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ORIGINAL ARTICLE

SMART IRRIGATION USING TRANSFER LEARNING IN IOT-BASED AGRICULTURAL NETWORKS

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Abstract
The management of water in agriculture is an important issue in contemporary agriculture, as the lack of water is growing, climatic changes are becoming apparent, and the volume of food production is increasing. The old method of irrigation usually is based on the fixed period or manual regulation resulting in the waste of water and the low optimization of crop production. To overcome these drawbacks, the present paper will suggest a transfer learning-based smart irrigation system to optimize the management of water in agricultural IoT-based networks. The suggested system incorporates distributed IoT sensors to monitor soil moisture, temperature, and humidity, among other environmental conditions continuously, and uses transfer learning to adapt the pre-trained deep learning models in order to make precise irrigation decisions with little agricultural data. Sensor data will be sent to a centralized platform where smart models are applied to compute the water needs of the crops and in real time dynamically turn the irrigation actuators. The experimental findings indicate that the proposed system has a great positive effect on the accuracy of irrigation and the amount of water used and the overall health of crops in comparison to the traditional methods of irrigation. Transfer learning combined with IoT allows converging models more quickly, more accurately, and scale to a wide range of agricultural scenarios, so the system becomes a viable and sustainable remedy to the precision agriculture and smart farming application.

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

1. Introduction
Agriculture is very important to the economy of the country since it is the source of food to all. It is related to one of the most important events that took place in the country. The country would be said to be financially and socially prosperous when the number of producers is large. In the majority of the countries, farming is the leading industry that creates employment opportunities. Big farms that have numerous individuals normally demand labor in planting and taking care of the animals. These large farms can boost and optimize their farm outputs with help of the nearby processing plants [1]. Human civilization has undergone a rapid transformation in the agricultural production. These modifications have made it possible to perform less work and use less of the resources. Regardless of this, the large population has ensured that demand and supply have not been in a position to match. The world is set to increase its population to 9.8 billion by 2050, which is a 25 per cent increment of the current population size [2]. Most of the growing populations are probably to be found in the emerging nations. Still, it is estimated that the world population in cities will reach 70 percent in 2050, compared to 49 percent currently [3]. There will be a rise in demand of food as incomes rise particularly in the emerging countries. Such countries will therefore become more aware of the nutritional content of their food and nutrition. As a result, the preference of people in food can change to grains and cereals to legumes and, finally, to meat. Water is an essential but scarce natural resource which is utilized in agriculture. The use of irrigation is a large water-consuming process in a country such as India [4]. The climatic factors that affect crop production include humidity, soil temperature, and air temperature, among others. Irrigation of crops is one of the factors contributing to crop productivity. The field harvesting is mostly carried out

by farmers and is directed and informed by human beings. The source of water in the field must be sealed [5]. Water shortage is a significant issue that is being experienced in the contemporary world. This situation can become even worse in the next several years. The term smart farming refers to a better and popular farming technique that is more common in the modern-day agricultural industry. The health and productivity of crops are tracked through use of farming and data collection technology. These include observing field crop situations and other indicators [6]. Finally, there is the goal of smart farming, which is to reduce the cost of inputs related to the production process but not decrease the quality of the resulting output. When fertilizer or a great deal of a herbicide is administered simultaneously over a large area, the whole area is treated as one unit. The major sources of natural water supplies include water on the surface, at the subsurface level, and precipitation [7].

The water found in oceans comprises 96.5 percent of the total water on the planet. The remaining fluid on Earth is found in clouds, mist, and snowfall, and only 0.001 percent of the total volume of water is found there or 1.7 percent of the overall water supply in the world. Most of the fresh water on earth exists in the ocean which is mainly salt water. Consequently, the issue of fresh water is becoming scarce in most countries across the globe. Water is a necessity to all environments. According to the predictions put forward by the World Resources Institute (WRI), most countries are bound to run out of water in coming years [8]. The fact that the industrial and agricultural use consumes the large portion of freshwater has a great impact on the downstream environments. The exploitation of freshwater resources should be controlled in order to ensure that the future generation is not affected adversely by the loss of the resources. The soil has numerous varieties which include clayey soils, salty soils and sandy soils. All types of soil possess advantages and disadvantages. The sand soil is a good example of such, it being able to drain extremely well. On the other hand, drainage quickly removes micronutrients in the soil [9]. Methods of data mining could be very beneficial especially in the situation involving farming occupations. One of such ways of controlling the use of water in the agricultural areas is restrictions made through association rules. The IoT has facilitated the use of diverse methods of gathering and storing information that have rendered smart farming viable [10]. On modern irrigation systems, there are advanced sensor networks that collect field values on the optimal irrigation of plants. Many real-world examples, such as smart farming, intelligent medicine, intelligent supply chain, and smart manufacturing use machine learning. The framework has soil and humidity sensors that gather data which are then stored in a centralized cloud server [11]. Machine learning algorithms are applied to complete various analytics on a cloud server. This model provides the exact amount of water required by a particular crop. This structure has been shown in Figure 1. One can imagine a global intelligent megacity with the help of IoT. Intelligence community is available in different ways; it is found in smart ecosystems, smart houses, smart agriculture, smart government, and smart fitness. The IoT is also used in the industrial, refining, and oil and gas extraction industries [12]. The IoT also boosts the productivity of the population, reduces costs, utilizes energy to the fullest extent, maintains precision of predictions, and provides the population with an unspeakable level of convenience. Technology and information handling is increasingly becoming diverse and thus safety issues are increasing. The main issue that will impair the growth of the IoT is the issue of privacy and security [13].

