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Intelligent Water Management in Agriculture Using IoT-Embedded Smart Irrigation Systems

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Abstract

Water scarcity and inefficient irrigation practices in agriculture have increased the need for smart water management systems capable of making irrigation decisions. In this paper, we propose an IoT embedded smart irrigation system for intelligent water management in agriculture, which includes sensor-based monitoring and optimization of predictive models. Firstly, the agricultural data are analyzed using the Adaptive Fast Desensitized Kalman Filter (AFDKF) to eliminate noise, minimize measurement uncertainty, and improve data consistency. Then, the pre-processed soil and environmental parameters are analyzed using the Kolmogorov-Arnold Recurrent Network (KARN), which is able to analyze the relationships between different agricultural parameters and make predictions regarding the crop needs for irrigation management. Weight parameters of the KARN model are optimized by means of the Arctic Tern Optimizer (ATO) to enhance prediction accuracy and convergence of the model. Moreover, the developed smart irrigation framework involves the use of an ESP32 based sensing unit equipped with sensors measuring soil moisture, temperature, humidity, and water level in real time. Evaluation of the AFDKF-KARN-ATO framework shows that it is able to demonstrate outstanding performance in comparison with existing RFL, ANN, and DNN algorithms with accuracy equal to 99.05%, precision—99.12%, recall—99.17%, specificity—98.4%, and AUC-ROC, 0.93. Besides, the developed smart irrigation framework ensures computation time equal to 97 seconds and throughput equal to 98.6.

Keywords

Water Management, Agriculture, Sensors, Adaptive Fast Desensitized Kalman Filter, Kolmogorov-Arnold Recurrent Network and Arctic Tern Optimizer

1. Introduction

In recent years, agriculture has become increasingly reliant on technology to meet the growing demands of a rapidly expanding population [1]. Global challenges such as urbanization, climate change, and resource scarcity have pushed the agricultural sector to adopt innovative solutions that can enhance productivity and sustainability [2]. Smart agriculture, leveraging technologies like the Internet of Things (IoT), sensors, cloud computing, and artificial intelligence (AI), has emerged as a transformative approach to modern farming [3]. These technologies enable real-time monitoring of crops, soil, water, and environmental conditions, allowing farmers to make data-driven decisions and optimize farm operations [4]. The integration of IoT in irrigation management, crop monitoring, and livestock health has paved the way for a more precise and efficient agricultural ecosystem. Intelligent water management using [5] IoT-based smart irrigation systems plays a critical role in addressing global agricultural challenges. Efficient water use is essential for ensuring food security, reducing operational costs, and minimizing environmental impact [6]. By continuously monitoring soil moisture, temperature, and humidity, smart irrigation systems provide precise water delivery to crops, preventing over- or under-watering [7]. Such systems not only conserve water resources but also improve crop yield and quality, contributing to sustainable agricultural development. The adoption of these technologies supports farmers in making timely and informed decisions, enhancing both productivity and profitability while reducing the overall ecological footprint of farming activities.

Despite the promising benefits of IoT-based smart irrigation systems, several challenges remain [8]. High initial investment costs, the complexity of integrating various sensors and devices, and the need for reliable internet connectivity can hinder adoption, particularly in rural or underdeveloped areas [9]. Technical issues such as sensor calibration, data accuracy, and system maintenance can also limit effectiveness [10]. Furthermore, farmers may lack awareness or training to fully utilize these advanced technologies, reducing their potential impact [11]. Cyber security concerns, data privacy, and interoperability of devices add additional layers of complexity to the implementation of smart agricultural solutions.

To overcome these challenges, it is essential to develop cost-effective, user-friendly, and scalable smart irrigation systems [12]. Simplifying the installation process, providing robust training programs for farmers, and offering technical support can increase adoption rates [13]. Integration of AI and machine learning can enhance predictive capabilities and improve decision-making based on sensor data [14]. Offline and low-power communication solutions can address connectivity issues, while standardized protocols and secure data management can mitigate technical and security challenges [15]. By addressing these limitations, intelligent water management systems can be effectively implemented to improve efficiency, sustainability, and resilience in modern agriculture.

Most important contributions of this research were abridged below:

- Development of IoT-embedded smart irrigation system to enhance water management and irrigation efficiency in agriculture.

- Data pre-processing with the Adaptive Fast Desensitized Kalman Filter (AFDKF) to get rid of noise and make the crop dataset more accurate for analysis.
- Prediction of crop water requirements using Kolmogorov-Arnold Recurrent Network (KARN) based on soil and environmental parameters.
- Optimization of KARN model using Arctic Tern Optimizer (ATO) to improve prediction accuracy through adaptive weight tuning.
- Demonstrated superior performance over existing methods (RFL, DNN, ANN) with high Accuracy, Precision, Recall, and F1-score, validating the system's effectiveness.

The novelty of this work lies in the integration of IoT-enabled smart irrigation with an optimized predictive framework for precise water management. By combining the Adaptive Fast Desensitized Kalman Filter (AFDKF) for data pre-processing, the Kolmogorov-Arnold Recurrent Network (KARN) for crop water requirement prediction, and the Arctic Tern Optimizer (ATO) for adaptive weight optimization, the proposed system achieves highly accurate and efficient irrigation planning. This integrated approach outperforms existing methods, providing a robust, automated, and intelligent solution for sustainable agriculture under varying environmental conditions.

The structure of this document is as follows: The literature review is presented in Section 2, materials and techniques are presented in Section 3, the suggested technique is presented in Section 4, the results are discussed in Section 5, and the article is concluded in Section 6.

2. Literature Review

Numerous studies that focused on water management in agriculture have already been published in the literature. Here are a few that were reviewed:

Morchid *et al.* [16] have developed a real-time intelligent irrigation system that uses embedded technology and the Internet of Things to improve water efficiency and advance sustainable agriculture. The main objective was to optimize irrigation management by monitoring climatic and soil conditions in real time. The system employed an ESP32 controller integrated with sensors such as DHT22, swater level and soil moisture sensors, with information sent over HTTP and Server-Sent Events to a web interface. However, the system's performance was limited by network reliability, sensor calibration issues, and scalability constraints in large agricultural areas.

Patole and Shrivastava [17] have presented a soil moisture prediction that is critical for crop recommendation but suffers from high time complexity and low accuracy due to spatial-temporal variability. IoT-enabled sensors provide soil and environmental data, improving monitoring and decision-making. Machine learning and deep learning, especially ensemble models like capture non-linear soil dynamics effectively. The proposed Intelligent Hunting Optimized Adaptive Light Gradient Boosting Ensemble Deep Neural Network integrates IoT data with adaptive ensemble learning and optimized SMOTE to enhance soil moisture prediction and crop recommendation accuracy.

Morchid *et al.* [18] have developed a real-time smart irrigation system integrating IoT, embedded systems, and WebSocket communication to address modern agricultural challenges. The main objective was to optimize irrigation management and enhance water-use efficiency for sustainable farming. The system utilized ESP32 microcontrollers with sensors to collect environmental data and enable real-time monitoring and remote control through a web interface. However, limitations such as dependence on stable internet connectivity, sensor calibration accuracy, and scalability in large farming areas were observed.

