Irrigation Iot Sensor Data Analytics Using Bio-Inspired Data Mining Techniques

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Abstract

Recently, irrigation management has been considered one of the most significant areas of research in smart vertical farming. Hence, it is essential to optimize freshwater usage for smart vertical farming management due to the lack of freshwater sources. It is observed that the soil moisture level and temperature data need to be appropriately examined and analyzed to predict the water irrigation level in a smart farming platform. Hence, in this work, the Internet of Things (IoT) sensors have been utilized to collect and monitor the soil moisture level, ambient temperature level, and humidity level data effectively. Besides, the collected sensor information has been analyzed and predicted to recognize the appropriate utilization of the optimum level of freshwater using Grey Wolf optimizer integrated recurrent network models. Therefore, this approach successfully analyzes the sensors' data and predicts the required level of irrigation based on motor ON and OFF conditions. The generated data from the sensor has been evaluated using the Keras model using the python language, and the performance is assessed based on the accuracy ratio. This model obtained a maximum of (0.995%) accuracy in forecasting the optimum irrigation level. The proposed system will utilize less voltage to minimize the power consumption ratio up to 35% in the irrigation process with 99.5% accuracy in forecasting the optimum irrigation level.

Keywords: Irrigation; Iot; Sensor; Data Analytics; g Bio-Inspired Data Mining

1. Introduction

In the recent past, the ecosystem's soil moisture level, temperature measurement, and humidity level have been considered for optimizing irrigation level and water usage in smart farming[1] management. This system uses IoT-based sensors [2] which refers to networked devices embedded in the environment that interact and collaborate to achieve common objectives [3]. The system include soil moisture sensors, temperature-monitoring sensors, and weather prediction sensors to get these parameters' information for smart farming monitoring accurately. Further, to measure the groundwater content, the soil moisture sensor is mounted in the soil of the farming land for analysis. The water observation level may vary based on the type of soil, and the pouring level varies based on the type of crop planted. Hence, the soil and plant cultivation type is considered based on the significant parameter, which includes fertilizers, pesticides, and other growth factors used in the soil for planting specific crops [4]. In smart farming, the sensors detect moisture levels up to 38mm depth into the ground, which consumes 2.0V to 5.0V power. Temperature and humidity monitoring sensors [5] were considered essential in an automatic irrigation system in a smart farming environment. Here, the humidity sensor is used for measuring the concentration of water stream in the air, and the level of humidity in the atmosphere decreases based on the vaporizing ratio of the water content in the soil. The high temperature in the environment increases the vaporizing rate of water content in the soil; in this case, more water is required for irrigation. Hence, temperature-monitoring sensors [6] play a vital role in irrigation management. This sensor gave temperature measurements in electrical signals and converted them into the

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required format. In General, the temperature scale is commonly represented in the form of Celsius℃, Fahrenheit °F, and Kelvin ‘K’. In this work, the Celsius scale describes the temperature values. Based on the firm survey, it is observed that DHT11 and DHT22 are the humidity and temperature monitoring sensors used in this research for smart farming monitoring [7]. The DHT11 measures humidity ranges between 20 - 80% with 5% of accuracy in detection, and it can detect the temperature range from 0 – 50^° C with 2^° C of accuracy. The DHT22 measures humidity ranges between 0 - 100% with 2 – 5% accuracy in detection, and it can detect the temperature range from 40-125^° C with 〖0.5〗 ^° C of accuracy [8]. These sensors consume 3.3V to 5.5V power. These sensor devices used two types of communication modes such as long-range and short-range wireless modes. The detailed soil moisture sensor, humidity, and temperature control system specifications are illustrated in table 1. The availability of the Internet of things (IoT) [9], wireless sensor technology, and machine learning approaches made the irrigation process cost-effective with less human power required to manage cultivation. These sensors are used for collecting information about the soil moisture level, temperature, and humidity level in the crop field. Further, these sensors produce analog or digital data as output, and it has been converted into the required format of sample data for evaluation.

Table 1: Communication technologies and sensors specification

Specification for the Soil moisture sensor	
Detection depth	38mm
Power	2.0V~5.0V
Dimension	20.0mm * 51.0mm
Mounting hole size	2.0mm
Specification for Humidity and Temperature sensors	
Humidity range	DHT11- (20 -80% /±5%), DHT22 – (0-100%/±2-5%)
Temperature range	DHT11- (0-50$^{\circ}C$ / $\pm 2^{\circ}C$), DHT22 – (40-125$^{\circ}C/\pm 0.5^{\circ}C$)
Power	3.3V~5.5V
Dimension	29.0mm * 18.0mm
Mounting hole size	2.0mm
Specifications for IoT communication	
For Long-range wireless	NB-IoT/Cat-M/ LoRa/ 4G/Cat-1/ GSM,/GPRS/ GNSS/ GPS
For Short-range wireless	Wi-Fi/Zigbee/ Bluetooth/ NFC/ RF

Abbreviations

TMS - Temperature Monitoring Sensor
SMMS – Soil Moisture Monitoring Sensor
HMS – Humidity Monitoring Sensor
WP – Water pouring Pipe
WPM – Water Pumping Motor
SRWC – Short Range Wireless Communication
LRWC – Long Range Wireless Communication
WF- Wi-Fi Network
GSM- Global System for Mobile Communication
GW- Gateway
CDB- Cloud Database
SR- Server
DAU- Data Analysis Unit
BT - Bluetooth
MD – Modem