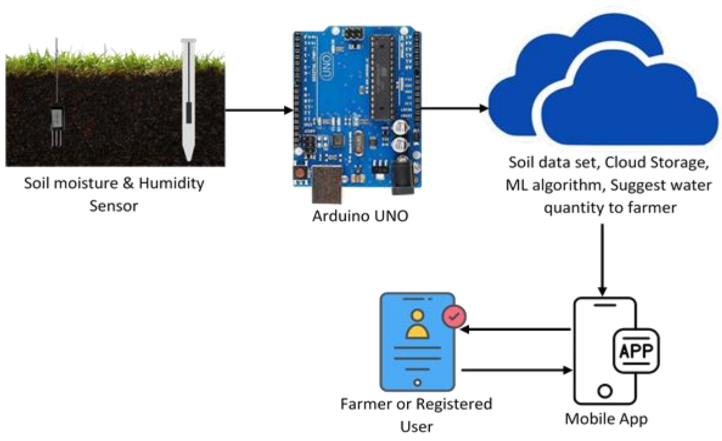


Figure 1: A framework for smart irrigation

A well-operating irrigation system in specifics is one that operates in the most efficient way possible in terms of water consumption and the least amount of energy consumption. WEF ecosystem nexuses are the way to achieve long-term ecological, economic and social objectives. Irrigation method could consume less water and guarantee a long term and sustainable water use. The water requirement of plants is tremendous due to climatic variations, lowered cost of precipitation, and global alterations [14]. The study on requirements evaluation and the administration of water to the plants is essential in the modern farming society. It is controlled by an irrigation system which incorporates the change in the nearby environment to regulate the needs of the plant in terms of water. In order to increase the yield of production, a number of water-saving strategies and effective hydration-management systems are used to reduce water usage and develop an effective system of forecasting the plant water-needs forecasting. Effective watering and planning systems are required in the society since they increase productivity with minimal consumption of water [15].

1.1 Problem statement

The existing irrigation practices are often inefficient in terms of agricultural irrigation, which leads to massive water wastage and poor crop production due to poor water distribution and monitoring. The traditional methods largely rely on human judgment and general irrigation strategies that do not consider the dynamic nature of the environment such as moisture content in the soil, weather patterns, and water needs of the crops. Smart irrigation systems based on IoT have evolved over time but most of the systems are still faced with inaccurate decision making and lack of flexibility in the decision making. Complexity and dynamism of agricultural ecosystems makes it hard to utilize the existing information effectively and worsens this ineffectiveness. Consequently, a new system that is more advanced, versatile, and capable of providing an immediate boost to water management is needed. The next advancement that can be applied to increase the effectiveness of the IoT-based smart irrigation system is the application of transfer learning that can use the pre-trained models in the related fields. The problem is to establish a low computing overhead and high capacity irrigation system that reduces water wastage and maximizes the crop yields by using sensor data and adapting to the environmental variations.

1.2 Motivation

The need to have sustainable farming methods and the increasing global concerns of the scarcity of water is what makes this study. As a significant portion of the freshwater supply in the world is utilized in agriculture, the solution to the problem of environmental and financial concerns should be to decrease the volume of water that is applied in the agricultural industry. Contemporary agriculture does not just require traditional irrigation methods, which are often a waste of water. This is particularly the case in places where there is water shortage or unpredictable weather. The introduction of the IoT-based sensors opens an opportunity to receive the information about the needs of crops, weather, and moisture levels in the soil in real-time, yet the existing smart irrigation systems are not always flexible and precise enough to help to use water efficaciously in various situations. Perhaps the more precise, scalable, and adaptable agricultural system may be created through incorporation of transferable learning, which allows models to gain knowledge by training on similar domains and situations. This study aims to enhance crop production by eliminating the existing gap between data irrigation methods and real farming needs to work towards promoting sustainability. The ability to dynamically adjust irrigation according to the real-time data provided by the sensors will equally make farmers gain profits as it will save them the expense of water and boost their output.

2. Related Works

Many industries use the Wireless Sensor Networks (WSN) including the military and agriculture. There is a lot of research on the power consumption of WSN. In their work, they also examined the life of WSN and metaheuristics. Offer a change, evaluation and solution process, which will help find the optimal solution to deal with the problem through metaheuristic methods. It is highly clear in their explanation that the metaheuristic approach requires a keen insight into the numerous field features and domain knowledge pertinent to the longevity problem. Metaheuristic algorithms have already been studied by many scholars [16]. Despite the increased success of the WSN due to these techniques, there are still a number of issues that should be addressed. Contingency planning could produce less sensors or cluster heads. Meta heuristic techniques do not work with scalable problems, rather they are oriented towards optimization. It is true that to enhance coverage and connectivity the nodes must be as small as possible [17]. The suggested solution is compared to the different existing solutions to perform the same job. The effectiveness of the suggested technique was proved through two known methods on four different cases. The developers make use of a decision system to process, store, and analyze information in an IoT structure. An intelligent application system, which utilizes an IoT system of different dimensions (e.g. moisture, evaporation of water, land slope, etc.) is considered to analyze the decision. Two models geography and climatology and make use of numerous forecast factors, which include humidity, wetness, rates of soil need on daily and monthly basis, transpiration of moisture and weather reports [18]. Demand of water is minimized through the use of the CWSI architecture that the authors propose to control temperature distribution-based irrigation. The needs are optimized with time intervals and the needs of the plants are constantly observed. An irrigation system which operates based on control-based scheduling to manage a number of parameters with the moisture content of the soil, wind direction, humidity and velocity being the most of them. Sensor-based predictions are used to sense various conditions in the soil in order to regulate irrigation and soil moisture sensors and monitor and track various watering system functions by mobile applications [19].

