Empowering Smart Irrigation : Predictive Soil Moisture Modeling for IoT - Driven Solutions

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ABSTRACT
In recent years, the fields of transportation, environment, business, and agriculture have witnessed revolutionary advancements with the introduction of Internet of Things. Agriculture, in particular, has benefited from the optimization of irrigation water usage through IoT and machine learning technologies. This integration has enabled the development of smart irrigation systems that can efficiently manage and optimize water usage based on real-time data and predictive analytics. The paper describes the use of machine learning strategies for refining irrigation practices through the Fore tend of future soil water content(SWC) within an Internet of Things-enabled smart irrigation system. Data gathered from sensors in the field (which measure air temperature, humidity, SWC, soil temperature) company with Climate pre prophecy information obtained from the cyberspace (webapp) are employed to forecast forthcoming soil water content levels. For the purpose of Measure forthcoming soil water content, a variety of machine learning algorithms are examined, and the GBRTM findings are rather positive. The advised methods may represent an important area of research for irrigation water optimization.

Introduction

According to research by the United Nations [1], the current global population of 8.1 billion people is expected to rise to 9.2 billion by 2040, 9.03 to 10.05 billion by 2060, and an astounding 11.2 billion by 2100, representing an annual growth of almost 83 million people. The critical problem of freshwater shortage is made worse by this worrying trend, which is exacerbated by population increase and inefficient water use habits. Nearly eighty percent of freshwater use in our nation(India), which deals with water scarcity, comes from agriculture. The increasing inefficiency of traditional irrigation systems has led to a need for precision agriculture and intelligent irrigation strategies to optimize water efficiency. Solutions based on IoT and MLM offers a lot of promise to enhance the agricultural environment.

The applications span diverse realms, such as intelligent irrigation, surveillance and regulation, agricultural product and resource management, as well as agricultural business administration [2]. IoT technology involves linking objects tailored for specific applications (Enabled with Sensing element and/or actuators) to the Network, and intellectual analyzing the data they generate to derive valuable insights. ML, a subset of AI, empowers machines to autonomously make decisions. In the modern era, smart irrigation techniques have become a focal point of interest, sparking innovation in irrigation systems that harness the power of technologies like WSN, IoT, and AI/ML [3]. A electronic structure board equipped with sensors to detect soil water content, temperature through thermocouples, and an active RFID transmitter has been proposed as part of a smart sensor system for irrigation scheduling.[4],[5] A groundbreaking advancement unveils an automated irrigation system seamlessly blending [6 -7] Wireless Sensor Network (WSN) technology with WiFi and mobile data (GPRS) communication modules, revolutionizing agricultural water management[8]. Various machine learning (ML) methodologies were explored to create intelligent models capable of predicting weekly irrigation schedules, leveraging the expertise of agronomists[9]. An avant-garde present time spontaneous With full irrigation framework, employing Cloud of Things(CoT) technology, was introduced. Specifically designed for cotton crops, it operates based on canopy temperature thresholds, exhibiting notable advancements in agricultural yield compared to conventional methods[10]. In Florida, a groundbreaking irrigation strategy integrates Evapotranspiration (ET), encompassing both land evaporation and leaf transpiration. This innovative system utilizes automated tensiometers to tailor irrigation schedules for papaya cultivation, drawing insights from historical weather patterns. By harnessing ET calculations, this approach revolutionizes irrigation management, achieving significant water savings compared to conventional techniques [11].

An innovative approach to irrigation management by integrating IoT technology with Machine Learning (ML) Goap et al. [12,13]. Their system offers automated soil moisture forecasting for upcoming days, utilizing field sensor data and weather fore tend. This predictive capability revolutionizes water resource management in agriculture. However, the intricate application of ML techniques for Predicted Soil Water Content remains an exciting and challenging frontier in research.

