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Sustainable Irrigation Requirement Prediction Using Internet of Things and Transfer Learning

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Abstract: Irrigation systems are a crucial research area because it is essential to conserve fresh water and utilize it wisely. As a part of this study, the reliability of predicting the usage of water in the present and future is investigated in order to develop an effective prediction model to communicate demand. In order to improve prediction, we develop a prediction model and share the updated model with nearby farmers. In order to forecast the irrigation requirements, the recommended model utilizes the Internet of Things (IoT), k-nearest neighbours (KNN), cloud storage, long short-term memory (LSTM), and adaptive network fuzzy inference system (ANFIS) techniques. By collecting real-time environmental data, KNN identifies the closest water requirement from the roots and its surrounding. In order to predict short-term requirements, ANFIS is used. To transfer the new requirements for better prediction, transfer learning is used. Time-series-data updates are predicted using LSTM for future forecasting, and the integrated model is shared with other farmers using cloud environments to enhance forecasting and analysis. For implementation, a period of nine to ten months of data was collected from February to December 2021, and banana tree was used to implement the planned strategy. Four farms, with measurements, were considered at varying intervals to determine the minimum and maximum irrigation needs. The requirements of farms were collected over time and compared to the predictions. Future requirements at 8, 16, 24, 32, and 48 h were also anticipated. The results indicated were compared to manual water pouring, and, thus, the entire crop used less water, making our prediction model a real-world option for irrigation. The prediction model was evaluated using R^2, MSLE and the average initial prediction value of R^2 was 0.945. After using transfer learning, the prediction of the model of Farm-2, 3 and 4 were 0.951, 0.958 and 0.967, respectively.

Keywords: sustainable irrigation system; IoT; LSTM; ANFIS; soil sensing; transfer learning

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1. Introduction

With increasing population growth and the need for food production, the agriculture sector utilizes around 70% of fresh water [1]. A huge amount of water and energy is wasted in irrigation systems. A total of 40% [2,3] of water is wasted because of evaporation, poor water management and poor irrigation systems. The water–energy–food (WEF) nexus is an interdependent approach which provides mutual integration for a sustainable ecosystem. Particularly, an effective irrigation system optimizes the usage of water and reduces the consumption of energy. WEF ecosystem nexuses provide the solution to achieve long-term environmental, economic and social goals. Effective, sustainable water utilization is achieved for irrigation systems and reduces water usage. In addition, due to global changes, lower rainfall rates, and climatic changes, a huge amount of water is also required for plants. Requirement analysis and management of water supply to plants are important to research in today's agricultural society. Based on varying environmental changes, water requirements for plants are managed using an irrigation system. Different water-optimization techniques and effective water-management systems are used to reduce water usage and achieve an effective water-requirements prediction system for plants, to increase production yields. Effective irrigation and scheduling systems are needed for society, and they increase productivity and reduce water usage.

Recent technologies are used to effectively manage sustainable irrigation systems and decision-making. Artificial intelligence plays a major role in decision-making and requirement predictions in recent technologies such as IoT. The combination of IoT, the cloud and artificial intelligence constitutes a new methodology for decision-making because interconnected technologies such as firmware and mechanical and programming techniques are used to manage irrigation systems. IoT devices are used to sense the data from their surroundings, a cloud environment is used to process the data, and artificial-intelligence techniques are used to make decisions and predict the time-series data. Importantly, recent machine-learning and deep-learning techniques play a vital role in decision-making systems. Dominant techniques for decision-making include neural networks, KNN, support vector machines, decision tree (DT), LSTM, deep neural networks, etc.

The combination of machine learning and IoT in a smart irrigation system has three layers for processing the entire application [4]: data gathering, data processing and intelligent system, and application layers.

1. Data gathering and transmission: in the first layer of an effective irrigation system, the layer collects all the information using sensors and transmits it using networking devices [5].
2. Data processing and intelligence layer: in the second layer, intelligence techniques are used for processing and decision-making.
3. Application layers: the third layer performs planning, optimization and implementations using the second layers' decision [6].

The data-processing layers are used to collect the data and perform the processing steps in the initial stages. The data-processing steps collect all the inputs from the sensors, atmosphere and other inputs. The data-processing layers apply the initial processing of surrounding information and intelligence techniques. The data-processing layer uses intelligence techniques such as machine-learning models and other statistical techniques to process the data. The application layer helps to connect to the real world. The first and second layers are interconnected to processing and decision-making.

Similarly, the second and third layers are connected to decision-making applied to the real world. The previous research [7] shows different challenges and limitations in irrigation systems. Some of the dominant limitations are as follows.

i. The irrigation system must be fully automated from the end-to-end process.
ii. The integrations of different functionalities of irrigation systems cannot be interconnected from data collection to processing.
iii. The real environment inputs (rain, soil moisture and atmosphere inputs) are not interconnected.
iv. The current- and future-requirements prediction is still one of the main research gaps in smart irrigation systems.
v. The predicted features and requirements are not shared with the neighbour farmers. .

To overcome the above challenges, the key contribution of the proposed work is as follows:

1. In this work, IoT sensors and k-nearest neighbours are used to sense and collect the requirements.
2. We also propose a system to predict the short- and long-term sustainable prediction requirements of the irrigation system using ANFIS and LSTM techniques.
3. The proposed model shares the sustainable requirements of the prediction using the cloud environment and shares the features with the nearest farmers for better requirements prediction using transfer learning.
4. The proposed model reduces and optimizes the sustainable irrigation requirements of the crops. It reduces by 42% to 50% the freshwater requirements compared to the previous traditional methods. The proposed work reduces water usage because the short- and long-term usage of irrigation requirements are calculated using the sensors, weather and history. Compared to the previous methods, the coefficient of determination (R^2) is better (0.955), and mean squared logarithmic error (MSLE) is less (0.439).
5. Compared to previous methodologies, this work is the first to introduce transfer learning to an irrigation system and forecast irrigation requirements using transfer learning to predict one farm from another. Compared to the previous method of irrigation requirements prediction [8], our method of LSTM and ANFIS with transfer learning reduces by 30.24% the water requirements in the single node of a banana tree in the implementations. Our method was tuned to consume 1.16% less water in a single banana-tree node than in ref. [8].

The rest of the manuscript is organized as follows. Section 2 presents different irrigation methods and requirement analysis methods. Section 3 presents the materials, working methodology, and optimized methods. Section 4 presents implementation results and comparison with dominant existing methods and the paper finishes with the Section 5.

2. Related Work

This section presents different existing smart irrigation models, frameworks, techniques, machine-learning and deep-learning techniques, transfer learning, and a comparison of different irrigation systems for supporting the proposed work. Different researchers have presented various works related to machine learning, deep learning, the Internet of Things, cloud computing, and highly integrated technologies for smart irrigation. Initial data processing and decision-making are performed using these technologies.

