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GOLDEN RESEARCH THOUGHTS

ISSN: 2231-5063
IMPACT FACTOR : 4.6052 (UIF)
VOLUME - 6 | ISSUE - 9 | MARCH – 2017

SMART AGRICULTURE-USING IOT IN FIELD MONITORING AND AUTOMATION FOR SOIL MOISTURE USING NAIVE BAYES PREDICTION

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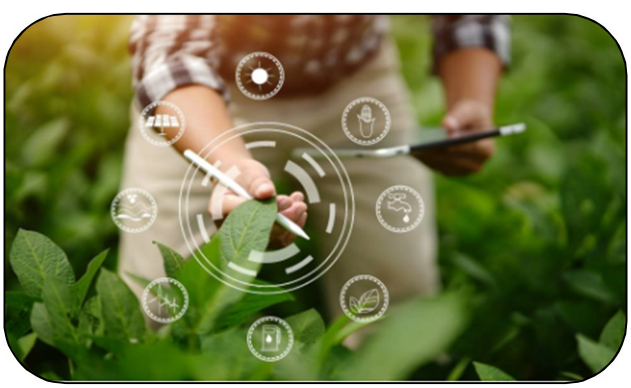
ABSTRACT :
Agriculture is the most important sector of Indian economy and majority of the people in rural areas depends on it. As the Technology in agriculture is changing rapidly noticeable changes are seen like low investment, high quality yielding at low risk. Several Prediction, Analysis and automation techniques were proposed and utilized at field level to improve the face of agriculture [1][2] [3] [4]. This paper proposes a data-driven methodology on improving soil moisture using collection and data modeling systems. Soil moisture also known as water present in soil is a key factor in the crop production cycle. MicaZ mote and VH400 soil moisture sensor are used to monitor the soil moisture. A soil moisture prediction framework is developed based on Naive Bayes Prediction. The framework predicts soil moisture based on the soil and whether attributes that are collected by our sensor nodes at Tadipathri, Ananthapur district, Andhra Pradesh. It is observed as low error rates (10%) and high correlations (90%) between predicted and actual values. Also it is expected that the predicted results can remain matching over a period of time (one crop duration).



KEY WORDS- *Agriculture, Prediction, Automation, Soil Moisture.*

I. INTRODUCTION

From the last 139 years, Ananthapur district faced normal and above normal rainfall during last 70 years (not sequentially) and poor rainfall in 69 years. The annual average rainfall in this region is 552.3 mm.

As per the records it is identified that ananthapur is the second lowest rainfall receiving district in India after Jaisalmer in Rajasthan. Farmers in this region cultivates groundnut. Water need of this crop is 400- 600 mm and duration is 90-120 days. The crop is usually exposed to mid or late season drought. Failure in supply of required water leads to 50 % yield drop approximately.

Lack of Moisture in groundnut crop results in

- Reduction in leaf area which directly decreases crop yield
- Poor plant height, fewer branches
- Reduction in yield up to 50 percent if the moisture scarcity is from 50 to 80 Days.

In order to overcome yield drops in cultivation more structured and automated management system is used to obtain better financial returns and effective use of resources. Smart Agriculture gives assurance to the farmers by effectively using technology to collect samples of data and applying prediction techniques. Internet of Things (IoT) simplifies our work for collecting data in various forms from various devices. A simple platform is required to assure that the data formats are reliable and that data are readily analyzable. Once data are collected, data mining techniques are applied to extract patterns creates estimation and prediction models that are applicable to field.

To develop an efficient model the following points has to be considered

- Data collection systems should to be developed to meet the requirement of Specific farms.
- Automated and simple systems need to be developed for farmers who don't know about software's and technical aspects.
- Low cost affordable devices.

In this paper, we have designed and implemented soil moisture analysis and prediction system by using Naive Bayes Prediction to solve the groundnut crop production problems due to lack of soil moisture. The reliability of this model depends on the following factors:

1) Data collected from farm
2) The procedure of data analysis and interpretation.

An integrated System is designed and developed by using a Wireless sensor network and machine learning techniques. A smart wireless device is developed to collect soil moisture, temperature and humidity data. Several nodes are set across the agriculture field to get the moisture, weather and humidity data. Naive Bayes Prediction is used to represent the results which are retrieved by hardware devices. After predicting the results from all the three factors if moisture levels are observed low (based on a threshold value) water sprinklers are automatically started for a specific time till the soil reaches to required moisture. The paper is represented in the following manner:

In Section 2, we provide overview of system. In Section 3 and 4, we present the design of detailed functionality of the collection and prediction, respectively. In Section 5, the proposed framework is evaluated under sample data. In Section 6, we discuss the related work details, and Section 7 includes our future work.
Our model achieves following operations:

1) A data driven methodology on soil moisture is proposed to address problems in groundnut cultivation.
2) Reactive sensor network is proposed to obtain moisture, temperature and humidity details and tested over the agriculture field
3) We present a unique soil moisture prediction framework. The proposed framework is built on basic models generated by the Naive Bayes Prediction algorithms and real time data set.