Morchid *et al.* [19] have developed an intelligent irrigation system integrating IoT, cloud computing, fuzzy logic, and embedded devices to improve agricultural sustainability and water management. The main objective was to minimize water wastage and maintain optimal soil moisture under varying climatic conditions. The system utilized ESP32 microcontrollers, environmental sensors, Thing Speak cloud analysis, and MATLAB-based fuzzy logic modelling for dynamic irrigation control. However, the system faced limitations such as dependency on stable internet connectivity, limited scalability for large farms, and potential delays in cloud-based data processing.

Ali *et al.* [20] have developed advances in precision and smart irrigation technologies to address the growing challenges of water scarcity in agriculture. The main objective was to analyze existing literature on water-saving and smart irrigation methods, including IoT, wireless sensor networks, deep learning, and fuzzy logic, to support sustainable agricultural practices. A comprehensive review of 150 articles from 2005-2024 was conducted, focusing on precision irrigation scheduling, monitoring systems, and decision-making techniques based on soil, plant, and weather data. However, the study identified limitations such as high implementation costs, technological complexity, and challenges in large-scale adoption of AI-based and precision irrigation systems.

Taibi *et al.* [21] have developed a cloud-based IoT smart irrigation system to enhance water efficiency and support sustainable agriculture in arid regions. The system integrated IoT devices, embedded controllers, low-cost wireless sensor networks, and cloud computing to centralize farm data and enable precise irrigation control. However, limitations included dependence on solar power availability, the complexity of big data management, and challenges in scaling the system to larger agricultural areas.

Bhardwal *et al.* [22] have developed a low-cost, secure, and smart IoT-based irrigation system to improve water management for agriculture and drinking water provision. The main objective was to enhance farming efficiency by enabling automated irrigation control based on seasonal and climatic conditions. The system employed four algorithms and water management rules, including automated alerts for device failures and water leakage, with alternative mode switching to maintain operation. However, limitations include reliance on network connectivity, potential sensor inaccuracies, and challenges in large-scale deployment. Below **Table 1** summarizes the literature review.

Table 1. Summary of literature survey.

Author	Objective	Advantages	Limitations
Morchid *et al.* [16]	To develop an intelligent irrigation system for sustainable water use in agriculture.	Enables continuous monitoring and automated irrigation control.	Limited by network reliability, sensor calibration issues, and poor scalability.
Patole & Shrivastava [17]	To improve soil moisture prediction and crop recommendation accuracy.	Provides enhanced prediction precision and adaptive learning capability.	Faces high computational complexity and sensitivity to environmental variability.
Morchid *et al.* [18]	To optimize irrigation management for efficient water utilization.	Enhances irrigation scheduling and supports smart water control.	Dependent on stable internet and accurate sensor functioning.
Morchid *et al.* [19]	To reduce water wastage and maintain soil moisture balance.	Promotes efficient water management and dynamic irrigation decisions.	Limited scalability for large agricultural fields and dependency on connectivity.
Ali *et al.* [20]	To analyze developments in precision and smart irrigation systems.	Provides a comprehensive review of AI-based and data-driven irrigation strategies.	Identifies challenges such as high implementation cost and technological complexity.
Taibi *et al.* [21]	To enhance water efficiency in arid regions through digital irrigation management.	Improves irrigation scheduling and promotes sustainable water use.	Dependent on solar power availability and complex data management.
Bhardwal *et al.* [22]	To create a low-cost and secure IoT-based irrigation and water supply system.	Enables automated irrigation and efficient water allocation.	Limited large-scale applicability and potential connectivity issues.

Research Gap

Despite significant advancements in IoT-based and smart irrigation systems, several research gaps and limitations remain that motivate this study. Existing methods, such as real-time irrigation systems using ESP32 controllers and sensors, improved water efficiency but suffered from network reliability issues, sensor calibration inaccuracies, and limited scalability for large agricultural areas. Machine learning and deep learning approaches enhanced soil moisture prediction and crop recommendations, yet they often faced high computational complexity and lower accuracy due to spatiotemporal variability. Cloud-based and fuzzy logic-integrated systems enabled dynamic irrigation control and big data analysis but were constrained by dependence on stable internet connectivity, solar power availability, and delays in cloud processing. Additionally, while low-cost IoT frameworks improved automation and provided fault alerts, challenges persisted in large-scale deployment and maintaining consistent sensor performance. These limitations highlight the need for a robust, scalable, and cost-effective smart irrigation system capable of reliable real-time monitoring, precise water management, and adaptability to diverse agricultural environments, which forms the motivation for this research.

3. Materials and Methods

In this work, an intelligent irrigation system is proposed to optimize water management in agriculture by leveraging soil and environmental data. The system collects key parameters such as soil moisture, temperature, humidity, pH, and rainfall using sensors interfaced with the ESP32 microcontroller and transmits the data to a web client for monitoring and informed decision-making. The system architecture integrates embedded systems, IoT, Server-Sent Events (SSEs), and web technologies to facilitate seamless data transmission, while the core algorithm uses the collected data to generate precise irrigation decisions. This approach promotes sustainable water management, improves crop yield, and supports resource-efficient farming practices.

3.1. System Modelling

The proposed intelligent irrigation system integrates the ESP32 microcontroller with a web server to facilitate efficient water management in agriculture. The ESP32 collects data from multiple sensors, including a DHT22 temperature and humidity sensor, a soil moisture sensor, and a water level sensor. These measurements are transmitted to the web client using Server-Sent Events (SSE), where the client dynamically updates the interface to display temperature, humidity, soil moisture, and water level in the form of informative maps. The web server, developed using HTML and CSS, ensures an intuitive and functional interface for monitoring environmental conditions. The irrigation management algorithm utilizes the collected data to control pumps and optimize irrigation schedules, promoting resource-efficient water use. The overall system architecture allows for continuous monitoring, informed decision-making, and enhanced water management in agricultural applications.

3.2. Embedded System and Sensor Integration

The embedded system in this intelligent irrigation framework is based on the ESP32 microcontroller, which serves as the central processing unit for collecting, processing, and transmitting real-time environmental data. It integrates multiple sensors to monitor key agricultural parameters:

- DHT22 sensor—measures ambient temperature and humidity, providing critical information for assessing crop and soil conditions.
- Soil moisture sensor—detects the water content in the soil, helping to determine when irrigation is required.
- Water level sensor—monitors the reservoir level to prevent water shortages and ensure continuous irrigation.

The ESP32 collects data from these sensors, processes it according to predefined thresholds (e.g., activating pumps when soil moisture is low), and transmits it to a web interface via HTTP and Server-Sent Events (SSE). This embedded system enables real-time monitoring, automated irrigation control, and efficient water management, ensuring sustainable agricultural practices with minimal manual intervention.

