Design of an efficient IoT based irrigation platform via fuzzy bioinspired multisensory analysis of on-field parameter sets

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Abstract:*Designing smart irrigation systems is a transdisciplinary task that includes choosing the best field-specific sensing devices, getting data from these devices, pre-processing the data, analysing and classifying the data, acting on the data using the Internet of Things (IoT), and getting feedback from the system. A variety of smart irrigation models, including IBM ThingSpeak, Tracxn, Farm Connect, Hydrawise, etc. have been proposed by researchers, and each of them have its own operational & deployment-specific characteristics. When applied to real-time irrigation situations, these models are either very complicated or have a slow response time and low efficiency. Moreover, these models have a higher cost, which limits their scalability levels. To overcome these issues, this present work discusses design of a novel efficient IoT based irrigation platform via fuzzy bioinspired multisensory analysis of on-field parameter sets. The proposed platform uses low-cost components for sensing moisture levels, temperature levels, rain probability, NPK (Nitrogen, Phosphorous, and Potassium) levels, and soil types. After the measured data have been evaluated by a Grey Wolf Optimizer (GWO) to determine the best kind of sensors to utilise, a fuzzy decision layer is activated to decide whether or not to water the area. The resulting growth of plants is fed-back into the model, and a Genetic Algorithm (GA) is applied to tune the fuzzy rules for better water-flow under multiple types of crops. Due to the integration of GWO with Fuzzy Logic controller, the proposed model improved yield efficiency by 8.5%, reduced computational delay by 4.9%, and reduced deployment cost compared to standard smart irrigation models. These benefits make the suggested approach suitable for use in a wide range of practical applications involving smart irrigation in real time.*

Keywords:Transdisciplinary, fuzzy bioinspired multisensor, IoT, irregation.

1 Introduction

Transdisciplinarity in a smart agriculture field is an essential sector for a country's economic and commercial development [1]-[2]. As a result of the fact that the demand for farming is increasing at a rate that is equal to the growth rate of the population, the agricultural sector has recently undergone a smooth transformation into an industry that is centred on productivity [3]-[4]. This transdisciplinary transformation has taken place relatively recently. As a result of the emigration of agricultural workers and the depletion of human resources [5]-[6], there has been a rise in the necessity to automate multi-level operations such as sowing, fertilizing, monitoring, and other related tasks [7]-[8]. The most recent information and communication technology developments have made it possible to accomplish this goal [9]. There is no shadow of a doubt that sensors and controllers are what make the activities of monitoring and controlling agricultural devices function so efficiently. The concept of "smart farming" comes into existence as a direct result of the interconnectivity of sensors installed in farms to monitor issues relating to crops and the surrounding environment [10]. The rate of crop growth, humidity, and water level are just few of the variables that are discovered during the monitoring process and then relayed to the controller unit that is located in the farm [11]. Wind speed is another one of the factors as depicted in figure 1 is identified during the monitoring process [12]. In order to interact with distant sources like the cloud, mobile networks, and the internet of things, smart farms depend on radios and other communication equipment located locally and in the immediate area (IoT) [13]-[14].

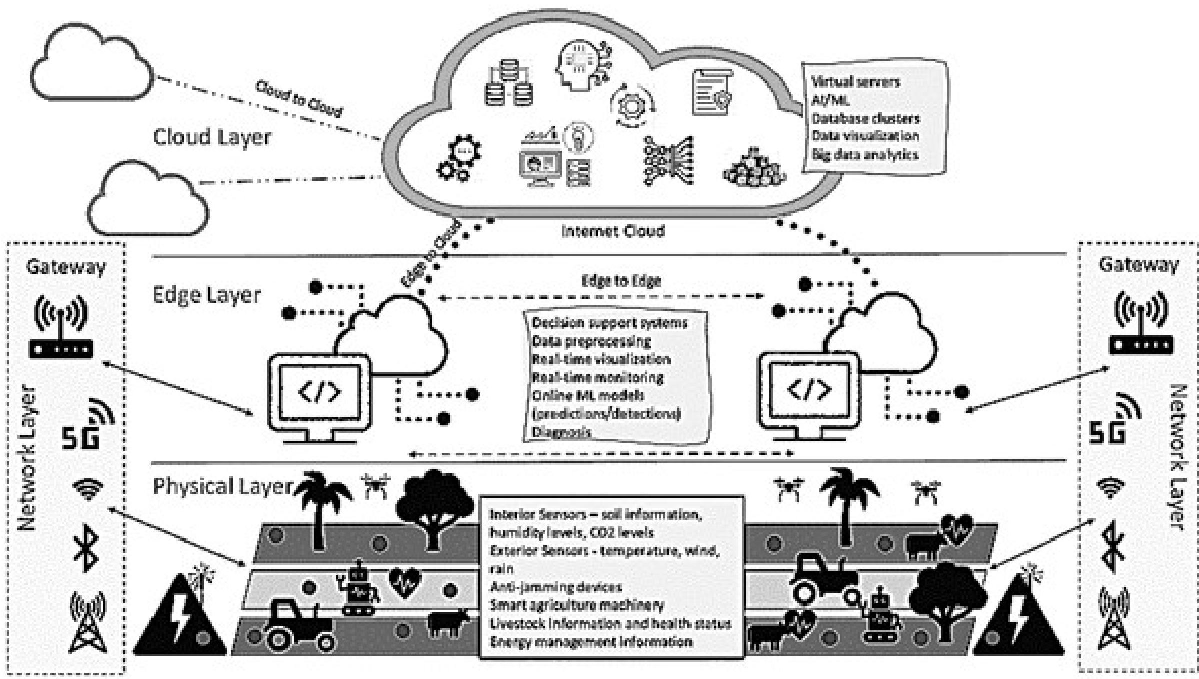

Figure 1: Design of a typical smart irrigation process.

