Water Resource Optimization by using a Hyper Parameter Tuned LSTM of a Smart Agriculture

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***Abstract*—The growing need for food and water throughout the world has put precision agriculture in the spotlight lately. In order to fulfil this demand, farmers will require access to water and fertile land. Farmers need a solution that alters their operations since both resources are scarce. The key to producing larger, better, and more lucrative crops with less resources is precision irrigation. To enhance water utilization efficiency, several machine learning-driven irrigation models have been proposed. However, these models face challenges in regions with unpredictable climates due to their limited learning capabilities. This study introduces an intelligent irrigation system for precision agriculture, leveraging the Internet of Things (IoT) and deep learning neural networks. This system, incorporating feedback mechanisms, exhibits sustained performance over time, independent of local weather conditions. A long short-term memory network (LSTM) is employed to predict irrigation schedules, required water amounts for agricultural land, and the geographic allocation of water. Simulation results unequivocally demonstrate that, in the experimental agricultural area, this model surpasses the efficiency of the most recent models in water utilization.**

Keywords— Precision agriculture geographical distribution, Internet of Things, long short-term memory network

I. INTRODUCTION

The global population is expected to reach 9.8 billion by 2050, up from its present 7.7 billion people, if growth rates of 1.1% per year are sustained[1]. Earth's freshwater resources and arable land are also at danger due to rising urbanisation and climate change. Agriculture is the key industry that will feed this massive population and support worldwide sustainable economic development. Freshwater makes up the remaining 3% of the world's water, with 97% of it being salty[2]. Approximately two-thirds of Earth's freshwater is confined within polar ice caps and glaciers, with only the remaining one-third contributing to the flow in rivers, lakes, or underground sources [3]. 70% of freshwater used for irrigation is used for agriculture in the majority of developing nations [4]. Efficient use of freshwater during irrigation is thus the most crucial factor to save expenses (such as power bills and time) related to increasing crop yields.

Around 50% of water is lost by typical irrigation systems since irrigation is timed globally based on farmers' eye inspections of the crops [5]. Water volume waste is decreased by 30–70% using controlled irrigation techniques as furrow, drip, and sprinkler irrigationthe open-loop design of these systems makes it impossible to precisely control the soil water content, leading to a decrease in crop yield and quality. This is because either too much or too little irrigation removes nutrients from the soil [6]. Achieving efficient water usage without compromising crop development requires feedback on integrated precision irrigation strategies. To maximise agricultural yields while lowering labour expenditures, precision irrigation takes meteorological data, rainfall depth, soil moisture, and crop type into account to predict the precise quantity of water and irrigation time required.

Smart agriculture is made possible by the Internet of Things (IoT), which connects various soil sensors wirelessly, as well as sensors that are aware of their surroundings, a variety of hardware (including sprinkler systems, water motors, solar system machinery, etc.), and applications for analysing data. This helps farmers with difficult agricultural tasks like soil preparation, water feed computation, yield forecasting, etc., all through the growing and harvesting cycles[7]. Using the main significant farmed field parameters—soil moisture content and climatic data—a number of mechanistic irrigation scheduling algorithms have been presented to predict the amount of water to be applied at certain intervals of time[8][9]. Programmable irrigation systems with an open-loop design can't keep soil nutrients in the soil and produce crops that show promise since they can't provide the best irrigation planning options. In addition, there aren't any models in these methods to deal with the real-time dynamics of soil moisture levels, which means that the irrigation system would ultimately be inflexible in the face of varying climates and geographical locations[10].

Data-driven machine learning (ML) models have gained popularity in recent years as a better way to estimate soil moisture content in irrigation [11][12][13][14] than physical/mechanistic models [10][15]. This is due to the comparison to mechanistic model calibration, data-driven approaches require fewer variables for calibration. Furthermore, machine learning models have superior predictive accuracy compared to physical models and can analyse spatial and temporal data with ease and speed. A closed-loop controller is a key component of machine learning model irrigation technologies. By comparing pre-processed data with real-time data captured over the same period, it compares and analyses feedback to provide calibration variables. Authors in[12][13]proposed a fuzzy-logic decision-making method to figure out the optimal watering schedule as well as assess volumetric soil moisture content, whereas in [14], For the purpose of estimating water, a Neural Network based model was created, applying a water stress threshold value. The previously described classical machine learning techniques work well on physical models but are not adaptable to changing environmental circumstances, that is, they can't be applied to other domains. These models can only be used to the places where the data needed to build and calibrate them was originally collected.

In complex agricultural systems with time-series dynamics, limited learning capacity causes conventional artificial neural networks to lose knowledge from previously processed data and become chaotic.

The capacity to use memory cells to store information from prior time steps is a feature that Recurrent Neural Networks (RNN) provide to the standard feedforward neural networks (FFNNs) [16]. The Long Short-Term Memory (LSTM) network, a specialized form of Recurrent Neural Network (RNN), leverages powerful learning capabilities by incorporating self-looping memory cells to effectively evaluate volumetric soil moisture content. Tailored for this particular application, the LSTM excels in analysing extended time series dynamics concurrently, allowing it to adeptly capture and depict the complex nonlinear relationships existing between input and output variables [17]. Within the framework of NASA's soil moisture active passive mission, the authors of [18]have proposed a deep learning-based algorithm for soil moisture content forecasting[19]. Using temperatures, precipitation, rainfall, and water diversions as temporal dynamics, predict the depth of irrigation. It takes time for the aforementioned algorithms to predict soil moisture content since they cannot self-adapt to new locations. The authors of [20]found that the performance of the LSTM-based framework is better to that of the standard NN model.

Addressing the existing challenges, the research presents a smart irrigation system for precision farming that uses deep learning neural networks and incorporates IoT features. Additionally, the model uses LSTM RNN models and analyses past soil and weather data to predict the volumetric soil moisture content for the next day. The suggested strategy employs a closed-loop methodology that incorporates input from climate and soil sensors to maintain greater functioning in any region's unpredictable environment.

