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Iot and Weather Based Smart Irrigation Monitoring And Controlling System for Agriculture

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Abstract*: Effective and successful agriculture requires effective water management. Irrigation at appropriate periods and at appropriate levels results in profitable yields. Technology can provide an effective solution for this domain. This work presents an IoT based prediction model that can be to create a smart irrigation system for farming. The proposed architecture is composed of three layers; the data collection layer, machine learning based rainfall prediction layer and the rulebased irrigation requirement identification layer. The data collection layer operates in multiple levels using sensors and APIs, obtaining ground based information and also weather information. The machine learning layer performs rainfall prediction based on past data and the final layer uses defined rules to identify the irrigation needs of crops. The major advantage of this model is that it is not fine tuned to a single crop. The model can be used for any crop and can also be used for multiple crops by the same farmer.

***Keywords* :Smart Irrigation, IoT, Random Forest, Precision Agriculture, Machine Learning.**

I. INTRODUCTION

Agriculture is one of the major requirements for human race to survive. Most of the food consumed by us is produced by agriculture. Water is considered to be the major concern for agriculture [1]. It was identified that water up to 100x more than personal use is consumed for agriculture. Further, 70% of river andgroundwater is being used for irrigation in farms [2]. This makes water one of the major requirements for effective farming. Effective water management leads to effective agriculture, which in turn leads to good production. Improper water management and un-effective usage of water sources has resulted in scarcity of water. Recent improvements in technology can be viewed as an effective solution for the water management issues.

The idea for smart irrigation originated with bloom of Internet of Things (IoT) [3]. Smart agriculture utilizing IoT devices for data collection and processing are on the raise. Sensors are deployed in agriculture fields and field based data are collected. The data corresponds to several aspects of the environment and details about crops [4, 5]. The devices can then use this data for effective decision making. The large amount of data collected by these sensors and devices can be stored in remote data centers. After collecting sufficient amount of data, artificial intelligence based models can be used for prediction. Such real-time data based predictions can provide necessary insights for growing crops effectively. Further cloud based computations can be used to perform intensive processing to make predictions more reliable and at lower cost. Predictions from the technology can be in terms of level of water, prediction of rainfall, calculation of minerals required for plants, etc. Technology based agriculture can effectively increase food production and hence handle the needs of the growing population [6].

This work presents an IoT based model that utilizes weather based predictions and local data obtained from sensors to provide decisions for irrigation. The smart irrigation based model inputs base requirements of crops and provides the level of water supply required for the crops. The model has been designed such that it can even be utilized for multiple crops planted at the same location and can also be used on several varied types of irrigation facilities. A fully automated irrigation model without human interaction is made possible with the proposed architecture.The remainder of this paper is structured as follows; section II provides the related works, section III presents the proposed IoT and prediction based irrigation model, section IV presents and discusses the results and section V concludes the work.

II. RELATED WORKS

Smart agriculture and smart irrigation are the essentials of tomorrow to compensate the demands for the ever increasing population. This section discusses some of the major and recent contributions in this domain.A deep reinforcement learning model for smart agriculture using IoT was presented by Bu et al. [7]. This model is composed of four major layers, the data collection layer, which collects details from the sensors, edge computing layer, which performs minimal computations on the collected data, data transmission layer, which transmits the computed data to the cloud and the cloud computing layer, which performs the major computations. Aggregation of artificial intelligence and deep reinforcement learning coupled with cloud computing resources enables smart and effective decision making for agriculture. A specific irrigation based model using IoT systems was proposed by Nawandar et al. [8].

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The model uses input data from IoT devices to perform irrigation scheduling and also incorporates artificial intelligence based decision making using neural networks for effective decision making.

A WSN based model using greenhouse crop management techniques for effective yield was proposed by Jimenez et al. [9]. The control techniques for green house was proposed by Genda et al. [10].

Several crop specific models have also been introduced for large scale farming requirements. A WSN based irrigation system for potato farming was proposed by Shinghal et al. [11]. The model is based on collecting information such as environmental factors and soil conditions from sensors and rules are used to provide recommendations. A water control based model to aid poor farmers was presented by Hussain et al. [12]. A soil moisture based model was proposed by Dong et al. [13]. This technique uses WSN based sensors to identify the soil parameters for effective irrigation.

