



ORIGINAL ARTICLE

TRANSFER LEARNING-ENABLED SMART IRRIGATION SYSTEM FOR OPTIMIZED WATER MANAGEMENT IN IOT-DRIVEN AGRICULTURAL NETWORK

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Abstract

Internet of Things (IoT) -driven sensor networks, smart irrigation systems have drawn a lot of interest lately as a way to improve managing water in agriculture. The ineffective control mechanisms accompanying conventional irrigation technologies frequently result in water waste. Promising solutions to this problem include integrating cutting-edge artificial intelligence technologies like transfer learning. By utilizing pre-trained information from related domains, transferable learning enables the model to greatly improve performance and shorten its training period when deployed to new contexts. In this paper, we demonstrate a transferable training-enabled intelligent watering system that tracks the condition of crops, the environment, and moisture in the soil using IoT sensors. The framework may be used in various farming setups since it can adjust to changing circumstances in the environment. We aim to maximize crop health and minimize water waste by offering real-time irrigation suggestions derived from sensor data analysis. The results show that productivity in agriculture and water usage effectiveness have improved, and the system outperforms conventional techniques in terms of accuracy and flexibility.

Keywords: *automation irrigation system, internet of things, machine learning, transfer learning*

1. Introduction

Agriculture is vital to the economy of the country since it is the source of food to all. It is related to one of the most considerable events that took place in the country. Any country is said to be financially and socially prosperous when it contains a substantial number of producers. Farming is the major job creation sector in most countries. Huge farms that have a lot of people are usually in need of help in planting and taking care of the animals. These large farms can complement and perfect their agricultural outputs with the help of the nearby processing plants [1]. Human civilization has had changes in its agricultural production. These changes have now made it possible to work less and use fewer resources. Despite this, the large population has ensured that the demand and supply have not been in the position to match. It is estimated that the world population will grow to 9.8 billion in 2050, which is 25 percent higher than the current population [2]. Most of the rising populations are probably to be experienced in emerging nations. Nevertheless, 70 percent of the population of the world is estimated to be living in urban settlements by 2050, compared to 49 percent currently [3]. Food demand will go up with the incomes, particularly in the developing countries. Such countries will therefore be more aware of nutritional value of their food and nutrition. Therefore, the dietary habits of people can change regarding the consumption of grains and cereals to legumes and eventually meat. Water is a useful yet scarce natural resource exploited in agriculture. In a country such as India, irrigation takes a lot of water [4]. There are many weather conditions that affect crop production including humidity, soil temperature and air temperature. Irrigation of crops is one of the factors that have a significant effect on crop productivity. Farmers largely undertake field harvesting as directed and instructed by human beings. The source of water in the field

must be secured [5]. Water shortage is a significant issue in the modern world. The situation can become even worse in the next few years. Smart farming is a term used to refer to a more advanced and popular agricultural practice that has become more common in the modern agricultural practice. The use of farming and data collection technology is in monitoring crop health and productivity. This includes observation of field crop situations and other indicators [6]. Finally, smart farming aims at minimizing the cost of inputs in terms of production but without compromising the quality of the end product. When a big volume of fertilizer or herbicide is applied at one time the entire field is considered as a unit. Natural water supplies are mainly provided by water on the surface, the subsurface fluid and rainfall [7].

There is 96.5 percent of all the water on the earth found in oceans. Only 0.001 percent of the remaining water is in clouds, mist and snowfall on Earth or 1.7 percent of the total water supply on the world. Most of the fresh water on the earth is in the ocean which is predominantly made up of salt water. Consequently, there is a lack of fresh water in most countries of the world. Every single place cannot exist without water. According to the projections of the World Resources Institute (WRI), most of the countries will have inadequate supply of water by the coming years [8]. This is because the fact that industrial and agricultural use of the great bulk of freshwater impacts downstream environments significantly. Freshwater resources should also be handled in a way that would not affect the future generation negatively because of their depletion. The soil has numerous varieties of soil including clay, salty and sandy soils. All types of soils have their advantages and disadvantages. A good example of this is sand soil that has a high capacity of drainage. On the other hand, drainage causes the rapid removal of the micronutrients in the soil [9]. Specifically in such an occupation as farming, data mining methods may prove to be rather beneficial. One of these methods of regulating water usage in agricultural areas is restrictions imposed by association rules. The smart farming has become possible because of the variety of gathering and storing information methods made possible by the IoT [10].

In modern irrigation networks, advanced sensor networks are used to collect field data on optimum plant irrigation. Machine learning is used in a variety of real-world applications such as smart agriculture, intelligent healthcare, intelligent logistics, and smart manufacturing. Within the framework, soil and humidity sensors gather data that are then stored on a centralized cloud server [11]. Machine learning algorithms are applied in order to achieve various analytics on a cloud server. The framework provides the exact quantity of water required in a particular crop. This structure is presented in Figure 1. A global smart metropolis with the aid of IoT is possible to imagine. There are many forms of the intelligence community; they include smart ecosystems, smart houses, smart agriculture, smart government and smart fitness. The IoT is used in the industrial, refining, and oil and gas mining industries as well [12]. The IoT benefits the population increases productivity, reduces costs, obtains maximum energy consumption, maintains predictions, and provides an immeasurable convenience. Due to the increased variety of technology and information handling, the safety concern becomes increasingly higher. The primary factors that prevent the growth of the IoT are the issues of privacy and security [13].

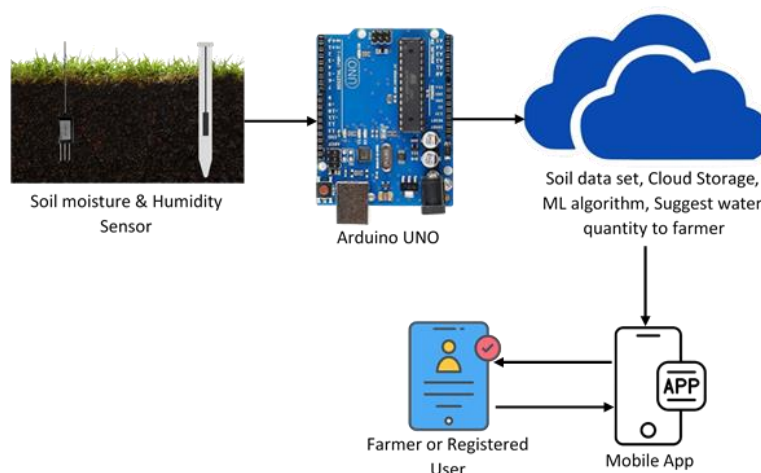


Figure 1: A framework for smart irrigation

Specifically, an efficient irrigation system optimizes water consumption and reduces the consumption of

energy. WEF ecosystem nexuses are the way of achieving the long-term ecology, economic and social objectives. Water consumption can be supported by less intensive irrigation methods and make water usage sustainable. The amount of water required by plants is huge due to climatic changes, lowering the cost of precipitation, and global modifications [14]. The investigation on needs evaluation and plant drinking water injection is vital in the current farming society. The irrigation mechanism is applied to regulate the water requirements of the plants according to the environmental changes around. In a bid to increase production yields, various water optimization methods and effective hydration-management systems are used to reduce the amount of water used and develop an effective plant water-needs forecast system. The society requires good watering and planning systems as they increase production at a lower consumption of water [15].