The following are the paper's main contributions:

- To start, a precision irrigation system model is shown, which consists of an IoT network sensor model for farms and a smart irrigation model.
- The second point is that the LSTM RNN model may be trained in a single step to forecast the volumetric soil moisture for the next day.
- The next step is to see how the irrigation scheduler can decide whether watering is required. When watering is required, the quantity of water to be utilised is calculated, and the time needed to water is evaluated by comparing the flow rate and the deployment of sprinklers.
- The fourth intelligent irrigation method is based on LSTM RNN and includes a temporal complexity study.
- In the end, real time-series data from three separate places are used to validate and fine-tune the proposed model. Furthermore, state-of-the-art algorithms that predict soil moisture, water deficit, and irrigation volume monthly are compared to the performance.

The rest of the document is structured like this: Section II evaluates relevant literature. Smart irrigation systems that are enabled by the Internet of Things are detailed in Section III. In Section IV, the findings are reviewed and addressed. The last section of the document is the conclusion.

II. LITERATURE REVIEW

This section provides a brief description of the smart irrigation systems found in the literature that showcase various approaches to water management. It notes the sources of these systems' field demonstrations, the technologies that have been adopted, and the different communication protocols that are used in their implementations.

In this paper, [21] Studies in different contexts have shown that the LSTM method outperforms Backpropagation in terms of prediction accuracy. In comparison to back propagation, which produces RMSE values of 0.10 for backpropagation and 0.8 for LSTM in smart agricultural applications, this research examines how LSTM improves predictions.

The study suggests,[22]a multi-tiered design called an anomaly detection systems to proactively handle the infrastructure hazards associated with smart agriculture. The proposed layout relies on a machine-learning algorithmic strategy that is built upon LSTM and multivariate linear regression (MLR). An authentic dataset collected from smart agricultural systems in Apulia, Italy, was used to test the anomaly detection method.

[23]Using RGB-D sensors, temperatures, and wetness, humidity of the air, and pH, a tracking system has been created by the researchers that uses WSN and cloud computing to control variables and collect data on the soil in the field. This approach aims to enhance agricultural yields. The sensors will gather data, which will then be uploaded to a cloud server for analysis. The field-installed sensor devices may sustain damage or cease to function, or another problem with our system—such as a compromised sensor's security—may arise.

In this paper,[24]The smart irrigation solution for the agricultural sector, the ARETh0U5A IoT platform was described in detail by the writers. The writers outlined the platform's IoT nodes. Experimental data shows that the constructed rectenna functions effectively as an ambient source harvester in an outdoor environment.

According to, [25]The "ACRIS: Agriculture Cultivation Recommender and Smart Irrigation System" that this research suggests will assist farmers in using IoT in precision agriculture to boost crop yield. In order to reduce water use and increase output, farmers who use precision agriculture may use this module to anticipate soil moisture and schedule irrigation. In order to guarantee ideal crop growth and water stability, the "AMOP System" module combines IoT technologies into agriculture and analyses water content at various stages of plant development.

A LoRa-based machine learning (ML) system for monitoring and scheduling precise irrigation via the Internet of Things is presented in the proposed work[26]. Utilising the data from the soil moisture sensors, we designed a separate irrigation method that would give the tomato and aubergine the exact quantity of water they needed. When compared to conventional watering, which needed 8755 mL for rice and 7541 mL for banana plants, the irrigation system watered the plants with a total volume of 4421.09 mL and 5010.745 mL in a single month.

This article suggests,[27]a smart system that integrates machine learning, IoT and long-range, low-power wireless sensor networks (LoRa) for precise crop planning and tracking. The suggested system is capable to anticipate when irrigation will be necessary since it makes use of machine learning techniques. A collection of soil and climatic characteristics acquired from sensor use is subjected to six different machine learning techniques; the most effective approach in terms of forecasting irrigation schedule is chosen.

This article reviews,[28] the wide range of research on deep learning applications in agriculture, covering basic DL methods and the detection of pests, diseases, yield, weeds, and soil. The study suggested a bootstrapping method for transfer learning that combines freshly constructed fully connected layers with optimised and enhanced VGG16 for pest identification. The findings demonstrate that, with an accuracy of 96.58% and a loss of 0.15%, the suggested model for pest identification works better than any other model.

In this article, [29]had provided an overview of the present status of IoT irrigation systems in farming. The criteria that are most closely watched to assess soil, weather, and irrigation water quality have been determined. In order to establish IoT and WSN systems for agricultural irrigation as well as the most widely used wireless technologies, and also determined which nodes are used the most.

This article presents,[30]the evolution of the (IoT) and irrigation, the elements that must be taken into account for efficient irrigation, the need of optimising irrigation, and the possibility of conserving water via dynamic optimisation of irrigation. The article covers a lot of ground, including the various models for deploying the IoT, detectors, and regulators employed in farming, current cloud platforms for the IoT, popular applications for scheduling watering and predicting water needs, and algorithms for irrigating that use machine learning and neural networks for learning.

The primary aim of this research, [31]aims to protect communication in intelligent irrigation systems by putting in place a lightweight security protocol. Among publishers and the MQTT protocol broker, and also amongst the broker and its subscribers, a secure channel is created using the approved encryption technique (Expeditious Cypher). We recommended using MQTT as the Internet of Things application protocol for communicating within the watering system since it is an energy- and bandwidth-efficient protocol.

In this article, [32]creating an intelligent watering system that takes weather and soil conditions into consideration respectively. A range of research papers in ML and Agriculture 4.0 are used to choose the weather and soil properties. The planned weather station and the many patents that have been produced are also contrasted in the text.

This article establishes, [33]an approach to detect and classify security incidents in agricultural IoT systems. Fundamental security and privacy concerns affect all Internet of Things (IoT) applications, including agricultural ones. The NSL KDD dataset is used as the input dataset for this approach. A numerical representation of the NSL-KDD data set's symbolic features is achieved by pre-processing. PCA is used to extract features.

This study, [34]every component of the deep learning predictor's sequentially two-level decomposing form, involving serially dividing the weather data into four parts, used trained gated recurrent unit (GRU) networks as sub-predictors. After some time of merging the GRU findings, the results for the medium- and long-term predictions were achieved. Using meteorological data from an IoT system in Ningxia, China, the tests of the suggested model were verified, allowing for the planting of wolfberries. Prediction results showed that the proposed predictors can meet the needs of farming by effectively predicting temperatures and humidity.

