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# Design of a Bioinspired Model for IrIoT Based Smart Irrigation Monitoring and Control operations

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**Abstract:**

Irrigation Internet of Things (IrIoT) networks consist of farm-based sensors that are connected to identify crop-based & soil-based parameters for yield enrichment purposes. These networks also use high-performance processing methods to predict future events like change in fertilization quantity, yield extraction, change in water flows, etc. Existing IrIoT network design models integrate multiple parameters, but have limited correlation capabilities, which restrict their usability under real-time conditions. These models are inconsistent in terms of their processing capabilities which affects the yield of underlying farms. These models are also observed to have limited actuation efficiency, which is due to lack of comprehensive recommendation models. To overcome these limitations, this text proposes design of a novel Bioinspired Model for IrIoT Based Smart Irrigation Monitoring and Control operations. The model initially uses a Grey Wolf Optimization (GWO) method to estimate data correlation between different on-field sensors. The model scans values for these sensors at different time instances, and estimates their effect on yield performance in farms. Based on the similarity in yield performance, correlation is estimated via single objective optimization process. This correlation assists in identification of sensors that are highly useful for monitoring, recommendation, and quality control purposes. Data from different identified sensors is further augmented via use of a high-efficiency recommendation engine, that uses environmental, geographical, and topological information to estimate optimum yield maximization operations. These operations include fertilizer type selection, water flow management, quantity of fertilizer to be used, and yield extraction, based on temporal analysis. The proposed model was tested on different farms, and its efficiency in terms of accuracy of fertilizer prediction, accuracy of water flow prediction, precision of monitoring, and accuracy of yield extraction were evaluated for multiple seasons. This performance was compared with various state-of-the-art models, and it was observed that the proposed model showcased 8.3% better recommendation accuracy, and 15.5% better control accuracy, due to which it is highly useful for a wide variety of smart farming application scenarios.

**Keywords:** Irrigation, IoT, Recommendation, GWO, Correlation, Water Flow, Yield, Temporal, Accuracy, Fertilizer

## 1. Introduction

Design of Irrigation IoT Networks is a multidomain task, that involves integration of farm-specific sensing interfaces, with processing & control models. These interfaces are useful for estimation of crop specific parameters, soil-specific parameters, and geography specific parameters, that allow the model to analyze and recommend yield maximization suggestions under different environmental conditions. These sensors also include livestock management devices that can detect different changes in livestock status. A typical layered model [1] for smart farming is depicted in figure 1, wherein the entire interface is segregated into physical, edge & cloud layers. Each of these layers performs a specific optimization task, which assists them in continuously monitoring & improving farm performance.