Fig 1 Agriculture Field view
Fig 1 represents installed nodes at agriculture field

II. SYSTEM OVERVIEW

The System was divided into two phases: Collection phase and prediction phase. The framework is user friendly and easily configured.

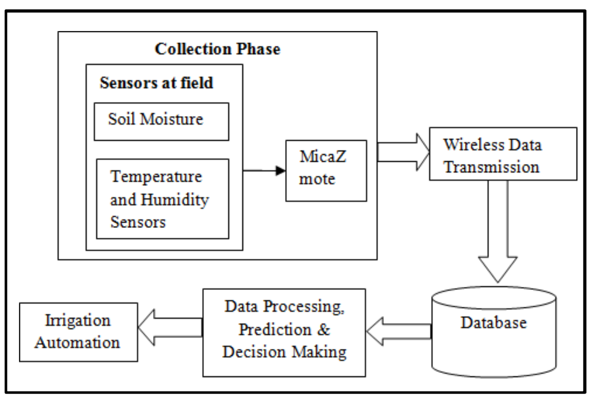


Fig 2 Overview of Smart Agriculture model

A. Collection Phase

In collection phase, soil moisture, weather and other meteorological data is gathered using wireless sensor nodes which are installed in various points at the agriculture field. These sensor nodes are responsible for collecting soil moisture and weather information. TinyOS [5] is a flexible application specific sensor network operating systems used in WSN, building automations.

B. Prediction Phase

A prediction phase is used to predict soil moisture and weather n days ahead.Meterological parameters like temperature, weather of previous day's soil moisture values are considered. Naive Bayes Prediction is applied on the data which is collected from collection phase.

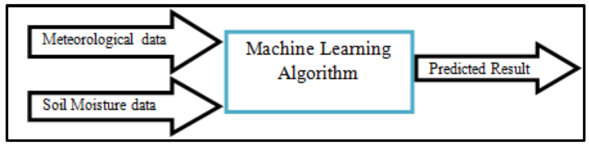


Fig 3 Prediction System

Fig 3 represents the process of prediction from meteorological data and soil moisture data

C. Data Source

The Data Source is agriculture fields in Tadipathri, Ananthapur district. Out of 15 acres land 8 nodes were installed in the agriculture field to monitor the moisture and weather related data.

III. COLLECTION SYSTEM DESIGN

Soil moisture and weather related environmental data is collected by the wireless devices for prediction purpose.

- User friendly interface which can be easily used by user.
- Data should be reactively sensed data based on environment changes.

Hardware Test

MicaZ [6] node with a MDA300CA [7] data acquisition board is prototyped in our Model. Initially, a hardware test was conducted at the agriculture field to test the response and functionality of the sensor network. In the experiment soil Vh400 [6] moisture sensors were connected to sensor node and inserted completely under the ground surface at 10 cm and 15 cm depths. The hardware was configured and the granularity level was 0.10 vwc, sample interval was 10 minutes.

The experiment was conducted for 80 minutes and results are shown in fig 4.Soil moisture readings 21 at 10 cm and 15 cm are represented by redline and blue line. Initially at the first readings both sensors have shown errors due to sensor warm-up stages. A small volume of water is poured at the testing area which in turn showed a change in 10cm sensor readings which is indicated or observed in the graph at point 40 later large volumes of water is poured at the same location at this point 40 the sensor at 15 cm showed a change in readings comparatively less than 10 cm sensor. When small amount of water was poured the moisture levels were changed at 10 cm level sensor whereas when high volume of water was poured it influenced the 15cm level sensor saturation at both levels in figure 4.