This helps contribute to the improvement of the efficiency of smart farms by using speedy calculations and distributed processing of information sensed from the fields. Independent of the factor of time, efficient computing and analysis of the information that is sensed may be used to construct the functions of the machinery used in smart farms, as well as the requirements for farming [15]. When information has to be gathered, a variety of different sensing gadgets are used, and each one is strategically positioned in a different part of the farm [16]. When evaluating the farms and crops, some of the elements that may be taken into account include the amount of time needed to harvest, irrigate, and fertilize the land [17].

However, in order to handle information in an efficient manner, more resources are required. These resources are easily accessible as a direct consequence of improvements in information and communication technology over the last several decades. When processing the information, there must be no instances of lateness, and when there are cases of lateness, the findings must be provided quickly [18]. In addition, the capacity for storage and the rate of processing are very important, but the infrastructure support provided by smart farms is insufficient to meet these requirements [19]. Information that has been detected is sent to platforms for distributed computing, such as the cloud, in order to allow frequent and confined research [20]. This is done in order to enable frequent investigation. These distributed computing systems are dependent on intelligent hardware and processing methods, some of which include machine learning, artificial intelligence, and smart computing, amongst others. Enhancing the information processing by automatically producing test cases and error reports using data from prior occurrences increases the efficiency of the operation [21]. This makes it possible to acquire an approximation of the solutions and makes it easier to choose choices that are either error-free or may result in fewer mistakes [22]-[23]. This makes it possible to get an estimate of the solutions. Because machine learning methods are able to provide correct results despite the complexity of the environment in which they are used, they have become more popular for use in a wide variety of real-time application settings [24]. It does this by first identifying the properties and contexts of the information, and then by using training sets to contextualize the features and circumstances [25]. The difficult task of processing very large amounts of information is made much easier as a result of this. This kind of processing contributes to the provision of dependable and accurate evaluations by using a number of different validation cycles. This intelligence is included into the data processing and decision-making systems that are connected to smart farms in order to increase the level of confidence associated with the responses that are supplied [26]. The analysis of sensor data by machine learning meets all of the requirements connected to each application scenario, including the criteria relating to ease of use and punctuality [27]. Rapid judgments are notably necessary for time- and instance-dependent solutions of the farm information [28], and they are needed so that automation may be made more effective.

In the last several years, a variety of intelligent and machine learning technologies have been used to prepare the back-end processing for smart farming. This preparation includes activities such as the processing of data and the making of decisions. This is because smart farming takes into account a number of different constraints at once. Real-time applications may benefit greatly from integrations of this kind since they strive to give correct responses [29]-[30] as well as synchronized judgments. In addition to this, it is observed that academics have presented a plethora of different models of intelligent irrigation, each of which has a one-of-a-kind combination of properties that are special to deployment [31]. When applied to real-time watering settings, these models either have a sluggish reaction time or a low efficiency, both of which are negative qualities. Neither of these attributes is desired. In addition, the rising expense of these models' places limits on the extent to which they may be scaled. In the next portion of this article, we will discuss the creation of a novel and efficient Internet of Things (IoT)-based irrigation platform that makes use of fuzzy, bioinspired, multimodal analysis of on-field parameter sets. Because of this, finding a solution to these problems will be achievable. The proposed model is then compared, using both empirical data and parametric analysis, to already available intelligent watering practices. With the assistance of this comparison, the reader will have the ability to verify the model that has been supplied in light of traditional smart irrigation tactics. This article comes to a close with some deployment-specific observations on the recommended model as well as some ideas for how it may perform even better in a variety of scenarios.

2 Methodology

2.1 Review of Existing Smart Irrigation Techniques

Researchers have come up with a broad number of different models for smart irrigation, and each of these models is distinct from the others in terms of the contextual subtleties, functional benefits, application-specific constraints, and deployment-specific future possibilities that they provide. For instance, the research presented in [28]-[30] suggests the utilization of the Hybrid Symbolic Aggregate Approximation Algorithm, the Back-Propagation Neural Network, and the Particle Swarm Optimization (BPNN-PSO) platforms, all of which contribute to an improvement in the computational performance of various use cases. Similar models are discussed b various researchers [32]-[35]. These models propose the use of mixed-integer linear programming (MILP), artificial neural networks (ANN), extended ANN, and Long Short-Term Memory Network with Recurrent Neural Network (LSTM RNN), which assists in incorporating multiple parametric sets during smart irrigation optimizations [32]-[33].