There are multiple recommendation systems being used such as deep learning, deep machine learning and statistical methods that are used to manage the forecasting process. To enhance the prediction rate, offer diversity of activities-based machine- and deep-learning, regression models, GBT and DNN methods. This model predicts more accurately by a margin of 93 using different variables. Explain a system of intelligence, which operates based on thermal imaging to evaluate various needs of an irrigated system. Between other variables, thermal pictures are applied to measure and calculate leaf potential [20]. The main weakness of this study is that it is difficult to quantify soil moisture due to a complicated process of the analysis. It is proposed to apply the machine learning and IoT methods to manage smart irrigation considering a range of conditions, temperatures, surrounding features, and various soil conditions that can be taken into account when the requirements are calculated. Propose a technique that would utilize the WSN and other node sensors to maximize the quantity of water that crops require [21]. The crop is controlled by using mobile and online applications. Mobile and online applications are used to calculate future requirements and soil moisture. The IoT is used in water management that involves numerous sensors to detect different variables, such as soil quality, moisture, temperature, and rain sensors. The forecasting and operation of the output in this activity are carried out by both automatic and manual operations. Different methods of agricultural systems control and monitoring are suggested [22]. To evaluate the parameters and apply a decision pumping schedule, a number of energy models and IoT platforms are applied. Using smart control, propose a LoRa net architecture that can support a range of 5 km with low-energy consumption. All the data are transported to different locations with the help of the LoRa framework. Using similar and related tasks to forecast and label problems is referred to as transferable learning which a knowledge-storing problem is. Learning transfer applications are in farming, knowledge transfer, problems of categorization among others. It is used in agriculture to forecast plant diseases, identify species, transfer knowledge of plants to plant domains, classify plants and exchange information.

Multiple problems regarding transfer learning in agriculture. A knowledge-transfer process was developed to classify different types of crops and reduce the amount of time required to retrain and labeling. The authors of this paper reduced their time by a half of what they would have done otherwise. Transfer learning with an accuracy rate of 99.29 to distinguish between different species including weeds. Similarly, deep transfer learning as an approach to rubbish categorization is postulated. The authors used multiple datasets which enabled them to achieve 94 percent and 98 percent accuracy in their model. Bales detection method involves transfer of the source photos to target domain photos by deep transfer training and domain adaptation. A Pest, CNN, and transfer-learning model can be offered to detect the pests that destroy crops in the initial stage. Transfer learning improves pre-trained models. Propose a technique known as transfer learning and transfer a base model, defined by a number of samples or features, to a different place. Features in this structure are mapped between sites in time series feature irrigation mapping. To better train the model based on the soil moisture and transfer the soil condition in one soil to another where the two soils have dissimilar distributions indicate the use of transfer learning with IoT.

3. Materials and Methods

The proposed research postulates the prediction of a drip irrigation system with storage in the cloud, LSTM, ANFIS, k-nearest neighbors (KNN) and IoT sensors. To find out the nearest requirements of the water in the root and environs and ANFIS to predict scenarios in the short-term, the IoT equipment would need to receive the data about the surroundings. The LSTM predicts time-series information revisions to be used in future forecasting and correlated the demands at different times using a Spearman rank correlation technique. The key goal of the proposed study will be to predict the current and future requirements at different times, such as 3 h, 8 h, 12 h, 24 h, and 48 h. The basic plan of the planned work is presented in Figure 2. The top three major parts of the proposed architecture of the predictions model include initial-value predictions, the integrated predictions approach, and the transfer of learning. The first needs estimate is done with the help of the set of sensors. This proposed study predicts various irrigation requirements with the help of meteorological data and IoT sensors and helps to develop both short- and long-term predictions. The depiction of the proposed work flow is indicated in Figure 3. The workflow of the planned work is divided into four major parts, including Gathering information on multiple sources, forecast sharing of knowledge with nearby farms (transfer learning), nearest need forecasting, short-term prediction (ANFIS), long time-series prediction (LSTM), and short-term prediction (ANFIS). The proposed work involves four phases of working: storage and processing of information, long- and short-term prediction, and characteristic transference with and learning between one source of information and other ones. In order to come up with predictions, KNN-based algorithms are employed to collect information on the sensors. Information is collected with the use of weather prediction and past information. The processed data are applied on ANFIS to make short-term prediction. The short-run projection of the irrigation recommends water pumping. Long-term prediction is performed with the help of the Long Short-Term Memory (LSTM) approach, which, in case of need, may propose water pumping. In this analysis, one farm is utilized in the short and the long-term predictions. The characteristics are shifted to a different farm to enhance the forecasts once the site of farming requirement is established.