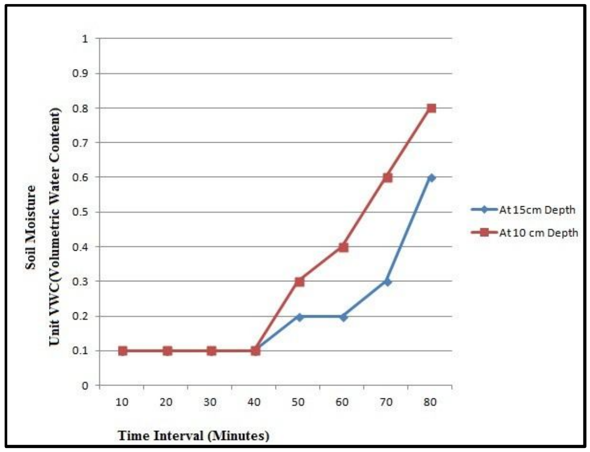


Fig 4 sensor node at field testing IV Prediction System

A soil moisture prediction framework is proposed to estimate and display soil moisture level over time based on meteorological data. A machine learning algorithm is applied to generate a prediction framework. Temperature, humidity and soil temperature are considered as meteorological data and these factors influence soil moisture value for the current day.

A looping model is created to manipulate inputs at any iteration by user. At every iteration environmental parameters are either the forecasting values or user provided values. Soil moisture input may be either data from soil moisture retrieval techniques or previous predicted values. For example, if drought condition stays more than n days our model will predict the future based on past data assumption. For a longer time to predict soil moisture data is received repeatedly. Data collected from day n can be sent to the prediction system to predict day n+1 soil temperature.

If all the sources are applied at input fields an effective prediction model can be achieved. In previous work [8, 9] on prediction of soil moisture, the model predicts values k days ahead where k is a fixed number. To predict n+k days soil moisture values and meteorological data at day n, day n-1, day n-2, and so on are considered which discards meteorological data between n and n+k.But the prediction result may become unreliable if there was heavy precipitation between n and n+k.As the forecasting of meteorological data is available to the public our system includes meteorological data between day n and n+k from weather forecasting. If both meteorological and actual values are integrated accuracy will be improved.

V. MODEL EVALUATION METHODOLOGY

After preprocessing the data, we are able to retrieve data from 8 nodes across the agriculture field for a time period. The data is parsed on split based at the field location so the values can be observed in a node specific model i.e values can be generated for individual node. Air temperature, humidity and soil moisture are considered in machine learning process.

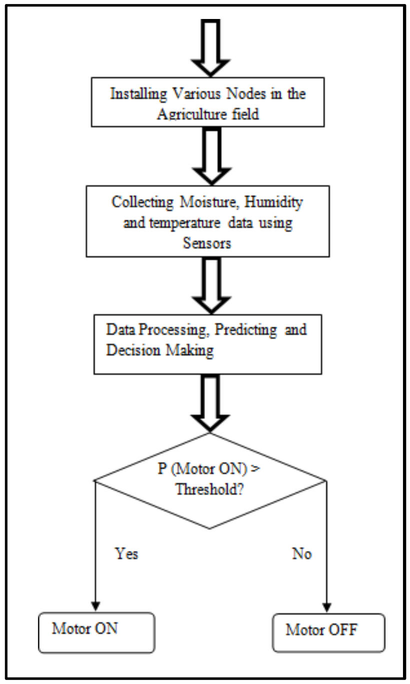


Fig 5 Flow Diagram of our model

Table 1 Sample Training data of our model

S No	Moisture	Temperature	Humidity	Motor ON/ OFF
1	0.3	0.7	0.7	ON
2	0.6	0.6	0.8	ON
3	0.7	0.4	0.7	OFF
4	0.5	0.5	0.7	OFF
5	0.5	0.8	0.8	ON
6	0.6	0.5	0.5	OFF
7	0.4	0.5	0.6	ON
8	0.5	0.5	0.6	OFF
9	0.2	0.5	0.7	ON
10	0.3	0.4	0.6	ON
11	0.5	0.6	0.7	ON
12	0.4	0.5	0.6	ON
13	0.4	0.5	0.7	OFF
14	0.3	0.5	0.6	ON
15	0.4	0.4	0.8	ON

Table 2 Moisture Frequency Table

Frequency Table		
Moisture	**ON**	**OFF**
0.2	1	0
0.3	3	0
0.4	3	1
0.5	2	2
0.6	1	1
0.7	0	1

Table 3 Moisture Likelihood Table

Likelihood Table				
Moisture	**ON**	**OFF**		
0.2	1	0	1/15	0.06
0.3	3	0	3/15	0.2
0.4	3	1	4/15	0.26
0.5	2	2	4/15	0.26
0.6	1	1	2/15	0.13
0.7	0	1	1/15	0.06
	10/15	5/15		

Table 4 Temperature Frequency Table

Frequency Table		
Temperature	**ON**	**OFF**
0.4	2	1
0.5	4	4
0.6	2	-
0.7	1	-
0.8	1	-