In this paper, [35]The four variables that are fed into machine learning approaches for categorization are soil moisture, temperature, humidity, and time. Given its excellent accuracy, random forest offers more promise than other methods for appropriately evaluating smart irrigation conditions (wet or dry), according to the trial findings.

In this paper,[36]An innovative blend of optimised smart irrigation systems is proposed in this study to improve the system's efficiency in energy management. Results from simulations run using the suggested method are checked for accuracy and contrasted with those from more traditional approaches. So, the developed model uses much less energy and has a longer network lifespan than the standard works, according to the findings of the suggested technique.

III. IOT-ENABLED INTELLIGENT-IRRIGATION SYSTEM

This section provides a detailed presentation of the suggested method's design.

A. System Model

The aesthetic perspective and fundamental structural architecture of the irrigation IoT network are further shown with the assistance of two models: one for sensing networks and another for irrigation.

1) Smart Irrigation Model

To back up the end user's (farmer's) choice to water the field adequately, the suggested irrigation model has four main components (see Figure 1). In the first part, we'll find a network of nodes that measure soil moisture, rainfall, and other environmental variables. It is believed that farms use strategically placed wireless sensor nodes to monitor air humidity, moisture content, and temperatures.

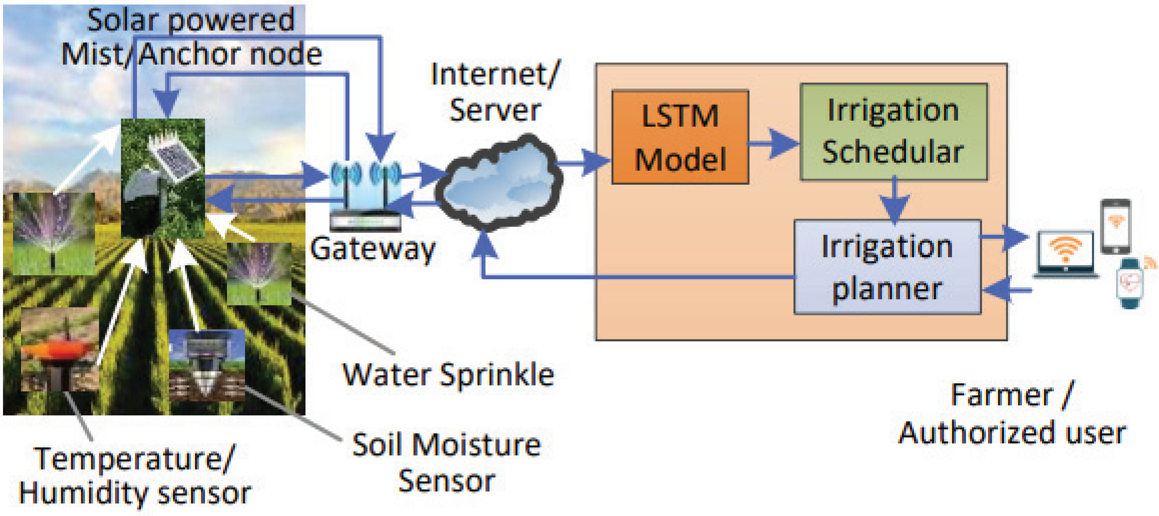

Fig. 1. IoT-LSTM network-based Irrigation Model

To regulate the sprinkler's water flow rate, actuator nodes are linked to water valves or sprinklers. Since the first component also includes the rain level, weather stations or rain-gauge sensors may be used to produce weather forecasts. Server and anchor nodes make up Section 2. Once the sensor data has been gathered by the anchor nodes, it is sent to a server for storage over the radio gateway. Step three involves building a deep LSTM RNN model that takes into account soil and meteorological data from the previous day in order to forecast the volumetric soil moisture content for the next day. To determine how much water is needed for irrigation, the watering schedule mechanism takes into account both the soil's water retention capacity and data on the crop, including its root development. In order to meet the projected water volume, the sprinkler planner also determines the irrigation time up to that point, when the sprinklers are turned on in accordance with the water flow rate. The fourth part, the authorised end-user interface (such a smartphone with an irrigation app), receives the third part's output. As a farmer or end-user, you get to decide in the fourth component whether to go with the irrigation planner's expected plan or make some adjustments. The planner then gets it back to you and you take care of applying the water. The irrigation planner takes input from the end-user/farmer and uses it to control the water network. The farmer has the option to either accept or modify the predicted plan. Through the anchor nodes, the irrigation planner communicates with the actuator nodes, instructing them to water the plants. Following that, the instructions are sent to the water valves and pumps.

2) Sensing Network Model

A field with an area of FL is assumed to have m,set of sensor nodes placed at predetermined locations. $q_m \triangleq (x_m, y_m \quad) \in FL, m = 1, \dots . N$In order to collect data that is both geographical and temporal, such air temperature$AirTemp^{t}(q_m, ti)$,air humidity $AirHum^{\hbar}(q_m, ti)$,soil moisture$SoilMois^{m}(q_m, ti)$,and soil temperature $SoilTemp^{t}(q_m, ti)$,ti represents the specific time point on a daily basis for the soil and its surrounding surroundings. Farmland $(Q_M \triangleq (x_M, y_M \quad) \in FL, M = 1, \dots . n)$ is home to a collection of anchor nodes that provide multipath wireless communication for receiving and transmitting data from sensors inserted into the land to a gateway. The actuator nodes are hooked to water valves and sprinklers that are positioned at predetermined locations$R_b \triangleq (x_b, y_b \quad) \in FL, b = 1, \dots . n.$ Furthermore, they are connected to the anchor nodes wirelessly. In addition, the anchor nodes supervise the actuator nodes, which in turn instruct the watering jets and outflows. The b^{th}actuator node is premeditated to function in binary i.e$\beta(b^{th}) = 0$, close the water valves or$1 = \beta(b^{th})$, Turn on the water valves. In order to detect the amount of precipitation, p_s=A rain gauge sensor node is positioned within the gates. It is identified by $RL^{l}(p_s, ti())$ where s is a rain-gauge sensor. Therefore, the IoT network contains of $N + M + A + 1$ sensor nodes.

Comprises the data obtained from the sensor nodes, i.e. $I_t = [AirTemp^{t}(ti), AirHum^{\hbar}(ti), SoilMois^{m}(ti), SoilTemp^{t}(T), RL^{l}(T)]$ is processed in each memory unit of the LSTM network layer.