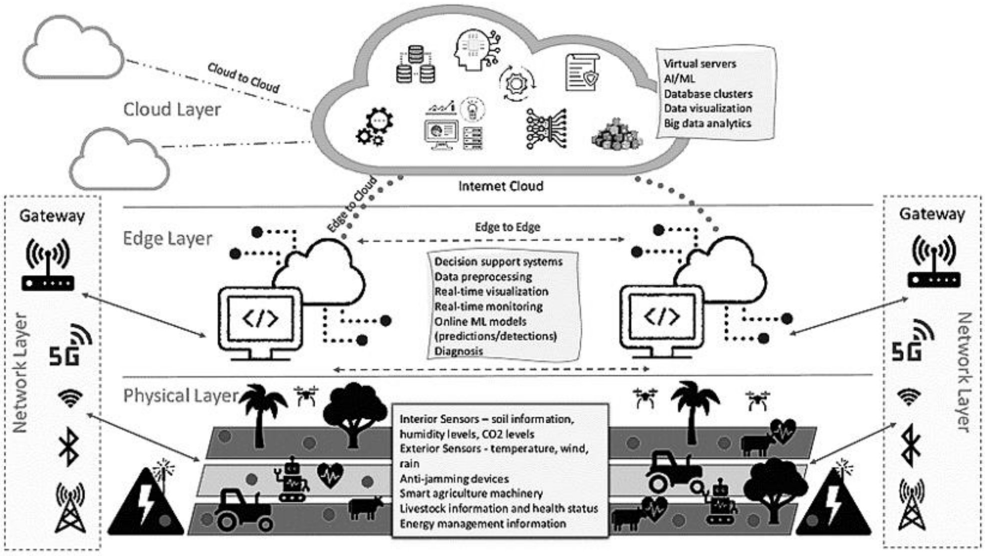


Figure 1. A typical Irrigation IoT Network Model

In this model, the physical layer estimates soil information via interior & exterior sensors, and combines it with energy information & livestock information, to create aggregated information vectors. These vectors are communicated to the edge computing devices, which process this data via decision support systems, real time monitoring & visualization, Machine Learning Models (MLMs), diagnosis models, etc. Data from different farms is collected, and used for edge-to-edge learning operations. This process enhances recommendation performance, thereby assisting in optimizing farm yield levels. Similar models are proposed by researchers [2, 3, 4], and they vary in terms of the internal operating characteristics. A survey of these models in terms of their functional nuances, contextual advantages, deployment-specific lacunas, and performance specific future scopes is discussed in the next section of this text. Based on this discussion, it can be observed that existing models are inconsistent in terms of their processing capabilities which affects the yield of underlying farms, and they are also observed to have limited actuation efficiency, which is due to lack of comprehensive recommendation models. To overcome these issues, section 3 proposes design of a novel Bioinspired Model for IrIoT Based Smart Irrigation Monitoring and Control operations. The model proposes use of GWO, with a high-efficiency recommendation engine, that assists in continuous optimization of farm performance. This performance was evaluated in terms of different accuracy measures, and compared in section 4 with various state-of-the-art models. Finally, this text concludes with some contextual observations about the proposed model, and recommends different fusion methods to further improve its performance under different farm types.

## 2. Literature Review

A large number of IoT models have been proposed for various irrigation applications, and each of them have their own internal working characteristics. For instance, work in [5, 6] propose use of dynamic irrigation scheduling model, and radiofrequency energy harvesting for agricultural applications. These models are observed to have lower efficiency when applied to large-scale farms, due to which they cannot be applied to real-time use cases. To overcome this limitation, work in [7] proposes use of discreteevent simulations for irrigation IoT deployments, which makes it easier for researchers to design & use IoT models for large-scale applications. Work in [8, 9] extend this model via use of Deep Learning Neural Network (DLNN), and fuzzy rules based irrigation controller (FRBIC), both of which assist in improving farm yield while reducing deployment costs for a wide variety of farm applications. These models must be extended via use of integration of renewable energy sources [9], greenhouse crop production [10], and their performance can be improved via use of ensemble classification methods [11], that assist in estimation of better yield & high efficiency recommendations for fertilization & yield extraction plans. Such integrated models are discussed in [12, 13, 14], which propose use of Naïve Bayes (NB), PenmanMonteith Optimization, and Model driven processes, which assist in continuously improving yield performance via pattern recognition & analysis for large-scale deployments.

Researchers in [15, 16] propose development of Buildout IoT Application Language (BIoTA), and extend it to farm applications. This language can be used for inter-communication between different farm sensors, which assists in estimating their sensing performance. This performance can be correlated with yield levels, fertilization levels, and water flow levels for recommendation of better yield opportunities under different weather & geographical conditions. An application of this process is described in [17, 18] which propose use of Ontology-Based Semantic Model, and Back-Propagation Neural Network with Particle Swarm Optimization (BPNN-PSO) for continuous learning from real-time farm environments. These models apply different pattern analysis methods to farm areas, and assist in identification of yield patterns under a wide variety of farm environments. Extension to these models is discussed in [19, 20], which propose use of Traceability models for Greenhouse Seedling Crops via block layers, and Automation for Precision Agriculture under area specific farm lands. These models showcase high-efficiency with low power requirements, which makes them highly useful for scalable irrigation applications. Models in [21, 22, 23] further explore these concepts, and propose Energy-Efficient Edge-Fog-CloudModels, and various deep learning methods to continuously optimize farming performance under different crop types. These models must be validated for large-scale crops, and can be used for incrementally improving performance of existing IrIoT deployments. Work in [24, 25] further extends these models, and proposes use of hydrokinetic converters, and Bidirectional Recurrent Neural Network (BiRNN), which aim at improving sensor accuracy for different farm sites. These models are useful when applied to multiple farm lands, that require sensing of similar parameters. But most of these models have limited sensor data correlation capabilities, due to which their usability is restricted under real-time scenarios. To overcome this limitation, next section proposes use of a Bioinspired Model for IrIoT Based Smart Irrigation Monitoring and Control operations. The proposed model was also tested & validated under different real-time conditions.

## 3. Design of the proposed Bioinspired Model for IrIoT Based Smart Irrigation Monitoring and Control operations

Based on the brief discussion about existing IrIoT models, it was observed that they have limited sensor data correlation capabilities, due to which their usability is restricted under real-time scenarios. This causes inconsistency in model deployment, which affects their yield estimation and optimization capabilities. These models also lack in terms of recommendation efficiency, which limits its actuation capabilities for maximization of yield levels. To overcome these limitations, this section discusses design of the proposedGWO based model for Smart Irrigation Monitoring and Control operations. Flow of the model is depicted in figure 2, wherein it can be observed that the model initially uses a Grey Wolf Optimization (GWO) method forestimation of data correlation between different on-field sensors. To perform this task, the model scans values of these sensors at different time instances, and estimates their effect on yield performance in farms. This is facilitated by temporal datasets, which assist in optimizing GWO performance under real-time conditions. The yield performance-correlation assists in identification of sensors that are highly useful for monitoring, recommendation, and quality control operations. A Genetic Algorithm (GA) based recommendation engine is deployed that makes use of environmental, geographical, and topological information for estimation of optimum yield maximization operations.