2.1. Irrigation Techniques

This section on related work presents how previous techniques are supported for centralized storage, data processing, and decisions. The authors of [9] present an IoT structure for processing, storing, and analyzing data using a decision system. An intelligence application system using an IoT system with different dimensions, such as moisture, water evaporation, and land slope, is considered for decision-making processing. The authors of [10] present two models, geography and climatology, and use different parameters for prediction, including moisture, wetness, daily and monthly soil requirements rates, evaporation of moisture and weather reports. The authors of [6] propose a CWSI framework for irrigation management using temperature distributions, and, with the help of this structure, water requirements are reduced. The requirement optimization is performed using time intervals and continuously checking the requirements of the plants. The authors of [11,12] propose an irrigation system using control-based scheduling to manage different factors such as humidity, wind speed, wind velocity, soil moisture, etc. The sensor-based prediction for managing irrigation and soil moisture sensor senses different soil conditions, and mobile applications are used to measure and monitor different activities of the irrigation system. Different recommendation systems such as statistical, machine-learning, and deep-learning models are used to manage the prediction. The authors of [13,14] present different activities-based machine- and deep-learning, regression model, GBT and DNN methods to increase the prediction rate. In this model, the accuracy of predictions is increased by 93%

using various parameters. The authors of [15] present an intelligence system which employs thermal images to analyze the various requirements of an irrigation system. Various parameters are measured using thermal images, and leaf potential is calculated. The main drawback of this work is that soil-moisture measurement is difficult to analyze.

The authors of [16] propose machine-learning and IoT techniques to manage smart irrigation with the help of different parameters, such as various soil conditions, environmental parameters, temperature and nearest features, which are considered for requirement calculation. The authors of [8] propose a system for optimizing the water requirement of crops using the WSN and different node sensors. Control devices are used to manage the crop using mobile and web applications. With the help of mobile and web applications, soil moisture and future requirements are calculated. The IoT with multiple sensors is used for water management [17,18] using different parameters such as soil properties, moisture, temperature, and rain sensors. In this work, the output is predicted and operated automatically and manually. The authors of [19,20] propose different monitoring and control systems for irrigation systems. Different energy models and IoT platforms are used to analyze parameters and use a decision pumping schedule. The authors of [21] propose a LoRa network structure with an energy-efficient model to cover up to 5 km with smart control. All the information is transferred to different places using the LoRa structure.

The various machine- and deep-learning approaches analyze the requirements, moisture analysis, and future recommendations of irrigation systems. The authors of [4] propose a model, with the help of genetic techniques, to increase yields and analyze various recommendations. The genetic model [22] provides the solution using sequential inputs and non-continuous scheduling. The authors of [9] propose a system using metrological data and created a weekly irrigation-requirement plan using regression and classifier techniques. This system achieves 95% and 93% accuracy using classification and regression techniques. The authors of [23] propose a location-based optimized irrigation system using a genetic algorithm with the help of previous data. The location-based water-requirement analysis for irrigation systems using the KNN algorithm with an intelligent IoT sensor is used to plan irrigation systems [5]. In addition, this work is fully automated with machine-to-machine data transmission for effective decision-making. The heterogeneous data management in irrigation systems uses machine learning and IoT, and this work predicts the requirement for irrigation using the related data. The time-to-time irrigation requirements are also calculated using logical regression analysis. The authors of [11,12,24] calculate humidity and temperature using a decision tree. The future requirements for the prediction of irrigation systems are calculated using the SVM algorithm, but the requirements for prediction accuracy are very low. The summary of the different IoT frameworks, models, and machine-learning algorithms is presented in Table 1. The authors of [25] presente a comparative study for precision agriculture using deep learning and IoT. In this work, authors have gathered and analysed disease, weeds, and soil yields using deep learning techniques. And also, the authors analysed different components of agriculture, such as sensors, UAVs, data acquisition, annotations and datasets used for predictions. Finally, pest detection is performed using VGG16 and transfer learning, which achieves 96.58% accuracy in prediction. The authors of [26] presented the state of the art for managing water using IoT devices. Using the connecting devices, the authors address water-planning and water-distribution issues. This case study is planned with the help of IoT-enabled devices. The author of [27] propose a smart and green irrigation system using gradients and regression trees, which are used for the implementation part. The authors of [28,29] use different parameters such as temperature, humidity and weather data, which are used for the prediction of irrigation requirement. The SVR and K-means are used for soil-moisture prediction.

The different limitations are summarized using the above-related works. Most of the work did not address the requirements of roots, and the nearest features were not considered for the irrigation-system requirement analysis. The recent works do not consider all parameters, such as wind, moisture, and temperature, for requirement prediction. The previous systems need to be integrated with the full automation system. In this work, we planned the different irrigation parameters to predict and analyze the requirement of the irrigation system based on the crop requirements.

Table 1. Summary of advantages and limitations of supporting works.

Previous Models	Advantages	Limitations
IoT framework [5,8,9,16,23]	The site-specific variable-rate sprinkler irrigation [9] (SS-VRT) used crop and soil conditions for irrigation, KMO [23] is used to analyse the factors of irrigations, SWAMP [5] architecture provides better scalability, Federated learning [16] is used for irrigation without sharing the data, using machine learning.	SS-VRT does not support long-term application, KMO is not considered as a real factor affecting the irrigation, SWAMP is not considered as one of the the multiple features for irrigation and the Federated learning [8].
Irrigation models [6,10,11,24,30]	A sprinkler–solid, centre pivot, travelling irrigator, and micro-spray are used for spatial-based irrigation. Automatic sensors and evaporation-based models are used to predict the requirements.	The spatial-based irrigation model is only supported at particular locations. Central data storage, irrigation scheduling, and root moisture are not considered for processing an effective system.
Recommendation system for irrigation [13]	Irrigation performed based on climate change, water availability, and a policy of productivity.	Considers area-wise irrigation and not irrigation technology, makes way for better decision-making.
Optimization and machine-learning algorithms [4,5,9,11,12,22–24]	Genetic algorithm, KNN, logical regression, SVM and decision-tree algorithms are considered for irrigation requirement predictions.	Effective sensor data and data on weather should be combined for effective predictions.

2.2. *Transfer Learning for Agriculture and Irrigation System*

Transfer learning is a knowledge-storing problem which applies similar and related tasks for prediction and classification problems. The transfer of learning is used in different applications, classification problems, knowledge transfer, agriculture, etc. In agriculture [31], it is used in plant disease prediction, species detection, plant-domain-knowledge transfer and plant classification and information sharing. Recently, different researchers have addressed different problems related to transfer learning in agriculture. The authors of [32,33] proposed a knowledge-transfer model to classify different crops and reduce the retraining and labelling time. In this work, authors reduced 20% of the time compared to the normal time.