B. The Hydrological Interpretation of LSTM Network

To forecast the volumetric soil moisture content for the next day, we propose using the hydrological part of the LSTM-RNN model. To forecast soil moisture levels for a specific future day, we integrate the LSTM network with hydrological components. Data related to hydrology, including soil moisture content, humidity, air temperature, and precipitation, is processed by the memory units of the LSTM RNN. The LSTM-RNN network follows a temporal input data flow for its operations,$I = [I_1, {}_2 \dots , I_t \, . \, . I_k]$ comprising linearly independent parameters for k consecutive days. In order to predict the output, the LSTM network processes these inputs simultaneously in its memory units, or soil moisture content$SoilMois^{m}(ti + 1)$, on the next day.

The current input vector at every single instant$(1 \leq ti \leq k)$

Theyare in that order, the averages for soil moisture, temperature, air $AirTemp^{t}(ti), AirHum^{\hbar}(ti), SoilMois^{m}(ti),$

$SoilTemp^{t}(T), RL^{l}(T)$ humidity, and precipitation on a certain day. Datanormalisation is essential for the suggested LSTM RNN model to train well. This is accomplished by dividing the daily data mean by the standard deviation. For data normalisation, the standard deviation and mean are solely computed from the training period.

In our suggested two-layer LSTM RNN architecture, k memory units will be used for each layer. The internal construction of the LSTM memory unit, which is responsible for evaluating the mapping from the input sequence. You may determine $\boldsymbol{Ub}$ and Ob by using Equations (1) through (6). Each LSTM unit has three gates, a hidden state vector (b), and a cell memory state vector (D) to regulate the input flow in the network. The initial gate, which is analogous to a forget gate, determines the need to erase and the extent to which the information from the previous cell memory state D_{b-1} must be deleted. Here is the forget gate's output path:

$$sf_T = \sigma(W_F I_t + Z_F h_{T-1} + B_F) \tag{1}$$

Whereas,$f_t \in \{0,1\}$ signifies the sigmoid function, $B_F$is the bias vector, W_F and Z_F are the flexible weight parameters, and these values are collectively referred to as learnable coefficients. When the network's user input parameters are specified,g_{ti} and D_{ti} are initialised with a zero-length vector for the first time instant (ti = 0). In the next stage, the hyperbolic tangent layer is used to re-equip the cell memory state vector, which may be expressed as

$$\check{d}_t = tanh(w_{\check{d}} I_{ti} + z_{\check{d}} g_{ti-1} + c_{\check{d}}) \tag{2}$$

In which $\check{d}_t \in \{0,1\}$ and $w_{\check{d}}, z_{\check{d}}, c_{\check{d}}$constitute additional learnable coefficients. In addition, some of the data used to alter the current state of cell memory is controlled by the output of the second gate, which is also called the input gate:

$$ɟ_{\bar{q}} = \sigma(x_ɟ I_t + z_ɟ h_{t-1} + c_ɟ) \tag{3}$$

Where $x_ɟ, z_ɟ, c_ɟ$ are additional sets of learnable coefficients for the input gate, and $ɟ_{\bar{q}} \in \{0,1\}ɫt \in \{0,1\}$ is the sigmoid function. Using the outcomes of Equations (1) and (3), the cell memory state route is now rationalized as:

$$d_q = g_q \odot d_{q-1} + ɟ_t \odot \check{d}_q \tag{4}$$

The sign for the product of the gate and cell memory state vector components is denoted by$\odot$. It is possible to interpret the first term in Eq. 4 as stating which data from the preceding cell memory state route $\check{d}_{q-1}$ should be kept (g_q near to one) and which should be disregarded (g_q close to zero).Comparably, the second term may be seen as indicating Fresh input data must be stored ($ɟ_{\bar{q}}$ near to 1) and the data that can be disregarded ($ɟ_{\bar{q}}$ close to 0).

The output gate (O_g), the amount of information transmitted from the current cell memory state vector to the following concealed state b is determined by the third gate, which is the final one. Here is how it is stated:

$$O_q = \sigma(x_O I_t + z_O h_{q-1} + c_O) \tag{5}$$

Where x_O, z_O, c_Oconstitute the collection of output gate learnable variables, and $O_q \in \{0,1\}$ is the sigmoid function. Additionally, using Equations (4) and (5), The following is a possible statement of the newly discovered hidden state:

$$g_{\bar{q}} = tanh(d_q) \odot O_q \tag{6}$$

In the end, the LSTM layer sends its signals and expected outputs to a dense layer featuring only one neurons, y_{pre}, is computed as follows:

$$y_{pre} = w_d \hbar_k + b_d \tag{7}$$

where $\hbar_k$stands for what the final LSTM layer produced, and w_d and $b_d$are the bijective function and weight ratios of the densely linked layer

C. *The Training Procedure*

In order to train the suggested LSTM RNN framework, the Indian Meteorological Department supplies variables such as soil temperature, atmospheric moisture, and relative soil moisture. Just one day after training, the model is saved to anticipate the measured soil moisture level. The model is trained using training data in a single iteration, as shown schematically in Figure 3. The ratio of a dataset's training and testing parts is 70:30 in order to prevent network over fitting. Every time around, the experience replaying recall (or mini-batch) is used to choose a random subset of the training sample. The mini-batch size is represented by a power of two (2^r), wherein a is the total number of specimens required to adjust the learnable network characteristics.

