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Smart Drip Irrigation System: A Novel Approach to Water Requirement Prediction Using Cascade Trio Gated Recurrent Networks

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Drip irrigation alleviates water scarcity challenges by delivering water efficiently and precisely on agricultural farms. The challenges posed by water scarcity especially in drip irrigation highlights the crucial importance of precise farm measurements for jasmine crop cultivation. Recognizing the need for innovative solutions, this work introduced a sophisticated hardware model flawlessly integrated with an Internet of Things (IoT) system. This integration enables the collection and analysis of dataset of an essential parameter used for enhancing the jasmine plant's health. The main agenda of this work is to evaluated an Irrigation Water Requirement (IWR) parameter which is a fundamental factor in addressing water scarcity concerns. To achieve an effective evaluation in IWR, the novel optimized Cascade Trio Gated Recurrent Unit (CTG) model is introduced. The CTG model is designed to leverage the strengths of recurrent neural networks for time-series data that offering enhanced accuracy in predicting irrigation water needs. This model is not only novel but also optimized using the RUNge Kutta (RUN) optimizer. The RUN optimizer is employed to fine-tune the CTG model's parameters that ensuring that it reaches an optimal configuration for accurately predicting IWR and also enhance its adaptability to the specific characteristics of jasmine cultivation. This proposed work is its comparative performance against existing models based on various performance metrics where optimised CTG model consistently outperforms other models. This showcasing superior performance and offering promise for more water-efficient and sustainable agricultural practices.

Keywords: water scarcity, water requirements, prototype, water level, CTG model, RUN optimizer, efficacy

1. Introduction

Agriculture is a keystone of global food production which plays a vital role in sustaining populations worldwide [1]. However, the increasing challenges of water scarcity and climate change are significantly impacting cultivation practices. Drip irrigation emerges as a crucial solution that mitigating water scarcity by enabling precise water distribution, enhancing resource efficiency and adapting to changing climatic conditions [2]. This method not only ensures the optimal use of limited water resources but also contributes to the resilience of agricultural systems in the face of evolving environmental challenges. India has a rich agricultural heritage with a significant portion of its population engaged in farming [3]. The sector not only contributes substantially to the country's GDP but also supports millions of livelihoods. However, the industry faces numerous challenges that including unpredictable weather patterns, resource scarcity and the need for sustainable practices [4].

Climate change has emerged as a formidable threat to agriculture that causing erratic weather conditions, altered precipitation patterns and increased frequency of extreme events [5]. These changes significantly impact crop yields that making it imperative for the farming community to adopt innovative solutions to mitigate risks and enhance productivity. The advent of smart agriculture has introduced cutting-edge technologies such as IoT devices and sensors into traditional farming practices [6-7]. These smart products enable real-time monitoring of environmental conditions, soil health and crop growth. Sensors collect vast amounts of data that providing farmers with valuable insights to make informed decisions and optimize resource utilization [8].

The explosion of sensors in agriculture generates vast datasets which paving the way for data mining and machine learning (ML) applications [9]. The ML algorithms analysed a historical and real-time data to make predictions that offering farmers actionable information for crop management, pest control and yield optimization. This data-driven approach enhances precision agriculture that are resulting in improved efficiency and sustainability [10].

The main concern and a critical challenge in agriculture are Water scarcity where the demand for water often exceeds the available supply [11]. In farming, water is an essential for crop growth and its scarcity can significantly impact agricultural productivity. The challenge is further aggravated by unpredictable weather patterns and the increasing frequency of droughts, both of which are attributed to climate change [12-13]. To address the challenge of water scarcity in agriculture, the ML algorithms can analyse vast amounts of data including historical weather patterns, soil moisture levels and crop characteristics. This not only conserves water but also ensures that crops receive the right amount at the right time, contributing to sustainable agriculture practices [14].

To address a challenge in Drip irrigation like climate change and resource constraints, proposed an integration of hardware set up and data mining by using a smart sensor and IoT technology and ML models [15]. The proposed work is framed with a hardware prototype, dataset generation, ML techniques. The main factor of this work is an IWR that is evaluated using novel model like RUN optimised CTG techniques. By harnessing the power of real-time data with this proposed model, the highly effective prediction is carried. This prediction supported the farmers that can make informed decisions, optimize resource utilization and enhance overall productivity.

The rest of the work is followed that the section 2 carried a related works and section 3 processed a materials and methods that has details of dataset samples and proposed prototype. The section 4 describes the IWR evaluation with proposed novel model and section 5 presents the result evaluation and its achievement over traditional models with proof. Finally the work is ended with section 6.

2. Related Work

Chaudhary et al [16] developed a ML based IoT system responsible for collecting data from diverse sources and transmitting it to a central processing system. The hybrid framework allows the integration of various technologies to create a cohesive and efficient system for precision farming

Karunathilake et al [17] offered a comprehensive overview of recent innovations, challenges and future scenarios in precision agriculture and smart farming. The analysis covers the present condition of precision agriculture that highlighting technological advancements such as drones, sensors and ML models.