Table 5 Tempe rapture likelihood Table

Likelihood Table				
Temperature	**ON**	**OFF**		
0.4	2	1	3/15	0.2
0.5	4	4	8/15	0.53
0.6	2	0	2/15	0.13
0.7	1	0	1/15	0.06
0.8	1	0	1/15	0.06
	10/15	5/15		

Table 6 Humidity Frequency Table

Frequency Table		
Humidity	ON	OFF
0.5	-	1
0.6	4	1
0.7	3	3
0.8	3	-

Table 7 Humidity Frequency Table Naive Bayes Prediction

Likelihood Table				
Humidity	ON	OFF		
0.5	0	1	1/15	0.06
0.6	4	1	5/15	0.33
0.7	3	3	6/15	0.4
0.8	3	0	3/15	0.2
	10/15	5/15		

$$P\left(\frac{c}{x}\right) = \frac{P\left(\frac{x}{c}\right)P(c)}{P(x)}$$

P(c|x) is the class (c, target) posterior probability of given predictor (x, attributes).
P(c) is the class prior probability.
P(x|c) is the likelihood which is the predictor probability of given class.
P(x) is the prior probability of predictor.

In order to implement the model the data are normalized between zero and one and split into training, testing and validating the data.

Let us assume if moisture is 0.3, temperature is 0.4 and humidity is 0.5.Our model predicts whether motor has to be ON or OFF and if the input data doesn't match the value in the table next value will be considered.

Moisture Probability

$$P\left(\frac{ON}{0.3}\right) = \frac{P\left(\frac{0.3}{ON}\right) * P(ON)}{P(0.3)}$$

Where $P\left(\frac{0.3}{ON}\right) = \frac{3}{15}, P(ON) = \frac{10}{15}, P(0.3) = \frac{3}{15}$

$$P\left(\frac{ON}{0.3}\right) = \frac{0.2*0.66}{0.2} = 0.66(high\ Probability\ i.e\ 1)$$

Temperature Probability

$$P\left(\frac{ON}{0.4}\right) = \frac{P\left(\frac{0.4}{ON}\right) * P(ON)}{P(0.4)}$$

$$\text{Where } P\left(\frac{0.4}{ON}\right) = \frac{2}{15}, P(ON) = \frac{10}{15}, P(0.4) = \frac{3}{15}$$

$$P\left(\frac{ON}{0.4}\right) = \frac{0.13 * 0.66}{0.2} = 0.42(low\ Probability\ i.e\ 0)$$

Humidity Probability

Here in our Training data set Motor ON occurrences for 0.5 is zero so, we calculate probability for Motor OFF

$$P\left(\frac{OFF}{0.4}\right) = \frac{P\left(\frac{0.4}{OFF}\right) * P(OFF)}{P(0.4)}$$

$$\text{Where } P\left(\frac{0.4}{OFF}\right) = \frac{1}{15}, P(OFF) = \frac{5}{15}, P(0.4) = \frac{1}{15}$$

$$P\left(\frac{OFF}{0.4}\right) = \frac{0.06 * 0.33}{0.06} = 0.33$$

$$P(ON) = 1 - P(OFF)$$

$$= 1 - 0.33$$

$$P(ON) = 0.67(High\ Probablity\ i.e\ 1)$$

P(Motor ON)=

= (P(Moisture)+P(Temperature)+P(Humidity))/3

= (1+1+0)/3

=(0.66)

Low probability (=<50) is considered as 0 and High probability (>50) is considered as 1.
Assumed Threshold value is 0.4 and the result is greater than threshold so motor should be ON
Out of these three factors Moisture and Humidity factors recommends Motor to be ON and Temperature recommends Motor to be OFF based on these results the motor will be ON.

VI. RELATED WORK

In [10] data is collected through sensors and water required is calculated on daily basis. Majority of the studies and research projected several seperate solutions on the collection, analysis and prediction. Analysis of soil moisture majorly depends on data- driven modeling, physically based modeling and more. In-depth knowledge of soil water, statistics background and machine learning are implemented for generating site specific models with training methodology and corresponding data set.[1] are implemented to predict soil moisture In past years vector machines [11, 12], neural networks [3], polynomial regression [4] and more on historical soil moisture datasets in the hydrology domain however none of them showed a common solution to both collection and analysis.

VII FUTURE WORK

Future work should focus on implementing our framework on a large scale. To reduce cost of the equipment, methodology should be improvised to show accurate results with less number of nodes in an agriculture field. Plant health with respect to various diseases in plants due to less moisture and more than moisture levels should be recorded to overcome the required moisture conditions.

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