Similarly, the authors of [34] use transfer learning for weed identification among different plants and achieved an accuracy of 99.29%. Similarly, the authors of [35] propose deep transfer learning for trash classification. In this framework, the authors achieved 94% and 98% accuracy using different datasets. The authors of [36] propose a model for identifying bale detection using deep transfer learning and a domain-adaptation approach, which transfers the source images to target domain images. The authors of [37] propose a CNN and transfer-learning model for identifying crop-attacking pests in the early stages of crop growth. Transfer learning is used to create fine-tuned pre-trained models. The authors of [38] propose a transfer learning for transferring a base model, characterized using different samples/features, from one place to another. In this framework, the transfer of features is performed in two places in the context of the irrigation mapping of time-series features in two locations. The authors of [39] propose transfer learning with IoT to train the model better using soil moisture and transfer the soil conditions from one soil to another, with the two soils having different distributions.

The previous works [31–37] on transfer learning are used in classification based on features, which are transferred within the framework and between the models. The authors of [38,39] proposed models for transferring the features from one spatial location to another spatial location using IoT technologies. In addition, the author of [39] transfers the soil features from one place to another using models.

3. Materials and Method

This section presents the materials and methods for the proposed work. The proposed work uses live data and historical datasets to predict the requirement for the present and future irrigation systems. Live weather data is used to correlate current and future requirements. IoT devices are interconnected for present-requirement collecting, and different components are used for future-requirement collections. The proposed method uses k-nearest neighbours, cloud storage, LSTM, and ANFIS to predict an irrigation system. The IoT devices must collect the data from the environments, for which KNN find the nearest water requirements from the root and surroundings, and ANFIS predicts short-term conditions. The LSTM is used to predict time-series-data updates for future prediction, and the transfer learning is used to transfer the learning features information from one cultivation field to another.

3.1. Materials

In the proposed method, materials are collected in three ways: IoT sensors, past data collected from previous years, and live data collected from the weather data. The IoT sensors and components to collect soil moisture, air moisture, temperature and soil moisture are presented in Table 2. The sensor and IoT devices are also used to transfer the data from one machine to another and to the cloud environment.

Table 2. Components and their usages.

S. No	Components	Usages
1	HPT675	Used to measure water level.
2	FC-28	Used to sense soil moisture.
3	HTM2500LF	Used to measure the humidity and water vapour.
4	THERM200	Used to sense soil temperature.
5	SHT11	Used to measure root moisture.
6	WSN	Used to surveil and manage the transmission of data and monitoring.
7	Digital inclinometer	Measures the gradient and slope of the land
8	M2M (ZigBee)	Personal communication network

The live-data collection location and the latitude and longitude of the experimental location is 8.2473502, 77.2743729, 345. The data was collected from Kanyakumari, Tamil Nādu, India. This location has seasonal rainfall, and basic requirements were collected using IoT devices. Three basic components, such as IoT devices, gateway and cloud, were interconnected to communicate and transfer data from the physical location to the cloud. Four different fields were used for collaboration and decision-making in the mentioned location.

The basic requirements for prediction were measured using various sensors. Figure 1 shows the different requirements predictions presented in 3 h time intervals. Similarly, the basic requirements were also measured between 5 h, 8 h and 10 h. The cultivation requirement of the Plantain Banana or Red Dacca (Australia) from the beginning to the end is represented in Table 3. The entire cultivation of the species started in February and ended in October. Table 3 [40,41] summarises the basic water requirement from the beginning of February till the end of the cultivation in October. This basic requirement is plotted manually with the help of farmers, and four farmers were involved in the cultivation.

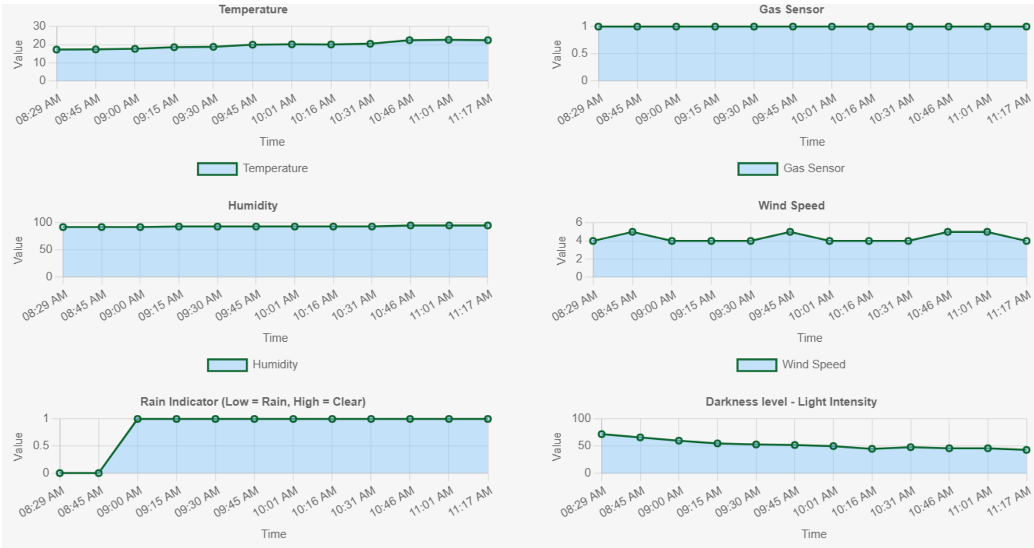

Figure 1. Collections of atmosphere requirements.

Table 3. Monthly water requirement for banana cultivation.

S. No	Month	Water Req Lit/Interval/Plant
1	February	3–4
2	March	4–5
3	April	5–6
4	May	6–8
5	June	10–12
6	July	8–10
7	August	6–8
8	September	10–12
9	October	12–14
10	November	16–18

3.2. Method

This proposed work used IoT devices, k-nearest neighbours, cloud storage, LSTM, and ANFIS to predict an irrigation system. The IoT devices must collect the data from the environments, for which KNN find the nearest water requirements from the root and surroundings, and ANFIS predicts short-term conditions. The LSTM is used to predict time-series-data updates for future prediction, and the Spearman rank correlation method correlates the needs in different intervals. The proposed work's basic goal is to predict current and future requirements for different time intervals, such as 3 h, 8 h, 12 h and 24 h and 48 h.

The basic structure of the proposed work is presented in Figure 2. The proposed structure of the prediction model consists of three main parts: initial-value predictions, integrated prediction model and transfer learning. The initial-requirements prediction is performed using the group of sensors. The group of sensors sensed soil-moisture, root-moisture, and weather data. In the integrated model, KNN, ANFIS and LSTM algorithms were used for sensing nearest values and short-term and long-term predictions. The prediction values and features were shared using transfer learning.

3.2.1. KNN Algorithm

KNN is a supervised algorithm to find the nearest values predicted using sensors with many assumptions [42,43]. The dataset inputs considered the real values, taking the values from the certain k nearest distance from the input dataset. The prediction output is the average distance between the input taken and the given sensed input using the average voting of the nearest prediction. The trained data of multiple inputs consist of multiple features, and different classes are labelled using a supervised KNN algorithm. The nearby sensed values depend on the discrete or continuous distance. The different features' relationship or distance between the features is predicted using Euclidean distance. The discrete values, such as soil moisture, atmospheric moisture and weather data, are evaluated using the Euclidean distance. The recommendation of the features is also evaluated and considered as the input value for the integrated prediction model. The Euclidean distance vector evaluated the different region-wise and root-moisture values considered as the input.