Priya et al [18] introduced a novel analytical system for extracting valuable visions from data patterns, aiding in understanding agricultural fields, identifying issues and proposing solutions. This study emphasizes the foundational concept of ML and systematic processes in applying it to agriculture.

Elashmawy et al [19] conducted joint investigations into empirical and statistical models that employing neural networks and Gaussian process regression models to find suitable physicochemical qualities of strawberries. This high level of accuracy facilitates the implementation of soil condition control that enabling data-driven decision-making for sustainable and high-quality strawberry production.

Radočaj et al [20] introduced a hybrid interpolation method to identify a sampled data using remote sensing data. The study emphasizes the significant role of remote sensing data and methods in enhancing fertilization practices in precision agriculture with increasing importance anticipated in the future.

Dakir et al [21] reviewed employing ML in precision agriculture through satellite remote sensing. The focus is on studies conducted in the years 2019–2020, highlighting the potential of AI in precision agriculture, addressing challenges, identifying future needs, and exploring trends in the field.

Cama-Pinto et al [22] provided a comprehensive review on the role of ML and emerging technologies in addressing current and future challenges in crop protection. The article also reviews the possibilities and advantages of AI in agriculture fields.

ohammed et al [23] presented the development and evaluation of four solar-powered micro irrigation systems under six irrigation levels for date palm irrigation. The systems utilized soil moisture sensor-based controllers for automated irrigation scheduling, powered by a solar photovoltaic (PV) system. The evaluation revealed that LSTM followed by XGBoost models exhibited greater accuracy than SVR and LR models in predicting optimum irrigation water and energy requirements. Experimental results on historical data set shows that LSTM model achieves minimum error rate than other models.

Samani et al [24] employed supervised ML technique to predict the Quantitative Water Flow (QWF) in the Chaghlondi Aquifer in Iran over a 14-year period (2007–2021) using monthly intervals. The study incorporated the wavelet transform (WT) technique to enhance QWF prediction quality for three lead months, utilizing datasets including QWF, precipitation, evapotranspiration, temperature, and Groundwater Level (GWL) signals. Five widely used ML models and their hybrid wavelet models were compared for effectiveness.

Akkem et al [25] provided a comprehensive review of ML techniques applied to crop datasets for tasks such as soil fertility classification, crop selection, time series analysis, and crop production forecasting. The review emphasizes the potential of ML algorithms in addressing crucial aspects of precision agriculture in response to the increasing global demand for food production.

Chaudhry et al. [26] discussed an automatic water supply system for farms based on crop IWR The system measures soil water levels, employs various machine learning algorithms to assess soil moisture content, and predicts IWR for the next cycle. The system aims to provide real-time sensing and control that eliminate manual intervention, and ensure uniform and efficient water supply to farms.

Yousaf et al [27] conducted a bibliometric analysis of research in Operations Research (OR) knowledge within Agriculture 4.0 over the past two decades. Utilizing advanced data mining tools, the analysis covered 1,305 articles from the Scopus database. The study highlights trends, gaps, and the application of UAVs and robotic units in optimizing resource allocation on farms, particularly in arid climate conditions.

McCarthy et al [28] reported field trials evaluating the accuracy of yield prediction using a biophysical model and comparing uniform irrigation with variable-rate irrigation strategies in cotton and perennial ryegrass crops. On-site weather data and field soil core information were crucial for accurately predicting yield. Model Predictive Control in cotton resulted in higher yield with reduced water application, demonstrating potential water-saving benefits through improved irrigation strategies.

3. *Materials And Methods*

Dataset collection

In the year 2023, a comprehensive dataset comprising 619 samples was precisely collected from a hardware prototype in the town of Batlagundu. Situated in the Nilakottai block within the Dindigul district, this town is nestled in the Madurai Region of the southern state of Tamil Nadu, India. The farming of jasmine is shown in Figure 1. The focus of this dataset is centred around the cultivation of jasmine crops during the months of June to September.

The collection of samples was conducted with the aim of gathering valuable insights into the various factors influencing the growth and development of jasmine crops within this specific geographical and temporal situation. The hardware prototype probably an agricultural sensing or monitoring system that provided a technological foundation for capturing and recording essential data related to the jasmine cultivation process.

Figure 1: Jasmine Farming located at Nilakottai

The dataset includes 619 samples that serves as a valuable resource for researchers, farmers, and agricultural practitioners that offering a nuanced understanding of the environmental conditions, agricultural practices and crop responses specific to the jasmine cultivation in the region during the specified time frame.

4. Proposed Experimental prototype

The proposed hardware prototype block diagram shown in figure 2 for evaluating soil properties employs an Arduino controller and a suite of specialized sensors to comprehensively assess key parameters influencing jasmine plant growth. The Arduino initiates the process by initializing the sensors including those for soil moisture, temperature, humidity, pH, Nitrogen (N), Phosphorus (P), Potassium (K), and wind speed [29]. Each sensor captures specific data, such as soil moisture percentage, air temperature, humidity levels, pH levels, and concentrations of N, P, K that are explained in the following.

