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Intelligent irrigation system using ML and IoT

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Abstract: To realize IoT promise in commercial-scale applications, integrated Internet of Things (IoT) platforms are required. The key challenge is to make the solution flexible enough to fulfill the demands of specific applications. A platform which is IoT-based which is used for smart irrigation with a adaptable design is created so that it allows developers to quickly link IoT and machine learning (ML) components to create application solutions. The design allows for a variety of customized analytical methods for precision irrigation, allowing for the advancement of machine learning techniques. Impacts on many stakeholders may be predicted, including IoT specialists, who would benefit from easier system setup, and farmers, who will benefit from lower costs and safer crop yields.

The typical irrigation procedure necessitates a large quantity of use of precious water, which results in waste of water. An intelligent irrigation system is in desperate need to decrease the wastage of water during this tiresome process. Using Machine learning (ML) and the Internet of Things (IoT),it is possible to develop an intelligent system that can accomplish this operation automatically and with minimum human intervention. An system which is enables using IoT and trained using ML is highly recommended and is suggested in this paper for optimum water consumption with minimal farmer interaction. In agriculture, IoT sensors are used to capture exact field and environmental data. The data being collected is transferred and kept in a cloud-based server that uses machine learning to evaluate the data and provide irrigation recommendations.

Keywords: IoT, ML, cloud, irrigation, water

I. Introduction

In our country where agriculture contributes for 60-70 percent of the GDP, there is a pressing necessity to modernize conventional agricultural techniques to increase yield. The groundwater table is lowering day by day as a result of uncontrolled water usage; lack of rainfall and shortage of land water also contribute to a drop in the amount of water on the planet. Water scarcity is currently one of the world ' s most pressing issues. Every sector requires water. Water is highly essential for our daily lives.

Agriculture is one of the industries that need a lot of water. Water wastage is a serious issue in agriculture. Every time there is a surplus of water, it is distributed to the fields. Climate change and its consequences are widely explored in academic studies on water resources and agriculture. Because of the potential repercussions of global warming, water adaptation Additionally, the safety of water for human consumption and return to the environment must be maintained. Increased water shortages, poor quality of water, higher water and soil salinity, loss of biodiversity, increased irrigation needs, and the expense of emergency and corrective action are all possible risks from climate change. As a result of these factors, most research are focusing on creating creative water utilization in irrigation. The Internet of Things (IoT) which was a concept earlier is now developed to a stage of implementation for real-world applications. Since then, the technological and application hurdles have been considerable.

IoT platforms permit complex real-time control systems by stacking communication infrastructure, hardware, software, logical approaches, and application knowledge. Recognizing the expected effects of IoT on systems is one of the most difficult technical problems because IoT allows systems to become amalgams of services, combining elements as services. The development of the system will become a dynamic mix of interoperable, off-the-shelf services, and the logic of the system will become the integration of the service accordingly.

An intelligent IoT-based irrigation system with an efficient machine learning algorithm is being developed to help farmers overcome rain uncertainty and increase production. This model provides a superior irrigation decision-making model. This research presents a Machine Learning (ML) strategy for successfully regulating irrigation and enhancing agricultural yield as a result.

II. Literature Review

Goldstein et al. (2017) [1] suggested a recommendation-based irrigation management system that combined machine learning with agronomic knowledge. According to the system, the best regression model with 93 percent accuracy, and the best classifier model with 95 percent accuracy, Gradient Boosted Regression Trees and Boosted Tree Classifier, provide superior irrigation prediction decisions than the linear regression model. To assist the agronomist in making better selections, the models were trained with eight

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separate sets of features. The Internet of Multimedia Things (IoMT) was proposed by Al Zu'bi et al. [2] (2019), which emphasis on the use of multimedia sensors in the area for irrigation optimization. To monitor crops and soil digital image processing is used.

The multimedia sensor sends the collected pictures of the crops to the image processing system, which makes the choice according to the proportion of cracks in the ground. This makes the Future No-Man irrigation management system possible.