4. Proposed Methodology

The proposed AFDKF-KARN-ATO framework is designed to provide accurate and efficient water management system through the use of IoT-based sensing and predictions. For this purpose, agricultural data will be filtered with the use of the Adaptive Fast Desensitized Kalman Filter (AFDKF) to reduce noise and minimize measurement uncertainties. No data augmentation will be done since Crop Recommendation dataset contains only structured tabulated observations. After that, pre-processed features will be used to train the Kolmogorov-Arnold Recurrent Network (KARN), which will enable us to detect any nonlinear dependencies between soil and environmental parameters and provide the basis for predicting the crop requirements. At the next step, we will use the Arctic Tern Optimizer (ATO) to optimize the weight parameters of KARN model and increase the efficiency of predictions and the rate of convergence. We will integrate our optimized model with IoT-based sensing unit based on the ESP32 microcontroller with temperature, humidity, soil moisture and water-level sensors. Depending on the crop requirement prediction and current soil moisture level, the irrigation pump will be controlled and adjusted in order to keep the required moisture level.The block diagram of the proposed methodology is given below in Figure 1.

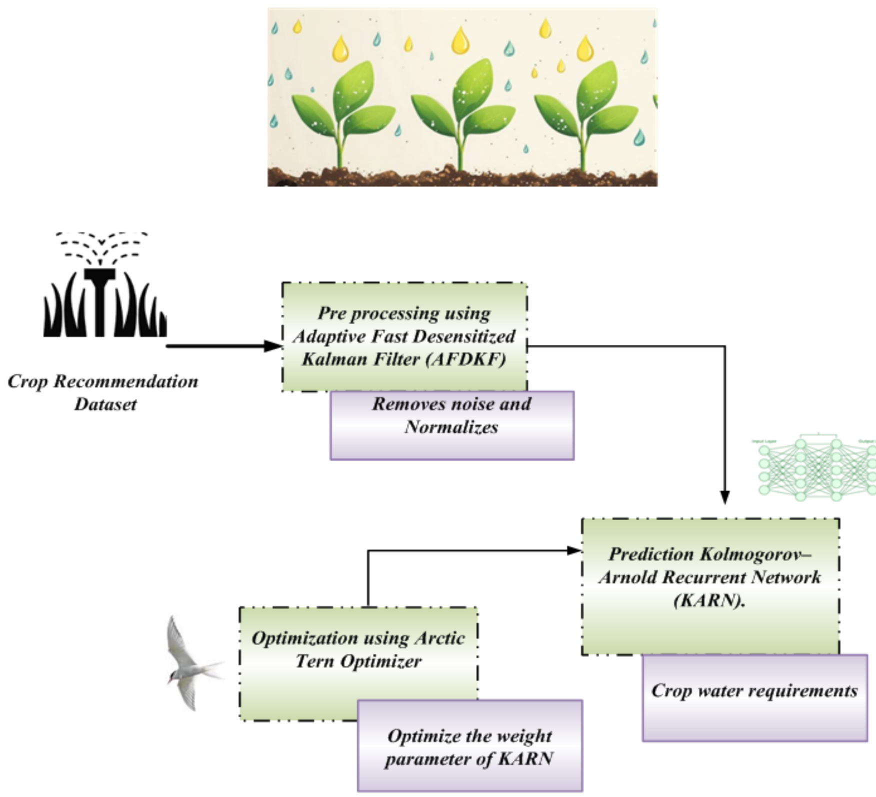

Figure 1. Block diagram of proposed methodology.

4.1. Data Collection

The Crop Recommendation Dataset [23] was used for the model development and evaluation purposes. This dataset has 2,200 agricultural observations with seven attributes, including nitrogen, phosphorus, potassium, temperature, humidity, pH value, and rainfall. The dataset also has one output attribute, which is the suggested crop type. The dataset was split into the training, validation, and testing subsets in a stratified 70:15:15 ratio with the fixed random seed value of 42. The training data were used for model training and ATO-based parameter optimization, while the validation data, for the model selection and parameter tuning. The test data were left independent and used for evaluation of the model performance. To prevent the data leakage, the AFDKF pre-processing and normalization parameters were calculated based on the training data set only and applied to the validation and test data afterwards. In addition, the ATO optimization was performed without involving the test data. The ESP32-based sensing unit was incorporated into the proposed irrigation system as the real-time data collection and monitoring module. The ESP32 module receives temperature, humidity, soil moisture, and water-level measurements from the connected sensors and sends the received data to the web interface for monitoring and irrigation control purposes. Thus, the dataset-based model and ESP32 module represent complementary components of the system, where the former is the source of the intelligence for the water management decisions, while the latter one serves for the real-time data collection and monitoring. The current evaluation of the performance was done by utilizing the public dataset, whereas the ESP32 implementation represents the proof-of-concept demonstration.

Irrigation Decision Rule

The predicted crop type from the AFDKF-KARN-ATO algorithm is integrated with the live soil moisture measurement from the ESP32 sensor to find the need for irrigation. Each crop type is assigned a defined soil moisture threshold, which defines the minimum moisture level that is needed. If the soil moisture is less than the defined threshold, then the ESP32 turns on the water pump. The water pump will be active until the soil moisture reaches the defined target value; afterwards, the water pump is turned off. If the soil moisture is in the required range, then the pump is not turned on.

4.2. Data Splitting, Validation Strategy, and Leakage Prevention

The data split for the Crop Recommendation Dataset was done through stratified sampling where each set comprised of 70%, 15% and 15% for training, validation and testing respectively. The training set was used for training the KARN model and for tuning the parameters of the model using ATO, while the validation set was used for model selection and parameter tuning. The test set was entirely kept out of this process and only used in the final performance evaluation step. The random seed of 42 was selected to provide reproducibility.

To prevent any data leakage, preprocessing of the datasets was done using only the training data and then applied to the validation and test sets without using test data at this stage. This includes the preprocessing through AFDKF and normalization as well as ATO optimization. The ATO optimization was also done using the training data and using the validation set for selecting the parameters of the model. The test set was not used at all in preprocessing, training and optimization steps.

4.3. Adaptive Fast Desensitized Kalman Filter (AFDKF) for Pre-Processing

In this section, the Adaptive Fast Desensitized Kalman Filter (AFDKF) is used to pre-process the Crop Recommendation Dataset by removing noise and normalizing the data [24]. Agricultural datasets often contain fluctuations and measurement errors in key features such as soil nutrients, water availability, rainfall, and humidity, which can reduce model accuracy. The AFDKF is chosen because it effectively suppresses random noise while preserving the true dynamics of the data, ensuring critical patterns in soil and water parameters are maintained. Its adaptive nature allows it to handle varying noise levels across different input features, and its fast computational performance is suitable for large datasets. By providing clean and normalized data, the AFDKF enhances the accuracy and reliability of deep learning models, leading to better crop recommendation and water management decisions in sustainable agriculture.

$$E\left\{\tilde{Z}_k + {}_j\tilde{Z}_k^T\right\} = 0,\ k = 1,2,\cdots, j = 1,2,3,\cdots \tag{1}$$

where, $\tilde{Z}_k$ represents the processed soil and water data at a specific time, ${}_j\tilde{Z}_k^T$ while captures the time-lagged or spatial interactions among soil moisture, which can reveal subtle patterns in water availability and usage. This approach enables effective noise removal and normalization, minimizing measurement errors and inconsistencies in the dataset, as expressed in Equation (2).