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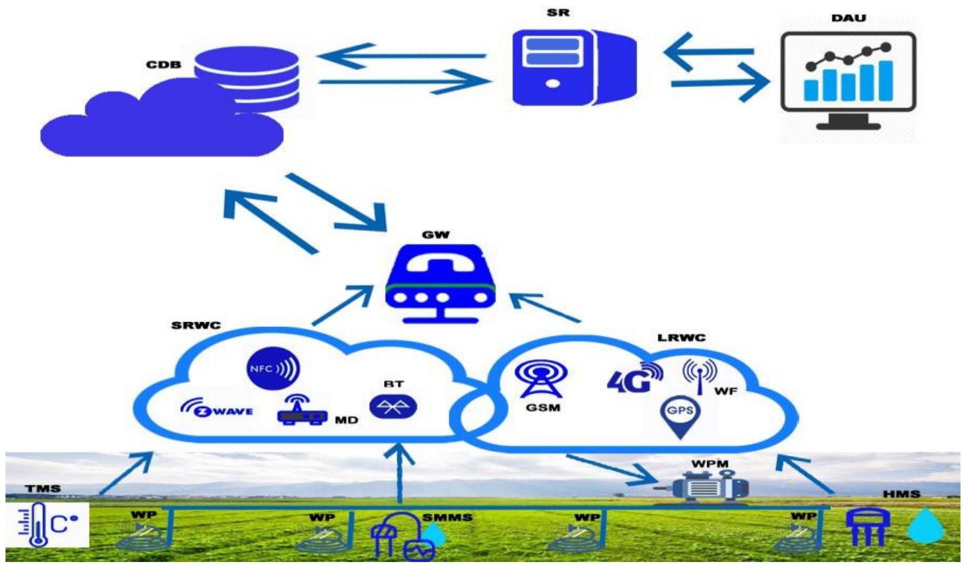

Figure 1. Internets of Things based Smart Irrigation System

Figure 1 illustrates the smart irrigation system, which includes three wireless sensors: a soil humidity monitor, environment humidity monitoring sensor, and temperature monitoring sensor. The collected field information from the sensor passes through the Long term or a short-term range of wireless communication technology to the gateway for evaluation [10]. The portal gives this information to the cloud database, and the agriculture server retrieves this information for analysis and validation. During the data analysis phase, sensor data is processed by a classifier, which predicts the required water utilized for the crop and analyzes water usage based on the threshold value. If the classifier predicts the plant requirement on water, the information will be communicated to the motor through data communication procedures. [11]. the soil humidity sensor continuously monitors the water content in the soil during the consumption of water into the field [12-14]. The classifier predicts the moisture content in the soil that meets the threshold level. Hence, the classifier will pass instructions to the water pumping motor, which helps to shut down the motor.

This research focused on IoT-assisted smart irrigation systems and their importance based on the discussion.

The paper is structured as follows; Section 2 analyzes the various researcher opinions regarding the irrigation monitoring process. Section 3 examines the introduced optimized, recurrent neural network-based irrigation system for smart farming management. Section 4 discusses the dataset utilized in this research work. Section 5 examines the efficiency of the introduced smart farming and irrigation management system based on simulation analysis. Section 5 concludes the research with future perspectives.

2. Review of literature

The literature reviews discuss the various related works based on useful technologies and machine learning algorithms utilized for smart farming and irrigation monitoring. (Annekethvij et al., 2019) [15] Developed a monitoring system to resolve the over-irrigation problem such as soil erosion and over-irrigation issues, effectively utilized for crop-specific irrigation. This work established a distributed wireless sensor network for each region of the form using various sensors to capture and transmit field information on a shared server—in which the machine learning techniques are utilized for analyzing and forecasting the irrigation pattern with better accuracy.

Mobasshir et al., 2020 [16] create the recommended systems for embedded systems, Internet of Things technologies, and wireless sensor network-based smart farming. It gave detailed descriptions of the electric circuit systems, distance monitoring equipment, and network protocols for intelligent agriculture. K Lova, et al., 2020 [17] analyzed and presented the current trends in various Internet of Things technologies, wireless sensors, equipment, and machine learning algorithms

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utilized to increase production in smart farming systems. K R Gsangaya, et al., 2020 [18] reported a precision agriculture system to capture and monitor the crop yield information using portable Internet of things based on wireless sensor networks.

Huiping Zhou, et al., 2020 [19] introduced the integrated high efficient irrigation strategy and the quality improvement of cash crops by analyzing the effects of various water and nutrient treatment. Quantitative simulation of crop quality and biophysical model were integrated to obtain more data about the mechanism of quality information by considering all analysis irrigation decisions, which can be made to acquire sustainable use of region water source. Ambarish G Mohapatra, et al., 2017 [20] developed a web-based notification system for testing, predicting, and notifying the farmer about the required amount of Nitrogen, Phosphorus, and potassium content in the soil, which helps in reducing the usage of fertilizer.

Jaiswal et al., 2020 [21] presented a model that reduced the electricity cost and wastage of water using IoT Sensors and a fuzzy inference system-based automatic water pouring system. Singh G Sharma, et al., 2020 [22] introduced the Internet of things and machine learning-based optimized utilization of water usage in irrigation. This system takes soil moisture parameter values as the main parameter for this prediction. Kondaveti R, et al., 2019 [18] projected a system for effective utilization of irrigation, saving electricity, and approximate rainfall detection. It focused on an automatic water pouring motors system based on machine learning algorithms. Ahmed S.M, et al., 2020 [23] represented a model that predicted soil moisture level-based water pump on the OFF system in smart irrigation. This system considered the measures of ambient temperature, daylight intensity, humidity, and rainfall prediction. K Venkata, et al., 2020 [24] introduced machine learning and sensor technology-based systems, which evaluated the connection between air temperature, soil temperature, and UV intensity with plant growth for conserved irrigation levels. Alqahtani, F. et al. [25] introduced a bio-inspired cuckoo search optimizer trained extended short-term memory network, which is used to reduce the prediction error for urban waste trace monitoring and truck tracking. This method uses the effective learning function and memory process that improves the overall IoT-based waster-monitoring process.

