of multimedia things	Automatic irrigation	CNN	N/A	The suggested model takes a very long time to train.
[54]/ 2020	Light intensity sensor, a temperature and humidity sensor, and a soil moisture sensor	IoT	Irrigation control system	Automatic irrigation	ANFIS	N/A	It has not been implemented in real systems using sensor parameters, as it has only done simulations.
[59]/ 2020	A humidity sensor, a	Wireless connection	Precision agriculture	Irrigation Automatic	ML	N/A	It needs real-time field monitoring.

	temperature sensor, a soil feed sensor, an ultrasonic sensor, a light-dependent resistor sensor						
[47]/2020	Soil moisture, humidity, air temperature, and water level sensors	GSM/GPRS	Fuzzy inference-based irrigation controller	Drip irrigation	Fuzzy	45%	The proposed system is expensive in terms of first-time installation.
[61]/ 2020	Moisture sensors, air temperature sensors, air humidity sensors, sensors for wind speed and sunlight	Zigbee, WiFi, GSM	Intelligent water irrigation and fertigation	Drip irrigation	Travelling salesman problem (TSP)	25.08%	System restrictions on high consumption of fertilizers as a result of improper fertilizer application and placement
[48]/ 2020	Soil moisture sensor air temperature and humidity sensor	Web server using RS232 data bus	Smart Irrigation System	Drip irrigation and manual irrigation	Fuzzy	N/A	Future research may incorporate IoT-based intelligent farming technology to help farmers and producers reduce waste and improve productivity across various metrics, from the calibre of fertilizers used to the volume of crops produced.
[39]/ 2020	Measure wind speed, water, humidity, temperature, soil moisture, and light sensors	Internet of Things and cloud computing	Intelligent Scheduling on the Cloud for IoT	Sprinkler	IrrSchedule	18.7%.	Executing in a small agricultural area with various crops is not easy.
[38] / 2020	Moisture sensor, a soil temperature sensor, and a moisture and air temperature sensor	ESP-12F8266	Irrigation monitoring and control	Automatic flow irrigation	Threshold-based value	60 %.	This technique was not used on large fields and was only active during one growing season annually.
[49] / 2020	Soil moisture sensors, infrared temperature sensors, humidity sensors, temperature sensors, and light sensors	NRF24L01	Intelligent Irrigation Scheduling System	Surface drip irrigation	Fuzzy	59.61%	There are limitations to the potential use of CWSI in practical implementations.
[55]/2021	Soil moisture sensors	Wire connection	Sprinkler irrigation system	Sprinkler	ANFIS	N/A	There has been no evaluation of the suggested system at temperatures greater than 30 degrees Celsius.
[50]/2021	Soil moisture, and temperature	RF communication	Zoning irrigation Smart system	Drip irrigation Furrow irrigation Sprinkler irrigation Flood irrigation	Fuzzy	26.41%	It is not easy to give an exact percentage of improvement because it needs to be compared in many aspects

[56]/ 2021	Rain gauge sensor, a soil moisture sensor, a sensor to measure air temperature and humidity	Internet	Deep Learning Neural Network	Sprinkler irrigation	DLiSA	44.28 %	a predictive irrigation plan that can also anticipate rainfall to maximize water availability using rainfall depths has not been developed.
[62]/ 2021	N/A	N/A	A Hybrid Methodology to Irrigation System	N/A	ES	N/A	The scenario with all pumps running was not studied because the experimental station did not use all the pumps during the field measurements.
[51]/ 2021	Air temperature and humidity sensor	Wire connection	Fuzzy Logic Controller for the Irrigation	Micro sprinkler irrigation	Fuzzy	N/A	The proposed design is a case that cannot be generalized because only one plant species and specific variants were used.
[60]/ 2021	Soil moisture sensors, and temperature sensors	Internet and LoRaWAN	Smart Irrigation System	Irrigation Automatic	ML	N/A	To assess its effectiveness, it needs to install a rectenna module in different IoT nodes inside an agricultural field.
[43] / 2022	-	Wireless connection	Phytoindication System	Center pivot irrigation	ANN	N/A	Their implementation and maintenance costs are so high that their use is limited.
[57]/ 2022	Soil moisture sensor air temperature and humidity sensor and neural sensor	Wireless connection	Sensor Modeling	N/A	Deep learning-based LSTM	N/A	1. Use large data sets as inputs during the training procedure. 2. There are few datasets available for farmers to work with.
[40]/ 2022	Soil moisture sensor, a temperature and humidity sensor, a soil conductivity sensor, a nutrient, phosphorous, and potassium (NPK) sensor, and a pH sensor	LoRaWAN	Smart Agriculture Decision Support System	Irrigation Automatic	Decision Support System (DSS)	N/A	The prototype is compatible in certain areas with a small range and cannot extract parameters from encoder sensors.
[52] / 2022	Soil moisture sensor air temperature and humidity sensor	Serial communication	Intelligent Control of Irrigation Systems	N/A	Fuzzy	N/A	The irrigation process is not automated for a variety of plants or soils.
[44]/2022	Soil moisture sensor, an air humidity and temperature sensor, and a wind speed and intensity sensor	Wireless connection	Agricultural Irrigation Recommendation and Alert (AIRA)	N/A	Combine k-NN with ANN and combine fuzzy with PSO	N/A	The proposed system adopted soil, water, and climate data without any plantations in the field.
[63]/2023	Soil moisture sensors and water level sensors	Nod MCU	Capillary irrigation system	Capillary	Kalman	56.3%	Soil salinity increases as salts accumulate in the cultivation medium due to the upward movement of water through fibrous capillary materials.