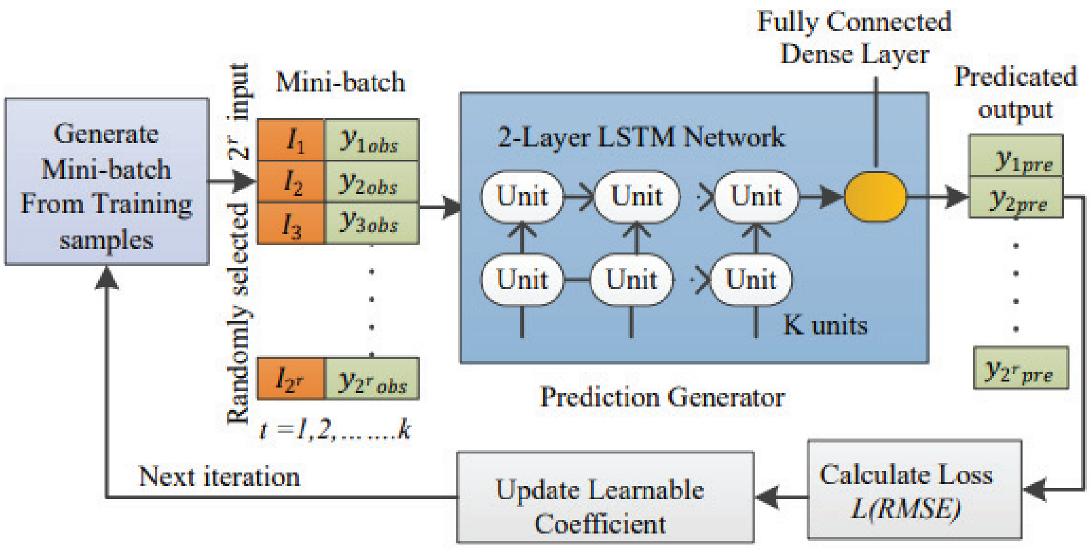

Fig. 2. A representation of a single stage of training

The suggested LSTM network is more amenable to learning when a random sample is used during the training phase. For the 'k' days before, every observation has one input (a normalised the data set, Jt) and one output (a normalised observed value, z_{obs}). In order to assess the actual value against the predicted output $zkfe$, the LSTM network uses the information that is given to it. The LSTM network's bias and accessible parameters are updated by the loss function that is found as a RMSE in relation to the concatenated set of weights E^q. You may get it from:

$$K(E^q) = \left[\frac{\sum_{q=1}^{r}(z_{obs}-z_{pre})^2}{r}\right]^{0.5} \tag{8}$$

The good prediction value is estimated by the loss function $K(E^q)$trending towards zero. Stochastic gradient descent is used to update the weight of the LSTM network by changing the network parameters twice 2^r(that is, the quantity of mini-batch random samples) in a single iteration. With learning rate$b \in \{0,1\}$, the network weight is changed using the following equation:

$$E^{q+1} = E^q + b\frac{\partial_K(E^t)}{\partial E^t} \tag{9}$$

D. Watering Schedules and Planners

Water distribution for agriculture the next day may be estimated with the use of online planners & schedulers that take into account variables like time and location.

1) Irrigation Scheduler

Maintaining soil moisture across lower & higher borders is the goal of the irrigation scheduling. The lower limit indicates the minimum acceptable soil moisture content, whereas the higher limit specifies the maximum allowable soil water retention capacity. Anything below the lower bound suggests that irrigation is necessary. The capacity of the soil to retain water is what determines when to start an irrigation plan on agriculture. The United States Department of Agriculture (USDA) predetermined set of soil labelled $(D_u; u = 1,\ldots\ldots U())$is used by the maximum likelihood estimate (MLE) approach to classify the soil category as follows:

$$D = \Delta\{d[avg(Soilmois^{M}(ti)), R^{Ł}(ti)]\}, D \in [D_u; u = 1,\ldots\ldots U[]] \tag{10}$$

Wherein the rate of diffusion of averaged volumetric soil moisture and the amount of precipitation are represented by d. The typical soil moisture content in weight is $avg(Soilmois^{M}(ti)) = \frac{1}{n}\sum_{n=1}^{N} Soilmois^{M}(q_m, ti)$. Following MLE's soil type classification,(So^{wat_r})the following is the maximum soil water retention capacity for the agricultural land:

$$So_{max}^{wat_r\left(D,avg\left(Soilmois^{M}(ti)\right)\right)|d=d_u} \tag{11}$$

δ(.)= seems to be a comparable empirical relationship between soil type and soil moisture. The amount of water stored by the soil at the roots of a crop$So_t^{wat_r}$ at a particular time instant b is directly relational to the level of the soil's contents (in mm of fluid) and is determined by:

$$So_t^{wat_r} = 1000 \times Soilmois^{M}(ti)\, q_s \tag{12}$$

Where qs is the unit of measurement for root depth in metres, and $Soilmois^{M}\left(\frac{n^3}{n^3}\right)$ is volumetric soil content. This is the formula for the agricultural land's water deficiency in the soil (mm) at time t:

$$So_t^{wat_d} = So_{max}^{wat_{r_t}^{wat_r}} \tag{13}$$

Assuming that irrigation is not necessary, the water deficit will be at its highest when the soil water retention capacity reaches its maximum value, which is represented by $yuaxwr - ymaxwr$. The water deficit $ybwth$ fluctuates as a function of the pace of crop growth. But in the current moment b, a threshold value is determined by utilising the expertise of farmers. In order to predict the water shortage yb+1 wd at time b + 1 (for the next day), the proposed LSTM RNN will be utilized. When soil moisture levels are low, (i.e. st+1 $wd \leq stwth$, In order to determine how much water will be required for irrigation the next day, the procedure is planned.

2) Water Volume Estimation

In this stage, the average water deficit from the rain level is subtracted to determine the volume of water required in volume $\left(\frac{1}{n^3}\right)$after the assessment scheduler chooses to irrigate the field.

$$W(ti) = \frac{1}{N}\sum_{n=1}^{N} V(q_m, ti) = \frac{1}{N}\sum_{n=1}^{N}\left[So_{\max}^{wat_r}(q_m, ti) - So_{t}^{wat_r}(q_m, ti)\right] - R^{Ł}(ti) \tag{14}$$

The water volume (ti) is an average volume that the sensors on the nodes put on the farms at location qm (where m = 1,...N) estimated.