The models that suggest using Genetic Algorithm (GA) to improve Back Propagation Neural Network [36], and ANN with computer vision [37] for smart irrigation, are highly optimized for a variety of different crop type situations. However, these models have a poor irrigation accuracy, which makes it difficult to use them to real-time use scenarios [38]. Deep learning with UNets, optimized LSTMs, deep reinforcement learning (DRL), and convolutional neural networks (CNN), all of which aim at augmenting different parameter sets for highly efficient irrigation operations, are proposed as a solution to these problems in the research published in [39]- [42], respectively. Because these models have accuracy levels of more than 95%, it is possible to utilize them for real-time deployments. Extensions to these models are explored in [43]-[46]. These references suggest the use of extended CNNs, deep CNNs, predictive Neural Networks, and Artificial Neural Networks for the estimation and prediction of various parameter sets. When applied to real-time irrigation settings, however, these models either have a delayed reaction time and poor efficiency or they have a high level of complexity. In addition, the increased expense of these models puts a limit on the levels to which they may be scaled. The next portion of this article will address the creation of a revolutionary efficient Internet of Things (IoT) based irrigation platform by using fuzzy bioinspired multisensory analysis of on-field parameter sets. This will allow for these problems to be resolved. The validity of the model that was developed was tested using a variety of use cases, and its effectiveness was evaluated using real-time examples.

2.2 Design of the IoT Based Irrigation Platform via Fuzzy Bioinspired Multisensory Analysis of On-Field Parameter Sets

Based on the review of existing smart irrigation techniques, it can be observed that these models are either highly complex or have slower response time and low efficiency when applied to real-time irrigation scenarios. Moreover, these models have a higher cost, which limits their scalability levels. To overcome these issues, this section of the text discusses the design of a novel efficient IoT based irrigation platform via fuzzy bioinspired multisensory analysis of on-field parameter sets. Flow of the model is described in Figure 2, where it can be observed that the proposed platform uses low-cost components for sensing moisture levels, temperature levels, rain probability, NPK (Nitrogen, Phosphorous, and Potassium) levels, and soil types. These sensed values are processed via a Grey Wolf Optimizer (GWO) for the identification of optimum sensor types, and then a fuzzy decision layer is used for the irrigation process. This layer assists in the identification of efficient water flow for different crop types. The resulting growth of plants is fed-back into the model, and a Genetic Algorithm (GA) is applied to tune the fuzzy rules for better water-flow under multiple types of crops.

The model initially collects large-scale datasets from in-farm sensors including Moisture levels, Temperature levels, Nitrogen levels, Phosphorous Levels, and other parameter sets. These sets are processed via a Grey Wolf Optimizer (GWO), which assists in the identification of sensor sets for obtaining maximum yield levels.

This is done via continuous monitoring of sensor values and validating them via a yield predictor under different scenarios. The GWO Model works as per the following process,

- To initialize the GWO Model, setup the following constants,
  - GWO iterations used for optimization (N_i)
  - GWO Wolves that will be generated and reconfigured (N_w)
  - Rate at which these Wolves will learn cognitively from each other (L_c)