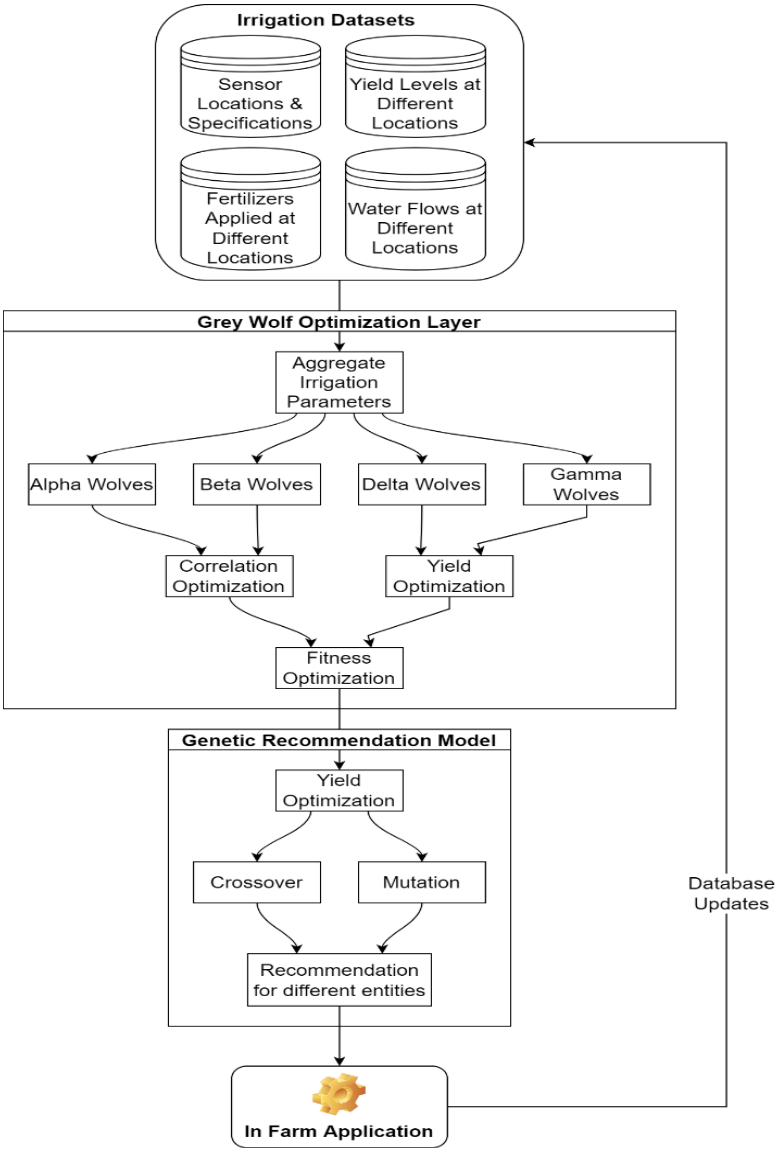


Figure 2. Overall flow of the proposed GWO & GA Based Model for IrIoT Optimizations

These operations include selection of fertilizer type & quantity, management of water flows, and yield extraction timelines, which are recommended based on temporal analysis. The model design is segregated into 3 different modules, which are described in different sub sections of this text. Researchers can refer these sub sections to deploy the proposed model in part(s) or as a whole, depending upon their application requirements.

### *3.1. Design of the GWO Model for selection of highly correlative sensors*

Data from multiple on-field sensors is collected and processed via the GWO Model, which assists in identification of sensors that can yield maximum yield performance. To perform this task, the following process is used,

- Initialize the following GWO Parameters,
  - Total number of Wolves ($N_w$)
  - Total GWO Iterations ($N_i$)
  - GWO Learning Rate ($L_r$)
  - Total number of sensors available ($T_s$)
  - Temporal yield data for the farm ($Y_d$)
- Initially mark all the wolves as 'Delta Wolves'
- Go to each iteration between 1 to $N_i$, and perform the following tasks,

- For each wolf in 1 to $N_w$, perform the following process,
- If the wolf is not marked as 'Delta Wolf', then go to the next wolf in sequence
- Else, generate new configuration for this wolf via the following process,
- Select $N_r$ stochastic sensors from the list of sensors via equation 1,

$$N_r = STOCH(L_r * T_s, T_s) \dots (1)$$

Where, $STOCH$ indicates a Stochastic Markovian Process.