According to the data mining technique, Rushika Ghadge et al. (2018) [3] created a system that employs ML algorithms [both supervised and unsupervised] to forecast soil and crop nature, quality and kind of land, as well as assess the nutrients present methods are being considered to assure water availability for food and human production as well as ecosystem sustainability.

in the soil to boost agricultural yield. This effort assists farmers in cultivating healthier crops in the proper soil to increase yield, as well as serving as a conduit for providing timely information to farmers regarding crop quality and nutrient requirements. For soil moisture estimation, a learning model based on Support Vector Regression (SVR) and K-means clustering was created. Humidity, radiation, soil moisture, air, and soil temperature were all captured in the field and sent into the training system of the SVR model.

To increase the precision and decrease the error rate, the output of the SVR model is sent to the K-means clustering. For optimum efficiency management, the final output from k-means is used to regulate the water pump controller. However, the majority of the older prediction models had a large variance, which causes the machine-learning model to perform poorly. Ensemble learning, as described by Zhao et al. (2018) [4], Catolino and Ferrucci[5] (2018), Joshi and Srivastava[6] (2014), and Ren et al.[7] (2016), may be utilized to deal with such significant variation. By combining different learning models to predict the output of a single system, ensemble approaches improve performance.

Some ensemble approaches, particularly bagging, have been shown to decrease the problem of over fitting and under fitting training data. The Bootstrap Aggregation approach improves single regression trees by using many models, each of which is trained using arbitrarily selected samples from the original dataset. The bagging approach has a smaller prediction error than the other single models. Gonzalez et al. (2014) [8] provide a bagging method for forecasting power price that is compared to the random forest approach for both classification and regression models.

A complete literature study was conducted, and the paper suggests few of the most capable feasible technologies and algorithms for the creation of a Smart Farm Monitoring System based on the findings of the literature research and experiments. Ersin et al.[9] suggested a microcontroller-based irrigation system that is more efficient and cost-effective than other traditional techniques. Liu et al. described precision irrigation technologies. [10]. Agrawal et al. presented a smart irrigation system using Raspberry Pi and Arduino. [11]. Koprda et al. presented a microcontroller-based irrigation solution. Ahouandjinou et al. discuss farm pest detection using ultrasonic sensors in their paper [12]. Goap et alprovided a full overall design for an IoT-based irrigation system.

Smith et alpresented machine learning algorithms for soil categorization. Wu et al. [16] investigated a farm vehicle and smart dispatching strategy. Ryu et al. presented an integrated method of smart farming. Kwok et al. proposed utilizing deep learning to recognize plants and then determining the optimal watering volume depending on plant type. Wang, Muzzammel, Raheel, and colleagues explored deep learning and an altitude-based economical irrigation technique. A WSN technique for precision farming was presented by Martinell et al. Izquierdo et al.

suggested a smart farming solution using cloud and edge computing.

III. Methodology

Existing Methods

In general, there is no automated irrigation method that is being used all over the world. However, some study has been done on the topic of automating the watering process. In most existing studies, the following is the basic method for Automated Irrigation: To begin, data is collected from several sensors to determine the moisture content of the soil and the temperature of the surrounding environment. They are attached to a breadboard that's wired up to the Arduino board. The Arduino IDE receives the information from the board. The programming language used executes the instructions to retrieve and reflect the data., i.e., a decision is made whether to turn the water pump "ON" or "NOT" based on the extracted data.

Proposed Solution

Step 1: As demonstrated in Fig. 1, irrigation can be automated by utilizing sensors, microcontrollers, Wifi modules, and the ThingSpeak platform. A controller is necessary to maintain all of the sensors and to drive the motor as needed. We utilized NodeMcu to accomplish this. The NodeMcu can output a maximum voltage of 5 volts. The moisture sensors module and DTH11 sensor can both be powered by 5 volts, but not the motor. We need at least 7 volts to run a motor. To solve this issue, we utilized a 9v battery to power the motor. We'll need a switch to regulate the motor whenever it's needed. We utilized a relay module to accomplish this.