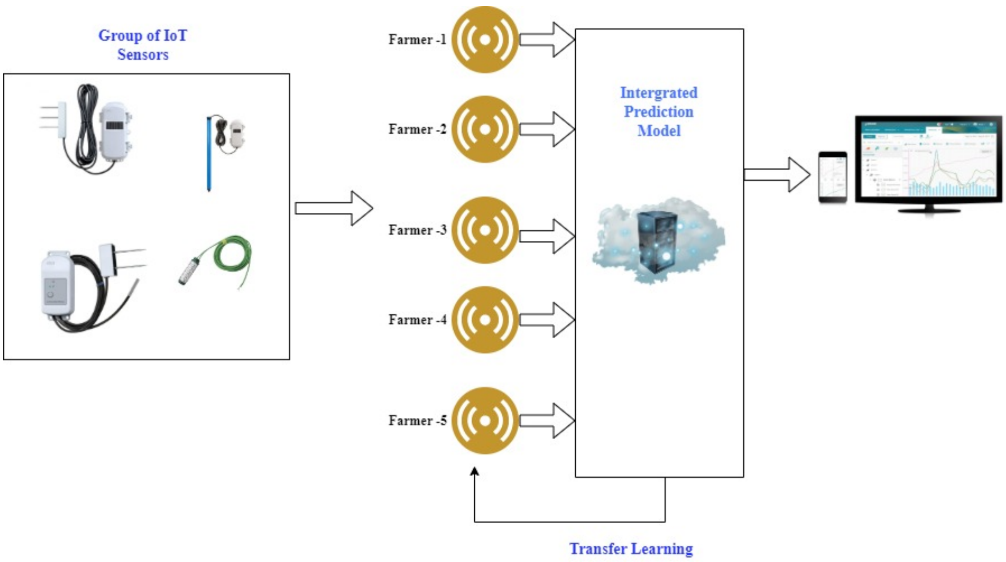

Figure 2. Structure of the proposed work.

3.2.2. ANFIS

The ANFIS is an artificial neural network with a combination of neural-network and fuzzy-logic properties. The inference system is a set of if-then rules with non-linear functions [44,45]. The ANFIS was constructed using five layers: an antecedent layer, three hidden layers, and a consequent layer. The antecedent layer is an input layer, and the consequent is an output layer. The three hidden layers are based on rule-based and fuzzy logic applied to these three layers. The first input layer between 0 and 1 is called the "premise parameter". The second layer estimates the income for each neuron using the product operator. The third layer normalizes the input signal, and the fourth layer is fuzzification. The fifth layer is a summarized weighted output layer. The ANFIS is an optimal and intelligent way to manage the energy system [46] .

3.2.3. Long Short-Term Memory

LSTM is a recurrent neural network which predicts and classifies data requirements using time-series data. It consists of input, output and forget gates. The different gates control the flow of information and help exit and enter the gates. The LSTM predicts future time-series data in short- and long-term predictions [47,48].

3.2.4. Transfer Learning

Transfer learning is used to train the system to perform the relevant similar learning of the existing model. The main part of the learning is generalized, and the different scenarios or relevant conditions are transferred from one model to another. The main advantages of transfer learning are saving resources, timing to complete similar learning, increasing the learning model's efficiency, and avoiding the negative prediction from the pre-trained model [38,49].

3.3. Working Principle

This proposed work predicts various requirements of irrigation using IoT sensors and weather inputs and helps in finding short- and long-term predictions. The flow of the representation of the proposed work is presented in Figure 3. The working process of the proposed work consists of four main parts: data collection from various sources, nearest requirement prediction, short-term prediction (ANFIS), long time-series prediction (LSTM) and predicted knowledge sharing to nearest farms (transfer learning). The working process of the proposed work uses four steps: processing the inputs and storage, short-term prediction, long-term prediction and transfer learning and sharing features from one data source to another data source. Initially, the data is collected from the sensors, with the help of KNN algorithms for predictions. With the collected data, weather forecasts and previous data are used as the input. The processed data is applied for short-term prediction using the ANFIS. The short-term prediction of irrigation recommends water pumping. For long-term prediction, the LSTM technique is used, and, if required, it recommends water pumping. This prediction is performed on a single farm for short- and long-term prediction. Once the farming location requirement is predicted, the features are transferred to another farm for better predictions. The second farm processes the new input data from a particular location and processes the farm 1 features for better performance.

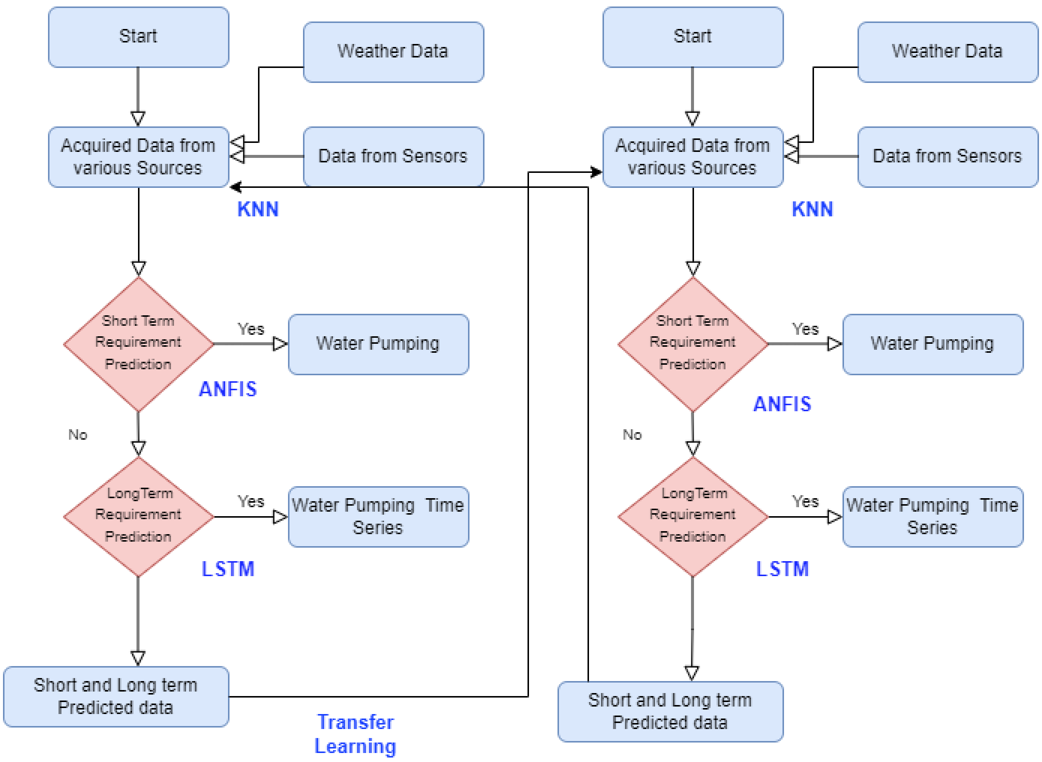

Figure 3. Workflow representation of proposed work.