This research delves into novel machine learning methodologies to project soil moisture levels for upcoming days. By synthesizing data from field-deployed sensors capturing current soil moisture, temperature, [13] environmental conditions, and coupling it with weather forecasts, it offers a distinctive approach to anticipate future soil moisture dynamics. The foretend is made using a variety of methods associated with ML, including Gradient Boosted Regression Tree Method (GBRTM), Method of Random Forest Regression (MRFR), and Method of Elastic Net Regression (MENR), and the findings are rather promising. The foot steps followed this Paper is, The system designing buildings and the setup for tests utilized in the work are covered in section II. The Emerging of Foretending Soil Water Content using various MLM approaches are shown in Section III. The fourth portion of the article finishes.

Intellectual Irrigation System : Demonstration Setup

In alignment with the "per drop more crop" mantra, innovative smart irrigation systems pursue the precise allocation of water resources for irrigation purposes. Ineffective water management practices and suboptimal irrigation techniques not only squander water but also jeopardize crop yield potential. In Company with assist in making decisions regarding crop and plant watering in real time, IoT-based smart irrigation systems are able to retrieve critical physical characteristics from the agricultural field. With their ability to make intelligent, independent decisions, MLM-based solutions can enhance the system. The method used in this paper is based on the foretend of SWC(Soil Water Content.)

This part covers the experimental system architecture, provides a brief overview of the MLMethods utilized in the Demonstration, and describes the specifics of the Demonstration setup. It also talks about the MLMethods applied in the trial.

1. Handward And System Architechture

In Fig. 1, the experimental configuration showcases the setup employed for this study. Crafted with the combined power of Raspberry Pi and Arduino Uno platforms, the sensor node is adept at calculative, Extracting, and Direct, seamlessly integrating sensors for of [14] SWC, soil_temperature, humidity, and air_temperature. Additionally, it incorporates a relay switch to regulate the Di-hydrogen Monoxide regulating machinery or pump, while data exchange between the field-deployed sensor node and the Cloud is facilitated through the utilization of web services. Additionally, internet-derived weather forecasts are harnessed to project SWC levels for the upcoming days. Figure 2 visually presents the sensor node in use.

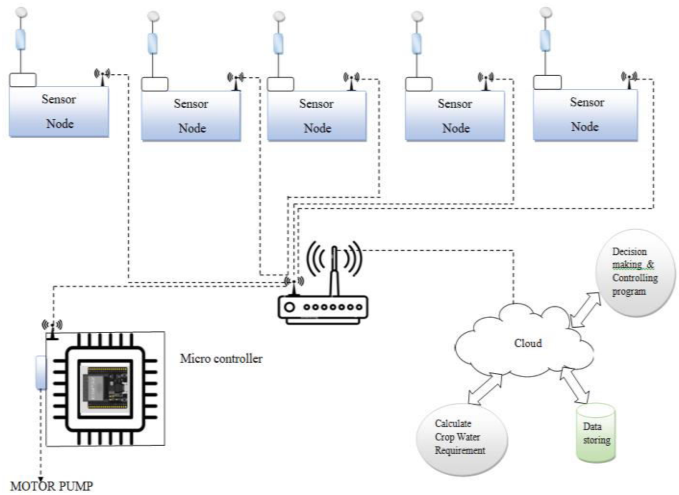

Fig. 1. System Architecture

Fig. 2. Image of the connected devices

Following this introduction, the section delineates the distinct Machine_Learning (ML) methodologies applied in the research.

- MENR – Method of ElasticNet Regression

Elastic Net emerges as a distinct regularization technique in regression, harmonizing the penalty traits of ridge and lasso regression. Its core objective lies in minimizing the loss function through a strategic fusion of these penalties, culminating in a unique convex amalgamation of ridge and lasso regression methodologies.

- MRFR- Method of Random Forest Regressor

Random Forest Regression is an ensemble learning method designed for both regression and classification tasks. It addresses the tendency of decision trees to over fit their training data [13]. This technique operates by aggregating foretend from a sequence of base models, akin to an additive model. In essence, it combines decisions from multiple base models to make foretends effectively.