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It's a switch in the electrical system. We must offer a strong pulse to the module to close the switch. Constant supervision of field is done using the soil moisture sensor. Node MCU is connected to the sensors. The measured data of the sensor is transmitted to the user via wireless transmission, on the received data that he can manage irrigation.

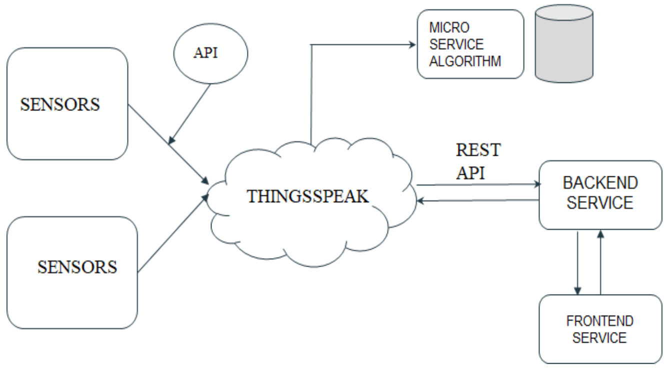

Fig. 1 Irrigation process

Step 2: Finally, all the data needs to be there in ThingSpeak for visualization. by using write API keys we will send the sensor data to the server. In ThingSpeak we can visualize the data of every sensor over time.

Step3: Fetching the data from ThingSpeak to our python script

1. Import all required libraries (json, urllib.request).

2. Create an API using READ_API_KEY and CHANNEL_ID of ThingSpeak.

3. Request the ThingSpeak website by using urllib.request module.

4. Store the json response from ThingSpeak.

5. Retrieve temperature, Humidity, and Soil moisture values from json data.

Step4:

1. The weather data was obtained through the Kaggle platform.

2. The performance of rainfall prediction is benchmarked using a variety of learning methods in this work. These are the supervised learning methods NB, C4.5, SVM, ANN, and RF.

3. An ensemble of the above models is used to train a Voting Classifier, which estimates an output (class) based on the maximum likelihood of output. It adds the results of each classifier that is fed to the vote classifier and the forecast of the output class with the most votes is carried out. We introduce a single model where several models can be trained and prediction of output based on the cumulative majority of votes for each output class is done, preferably as building separate specialized models and determining their performance.

Step5: Taking the final decision

When the soil moisture falls below a certain threshold, a motor will switch on. Instead of turning on the motor immediately, we examine the probability of rain using the above-mentioned ensemble methodologies, and if rain is likely to occur during that period, we wait a while. From crop to crop, the threshold level will differ. If a crop needs more water, we will increase the high threshold level so that the crop receives more water. Alternatively, if the crop requires less water, we will specify a low value.

IV. Implementation

Hardware used:

1. NodeMcu ESP8266

2. Soil Moisture Sensor Module

3. Submersible DC motor

4. DTH11 sensor

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5. Relay module

Software used:

1. Arduino IDE

2. ThingSpeak

3. Google Sites

NodeMcuEsp8266: It's an IoT gadget that's open-source. It's a 32-bit microcontroller that allows Wi-Fi-connected gadgets to perform 2-way communication between each other. It's a low-cost semiconductor with TCP/IP networking software built in. There are 17 GPIO pins on this board. It contains a Tensilica L 106 RISC CPU that uses very little electricity. It's compatible with ADCs, power amplifiers, and certain power management modules are all available. It contains 4KB of memory storage. Figure 1 depicts NodeMcu in its most basic form.

Fig 1: NodeMcu

Soil Moisture Sensor Module: A soil moisture meter is used to determine the amount of water in the soil. It consists mainly of a pair of conducting probes. The resistance variation among these probes is used to calculate the moisture content. The quantity of moisture in the soil has an inverse relationship with resistance. It transmits analog data.

The value will vary from 0 to 1023 after feeding this into ADC. As a result, if there is no water in the soil, the value decreases. 1023 will be the number. So for changing this value into percent we need a map (0,1023) to (1,100) which can be done using the map function.