The entire working procedure is described in Algorithm 1. The processing steps of the algorithms consist of data processing, and prediction and sharing of knowledge gained from other farmers, as well. Initially, the sensor data from farm 1 and weather data are transferred to the cloud storage. The history data and collected data are initially processed for the prediction of requirements. The processed data predicts the short-term (Sp) and long-term (Lp) requirements using ANFIS and LSTM techniques. Using these techniques and collected data, initial requirements are predicted in the long term and short term. The first farm (X1) gains the knowledge, and so the stored model weight is shared with the nearest second farm for better prediction. A detailed description of the working process is as follows.

Algorithm 1 Requirement Prediction and Features Transfer

Input:
Xm: Data Collection Using Sensors (Moisture);
Xw: Weather details ;
TT: Temperature ;
$X1$, $X2$, $X3$, and $X4$: Farms Prediction Details;
Output:
Short- and Long-term Prediction Details (Sp, Lp);
Generating algorithm Begin:
Moisture (Xm), Weather details (Xw), Temperature (TT) > 0
$X1$, $X2$, $X3$, and $X4$ > 0
Calculate (Xm), (Xw), (TT);
{
if $Xm, Xw, TT > 0$
Predict of Each Farm Requirements Details
N = C (Prediction of Nearest features with respect to weights and time)
D = Prediction of distance features between two terminals
Sp = Tp -AP // Short- term prediction
Lp = Tp -AP // Long- term prediction
}
End of Each Farm Prediction
Share the month-wise history data
$Y = X1$ (End prediction of single Farm)
Share $X1$ to $X2$
T = [Y, f(.)] //Start Transfer Learning
if $X1 > X2/X2 > X1$
State Share the Y values
if Xw = Rainy
Stop // Stop sharing, Sensors in Sleep Mode
end

Initially, the input collected from various input sources is real data, with the help of IoT devices, past data and weather information from the nearest weather stations. In this work, four farms for banana cultivation were considered. Each farm is considered as $X1$, $X2$, $X3$, and Xn. The output of four farms with the input process model is represented in Equation (1).

$$Y = X1, X2, \ldots\ldots Xn \tag{1}$$

Each farm used three input sources: past cultivation data ($x1$); weather data ($x2$); and current data, collected with the help of IoT and sensors ($x3$). The combination of inputs and output is represented in Equation (2).

$$Y = X1(x1, x2, x3), X2(x1, x2, x3), X3(x1, x2, x3), and\ X4(x1, x2, x3) \tag{2}$$

The $x3$ combines the nearest features, short-term requirement predictions, long-time predictions and knowledge transfer from one farm to another. Initially, the nearest features are predicted using the KNN algorithms. The nearest features are calculated based on the distance between the roots from the initial prediction to the next nearest prediction. The distance is calculated using the Euclidian distance. The mathematical representation of nearest features calculation and distance measurement between the features are represented in Equations (3) and (4).

$$N = C_n^w(x1, x2, \ldots\ldots x3) \tag{3}$$

N denotes the predicted nearest values, C denotes features, n denotes different features, w denotes weight, and $x1, xn$ denotes different input features. The distance between the initial root prediction features and the next feature distance is as follows.

$$D = \sqrt{(x_2 - x_1{}^2) - (y_2 - y_1{}^2)} \tag{4}$$

D denotes distance features. The moisture is measured based on the starting and ending points of the roots. Based on the nearest features, past data and weather information, short-term inferences are calculated using ANFIS. The inference model and short-term learning prediction are represented in Equations (5) and (6).

$$S_p = \sum_{i=0}^{n} (T_p - A_p)^2 \tag{5}$$

S_p denotes short-term prediction, T_p denotes the targeted prediction, and A_p denotes actual prediction. Similarly, the learning rate of ANFIS representation is as follows.

$$\sigma = \frac{k}{\sqrt{\frac{\delta E}{\delta \sigma}}} \tag{6}$$

σ denotes the learning rate, k denotes the learning size, δE denotes the error rates and $\delta\sigma$ denotes the training data. Based on Equations (5) and (6), the short-term inference result is calculated. If the short-term inference result is not required, long-term prediction is performed using the LSTM algorithm. The LSTM algorithm predicts long-term series data [27,28] with the help of three types of inputs, as mentioned earlier. The LSTM algorithm consists of three gates: forget gate; remember cell; activation sigmoid function and new states of prediction, represented as 7 to 10.

$$f_t = \sigma_q(w_f x_t + u_f h_t - 1 + b_f) \tag{7}$$

f_t—activation function, $h_t - 1$ denotes previous unit output $t - 1$, x_t denotes input data, b_f denote bias. Sigmoid function, denoted as $S(t)$, is represented as follows.

$$S(t) = \frac{1}{1 + e^t} \tag{8}$$

The remember cell and new state function are as follows.

$$i_t = \sigma(w_t(h_t - 1) + b_t) \tag{9}$$

$$S(n) = f_t * S_t - 1 + t_t \tag{10}$$

With the help of KNN, ANFIS and LSTM, prediction is performed using the short-term and long-term prediction of the requirements. The requirements of $X1$, $X2$, $X3$, and $X4$ are shared using the knowledge transfer. The knowledge transfer is represented in Equation (11) [50]. The initial learning is performed from the $X1$ ($x1$, $x2$, $x3$) and predicted values or known values are considered as Y. The transferring learning is denoted as

$$T = [Y, f(.)] \tag{11}$$

T denotes the learning task transferred to the next node or prediction task, Y denotes the prediction output, and $f(.)$ denotes the prediction function with the different instances. This predicted task is transferred to the other farm using different thresholds or different conditions.

4. Result and Discussion

For experimental and implementation requirements, the specification is described in Tables 2 and 3. Data was collected from India's metrological deportment and banana cultivation research centre. Initially, the requirements, such as X1, were collected from the IoT sensors. Using the sensor, surrounding moisture, root moisture and humidity values were also collected. In addition, minimum and maximum water requirements were collected manually from the farmers. The maximum 50 L of water requirements for a month and intervals of irrigation of 5 to 7 days were collected for fixing the threshold values for training and testing. Some of the fixed and basic parameters considered for irrigation are shown in Table 4.

Table 4. Basic parameters for irrgation.

S. No	Parameters and Requirements	Values
1	Number of farms	4
2	Number of trees in each farm	300
3	Maximum requirement of water per month	50 L
4	Irrigation interval	Feb to November
5	Minimum temperature	0 °C
6	Maximum temperature	37 °C
7	Interval of irrigation	7 Days
8	Average requirement of water per month	36 L

In our work, cloud computing is used for data storage and sharing of data. Using cloud computing, we deployed models and real predictions are shared with farmers for betterment. With the help of artificial intelligence as a service (AIaaS), the model was deployed and executed for better predictions. The predicted results were transferred for decision-making using IoT devices. For the implementation process of cloud computing in our work, we employed data collection using sensors; Raspberry Pi (ThingSpeak), which transfers the data from the physical devices to cloud environments; and AIaaS to predict data which has to be transferred to controlling devices and farmers.