$g(x)=f0(x)+f1(x)+f2(x)+f_3(x)+f_4(x)\ldots\ldots$

In this formulation, the ease Fundamental models are denoted as fi, while the last phase of model is denoted as g. These Foundative classifiers typically represent straightforward decision trees. Random Forest Regression employs multiple models, known as model ensembling, [13] to enhance predictive accuracy. Each base model is constructed independently within the random forest framework, utilizing distinct subsamples of the data.

- GBRTM - Gradient Boosting Regression Trees Method

Gradient boosting stands as a resilient non Characteristic statistical approach applicable to classification and regression scenarios. It assembles a Foretend Sample comprising weak predictive entities, typically decision trees. This method constructs models incrementally, allowing for optimization of diverse differentiable loss functions. Gradient Boosting orchestrates an summative model formation through a result, stage-wise process. At every phase, a regression tree is tailored to the negative gradient of the designated loss function, with subsequent models endeavoring to rectify errors introduced by prior iterations.

1. Model preparation setting

Sensor nodes placed around the field collected data on an hourly basis for 37 days straight. The analysis included a daily average of the minimum recorded SWC value for each day, as well as the soil temperature, humidity, and air temperature. Additionally, the information is derived from a weather foretend website to estimate the SWC content of the next several days.

The data is moved to the cloud. These ML:Algorithms are used to the obtained data for analysis. Pandas, Matplotlib, and Scikit-learn are some of the Python libraries used for the article. Soil temperature prognosis involves the application of Method of Elastic Net Regression (MENR) and Method of Random Forest Regression (MRFR). Their results underwent a thorough comparison, with the superior method proceeding to subsequent analysis. Utilizing the forecasted soil temperature as a pivotal parameter, Foretend for SWC were made. A comprehensive evaluation ensued, featuring MENR, MRFR, and Gradient Boosted Regression Trees Method (GBRTM). GBRTM implementation comprised 1000 boosting stages (no_estimators), a maximum node depth set at 4 (maxi_depth), Huber loss function integration, a minimum split requirement of 2 samples for internal nodes (mini_test_split), and a understanding rate of 0.01. In Method of Random Forest Regression (MRFR), the Counting of boosting phases (no_ evaluaters) is set to 210, and the peak counting of nodes (maxi_depth) is restricted to 4. For EN, the alpha value is 0.1, and the l1_ratio is determined as 10 through cross-validation using the scikit:learn library in Python. The forecasted SWC levels for future days offer valuable insights for efficient water irrigation scheduling. Furthermore, a web service could be developed to manage the aqua motor, toggling it ON/OFF based on predefined thresholds of SWC values Discussion And Outcomes Of SMP Using Method Of ML.

As was previously said, the pre prophecy the field's soil water content for the next several days can be useful in providing and organizing irrigation that is both efficient and effective. Online weather forecast data can be useful in obtaining environmental elements and circumstances (such as temperature, humidity) over the next several days. The information obtained from the sensors may be used to build ML-based foretend models, which can then be used to estimate SWC levels for the next few days depending on the weather and the surrounding circumstances. This research provides a straightforward approach for predicting the SWC levels over the following several days. Considering air temperature and humidity, among other weather-related forecasts.