1.1 Problem statement

As it often happens, the existing agricultural irrigation systems are relatively useless and lead to excessive water wastage and poor crop production due to poor water distribution and monitoring. Most of the traditional methods rely on human observation and general irrigation patterns, which fail to consider the dynamic environmental conditions such as the soil moisture content, weather patterns as well as the specific water needs of crops. The IoT-based smart irrigation systems have come far yet most of the systems still fail to provide good decision-making accuracy and flexibility. The complex and dynamic nature of agricultural ecosystems is what complicates the utilization of the existing information and adds to the ineffectiveness. This has led to the need to have a more advanced, dynamic system which can improve water management immediately. A new way to enhance the effectiveness of IoT-based systems of smart irrigation is the application of transfer learning, which can utilize the pre-trained models in the related fields. The problem is how to design a low computing overhead, and a high capacity of the irrigation system that delivers minimal water waste and maximum crop production through efficient use of sensor information and adaptation to the change in the environment.

1.2 Motivation

This study is driven by the need to have sustainable methods of agriculture and the increasing global concern over the lack of water. The fact that agriculture consumes a significant portion of freshwater supply in the globe makes it necessary to lower the volume of water utilized in irrigation as a way of addressing the environmental and financial problems. The contemporary agriculture practices require beyond the traditional methods of irrigation, which often wastes water. This is particularly so in places where there is a shortage of water or unpredictable climatic conditions. The IoT-based sensors provide an opportunity to gather information on the needs of the crop, the weather, and the soil moisture in real-time, but the contemporary systems of smart irrigation are not always as adaptable and accurate in order to use water efficiently in diverse settings. The agricultural system can also be more specific, scalable and adaptable by incorporating transferable learning, which allows models to attain learning in similar domains and contexts. By closing the disconnect between the data irrigation techniques and the actual farming needs, the study will contribute to the higher yields of crops and the enhancement of sustainability. The ability to give the farmers real time information through sensors to dynamically adjust irrigation will also benefit the farmers in the sense that they will save money on water and boost production.

2. Related Works

Many industries e.g. the military and agricultural make use of Wireless Sensor Networks (WSN). Power consumption of WSN is an issue of research. The WSN life durations and metaheuristics were also studied by them. Offer change process, assessments and resolutions process that assists in searching the most appropriate solution to the problem through metaheuristic approaches. As they explain, it is quite clear that the metaheuristic method requires extensive knowledge of the numerous field characteristics and domain knowledge on the longevity issue. Metaheuristic algorithms have already been studied by many researchers [16]. Even though the success of the WSN has become more successful due to these techniques, there are still a number of issues that must be addressed. The contingency planning can lead to the reduction of the number of sensors or cluster heads. Scalable problems cannot be solved by the use

of metaheuristic techniques; they are oriented at optimization. Say that to enhance coverage and connectivity, the nodes are to be as small as possible [17].

The suggested method is compared with other existing methods to perform the same job. The effectiveness of the proposed technique was proved through four different cases with the help of two commonly-known methods. The developers use a decision system to process, store, and analyze information in an IoT structure. An intelligent application system, which utilizes an IoT system with different dimensions, including moisture, water evaporation, and land slope, is considered in order to analyze decisions. Two models geography and climatology and use numerous forecast factors e.g. humidity, wetness, rates of need of soil in everyday and monthly basis, transpiration of moisture, and report on the weather [18]. It reduces the requirement of water by use of the CWSI architecture which the authors propose to control temperature distribution-based irrigation. Optimization of needs is done through time intervals and plant needs are checked on a continuous basis. An irrigation system wherein the irrigation is carried out with the help of control-based scheduling in order to control numerous parameters, such as the moisture content of the soil, wind direction, humidity, and wind velocity. Predictions of the conditions in the soil by sensors control the irrigation and soil moisture sensor, and the operations of different watering systems are monitored and measured by using mobile applications [19]. The forecasting process is handled with various systems of recommendation such as deep learning, deep machine learning and statistical approaches. Enhance the rate of prediction offer diversified activities-based machine- and deep-learning, regression models, GBT, and DNN methods. This model can be used to predict better by 93 percent, using different variables. Explain a system whereby thermal imaging is used to evaluate various demands of an irrigated system by use of intelligence. Various variables are measured through thermal pictures and calculated on the potential of leaves [20]. The main weakness of this study is that measuring soil moisture is an analysis that is complicated. Recommend machine learning and IoT-based solutions which should be used in managing smart irrigation by considering a wide range of factors, such as temperature, nearby features, and a spectrum of soil conditions all of which are considered in determining requirements. Propose an approach that will utilize the WSN and other node sensors to optimize the quantity of water requested by crops [21].

There is the use of mobile and online apps to control the crop through control devices. The mobile and online applications are used to compute future requirements and soil moisture. The IoT is used in water management and has numerous sensors to measure different aspects; these include soil characteristics, moisture, temperature, and rain sensors. The forecasting and operation of the output in this activity are both done using both automatic and manual operations. Different methods of control and monitoring of the agricultural systems are presented [22]. Using smart control, propose a LoRa network design with a range of 5km with energy-efficient architecture. All the data is transported to different locations using the LoRa framework [23]. This prediction and labeling of problems is a type of knowledge that is stored by applying similar and close tasks to analogous problems, which is called transferable learning. Applications in learning transfer are farming, transfer of knowledge, categorization issues among others. It is used in farming to predict plant diseases, identify the species, transfer knowledge about plants to different domains, categorize plants and exchange information.

