JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Smart Irrigation System

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Abstract

Ingenious, frugal, and cost-effective irrigation techniques have developed to meet the world's population's need for sweet water. Put differently, one should use water sparingly enough to preserve the limited supply of sweet water. The majority of the water was squandered as a result of poor irrigation techniques. We used a clever strategy that is expertly capable of employing ontology to make half of the decisions; the remaining half is based on the values of the sensor data. The final decision, which is the outcome of a machine learning algorithm, is derived from the choice made by the ontology and the sensor values taken together (KNN). Additionally, a new edge server is placed in between the GSM module and the primary IoT server. This approach will lower the delay rate in addition to preventing the IoT server from being overworked when processing data. In order to predict the amount of water required for a field of crops, this method links the Internet of Things with a network of sensors. It then uses an Android application edge to display the results. The data is cleverly traced, analyzed, and only a portion is transferred to the main IoT server.

Keywords
Smart Irrigation, Water Harvesting, C4.5, KNN, IOT System

Introduction

Growers all around the world are utilizing the Internet of Things to decrease waste, improve the quality or yield of their products, and use less water and fertilizer—from large agribusiness heavyweights like India to tiny organic farms. In order to maximize shelf life and reduce waste, examples include measuring microclimates throughout fields and closely observing temperature and humidity variations when perishable commodities are moved from field to warehouse to storage. Many producers in California were compelled to look for ways to use less water due to the current and record drought. Tech companies are assisting them with real-time condition measurement tools like soil sensors and drone footage. The Nature Conservancy claims that with this kind of precision farming, farmers can reduce their usage of fertilizer and water by up to 40% without sacrificing yields. Enhancing irrigation efficiency in the agriculture sector makes this business more sustainable and competitive. In arid regions devoid of adequate precipitation, adequate irrigation is unattainable. Therefore, by using this irrigation system and keeping an eye on the soil's moisture level, we can meet the field's water needs. Water and time are crucial factors to consider when trying to save farmers' labor. They have to wait till the field is completely irrigated under the current situation. It prevents them from engaging in other things. This concept is intended for plant watering as well as farming. Nowadays, farmers irrigate their crops on a regular schedule. Their methods will lead to water logging and waste, which will increase water use. The tension associated with manual labor will be totally eliminated by the solution we devised. It has been tested on two different types of soils, and it only functions under dry soil conditions. All developed nations rely heavily on agriculture. It consumes 85% of the fresh water resources that are available globally, and because of rising food prices and population growth, this proportion of water use remains dominant. As a result, effective water management is a top priority for many cropping systems in arid and semi-arid regions. An Arduino-based plant communicator assists farmers by monitoring soil moisture levels and automatically adjusting irrigation when necessary. Water pollution is caused by improper disposal or handling of waste water, which leads to over-irrigation.