3) Irrigation Planner

The irrigation planner establishes the necessary water distribution, both in terms of time and space, over the fields in this stage. Accurate information on the location, quantity, and water flow rate of the actuators is required for this task. The water flow from every sprinkler is controlled by actuators, as mentioned before$\beta(b^{th}) \in \{0,1\}$). For distributional reasons, the field is split into a few square sub-farmlands. Actuator nodes are found in every sub farmland because they function differently based on the approximate water volume required in each sub farmland. Let us define $G_b \in G, b = 1,\ldots B$ such as sub-farmland watered by pre-set actuators$w_b \in H_b, A = 1,\ldots a$. When placed in sub-farmland areas, the sensor nodes may$S = \sum_{b=1}^{B} S_b$, where N_a, a = 1 … Aconstitute a subset of the locations of nodes in$q_m \in g_m$. The time that each actuator node has to be irrigated is shown as:

$$\varphi^b(ti) = \frac{1}{M_c}\sum_{m=1}^{M_a}\varphi^n(q_m, ti)\,|q_m \in F_c, c = 1,2,\ldots\ldots, C, \tag{15}$$

where$\varphi^n$is the amount of time that each sensor node at its location calculates for irrigation as:

$$\varphi^m(q_m, ti) = \frac{V(q_m, ti)}{\omega_{spr}(q_m)} = \frac{\varphi^{opt}(ti)\times\omega^{opt}(q_m, ti)}{\omega_{spr}(q_m)}$$

where V(q$_m$,ti) is the amount of water that is best used during the irrigation season$\varphi^{opt}(t)$ within the ideal sprinkler water circulation rateω_{opt}(q$_m$,t) when the sensor is set up.

The occurrence scheduler's irrigated scheduling is reflected in all of the actuators with an irrigated duration. $\varphi^a(t)$, $a = 1, A$, that is, below the critical value, the soil moisture content is found. As a result, this data reaches the authorised users or farmers' application smartphones. It is then that farmers estimate the water capacity using the current capacities of water tanks and lakes. With this data in hand, farmers can make informed decisions about water use and tell the irrigation scheduler to turn on the water. If there isn't enough water in the reservoirs to fill the tank to its predicted volume, the motor pumps need to fill it up to at least 80% of its capacity.

E. The LSTM RRN-based Irrigation Algorithm

Pseudocode (Algorithm 1) and Figure 4 describe the proposed intelligent irrigation system. As input variables, we feed them into the training LSTM network. $I_t = [AirTemp^{t}(ti), AirHum^{h}(ti), SoilMois^{m}(ti), SoilTemp^{t}(T), RL^{l}(T)]$in order to estimate the volumetric soil moisture $Soilmois^{M}(t+1)$ content one day in advance. In the end, farmers may maximise their financial gain by using data on root growth, anticipated volumetric soil moisture content, and irrigation schedule estimates to support healthy crop development.

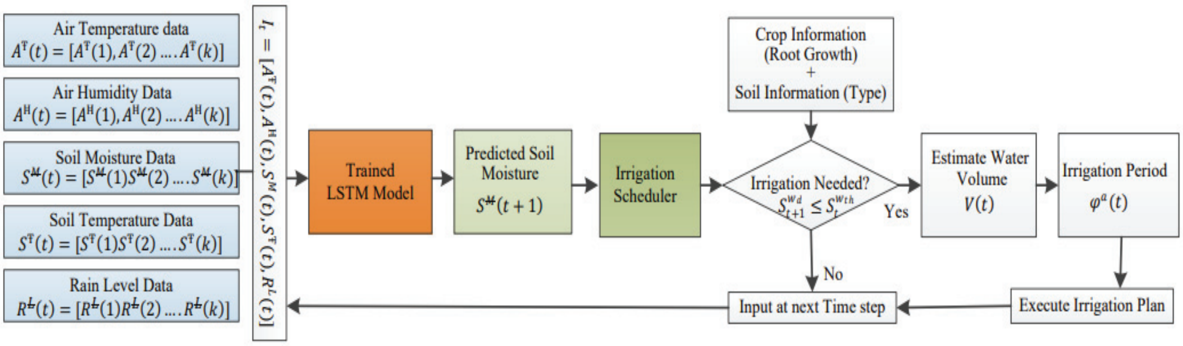

Fig. 3. Block Diagram of Predictive Irrigation Schedule

Algorithm 1 LSTM RRN-based intelligent irrigation algorithm

1. **Training:**
   1. Set the maximum number of episodes and experience replay memory
   2. Set random weights to begin the learnable coefficient E^t
   3. Initialize $\hbar_0$, $\mathbb{C}_0 = 0$ of length k
   4. For $E_{ps} = 1, \dots\dots\dots E_{ps}^{max}$
   5. Examine the arbitrary mini-batch size 2^r
   6. For each $t = 1,2 \dots .. k$
   7. Take any arbitrary sample from the mini-batch
      $I_t = [AirTemp^{t}(ti), AirHum^{\hbar}(ti), SoilMois^{m}(ti), SoilTemp^{t}(T), RL^{l}(T)]$and y_{obs}
   8. Evaluate (Equation 1,2 and 3)
   9. re-equip cell memory state d_tEquation.4
   10. Evaluate (Equation. 5 and Equation 6)
   11. End for
   12. Output : $\hbar = \{\hbar_1, \dots\dots \hbar_n\}$
   13. Calculate simulatedpredicted output y_{pre} (Equation.7)
   14. Estimate loss function Equation.(8)
   15. Utilising Equation (9) for stochastic gradient descent loss optimisation, update the LSTM weight parameterE^{ti}
   16. End for
2. **Prediction:**
   1. Examine your surroundings and gather data about the current day
      $$I_t = [AirTemp^{t}(ti), AirHum^{\hbar}(ti), SoilMois^{m}(ti), SoilTemp^{t}(T), RL^{l}(T)]$$
   2. Give the trained LSTM model the current day as input.
   3. Estimate the soil moisture content one day in advance $S(t+1)$
   4. The input and output tuple should be saved in the experience's replay memory set.
3. **Irrigation Schedule:**
   1. Categorise the soil Eq. (10)
   2. Compute maximum water capacity of farmland Eq .(11)
   3. Use the kind of soil and crop root growth data as inputs to calculate the water deficit $s_{t^{w}+1}^{d}$ Eq. (13)

4. If stw+$d1 \leq stwth$
5. Determine the irrigation water volume $V(b)$ by using Eq. (14)
6. Else
7. Step 2 inputs (i.e., go to Step 2), prediction

4. **Irrigation Planner:**
    1. Consider the input of sprinkler water flow rate.
    2. Irrigation time estimate for each actuator using Equation (16)
    3. Implement the irrigation plan

a) Complexity Analysis

Initialization from line 1 to line 3 requires a constant amount of time of order (1), which is mostly dependent on the training technique and thus the time complexity of the proposed approach. The input ak is trained using a 2-stage mini-batch with a total of k LSTM units, as shown in line 6 through line 11. The overall weight of the LSTM elements in the layer also affects the time complexity. The four recurrent connections found in each LSTM unit are as follows: input gates, output gates, forget gates, and the direct link between the input and output layers.