The dataset consists of Year, Month, Date, Hour, minute, moisture0 (Atmosphere), moisture1 (Plant Surface Moisture), Soil Moisture (Sensor 1), Root Moisture (Sensor 2), Temperature, Humidity, Wind Speed (mph), Rain, and irrigation. The dataset should be pre-processed using the one-hour time interval and the data should be mapped within one hour. All the data fields converted the data a pure value and dimensionless value. Finally, different magnitudes or units, comparisons of indexes and weighing, were considered in the pre-processing of the dataset. In this research work, a zero-mean standardization pre-processing method was used for processing the raw-data fields. The missing values happened due to maintenance, failure of instrumentation, invalid values and manual check-in. Our work uses the Akima [51] method for supplementary values, for time-series data and filling in the missing values for smooth curves. In our work, we validated the proposed method using accuracy, coefficient of determination (R^2), mean squared logarithmic error (MSLE) and earned values (EV).

Initially, the basic requirement of prediction training, testing and validation accuracy was predicted using the combination of ANFIS and LSTM. Figure 4 represents the training and testing accuracy of 97 iterations and 100 nodes' data. The implementation hyperparameters are presented in Tables 5 and 6.

Table 5. Hyperparameters of LSTM.

S. No	Hyperparameters of LSTM	Values
1	Number of layers	2 Layers
2	Units	96 (64 + 32)
3	Feature points	10
4	Activation function	Sigmoid
5	Time steps	20
6	Loss function	Binary cross entropy
7	Total parameters	34,242

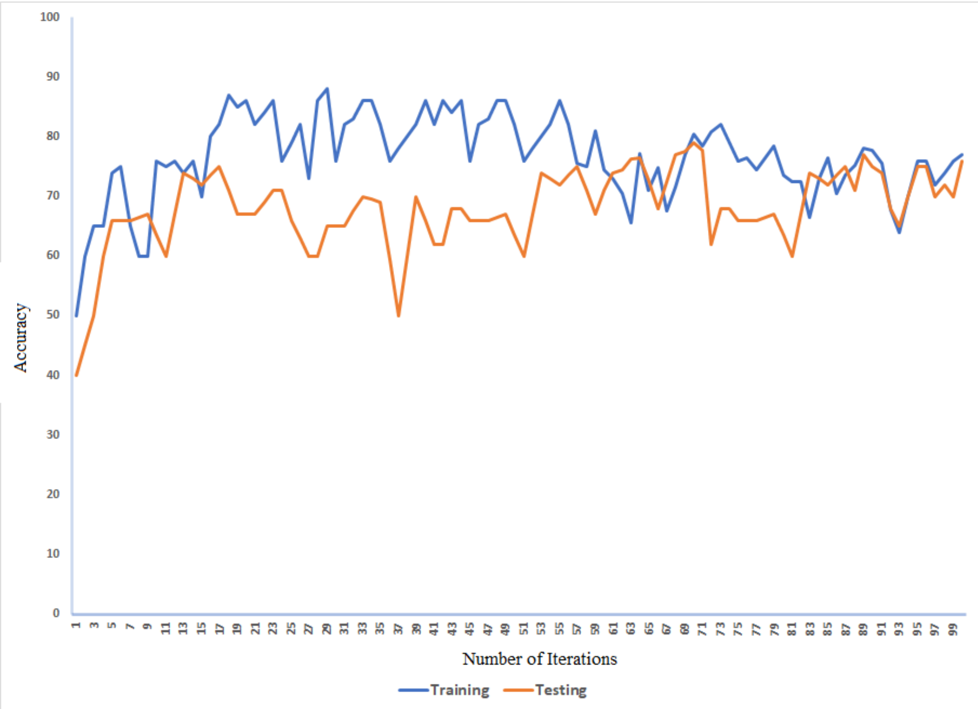

Figure 4. Training and testing accuracy of prediction.

Table 6. Hyperparameters of ANFIS.

S. No	Hyperparameters of ANFIS	Values
1	Hidden layer size	2 Layers
2	Input layer size	10
3	Activation function	Sigmoid
4	Time steps	20
5	Range of influence	0.7
6	Acceptance ratio	0.5
7	Number of maximum iterations	100

Figure 1 shows various live indicators, such as temperature, humidity, rain possibility, and wind speed, taken from three calculations. The past cultivation data ($x1$), weather data ($x2$), and current data collected with the help of IoT and sensors ($x3$) and root moisture were also calculated continuously with the help of THERM200 and SHT11. In this work, irrigation requirement is predicted in terms of 8 h, 16 h, 24 h, 48 h and 60 h. Two main requirements directly affect the requirements: temperature and humidity.

In this work, three types of requirements are predicted: short-term (8 h, 16 h), long-term (24 h, 48 h and 60 h) and changes implemented after transferring learning from one farm to another. The shortest inference result is predicted with the help of ANFIS, and long-term prediction is carried out with the help of LSTM. The shortest term prediction analysis was carried out in two months, March and July. The reason for the prediction of March and July is that rainfall is low during March. Similarly, in July, the rainfall starts, and, thus, the atmospheric temperature is low. The moisture and humidity of the current and the short-term requirement prediction of March and July's requirement prediction, using ANFIS, are presented in Table 7. The shortest term prediction requirements are shown in Figure 5. The month-wise temperature and humidity are the two main requirements of short- and long-term predictions, such as temperature and humidity for 8, 16, 24, 32, and 48 h. The figure describes the minimum and maximum temperature and humidity, starting from 8 am and continuously measuring up to 48 h. Transfer learning is used for knowledge gained in the initial model in farm 1 and the knowledge gained by farmer 1 is used to retrain the farmer-2 models for better prediction using the changes from the farmer-1 data.

Table 7. Short-term prediction of requirements.

Months	Min and Max/Time Interval	8	16	24	32	48
March	Min (Litres)	8	3	1	2	3
July	Min (Litres)	0	1	1	3	1
March	Max (Litres)	3	4	2	3	4
July	Max (Litres)	1	2	2	1	2

Based on the minimum and maximum temperature and humidity, the requirements of irrigation for March and April are summarized in Table 7. Compared with Table 3, the maximum requirement per day in March is 6 to 7 L, and in the requirement, prediction is also according to the maximum requirement per day, which is about 6 to 7 days. Similarly, July received 2 to 3 L per day based on the ANFIS prediction. Similarly, the long-term prediction was performed with the help of the LSTM algorithm, and prediction intervals are 24, 48, 72, etc. Using the long-term prediction, irrigation is performed because generally banana-irrigation intervals are between 3 days to 5 days. Based on the long-term prediction, irrigation was scheduled. The long-term prediction of farm-1 is presented in Table 8.