- For each sensor, estimate its correlation with yield levels via equation 2,

$$C = \bigvee_{i=1}^{N_s} \frac{var(SV_i)}{Max(SV)} + \frac{var(Y_i)}{Max(Y)} \dots (2)$$

Where, $N_s$ represents number of temporal samples used for analysis, $SV$ & $Y$ represents sensor values & yield levels for these temporal samples, while $var(X)$ represents variance levels, and are estimated via equation 3,

$$var(X) = \frac{\sqrt{\sum_{i=1}^{N}\left(X_i - \sum_{j=1}^{N}\frac{X_j}{N}\right)^2}}{N} \dots (3)$$

- Based on these correlation values, fitness is estimated for each wolf via equation 4,

$$f_i = \sum_{i=1}^{N_r} \frac{C_{y_i}}{N_r} \dots (4)$$

- Repeat this for all wolves, and evaluate iteration threshold via equation 5,

$$f_{th} = \sum_{i=1}^{N_w} f_i * \frac{L_r}{N_w} \dots (5)$$

- At the end of each iteration perform the following process,
- If $f_i < f_{th} * L_r$, then mark the wolf as 'Delta Wolf'
- If $f_i < f_{th} * \frac{L_r}{2}$, then mark the wolf as 'Gamma Wolf'
- If $f_i < f_{th} * \frac{L_r}{4}$, then mark the wolf as 'Beta Wolf'
- Else, mark the wolf as 'Alpha Wolf'
- At the end of all iterations, select the Wolf with maximum fitness, and use its sensors for maximization of yield at different locations

Based on this process, multiple sensors are selected, and their values are used for maximizing farm yields. These sensors are further augmented via a GA Model, which assists in recommendation of fertilization, water flow, and yield extraction timelines. Design of this model is discussed in the next section of this text.

### *3.2. Design of the GA Model for recommendation of different entities*

After identification of sensors that are used for maximizing farm yield performance, a GA Model is used to estimate fertilization, water flow and yield extraction timelines. This model works via the following process,

- Initialize the following parameters for GA,
- Total number of GA Iterations ($N_i$)
- Total number of GA Solutions ($N_s$)
- GA Learning Rate ($L_r$)
- Temporal data for fertilization, water flow & yield extraction timeline for previous evaluations
- Initialize all solutions by marking them as 'to be processed'
- Go to each of the iterations in 1 to $N_i$, and perform the following,
- Go to each of the solutions in 1 to $N_s$, and perform the following process,
- If the solution is marked as 'not to be processed', then skip it and go to the next solution

- Else, generate a new solution via the following process,
- Select fertilizer for the given crop, and generate stochastic values for fertilizer quantity ($F_q$), water flow level ($W_{fl}$), and yield extraction timeline ($Y_{et}$) via equation 6, 7, & 8 as follows,

$$F_q = STOCH\left(L_r * Max(F_q), Max(F_q)\right) \dots (6)$$

$$W_{fl} = STOCH\left(L_r * Max(W_{fl}), Max(W_{fl})\right) \dots (7)$$

$$Y_{et} = STOCH\left(L_r * Max(Y_{et}), Max(Y_{et})\right) \dots (8)$$

- Based on these values, identify yield levels from the temporal database, and estimate fitness for this solution via equation 9,

$$f_i = f\left(F_q, W_{fl}, Y_{et}\right) \dots (9)$$

Where, $f$ represents yield function, which is calculated from temporal instances of previous yield extraction states. This value is estimated by the farmers based on environmental, geographical, and topological information about the farms.

- Evaluate fitness levels for all solutions.
- At the end of each iteration, evaluate fitness threshold via equation 10,

$$f_{th} = \sum_{i=1}^{N_s} f_i * \frac{L_r}{N_s} \dots (10)$$

- Check for solution fitness, and perform the following tasks,
- If $f_i > f_{th}$, then mark solution as 'not to be processed', and crossover it to the next iteration
- Else, mark solution as 'to be processed', and mutate it in the next iteration
- Repeat this process for all iterations

Select the solution with maximum fitness levels, and use its fertilizer quantity ($F_q$), water flow level ($W_{fl}$), and yield extraction timeline ($Y_{et}$) levels for optimizing farm yield under current environmental conditions. These values are further processed via a correlation engine, which assists in continuous optimization of model performance under real-time conditions.

### *3.3. Design of a correlation model for continuous database updates*

The GWO Model assists in identification of on-field sensors ($FS$) that can maximize the yield, while GA assists in identification of fertilizer quantity ($F_q$), water flow level ($W_{fl}$), and yield extraction timeline ($Y_{et}$) levels. This information is given to a correlation model, which estimates similarity between currently selected values, and values in the database. This correlation is estimated via equation 11 as follows,

$$Corr = \frac{\begin{matrix}\sum(FS - \overline{FS})\left(F_q - \overline{F_q}\right) \\ (W_{fl} - \overline{W_{fl}})(Y_{et} - \overline{Y_{et}})\end{matrix}}{\sqrt{\begin{matrix}\sum(FS - \overline{FS})^2\left(\sum F_q - \overline{F_q}\right)^2 \\ \left(\sum W_{fl} - \overline{W_{fl}}\right)^2(\sum Y_{et} - \overline{Y_{et}})^2\end{matrix}}} \dots (11)$$

If the value of $Corr > 0.999$, then the sensor readings are matching with the database, and thus are added back to the database for incremental learning operations. Other values are discarded, because they do not confidently estimate entity values, thus cannot be used for incremental learning operations. Due to these operations, the model is capable of improving accuracy of fertilizer prediction, accuracy of water flow prediction, precision of monitoring, and accuracy of yield extraction for different seasons. These parameters were evaluated & compared with various state-of-the-art models in the next section of this text.

