Scientific Journal of Impact Factor (SJIF): 5.71

e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 5, Issue 08, August -2018

A DATA-DRIVEN APPROACH TO SOIL MOISTURE COLLECTION AND PREDICTION USING A WIRELESS SENSOR NETWORK AND MACHINE LEARNING TECHNIQUES

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Abstract —*Agriculture has been one among the foremost under-investigated areas in technology, and therefore the development of exactitude Agriculture (PA) continues to be in its early stages. This paper proposes a knowledge-driven methodology on building PA solutions for assortment and data modeling systems. Soil wetness, a key consider the crop growth cycle, is chosen as AN example to demonstrate the effectiveness of our data-driven approach. On the gathering aspect, a reactive wireless sensing element node is developed that aims to capture the dynamics of soil wetness mistreatment soil wetness sensing element. The prototyped device is tested on field soil to demonstrate its practicality and therefore the responsiveness of the sensors. On the info analysis aspect, a unique, site-specific soil wetness prediction framework is constructed on high of models generated by the machine learning techniques SVM Regression. The framework predicts soil wetness n days ahead supported a similar soil and environmental attributes which will be collected by our sensing element node. Thanks to the massive knowledge size needed by the machine learning algorithms, our framework is evaluated underneath the Illinois historical knowledge, not field collected sensing element knowledge. It achieves low error rates (10%) and high correlations (98%) between foreseen values and actual values.*

Keywords- *SVM Regression, Weka Forecasting, Soil Moisture, Soil Temperature, Support Vector Machine*

I. INTRODUCTION

All Soil moisture is one of the basic physical features of soil. Growth and development of crops are closely related to soil moisture. If soil water content is too high, it not only will produce soil deep percolation, results in the loss of nutrients and trace elements, but will also cause pollution of groundwater resources. On the other hand, if soil water content is too low, it will affect crops absorbing water and nutrients, will not be conducive to crop growth and development. Accurately grasp the dynamics of soil moisture enable one to react accordingly to the crop water demand to a certain extent. Therefore, objective and dynamic soil moisture prediction methods have important practical significance for adjusting the irrigation scheduling policy, planning and management of water resources, the development of water-saving agriculture and improving agricultural water management measures.

The average farm size in the U.S. is increasing every year despite a continuously decreasing farmer population [1]. As a result, more and more cropland is shifting to large farms. Large farms rely on a more structured and automated management system to realize better financial returns and use of resources.
Precision Agriculture (PA) promises to deliver the next generation of agriculture by actively using technology to collect various types of data and applying site-specific, sensor based treatment to the farm. As the world moves into the era of the Internet of Things (IoT), data are collected in various forms from different types of devices. A unified platform is needed to ensure that the data formats are consistent and that data are readily analyzable. Once data are collected, data mining techniques can be applied to extract patterns and build estimation and prediction models that are valuable to farm management. Data-driven agriculture is still at an early stage of development and faces many challenges. As pointed out in [2, 3, 4] the major problems for PA to become reality include:

- Crop management decisions and data collection systems need to be designed to meet the needs of specific farms.
- Automated and user-friendly systems need to be developed for users with less software experience.
- The introduction of expert knowledge must be possible. Systems should allow the inclusion of new automated methods for user-defined terms.
- Devices need to be affordable and scalable for large farm deployment.

In this paper, we designed and implemented a soil moisture collection and prediction system to address parts of the above problems using a data-driven approach. The success of the data-driven approach depends on two factors:

1. The quality of the data gathered and
2. The effectiveness of its analysis and interpretation.

By using a wireless sensor network and machine learning techniques in collection and prediction respectively, an integrated system focused on soil moisture is presented [5, 6]. Soil moisture, a key factor in the crop growth cycle, is selected as an example to demonstrate the effectiveness of our data-driven approach. Soil moisture is a preferable target for using data driven methods, since large volumes of data related to soil moisture and climate have been collected for decades and are easy to retrieve. We build a smart wireless device that can collect fine-grained soil moisture and related meteorological data. Two regression supervised machine learning algorithms—support vector machine Regression (SVMReg) —are used to show the effectiveness of data-driven tools of building soil moisture prediction model by using the same attributes that can be collected from our hardware devices.

