A SMART IRRIGATION SYSTEM BASED ON MACHINE LEARNING FOR EFFICIENT PLANT DEVELOPMENT

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ABSTRACT

Adavnced automation skills are transforming many sectors of human endeavour, including transportation, the environment, business, and agriculture. Many countries utilise an excessive quantity of already limited fresh water resources. This work demonstrates how to apply ML algorithms in an automation network based irrigation structure to predict soil moisture in order to optimise irrigation water use. Field data from installed sensors (humidity,moisture, temperature ,radiation) and virtual climate prediction information are used to forecast future soil moisture. The efficiency of numerous ML approaches for predicting soil moisture is investigated, and the GBRT results are encouraging in both accuracy and prediction. The approaches proposed can be an important area of research for maximising irrigation water usage.

1. Introduction

One of the most pressing concerns confronting many nations throughout the world is a scarcity of fresh water, which is worsening with time as a consequence of expanding population and inefficient fresh water consumption [1]. Water is used extensively in agricultural irrigation operations. In India, which has a water scarcity, the agriculture sector consumes over 80% of the country's fresh water resources. Precision agriculture need smart irrigation since traditional irrigation systems waste water [2].

The usage of information and communication technology (ICT) in rural areas has expanded dramatically in recent years [3]. Machine learning , a branch of AI, allows computers to make independent decisionsc[4].

A work provided a sophisticated approach of sensor collection for irrigation scheduling. A circuit integration setup is supplied with thermocouple, active RFID (Radio Frequency Identification), and soil moisture (M_s) sensors in this system [5]. Another work introduced an autonomous smart watering technique. In its smartphone irrigation sensor, this device employs necessary sensor nodes. One research work utilised agronomist information to build a smart model that could anticipate the weekly irrigation plan using a range of machine learning (ML) methodologies [6], [7].

Evapotranspiration (ET), which accounts for both leaf transpiration and groundwater evaporation, is a critical component of irrigation The ET was intended using historical weather data to water papaya plants. In comparison to more traditional ways, irrigation systems based on ET used less water [8]. The system takes use of weather data from weather prediction websites as well real word information by sensors deployed in a land. Future soil moisture projections might be very useful for optimal water supply and irrigation use [9].

This work investigates machine learning approaches for forecasting moisture in the next days using field sensor data and weather prediction. The prediction results using a range of machine learning algorithms, including

- Gradient Boosted Regression Tree (GBRT)
- Random Forest Regression (RFR)
- Multiple Linear Regression (MLR), and
- Elastic Net Regression (ENR), are highly favourable [10].

2. A creative irrigation system installation

Smart irrigation systems aim to maximise water use during irrigation in order to yield more crop per drop.