4. IoT in Irrigation Systems

The IoT is an ecosystem of connected devices that can collect and share data via the Internet. In an irrigation system, IoT can significantly increase efficiency, reduce water waste, and improve crop yield [64]. Here are some ways in which IoT can be used in irrigation systems. Soil Moisture Sensors: IoT-enabled soil moisture sensors can be used to monitor the moisture content of the soil in real-time [65, 66]. This allows farmers to apply water precisely when needed, avoiding water waste and reducing the risk of overwatering, which can lead to plant diseases and stunted growth. Weather Stations: Weather data is critical in determining when to water crops. IoT-enabled weather stations can provide accurate, up-to-date temperature, humidity, wind speed, and precipitation information. This information can help farmers decide when and how much to water their crops [67]. Automated Irrigation Systems: IoT can automate irrigation systems, saving time and labour costs [68]. An automated system can be programmed to turn on and off at specific times or when specific conditions are met, such as when soil moisture levels reach a certain threshold. Remote Monitoring: IoT-enabled irrigation systems can be remotely monitored and controlled using a smartphone or computer [69]. This allows farmers to monitor their crops and adjust the irrigation system as needed, even when not on the farm [70]. Predictive Analytics: By analyzing data collected from IoT sensors and weather stations, predictive analytics can be used to forecast crop water needs. This can help farmers plan irrigation schedules and conserve water [66, 71].

5. Challenges and Limitations

This section will discuss the challenges and limitations of implementing WSN, AI, and IoT in irrigation applications.

5.1. Challenges and limitations of WSN in irrigation

The use of WSN in intelligent irrigation systems has the potential to significantly improve the efficiency of water usage and crop yields [24, 72]. However, implementing such systems must address several challenges and limitations [73, 74]. Here are some of them:

- Sensor Deployment: Sensor deployment is one of the most critical factors affecting the performance of the WSN-based irrigation system. Proper placement and calibration of sensors are essential for accurate data collection and interpretation.
- Energy Constraints: Wireless sensors require a power source, and batteries have limited lifespans. In agricultural settings, limited access to a stable power source can pose a challenge.
- Communication Challenges: Communication in agricultural settings can be challenging due to obstacles such as trees, hills, and other environmental factors. This can lead to delays in communication or data loss, which can impact the system's performance.
- Sensor Accuracy and Maintenance: Sensor calibration and maintenance can be time-consuming and require specialized knowledge. Sensors must be calibrated regularly to ensure accurate data collection, which can be difficult and expensive to implement in large-scale systems.
- Data Processing and Analysis: Collecting data from multiple sensors can result in a vast amount of data that needs to be processed and analyzed in real-time. This requires powerful AI algorithms and computing infrastructure, which can be expensive and challenging to implement in remote agricultural settings.
- System Complexity: Implementing a WSN-based irrigation system requires expertise in both fields, which may be difficult to find in rural agricultural areas. The system also needs to be user-friendly for farmers to use and maintain.
- Cost: Implementing a WSN-based irrigation system, especially for small-scale farmers, can be expensive. The cost of sensors, communication infrastructure, and computing resources can be significant barriers to adoption.
- Compatibility with existing irrigation systems: In many cases, WSN-based systems must be integrated with existing irrigation infrastructure. This can be challenging due to the different protocols and technologies used in the systems.