Fig 2 shows the Soil Moisture Sensor.

Submersible DC: the motor can be completely immersed in water. In order to prevent water from entering the motor, it is hermetically sealed. It converts rotational energy into kinetic energy, which is then converted into pressure energy, which pushes water to the surface. This engine will be submerged in water, with a conduit connecting it to the water's output.

Fig 3: Submersible pump

DTH11 sensor: It's a multi-purpose sensor that measures temperature and humidity in the environment. It is made up of humidity-detecting material and a temperature-sensing thermistor. A humidity-detecting material is a capacitor with humidity as a dielectric

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substance between them, causing the capacitance to alter as the humidity changes. We understand how thermistors function. The resistance value fluctuates as a function of temperature. It operates at 3-5 volts, which we can acquire from the NodeMcu

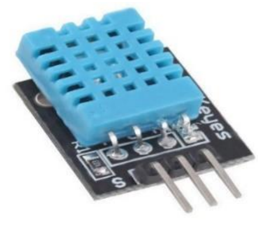

Fig 4: DTH11 Sensor

Relay Module: It's a type of electrical switch that works by using magnetism. The Relay module's primary function is to control the motor. The NodeMcu's maximum output voltage is 5 volts, which is insufficient to drive the motor. So, to drive the motor, we'll connect the relay module to the NodeMcu, and power the module with a 9v battery. A high to-low pulse can be sent to the relay module anytime when we want to turn ON the motor, the switch will shut, and 9V will be sent to the motor. The 1-channel Relay module is shown in Fig 5 as an example.

Fig 5: Relay Module

V. Algorithms

The categorization technique C4.5 is one of the most effective. C4.5 generates a decision tree, where each node divides the classes according to the information. The property with the highest normalized information gain is used to determine the splitting criteria. Humidity and temperature, for example, are included in our data collection. The C4.5 algorithm first examines these aspects to determine which is best for data splitting (a feature with maximum information gain). After that, the feature is used to partition the dataset into the following feature until it reaches the final destination. The algorithm's output is shown in Table.

Naïve Bayes

Naïve Bayes is a supervised machine learning model belonging to the probabilistic classifier family that applies naive theory to assumptions about the independence of the data set between features. By calculating the assumptions, Naïve Bayes determines the probability of each characteristic within the dataset. Naive determines each conditional attribute probability on a class label for each known class label. The product rule is then used to calculate the joint conditional probability for labeling characteristics. The Naïve model is then used to derive the conditional probability for the class characteristics. The class with the highest probability is provided after performing this method for each class value. The results of the algorithm are shown in Table II.

Support Vector Machine

SVM is a supervised computer learning algorithm that is widely used for classification or regression issues. The support vector machine uses a hyper plane to partition a dataset into two pieces. This partitioning procedure treats each class label separately, and it may be done by considering two class labels A and B, and classifying the data into class A and not class B. The calculation of the Euclidean distance between each data point and the hyperplane margin is used for data classification. When data cannot be separated linearly in a lower-level space, the support vector machine model employs a kernel, which is a set of scientific functions, to allow for data categorization in a complicated dimensional space. In machine learning, many kernel functions, such as radial, are available to regulate the above.

Neural Networks

Exhibit machines that mimicked the brain's functions influenced the development of neural networks. Every brain unit is linked to a slew of others. In terms of the initial state effect of the linked neuronal units, links might be either enforcing or inhibitory. A summing function might be used to unite the input values of each individual brain unit. This model is utilized in regression and classification, as well as prediction and clustering. There are two primary factors that have a significant impact on neuronal network

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classifier performance. One of which is the hidden layers, and another one is the learning rate. Findings from the algorithm are presented in Table IV.