Literature Review

A recommendation-based irrigation management system that integrated agronomic expertise and machine learning was proposed by Goldstein et al. (2017) [1]. The system indicates that the Gradient Boosted Regression Trees and Boosted Tree Classifier, the top classifier and regression models with 93% and 95% accuracy respectively, outperform the linear regression model in irrigation prediction. The models were trained using eight distinct sets of features to help the agronomist make better decisions. Al Zu'bi et al. (2019) introduced the concept of the Internet of Multimedia Things (IoMT), which centers on the application of multimedia sensors for irrigation optimization. Soil and crops are monitored by digital picture processing. The image processing system receives the photographs of the crops gathered by the multimedia sensor and makes a decision based on the percentage of soil fractures. This enables the Future No-Man irrigation control system to be implemented. Rushika Ghadge et al. (2018)[3] developed a system that uses supervised and unsupervised machine learning algorithms in accordance with data mining techniques to forecast crop and soil quality and kind of land, as well as evaluate the nutrients present in the soil to increase agricultural productivity. In addition to helping farmers grow healthier crops in the right soil to boost output, this initiative acts as a channel for timely information about crop quality and nutrient requirements. A learning model based on Support Vector Regression (SVR) and K-means clustering was developed for soil moisture estimation. Air, soil temperature, humidity, radiation, and moisture were all recorded in the field and fed into the SVR model's training system. Kmeans clustering is used to process the SVR model output in order to improve accuracy and decrease error rate. The water pump controller is controlled by the k-means final output for the best yield management. But most of the previous prediction models have a high variance. It results in subpar performance from the machine learning model. To address such substantial variation, ensemble learning can be used, as suggested by Zhao et al. (2018)[4], Catolino and Ferrucci (2018), Joshi and Srivastava (2014), and Ren et al. (2016). Through the combination of When using many learning models to forecast a single system's output, ensemble techniques yield better results. It has been demonstrated that certain ensemble techniques, in particular bagging, lessen the issue of training data overfitting and underfitting. The Bootstrap Aggregation method uses many models, each of which is trained using randomly chosen samples from the original dataset, to improve single regression trees. Compared to the other single models, the prediction error of the bagging strategy is lower. A bagging technique for power price forecasting is presented by Gonzalez et al. (2014)[8] and is contrasted with the random forest method for both regression and classification models. After a thorough review of the literature, the study's conclusions and experimental results are used to propose some of the most practical and effective technologies and algorithms for the development of a smart farm monitoring system. A microcontroller-based irrigation system that is more economical and efficient than other conventional methods was proposed by Ersin et al. [9]. Technologies for precision irrigation were described by Liu et al. [10]. Agrawal et al. demonstrated an Arduino and Raspberry Pi-based smart watering system. [11]. A microcontroller-based irrigation solution was presented by Koprda et al. In their study, Ahouandjinou et al. address the use of ultrasonic sensors for farm pest monitoring.

An IoT-based irrigation system's complete overall design was made available by Goap et al. Machine learning algorithms for soil categorization were presented by Smith et al. Wu et al.'s research focused on smart dispatching and agricultural vehicles. Using an integrated approach, Ryu et al. introduced smart farming. According to Kwok et al. , deep learning might be used to identify plants, and based on the type of plant, determine the ideal watering volume. Wang, Muzzammel, Raheel, and associates investigated an altitude-based cheap irrigation method as well as deep learning. Martinell et al. presented a WSN method for precision farming. A cloud and edge computing-based smart farming approach was proposed by Izquierdo et al. In their research endeavor, Bacco furnished an elaborate approach to smart farming, encompassing all impediments, facilitators, and opportunities. This essay highlights and provides a detailed, accurate image of the workable solution for agricultural needs after a careful examination of the literature that is now available and addresses the issues facing modern farmers. their corresponding fixes. The prototype for the distributed sensor network field described in the paper was made specifically for this study.

Proposed System

There are four main parts to the smart irrigation system. As seen in Figure 1, these are the pumping system, the communication network, the controller, and the power supply. Off-grid solar photovoltaic energy serves as the power source, and readily available, reasonably priced Arduino controllers make up the control unit. In a similar vein, transmitters and receivers based on Arduino Uno make up the communication network. Lastly, the pumping system is made up of an ultrasonic water level sensor, relays, DC water pumps, and a water tank. Lastly, temperature and moisture sensors make up the sensing system.