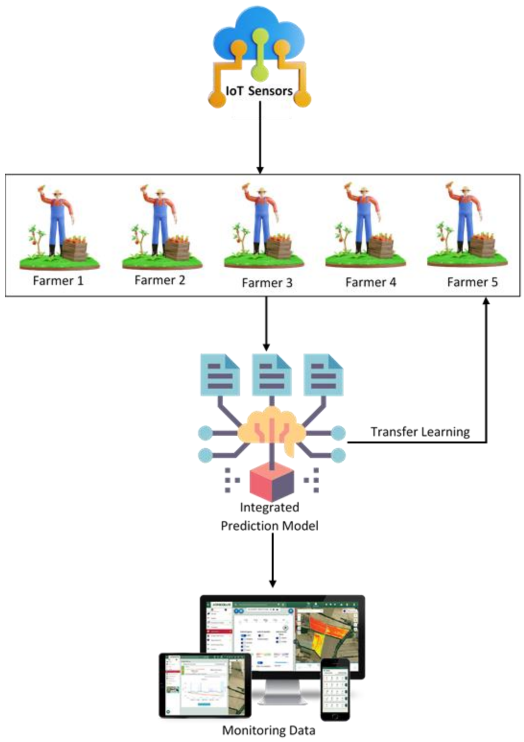


Figure 2: Fundamental layout of the planned work

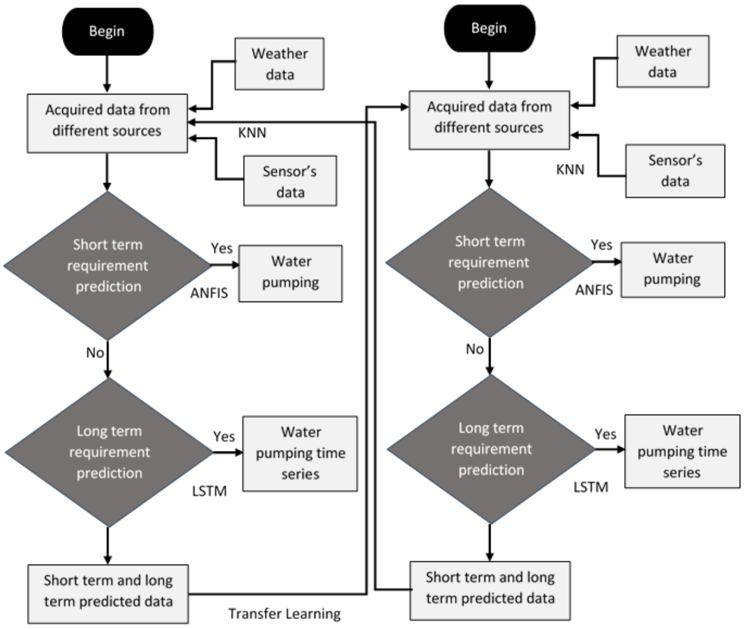


Figure 3. Workflow representation of proposed work

The processing phases consist of processing data, forecasting, and sharing information acquired by other farmers. To begin with, the meteorological and sensor data at the farm 1 are transferred to the cloud storage. First, the historical and purchased data are evaluated in order to project the needs. Processing of the information with the help of LSTM and ANFIS algorithms predicts the short-term (Sp) and the long-term (Lp) requirements. These techniques and the obtained information are used to project the short- and long-term initial demands. When information is received the first farm (X1) transfers the stored model weight to the nearest second farm to enhance prediction. A smart irrigation system that has transfer learning is composed of a set of characteristics collected by IoT sensors located within the fields. Temperature and moisture content of soil are important parameters which can be used in estimation of crop water requirements. These sensors measure the temperature and the moisture content of the soil at varying depths to ensure proper watering. Moreover, air temperature and humidity provide data on the environmental conditions which may influence the development of plants and speed up the rate of evaporation. In order to consider natural sources of water and the availability of energy sources that could influence the need to use artificial irrigation, the dataset also contains data about rainfall and sun rays. In order to streamline the decision-making process, wind speeds are added in order to consider the evaporative water loss. A classification variable named crop type is employed to determine the specific crops that are being grown because of the different amounts of water required by the different plants Report Word. Continuous variables of the amount irrigated and irrigated time, respectively, are used to monitor the amount of water used and durations of irrigation events. To give the additional context to the irrigation schedule, the weather condition is a category property, which describes the overall weather condition, which may be bright, overcast or rainy. A combination of such numerous data sources can provide the system with an efficient real-time monitoring and optimization of water consumption. This enables proper application of irrigation at appropriate time and place; reduced wastage and health of crops is improved.

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	Continuous	-10 to 50	Degrees Celsius (°C)

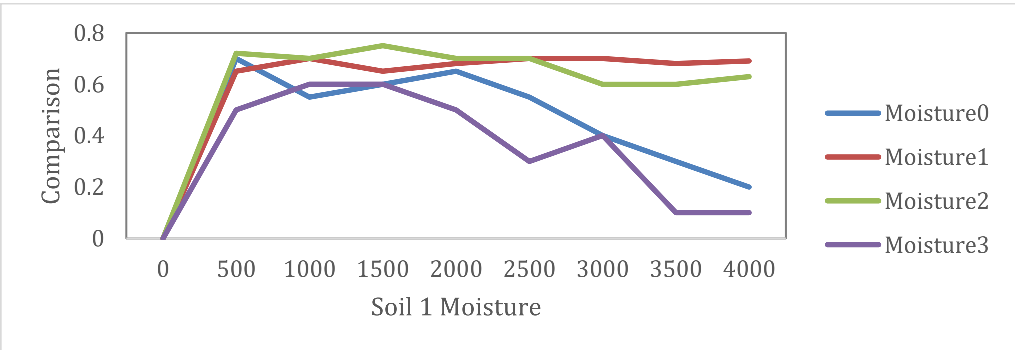
	measured near crops			
Humidity	Relative humidity in the air surrounding the crops	Continuous	0 to 100	Percentage (%)
Rainfall	Precipitation levels collected by rain gauge sensors	Continuous	0 to 200	Millimeters (mm)
Solar Radiation	Amount of solar energy received at the farm	Continuous	0 to 1500	Watts 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 training and testing

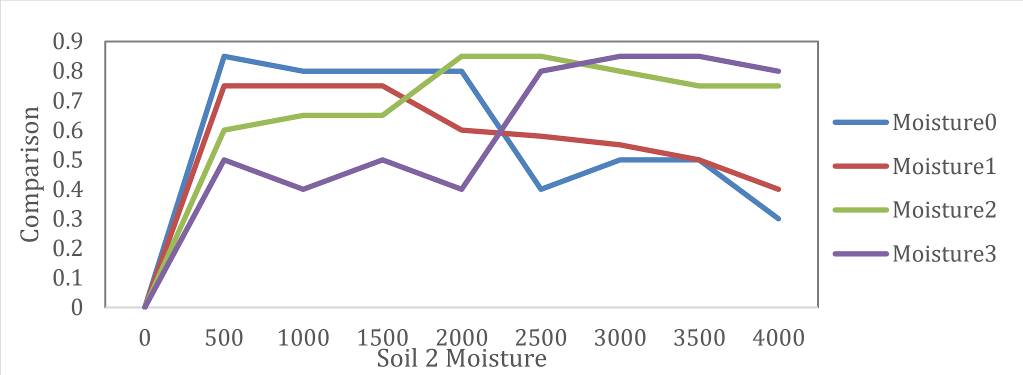
The analysis of datasets that were gathered in two different pots, which were referred to as Soil1 and Soil2. There are four soil moisture sensors at a distance of 10 cm between each other in both soils indicated in Table 1. These are the sensors that are marked by Moisture 0 (first layer) to Moisture 3. The periods did not subject the soils to irrigations and this can be used to further indicate the disparity. After every two to three minutes, there is a saving of information. 26,000 points of data have been collected altogether. Public data are available on the internet and additional illustrative 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 step that will be made to compare the two soils (Soil1 and Soil2) and bring out the differences is plotting each soil moisture level. (Figure 4). Whereas the first layer of Soil 1 loses water slowly, the first layer of Soil 2 can retain a lot of water. Whereas water passes through the second and the third level faster in Soil 1, it passes through the final layer slower in Soil 2. These clearly illustrate the difference in the rate of water uptake of the two pots. The level of absorption differs in the different layers of soils. Figure 4 presents the general workings of the proposed model. The IoT structure is being offered with four layers, namely, perception, implementation, manufacturing, and transport. The perception layer is referred to as physical layer implying that it can serve as an information gathering sensor. It can detect humidity of air, soil moisture and warmth. The transport layer provided the source of sensed data which was already gathered and transmitted to the computation layer over networks such as LAN, WiFi, 2G, and 3G. The analysis layer examines, stores and develops a vast amount of information that reaches the transport layer. It utilizes the techniques such as CC, databases alongside, and edge computing. The application layer aims at providing end users with application-specific services.