Xiaobin W. et al., [26] is incorporated based on the genetic algorithm in neural networks to identify the characters in vehicle license plates. The optimizer predicts the minimal weight and threshold in predicting the characteristics. The adaptive mutation rate ensures the diversity of the species and makes the algorithm reach the network model at the global standard. The experimental results show that the classification approach has improved convergence speed. Salama et al., 2015 [27] developed a learning neural network structure with the help of an ant colony optimizer. The new classification approach has been tested with 40 benchmark datasets, and the performance is compared with other optimizers' trained classification methods. The results and discussion shows that the new algorithm performs well with comparison algorithms. Jha, G. K., et al. [28] introduced particles swarm intelligent optimizers, which are utilized for training the neural network model to predict the time series data. The efficiency is compared with standard backpropagation networks, in which the evaluation results show that the new classification techniques provide superior performance to classical network models. According to the above- study, most of the related works focused on utilizing IoT and wireless sensor technology-based monitoring systems to improve the crop yield in smart farming. This paper focuses on monitoring and controlling over-irrigation problems by enabling deep learning analysis, IoT, and wireless sensor network techniques.

3. IoT Sensors Data Analyzing Bio-Inspired Optimizer Utilized Gated Recurrent Network Based Smart Irrigation System

This section uses a bio-inspired optimized **neural** network to discuss the smart irrigation management process. The system uses the three IoT sensor data for collecting irrigation data; the collected data is processed by applying different steps such as data preprocessing, classification, and alert system. The detailed working process is illustrated in figure 2.

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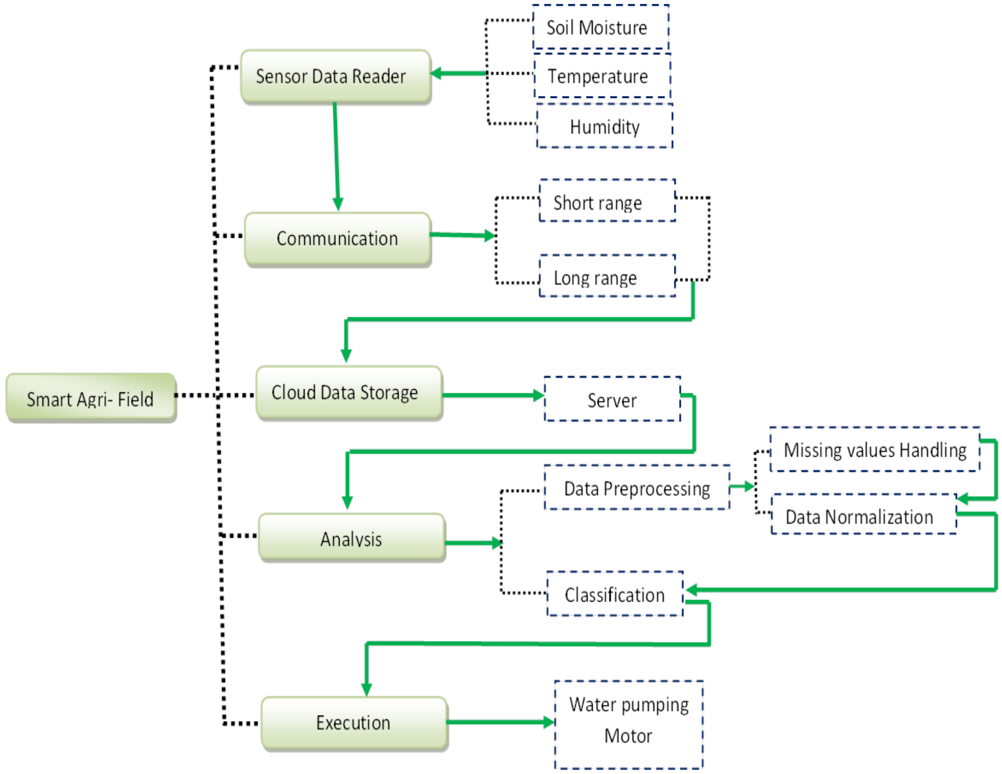

Figure 2. Workflow Diagram of the Smart Irrigation System

The manuscript uses the bio-inspired optimizer that was utilized by gated recurrent unit network-based prediction in the irrigation monitoring system. Initially, the IoT sensors collect the soil moisture level, soil humidity data, and soil temperature data from the crop field. From the sensor-reading device, the communication network module retrieves the sensor-captured information. The communication modules pass this information to cloud storage through the gateway. The agricultural data analytics sever this information from the database for analysis. The IoT irrigation data analytic system has two phases: data preprocessing and classification. In preprocessing, the sensor recorded input data and verified for noisy records. Here, the noise removal technique applied to remove or replace that record transformed into an appropriate range using the classifier. After normalizing the data, it has been passed to the classification model to forecast water-pouring decisions using the sensor-predicted moisture, temperature, and humidity information. The classifier sends the instruction to the water pumping motor to pour water into the crop until it reaches enough water levels. Finally, once the water level reaches the maximum threshold value, the classifier will instruct the pumping motor to switch off. The IoT-based wireless sensor will continuously monitor the crop field to monitor irrigation status. The machine learning-based smart irrigation system was developed to reduce the farmers' work.

3.1. Methods

3.1.1. Preprocessing

This section discusses the optimized method used for preprocessing. The classification process is an essential step in the machine-learning model. Further, in electronic devices, missing or noisy data occurs due to several reasons such as power failure, power fluctuation, and so on. Therefore, before the data has been processed in a classification algorithm, the dataset needs to minimize the noisy and missing data to achieve an accurate prediction ratio. In this work, the mean or average value of previous and next records data taken as a replacer for those missing data is represented as follows in the equation (1),

$$Average\ \text{value} = \frac{\text{previous record value} + \text{Next record value}}{2} \tag{1}$$

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It is observed that this dataset may contain high and low values based on weather conditions, and it may increase the burden of classification algorithms during training and testing. Therefore, the Min-Max normalization approach has normalized the input data between 0 and 1.

$$\left.\begin{aligned} A &= \frac{\text{Original value} - \text{Minimum value(attribute)}}{\text{Maximum value(attribute)} - \text{Minimum value(attribute)}} \\ B &= \big(\text{NewMaximum(attribute)} - \text{NewMinimum(attribute)}\big) + \text{NewMinimum(attribute)} \quad (2) \\ \text{Normalized value} &= A * B \end{aligned}\right\}$$

In Equation (2), the minimum and maximum ranges have been taken to analyze the input values normalized by Min-max normalization. The normalized dataset is further processed to extract different features such as mean, standard deviation, energy, entropy, and other statistical features. The derived features are handled using a classification model to classify the irrigation data. The next section discusses in detail the classification model used in this work.