Different problems on transfer learning in agricultural domain. Knowledge-transfer methodology was developed in order to classify different crops and reducing the time required to retrain and label. The authors of this paper saved half of the time that they would have used otherwise. Applied transfer learning to classify weeds under different species with an accuracy of 99.29. Similarly, deep learning on categorization of rubbish is suggested. The authors could achieve 94% and 98% accuracy in their framework using several datasets. Bale detection method involves transferring the source photos to the target domain photos using deep transfer training and domain adaptation. Objective A CNN and transfer-learning model is suggested in detecting the pests which destroy crops at an early stage. Transfer learning optimizes pre-trained models. Propose a technique known as transfer learning when relocating a base model, which is characterized by a number of samples or features. In this model, the features are relocated to two locations in terms of time-series feature irrigation mapping. To better train the model with soil moisture and be able to transfer the soil conditions between two soils, where they have different distributions, propose to use transfer learning with the IoT.

3. Materials and Methods

The proposed research foresees the creation of a drip irrigation system based on cloud storage, LSTM, ANFIS, k-nearest neighbors (KNN) and IoT sensors. To enable KNN to calculate the most similar requirements of water between the root and the surrounds and ANFIS to predict the situation in the nearest future, the IoT devices should capture the data within the surroundings. The LSTM predicts time-series information revisions to use in future forecasting and correlated the demands at different times based on a Spearman rank correlation approach. The primary aim of the proposed study is to predict the current and possible needs at different times, such as 3 h, 8 h, 12 h, 24 h, and 48 h. The basic plan of the intended work is depicted in figure 2. The three main components of the proposed architecture of the predictions model are initial-value predictions, integrated predictions approach, and the transfer of learning. The first needs estimate is done by the set of sensors.

This proposed study predicts the various irrigation requirements using a meteorological data and the IoT sensors and assists in the formulation of both short-term and long-term prediction. The depiction of the flow of proposed work is demonstrated in figure 3. The workflow of the planned work is split into four main parts; Gathering information about multiple sources, forecast knowledge sharing with farms nearby (transfer learning), nearest needs forecasting, short-term forecasting (ANFIS), long-time series forecasting (LSTM), short-term forecasting (ANFIS). The operation of the proposed work is carried out in four phases, namely, information storage and processing, long-term and short-term prediction, characteristic transference and learning one type of information by another. Algorithms for KNN are then applied to retrieve sensor information in order to make predictions. The inputs used with the information gathered are weather predictions and past information. The processed data is applied using the ANFIS to make short-term prediction. The short-term project of irrigation recommends water pumping. Long-term prediction and the subsequent proposal of water pumping when required makes use of the Long Short-Term Memory (LSTM) approach. The short- and long-term predictions in this analysis are done using one farm. The characters are transferred to a different farm to enhance predictions once the need of the farming site has been established.