5.2. Challenges and limitations of AI in irrigation

AI can potentially improve the efficiency and effectiveness of irrigation systems [75]. However, several challenges and limitations must be addressed to implement AI in irrigation [76, 77] successfully. Here are some of them:

- Data availability: AI algorithms require large amounts of data to learn and make accurate predictions. However, in many regions, data on soil moisture, weather patterns, and crop growth may be limited or unreliable, which can impact the accuracy of the predictions.
- Sensor reliability: Sensors collect data on soil moisture and other environmental factors. However, sensors can be expensive to install and maintain, and their accuracy can be affected by temperature, humidity, and electromagnetic interference.
- Power supply: Many irrigation systems are located in remote areas with limited or no access to electricity. AI-powered irrigation systems require a stable and reliable power supply to operate effectively.
- Cost: Implementing an AI-powered irrigation system can be expensive, and the initial investment may be difficult to justify for small-scale farmers.
- Limited technical expertise: Farmers may lack the technical expertise required to operate and maintain AI-powered irrigation systems, which can limit their adoption.
- Unforeseen challenges: AI algorithms can be affected by unforeseen events, such as extreme weather patterns or pests, which can impact their accuracy and effectiveness.
- Privacy and security concerns: The data collected by AI-powered irrigation systems may be sensitive, and there are concerns about how this data is stored, processed, and shared. There is also a risk of cyber-attacks that could compromise the system's security.

Addressing these challenges and limitations is essential for successfully implementing AI in irrigation systems.

5.3. Challenges and limitations of IoT in irrigation

Several challenges and limitations are associated with using IoT in irrigation systems [78, 79]. Some of them are:

- Data Security: Since IoT devices are connected to the internet, they are vulnerable to cyber-attacks, which can compromise the security of the data collected. This is a significant concern for farmers who rely on IoT devices for irrigation management.

- High Initial Cost: The initial cost of installing IoT devices can be high, which may deter some farmers from adopting this technology. However, it is essential to note that the long-term benefits of IoT in irrigation can outweigh the initial cost.
- Technical Complexity: The implementation and maintenance of IoT devices can be technically complex, requiring specialized skills and knowledge. This can be a challenge for farmers who may not have the technical expertise required.
- Limited Connectivity: In some rural areas, internet connectivity may be limited or unreliable, making it challenging to use IoT devices effectively.
- Data Overload: The large volume of data generated by IoT devices can be overwhelming, making it difficult to interpret and use effectively. This requires using advanced analytics tools to derive meaningful insights from the data.
- Power Supply: IoT devices require a continuous power supply to function effectively, which can be challenging in areas with limited or unreliable power supply.

6. Maturity evaluation

This paper aims to provide a comprehensive overview and analysis of the current state of knowledge regarding the performance evaluation of intelligent irrigation systems to promote the sustainable future of irrigated agriculture. The article focuses on the principles, techniques, and methodologies employed in assessing the effectiveness of intelligent irrigation projects. The evolution of ideas for evaluating irrigation effectiveness and various models used for this purpose is presented. Multiple techniques have been developed and utilized to measure and analyze the efficacy of intelligent irrigation systems, including FL, NN, ML, ES, and ANFIS, each of which is discussed in detail. However, despite the variety of suggested criteria in the literature for characterizing performance assessment, there is no single unified method for comparing the effectiveness of different intelligent irrigation systems. Thus, factors such as irrigation systems, soil types, plant varieties, and climate conditions are crucial in determining the appropriate assessment framework and approach to utilize.

7. Conclusions

Iraq is among the countries facing severe water shortages, underscoring the importance of having an effective water management system. Agriculture, which consumes significant water, is one of the most pressing water waste problems. In response to climate change, there have been discussions on implementing water management technologies to ensure adequate water supply for agricultural use. To reduce water wastage in irrigation, numerous studies have focused on developing solutions to this issue. This study aims to provide insight into IoT irrigation systems for the agricultural sector. We have compiled a list of the most common irrigation water quality, soil, and climate characteristics and the most popular wireless technologies and nodes for deploying IoT systems and WSNs in agricultural irrigation. Additionally, we have examined the most prevalent AI algorithms utilized in irrigation management planning over the past four years. The ultimate goal is to develop an intelligent and efficient irrigation system that conserves water and energy.

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