3.1 Sensor Data

Initially, the sensors receive input. This step involves gathering of information about the humidity, temperature, and moisture of the soil. Microcontroller is the actuator and sensors are elements of the perception layer. Transport and Processing levels give crop watering plans, proposals and supervision. The second step will involve the collection of information in the data centers to be evaluated after the initial data collection. The picture suggests the entire design study of the physical element utilized. All the parts are readily accessible on the market and of a fair price. Consequently, the device that is located in the real world can be produced easily. The layers of sensors in these implants are the illumination, humidity and temperature sensors. The Arduino board receives the digital signal of this sensor through the microcontroller set in the board and in a duration of thirty seconds the sensor value is transmitted to the information center through the model of GSM SIM808. An android-based application gave the customer an opportunity to visualize the results of the process of making choices exhaustively. The customer was then in control of the whole actuator, and made the valve to close and discharge water. HL-69 Soil Hygrometer Sensor applied moisture sensors of an HL-69 soil hygrometer to determine the humidity of the soil. The main objective of HL-69 soil hygrometer moisture sensor is to record the best reading when compared to the moisture sensor of another soil. This is done to monitor the real soil moisture content of plants planted in tunnel farms using the sensors. Due to the water content in the ground, the voltage current in the output of the sensor's changes. It has several ways in common with the HL-69 soil hygrometer sensors. Thereafter, the voltage produced reduces with the content of soil moisture; however, the voltage produced rises with the content of soil moisture that is lower. The analog signal provided by the hygrometer sensors that detect the soil moisture must also be converted to a digital version with the help of an Arduino board. These detectors have two plates that identify presence of water and an electrical board. On the circuit board place the LM393 comparator chip. It has two lights, including a red light that indicates the power indicators and a green light that indicates the output indicators of computerized changeover.

DHT22 sensor is an AM2302 DHT11 Sensor normal temperature-humidity detectors that measure the moisture and temperature of the air. DHT22 sensor is composed of the humidity sensor and the thermostat. It has some common aspects with the DHT22 sensor which include the following: DHT22 sensor is less costly. The DHT22 sensors have a voltage scale of [3, 5 V] as their input or output voltage range. At the change the maximum current use to be applied to information is 2.5 mA. The DHT22 sensor has four pins that have a distance of 0.1. The size of the body of DHT22 sensor is approximately 15.1 xtimes 25 xtimes 7.7 mm. The BH1750 is a common digital light sensor that is able to measure the number of light concentrations. The digital light sensor BH1750 can measure the smallest light traces and transform them into a 16-digit numerical figure, this is possible due to their calibration. Overall, smartphones can be exploited to adjust the brightness of the screen concerning the level of light. The BH1750 value of light intensity limit is [065, 535] lux (L). It also has several major BH1750 sensor features which are availed by: The BH1750FVI chip belongs to the BH1750 sensor. The power supply of the BH1750 sensor was [3.3 V -5 V]. The sensor is a BH1750, which contains on board a 16-bit analog-to-digital converter which converts the light sensing into 16-digits of numerical data.

Algorithm: Transfer Learning-Based Smart Irrigation System to Optimize Water Management in IoT-Based Agricultural Networks.

The algorithm takes advantage of transfer learning to conduct optimal irrigation scheduling using real time loT sensor data and pre-trained models to manage water efficiently. The step-by-step process is as described below and equations given to demonstrate important points about 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).

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

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

$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$ (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 8. The model is optimized for the new task by fine- tuning the parameters θ':

$\theta' = \theta + \Delta\theta$ (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):

$IR = f_\theta(I)$ (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 (Wwaste) and maximize irrigation efficiency (Eirrigation)

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

$W_{applied} = \{W_{required}\ if\ IR > \beta\ 0\ otherwise$ (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 was also used to measure values of humidity, root wetness, and ambient moisture. Moreover, the minimum and maximum water requirements of the farmers were also compiled. In order to identify the threshold values in both testing and training, maximum 50 L water required in a month and five- to seven-day intervals during the process of irrigation were collected. Some of the basic and fixed features considered when watering is shown in table 3. The proposed model is tested with the help of three sensor data, such as soil moisture, temperature, and humidity. The dataset has five labels of classes, namely extremely unnecessary, highly needed, needed and medium. Figure 5 defines the range of information in sensor information alongside the labels.

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.