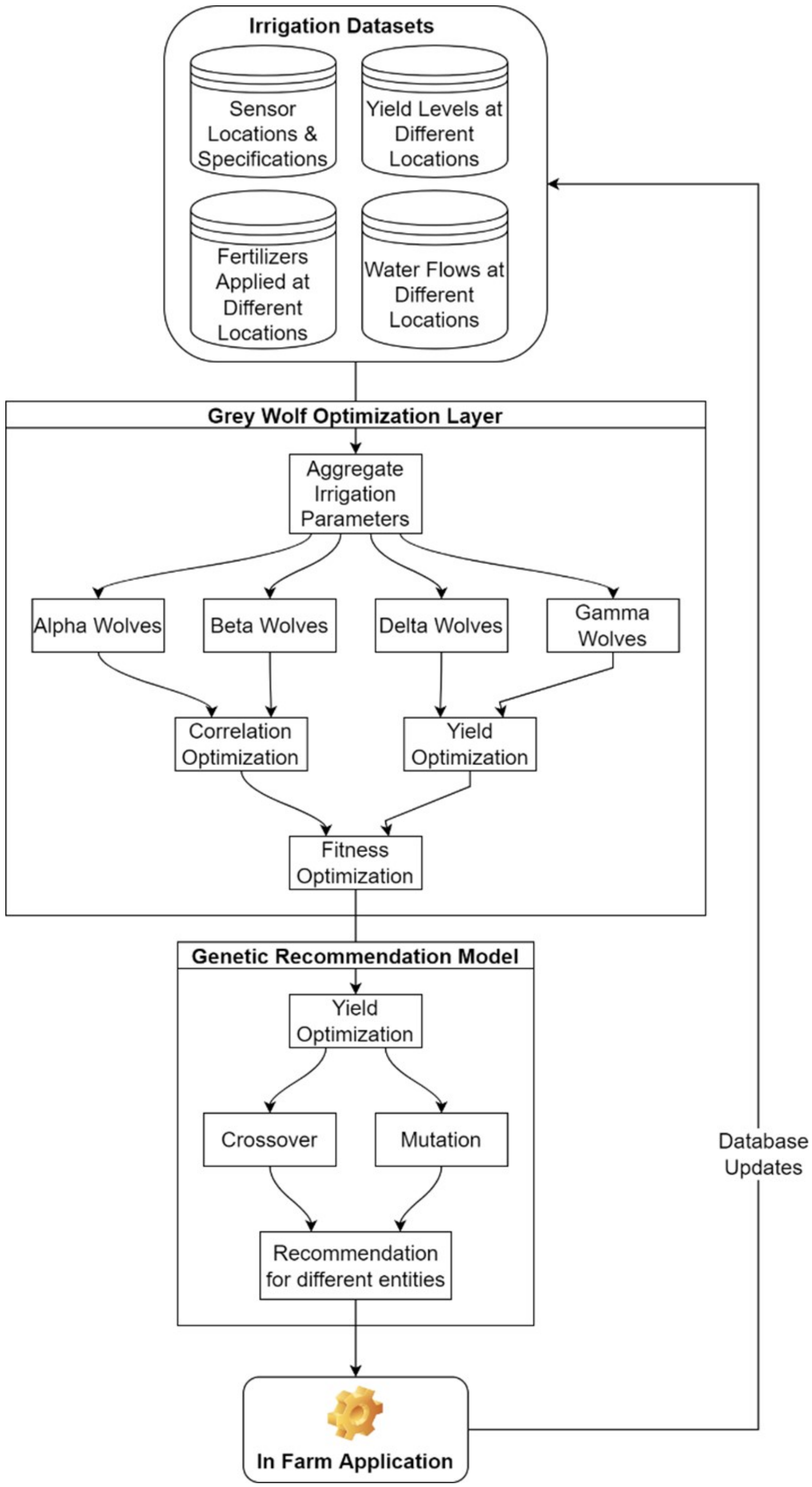

Figure 2: Design of the proposed smart farming process.

- Total number of sensors used in the field (N_s)
- Temporal value sets from these sensors (TV_s)

- To start the optimization process, generate N_w Wolves as follows,
  - Select $N_{sensors}$ number of sensors stochastically via equation 1 [15],

$$N_{sensors} = chandraSTOCH(L_c * N_s, N_s) \tag{1}$$

  Where, STOCH is a stochastic process that generates numbers via Markovian operations.
  - o The temporal value sets from these sensors are collected, and yield prediction is done based on these value sets.
  - As per the yield prediction, Wolf fitness is evaluated via equation 2 [15],

$$f_w = \sum_{i=1}^{N_f} \frac{T_{c_i}}{T_{p_i} * N_f} \tag{2}$$

  Where, T_c, T_p and N_f represents correctly predicted yield levels, total predicted yield levels and the number of fields for which these yield levels were predicted via temporal evaluations.

- Once all Wolf configurations are generated, then estimate Wolf fitness threshold as per equation 3 [14],

$$f_{th} = \frac{L_c}{N_w} \sum_{i=1}^{N_w} f_{w_i} \tag{3}$$

- As per this fitness level, segregate Wolves into the following 4 categories,
  - Alpha Wolves, which have achieved $f > 2 * f_{th}$
  - Beta Wolves, which have achieved $f > f_{th}$
  - Gamma Wolves, which have achieved $f > L_r * f_{th}$
  - Delta Wolves, which have achieved $f < f_{th}$
- Based on this evaluation, reconfigure all 'Delta' Wolves via equations 1 and 2, and repeat the process for N_i iterations

At the end of the final iteration, select Wolf with the highest fitness levels. Based on this selection, sensor sets that can be used for the highest accuracy levels are identified and can be used for real-time scenarios. Based on the selected sensor sets, Fuzzy Rules are applied and are tuned via a Genetic Algorithm (GA) based optimization process. The flow of the proposed Fuzzy Logic Controller is depicted in Figure 3 as follows,

Values obtained from the selected sensor sets are given to the proposed Fuzzy Logic Controller (FLC), which assists in the application of fuzzy rules to different sensor values under multiple crop types. The fuzzification process is controlled via equation 4, where each of the sensed values are quantized into 3 fuzzy levels [14],

$$FL_i = \frac{VS_i}{Max(VS_i)} * 3 \tag{4}$$

Where, VS_i represents value of the i^{th} sensor, which was selected by the GWO process. For s selected sensors, as^3 rules can be obtained, where a represents a number of connected actuator units. To optimize these rule sets, a Genetic Algorithm (GA) based optimization process is used, which assists in selecting optimum actuation for different crop types. The GA works as per the following process,