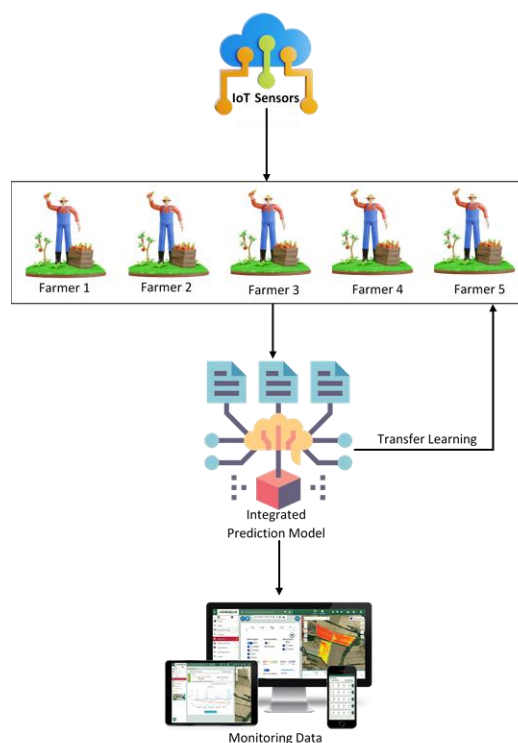


Figure 2: Fundamental layout of the planned work

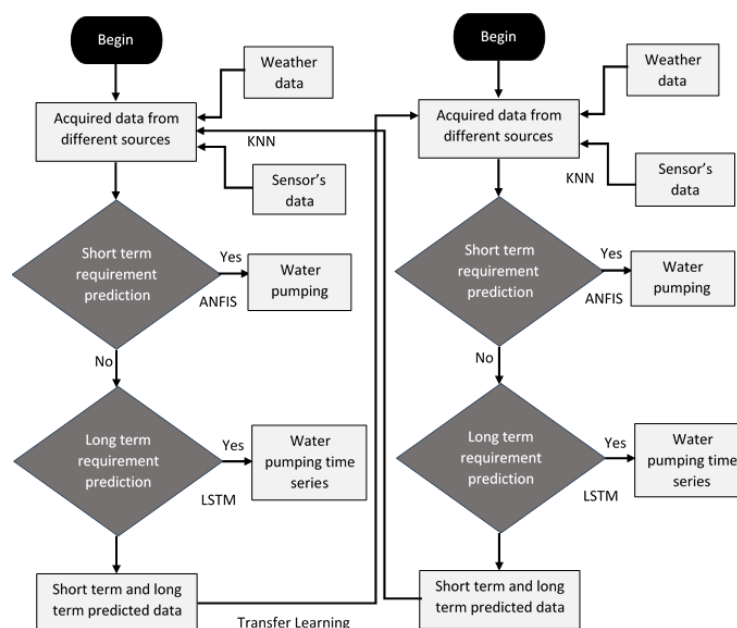


Figure 3: Workflow representation of proposed work

The stages of processing involve processing of data, forecasting, and sharing information that other farmers have learnt. Meteorological data of farm 1 and sensor data are first transferred to the cloud storage. The analysis of the acquired and historical data is done first to estimate the needs. Information processed using ANFIS and LSTM algorithms forecasts both the short-term (Sp) and the long-term (Lp) requirements. The short and long-term initial demands are estimated using such techniques and the information gathered. When information is obtained, the first farm (X1) is able to share the model weight that is stored with the nearest second farm to enhance prediction. A smart irrigation system with transfer learning abilities is comprised of a dataset that consists of a number of characteristics that are obtained by the use of IoT sensors installed in agricultural fields. Among the important parameters are the temperature and moisture content of soil, which is required in estimating the water requirement of crops. They are used to ensure that watering is done accurately by measuring temperature and moisture content in various levels. More than this, the air temperature and the humidity provide data concerning the environmental conditions that could influence the growth of plants and their evaporation rates. The dataset also contains data on sun radiation and rainfall to calculate the demand of artificial irrigation taking into consideration natural water supply and energy availability. To maximize the decisions making process, the data on wind speeds is incorporated to consider the evaporative water loss. A classification variable is required to determine the specific crops being grown since different plants require different amounts of water and this is termed as crop type. Continuous variables are used to monitor the amount of water used and the duration of irrigation periods; they are irrigated amount and irrigated time respectively. In order to give irrigation schedule additional context, the weather condition is a category property, which represents the overall weather condition, including: bright, overcast, or rainy. These numerous data sources can be combined to provide the system with an efficient and real-time monitoring and optimization of water consumption. This enables proper irrigation to be applied at the correct time and place reducing wastage and improving crop health.

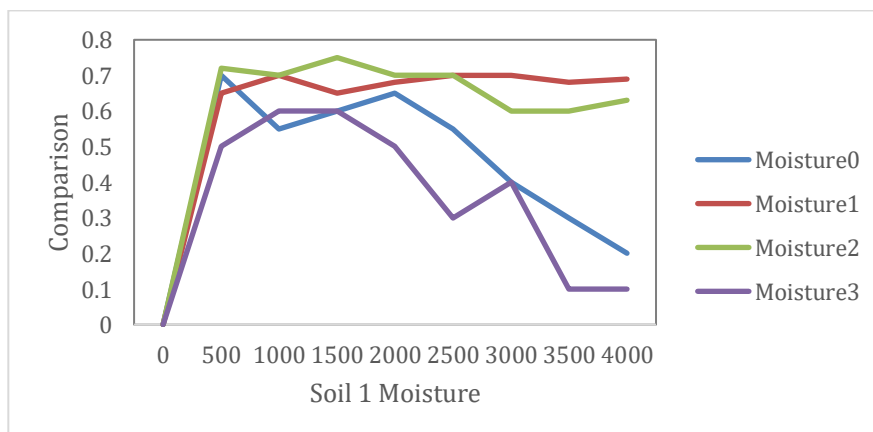
Attribute	Description	Data Type	Range/Values	Units
Soil Moisture	Measures the moisture level of the soil at different depths	Continuous	0 to 100	Percentage (%)
Soil Temperature	Temperature of the soil at sensor locations	Continuous	-10 to 50	Degrees Celsius (°C)

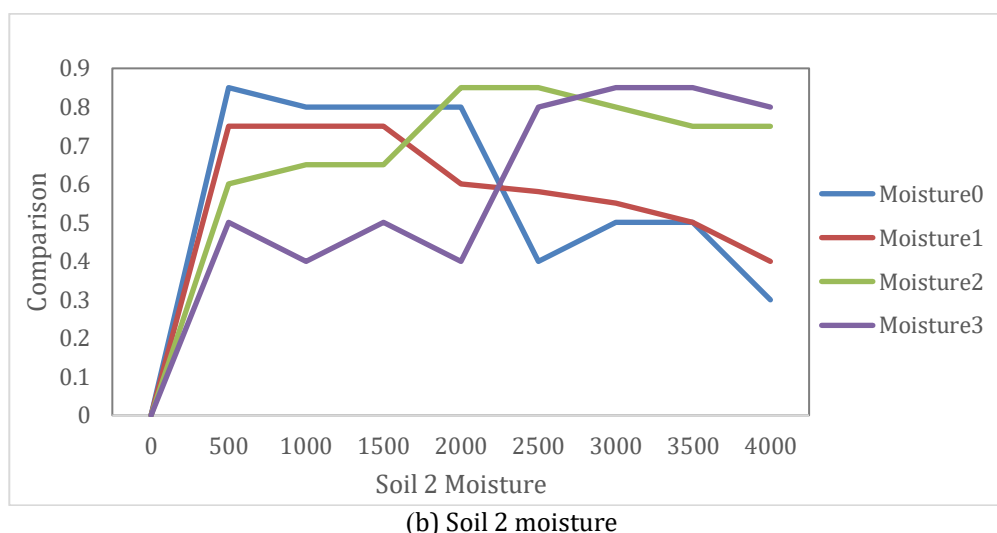
Air Temperature	Ambient temperature measured near crops	Continuous	-10 to 50	Degrees Celsius (°C)
Humidity	Relative humidity in the air surrounding the crops	Continuous	0 to 100	Percentage (%)
Rainfall	Precipitation levels collected by rain gauge sensors	Continuous	0 to 200	Millimeters (mm)
Solar Radiation	Amount of solar energy received at the farm	Continuous	0 to 1500	Watts per square meter (W/m ²)
Wind Speed	Speed of wind that may affect evaporation rates	Continuous	0 to 100	Meters per second (m/s)
Crop Type	Type of crops being irrigated	Categorical	Wheat, Corn, Rice, etc.	N/A
Irrigation Amount	Water volume applied during irrigation events	Continuous	0 to 1000	Liters (L)
Weather Condition	Weather status at the time of irrigation	Categorical	Sunny, Cloudy, Rainy, etc.	N/A
Irrigation Time	Duration of irrigation applied	Continuous	0 to 360	Minutes (min)

Table 1: Dataset description

The data were analyzed using datasets that were obtained in two different pots that were named Soil1 and Soil2. Four soil moisture sensors have been placed at a distance of 10 cm between each other in both soils as illustrated in Table 1. These are the sensors that are referred to as Moisture 0 (first layer) to Moisture 3. There was no irrigation done to the soils at the periods, which is another way of demonstrating the inequality. Saving of information is done every two or three minutes and a total of 26,000 points of information have been collected. The data used as a sample is available online under the form of public datasets, and additional example updates can be located in dataset is exemplified in Table 2.

Year	Month	Day	Hour	Minute	Second	Moisture0	Moisture1	Moisture2	Moisture3
2024	3	12	15	45	42	0.60	0.64	0.52	0.46

Table 2: The Moisture in table is in the top layer of soil and the others increase in depth**(a) Soil1 moisture**



(b) Soil 2 moisture
Figure 4: Two types of soil moisture comparison.