## 4. Result analysis & comparison

The proposed model uses a combination of GWO & GA with continuous optimization in order to improve yield levels for different farms. To estimate the performance of this model, it was initially trained on the following datasets,

- Historical Irrigation Dataset, which is available at https://aquaknow.jrc.ec.europa.eu/en/content/historical-irrigation-dataset-hid
- Earth System Science Data, which is available at https://essd.copernicus.org/articles/13/5689/2021/
- Intelligent Irrigation System Data, which is available at https://www.kaggle.com/datasets/harshilpatel355/autoirrigationdata

After training the model on these sets, it was evaluated on farm lands near Mumbai, Maharashtra, India region, for different seasons. A total of 40 different farms, were evaluated with 3 years of temporal datasets in order to estimate accuracy of fertilizer prediction ($A_f$), accuracy of water flow prediction ($A_w$), precision of monitoring ($P_m$), and accuracy of yield extraction ($A_y$) for over 5000 different samples. This evaluation was compared with the models proposed in DLNN [8], FR BIC [9], and BPNN PSO [18], which assisted in estimating current model's performance under real-time use cases. Based on this strategy, the accuracy of fertilizer prediction ($A_f$) w.r.t. Number of Farm Samples (NS) can be observed from table 1 as follows,

| NS | Af (%) DLNN [8] | Af (%) FR BIC [9] | Af (%) BPNN PSO [18] | Af (%) BMSICM |
|---|---|---|---|---|
| 500 | 86.50 | 90.50 | 91.50 | 96.50 |
| 750 | 86.90 | 90.56 | 91.55 | 96.80 |
| 1000 | 87.50 | 90.59 | 91.56 | 97.10 |
| 1250 | 88.30 | 90.65 | 91.59 | 97.20 |
| 1500 | 88.50 | 90.90 | 91.61 | 97.30 |
| 1750 | 88.90 | 91.20 | 91.65 | 97.50 |
| 2000 | 89.10 | 91.30 | 91.67 | 97.80 |
| 2250 | 89.20 | 91.40 | 91.70 | 97.90 |
| 2500 | 89.30 | 91.50 | 91.73 | 97.95 |
| 2750 | 89.35 | 91.66 | 91.75 | 98.01 |
| 3000 | 89.38 | 91.80 | 91.78 | 98.05 |
| 3250 | 89.39 | 91.95 | 91.81 | 98.06 |
| 3500 | 90.22 | 92.09 | 91.84 | 98.10 |
| 3750 | 90.48 | 92.23 | 91.86 | 98.15 |
| 4000 | 90.74 | 92.37 | 91.89 | 98.51 |
| 4250 | 91.00 | 92.51 | 91.92 | 98.64 |
| 4500 | 91.26 | 92.65 | 91.95 | 98.76 |
| 4750 | 91.52 | 92.80 | 91.97 | 98.88 |
| 5000 | 91.78 | 92.94 | 92.10 | 99.10 |

Table 1. Accuracy of fertilizer prediction for different farm samples & different models

Based on this evaluation, it was observed that the proposed model showcases 8.5% improvement in accuracy of fertilizer prediction when compared in DLNN [8], 5.9% improvement when compared with FR BIC [9], and 6.5% improvement when compared with BPNN PSO [18], which is due to use of GA Model, that assists in continuous optimization of fertilizer prediction under different farm-based use cases. Due to this, the model is capable of improving farm yield, while minimizing fertilization costs. Similar evaluation for accuracy of water flow prediction can be observed from table 2 as follows,

| **NS** | **Aw (%) DLNN [8]** | **Aw (%) FR BIC [9]** | **Aw (%) BPNN PSO [18]** | **Aw (%) BMS ICM** |
|---|---|---|---|---|
| 500 | 84.16 | 89.07 | 85.82 | 96.80 |
| 750 | 84.74 | 89.11 | 85.84 | 97.03 |
| 1000 | 85.26 | 89.23 | 85.86 | 97.20 |
| 1250 | 85.71 | 89.43 | 85.89 | 97.33 |
| 1500 | 85.97 | 89.64 | 85.92 | 97.53 |
| 1750 | 86.19 | 89.80 | 85.94 | 97.73 |
| 2000 | 86.32 | 89.90 | 85.97 | 97.88 |
| 2250 | 86.40 | 90.02 | 85.99 | 97.95 |
| 2500 | 86.46 | 90.15 | 86.02 | 98.00 |
| 2750 | 86.49 | 90.30 | 86.05 | 98.04 |
| 3000 | 86.77 | 90.44 | 86.07 | 98.07 |
| 3250 | 87.12 | 90.58 | 86.10 | 98.10 |
| 3500 | 87.56 | 90.72 | 86.12 | 98.25 |
| 3750 | 87.81 | 90.86 | 86.15 | 98.43 |
| 4000 | 88.06 | 91.00 | 86.17 | 98.64 |
| 4250 | 88.31 | 91.13 | 86.20 | 98.76 |
| 4500 | 88.56 | 91.27 | 86.26 | 98.91 |
| 4750 | 88.82 | 91.41 | 86.29 | 99.04 |
| 5000 | 89.07 | 91.55 | 86.32 | 99.17 |