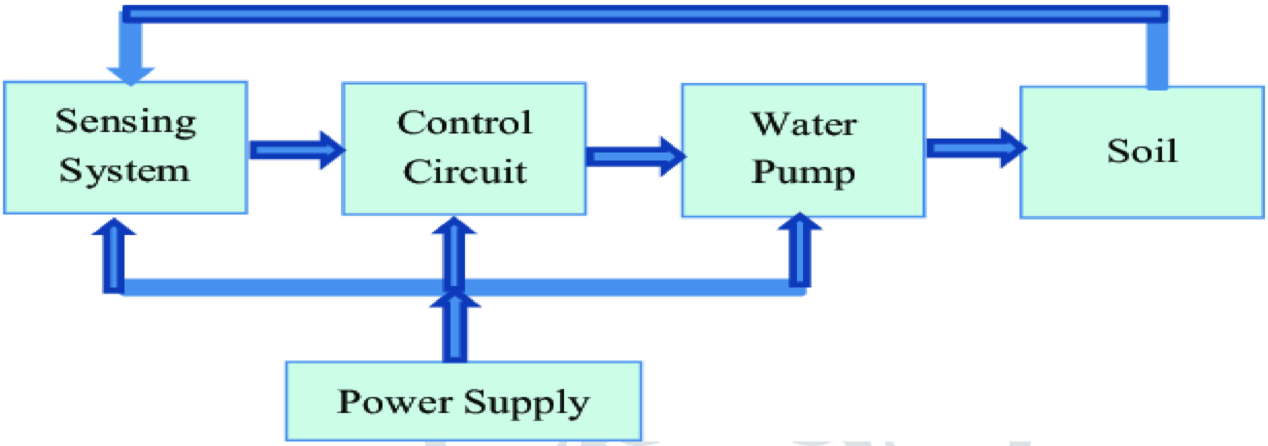

Figure 1 Proposed System Architecture

Operation of irrigation systems

The controller continuously reads the signal from the water level sensors to ensure that the water tank is filled during the irrigation procedure. The controller measures the volumetric water content and determines the moisture content. Watering is not necessary if the moisture content is higher than the threshold value. If not, it will measure the ambient temperature. For example, irrigation is not allowed if the latter is greater than 30C. If not, irrigation is started and the water pumping relays are turned on. The moisture level is monitored while the pumping is happening, and the water pumping is halted when the moisture level hits the threshold.

Smart irrigation system component

The following subsections describe each of the component functions.

Power supply

There are three primary parts to the off-grid power supply system. The charging controller, storage batteries, and solar panels are these. The charge controller is the fundamental component of the solar power supply. The latter regulates the flow of electricity into and out of the communication network, controllers, water pumping system, and storage batteries. The daily electricity consumption for the Arduino controllers, water pumps, and communication network determines the quantity of solar panels, the size and kind of batteries, and the charge controller.

The controller Arduino Uno

The ATmega328 is the foundation for the Arduino Uno depicted in Figure 4. It contains an ICSP header, 6 analog inputs, a 16 MHz crystal oscillator, a USB port, a power jack, a reset button, and 14 digital input/output pins. The latter makes it easier to program while the Arduino is attached to the board.

Algorithms

C4.5

The C4.5 categorization technique is among the best. C4.5 creates a decision tree in which the information is used by each node to split the classes. The splitting criteria are based on which attribute has the biggest normalized information gain. Examples of the data we collect include temperature and humidity. To decide which of these factors is best for data splitting (a feature with maximum information gain), the C4.5 algorithm looks into them first. Subsequently, the feature is employed to divide the dataset into the following feature till the ultimate goal is reached.

Naïve Bayes

The supervised machine learning model Nave Bayes is a member of the probabilistic classifier family that applies the Nave Bayes theory to the independence assumption of the dataset. Nave Bayes calculates the assumptions and uses them to calculate the likelihood of each feature in the dataset. For each known class label, Nave Bayes calculates each attribute's conditional probability on the class label. Next, the joint conditional probability for a label's characteristics is determined using the product rule. After that, the conditional probability for the class characteristics is obtained using the Nave Bayes model. For every class value, this technique is applied to offer the class with the highest likelihood.

By Chance

Among other things, the machine learning model Random Forest can be applied to classification, regression, and prediction. This algorithm is an ensemble of decision tree models that tries to construct a plurality of decision tree models from the same training data and generate the final class as the output. The number of attributes to freely explore (Num Features), maximum depth of the tree (Max Depth), and number of trees (Num Tree) parameters are changed in the random forest classifier. The results of the study demonstrate that as features, trees, and depth increase, so does the Random Forest classifier's classification performance.