The initial stage to the comparison of the two soils (Soil1 and Soil2) and the identification of their differences is plotting of the level of moisture in each soil. (Figure 4). Although in Soil 1 the first layer in the soil loses water gradually, in Soil 2 the first layer of the soil holds water longer. Although the movement of water in the second and third levels is faster in the Soil 1, it is slower in the final layer in Soil 2. These clearly show that the rate of absorption of water by the two pots are not equal. The absorption of different strata of soil is different. Figure 4 illustrates the way the proposed model works in general. The IoT structure presents four layers which are being offered, namely perception, implementation, manufacturing, and transport. The perception layer is referred to as physical layer implying that it can be used as a sensor to collect information. It can feel the humidity of the air, moisture levels of soil and warmth. The transport layer was the origin of sensed data which was earlier gathered and transmitted to the computation layer via networks such as LAN, WiFi, 2G and 3G. The analysis layer analyses, stores, and develops a large amount of transport layer information. It utilizes such techniques as CC, databases in addition, and computing at the edge. Application layer is meant to provide end users with application-related services.

3.1 Sensor Data

Initially, the sensors receive information. This step involves the gathering of data about humidity, temperature and moisture in the soil. Microcontroller is the actuator and perception layer components are sensors. Processing/Transport level offers watering plans, advice and supervision of crops. The second step involves collection of information based on data centers to be evaluated after the initial data collection. The picture suggests the entire design study of the physical part utilized. All the parts are readily found on the market and affordable. Consequently, the device that is located in the physical world can be produced conveniently. The sensors layers of the implanted devices are the illumination sensors, humidity sensors and temperature sensors. The digital signal of this sensor is received by the microcontroller set in the Arduino board and after thirty seconds, the signal is passed to the information center through the GSM model SIM808. One of the applications in Android gave the customer the ability to visualize the final result of the process of making choices fully. The customer was then able to operate the whole actuator and this made the valve to open and discharge water.

HL-69 Soil Hygrometer HL-69 soil hygrometer products were moisture sensors attached to a HL-69 Soil Hygrometer. The main objective of the HL-69 soil hygrometer moisture sensor is to deliver a perfect reading as compared to the moisture sensor of another soil. The sensors are applied in monitoring the real soil moisture of plants cultivated in tunnel farms. Due to the quantity of water in the ground, the voltage of the sensors output varied. It resembles HL-69 hygrometer sensors of soil sensors in some main aspects. Then the output voltage reduces as the content of soil moisture becomes larger; however, the output voltage becomes larger as the content of the soil moisture becomes smaller. The analog signal that comes out of the hygrometer sensors measuring soil moisture must be digitized with an Arduino board. These sensors contain 2 pads which detect the availability of water and an electric board. Install the LM393 comparator chip on the circuit board. it has two lights, a red light used to display the power indicators, and a green one used to display the output indicators displayed in computerized changeover. **DHT22 sensor** DHT11 Sensor normal temperature-humidity detectors are applied to gauge the humidity and temperature of the air. The DHT22 sensor consists of the humidity sensor and the thermostat. It has some similarities with the DHT22 sensor namely: the DHT22 sensor is cheaper. The voltage range of the

input or output of the DHT22 sensors is [3, 5 V]. The highest current that can be used in the change when applied to the information is 2.5 mA. DHT22 sensor has 4 pins and the spacing between them is 0.1. DHT22 sensor has the body size of approximately 15.1 25 7.7 mm.

The BH1750 FVI Light Sensor is a typical digital light sensor which is capable of measuring light intensities. The digital light sensor BH1750 is calibrated with an ability to sense even the slightest traces of light and transform them into 16 digit numerical value. Overall, smartphones can be utilized to utilize the screen brightness depending on the lighting. The intensity light threshold as determined by BH1750 is [0-65,535] lux (L). It has some major characteristics of the BH1750 sensor which are supplied by: The BH1750FVI chip belongs to the BH1750 sensor. The power supply of the BH1750 sensor was [3.3 5 V]. The BH1750 sensor has an inbuilt 16-bit analog-digital converter which transforms the light sensing into 16-digit numerical data.

Algorithm: Transfer Learning-Enabled Smart Irrigation System for Optimized Water Management in IoT-Driven Agricultural Networks

This algorithm leverages transfer learning to optimize irrigation scheduling based on real-time IoT sensor data and pre-trained models for efficient water management. Below is the step-by-step process, with equations illustrating key aspects of the algorithm.

Step 1: Data Collection

Collect real-time data from IoT sensors installed in the field.

Sensor data includes soil moisture (SM), soil temperature (ST), air temperature (AT) humidity (H), rainfall (R), solar radiation (SR), wind speed (WS), and weather condition (WC).

$$I = [SM, ST, AT, H, R, SR, WS, WC] \quad (1)$$

Step 2: Preprocessing: Normalize the collected sensor data to ensure compatibility with the pre-trained model. Use Min-Max Normalization for continuous variables:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (2)$$

where I_{norm} is the normalized sensor data, I_{min} and I_{max} represent the minimum and maximum observed values of each sensor attribute.

Step 3: Transfer Learning Model Setup: Utilize a pre-trained deep learning model (e.g., a Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) network) from a similar domain, such as smart irrigation or environmental control.

Transfer the learned weights from the source domain to the target domain, freezing the initial layers to retain the pre-trained knowledge and fine-tuning the later layers using the new dataset.

Let $f_{\theta}(I)$ represent the model with parameters θ . The model is optimized for the new task by fine-tuning the parameters θ' :

$$\theta' = \theta + \Delta\theta \quad (3)$$

where $\Delta\theta$ is the update after training with the target domain data.

Step 4: Water Requirement Estimation: The pre-trained model outputs the predicted irrigation requirement (IR) based on the input sensor data (I):

$$IR = f_{\theta}(I) \quad (4)$$

Step 5: Irrigation Scheduling Optimization: Optimize irrigation timing and volume to minimize water usage while ensuring crop health. Define the objective function to minimize water wastage (W_{waste}) and maximize irrigation efficiency ($E_{irrigation}$)

$$\min(W_{waste}) \text{ subject to: } E_{irrigation} = \frac{\text{Water Delivered}}{\text{Water Required}} \geq \alpha \quad (5)$$

where α is the threshold for irrigation efficiency.

Step 6: Control Decision: Based on the model's output and optimization constraints, the system determines whether to irrigate, and if so, the amount of water ($W_{applied}$) to be delivered:

$$W_{applied} = \{W_{required} \text{ if } IR > \beta \text{ 0 otherwise} \quad (6)$$

where β is a threshold value that ensures irrigation is only applied when necessary.