Random Forest

Random forest is one of the popular machine-learning model that is mainly used for prediction, regression, and classification, among other things. This algorithm is an ensemble of decision tree models that aims to produce a multiplicity of decision tree models from the same training data and develop the final class as the output. The number of characteristics to freely study (Num Features), the maximum depth of the tree (Max Depth), and the number of trees (Num Tree) parameters are modified in the random forest classifier. The findings of the research show the Random Forest classifier's classification performance improves as the number of features, trees, and depth grows. The results of the algorithm are shown in Table V.

VI. Results and Discussions

A. C4.5 Algorithm

Accuracy: 0.77

	Precision	Recall	F1-Score	Support
0	0.80	0.88	0.84	274
1	0.64	0.50	0.56	118
Average	0.72	0.69	0.70	392

Table I: Results for the C4.5 Algorithm

B. Naïve Bayes

Accuracy: 0.81

	Precision	Recall	F1-Score	Support
0	0.84	0.91	0.88	280
1	0.72	0.56	0.63	112
Average	0.78	0.74	0.75	392

Table II: Results for the **Naïve Bayes** Algorithm

C. Support Vector Machine

Accuracy: 0.82

	Precision	Recall	F1-Score	Support
0	0.84	0.95	0.89	291
1	0.76	0.47	0.58	101
Average	0.80	0.71	0.73	392

Table II: Results for the Support Vector Machine Algorithm

D. Neural Networks

Accuracy: 0.77

	Precision	Recall	F1-Score	Support
0	0.81	0.88	0.83	274
1	0.76	0.64	0.72	118
Average	0.78	0.76	0.77	392

Table IV: Results for the Support Vector Machine Algorithm

E. Random Forest

Accuracy: 0.75

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	Precision	Recall	F1-Score	Support
0	0.81	0.85	0.83	278
1	0.58	0.50	0.54	114
Average	0.69	0.67	0.68	392

Table V: Results for the Random Forest Algorithm

Machine learning-based prediction performance varies amongst algorithms, with the artificial neural network approach having a modest performance edge over other categorization models. Each model has certain flaws, but the overall outcome is always better since the error rate is reduced. When one model fails, other models will step in to help. Because we're employing ensemble learning, we'll take into account a mix of model knowledge. a majority of people A voting model is constructed that trains on a mixture of the aforementioned models and predicts an output (class) based on the majority of the high probability of each model's preferred class as the output. It clearly aggregates the results of each of the machine learning model which is fed to the Voting Classifier and based on the most votes it will predict the output class.

The representation of detected data via sensors in ThingSpeak is shown in Figure 11,12,13. It aids in the interpretation of data. We may use this data to combine, transform, and create new data, and we can use built-in charting algorithms to graphically grasp the relationships between the data. In the future, we'll be able to combine data from numerous sources to provide a more complex study.