Soil Moisture: Soil Moisture Sensor is used to predict the moisture level. This sensor monitors the moisture content in the soil, helping to determine when and how much to irrigate the jasmine plants. Maintaining optimal soil moisture is crucial for healthy plant growth.

Temperature: Temperature Sensor DHT11 is used for it that measures the air temperature around the jasmine plants. Temperature affects plant metabolic processes, growth, and flowering. Monitoring temperature helps optimize growing conditions.

Humidity: Humidity Sensor is used that measures the relative humidity in the air. Jasmine plants, especially certain varieties like Madurai Malli, are sensitive to humidity levels. Monitoring humidity aids in understanding the local microclimate and potential risks of diseases.

pH (Soil Acidity/Alkalinity): pH Sensor is used that determines the acidity or alkalinity of the soil. Jasmine plants prefer slightly acidic to neutral soil conditions. Monitoring pH levels ensures that the soil is within the optimal range for nutrient uptake.

N (Nitrogen), P (Phosphorus), K (Potassium): Individual N, P, K sensor is used to measures the concentrations of essential nutrients in the soil. Nitrogen promotes leafy growth, phosphorus supports flowering, and potassium aids in overall plant health. Monitoring nutrient levels guides fertilization practices.

Wind Speed: wind Speed Sensor is used to measures the speed of the wind. Wind speed can affect the physical structure of jasmine plants, especially if it is climbing varieties. Monitoring wind speed helps in understanding potential stress on plants and supports proper trellising.

Water Level: Liquid Level Sensor specifically used to detect and indicate the presence or absence of a liquid at a certain level within a container.

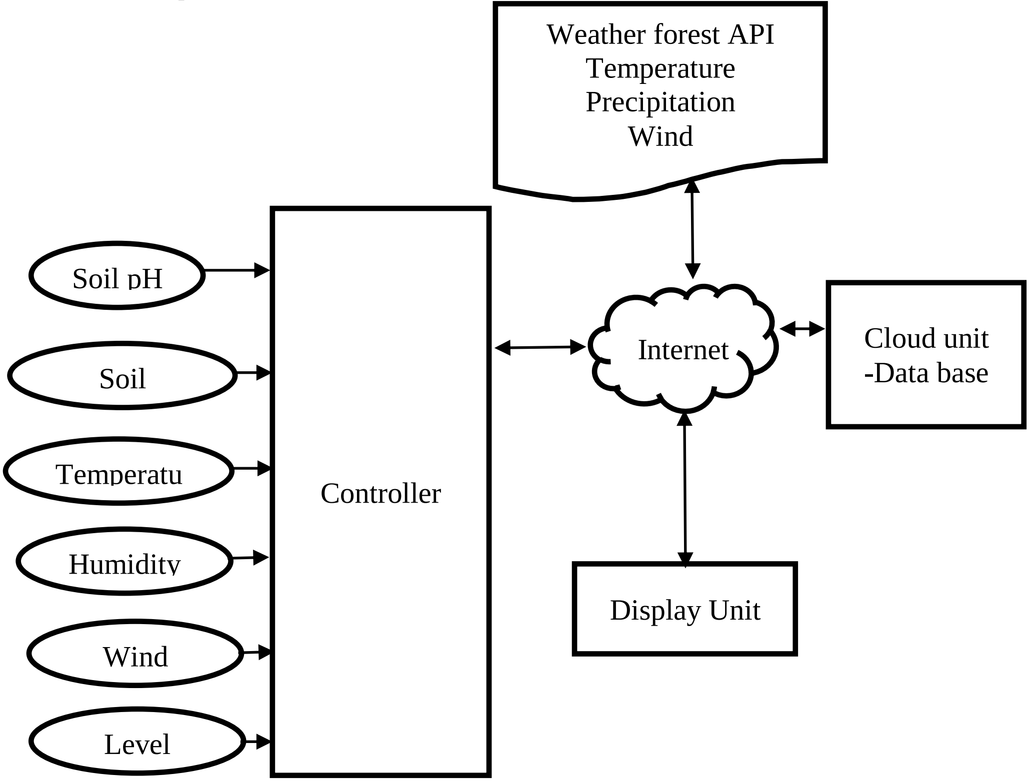

Figure 2: proposed Hardware Block Diagram (change IWR as LEVEL sensor)

All these data are fed into Arduino controller where Arduino processes this raw data converting it into calibrated values. Additionally, an algorithm embedded in the Arduino calculates the water requirement based on the collected parameters considering factors like soil moisture, temperature, humidity and water level. The prototype integrates with an IoT module to transmit the processed data to a cloud based IoT platform for storage and analysis. Users can access the platform through a web-based dashboard enabling real-time monitoring and historical data analysis. The system is designed to enhance precision agriculture that offering insights that optimize irrigation and nutrient management that ultimately contributing to resource efficiency and sustainable agricultural practices. Additionally, the IoT integration facilitates remote monitoring that allowing for efficient management of large agricultural fields. The prototype's ability to generate alerts and notifications ensures prompt responses to deviations from optimal soil conditions. This innovative hardware prototype provides farmers with crucial data for informed decision-making and enhanced agricultural productivity.