In addition, there is a total for each unit $y_k + ŧ_k$quantity of inputs for the present time intervals. Given that a total of four recurrent connections $4(y_k + ŧ_k)$ weight that comes with every single item. Additionally, there are $ħk$ LSTM units in each layer, thus in total, $4ŧ_k(y_k + ŧ_k)$attached to that LSTM layer. Assuming an aggregate of Ok outputs created by the result level, the weight linked to the outputs level is $k \times Ok$. The sum of the three gates' weights is$ŧ_k \times 3$. This leads to the computation of total weights connected$weig_{Tot}$ with each LSTM layers as:

$$weig_{Tot} = 4ŧ_k(y_k + ŧ_k) + ŧ_k \times O_k + ŧ_k \times 3 \qquad (17)$$

The lines 12–15 make predictions, and the time it takes to update the network weight using stochastic gradient descent optimisation is constant (1). The training process continues until convergence occurs or until the maximum number of episodes has been reached. Training as a whole takes a lot of time since $(train) = (W_{Tot})$.

If you have an already-trained LSTM RNN model, predicting the next day using line 3 of the approach will take (1) time. Irrigation planners and schedulers, on the other hand, use equations and if-else statements, and they run at a fixed order time (1). Consequently, the suggested algorithm's total time complexity is assessed as $(weig_{Tot})$.

F. Hyper parameter Tuning

Hyper parameters are selected before machine learning is performed. Instead of discovering model weights during training, data analysts or researchers specify hyper parameters. Hyper parameter selection may affect model performance, convergence speed, and generalizability. Hyper parameters include learning rate, batch size, layers, hidden units, dropout rate, and others.

1) Rate of Learning (η):

The learning rate is a crucial hyper parameter that controls the gradient descent step size for each iteration. It regulates the speed at which the model changes its internal settings to reduce the loss function. $\theta_{new} = \theta_{old} - \eta.\nabla J(\theta_{old})$

Where,

$\theta_{new}$is the updated parameter value?

$\theta_{old}$is the current parameter value?

Batch Size (B):

The batch size defines how many training examples are utilized in each training iteration. For a batch gradient descent step having batch size B, the update equation is:

$$\theta_{new} = \theta_{old} - \frac{\eta}{B}\sum_{i=1}^{B} \nabla J_i(\theta_{old})$$

Where,

- B is the Batch Size
- $\nabla J_i(\theta_{old})$ is the gradient of the loss function in relation to the parameter θ_{old} calculated for the batch's i-th training sample.

Layer count and hidden units:

Our neural network's architecture is determined by the amount of layers & the count of hidden elements in each layer. Deeper networks may capture more complicated interactions, but they may also be vulnerable to over fitting. The equation for propagation information across a single layer in a network of neurons (e.g., a fully interconnected layer) is:

$$h^{(l+1)} = \sigma(W^{(l)}h^{(l)} + b^{(l)})$$

Where,

- $h^{(l+1)}$ Represents the output of layer l+1
- σ is the function of activation
- $b^{(l)}$ Is a bias vectors of layer l
- $W^{(l)}$Is the weight matrices of layer l
- $h^{(l)}$Is an input to layer l

Dropout Rate (p):

Dropout is a regularization strategy that removes a percentage of neurons at random throughout each training cycle. It aids in the prevention of over fitting. The drop-out equation is as follows:

$$h_{dropout} = h \odot mask$$
$$mask_i \sim Bernoulli(p)$$

Where,

- $h_{dropout}$ is the result of dropout?
- H is the input
- Mask is a binary mask where each element comes from a p-parameter Bernoulli distribution.

To refine hyper parameters effectively, we've integrated the innovative LSTM Algorithm into our implementation. This algorithm strategically navigates parameter spaces, enhancing the model's performance. By leveraging the unique capabilities of the LSTM Algorithm, we aim to achieve superior results in tuning key model parameters for optimal performance.

IV. RESULTS

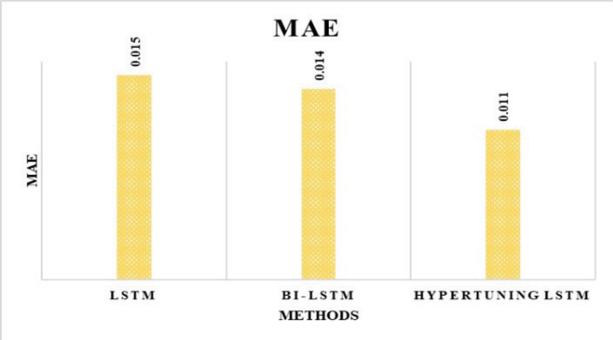

Fig. 4. MAE

The picture above depicts the mean absolute error (MAE) values associated with several approaches used to optimise water resource management. In the framework of smart agriculture, the effectiveness of three different methods—LSTM, Bi-LSTM, and Hyper parameter-Tuned LSTM—was assessed in terms of how well they predicted water resources. Lower values of the MAE indicate more accuracy, therefore they are used as performance measures. While the Bi-LSTM model fared marginally better with an MAE of 0.014, the Hyperparameter-Tuned LSTM model surpassed the other two models with the lowest MAE of 0.011. The LSTM model produced an MAE of 0.015. According to these findings, the LSTM model's predictive power was considerably improved by the hyperparameter tuning procedure, demonstrating the model's potential as a useful instrument for managing water resources optimally within the framework of smart agriculture. The results emphasise how crucial it is to use cutting-edge machine learning methods—specifically, hyperparameter tuning—to raise the prediction model accuracy in the field of agricultural water resource enhancement.