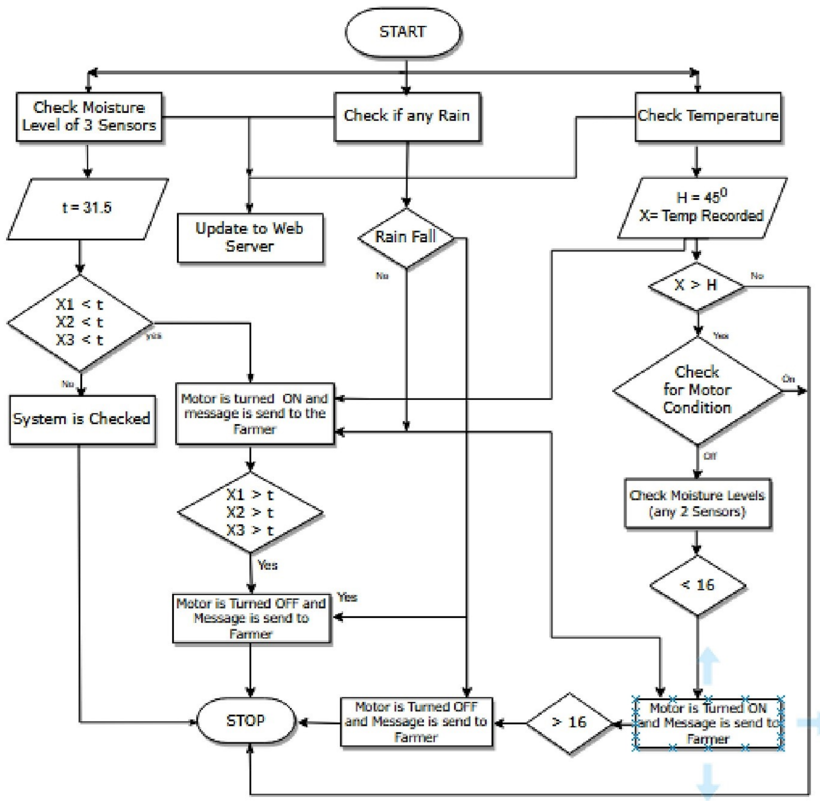

Figure 3: Design of the fuzzy rule engine for smart farming optimizations.

- To initialize the GA optimizer, setup following constants,
  - Total GA iterations for optimization (N_i)
  - Total GA solutions for optimization (N_s)
  - Learning rate for social learning (L_r)
- Setup all solutions as 'mutated', and repeat the following process for N_i iterations,
  - Out of the as^3 rules, remove N rules as per equation 5 [15],

$$N = STOCH(L_r^2 * as^3, as^3) \tag{5}$$

  - Based on the removed rules, generate actuation schedules of sensors on the field, and identify their fitness levels via equation 6,

$$f = \frac{\sum_{i=1}^{N_{sen}} Y_i}{N_{sen}} \tag{6}$$

Where, Y_i is the yield level for the connected N_{sen} sensor sets.

  - Evaluate these fitness levels for all solutions, and estimate fitness threshold via equation 7 [15],

$$f_{th} = \sum_{i=1}^{N_s} f_i * \frac{N_s}{L_r} \tag{7}$$

  - Reconfigure solutions with $f < f_{th}$ via marking them as 'mutated', while pass other solutions to next iteration via marking them as 'crossover'

- Repeat this process for N_i iterations and regenerate different configurations of fuzzy rules

Once all iterations are completed, then solutions with fitness levels more than $f_{th} * 2$ are selected for reconfiguration of fuzzy rules. These solutions provide higher accuracy levels, with and can achieve faster response due to reduced number of rules. Based on this process, the proposed model was deployed on real-time fields, and its efficiency levels were estimated under different scenarios. A comparative analysis of these efficiency levels is shown in next section.

3 Results and Discussion

The proposed model uses a combination of multiple optimizations including GWO for sensor selection, fuzzy rules for actuation, and GA for optimization of fuzzy rules. The proposed was deployed on an Arduino Uno based IoT platform for multiple smart irrigation scenarios. The model is depicted in Figure 4, where overall circuit connections along with different Water Flow Sensors (WFS) can be observed as follows,