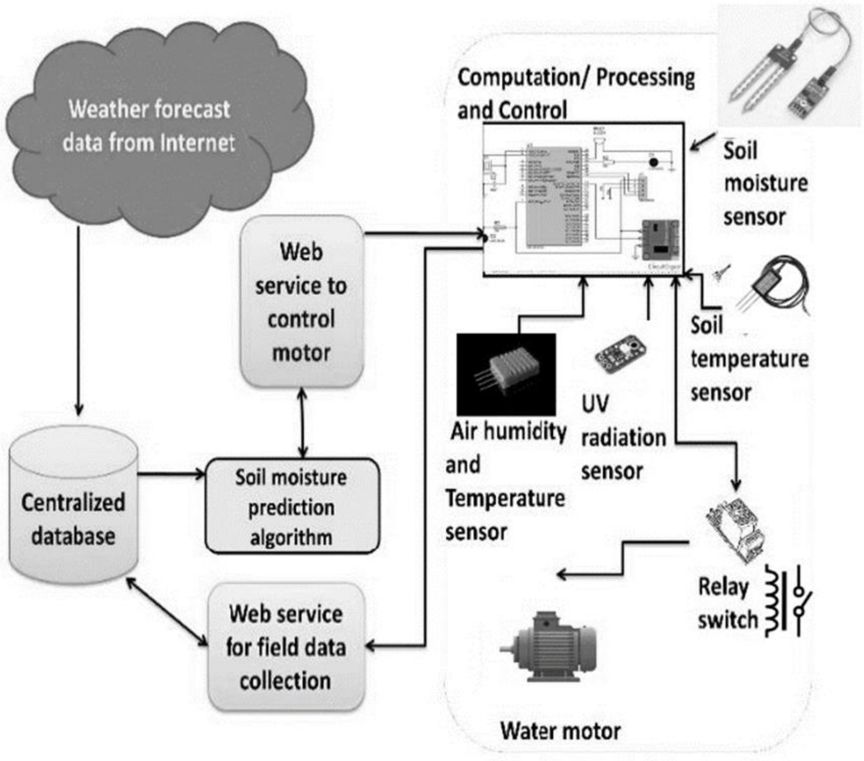

Figure 1. System structure

Inefficient irrigation practises and water resource mismanagement waste water and/or lower agricultural production. ML-based techniques to intelligent autonomous decision making might be used to improve the system. Thermal imaging and the soil moisture of the field are the two basic approaches for calculating the optimal watering demands. This research employs a method for forecasting soil moisture. System structure is presented in the figure 1.

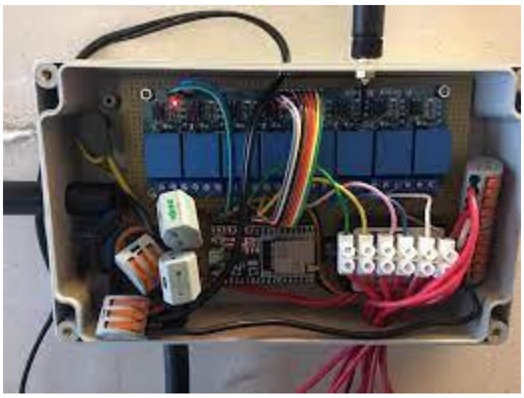

Figure 2. Setup of the proposed system

This chapter covers the setup utilised for the test in addition to giving description of the methods used in the experimentation and information on the experimental setup. The demonstration setup utilised in the study is shown in Fig. 2. The Raspberry Pi and Arduino

Uno computer are used in the sensor node. It contains sensors that measure soil moisture, temperature difference, air humidity, air temperature, and ultraviolet) radiation, as well as a relay switch that controls a water pump or motor. Data is sent between the centralised database and the detection devices using web services.

3. Simulated Environment

The facts are transmitted to the local cloud computer through a web. The mentioned machine learning techniques are subsequently applied to the freshly received data. Scikit-learn, Pandas, and Matplotlib are Python-based analytic tools. ENR and MLR are used to forecast soil temperature (T_s). The results of the two techniques have been compared, and the one with the better results will be employed in the future. The expected T_s is used as a metric to forecast M_s. ENR, RFR, and GBRT have all been compared. There are 1000 boosting stages (n estimators) in GBRT, a lowest number of examples mandatory to divide an interior node, and a wisdom rate of 0.015. There are 200 boosting steps (n estimators) and a maximum of 4 nodes in RFR (max depth). The Elastic Net has an alpha value of 0.11 and a 12 ratio of 20 built on fractious proof using the scikit-type-learn package in Python programming. Using the expected M_s values for the following several days, effective water irrigation scheduling may be done. In addition, a web service might be developed to regulator the motor and shift, turning them on/off when the M_s value reaches a specified limit.

4. Result and Discussion

As previously stated, forecasting a field's soil moisture over the following several days might help with planning and providing for adequate watering. Online weather prediction information may help you learn about the environmental conditions and elements that will affect you in the next days. Machine learning-dependent estimation models may be developed using sensor data gathered over time, and the models can be used to forecast soil moisture for the next few days based on projected weather/environmental conditions. This study discusses two strategies for predicting soil moisture. The predicted soil temperature, together with other weather forecasted parameters, is utilised in the first approach to estimate the soil moisture for the following several days (air temperature, humidity, and UV). The second approach for anticipating soil moisture takes soil temperature into account. Two machine learning techniques, they are, MLR and ENRR, are used to facts composed completed time to anticipate the field's soil temperature for the following days. Table 1 displays last set outcome.

Date	Soil temperature actual	ENR Predicted temperature	MLR Predicted temperature
Day 1	20.33	20.78	21.33
Day 2	21.22	21.89	22.22
Day 3	17.31	17.22	18.78
Day 4	18.22	19.72	18.98
Day 5	19.33	18.56	18.6

Table 1. Soil temperature comparison

Figure 3 shows the results of the soil temperature forecast.