Precision Agriculture, which identifies the soil properties and performs related recommendations is also on the raise. A precision agriculture based model that works in greenhouse environments was proposed by Srbinovska et al. [14]. IoT based decision making for precision agriculture was proposed by Patokar et al. [15]. An irrigation based model that also considers soil properties was proposed by Severino et al. [16]. The model aims to utilize recycled water and provides an irrigation model that can analyse the risks associated with such a model. Considering multiple properties like soil properties, water type and environmental conditions make the model effective. Support Vector Machines (SVM) has also been used for prediction in agriculture scenario. Some models using SVM include models by Rajagopalan et al. [17] and Putjaika et al. [18]. A case study for IoT based smart systems to support agriculture was proposed by Pathak et al. [19]. This technique uses Cuckoo Search Algorithm for prediction and Arduino for the processing. Other models using machine learning for smart agriculture includes IoT based models by Goap et al. [20], Sharma et al. [21] and Shang et al. [22].

III. MACHINE LEARNING BASED IRRIGATION CONTROL SYSTEM

Irrigation is one of the biggest concerns in agriculture. Effective irrigation results not only in better yield, but also better conservation of water. This work presents an effective prediction based architecture that utilizes current environmental parameters, crop requirements and future predictions to identify the water level to be supplied for the crops. The proposed architecture is composed of three layers; the data collection layer, machine learning based rainfall prediction layer and rule based irrigation requirement identification layer. The model has been designed to provide minimal interactions from the farmer in the initial stages and no interactions in the further stages. The output is directly connected to the IoT devices for water supply. Further, the entire data is stored in cloud and all the sensors and IoT devices for watering are connected to the cloud. The prediction model also operates in the cloud. The sensor data(input) and the result (water supply level for irrigation) are the only transmission parameters. Hence interactions are also minimal, leading to a cost effective model.

A. Data Collection

Data related to the crops and the weather information correspond to the input parameters. The inputs are obtained in three independent modules. The first module corresponds to the water requirements for a crop, the second module obtains the weather information and the last module deals with obtaining the sensor data.

Crop Requirement Identification

Irrigation deals with providing a crop with the essential and required water such that the plat ins not over-watered or under-watered. Requirement of every crop differs considerably. Water requirement for a crop *ETcrop* is identified using the below equation.

$$ETcrop = kc * Eto$$

Where *ETcrop* is the water requirement for a crop in mm, *kc* is the crop factor determined by the type of the crop and *Eto* is the evapotranspiration rate [23] of the crop in mm.

Crop factor is the water requirement for a crop at each stage of its growth cycle. This value usually differs with the stage of the crop. Crops usually fall into any of the four stages; initial stage, where the water requirement is low, crop development stage, where the water requirement increases, mid-season stage, where the water requirement is the highest and the late season stage, where the water requirement is low. The values for these stages varies with the crop. This data has to be provided by the farmer, or standard values can be used. Shown below (Figure 1) is a sample of the standard values for some crops obtained from the Food and Agriculture Organization of the United Nations [24].

The proposed architecture uses specific values for each growth stages and can also operate on the season values for crops whose specific values are not available.

Eto is the evapotranspiration rate (mm) for a crop per unit time. Evaporation rate is manually calculated using either of the standard methods; the Pan Evaporation method [25] and Blamey-Criddle method [26]. However, in scenarios where this is not possible, general *Eto*values can be used for analysis. A tabulated view of the general values is shown in Table 1.

Crop Info

```
kc=pd.read_csv("kc.csv").set_index('Crop')
kc
```

Crop	Initial stage	is days	Crop dev. stage	cd days	Mid-season stage	msdays	Late season	lsdays	Season average
Cotton	0.45	30	0.75	50	1.15	55	0.75	45	0.82
Maize	0.40	20	0.80	35	1.15	40	0.70	30	0.82
Millet	0.35	15	0.70	25	1.10	40	0.65	25	0.79
Sorghum	0.35	20	0.75	30	1.10	40	0.65	30	0.78
Grain/small	0.35	20	0.75	30	1.10	60	0.65	40	0.78
Legumes	0.45	15	0.75	25	1.10	35	0.50	15	0.79
Groundnuts	0.45	25	0.75	35	1.05	45	0.70	25	0.79

Fig. 1. Crop Information

Table-I: General Temperature Values for Eto

Climatic Zone	Mean Daily Temperature		
	15°	15°-25°	25°
Desert/ Arid	4-6	7-8	9-10
Semi-arid	4-5	6-7	8-9
Sub-humid	3-4	5-6	7-8
Humid	1-2	3-4	5-6

Total amount of water required for irrigation can be calculated using these values. For example, if the crop is a millet, the season average of crop is 0.79, the *Eto*for a humid location > 25° is 6. Hence,

$$ETcrop = 0.79 * 6 = 4.74\ mm\ per\ day$$

The crop takes 105 days in total, hence requires 497.7 mm water in total.This can provide an overall crop requirement for the growing season. Hence an average estimate for the crop can be identified.