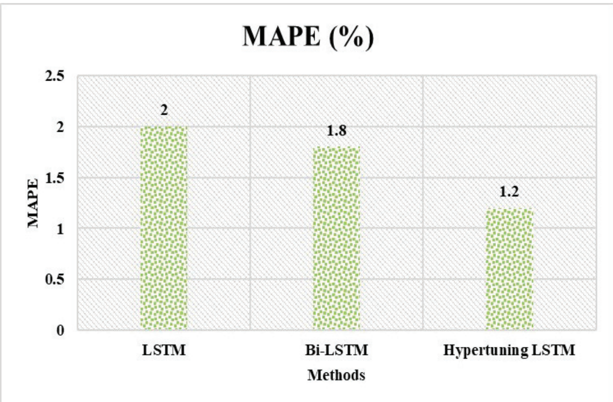

Fig. 5. MAPE (%)

The Mean Absolute Percentage Error (MAPE) is a performance indicator that is shown in the figure for several LSTM architecture modifications. With a remarkable MAPE of 2%, the typical LSTM model displays how well it can anticipate and optimise the use of water resources. With a lower MAPE of 1.8%, the Bidirectional LSTM (Bi-LSTM) has even higher accuracy, demonstrating the improved predictive abilities provided by the bidirectional nature of the model. Moreover, the LSTM model with hyperparameter tuning is the most accurate, with a very low MAPE of 1.2%. This shows that, in the context of smart agriculture, optimising hyperparameters is critical to improving the prediction accuracy of the model and developing more accurate and effective water resource management plans.

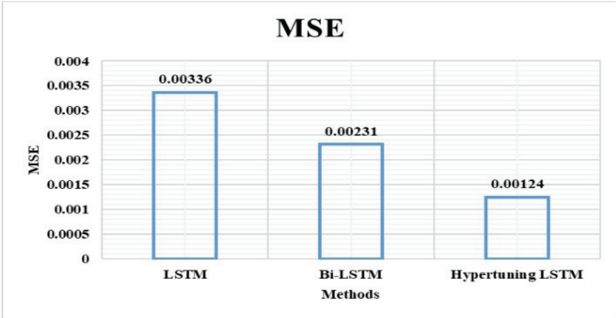

Fig. 6. MSE

The performance measure shown in the figure is Mean Squared Error (MSE) values.Each model's predicted accuracy is shown by its Mean Squared Error values, where lower values indicate greater performance. The Bidirectional LSTM showed improvement with an MSE of 0.00231, compared to the regular LSTM's 0.00336 MSE. With the lowest MSE of 0.00124, the hyperparameter-tuned LSTM demonstrated stronger prediction ability and beat the other model.

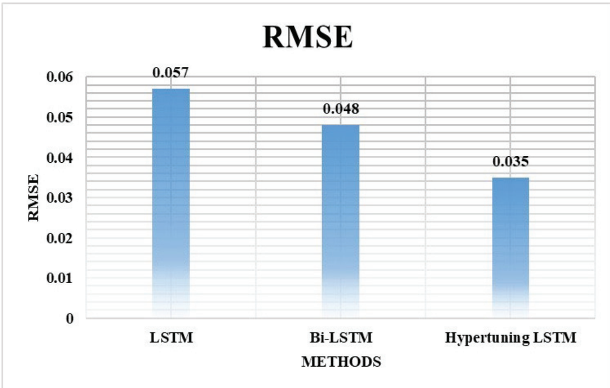

Fig. 7. RMSE

The Root Mean Square Error (RMSE) measure is used to assess each model's performance, as seen in the above figure. The Bidirectional LSTM showed better accuracy with an RMSE of 0.048 compared to the standard LSTM's 0.057 RMSE. But the most notable improvement in performance was obtained by adjusting the LSTM's hyperparameters, which led to a much lower RMSE of 0.035.

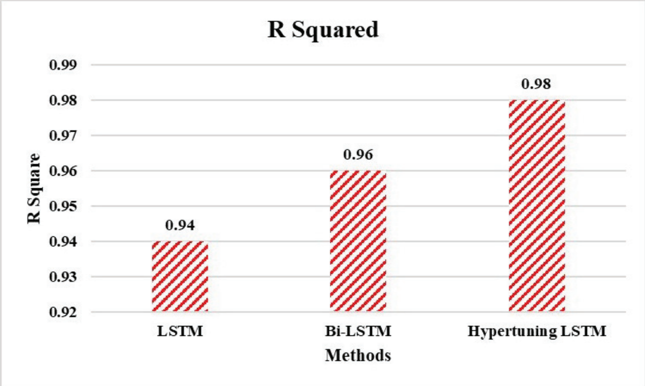

Fig. 8. R Squared

The coefficient of determination (RSquared) performance is evaluated using a statistic in the above figure. With an outstanding R-squared value of 0.94, the LSTM model demonstrates its effectiveness in forecasting and optimising the use of water resources. With an even higher R-squared value of 0.96, the Bi-LSTM model outperforms this performance, demonstrating the advantages of bidirectional processing in capturing intricate patterns. The Hyperparameter-Tuned LSTM is the standout feature of the table, exhibiting exceptional optimisation capabilities with an impressive R-squared value of 0.98. This emphasises how important hyperparameter tweaking is to improving the predictive capability of LSTM models for applications related to smart agriculture, especially in the crucial area of water resource management.

V. CONCLUSION

Using a variety of LSTM-based models, by exploring the field of water resource optimisation can be done in smart agriculture. The outcomes of the experimental assessment demonstrate how well these models forecast and optimise the use of water resources. The R-squared score of 0.94 for the basic LSTM model was impressive, suggesting that it performed robustly. With its ability to handle data in both directions, the Bi-LSTM model beat the normal LSTM, obtaining a better R-squared value of 0.96, highlighting the benefits of capturing intricate patterns in the context of agriculture. But the Hyperparameter-Tuned LSTM, with its outstanding R-squared value of 0.98, is the real star of this study. It demonstrated incredible optimisation skills. This highlights the vital role that hyperparameter adjustment has in improving the prediction accuracy of LSTM models for applications related to smart agriculture, especially in the crucial area of water resource management. The results together point to the possibility of greatly enhancing the sustainability and efficiency of water resource utilisation in smart agriculture via the incorporation of sophisticated LSTM architectures and careful hyperparameter optimisation. These findings provide important insights into the possibilities of cutting-edge methods for attaining ideal water management in the agricultural sector as we traverse the difficulties of contemporary agriculture and the need to improve resource efficiency.

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