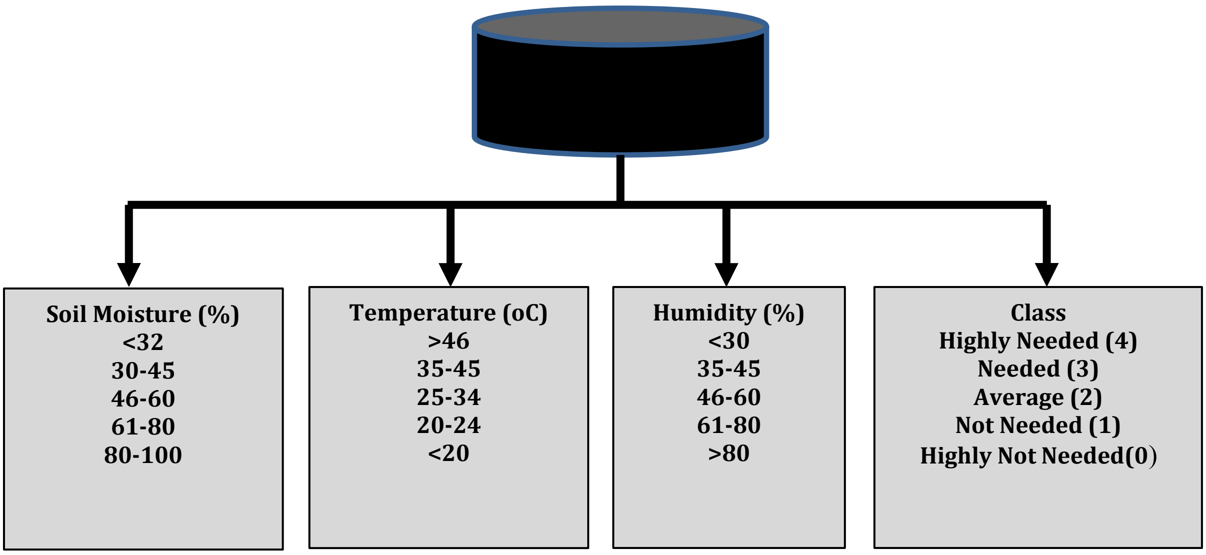


Figure 5: Dataset descriptions

Figure 6 shows a set of confusion matrices obtained with the use of the IoTML-SIS method in multiple test runs. On the initial execution run, 90 samples have been rated 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 classified as Highly Not Needed, 93 samples as Not Needed, 94 samples as Average, 93 samples as Needed, and 94 photos as Highly Needed by the IoTML-SIS technique on execution run-2.

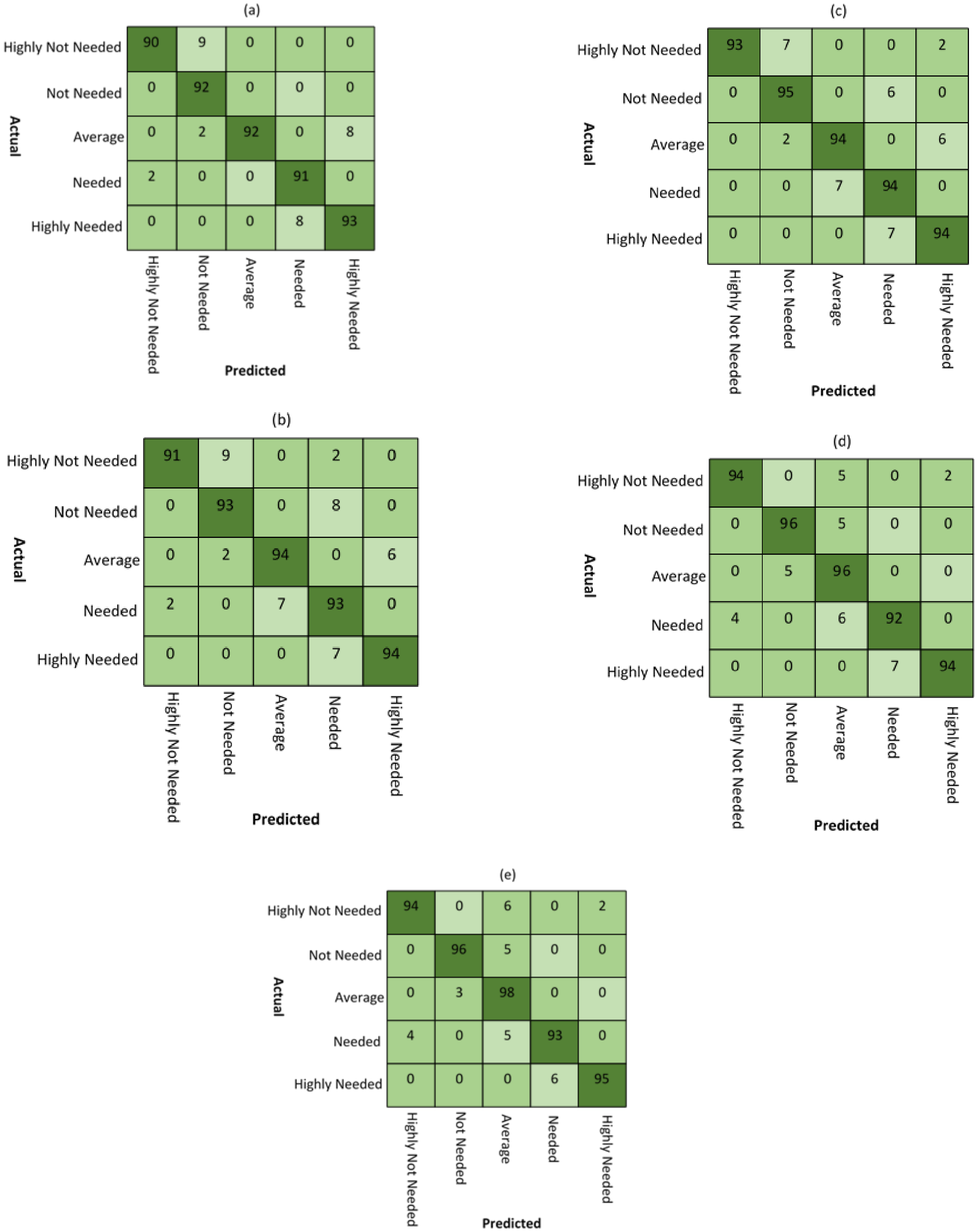


Figure 6: Confusion matrix of proposed IoTML-SIS method on different runs (a) Run-1, (b) Run-2, (c) Run-3, (d) Run-4, and (e) Run-5

The approach based on the use of IoTML-SIS finally assigned 93 samples to Highly Not Needed, 95 to Not Needed, 94 to Average, 94 to Needed and 94 to Highly Needed on execution run-3. Simultaneously, the IoTML-SIS approach has determined 94 Highly Not Needed, 96 Not Needed, 96 Average, 92 Needed and 94 photo examples on the execution run-4. Lastly, on implementation run-5, 94 examples were defined as

Highly Not Needed, 96 examples as Not Needed, 98 examples as Ordinary, 93 samples as Required and 95 photos as Highly Needed.