2. Pseudocode for Foretend the Soil Water Content(SWC) Analysis Using GBRTM

```
Step 1: Load and Preprocess Historical Data

LOAD historical_data
PREPROCESS historical_data
HANDLE missing_values in historical_data
NORMALIZE historical_data
Split historical_data into training_set (70%) and validation_set (30%)

Step 2: Train Models Using Historical Data

FUNCTION train_temperature_only_model(training_set)
SET features = training_set['Temperature']
SET target = training_set[SWC]
INITIALIZE GBRTM model with parameters
TRAIN model GBRTM (temperature_data, temperature_target)
FUNCTION train_SWC_only_model(training_set)
SET features = training_set['SWC ']
SET target = training_set[SWC']
INITIALIZE GBRTM model with parameters
TRAIN GBRTM (soil_moisture_data, soil_moisture_target)

FUNCTION train_combined_model(training_set)
SET features = training_set[['Temperature', 'SWC']]
SET target = training_set[' SWC']
INITIALIZE GBRTM model with parameters
TRAIN GBRTM (combined_data, combined_target)

Step 3: Collect Real-Time Sensor Data

FUNCTION collect_sensor_data()
current_temperature = GET current temperature from sensor
current_ SWC = GET current SWC from sensor
current_humidity = GET current humidity from sensor
RETURN (current_temperature, current_SWC, current_humidity)

Step 4: Prepare Data for Prediction

FUNCTION prepare_prediction_data(historical_data, current_sensor_data)
last_temperature = GET last_temperature from historical_data
last_SWC = GET last_SWC from historical_data

Create prediction datasets
temperature_only_dataset = [last_temperature, current_ temperature-
```

```
_sensor_data[0]]
SWC_only_dataset = [last_soil_moisture]                    combined_dataset =
[last_temperature, last_SWC, current_sensor_data[0], current_sensor_data[2]]
RETURN (temperature_only_dataset, SWC_only_dataset, combined_dataset)

Step 5: Generate Predictions Using Real-Time Data

FUNCTION            generate_predictions(models,            prediction_data)
temperature_only_model = models['temperature_only']
SWC_only_model = models['SWC']
combined_model = models['combined']

Foretend                         _temperature_only                         =
temperature_only_model.PREDICT(prediction_data[0])
predicted_SWC_only = SWC_only_model.PREDICT(prediction_data[1])
predicted_combined = combined_model.PREDICT(prediction_data[2])

 RETURN (predicted_temperature_only, predicted_SWC, predicted_combined)

Step 6: Evaluate Model Performance
FUNCTION evaluate_predictions(actual_SWC, predictions)
metrics = {}
metrics['temperature_only'] = CALCULATE RMSE(actual_SWC, predictions[0])
metrics['SWC_only'] = CALCULATE RMSE(actual_SWC, predictions[1])
metrics['combined'] = CALCULATE RMSE(actual_SWC, predictions[2])
RETURN metrics
```

Results:

A. Foretend the Soil Water Content(SWC)

Table I presents Foretend of SWC for the next several days based on GBRTM, without account the soil temperature.

Table 1 Predictied SWC Using GBRTM

DATE	Actual SWC	Estimated SWC with GBRTM
4/25/2024	31.46	30.69
4/26/2024	2.93	6.46
4/27/2024	9.23	10.94
4/28/2024	11.61	12.33
4/29/2024	12.63	11.25
4/30/2024	11.59	12.28

B. Foretend the Soil_Tempature

Table II showcases the outcomes of the test set, where the forecasting of soil temperature in the field for the forthcoming days was conducted using two ML techniques, namely MRFR and MENR.

Table 2 Resembles Of Exact_Soil_Temparature And Foretend_Soil_Temperature(FST) Using MENR & MRFR

DATE	Actual ST	FST using MRFR	FST using MENR
4/25/2024	20.74	20.45	19.17
4/26/2024	18.35	19.34	20.15
4/27/2024	22.30	20.58	21.35
4/28/2024	20.65	20.84	19.99
4/29/2024	18.81	20.99	21.14
4/30/2024	22.31	23.47	20.36

Table III compares the R_squared values of the used ML approaches in order to determine their accuracy. The outcomes demonstrate that when compared to the MENR, the MRFR performs better.