$$\Lambda_k = P_k^- \bar{H}_k^T - K_k V_k \tag{2}$$

where, Λ_k represents the updated estimate of uncertainty in soil moisture and water data at time step k, P_k the prior uncertainty before incorporating the latest measurement, denotes a weighting factor that balances the influence of new water or soil observations with previously estimated conditions, K_k represents the difference between the actual measurement and the predicted water availability, and is the transpose of the observation matrix linking the internal water-soil state, V_k This method applies normalization to the data, standardizing soil and water measurements across different fields and sensors for consistent analysis, as expressed in Equation (3).

$$W_k^a = \lambda_k W_0 \tag{3}$$

where, W_k^a represents the adaptive weight at time step k, λ_k represents a denotes a scaling or adaptation factor that changes over time based on variations in soil moisture or water availability, W_0 represents the initial or baseline weight set during normal irrigation or soil conditions. This approach improves the clarity of underlying water patterns, making anomalies in water distribution or irrigation efficiency more distinguishable, as expressed in Equation (4).

$$g(\lambda_k) = \sum_{i=1}^{l}\sum_{j=1}^{l}\Lambda_{i\,j,k}^{2} \tag{4}$$

where, $g(\lambda_k)$ Here, represents a function of the adaptive factor that quantifies overall changes in soil moisture or water availability at time step λ_k step k, $\Lambda_{i\,j,k}^{2}$ denotes the squared element of the covariance matrix at row i, column j, and time k. The AFDKF can adaptively adjust filter parameters to accommodate sudden changes in irrigation patterns or unexpected variations in water distribution, as expressed in Equation (5).

$$\lambda_k = \max\left\{1, \lambda_k^{*}\right\} \tag{5}$$

where, λ_k^{*} represents a function of the adaptive factor that quantifies overall changes in soil moisture or water availability at time step. Finally, the AFDKF has cleaned the data, removed noise and normalized the data. After that, the pre-processed data is given to deep learning segment.

4.4. Crop Water Needs Kolmogorov-Arnold Recurrent Network (KARN) Prediction

The KARN-Based Model is used for classification of appropriate crop categories using the available data from the soil and environment from the dataset [25]. As the Crop Recommendation Dataset consists of independent data entries and not time-stamped sequences, the model does not apply any form of recurrence or memory from past observations. Rather, each entry is individually mapped from the available agricultural properties to the respective crop categories. The choice of the KAN-Based Model is based on the fact that the nonlinear function-learning capacity of the model enables representation of complex interactions among the soil nutrients and environmental parameters as shown in **Figure 2**.

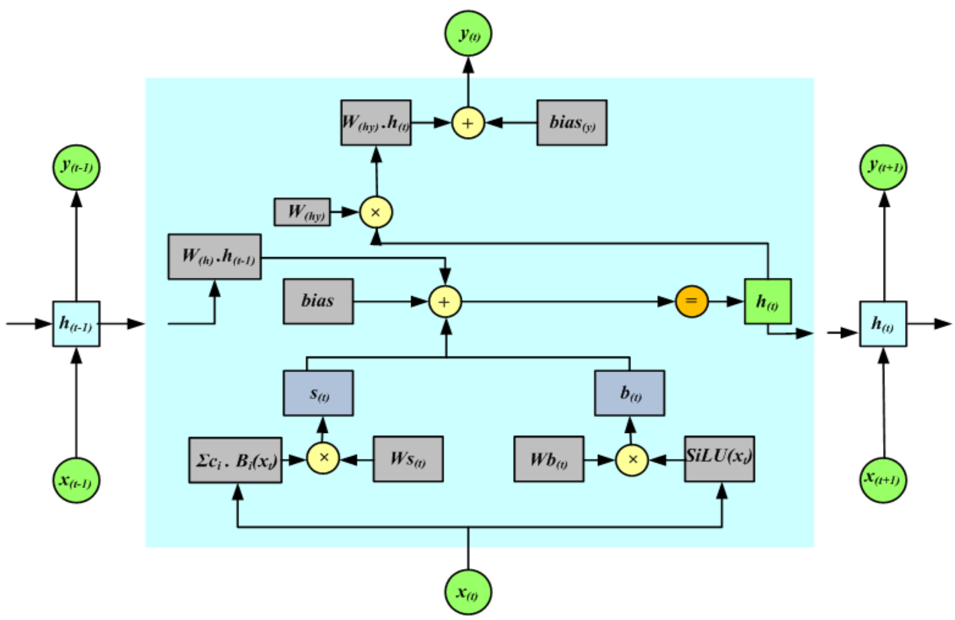

Figure 2. Architecture of KARN.

The KARN model is applied to predict crop water requirements and support efficient irrigation management using soil and environmental data. It handles input data in time series format, including soil moisture, temperature, humidity, pH, and rainfall, using kernel-based input transformations with non-linear SiLU activations, enabling it to capture complex, non-linear relationships affecting crop water needs. KARN employs a recurrent architecture that merges past soil and environmental states with the transformed inputs, resulting in accurate predictions for irrigation scheduling and water allocation. This provides AI-enabled water management systems the ability to optimize irrigation, conserve water resources, and support sustainable crop growth while maximizing yield.

The KARN begins with an input layer that receives time-series data related to soil and environmental variables, as stated, including soil moisture, temperature, humidity, pH, and rainfall in Equation (6).

$$SiLU\left(x\right)=\frac{x}{1+\mathrm{e}^{-x}} \tag{6}$$

where x is the is the input feature representing system state, and e is the mathematical constant used in the activation function, this enables modeling of complex nonlinear relationships to accurately predict crop water requirements based on soil and environmental parameters. The model utilizes earlier hidden layers to retain temporal dependencies and contextual information from previous soil moisture, temperature, humidity, pH, and rainfall measurements, enabling precise irrigation scheduling and efficient water management, as shown in Equation (7).

$$a_{(t)}=w_{b(t)}\cdot SiLU\left(y_{(t)}\right) \tag{7}$$

where, $w_{b(t)}$ are Learnable weights that enable the model by matching the input at a specific time to adaptively respond to temporal trends in soil moisture, temperature, humidity, pH, and rainfall. As contained within the hidden states of the model, these predictions are aligned to support earlier and more accurate crop water requirement estimation and efficient irrigation scheduling, as shown in Equation (8).

$$S_{(t)}=w_{s(t)}\cdot\sum_{i}c_i\cdot B_i\left(x_{(t)}\right) \tag{8}$$

where, B_i represents the B-spline basis function used to model crop water requirements, c_i are the soil and environmental input parameters (such as soil moisture, temperature, humidity, pH, and rainfall), and $w_{s(t)}$ are the are the adaptive weights optimized to improve the accuracy of water requirement prediction for crops. In this context, KARN computes a new hidden state that reflects updated water demand trends and soil moisture dynamics based on incoming environmental and soil data. The data set is defined as a multiclass classification task where the output label denotes the type of crop that grows in the soil and environmental conditions, as shown in Equation (9).

$$J_{(t)} = w_{(h)} \cdot J_{(t-1)} + b_{(t)} + V_{(t)} + bias \quad (9)$$

where, $w_{(h)}$ is a learnable weight matrix that aids in the retention of data from the irrigation condition prior to the current forecast. $J_{(t-1)}$ to the current prediction $J_{(t)}$. The term $b_{(t)}$ The term denotes the output obtained from the temporal analysis of soil and environmental input data at time step t, while $S_{(t)}$ denotes the objective function of location K. In order to accurately estimate water requirements and crop development patterns across time, while represents the output of the temporal function applied to the same input. The output layer then generates the predicted irrigation levels and water distribution schedules, supporting intelligent decision-making for efficient water management and sustainable agricultural practices, as expressed in Equation (10).

$$y_{(t)} = w_{(hy)} \cdot h_t + bias_{(y)} \quad (10)$$

where, w_{hy} is a learnable weight matrix that aids in remembering the previous crop's information water requirement state $bias_{(y)}$ to the current prediction. Table 2 shows the parameter table for KARN.