Step 7: Continuous Monitoring and Learning: Continuously monitor the field conditions and update the model as more data becomes available. The model uses online learning to improve over time based on new environmental conditions and crop responses.

Final Equation for Optimized Water Management: The final irrigation decision is based on the learned model and optimized constraints, ensuring that water usage is minimized while maintaining efficient irrigation:

$$W_{applied} = f_{\theta}(I_{norm}) \times \frac{E_{irrigation}}{\alpha} \quad (7)$$

This algorithm enables dynamic, real-time irrigation control, improving water management efficiency in IoT-driven agricultural systems through the use of transfer learning.

4. Results and Discussions

The sensor also collected values of the humidity, root wetness and ambient moisture. Moreover, minimum and maximum water requirements of the farmers were also collected. The maximum amount of 50 L of water required during a month and the irrigation periods during five to seven days were collected to arrive at the threshold values of both testing and training. Some of the basic and fixed characteristics that are considered in the watering are as shown in Table 3. The proposed model is tested using three sensor data namely, soil moisture, temperature, and humidity. The dataset has five class labels namely, extremely unnecessary, highly needed, needed, and medium. The information ranges of the sensor information and labels are listed in figure 5.

S.No	Parameters and Requirements	Values
1	Number of farms	5
2	Number of trees in each farm	350
3	Maximum requirement of water per month	55L
4	Irrigation interval	Jan to Oct
5	Minimum temperature	0oC
6	Maximum temperature	38oC
7	Interval of irrigation	8days
8	Average requirement of water per month	37L

Table 3: Basic parameters for irrigation.

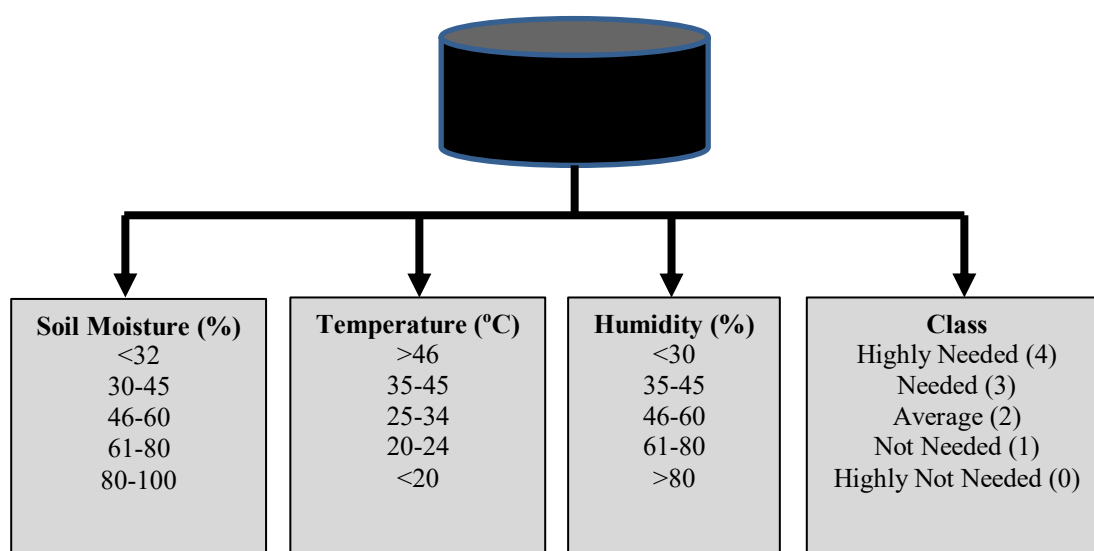


Figure 5: Dataset descriptions

Figure 6 shows a set of confusion matrices generated by the IoTML-SIS method on various test runs. The first execution run of the IoTML-SIS approach has ranked 90 samples as Highly Not Needed, 92 samples as Not Needed, 92 samples as Average, 91 samples as Needed and 93 photos as Highly Needed. Meanwhile, 91 samples are of Highly Not Needed, 93 samples are of Not Needed, 94 samples of Average, 93 photos of Needed, and 94 of Highly Needed by the IoTML-SIS technique on execution run-2.

(a)

Actual	Highly Not Needed	90	9	0	0	0
	Not Needed	0	92	0	0	0
	Average	0	2	92	0	8
	Needed	2	0	0	91	0
	Highly Needed	0	0	0	8	93
		Highly Not Needed	Not Needed	Average	Needed	Highly Needed
		Predicted				