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Measures	Precision	Recall	Accuracy	F-Score	MCC
Run-1					
Highly Not Needed	0.990	0.901	0.979	0.943	0.931
Not Needed	0.894	0.921	0.963	0.907	0.884
Average	0.921	0.921	0.969	0.921	0.901
Needed	0.860	0.911	0.953	0.885	0.855
Highly Needed	0.931	0.931	0.973	0.931	0.914
Run-2					
Highly Not Needed	0.90	0.911	0.981	0.949	0.938
Not Needed	0.913	0.931	0.969	0.922	0.902
Average	0.941	0.941	0.977	0.941	0.926
Needed	0.870	0.931	0.959	0.900	0.874
Highly Needed	0.951	0.941	0.979	0.946	0.932
Run-3					
Highly Not Needed	1.00	0.931	0.987	0.965	0.957
Not Needed	0.932	0.951	0.977	0.942	0.927
Average	0.941	0.941	0.977	0.941	0.926
Needed	0.896	0.941	0.967	0.918	0.897
Highly Needed	0.941	0.941	0.977	0.941	0.926
Run-4					
Highly Not Needed	0.970	0.941	0.983	0.955	0.944
Not Needed	0.961	0.961	0.985	0.961	0.951
Average	0.882	0.961	0.967	0.920	0.900
Needed	0.940	0.921	0.973	0.930	0.913
Highly Needed	0.980	0.941	0.985	0.960	0.951
Run-5					
Highly Not Needed	0.970	0.941	0.983	0.955	0.944
Not Needed	0.981	0.961	0.989	0.971	0.963
Average	0.884	0.981	0.971	0.930	0.913
Needed	0.950	0.931	0.977	0.940	0.926
Highly Needed	0.991	0.951	0.989	0.970	0.963

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

Concerning the different parameters in Table 4, the thorough results analysis of the IoTML-SIS approach is carried out. Also, the results are examined using varying run counts. Based on the results of the trial, the IoTML-SIS methodology has resulted in positive outcomes in all the applications operated.

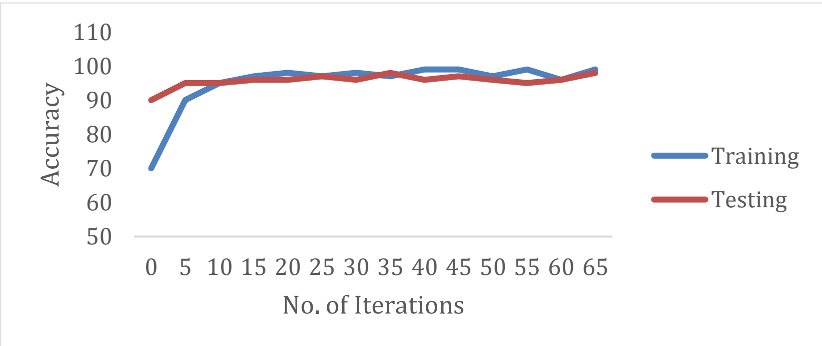
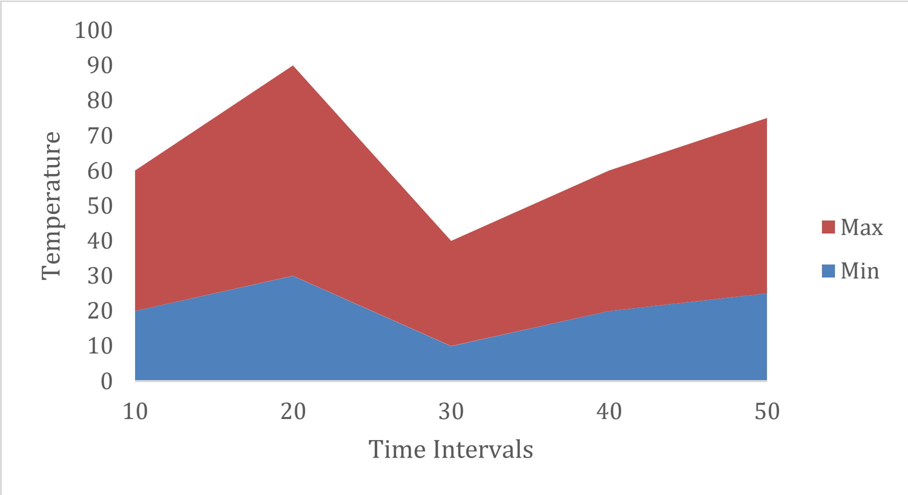
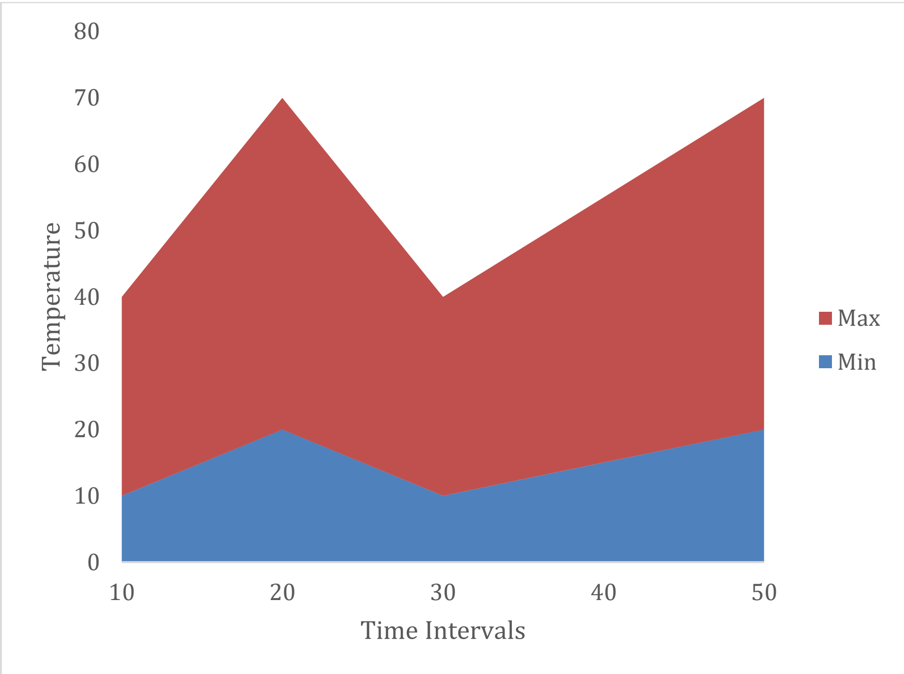