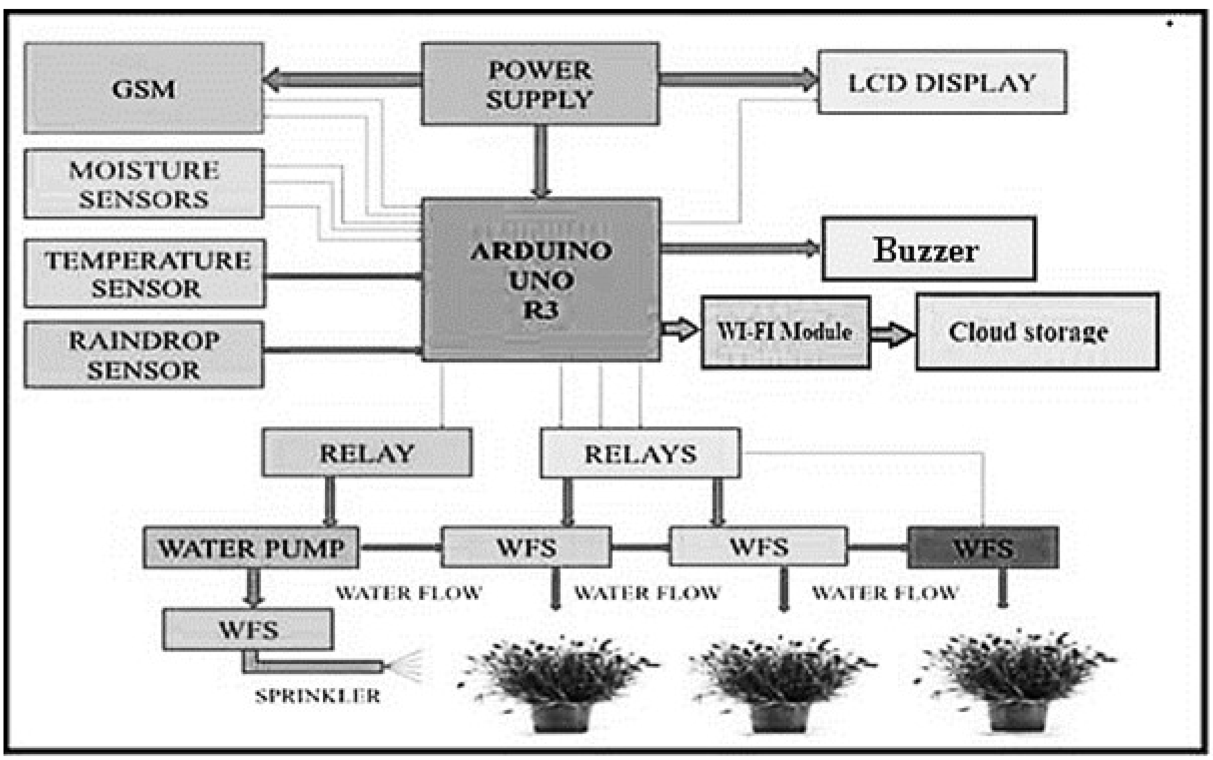

Figure 4: Design of the proposed model for real-time smart agriculture applications.

The proposed model was tested using Moisture and Temperature Sensor (LM35), Raindrop Sensor (LM393 based sensor), Gas Sensors (MQ5, MQ24, MQ35, and MQ214) for sensing different atmospheric gas levels. These sensors were deployed on different fields, and their yield efficiency was evaluated via equation 8 [14, 15],

$$Y_{eff} = \frac{C_p}{T_p} \tag{8}$$

Where, C_p and T_p represents correctly predicted yield levels, and total predicted yield levels. These yield levels were evaluated w.r.t. total evaluation iterations (TEI) and compared with BPNN PSO [28], ANN [33], and LSTM RNN [35] in Table 1 as follows,

Table 1: Yield prediction efficiency for different iterations

TEI	**Y (%)** **BPNN PSO [28]**	**Y (%)** **ANN [33]**	**Y (%)** **LSTM RNN [35]**	**Y (%)** **Present Work**
10	91.50	90.40	90.50	96.50
20	91.60	90.60	91.20	96.80
30	91.75	90.95	92.40	96.95
40	91.83	91.20	92.50	97.30
50	91.96	91.48	92.70	97.90
75	92.07	91.75	92.90	98.20
100	92.18	92.03	93.10	98.35
200	92.30	92.30	93.83	98.49
300	92.41	92.58	94.24	98.68
400	92.53	92.85	94.65	99.20
500	92.64	93.13	95.06	99.30
750	92.75	93.40	95.47	99.35
1000	92.87	93.68	95.88	99.42
2500	92.98	93.95	96.29	99.48
3500	93.10	94.23	96.70	99.54
5000	93.21	94.50	97.11	99.60

Based on this evaluation, and Figure 5, it can be observed that the proposed model showcased 6.5% better yield efficiency than BPNN PSO [28], 5.3% better yield efficiency than ANN [33], and 2.5% better yield efficiency than LSTM RNN [35] under different iterations.

This is due to use of GWO and GA for yield optimization operations. Similarly, the delay needed to perform these optimizations can be observed in Table 2.

Based on this evaluation, and Figure 6, it can be observed that the proposed model showcased 16.5% higher speed than BPNN PSO [28], 14.2% higher speed than ANN [33], and 15.4% higher speed than LSTM RNN [35] under different iterations. This is due to use of fuzzy rule optimizations via GA for yield optimization operations. Similarly, the precision of yield prediction obtained via these optimizations can be observed in Table 3.