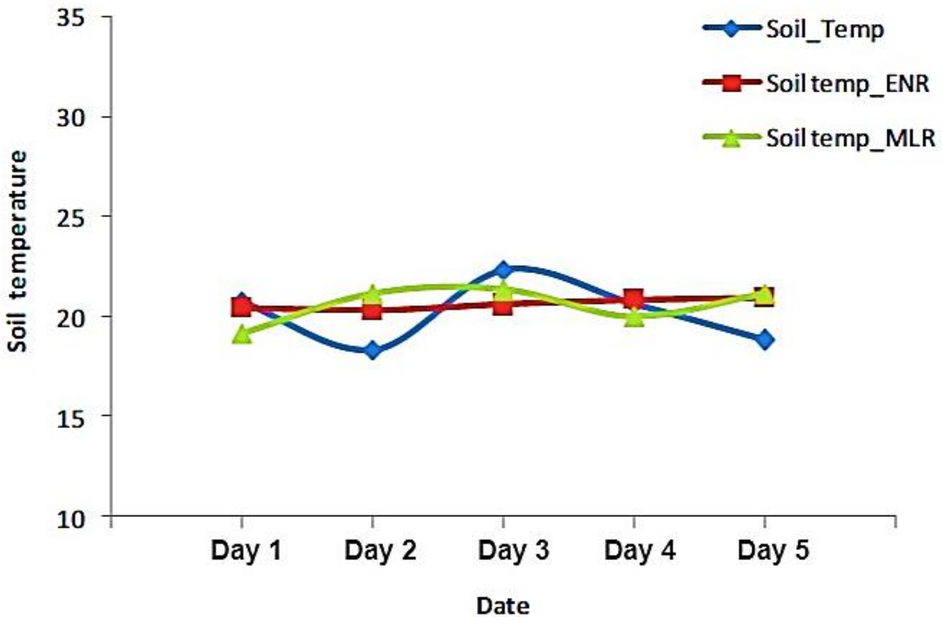

Figure 3. Soil temperature changes in date wise

Table 2 compares the R-squared values of the applicable machine learning algorithms to measure their accuracy. The results show that the ENR outperforms the MLR.

Table 2. Temperature mean error

Parameter	ENR Predicted temperature	MLR Predicted temperature
Mean error (squared)	2.67	3.43

Based on the measuring parameters , this section estimates the M_s for the next few days and provides the projected soil temperature. It investigates the outcomes of many approaches, including the mentioned three approaches. Table 3 shows the results of the M_s prediction for the next several days.

Table 3. Moisture comparison

Date	M_s actual	GBRT-Forecast moisture	ENR- Forecast moisture	RFR - Forecast moisture
Day 1	3.33	4.38	2.78	2.98
Day 2	7.90	8.09	6.89	7.22
Day 3	12.31	12.99	11.27	11.88
Day 4	10.29	10.56	11.72	10.98
Day 5	9.63	10.98	10.63	9.45

Figure 4 shows the expectation outcomes for M_s for the next several days based on the various methods.

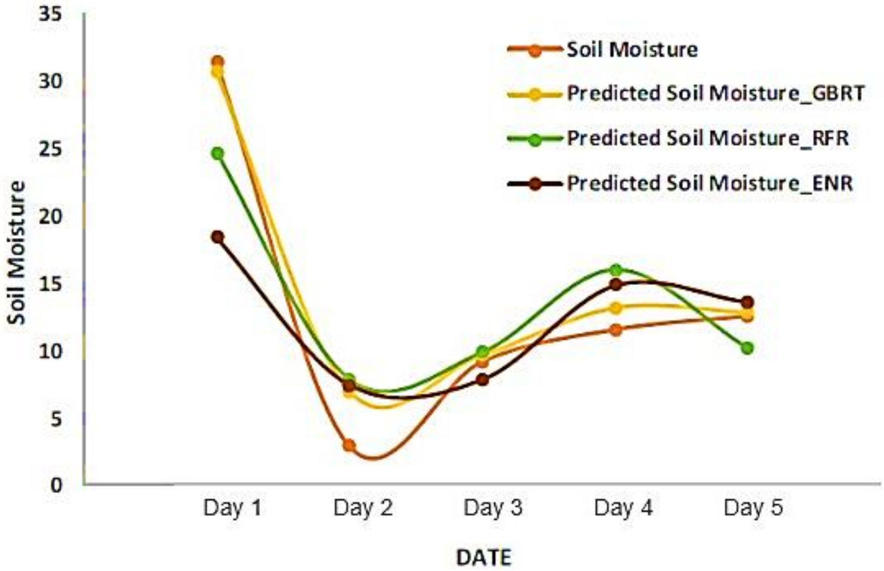

Figure 4. Soil moisture changes in date wise

Table 4 compares the R^2 accuracy and Mean Squared Error of the procedures used to measure their accuracy. The findings show that the GBRT outperforms the RFR and ENR.