Accurate estimation and management of IWR play a pivotal role in mitigating water scarcity. When farmers apply the right amount of water precisely where and when it is needed, it contributes to sustainable water use. Drip irrigation when coupled with precise knowledge of IWR, becomes a powerful tool in reducing water scarcity by maximizing the efficiency of water utilization in agriculture.

5. IWR Evaluation

In modern agricultural practices, the precise determination of IWR is paramount for efficient water management. A sophisticated approach involves leveraging advanced technologies, such as the Optimised CTG model. This model utilizes a combination of cascading GRU to effectively capture temporal dependencies within the dataset. The parameters considered for this irrigation water requirement model include N, P, K, soil moisture, humidity, temperature, water level, pH and wind speed. By integrating these diverse factors, the optimised CTG model not only calculates but also evaluates the optimal irrigation water needs for crops. This innovative application of deep learning in agriculture underscores the importance of leveraging technology to enhance precision and sustainability in irrigation practices

Novel Optimised CTG Model

For an effective and accurate IWR evaluation, the proposed novel RUN optimised CTG model is used that is explained in the following.

GRU Model

The GRU is a type of RNN architecture designed to address challenges associated with vanishing gradients in traditional RNNs [30]. The GRU architecture shown in Figure 3 that includes crucial components such as the Update Gate (zt), Reset Gate (rt), Current Memory Content (h’t), and Hidden State Update (ht). The Update Gate determines how much past information should be carried over to the present, while the Reset Gate decides how much past information should be forgotten. The Current Memory Content represents new information that will be added to the memory, and the Hidden State Update combines the old and new information to produce the updated hidden state. This architecture allows the GRU to effectively capture long-term dependencies in sequential data, making it particularly useful for tasks involving time-series analysis and natural language processing. The use of gating mechanisms enables the GRU to mitigate the vanishing gradient problem, allowing the model to determine what information is relevant to propagate through time. As a more streamlined alternative to the Long Short-Term Memory (LSTM) network, the GRU has proven to be effective in various applications where understanding and processing sequential data are crucial.

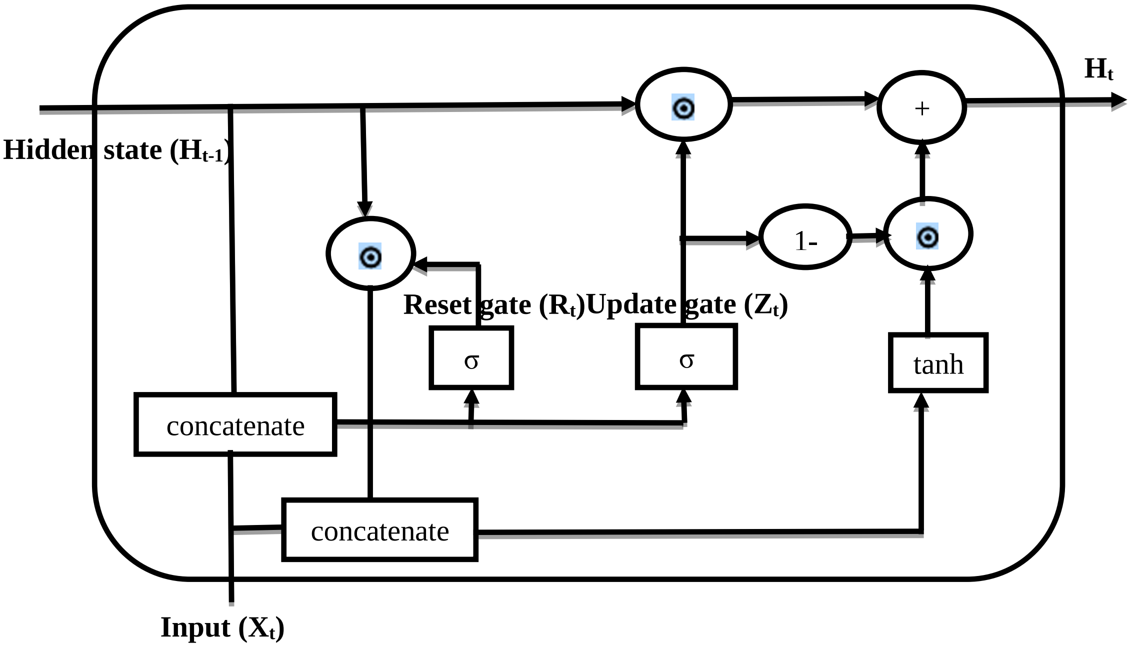

Figure 3: GRU Architecture

The GRU is characterized by its gating mechanisms which control the flow of information through the network that is given in the following equation (1-4).