Table 2. Parameter table for KARN.

Parameter	Value
Hidden layer	128
No. of layer	2

4.5. Optimization Using Arctic Tern Optimizer

In this section, Optimization using Arctic Tern optimizer (ATO) [26] is discussed. The Arctic Tern Optimizer (ATO) is employed to optimize the weight parameters of the KARN model to enhance prediction accuracy and convergence efficiency in agricultural water management. This optimizer is inspired by the migratory behavior of Arctic terns, which follow the most efficient and adaptive flight paths between regions a behavior analogous to optimal search and exploitation in optimization problems. ATO is chosen because it provides a strong balance between exploration and exploitation, effectively preventing the model from getting trapped in local minima. Its adaptive learning mechanism allows dynamic adjustment of search paths, resulting in faster convergence and better generalization performance. By integrating ATO with KARN, the model achieves improved parameter tuning, enhanced stability, and more accurate prediction of crop water requirements under varying soil and environmental conditions.

Step* 1: *Initialization

The ATO is a population-based optimization algorithm, where a set of potential solutions is initialized to begin the optimization process. For optimizing the KARN weights in agricultural water management, this involves placing multiple search agents randomly within the high-dimensional weight space, enabling the algorithm to explore diverse regions and identify optimal parameter configurations for accurate crop water requirement prediction. The initialization process helps capture variations in soil moisture, temperature, humidity, pH, and rainfall data, allowing the KARN model to achieve better convergence and adaptability to environmental fluctuations. The initialization is mathematically represented in Equation (11).

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & X_{1,3} & \cdots & \cdots & X_{1,d} \\ X_{2,1} & X_{2,2} & X_{2,3} & \cdots & \cdots & X_{2,1} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ X_{M,1} & X_{M,2} & X_{M,3} & \cdots & \cdots & X_{M,d} \end{bmatrix} \tag{11}$$

where d represents the number of variables in the problem; X represents a collection of current potential solutions.

Step* 2: *Random generation

The input weight parameter $t_{\mu-1}$ and Ω_k^μ developed randomness through ATO method.

Step* 3: *Assessment of fitness

Random replies and initialized assessments determine the result. Equation (12) is then used to calculate the fitness.

$$\text{Fitness function} = \text{optimizing}\left[W_{(h)} \text{ and } S_{(t)}\right] \tag{12}$$

where, Q_{HF} is used for increasing the accuracy and N_1 is used for increasing the recall.

***Step* 4: *Positioning and migration movements for optimizing* $W_{(h)}$**

The Arctic Tern Optimizer determines new positions of search agents based on the terns' current, previous, and optimal locations, inspired by their migratory behavior and adaptive navigation toward favourable conditions. In the context of KARN weight optimization for agricultural water management, this mechanism directs each search agent toward promising regions in the weight space by considering both local and global best positions. This process ensures efficient exploration and exploitation, enabling the model to identify optimal weight configurations for accurately predicting crop water requirements and achieving balanced irrigation management, as expressed in Equation (13).

$$K_{(l+1)} = K_t + W_{(h)}\left(i_b \times rand \times K_n - K_{best}\right) \tag{13}$$

where, $K_{(l+1)}$ represents the updated positions of a search agent moving towards the most successful search agent K_{best}; i_b denotes the random variable that enhances exploration.

***Step* 5: *Walking during stopover for optimizing* $S_{(t)}$**

The Arctic tern at K_t travel towards K_j and if the Arctic tern is found, the search agents take the route of the closest search agents at K_j is more enticing than the other Arctic tern at K_t. According to Equation (14), this behaviour is the Arctic tern's random translocation.

$$K_{(l+1)}^{C} = \begin{cases} K_j - K_t & \text{if } y(K_t) \geq S_{(t)}(K_j) \times N_1 \\ K_t - K_j & \text{if } y(K_t) < S_{(t)}(K_j) \times N_1 \end{cases} \quad (14)$$

where, $S_{(t)}$ denotes the objective function of location K; $K_{(l+1)}^{C}$ represents the positions of the search agent for finding food by walking.

Step 6: Termination

The parameters from RMFNN are optimized with the help of ATO, iteratively repeat the step 3 until fulfil the halting criteria $W = W + 1$ is met. Then ECG-IoT-EFCC-RMFNN has managed the classification of ECG anomaly with higher accuracy. The pseudo code depicting the ATO algorithm can be observed in Algorithm 1. Table 3 shows the hyperparameters of ATO.

Algorithm 1. Pseudo code for the ATO algorithm.

```
Initialize the population of the search agent
Calculate the new position of the search agent
Find the path of the finest Neighbor search agents and calculate the best search agent
K_best
While (iter < Maxiter) do
for each search agent do
Determine the stopover (walking) random relocation's location.
Update the search agents' positions end for
Calculate the fitness value of each search agent
Update K_best if there is a better solution than the previous optimal solution
t ← t + 1
End while
Return K_best
End
```

Table 3. Hyperparameters of ATO.

Hyperparameter	Value
Total population size	50
Max Iterations	500

5. Result and Discussion

This section discusses the research results of the suggested method KARN-ATO (proposed). The testing system has an Intel Core i3-3220 CPU operating at 3.30 GHz and 4 GB of installed RAM. It uses a 64-bit Windows operating system's x64-based CPU architecture, which offers it the perfect platform for successfully completing the suggested tests. Under this unified experimental design, the performance of the suggested methodologies is assessed and contrasted with current methods, such as RFL, DNN, and ANN.

5.1. Performance Measures

This is an essential stage in figuring out the best prognosis. Performance metrics including accuracy, precision, recall, F1-score, specificity, confusion matrix, and ROC are assessed.

5.1.1. Accuracy

Accuracy is a fundamental metric that estimates the proportion of proper predictions a model makes out of all forecasts. It essentially displays how frequently the model is correct when sorting illustrations into different categories, which is done using Equation (15).

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{15}$$

where, TN is the True Negative, FN is the False Negative, TP is the True Positive, and FP is the False Positive.

5.1.2. Precision

That is, it evaluates the predictive power of the model, determining how effectively it distinguishes between different irrigation requirement classes. This metric reflects the model's ability to identify the correct category whether a crop requires low, moderate, or high water input based on the input parameters. Depending on the class for which it is assessed, the computed value as defined in Equation (16) may be either positive or negative indicating the direction and strength of the prediction.