3.1.2 Irrigation data classification using Bio-inspired neural networks

Bio-inspired: Grey Wolf Optimization

The Grey wolf hunting optimizer is considered one of the meta-heuristic-based optimization techniques. In General, grey wolves live as a group, in which the group leader is named the alpha and responsible for entire activities like hunting and sleeping place decisions. The next wolf is named beta, which helps alpha make his or her own decisions promptly. The last wolf is named omega, which is responsible for collecting the information from the group and providing it to other wolves for further processing. Other than three, the remaining wolves are named a delta. Then, the grey wolves are worked according to three steps: prey tracking, chasing, prey pursue-encircle-harass, and attack towards the prey. The mathematical representation of the grey wolf is as follows in the equations (3,4 and 5),

$$\text{Computed the Coefficient vectors as } [A_1\ A_2\ A_3\ \ A_4\ ]\ ,\ [B_1\ B_2\ B_3\ \ B_4\ ] \quad (3)$$

$$\text{Calculate the Distance vector as } \left[D_\alpha\ D_\beta\ D_\gamma\ \ D_\delta\ \right] = \left|[B_1\ B_2\ B_3\ \ B_4\ ]^\circ \left[TV_\alpha\ TV_\beta\ TV_\gamma\ \ TV_\delta\ \right] - \ [X_1\ X_2\ X_3\ \ X_4\ ]\right|, \quad (4)$$

$$\text{Compute position vector for each input values } [IV_1\ IV_2\ IV_3\ \ IV_4\ ] = \left[TV_\alpha\ TV_\beta\ TV_\gamma\ \ TV_\delta\ \right] - [A_1\ A_2\ A_3\ \ A_4\ ]^\circ\left[D_\alpha\ D_\beta\ D_\gamma\ \ D_\delta\ \right] \quad (5)$$

The simplified form of equation (3), equation (4), and equation (5) are represented as follows,

$$\left.\begin{aligned} D_\alpha = |B_1{}^\circ\, TV_\alpha - IV|, D_\beta = \left|B_2{}^\circ TV_\beta - IV\right|, D_\gamma = \left|B_3{}^\circ\, TV_\gamma - IV\right|, \dots, D_\delta = \left|B_3{}^\circ\, TV_\gamma - IV\right| \\ IV_1 = TV_a - A_1{}^\circ\, D_\alpha, IV_2 = TV_\beta - A_2{}^\circ\, D_\beta, IV_3 = TV_\gamma - A_3{}^\circ\, D_\gamma, \dots, IV_n = TV_\delta - A_n{}^\circ\, D_\delta \end{aligned}\right\} \quad (6)$$

$$IV_{(t+1)} = \frac{IV_1 + IV_2 + \cdots + IV_n}{n} \quad (7)$$

In Equation (6) the $D_\alpha, D_\beta, D_\gamma, D_\delta$ represents the Distance vector from the target, where α- denotes the first value, β-denotes second value, γ - denotes the third, and δ- indicates the last value. Here, each iteration candidate solution was updated by calculating the distance from the target. In which t represents iteration; the Position vector of the target value is defined asTV_p, A and B represent Coefficient vectors. The position vector of input values is represented as IV in eq(7). A takes a random value from the first candidate value $|-\alpha, \alpha|$, and B takes random values |-1, 1|. In stopping criteria, when the candidate solution reaches target $If\,|A| \geq 1$, otherwise can optimize$If\,|A| \leq 1$.

A Gated recurrent unit is a type of recurrent network used in the LSTM network as an extended version for data processing. The Gated Recurrent Unit is faster and less expensive than the Long Short Term Memory network. Here, both network models work similarly to pass information for the optimization process. Initially, the hidden values are taken as input to perform calculations during training mode. Then the next epoch, the following training, and current hidden values are taken for further analysis. In each epoch's stage, the current hidden values are estimated by the maximum amount of stored or processed information.

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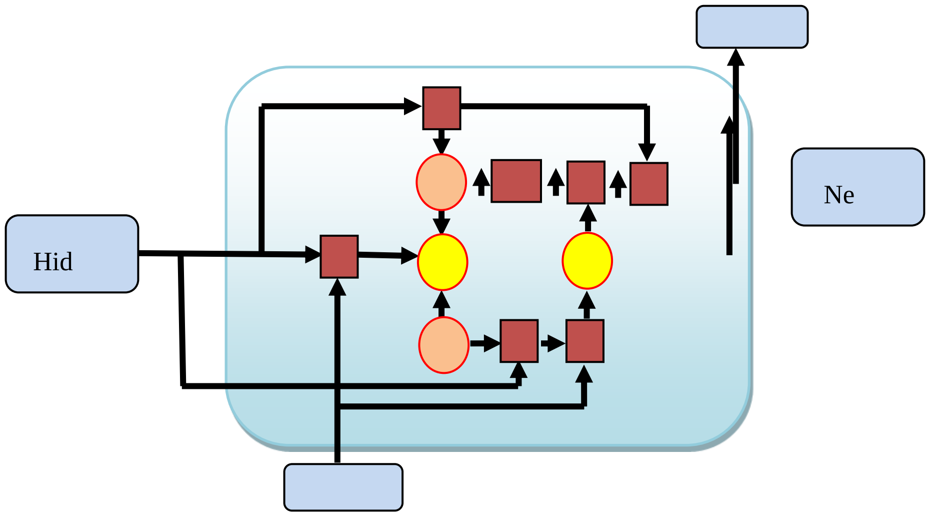