Results

1. **Register Page**

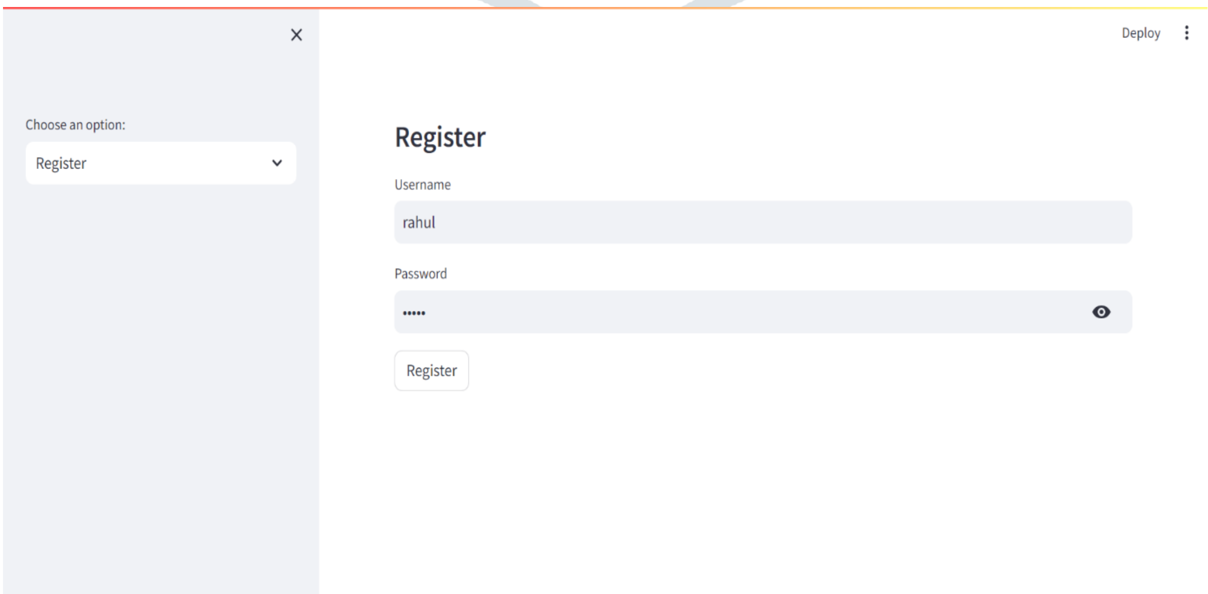

Figure1 Register page

The figure1 shows the register page

2. Crop Prediction

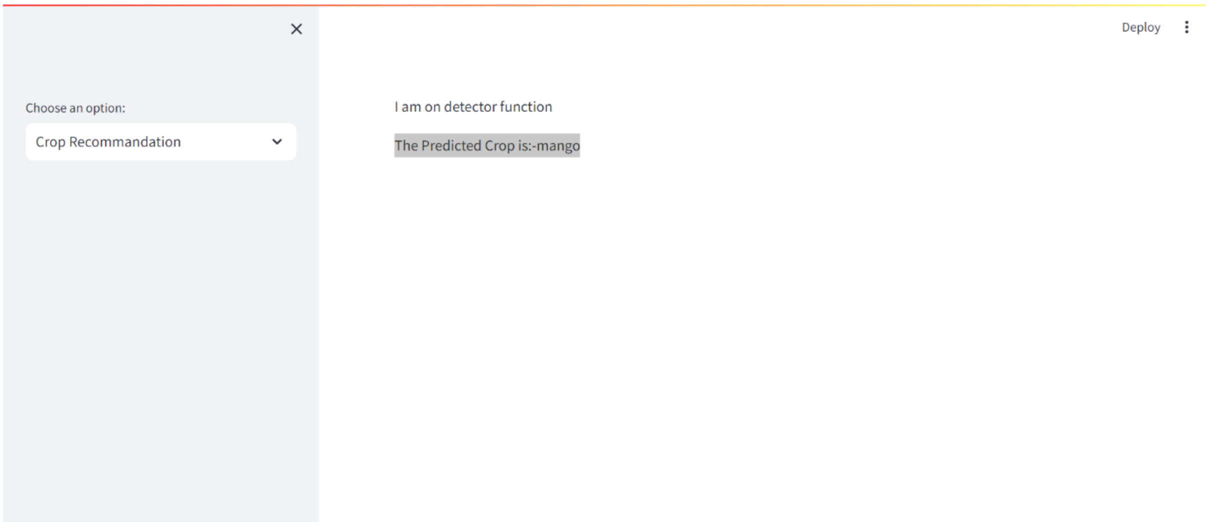

Figure2 crop prediction

The figure2 shows the crop prediction

3. Actual VS Predicted Crop

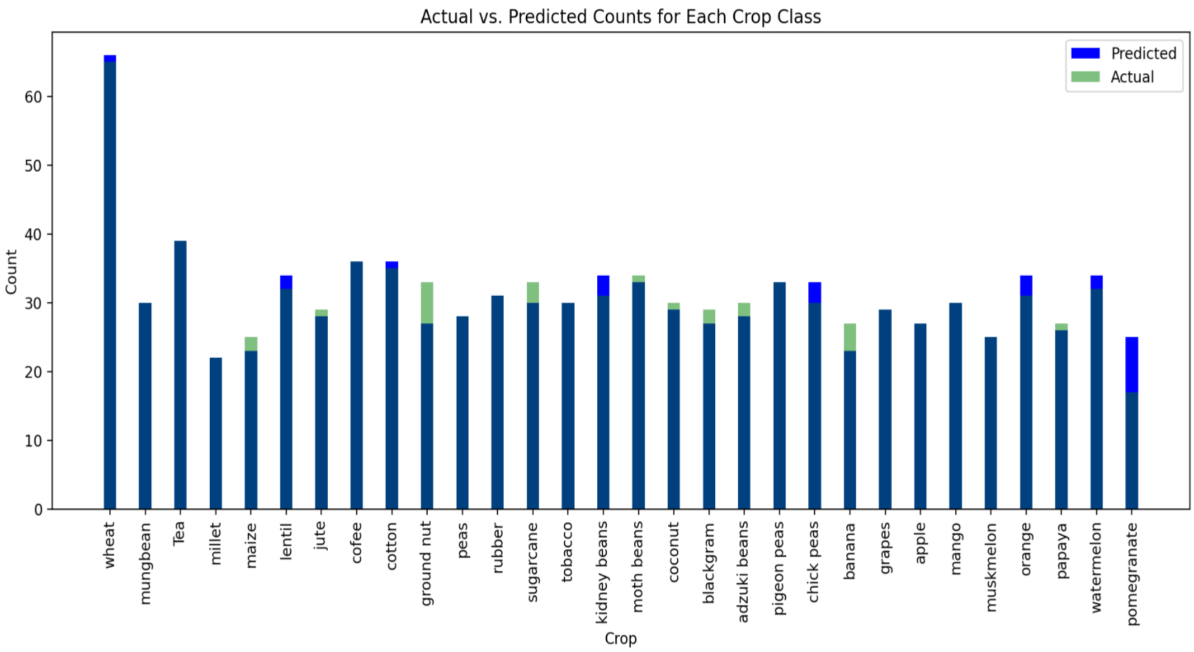

Figure 3 Actual and Predicted crop

The figure3 shows the actual vs predicted crop.

X-axis: This axis represents the different crop classes. Each bar corresponds to a specific crop, such as wheat, mungbean, tea, etc.

Y-axis: This axis represents the count of occurrences of each crop class. The height of each bar indicates how many times that particular crop class was predicted or occurred in the actual data.

Blue bars (Predicted): These bars show the count of each crop class as predicted by your model.

Green bars (Actual): These bars show the count of each crop class as it actually occurred in the test dataset.

Conclusion

In agriculture, it is essential to regularly update crop parameters including temperature, humidity, and moisture. Technology breakthroughs have led to a huge increase in the accuracy of climate forecasting data, which can now be used to estimate rainfall in a particular area. This paper proposes an Automated Irrigation System that makes use of ensemble learning and the Internet of Things to forecast rainfall chances. The proposed method uses a combination of weather predicted data and sensor data from the recent past to predict the likelihood of rain in the near future. To predict the chance of rain on that specific day, we used the ensemble learning approach. The fundamental goal of this technique is to create a single model that trains many models and classifies the output based on their aggregate majority of votes for each output class, as opposed to building separate specialized models and computing classification metrics for each of them. Predicted likelihood of rainfall is better in terms of precision and error rate. The prediction method can also be applied in a solo system prototype. Since the system prototype is built using open-source technologies, it is inexpensive. In the future, we'd like to carry out water-saving research using the recommended method, but with more nodes and a less expensive system. Our concept included irrigation system automation, which worked incredibly well. It's also reasonably priced. We can lower the number of workers required in the fields for maintenance by using this method. This method will automatically irrigate the land based on the soil's moisture content and the likelihood of rain, and it will also transmit the data to the MYSQL server so the farmer can monitor the condition of the land.

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