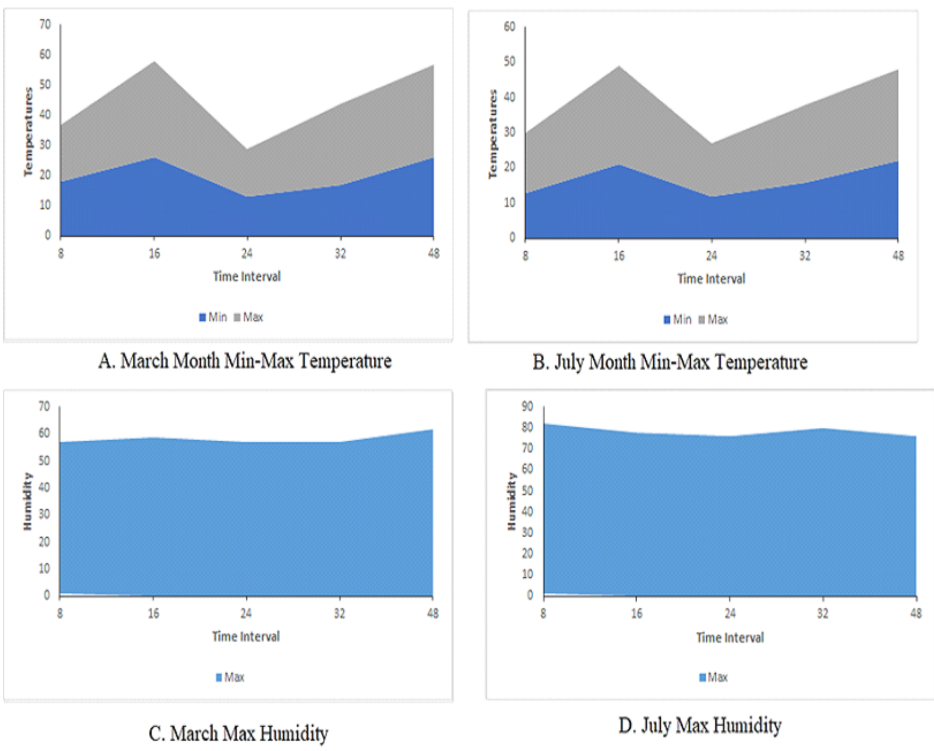

Figure 5. Minimum and maximum temperature and humidity in March and July.

Table 8. Long-term prediction of requirement.

Months	Min and Max/Time Interval	24	48	72	96
March	Min (Litres)	2	3	1	2
July	Min (Litres)	0	1	1	0
March	Max (Litres)	3	4	2	3
July	Max (Litres)	1	2	2	1

Based on Tables 7 and 8, the entire prediction requirements of irrigation in March and April are in Table 9. This prediction requirement is calculated between four-day intervals. Four-day intervals correlate the short-term and long-term prediction. Table 9 and Figure 6 present the minimum and maximum requirements of irrigation.

Table 9. March and July irrigation dates and requirement.

Months	March/July Dates Interval	4/2	8/6	12/10	16/15	20/18/	24/22	28/26	Total Requirements
March	Min (Litres)	2	4	5	4	4	5	4	28
March	Max (Litres)	3	5	6	5	5	5	5	34
July	Min (Litres)	0	1	1	0	1	2	2	7
July	Max (Litres)	1	2	2	1	3	3	3	16

Tables 7–9 are the short, long and month-wise requirement prediction of farm 1's prediction. In this prediction, ANFIS and LSTM are used. In addition, based on these two techniques, the month-wise prediction is presented in Table 9. Table 9 presents the minimum and maximum irrigation requirements in four-day time intervals. The four-day time interval is measured with the help of ANFIS and LSTM and the corresponding correlation of long- and short-term prediction. In March, the humidity, temperature and other parameters such as weather, wind speed and previous-year information are considered for prediction. Generally, the parameters mentioned earlier are very high in March, and wind speed is also very low compared to the other months in the specified location. The maximum irrigation requirement was higher that year, and the minimum requirement is similar to the maximum requirements. The difference between the minimum and maximum requirements is 8 L. Similarly, July is monsoon season, and if it rains in the specified location, the requirements for irrigation decrease automatically. The requirements mostly decrease in July, as the humidity is very low.

Our proposed work was used different combinations of data, such as root moisture, atmosphere moisture, temperature, humidity, and weather data. While taking all these data, normal model prediction produces prediction error. To avoid the prediction error, our model used the ANFIS method and error rates for short-term predictions. The ANFIS used forward and backward passes in each layer for processing different data.

The minimum irrigation requirement is nine, and the maximum is 16. Similarly, requirements are very low in the next three months, but during the summer, the irrigation requirements are very high in April, May and the middle of July. The entire year-wise irrigation requirements of farm 1 are presented in Figure 6. In this Figure 6, minimum and maximum requirements are summarized for farm 1. The maximum requirements are higher in March, April and May.

Similarly, with the help of transfer learning, from farm 1 prediction is transferred to farm 2. Based on farm 1, the basic information is shared with farm 2. The basic irrigation requirements in March and April are shown in Table 10, and year-wise predicted results are presented in Figure 6. Transfer learning helps to reuse the model for new task prediction. Table 10 and Figure 7 show the differences after applying the first prediction and after transferring the prediction features of farm 1 and the new prediction of farm 2. Figure 7 shows the difference between applying transfer learning and reducing the consumption of water usage. Comparing Tables 9 and 10, the requirement prediction is reduced because it produced better optimization and saved the irrigation requirements of two months. Overall requirements are also reduced in farm 2.

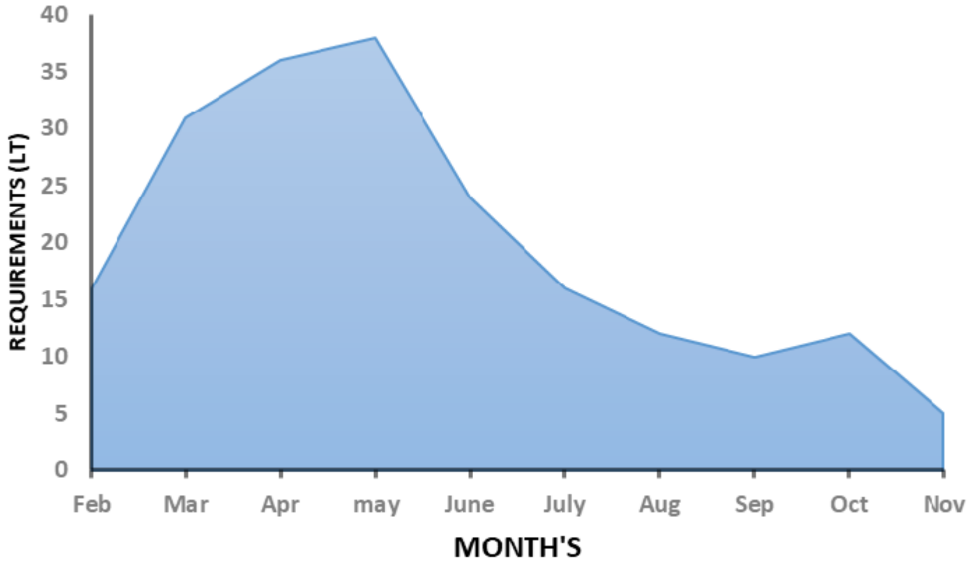

Figure 6. Month-wise requirement prediction of irrigation—Farm 1.