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{16}$$

5.1.3. Recall

Out of all the positive forecasts, recall is a measure that counts the number of accurate projections. Equation (17) below, which quantifies it,

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{17}$$

5.1.4. F1-Score

Recall and accuracy are averaged to get the F1-Score. The initial step is to ascertain both of these criteria. Consequently, Equation (18) is given.

$$\text{F1- Score} = \frac{\text{Precision} * \text{Recall} * 2}{(\text{Precision} + \text{Recall})} \tag{18}$$

5.1.5. Specificity

Selectivity, also known as the True Negative Rate (TNR) or specificity, can be defined as the proportion of actual negative instances that are correctly identified by the model. In the context of water management prediction, it measures how effectively the model avoids falsely classifying a crop or field as requiring irrigation when it actually does not. Mathematically, it is expressed as:

$$\text{Specificity} = \frac{\text{TN}}{\text{FP} + \text{TN}} \tag{19}$$

5.2. Performance Analysis

Figures 3-10 display the imitation results of proposed method. The method is compared with existing RFL, DNN and ANN method.

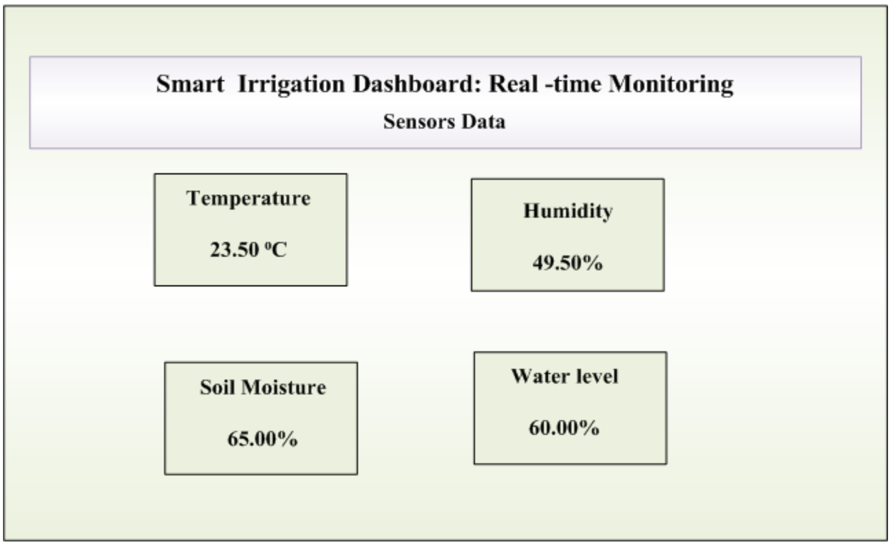

Figure 3. Examining the web server's real-time monitoring dashboard for intelligent irrigation.

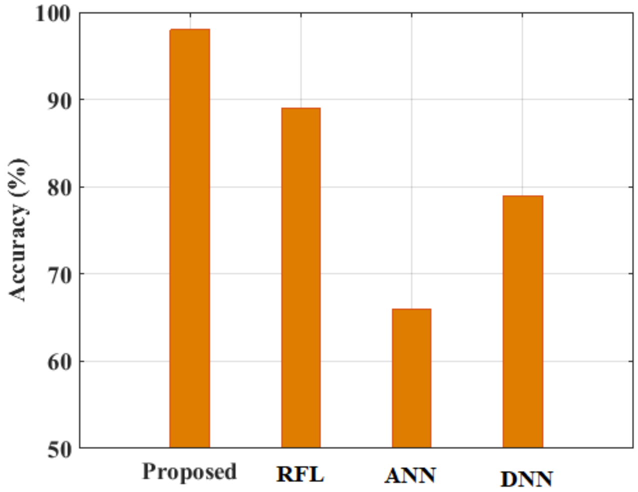

Figure 4. Analysis the performance of accuracy value with proposed and exiting.

Figure 4 illustrates the comparative analysis of accuracy performance between the proposed IoT-embedded smart irrigation model and existing techniques, including RFL, ANN, and DNN. The proposed method, which integrates the KARN optimized by the ATO, achieves the highest accuracy of 99.05%, significantly outperforming the other models. In comparison, the RFL model achieves approximately 89%, while the DNN and ANN models attain around 79% and 66%, respectively. This substantial improvement demonstrates the effectiveness of the proposed ATO-KARN framework in accurately predicting crop water requirements and optimizing irrigation efficiency, leading to superior performance in intelligent water management for agricultural applications.

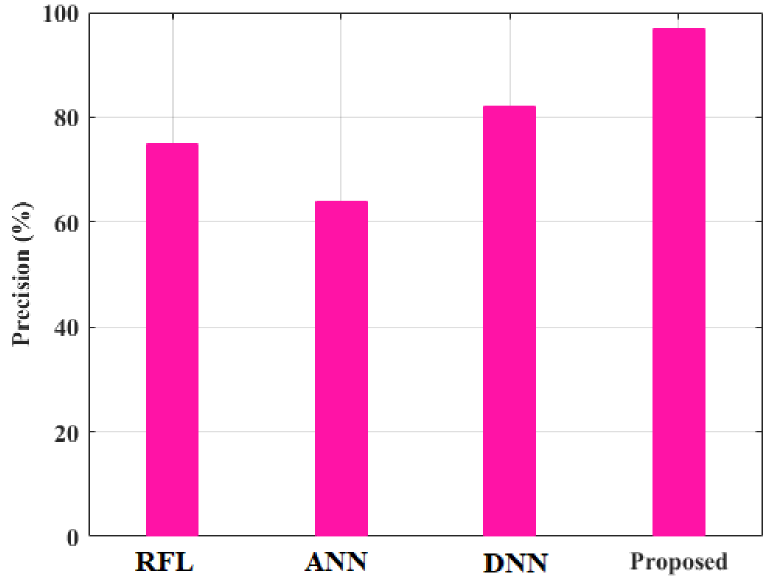

Figure 5. Analysis the performance of precision value with proposed and exiting.

Figure 5 shows the performance analysis of Precision (%) for the proposed model compared with existing methods such as RFL, ANN, and DNN. The proposed model achieves the highest precision of 99.12%, while RFL, ANN, and DNN obtain approximately 75%, 65%, and 82%, respectively. The result clearly indicates that the proposed method provides more accurate prediction outcomes with reduced false positives, ensuring effective water management and reliable irrigation control in smart agricultural systems.