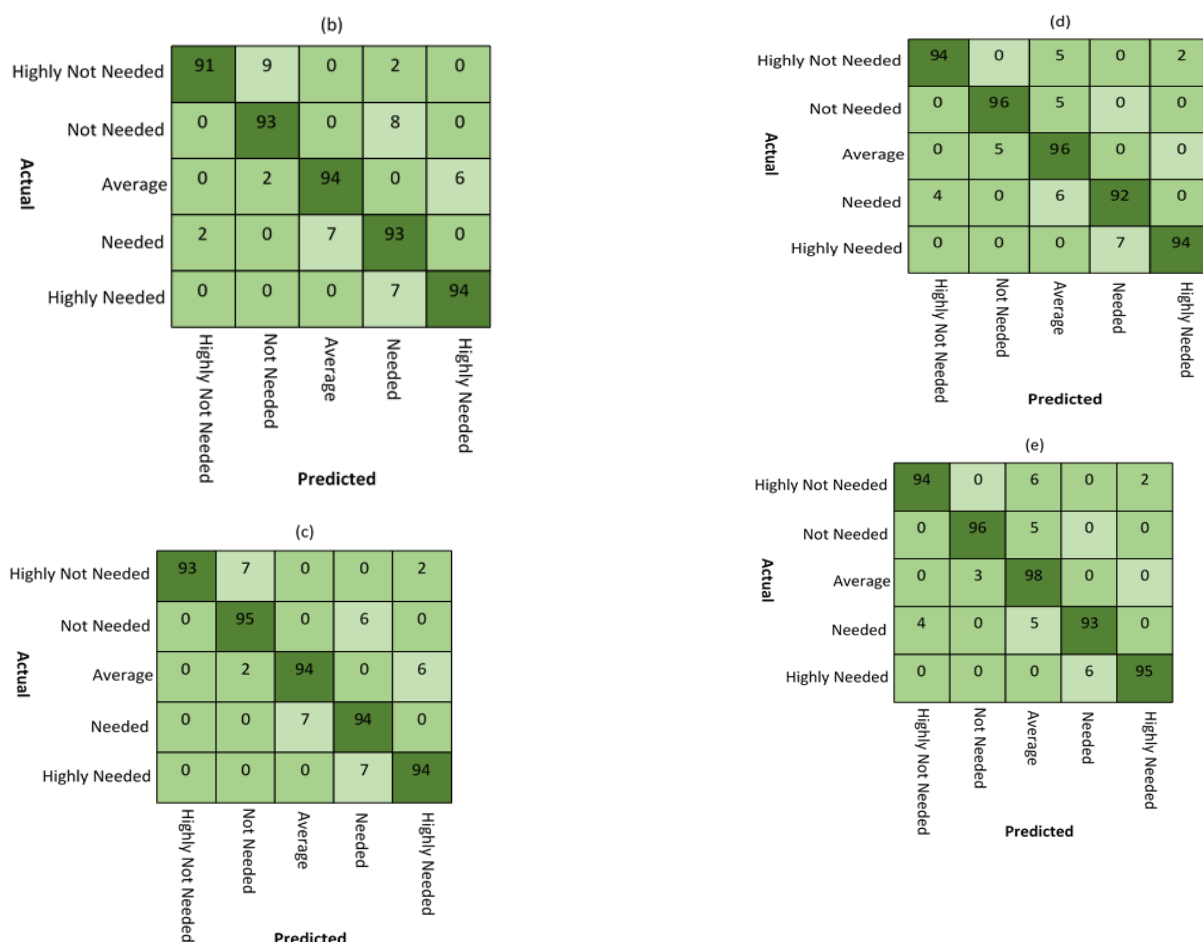


Figure 6: Confusion matrix of proposed IoTML-SIS method on different runs (a) Run-1, (b) Run-2, (c) Run-3, (d) Run-4, and (e) Run-5

The final classification of the 93 samples on the Highly Not Needed category, 95 samples on the Not Needed category, 94 samples on the Average category, 94 images on the Needed category, and 94 images on the Highly Needed category on the execution run-3 was the IoTML-SIS approach. Simultaneously, with the IoTML-SIS approach, 94 samples are classified as the Highly Not Needed, 96 samples as the Not Needed, 96 as the Average, 92 as the Needed, and 94 as Highly Needed on the run-4 of execution. Lastly, IoTML-SIS method has identified 94 items as Highly Not Needed, 96 items as Not Needed, 98 items as Ordinary, 93 items as Required and 95 photos as Highly Needed on implementation run-5.

Measures	Precision	Recall	Accuracy	F-Score	MCC
Run-1					
Highly Not	0.990	0.901	0.979	0.943	0.931
Needed	0.894	0.921	0.963	0.907	0.884
Not Needed	0.921	0.921	0.969	0.921	0.901
Average	0.860	0.911	0.953	0.885	0.855
Needed	0.931	0.931	0.973	0.931	0.914
Highly					
Needed					
Run-2					
Highly Not	0.90	0.911	0.981	0.949	0.938
Needed	0.913	0.931	0.969	0.922	0.902
Not Needed	0.941	0.941	0.977	0.941	0.926
Average	0.870	0.931	0.959	0.900	0.874
Needed	0.951	0.941	0.979	0.946	0.932
Highly					
Needed					
Run-3					
Highly Not	1.00	0.931	0.987	0.965	0.957
Needed	0.932	0.951	0.977	0.942	0.927
Not Needed	0.941				

Average	0.896	0.941	0.977	0.941	0.926
Needed	0.941	0.941	0.967	0.918	0.897
Highly		0.941	0.977	0.941	0.926
Needed					
Run-4					
Highly Not	0.970	0.941	0.983	0.955	0.944
Needed	0.961	0.961	0.985	0.961	0.951
Not Needed	0.882	0.961	0.967	0.920	0.900
Average	0.940	0.921	0.973	0.930	0.913
Needed	0.980	0.941	0.985	0.960	0.951
Highly					
Needed					
Run-5					
Highly Not	0.970	0.941	0.983	0.955	0.944
Needed	0.981	0.961	0.989	0.971	0.963
Not Needed	0.884	0.981	0.971	0.930	0.913
Average	0.950	0.931	0.977	0.940	0.926
Needed	0.991	0.951	0.989	0.970	0.963
Highly					
Needed					

Table 4: Results analysis of proposed IoTML-SIS method in terms of different runs

Concerning the different parameters in Table 4 comprehensive classification outcomes analysis of the IoTML-SIS strategy is performed. Also, the results are explored using various run numbers. The trial data reveals that the IoTML-SIS has yielded positive results in all applications it has been used in.

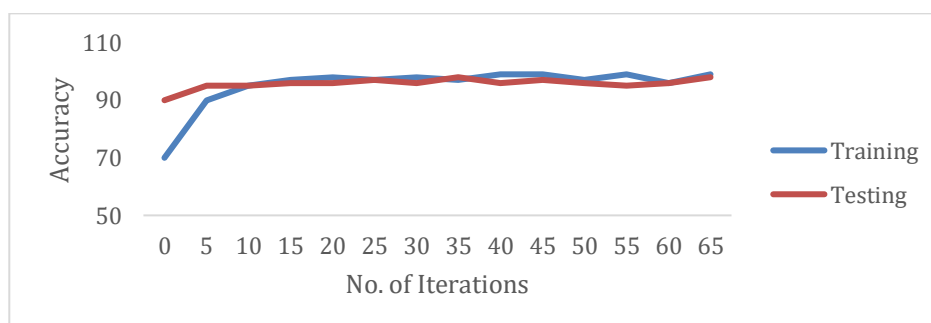
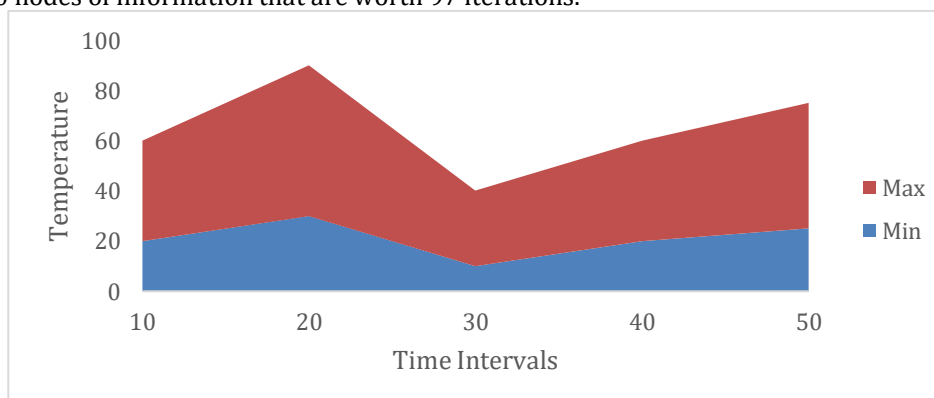


Figure 7: Training and testing accuracy of prediction.