Figure 7. Training and testing accuracy of prediction.

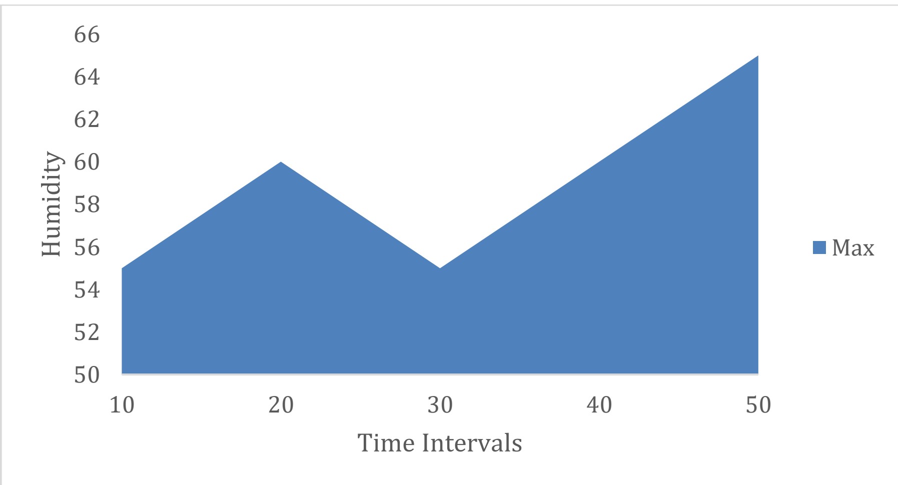
In the first step, ANFIS and LSTM were merged to predict the basic need of prediction education, validation and correctness of testing. Figure 7 presents the training process and the accuracy of the testing of 100 nodes of value and 97 repetitions.



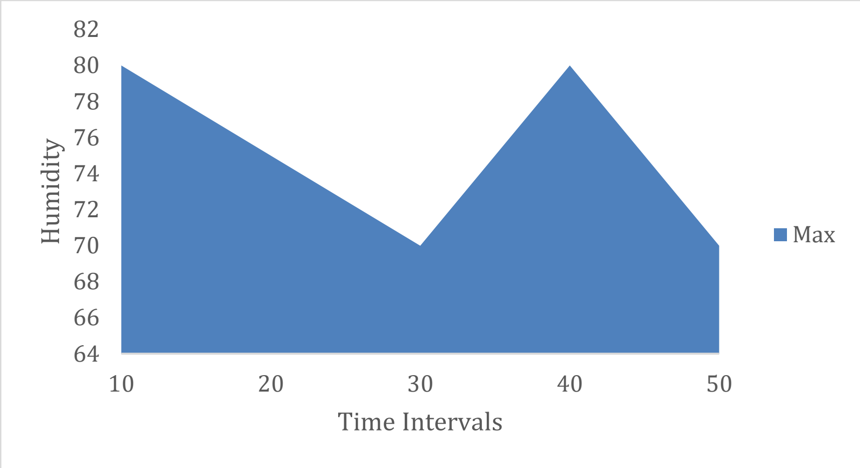
A. March Month Min-Max Temperature



B. July Month Min-Max Temperature



C. March Max Humidity



D. July Max Humidity

The Figure 8 shows the requirements of the shortest-term forecast. The month-wise relative humidity and temperature are the two main requirements of both short- and long-term predictions like the humidity and temperature projections of 8, 16, 24, 32 and 48 hours ahead. The humidity, lowest and highest temperatures were recorded the entire 48 hours starting at 8 am, as shown in the graphic. The knowledge that Farmer 1 learns is applied to retrain the farmer-2 models to do better prediction using the corrections made by the information of farmer-1. Transfer learning is implemented on the information collected in the original model on farm.

6. CONCLUSION

To conclude, one of the most effective methods of optimizing water management in intelligent agricultural networks posed by IoT is the development of a smart irrigation system having transferred learning. By using the pre-trained models of the adjacent areas and adapting them to the environment, the system allows increasing the precision of irrigation schedules, reducing excessive water loss. The irrigation decisions are dynamic and specific to the needs of the particular crop and environment based on real-time sensor data of soil moisture, temperature, humidity, and meteorological variables. This plan addresses significant problems of water scarcity and resource sustainability besides the improvement of the health and production of crops. The ability to keep learning with the changing environmental conditions over time enables the system to adapt to it making it a scalable and useful tool in modern day agriculture. Everything said and done, combining transfer learning with IoT in smart irrigation systems is a legitimate way to achieve sustainable water consumption and increase agricultural production.

Conflict of Interest Statement

There is no conflict of interest

Data Availability Statement

Data not available due to commercial restrictions

Ethical Approval

Not applicable

Funding

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