$zt=\sigma(Wz\cdot[ht-1,xt])$ (1)
$rt=\sigma(Wr\cdot[ht-1,xt])$ (2)
$h't=\tanh(W\cdot[rt\odot ht-1,xt])$ (3)
$ht=(1-zt)\odot ht-1+zt\odot h't$ (4)

where xt is the input at time t, Wz, Wr,W are the weight matrices for the update gate, reset gate, and memory update, respectively. σ is the sigmoid activation function, tanh is the hyperbolic tangent activation function and ⊙⊙ denotes element-wise multiplication [31].These equations collectively define how the GRU processes sequential data, incorporating information from the current input xt and the previous hidden state ht−1 to update the ht. The gating mechanisms, controlled by zt and rt, enable the GRU to selectively retain and update information, making it particularly effective for capturing long-term dependencies in sequential data.

The proposed CTG model is presented in figure 4 which performed the feature extraction. Each feature extractor consists of three GRUs, with input features encompassing N,P ,K, PH, humidity, soil moisture, and wind speed. Additionally, the feature extractor incorporates historical data on water requirements from the same period in the preceding year. The first two GRUs within the feature extractor focus on extracting long-term trend features and short-term change features, respectively. These features are then amalgamated through the third GRU to yield site-specific features.

Subsequently, the output features from each station's feature extractor and the historical water requirement data with a step length (s) are combined using a residual connection technique. This approach enhances the model's ability to capture intricate dependencies by preserving information from previous time steps. Following this combination, an additional GRU layer is employed to forecast IWR at time (t) for drip irrigation. The inclusion of historical water requirement data not only serves as a valuable reference but also establishes constraints for boundary conditions. This strategic integration disrupts the network's symmetry, thereby bolstering the overall characterization capabilities of the GRU model that ensuring precise predictions for effective management of IWR in drip irrigation. This holistic architectural framework underscores the nuanced process of feature extraction and application within an enhanced GRU model specifically designed for predicting IWR in the domain of drip irrigation.

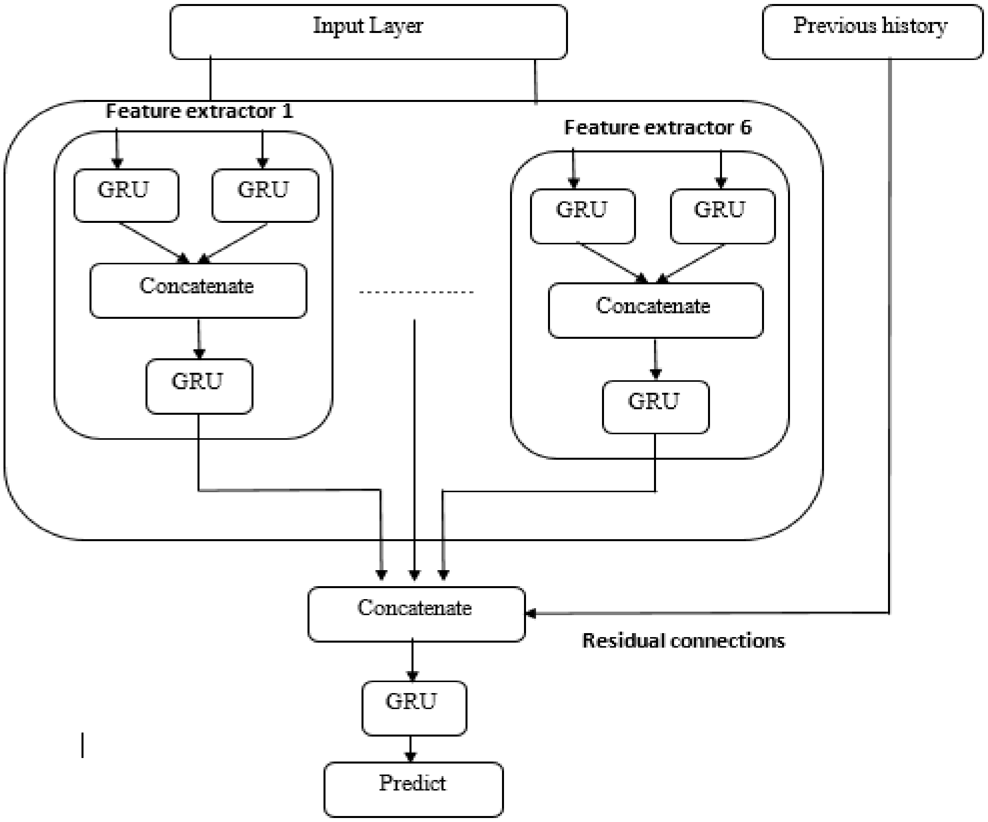

Figure 4: CTG Architecture

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6. Hyperparameter tuning

A hyperparameter is nothing that the configuration is setting externally to the model before training. Some of the hyperparameter of CTG are represented in the table. These hyperparameters play crucial roles in training proposed model where the RUN optimization is used for hyperparameter tuning. It would likely adjust these values iteratively to find an optimal configuration for the specific task.