II. SYSTEM OVERVIEW

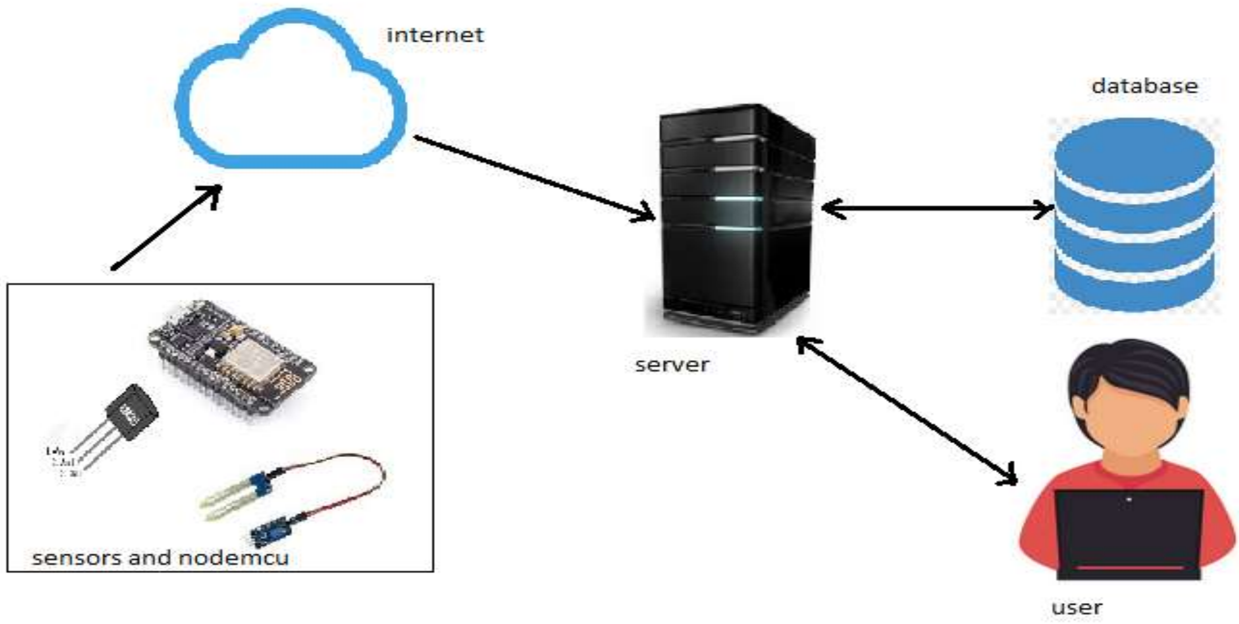

Fig 1: System Architecture

Fig. 1 shows an overview of the system, which can be separated into two parts: collection and prediction. The design principle is to create a framework that allows users to easily configure the system to be site-specific.

2.1 Collection System

In the collection system, a nodemcu based micro controller is prototyped that implemented our proposed framework for sensing soil moisture and other meteorological data. The sensor node is an intelligent reactive device that focuses on collecting soil moisture dynamics data with respect to surrounding environment changes. Programmed under open source platform Java and c language, the node can be easily reconfigured. It offers two user-defined variables regulating the level of data granularity and sample intervals. The nodemcu based micro controller can be used for applications such as in-field soil moisture collection and other kinds of remote site data collection, since it is specifically designed for applications that require a long lifetime. Lm 35 sensor used to get temperature and soil moisture sensor is used to get soil moisture

2.2 Prediction System

A prediction system is built on top of the machine learning models to predict soil moisture n days ahead. The models predict the soil moisture value based on meteorological parameters including temperature, humidity, wind speed, solar radiation, precipitation, and soil temperature together with previous days' soil moisture values. The sparse and well-studied machine learning techniques SVM regression applied on the historical data to derive mathematical models. Designed from a Precision Agriculture perspective, the sites specific model is able to incorporate data from other sources at the granularity of one day. The feature of taking user-provided data makes the system more robust by allowing the model to interact with human knowledge or reliable soil moisture data from other sources at fine granularity. Due to the large data size required by the machine learning algorithms, field-collected data from our sensor node are not used in our prediction experiments. However, the soil and meteorological attributes collected from the hardware devices are the same attributes that are used for deriving prediction models.

2.3 Data Source

The data used in this paper are from the Illinois Climate Network (ICN) [8] program, which monitors weather and soil conditions at 17 different locations across Illinois. Out of 17 sites, 1st sites are selected as our data source sites. ICN program offers soil moisture data with hour granularity and meteorological data with day granularity. Both soil moisture and meteorological raw data are preprocessed and manually examined to ensure they are error-free and well formatted.

2.4 Prediction System

In the prediction part, we propose a soil moisture prediction framework to estimate and forecast soil moisture level over time based on meteorological data. The prediction framework is built on basic models generated by machine learning algorithms. To establish a well-performed basic model, input data are parsed from the ICN database and fed to machine learning algorithms for training and validating purposes. The inputs are meteorological data: temperature, humidity, wind speed, solar radiation, precipitation, and soil temperature, together with the previous day's soil moisture values. The output is the soil moisture value for the next n days. Weka forecasting library is used to forecasting soil moisture.

III. RESULTS

Id	Date	Wind Speed	Solar Radiation	Air Temp	Humidity	Precipitation	Soil Temp
1	2018-01-01	7.9	10.4	-11.5	72.1	0	32
2	2018-01-02	8.6	11.3	-4.1	72.3	0	31.8
3	2018-01-03	9.1	10	10	75	0.01	31.6
4	2018-01-04	5	9.4	0.8	76.5	0	31.3
5	2018-01-05	4.5	10.9	0.8	75	0	31.1
6	2018-01-06	4.7	12.1	-4.6	76.6	0	30.5
7	2018-01-07	8.8	2.5	25.4	80.9	0.05	30.7
8	2018-01-08	6.2	9.1	33.5	89.8	0.12	31.6
9	2018-01-09	8	4.5	28.9	96.7	0	31.9
10	2018-01-10	12.5	2.9	40.8	98.7	0.07	32.1
11	2018-01-11	10.5	1.4	34.4	92.2	0.2	32.2
12	2018-01-12	11.2	7.1	14.9	77.4	0	32.1

Fig 2: Training data

Id	Air Temp	Soil Temp
1	25	56

Fig 3: Sensor Data

Days	Soil Temp
1	73.53869[illegible]3825229
2	69.4[illegible]22501626345
3	73.75839093172519
4	70.22889296975302
5	76.65943876098454

Fig 4: Forecast for next 5 days tabular form

Fig 5: Forecast for next 5 days graphical form

IV. CONCLUSION

A Nodemcu microcontroller based node is used to collect data from sensors. Nodemcu get data from sensors and send to the server. Lm 35 sensor used to get temperature and soil moisture sensor is used to get soil moisture. Weka forecasting library is used to forecasting soil moisture. SVM Regression is used for prediction.

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