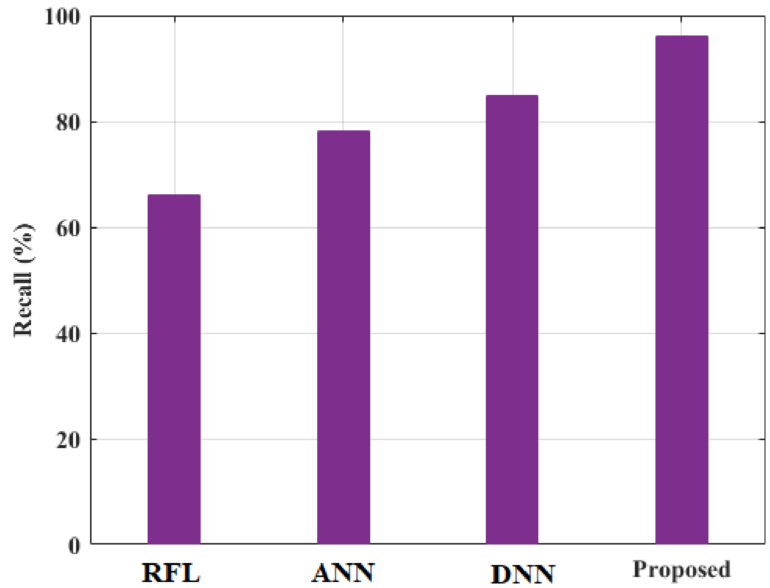

Figure 6. Analysis the performance of recall value with proposed and exiting.

Figure 6 shows the performance analysis of Recall (%) for the proposed model compared with existing methods such as RFL, ANN, and DNN. The proposed model attains the highest recall value of 99.17%, while RFL, ANN, and DNN achieve around 67%, 78%, and 85%, respectively. The higher recall rate of the proposed method indicates its strong capability in correctly identifying relevant irrigation needs, minimizing false negatives, and ensuring accurate water distribution for efficient agricultural management.

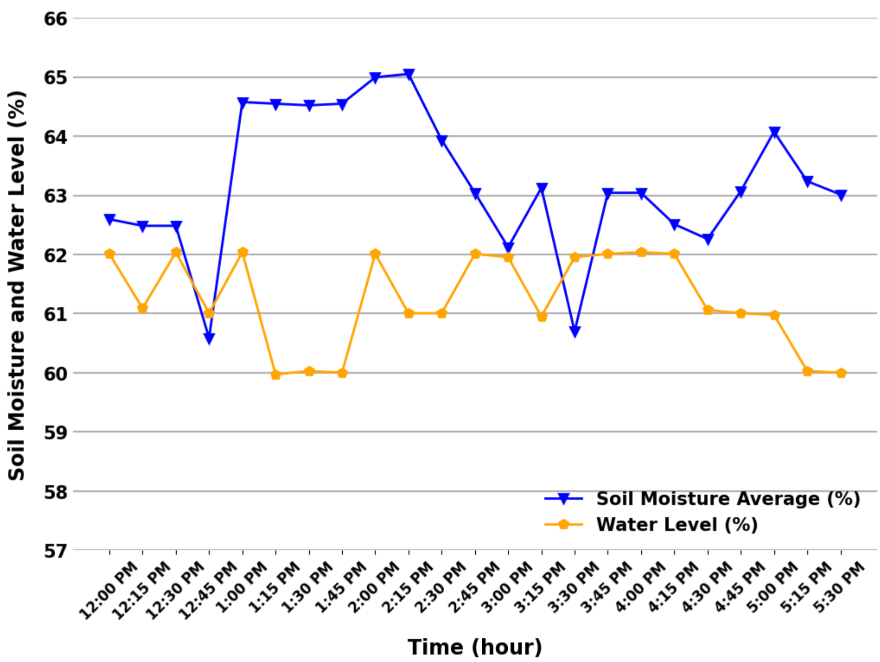

Figure 7. Analysis the performance of soil moisture and water level over time.

Figure 7 shows the variation of soil moisture and water level over time, as monitored by the proposed IoT-embedded smart irrigation system. The soil moisture percentage (blue line) shows slight fluctuations between 61% and 65%, while the water level (orange line) remains stable around 60% - 62%. This consistency indicates the system's intelligent control mechanism, where irrigation is automatically adjusted based on real-time soil conditions. When soil moisture decreases, the system activates irrigation to restore optimal levels, and once adequate moisture is achieved, it halts water flow to prevent wastage. This demonstrates the system's effectiveness in maintaining balanced moisture conditions and optimizing water usage through accurate prediction and automated regulation.

Figure 8 shows the relationship between temperature and humidity over time, as observed in the IoT-embedded smart irrigation system. The red line represents the temperature, which gradually decreases from around 28˚C to 23˚C, while the green line shows humidity increasing slightly and stabilizing at approximately 45%. This inverse relationship demonstrates the system's environmental response, where irrigation and moisture regulation help maintain favorable microclimatic conditions for crops. As irrigation progresses, soil evaporation contributes to reduced temperature and increased humidity, reflecting the system's efficiency in maintaining optimal environmental balance for healthy crop growth and sustainable water use.

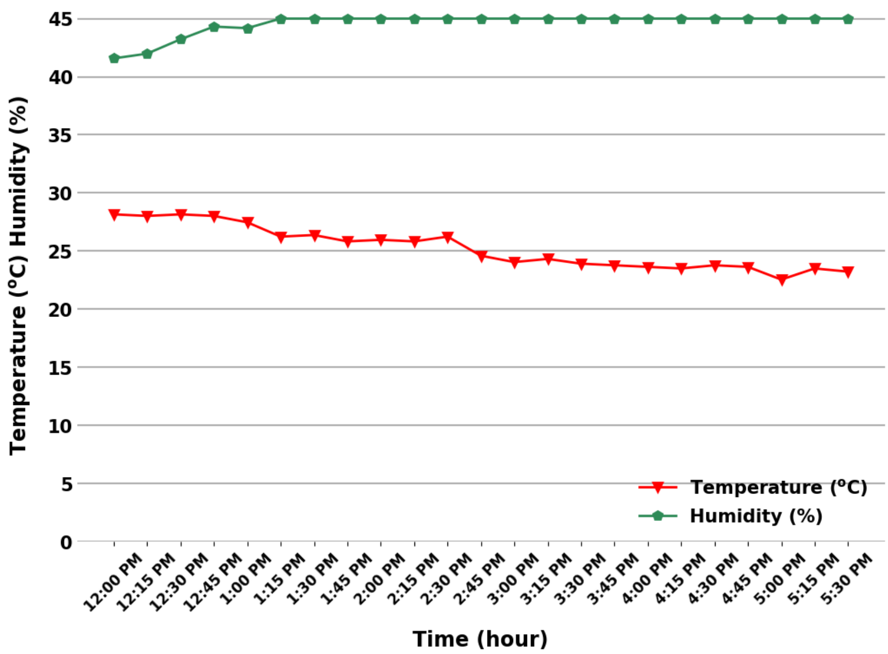

Figure 8. Analysis the performance of temperature and humidity over time.