Table 2. Accuracy of water flow prediction for different farm samples & different models

Based on this evaluation, it was observed that the proposed model showcases 10.5% improvement in accuracy of water flow predictionwhen compared in DLNN [8], 8.5% improvement when compared with FR BIC [9], and 12.5% improvement when compared with BPNN PSO [18], which is due to use of GA Model, that assists in continuous optimization of water flow predictionunder different farm-based use cases. Due to this, the model is capable of improving farm yield, while minimizing watering costs. Similar evaluation for precision of monitoringcan be observed from table 3 as follows,

| NS | Pm (%)<br>DLNN [8] | Pm (%)<br>FR BIC [9] | Pm (%)<br>BPNN PSO [18] | Pm (%)<br>BMS ICM |
|---|---|---|---|---|
| 500 | 83.49 | 87.62 | 86.51 | 94.42 |
| 750 | 84.00 | 87.68 | 86.54 | 94.67 |
| 1000 | 84.58 | 87.78 | 86.56 | 94.84 |
| 1250 | 84.99 | 87.96 | 86.59 | 94.97 |
| 1500 | 85.26 | 88.18 | 86.61 | 95.14 |
| 1750 | 85.49 | 88.34 | 86.64 | 95.35 |
| 2000 | 85.62 | 88.44 | 86.67 | 95.50 |
| 2250 | 85.70 | 88.55 | 86.69 | 95.56 |
| 2500 | 85.76 | 88.69 | 86.72 | 95.61 |
| 2750 | 85.85 | 88.83 | 86.75 | 95.65 |
| 3000 | 86.02 | 88.97 | 86.77 | 95.68 |
| 3250 | 86.41 | 89.10 | 86.80 | 95.74 |
| 3500 | 86.84 | 89.24 | 86.82 | 95.84 |
| 3750 | 87.09 | 89.38 | 86.85 | 96.03 |
| 4000 | 87.34 | 89.52 | 86.87 | 96.23 |
| 4250 | 87.59 | 89.65 | 86.91 | 96.36 |
| 4500 | 87.84 | 89.79 | 86.94 | 96.48 |
| 4750 | 88.09 | 89.93 | 87.00 | 96.63 |
| 5000 | 88.34 | 90.06 | 87.02 | 96.75 |

Table 3. Precision of monitoring for different farm samples & different models

Based on this evaluation, it was observed that the proposed model showcases 8.3% improvement in precision of monitoring when compared in DLNN [8], 6.5% improvement when compared with FR BIC [9], and 9.5% improvement when compared with BPNN PSO [18], which is due to use of GWO Model, that assists in continuous optimization of sensor selection under different farm-based use cases. Due to this, the model is capable of improving farm yield, while minimizing sensor activation costs. Similar evaluation for accuracy of yield extractioncan be observed from table 4 as follows,

| NS | Ay (%) DLNN [8] | Ay (%) FR BIC [9] | Ay (%) BPNN PSO [18] | Ay (%) BMS ICM |
|---|---|---|---|---|
| 500 | 86.15 | 90.57 | 89.43 | 96.55 |
| 750 | 86.66 | 90.63 | 89.47 | 96.81 |
| 1000 | 87.23 | 90.71 | 89.49 | 97.03 |
| 1250 | 87.80 | 90.86 | 89.51 | 97.15 |
| 1500 | 88.04 | 91.09 | 89.54 | 97.31 |
| 1750 | 88.33 | 91.30 | 89.57 | 97.51 |
| 2000 | 88.49 | 91.41 | 89.60 | 97.71 |
| 2250 | 88.58 | 91.52 | 89.62 | 97.79 |
| 2500 | 88.65 | 91.64 | 89.65 | 97.84 |
| 2750 | 88.71 | 91.79 | 89.68 | 97.89 |
| 3000 | 88.87 | 91.94 | 89.70 | 97.92 |
| 3250 | 89.13 | 92.08 | 89.73 | 97.95 |
| 3500 | 89.70 | 92.22 | 89.76 | 98.05 |
| 3750 | 89.96 | 92.36 | 89.78 | 98.19 |
| 4000 | 90.22 | 92.50 | 89.81 | 98.45 |
| 4250 | 90.48 | 92.64 | 89.84 | 98.57 |
| 4500 | 90.73 | 92.79 | 89.88 | 98.71 |
| 4750 | 90.99 | 92.93 | 89.92 | 98.84 |
| 5000 | 91.25 | 93.07 | 89.98 | 99.00 |

Table 4. Accuracy of yield extractionfor different farm samples & different models

Based on this evaluation, it was observed that the proposed model showcases 6.5% improvement in accuracy of yield extractionwhen compared in DLNN [8], 5.9% improvement when compared with FR BIC [9], and 9.5% improvement when compared with BPNN PSO [18], which is due to use of GWO& GA Model, that assists in continuous optimization of yield extraction timings under different farm-based use cases. Due to this, the model is capable of improving farm yield, while optimizing yield extraction timings & deployment costs. Thus, the model is suitable for low cost, high precision, and high-performance farm deployments, with high efficiency of yield extraction under real-time use cases.