API based Weather Detail Identification

Weather plays a vital role in determining the watering requirements of a crop. Effectively determining the weather and providing calculated water supply for the plans results in cost effective irrigation that also conserves water. Weather details have been obtained from the OpenWeatherMap [27].The API key can be used to perform 60 free queries per day, which is sufficient for the current work. The API requires a location as the input and results are obtained in JSON format. A sample of the results is shown below (Fig. 2).

Weather Details from API

```
In [120]: # Enter your API key here
          api_key = "66f11e9c15a8d24e408ffa16c8e82329"

          base_url = "http://api.openweathermap.org/data/2.5/weather?"

          complete_url = base_url + "appid=" + api_key + "&id="+ str(cityID)+"&units=metri

          response = requests.get(complete_url)

          x = response.json()
          x
```


```
Out[120]: {'coord': {'lon': 78.7, 'lat': 10.8},
 'weather': [{'id': 721,
   'main': 'Haze',
   'description': 'haze',
   'icon': '50d'}],
 'base': 'stations',
 'main': {'temp': 31,
  'pressure': 1012,
  'humidity': 66,
  'temp_min': 31,
  'temp_max': 31},
 'visibility': 3000,
 'wind': {'speed': 3.1, 'deg': 10},
 'clouds': {'all': 40},
 'dt': 1572853513,
 'sys': {'type': 1,
  'id': 9227,
  'country': 'IN',
  'sunrise': 1572827827,
  'sunset': 1572870020},
 'timezone': 19800,
 'id': 7603116,
 'name': 'Trichy',
 'cod': 200}
```


Fig. 2. Weather Details using API

Sensor based Environmental Condition Identification

Sensors are deployed in the farms to identify the soil properties. Some rrepresentative environmental parameters include the carbon dioxide concentration, soil moisture and temperature, and light intensity, etc. Specially, these parameters are collected every five minutes. The collected data is pre-processed and is sent to the cloud. This transmission is performed every 4 hours. The time period of four hours is determined based on the watering cycles and can be modified based on the requirements for the crop and based on the type of irrigation adopted by the farmer. Since data is sent only at specific intervals, it has to be pre-processed prior to transmission.

Data aggregation is performed prior to transmission and the average values for the time period is passed to the cloud. This however, is not constrained to the cycle, instead, during sudden changes in the weather parameters like rain or increase in temperature, the data is sent to the cloud immediately irrespective of the time.

Machine Learning based Rainfall Prediction

Data obtained from the API and sensors provide current data only. Predicting future weather can provide better watering solutions. Saving water is a major requirement for the current scenario. Predicting rainfall prior to watering can provide huge help to manage irrigation and avoid wastage of water. This section presents the machine learning based rainfall prediction model using the past data. Data for analysis has been obtained from data.gov.in [28]. The site provides month wise rainfall data. This data is used for the training process and future rainfall levels are predicted.

Random Forest Regressor is used for the prediction process. Random Forest is a tree based prediction model that uses multiple Decision trees for the prediction process. This is based on boosting ensemble model. Rainfall prediction requires the current rainfall level to be provided as the result. Hence, regression model is used for the process.

The input training data is composed on year wise data providing monthly rainfall levels. Although the month and year values are numerical in nature, they actually correspond to categorical data. Hence, the data is preprocessed by applying one-hot-encoding values for the month and year parameters. The preprocessed data is used for training the Random Forest model. Similarly, every time a watering requirement arises, the probability of rainfall is calculated and used as a deciding factor for determining the watering levels.

Rule based Irrigation Requirement Identification

The above modules identify the required values for the decision making process. After identifying all the parameters, the provided rule set is used for the identification of the actual watering level. It should also be noted that general water requirements are formulated at ideal conditions, hence they should not be entirely relied upon. Plants are prone to transpiration, which makes the plants lose water through stems and leaves. Humidity and temperature play vital role in transpiration. These are also considered and along with general requirements, this water loss should also be compensated to achieve effective growth in plants. The rule set provided for irrigation is presented below.