Learning Rate	The step size at which the optimizer adjusts model weights during training.
Dropout Rate	A regularization technique where a fraction of connections is randomly dropped during training.
Batch Size	The number of samples processed in one iteration during training.
Sequence Length	The length of input sequences in a RNN or time series model.
Activation Function	A mathematical operation applied to the output of a neuron, such as 'tanh' or 'relu'.
Optimizer	Adam optimizer model used to minimize the model's loss function during training
Gradient Clipping	A technique to prevent exploding gradients by capping the gradient values during training.
Initialization	glorot_uniform method used to set the initial weights of the neural network.

7. RUN optimizer

In this work, a swarm-based optimization model with stochastic components referred to as the RUN method is applied [32]. Unlike traditional approaches, the RUN method avoids clichéd inspiration and emphasizes a metaphor-free language that focusing on the mathematical core and activated rules at specific times. Rejecting the use of metaphors in population-based models, the RUN method incorporates the main logic of the Runge-Kutta (RK) technique and population-based evolution of agents.

The RUN method applies K4 method to find an optimal solution. It uses calculated slop to explore a best solution in search space. The algorithm initializes a population randomly within specified bounds and apply searching strategy based on RK methods to conduct global and local searches.

The search mechanism involves calculating coefficients (k1, k2, k3, k4) using random solutions, determining the best and worst positions, and updating solutions iteratively. The algorithm balances exploration and exploitation by adapting the step size and employing an enhanced solution quality (ESQ) mechanism. ESQ combines the average of random solutions with the best location to produce improved solutions that emphasizing both exploration and exploitation stages based on a random condition. Therefore, the step-by-step explanation of the algorithm is given in the following [32].

Stage 1: Initialization

- Parameters Setup: Initialize parameters a, b, and other constants.
- Population Initialization: Generate a population Xn (where n=1,2,…,N), where each member Xn represents a solution to the optimization problem.
- Objective Function Calculation: Evaluate the objective function for each member of the population.
- Best and Worst Solutions: Determine the best (xb), worst (xw), and best-so-far (xbest) solutions.

Stage 2: RUN Operators (Iterative Process)

- Iterate through generations: Loop for i=1 to Maxi (maximum number of iterations).
- Iterate through population: Loop for n=1 to N (population size).
- Position Update: Calculate the position for the next iteration (xn+1,l) for each dimension (l=1 to D) using the exploration and exploitation phases
- ESQ:

1. If rand<0.5, calculate a new solution (xnew2) end
2. If f(xn)<f(xnew2), further refine xnew2 to xnew3

Stage 3: Termination

- Finish the algorithm after completing the specified number of iterations (Maxi).
- Position Update (Exploration and Exploitation) is determined by a conditional statement:

1. If rand<0.5, a global search is applied around the current solution xc (exploration phase).
2. If rand≥0.5, a local search is applied around the historical best solution xm (exploitation phase).

- ESQ aims to improve solution quality and prevent local optima:

1. Calculate the average of three random solutions (xavg).
2. Generate a new solution (xnew1) based on a combination of xavg and the historical best solution (xbest).

3. If rand<0.5, determine xnew2
4. Refine xnew2 to xnew3 under certain conditions

The RUN optimizer provides a balance between exploration and exploitation that employs a dynamic step size and incorporates an enhanced solution quality mechanism to refine solutions iteratively. It aims to efficiently explore the search space and converge to high-quality solutions in optimization problems.

However, proposed novel RUN optimised CTG model represents a notable advancement in the field of irrigation management. By incorporating key parameters such as N,P,K, soil moisture, humidity, temperature, pH, and wind speed, this model provides a comprehensive understanding of the factors influencing IWR factor. Then optimised CTG model effectively capture an intricate temporal relationship within the dataset that enabling accurate predictions. Also, this proposed technology underscores the significance of harnessing data-driven visions for optimizing irrigation does that ultimately contributing to resource efficiency and improved crop yields of modern agriculture.

8. Result And Discussion

The hardware prototype for collecting data set is shown in Figure 5. The Arduino control collects data from the sensors and updated to the cloud. The sensor readings in cloud visually shown in Figure 6. The evaluation of the proposed Optimized CTG model for IWR involves training and testing on a dataset of 619 jasmine samples with a 70% training and 30% testing split. After training, the model's performance is compared with an existing model using various metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Bias Error (MBE), Standard Deviation (SD), T-Statistic (Tstat), Uncertainty with 95% Confidence Level (U95) and Nash-Sutcliffe Efficiency (NSE) [33].