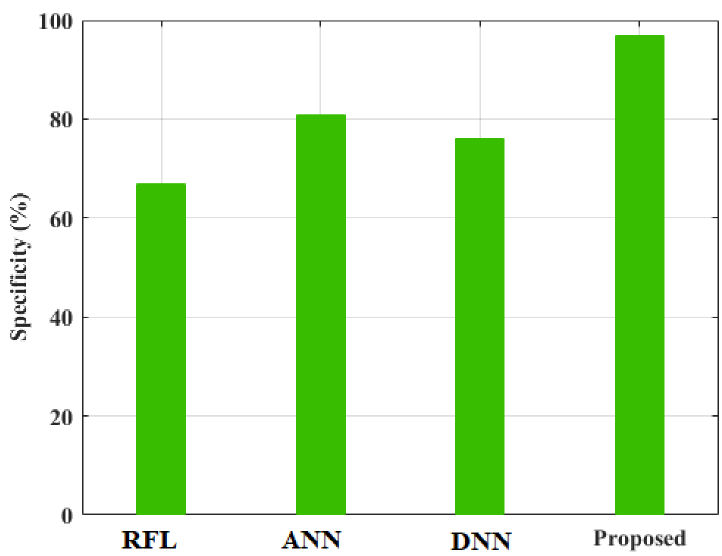

Figure 9. Analysis the performance of specificity of proposed and exiting methods.

Figure 9 shows the specificity performance of the proposed IoT-embedded smart irrigation system with existing models such as RFL, ANN, and DNN. The proposed method achieves the highest specificity, nearing 98.4%, indicating its superior ability to accurately distinguish relevant irrigation conditions and avoid false detections. In contrast, the ANN and DNN models show moderate performance with around 80% - 85% specificity, while the RFL model records the lowest value at approximately 68%. This significant improvement demonstrates that the proposed AFDKF-KARN model optimized by the Arctic Tern Optimizer (ATO) enhances prediction precision, ensuring reliable and efficient irrigation control for intelligent water management in agriculture.

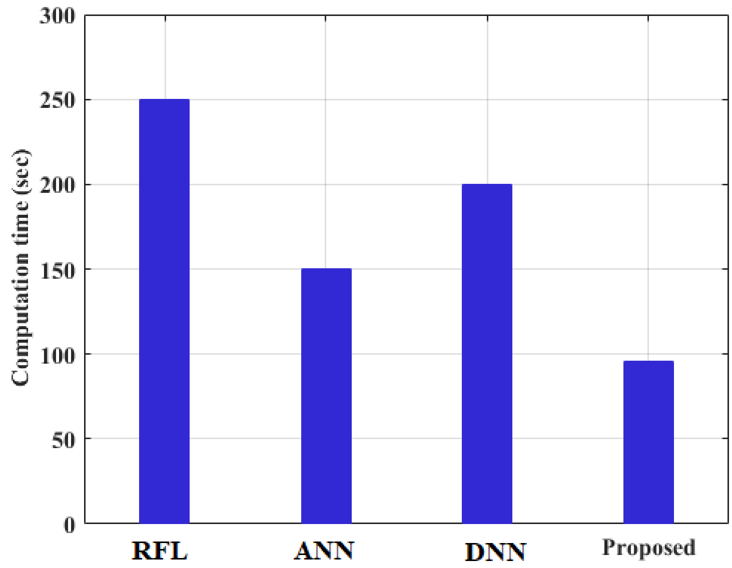

Figure 10. Analysis the performance of computation time with proposed and exiting.

Figure 10 demonstrates the computing time performance analysis of the suggested approach in comparison to current techniques such RFL, ANN, and DNN. The proposed method achieves the lowest computation time of 97 seconds, whereas RFL, ANN, and DNN record 249 seconds, 150 seconds, and 200 seconds, respectively. This significant reduction in computation time demonstrates that the proposed model is more efficient and faster in processing and prediction, making it highly suitable for real-time intelligent irrigation and effective water management applications.

Table 4. Comparison results of the AUC-ROC and MCC analysis.

Method	Throughput	Area Under the ROC Curve (AUC-ROC)
Proposed	98.6	0.93
RFL	94.2	0.89
ANN	95.4	0.90
DNN	96.1	0.91

Table 4 presents the comparison results of the AUC-ROC and Throughput analysis for the proposed model and existing methods such as RFL, ANN, and DNN. The proposed IoT-embedded smart irrigation model achieves the highest throughput of 98.6 and an AUC-ROC value of 0.93, outperforming all other meth-

ods. In comparison, RFL, ANN, and DNN record lower AUC-ROC values of 0.89, 0.90, and 0.91, respectively. The higher AUC-ROC value of the proposed method indicates its superior ability to accurately distinguish optimal irrigation decisions, while the higher throughput reflects faster and more efficient processing. These results confirm the robustness and reliability of the proposed model for intelligent water management in agricultural applications.

5.3. Discussion

The study's conclusions demonstrate how successful the suggested IoT-embedded smart watering system in improving water management and crop productivity. The system successfully integrates IoT sensing, intelligent data analysis, and automated irrigation control to optimize water utilization and reduce wastage. The performance comparison with existing models such as RFL, ANN, and DNN clearly demonstrates that the proposed method delivers superior results across all key evaluation metrics. High accuracy (99.05%), precision (99.12%), recall (99.17%), and specificity (98.4%) confirm that the model is capable of making reliable irrigation predictions and effectively identifying crop water requirements under varying soil and environmental conditions. The computation time analysis shows that the proposed system requires only 97 seconds, which is considerably lower than other techniques, indicating improved computational efficiency and faster decision-making. The consistent soil moisture and water level readings between 60% and 65% further validate the system's ability to maintain optimal soil conditions through automated control. Similarly, the observed correlation between temperature and humidity confirms the system's adaptability in maintaining favorable microclimatic conditions that support healthy crop growth. In addition, the proposed system achieves a higher throughput (98.6) and AUC-ROC value (0.93) than existing models, indicating strong discrimination ability and overall system robustness. These results collectively demonstrate that the proposed model not only enhances irrigation efficiency but also promotes sustainable water use in agriculture. By ensuring precise irrigation scheduling and adaptive environmental control, the system contributes significantly toward resource conservation, improved yield quality, and eco-friendly agricultural practices.

6. Conclusions

The proposed IoT-embedded smart irrigation system effectively enhances water management and irrigation efficiency in agriculture by integrating intelligent sensing, data processing, and automated control mechanisms. The model achieved superior performance compared to existing methods such as RFL, ANN, and DNN, attaining high accuracy (99.05%), precision (99.12%), recall (99.17%), and specificity (98.4%), with reduced computation time of 97 seconds. The consistent monitoring of soil moisture, water level, temperature, and humidity demonstrates the system's capability to maintain optimal conditions for crop growth while minimizing water wastage. The high throughput (98.6) and AUC-ROC value (0.93) further confirm the reliability, robustness, and efficiency of the proposed approach in intelligent irrigation decision-making and sustainable water utilization.

The proposed system can be widely applied in precision agriculture, smart farming, greenhouse management, and large-scale irrigation networks to ensure efficient water distribution and improved crop productivity. However, the system's performance may depend on sensor calibration, communication network stability, and variations in soil and climatic conditions. Future research can focus on integrating advanced predictive models, low-power IoT devices, and satellite or drone-based monitoring to enhance scalability and accuracy. Additionally, the incorporation of real-time weather forecasting and adaptive learning algorithms could further improve irrigation scheduling, enabling a fully automated and sustainable agricultural water management framework.

Author Contributions

All authors contributed to the study conception and design. Manuscript preparation, data collection and analysis were performed by Valuskar A, Tavare A, Pundlik M. The first draft of manuscript was written by Valuskar A, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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