Figure 3. Gated Recurrent Unit Network Architecture

Figure 3 illustrates the gated recurrent unit network architecture. The systematic mathematical representation of the model is shown as follows in the equations (8,9 and 10). Initially, t and h values were assigned as t=0, h_0=0.

$$\left.\begin{aligned} r_t &= \sigma(W_r x_t + L_r h_{t-1} + b_r) \\ Z_t &= \sigma(W_z x_t + L_z h_{t-1} + b_z]) \end{aligned}\right\} \quad (8)$$

$$\check{h}_t = (W_h x_t [r_t \circ L_h h_{t-1}] + b_h) \quad (9)$$

$$h_t = h_{t-1} \circ (1 - Z_t) + Z_t \circ \check{h}_t \quad (10)$$

In the above derivations, Z_t represents update gate vector, r_t represents reset gate vector, 〖ȟ〗 _t denotes candidate vector, h_t represents output vector and h_(t-1) denotes the current hidden state. The sigmoid and tangent activation function is defined as σ, ρ. The hyper-parameters such as weight, learning rate, and bias are represented as W, L, and b. In eqn (8), the reset gate and update gate calculate the sigmoid for '+' element-wise addition of weighted input, currently hidden with learning rate, and bias values help decide the state activation decision. In eqn (9), to obtain a candidate solution, the tangent for '∘' is calculated based on the element-wise multiplication of the reset gate vector current hidden state based on the parameter values. Finally, eqn (10) is estimated based on the element-wise propagation for the candidate solution vector to analyze the current hidden state with 1- updated gate vector and element-wise addition to obtain the output.

In this, activation functions decide which state should be active by calculating the weighted sum and adding bias. The Gated recurrent unit commonly used sigmoid and tangent activation functions for state activation. A general derivation of the sigmoid activation function is denoted by follows in the eq(11),

$$\sigma(v) = (1 + exp^{-v})^{-1} \quad (11)$$

Where v and –v denoted the actual and predicted values, respectively, the range of predicted values is between 0 and 1. Here, 0 is indicated as invalid, and one is valid. A general derivation of tangent activation function is indicated as follows in the equation (12),

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$$sin\ sin\ (v) = \frac{exp^{io} - exp^{-io}}{2i} \quad cos\ cos\ (v) = \frac{exp^{io} - exp^{-io}}{2} \quad (v) = \frac{sinsin\ v}{coscos\ v} = \frac{exp^{o} - exp^{-o}}{exp^{o} + exp^{-o}} \} \quad (12)$$

In this equation, the actual and predicted output values are represented as –o and o, respectively. In tangent activation, the state activation ranges between -1 and 1. During the backpropagation in the neural network model, the weight of each input value must be updated in iterations to obtain a target output with minimum error. The default optimization technique utilized by the neural network model is the Gradient descent technique. However, this gradient approach took much time to reach the global minimum. Bio-inspired optimization techniques are utilized to overcome this issue in new research to replace the gradient approach. In this work, to update the weight of input vectors in the Gated recurrent unit network, the grey Wolf hunting optimization technique reduces the error rate. The derivation to calculate optimum is denoted in eqn (4), which is used during each iteration's weight update. This optimized process helps to classify the irrigation data effectively. Based on the results, the irrigation monitoring system has been created.

3.1.3 Continuous monitoring and Analyzing

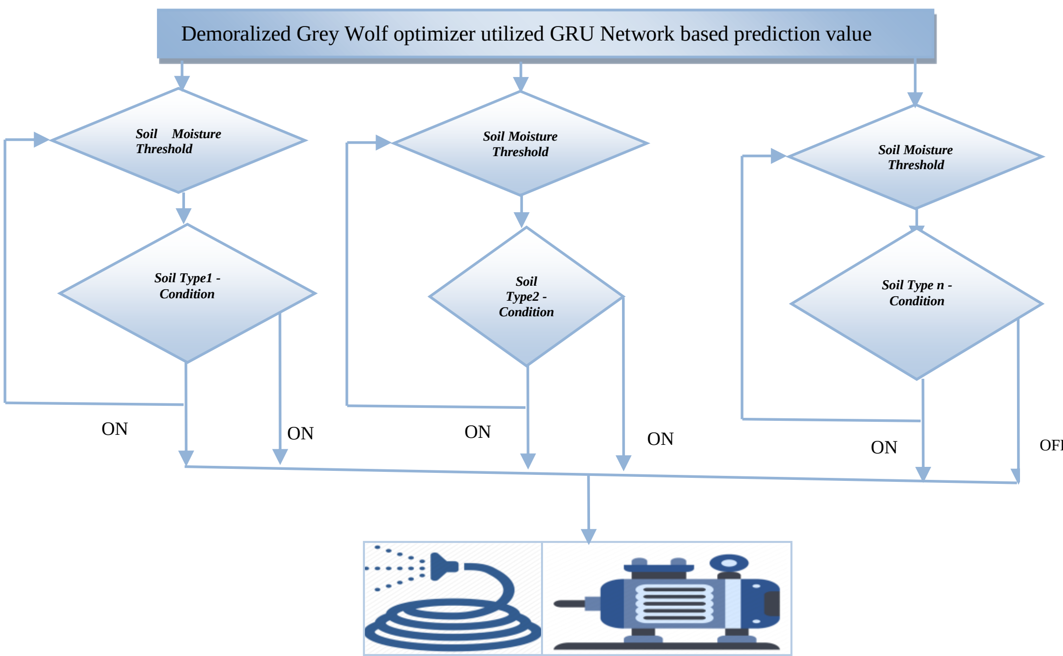

Figure 4. Monitoring and Irrigation Decision made by Grey Wolf Hunting Optimization utilized Gated recurrent unit Network

According to figure 4, the demoralized Grey Wolf optimizer used GRU Network-based prediction value. Here, the soil moisture level and the temperature or humidity reach the threshold value in which the classifier system instructs to control the water pumping motor state based on the soil moisture threshold limit. After reaching the maximum limit, the classifier tells the engine to switch OFF. The detailed Soil type based moisture threshold, temperature, and humidity threshold Conditions are explained as follows,

Soil Type1 - Condition:

If (Sensore type==Sandy)→If ((Moisture≤80) AND((Temperature ≥ -12^°C)OR(Relative humidity ≤35%)))→ON

else

If (Moisture ≥160)→OFF

In soil type 1 condition, from the predicted output vector, if the soil type is 1 – sandy, it will check the soil moisture level, temperature, and humidity level. If the soil moisture level ≤ 80 and temperature value ≥ -12^°C Or humidity value ≤ 35%,

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the system will pass instructions to the water pumping motor to switch ON and continuously check and predict the soil moisture until it reaches the maximum threshold, which is 160. Once it reaches the maximum limit, it will pass switch OFF instruction to the water pumping motor.