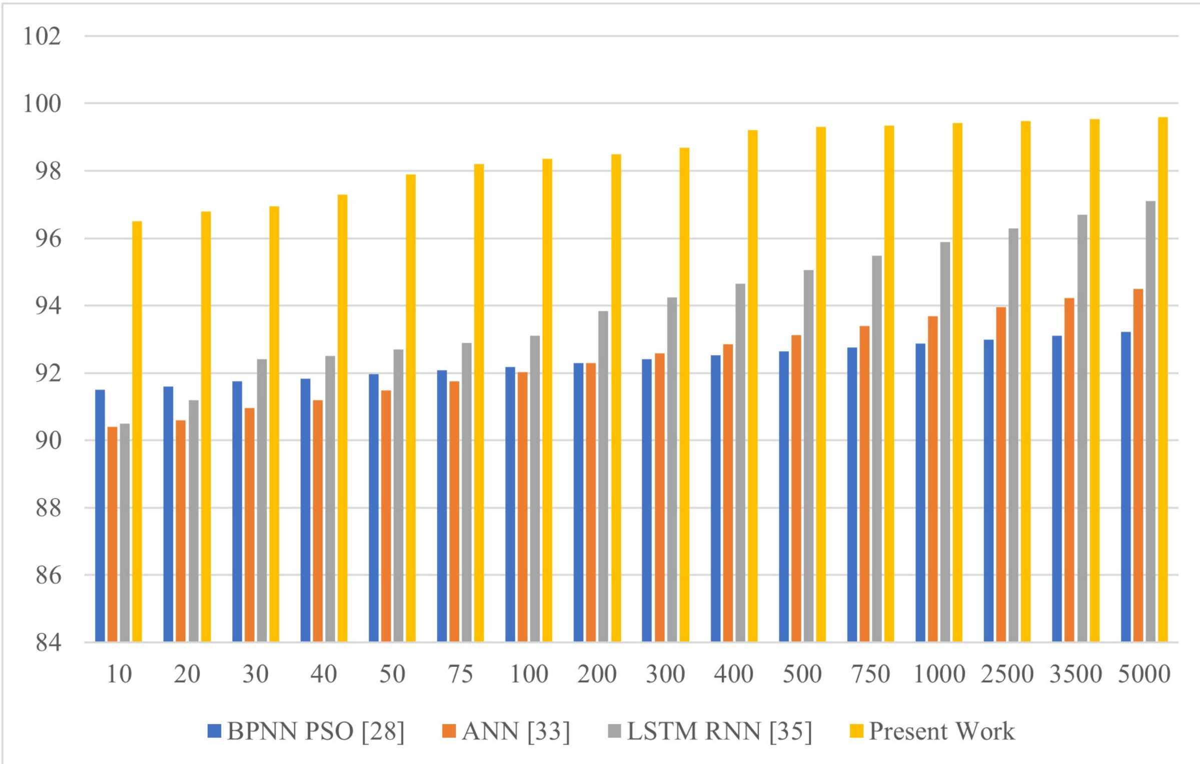

Figure 5: Yield prediction efficiency for different iterations.

Table 2: Delay needed to perform high efficiency irrigation for different iterations

TEI	D (ms) BPNN PSO [28]	D (ms) ANN [33]	D (ms) LSTM RNN [35]	D (ms) Present Work
10	120.22	99.98	111.78	76.25
20	120.36	100.24	112.48	76.49
30	120.53	100.59	113.49	76.66
40	120.65	100.88	113.74	76.91
50	120.81	101.18	114.08	77.28
75	120.96	101.48	114.44	77.49
100	121.11	101.79	114.82	77.62
200	121.26	102.09	115.56	77.75
300	121.41	102.39	116.06	77.89
400	121.56	102.70	116.56	78.15
500	121.71	103.00	117.07	78.22
750	121.86	103.30	117.57	78.26
1000	122.01	103.61	118.07	78.31
2500	122.16	103.91	118.57	78.36
3500	122.31	104.21	119.08	78.41
5000	122.46	104.52	119.58	78.46

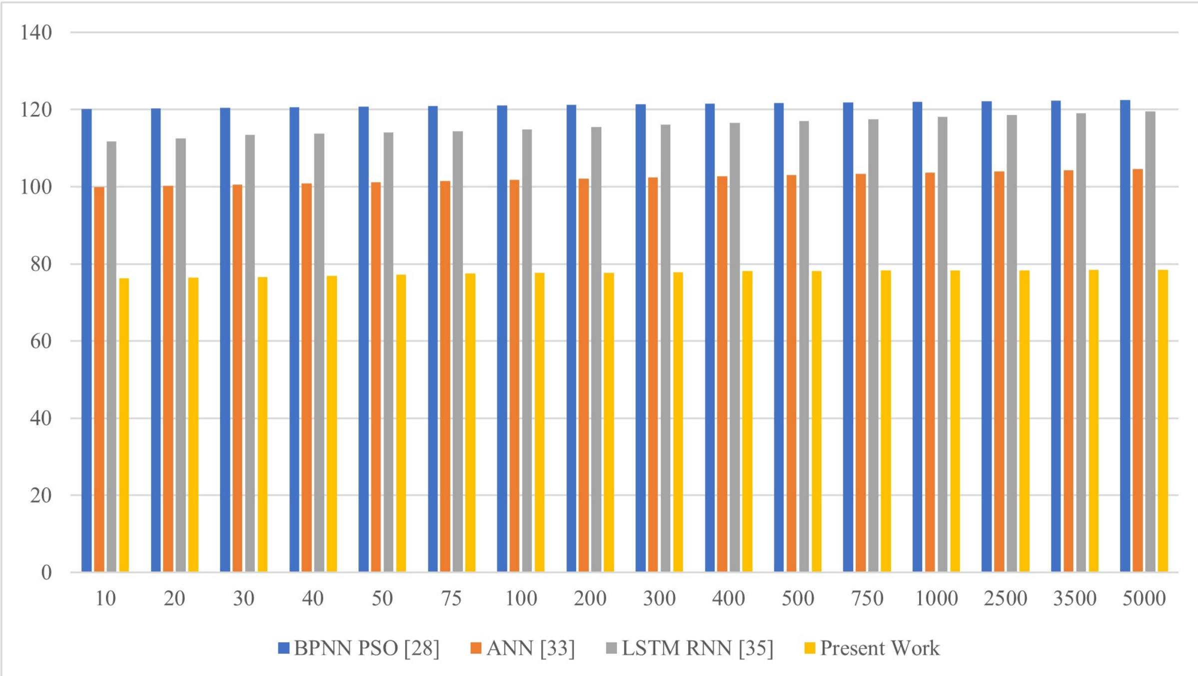

Figure 6: Delay needed to perform high efficiency irrigation for different iterations.