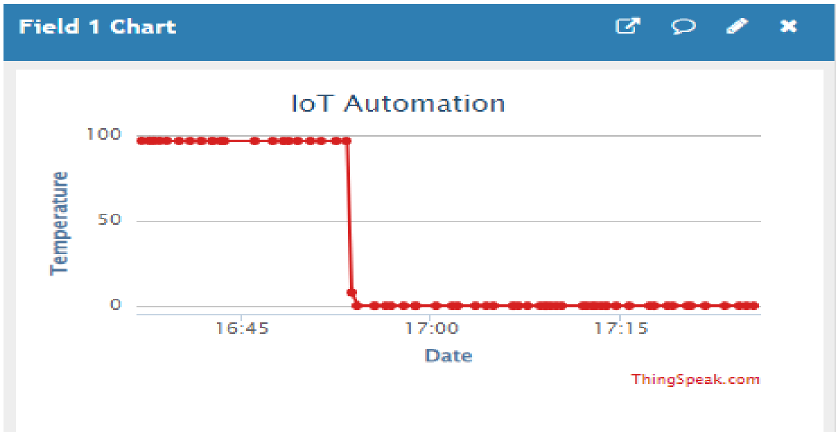

Fig 6: Field Chart 1

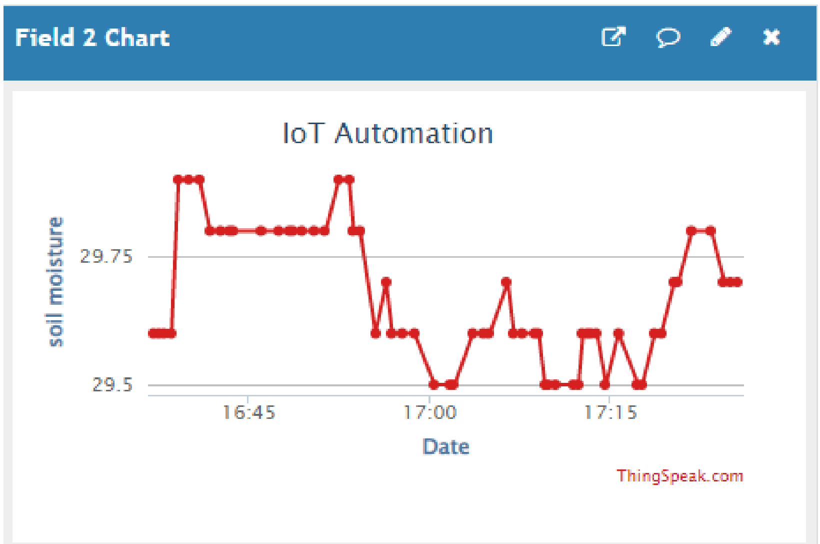

Fig 7: Field Chart 2

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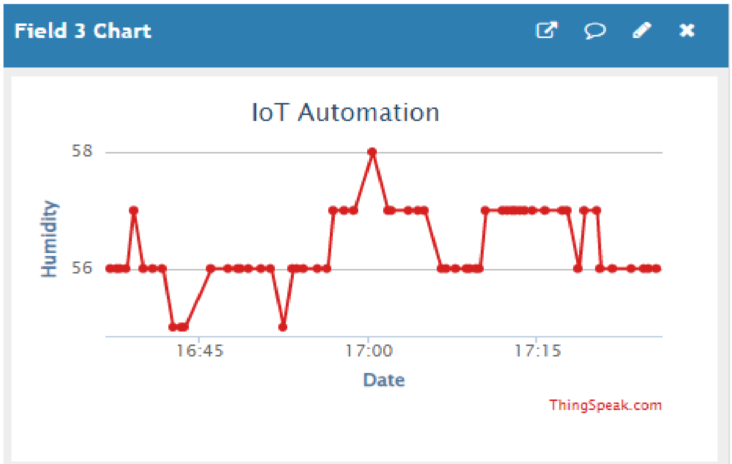

Fig 8: Field Chart 3

VII. Conclusion and Future Enhancement

Regular crop updates, such as moisture, humidity, and temperature, are critical in agriculture. Climate forecasting data accuracy has increased dramatically as a result of technological advancements, and weather forecasting data may now be utilized to estimate rainfall in a specific location. To estimate rainfall possibilities, this study suggests an Automated Irrigation System that uses the Internet of Things and Ensemble Learning techniques. The suggested technique predicts rainfall soon by combining sensor data from the recent times with projected data of weather. We utilized the Ensemble learning approach to forecasting the likelihood of rain on that particular day. Instead of constructing separate specially designed models and calculating classification matrices for each of them, the main purpose of this technique is to a single model that forms multiple models and classifies the result according to their overall majority of votes for the individual output class.

Forecasted rainfall possibilities are superior in terms of accuracy and mistake rate. A solo system prototype can also use the prediction method. The prototyping of the system is inexpensive because it is based on open-source technologies. We'd like to perform a water-saving study based on the suggested technique in the future, with more nodes and a lower system cost. The irrigation system automation we provided as part of our strategy performed wonderfully. It's also cost-effective. Using this technique, we can reduce the number of people needed in the fields for upkeep. This approach will not only ensure that the soil is irrigated automatically according to the moisture content of the soil and the possibility of rain, but it will also transmit the data to the Thingspeak server, enabling the farmer to monitor the condition of the land.

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