Soil Type2 - Condition:

If (Sensore type==Clay)→If ((Moisture≤60)AND((Temperature ≥ -12^°C)OR(Relative humidity ≤35%))→ON

else

If (Moisture ≥120)→OFF

In the soil type 2 condition, from the predicted output vector, if the soil type is '2' – Clay, it will check the soil moisture level, temperature, and humidity level. If the soil moisture level ≤ 60 and temperature value ≥ -12^°C Or humidity value ≤ 35%, the system will pass instructions to the water pumping motor to switch ON and continuously check and predict the soil moisture until it reaches the maximum threshold, which is 120. Once it reaches the maximum limit, it will pass switch OFF instruction to the water pumping motor.

Soil Type3 - Condition:

If (Sensore type==Loamy)→If ((Moisture≤70)AND((Temerature ≥ -12^°C)OR(Relative humidity ≤35%)))→ON

else

If (Moisture ≥140)→OFF

In soil type 3 condition, from the predicted output vector, if the soil type is loamy, it will check the soil moisture level, temperature, and humidity level. If the soil moisture level ≤ 70 and temperature value ≥ -12^°C If or humidity value is ≤ 35%, the system will pass instructions to water the pumping motor to switch ON and continuously monitor and predict the soil moisture until it reaches the maximum threshold as limited as 140. Once it reaches the maximum limit, it will switch OFF instruction to the water pumping motor. Then the gated recurrent network working algorithm steps are depicted in algorithm 1.

begin

Step 1: Initially assign t=0, $h_0=0$ and compute the new weight for the input vector values using the below derivation.

$$IV_{((t+1))}=(IV_1+IV_2+\cdots+IV_n)/n$$

Step 2: Calculate the element-wise addition in the vector gate, and the decision is taken according to the sigmoid function

$$Z_t=\sigma(W_z x_t + L_z h_{(t-1)}+ b_z])$$

Step 3: Again, compute the element-wise addition in the reset vector gate as follow,

$$r_t=\sigma(W_r x_t+ L_r h_{(t-1)}+ b_r)$$

Step 4: Compute the element-wise multiplication process in the candidate vector gate by using the tanH value.

$$\check{h}_t=(W_h x_t [r_t \circ L_h h_{(t-1)}] + b_h)$$

Step 5: Estimate the output value using the above-computed step 2,3, and 4.

$$h_t=h_{(t-1)} \circ (1-Z_t)+ Z_t \circ \check{h}_t$$

Step 6: Once the predicted output value is correctly classified actual value, then go for the next iteration; otherwise, backpropagate by Repeat this steps (1) to (5) till it fits the actual output

Step 7: when the classifier correctly predicts a newly coming input value, it will check for the soil moisture level condition to decide the activation of water pumping motors.

End.

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Based on algorithm 1, the gated recurrent unit processes the incoming irrigation data to predict the soil's quality effectively. The efficiency of the classifier model was tested with an agricultural field irrigation monitoring dataset, which is described in detail in the next section.

4. Dataset Description

This section discusses the detailed description of the dataset for the IoT irrigation data analytic process. To train and test this classification model, soil moisture, humidity, and temperature information was collected from [30] and [31]. The dataset was utilized and gathered manually to the appropriate format for analysis and test, shown in below table 2. It contains multi-variant attribute information. The input dataset contains soil moisture level, soil type, and soil temperature and humidity information. In this Soil type-based moisture threshold value is the decision attribute.

Table 2: Sample Dataset

Date and Time	Soil Moisture	Temperature	Humidity	Soil type based Moisture Threshold
2019-06-04 04:26:06	90	30	14	60
2019-06-05 08:33:05	85	32	16	70
2019-06-05 12:15:03	92	30	16	60
2019-06-05 14:56:01	122	29	14	80
2019-06-07 15:33:04	76	30	15	60
2019-06-06 04:02:02	95	30	15	70
2019-06-0808:56:06	55	29	14	60
2019-06-0612:41:03	105	30	15	80
2019-06-0614:46:05	99	30	14	60
2019-06-0912:23:08	166	31	15	70
2019-06-0714:12:09	89	30	15	60
2019-06-1118:32:02	178	30	15	80

With the help of the collected irrigation data, the introduced bio-inspired gated recurrent neural network working process efficiency is evaluated, which is explained in the experimental section.

5. Experimental Results and Discussion

This section describes the performance evaluation results of Grey Wolf Optimization integrated Gated Recurrent Unit Neural Network (GWO-GRUNN) in comparison with bio-inspired optimizer which includes Cuckoo learned Long Short Term Memory (Cuckoo-LSTM) [25], Genetic optimizer determined Neural Network (GA-ANN) [26], Ant Colony Optimization learned Neural network (ACO-ANN) [27], Particle Swarm Optimization learned Neural Network (PSO-ANN) [28]. The implementation part of the system has been accomplished with the help of Keras deep neural network library support. This platform supports the creation of custom optimizers and loss functions based on sensor information. As discussed earlier in the previous section, the smart irrigation-based dataset contains time series values that have been stored in the database. In this work, 75% of data was used for training and 25% for testing purposes. The prediction accuracy [29] was evaluated using the following metrics, which are described in detail.