## 5. Conclusion and future scope

The proposed BMSICM Model uses a combination of GWO with GA for continuous optimization of sensor selection, water flow estimation, fertilizer quantity estimation, and yield extraction time lines. The model also proposes use of a correlation engine which assists in continuous optimization of the IrIoT deployments. Due to these optimizations, it was observed that the proposed model is capable of showcasing8.5% improvement in accuracy of fertilizer prediction when compared in DLNN [8], 5.9% improvement when compared with FR BIC [9], and 6.5% improvement when compared with BPNN PSO [18], which is due to use of GA Model, that assists in continuous optimization of fertilizer prediction. It was also observed that the proposed model showcased10.5% improvement in accuracy of water flow prediction when compared in DLNN [8], 8.5% improvement when compared with FR BIC [9], and 12.5% improvement when compared with BPNN PSO [18], which is due to use of GA Model, that assists in continuous optimization of water flow prediction. The model also showcased8.3% improvement in precision of monitoring when compared in DLNN [8], 6.5%

improvement when compared with FR BIC [9], and 9.5% improvement when compared with BPNN PSO [18], which is due to use of GWO Model, that assists in continuous optimization of sensor selection. It was also observed that the model showcases 6.5% improvement in accuracy of yield extraction when compared in DLNN [8], 5.9% improvement when compared with FR BIC [9], and 9.5% improvement when compared with BPNN PSO [18], which is due to use of GWO & GA Model, that assists in continuous optimization of yield extraction timings under different farm-based use cases. In future, the model must be validated on larger farm scenarios, and can be extended via use of Q-Learning, & Reinforcement Learning based methods. The model performance can also be improved via use of large-scale Convolutional Neural Networks (CNNs), Region based CNNs (RCNNs), and Recurrent NNs (RNNs), which will assist in further optimizing its performance under different real-time farm-based use cases.

## 6. References


[1] S. Qazi, B. A. Khawaja and Q. U. Farooq, "IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends," in IEEE Access, vol. 10, pp. 21219-21235, 2022, doi: 10.1109/ACCESS.2022.3152544.

[2] T. Ojha, S. Misra and N. S. Raghuwanshi, "Internet of Things for Agricultural Applications: The State of the Art," in IEEE Internet of Things Journal, vol. 8, no. 14, pp. 10973-10997, 15 July15, 2021, doi: 10.1109/JIOT.2021.3051418.

[3] A. Sharma, A. Jain, P. Gupta and V. Chowdary, "Machine Learning Applications for Precision Agriculture: A Comprehensive Review," in IEEE Access, vol. 9, pp. 4843-4873, 2021, doi: 10.1109/ACCESS.2020.3048415.

[4] S. I. Hassan, M. M. Alam, U. Illahi, M. A. Al Ghamdi, S. H. Almotiri and M. M. Su’ud, "A Systematic Review on Monitoring and Advanced Control Strategies in Smart Agriculture," in IEEE Access, vol. 9, pp. 32517-32548, 2021, doi: 10.1109/ACCESS.2021.3057865.

[5] S. K. Roy, S. Misra, N. S. Raghuwanshi and S. K. Das, "AgriSens: IoT-Based Dynamic Irrigation Scheduling System for Water Management of Irrigated Crops," in IEEE Internet of Things Journal, vol. 8, no. 6, pp. 5023-5030, 15 March15, 2021, doi: 10.1109/JIOT.2020.3036126.

[6] A. D. Boursianis et al., "Smart Irrigation System for Precision Agriculture—The AREThOU5A IoT Platform," in IEEE Sensors Journal, vol. 21, no. 16, pp. 17539-17547, 15 Aug.15, 2021, doi: 10.1109/JSEN.2020.3033526.

[7] R. Gomes Alves, R. Filev Maia and F. Lima, "Discrete-event simulation of an irrigation system using Internet of Things," in IEEE Latin America Transactions, vol. 20, no. 6, pp. 941-947, June 2022, doi: 10.1109/TLA.2022.9757736.

[8] P. K. Kashyap, S. Kumar, A. Jaiswal, M. Prasad and A. H. Gandomi, "Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network," in IEEE Sensors Journal, vol. 21, no. 16, pp. 17479-17491, 15 Aug.15, 2021, doi: 10.1109/JSEN.2021.3069266.

[9] F. B. Poyen, A. Ghosh, P. Kundu, S. Hazra and N. Sengupta, "Prototype Model Design of Automatic Irrigation Controller," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-17, 2021, Art no. 9502217, doi: 10.1109/TIM.2020.3031760.

[10] E. -T. Bouali, M. R. Abid, E. -M. Boufounas, T. A. Hamed and D. Benhaddou, "Renewable Energy Integration Into Cloud & IoT-Based Smart Agriculture," in IEEE Access, vol. 10, pp. 1175-1191, 2022, doi: 10.1109/ACCESS.2021.3138160.