At first, ANFIS and LSTM were integrated to predict the underlying needs of prediction education, validation, and testing accuracy. Figure 7 demonstrates the training process, as well as the accuracy of testing 100 nodes of information that are worth 97 iterations.



A. March Month Min-Max Temperature

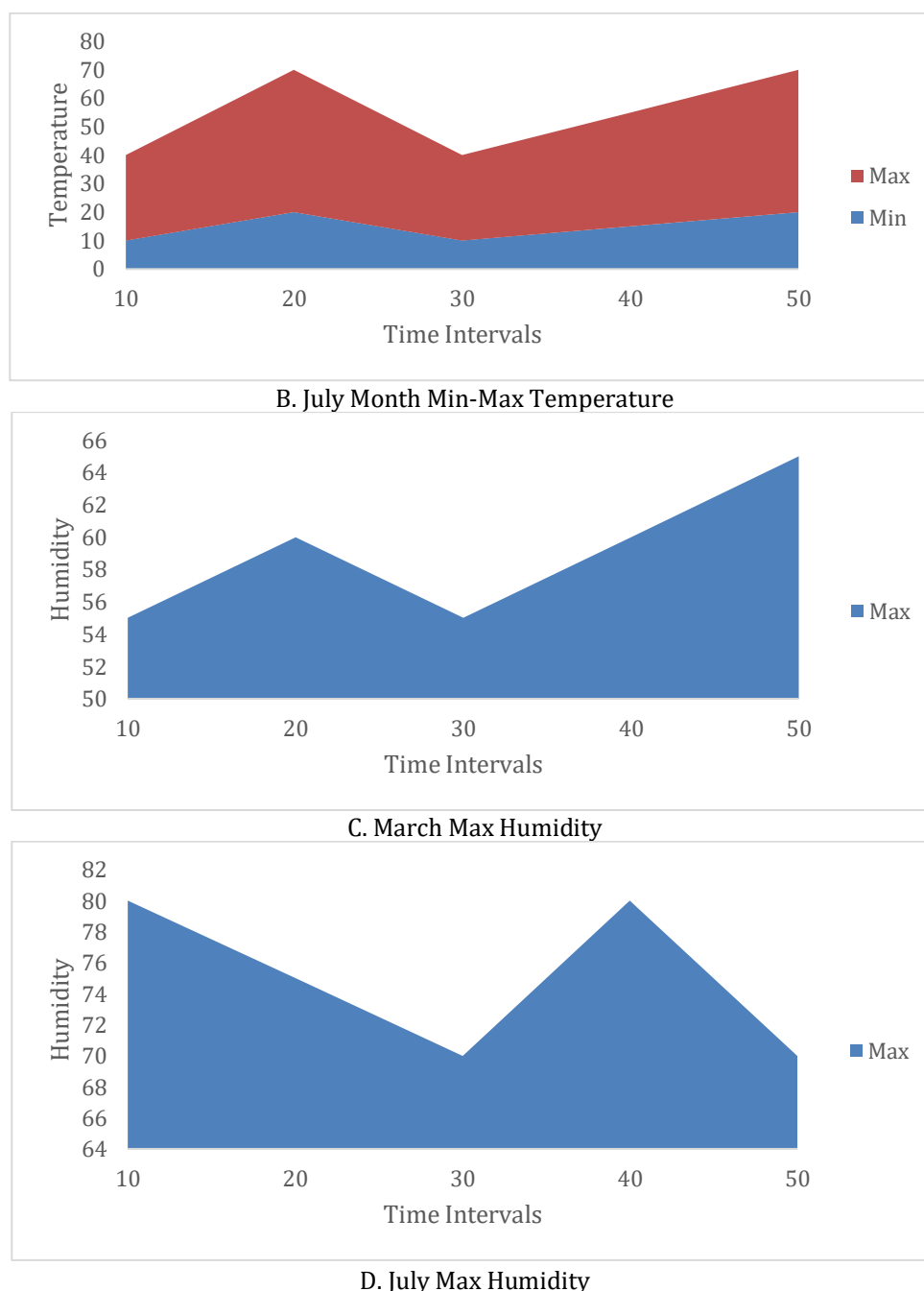


Figure 8: Minimum and maximum temperature and humidity in March and July.

At first, the prerequisites of shortest-term forecast are in figure 8. Month-wise relative humidity and temperature are the two main requirements of both the short-term and the long-term forecasts including relative humidity and temperature forecasts of the 8, 16, 24, 32 and 48 hours. The humidity, the lowest and highest temperature are indicated in the graphic and recorded at the same time, 48 hours starting at 8 am. The data received by Farmer 1 is used to retrain the farmer-2 models to give better prediction with the modifications achieved with the use of the farmer-1 information. Transfer learning is used in information collected in the first model in the farm.

5. Conclusion

In summary, a very efficient way to optimize water management in IoT-driven agricultural networks is to build a smart irrigation system with transferred learning capabilities. Through the utilization of pre-trained models from related domains and their adaptation to the surroundings, the system improves irrigation schedule accuracy while minimizing water waste. Real-time sensor data, including soil moisture, temperature, humidity, and meteorological variables, is used to make irrigation decisions that are dynamic and tailored to the unique requirements of various crops and settings. This strategy solves important issues with water shortage and resource sustainability in addition to enhancing crop health

and output. The system's capacity to learn continuously allows it to adjust to shifting environmental circumstances over time, which makes it a scalable and effective tool for contemporary agriculture. All things considered, integrating transfer learning with IoT in smart irrigation systems is a viable path toward attaining sustainable water consumption and raising agricultural output.

Conflict of Interest Statement

There is no conflict of interest

Data Availability Statement

Data not available due to personal restrictions

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