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The elapsed time is defined as the time taken to execute the algorithms. The root mean square error specifies the variation between two vector values which is calculated by calculating it as follows,

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{NS}(AML-PML)^2}{NS}} \qquad (13)$$

When AML is the actual soil moisture level, and PML is the predicted level of soil moisture (PML). The NS indicate the number of samples in this vector.

The correlation coefficient used for finding the dependency between two attribute values could be used to calculate the dependence between actual and predicted values. The derivation for correlation coefficient (CC) is represented as follows,

$$cc=\frac{NS(\sum(AML*PML))-(\sum AML)(\sum PML)}{\sqrt{[NS(\sum AML^2)-(\sum AML^2)][NS(\sum PML^2)-(\sum PML^2)]}} \qquad (14)$$

The formula to calculate the fit value described in equation (14) is below. The higher Fit value indicates the better performance of the classifier, which is represented as follows, in equation (15)

$$Fit=\left(1-\frac{RMSE}{\sqrt{1/NS}\sum(AML-AML_{mean})}\right)*100\ \% \qquad (15)$$

Commonly used fundamental confusion matrix based accuracy Metrics for calculating error and accuracy are represented as follows in equation (16),

$$\left.\begin{array}{l} \text{True Positive} = \frac{TP}{TP+FN} = 1-FN \\ \text{False Positive} = \frac{FP}{TN+FP} = 1-TN \\ \text{False Negative} = \frac{FN}{TP+FN} = 1-TP \\ \text{True Negative} = \frac{TN}{TN+FP} = 1-FP \\ \text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} = \frac{TP+TN}{P+N} \end{array}\right\} \qquad (16)$$

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (17)$$

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (18)$$

According to the performance parameters, the proposed classification approach helps to predict the soil condition based on the introduced grey wolf optimizer trained gated recurrent unit network. The proposed method indicates the soil type based on moisture level and threshold limit. It helps to control the switching condition of the motor. The graphical representation of the values, as shown in figure 5, figure 6, figure 7, and figure 8, is below.

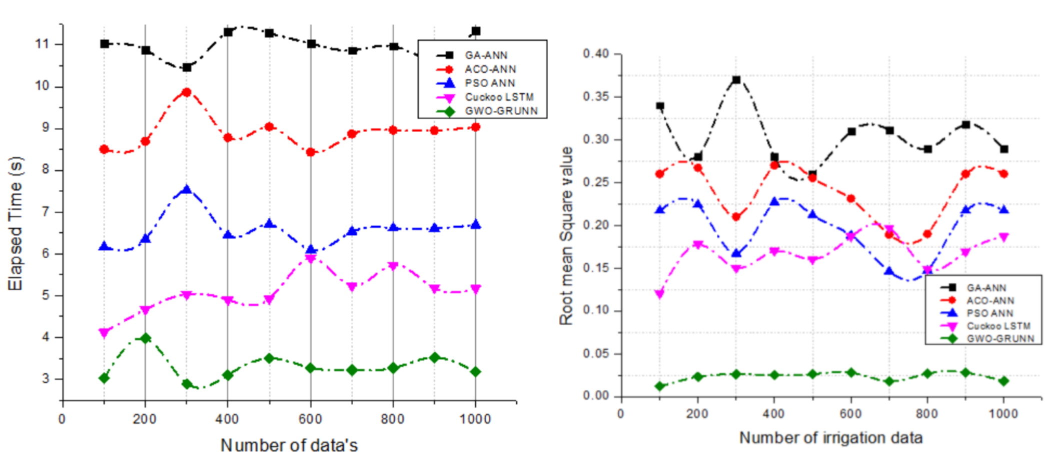

Figure 5. Analysis of Root mean square and Elapsed time for predicted value vs. predicted

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The sufficient weight has been updated through a grey wolf optimizer, which helps optimize the error rate in predicting the soil type based on the threshold value. The reduced error rate is calculated by estimating the average root mean square error, as shown in Figure 5. It described that every optimizer utilized in updating hyper-parameters in the neural network works efficiently based on the weight updating learning technique, which is obtained via minimum means square error rate ratio of (4.8%) compared to other classifiers such as Cuckoo-LSTM (7.91%), GA-ANN (9.34%), ACO-ANN (8.26%), PSO-ANN (7.54%). The minimal error helps to increase the overall accuracy of the classifier. Due to the less complicated calculation in the gated recurrent unit model, the GWO-GRU reduced the overall processing time (3.025003s) compared with other classifiers such as Cuckoo-LSTM (4.125066s), GA-ANN (11.023006s), ACO-ANN (8.502605s) and PSO-ANN (6.016002s). It helps send faster ON or OFF instructions to the water pumping motor[32].

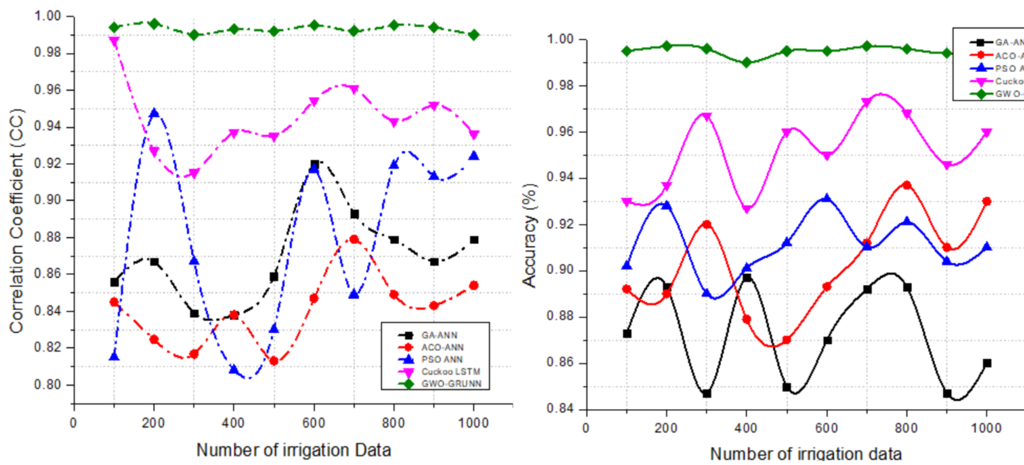

Figure 6. Analysis of Correlation Coefficient value and accuracy value for actual vs. predicted threshold**.**