[11] M. Muñoz, J. L. Guzmán, J. A. Sánchez-Molina, F. Rodríguez, M. Torres and M. Berenguel, "A New IoT-Based Platform for Greenhouse Crop Production," in IEEE Internet of Things Journal, vol. 9, no. 9, pp. 6325-6334, 1 May1, 2022, doi: 10.1109/JIOT.2020.2996081.

[12] G. Nagasubramanian, R. K. Sakthivel, R. Patan, M. Sankayya, M. Daneshmand and A. H. Gandomi, "Ensemble Classification and IoT-Based Pattern Recognition for Crop Disease Monitoring System," in IEEE Internet of Things Journal, vol. 8, no. 16, pp. 12847-12854, 15 Aug.15, 2021, doi: 10.1109/JIOT.2021.3072908.

[13] R. N. Bashir, I. S. Bajwa and M. M. A. Shahid, "Internet of Things and Machine-Learning-Based Leaching Requirements Estimation for Saline Soils," in IEEE Internet of Things Journal, vol. 7, no. 5, pp. 4464-4472, May 2020, doi: 10.1109/JIOT.2019.2954738.

[14] D. Alghazzawi, O. Bamasaq, S. Bhatia, A. Kumar, P. Dadheech and A. Albeshri, "Congestion Control in Cognitive IoT-Based WSN Network for Smart Agriculture," in IEEE Access, vol. 9, pp. 151401-151420, 2021, doi: 10.1109/ACCESS.2021.3124791.
[15] J. E. Plazas et al., "A Conceptual Data Model and Its Automatic Implementation for IoT-Based Business Intelligence Applications," in IEEE Internet of Things Journal, vol. 7, no. 10, pp. 10719-10732, Oct. 2020, doi: 10.1109/JIOT.2020.3016608.
[16] F. F. Borelli, G. O. Biondi and C. A. Kamienski, "BIoTA: A Buildout IoT Application Language," in IEEE Access, vol. 8, pp. 126443-126459, 2020, doi: 10.1109/ACCESS.2020.3003694.
[17] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour and E. -H. M. Aggoune, "Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk," in IEEE Access, vol. 7, pp. 129551-129583, 2019, doi: 10.1109/ACCESS.2019.2932609.
[18] M. H. Mughal, Z. A. Shaikh, A. I. Wagan, Z. H. Khand and S. Hassan, "ORFFM: An Ontology-Based Semantic Model of River Flow and Flood Mitigation," in IEEE Access, vol. 9, pp. 44003-44031, 2021, doi: 10.1109/ACCESS.2021.3066255.
[19] S. K. Sah Tyagi, A. Mukherjee, S. R. Pokhrel and K. K. Hiran, "An Intelligent and Optimal Resource Allocation Approach in Sensor Networks for Smart Agri-IoT," in IEEE Sensors Journal, vol. 21, no. 16, pp. 17439-17446, 15 Aug.15, 2021, doi: 10.1109/JSEN.2020.3020889.
[20] C. A. González-Amarillo et al., "An IoT-Based Traceability System for Greenhouse Seedling Crops," in IEEE Access, vol. 6, pp. 67528-67535, 2018, doi: 10.1109/ACCESS.2018.2877293.
[21] N. Lekbangpong, J. Muangprathub, T. Srisawat and A. Wanichsombat, "Precise Automation and Analysis of Environmental Factor Effecting on Growth of St. John’s Wort," in IEEE Access, vol. 7, pp. 112848-112858, 2019, doi: 10.1109/ACCESS.2019.2934743.
[22] H. A. Alharbi and M. Aldossary, "Energy-Efficient Edge-Fog-Cloud Architecture for IoT-Based Smart Agriculture Environment," in IEEE Access, vol. 9, pp. 110480-110492, 2021, doi: 10.1109/ACCESS.2021.3101397.
[23] M. S. Farooq, S. Riaz, M. A. Helou, F. S. Khan, A. Abid and A. Alvi, "Internet of Things in Greenhouse Agriculture: A Survey on Enabling Technologies, Applications, and Protocols," in IEEE Access, vol. 10, pp. 53374-53397, 2022, doi: 10.1109/ACCESS.2022.3166634.
[24] R. C. F. Mendes, R. R. Mac Donald, A. R. S. Miranda, R. H. van Els, M. A. Nunes and A. C. P. Brasil Junior, "Monitoring a hydrokinetic converter system for remaining energy in hydropower plants," in IEEE Latin America Transactions, vol. 18, no. 10, pp. 1683-1691, October 2020, doi: 10.1109/TLA.2020.9387638.
[25] P. Pal, S. Tripathi and C. Kumar, "Single Probe Imitation of Multi-Depth Capacitive Soil Moisture Sensor Using Bidirectional Recurrent Neural Network," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-11, 2022, Art no. 9504311, doi: 10.1109/TIM.2022.3156179.