Table 3 Resembles Of MSE Based On Foretend Algorithm

Parameter	FST using MRFR	FST using MENR
Mean Squared Error	2.58	3.4

C. SWC Foretend with Soil_Temperature

This section pre prophecy the field's SWC for the upcoming particular days based on the air temperature and humidity, as well as the projected soil temperature. It examines the results of different machine learning techniques, including MENR, MRFR, and GBRTM. Table IV shows the SWC forecast findings for the future days.

Table 4 Resembles Of Exact SWC And PSWC (Predicted Soil Water Content)

DATE	SWC	PSWC using GBRTM	PSWC using MRFR	PSWC using MENR
4/25/2024	31.45	30.65	24.71	18.46
4/26/2024	3.93	7.02	7.92	7.43
4/27/2024	9.23	9.71	9.91	7.82
4/28/2024	11.60	13.21	16.01	14.87
4/29/2024	12.63	12.78	10.20	13.61
4/30/2024	11.59	12.28	12.45	13.75

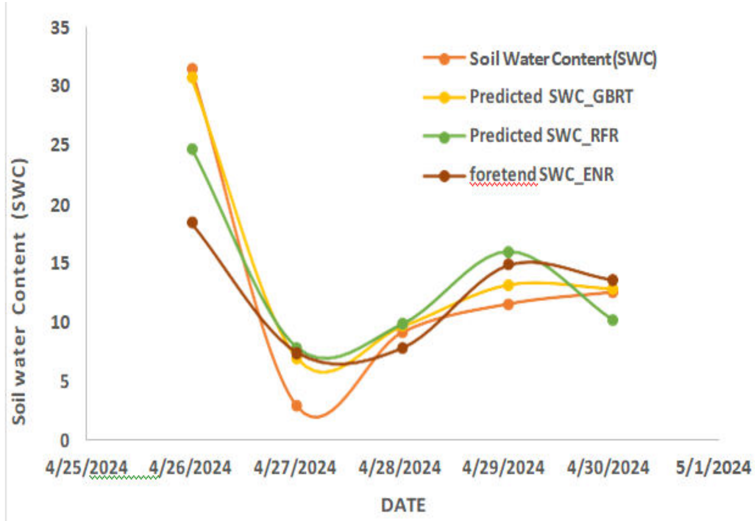

Fig. 3 depicts the Foretend SWC for the future days using several ML approaches.

Table 5 Squared Error Of PSWC Using MENR , GBRTM And MRFR Resembles Of R Squared And Mean

Parameter	PSWC using GBRTM	PSWC Using MRFR	PSWC using MENR
MSE(Mean Squared Error)	4.03	19.16	40.49
Accuracy (R squared)	0.93	0.76	0.54

In the analysis presented in Table V, the effectiveness of different ML:Algorithms is evaluated based on their R-squared and Mean Squared Error values. Notably, the results highlight GBRT's superior performance, especially when factoring in temperature as a parameter for soil water content estimation .

Table 6 Working Result Resembles Based On R_Squared And MSE

Parameter	PSWC using ST	PSWC not using ST
MSE	4.03	5.76
Accuracy_ R_squared	0.93	0.91

Conclusion :

The freshwater resources that are essential to human survival are scarce and valuable resources on our planet. Much freshwater is used in the agricultural industry. Numerous nations have been seen to not make the best use of their water resources for irrigation. In addition to wasting water, it may result in a reduced output of agricultural products. This study presents a strategy based on IoT and ML to improve irrigation water utilization. ML algorithms are used to anticipate the Soil water content in the following days using information collected by field sensors and weather Foretends.

This forecasting is essential for optimizing water usage in irrigation, as SWC greatly influences the most effective irrigation practices. The outcomes are examined using plenty of ML solutions, and the GBRT-based approach yields extremely positive findings. Utilizing such techniques could maximize the efficient use of scarce freshwater resources for irrigation in countries facing water stress, such as India, thereby providing vital assistance in alleviating pressing water scarcity challenges.

(ST: Soil_Temperature , FST : Foretend Soil_Temperature , MSE: Mean_Squared_Error)

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