Figure 6 shows that the newly introduced grey wolf optimized trained gated recurrent unit network (GWO-GRUN) helps to improve the maximum accuracy and correlation coefficient value. The overall recognized efficiency of grey wolf optimization utilized gated recurrent unit network is (99.5%) compared with other optimizer-based approaches such as Cuckoo-LSTM (99%), GA-ANN (87%), ACO-ANN (85%), PSO-ANN (89%). The introduced grey wolf optimizer trained gated recurrent unit network attained a maximum correlation coefficient value (99%) than other compared approaches. The correlation coefficient values obtained by different methods such as Cuckoo-LSTM, GA-ANN, ACO-ANN, and PSO-ANN are 98.7%, 85.6%, 84.5%, and 86.4%, respectively.

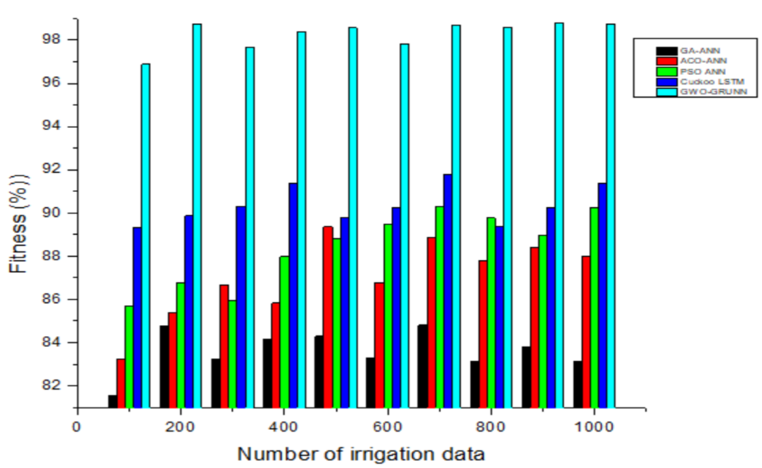

Figure 7. Analysis of Fit values for actual vs. Predicted

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According to figure 7, the Fit values of the soil moisture level have been analyzed using a grey wolf optimizer utilized gated recurrent unit, which obtained the maximum fit value of (90.20%) compared with other optimizer based network models; it indicates that the performance of the newly introduced grey wolf optimizer utilized gated recurrent unit network predicting excellently. The Fit values obtained by optimizer-based network approaches such as Cuckoo-LSTM, GA-ANN, ACO-ANN, and PSO-ANN were 89.33%, 81.54%, 79.23%, and 80.32%, respectively.

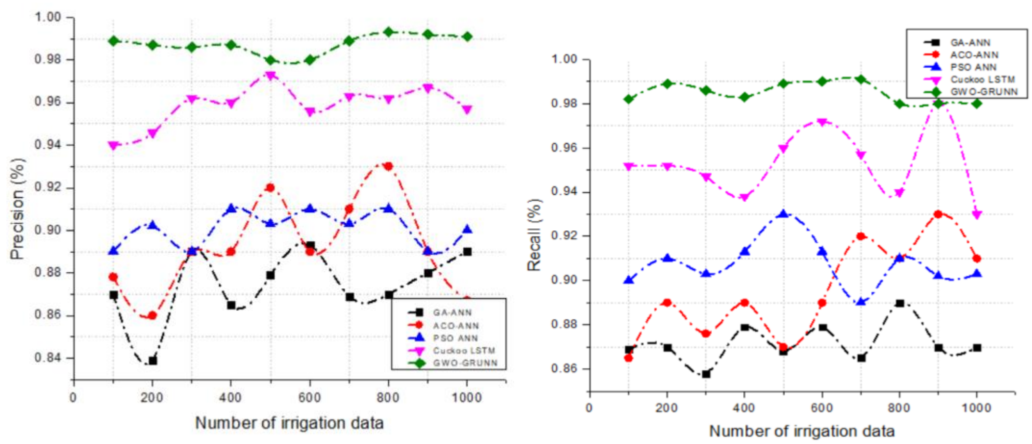

Figure 8. Analysis of Precision and recall values

Figure 8 illustrates the analysis results of precision and recall values for the introduced grey wolf optimizer, which utilized gated recurrent unit neural network GWO GRUNN and other compared bio-inspired neural network approaches. It clearly shows that the new classification approach obtained a maximum precision value (98.9%) than ACO-based ANN, PSO-based ANN, Cuckoo-based LSTM, and Genetic algorithm-based NN. The new bio-inspired classification obtained a maximum recall value of 98.2%, which is maximum than conventional algorithms. The maximum recall value helps in predicting moisture threshold value efficiently compared to other classification approaches.

6. Conclusion

As a result, in this research, the performance of the grey wolf optimization algorithm has been utilized based on the gated recurrent unit network for smart irrigation on IoT data analytics systems. Initially, soil moisture, temperature, and humidity data were collected from a publicly available database to train and test this model. The collected data are preprocessed by removing noisy or missing values, and data normalization has been introduced for validation. From this normalized dataset, 75% of records were taken to train the newly introduced neural network model, and the remaining 25% were utilized to test the model. Hence, according to the overall evaluation results, the recently introduced grey wolf optimizer integrated gated recurrent unit network models outperforms bio-inspired optimizers approaches such as cuckoo search optimization trained neural network, particle swarm optimization utilized neural network, ant colony optimization learned neural network, and genetic optimization algorithm based neural network. The introduced model helps to improve the accuracy by 99.5% and classifies the soil type based on the threshold limit for smart irrigation decisions. Data analysis in the sensor system has been planned to optimize further to show-improved performance in the smart farming system.

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