Table 3: Yield prediction precision levels for different iterations

TEI	P (%) BPNN PSO [28]	P (%) ANN [33]	P (%) LSTM RNN [35]	P (%) This Work
10	88.82	89.57	88.35	94.14
20	88.93	89.84	88.77	94.44
30	89.05	90.11	89.19	94.71
40	89.15	90.38	89.48	94.99
50	89.26	90.65	89.83	95.29
75	89.37	90.92	90.20	95.52
100	89.49	91.19	90.62	95.70
200	89.60	91.46	91.06	95.88
300	89.71	91.73	91.46	96.04
400	89.82	92.00	91.85	96.17
500	89.93	92.27	92.24	96.24
750	90.04	92.55	92.64	96.30
1000	90.15	92.82	93.03	96.36
2500	90.26	93.09	93.43	96.42
3500	90.37	93.36	93.82	96.48
5000	90.48	93.63	94.22	96.54

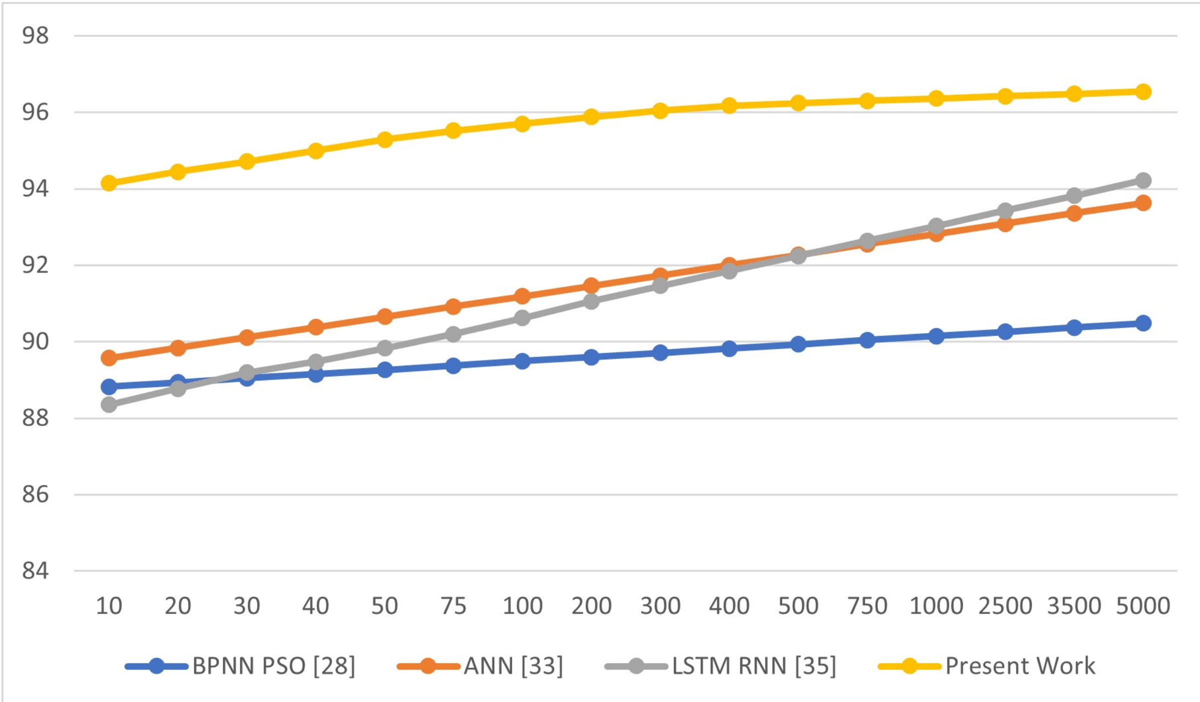

Figure 7: Yield prediction precision levels for different iterations.

Based on this evaluation, and Figure 7, it can be observed that the proposed model showcased 5.9% better yield precision efficiency than BPNN PSO [28], 2.8% better yield precision efficiency than ANN [33], and 1.6% better yield precision efficiency than LSTM RNN [35] under different iterations.

This is due to use of continuous optimizations via GWO and GA while predicting yields for different crop types. Due to these optimizations, the proposed model is capable of deployment for a wide variety of real-time use cases.

4 Conclusions

The model that is being presented makes use of a mix of several optimization techniques, such as GWO for the selection of sensors, fuzzy rules for the actuation, and GA for the optimization of fuzzy rules.The proposed was deployed on an Arduino Uno based IoT platform for multiple smart irrigation scenarios. Based on the evaluation of this model, it can be observed that the proposed model showcased 6.5% better yield efficiency than BPNN PSO [12], 5.3% better yield efficiency than ANN [16], and 2.5% better yield efficiency than LSTM RNN [18] under different iterations. This is due to use of GWO and GA for yield optimization operations.

Fuzzy logic with GA assists in improving operational speed, due to which it can be observed that the proposed model showcased 16.5% higher speed than BPNN PSO [12], 14.2% higher speed than ANN [16], and 15.4% higher speed than LSTM RNN [18] under different iterations. This is due to use of fuzzy rule optimizations via GA for yield optimization operations. While, in terms of precision of prediction it can be observed that the proposed model showcased 5.9% better yield precision efficiency than BPNN PSO [12], 2.8% better yield precision efficiency than ANN [16], and 1.6% better yield precision efficiency than LSTM RNN [18] under different iterations. This is due to use of continuous optimizations via GWO and GA while predicting yields for different crop types. Due to these optimizations, the proposed model is capable of deployment for a wide variety of real-time use cases.

In the future, the performance of the model may be enhanced by the integration of deep learning models, as well as Q-Learning and autoencoders for yield prediction operations. The model has to be tested on bigger fields, and it is possible to further improve it by making use of hybrid bioinspired approaches. These techniques integrate swarm optimization models with regression models in order to achieve continuous efficiency optimization in large-scale

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