Rules for Irrigation (Pseudocode)

1. *Input the required parameters from API and Sensors*
2. *Identify rainfall level from the prediction model*
3. *Set humidity tolerance ($tolerance_H$) and temperature tolerance ($tolerance_T$)*
4. *Calculate the ETcrop, the general water requirements of the crop*
5. *Obtain the transpiration level of crop based on humidity (tH) and temperature (tT) (differs with crop)*
6. *If ETcrop<rainfall level*
   a. *Return 0*
7. *Else ETcrop = ETcrop -rainfall*
8. *If humidity level is between ± $tolerance_H$ of required humidity goto step 11*
9. *If humidity < required humidity- $tolerance_H$ then increase water level based on tH*
10. *Else if humidity > required humidity + $tolerance_H$ then decrease water level based on tH*
11. *If temperature is between ± $tolerance_T$ of required humidity goto step 14*
12. *If temperature < required temperature - $tolerance_T$ then increase water level based on tT*
13. *Else if temperature > required temperature + $tolerance_T$ then decrease water level based on tT*
14. *ETcrop = ETcrop + aggregate increase in water level – aggregate decrease in water level – (soil moisture/100)*
15. *If ETcrop< 0 return 0 else return ETcrop*

The process of identifying ETcrop is performed in the cloud and data is sent back to the irrigation system. The value of ETcrop varies based on crops. The model is flexible and can be used for multiple crops. The IoT device is programmed such that the soil moisture is monitored. When the desired moisture level is achieved, the watering for a plant is stopped.

IV. RESULTS AND DISCUSSION

Interface for the proposed model has been developed with python. Requirements from farmers regarding crops are obtained and coded in the model. Sensors are to identify soil conditions and environmental conditions. The entire processing is performed in cloud. Hence the devices and sensors are connected to cloud. Further, sensors are deployed to control the water flow for automated irrigation. The sensor data is passed to cloud and is used by the python module for prediction. Weather details are obtained from the API. Crop requirements, climatic details, watering type required and location details to be provided by farmer. Crop requirement details and the required watering parameters are used for the calculation of the kc value and climate details used for calculating the Eto. Watering parameters determine the type of watering followed like localized irrigation, drip irrigation [29], sprinkler irrigation [30], central pivot irrigation, lateral move irrigation etc. [31]. The proposed architecture can be effectively deployed in localized irrigation, sprinkler irrigation and also manual irrigation without support for IoT devices. Sample screenshots for various crops is shown below (Fig. 3).

```
Location :Trichy -- {'lon': 78.7, 'lat': 10.8}
Temperature :32 C
Pressure :1008 mod
Humidity :59 %
Soil Moisture :20 %
Rainfall Expected: 5.28 mm

Crop  Cotton

'Today Irrigation Requirement: 0 mm - Actual Requirement: 4.92 mm'

Location :Trichy -- {'lon': 78.7, 'lat': 10.8}
Temperature :32 C
Pressure :1008 mod
Humidity :59 %
Soil Moisture :40 %
Rainfall Expected: 0 mm

Crop  Millet

'Today Irrigation Requirement: 1.64 mm - Actual Requirement: 4.74 mm'

Location :Trichy -- {'lon': 78.7, 'lat': 10.8}
Temperature :32 C
Pressure :1008 mod
Humidity :59 %
Soil Moisture :40 %
Rainfall Expected: 0 mm

Crop  Grain/small

'Today Irrigation Requirement: 1.58 mm - Actual Requirement: 4.68 mm'
```

Fig. 3. Screenshot of Prediction Process

V. CONCLUSION

Effective irrigation is a major aspect for agriculture. This not only results in effective production, but also results in effective conservation of water to avoid wastage. This work proposes an effective prediction based architecture for irrigation. The model is based on cloud architecture and performs data collection through sensors, IoT devices and weather API. Further, the rainfall prediction module uses machine learning to predict possibilities of rainfall. The model is flexible and is not constrained to a single crop. It can be used even by a single farmer growing multiple crops. It is sufficient to add the additional crop details. The proposed architecture can be effectively deployed in localized irrigation and sprinkler irrigation. It can also be used for manual irrigation scenarios without support for IoT devices. Further, the model can be extended to drip irrigation by increasing frequency of data transmission and irrigation frequency. The model can be extended to completely automated irrigation types like center pivot irrigation and lateral move irrigation by adding additional IoT devices to facilitate movement of the watering equipment.

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