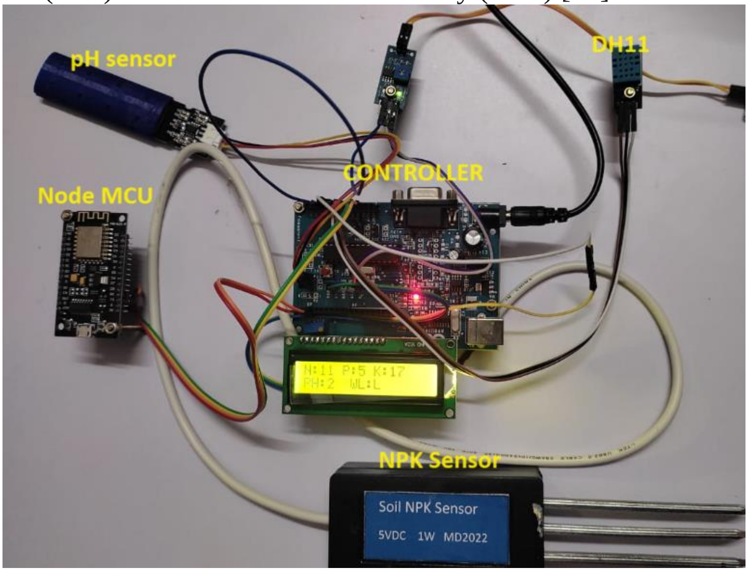

Figure 5: Hardware implementation

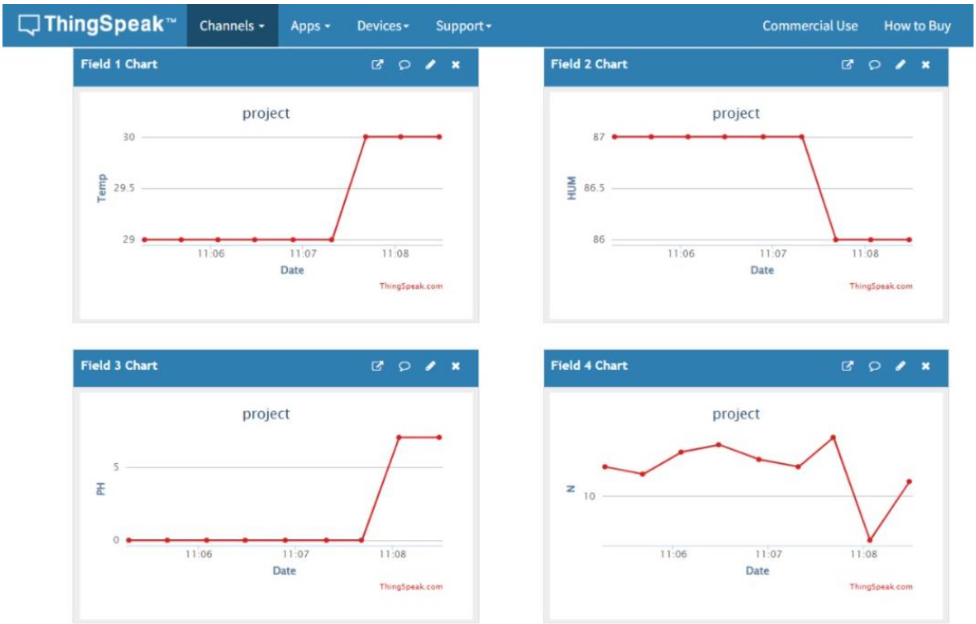

Figure 6: Updates sensor values in cloud

The MAE assesses the average absolute difference between predicted and observed values, with lower values indicating better accuracy. RMSE provides a similar measure but with greater penalty for larger errors due to the square term. The MBE calculates the average difference between predicted and observed values, with positive or negative values indicating overestimation or underestimation, respectively.

SD measures the variability in the predicted values. Tstat evaluates the significance of differences between the proposed and existing models. U95 accounts for uncertainty in predictions, incorporating SD, RMSE and the number of observations. NSE assesses the model's efficiency in simulating observed values, with a value of 1 indicating a perfect match. Also Considering R2 as an additional metric to evaluate the goodness of fit between observed and predicted values. A higher R2 value indicates a better fit and predictive performance of the model. It complements the other metrics in providing a comprehensive understanding of the model's accuracy.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |O_i - P_i| \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (P_i - O_i)^2} \tag{6}$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n} (O_i - P_i) \tag{7}$$

$$\mathrm{SD} = \frac{\mathrm{RMSE}}{\bar{O}} \tag{8}$$

$$\mathrm{Tstat} = \sqrt{\frac{(1-n)\mathrm{MBE}^2}{\mathrm{RMSE}^2 - \mathrm{MBE}^2}} \tag{9}$$

$$\mathrm{U95} = 1.96\sqrt{\mathrm{SD}^2 + \mathrm{RMSE}^2} \tag{10}$$

$$\mathrm{NSE} = 1 - \frac{\sum(P_i - O_i)^2}{\sum(\overline{O_i} - O_i)^2} \qquad (11)$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{(\sum_{i=1}^{n}(O_i - \overline{O_i}))^\wedge 2\ (\sum_{i=1}^{n}(P_i - \bar{P})^\wedge 2\ )}}\right]^2 \qquad (12)$$

Where n indicates Total number of observations, Oi denotes Observed (actual) value for the i-th data point, Pi denotes Predicted value for the i-th data point and |x| indicates an Absolute value of x, O¯ denotes Mean of the observed values. P¯ indicates Mean of the predicted values. The real versus predicted plot of proposed model is shown in Figure 7.