Table 4. Moisture error

Parameter	GBRT Predicted moisture	ENR Predicted moisture	RFR Predicted moisture
Mean error (squared)	5.22	18.33	38.22
Accuracy needed (R^2)	0.93	0.68	0.89

The GBRT is used to predict soil moisture for the next several days without taking soil temperature into consideration. Table VI summarises the results.

Table 5. Soil moisture comparison with GBRT

Date	Soil moisture actual	GBRT Predicted moisture
Day 1	3.33	4.67
Day 2	7.90	9.98
Day 3	12.31	11.99
Day 4	10.29	10.96
Day 5	9.63	11.11

Figure 5 shows the results of the M_s forecast not considering T_s.

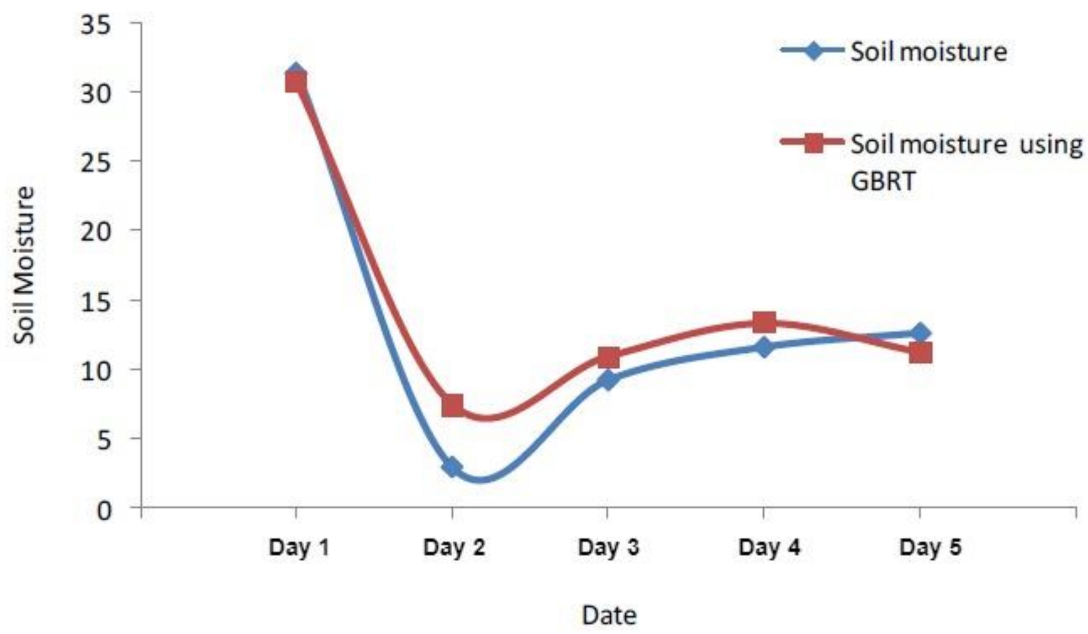

Figure 5. Soil moisture with respect to GBRT

Table 6 relates the R^2 accuracy values and Mean Squared Error of the relevant machine learning algorithms to estimate their accuracy. The results revealed that the GBRT works better-quality when temperature (T) is considered as the a part of criteria used to assess soil moisture.

Table 6. Soil moisture with and without considering soil temperature

Parameter	Soil moisture 1	Soil moisture 2
Mean error (squared)	4.22	5.33
Accuracy needed (R^2)	0.95	0.97

5. Conclusion

Humanity is dependent on fresh water, which is both important and rare on our world. Agriculture consumes a significant amount of fresh water. Many countries have been seen to waste irrigation water resources. Not only does it waste water, but it may also reduce agricultural product productivity. This study proposes an IoT and ML-based method to enhance irrigation water consumption. Because soil moisture is an important aspect in predicting how much water should be utilised for irrigation, ML techniques are used to anticipate soil moisture for the next few days using data from field sensors and weather predictions. When the results of other ML techniques are compared, the findings of the GBRT-based method are highly promising. Such technologies might help to maximise the use of valuable ground water possessions for irrigation, especially in many countries like India.

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