Table 10. March and July irrigation dates and requirements (farm 2) using transfer learning.

Months	March/July Dates Interval	4/2	8/6	12/10	16/15	20/18/	24/22	28/26	Total Requirements
March	Min (Litres)	2	3	3	4	4	3	4	23
March	Max (Litres)	3	4	4	5	5	5	5	31
July	Min (Litres)	0	1	1	0	2	3	2	9
July	Max (Litres)	1	2	2	1	3	4	3	16

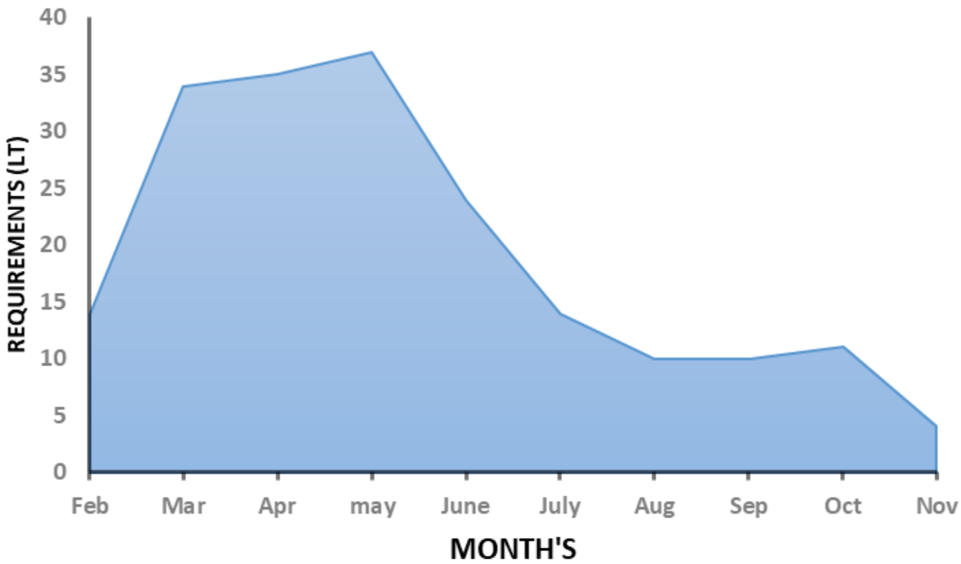

Figure 7. Month-wise requirement prediction of irrigation—farm 2.

Comparing farm 1 to farm 2, the irrigation requirements are reduced to 7 L per banana plant. Farm 1's total requirement was 200 L per plant, and after applying the transfer learning, the total requirement of irrigation was 193. After applying transfer learning, the 7 L irrigation requirement was reduced in farm 2. In the overall irrigation process, everyday prediction was transferred from farm 1 to farm 2 at a delay of 5 min time intervals, and, after that, farm 2's irrigation requirement was predicted.

The proposed work was evaluated using the coefficient of determination (R^2). The R^2 determines the model prediction measurements when increasing the iterations. Initially, the model was predicted to be 0.920 at 15 epochs and 0.958 at the 75th epochs. After applying the transfer learning, the farm-2, farm-3 and farm-4 values gradually increase. Figure 8 shows that the model prediction and relationship accuracy values increase after transferring the features.

	Farm-1			Farm-2			Farm-3			Farm-4		
Epochs	R2	MSLE	EV	R2	MSLE	EV	R2	MSLE	EV	R2	MSLE	EV
15	0.92	0.52	0.92	0.93	0.51	0.93	0.94	0.56	0.94	0.95	0.49	0.95
30	0.945	0.48	0.945	0.947	0.48	0.947	0.954	0.47	0.954	0.954	0.45	0.954
45	0.946	0.46	0.946	0.956	0.4	0.956	0.964	0.46	0.964	0.974	0.46	0.974
60	0.95	0.42	0.95	0.96	0.4	0.96	0.967	0.44	0.967	0.977	0.34	0.977
75	0.958	0.38	0.958	0.962	0.38	0.962	0.968	0.35	0.968	0.981	0.33	0.981

Figure 8. Comparison of R^2, MSLE and EV.

Comparison with Other Methods of Estimation and Transfer of Learning

The proposed method was compared to the existing approach, which decreased the water consumption of a single node by 31.4% in the period of 2020. When compared to the previous approach, our method optimized 30.24% of water after applying transfer learning on a single node of the banana tree. Our method was tuned to consume 1.16% less water in a single node of a banana tree. Comparing our suggested method to the manual and technology-based approaches, we find that it optimized 41% to 50% more water in the farm. Using transfer learning, the proposed method reduced from 31.4% to 30.24% the water of a single node tree. Tables 9 and 10 clearly illustrate the optimization of water usage following the implementation of transfer learning. Our proposed work was compared with the recent work [8,27–29], and it optimized the irrigation requirements. Compared to previous work, total water usage is reduced. Table 11 shows the water usage of our work and its comparison with previous work. Compared to the previous work, total irrigation requirements were reduced.

Table 11. Comparison of requirement predictions.

S.No	Methods	Accuracy
1	GBRT [27]	87.23
2	SVR + K means [28]	88.13
3	LSTM + GBT [8]	92.04
4	RBFN [29]	89.0
5	Our Method	94.0

5. Conclusions

This work integrates IoT, machine-learning and transfer-learning techniques to achieve sustainability and predict irrigation-system water requirements. The main finding of this work is that it reduced water usage and transferred the features of the prediction model and exchange for better prediction and requirement analysis. IoT sensor devices collected basic requirements such as humidity, temperature, and moisture. The weather data and past data collected from the banana research centre were used for implementation. The proposed work used ANFIS for short-term predictions, such as 8, 16, 24, etc. The LSTM predicted long-time requirement predictions such as 24, 48, 72, etc. Based on short- and long-term predictions, the entire requirement was predicted in 4 days. In this work, data of two months, March and July, was predicted and analyzed. The entire requirement of overall cultivation was predicted and calculated in the short and long term, with the help of weather and past data. The farm-1 data features were transferred to farm two, and, thus, it predicted the irrigation requirement. Comparing farms 1 and 2, after irrigation, farm 2 had lower irrigation requirements in July, a change from 16 to 15; during May, the requirement increased from 31 to 34. Similarly, comparing the year-wise requirement of farm 1 to farm 2, we see that it reduces the requirements from 200 to 193 for a single banana tree. This work reduces the irrigation requirement and predicts the short- and long-term requirements of an effective irrigation structure at a particular interval. In the future, this approach will be extended to multiple farms. Based on that, the requirements can be optimized. In addition, further implementation of this work is being carried out using Federated learning, sharing the farm data, which predicts and shares the model for further irrigation.

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