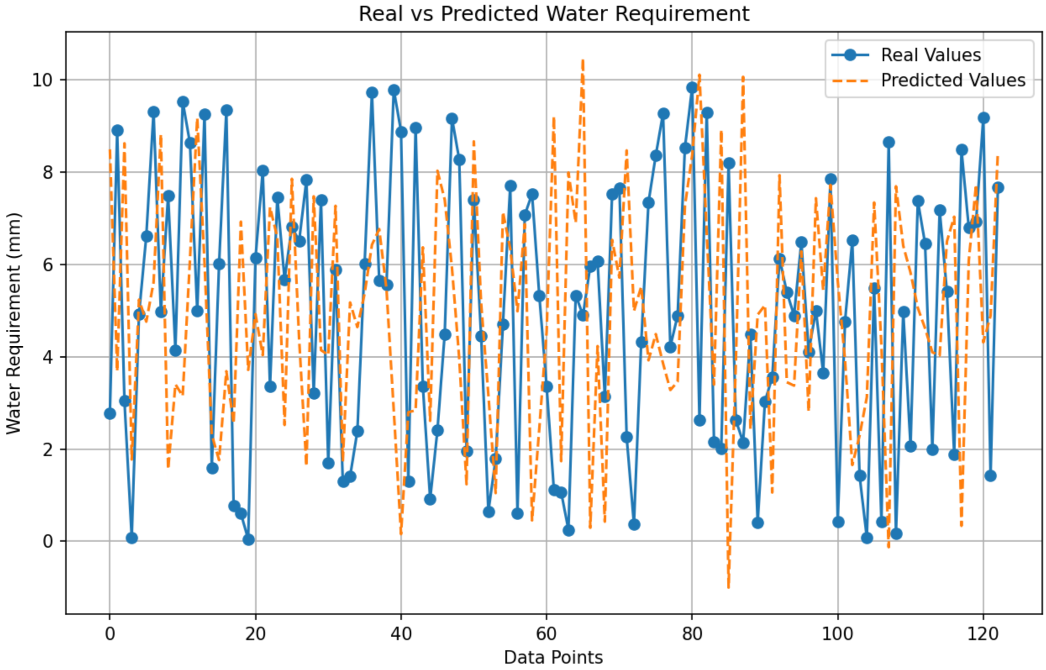

Figure 7: Real versus predicted plot

Model	**MAE**	**RMSE**	**SD**	**Tstat**	**U95**	**NSE**	**R^2**
Proposed	4.50	6.80	2.50	2.50	5.80	0.85	0.80
Optimised LSTM	6.50	8.90	3.80	1.80	7.20	0.75	0.68
GRU	7.80	9.50	4.20	1.50	8.10	0.70	0.65
LSTM-CNN	8.50	10.20	4.80	1.20	9.00	0.65	0.60
RNN	9.20	11.00	5.50	1.00	9.80	0.60	0.55
Random Forest	10.50	12.50	6.50	0.80	10.50	0.55	0.50
CNN	11.80	13.80	7.80	0.60	11.20	0.50	0.45

Table 1: Performance analysis

In this comparison table 1, various ML models including the proposed optimised CTG model are evaluated based on performance metrics. The proposed model is highlighted for its superior performance that showcasing minimal errors across different criteria. Specifically, it achieves a MAE of 4.50, RMSE of 6.80, SD of 2.50, Tstat of 2.50, U95 of 5.80, NSE of 0.85 and a R2 of 0.80.

Comparatively, other models such as Optimized LSTM, GRU, LSTM-CNN, RNN, Random Forest, and CNN exhibited a higher error value across these metrics. Lower MAE, RMSE, SD and Tstat values in the proposed model indicate improved accuracy and precision while a lower U95 implies reduced uncertainty. Additionally, higher NSE and R2 values highlight the proposed model's enhanced efficiency and goodness of fit.

This illustrative showed that the proposed model outperforms its counterparts by showcasing its potential for more accurate and reliable predictions than the conventional methods. Therefore, the Proposed underscores its superior performance that making it a promising performance for further consideration and application in practical scenarios.

9. Conclusion

In this work, a experimental prototype is successfully implemented to generate a comprehensive dataset for jasmine plants for a various crucial parameters N, P, K, PH, Moisture, Humidity, Speed and Water Level. By Leveraging this dataset, the IWR is accurately calculated through the application of a novel CTG model. This model experienced fine-tuning with the RUN optimizer that resulting in enhanced precision in IWR identification. The proposed model showcases exceptional performance in IWR evaluation by attaining the lowest error values across all evaluated metrics. With a remarkable value i.e., MAE as 4.50, RMSE as 6.80, SD as 2.50, Tstat as 2.50, U95 as 5.80, NSE as 0.85 and R2 as 0.80 respectively. This model consistently outperforms others in accuracy, precision, bias reduction, statistical significance, uncertainty management, efficiency and goodness of fit among all the conventional models. The precise calculation of IWR serves as a pivotal component in drip irrigation that optimizing the yield and growth of jasmine plants. By combining hardware implementation, dataset generation, and advanced CTG modelling, this work found as a footing for effective and data-driven strategies in jasmine cultivation contributing to more efficient drip irrigation based agricultural practices.

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